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Simulation for Industry 4.0

Past, Present, and Future

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Murat M. Gunal
Editor

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Editor
Murat M. Gunal
Barbaros Naval Science and Engineering Institute
National Defense University Tuzla
Istanbul, Turkey

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Foreword

I count myself lucky to have been born in the 1960s as I have experienced much of our contemporary computing history. At school, I was in the last year to use a slide rule and one of the first to use one of the new microcomputers emerging on the market. I certainly caught the "bug"—so did my Uncle! He brought an early Atari and the wonderful ZX80, the computer I really cut my programming teeth on. The ZX81 and ZX Spectrum followed as did the Sinclair QL (he wrote an inventory control system for his shop without any training!). Thanks to my parents wanting to nurture their teenage "geek", I managed to get hold of a Commodore 64, a Dragon, and an Atom. I remember buying computer magazines full of program code typing them into to whatever I could get hold of (which was always fun with the ZX Series!). In those days, we saved things onto a tape cassette player—the soundtrack of my early years was the sound of a program loading from a tape feed and quite possibly Manic Miner.

After school, I did a degree in industrial studies (I'm from Yorkshire (UK)—lots of heavy industry at the time). Computing was not a career path at the time, but things were changing rapidly. Remember this was in the mid-1980s—the twin floppy disc drive IBM PC XT had just come out. The Internet was there, but tools (and games) were difficult (but fun) to use. The degree had a small computing element, but more importantly it has a final-year module on operational research. This is where I first encountered simulation (specifically activity cycle diagrams). I could not really see me working at British Steel in Sheffield (I was completely unaware of the connection to KD Tocher at the time!) so I did a Master in Computing to try to change my career path. This was a great degree, especially as we were introduced to parallel computing. Towards the end of this, I spotted a research assistant post on speeding up manufacturing simulation with parallel computing. I applied, was successful and then spent the next few years with all sorts of simulation software, distributed simulation, and specialist parallel computing hardware (anyone remember transputers?). In the 1990s, I continued with this work at the Centre for Parallel Computing at the now University of Westminster (with whom I still work) and the great people in my Modelling and Simulation Group at Brunel University London and many collaborations with friends across the world.

It has been a fascinating time—experiencing the impact of the World Wide Web, new enterprise computing architectures, multicore computers, virtualization, cloud computing, the Internet of things and now the rise of big data, machine learning, and artificial intelligence (AI).

What I find remarkable is that every new advance in digital technology has been closely followed by some new simulation innovation. Researchers exploited the new personal computers of the 1980s with new simulation environments, the World Wide Web with Web-based simulation, distributed computing and high-performance computing technologies with parallel and distributed simulation, etc. These advances have been continuous and overall have strongly influenced and led to the evolution of mainstream commercial simulation. The digital technology of Industry 4.0 is especially exciting. Arguably, it has been made possible by the relative ease of interoperability between elements of cyber-physical systems such as automation, data infrastructures, the Internet of things, cloud computing, and AI. This new "Industrial Revolution" has tremendous potential for the world, and given the above trend, I am confident that this will be followed closely by new, creative advances in simulation that will further fuel the revolution. This book captures the state of the art of simulation in Industry 4.0, and I am sure it will inspire and inform many new innovations in this golden age of technology.

Greater Yorkshire, UK
February 2019

Prof. Simon J. E. Taylor

Preface

Technological developments have transformed manufacturing and caused industrial revolutions. Today, we are witnessing an Industrial Revolution so-called Industry 4.0. The name was coined in Germany in 2011, and later many countries adopted the idea and created programs to shape manufacturing for the future. The future of manufacturing is about smart, autonomous, and linked systems, and custom and smart products.

Industry 4.0, the Fourth Industrial Revolution, comprises of advanced technologies such as robotics, autonomous production and transportation machinery, additive manufacturing, Internet of things (IoT), 5G mobile communication, sensors, integration of systems, the cloud, big data, data analytics, and simulation. These technologies are used for increasing product quality and diversity, optimizing processes, and decreasing costs with smart systems. The goals of Industry 4.0 are to achieve smart factories and cyber-physical systems (CPSs).

Simulation has been used in manufacturing since its birth in the 1950s for understanding, improving, and optimizing manufacturing systems. Many techniques, methods, and software for simulation including, but not limited to, discrete-event simulation (DES), system dynamics (SD), agent-based simulation (ABS), simulation optimization methods, heuristic algorithms, animation, and visualization techniques have been developed and evolved in years.

This book is written to signify the role of simulation in Industry 4.0 and enlighten the stakeholders of the industries of the future. The Fourth Industrial Revolution benefits from simulation for supporting developments and implementations of manufacturing technologies associated with Industry 4.0. Simulation is directly related to CPS, digital twin, vertical and horizontal system integration, augmented reality/virtual reality (AR/VR), the cloud, big data analytics, IoT, and additive manufacturing. This book is organized around related technologies and their intersection with simulation.

I see *simulation* at the heart of Industry 4.0. As we get more digitized, we will see more simulations in the future. New uses of and the need for simulation will emerge in manufacturing in Industry 4.0 era, and simulation research and development community will respond accordingly with new approaches, methods, and applications.

Istanbul, Turkey
February 2019

Murat M. Gunal

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About This Book

The book shows how simulation's long history and close ties to industry since the Third Industrial Revolution have led to its growing importance in Industry 4.0. It also emphasizes the role of simulation in the New Industrial Revolution, and its application as a key aspect of making Industry 4.0 a reality—and thus achieving the complete digitization of manufacturing and business. It presents various perspectives on simulation and demonstrates its applications, from augmented or virtual reality to process engineering, and from quantum computing to intelligent management.

Simulation for Industry 4.0 is a guide and milestone for the simulation community, as well as for readers working to achieve the goals of Industry 4.0. The connections between simulation and Industry 4.0 drawn here will be of interest not only to beginners, but also to practitioners and researchers as a point of departure in the subject, and as a guide for new lines of study.

Chapter "Simulation and the Fourth Industrial Revolution" is the introductory chapter which sets up the scene for the book and gives a background information including a historical review of the industrial revolutions and historical perspective of simulation. Concepts within Industry 4.0 are introduced, and their interaction with simulation is evaluated. This chapter reveals that simulation has a significant role in Industry 4.0 concepts such as cyber-physical systems (CPSs), augmented reality/virtual reality (AR/VR), and data analytics. Its role will continue in analysis for supply chains, lean manufacturing and for training people.

Chapter "Industry 4.0, Digitisation in Manufacturing, and Simulation: A Review of the Literature" is a review of the literature written by Gunal and Karatas (2019). Their review is conducted in two parts; first, selected publications between 2011 and 2019 are critically evaluated, and second, Google Scholar is used to count studies with selected keywords. Their review revealed that the number of papers on Industry 4.0 increased exponentially in recent years and these papers are not only from Europe but also from other countries in the world. This suggests that "Industry 4.0" is adopted by the whole world.

Chapter "Traditional Simulation Applications in Industry 4.0" is presenting traditional simulation applications in Industry 4.0, written by Sturrock (2019).

He emphasizes that DES products are routinely used for purposes supply chain logistics, transportation, staffing, capital investment, and productivity. He presents case studies in health care, iron foundry, logistics, and manufacturing. He discusses that a smart factory can benefit from simulation to assess the impact of any specific advanced features. Furthermore, with DES, decision-makers can identify areas of risks before implementation and evaluate the performance of alternatives. He also gives a tutorial for building a simple model using Simio simulation software. In this model, a simple production system is built. A Gantt chart is generated and optimized for scheduling which is an important feature desired in smart factories of the future.

Chapter "Distributed Simulation of Supply Chains in the Industry 4.0 Era: A State of the Art Field Overview" is discussing distributed simulation of supply chains in Industry 4.0 context and written by Katsaliaki and Mustafee (2019). They highlight the significance of distributed simulation for supply chain analysis and review simulation techniques including parallel simulation, DES, ABS, and SD. They present distributed simulation around two scenarios, first as an enabler of large and complex supply chain models, and second, as an enabler of inter-organizational supply chain models. Although they point out that parallel DES is dominant in most of the studies, potential of ABS and hybrid modelling is great in terms of modelling autonomy, complexity, and scalability in the problem domain.

Chapter "Product Delivery and Simulation for Industry 4.0" is debating on product delivery and simulation issues in Industry 4.0 context, written by Cruz-Mejia, Marquez, and Monsreal-Barrera (2019). They propose "Smart Coordinated Delivery" (SCD) within supply chain players to re-balance the workload and increase the efficiency. Simulation can be used to assess the performance of SCD and to help design "standard interfaces" to enable coordination. They put forward "merge in transit" operations are needed to consolidate multi-item shipments, and this could be implemented using technology such as IoT. The role of simulation here is to help design such systems since simulation is a powerful tool when data availability is limited or problematic. For improving the "last mile delivery" performance, the authors highlight the potential of "what3words.com" concept and using VR/AR. Furthermore, ABS is mentioned as an excellent option for business modelling since it is about autonomous decision-making entities as in the real-life examples. They point out that simulation software vendors should adapt the software to Industry 4.0 to answer the needs emerged by the new concepts. For example, a new dynamic and intelligent queueing objects must exist in the software to mimic smart factory operations such as picking the next part to process on a machine from a que of jobs with some prespecified rule.

Chapter "Sustainability Analysis in Industry 4.0 Using Computer Modelling and Simulation" is written by Fakhimi and Mustafee (2019) and is discussing sustainability in manufacturing and supply chain systems from Industry 4.0 and modelling and simulation point of views. They point out that modelling and simulation techniques could provide significant insights in coping with the uncertainty associated with triple-bottom-line (TBL) management and highlight that there are opportunities for the realization of sustainable development in using simulation in Industry 4.0.

Chapter "Interactive Virtual Reality-Based Simulation Model Equipped with Collision-Preventive Feature in Automated Robotic Sites" is written by Alasti, Elahi, and Mohammadpour (2019) and demonstrates how a DES model of a manufacturing facility with robot arms can work with a robot arm simulation software. The VR created can help design robot operations in a facility. Their approach is a template for modelling manufacturing with robots. This chapter also summarizes the use of VR in manufacturing including in design and prototyping phase, planning phase, simulation, workforce training, machining process, assembly, inspection, and maintenance phases.

Chapter "IoT Integration in Manufacturing Processes" presents an implementation Event Graphs methodology called TAO, written by Adduri (2019). A novel feature is the "pending edge" which is an entry to Future Event List (FEL). TAO allows editing FEL in simulation. An event can be scheduled when an earlier event is scheduled. This feature can be useful in cases such as an IoT device is to be fed to a simulation model. Real-time data, for example provided from IoT devices, could be used in models. Simulation is suggested as a production management software rather than being a tool to design the production system. This way of use is a novel approach.

Chapter "Data Collection Inside Industrial Facilities with Autonomous Drones" is a conceptual study of a drone-based data acquisition and processing system, written by Gunal (2019). To achieve Industry 4.0 targets, a manufacturing facility can benefit from such system in sensing and collecting data at the shop floor. In the proposed system, there is an autonomous drone which can fly over predefined path inside a facility and collect visual data. The data is processed on the return, and useful managerial information is obtained by processing vision data. The system can be a solution for SMEs to increase their Industry 4.0 maturity levels.

Chapter "Symbiotic Simulation System (S3) for Industry 4.0" is presenting symbiotic simulation system (S3) and written by Onggo (2019). S3 is a tool designed to support decision-making at the operational management level by making use of real-time or near-real-time data which is fed into the simulation at run-time. Symbiotic simulation is very relevant to Industry 4.0 as it makes use of real-time data, and can be a significant part in CPS. This chapter includes the architecture of S3, three types of S3 applications for Industry 4.0, and challenges for adoption.

Chapter "High Speed Simulation Analytics" is written by Taylor, Anagnostou, and Kiss (2019) and presents high-speed simulation analytics from an Industry 4.0 perspective. They see that distributed simulation and high-speed experimentation with cloud computing are the keys to achieve high-speed analytics. A novel commercial system has been presented that demonstrates how cloud computing can be used to speed up simulation experimentation. This chapter highlights the role of simulation in data analytics as one of the comprising technologies of Industry 4.0.

Chapter "Using Commercial Software to Create a Digital Twin" is presenting how a digital twin using a commercial simulation software can be constructed, and written by Sturrock (2019). First, he discusses the digital twin concepts and how it addresses the challenges of Industry 4.0. Secondly, he evaluates how modern simulation software can be used to create a digital twin of the entire factory. Finally, Risk-based Planning and Scheduling (RPS) system which provides a unique solution to achieve smart factory is presented.

Chapter "Virtual Simulation Model of the New Boeing Sheffield Facility" is presenting a virtual simulation model of Boeing Company's facility in Sheffield, UK, and written by Hughes (2019). The factory is expected to become an Industry 4.0 flagship facility for Boeing, with robust IT infrastructure and a fully connected virtual simulation model working between its digital and physical systems—a "digital twin" factory. The digital twin is built using commercial simulation software. This chapter presents the key elements in the simulation model and discusses the approach of linking the model to physical systems.

Chapter "Use of a Simulation Environment and Metaheuristic Algorithm for Human Resource Management in a Cyber-Physical System" is a study conducted on workforce planning problems in Industry 4.0 and written by Hankun, Borut, Shifeng, and Robert (2019). They presented 5C CPS architectural model and applied five-level architecture implemented with simulation. Heuristic Kalman algorithm (HKA) and improved HKA are presented as evolutionary methods for determining the number of workers in a virtual factory. They demonstrated the benefits of these algorithms with a simulation model. Their algorithms can help determine an optimum number of workers in a CPS.

Chapter "Smart Combat Simulations in Terms of Industry 4.0" is presenting the concepts in military and their links with Industry 4.0, from Command, Control, Computer, Communication, Intelligence, Surveillance, and Reconnaissance (C4ISR) point of view, and written by Hocaoglu and Genc (2019). Their study shows that data sharing, fusing data received from different sources, distributed decision, automated decision-making, integration of systems, and handling big amount of data are common points for both C4ISR and Industry 4.0. They also discussed agent-based simulation technologies and demonstrated an application of C4ISR concepts in a simulation environment.

Chapter "Simulation for the Better: The Future in Industry 4.0" is the final chapter and a conclusion of the book, written by Gunal (2019). This chapter states the role of simulation in Industry 4.0 era and links the concepts of Industry 4.0 with simulation. A discussion is included on how simulation can contribute to designing, developing, and improving manufacturing systems of the future.

Contents

Editor and Contributors

About the Editor

Murat M. Gunal worked in simulation and operational research (O.R.) since 1999. He received his M.Sc. and Ph.D. degrees in O.R. from Lancaster University, UK, in 2000 and 2008, respectively. His main area of research is simulation methodology and applications particularly in health care, service sector, and the industry. His Ph.D. thesis was funded by EPSRC and titled District General Hospital Performance Simulation. His simulation models are being used in various National Health Service (NHS) hospitals in the UK for performance improvements. In his M.Sc. study, he wrote a dissertation on call center operations and developed a simulation model for NTL digital TV company. He took part in research projects funded by Istanbul Metropolitan Municipality, Turkish Science and Technology Research Council (TUBITAK), and Ministry of Health in Turkey. He conducts research and works in consultancy projects for industrial, health care, and service systems.

He published scholarly papers in academic journals and chapters in edited books. He also attends conferences regularly and publishes at conference proceedings including Winter Simulation Conference (WSC) and Spring Simulation Conference. He has one book translation published in Turkish.

He worked as Associate Professor at Barbaros Naval Science and Engineering Institute, in Turkey, and was Director of Master of Science in Naval Operational Research. He taught simulation, probability, facility planning, service science, decision analysis, mathematical modelling, and O.R. applications at graduate and undergraduate levels in several universities in Istanbul since 2008. He is Associate Editors of *Journal of Simulation* and *Health Systems*.

Contributors

Abhinav Adduri Computer Science, University of California, Berkeley, CA, USA

Hadi Alasti Department of Computer, Electrical and Information Technology, School of Polytechnic, College of Engineering, Technology, and Computer Science, Purdue University Fort Wayne, Fort Wayne, IN, USA

Anastasia Anagnostou Department of Computer Science, Modelling & Simulation Group, Brunel University London, Uxbridge, Middx, UK

Borut Buchmeister Faculty of Mechanical Engineering, University of Maribor, Maribor, Slovenia

Oliverio Cruz-Mejía Universidad Autónoma del Estado de México, Nezahualcoyotl, México

Behin Elahi Department of Manufacturing and Construction Engineering Technology, School of Polytechnic, College of Engineering, Technology, and Computer Science, Purdue University Fort Wayne, Fort Wayne, IN, USA

Masoud Fakhimi Surrey Business School, University of Surrey, Guildford, UK

İbrahim Genç Faculty of Engineering and Natural Sciences, İstanbul Medeniyet University, İstanbul, Turkey;
Agena Information and Defense Technologies LLC, İstanbul, Turkey

Murat M. Gunal Barbaros Naval Science and Engineering Institute, National Defense University, Turkish Naval Academy, Tuzla, Istanbul, Turkey

M. Fatih Hocaoğlu Faculty of Engineering and Natural Sciences, İstanbul Medeniyet University, İstanbul, Turkey;
Agena Information and Defense Technologies LLC, İstanbul, Turkey

Ruby Wai Chung Hughes Advanced Manufacturing Research Centre, University of Sheffield, Sheffield, UK

Mumtaz Karatas Industrial Engineering Department, National Defense University, Tuzla, Istanbul, Turkey;
Industrial Engineering Department, Bahcesehir University, Istanbul, Turkey

Korina Katsaliaki School of Economics, Business Administration and Legal Studies, International Hellenic University, Thessaloniki, Greece

Tamas Kiss Department of Computer Science, Centre for Parallel Computing, University of Westminster, London, UK

Shifeng Liu School of Economics and Management, Beijing Jiaotong University, Beijing, People's Republic of China

Alberto Márquez Lamar University, Beaumont, USA

Atefeh Mohammadpour Department of Manufacturing and Construction Engineering Technology, School of Polytechnic, College of Engineering, Technology, and Computer Science, Purdue University Fort Wayne, Fort Wayne, IN, USA

Mario M. Monsreal-Barrera Texas A&M Transportation Institute, College Station, USA

Navonil Mustafee Business School, University of Exeter, Exeter, UK;
Centre for Simulation, Analytics and Modelling (CSAM), University of Exeter Business School, Exeter, UK

Robert Ojstersek Faculty of Mechanical Engineering, University of Maribor, Maribor, Slovenia

Bhakti Stephan Onggo Southampton Business School, Centre for Operational Research, Management Sciences and Information Systems, University of Southampton, Southampton, UK

David T. Sturrock Simio LLC, Sewickley, PA, USA

Simon J. E. Taylor Department of Computer Science, Modelling & Simulation Group, Brunel University London, Uxbridge, Middx, UK

Hankun Zhang School of Economics and Management, Beijing Jiaotong University, Beijing, People's Republic of China

Abbreviations

ABS	Agent-based simulation
AGV	Automatic guided vehicle
AI	Artificial intelligence
AR	Augmented reality
BDI	Belief, desire, intention
C4ISR	Command, Control, Computer, Communication, Intelligence, Surveillance, and Reconnaissance
CDM	Content distribution management
CPS	Cyber-physical system
CV	Computer vision
DA	Data analytics
DES	Discrete-event simulation
DIS	Distributed Interactive Simulation
DSCS	Distributed supply chain simulation
DVE	Distributed virtual environments
ERP	Enterprise resource planning
HKA	Heuristic Kalman algorithm
HLA	High-level architecture
HRM	Human resource management
ICT	Information and communication technologies
IoT	Internet of things
KPI	Key performance indicator
MCS	Monte Carlo simulation
MES	Manufacturing execution system
MIS	Manufacturing information system
ML	Machine learning
MR	Mixed reality
PADS	Parallel and distributed simulation
RFID	Radio-frequency identification
RTI	Run-time infrastructure

S2	Symbiotic simulation
S2M	Symbiotic simulation model
S3	Symbiotic simulation system
SaaS	Software-as-a-service
SBL	Scenario-based learning
SCM	Supply-chain management
SD	System dynamics
SDEV	Sustainable development
SME	Small and medium-sized enterprise
SOA	Service-oriented architecture
SOM	Sustainable Operations Management
TBL	Triple bottom line
UAV	Unmanned aerial vehicle
URL	Unified Modeling Language
VR	Virtual reality
WSC	Winter Simulation Conference
XML	Extensible Markup Language

Simulation and the Fourth Industrial Revolution

Murat M. Gunal

Abstract Through history, advancements in technology have revolutionised manufacturing and caused a leap in industrialisation. Industry 4.0, the Fourth Industrial Revolution, comprises of advanced technologies such as robotics, autonomous transportation and production machinery, additive manufacturing, Internet of Things (IoT), 5G mobile communication, sensors, systems integration, Cloud, big data, data analytics, and simulation. Such technologies are used in the production of quality goods, which increased product diversity, and often at lower costs achieved through optimisation and smart production techniques. The goals of Industry 4.0 are to achieve Smart Factories and Cyber-Physical Systems (CPS). The introductory chapter presents concepts from Industry 4.0 and contextualises the role of simulation in bringing about this new industrial age. The history of the industrial revolutions and simulation are discussed. Major concepts in Industry 4.0, such as CPS, vertical and horizontal system integration, Augmented Reality/Virtual Reality (AR/VR), Cloud, big data, data analytics, Internet of Things (IoT), and additive manufacturing are evaluated in the context of simulation. The discussions show that computer simulation is intrinsic to several of these Industry 4.0 concepts and technologies, for example, the application of simulation in hybrid modelling (e.g., digital twins), simulation-based training, data analytics (e.g., prescriptive analytics through the use of computer simulation), designing connectivity (e.g., network simulation), and simulation-based product design. Simulation has a pivotal role in realising the vision of Industry 4.0, and it would not be farfetched to say that simulation is at the heart of Industry 4.0.

Keywords History of simulation · Industrial revolution · Industry 4.0 · Hybrid modelling · Cyber-Physical Systems · Digital twin

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M. M. Gunal (✉)
Barbaros Naval Science and Engineering Institute, National Defense University, Tuzla, Istanbul, Turkey
e-mail: m_gunal@hotmail.com

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1 Introduction

Technological advancements through the last decades have radically transformed our daily lives. Taking the example of the Internet and mobile telephony, the latter made it possible for people to be connected 'on the move' through voice calls and text messages, whereas mobile Internet allowed access to the *World Wide Web* without the need for either a wired or a static Internet connection. Technologies such as these have created a new kind of economy; an economy that is characterised by the speed of access to information, an economy where consumers demand faster deliveries and up-to-the-minute information on products, prices/sale, user comments and feedback, tracking information and so on so forth. To cater to such evolving dynamics of the market economy, businesses have been forced to redesign their business models and the underlying systems for the manufacture and delivery of goods.

Industrial revolutions take place as a result of significant changes in technology and the way people live. The first Industrial Revolution was triggered by inventions of machines powered by steam engines, and this led to an increase in production. The second revolution was about electricity and mass production of goods. The third revolution was mostly about the use of electronics in production. As manufacturing systems were increasingly controlled through electronics, this reduced the need for labour—however, production continued to increase. The first three revolutions were not explicitly started, or they did not expressly end. Indeed, they were named as "revolutions" subsequent to the industrial transformation having begun or after they had ended. These were silent revolutions which, over the subsequent years and decades, have continued to increase welfare.

The fourth Industrial Revolution, Industry 4.0, is about revolutionising manufacturing by making machines that are connected and smarter. The main objective of Industry 4.0 is to create "smart factories" and "Cyber-Physical Systems (CPS)". In smart factories, there are autonomous machines which can convey routine jobs as well as decide what to do in exceptional situations. They can inform the time to replenish stock and the inventory-level to maintain, and switch between different tasks easily. Rüssmann et al. [19] emphasise nine technologies which will drive the new industrial revolution. These are big data and analytics, autonomous robots, simulation, horizontal and vertical integration, industrial Internet of Things (IoT), cybersecurity, the Cloud, additive manufacturing, and augmented and virtual reality (AR/VR). Although the aforementioned technologies already exist, we are going to need more of this to achieve Industry 4.0 objectives; it is therefore expected that the next decade will witness major advancements in these technologies and indeed the development of new Industry 4.0 technologies. For example, robots are common in manufacturing, but robots in the future will not require human intervention for decision making. This is rather difficult today but the advancements in Artificial Intelligence (AI) and sensor technology has the potential to make this happen. We will have changes in way of thinking in manufacturing, for example, there will be a change from preventive maintenance to predictive maintenance. "Predictive maintenance" will alleviate the need for periodic maintenance, since machines will "predict" when they are going to need maintenance to be scheduled. A comprehensive review of the academic literature and introduction to the Industry 4.0 concepts is presented in Liu and Xu [15].

Compared to the first three industrial revolutions, Industry 4.0 is a very different revolution. First, it is announced in 2011 and therefore it has an explicit start date. Although the name was coined in Germany, it is adopted by many other nations. Secondly, it is an industrial revolution which arises from one of the greatest inventions of mankind, the Internet. Thirdly, this new revolution is associated with autonomous machines. Humans controlled machines in earlier industrial revolutions, but with Industry 4.0, machines have gained intelligence and autonomy. The control is thus handed over to machines in manufacturing.

The impact of Industry 4.0 on the global economy is expected to be transformative. A survey conducted by *PwC* [9] with over 2000 participants in 26 countries reveals that companies are likely to invest \$907 Billion per year on digital technologies such as sensors, connectivity devices, and software for their manufacturing systems, and expect \$421 Billion reductions in their costs and \$493 Billion increase in annual revenues. Moreover, *Boston Consultancy Group* (BCG) predicts that the new industrial revolution will make production systems 30% faster and 25% more efficient. Furthermore, it will create 390,000 new jobs and an investment of €250 Billion specific to manufacturing [19].

After the announcement of Industry 4.0 (in Germany), working groups were formed. Guides were published for decision makers to provide them information on realising the potential of transformative technologies associated with this revolution. Kagerman et al. [13] report the current situation of manufacturing in Germany and recommends steps for change. Other nations responded to Germany's move, but mostly accepting the idea of revolutionising manufacturing and going digital. In the USA, *Advanced Manufacturing Partnership* (*AMP*) initiative was formed in 2011. This was a government initiative which aimed at bringing together industry and improving manufacturing in the US. Non-profit organisations, such as The *Smart Manufacturing Leadership Coalition* (*SMLC*), also formed with similar objectives. In China, a strategic plan called "*Made In China 2025*" was developed with the aim of upgrading manufacturing systems and focusing on producing higher value products in China. This initiative increased the use of robots in China. South Korea's perspective on Industry 4.0 is presented in Sung [22]. Japan proposed "*Society 5.0*", which is essentially an idea for making the society ready for the new digital era. Russia also discusses improving the use of technology in manufacturing with initiatives such as *National Technology Initiative*. Turkey has announced a road map for digitisation of the country, including the industry [16].

A key technology associated with Industry 4.0 is computer simulation. The word *simulation* comes from a Latin word called "*Simulāre*" which is the infinitive form of "*Simulō*", also in Latin. "*Simulō*" means "*I make like*" or "*I behave as if*". The action for "*making like*" or "*behaving as if*" is done either physically or virtually. For example, before the Age of the Computers, commanders simulated their war tactics and strategies using the physical representation of objects (such as battlefield assets) and placed them on maps. They wanted to rehearse the actions they would do during the war and discuss possible situations with their commanders. With the advent of the computers, such war simulations based on moving physical objects on maps have mostly ceased to exist; however, physical simulations continue to be used in other domains. For example, for medical training, healthcare simulations are used to train healthcare professionals using dummy human figures to mimic injuries. Even the hardware in simulators (human-in-the-loop and machine-in-the-loop simulations) are controlled mostly by computers.

The book is written to inform stakeholders of the industries of the future, of the significant role of simulation in the fourth industrial revolution, including its application for supporting developments and implementations of manufacturing technologies associated with Industry 4.0. Simulation is directly related to CPS, digital twin, vertical and horizontal system integration, AR/VR, the Cloud, big data analytics, IoT, and additive manufacturing. Indeed, simulation is at the heart of Industry 4.0. This chapter is organized around related technologies and their intersection with simulation, after a historical outlook which evaluates industrial revolutions and simulation perspective.

2 Historical Outlook

2.1 A Brief History of Industrial Revolutions

A revolution is, in an industrial sense, an extraordinary growth and change in technology, or a leap in science. It is closely linked with scientific growth, both in terms of theory and application. The first revolution, the Industrial Revolution (1750–1870), caused an increase in the application of science to industry [5]. The change in the way how we produce was from agrarian and handicraft to manufacturing with machinery. Man-powered tasks could be done by machines which were powered by some other sources of energy, such as steam produced by burning coal. Steam engines, and later internal combustion engines which burn oil, produce power to drive machines of manufacturing.

During the first Industrial Revolution, the change was not only in science and technology, but it was also in the economy, social life, politics, and culture. Large-scale production meant more products at lower prices, and which translated to a new customer base. People became urban, and there was an increase in the living standard.

Exact beginning and ending dates for industrial revolutions are difficult to present as there are different views as to the start and the end of the revolutions. Figure 1 presents a timeline with the most agreed dates. For the first one, for example, the beginning date is related to the textile industry which was developed in Britain. It is said to end by the end of the 19th century with the inventions such as electricity and steel making process. These inventions and many others caused the second industrial revolution which eased manufacturing and enabled mass production. Some say the

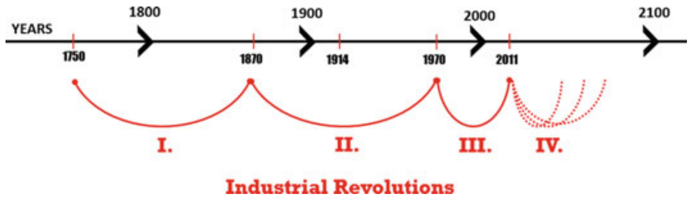

Fig. 1 Timeline of the industrial revolutions

second revolution lasts until the beginning of World War I (WWI) in 1914; however, its effects continued until the beginning of the third industrial revolution.

During the two World Wars and the Cold War period, the technology continued to develop in different parts of the World. Two most important innovations of the modern world occurred in this period; Digital computers and the Internet. By the 1950s, digital computers started to appear in many areas, including manufacturing. However, the beginning of the third Industrial Revolution is attributed to the invention of Programmable Logic Controller (PLC) in 1970. PLC had a great impact on automation in manufacturing. By the end of the 1980s computers started to appear in business which even supported the deployment of PLC in manufacturing. In 1960s, as part of the ARPANET project (defense), strides were made in computer networking that allowed computers to exchange messages. But the diffusion of this technology and its commercialisation only happened in the 1980s. Later in this era, the Internet has evolved and became a communication medium and information megastore. Personal mobile phones and "smart" mobile devices amplified the wind of change. Eventually we ended up with Information and Communication Technologies (ICT) era.

ICT helped improve manufacturing systems significantly in many ways. We did not need to spend time in front of machines anymore, but still, we needed to start machines and observe how things were going. Today, most manufacturing systems work like this, that is we still control manufacturing. In the fourth industrial revolution, however, the basic idea is to hand over the control in manufacturing to "smartness in machines". "Smartness" is a difficult term in many ways. At least, it requires awareness, synthesis, and rational decisions. Industry 4.0 technologies aims at achieving all these to end up with "smart factories".

The latest industrial revolution's beginning date is 2011. Germany is the founding nation, and the naming nation, of the Industry 4.0. Germany has thought that such a move was necessary to be able to meet the increased global competition. Rising production costs and improved quality in the competition have forced Germany to act and to create a road-map. Germany's objective is to achieve production of customised products and to lower fast time to market.

Is Industry 4.0 an Industrial Revolution? Most say "yes" to this question as many other nations made moves to reshape their manufacturing philosophies. The global economy and the level of technology support this idea that we are really in an era where we demand products differently than we did in the past. We want a product just like we want it to be (colour, shape, and configuration), and we want it right now. It is normal that the manufacturing must adjust itself accordingly. Industry 4.0 is, therefore, a revolution in the industry. Not only in terms of how humans demand the end product but also how we manage, transport, and produce things, and live.

Thinking of “4.0”, a couple of sentences can be written about it. Versioning the technology-related products and concepts, which originally comes from the software world, is a fashion. For example, Web 2.0 is used to name the new developments in web standards. It is true that once a version of a product or idea is released, it can affect its surrounding domains. Health 2.0 and Medicine 2.0 [25] are developed as a result of Web 2.0. This behaviour is similar for Industry 4.0. We have now Retail 4.0 [11], Telecommunication 4.0 [27], and Health 4.0 [24]. These ideas are influenced by the Industry 4.0. Signifying an idea with versioning is common today. The government in Japan introduced a plan named Society 5.0 to transform society [6]. The program claims that it is now time for a new kind of society (5.0) since industrial (3.0) and information (4.0) societies are no longer exist.

Causes and effects of four industrial revolutions are summarised in Table 1. The third revolution is over since we are ready for something very different in the industry. We have now “smart digital signals” in place as our machines can decide what to do next. The technology’s current state allows us to make manufacturing transform. For a more detailed evaluation of the first three revolutions, from governance and technology perfective, please refer to von Tunzelmann [26].

Industry 4.0 is different than previous industrial revolutions in terms of its beginning. No other industrial revolution had been explicitly announced. Industry 4.0 might seem curious in this regard, but this also indicates its two attributes; proactive-

Table 1 Cause and effect relation of industrial revolutions

	Causes	Effects
First revolution 1750–mid 1800s	Steam engine powered by **water**	Mechanize production, iron and textile production
Second revolution 1870–1914 (start of WWI)	Electrical motors powered by **electricity**	Mass production, steel making process, large scale machine tools manufacturing
Third revolution (1970–2011)	Electronics circuits, Programmable Logic Controller (PLC) and Information and Communication Technology (ICT) derived by **digital signals**	Production automation, human controlled manufacturing
Fourth revolution (2011–)	Cyber-Physical Systems (CPS), advanced automation and robotics, Artificial Intelligence, Internet of Things (IoT) derived by **smart digital signals**	Autonomous manufacturing, connected businesses

ness and creating a vision for the future. We have not seen the effects yet, but with its vision, we are expecting to see the desired future.

Do we know when this revolution will end, or what and when will be the next industrial revolution? We do not know the answer to this question. But examining the time between industrial revolutions, the hops in Fig. 1, we see them getting shorter. Does this mean we are going to see new industrial revolutions soon, and frequently?

2.2 Simulation Perspective in Industrial Revolutions

Computer simulation, as we know simulation today, dates back to the beginning of the 1950s, the post-World War era. There was a need for analysis of randomness in military problems and stochastic simulation foundations laid down by mathematicians. Computer simulation was started to be used by steel and aerospace corporations to solve complex problems with very complex models. These models could be run by highly skilled people and on mainframe computers. General purpose programming languages, such as FORTRAN, and later specialised simulation languages and software, such as "General Purpose Systems Simulator (GPSS)" and SIMSCRIPT were used to create simulation models. Discrete Event Simulation (DES) was in the heart of these languages, and indeed it is still in there in most modern simulation software.

Although the emergence of simulation has been during the second Industrial Revolution, its use and spread had started with the third Industrial Revolution, in the late 1970s and early 1980s. It was first used in automotive and heavy industries. More people showed interest and large events were organised, e.g., the *Winter Simulation Conference*. The conference program included tutorials, which helped to disseminate "simulation" in these conferences to the people in the industry. Simulation courses were designed and students could enrol in such courses at universities.

During the 1980s, simulation community was interested in Material Requirement Planning (MRP) and process planning in factories. There were very limited graphical representations and most simulations were run textually or numerically. With the advancements in computer graphics in the 1980s, animation became an integral part of programs that were used to develop computer simulations. Factory processes could now be simulated with animation added so that the stakeholders (e.g., factory managers, workers) were able to observe how their factories would function when some changes were done to the underlying processes. Animation helped in further dissemination of simulation as a tool for decision making.

Computer graphics revolutionised simulation. Simulation by numbers turned to iconic animations, and then to 2 dimensional (2D) animations. First simulation software with graphical user interfaces (GUI) such as Arena and Micro Saint could run on personal computers with Windows operating system. They had, which they still have, drag and drop modelling objects on the screen to build simulation models, and iconic and 2D animations to show models run. In the early 1990s, these features were remarkable for modellers and decision makers. In today's simulation software world, there are many simulation software in the market. The web site https://www.capterra.com/simulation-software/ is a good source for a list of simulation software.

The first decade of the Millennium, the 2000s, were the years of Computer Aided Design (CAD) and Computer Aided Manufacturing (CAM) software. CAD/CAM software became a part of product design and manufacturing. Advancement in these software products created a base for Industry 4.0. Simulation also evolved with CAD/CAM software, and 3D visualisation became a standard feature in DES software. 3D Models can now be used in simulation models and create realistic visualisations. Inversely, some CAD/CAM software can simulate dynamics of the objects they represent. The integration between simulation software and other utility software can also be seen in Enterprise Resource Planning (ERP) software.

Simulation has grown with the third industrial revolution and made itself ready for the fourth revolution. In the Industry 4.0 era, it is expected that computer simulation will become a significant driver of the progress.

3 Simulation and Concepts of Industry 4.0

Industry 4.0, as it was introduced in 2011, has many concepts and technologies involved, and it is difficult to come up with an all-encompassing list. Here, we list some of the concepts and technologies agreed in the literature [4] and discuss their intersection with simulation. We can extend the list, since Industry 4.0 and digitisation in manufacturing are evolving with more ideas which are going to affect the future.

3.1 Cyber-Physical Systems (CPS) and Digital Twin

CPS is a platform of collaborative industrial business processes and networks which regard smart production systems, storage facilities, supplier organisations, final demand points at people's fingertips. CPS include smart machines, processes, factories and storage systems which can autonomously exchange information and take necessary actions such as running, replenishing, ordering, and transferring tangible goods [13]. Another definition of CPS is about the marriage of mechanics, electronics and software. It is the blend of software with mechanical and electronic devices which can communicate through a data exchange medium.

"Digital Twin" is used as a term which denotes controlling software part of CPS. In CPS, physical devices can be controlled by a software replica which can communicate with these devices in real-time. For example, a button in Digital Twin can make a machine on and off.

A Digital Twin is not only for controlling devices but also for processing the data collected from devices. Talking about "software replica", a Digital Twin is a simulation of the system that is replicated. A Digital Twin cannot only act in real-time but also can predict the effects of the action. In CPS, the role of a Digital Twin

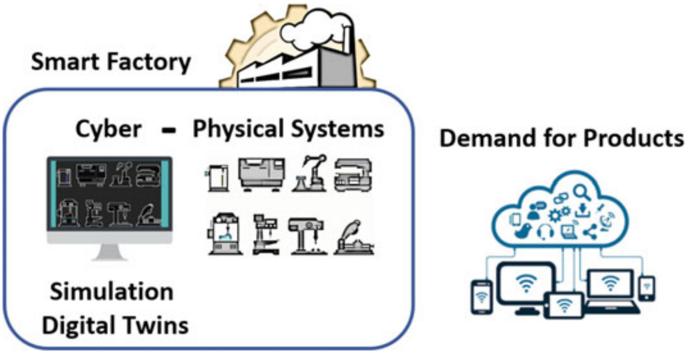

Fig. 2 Cyber-Physical Systems and simulation

is to simulate in the virtual world and predict the possible outcomes of that action. Human users, or Artificial Intelligence (AI), will be aware of risks before the action is taken, and eventually, make the right decisions.

In the CPS concept, there is an exchange of data between devices and Digital Twin. This exchange makes Digital Twins "real-world aware" and therefore valid representations of reality. Simulation is valuable with real-world data (Fig. 2).

3.2 *Vertical and Horizontal Systems Integration and Hybrid Modelling*

Factory of the future, the Smart Factory in Industry 4.0, must have tightly coupled systems which require two types of integration; vertical and horizontal. Vertical integration means that the systems within a smart factory must be aware of each other, and manufacturing systems and products must be hierarchically organised. Horizontal integration means that smart factories, and businesses, must be networked and cooperate.

Figure 3 illustrates that comprising systems in a smart factory work individually but also collaboratively. They are linked via high-speed connection systems, and exchange information obtained by sensors. Machines up-stream and down-stream processes tell their states to other machines. Machine states and times of state changes are significant to make machines prepared for future jobs. Sensors are critical components because they collect real-time data from machines, which are then transmitted using Internet of Things (IoT) technologies.

Vertical integration is about linking machines, making them aware of other machines, and more importantly, governing them centrally. The governance does not mean taking full-control of machines but rather orchestrating them to increase efficiency and reduce waste. Lean Manufacturing concepts, therefore, are very appli-

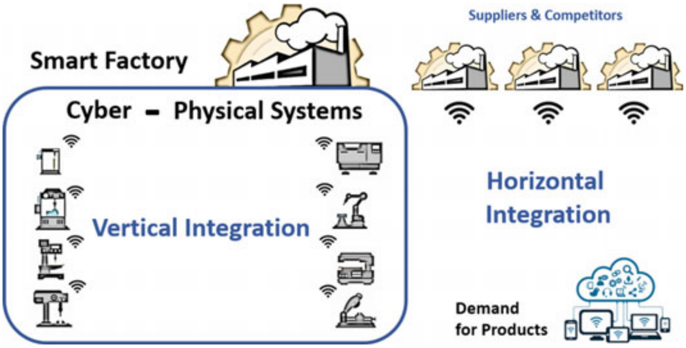

Fig. 3 Vertical and horizontal integration

cable to Industry 4.0 concepts in general. CPS represents not only the comprising components of a factory but also a central authority to govern a factory.

Horizontal integration is about linking factories and customers. This type of integration is difficult for many reasons. First, we are opening our factory information to the outside world and therefore confidentially might be breached. This brings the need for information security or cybersecurity. We need integration with suppliers for speed; however, we must carefully evaluate cybersecurity issues.

Simulation is used to make vertical and horizontal integration happen. It can be used for designing, testing, and evaluating integration systems. For vertical integration, a digital twin includes machine models which can help evaluate how machines can integrate. Simulation models can tell what data a machine is needed to generate and why is that needed. This type of use of simulation is for pro-active purposes. Simulation is used before integrating machines so that the level of vertical integration can be designed and evaluated. Questions such as "Do we really need this sensor on this machine?" or "What will we achieve if we integrate our machines?" can be answered by using simulation models. Simulation can also answer questions for re-active purposes, such as "What happens to our throughput if a machine breaks down unexpectedly?"

For horizontal integration, we mainly talk about "Supply Chain simulation". A factory needs raw materials, or components, from suppliers and it is crucial for manufacturing to have them ready on-time. Supplier relations are also important for maintaining quality. You depend on your suppliers' quality. Supply Chain simulation models can help design and evaluate your integration with your suppliers. Questions such as "which suppliers should we work with to reduce our costs?" or "What information should our suppliers get to integrate with us?" can be answered by using simulation models.

Another type of simulation models we need is about integration with customers. In this new era, as discussed before, the type of demand from customers has changed. Products demanded are now customised and required instantly. Simulation models can be used to evaluate the effects of changes in the market.

The need for simulation is obvious but how do we simulate all these? We talk about multi-level of details in systems. The answer could be in hybrid modelling [17, 18] methods and multi-resolution/hybrid simulation models [3]. For example, we need different time granularities in models; milliseconds for the physics of goods in manufacturing, seconds for the operations at the machine level, and minutes for the process level. Likewise, we need different way of modelling; DES for modelling factory processes, and System Dynamics (SD) and ABS for understanding customer dynamics.

3.3 Augmented Reality/Virtual Reality (AR/VR) and Training People

The term Augmented Reality (AR) is first used in 1992 by Caudell and Mizell [7] to describe a technique which superimposes computer-generated graphics onto real objects with displaying devices such as goggles, helmets, monitors, or hand-held devices. AR devices are first produced for the aerospace industry and applied on heads-up displays. Azuma [1] state that AR systems have mainly three characteristics. They can combine real and virtual objects, they can interact in real-time, and they use 3D computer generated objects. Syberfeldt et al. [23] classifies AR hardware into three groups; Head-worn, hand-worn, and spatial. The technology is not new, however recent trends show that AR is becoming more popular. Billinghurst et al. [2] survey 50 years of computer-human interaction in AR research context.

Karlsson et al. [14] is an example of decision support tool capable of AR. They displayed a traditional DES model's 3D view on a table with Microsoft's HoloLens. On their display, they showed a 3D view of a manufacturing facility and a score for the cause of bottleneck on each machine. Rather than displaying the simulation execution in real-time, they displayed pre-executed simulation results on a table. This is ideal for a group of decision-makers who evaluate options for better manufacturing. They claim that AR provides better comprehension than traditional visualisation tools such as bar charts, and AR can be used in training, collaboration, production planning. They report an increase in performance of trainees using AR devices.

In Virtual Reality (VR), the user is immersed in a virtual world made of computer-generated graphics. The user can visually, through eyes, sense the virtual world and interact with virtual objects. It is an improved way of visualisation in a simulation. Rather than observing virtual objects on a 2D screen, the user feels the sense of the 3D world.

AR/VR, as illustrated in Fig. 4, are a part of CPS. They are seen as optional today, however, in the future, they are going to be required in CPS. With VR, the simulated world can better be displayed so that the users can comprehend the cyber world and make changes in the physical world. "Fidelity" in VR is an issue to tackle. In fact, the fidelity issue is solved with AR. In AR, computer graphics is supported by the objects in the real world, and only necessary cyber, and visual, objects are created. It

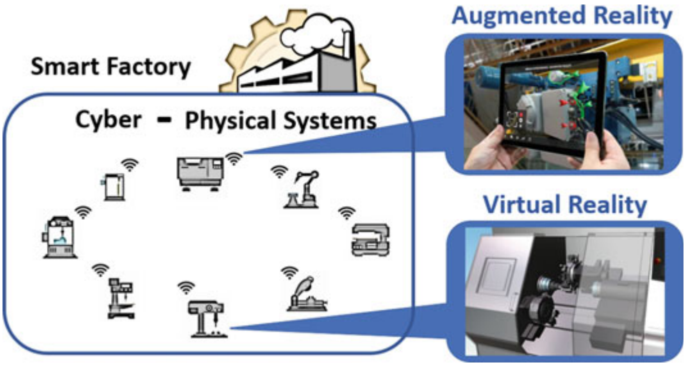

Fig. 4 Augmented Reality (AR) and Virtual Reality (VR)

can be speculated that if we had high fidelity VR systems with the ability to interact with the real physical world then we would not need AR.

Other than AR/VR, there are physically established simulation centres to train people who work in Industry 4.0 enabled factories. Faller and Feldmüller [8] reports a training centre for SMEs in Germany to make them ready for Industry 4.0. They use simulation in the training centre to mimic a few processes in a factory, such as robotic actions.

3.4 Cloud, Big Data Analytics and Simulation Input Modelling

The Cloud and Big Data are the two terms which are frequently discussed today. It is true that, because of electronic devices, there is more data available today than we had before. The devices and services we use, such as mobile phones and the Internet, produce data and presents an opportunity for scientists. Data Analytics (DA) is a growing field in computing science which deals with the analysis of non-trivial amounts of data. It relies on methods and algorithms which can deal with large data sets.

Simulation models require data from the systems they represent. This requirement is due to the need for making models realistic. Historical data is used to create statistical inference which provide inputs to simulation models. Overall process is named as “Input modelling” in simulation literature. Input modelling is as old as simulation itself. In the early days of simulation, data from the system on hand was analysed to study probability distributions in stochastic processes. Probability distributions are needed in systems where there exists variability and randomness, such as in random arrivals of supplies and orders, the occurrence of failures, and process times of jobs.

There is still a need for data analysis for increasing our understanding of systems, not only for simulation but also for comprehension.

In an era where more data is available, we can create “better” simulation models, “better” in the sense of realistic data collected from industrial systems. The task of data collection is now fulfilled by using technologies such as sensor and IoT. However, standardisation in data collection is an issue. For this purpose, there are studies conducted by organisations such as the *Simulation Interoperability Standards Organization* (*SISO*). SISO [21] publishes standards such as “*SISO-STD-008-01-2012*” for creating *Core Manufacturing Simulation Data* (*CMSD*) file in XML format. Likewise, as a result of international efforts, the standard *STEP-NC AP238* is created as a communication medium between CAD files and machining requirements in Computer Numerical Controlled (CNC) processes. Another international organisation, International Society of Automation (ISA), founded in 1945, develops standards for automation, such as “Enterprise-control system integration—Part 1: Models and terminology” in *IEC 62264-3* [12].

Simulation can also be used in DA, as summarised in Shao et al. [20]. Simulation can be used to analyse data for diagnostic, prediction, and prescriptive analytics. To diagnose an incidence in a manufacturing system, and to understand why this happened, sensitivity analysis using a simulation model can help answer questions. To predict the effects of a change in a system, and to estimate what this change cause, a model can simulate changes and tell what is going to happen. To enhance benefits gained in DA, a simulation model can run what-if scenarios and many alternative solutions can be evaluated.

3.5 Internet of Things (IoT) and Designing Connectivity

IoT makes objects communicate with each other and with humans. Although there are many other related terminologies such as the Internet of Everything (IoE), Internet of Goods (IoG), Industrial Internet, and Industrial Internet of Things (IIoT) [10], there seems to be a consensus on “IoT” in Industry 4.0 context. Manufacturing machines, transporters, storage systems and even products can communicate and exchange information with IoT technology.

With IoT, Peter Drucker’s dreams may come true as once he said, “If you can’t measure it, you can’t improve it”. From a management point of view, IoT provides real-time data from resources and processes which are needed for measuring things. We can keep track of our manufacturing assets including equipment, raw materials, goods from suppliers, and workforce. This valuable data can be used for utilizing things more efficiently.

IoT helps things to be smarter. Machines can be aware of their parts, with embedded sensors, and can predict when maintenance is required. This helps manufacturers do predictive maintenance rather than preventive maintenance. Raw materials stored on racks can be tracked and when they run out, new orders from suppliers can be given. Self-ordering supply systems are possible with IoT technology. Even products on production lines in factories can be aware of itself, and be smart. A product can question itself if anything is missing on it and can ask process control to complete the missing parts or help control the sequence of jobs in the production line.

Simulation can be used for designing and implementing IoT technology. Expected benefits of using IoT in factories can be tested using simulation modelling. A simulation model of a factory with and without IoT can show differences between the two worlds, and help investment decisions. Since simulation models are scalable, partial IoT implementations can also be evaluated with simulation. For example, a question like "what benefit can we gain if we track our finished products in our warehouse" can be answered by using simulation.

Simulation is a preferred method for designing IoT technology. There are simulation packages available in the market which helps developers to test IoT hardware. Using this simulation software, tuning IoT devices is possible. Additionally, research for 5G (5th Generation) mobile communication technology also use simulation for designing.

3.6 Additive Manufacturing and Product Design

Additive Manufacturing (AM) is a general term used for making 3D objects by adding forming material layer-upon-layer. It is a new way of manufacturing. It is mostly known with 3D printers. The material used in 3D printers today is typically a type of plastic which can melt, shaped, and cooled down. When the material is melted, semi-liquidised material is laid on a surface in a controlled way. CAD software, to design the object and layer laying device to shape the object are the two main elements of AM.

The material in AM has a substantial role since a "mould" does not exist in AM. Today we even see metal material used in AM. The future of AM is about new composite materials that can compete with materials in conventional manufacturing (Fig. 5).

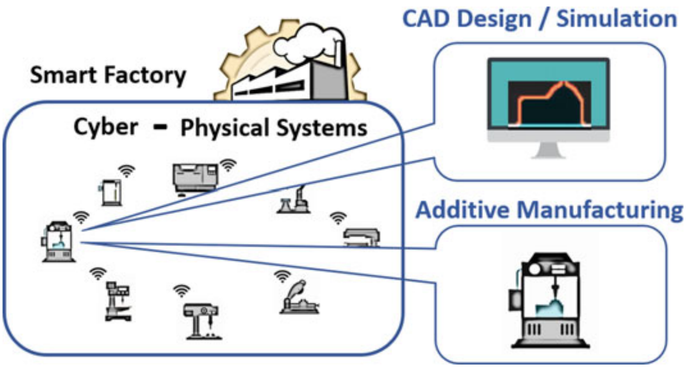

Fig. 5 Additive manufacturing and simulation

Simulation in AM takes place in the design phase and pre-manufacturing phase. Design of the object to be manufactured is done using CAD software. If the object is a component of a product, then the object's mechanics, such as moving area and assembly status, can be simulated in CAD software.

In the pre-manufacturing phase, 3D Printers software simulate the printing job, to avoid material loses and to test stability. These software work with CAD software and simulate layer forming process.

4 Conclusion

Industry 4.0 encapsulates many advanced technologies and aims at using these technologies to make manufacturing smarter, autonomous, cyber, and integrated. Smart Factories and CPS will realise these objectives by using robotics, big data analytics, cloud computing, IoT, systems integration, AR/VR, and simulation.

CPS is about digitising physical resources, mechanical and electronic parts of machines, with software and creating a replica, Digital Twin, in cyberspace. A Digital Twin is a simulation model of the manufacturing facility. It gets data from the real world and manipulates to create actions. Before taking action, systems can be simulated with Digital Twin to observe the effects of possible changes.

Vertical and horizontal integration in CPS is required to connect physical world entities. Vertical integration is to make a factory's components to be aware of each other to create a smart factory. Horizontal integration deals with inter-smart factory communication. Hybrid modelling and hybrid simulation could be used to realise these connections by testing alternative integration modes and operation scenarios.

AR and VR have great potentials in Industry 4.0 since they help create a cyber world in manufacturing. In this world, decision making and training can be done non-traditionally with more visual features. AR and VR are methods that create simulations of reality.

We need data analytics for obtaining inferences with data collected through IoT. Simulation helps create inferences. Additionally, simulation is a tool for designing connectivity using IoT devices. Simulation has been used in designing computer networks in the past.

Additive Manufacturing is transforming conventional product design process. With CAD software, a product, or a component, can be designed and simulated for its dynamics. Although 3D printers are used today mostly for rapid prototyping, they will be the main manufacturing machines in the future. The print process is simulated before physical activity, to increase efficiency.

For reasons discussed earlier on versioning (refer to the section on the history of industrial revolutions), we are not going to call this era "Simulation 4.0". However, we can prognosticate that simulation is entering a new era with the advent of Industry 4.0. As we get more digitised, we will see more simulations in the future. New uses and needs of simulation will emerge in manufacturing in Industry 4.0 era, and simulation research community must respond with new methods, algorithms, and approaches.

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Industry 4.0, Digitisation in Manufacturing, and Simulation: A Review of the Literature

Murat M. Gunal and Mumtaz Karatas

Abstract Simulation is perhaps the most widely used approach to design and analyze manufacturing systems than to any other application area. Industry 4.0, the latest industrial revolution, also involves the use of simulation and other related technologies in manufacturing. In this study, our main ambition is to provide readers with a comprehensive review of publications which lie within the intersection of Industry 4.0, digitization in manufacturing, and simulation. To achieve this, we follow a two-stage review methodology. Firstly, we review several academic databases and discuss the impact and application domain of a number of selected papers. Secondly, we perform a direct Google Scholar search and present numerical results on global trends for the related technologies between years 2011 and 2018. Our reviews show that simulation is in the heart of most of the technologies Industry 4.0 utilises or provides. Simulation has significant role in Industry 4.0 in terms of supporting development and deployment of its technologies such as Cyber-Physical System (CPS), Augmented Reality (AR), Virtual Reality (VR), Smart Factory, Digital Twin, and Internet of Things (IoT). Additionally in terms of management of these technologies, simulation helps design, operate and optimise processes in factories.

Keywords Industry 4.0 · Simulation · Manufacturing

1 Introduction

Technological innovations in the history affected human life in different scales. Some innovations, collectively, caused a landmark in the industrial history and named as

M. M. Gunal (✉)
Barbaros Naval Science and Engineering Institute, National Defense University, Turkish Naval Academy, Tuzla, Istanbul, Turkey
e-mail: m_gunal@hotmail.com

M. Karatas
Industrial Engineering Department, National Defense University, Tuzla, Istanbul, Turkey
e-mail: mkaratas@dho.edu.tr

Industrial Engineering Department, Bahcesehir University, Istanbul, Turkey

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revolution. Industry 4.0 is the latest industrial revolution which is founded in 2011 by the German government. It is indeed including multiple technologies and more importantly philosophy of how these technologies is to be used in manufacturing. This step forward is followed by other nations and caused them express explicitly how their manufacturing is going to evolve. Although many nations other than Germany, who is the name father of this industrial revolution, use different names there seems to be a consensus on the name Industry 4.0.

The first industrial revolution was triggered by the invention of the steam engine. It produced power to run machines for manufacturing. Electricity and internal combustion engine inventions had similar effects which caused mass production and the second industrial revolution [1]. The third revolution was about electronics and hence the computer. Computers have been started to be used in manufacturing where they ease human involvement and increase automation. All of these revolutions caused more products to be produced with less cost, and therefore more people accessed to products. The fourth revolution is also aiming at this, better products, more amounts, and less cost. Industry 4.0 involves advanced technologies to be benefited in manufacturing. In fact, the ultimate objective is, although it is a myth for now, to let machines produce by themselves.

Technological innovations within Industry 4.0 include autonomous manufacturing systems, industrial Internet of Things (IoT), the cloud, big data analytics, additive manufacturing, horizontal and vertical system integration, cybersecurity, augmented reality (AR), and simulation. Many of these technologies are already on their way in manufacturing and in other sectors. Smart cities concept, for example, involves using these technologies. Additionally, more technologies can be included to this list as new ones are emerging on the way of digitisation.

This chapter reviews the publications on the intersection of Industry 4.0, digitization in manufacturing, and simulation. Simulation has been a method to design and analyze manufacturing systems since 1950s. There are several reported success stories and reviews of the literature. One such review, Mcginnis and Rose [2], highlights five pioneering papers in one of which job-shop scheduling problems were simulated in late 1950s. In later decades, with the advancements in computer hardware, many software tools and languages were developed, such as GPSS, SIMON, PROLOG. Scholars published their studies in the Simulation Journal of the Society for Modeling and Simulation International, and in other journals and conferences. Increasing trend in using simulation in manufacturing continued in following years. They identified more than 25,000 papers which reported use of simulation between 1960s and 2015. The numbers have grown exponentially. The trend reciprocates the situation in Winter Simulation Conference (WSC) proceedings. In fact, WSC proceedings revealed new sub-areas of simulation in manufacturing, such as data issues, interoperability, and algorithms for optimization and new challenges emerged for the simulation community. Fowler and Rose [3] identified three challenges and made recommendations; simulation community must (1) reduce problem solving cycles including simulation model building times, (2) develop real-time problem-solving capabilities by using simulation, and (3) provide plug-and-play capabilities to simulation models to be able to link with other software, known as “Interoperability”.

This review is conducted in two parts. In the first part, we used academic databases and search engines (ScienceDirect, Web of Science, Scopus, and Google Scholar) to track papers on "Simulation and Industry 4.0". Since the term "Industry 4.0" was founded in 2011, we narrowed the scope of our search between years 2011 and 2018, inclusively. We then selected 82 papers from the search and reviewed them in detail to examine their impact on simulation theory, methodology, and practice.

In the second part, we performed Google Scholar search by using some of the related keywords and phrases, excluding patents and citations. This search relies on Google Scholar's search algorithms since their reach is deeper than the other academic search engines. This means that grey literature is included in the search as we explicitly wanted to know how much our search terms are mentioned.

2 Review of the Selected Publications Between 2011 and 2019

Using academic databases and search engines, we identified a total of 82 papers. Our selection was based on our personal evaluations considering the papers' level of theoretical, methodological contributions and practical impacts. We did not ponder any formal criteria for selection, however, we specifically sought for papers which present methods for running simulation models faster, building simulation models quicker and easier, analysing input and output data quicker and easier, collecting data with new technologies, and simulating new areas in manufacturing processes.

Figure 1 shows the number of papers in our survey grouped with respect to the time of publication (2013–2018) and originated country (papers from Germany, the EU, and outside the EU). Since the idea of Industry 4.0 concept originated in Germany, we've depicted the papers from Germany separately. The figure reveals that, European Union (EU) countries are influenced with the industry 4.0 idea significantly.

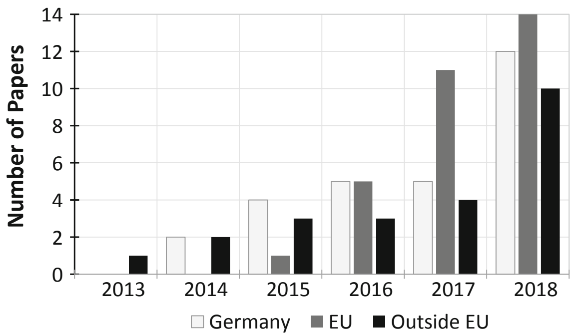

Fig. 1 Number of papers in the survey by the origin country and year

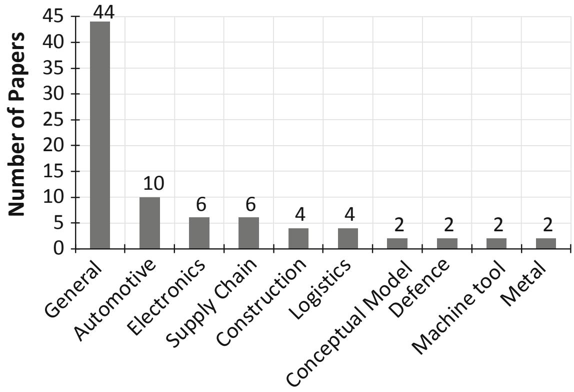

Fig. 2 Number of papers in the survey by application domain

It is clear that the number of studies increased exponentially and most of them are written by German authors. EU countries have also contributed to the literature on simulation and Industry 4.0. It is interesting that non-EU countries have also accepted the idea and started thinking and writing about Industry 4.0. This may be a sign of global recognition of an industrial revolution. We can further evaluate that the papers in our survey mentioned Industry 4.0 concepts positively and recognized as a revolution. However, there seems to be many works to do as the transformation in manufacturing will not happen effortlessly.

We also examined the manufacturing domains in surveyed papers. Figure 2 shows the distribution of the papers by application domain. Majority of the studies did not aim at any manufacturing domain since more than half of them are broadly written without aiming at any specific area. This suggests that the authors are on the search for general guidelines of how to apply and manage the concepts in manufacturing. This may also mean that simulation is a generic method for making things better in manufacturing. Industry 4.0 will benefit from simulation in many ways and domain specificness is not valid for simulation. In the surveyed papers we also identified papers mentioning simulation with the terminologies AR, Virtual Reality (VR), and other technologies of Industry 4.0.

After the general papers, most studied application domains are automotive, electronics and supply chain. Germany, as the world's technology leader in automotive industry, may have influenced the distribution. Also, the automotive and electronics industries might be ready for Industry 4.0 since these industries are using automation and robotic technologies for decades.

2.1 Literature Reviews

For the detailed evaluations of the surveyed papers, we start with literature review papers. An early one, relatively to the start of Industry 4.0 in 2011, Brettel et al. [4]

reviews the literature and points out that the role of simulation is observed in the rapid product development. Furthermore, they identified four research areas related to Industry 4.0; Individualization, virtualization, hybridization and self-optimization. With regards to individualization, they see modularization in products as the key to achieve fast time-to-market. Their claim is that the concept of "modular" product design is influenced from "simulation" world. Reusability and modularity in production simulation models and value-stream mapping in lean manufacturing simulations supported "modularization in production" concept. Although not directly related to simulation, they also point out the importance of collaboration among companies, including SMEs which are the primary suppliers of main producers. Furthermore, they see significant role of simulation and modelling in end-to-end digital integration which is information sharing through simulation between suppliers and production organisations.

Their survey of literature is conducted for the period 2007 and 2012 and a total of 548 papers in 8 academic journals are included. The cluster analysis showed that "End-to-End Digital Integration" is one of the 3 clusters in emerging research areas in Industry 4.0, and there are 249 papers in this cluster. Within this cluster, there are 64 studies related to modelling and simulation which has the dominant role.

Additionally, Brettel et al. [4] surveyed a few people from the industry in Germany. The survey revealed that use of simulation technologies, such as in prototyping, is still very difficult for SMEs. They do not have expertise to use these technologies and this is going to be the strongest barrier in Industry 4.0. Likewise, another responded mentioned that "Industry 4.0 will only work if machines can communicate via Cyber-Physical-Systems (CPS) and commodity flows can be tracked via RFID". This statement indicates the importance of inter-machine communication and also the need for CPS.

Qin et al. [5] review the concepts and highlights the gaps in the current research and the needs in the future. Smart factory as an enabler technology of Industry 4.0 can be achieved using simulation. Likewise, Roblek et al. [6] presets a general literature review and specifically researched the influence of Industry 4.0. With the data collected through Industry 4.0 technologies, more information will be available and therefore Knowledge Management 4.0 (KM 4.0) is required to create value.

Jain and Lechevalier [7] review the literature on virtual factory and stated that the idea is not new and has been studied in the past. The term generally refers to high fidelity simulation of a factory's manufacturing processes. They state that VR is used interchangeably with virtual factory and digital factory. In their work, they propose a framework for automatic generation of virtual factory simulation models, using standards of machine manufacturers. There are three levels of modelling elements; cell, machine, and process. International Society for Automation (ISA) standards ISA-95 and 88 recognize a cell as "work center", a machine as "work unit", and a process as "production process". Authors simulate a cell with DES, a machine with DES/ABS, and a process with continuously based on equations. Their automated framework reads a Core Manufacturing Simulation Data (CMSD) file, which is a standard provided by Simulation Interoperability Standards Organization [8]. The file includes the inputs for machines, logic network, layout, and output data interface.

Hofmann and Rüsch [9] is a review of papers in logistics and special focus on Industry 4.0. They point out that simulation can be used in logistics and particularly in analyzing delivery systems. For intelligent manufacturing systems, Zhong et al. [10] reviewed the literature in a period between 2005 and 2016. They identified an increasing trend in number of papers published and focused on 165 papers in this period. Furthermore, they grouped the studies into three; intelligent, IoT-enabled, and cloud manufacturing. They considered simulation as part of CPS.

The paper by Strozzi et al. [11] adopts Systematic Literature Network Analysis (SLNA) to review papers on smart factory concept. Upon clustering the papers, the authors reviewed and concluded that simulation is in the cluster of methods to increase efficiency.

Vieira et al. [12] is a recent literature review to position DES in Industry 4.0 context. They created an agenda for research and development and pointed out that DES is needed to create insight on businesses, and to assess the added-value of Industry 4.0. Furthermore, digital twins which are real-time representations of entire factory operations, and real-time supply chains simulations are needed for the future. Although Industry 4.0 will help provide data, we still need reusable full models, or sub-models, to achieve these goals.

Other review papers include Liao et al. [13], Jain et al. [14], Oztemel and Gursev [15]. We also note that Jahangirian et al. [16] is a review of simulation in manufacturing which was done prior to start of Industry 4.0.

2.2 Cyber Physical Systems (CPS), AR/VR, Visualisation

In our review of the literature pertaining to the CPS concepts and the use of AR and VR, we encountered a number of studies. Lee et al. [17] proposes a 5-level architecture for creating CPS. In their architecture they suggest simulation methods as a synthesis tool to optimise future steps in organising manufacturing assets. Zhou et al. [18] argue that simulation can help create CPS. Likewise, Saldivar et al. [19] discuss the integration issues for CPS. There are 6 dimensions of integration; methodology, dimension, view, method, model, and tool integration. For the tool integration, they emphasize High Level Architecture (HLA) for connecting simulation software which are used for product design.

Scheifele et al. [20] present a case study which use simulation in a hardware in the loop system. The machine tooling case is an example of how CPS can be created. They merge hardware settings with software settings and how they communicate and create value.

Mueller et al. [21] analyse the shortcomings of the Industry 4.0 applications with an emphasis on CPS in different countries based on the state of the art and practice reviews. For this purpose, they develop a reference architecture with four main perspectives as manufacturing process, devices, software and engineering. They later study a number of cases for the potential applications of CPS with the purpose of closing the gap between research and practice. Some of the cases include selfsustaining intelligent sensor networks for production, virtual space for the controlling of double-arm robot, synchronous production through semi- autonomous planning and human-cantered decision support, and resource-cockpit for socio-cyber-physical systems. They report that, for an efficient application of Industry 4.0, both horizontal and vertical collaborations among companies is essential, and thus, further opportunities for such collaborations should be studied.

Based on the fact that, as the Industry 4.0 revolution takes shape, human operators are expected to operate more flexibly in dynamically changing environments, Longo et al. [22] propose a human-centered approach for smart factories. Hence, this study introduces a visionary and user-centered solution method which is designed to operate efficiently in the framework of Industry 4.0 concept. In particular, the authors design and develop of a practical tool, called the "Sophos-MS", which integrates AR and intelligent tutoring systems. The tool basically assists operators by providing them with quick and practical information flow through a Q&A design. The tests to measure the training potential of the tool showed that operators trained by SOPHOS-MS outperform traditionally-trained operators with respect to their learning curve performances.

Syberfeldt et al. [23] highlight that the concept of "smart factory" refers to future factory designs which combine people, machines, products and other components such that they share information via internet to perform intelligently. Such factories are expected to act flexibly in complex and customized production processes which may require short product life-cycles. One way of enhancing human performance in smart factories is the AR. With AR, virtual information can be used in real-world with the purpose of improving a human's perception of reality. This paper assesses several AR implementation approaches from a shop-floor operator's perspective. The authors perform their analysis in collaboration with a number of companies including Volvo Cars and Volvo GTO. They point out that there are still big opportunities for successful implementation of this technology on the shop floor. They state that major topics and challenges that are crucial in conducting the research are (1) privacy, (2) data security, (3) information content, (4) location awareness, and (5) tailor-made solutions for human-robot collaboration.

Gorecky et al. [24] study the interaction between human and machines and points out that VR plays an important role for this interaction since VR allows users to interact with CPS. Furthermore, Herter and Ovtcharova [25] propose a new integrated visualization framework for interdisciplinary communication. This theoretical framework enables experts from different and related disciplines communicate directly in Industry 4.0 product development scenarios. The proposed visualization feature is realized on a 3D environment where connected models are displayed and arranged.

Karlsson et al. [26] is a good example for using AR in detecting bottlenecks in a manufacturing facility. They incorporated an AR device (Microsoft's HoloLens) with a simulation model's 3D visualization. They conclude that AR provides better support for decision making.

Nunes et al. [27] review and evaluate the approaches for Smart Product Development (SPD) in the new industrial era. For rapid prototyping and product deployment, emerging technologies such as VR and AR are discussed. The term "smart product" refers to a product which is aware of itself, its environment, and its users. A product can be aware of itself when it knows about its characteristics, functionalities, and history. This gives a product measurability and traceability. When a product interacts with its environment, it can get information and send information to other surrounding devices. Likewise, when a product is aware of its users, it can be tracked in its whole life-cycle and can provide maintenance information.

Akpan and Shanker [28] evaluate cost and benefit of visualization (2D, 3D, and VR) in a DES model and highlight the potential to improve benefit.

2.3 Data Analytics

With regards to Data Analytics (DA), simulation can play a significant role. Note that DA is an emerging field in this new era as we talk about Big Data and ways of its analysis. There are predictions about increase in volume, variety, and velocity of data in manufacturing. The use of simulation in DA is discussed by Jain et al. [29] and Shao et al. [30]. Shao et al. [30] suggest that simulation can be used as a tool in DA to perform diagnosis and analysis for prediction and prescription in manufacturing context. Jain et al. [29] demonstrated the link between DA and simulation in virtual factory context. In their definition a "virtual factory" is "an integrated simulation model of major subsystems in a factory that considers the factory as a whole and provides an advanced decision support system". A virtual factory requires multi-resolution simulation modelling that is a model with different levels of detail. For example, a manufacturing cell model is a DES model with machines in focus, and a machine model is an ABS model which individual parts can be tracked. Another common terminology for multi-resolution simulations is called "Hybrid simulation". This involves use of multi-simulation approaches such as System Dynamics (SD) and DES [31].

Weyer et al. [32] emphasize the importance of standardization for data communication between automated machines and modularization in production systems. They see Industry 4.0 as three concepts; smart product, smart machine, and augmented operator. Operators must work flexibly within the production system to be able to cope with different tasks machines are performing. The expertise they need will be more than in the past. AR can help companies develop such expertise.

Theorin et al. [33] propose an architecture for information gathering from machines which they call Line Information System Architecture (LISA). With LISA, machine data can be collected via RFID and IoT devices.

Srewil and Scherer [34] propose a framework to enable the link between physical and cyber objects, particularly developed for construction sector. The framework utilizes RFID devices to track construction objects.

Digital twins can be created using ERP and MIS data, as Rodič [35] discusses. This points out that digital twins are a must of the future manufacturing systems however there are obstacles in creating them. To overcome the challenge, new software to create simulation models from data must be available.

2.4 Supply Chain

Timm and Lorig [36] argue that the logistics sector will shift from hardware-oriented to a software-oriented logistics. They name this “Logistics 4.0”, or “Smart Service World”. Autonomous sub-logistics systems can depend on individual actors. For simulating logistics systems, they propose two approaches: First, existing material flow simulation models can be modified to be able to make decisions. A CPS is attached to a real system. In the second approach, more sophisticated Multi-Agent Systems (MAS) are developed to represent individual entities in logistics systems, and the autonomy in these systems are built upon these systems.

Dallasega et al. [37] review the literature on supply chain within Industry 4.0. They cluster the studies and simulation appears in “digitization” and “tracking and localization” clusters. Tjahjono et al. [38] focus on supply chains and simulation.

2.5 Lean Manufacturing

Lean Manufacturing is a well-established manufacturing philosophy and appears to continue its strength in Industry 4.0. Sanders et al. [39] investigate the link between Lean Manufacturing and Industry 4.0 and point out that the two are actually mutually exclusive. High investment levels required to make Industry 4.0 real, companies should still need to implement Lean concepts to avoid waste and to streamline their production processes. Industry 4.0 will provide data on how much the company actually made progress on improving their processes. Additionally, they think that simulation can have a role in providing Just-in-time delivery of suppliers.

Wagner et al. [40] see most of the current manufacturing systems as lean systems and argue that what Industry 4.0 will bring to these systems as a complementarity of lean concepts, though with more complexity. Their framework helps implement Industry 4.0 concepts in a lean manufacturing system.

Zúñiga et al. [41] report a study conducted in a company which decided to use IoT, automatic guided vehicle (AGV) technologies. Simulation models showed potential benefits. The paper presents the concepts of lean manufacturing and simulation optimisation within industry 4.0 principles. The lean production philosophy has been adopted especially in automobile industry. It states that the success in manufacturing is achieved only with all parties in the production and supply chains by developing the people, partner organisations and their processes. The progress should be continuously achieved and address the root-problems. A lean system must emphasize value adding processes and ways of waste identification and reduction.

They identified three areas where Industry 4.0 concepts can be applied: Buffers and storage, material flows, internal logistics. For the buffers and storage areas, they consider monitoring and control of storage levels with IoT technologies. For managing material flows, they simulated the production with RFID and barcode readers installed. For the internal logistics, they considered Automated Guided Carts (AGC). The company saw the benefits of adopting Industry 4.0 concepts through simulation and decided to adopt new technologies in their facility.

The automation technology has already been applied to lean production systems since 1990s, and this concept is known as "Lean Automation". Today, with the rise of the Industry 4.0 technologies, many other lean production problems are regarded as new potential improvement areas. Motivated from this fact, Kolberg and Zühlke [42] gives an overview of possible application areas of the Industry 4.0 within the Lean Production and Automation technology. They discuss new ways and frameworks for implementing Industry 4.0 to Lean Production in the future. The Industry 4.0 solution methods are demonstrated over a Kanban production scheduling example for smart watch production systems. The possible methods are grouped under four different titles as (1) smart operator, (2) smart product, (3) smart machine, and (4) smart planner. Finally, they argue that Lean Production and Industry 4.0 together can add value to users.

Furthermore, for sustainable business models for Industry 4.0, options are discussed by Man and Strandhagen [43].

2.6 Training People

Simulation centers are also being developed as to help train people and develop ideas in this era. For example, Erol et al. [44] propose a scenario-based learning factory approach to improve competences which they categorized into four; personal, interpersonal, action-related, and domain-related. In their proposed learning factory, they rely on Scenario-Based Learning (SBL) theory which claims that learning is most effective when it takes place in its natural context. They report a pilot factory which was established in Vienna as a teaching and training platform. This center is, in a way, simulation center to train future or current employees of factories which adopts Industry 4.0 concepts. Furthermore, in this center, developers do also try and develop their ICT systems.

Faller and Feldmüller [45] discuss the case of SMEs in Industry 4.0. They point out that SMEs generally do not have enough manpower skills to look ahead and beyond their current products and processes. In their paper, they report a training centre within a university in Germany which aims at helping SMEs establish Industry 4.0 concepts in their facilities. For example, they simulate robot actions in the training centre's shop floor.

Prinz et al. [46] report a development of a learning factory system to train people in production sector for adopting their processes to Industry 4.0. They also use simulation to mimic manufacturing processes and use it for testing planning and scheduling system components.

Wang et al. [47] propose a smart factory design of distributed self-decision making and intelligent negotiation mechanisms for manufacturing system. The proposed system incorporates industrial network, cloud, and supervisory control terminals that are self-organized via a multi-agent system which is assisted with big data based feedback and coordination. They also analyse the conditions which cause deadlocks, and develop a number of strategies to prevent them by improving decision-making processes. Finally, they use a simulation program developed in Microsoft VS integrated development environment (IDE) with for purpose of verifying their proposed approach.

2.7 Scheduling and Optimisation

Simulation optimisation is needed to make CPS intelligent. Software vendors develop products to make this possible. Zaayman and Innamorato [48] present a DES model in SIMIO simulation software. They believe the scheduling is another cornerstone of Industry 4.0 and to achieve smart factory target, we need self-optimized manufacturing systems. They explain the difference between planning and scheduling in manufacturing context, although the two terms are used interchangeably. Planning is to create an order of works to do in time and allocate resources to these works. Scheduling is to sequence the tasks in the works defined. By sequencing, start and end times are determined and a resource allocation plan is made.

Mathematical models for scheduling seek to find optimal, or best feasible schedules for the manufacturing components. Simulation models have advantage over mathematical models in the sense of modelling detail, visualization, and eventually convincing decision makers.

In scheduling context, there are two critical decisions to be made during simulation execution: Resource selection, and job selection. A resource selection is about selecting a resource when a job can be done by multiple types of resources. A job selection is on the opposite site of a resource selection decision. When a resource is free, it must choose where to work next.

The software incorporates Risk Based Planning and Scheduling (RPS) approach. In RPS, a deterministic schedule is run with a simulation model to assess variations and uncertainty in the system, such as machine failures, delivery delays, variable machine operating times.

Ivanov et al. [49] present a flow-shop mathematical model to help schedule coordinated machines in a factory.

2.8 Trends

As a result of the Industry 4.0 revolution, concepts such as CPS, big data, and IoT created new process improvement possibilities for manufacturing companies. Tamas and Illes [1] first give an overview of the history of industrial revolutions and discusses the key terms of the Industry 4.0 concepts. Next, the authors discuss the utilization of Industry 4.0 concepts in manufacturing systems. In particular, they define the main aim of the 4.0 revolution as the "realization of the intermittent manufacturing with mass production's productivity and specific cost". And to achieve this goal, they argue that simulation modelling is one of the most important tools to cope with the increased process complexity which is mainly caused by high product type variability and customization requirements. With an effective use of simulation models in system processes, it may be possible to eliminate planning failures, improve the performance of manufacturing and logistics systems, assess the expected outcome of different courses of actions before actually implementing them, etc. Moreover, these advantages provided by simulation models can be further improved with the combination of value stream mapping method and new intelligent logistics solutions.

Oesterreich and Teuteberg [50] are being motivated from the fact that digitisation and automation of the manufacturing environment has not gained attention in the construction industry, this study provides the state of the art and practice of Industry 4.0 applications in the construction industry. To achieve this, the authors first discuss the implications of adopting the Industry 4.0 concept in terms of multiple perspectives, i.e. political, social, technological, economic, environmental and legal. Next, they use a data triangulation approach for data collection to achieve comprehensive results. The triangulation approach consists of a systematic literature review, a case study research, and a value chain model. The results of the case studies show that: (1) there are a plenty of possibilities and a big potential for digitisation, automation and integration of the construction process in terms of Industry 4.0 concept, (2) While some of the technologies are currently used in the industry, some are still in the process of reaching a certain level of maturity and some are at the formative stage, as prototypes, (3) Although these technologies are not adopted by the construction industry at a high level, there exists opportunities and potential practice areas to adopt them in the construction process.

Lee et al. [51] researched how current manufacturing systems will evolve in the upcoming era and propose key technologies to help cope with the change. They point out two major trend; "Servitization", which is a shift from selling what is produced to selling an integrated product, and service with the product, and second, industrial big data which are generated by machines. CPS is seen as control or "simulation" oriented and can be extended to help decisions on machines' maintenance. Their paper includes a case study in a heavy-duty equipment vehicle manufacturer in which a system is created to predict and assess the status of the diesel engine in vehicle.

Liu and Xu [52] highlight an upward trend in Industry 4.0 and cloud manufacturing. CM is part of CPS and is defined as a new manufacturing paradigm which organizes manufacturing resources on a network to be able to satisfy consumers' needs. Their view is that simulation has an important role in CPS to be able to have great variety of models of production systems. They list the technologies to underpin CPS. The technologies are additive manufacturing, robotics, AR, simulation, big data analytics, cloud, cyber security, IoT, and horizontal and vertical system integration.

As the manufacturing systems get more and more complicated, simulation becomes a method for cost-avoidance insurance. Mcginnis and Rose [2] mention that simulation can test decisions made for designing facilities. Simulation costs significantly less than actually implementing the options for change.

Although there is growing interest in simulation for making manufacturing systems better, they point out why we see limited applications. Main reason they raise is related to the "math-dependent" analysis approaches. As in other abstraction-base analysis approaches, there are people who are skeptical. This is not specific to simulation. The sceptics are either unaware of the successes these approaches have achieved, or, are aware of unsuccessful ones. The authors think that skepticism in manufacturing industry limits the dissemination of simulation.

Pereira and Romero [53] review the concepts in Industry 4.0 and highlights that the future of manufacturing is about making factories and products smarter, business models connected, and customers more engaged. Furthermore, the key technologies are CPS, IoT and the new revolution will have impact on the industry, products, business models and markets, and overall economy.

Finally, when we examine the papers published in 2018, topics covered are simulations for autonomous vehicles, cloud-ready technologies, occupational health and safety issues, smart manufacturing, CPS, digital twin, supply chain and market integration, sustainable production, teaching related systems and concepts.

3 Google Scholar Searches

In the second part of our review, we used Google Scholar search engine to seek the key words listed in Table 1. Our search aims at observing the global trends for the related technologies. We cover years between 2011 (the announcement of Industry 4.0) and 2018 (including).

The first phrase we seek is the obvious intersection of simulation and Industry 4.0. In some countries it is pronounced as "Industrie 4.0". Since "simulation" has been a preferred method in manufacturing for decades, we wanted to see the trends in simulation and manufacturing. New terminologies, such as CPS, Digital Twin, Smart Factory, and Virtual Factory have emerged. We also wanted to see how AR/VR/MR and the other technologies and concepts (additive manufacturing, IoT, analytics, and autonomy) are utilised in manufacturing context. Figure 3a–e shows the results of the searches.

In Fig. 3a, it is clear that simulation has a growing role in Industry 4.0. It is also interesting that on the contrary to this upward trend, in Fig. 3b, the intersection of manufacturing and simulation is diminishing. This does not mean that simulation is being used in manufacturing context less than before, but rather this drop can

Table 1 Search phrases in Google Scholar

Simulation and “Industry 4.0” or “Industrie 4.0”
Simulation and Manufacturing
“Cyber Physical Systems”
“Digital Twin”
Simulation and “Digital Twin”
“Smart Factory”
“Virtual Factory”
“Augmented Reality” and Manufacturing
“Virtual Reality” and Manufacturing
“Mixed Reality” and Manufacturing
Simulation and “Additive Manufacturing”
Simulation and “Internet of Things”
Simulation and Analytics and Manufacturing
Simulation and Autonomy and Manufacturing

be explained with the introduction of new terminologies. That is, rather than sole “manufacturing” word, nowadays in most studies, new phrases such as “Cyber physical systems-(CPS)” and other new terminologies are being used interchangeably in manufacturing context. In (a), CPS has a significant growth.

“Digital Twin” is perceived as a simulation model of a factory. In Fig. 3c, “Digital Twin” and “Simulation and Digital Twin” curves grow almost together, although in 2018 they separated. We must observe how the digital twin concept will evolve in the future. “Smart Factory” mean more than “Digital Twin”, as its curve is significantly above the “Digital Twin” curve. This is plausible since a “Smart Factory” does not only mean a digital representation of a factory but also mean a factory with self-deciding machines.

VR, AR, and MR are the derivatives of simulation and used in manufacturing context. In Fig. 3d, the lines show that VR is more popular than AR and MR in manufacturing, though the use of AR is growing faster than VR. There seems to be more interest in AR than VR in the future. MR is in its infancy period yet.

Finally, in Fig. 3e, search results for using simulation with other technologies of Industry 4.0 are shown. Simulation has been used for IoT mostly, and the growth is exceptional. “Additive manufacturing” and simulation has also grown. Simulation is supporting these two technologies.

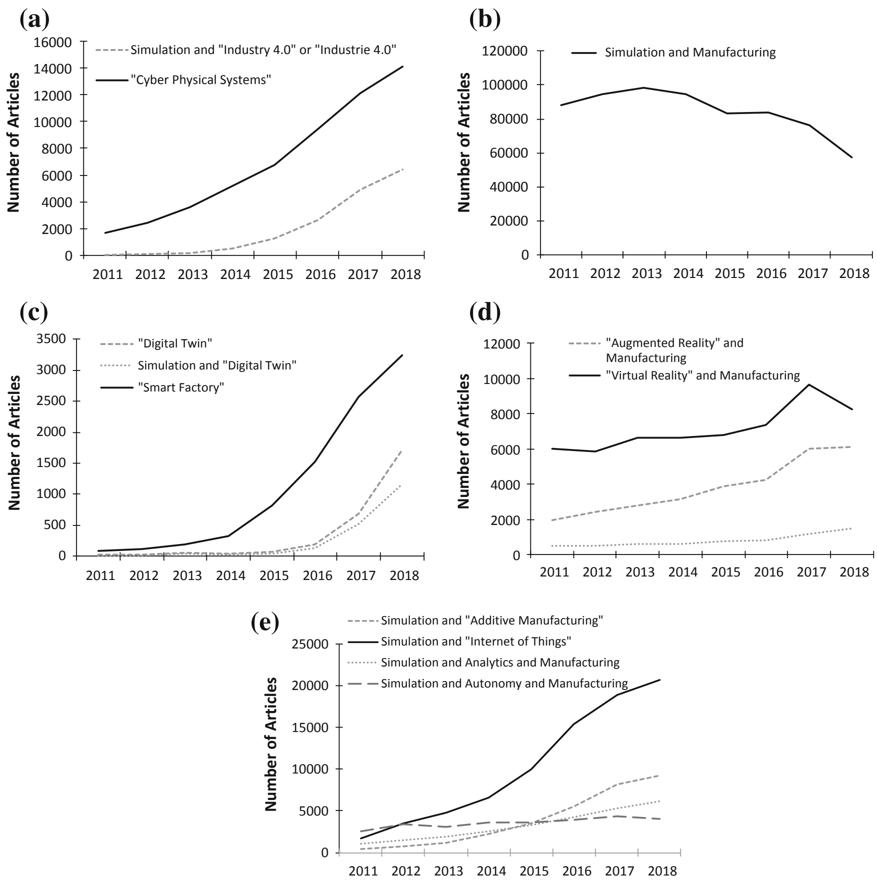

Fig. 3 Google Scholar keyword search results

4 Conclusion

We reviewed the simulation literature to evaluate the trends in Industry 4.0. Our review was conducted in two parts; selected publications were examined in detail and Google Scholar's counts for the related key words were analysed.

Our review of the selected literature revealed the topics and conveyed messages in Table 2. The table is alphabetically sorted.

The results of our review provide valuable insights on the current and potential implementations of the Industry 4.0 philosophy to manufacturing and related technologies. In particular, simulation lies in the intersection of many Industry 4.0 related concepts such as CPS, process optimisation, system design, data analytics, supply chain, and VR/AR. It plays a crucial role in both designing and improving manu-

Table 2 Topics and conveyed messages in the surveyed papers (in alphabetical order of topics)

Topic	Message
ABS	• Agents can represent manufacturing systems' elements
AR	• AR can help human operators to create expertise • AR is for better and quick decision making
Conceptual model	• Conceptual models need to be visualised
CPS	• Simulation can help create CPS • Simulation can be used for CPS integration • Simulation is to enable CPS • CPS means hardware in the loop • Multi Agent Systems (MAS) can help create CPS • RFID devices can generate simulation data • Simulation is needed to optimise processes
CPS and VR	• VR can help humans interact with CPS
DES	• Digital twins can be created using ERP and MIS data and DES • Scheduling is a feature that is needed in digital twins • Simulation can be used for Data Analytics • Simulation has potential in analysing Supply Chains
DES-ABS-Continuous	• Hybrid models capture complex relations in systems
SD-DES	• Hybrid methodologies can better manage simulated time
Smart factory	• Smart factory is enabled with simulation
Visualisation	• Simulation has value in construction industry
VR	• VR can help humans interact with CPS
Other topics	• Data collection frameworks, knowledge management, implementation in SMEs, Lean Manufacturing can better implement Industry 4.0 concepts, simulation to test vertical and horizontal integration, logistics can benefit from simulation • General concepts and views, review of literature • Modular simulation techniques allow rapid product innovation • Learning factory concept to train people • Simulation plays an important role in designing Industry 4.0 systems • Simulation for sustainable business development

facturing processes. Visualized conceptual models, ABSs of manufacturing systems, CPS integration and smart factory operations are some of the prominent domains that simulation can be used to improve the quality and efficiency of Industry 4.0 concept.

Throughout this literature review, we identified and highlighted several selected papers in various Industry 4.0 related concepts, i.e. CPS, AR/VR, visualisation, data analytics, IoT, supply chain, lean manufacturing, training people, scheduling and optimisation and trends.

In conclusion, our review shows that there is still a lot of room for the development of both simulation applications and Industry 4.0 oriented process improvement technologies in manufacturing domain. We hope that as the number of success stories of simulation applications in manufacturing systems around the world increase, the motivation for future attempts will also increase. We also believe that, the challenges presented in our chapter arouse interest in readers and encourage them to conduct further research in this area.

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Traditional Simulation Applications in Industry 4.0

David T. Sturrock

Abstract For decades, simulation has been used primarily for facility design improvements. Domains like manufacturing, airports, mining, ports, call centers, supply chains, and military have provided a rich set of case studies describing how simulation has been used to save hundreds of thousands, sometimes even millions, of dollars per project. These are well accepted and documented applications of Discrete Event Simulation (DES). We will first discuss those typical benefits and how those same design-related benefits can be realized in Industry 4.0 applications. But Industry 4.0 introduces many new modeling demands. This chapter also discusses some of those new demands and how mainstream DES technology can be used to help assess the impact of advanced features, identify areas of risk before implementation, evaluate the performance of alternatives, predict performance to custom criteria, standardize data, systems, and processes, establish a knowledgebase, and aid communication. We will illustrate these concepts with four case studies as well as provide a brief tutorial on building a model of such a system using the Simio DES product.

Keywords DES · Design simulation · Simulation benefits · Industry 4.0 · Risk reduction · Performance prediction · Standardization · Communication · Digital transformation · Simio

1 Introduction

For decades, simulation has been used primarily for facility design improvements. Domains like manufacturing, airports, mining, ports, call centers, supply chains, and military have provided a rich set of case studies describing how simulation has been

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D. T. Sturrock (✉)
Simio LLC, 504 Beaver St, Sewickley, PA 15143, USA
e-mail: dsturrock@simio.com

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used to save tens or hundreds of thousands of dollars—sometimes even millions of dollars—per project. These are well accepted and documented applications of Discrete Event Simulation (DES). Almost 50 years of such case studies can be found on-line at the Winter Simulation Conference (WSC) Archive [1]. But Industry 4.0 introduces many new modeling demands. This chapter discusses some of those new demands and how mainstream DES technology can be used with Industry 4.0. Some material in this chapter is adapted from similar material in the book *Simio and Simulation: Modeling, Analysis, Applications* [2] and is included with permission.

There are many DES products on the market. Two popular sites that list and compare simulation software are Capterra [3] and the Informs Simulation Software Survey [4]. AnyLogic (Russia), Arena (USA), Plant Simulation (Germany), Simio (USA), and Witness (UK) are among the most widely used. Some DES products use the latest object-oriented technology, others are based on older procedural programming. Some have particular functional strengths like debugging tools or data handling, while others specialize in domain strengths like material handling or healthcare. What they all have in common is demonstrated strengths in providing value when used in the broad system design space. They are routinely used for purposes like:

Supply Chain Logistics: Just-in-time, risk reduction, reorder points, production allocation, inventory positioning, contingency planning, routing evaluations, information flow and data modeling
Transportation: Material transfer, labor transportation, vehicle dispatching, traffic management (trains, vessels, trucks, cranes, and lift trucks)
Staffing: Skill-level assessment, staffing levels and allocation, training plans, scheduling algorithms
Capital investments: Determining the right investments in the right things, at the right time. Investing for growth. Objective evaluation of return on investment
Productivity: Line optimization, product-mix changes, equipment allocation, labor reduction, capacity planning, predictive maintenance, variability analysis, decentralized decision-making.

A few of these usage areas, like human resource management, supply chains, and sustainability analysis are discussed in other chapters. While these DES tools have demonstrated significant value in traditional design-oriented applications, can these same tools provide useful value to Industry 4.0 implementations? And if so, how?

The first answer to how simulation can assist with Industry 4.0 is ‘all of the above’. At its simplest, a smart factory is just a factory—it has all the same problems as any other factory. Simulation can provide all the same benefits in the same areas where simulation has traditionally been used. In general, simulation can be used to objectively evaluate the system and provide insight into its optimal configuration and operation.

2 Simulation Case Studies

In this section we will illustrate the more traditional role of simulation with a few brief case studies. Some of these are drawn from material published in Pegden [5].

2.1 Healthcare—Denmark Health

The health system in the Capital Region of Denmark is a world-class automated health system that includes two Central Sterile Services Departments (CSSD), and two distribution centers that handle the receipt and dispatch of goods for the two CSSDs. The CSSDs and distribution centers are automated (Fig. 1) by robots for loading and unloading of storage goods and AGVs. Besides the transport of sterile goods, the distribution centers also handle other goods such as medicine, linen, uniforms, and waste. The CSSDs also supply other hospitals in the system with surgical equipment, ensuring the right equipment will be in the right place at the start of each day.

This system was modeled in two phases. The first phase was to access and fine-tune the system design using a Logisim model developed by ALECTIA. After the

Fig. 1 AS/RS system in Denmark Health CSSD

basic design was complete, a second simulation was created using a Simio model created by CGI for more detailed design and for operational control.

From the goods receipt, SAP system, or the sterile system, the Wonderware MES system receives information about items in the distribution center that must either be delivered within the hospital or sent by external transport to additional hospitals. Planning and scheduling of all transports is done using Simio, which directly integrates with the MES system. The schedule considers the type of object that must be transported, the expected transport time, and the capacity constraints in the facilities. Simio then creates an optimized plan for execution that is based on the simulated model of the system. Scheduling and re-scheduling is carried out automatically in response to events, and it reflects the current load of the facility.

2.2 Manufacturing—John Deere Cast Iron Foundry

Simio's RPS was implemented to improve the production scheduling at the John Deere Cast Iron Foundry (Fig. 2) in Waterloo Iowa. Many industries demand complex sequencing that involves multiple constraints in order to find the most feasible production schedule. This is particularly true for the highly automated and complex John Deere Cast Iron Foundry, which produces several hundred parts with various iron recipes and production constraints. The challenge was to have an integrated production scheduling system that allows for real-time data exchange between the Wonderware MES, and SAP ERP, as well as a system that could create a schedule based on the actual status of the production line with complex production constraints. The solution was implemented using Simio's RPS, and it has allowed us to consider complex material requirements, equipment resource availability, due dates, and nine different sequencing constraints.

2.3 Logistics—Shell Exploration and Production Company

In the Gulf of Mexico, Shell moves more than 50,000 tons of materials and equipment to offshore facilities (Fig. 3) each month using more than 40 offshore supply vessels. The shipments are broken into voyages, which include loading of the vessel, transiting to offshore locations, transferring materials offshore, returning to port, unloading, and possibly tank cleaning. In a typical month, Shell will schedule over 200 voyages that transport more than 9000 tracked items—anything from a simple pallet of chemicals to 20,000 feet of tubular goods.

The offshore supply vessels employed come in a variety of sizes and configurations: the vessels range in length from 100 to over 350 feet, with cargo capacities ranging from 500 to 6000 tons. Open back deck areas and below deck storage vary in terms of capacities and types of storage. Vessel travel durations are determined

Fig. 2 Casting Iron at John Deere Cast Iron Foundry

Fig. 3 Offshore Drilling Logistics

based on the distance between the port and rigs, and the travel rate of the vessel is dependent upon weather and location.

The complex scheduling process revolves around shipping requests, which identify the materials and equipment that need to be shipped within the next 5–10 days. Requests include the pickup and delivery points, quantities, dimensions, weights, and time constraints. Each port has a number of loading, unloading, and tank cleaning slips, and information about the slips' capabilities, vessel capacity, selection ranking, and load and unload times are configured for each slip.

Because of the enormity of the system and the presence of so much variability, Shell selected Simio's RPS for the solution. RPS has allowed Shell to generate schedules that meet their complex constraints, and to assess the risk associated with the schedules. The results from RPS are displayed in Gantt charts that visually display the details of each rig, slip, vessel, and demand item, and customized reports and dashboards are used to view the schedule from different perspectives.

2.4 Manufacturing—Defense Contractor

As a defense contractor, BAE Systems must reliably plan and predict production resources to meet the military's needs—items such as illustrated in Fig. 4 must be produced with on-time delivery and within budget. What their managers needed was more effective methods for production resource risk mitigation.

Fig. 4 Large gun barrels deployed on a ship

BAE Systems used Simio's RPS solution to provide planners and schedulers with a customized interface for generating schedules, performing risk and cost analysis, investigating potential improvements, and viewing 3D animations. Gantt charts now make it easy for their managers to see the timing of processes and to explore how changes in equipment or employees affect that timing. BAE Systems can run additional simulations whenever one or more factors change, resulting in a "finger on the pulse" awareness that allows quick adjustments and assures confident decision making.

Simio's RPS helps BAE Systems meet production deadlines and is now used for a variety of forecasting and scheduling challenges including decreasing overtime, managing equipment reliability issues, developing training goals, writing proposals, and evaluating capital investments.

3 More Than just a Factory

We said above that at its simplest, a smart factory is 'just a factory', and so can benefit from simulation in all the same ways as a typical factory could. But of course, a smart factory implementation is much more than 'just a factory' and differs in many important ways. A smart factory is generally larger and has not only *more* components, but more *sophisticated* components. While an optimist might read 'sophisticated' as 'problem free', a pessimist might read that as 'many more opportunities to fail'. Either way, a larger system with more interactions is harder to analyze and makes the traditional application of simulation even more important. It is difficult **to assess the impact of any specific advanced feature**. Simulation is possibly the only tool to allow you to objectively evaluate the interactions and contributions of each component, design a system that will work together, and then tune and optimize that system.

In a smart factory, IT innovations such as Big Data and Cloud Operation make real time data much more available. Although effectively handling large amounts of data is not a strength of all simulation products, more modern products allow incorporating such data into a model. While this enhanced data access potentially enables the system to perform better, it also exposes still more points of failure and the opportunity for a model of sufficient detail to **identify areas of risk before implementation**.

Another way that a smart factory differs is its level of automation and autonomy. The dynamic processes in a smart factory enable operational flexibility such as intelligently responding to system failures and automatically taking corrective action both to correct the failure and to work around the failure with appropriate routing changes. Again, this is an opportunity for a simulation to help assess those actions by **evaluating the performance of alternatives**.

Just as in a normal factory, a smart factory can't readily be run over and over with different configurations and settings. Simulation is designed to do just that. It projects future operations, **compressing days into just seconds**. Further, the simulation model can be easily adjusted when the effects of scaling up or down need to be studied. The resulting information answers fundamental questions about the processes and overall system, for example how long a process takes, how frequently some equipment is used, how often rejects appear, etc. Consequently, it **predicts performance criteria** such as latency, utilization and bottlenecks for direct improvement.

A benefit for larger organizations using this virtual factory model is **standardization of data, systems, and processes**. Typically, each factory within a large corporation has implemented their systems differently. These differences cause big problems when moving these facilities to single instances of ERP or attempting to implement other consistent operational controls. People need to be using the same processes and workflows, but how do they decide what process is the best and what data is correct or preferable? Using the virtual factory model to test different operational policies and data is the best way to determine the single best global process and adjust all factories accordingly. Using simulation with a data generated approach is valuable and interesting to these large corporations with multiple global factories.

Two other benefits of simulation are particularly applicable to smart factories—**establishing a knowledgebase** and **aiding communication**. It is very difficult to describe how a complex system works, and perhaps even more difficult to understand it. Creation of a model requires understanding of how each subsystem works and then representing that knowledge in the model. The simulation model itself becomes a repository of that knowledge—both direct knowledge embedded in its components as well as indirect knowledge that results from running the model. Likewise, the 2D or 3D model animation can be an invaluable way of understanding the system so stakeholders can better understand how the system works, more effectively participate problem resolution, and hence have better buy-into the results.

Although time consuming, the modeling stage requires the involvement of operators and personnel who are intimately familiar with the processes. This imparts an immediate sense of user involvement and ownership that can help in the later stage when implementing findings. To that end, a realistic simulation proves to be a much easier and faster tool for testing and understanding performance improvements in the context of the overall system. This is especially true when demonstrating to users and decision makers.

In these ways, simulation assists with:

- predicting the resulting system performance,
- discovering how the various parts of the system interact,
- tracking statistics to measure and compare performance,
- providing a knowledgebase of system configuration and its overall working, and
- serving as a valuable communication tool.

In summary, use of simulation in its traditional design role can provide a strong competitive advantage during development, deployment and execution of a smart factory. It can yield a system that can be deployed in less time, with fewer problems, and yield a faster path to optimal profitability.

4 Building a Simple Model

Each of the DES tools mentioned in the introduction have their own strengths and weaknesses for building design-oriented models of an Industry 4.0 system. But since Simio has some unique capabilities (see Chapter "Using Commercial Software To Create a Digital Twin") in being used in a highly integrated role in Industry 4.0, we will include here a brief example of building a Simio-based model of a simple system for design and operational purposes. You can build this model with the Simio Personal Edition—available by download at no charge from https://www.simio.com/free-simulation-software/.

When you first load Simio you will be presented the option to view a Quick Start video. Watching this short, 15 min, video will introduce you to the basics of navigation, model-building, and experimentation in Simio. We will assume that you have carefully watched that video and so already know the basics of model building. If you accidentally dismissed that video, you can locate it on the Support Ribbon—it is the first video listed under the "Videos" button.

Now that you have watched the Quick Start video, you should see a new Simio project. If not, create a new model by clicking on the "New" item in the File page Fig. 5 shows the default initial view of a new Simio project, looking at the blank model. Although you may have a natural inclination to start model building immediately, we encourage you to take time to explore the interface and the Simio-related resources provided through the Support ribbon (described in the video).

Using Standard Library objects (Table 1) is the most common method for building Simio models. These pre-built objects will be sufficient for many common types of models. Start with a new project and place a Source, three Servers, and a Sink, then name the servers and connect them with paths as illustrated in Fig. 6. As you build the model, leave all the object properties at their default values. Group select the three servers and in the Advanced Options property group set Log Resource Usage to True. Set the Ending Type on the Run ribbon to a Run Length of 1 h.

Select the Planning Tab and the Operational Planning Ribbon and click the Create Plan button. When you view the Resource Plan (click top button on the left) you will see each resource listed and on the right side you will see the activity on each resource—more specifically, you will see when each entity started and stopped processing on each resource. If you use the Zoom In or Zoom Range functions on the Gantt ribbon, or simply scroll the mouse on the Gantt time scale, you will be able to more closely examine the activity in a view that looks like Fig. 7.

Click the Entity Workflow button on the left, to see a different Gantt view displaying all entities in separate rows, which resources it used, and when it started and stopped processing on each resource. Again, you can use the Zoom features to zoom in, so you can see the detailed activities of the first few entities listed (Fig. 8). Note that the entity ID's are sorted as strings (not numerically)—so the first entity created 'DefaultEntity.19' comes between 'DefaultEntity.189' and 'DefaultEntity.190'—perhaps not intuitive, but we will address that shortly.

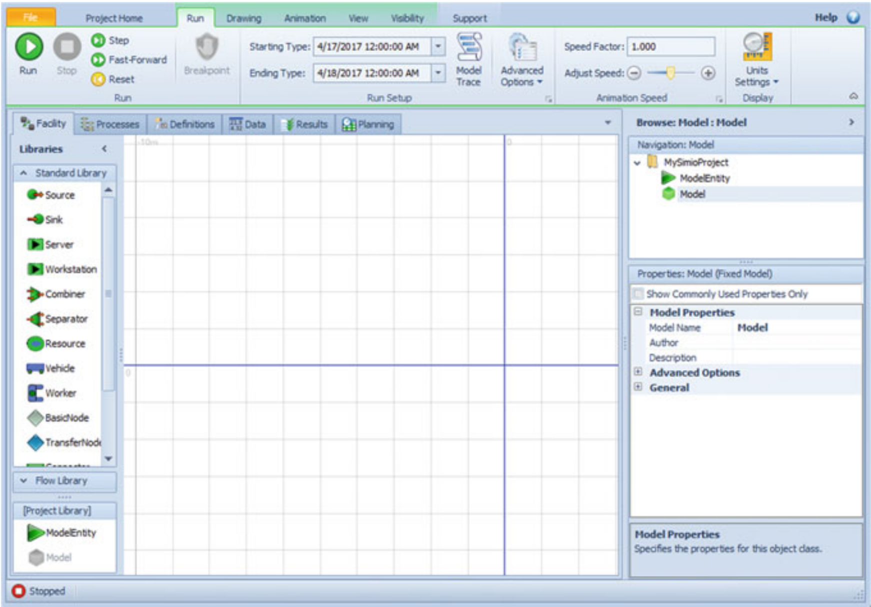


Fig. 5 Facility window in a new Simio model

Table 1 Simio Standard Library

Source	Generate entities of a specified type and arrival pattern
Sink	Destroy entities
Server	Capacitated process, such as a machine
Workstation	Capacitated process, includes setup, process, tear-down
Combiner	Batches entities with a parent entity (e.g., pallet)
Separator	Splits batches or copies entities
Resource	Seized/released by objects
Vehicle	Fixed route or on-demand pickups/drop-offs
Worker	Moveable resource, for stationary and non-stationary tasks
Basic node	Simple intersection, fixed object input
Transfer node	Change destination/get rides, fixed object output
Connector	Zero travel time
Path	Entities independently move at their own speeds
Time path	Entities complete travel in a specified time
Conveyor	Accumulating/non-accumulating conveyor devices

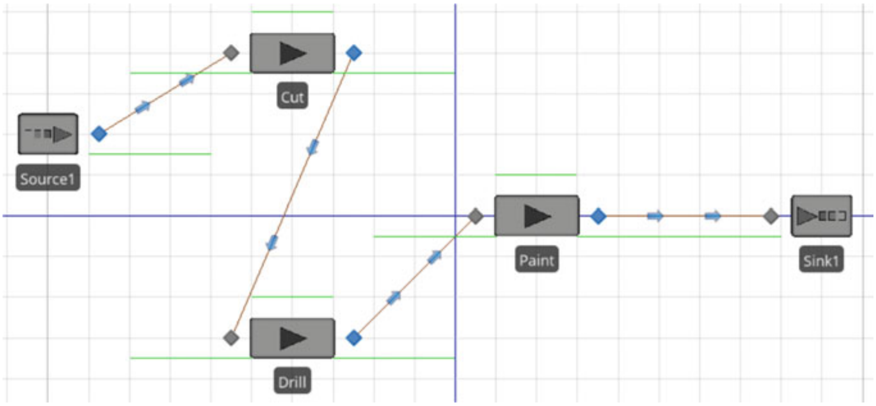


Fig. 6 Facility window of our simple Simio model

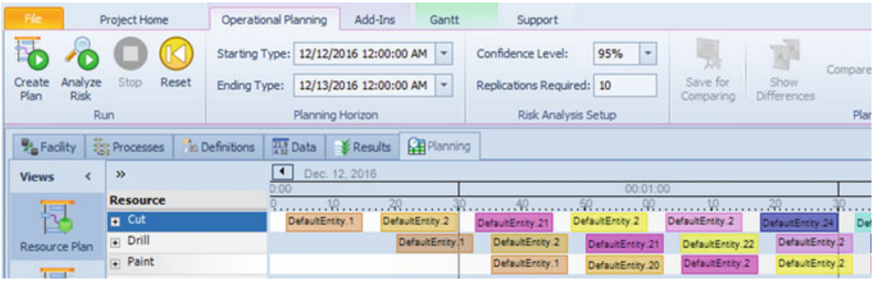


Fig. 7 Resource Plan zoomed to show entity details

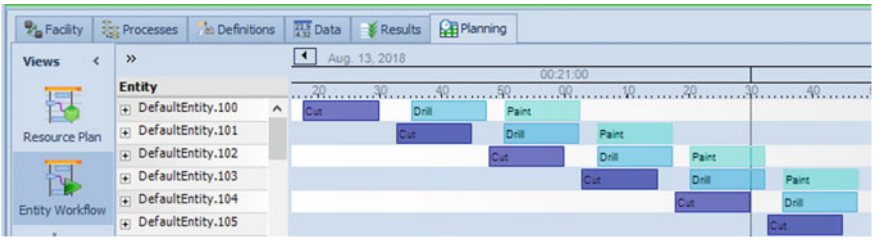


Fig. 8 Entity Workflow Gantt zoomed to show resource details

5 Creating a Data-Driven Model

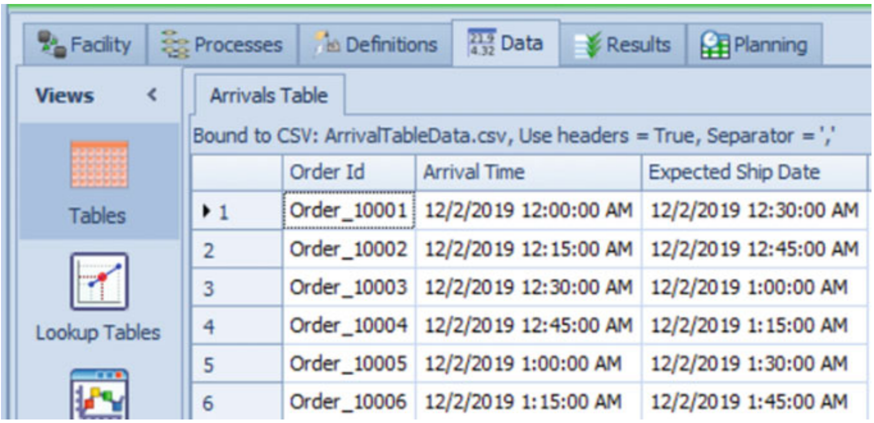
A Simio *Data Table* is similar to a spreadsheet table. It's a rectangular data matrix consisting of columns of properties and rows of data. Each column is a property you select and can be one of about 50 Simio data types, including Standard Properties (e.g., Integer, Real, Expression, Boolean), Element References (e.g., Tally Statistic, Station, Material), or Object References (e.g., Entity, Resource, Node). Typically, each row has some significance; for example, the row could represent the data for a particular entity type, object, or organizational aspect of the data.

Data tables can be imported, exported, and even bound to an external file. They can be accessed sequentially, randomly, directly, and even automatically. You can create relations between tables such that an entry in one table can reference the data held by another table. In addition to basic tables, Simio also has Sequence Tables for creating process plans and Arrival Tables for scheduled arrivals, each a specialization of the basic table. Refer to Simio help for more information on these topics.

While reading and writing files interactively during a run can significantly slow execution speed, tables hold their data in memory and so execute very quickly. Within Simio you can define as many tables as you like, and each table can have any number of columns of different types—you can define any table schema you need. You'll find tables to be valuable in organizing, representing, and using your data as well as interfacing with external data.

Let's make our model more realistic by using a data file containing orders we want to produce and using more appropriate processing times. First, back in the Data tab, we want to go to the Schema ribbon, add a table (Add Table button) and name this new table ArrivalTable. You will find a CSV file named ArrivalTableData.csv from the folder named DataDrivenModelDataFiles found in the student downloads files. Use the Create Binding button on the Content ribbon to bind this CSV file to your new table. This action establishes a relationship between the table and the file, as well as creates the schema (column definitions) so we can import the data. With this established, we can now Import the file into the table (Fig. 9). Since this table has actual calendar dates in it, the model must be configured to run during those dates. On the Run ribbon, set the Starting Type to Specific Starting Time matching the first arrival (12/2/2019 12:00:00 AM) and set the Ending Type to Run Length of 1 Days.

In the Facility view select the Source1 object so we can configure it to create entities using the new table. Set Arrival Mode to ArrivalTable and set the Arrival



	Order Id	Arrival Time	Expected Ship Date
1	Order_10001	12/2/2019 12:00:00 AM	12/2/2019 12:30:00 AM
2	Order_10002	12/2/2019 12:15:00 AM	12/2/2019 12:45:00 AM
3	Order_10003	12/2/2019 12:30:00 AM	12/2/2019 1:00:00 AM
4	Order_10004	12/2/2019 12:45:00 AM	12/2/2019 1:15:00 AM
5	Order_10005	12/2/2019 1:00:00 AM	12/2/2019 1:30:00 AM
6	Order_10006	12/2/2019 1:15:00 AM	12/2/2019 1:45:00 AM

Fig. 9 ArrivalsTable after import from CSV

Time Property to ArrivalTable.ArrivalTime. Let's also make the server processing times more realistic. Group select (select, Ctrl-select, Ctrl-select) the three servers and change the Units on Processing Time to be Hours instead of Minutes.

The last thing we want to do for now is to use the OrderID listed in the table to identify our entities. Drag a ModelEntity into the Facility view so we can edit its properties. In the Default Entity Advanced Options category set the Display Name to ArrivalTable.OrderId. Under the Animation category also set the Dynamic Label Text to ArrivalTable.OrderId. These two changes will let Simio identify each entity with the information in the data table rather than its default (e.g., Order_10001 instead of DefaultEntity.17).

We are done with this series of enhancements, so let's examine our results. Navigate back to the Entity Workflow Gantt under the Planning tab. You should see a bright red bar indicating that we have changed the model since we last ran it, so let's refresh the Gantt chart by clicking the Create Plan button. After zooming again to adjust to the new times, you should see all your entities listed, now with more meaningful names based on how they were identified in the ArrivalTable (Fig. 10). And in the Resource Plan, you should see each of your resources as they were, but now the entities again have more meaningful names (Fig. 11).

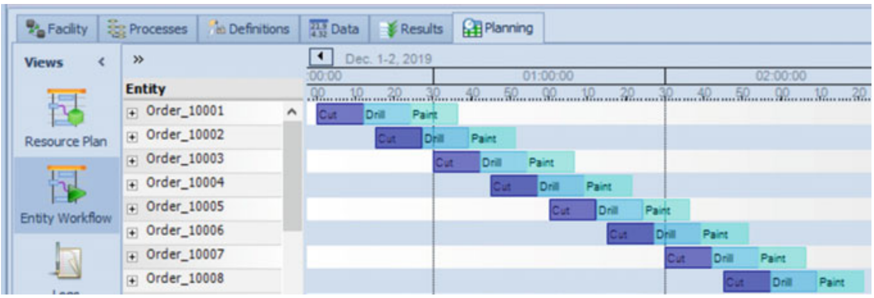


Fig. 10 Entity Workflow Gantt with better times and entity labels

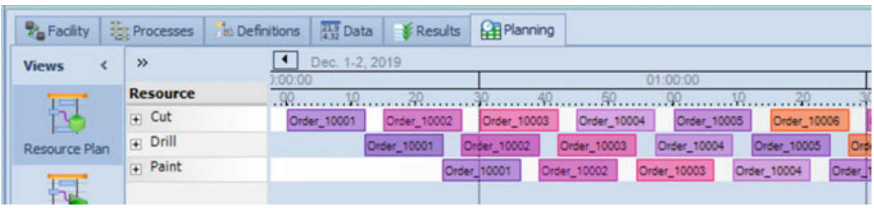


Fig. 11 Resource Plan Gantt with better times and entity labels

6 Adding Performance Tracking and Targets

Now that our model is working, let's add a few features to help us evaluate how well our schedule is working. One important item is to record when each order is planned to ship. We do that by first adding a State to our table. Navigate back to the table and select the States. Select a DateTime state to add it to the table. Name this column ScheduledShipDate. This is an output column that is assigned values during the run, so initially it will show errors indicating no data yet. We must assign those values in Sink1, where orders go when they are completed. In the State Assignments section of Sink1 assign ArrivalTable.ScheduledShipDate to TimeNow.

Another important item is to evaluate whether the order is scheduled to be shipped on time. We do that by adding a Target to the table. Navigate back to the Table and open the Targets ribbon. When you click on the Add Targets button, two columns are added to the table—a Value and a Status for that target. Name this target Target-ShipDate. The Expression we want to evaluate is ArrivalTable.ScheduledShipDate which has the Data Format of DateTime. The value we want to compare this to is ArrivalTable.ExpectedShipDate—we don't want to exceed that value, so we make it the Upper Bound. You will typically want to replace the default terminology for clarity. Under the Value Classification category set the values of Within Bounds to On Time, Above Upper Bound to Late, and No Value to Incomplete. If you run the model now, you will see that the status of all the orders is Late.

Let's balance the system by changing the Processing Time for all the servers to be Random.Triangular(0.05, 0.1, 0.2) Hours. Rerun the model and look at our table again. You will see that now all orders are On Time. If we move over to the Entity Workflow on the Planning tab and run Create Plan, you will see that the plan now has a gray flag on each entity indicating the Target Ship Date. When that flag is to the right of the last operation, that indicates a positive slack time (e.g., the plan calls for that order to complete early). But we don't yet know how confident we can be in those results. If you click the Analyze Risk button the model will run multiple replications with variability enabled and those flags will change color and display a number that is the likelihood that the order will be On Time.

This model does not yet include much variation, so let's add variation in three places. First, let's allow for variability in order arrival times. If orders typically arrive up to a quarter hour early or up to a half hour late, we would represent that on the Source by setting the Arrival Time Deviation under Other Arrival Stream Options to Random.Triangular(−0.25, 0.0, 0.5) Hours. Second, let's assume that the Drill is a bit longer and less predictable than the others and set its Processing Time to Random.Exponential(0.2). Finally let's recognize that all three servers have some reliability problems. Under Reliability add a Calendar Time Based failure to each, leaving the default Uptime Between Failures and Time to Repair. Return again to the Entity Workflow Gantt, click Analyze Risk, and now you will see that even though most orders are still projected to be on time in the deterministic plan, when the variability is considered most of them have a low probability of actually being on-time (Fig. 12).

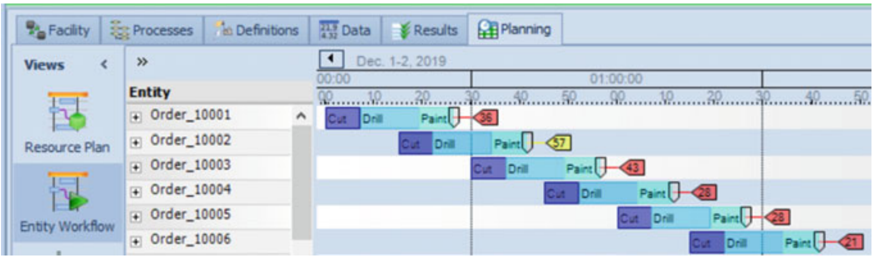


Fig. 12 Higher variability system with risk analysis

7 Summary

This chapter provided only a brief introduction into model-building, illustrated with Simio. We created a very simple model, imported a data table to drive the model, generated a schedule, and performed basic risk analysis. While we did not take the time to animate our simple model, Fig. 13 illustrates the 3D animation that is possible for a large system.

Simulation can be used in all aspects of design analysis including the inclusion of more complex modeling features like AGVs, ovens, conveyors, and overhead cranes. Simulation can also represent complex interactions like and worker scheduling, skill-based worker selection, and sophisticated resource and routing rules, and then be used to objectively evaluate system design and performance. All of these encompass

Fig. 13 Sample 3D animation (model created by Mosimtec)

traditional design-oriented use of simulation, in support of modeling Industry 4.0 applications to design and implement the most effective systems.

In Chapter "Using Commercial Software To Create a Digital Twin" we will build on these concepts, to explore the additional benefits of using simulation in support of a digital twin. You can obtain more detail about Simio features and building Simio models by accessing one of the popular Simio textbooks [2, 6] or the videos, examples, SimBits and other training materials available with the Simio software (see the Support ribbon).

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Distributed Simulation of Supply Chains in the Industry 4.0 Era: A State of the Art Field Overview

Korina Katsaliaki and Navonil Mustafee

Abstract Simulation approaches have long been used in the context of supply-chain management (SCM). Unlike the conventional approach which models the different stages of SC as a single simulation, a distributed supply-chain simulation (DSCS) enables coordinated execution of existing models through use of distributed simulation middleware. The new era of Industry 4.0 has created the "smart factory" of cyber-physical systems which controls the route of products' assembly line for customised configuration. The collaboration of all supply-chain players in this process is essential for the tracking of a product from suppliers to customers. Therefore, it becomes necessary to examine the role of distributed simulation in designing, experimenting and prototyping the implementation of the large number of highly interconnected components of Industry 4.0 and overcome computational and information disclosure problems amongst supply chain echelons. In this chapter, we present an overview and discuss the motivation for using DSCS, the modelling techniques, the distributed computing technologies and middleware, its advantages, as also limitations and trade-offs. The aim is to inform the organizational stakeholders, simulation researchers, practitioners, distributed systems' programmers and software vendors, as to the *state of the art* in DSCS which is fundamental in the complex interconnected and stochastic environment of Industry 4.0.

Keywords Supply chain management · Distributed simulation · Industry 4.0 · Simulation methods · Overview

K. Katsaliaki (✉)
School of Economics, Business Administration and Legal Studies, International Hellenic University, 57001 Thessaloniki, Greece
e-mail: k.katsaliaki@ihu.edu.gr

N. Mustafee
Business School, University of Exeter, Rennes Drive, Exeter EX4 4ST, UK
e-mail: n.mustafee@exeter.ac.uk

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1 Industry 4.0 and Supply Chains

The new era of Industry 4.0 has created the, so called, "smart factory" of cyber-physical systems, such as internet-connected workstations, conveyors and robotics which autonomously control and monitor the route of products' assembly line for customized configuration.

These cyber-physical systems communicate with each other to support production line automation and are capable of analyzing, understanding and solving certain production problems when arise with minimum human intervention. This is achieved through inter-connected machines and "Internet of Things (IoT)" devices which send real-time data to platform services and databases. The expanding corpus of data, with data-driven algorithms and 'fast' and 'cheap' commodity hardware make possible big data analytics. Artificial Intelligence and Machine Learning algorithms rely on such humongous data source to make predictions and corrections, and which are communicated back to the networked machines belonging to the different echelons of the supply chain.

For example, a smart factory of shoes production in China that exports its products to the EU market could acquire more accurate and detailed demand forecasts for the coming season by analyzing big data reports about the market, financial and weather conditions of these countries throughout the year. These forecasts can then be translated to capacity requirements and production runs of (small) lot sizes which the interconnected machines can handle without necessarily requiring re-programming, just parametrization and self-recognition by the machine of the raw materials. Following production, a flexible distribution system must be in place to move the right stock, in the right quantity, to the right targeted markets in a timely manner.

From the above example, it is understood that the collaboration of all supply chain players in this process is essential for the tracking of a product's life cycle from suppliers to customers and back and for increasing the transparency of all supply chain steps. According to the study of Tjahjono et al. [85], warehouse, transport logistics, procurement and fulfilment functions will be critically affected by the implementation of Industry 4.0 technologies, with order fulfilment and transport logistics processes having the greatest impact. Increased flexibility, quality, and productivity are some of the advantages of Industry 4.0 in the supply chain of a product/service which can enable optimized decision-making, mass customization, and the introduction of new products/services for meeting higher customers' expectations. It is said that the implementation of Industry 4.0 technologies and in particular of, virtual and augmented realities, 3D-Printing and simulation will all result in supply chain management opportunities [85]. Simulation approaches provide a general and powerful decision-making paradigm for the control of industrial systems in the Industrial 4.0/Industrial Internet era [91].

Simulation approaches have long been used in the context of supply chain management (SCM) for designing new supply networks, for performance evaluation of existing supply chains, and for experimenting with alternative configurations through what-if scenarios. In conventional supply chain simulation (SCS), the underlying constituents of the system like manufacturing, distribution, retail and logistics processes are often modelled and executed as a single model. However, runtime and other operational problems of these huge and complex conventional models lead to the development of new simulation modes. Therefore, unlike the conventional approach, a distributed supply chain simulation (DSCS) enables coordinated execution of existing models through use of distributed simulation middleware.

Therefore, faced with the challenges that Industry 4.0 imposes, it is, as ever, important to examine the role of distributed simulation in designing, experimenting and prototyping the implementation of the large number of highly interconnected components and subsystems of Industry 4.0 and overcome computational and information disclosure problems amongst supply chain echelons that traditional simulations face.

2 Supply Chains and Simulation

Supply Chains, from their very nature, are usually complex as they entail, (a) all the processes from procurement and manufacturing to sales and support [73], (b) there are forward and backwards flows of information and funds that influence the behaviour of the chain, and (c) supply and demand are often variable. Moreover, modern supply chain management approaches favour a global, holistic view in which the individual echelons share information and trust each other, rather than simply trying to optimise their own local processes independently of its neighbours [9]. Most of these multi-echelon and complex supply chains can benefit from Operational Research (OR) techniques, such as 'simulation', which is recognised as the second most widely used technique after 'Modelling' in the field of Operations Management [60]. In the context of decision support within a stochastic supply chain environment, simulation is widely regarded as a powerful analytical technique [4, 84] as it is a tool which can provide multi-decisional support with regard to "what-if" analysis and evaluation of quantitative benefits. However, there are two specific problem scenarios which may severely limit the application of the conventional simulation (by conventional we mean a standalone one-computer simulation execution) for decision making, and we argue that such a limitation may be alleviated through the execution of simulation over multiple processors. We refer to the latter as 'distributed simulation'. The two important problem scenarios are now presented, both of which can be considered as major drivers for the application of distributed simulation to supply chains.

- **Scenario One—Distributed Simulation as an enabler of large and complex supply chain models**: The size of a supply chain can be potentially quite large and can consist of many complex elements. The simulation of a supply chain can therefore demand the creation of large models that, it is argued, are beyond the capability of a single computer to simulate [24, 33, 55, 78].
- **Scenario Two—Distributed Simulation as an enabler of inter-organisational supply chain models**: In recent years, the scope of SCM has evolved to cross the enterprise boundaries, as vertical integration is no longer the emphasis of large

corporations [1]. In order to increase performance over the supply chain, accurate simulation models have to be built. There are generally two strategies for creating an overarching simulation model that encompasses the individual supply chain processes. The first strategy is to create a single simulation model—this is the conventional approach and is not the focus of this chapter (unless the solitary simulation is large and complex and thus requires the use of distributed simulation—this is scenario one). The second strategy is to develop different models for the individual supply chain elements and then to use distributed simulation technology to execute the models in sync. The latter approach, which, together with scenario one, is the focus of this chapter, is arguably better equipped to tolerate the physical changes that may take place in the underlying supply chain structures (for example, a change in the logistics provider can be modelled by replacing the former logistics model with a new model that simulates the processes of the new provider. This alleviates the need for creating a new supply chain model). However, although such detailed models do not pose a problem when the chain involves only a single enterprise, not many participating companies are willing to share detailed model information when the chain crosses the enterprise boundaries. Distributed simulation techniques enable technology that allows corporations to construct a cross enterprise simulation while hiding model details within the enterprise. An informative example is given by Gan and Turner [24].

The purpose of the literature review presented in this book chapter is to review the extant literature in distributed supply chain simulation as a useful modelling tool for the Industry 4.0 era. This is achieved through a methodological review and categorization of literature pertaining to this topic. More specifically, we have undertaken a search for relevant articles using the ISI Web of Knowledge^{SM} citation and journal database. We have complemented this "search, retrieve and read" process with our domain-specific knowledge, and have presented the results of this literature review in well-defined categories. Our main purpose of undertaking this review is to inform the researchers, stakeholders in supply chains, simulation practitioners, distributed systems' programmers, etc. as to the *state of the art* in distributed simulation of supply chains. We hope that this would enable those interested in modelling such supply chains to refer to the existing studies with the objective of identifying the most suitable modelling techniques, the underlying technologies and the expertise required, its potential advantages, as also its limitations and the trade-offs that may be associated with this distributed modelling approach.

This section has presented an overview of distributed simulation in the context of supply chains. Furthermore, it has highlighted the motivation of this literature review. The rest of this book chapter is organised as follows. Section 3 is on distributed simulation—it discusses the terminologies, its potential benefits, application areas and the underlying protocols. Section 4 sets the scope of this study. This is followed by an overview of three simulation techniques that were identified in the context of distributed supply chain simulation (Sect. 4). The following three sections present a review of literature on distributed supply chain simulation. The sections are classified on the basis of the underlying simulation technique that was used for modelling—thus, Sects. 6, 7 and 8 refer to Discrete Event Simulation, Agent-Based Simulation and System Dynamics (including Hybrid Simulation) respectively. The studies that fall under each of these sections are organised into two subsections according to the scenarios defined earlier in this section, namely, (a) studies of distributed simulation enabling large and complex SC models, and (b) studies of distributed simulation enabling inter-organisational SC models. Section 9 is the concluding section of this chapter with a discussion around the implementation of DSCS.

3 Distributed Simulation

Professor Richard M. Fujimoto is one of the major contributors in the area of Parallel and Distributed Simulation (PADS). His books [19, 20] are *state of the art* guides for the implementation of PADS technology. We therefore predominantly refer to the work of Prof. Fujimoto while progressively analysing and defining the term 'distributed simulation'. PADS is a technique where models are implemented over many computers in a parallel or distributed fashion with the goals of reducing the execution time of a single simulation run, sharing the memory needs of a simulation across several computers and the linking of simulations sited in different locations [21, 22]. This definition of PADS makes reference to the terms 'parallel' and 'distributed' and it is important to distinguish between them. In the context of PADS, Fujimoto [19, 23] distinguishes between parallel simulation and distributed simulation based on the frequency of interactions between processors during the simulation execution. A parallel simulation is defined as running a simulation on a tightly coupled computer with multiple central processing units (CPUs) where the communication between the CPUs can be very frequent (e.g., thousands of times per second). A distributed simulation, on the other hand, is defined as executing simulations on multiple processors over loosely coupled systems (e.g., a network of PCs) where the interactions take more time (e.g., milliseconds or more) and occur less often. Sometimes the terms parallel simulation and distributed simulation are used interchangeably [65]. In one of his more recent papers, Fujimoto [22] uses the term distributed simulation to refer to both the parallel and distributed variants of PADS. The rationale presented is that, although historically, the terms 'distributed simulation' and 'parallel simulation' referred to geographically distributed simulations and simulations on tightly coupled parallel computers respectively, new distributed computing paradigms like clusters of workstations and grid computing has made this distinction less obvious. The study presented in this chapter takes a similar view and therefore does not distinguish between the parallel and distributed variants of PADS. The term distributed simulation will henceforth be used to refer to the execution of distributed simulation on both multiprocessor machines and over network of PCs.

For the purposes of the book chapter, we define distributed simulation as the distribution of the execution of a single run of a simulation program across multiple processors [19]. The following extract is taken from previous work by the authors on the motivations and barriers in using distributed supply chain simulation [55]. For

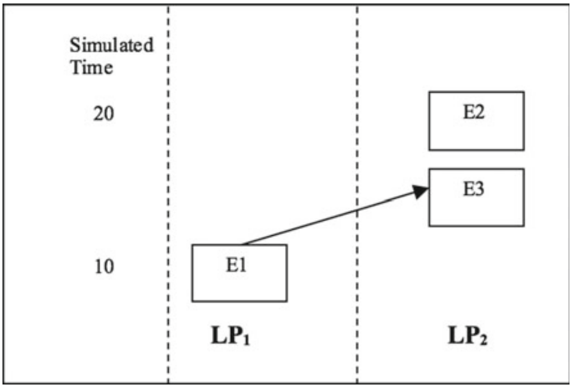

Fig. 1 Execution of events in a distributed simulation (adapted from [18])

coordinated execution of the simulation, time management algorithms (see Sect. 3.3) need to be implemented to guarantee that an event with a lower simulation timestamp is executed prior to an event with a higher timestamp. Failure to do so will lead to causality error. A distributed simulation executing over multiple machines will have several logical processes. These logical process can be mapped to physical process in the hardware. In the context of supply chains, the physical processes may characterise the activities of manufacturing organisations or they may represent processes associated with storage, transport and logistics. All the interactions between the physical processes (e.g., material movement from one supply chain component to the other) are modelled as messages that are exchanged between their corresponding logical processes. Each message will have a time stamp associated with it. Figure 1 shows that the simulation represents a physical system that has two physical processes, say, PP_1 and PP_2. Logical simulation processes LP_1 and LP_2 model the two physical processes. Each of these logical processes have their own simulation engine, simulation clock and an event list. During simulation initialisation the event lists of both LP_1 and LP_2 are populated with the events $E1$ and $E2$ respectively. The timestamps for $E1$ and $E2$ are 10 and 20 respectively. It will be possible for LP_1 to process event $E1$ without any causality error since the timestamp of $E1$ < timestamp of $E2$. But LP_2 will not be able to execute event E2 at time 20 because causality error may then occur. The reason for this is that execution of $E1$ might schedule another event $E3$ for LP_2 at time 15. In such a case, if LP_2 had been allowed to execute $E2$ at simulated time 20 then it would have resulted in a causality error because the time stamp of $E3$ < the time stamp of $E2$. Different synchronisation protocols are proposed for distributed simulation that prevent or correct such causality errors. These are discussed in Sect. 3.3.

3.1 Advantages of Distributed Simulation

Potential benefits of using distributed simulation can be [21, 22], (a) a reduction in the time required to execute large and complex models by using larger number of processors and more memory, (b) facilitating the building of reusable models by 'hooking together' existing simulations into a single simulation environment, (c) reduction in costs associated with creating new models through reuse of existing interoperable model components (it is usually far more economical to link existing simulations to create distributed simulation environments than to create new models within the context of a single tool or piece of software), (d) integrating "inherently separated" simulators by executing simulations on a set of geographically distributed computers and thus facilitation wider user participation in the simulation experiments, e.g., co-operative development and execution of simulations, (this also alleviates the cost and time that is normally associated with bringing participants to one physical place for conducting a joint simulation exercise), (e) integrating proprietary simulators, e.g., Commercial-Off The Shelf tools—refer to Mustafee and Taylor [53], and (f) realizing enhanced functionality, e.g., composing multiple disparate models.

3.2 Application Areas of Distributed Simulation

Military applications have traditionally been the primary benefactor of distributed simulation, and indeed most of this technique's protocols have been developed by the military (like the US Department of Defence Modelling and Simulation Coordination Office) and for the military (e.g., distributed simulation of war scenarios, analytical war games simulation, simulation-based acquisition, interoperability and reuse of existing simulation created by, for example, the NATO member countries). Another application of distributed simulation in the military is for training, and Test and Evaluation (T&E) [15]. These are conducted in Distributed Virtual Environments (DVE) where both humans (*human-in-the-loop*) and devices (*hardware-in-the-loop*) take part in the simulation. Other application areas of distributed simulation includes, (a) network simulation, e.g. internet protocols, network security, P2P designs, (b) traffic simulation, e.g. emergency planning/response, environmental policy analysis, urban planning, (c) social dynamics simulation, e.g. operations planning and supply chain management, marketing, foreign policy, (d) organisation simulations, e.g. business processes, command and control, (e) sensor simulations, e.g. wide area monitoring, situational awareness, border surveillance and a few others. One of the emerging application areas of distributed simulation in the civilian domain, presented here under the social dynamics simulations category, is its use in supply chains which is indeed the focus of this chapter.

3.3 Distributed Simulation Protocols and Middleware

A simulation has to process events in increasing timestamp order. Failure to do so will result in causality errors. A causality error occurs when a simulation has processed an event with timestamp $T1$ and subsequently receives another event with timestamp $T2$, wherein $T1 > T2$. Since the execution of the event with time stamp $T1$ will have normally changed the state variables that will be used by the event with timestamp $T2$, this would amount to simulating a system in which the future could affect the past [18]. Synchronization protocols are used to prevent causality errors from occurring. They can be broadly divided into conservative (pessimistic) synchronization protocols and optimistic synchronization protocols. In a conservative protocol a processor is never allowed to process an event out of order; whereas in an optimistic protocol a processor is allowed to process an event out of order, provided it can revert back to its previous state in the case of a causality error [57]. A pessimistic protocol like Chandy-Misra-Bryant [6, 7] implements the conservative synchronization protocol. Synchronization here is achieved through propagation of "null" messages [7] or through deadlock detection and recovery mechanisms [8]. An optimistic synchronization protocol like Virtual Time, and its implementation called the Time Warp mechanism, executes events without considering the event time ordering [32]. It has to save its state frequently so that a rollback to a previous state can occur when an event with a time stamp less than the current simulation time is received.

A distributed simulation middleware is a software component that implements the conservative and optimistic algorithms to achieve synchronization between the individual running simulations. Examples of such middleware include, Aggregate Level Simulation Protocol (ALSP), Distributed Interactive Simulation (DIS), IEEE 1516 High Level Architecture—Run Time Infrastructure (HLA-RTI), FAMAS, GRIDS and CSPE-CMB. The reader is referred to Mustafee [50] for a discussion on these middleware. For the purposes of the study presented in this book chapter, we do not discriminate among the alternative distributed simulation middleware that may have been used to model supply chains. However, we would like to draw the readers' attention to a few of our observations: (a) Distributed simulation middleware like Aggregate Level Simulation Protocol (ALSP) [17] and Distributed Interactive Simulation (DIS) [48] have been used widely in defence training simulations. However, there has been no reported application of these technologies to civilian simulations; (b) The High Level Architecture (HLA) [29], although originally proposed to address the need for interoperation between existing and new simulations within the U.S Department of Defense, is now generally accepted as the de facto standard for distributed simulation. It is now an IEEE standard. There are several examples of using the HLA standard and the accompanying middleware (Run Time Infrastructure, or RTI for short) for creating distributed simulation in the civilian sector; (c) Several middleware have been developed in the academia with the objective of facilitating distributed simulation in the industry, e.g., GRIDS [78], CSPE-CMB [49] and FAMAS [5]. However, much of this software is developed for a specific project and is not available for download. One exception to this is the Service-Oriented HLA RTI [59], SOHR for short, that has been developed by the *Parallel and Distributed Computing Centre* (*PDCC*), *Nanyang Technological University, Singapore*.

3.4 Distributed Supply Chain Simulation (DSCS)

The following extract is taken from previous work by the authors on the motivations and barriers in using distributed supply chain simulation [55]. Figure 2 illustrates a possible supply chain scenario where DSCS could be applied and shows three organisations (X, Y and Z), each engaging in a specific activity. Here there may be concerns regarding information security since each company may not wish to reveal its data and internal processes to another company that it is happy to work with. If this supply chain was represented as a single model then these 'secrets' would be revealed as they would be specified explicitly in the model. In addition to *privacy*, further problems include problems associated with data transfer (e.g., companies 'X', 'Y' and 'Z' may be happy to share data, however, data once imported becomes instantly out of date) and long execution time associated with large models.

In the above cases, an alternative approach is needed. Here we create separate DES models for processes representative of each organisation. Linking the models together over a network such as the Internet using distributed simulation technologies and techniques creates a DSCS. This allows the models to be executed separately

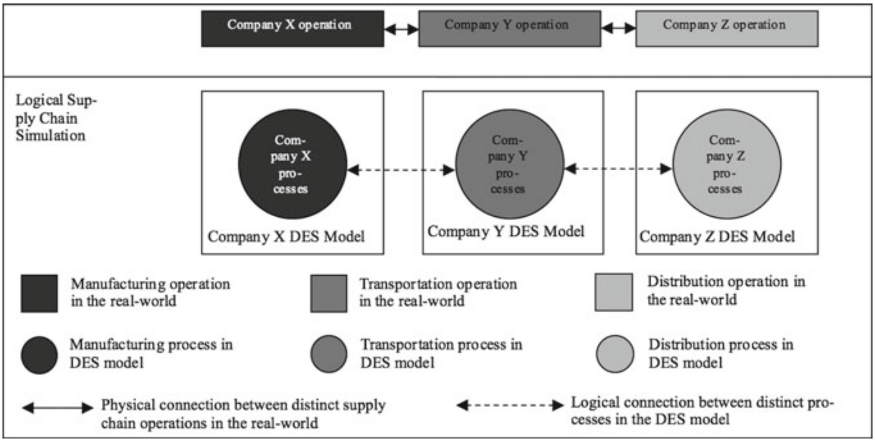

Fig. 2 Modern supply chain with organisations X, Y and Z involved in manufacturing, transportation and distribution operations respectively. The logical simulation processes representing these operations are contained in three different DES simulations, each representative of the physical operation associated with a specific organisation [55]

and privately by companies X, Y and Z respectively, to simulate organisation-specific processes while accessing local data, and avoiding many model composability issues.

4 Defining the Scope of the Study

It is important that we define the scope of this study at this point; the scope determines the articles that are selected for the subsequent literature review. Towards this end, it is useful to set the boundaries of this literature review by defining the terms 'distributed simulation' (refer to the next paragraph) and 'simulation modelling'(discussed in the subsequent paragraph).

In Sect. 3 we define the term distributed simulation and state that it refers to the distributed execution of simulations on both multiprocessor machines and over network of PCs. For the purposes of the literature review presented in this book chapter, the simulation studies that we are focussing on are those which *implement distributed simulation protocols, algorithms and middleware*, and which are executed *faster-than-real-time*. Thus, real-time simulations that are generally executed as per wall-clock time are outside the scope of this study. These simulations are often referred to as Distributed Virtual Environments (DVE)/Distributed Virtual Reality (DVR) simulations, which may either reflect reality (e.g., pilot training) or may be completely fictitious (e.g., DVR games), where both humans and machines (e.g., a physical cockpit simulator for training pilots) may interact with each other in a simulated environment. Our focus on distributed simulation protocols, algorithms and middleware has meant that we also ignore some simulation studies that only make use of distributed systems concepts (e.g., sockets, Web Services) for message passing among computers, without any underlying need for causality detection and correction. An important example of this is the beer game [71].

Computer simulation models are decision support techniques that allow stakeholders to conduct experiments with models that represent real-world systems of interest [61]. It can be used as an alternative to "learning by doing" or empirical research [68]. Furthermore, simulation modelling gives stakeholders the opportunity to participate in model development and, hopefully, gain deeper understanding of the problems they face. As a result, decision-makers and stakeholders can gain a new perspective on the relationships between the available parameters, the level of systems' performance, the cost-effectiveness and its quality or risk association. In light of the above, our interest starts by identifying the different simulation methods which have been used over the years in addressing supply chain issues. The review of simulation techniques in business and manufacturing by Jahangirian et al. [30] has identified the following simulation techniques: Discrete-Event Simulation (DES), System Dynamics (SD), Agent-Based Simulation (ABS) and Monte Carlo Simulation (MCS), Intelligent Simulation, Traffic Simulation, Distributed Simulation, Simulation Gaming, Petri-Nets and Virtual Simulation, excluding simulation for physical design. According to this study the first five techniques were the most commonly presented/used in the selected papers for that review.

The simulation modelling techniques that were found appropriate and for which relevant work is available both in the area of distributed simulation and supply chains are DES, ABS and SD. Having identified the specific simulation techniques, we restate the scope of our study as follows: *In our literature review of the state of the art in distributed supply chain simulation, the studies that we are focussing on are those that have used* ***Discrete Event Simulation***, ***Agent-Based Simulation*** *and* ***System Dynamics to model supply chains, are executed faster-than-real-time, and which implement distributed simulation protocols, algorithms and middleware***.

5 An Overview of the Simulation Techniques

Our literature review examines simulation studies that have designed, applied, described, analysed or evaluated supply chain topics with the use of distributed simulation. In the previous section we identified three specific simulation techniques that were considered as relevant for the purpose of the study presented in this book chapter. A brief overview of these simulation techniques are presented in separate paragraphs below.

DES is a simulation technique that emerged in the UK in the late 1950s. DES is used to model systems in greater detail (when compared to SD) and with more complex temporal dependencies (when compared to MCS). It involves the modelling of a system as it progresses through time and is particularly useful for modelling queuing systems [66]. A DES model includes the following elements: a clock, an event list, a random-number generator, statistics and ending conditions.

Agent-Based Simulation, or ABS, is a computational technique for modelling the actions and interactions of autonomous individuals (agents) in a network. The objective here is to assess the effects on these agents on the system as a whole (and "not to" assess the effect of individual agents on the system). ABS is particularly appealing for modelling scenarios where the consequences on the collective level are not obvious even when the assumptions on the individual level are very simple. This is so because ABS has the capability of generating complex properties emerging from the network of interactions among the agents although the in-build rules of the individual agents' behaviour are quite simple. It is the most recent of the other simulation methods and is being used since the mid-1990s to solve a variety of financial, business and technology problems.

System Dynamics, or SD, comes from Industrial Engineering in the 1950s and is a modelling approach to understanding the behaviour of complex systems over time. It deals with internal feedback loops and time delays that affect the behaviour of the entire system. SD takes a holistic view of the problem and uses stocks, flows and feedback loops to study complex systems [72]. These elements differentiate it from other simulation techniques and help in the understanding of how even apparently simple systems display inexplicable nonlinearity.

The following three sections of this book chapter present studies that report on the creation, evaluation and improvement of the methodology applied to distribute and execute a supply chain simulation model which is modelled using DES (Sect. 6), ABS (Sect. 7) and/or SD respectively (Sect. 8).

6 Discrete Event Simulation (DES) Supply Chain Studies

There have been several attempts to create distributed simulations of supply chain and manufacturing systems using the IEEE standard on Distributed Simulation—the Higher Level Architecture [29]. The HLA was originally proposed to address the need for interoperation between existing and new simulations within the U.S Department of Defense (DoD). This came from the need to reduce the cost of training military personnel by reusing computer simulations linked via a network. The first major work in the application of this primarily military technology to civilian domain was done by Straßburger [74]. Various strategies have been investigated since then in several supply chain application areas. In the following two sub-sections, we present 30 studies which deal with distributed DES models in supply chains.

6.1 DES Studies Enabling Large and Complex SC Models

Hibino et al. [26] developed a distributed simulation system to easily evaluate a very large manufacturing system by synchronising several simulators. Three commercial object-oriented discrete event simulation tools of manufacturing systems (SIMPLE++, QUEST, GAROPS) were connected using the developed manufacturing adapter. Linn et al. [39] describe a successful two-machine implementation of a distributed simulation model for an international transportation system in a supply chain network operation using the HLA-RTI and the ARENA simulation tool. Rabe and Jäkel [63] analysed the requirements for distributed simulation in production and logistics. Taylor et al. [79] describe how a distributed model, the COTS Simulation Package Emulator (CSPE), was used in the planning process of a new production line in the Ford automobile company to determine if it can meet expected demand. The paper investigates the benefits from the use of distributed simulation at Ford.

Lee and Wysk [36] present a development of a top-down mapping mechanism for modeling and coordinating a federation of distributed DES models representing intra supply chain entities using an Enterprise Resource Planning (ERP) system as the federation coordinator. The ERP or Supply Chain Management (SCM) system uses a traditional coordination cycle to correct infidelities in data and status. The ERP system, which is typically used as a coordination tool for interactions between complex highly variable manufacturing systems, serves to coordinate and synchronize complex highly variable simulation models of these same systems. Before implementing the ERP-based coordination methodology for a federation, a formal information model, which contains static and dynamic information of the problem domain using Unified Modeling Language (UML) and Supply Chain Operations Reference

(SCOR) model, is developed to provide formal semantics and ontological characteristics of the system. From this formal model, a top-down mapping mechanism of the federation objects and processes with potentially different granularities is presented in order to make an entire federation functional. Similarly, Fayez et al. [16] describe an approach which is based on ontologies to integrate several supply chain views and models, which captures the required distributed knowledge to build simulation models. The Ontology core is also based on the SCOR model. The ontology can define any supply chain and help the user to build the required simulation models.

The study by Bandinelli and Orsoni [3] illustrates the design and use of a distributed simulation system for the assessment of competing outsourcing strategies in the context of large scale manufacturing. The work consists in the evaluation of modelling approaches for the systematic assessment of the candidate solutions in terms of their direct production costs and estimated production losses. The paper mainly focuses on the development of a simulation framework to describe a typical production system including a main contractor and several suppliers where jobs are exchanged on a daily basis. A simple application concerning a single contractor and four suppliers was built for testing purposes.

Virtually every author cited above used a different approach to distributed simulation of manufacturing and supply chains. Bandinelli et al. [2] present an overview of standards, models and/or architectures, describing the technological choices of distributed supply chain simulation and propose how and when a distributed supply chain simulation framework is to be used. In an attempt to standardise the approach, an international standardisation group, have produced a set of draft standards in this area and are described in Taylor et al. [80, 83].

Continuing with DES studies in the supply chain application areas Chong et al. [12] developed a distributed simulation model that can be used to study a complex supply chain. They fine-tuned the execution speed of the model, and then used the model to investigate on how the frequency of inventory updates and demand changes affect the on-time-delivery (OTD) performance of the entire supply chain.

The study of Rossetti and Chen [67] presents the structure and elements and their relations of a prototype Cloud Computing Architecture for supply chain network simulation. The discrete-event simulator written in Java allows the user to specify the network structure (which can be large-scale and multi echelon), the inventory stocking policies and demand characteristics so that supply chain performance can be estimated (e.g. average inventory on hand, average fill rates, average backorders, etc.) for each stock-keeping-unit.

Tammineni and Venkateswaran [77] propose an advanced look-ahead based approach (ALBA), a hybrid conservative approach for time synchronization that allows the models to run as-fast-as-possible to the nearest interaction event. This is achieved using an improved supply chain domain specific look-ahead algorithm that handles multiple types of interactions. Experimental results using a four-player distributed supply chain simulation show that ALBA functions better than the other approaches in terms of network communication load and execution time.

Moreover, Lee et al. [37] present a dynamic epoch time synchronisation method for distributed simulation federates. The proposed approach allows federates to advance their local times at full speed to the global safe point, which is dynamically estimated using the look-ahead function for each federate. The simulation then slows for an interaction between federates. This approach aims to reduce the number of time synchronisation occurrences and duration of the conservative phase. The distributed simulation is implemented using the web services technology. The experimental results reveal that the proposed approach reduces simulation execution time significantly while maintaining complete accuracy as compared with two existing methods.

An application of a distributed DES in the food supply chain is presented by Mao et al. [44]. Aiming at improving the efficiency of the food supply chain management by preventing system deadlock, they examined a simplified discrete parallel system simulation model of the supply chain's information management. The distributed simulation approach improved computation efficiency and met high efficiency of the real time operation system.

In the semiconductor sector, Chong et al. [11] describe how a distributed simulation test bed enable a very detailed supply chain simulation to study a customer-demand driven semiconductor supply chain. Gan et al. [25] present a case study in the use of the standards to support semiconductor supply chain analysis using the simulation package Autosched. They run scenarios with different types of time synchronization mechanisms to set the requirements that the simulation package needs to satisfy in order to be made interoperable. Turner et al. [86] describe their experiences on employing the HLA to support reusability and interoperability of this application area. Their experiments show that by fine-tuning the integration of the application with the HLA-RTI, considerable performance improvements can be achieved.

In the area of healthcare supply chains, Mustafee et al. [55] and Katsaliaki et al. [33] present a distributed simulation model which facilitates the analysis of the supply chain of blood from blood services to hospitals using the Simul8. They share experiences of the execution times between the implementation of a "conventional" simulation model and a distributed approach.

6.2 DES Studies Enabling Inter-organisational SC Models

Mertins et al. [47] discuss the advantages of distributed simulation to assist DES models in analysing the behaviour of supply chains, especially those in which several enterprises are involved. Integrating local models of the supply chain into one complete model is time consuming and error prone. Even more critical, local maintenance of partial models is generally inhibited. Distributed simulation solves this problem and, furthermore, provides encapsulation, if supply chain partners do not wish to publish details of their node to other partners. The interfacing description is based on the HLA and generates Extensible Markup Language (XML) files, which provide a specification of each supply chain node and its interfaces. Justifying that a distributed approach could be successful in modeling supply chains across multiple businesses where some of the information about the inner workings of each organisation may be hidden from other supply chain members, McLean and Riddick [46] attempt to integrate distributed manufacturing simulation systems with each other, with other manufacturing software applications, and with manufacturing data repositories. More recently, Li et al. [38] present a distributed simulation framework to facilitate collaborative cluster supply chains simulation. The proposed integrated framework constructs a cross-chain simulation while hiding model details within the enterprises. This is realized by building the simulation components as web service agents on top of the HLA-RTI and integrating simulation application on top of SOA (Web Service-Oriented Architecture).

Enjalbert et al. [14] presents a tool for distributed simulation of geographically dispersed manufacturing units/workshops. The proposed architecture, which uses the HLA-RTI protocol, guarantees the synchronisation and the chronology of events of the production operations for the distributed workshop network, which are simulated using the SIMBA software. The simulation tool can handle any kind of distributed scheduling by preserving the independence of each partner.

Chen et al. [10] analyse supply chains that produce and distribute computer servers. These are usually globally dispersed and have a high degree of uncertainty. To excel at servicing customers, a supplier must be highly skilled in matching the assets in the system with customer demand. DES has been proven valuable for system state estimation of supply chains. However, irregularities and disruptions occurring at any site along the system and the resulting bullwhip effects can lead to significant departures of simulation-based estimation from the performance of the real system. These departures reduce the ability of the model to assist in making correct decisions. In these terms, they propose an adaptive distributed simulation framework for a server fulfilment supply chain, and a Kalman filter to improve estimates of job completion times.

Jain et al. [31] present a distributed simulation based approach for supply chain interoperability testing. Simulations are used to represent real life organisations to serve as sources and consumers of dynamic data. The data can be encapsulated per the standard under consideration and exchanged with other organisations directly or through selected applications for testing. Furthermore, Iannone et al. [28] propose an efficient architecture (SYNCHRO) which is able to synchronize, simply and securely, simulation models which are located in different geographical areas. The architecture, developed by the authors, has been tested to establish its efficiency when using a variable number of connected units and has demonstrated it can be successfully applied in supply chain contexts.

Hongyu et al. [27] propose a HLA distributed simulation method (WS-HLA) which combined Web Service technologies in order to support analyzing bullwhip effect and information sharing in supply chain. This method takes each supply chain node as a simulation federate, and wraps these federates as web services that could be run under the control of the HLA-RTI. They built a model of the Beer Game to verify the feasibility of the WS-HLA-based simulation method. Also, Taejong et al. [76] proposed a supply chain simulation framework through a combination of PADS and Web services technology. In this framework, PADS provides the infrastructure for supply chain simulation execution while Web services technology makes it possible to coordinate the supply chain simulation model. A prototype implementation with a simple supply chain simulation model demonstrates the viability of this supply chain simulation framework.

For the automobiles distribution network, Dalal et al. [13] presents VinLogic for predicting future network performance and status. It is an integrated tool, which is implemented in an extension of Extend simulation software, integrated with a database containing the status of all vehicle shipments. The information in the database which entails (live) data from assembly plants, rail (un)loading facilities, ports and dealers, is used to distribute vehicles and resources through the network at a model run, and then the model can project demand and expected times of arrival.

7 Agent Based Simulation Studies

The Agent-based approach is used for creating more adaptive and flexible supply chain models. Below we present 13 studies which deal with aspects of distributed ABS models in supply chains.

7.1 ABS Studies Enabling Large and Complex SC Models

One of the notable studies in distributed agent based simulation of supply chains is the work of Maturana et al. [45]. They propose an agent-based approach for creating and managing agent communities in distributed and changing manufacturing environments. The authors introduce an adaptive multi-agent manufacturing system called MetaMorph. Their system facilitates multi-agent coordination and includes adaptation through organisational structural change and various learning mechanisms.

Xu and Lin [92] propose an advancing mechanism that integrates HLA with multi-agent distributed simulation to meet time management in supply chain simulation. In the same direction, Wen-guang and Jie [90] introduce a time management mechanism of HLA into MAS to construct a multi-agent based distributed simulation platform for supply chain; this platform is realized using JADE (Java Agent Development Framework), a developing kit for intelligent agents. Next, Qing-qi and Jie [62] propose a multi-agent simulation model for optimising supply chains. Based on this model, two types of agents and a time synchronization mechanism for distributed simulation were designed. Aligned with this, Long et al. [41, 42] presented a multi-agent based distributed simulation platform for a generic complex supply chain. The simulation platform comprises of a network communication layer, a Java agent development framework middleware, the simulation model and a graphical user interface, It is easy and fast to develop and has a visual display.

Finally, the FAMASS (FORAC Architecture for Modelling Agent-based Simulation for Supply chain planning) project [70] provides a methodological framework of distributed SC planning and scheduling systems using agent technology to support simulation analysts in defining what the functional requirements of possible simulation scenarios are. Their developed framework shows the way forward for agent-based SC systems to simulate complex and realistic scenarios.

7.2 ABS Studies Enabling Inter-organisational SC Models

Saad et al. [69] introduce a new approach to Distributed Manufacturing Simulation (DMS) with the goal of providing a simple cost-effective solution for evaluating viability of a proposed enterprise to enter into alliances forming enterprise partnerships as well as how a company's operations are affected by the proposed virtual enterprise. The authors underline that enterprises are moving towards a more open architecture that enables integration of activities of suppliers and customers.

Makatsoris et al. [43] introduce the concepts and design of a distributed order promising system that focuses on Available-To-Promise (ATP) and Capacity-To-Promise (CTP) for distributed enterprises. Their system essentially consists of three key levels: order intakes, order coordination and brokering and capacity handling. The architecture created in this article aims to help complex decision-making processes that take place at the order taking and fulfilment stages. Their design helps an enterprise make optimal decisions by checking customer demand against the supply chain constraints.

Nurmilaakso [58] proposes a distributed supply chain scheduling in the agent architecture instead of centralised supply chain scheduling. The companies communicate through their agents that share only the information relevant to the supply chain scheduling. This scheduling relies on distributed parallel forward simulation in which simple messages are exchanged between the agents periodically. According to these messages, each agent simulates the production orders of its company and receives and sends messages about the purchase and sale orders. This synchronises the simulation of the agent with the simulations of the other agents. Although distributed simulation does not optimise the schedules, it is capable of finding feasible schedules.

Nfaoui et al. [56] present a modeling work based on the Agent Unified Modeling Language (AUML) for distributed architecture of simulation and decision-making in the supply chain. The environment of supply chain is rich in negotiation protocols. They use AUML to model exchange and negotiation protocols for agents within the supply chain context and show through an example that AUML language could be used for specifying and modeling real-world agent-based applications.

Kiralp and Venkatadri [34] in their article present an optimisation-based multi-agent decision support platform (DSOPP) for integrated order promising and production planning in a multi-enterprise supply network environment. The DSOPP platform may be run either in real time or in simulation mode. Its goal is to demonstrate the viability of collaborative decision making. The DSOPP framework is built around a scalable multi-period optimisation model that may be used across enterprises. The DSOPP platform architecture consists of a distributed network control centre (DNCC) and individual supply chain control centres. Intelligent agents are embedded in both types of centres. The role of the DNCC is to coordinate the planning cycle clock and facilitate the transfer of information and inventory through a central mailbox mechanism. An individual supply chain centre comprises agents for demand management, planning and production execution. The platform can be used effectively to coordinate the planning activities across supply chain networks by providing the ability to analyse and understand the effects of various supply chain parameters.

To deal with the result data of the supply-chain simulation, such as data storage, analysis and display, Sun and Lin [75] developed a multi-agent distributed simulation platform. The system utilises agent's intelligence and interaction; realises the dynamic display of the real-time simulation status and performs statistics analysis. This enables the decision makers to view and analyze simulation performance.

Long [40] developed a research methodology for modelling multi-dimensional flows in the multi-stage supply network collaboration. The methodology integrates a three-dimensional flow model with a SCOR-based process modeling approach, a multi-agent system and a system-distributed simulation, which is performed until the final decision-making is formulated. The case for a five-stage make-to-order supply network is studied for the application of the methodology and to verify its effectiveness.

8 System Dynamic Studies (Including Hybrid Models)

Finally, there are a few studies of distributed system dynamics models in the supply chain area. Basically there are hybrid models which usually integrate system dynamics and DES models. Here we present four such studies.

8.1 SD Studies Enabling Large and Complex SC Models

The work of Venkateswaran and Son [87] discusses multi-plant production planning problems that deal with the determination of type and quantity of products to produce at the plants over multiple time periods. Hierarchical production planning provides a formal bridge between long-term plans and short-term schedules. Their research presents a hybrid simulation-based hierarchical production and planning architecture consisting of System Dynamics (SD) components for the enterprise level planning and DES components for the shop-level scheduling. The architecture consists of the Optimizer, Performance Monitor and Simulator modules at each decision level. The Optimizers select the optimal set of control parameters based on the estimated behaviour of the system. The enterprise-level simulator (SD model) and shop-level simulator (DFS model) interact with each other to evaluate the plan. Feedback control loops are employed at each level to monitor the performance and update the control parameters. Functional and process models of the proposed architecture are specified using IDEF. The internal mechanisms of the modules are also described. The modules are interfaced using HLA. Their research demonstrates results from a multi-product multi-facility manufacturing enterprise demonstrate the potential of the proposed approach. Furthermore, Venkateswaran et al. [88] present an innovative approach of integrating the Vendor Managed Inventory (VMI) strategy with a hierarchical approach to production planning decisions within a supply chain environment. The proposed architecture is divided into three stages: plan optimisation, schedule optimisation and decision evaluation. To implement this architecture, they use SD simulations, DES simulations and the HLA as a distributed infrastructure. Taking this even further, Venkateswaran and Son [89] analyse the interactions between the planning decisions that are spread across deferent members of the supply chain, considering the operational aspects at each member as well as the robustness of the plan. They propose a conceptual framework, which involve a multi-scale federation of inter-woven simulations and decision models to support integrated analysis of stability and performance in hierarchical supply chain planning and further develop and implement via experiments a realistic three-echelon conjoined supply chain system. The study presents the advantage of the hybrid models framework in robust supply chain planning.

8.2 SD Studies Enabling Inter-organisational SC Models

A study of Rabe et al. [64] explains techniques which support cross-enterprise design and configuration based on Reference Models. Thereby, different approaches such as SCOR (Supply-Chain Operations Reference), the Integrated Enterprise Modelling (IEM) and a specific distributed simulation method are used and integrated into a consistent reference model approach. The application of this approach is illustrated with different projects which each focus on a specific aspect of the supply chain design and configuration.

Table 1 summarizes the volumes of the around 50 distributed supply chain simulation studies which were identified and examined in this book chapter. They are analysed per simulation method and based on the drivers for the application of distributed simulation to supply chains. The trends are clear.

Table 1 Analysis of the % of distributed supply chain simulation studies examined in this review

DSCS	DES (%)	ABS (%)	SD/hybrid (%)
Enabling large and complex SC models	42.6	12.8	6.4
Enabling inter-organisational SC models	21.3	14.9	2.1
SUM	63.8	27.7	8.5

9 Discussion and Conclusions

It is evident that much work has been done in distributed supply chain simulations, with the majority of the studies focusing on Distributed DES models. This is to be expected since DES is more often used to model supply chain environments. Most of the examined research focuses on developing a framework for message exchange amongst processors trying to achieve faster model execution; while some research focuses on reusability and interoperability of models. However, it is also apparent that the most recent studies focus on ABS, which presents an advantageous environment for distributed simulation. It provides an outstanding mechanism for modeling the supply chain's need for autonomy as well as coordination, by enabling also decision making and scenario testing. From our review, it is also clear that only very few studies are based on systems dynamics for distributed simulation of supply chains. This is also true for the modeling of conventional simulation not in a distributed mode. So, although the development of supply chain simulations was originally based on SD because the performance of a supply chain is determined by its structure and flow control [42], DES was later proven a more effective tool due to its realistic modeling and analysis capabilities [93]. In the distributed mode, it seems that DES together with the events synchronization middleware is capable of correctly modelling supply chains and enabling both large scale, complex configurations and balanced information disclosure for effective inter-organizational communication. Additionally, if the SC players already simulate their operations then these models can be linked together by slightly modifying the existing models and adding a middleware. The cost involved for additional technologies such as for middleware is minimum as some of these are integrated into Windows operating systems and programming languages can be interconnected into simulation packages.

From the literature review, the ABS presents an even bigger potential since Agent-based modeling and simulation can further extend the capabilities of DES for both enablers in the context of complex and intensive information-sharing supply chains [35].

Development of hybrid simulation models using DES and ABS offers yet another opportunity. For example, Mustafee et al. [52] present the architecture of a DSCS which combines an ABS models of wind farms with a DES model of Maintenance, Repair and Operations (MRO), one component of which is a supply chain of spare parts for the wind turbines. Industry 4.0 provides the opportunity to work with data-driven models, and to combine simulation approaches with predictive modelling for hybrid systems modelling. Unlike hybrid simulation, which is the application of multiple simulation techniques to a given problem situation, hybrid systems modelling refers to the combined application of various analytical techniques (including simulation) to best model the system in question. Thus, hybrid systems models using real-time data being output from Industry 4.0 supply chain systems, could be combined with computer simulation to realise a real-time supply chain simulation for short-term decision making.

Overall, several of the studies that were reported about DSCS were general/broad-ranging (e.g. grand challenges, new research direction, inter-disciplinary research, methodological improvements applicable to a field, new tool/language development) and other were specific to work being reported by the authors (e.g. extension/enhancement to the algorithm/architecture presented, further implementation of research artefact, further experimentation and validation, extending the modelling approach to a larger supply chain with more players involved, application of the proposed approach to other problems in either the same domain or a different domain). A frequently repeated future direction for research is on the need of improving time synchronization algorithms.

However, the implementation of distributed supply chain simulation models is challenged by certain factors. A question which emerges after reading the literature is whether all large, complex supply chain simulations could equally benefit from a distributed approach. The answer mainly depends on the problem that distributed simulation is employed to solve. The literature has shown that distributed simulation offers a great deal by modelling supply chains across multiple businesses, setting up interconnections between multiple applications and integrating simulation systems and software applications. However, in the situations where a distributed model is built with the purpose of accelerating execution time then the answer is not that straightforward. The development of a distributed simulation requires extra investment in time which is hopefully balanced by an increase in execution speed and therefore a decrease in the time taken to get results from experimentation with the simulation [33]. Moreover, the simulation model needs to have the right characteristics to benefit from a distributed approach. Often, supply chain configurations fulfil the criteria, however, it appears that the supply chain ‘topology, the relationship of the sub-models and their interconnection (how the entities are passed between sub-models), and the relationship between processing and synchronisation loads play an important role. The development of metrics to indicate what could be distributed and what should not be distributed will help bring this technology closer to the simulation practitioner [33, 51]. Moreover, most of the proposed approaches for implementing distributed simulation environments are not compatible with the use of Commercial of the Shelf simulation packages and this is problematic for the wider adoption of DS in the industry [54, 81]. Nevertheless, a future where packages and models can be connected together in a “plug & play” manner in such a way to exploit the resources of a Grid/Cloud is almost feasible [82].

The success of the implementation of DSCS is based on the effective inter-disciplinary collaborations between operations researchers, computer scientists and package vendors. Performance improvements will derive from industrial-strength application of such DSCS frameworks, especially in highly dynamic, multi-enterprise networks (i.e. virtual enterprise). Increasingly manufacturers are turning to simulation tools to help them make long-term, evidence-based decisions, as they are faced with the implementation of new production technologies, intense global competition and changing customer needs. In this chapter, we have outlined examples of how distributed simulation has been developed to support the principles of Industry 4.0 in supply chains.

We hope that the presentation of the DSCS papers by technique and capability mode are useful to the supply chain participants, simulation practitioners, researchers, and distributed systems' programmers. Especially those interested in modelling such supply chains will refer to the existing studies with the objective of identifying the most suitable modelling techniques, the underlying technologies and the expertise required and its existing and potential advantages. This utility derives not only from general observations of the related studies, but also from questions that arise and which may need to be considered as the research in distributed simulation in the industry 4.0 era continues to evolve. The challenges associated with this distributed modelling approach were realized and recommendations were provided for overcoming the obstacles of further utilizing this technique by the industry.

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Product Delivery and Simulation for Industry 4.0

Oliverio Cruz-Mejía, Alberto Márquez and Mario M. Monsreal-Barrera

Abstract Industry 4.0 is having machines working connected as a collaborative community, both inside and outside the walls of the manufacturing sites. Manufacturing, sourcing, and delivery supply chains are now connected, making synchronization possible. Physical product delivery has changed significantly. Smart deliveries are now possible by directing end customer location in dynamic conditions. The capabilities of the delivery system can be simulated using discrete event simulation to compromise on-time delivery. Big data analytics are now a fundamental tool for product delivery analysis of optimal vehicle routing conditions and resource allocation. As companies have improved product delivery capabilities, more complex supply chains have been created. Analytic tools can tackle this complexity in estimating delivery time and product delivery windows under different workload scenarios.

Keywords Product delivery · Computer simulation · Lead-time analysis · Discrete-event simulation · Last mile delivery

1 Introduction

The technologies of Industry 4.0 (sensors, big data, analytics, artificial intelligence) blur the lines between the digital and physical world. In a world that demands better

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O. Cruz-Mejía (✉)
Universidad Autónoma del Estado de México, Nezahualcoyotl, México
e-mail: ocruzm@uaemex.mx

A. Márquez
Lamar University, Beaumont, USA
e-mail: alberto.marquez@lamar.edu

M. M. Monsreal-Barrera
Texas A&M Transportation Institute, College Station, USA
e-mail: m-monsreal@tti.tamu.edu

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customer service and transparency, knowing product and resources locations in real time gives power to manufacturers and distributors in modern supply chains.

These technologies facilitate real-time system status, including orders, product, availability of transportation resources, and availability of storage resources. Simulation can be used to model the impact of implementing Industry 4.0 technologies in resource coordination. For instance, delivery on the last mile means coordinating the picking of different products to assemble the order [1]. Trucks, lift trucks, hand picking personnel, product, and order information may all have to be present in a coordinated fashion to pick the product from the warehouse and prepare the shipment. The current operations decision-making process is to independently schedule each resource. In case of conflicts, priority rules are used to solved conflicts. In Petersen and Aase [2], results show that order batching yields the greatest savings, particularly when smaller order sizes are common. Results also show using either a class-based or volume-based storage policy provides nearly the same savings as batching, while being less sensitive to the average order size. In other cases [3] heuristics can enhance order picking efficiency when they replace a simple first-come-first-serve method.

2 Applications of Simulation in Real World Product Delivery

Industry 4.0 promises a more coordinated work where rather than conflict, resources work in unison, as if simultaneously orchestrated to be in a specific place at a particular time. Simulation can be used to optimize the number of resources that increases productivity, without blocking each other or designing optimal workload for type of product, location of the product for order assembly, etc. This type of coordinated effort will require simulation packages, which instead of solving conflicts by queues, use an advanced logic to emulate resources coordination. Simulation packages today depend on the user to create advance logic subroutines to control any type of sophisticated coordination. In the future, key coordination algorithms may be available off the shelf to be implemented both in simulation and the Industry 4.0 real world.

Barreto et al. [4] explain that Industry 4.0 logistics will highly need transparency (supply chain visibility) and integrity control (right products at the right time, place, quality condition, and at the right cost) in the supply chains. For distribution, new coordination schemes could be simulated, including smart coordinated delivery using fleets that re-balance the workload using the latest information available within the system.

These coordination efforts could include disruptions in the distribution network. For instance, in the case of road blockage due to accidents, the best algorithms for re-routing and re-scheduling in real time can be tested in a simulated environment. Similarly, extreme weather conditions (rain, fog, snow) can be simulated to test the system under stress. During Hurricane Harvey, large parts of the state of Texas were affected. The simulation of how the water would affect the roads and when

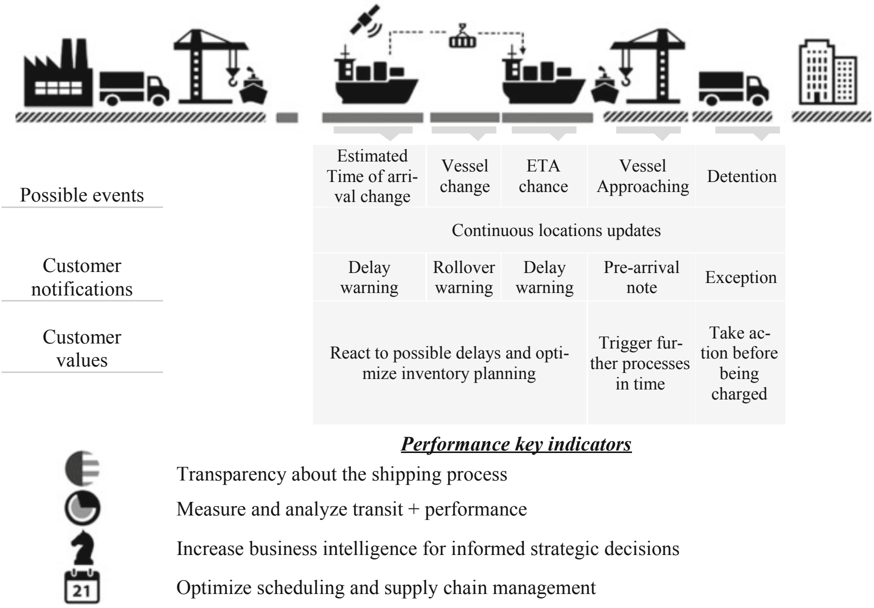

Fig. 1 Smart coordinated delivery

would have allowed a better response. Some places were inundated; others did not have potable water. Anticipating losing running water would have prevented water shortages, reducing the population distress during the peak of the predicament.

Figure 1 shows a prototypical supply chain that is fully integrated and coordinated. In the figure, the sharing of valuable information in real time can help stakeholders in the whole supply chain. An example can be the estimated arrival time of a product; this time can change due to weather conditions or delays so delivery systems are able to update shipment locations and provide notifications to the companies linked in the supply chain. Customers value this flow of information as the supply chain can react to inventory planning conditions and trigger contingency plans if needed.

Another important aspect under consideration is the environmental impact of distribution. Simulation can be used to predict air quality, noise, and waste products, especially with sensors and other technologies of Industry 4.0. Some efforts have been made to address the opportunities and gaps to integrate environmental protection and Industry 4.0 [5]. Smart deliveries and coordination can be simulated to reduce the environmental impact of last mile delivery, reducing carbon dioxide emissions [6].

Societal impact and quality of life can also be included. Fast delivery can be a life or death situation. Simulation could consider accidents, safety standards, reverse logistics, and similar efforts to improve the standard of living.

Naturally, the development of smart algorithms is expected to have an evolution, as the technology is improved, better coordination between players is implemented, and smarter decisions can be built into the system. Researchers have proposed that Industry 4.0 will have self-optimization and self-training behaviors [7]. Simulation can model the introduction of the scheduling and coordination algorithms from the simplest to the most sophisticated, effectively helping the self-optimization and self-training algorithms.

Particularly the delivery of foods [8], drugs DNA and other biological samples, and other sensitive material can be improved with Industry 4.0. Simulating the delivery of these specialized supply chains will promote the rapid development of policies and algorithms to fully integrate and coordinate its agents.

3 Smart Deliveries

As traditional manufacturing is transferred to developing countries, advanced countries move to higher value supply chains. That means it will be ever more important to track individual products with utmost precision. GPS is a standard feature included in logistic coordination of vehicles and tracking cargo at the bulk level. In the future, combining conventional transaction tracking (bar code and RFID) blockchain and GPS technologies, along with omnipresence of sensors, promise an unparalleled product tracking capability. Simulating tracking an individual product will allow for better planning for the cases where a robust response on tracking is needed (Fig. 2). How do we design a system that, even in the case of misinformation, each product can be tracked back in the path without making it very costly or redundant?

Industry 4.0 technologies could factor in fuel efficiency, cost effective solutions for delivery, and self-driving vehicles to determine the most cost effective route and acceleration and deceleration patterns. Then the algorithms, routes, and implementation could be tested using the virtual spaces created by simulation.

Capital expenditure in last mile delivery equipment can be justified by using simulation. The integration of new capabilities can be scaled or scheduled in a progressive way, indicating the possible scenarios in which to introduce new features that will coordinate final delivery with other functions within the supply chain. Further, the financial justification for additional capital needed in implementing Industry 4.0 technologies requires computing its positive impact.

With the implementation of Industry 4.0 technologies, researchers expect the infrastructure (roads, bridges, ports, airports, etc.) will integrate this technology too, motivated by higher efficiency, safety, and the proven interfaces between the different users of such infrastructure. Simulation of the coordination enabled by Industry 4.0 infrastructure can help in designing standard interfaces and can justify the prioritization of Industry 4.0 capabilities in current and future infrastructure investments.

On a global scale, a recent development that promises to change the nonurban delivery of products is the concept of what3words location. This is a 3×3 m location capability for the whole surface of the earth. The idea is that every 3×3 m can be identified by simply using three consecutive words in the English language. The number of possible combination of words allows for all the 3×3 m sections to

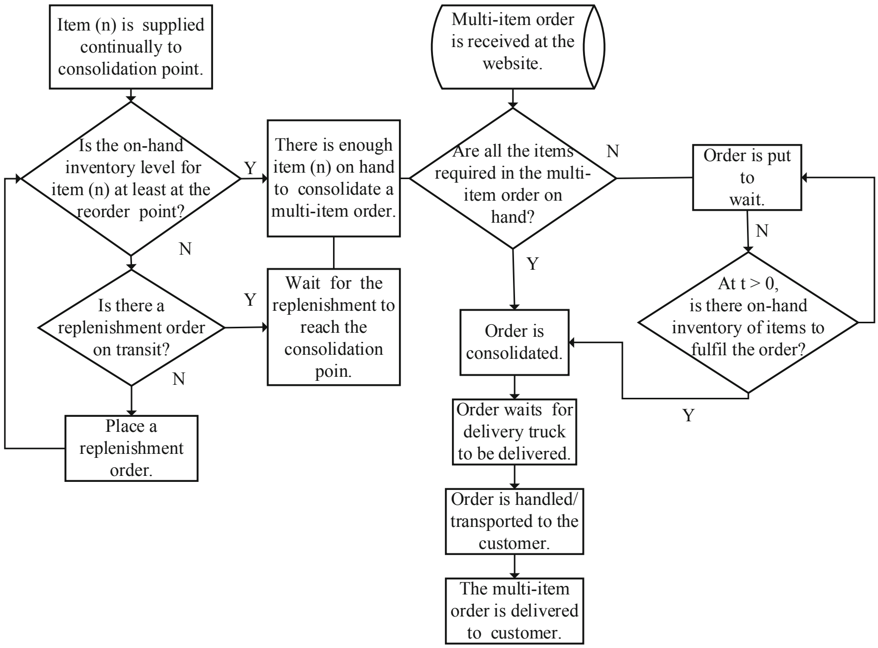

Fig. 2 Multi-item consolidation flow diagram

be individually tagged in a grid that covers the planet. This adds precision for all sorts of potential last mile delivery in nonurban settings, where there may not be even a road, address, post office, or mailbox. This, combined with drones, GPS, and other capabilities bring nonurban settings to modern times without the need for a conventional address. Naturally this will improve the last mile delivery performance under those settings. It is conceivable that simulation packages can have a default setting for what3words.com to simulate the requirement of an efficient delivery of nonrural areas.

Multimodal last mile delivery is not impossible in settings where ferries are needed or at least are an option to be considered. Simulation of this transportation mode can be simulated, creating the most coordinated system possible.

With augmented reality and virtual reality (AR/VR), simulation packages can be used for design and training operations. Companies can use simulation-based games to train their personnel on human interaction with clients, assessing issues and solutions of different positions, etc.

Using simulation for product delivery optimization will have to take into consideration the requirements for creating new added value in the long run, while remaining competitive with optimized operations in the short term. Simulation then will be used to anticipate the potential impact of new technological proposals implemented first in an exclusively virtual world and then deployed in the digitized world of Industry

4.0. In the short term, simulation can help synchronize the organizational resources in real time, maximizing the potential of sensors and the capacity for interconnection.

With the digitization of the economy, many changes are happening in the retail and last mile delivery domain. Brick and mortar stores are reducing their pedestrian traffic and revenue, while multiproduct and automated warehouses are growing in number, size, and sophistication. Miyatake et al. [9] used simulation for comparing the cost of online shopping versus brick and mortar stores. Their conclusion was that an online store saved in rent and labor costs.

For the future, value added operations near the customer will create a white glove service, in which companies can deliver prime branding products using the benefits of integrated coordinated logistics. These value-added activities will require fast and efficient training. AR/VR capabilities will enable the required sophistication of the operations through training and anticipating customer needs. Simulation will include virtual spaces and virtual-real interaction.

With the transformation of the economy, an important change is the need for hassle-free returns. Supply chain optimization will include the reverse logistics both for customer service and good sustainable practices. The typical challenges for expanding reverse logistics include the lack of real-time accurate logistics information and demands toward sustainable operations logistics [10]. Liu et al. [10] suggest a bottom-up logistics strategy that aims to achieve the real-time information-driven dynamic optimization distribution for logistics tasks. They propose an Internet of Things (IoT)-enabled real-time information sensing model designed to sense and capture the real-time data of logistics resources, which are shared among companies after the value-added processes. The main idea is to use a real-time information-driven dynamic optimization to optimize the configuration of logistics resources, reduce logistics cost, energy consumption and the distribution distance, and alleviate the environmental pollution. With this contribution in mind, reverse logistic policies can be tested using simulation. The optimization algorithms can be customized and tested using simulation.

4 Big Data Analytics and Artificial Intelligence for Product Deliveries

Artificial intelligence, big data, and analytics will combine with sensors and connectivity, enabling the representation of virtual worlds for simulation. Simulation packages today already come prepared for system design optimization of several resources, transporters, and other parameters. Simulation will have to keep integrating continuous improvement processes into their packages. In product delivery, smart agents will synchronize activities and products, creating a seamless operation in customers' eyes. Such synchronization algorithms will be common in the market place as the IoT and Industry 4.0 becomes the standard. In order to make the simulation packages relevant, the same synchronization algorithms will have to be available for the simulation software packages off the shelf to be ready to be applied for long-term planning and short-term operation optimization.

Additional new technologies will create new models of delivery operations. Self-driving vehicles and drone delivery are promising to be available soon. AR/VR could help the final user be prepared to make full use of the features of the product that is yet to be delivered in the physical world. Simulation will be present in the creation of this anticipated customer experience. Blockchain technologies will bring trust, increased security, removal of middlemen, and faster transactions. In the competitive market, simulators will have to integrate to the criteria the speed of the transactions, and tracking capability, that block chain bring to the table where the shake of hands at each transaction is important for security and validation purposes.

Industry 4.0 will affect how inventories are managed just before or at the delivery to the client. Concepts like vendor managed inventory will turn into autonomous inventory management with the help of sensors and interconnectedness. The next step will be predictive logistics based on integrating artificial intelligence in the decision-making process. Similarly, automated warehouse operations will yield to automated warehouse networks, and eventually it is possible to conceive synchronic distribution without an intermediate warehouse. The simulation of this highly sophisticated alternative will require more than randomized events within simulation but should bring the same capabilities of artificial intelligence coordination within the simulation models.

5 Internet of Things and Delivery Supply Chains

In the context of Industry 4.0, the IoT is progressively getting public and private sector attention to increase supply chain performance and boost economic growth [11]. The major evolutionary change promised by the IoT is the integration of networks that contain sensor and tracking devices, also known as Auto-ID technologies. The IoT enables each device to be directly accessible through the Internet. For example, RFID has been used for years to track products through certain parts of the supply chain. However, once the product left the shelf of a retail outlet, the manufacturer's ability to track the object was lost. Likewise, consumers were unable to gain access to the lifecycle information of products they purchased. In the IoT concept, devices can communicate with one another with point-to-point, point-to-multipoint, or multipoint-to-multipoint communication. By giving each product a unique identifier and making its data available through the web, the IoT promises to enable product traceability throughout the entire product lifecycle [12].

The IoT will also change the way businesses interact with customers and receive feedback about products [13]. Therefore, the use of the IoT concept and Information and Communication Technologies (ICTs) is considered a valuable asset in supply chain management because it enables seamless communication throughout different levels of the supply chain. With the advent of IoT, Internet connections now extend to physical objects that are not computers in the classic sense and serve a multiplicity of other purposes.

One main purpose of this seamless communication is the measurement of supply chain performance to provide precise and on-time decision-making information. Product delivery, which is the ultimate supply chain activity where the overall performance of the supply chain, reflects if anything that went wrong upstream the supply chain (lack of delivery being the worst-case scenario). Research firm Gartner states that the IoT will dramatically change delivery operations. By the year 2020, 30 times more Internet connected physical devices will significantly alter how the supply chain works [14]. Morgan Stanley estimates that 75 billion devices will be connected to the IoT by 2020 [14].

With the exponential growth of e-business, a lot of pressure is put on product delivery and its supporting activities, especially on the online transaction process: The relationship between e-retailers and product delivery service providers is complicated mainly due to the online transaction process. E-retailers and product delivery service providers are partners. Yet e-retailers are evaluated by end customers, whose satisfaction level is of essence for returning to the same e-retailer.

There are several examples of IoT used to improve product delivery. For instance, Yu et al. [14] integrated the IoT with innovative selection criteria for a product delivery service supplier, using the Asset-Process-Performance framework and a triadic model that includes e-retailers, product delivery service providers, and customers. Figure 3 shows a diagram on how the merge-in-transit operations need to be executed for the coordination of consolidated multi-item shipments. The flow diagram can be read from left to right beginning with the product sourcing operations. The system can track both make-to-order and make-to-stock products that will be assembled downstream in the supply chain. Sourcing policy and transportation time are key elements to be evaluated. After that, the merging operation takes place were orders are configured according to purchase orders. Finally, the order delivery operations are scheduled according the customer needs.

"This study finds that flexibility is a key criterion that will strengthen the relationship between e-retailers and product delivery service providers to improve the competitiveness of e-retailers as well as to satisfy the customers" [14]. Despite that various practitioners' guidelines have highlighted the importance of infrastructure and flexibility for product delivery service providers, this is one of the first studies that provides theoretical foundations and empirical validations of these general opinions. In addition, this study's framework proves the suggestions in previous studies that the combination effect of hard infrastructure assets and soft infrastructure assets have positive influence on flexibility, which in turn has a positive impact on customer satisfaction.

One of the factors preventing a more rapid adoption of the IoT and a wider spread of the Industry 4.0 concept in activities such as product delivery is the lack of understanding of new technologies. However, the understanding of the IoT concept can be increased by demonstrating its impacts and benefits on supply chain performance. Given the omnipresent challenge of data constraints, developing a thorough comprehension of the IoT concept and its impacts on supply chain performance could

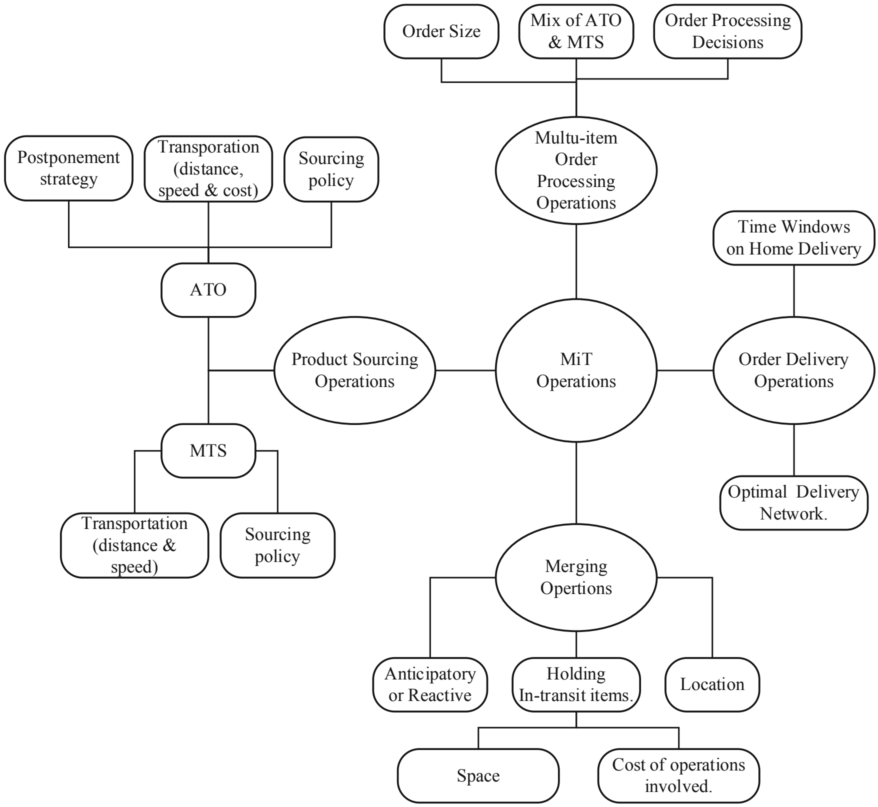

Fig. 3 Merge-in-transit operations

be better accomplished by simulation. Simulation is a powerful tool that helps when data availability is limited or problematic. Also, simulations are adequate to study new technologies, given the aforementioned data constraints [15]. In addition, simulations—especially system dynamics simulations—facilitate capturing the dynamics of complex systems, which is the case of supply chain activities such as product delivery, where actions taken by one actor can impact the entire supply chain. For instance, levels of upstream, internal manufacturing and downstream complexity will have a negative impact on plant performance. Bozarth et al. [16] performed an empirical analysis, based on a sample of 209 plants from seven countries. The outcomes of the analysis support these complexity hypotheses. Three supply chain complexity drivers stand out in terms of their impact on performance: long supplier lead times, instability in the master production schedule, and variability in demand [16].

6 Complexity in Supply Chains and Agent-Based Simulation

Vachon and Klassen [17] showed that the complexity of the supply chain had an impact on delivery performance. In particular, strong statistical evidence was found for a relationship between delivery performance and both process technology complicatedness and management systems uncertainty. For instance, the recent trend toward outsourcing (less vertical integration) is very consistent with findings that reduced complexity can improve delivery performance. The simpler processes and greater specialization that result, likely coupled with increased flexibility, serve to improve this aspect of operational performance. Moreover, these results were consistent, regardless of the economic context and level of development that a particular firm faced [17].

As shown by Birkinshaw and Heywood [18], complexity kills supply chains. The main message for practice seems straightforward: simplify your supply chains (within the limits of your business model)! Birkinshaw and Heywood [18] also noted that: "Despite widespread agreement that organizational complexity creates big problems by making it hard to get things done, few executives have a realistic understanding of how complexity actually affects their own companies." In this respect, complexity is driven by observable supply chain characteristics such as the number of direct suppliers or the geographic distances between a focal firm and its suppliers. These results offer hints to managers about the aspects of supply chain design that lead to more disruption-prone supply chains. All three structural drivers of supply chain complexity amplify the frequency of disruptions, and decision-makers are well advised to be attentive to these aspects when they organize their supply chains. In other words, the study's insights assist practitioners in assessing the impact of supply chain management strategies, like outsourcing or supply base reduction, on the exposure to supply chain risk, but most importantly, hints the use of tools to reduce complexity in the supply chain [18].

Supply chain complexity increases as supply chains become more exposed to various sources of risk, and not since the end of World War II have supply chains been as exposed to risks as they are now [19]. Higher demand volatility, unprecedented technological changes, and supply chain speed intensify risk exposure. Again, this complexity lumps and reflects in the final stage of forward supply chain operations—product delivery. Managing this complexity requires visibility.

Visibility is one feature of supply chain management that helps improve supply chain performance, but it is not the only feature of supply chain management that could facilitate better performance. Also, the IoT is a technology tool to improve visibility through integration, but visibility may be attained by other means without IoT. Simulation supports the analysis, planning, and assessment of product deliveries and other supply chain activities by enabling the isolation of specific impacts stemming from different sources, such as enhanced visibility using the IoT or other means.

The use of models/simulations has a long history at some stages in the product life and has proved to be a helpful tool for reducing complexity. For instance, models and simulations of a real time cylinder testing system create and reproduce results that sufficiently represent the real world. The simplified model/simulation can be used to evaluate parts of the control before commissioning. In addition, the use of one simulation across all engineering teams facilitates communication in early stage product development that causes improvements in design efficiency and project management [20].

Simulation also provides improved process planning because it confirms feasibility, time analysis, and other considerations. This activity, now being an integral part of the entire process, facilitates having a faster and more flexible approach when resolving complex issues within the product delivery environment. The time from plan to execution has been reduced, and the actual execution duration has been reduced, which means that assets get higher utilization, which in turn creates a virtuous cycle helping to reduce product delivery time. This is especially important in make-to-order and customizable products, for instance, where there has been a reduced number of changes due to assembly issues. An added benefit is the reduced number of prototypes required for manufacturing. Simulation relays much more confidence to only build a few of those because of the improved work done during the design activities [21].

A different application of simulation for product delivery is assessing on-street parking strategies. Urban scenarios are extremely complicated for distribution for several reasons. The urban structure induces accessibility constraints and logistical efficiency problems. One of these reasons is a place to park the distribution vehicle. Although parking seems simple, it is a major factor for goods delivery. The parking problem results in the increase of trip delays, a lower reliability, and in some cases inefficient logistical systems by using more vehicles than necessary, which in turn increases the problem. Simulation helps to assess different scenarios, factors, and impacts of the parking issue. For instance, Boussier et al. [22] used simulation to evaluate consequences of interactions between different actors of transportation systems with their environmental benefits. Specifically, they "simulate the traffic and environmental consequences of several scenarios for different infrastructures, occupancy rate of the places reserved for goods delivery and durations of the delivery process" [22].

On-time delivery is one of the always-present challenges most industries face. Service is mostly measured by the ability to meet on-time deliveries. Nowadays, distribution operations move in fast-changing environments, and standard and static analysis cannot reflect the dynamics of these changes. On-time delivery becomes more challenging in businesses focused on home-delivery, such as the e-commerce industry [23].

Simulation many times entails a causal analysis to determine means to improve processes; however, evaluating causes also enables users to build and answer what-if scenarios and questions. This type of simulation analysis helps effective planning for different future possibilities, because it can easily and quickly show the consequences over time of changing any input assumption or parameter. What-if analysis measures how changes in a set of independent variables impact on a set of dependent variables with reference to a simulation model offering a simplified representation of the business, designed to display significant features of the business, and tuned according to the historical enterprise data [24]. Therefore, what-if simulation analysis can be used rapidly to explore a wide range of options and scenario changes. Thus, managers can use what-if analyses to anticipate the most likely future situations they will need to manage and then plan accordingly.

One simulation technique that has proven useful to real-world business problems such as product delivery is agent-based modeling (ABM). This simulation technique is typically focused on four areas or application: flow simulation, organization simulation, market simulation, and diffusion simulation [25].

ABM represents a system as a collection of autonomous decision-making entities known as agents. These agents carry out activities or tasks pertaining to the system they belong (e.g., producing, consuming, selling). The interactions between these agents are the main feature of agent-based modeling, which relies on the power of computers to explore dynamics impossible to attain by pure mathematical methods. The main advantages of ABM are its abilities to capture the results of these interactions, the description of complex system (such as systems compound by behavioral agents), and its flexibility.

Product delivery operations show features and requirements that may benefit from what-if simulation analysis and ABM techniques. Some of these features stem from the fact that product delivery is strongly influenced by demand, policy, infrastructure, fuel/energy prices, and transportation modes. In addition, the impacts of product delivery are significant in areas such as energy consumption and the environment.

Since one application area of ABM is flow simulation, within this area specific what-if questions on delivery flows may be addressed, such as:

- What if demand changes? Delivery is driven by end demand, which is extremely difficult to predict accurately. Reasons for this are data limitations and the complexity of the interacting factors that determine demand. ABM simulation may help supplementing demand uncertainty by providing flexible analysis in terms of impacts from different demand scenarios.
- What if policy changes? As with demand, the changes in policy and the impact of these changes are hard to visualize with clarity. Generally, policy translates into constraints for operations purposes. The ability to relax these constraints by changing operation practices is vital for mitigating unwanted effects in delivery flows. Once again, the simulation of these policy impacts, and the building of model scenarios on how to address them, may provide a sound base for planning.
- What if infrastructure changes? Infrastructure establishes the physical boundaries of delivery flows. Regardless of changes in policy and demand, infrastructure leaves no room for slack and is costly and time demanding. This type of hard, lengthy, and costly changes is where simulation may provide the most benefit. For instance, impacts from different routing scenarios reflecting infrastructure implementation, changes in infrastructure capacity, or changes in road network

structure in terms of links and nodes are just a few of the specific situations that could be evaluated through simulation.

Other what-if questions like fuel costs and combinations of transportation modes are highly regarded as important for delivery flows. Currently, fuel costs have a high variability and uncertainty, and they represent a large portion of the total delivery cost. This relates to the different transportation modes that are involved in product delivery. Supply chain managers attempt using and balancing multimodality to keep high costs at bay, while providing a high level of service. To achieve the right balance, many factors and actors need to be considered, as well as the relationships among these factors and actors. Simulation, and specifically ABM simulation, enables users to assess the dynamics of all these elements and produce balanced configurations for costs and multimodal operations.

Techniques such as ABM allow model building to be iterative. For instance, adding layers with some energy consumption or environmental (e.g., carbon-foot print) measures could simulate different energy-scenarios. Moreover, the resulting behavior can have properties that are decoupled from the properties of the parts (i.e., the agents). In other words, in ABM, each agent is modeled as an autonomous unit following specific rules; this allows predicting the emerging collective behavior. In addition, ABM not only helps in assessing time steady behavior, but also enables dealing with more complex individual behavior, including learning and adaptation [25].

As previously mentioned, enhanced visibility using the IoT or other means may be adequately analyzed by isolating specific effects or impacts stemming from agents' activities and capabilities, such as technology usage. The latter is of essence for planning and assessment of product deliveries and other supply chain activities.

7 Conclusion

Product delivery is an area where operations simulation can be an aid for evaluating coordination and performance assessment. Digitalization of information allows multiple information flows that make coordination of delivery supply chains very effective. In practical terms, last mile delivery has been subject to an extensive effort to improve customer satisfaction, not only in due date management and coordination but also the management of returns, drop off delivery windows, and optimal routing for parcel companies. Operation simulation with Industry 4.0 has a vital role in evaluating on-time delivery of products. Specifically, discrete event simulation is being used to evaluate due dates for made-to-order products that include many uncertainties. This variability can be evaluated in simulation scenarios were inventory conditions and replenishment policies can be evaluated not only for fulfilling customer expectations but also to make delivery operations at minimum cost. Discrete event simulation is an efficient tool for capturing all sources of variability, so it produces good time and cost estimates. The configurations on complex products with many combinations have been helped by big data analytics that are able to sort large amounts of combinations. These combinations can come from much data for product personalization to the complex combinations of a delivery vehicle scheduled to visit end-customers.

Computer simulation has the potential to deliver more solutions to the product delivery analysis; some areas with potential are the web-based simulation that can help in estimating lead times from product customization to the delivery at a customer's house. The further integration of manufacturing operations and design to the adding value activities in product delivery is an area under development for Enterprise Resource Planning providers. ABM is being used for the development of more detailed solutions.

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Sustainability Analysis in Industry 4.0 Using Computer Modelling and Simulation

Masoud Fakhimi and Navonil Mustafee

Abstract Industry 4.0 proposes the use of digital and connected manufacturing technologies for enhanced value creation. The measures that are traditionally associated with value creation include the reduction in waste, increased productivity and efficiency improved profitability, etc. With a growing interest in sustainability, it is important to supplement the conventional definition of value-creation with factors related to the environment and the society. This inclusive definition could help the realisation of sustainable development. Computer simulation and modelling (M&S) could be valuable in providing the understandings and insights necessary for coping with such all-inclusive systems which have high levels of complexity. In addition, M&S could also provide immense opportunities for stakeholders to understand the underlying dynamics of industry 4.0's contribution to sustainable development targets. Although, the researchers have recently been applying M&S to plan and test industry 4.0 approaches but our findings show that using M&S for analysing the contribution of industry 4.0 on sustainable development are scarce. The outcome of this chapter provides insights toward future research directions and needs. Finally, this research argues for a shift from normal to post-normal M&S paradigms for sustainability analysis this is achieved through a discussion on normal and post-normal science concepts and assumptions.

Keywords Industry 4.0 · Modelling and simulation · Sustainable development · Triple bottom line

M. Fakhimi (✉)
Surrey Business School, University of Surrey, Guildford GU2 7XH, UK
e-mail: Masoud.fakhimi@surrey.ac.uk

N. Mustafee
Centre for Simulation, Analytics and Modelling (CSAM), University of Exeter Business School, Exeter EX4 4ST, UK
e-mail: N.mustafee@exeter.ac.uk

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1 Introduction

Industry 4.0 is known as Manufacturing 4.0 or the fourth industrial revolution. While the hallmarks of Industry 3.0 were the automation of individual machines and processes, Industry 4.0 promises not only the end-to-end digitisation of business processes and physical assets (vertical alignment) but also emphasises the integration of these digitised internal processes with that of their suppliers, customers and key value chain partners (horizontal alignment). Industry 4.0 is data-driven and is reliant on key technologies, including, standards for industrial engineering, automation and robotics, real-time data and acquisition through sensors/Internet-of-Things, high-speed networking, cloud computing, computational infrastructure to enable real-time analysis of high velocity -high volume data, business intelligence and real-time monitoring and predictions. However, the focus of this chapter is not on the technology or its promise of new business models, radical innovations or increasing efficiency, but instead, in understanding the implications of Industry 4.0 for sustainable development (SDEV) and the triple-bottom line (TBL) of sustainability. It enables us to identify underlying system-wide characteristics that contribute to achieving resilience through a balanced treatment of societal, environmental and economic factors.

Computer modelling and simulation (M&S) is widely used in the industry to develop future state models and to perform experiments by simulating candidate strategies. In the context of manufacturing and supply chains, computer models could be used for the identification and (ultimately) removal of bottlenecks, inventory management, waste reduction, logistics and supply chain network design. Similarly, such models can be used for planning an organisational transition from existing Industry 2.0/3.0 automation-levels to that necessitated by the fourth industrial revolution. Industry 4.0 models could be used for experimenting the impact of future automation and availability of real-time data in relation to horizontal and vertical integration, analysing the efficacy of existing logistic networks with simulated location updates (to mimic Radio-frequency identification (RFID) data), experimenting the impact on inventory levels with real-time data on sales (e.g., through Point of Sales terminals with retailers) made available by the supply chain echelons. We argue that, in the industry, the overwhelming majority of simulation models are developed from the perspective of the productivity optimisation and consequently the processes that are of interest are mostly related to business-specific functions with outcome variables/Key Performance Indicators (KPIs) often defining metrics related to efficiency, productivity, throughput, profitability, and so on so forth. Our previous work [1] has criticised such organisation-centric models as it fails to appreciate the interplay of the overarching environmental, social and economic factors (also referred to as the TBL of SDEV), within which an organisation operates (see Fig. 1). TBL is a framework that guides organisations to harness their strategies towards a balanced treatment of their social, environmental and economic responsibilities [2].

With Industry 4.0, end-to-end digital manufacturing technologies will lead to enhanced economic success; however, it is also vital to consider the environmental

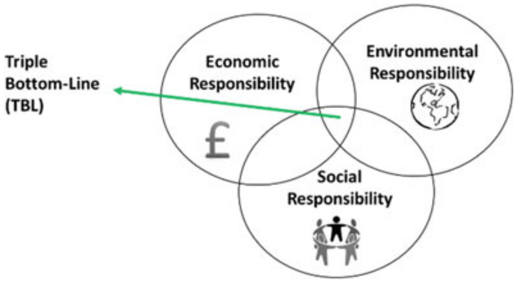

Fig. 1 The spheres of sustainable development

and social related KPIs to ensure organisations' sustainable success [3]. This book chapter extends our previous work on modelling approaches for sustainability analysis and applies this in the context of Industry 4.0.

2 Sustainable Development and Industry 4.0

The "Brundtland Commission" defines sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [4]. In recent years, the concept of "sustainability" has gained increasing attention in organisational and managerial disciplines. Such shifts in organisational paradigms placed demands on stakeholders to revise their priorities from productivity focused management to TBL [5]. Therefore sustainable manufacturing has emerged as an evolving field and has been the focus of numerous studies in operations management and sustainable development research communities [6]. Sustainable manufacturing can be defined as the planning, coordination, and control of a system that adds value to the stakeholders through the most cost-effective approach while striving to protect the environment and respecting social norms and responsibilities [7]. Linton et al. [8] argue that, in essence, the implementation of sustainable development requires a major shift in current conventional managerial disciplines and practices.

In organisations that implement Industry 4.0 technologies, real time access to data and information play a significant role in ensuring quick decision making. This also contributes towards cost savings. The use of real time data could also provide manufacturers with more accurate demand forecasts which lead to an increase in the resource utilisation and waste reduction [9]. The also numerous possibilities to analyse and improve sustainable manufacturing using the Industry 4.0 capabilities. For example, the use of IoT changes the sustainable operations management paradigms and provides manufacturers with the privilege of data source to "trace, extract and influence" the processes related to either of TBL (such as energy use and pollution) or material flows.

In summary, Industry 4.0 is transforming businesses by creating more efficient manufacturing methods, optimised supply chain and life cycle traceability and information management. In this new setting, with plentiful opportunities arising for manufacturers, the question is how it can contribute to the implementation of organisations' sustainable development strategies against TBL framework.

We argue that M&S could provide a valuable tool for analysing sustainable manufacturing strategies within the industry 4.0 setting. However, our findings show that most of the existing research on sustainable manufacturing led by Industry 4.0 relates to literature reviews e.g., [10, 11] with only a small number of empirical research having been reported e.g., [12–14]. There are limited number of studies which have explained the application of M&S for Industry 4.0 for SDEV analysis i.e. [15, 16]. The next section discusses the application of M&S for sustainability analysis in Industry 4.0 setting and how industry 4.0 capabilities could help the modellers to tackle some of the challenges of developing models for sustainability analysis.

The remainder of this chapter is organized as follows. The next section provides an overview on application of M&S for TBL modelling using Industry 4.0. Section three articulates a need to shift from normal to post normal modelling for sustainable development analysis. Section four is the concluding section and summarises the chapter.

3 TBL Modelling and Industry 4.0

3.1 Overview of Application of M&S for Sustainable Development Analysis

Tackling issues related to Sustainable Development (SDEV) has become increasingly crucial for organisational success. The initial pragmatic solution is to incorporate TBL criteria for any decision making process across the organisation. Over the last two decades, research in sustainable operations management (SOM) has made significant contribution towards the understanding and implementation of TBL in manufacturing. Modelling and Simulation is a frequently applied decision-making technique for representing and analysing complex systems. Hence, TBL-based systems, being complex, uncertain and having multiple system outputs, could leverage the abilities of M&S techniques to capture multiple perspectives and the effect of quantifiable and non-quantifiable TBL metrics for analysing systems.

In previous work we have shown that M&S allows for the experimentation of alternate TBL-centric strategies and to compare the results of the simulation in a meaningful way. M&S studies have been widely used in industry to gain insights into existing or proposed systems of interest. However, our review of the literature [1] shows the dearth of empirical research on integrating sustainability factors with systems' modelling studies. It is with this aim of addressing this gap that we have conducted a review of literature which attempts to provide a synthesised view of M&S approaches which have previously been used to model sustainable development issues. Note that this study was not specific to Industry 4.0 but included studies that focussed on both SDEV and M&S. As several of the studies identified in the review were to do with manufacturing, we consider it important to summarise the findings from this paper as it is of relevance to Industry 4.0 manufacturing.

Our study [1] found that system dynamics (SD), mathematical modelling (MM), discrete-event simulation (DES) and agent-based simulation (ABS) were the most widely applied techniques addressing sustainable development related issues. Every technique has a methodological foundation, for example, SD adopts a holistic systems perspective and uses stocks, flows and feedback loops to study the behaviour of complex systems over time; ABS takes a bottom-up approach to modelling wherein the overall behaviour of the system emerges from the underlying dynamic interaction between the agents; DES is used to model queuing systems [17]. Finally, MM uses mathematical notations and relationships between variables to model the behaviour of a system (for example, MM approaches like linear programming and integer programming can be used for optimization). MM can also refer to statistical approaches to model system behaviour, for example, Monte Carlo simulation relies on repeated random sampling from known probability distributions and which are then used as variables values. It, therefore, follows that certain techniques may be more appropriate for modelling particular classes of SDEV's problems.

Our findings also reveal that despite the recent endeavours to apply M&S for sustainability analysis, in many cases at least one of the pillars of the TBL framework (Economy, Society and Environment) has been neglected. Most empirical studies focused on economy-related measures to evaluate system performance and consideration of all three sustainability dimensions (TBL) has been underrepresented. This shows that existing studies have continued to ignore the interconnected impact of the TBL pillars on the success of short term and long term productivity. This excessive focus on productivity may need to change, since the decisions being made based on such models would not be aligned with the discipline of sustainable development discipline, but also can be very misleading for the whole organisation.

The recent increase in the number of publications in this area notwithstanding, our findings have shown that there is a lack of studies on the application of M&S for sustainable manufacturing incorporating all TBL factors of underlying systems, and many challenges still remain unaddressed in developing and validating such models. The development of models that respond to these TBL-based systems complexities is a particularly arduous task for modellers, since they require to ensure that the models are: (a) applicable to the real world, (b) capable of dealing with variables at different levels (strategic level and operational level), (c) considering all three sustainability pillars (TBL) in their analysis, and (d) capable of dealing with high level of uncertainty and complexity. Therefore, it is not surprising that a variety of limitations and drawbacks of the models was found in this literature review. Table 1 indicates the list of limitations exhibited by the TBL-based models that were developed for the studies reviewed for this research. The limitations found in the literature have been classified based on the simulation techniques they used.

Our findings advocate that a combination of M&S techniques (Hybrid Simulation) lends itself to a closer representation of the TBL-system (when compared to using single techniques). Our previous work shows that DES-SD [27] and ABS-SD [28]

Table 1 Limitations of the developed models addressing the sustainability issues

M&S techniques	Limitations for modelling the TBL-based systems	Example studies
System Dynamics (SD)	– Complexity of finding interconnections between TBL KPIs that are not essentially homogenous – More focus is on system rather than solving problems – More efficient for representing outside of the system rather than the inside	i.e. Shen et al. [18], Halog and Manik [19], Jain and Kibira [20]
Mathematical Modelling (MM)	– It is hard to quantify immeasurable TBL KPIs (i.e. social responsibility related KPIs) – Lack of feedback analysis in implementing TBL intervention – Tends to ignore the interconnections with high level and low level operations – Hardly capable of covering the whole TBL-based system	i.e. Sander et al. [21], Hashmi et al. [22]
Discrete-event Simulation (DES)	– Does not cover the whole TBL-based system – Tends to ignore the interconnections with high level and low level operations – Does not support proactive behaviour (which is important when simulating social factors of TBL) – Mostly used at operational level of abstraction rather than at strategic level	i.e. Widok and Wohlgemuth [23], Shao et al. [24], Jain and Kibira [20]
Agent-based Simulation (ABS)	– TBL-based model will be complex and difficult to completely understand – Heavily dependent on data – Developing model showing the details in high level resolution will be complicated and the size of model will be large	i.e. Yang, et al. [25], Memari et al. [26]

to be the preferred hybrid approach for TBL modelling as they could model most underlying characteristics of TBL-based system.

3.2 Application of M&S for TBL Modelling for Industry 4.0 SDEV Analysis

M&S has been used for SDEV analysis in most major industries such as Healthcare i.e. [29, 30], Manufacturing i.e. [31, 32], Food and Agriculture i.e. [33, 34], Construction Industry i.e. [35, 36], Transportation i.e. [37, 38], and etc. It is arguable that sustainable Industry 4.0 could also benefit from the use of M&S. However, as noted by Rodic [39] the potential of M&S is yet to be fully exploited in this new industry.

We define a TBL-based model as an abstraction of an underlying system of interest that is developed to analyse the system pertaining not only to the productivity criterion (e.g., resource utilization, service time) but also on environmental and social criteria. The development of suitable models is response to such complexity is reliant on aligning the specification, analysis and evaluation processes, the infrastructure and the surrounding subsystems of social valuation (here the three TBL component systems) and policy context. Moreover, reconsideration of the methodological aspects of M&S techniques is essential in relation to the development of TBL-based systems.

It has become necessary for manufacturers to abandon traditional design practices in favour of a systems-design approach as a result of shortened product development cycles and the negative impact on TBL. However, this has been difficult to achieve without the elements offered by Industry 4.0. During the initial development stages of TBL models, manufacturers are able to authenticate the design alongside TBL targets. An automated operation can considerably facilitate and ease the development of models for complex and uncertain systems [40, 41]. By modifying the structure of a model, TBL-based improvements can be made by creating multiple versions of the model and input data, alongside a comparison of the simulation outcomes. Algorithms can be devised to construct or adjust simulation models in relation to the input data; thereby speeding up the process of developing the TBL-based model. This is particularly pertinent to TBL-based models where the simulations are dealing with large and complex systems holding several immeasurable variables. However, automation demands modification of the model composition using an algorithm that has no manual intervention [42].

Furthermore, within an organisational context, SDEV arguably is a primarily strategic concept [43]. Nevertheless, decision pertaining to strategy or policy can be realised only through their implementation at an operational level. For example, in Industry 4.0, a modeller must comprehend the strategic interaction of TBL while simultaneously being sympathetic towards the operational aspects of the system. Ideally, the method selected to conduct SDEV analysis should epitomise, at appropriate levels of detail, the strategic and operational elements of the system under investigation. This will ensure it can predict candidate policies; thereby facilitating a choice of policy.

Moreover, it is vital to contemplate the short and long-term impact sustainability for analysing TBL-based systems because policy dilemmas will quite frequently emerge from their conflicting requirements. In the long-term, the impact will come primarily from strategic decisions, which are, by nature, more holistic [44]. Processes with long-term effects should ideally be composed into an aggregate level of analysis in TBL modelling. Conversely, the short-term effects arise generally from decisions made at the operational level, although some decisions are conceived of as being strategic and therefore long-term, can also have immediate unexpected effects in the short term. Processes with short-term effects may be composed into an individual level of analysis in TBL modelling. Nevertheless, our findings suggest that there are few studies that have used M&S in the context of sustainable Industry 4.0 and that have taken into account the strategic and operational-level strategies that may be necessary for experimentation within a simulated environment and analysis before implementation occurs.

It has been argued by some critics that sustainability cannot be modelled due to its size, complexity, ambiguity and the fact that no adequate definition has been provided [45]. However, we argue that combination of Digital Twin and Virtual Testbeds promoted by industry 4.0 [46] extends the use of simulation modelling for TBL modelling in manufacturing especially with regards to TBL-based Product lifecycle management (PLCM). "Digital Twins" refers to the virtual substitutes for real objects consisting of virtual representations and communication capabilities comprising smart objects that act as intelligent nodes within the internet of things [47]. Integrating real-world data with the simulation yields precise predictions of relating to productivity or maintenance alongside green and social influences of products across its lifecycle based on the circulation of real-world data. When Virtual Testbeds and Digital Twins are combined, a new type of dynamic and experimental Digital Twin is created, which is ground-breaking in the simulation of large and complex systems [47]. The real value of Digital Twins lies in their ability to be tested extensively beyond the scope of the real world [39, 48]. Moreover, Digital Twins is a trusted system in a field where automated systems change continuously as it can offer a reliable analytics sandbox where the "what-if" scenarios can be analysed and experimented with low cost and complexity. Therefore, the TBL-based model could represent the operation of the system using real-time (or near real-time) data, or thereabouts, yielded from the TBL-based system. Furthermore, this will enable the modeller to analyse the system with high and low resolution by clicking on model objects and excavate a broad range of economic, environmental and social data, and perform an operational and holistic analysis.

In summary, Industry 4.0 application could help the modellers to tackle some of the challenges of TBL modelling which can hardly be resolved in traditional industries:

(1) Industry 4.0 can help the modellers and decision makers to understand, analyse the integration of all TBL measurable success factors within the system.

(2) In TBL modelling the modellers should be able to represent and analyse the system at high and low level of resolution. Industry 4.0 facilitates representation of more aspects and details of the underlying TBL-based model at different level.
(3) Industry 4.0 also could automate the modification (testing what-if questions) thanks to its reliable and real-life (or close to real life) data and analytics sandbox.

Notwithstanding the several benefits that Industry 4.0 could offer to TBL modelling, this research argues that due to the unique characteristics of Sustainable Development, TBL modelling still may require major re-thinking on traditional M&S disciplines. The next section argues for a shift from normal to post-normal M&S paradigms for sustainability analysis; this will be achieved through a discussion on normal and post-normal science concepts and assumptions.

4 From Normal to Post Normal Modelling for Industry 4.0 Sustainability Analysis

On the basis of the knowledge gained from the literature and limitations of existing empirical studies on TBL modelling, this research argues for a shift from normal to post normal modelling for Industry 4.0 sustainability analysis. We argue that modelling for sustainability based on classical science disciplines is not feasible to understand a phenomenon like Sustainable Development. The rest of this section explains this argument. We will further discuss why modelling for sustainability may become a Holy Grail for modellers.

The normal (classical) science is dominated by the concepts emerging from equilibria and optimality; thus, perception and treatment of changes for scientists are rather easy to formulate and predict. According to the principle of distinction conservation [49], "Classical science initiates with making as precise as possible distinction between the different components, properties and states of the system under observation". Normal science is grounded in the Newtonian worldview (reductionism concept), which implies that to understand any complex phenomenon, you need to take it apart [50]. Newtonian reductionism idea advocates that mathematical models are reducing the elements of system variables to a "machine" to represent the observing system in a set of differential equations [49, 51]. Bagheri and Hjorth [52] argues that normal science is mainly based on Equilibrium and Optimality. Meaning there is only one rigid solution for all differential equations and there is only one optimum point for a system. Due to these reasons, the logic behind it is not valid for open systems, which include unpredictable, uncertain and sometimes idealistic factors that do not have a unique final state as "optimum or minimum". Moreover, using a reductionism view for studying complex systems coping with unpredictable and immeasurable factors (human, environment, etc.) factors which naturally cannot be studied separately and do not obey mechanistic laws, is not practically possible. This explains the reason why normal science ignores all issues related to social and ethical values. Clark et al. [53] argue that since traditional mathematical (quantitative) systems are only capable of functioning but not of evolving. So they are not capable of coping with structural changes in open system. Thus, dealing with such open systems' shift to a post-normal mode is a critical change [54].

Post-Normal Science (PSN) was initially established to critique the Newtonian reductionism world view, which eliminates some uncertainties and social values associated to the observing system [55, 56]. PNS is a problem-solving framework developed by Silvio Funtowicz and Jerome Ravetz in 1990 [57] in order to study the underrepresented parts, the management of complex science-related issues. Funtowicz and Ravetz developed an argument claiming that the sciences tackling sustainability issues are profoundly different from those sciences that are involved in generating them (such as the applications of physics and molecular biology [58]. Bagheri and Hjorth [52] argue that classical science is all about treating the "symptoms", but the post-normal science is exclusively concerned with treating the "cause".

Therefore, we argue that, the most important factor for low adoption of M&S for sustainability analysis in Industry 4.0 is the fact that M&S methodologies are mainly applying mechanical concepts relying on equilibria and optimality, while TBL-based systems entail constantly moving processes where the optimal point is not known in advance; therefore using traditional M&S disciplines is less likely to be useful when analysing sustainability in Industry 4.0 systems, which are governed by large numbers of immeasurable factors that do not necessarily obey such disciplines. Therefore, the challenges and complexity of TBL modelling arguably are due to modellers trying to deal with these issues using normal science disciplines; it is like measuring length using scales.

5 Summary

M&S tools are one of the key element for the development of Industry 4.0. M&S play a significant role for modernising processes and designs as well as piloting and testing new products or services. Sustainable manufacturing principles used in tandem with M&S techniques could provide significant insights in coping with the uncertainty associated with TBL management. However, the application of M&S for analysing SDEV in Industry 4.0 is still at its infancy. According to the findings of this research, the most important factor for low adoption of M&S for industry 4.0 sustainability analysis is the fact that M&S methodologies are mainly applying mechanical concepts relying on equilibria and optimality, while sustainability systems entail constantly moving processes where the optimum point is not known in advance; therefore using traditional M&S disciplines less likely to be useful when observing sustainable systems entails a large number of immeasurable factors that do not necessarily obey such disciplines. This research presented a review of M&S and recent developments on applying M&S for sustainability purposes. The aim of this research was to investigate the challenges in developing models for sustainability analysis in Industry 4.0. Understanding and tackling these challenges provides immense opportunities for the realisation of sustainable development in using M&S

in industry 4.0. This research also showcased the opportunities which Industry 4.0 offers to TBL modelling.

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Interactive Virtual Reality-Based Simulation Model Equipped with Collision-Preventive Feature in Automated Robotic Sites

Hadi Alasti, Behin Elahi and Atefeh Mohammadpour

Abstract Technological changes have made historic moves in the industry trajectory towards industry 4.0. Simulation of the work environment is one of the effective tools in an automated robotic site. It contributes to a better work environment's awareness toward the machines' and robots' behavior, enhancement of the monitoring and troubleshooting of processes, and selection of the optimum adaptable design for the system. This book chapter mainly focuses on proposing an innovative interactive VR-based simulation model for automated robotics sites. Consolidating all features of an effective VR tool, a system design simulation software (SIMIO) and a robot programming simulation software (Epson RC+) results in an effective VR-based simulation for the entire manufacturing system. Such a proposed model, interacts with workforce and decision makers effectively. Decision makers will be able to test and evaluate various design scenarios and potential states in the whole response space. In this way, the optimum alternative, which optimizes the performance measures' values, will be captured in a timely manner. Such a model, proactively recognizes the potential collisions via simulation. Utilizing such a tool will improve the scheduling process, reduce down-time and delays, enhance the system productivity and reliability, and detect maintenance time of robots and machines in a faster way, which are among the main goals of systems' automation.

H. Alasti
Department of Computer, Electrical and Information Technology,
School of Polytechnic, College of Engineering, Technology, and Computer Science,
Purdue University Fort Wayne, 2101 East Coliseum Boulevard, Fort Wayne,
IN 46805-1499, USA
e-mail: alastih@purdue.edu

B. Elahi (✉) · A. Mohammadpour
Department of Manufacturing and Construction Engineering Technology,
School of Polytechnic, College of Engineering, Technology, and Computer Science,
Purdue University Fort Wayne, 2101 East Coliseum Boulevard, Fort Wayne,
IN 46805-1499, USA
e-mail: belahi@purdue.edu

A. Mohammadpour
e-mail: atefeh@purdue.edu

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1 Introduction

Industry 4.0 signifies an industrial revolution in global manufacturing based on the internet of things leading to a fully connected and automated manufacturing system, or smart factory. In other words, the key idea of Industry 4.0 is creating functional cyber physical systems by connecting all parts of machines (physical systems, embedded systems, sensors, actuators, electronic hardware, software etc.) via integrated data chains [17]. In Industry 4.0, robots and the other equipment are networked which enables robots to communicate with each other and data is continually being produced and processed by sensors. Smart embedded sensors in robots, interface with the physical environment to detect and forecast the hazards (i.e. collision, failure due to aging, accuracy and precision deterioration, etc.). The collected data via sensors are shared to the smart work environment to align the workload and timing among all the machines and system elements. Sophisticated algorithms and tools enables the networked robots and equipment, to work more efficiently, collaboratively, and resiliently. All industries are subject to the new trend and changes that will evolve their work environment.

Smart sensing, communications, cyber environment, and industrial manufacturing form the foundations of industry 4.0. As collaboration of organizations has increased internationally, setting a common standard is essential. The standardization roadmap for industry 4.0 provides an overview of the conducted activities within the industry 4.0 domain and its effective implementation [2, 12]. In sensor-enabled, smart work environment, a cyber-physical system is designed as a platform for managing networks of interacting elements between computational and physical components [22]. Within the smart work environment, a cyber-physical system monitors physical processes, generates a virtual copy of the physical environment which can be used for decision making in a decentralized way.

Utilizing Virtual Reality (VR) technologies, which are currently regarded as the interactive technology of the future, could be a powerful tool in smart factories where information, communication, and automation technology are fully integrated. Reviewing the literature verifies that VR simulators such as flight, driving, battlefield and surgery simulators have been used for a long time, however an interactive VR-based model that controls robots motion and the entire manufacturing system simultaneously in automated robotic sites, has not been presented. In this chapter, such a novel interactive model will be introduced which helps decision makers control the potential impacts and collisions in an automated system. In this way, it can be considered as a collision-preventive model. The objectives of this chapter includes (a) elaborating on general application of VR in manufacturing systems' phases of an automated robotic site, (b) explaining safety 4.0 and risk-preventive workforce training, and (c) focusing on a particular VR application in automated robotics sites and proposing a novel integrated VR-based simulation model equipped with collision-preventive feature with application in automated robotic sites.

This chapter is organized as follows. Section 2 and its subsections describes general application of VR in manufacturing systems' phases of an automated robotic site. Section 3 and its subsection elaborates on safety 4.0 and risk-preventive workforce training. Section 4 mainly introduces the proposed interactive VR-Based simulation model equipped with collision-preventive feature. It also focuses on presenting a simple geometrical modeling to simulate potential collisions and impacts to avoid collision incidences. Moreover, it describes the importance of workforce and decision makers' training to work with the proposed VR-based simulation model effectively. Finally, summary of this chapter is presented in Sect. 5.

2 General Application of VR in Manufacturing Systems' Phases and Processes of an Automated Robotic Site

The definition of VR originates from the definitions for both "virtual" and "reality". The definition of "virtual" is near and reality is what we experience as human beings. Thus, the term 'virtual reality' basically means 'near-reality'. VR tools have seen remarkable advancements in recent years. VR applications include a wide range of industrial areas from product design to analysis, from product prototyping to manufacturing. The design and manufacturing of a product can be viewed, evaluated and improved in a virtual environment before its prototype is made, which is a significant cost saving. The following subsections describes the application of VR in manufacturing systems' phases of an automated robotic site.

2.1 Design and Prototyping Phases

One of the key goals of utilizing a VR system for design verification is the potentially high degree of reality that can be experienced while immersed in a virtual environment. Virtual prototyping is a key aspect, where a digital model of a system in development can be experienced prior to construction [9].

2.2 Planning Phase

VR offers very valuable task visualization aids for planning and previewing robotic systems and tasks [9]. VR can result in an optimal planning of an automated manufacturing system by offering a visual environment to the all engineers, managers, and staffs involved in the planning process. In this way, significant factors that lead to inefficient planning and postpone the start of products can be monitored in an effective way.

Moreover, real-time visual comparison of potential scenarios and solutions based on decision makers' experiences and statistics initiate a rapid start of production and robust automated manufacturing processes [5].

2.3 Simulation Process

The logic of simulation model can be verified by using VR as an effective tool. VR can provide a visual trace of incidence as they occur. A virtual environment is provided by VR for engineers, managers, and all staffs to understand the statistical outcome of a simulation.

VR helps understand the results and dynamic behavior of the simulation model. Virtual model of the proposed work cell could bring to enlighten the hidden errors whose elimination in later stage of the new work cell creation should cause significant problems.

2.4 Workforce Training

The adoption of Industry 4.0 has an impact on the workforce training and will change their needs and professional development requirements as the required skills of the workforce will be different [18]. Furthermore, combining digital and physical technology requires that the workers have the ability to incorporate technologies in daily work exercises which means new training essentials. It is necessary for the worker to be trained on how to navigate and interact with new technologies in the smart work environment.

VR with its interactive and real-time application can be used for training purposes [28]. Workers can learn smarter, better and more efficient. Moreover, it gives them the opportunity to practice their job virtually before they do it in the real-world in a hazard-free environment. Using VR for training, increases the workers' performance and reduces their tentative mistakes and errors. The level of virtualization depends on the type of industry as well as company size [1].

Different game engines can be used to combine with VR for training and education of the workforce [27]. Playing games allow workers to learn concepts and develop necessitated skills. It provides an interactive environment with the possibility of practice or compete with other colleagues that enhance the retaining information and applying in their work practices.

One of the advantages of training games, is to obtain feedback on workers' performance, learning process, and effectiveness of the training. It also presents an effective and adaptable learning environment that potentially reduces the cost and the overall training period.

VR helps predict robotic actions, training robotic system operators, and have a visual perception of non-visible events like contact forces in robotic tasks [9].

2.5 Machining Process

Based on the application, the machine simulation, including material removal and collision detection, can occur in the VR with the correlated requirements regarding real-time. Furthermore, with the knowledge of the process forces and with the aid of the axial values, the tool deflection and the static flexibility of a machine tool can be computed by using a multibody simulation. Dynamic simulation of multibody systems plays a significant role in a wide range of arenas, from robotics to computer animation, and from digital prototyping to VR [20].

2.6 Assembling Phase

VR plays a vital role in simulating advanced 3D human-computer interactions, especially for mechanical assemblies, by allowing users to be completely immersed in a synthetic environment.

2.7 Inspection Phase

Remote monitoring of hazardous conditions can be accomplished by using VR tools. In addition, in automated manufacturing systems, robots have been integrated with inspection equipment to perform inspection tasks. The robot actively carries a sensor to inspect a work piece or passively loads an inspection station with a work piece. Such an approach increases productivity and quality and reduces labor costs [13]. As an example, to enhance flexibility in passive robot inspection, using a VR-based point-and-direct system can be incredibly helpful. Such a system can productively establish two complementary technologies: (1) Flexible material handling using virtual tools: a human-machine interface has been created therefore robots are taught by manipulating virtual grippers utilizing an instrumented glove to point to key locations while giving directives. (2) Skeletons in a neural network-based inspection to achieve efficient rotational and translational invariance: the number of pixels counted in each sub-skeleton on an image are considered as neural network input for flaw identification. Such a technique is followed to achieve position and orientation invariance to support the flexible robotic material handling approach.

2.8 Maintenance Phase

VR tools offer a promising platform for the maintenance process as they can provide learner experimentation, real-time personalized task selection, and exploration. Utilizing VR during the maintenance process allows individuals to engage in repeated experiential learning, practice skills, and participate in real-life scenarios without real-life repercussions [19].

3 Safety 4.0 and Risk-Preventive Workforce Training

Work area accidents results in major workforce casualty, where it leads to huge monetary consequence to the companies and the governor. According to the released report of the U.S. Department of Labor, Bureau of Labor Statistics, the average workforce fatal occupational injuries among the careers in 2006 was around 3.9%, where this rate in construction and manufacturing site are around 10.8 and 2.7%, respectively [24]. In the same sectors, these rate in 2016 dropped to 10.1 and 2%, respectively, while the average casualty rate increased to 4.33% [25]. Moreover, the released statistics of fatal accidents at work related to the countries of the European Union in 2013 indicates an average 1.71% casualty rate in these countries [4]. Another example refers to the reported cases in Brazil which shows that 0.4% of accidents lead to worker death and in 2.15% of the accidents, permanent disability [14].

In the course of incidents, besides casualty, the equipment damage, total loss, and manufacturing plant down-time should be accounted as losses. The accident rate in the construction industry is higher than other similar industries and it significantly makes delay and accompanies with costs like overrun costs. Consequently, investing to improve the safety of the work environment helps reduce companies' expenditures. Workforce training is one of the common cost saving means to drastically reduce the aforementioned expenditures. Virtual training has attracted attentions these days due to their special attributes, such as low-cost scalability, repeatability, experience of well-trained staff, and ease of changing training scenarios.

People react to risky situation based on their beliefs, their motivation and in short based on their mental model of the risk potential. Digital technology has made it possible to use VR for comprehensive and immersive training environment. The safety methods and tools that are used in work environments need to be changed when adapting to new technologies. Advancing new technology at job sites without adapting it to the existing culture and leadership style can be very harmful. For example, in the smart work environment where sensor-enabled robots are the new normal, it is necessary for employers to take preventive measures to the next level by fostering new forms of safety and health management systems as part of their management process. The traditional safety approach can put workers at risk, especially at places that dealing with high-tech machinery [7].

The smart work environment provides an opportunity to bring more automation into the safety management system of the manufacturing industry where safety 4.0 needs to be developed. It is vital to make the safety measures smarter and at the same time be captured at a real-time. To be accommodated with emerging new technologies for safety compliances, it is required to become familiar with safety related technologies that promote a safer work environment.

There are many new products, tools, and technologies that have been developed recently such as wearable technologies (activity trackers, smart hat), drones, robots, and smart personal protective equipment. For instance, by adding sensors to personal protective equipment, they become part of internet of things at the job site that results in real-time data collection. Safety-related data are used in internet of things with the desired scale and speed which transforms and adopt safety to industry 4.0 criteria.

In addition, safety is an important issue in human-robot interaction in an automated and smart work environment. Robots mobility may cause incidents with people around them. To avoid the hazardous situations, it is essential to identify sources of the potential hazards [26].

3.1 Selection of a Safe Adaptable System Design

Together with machinery, the work environment will also change, and create the workforce a greater work responsibility [22]. Work organization should enable workers to combine work, private lives, and professional development more productively [23].

The previous studies identified four design principles instructing on "how to do" Industry 4.0, which supports companies in identifying and performing Industry 4.0 scenarios [11]:

- Interoperability: The ability of equipment and people to connect and communicate each other via the internet of things or the internet of people.
- Information transparency: The ability of information systems to create a virtual copy of the physical world by improving the quality of digital plant models with the data gathered from sensors. The aggregation and analysis of raw sensor data to higher value information is required.
- Technical assistance: In the Industry 4.0 smart factories, workers' position shifts from machine operator to a decision maker and problem solver. The existing technical assistance systems help workers to aggregate and visualize information extensively for making decisions strategically and solving problems quickly.
- Decentralized decisions: The cyber physical systems' ability helps workers to make decisions on their own and perform their tasks as independently as possible. In case of interference, or goal conflicts, the tasks will be given to a higher level.

In order to generate a comprehensive software for manufacturing/construction plant design and workforce training, in the next section the idea of merging the positive attributes of a VR tool and two simulation software pieces such as SIMIO and EPSON RC+ is presented. The proposed integrated model simulate, evaluate, and test potential designs and by means of accurate computations associated with a reach of robotic arms mimics the robot arm motions effectively. In this way, by evaluating all potential designs and considering all possible states, the decision maker will come up with the more focused states and feasible designs in the response space. The proposed integrated model can also prepare decision makers with a detailed simulation as it considers the motion parameters of the robot arms such as a motion range of the auxiliary arms' joint angle. It also takes the proximity of robots into consideration and computes the probability of impacts and potential accidents that can occur among the arms of various robots or between the robot's arms and other physical objects in the working environment. In this way, it can be helpful to decrease the risk of accidents' occurrences.

4 A Proposed Interactive VR-Based Simulation Model Equipped with Collision-Preventive Feature

Controlling the robotic systems is a challenging task, especially when multiple robots are integrated to accomplish certain tasks for an automated manufacturing system. Moreover, training the operators of such complex systems is time-consuming and costly [3, 6]. In the era of industry 4.0, integrating VR tools with real-time simulations can be very effective. In this way, various manufacturing system processes and robot motions can be simulated virtually. Such a VR-based, task-level robot control system offers a great help for training of operators on a complex robotic system and robot control during hazardous/remote robot applications [9, 15].

The literature on VR display technologies demonstrates that there are two main categories for such a display, including (a) partial-immersive VR and (b) full immersive VR. Partial immersive VR devices such as vision-head mounted displays (HMDs) supports the feeling of "looking at" a virtual environment while full immersive VR devices such as a successful projection technology called the cave automatic virtual environment (CAVE), supports the feeling of "being in" that environment [10]. In an HMD, displays and imaging optics mounted on a headset offer a virtual image in front of the eyes. Such a device provides the viewer with a view of the virtual environment while blocking out the user's real environment. The CAVE system is one of the most immersive display devices in VR domain. Selecting the name of CAVE refers to Plato's allegory in which prisoners confined to a cave interpreted external events from the shadows and echoes experienced within the cave. Most interpretations of the allegory focus on the idea that human being's perception of reality is, similarly, not reality itself but a construct of reality created by his/her minds. CAVE consists of a cube-shaped VR room in which the walls, floors and ceilings are projection screens. The user typically wears a VR headset or a head-up display and interacts via input devices such as pointers, joysticks or data gloves. The user, whose headgear is synchronized with the projectors, can walk around an

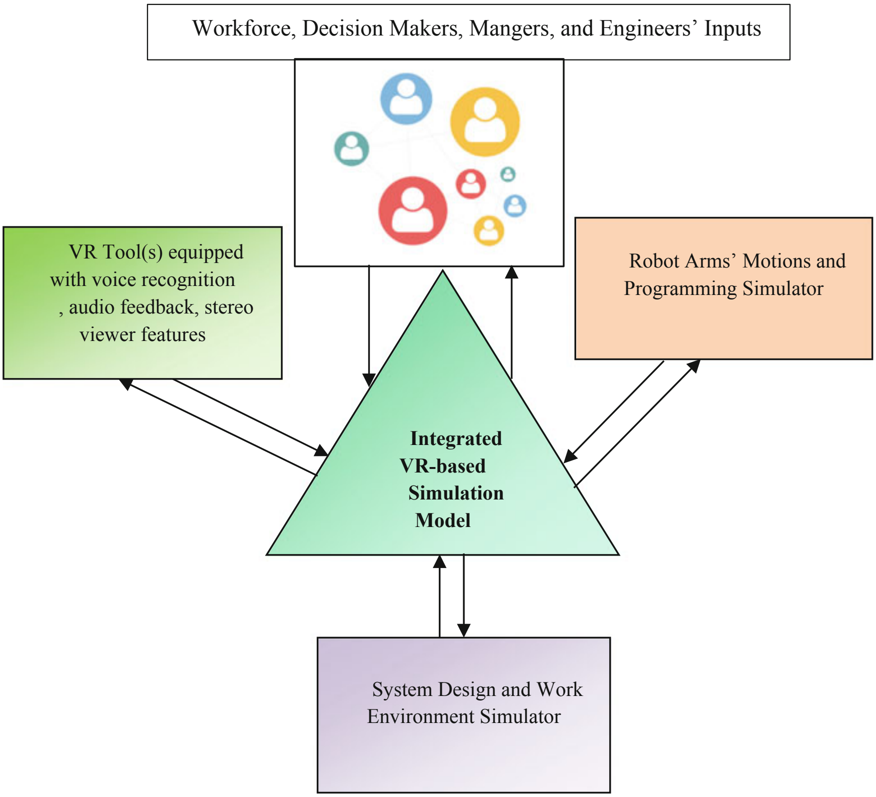

Fig. 1 Architecture of the proposed interactive VR—based simulation model

image to study it from all angles. Sensors within the room track the user's location to align the perspective correctly [8]. Thus, the use of VR display devices can be taken into account as a helpful tool in real-time simulation and visualization of automated manufacturing systems.

Here, a proposed VR-based simulation model, which integrates a VR tool, a system design simulation software (SIMIO), and a robot programming simulation software (Epson RC+), is discussed. Figure 1 shows the architecture of the proposed model. Moreover, an exact simulated instance of a real-life robot is programmed in the presence of obstacles with approximately the same distance as in real environment. Such information can be collected by the autonomous wireless sensory mechanism, embedded in a manufacturing plant.

The proposed VR-based simulation model have the capability to visualize object behaviors at interactive frame rates and provide efficient geometrical and spatial analysis. It plays the role of a collision-preventive tool which tracks the work environment and work cells for the objects to move and analyzes the robot arms' motions. When

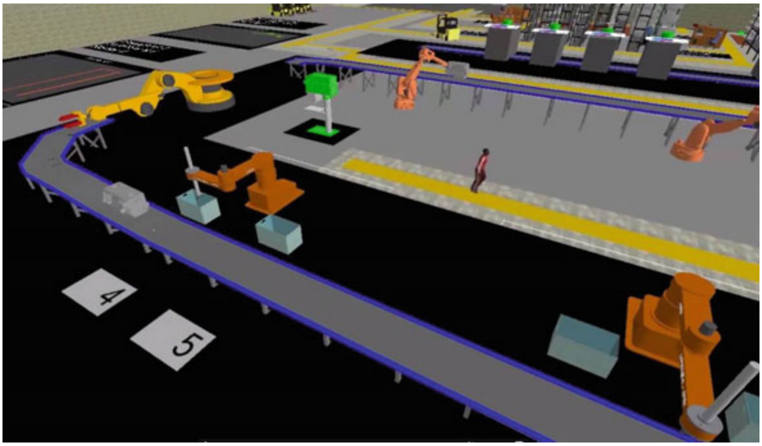

Fig. 2 A virtual model of an automated factory created in SIMIO version 9.147 software environment

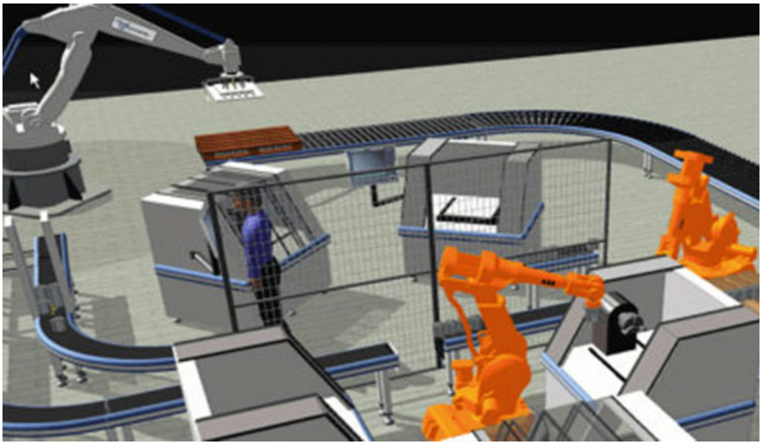

Fig. 3 A virtual model of a manufacturing cell created in SIMIO version 9.147 software environment

collisions occur, two tasks are handled in a timely manner: (a) collision detection and (b) collision handling.

Considering the aforementioned points, Figs. 2 and 3 refer to virtual models of an automated factory and manufacturing cell created in SIMIO Version 9.147 software environment in order. Figure 4 demonstrates a robot model before collision detection that is created in Epson's RC+ software while a collision error message is shown in Fig. 5.

The proposed integrated VR-based simulation model is a collision-preventive tool and in the next subsection, a simple geometrical modeling is presented to

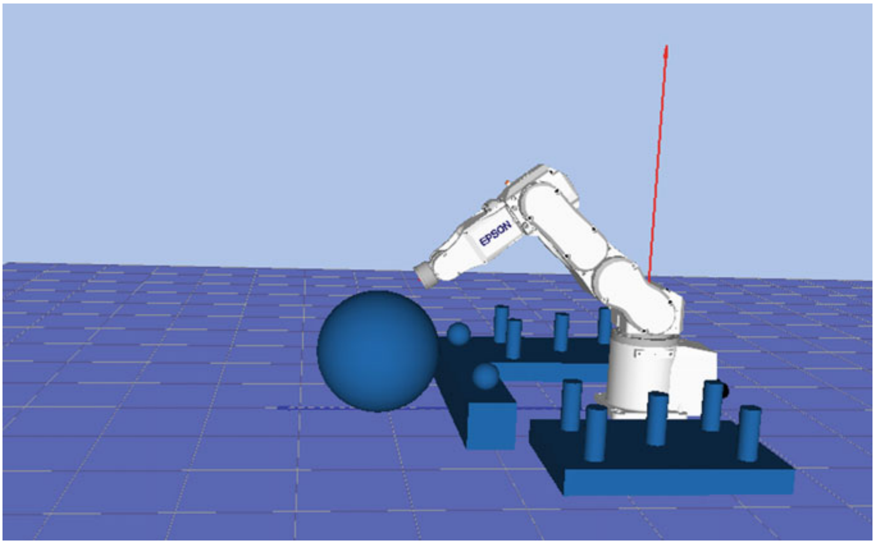

Fig. 4 Model of robot created in Epson's RC+ software

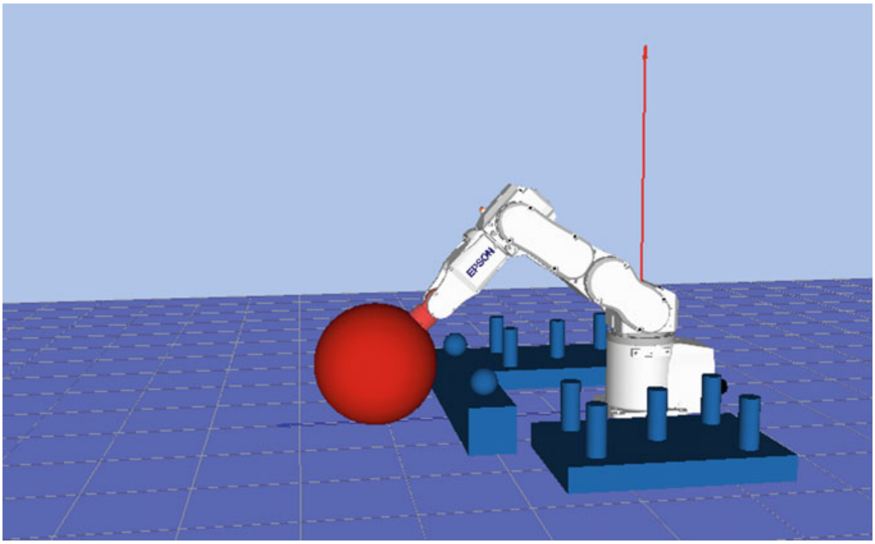

Fig. 5 Example of a collision error message created in Epson's RC+ software

simulate robot arms' motions with the objective of potential collision avoidance. Such incidences can occur due to machine-machine, robot-robot, machine-worker, robot-worker, machine-site objects (work pieces), robot-site objects (work pieces), machine-building, robot-building, machine-material, and robot-material collisions. To avoid potential collisions, the proposed model incorporates various factors in its analysis, such as region of a space that a robot can encompass (when the arms are extended) and the region in a space that a robot can fully interact with.

4.1 A Simple Geometrical Modeling to Simulate Robot Arms' Motions to Avoid Potential Collisions

Developing a tangible mathematical model for technician workforce who intend to program the automated manufacturing can simplify their training steps. In this section, multi-axis and SCARA robots are considered as two common robot types for manufacturing sites. Each robot in its simplest form can be modeled with a system of multiple vectors of different lengths and angles in three dimensional (3D) space. Figure 6, illustrates this geometrical model.

In the course of the task as the robot moves, the vectors' relative angle and accordingly the formation of the connected vectors varies, as it is shown in Fig. 7. Each vector has its own thickness and allowed angle of rotation in given directions. The majority of the SCARA robot parts have planer or two-dimensional (2D) move, where it simplifies the model for this robot type to multiple 2D vectors and one perpendicular vector to the plane of other 2D ones for the end effector. For clarity,

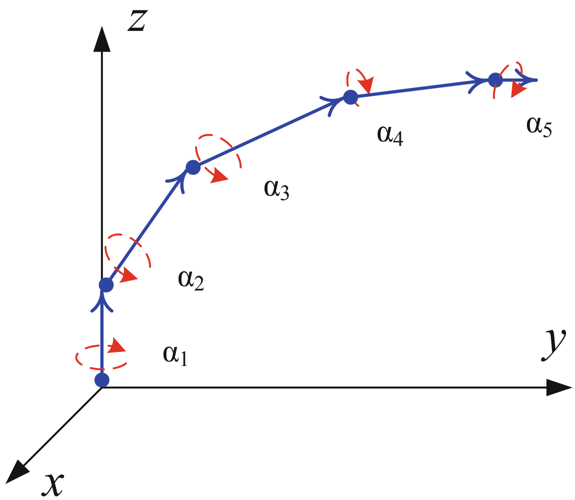

Fig. 6 Modeling a multi-axis or SCARA robot with vectors

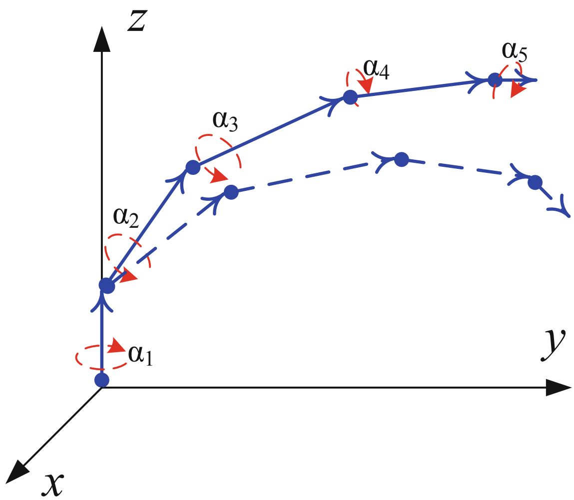

Fig. 7 Modeling the dynamic of change in robot using multi-axis model

Figs. 8 and 9 illustrate one simulated 6-axis EPSON robot arm and one EPSON SCARA robot, respectively.

In the accelerated process of manufacturing in the multi-robot environment, avoiding incident can be challenging. Once a robot is programmed to go from a given known endpoint to another one, the body of the robot trajectory may pass through some unexpected locations, where it might results in a collision.

Based on the above proposed model, the following approaches are proposed to eliminate or highly reduce the risk of collision:

(a) Moving one arm or piece of robot at a time and specifying the risk-involved zones. With this approach the risk zones become limited and it directly reduces the risk of concurrent operations in the same zone that can collide.
(b) Moving arms in their allowed angular range, i.e. α_k in Fig. 7.
(c) Time scheduling to isolate the operation time of the distinct arms or moving pieces. This approach is highly effective in preventing collisions.
(d) Using smart sensing mechanisms such as proximity sensors (ultrasonic, optical, magnetic, reflection, etc.), motion sensors, etc. to individually detect the presence of another in-range part and prevent the collision risk.
(e) Using sensing and communication mechanisms to collaboratively share the physical area, and time among the machines.

The final solution is normally a supportive combination of the aforementioned approaches. The VR-based scenario-simulator considers all the possible tentative collisions and based on priorities, it proposes an optimum design scenario.

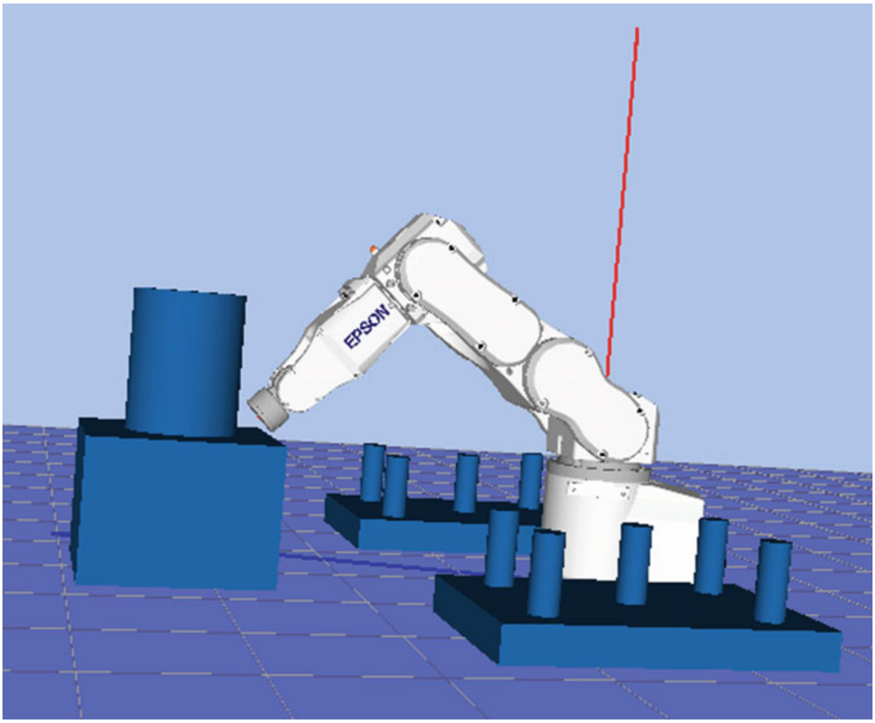

Fig. 8 A simulated 6-axis EPSON robot arm in EPSON RC+

4.2 Workforce Communication with Robots and System

Numerous manufacturing tasks require a physical presence to operate machinery. But supposing such tasks could be done remotely. VR techniques have paved a path in robot tele-operation. System and robot tele-operation embeds the decision maker in a virtual environment with multiple sensor displays. By using gestures, the decision maker can match his/her movements to the robots to perform various tasks. In this way, workforce and decision makers can tele-communicate with robots and the entire system design. Literature on tele-operation demonstrated that there are two main approaches to using VR techniques for tele-operation including (a) direct model: in this model, the user's vision is directly coupled to the robots and systems' states and positions. (b) Cyber-physical model: the user is separate from the robots and the system. He or she interacts with a virtual copy of robots and system using a VR tool. Such a feature (tele-opration) with robots and the entire system can be added to the proposed model.

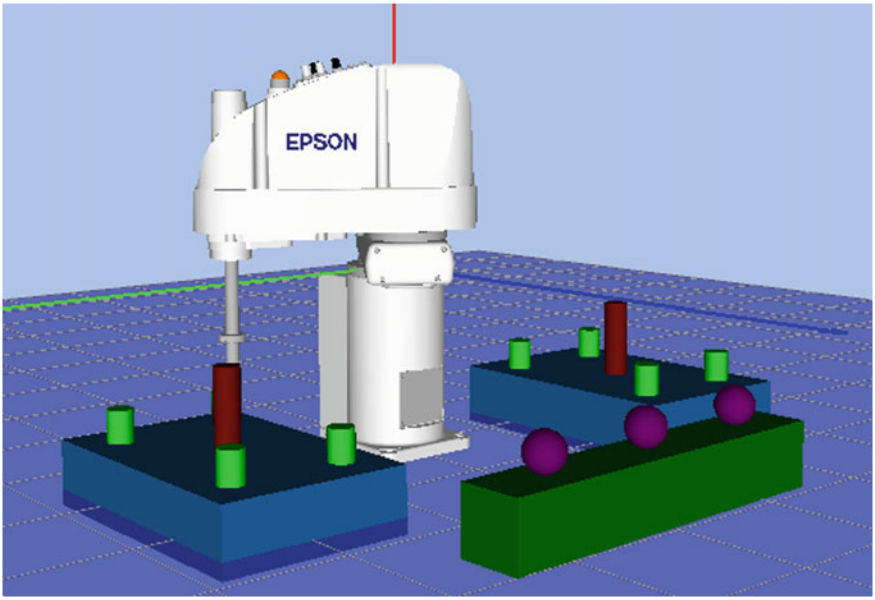

Fig. 9 A simulated SCARA EPSON robot in EPSON RC+

4.3 VR-Based Scenario Test in Sensor-Enabled Robotic Site

With the advent of industry 4.0 and industrial internet of things, employing multi-purpose sensor sets along with communication facility is inevitable. Such sensing sets may include proximity sensors, motion sensors, vision sensors, force sensors, touch sensors, orientation sensors, position sensors, velocity sensors, light sensors, radio frequency identifier sensors, chemical detection sensors, thermal sensors, and flame sensors. They are helpful in collecting, processing, and sharing data through the available communication facilities with the other robots of the site.

Embedding the sensor observation outcomes with the next step interaction of the robot in a real-time machinery process, allows the manufacturing and construction site to (a) avoid the accidental and unexpected incidents, (b) reduce the risk of site shut downs and damages to the site facilities, workforce casualties, and quality product rate drop.

In work area collision prevention, the sensors play a pivotal role, while they collect the environment data in real-time. The mixture of the multi-purpose sensor set's data allows the decision system to predict the upcoming incidents.

The proposed interactive VR-based simulation software can smooth the workforce's practice with the different types of sensors. In this way, workforce will decide to embed them in the structural design of the manufacturing/construction sites, under various scenarios, such as performance improvement, minimum incident risk, etc.

Luckily today, the prevailing companies' robotic machineries can support and employ multiple types of sensors, where some of them are wireless and can transfer the variables of the environment to the other machines for mutual decision makings and real-time reactions. High quality proximity sensors, vision sensors, force and touch sensors are among these instruments. Sensor-enabled robots can work and communicate together using wired or wireless communication channels. Networking of robots can function to improve efficiency, production and safety of a smart work environment. According to Occupational Safety and Health Administration [16], having a safety management system at the workplace provides a proactive method to prevent workplace accidents. In a smart work environment, workers and equipment can be monitored and it is suggested that an automated safety procedures with the help of decision support system can provide preventive strategies for the work environment [21].

Therefore adding the scenario-evaluation feature in training of the workforce during the programming and the assembly line design, allows the trainees to employ various sensors and test them in the scenario.

5 Summary

This book chapter dealt with proposing a novel VR-based simulation model which enables workforce to test all possible design scenarios and avoid any potential collisions that can happen in automated robotic sites. It specifically focused on the integration of a VR tool, a system design simulation software (SIMIO), and a robot programming simulation software (Epson RC+). Alongside this context, a simple geometrical modeling to simulate robot arm' motions is presented to show how the proposed model will work to avoid potential collisions.

Integrating the manufacturing and construction mechanisms (i.e. robot arms, track belts, etc.) in assembly module; as an instance along with condition aware embedded sensory system in simulated VR software that is closely incorporating with the real-life plant for training purpose, not only reduces the work environment casualty and its related costs, but also improves the manufacturing and construction site's productivity and its production speed.

Furthermore, if the manufacturing system is equipped with machine-to-machine communication technologies, the sensor-enabled robots can convey information in a timely manner. They can also detect the required maintenance for the associated robots. As an example, sensors can perform proactively and be sensitive toward the life cycle, fatigue, and fracture mechanics of robot arms. Meanwhile, heuristic techniques such as an ensemble of neural networks and genetic algorithms can be added to the proposed model as a module to enhance and expedite the optimization process in finding the most adaptable scenarios.

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IoT Integration in Manufacturing Processes

Abhinav Adduri

Abstract In manufacturing processes, simulation parameters such as arrival times have traditionally been drawn from statistical distributions or from empirical datasets. Although this approach may lead to relatively accurate parameters, there may be applications in which a more precise methodology is required. IoT is a technology that enables for the processing of real time data through microcontrollers and servers. A simulation may ingest this real-time data to modify downstream simulation parameters towards values that will produce higher yield. This chapter will introduce two techniques that are made possible by the availability of real-time data in simulation. First, the chapter will discuss possible optimizations that may be made by selectively choosing parameters that lead to higher production based on real-time data input. Then, the chapter will focus on the ability of IoT-based simulations to dispatch real-time instructions to robots placed in the manufacturing process. The chapter introduces these concepts by the model construction of a drug manufacturing process using a discrete-event simulation software called Tao.

Keywords Internet of things · Discrete event simulation · Modeling

1 Motivation

In recent years, the cost of IoT compliant devices has gone down considerably, and the interconnectivity between these devices has been simplified. Remote computers and microcontrollers on these IoT devices can send messages to one another through a variety of protocols, such as the HTTP protocol. This allows users to access real-time info that can then be used to make automated decisions in the field. The improved feasibility of these methods makes the incorporation of IoT in discrete-event simulation a natural next step in the industry. This chapter will detail a method by which simulations might query for real-time data, and also describes two possible uses for IoT in a traditional discrete-event simulation setting.

A. Adduri (✉)
Computer Science, University of California, Berkeley, CA 94720, USA
e-mail: abhinadduri@gmail.com

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2 Background

Before starting a discussion on the model development process, it will be helpful to provide context on the Tao software. Tao [1] is heavily inspired by Sigma [2], which was the first graphical discrete-event simulation software developed for the DOS operating system. Sigma has since been used by thousands of students in classrooms and has been used in the industry to make fast simulation engines for various commercial applications. Unlike Sigma, which exclusively runs on Microsoft Windows, Tao has been developed to run on a modern web browser, leveraging existing libraries in the environment to make tasks such as IoT integration easier. The engine and graphical interface are both written in Javascript, a popular language that is used on almost all webpages today. This allows for easy cross-platform use, which is a desirable trait when deploying simulations across multiple devices. The source code also allows for the application to be exported as a native Microsoft Windows, Mac OS, or Linux executable for those who prefer not to use a web browser. The code for Tao is open source and available at https://github.com/abhinadduri/tao-app.

Although Sigma had adopted a stance of minimalism regarding its available features, Tao has opted to give users full flexibility and control over every aspect of a simulation. Sigma and Tao are similar internally in their implementations, but Tao makes certain tasks easier for the modeler. Traditional discrete-event simulation software such as Sigma use event graphs to represent the various state changes that can take place in a system. An event graph is a representation of a system using a directed graph, where events that are executed can schedule other events with a specified delay. These scheduled events are placed in a "future events list", which is a priority queue that is organized by the scheduling time plus the delay. In Sigma, these events contain state changes that modify user-specified global variables. The directed edges between events represent conditions which, if fulfilled, place the target event into the future events list. In Sigma, this edge condition may be a function of global variables or parameters to the event. Such edges are called "scheduling edges". Tao allows for arbitrary code to be executed within each event. This means users can define private variables within an event execution scope and use these variables in edge conditions or as parameters for target events. A user may use existing Javascript libraries present in the web browser, such as HTTP requests, to communicate over the internet during the execution of an event. By storing the value contained in the response, a modeler may pass on this value as a parameter to other events.

The cardinal design decision behind Tao was to give the modeler complete control over the underlying engine. For example, the user has access to the future events list in the simulation, and can directly modify it if s/he so wishes. All attributes—including scheduler logic, global variables associated with the simulation, events and edges—are attached as attributes to one central simulation object. This means a user can dynamically add new global variables or create new events and edges in the middle of a simulation run. A user can also schedule events using Javascript code, meaning an event may be scheduled without an edge pointing to it if necessary. As an example of the freedom provided to the modeler, the simulation might receive a piece of code as a HTTP response and create a new event using that code while the simulation is running. In this manner, a modeler might be able to remotely modify a simulation. If security is a concern, it is also possible to make the central simulation object immutable, which would prevent anyone from changing any simulation parameters (such as events, edges, delays, etc.) after initialization. These features make Tao a great choice when choosing a software to incorporate internet-of-things with discrete-event simulation.

3 Drug Pipeline Introduction

Consider a three-stage drug production pipeline, where each stage represents a critical operation. For the completion of each critical operation, certain conditions must be met. If not, the pipeline is blocked and results in yield loss in the later stages of the pipeline. Let these dependencies of the critical operation be denoted as preceding, or ancillary, operations. A concrete example of one stage of this pipeline might be to heat a chemical compound to a certain temperature and mix it with water. In this case, possible preceding events would be to obtain the stoichiometric amount of water, as well as preparing a heat bath. One can see that if these operations take longer than expected, then there is a delay in the completion of this critical operation, which may lead to yield loss. Figure 1 describes a basic process flow diagram of one cycle of the proposed drug pipeline.

In the language of event graphs, the critical operations are denoted as events, and the preceding operations are denoted as "preceding events", or events that are placed into the future events list before the main event. It follows that the yield loss mentioned above can be thought of as these preceding events taking longer than expected. This requires an event graph analog for the critical event to "wait" for its dependencies before being executed. In Sigma, this may be done by scheduling the critical event, and cancelling it if the necessary conditions are not met by the scheduled time of

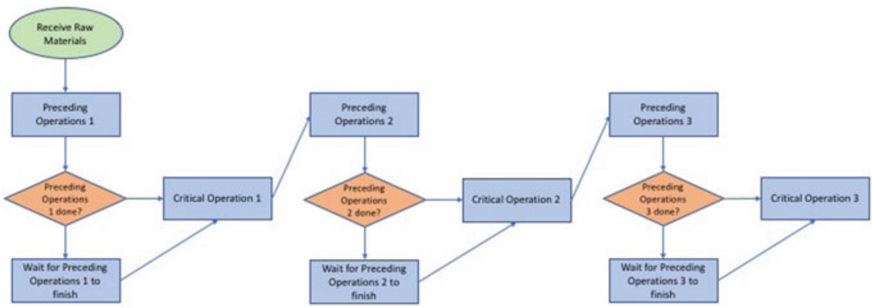

Fig. 1 It is assumed that a critical operation must be completed before the preceding operation of the next critical operation can begin

execution. To model the preceding events, one would first schedule a preceding event and then schedule a critical event. This may prove to be difficult if there are many independent preceding events for a single critical event.

Although the techniques used may be generalized to work with most simulation software, this chapter will focus on using Tao features to create a model. The most important of these features is the pending edge, which is a generalization of the scheduling edges found in Sigma. Intuitively, a pending edge places a condition on the future events list, and checks to see if the condition is fulfilled at each time step before executing the next event. If the condition is ever fulfilled, the target event of the pending edge is placed on the future events list with the specified parameters. The condition can only involve global variables and the parameters of the source event of the pending edge. If there are no more events on the future events list and there are still pending edges whose conditions have not been fulfilled, the simulation continues to step the global clock until the specified end time for the simulation is reached. This is to accommodate for pending conditions that involve the global clock, such as “wait until the clock reaches 100 time units”. The pending edge construct immediately presents a more elegant modeling solution to the drug pipeline described above, where critical events must wait for preceding events to complete. A helper event may schedule the critical event with a pending condition requiring that all preceding operations are completed. Once a pending edge condition is fulfilled, the critical event is placed in the future events list with a specified delay.

Tao also allows for relative scheduling, which is a technique that allows a modeler to schedule events relative to the scheduling of another event. This can be valuable in situations where a modeler is waiting for real-time data and wants to schedule several events upon the arrival of the data. It is difficult to keep track of simulation state if a main event has many independent preceding events that must all complete before scheduling the main event. The complexity increases greatly if these preceding events themselves have dependencies on one another. Using relative scheduling, the independent events do not need to be aware of one another, as Tao calculates the relative schedule for each of these events during the scheduling of the critical event. In the example of the drug manufacturing pipeline, a modeler may schedule a critical event, and then have “preceding edges” to each of the preceding events, which would place the preceding events in the future events list before the critical event.

In combination with pending edges, relative scheduling allows for the ability to schedule events before or after events that have an undetermined execution time, as any preceding events are placed in the future events list once the pending edge condition is fulfilled. This is extremely convenient, and can help greatly in modeling systems using real-time data. One nuance here that should be noted is that Tao does not currently allow the global clock variable to run backwards. So, a critical event scheduled 20 time units after its pending edge condition is fulfilled can have preceding events up to 20 time units before it. If the user specifies that a preceding event should be 25 time units before the critical event, the negative delay is floored to 20 time units.

4 IoT in Simulation

There is great versatility and power in using IoT with simulation. A simulation would be able to query information from remote machines to update parameters, and notify remote machines of status changes within the production pipeline. Additionally, a simulation might make use of robots by sending commands and receiving status updates. Incorporating IoT devices with simulation, which would allow for the aforementioned features, requires processing real-time data. Upon first inspection, such a method seems rather counterproductive as it would greatly reduce the speed of running a model. One might argue that once real-time data is available, it is too late to use simulation as a meaningful tool. This is true to an extent, and as such, techniques that require real-time data to adjust their own parameters are not applicable to all processes. For a manufacturing pipeline with multiple discrete stages, real-time data for the earlier stages can replace simulation parameters, such as wait times drawn from statistical or empirical distributions, and aid in optimizing later stages. An example is presented in the next section. Additionally, using real-time data allows for a simulation to issue real-time instructions.

An IoT-based simulation allows for a fully connected and automated production pipeline, using robots that are commanded by a central, synchronized simulation. The robots would contain microcontrollers, which are programmable to communicate with a simulation over a common network. There are exciting possibilities in the future of the field; as there are no restrictions on the devices with which the simulation will communicate with, a distributed system of several Tao simulation instances may be developed. For example, one computer running the simulation software might be in charge of a particular stage of the medicine production pipeline. It may communicate with other stages of the pipeline by routing requests to computers in charge of those stages, rather than directly to the robots involved in those stages. Such a division of labor would allow for easy division of tasks. One complication of this method is that it would require maintaining global state across several different machines, introducing additional complexity to the model.

The benefit of the abstraction provided by using the centralized IoT-based simulation is substantial. If a production line had robots directly communicating to one another, replacing or upgrading a machine would require notifying all other robots that directly communicate with the replaced hardware. If there is a centralized system, the robot may be represented as an object in the simulation. Rather than changing all connected robots, a modeler may simply change the value of the IoT endpoint for the particular object that is being replaced. Such abstraction, in some cases, may warrant the increased overhead of sending requests through the central simulation.

There are several methods of gathering data from the outside world to be used with a simulation. No matter the method of compiling the data, polling to receive the data is not feasible from a performance standpoint. An example of polling would be continuously scheduling an event that checks to see if new information has arrived through the internet during the execution of this event. The future events list is unnecessarily filled with these polling events, leading to slower overall simulations.

The problems that arise from polling are similar to those in systems programming as well. Instead, it is preferable to use an event-callback method to be notified of new data. The approach is as follows: the simulation sets up a server that is notified when any requests are made to it. The modeler can create and register functions that are executed when the server is notified of new incoming data. Such functions are known as callback functions [3]. When a robot or similar IoT device sends a message to the server listening in the simulation, the model will invoke the callback function defined by the modeler.

Consider a source event that wants to schedule a target event only when it ingests new data from a data source. The source event can register a callback function that will change some flag to be true. This flag may be either a global variable or a parameter and should be initialized to false. The source event can also register a pending edge to its target event, whose condition for success is that the same flag mentioned above is true. Once the server notices incoming data and invokes the callback function, the global flag is changed to true, and the pending edge condition evaluates to true, leading to the execution of the target event. Once the target event executes, it can change the flag back to false to facilitate further loops of this model. Such an approach allows for relative scheduling to the target event as discussed earlier, since it was scheduled by a pending edge. It avoids unnecessarily filling the future events list with data ingestion events, and allows for critical operations to be scheduled based on real-time data. This is described in Fig. 2.

It is important to define exactly what is meant by fine tuning parameters further down a pipeline. Consider a scenario in which the early stages of a production pipeline have already been planned, and a modeler is tasked with finding parameters for downstream processes. In this case, using real-time data as a sort of realistic stress test for the downstream process will allow the modeler to accurately make design decisions. One example in the case of drug production might be the amount of time between heating a solution and using it in a downstream reaction. Although there are several physical considerations that must be taken into account, such as

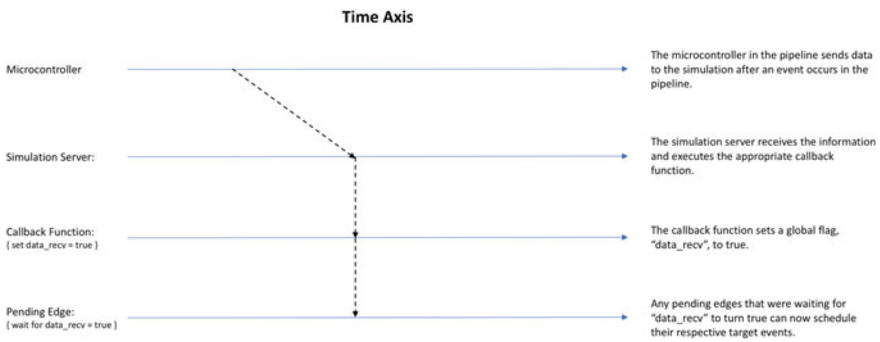

Fig. 2 A schematic representing the data transfer mechanism. The simulation can set up pending edges that wait for incoming data. Once the data arrives, registered callback functions can set the global flag to true, scheduling the targets of the pending edges

the fact that waiting too long might invalidate the solution for further reactions, this method provides a preliminary method by which to optimize the later stages of the production line.

4.1 Drug Manufacturing Pipeline Optimization

The scheduling concepts, in conjunction with IoT devices, can be used to build out a traditional production pipeline in a novel way. Consider the drug manufacturing pipeline described earlier in this chapter that has three critical operations, each with its own preceding and succeeding operations. Each critical operation is a blocking operation, meaning a unit quantity of medicine cannot be produced without going through all of the critical operations, and a downstream critical operation cannot start before an ongoing critical operation is completed. For example, the second critical operation cannot begin until the first critical operation has begun. This does not apply to the preceding operations required to begin the second critical operation, as it is often the case that such preceding operations for the second critical operation are run in parallel with the first critical operation. In the case of medicine production, the first critical operation might produce Compound A, which is a necessary reagent to begin the chemistry of the second critical operation. A preceding operation that may be run in parallel with the first reaction might be to heat up a buffer or a solution in preparation for the second reaction.

Let there be two preceding operations per critical operation in this pipeline. Consider the case in which the first stage of the pipeline has been finalized, and yield loss is being incurred in the second and third stages of the pipeline, which are still in development. As a result, total production of the final product is reduced. With the advent of the internet of things, microcontrollers can be programmed to send messages to connected devices. In this case, one method by which real-time data can be acquired would be to connect a microcontroller to the production of Compound A, so that it can send out a message per unit production of the desired compound. Although specialized protocols for this communication may be developed, Tao leverages HTTP requests as they are general purpose and are already integrated nicely with Javascript. The Tao model would set a pending edge between the first critical operation and the beginning of the second one, with the condition being the completion of the first critical operation. Note this inherently requires all of the ancillary operations for the first critical operation to be complete, as the system is taking in live data.

The modeler may set up a global flag to describe the transition from the first critical operation to the second, and once an incoming HTTP request from the microcontroller is detected, this flag is set to true. The second critical operation may then commence in the simulation, setting off any ancillary operations through relative scheduling. It is critical to reset this flag to false as soon as possible to facilitate further processing of live events. If this is not possible, the modeler may consider using an integer counter and changing the pending edge condition to look for an increase in the global counter from one timestamp to the next. With the initial setup done, the simulation is now effectively running an arrival process where the arrivals are determined by the microcontroller as opposed to being drawn some empirical distribution. The modeler may then measure the theoretical output of the pipeline by noting the output of the third critical operation in the simulation.

This simulation scheme is seen in Fig. 3. The event named "Crit_A" sets up a callback function and waits for incoming data. It has a pending edge to "Sched_B", whose condition is for a global flag, such as "First_Crit_Op_Done", to be set to true. The registered callback function will set this flag to true once data has arrived. Once "Sched_B" is scheduled, it also schedules the preceding events "Pred_B" and "Pred_BB" (signified in Tao by setting the edge type to "Preceding" in the user interface). "Sched_B" also sets up a pending edge to "Crit_B", whose condition is to wait until the necessary preceding operations are completed. In this example, both stages B and C, which include the respective critical operation and necessary preceding events, are downstream operations relative to stage A. The event "Sched_B" should set the global flag "First_Crit_Op_Done" to false, and immediately schedule the event "Crit_A" so that it can set up another callback function to listen for more incoming data. Note that in this diagram, "Crit_A", "Crit_B", and "Crit_C" are the same critical operations described in the beginning of this chapter.

This allows a modeler to conduct stress testing on the system using real-time data for the first critical operation. From this point on, optimization may involve looking through output logs and identifying the bottleneck areas of the pipeline downstream relative to the first operation. One example of a bottleneck in the process described above could be that the transfer mechanism to take the output of "Crit_A" to "Crit_B". If the time to transfer the output is larger than the time for the preceding operations of "Crit_B", then the output transfer is a bottleneck, since "Crit_B" is blocked until this step is done. The efficiency gained by tuning parameters in this manner can be considered theoretically equivalent to identifying and fixing bottlenecks in the pipeline. By ensuring that preceding operations are started early enough to not delay the critical operations, the production of the final product will increase. Using real-time data in a simulation allows a modeler to view each critical segment of the pipeline in isolation, and make adjustments to delays and other parameters to lower yield loss. If a user was to optimize the pipeline, then each stage of the pipeline would change based on design decisions earlier in the process.

By abstracting the earlier stages using the arrival data from the real world, the modeler can optimize the next stage of medicine production without worrying about parameters in earlier stages. In the event graph above, the model is effectively drawing wait times, signifying how long the first critical operation will take, from the exact distribution that describes the real process. Another added benefit of incorporating IoT in simulation is that it allows for an easy comparison between the currently implemented production line and the idealized simulation output. Because the model is synchronized with the production of compounds in the drug manufacturing pipeline using microcontrollers, it becomes easy to compare where the model diverges from reality.

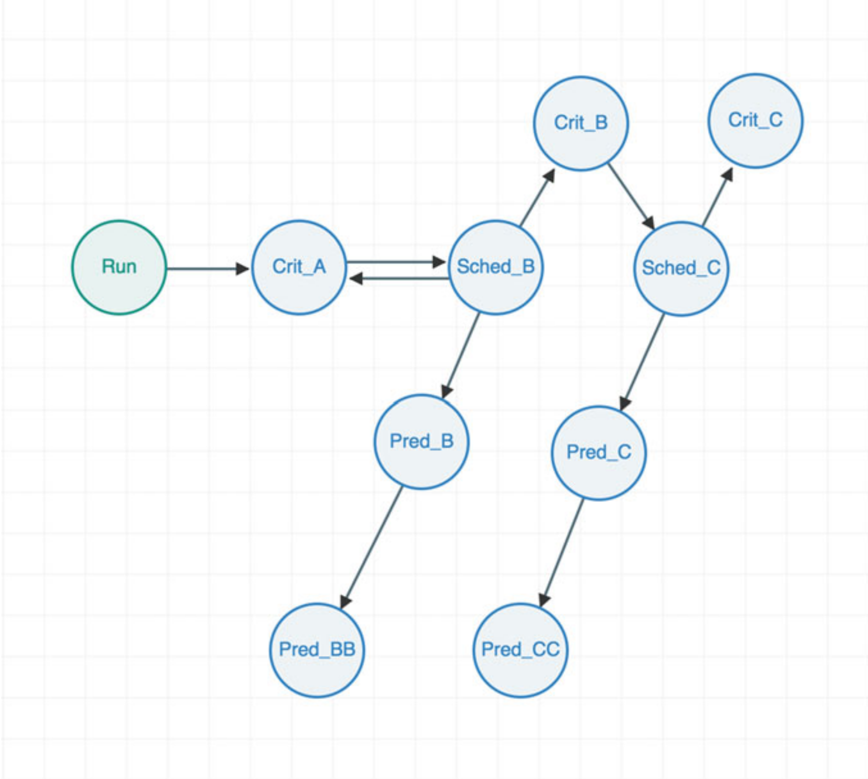

Fig. 3 A sample simulation event graph, built in Tao

5 Dispatching Real Time Instructions to Robots

It is also possible to dispatch instructions through the simulation to various robots set up in the pipeline. These instructions may be dispatched from any event in the simulation, including preceding and succeeding events. A modeler would send an HTTP request to a robot equipped with a microcontroller, which can send back a response after finishing the task it was given. Using a centralized simulation to control the interaction between robots allows for fine control and easy modification of the pipeline. In the medicine example above, let there be a robot that must carry the output of the first stage of the pipeline to the second stage within a certain time limit. If this time limit is exceeded, the output might become invalidated and would no longer be usable to facilitate further downstream reactions. Upon reaching the time limit, the robot may dispose of the solution and go back to its original location. It must also notify the central simulation of success or failure.

Once the first critical operation finishes, the simulation may immediately notify the robot responsible for carrying the solution to go to the second critical operation. Or, the simulation might note that the second critical operation is backlogged by several other tasks (such as dealing with earlier output from the first critical operation), in which case the simulation might tell the robot to move the solution to a preservation tank to prevent invalidation. In this case, the robot need only to listen for instructions from the simulation, and it does not need to query lots of devices to figure out its best course of action. The logic and code for the behavior of the robot is entirely kept in the simulation, reducing the cost and overhead of replacing a broken robot. The second stage of the simulation would then continue as before, with the inclusion of other robots similarly equipped with microcontrollers. For example, upon scheduling the second critical operation, the simulation may dispatch an event to a robot in charge of a preceding event. In this manner, the pipeline may be converted to using fully connected network of robots. The simulation, which is connected to a network, may also query remote databases or any other sources of knowledge it might need.

In this case, the simulation is in charge of running production, rather than being a tool to help design it. It may also be possible to self-optimize various parameters as the run goes on, based on the responses sent by the robots. It is a simple task to notice when the pipeline is slowing down, since the simulation in charge of controlling the robots would notice any considerable delays in success responses. If so configured, the simulation may also notify idle robots to help with a particular step that is causing delays. The pipeline is entirely programmable, and has access to the power of discrete-event simulation as it is running.

It is necessary to consider the additional points of failure that incorporating IoT might create. In particular, a network outage would devastate the production pipeline as it is setup. One possible solution for this is to program the robots so that they may remember previous history of actions and act according to that history. For example, the robot may notice that it is transporting the output of the first stage to the second stage every five minutes, and continue to do so in the case of a network outage. The pipeline built out using the scheduling techniques discussed above attempts to optimize the process through pending edges. Such techniques cannot be employed during a network outage, and this will likely lead to less than optimal production output after some time. If a modeler sends and receives encrypted data, and ensures that the microcontrollers can only receive instructions from the central simulation, then the risk of malicious security attacks is minimal.

6 Conclusion

Although the techniques described in this chapter are yet to be adopted by most production lines, the appropriateness and effectiveness of analytic approaches involving the internet-of-things is immediately notable. In the future where integrated devices are more commonplace and cheap, it may be favorable to run real-time simulations alongside production processes to note where slowdowns are occurring. Using discrete-event simulation to control connected robots would allow for a modeler to optimize production processes in a completely novel way. Data from around the world can be ingested in real-time. The connection of simulation software and the internet allows for limitless possibilities, and there is no doubt that in the future, novel and advanced techniques relying on such technologies will be developed. Such techniques need not compete against traditional discrete-event simulation modeling software, as they can complement existing techniques and help aid the modeler in making key design decisions.

Additionally, this chapter briefly discussed the usage of robots equipped with microcontrollers in manufacturing pipelines. The interconnectivity between various devices in a simulation allows for a simple, centralized automated system for production. The central simulation, which receives data from all of the connected robots, can then reallocate resources as needed. The modeler may use real-time data as a replacement for edge wait-times, and even change the model structure itself by changing events. Although this chapter was primarily written in the language of the Tao software, any discrete-event simulation software tool that allows for network communication can incorporate the same methods described in this chapter. In the case of Tao, which is written specifically for the web browser platform, it is simple to leverage the existing HTTP protocol. Other simulations tools might accommodate different network protocols to communicate with microcontrollers.

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Data Collection Inside Industrial Facilities with Autonomous Drones

Murat M. Gunal

Abstract Advancements in drone and image processing technologies opened a new era for data collection. Comprehension by visual sensors is an emerging area which created a completely new view point to many sectors including the production industry. New dimensions are added to abilities of visual human sensors with these technologies. Image processing provide fast, reliable, and integrated information that the industrial facilities require for improving efficiency. On top of this, drones can extend these properties by providing multi-dimensional and continuous view. In this chapter, we propose a new approach for data collection in industrial facilities. Our approach utilises autonomous drones that can fly over the production lines, collect indoor aerial image and video, processes the visual data, and converts it to useful managerial information. Although developing such a system for different manufacturing domains is a challenge, especially Small and Medium-Sized Enterprises (SMEs) can utilise this approach to help achieve Industry 4.0 goals in their manufacturing facilities.

Keywords Drone · Autonomous vehicle · Industrial applications · Computer vision · SMEs

1 Introduction

Drones are utilised in many areas today for various purposes. In military, drones, also known as Unmanned Aerial Vehicles (UAV), are utilised not only for surveillance but also for taking armed action. Non-military usage of drones are evolving, and new uses are being emerged. For example, in energy sector, drones carry out inspections on energy infrastructure by collecting visual static and thermal data of assets. The data is processed in specially designed software which can detect anomalies, cracks and defects in lines. The information is then used to build maintenance schedules. In agriculture, drones help farmers detect parts of a field which need extra

M. M. Gunal (✉)
Barbaros Naval Science and Engineering Institute, National Defense University, Turkish Naval Academy, Tuzla, Istanbul, Turkey
e-mail: m_gunal@hotmail.com

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care or irrigation. Other examples include shipping and delivery, filming and journalism, humanitarian operations and healthcare, archaeological surveys, geographic mapping, weather forecasting, and wildlife monitoring.

Drone technology is one of the most significant technologies which will revolutionize businesses in the near future. Their use in business is estimated to grow rapidly and its economy will exceed $128 billion by 2020 [1]. Furthermore, Artificial Intelligence (AI) technology will extend the capabilities of a drone since this companionship will create flying and self-deciding machines. When such machines operate together with coordination, their capabilities increase.

Image processing is a popular field in computer science and many algorithms and methods have been developed in years. "Computer Vision (CV)" extends the objectives of image processing and allows real-time image processing in videos as well as in images. Many applications exist in our daily lives today, such as person tagging in social networks, surveillance in security cameras, authorisation by human face in computer networks and mobile devices and so on. Advance and emerging applications of CV do also exist, such as in robotics, autonomous vehicles, industrial inspection.

Industrial applications of image processing include automated visual inspection, process control, part identification, and robot control. For example, in quality control, visual inspection is performed by workers and this process relies on workers' eyes. Although human operators have some advantages over machines and algorithms, machines can work in visual inspection, which incorporate CV, faster and longer than humans. Visual inspection is needed for two purposes; To inspect the quality, and to inspect the quantity. For quality control purpose, a visual inspection system can be used for verifying the quality of products on a static or moving surface, such as a table or a conveyor belt. Such systems can choose uncompliant items and direct them out of the production line. We see these systems particularly in high speed production lines, such as for snacks and bottled drinks. For inspecting the quantity, a visual automated system can count the number of items on a static or moving surface, or in a container.

Integration of CV and drone technologies will create a flying visual inspection system for the industry. Real time information with high level accuracy can be obtained. Integration with data processors and data acquisition will make such systems an indispensable part of data processing. Furthermore, dangerous tasks can be assigned to intelligent drones, so that they can help decrease human injuries in the industry.

In this chapter, a drone-based data acquisition and processing system is conceptually presented. To achieve Industry 4.0 targets, a manufacturing facility can benefit from such system in sensing and collecting data at the shop floor. A short review of the academic literature is given in the next section. In Sect. 2, Flying Eye System (FES) is presented with its components and requirements. The chapter concludes with potential benefits the FES will bring.

1.1 A Glimpse of Academic Literature

Some of the technological developments in this area come from academia and are reported in the literature. These developments are generally reporting a system conceptually or necessary algorithms as part of a whole system. For example, Malamas et al. [2] demonstrated components of an automated visual inspection system. Their system includes image processing hardware, illumination, camera, manufacturing process control system, and a network backbone to enable data flow between these components. Likewise, Golnabi and Asadpour [3] reports a generic machine vision model for developing industrial systems. Such a system has four stages including capturing of images, analysis of these images, recognition of objects of interest within images, analysis of the objects in focus to recognise objects and features within images.

Ciora and Simion [4] presents the steps of an industrial inspection with image processing system. After an image acquisition, images which capture the area of interest in the production line are processed. The process mainly removes the noise and non-uniform lighting. Some image operations can be included to the process. There are five groups of image operations; Point operations including brightness and contrast modification; Global operations including histogram equalisation; Neighbourhood operations including image smoothing and sharpening; Geometric operations including display adjustment, image wrapping, magnification, and rotation; Temporal operations including frame-based operations. Segmentation is the next step in which region of interest in images are identified and focused. The feature extraction phase in industrial image processing aims at reducing the amount of information in images so that they are analysed using statistical, structural, neural network and fuzzy logic operations. Finally, decision is made to extract the information in images.

Application area include food industry, automotive industry, medical sector, electronic circuit manufacturing, steel and wood manufacturing, and robot design. In robot design vision-guided automated guided vehicles are being developed.

Use and design features of UAVs, and drones, are reported in the literature as well. For example, Cermakova and Komarkova [5] developed a framework for generating automatic landscape map production using imagery collected by UAVs. Beul et al. [6] presents a study conducted for a warehouse in which Micro Aerial Vehicles (MAVs) autonomously operate to collect data among shelves. MAV's task is to detect, identify, and map the inventory stored in the warehouse. Autonomy is required in such operations since the environment is dynamically changing and obstacles are emerging. Main sensor technology they used in the application is "Lidar" that is a laser beam scanning the surrounding environment like a radar. The Lidar system, as reported, is capable of sensing MAV's environment, avoiding obstacles, creating allocentric map of warehouse. Note that allocentric is to localise objects relative to other objects, and its opposite, egocentric, is to localise objects relative to the observer, the drone in this case. In addition, the warehouse is equipped with fiducial markers and Radio Frequency Identification (RFID) tags. They pointed out that in most of the current applications, drones are operated by human pilots in warehouses, however autonomy provides time and cost efficiency in these tasks.

Just to give another view from the literature related to drones, Vidyadharan et al. [7] presents a modelling approach to evaluate key factors in performing Unmanned Aerial Systems (UAS) tasks. Their model use attributes of autonomy and technology readiness levels of UAS. The evaluation model can be used for developing state regulations, and therefore it is an example of how drones is to be managed. In the future, with the increase in the use of drones, such regulations at state or international levels are necessary.

Since the CV and drone technologies are very active research areas with the advent of Industry 4.0, with this very limited literature review, we aimed at giving a glimpse of the literature and wanted to guide the readers to the academic world. There are many ideas in the literature and the material in this review is even not the tip of the iceberg. The developers and entrepreneurs of the fourth industrial revelation can benefit from academic literature.

1.2 A Glimpse of Related Terminology

As in the review of the literature, we review some of the related terminology in this domain, although we acknowledge that the technology is already vast and emerging.

A drone can only fly if its motors generate enough thrust to lift itself and the payload. A drone's payload depends on the intended use of drone. For example, for a delivery drone the payload is the parcel and therefore the drone should able to lift the parcel. Thrust-to-Weight ratio (T/W) is a measure of how powerful a drone is in terms of its lift force. If T/W is greater than 1.1 then the drone is said to be "flyable". A drone with T/W greater than 2 is a powerful one and suitable for lifting its payload, as well as suitable for tough weather conditions.

A drone must be capable of odometrical sensors for autonomy. Odometry is the ability of a robot, or a drone, to estimate change in position in time of itself and the objects in the surrounding area. Drone odometrical sensors are based on;

- Radio (Radar)
- Sound (Sonar)
- Laser (Lidar)
- Visual (Vision)

Visual Odometry (VO) is a type of odometry in which position estimation is done by using visual sensors such as cameras. Note that in the list above, tactile sensor is not included since physical touch to objects in drones is not practical way of sensing.

An autonomous drone must have one or more of these types of sensors for at least sensing its surrounding area. The weight of such sensors, for example a camera for VO, is to be added to the payload. Other sensor types require heavier devices than a camera. An autonomous drone's task is not only to fly by itself but also to perform the given mission, for example collecting data.

Furthermore, for autonomy and performing the mission, computing power is required for calculating avoidance paths and detecting objects in interest. Performing these tasks is possible with onboard computers or with a ground station which has computing power.

"Image segmentation" is the terminology for detecting the object of interest in an image or video. If there are many objects with the same attributes in the scene, instances of the objects can be counted. This is quite useful for obtaining dynamic tally statistics. Segmentation can also be used to detect workers in the scene and recognize the process in which they are working in.

2 Flying Eye System © (FES)

The Flying Eye System © (FES) proposed here includes an autonomous drone which can fly on a predefined path inside industrial facilities, collect visual data and process the data to convert to useful information. A flow diagram for the system is given in Fig. 1. In this system, the drone, or drones, fly inside the facility starting from a base station, follow the flight path, collect visual data on focus points, and uploads the data on its return to base station. The visual data is processed, and useful information is obtained and these are fed to the Manufacturing Information System (MIS) and/or Enterprise Resource Planning (ERP) software.

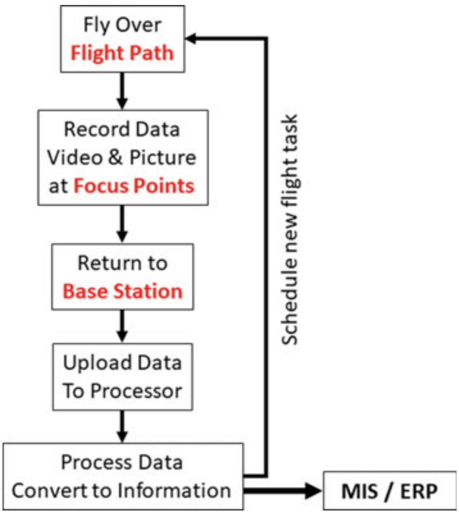

Fig. 1 Flow of drone data collection system

2.1 Operations

The flight path is a predefined path which includes the point of interests inside the facility. The Z-dimension (the altitude) is set appropriately in order not to obstruct manufacturing operations and people underneath. However, to improve the quality of the vision data taken at the Focus Points, the drone may descend to a plausible altitude at Focus Points. During the flight on the flight path, the drone is autonomous, meaning that it can avoid unpredicted obstacles along the path. Although initially the flight path is created by considering possible stationary obstacles inside, such as over-height machines and the building's columns, there may appear some unpredicted "dynamic" obstacles along the path. The drone must be able to sense dynamic obstacles and manoeuvre to avoid from them and return to the flight path. For the autonomous flight, necessary sensors must be onboard. These increase the payload and hence more power is needed.

Data recording is done by either still images or continuous video with the cameras onboard. The recorded data is processed on the ground base station and therefore image processing capabilities on board is not needed. However, there must be enough memory to record the data. In the basic configuration, the data processing is done on the ground base station for making the drone lighter. Because to process visual data, and sending the information wirelessly, require computing power. Although the technology today is available to accomplish onboard computing, it will increase the drone's payload. The autonomy feature, equipped with necessary sensors, is required more than online visual data processing feature.

In the base station, the drone recharges its batteries when it is in pre-flight state. The drone must have equipment, such as probes, to contact to charging pads in the base station, and indicators which signals to controlling system to alter the drone's state to "ready for mission". Initially, when the drone is in this state, the battery is charged, and the drone can start flying over the path and record data without battery loss. Some extra battery power, such as 20% more than a mission requires, must be allocated for the manoeuvres to avoid dynamic obstacles. In case the drone loses its power on the flight path to a level where it cannot accomplish the mission, the mission is ceased, and the drone returns to the base station for recharging. After the recharge, the mission continues from where it is ceased.

The processor is a powerful computer situated at the base station. When the drone lands on the base station, and start to recharge, it also uploads the visual data to the processor. The drone's recharging equipment must also include a channel for data transfer. When the visual data is transferred to the processing unit, the memory at the drone is cleared for the next mission.

As we discussed in the literature review, there are many algorithms and methods to process visual data. The data processing software will utilise necessary methods to facilitate data to information conversion. The objective of this chapter is not to give design details of such software. We must acknowledge that, however, designing and implementing such a software requires expertise on vision and this expertise is difficult to find. In fact, we speculate that in the near future, the need for expertise on vision will increase exponentially as the need for Artificial Intelligence (AI) increases.

After processing the data, useful managerial information is obtained, and they are fed to MIS and/or ERP. MIS is a general term for software that can plan, manage, and operate systems in a production facility. There are different implementations depending on the technology used in facility. In most of the production systems, the machines operate with local management consoles which has no interface to the systems outside. Commands to run the machine can be entered on these consoles and when machines run, they generate data and store it locally. In such systems the data, such as number of items produced, can be collected manually. An operator can read the local data and record it to a central MIS. The system proposed here is most useful for such cases, since we aim at collecting data based on physical activities, and remove the human data collection procedures.

An MIS, or Manufacturing Execution System (MES), is ideally capable of collecting data, automatically and without human intervention, processing the data, commanding and managing the production systems. Industry 4.0 objectives aims at achieving such features by providing sensors in machines, for example to count the products produced and sense the state of machines, and to take action with actuator systems, to operate machines. Today, most of the manufacturing systems are away from this ideal world. Machines can be operated locally and their data is either not collected at all or collected but has never been used. The system proposed here aims at filling the gap between the ideal world of Industry 4.0 and the world today.

Once an MIS provides data, and process it to take operational level action, it can be used to plan further with an ERP software. An ERP is an integrated software which links many functions of an enterprise. MIS, or MES, provide data to ERP. ERP is aware of the production capacity of the facility, and hence can manage the raw materials. It orders right amount of raw material so that the machines never starve (stops due to the lack of raw material). Likewise, ERP creates plans to allocate jobs (orders from customers) to machines, so that the orders are produced for on-time delivery.

In Fig. 2, a fictious manufacturing facility is shown, with the proposed system diagrammatically presented. In this facility, there are three sequential processes; Cut-Shape-Drill, weld, and paint. In this machine park there are two cut-shape-drill machines, three welding robotic arms, and two painting machines.

The drone commences its flight from the base station and follows the flight path. This path includes the focus points determined with points on interest, near the machines. A requirements analysis is done before implementing the system to discover what data is to be collected, and where this data is available at. For example, at the finished parts point of the cutting machines, number of parts can be counted. Likewise, painted parts at the exit of the painting machine can be counted.

Number of focus points and the length of the flight path are determined by the needs and the physical properties, however the flight time is a limiting factor. If the flight time is not enough to cover whole points and the path, then successive flight missions can be scheduled. The feedback loop in Fig. 1 represents the successive tasks, and the task to be executed in every T time. Time T is the time between flight

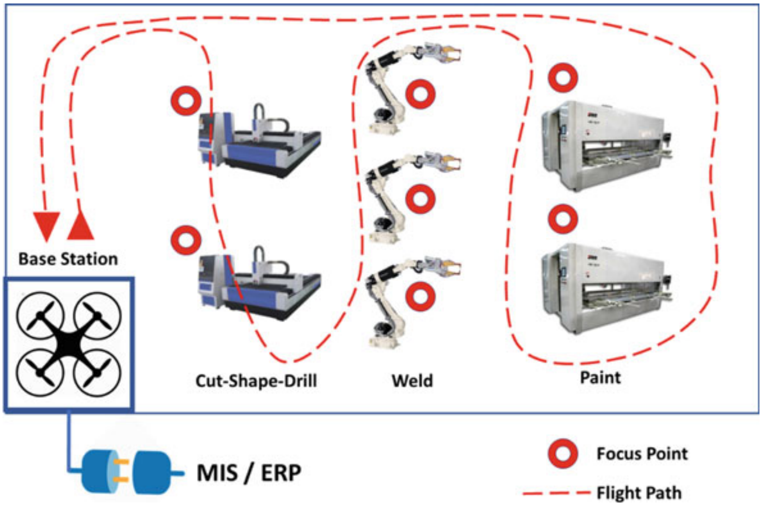

Fig. 2 A fictional facility's bird's-eye view and concepts in the proposed system

tasks. It can be regular, such as an hour, or irregular, such as based on labour shifts or machine schedules. The data collected is discrete. In every T, some information will be produced and fed to MIS/ERP. Managing discrete data as time series is easier than real-time semi-continuous data. The data can tell averages, variances, trends and many others for statistical inference. Retrospective data analysis creates past information. Using the past, we can plan for the future.

2.2 Example Data and Outputs

The FES collects visual data such as the ones in Figs. 3 and 4. The factory in these pictures is a kitchenware manufacturer which has metal, bakelite and plastics production processes. Their production system is clustered based on the material being processed, and additionally there are painting and assembly processes. In Fig. 3, a scene in the final assembly process is shown. After this picture is taken by the drone, it is uploaded to the vision processor in the base station and objects of interest are detected. In this case, finished product boxes are marked, and the information on them is recorded. For example, on the upper assembly line there are 15 finished boxes of medium size, and on the lower assembly line, there are 11 big size boxes on a palette. More information in this picture can be obtained, such as number of workers and number of boxes on the shelves.

In Fig. 4, a scene from a machine park is shown. The drone takes this image from wide angle, before it reaches the focus point. The object of interest, in this case, is the labour force, and three workers are marked on the image. Since the locations of

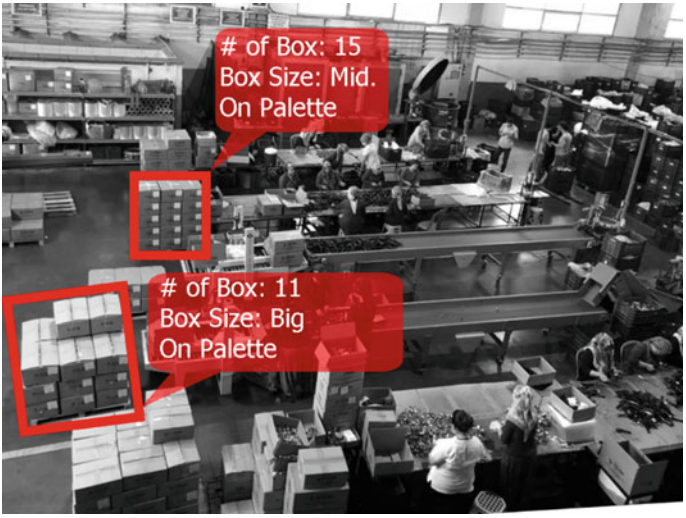

Fig. 3 Aerial photo processed to extract attributes to count the number of boxes

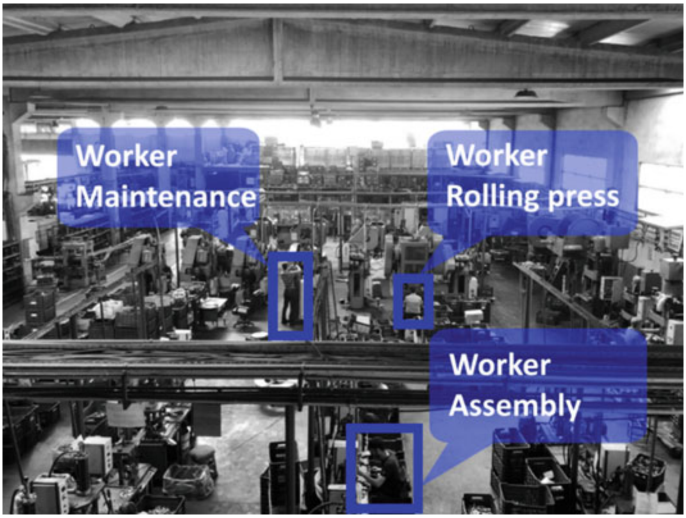

Fig. 4 Aerial photo processed to extract workers

machines are known by FES, and we can get the human body gesture, the processor software can estimate the status of the workers. For example, the worker in the upper left is standing by the rolling press number 1. This gesture is not suitable for this machine's working principle, as this machine is operated while the operator is sitting. The proximity of the standing worker to the machine is indicating that the man is working on the machine, suggesting it is doing maintenance. This approach is not precise, since it can be cheated, however it gives a good guess. The second worker in the upper right is sitting by the rolling press number 2. This suggest that the worker is working in production. The third worker in the lower side of the picture is by the assembly machine and sitting position.

Imagery data can tell many other things and keep an eye on the processes and workers. Work-in-progress (WIP), which is partially finished goods awaiting completion in production systems, data can also be obtained. If the focus points are set before and after the machines, or conveyors, WIP can be recorded regularly. Furthermore, machine utilisations and worker utilisations can be obtained.

Note that the vision data is taken at time T and reflects the situation at time T. In the next flight the situation will be different. To find the differences obtained at different times, the processor software must be able to detect what has changed so far. There needs to be intelligent processing to avoid repetitions and false alarms. One possible solution is to use "tagging", such as square codes, on WIP and finished goods. The tags can be visible from above and drone's camera can read them to know that they are objects in interest with the ID embedded in the tag.

3 Conclusion

The system proposed in this chapter, Flying Eye System (FES), is a drone-based data collection system which includes an autonomous drone, a base station, and a software to analyse visual data that is taken in regular intervals. The drone can fly inside a production facility and collect visual data at points of interest. The points are located where there are possible WIP and workers are operating machines.

FES is presented conceptually with design features and application principles. Expected advantages, benefits and possible uses of FES are as follows;

- Inventory control by measuring finished products, WIP, and raw materials.
- Management of supplies in manufacturing processes by controlling stock levels and signalling for replenishment.
- Monitoring machine states and signalling for acting to solve machinery problems.
- Observing labour force for allocating to tasks and improved efficiency.
- Inspecting and monitoring quality of finished goods and semi-products.
- Examining material handling systems and product transfers.
- Early detection of machine failures.

Potential uses of FES are not limited with the list above. Dangerous and unsafe tasks in facilities can be assigned to drones. New uses will emerge with the advancements in technology, for example with light robotic arms equipped in drones, abilities of FES will be extended from surveillance to taking action.

The FES will help SMEs measure their processes and increase efficiency with low cost. SMEs may have a long journey ahead to achieve Industry 4.0 goals and technologies like FES will provide interim solutions.

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Symbiotic Simulation System (S3) for Industry 4.0

Bhakti Stephan Onggo

Abstract This chapter discusses symbiotic simulation system, a simulation system that is designed to support online short-term operations management decision. The prevalence of real-time data and the advances in Industry 4.0 technologies have made the real-world implementation of the vision of using simulation to support real-time decision making a reality. The main contributions of this chapter are to provide a review of similar concepts in simulation, to provide the architecture of symbiotic simulation system at the conceptual level, to classify the types of symbiotic simulation applications, and to highlights research challenges in symbiotic simulation.

Keywords Symbiotic simulation · Industry 4.0 · System architecture · Operations management

1 Introduction

Based on their planning horizons, management decisions can be grouped into three categories: strategic, tactical and operational. Strategic management decisions often have a long planning horizon (e.g. several years). A strategic management decision (or strategy) is then translated into one or more tactical management decisions. Each has a medium-term planning horizon (e.g. one year, six months). Finally, a tactical management decision is implemented in one or more operational management decisions. Each has a short-term planning horizon (e.g. monthly, weekly, daily). Given the shorter planning horizon, the time needed to make operational management decisions is limited. Hence, a tool to support short-term operational management decision-making is important, especially when dealing with complex operational problems. The symbiotic simulation system (S3) is a tool designed to support decision-making at the operational management level by making use of real-time or near-real-time data which are fed into the simulation at runtime.

B. S. Onggo (✉)
Southampton Business School, Centre for Operational Research, Management Sciences and Information Systems, University of Southampton, Southampton, UK
e-mail: b.s.s.onggo@soton.ac.uk

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1.1 Symbiotic Simulation System Definitions

The idea of using simulation as a real-time decision support tool is not new. For example, in 1991, Rogers and Flanagan used the term "online simulation" to describe their proposed real-time simulation-based decision-support tool for manufacturing systems (cited in [1]). A few years later, Davis [2] provided one of the earliest descriptions of the architecture of online simulation and generalised it as a simulation system that could be used to control a physical system (not just a manufacturing system).

A similar concept, called "co-simulation", has also been used in electrical and computer engineering to describe an experiment in which a hardware simulator (e.g. integrated circuit simulator) communicates with a software component (e.g. firmware) with the objective of verifying that both hardware and firmware function correctly before the hardware is produced. There are several variations of this hardware/software co-simulation (see [3]). Later, some researchers also used it to describe a real-time simulation-based decision-support tool (e.g. [4]).

Another related term is "real-time simulation". A real-time simulation refers to a simulation that can run as fast as "wall-clock" time. Hence, a real-time simulation enables us to use it to test a hardware component (i.e. hardware-in-the-loop simulation). Since more digital devices contain both hardware and software components, real-time simulation has also been used to test software components, too (i.e. software-in-the-loop simulation). Real-time simulation has also been used to describe a simulation that interacts with a physical system in real time. IEEE and ACM have jointly run an international symposium on this topic since 1997 (see http://ds-rt.com).

With the introduction of Dynamic Data-Driven Application Systems (DDDAS) in 2000 [5], the term Dynamic Data-Driven Simulation has also been used to describe similar applications of simulations. It puts emphasis on the ability of a simulation to (1) react to additional data from the physical system while the simulation is running and (2) control the physical system. At the 2002 Dagstuhl seminar on Grand Challenges for Modelling and Simulation, the term symbiotic simulation was coined [6]. The initial definition was heavily influenced by research in DDDAS, which put emphasis on the ability of a simulation to control a physical system. Aydt et al. [7] propose a new definition of symbiotic simulation that is less restricted, i.e. "a close association between a simulation system and a physical system, which is beneficial to at least one of them". A close association is less restrictive than the ability to directly control a physical system. This close association is enabled by communication channels between the simulation system and the physical system which allow them to interact in real or near-real time. This chapter adopts the term symbiotic simulation from Aydt et al. [7] and refers to it as a *symbiotic simulation system* (S3). S3 is also referred to as a virtual system or digital twin. We will discuss the architecture of S3 in Sect. 2.

1.2 Symbiotic Simulation System and Industry 4.0

Historically, industrial revolutions were triggered by the introduction of new technologies. The first industrial revolution was triggered by the introduction of water- and steam-power engines. If the first industrial revolution is seen as Industry 1.0, then subsequent phases, Industry 2.0 and Industry 3.0, are associated with the introduction of electrically-powered mass-production technologies and automation using Information Technology (IT), respectively. The term Industry 4.0 was first announced at the "Hannover Messe" industrial trade fair in 2011. It was taken from the Germans' strategic initiative to establish Germany as a leader in advanced manufacturing solutions. Since then, the term has spread and been adopted in various industries outside manufacturing.

Like many new terms, there have been several definitions proposed for Industry 4.0, as discussed in Chap. 1. However, these definitions agree that Industry 4.0 is a new paradigm that puts emphasis on real-time (or near-real-time) situational awareness to address the increasing complexity of products and processes in industry by making use of Cyber-Physical Systems (CPS). In addition to CPS, Industry 4.0 is also enabled by technologies across four groups [8]: data and communication (e.g. Internet of Things (IoT), big data, cloud), advanced analytics (e.g. Artificial Intelligence (AI), data mining), advanced man-machine interface (e.g. augmented reality) and advanced actuators (e.g. robotics, 3D printers).

CPS has been perceived as the core foundation of Industry 4.0 [9, 10]. There are several definitions of CPS. If we look at the definition in [11], CPS is a system of collaborating computational entities (i.e. virtual system), which have an intensive connection with the surrounding physical system and its ongoing processes. This is exactly what we have in symbiotic simulation, where a physical system and an S3 that represents the physical system form a symbiotic system. In both CPS and S3, the combined virtual-physical (or symbiotic) system provides benefits that would otherwise be unavailable if used separately. Hence, from the perspective of academia, S3 is closely linked to Industry 4.0 in at least two ways. First, S3 is a special form of CPS, which is the core foundation of Industry 4.0. Second, S3 uses the same technologies that support Industry 4.0. Hence, S3 and Industry 4.0 share the same design methodology and most of the challenges. These will be discussed in later sections.

From the perspective of industry, several simulation software vendors have marketed their products and services in the context of Industry 4.0. For example, the Simio homepage (www.simio.com) has Industry 4.0 as one of its main menu items (see Fig. 1). Lanner has produced a briefing paper outlining how their product fits into Industry 4.0 and provided several case studies [12]. Flexsim has written about their successful Industry 4.0 projects in Italy [13]. AnyLogic has also written about their Industry 4.0 project at CNH Industrial, which was presented at the AnyLogic Company Conference in Baltimore [14]. These are only a few examples of how simulation vendors have prepared themselves to provide simulation-based solutions to support Industry 4.0. The most commonly used term for S3 in industry is digital twin

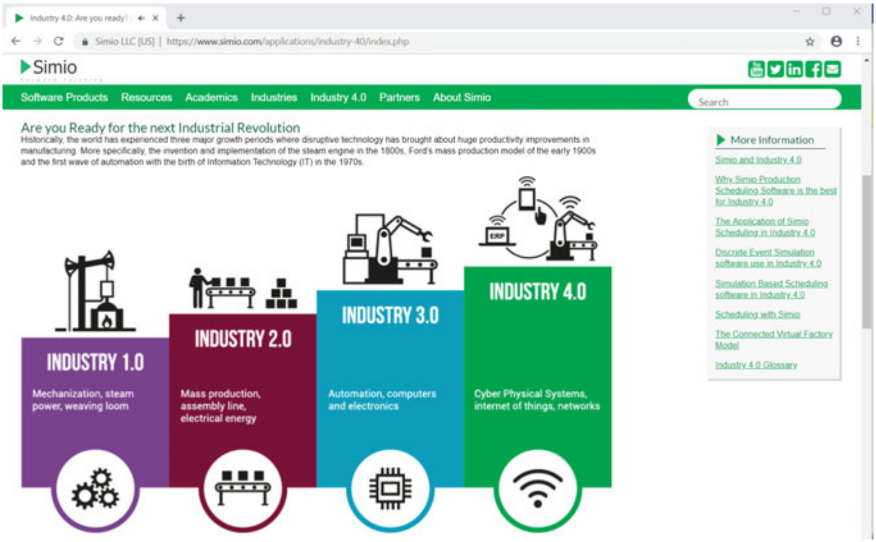

Fig. 1 Industry 4.0 web page at Simio

[15]. Hence, both academia and industry believe that S3 will play an important role in Industry 4.0.

1.3 Objective and Structure

The objectives of this chapter are to present the architecture of S3 (Sect. 2), introduce three types of S3 applications for Industry 4.0 (Sect. 3) and highlight the challenges that need to be addressed for the real-world adoption of S3 (Sect. 4). Finally, Sect. 5 summarises this chapter.

2 Symbiotic Simulation System Architecture

In this chapter, we use the following definitions: A *symbiotic system* is a system that is formed by a physical system and a *symbiotic simulation system* (S3) that represents the physical system. S3 is formed by a *symbiotic simulation model* (S2M) and other components, such as data acquisition, optimisation and machine-learning. The execution of S2M is referred to as *symbiotic simulation* (S2). A diagram showing the components of a symbiotic system and their relationship is shown in Fig. 2.

As shown in Fig. 2, an S3 extracts, transforms and loads real-time (or semi-real-time) data from a physical system using the data acquisition component. The

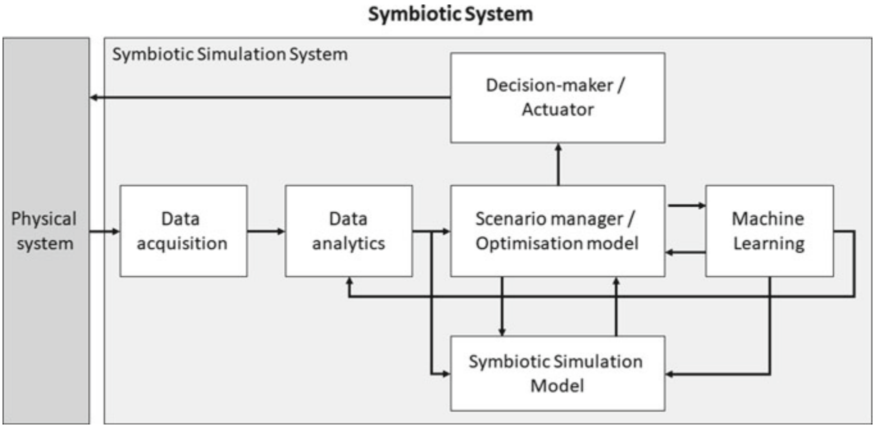

Fig. 2 Symbiotic system formed by a physical system and its symbiotic simulation system [16]

loaded data are then analysed using appropriate analytics methods. The objective of analytics methods is to select the best way to use a combination of historic data when developing a model and new data that are only available when the model is running. The information extracted by analytics may be used to update the scenario manager, optimization model or S2M. Machine learning (ML) methods can be used to adapt the scenario manager, optimization model, S2M and analytics methods to make them perform better. Finally, the results from the scenario manager/optimization model are communicated to an actuator or a decision-maker, leading to changes being made to the physical system. These components work together to achieve a common system objective, e.g. maintain the stability of the physical system when facing external perturbations or make the physical system react in time in anticipation of a drop in its performance. The remainder of this section explains the main components of S3. A more detailed explanation and examples can be found in [16].

2.1 Data Acquisition

The data-acquisition component is responsible for extracting, transforming and loading data (ETL) from the physical world to S3. The data can be read online (direct communication with the sensors) or off-line (the data from sensors are stored in a file, and the file is read by the data acquisition component) through a Web service, Web application or mobile application. The data can be real-time (always connected) or semi-real-time (connected at certain times or regular intervals).

2.2 Data Analytics

One of the characteristics that differentiates symbiotic simulation from non-symbiotic simulation is that symbiotic simulation is designed to respond to data when the simulation is running. The data may come in different volumes, velocities, varieties and veracities. Hence, there is a need for analytics methods to determine the best way of using various data sources to update the appropriate parts of S3. Typically, the data analytics methods used in S3 belong to time-series models or data-mining models.

2.3 Scenario Manager

The role of a scenario manager is to implement various what-if analyses using a symbiotic simulation model. Typically, the scenario manager implements analyses such as sensitivity analysis and the design of experiment analyses.

2.4 Optimisation Model

An optimisation model may be used instead of a scenario manager, especially when it is impractical to define a set of scenarios (e.g. too many possible solutions). In this case, the optimisation model explores the solution space and tries to find the best solution based on a predefined objective function (or functions, when there is more than one objective). The function is estimated by running the simulation model. This combination of simulation and optimisation models is referred to as simulation optimisation or optimisation-via-simulation [17].

S3 is a tool designed for making short-term operational management decisions. Hence, the time to find a solution is relatively short. For this reason, the simulation model has to run fast. Many complex short-term operational decisions belong to a *combinatorial optimisation problem* (COP). A COP is a problem in which there are countable-but-vast possible solutions to choose from, e.g. staffing level to minimise waiting time, job scheduling to maximise throughput, inventory management to minimise stock-outs. Finding the best solution to a COP is known to take a long time and is impractical in practice. Hence, alternative methods are needed to find good enough solutions that can be achieved over a short planning horizon. The alternative methods include simheuristics [18], multi-fidelity modelling [19] and parallel computing [20].

2.5 Simulation Model

The core model of S3 is the simulation model of the physical system (i.e. S2M). This S2M needs to be designed to communicate with the data-acquisition component at runtime and to make an appropriate response as specified by the modeller. The response can be in the form of:

- re-initializing the system states in the simulation using the latest data from the physical system
- adjusting the remaining service times for entities that are already in the system at the point of simulation re-initialization
- adjusting the parameters used in the simulation, such as input distribution functions and number resources
- updating the structure of the simulation model.

Any simulation needs to maintain a set of system states (e.g. queue lengths and whether a server is busy in a discrete-event simulation, or the accumulated values of each stock in a system-dynamics simulation). In a non-symbiotic simulation, system states are initialised at the start of the simulation. In symbiotic simulation, the system states may be re-initialised a few times during a simulation run. Re-initialising system states is straightforward. Most simulation software has this functionality. The task of a modeller is to define the system states that need to be re-initialised and the mechanism that triggers the re-initialisation (e.g. periodically or when a value from the physical system is outside a certain range).

Re-initialisation means that the service time of an existing entity that is being served when the simulation is initialised should be sampled based on the time already spent in service. This requires the simulation software to support a conditional-distribution probability function. Most simulation software provides a capability for modellers to create user-defined functions which can be used to implement the required conditional-distribution probability functions.

Adjusting simulation parameters is also straightforward. Most simulation software provides this functionality. However, methodologically, this requires the model to be revalidated. When the adjustment happens regularly, a manual validation process becomes impractical. The simulation software needs to support an auto-validation mechanism. The validation suite in test-driven simulation modelling [21] provides a promising approach for the auto-validation of a symbiotic simulation model. A modeller needs to define a condition that triggers parameter adjustment.

The ability to adapt the structure of a model at runtime in response to a structural change in the physical system is probably the most challenging, methodologically. Only a few simulation tools provide the functionality that allows us to change a simulation model at runtime. Nevertheless, it shows that, technically, such functionality can be implemented. Methodologically, however, the need for an auto-validation is even greater because the model structure can change during a simulation run. A modeller will also need to define a condition that triggers the change in the model structure.

2.6 Machine-Learning Model

The above components of symbiotic system provide an infrastructure that allows us to collect data about expected S3 outputs and the real output from a physical system over time. Hence, every time we run S3 we can collect data about the expected outcome of an operational management decision (from S3) and, after some delay, the real outcome from the physical system. These data, with an appropriate ML method, enable the simulation, optimization and analytics models to learn and make the necessary adjustments to make them perform better in the future (e.g. more accurate, faster).

3 Symbiotic Simulation System Applications in Industry 4.0

Moeuf et al. [22] list four levels of managerial capacities that are aligned with the concept of Industry 4.0, namely: monitoring, control, optimisation and automation (see Fig. 3). The lower level provides components or data needed for the upper levels. Internet of Things (IoT) enables us to monitor the various parts of a physical system. IoT also provides the data needed for the upper levels. Based on monitoring data, we can define the standard behaviour of the physical system. This "standard" behaviour will be used to control the behaviour of the physical system. The optimisation level uses monitoring data and behavioural data to find the most optimal decision. Finally, ML can be used to create autonomy in which the system can learn from its behaviour and past performance. S3 can be used to support the top three levels of managerial capacities (i.e. control, optimisation and autonomy).

3.1 S3 for Control

When the term symbiotic simulation was introduced in 2002, there was a strong emphasis on its application as a control system. Hence, the idea of using S3 for

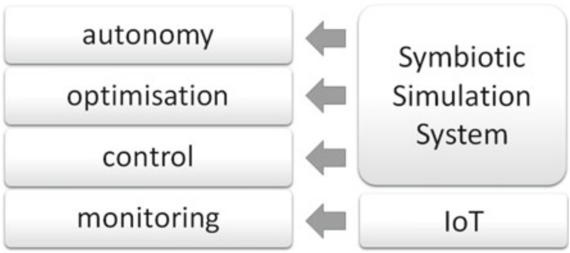

Fig. 3 S3 supports the top three levels of managerial capacities

control has been around since its inception. The way S3 is used to control a physical system can take several forms.

First, S3 can be used to create a reference model of a physical system (Aydt et al. [7] refer to this type of application as an anomaly-detection system). When the behaviour of the physical system deviates from the model, a trigger is activated to investigate whether this is due to changes in the physical system or an inaccuracy in the model. The first case allows decision-makers to make a necessary plan to deal with the changes (indirect control via human decision-makers). The latter case enables the model to learn to improve its accuracy by comparing its outputs against outputs from the physical system. For example, Katz and Manivannan [23] developed an S3 to detect discrepancies between what happens on a shop-floor and expected behaviour or performance (e.g. the number of operational machines and the length of a queue).

Second, S3 can be used to predict the behaviour of a system under the current settings [7]. One important application is to use S3 as an early-warning system if the expected (future) performance is outside an acceptable range. An example of S3 used as an early-warning system in a hospital to help hospital managers cope with potential overcrowding is given in Oakley et al. [24]. Hospital managers need to manage resources, such as beds and equipment, to be shared between emergency and elective patients. Emergency patients must be dealt with as they arrive, while elective patients require care scheduled in advance. Hence, some proportion of each resource must be set aside for emergency patients when planning for the number and type of elective patients to admit. S3 produces outputs that show the risk of overcrowding for a given elective patient schedule. To take another example, Patrikalakis et al. [25] built a symbiotic simulation to predict the state of an ocean.

Third, S3 can be used to assist decision-makers in comparing different scenarios. This will include predicting the behaviour of the system under two or more scenarios. This is what the scenario manager in Fig. 2 is for. In this case, decision-makers need to define the scenarios that will feed the simulation so that the scenarios' expected performances can be compared. The final decision is made by decision-makers based on the simulation results. For example, Rhodes-Leader et al. [26] developed an S3 that is used to compare decisions to recover airlines operations from disruption. The S3 uses data from FlightRadar24 of a small airlines company. The case they consider is that, one morning, one aircraft needs urgent maintenance at an airport. S3 is used to compare decisions, such as wait until the aircraft is available, replace the aircraft with another aircraft (may require further aircraft swaps) or cancel the flight. Oakley [24] describes a case where hospital managers can compare three elective patient schedules using their S3. They show how hospital managers need to trade-off the risk of overcrowding and the risk of elective patient cancellation. Xu et al. [9] demonstrate that dynamic data-driven fleet management strategies for emergency vehicles perform better than a static strategy.

3.2 S3 for Optimisation

When the number of possible decisions is too big to do a scenario comparison, an optimisation model can be used to replace the scenario manager in Fig. 2. The optimisation model will search the decision space to find the optimal result. Since a model is subject to assumptions and simplifications, decision-makers will need to decide if the solution would work in the physical system. Hence, the final decision is still taken by decision-makers. For example, we can replace the scenario manager in Oakley et al. [24] with an optimisation model that finds the optimal elective patient schedule. In their subsequent work, Rhodes-Leader et al. [19] replace the scenario manager in [25] with an optimisation model that finds a tentative optimal schedule so that the normal schedule can resume as soon as possible.

3.3 S3 for Autonomy

The S3 applications in Sects. 3.1 and 3.2 require a certain level of human involvement in the decision-making process. However, it is technically possible to use an S3 to automate a physical system. In this case, ML and advanced analytics methods are used to replace human decision-makers. This may be suitable for routine cases. When a case is too complex or unusual, S3 can alert human decision-makers to intervene. If this happens, the decisions made by human decision-makers can be used to train S3 so that it can handle similar cases in future. Although we have not seen any research papers on this topic, work on this has been reported. For example, Parashar et al. [27] explain the infrastructure needed to achieve an autonomic self-optimising oil-production management process. Kotiadis [28] explains her vision of self-adaptive discrete event simulation in which a simulation model can adapt with minimum human intervention to the changing physical system and its environment. Like symbiotic simulation, her vision is influenced by DDDAS.

4 Challenges

S3 combines several technologies, such as data acquisition, analytics and machine-learning. Hence, the first challenge is that S3 needs an integration framework. An integration framework is needed to make the S3 components interoperable (i.e. meaningful collaboration between S3 components to achieve common system-level objectives). Onggo et al. [16] identify the challenge in integrating various analytics models (descriptive, predictive and prescriptive) and machine-learning methods in an S3. However, the integration challenge does not stop there because the virtual system needs to communicate with the physical system. Hence, the framework should cover integration between the virtual system and the physical system. The vision of

Industry 4.0 includes end-to-end digital integration across organisations in a value chain including end-customers. Hence, integration should not stop at one symbiotic system, but all symbiotic systems across the entire value-chain.

Standardisation is important in an integration framework. Simulation standards related to distributed simulation (e.g. high-level architecture) and simulation interoperability (e.g. those managed by the Simulation Interoperability Standards Organisation) will play an important role in S3 implementation. Standards related to Industry 4.0, such as Industrial Internet Reference Architecture and Reference Architecture Model for Industry 4.0, will provide a good starting point for the development of standards for the real-world implementation of S3.

As computing and communication capabilities are embedded in more devices, they provide potential data sources for S3. However, as more devices feed data into S3, scalability issues may arise. Hence, there is a need for research into how S3 can effectively manage the amounts of data that arrive at high frequency in various forms (e.g. text, numbers, images etc.), which may contain noise. Furthermore, analytics methods suitable to analyse these data are needed so that S3 can make the best use of such data.

McKinsey interviewed more than 300 respondents working in production and service industries in Germany, Japan and the USA [29]. According to the respondents, security and data-privacy issues are amongst the main obstacles to the implementation of Industry 4.0. Given the close relation between Industry 4.0 and S3, we can see that security and data privacy issues may hinder the adoption of S3 in the real world. As virtual and physical systems become more integrated, the risk of physical systems being attacked or hacked is greater. In the case of end-to-end digital integration, data-privacy issues arise due the sensitive nature of the data and models used by organisations in a value-chain. Hence, research on the security and data-privacy aspect of S3 is important.

Finally, apart from the need for integration frameworks, there are other methodological challenges for S3 [16], namely: how to deal with changes in a highly dynamic physical system, the need for algorithms suitable for short-term-operation management decision making, and how to make simulation models adaptive to reflect changes in physical systems.

5 Summary

This chapter has explained symbiotic simulation systems (S3) and highlighted their relevance to Industry 4.0. S3 is a special form of cyber-physical system that forms the core foundation of Industry 4.0. We have explained how S3 can be used in three Industry 4.0 application types, namely: control, optimisation and autonomy. The technological and methodological challenges that may hinder the adoption of S3 in industry have also been presented.

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High Speed Simulation Analytics

Simon J. E. Taylor, Anastasia Anagnostou and Tamas Kiss

Abstract Simulation, especially Discrete-event simulation (DES) and Agent-based simulation (ABS), is widely used in industry to support decision making. It is used to create predictive models or Digital Twins of systems used to analyse what-if scenarios, perform sensitivity analytics on data and decisions and even to optimise the impact of decisions. Simulation-based Analytics, or just Simulation Analytics, therefore has a major role to play in Industry 4.0. However, a major issue in Simulation Analytics is speed. Extensive, continuous experimentation demanded by Industry 4.0 can take a significant time, especially if many replications are required. This is compounded by detailed models as these can take a long time to simulate. *Distributed Simulation* (DS) techniques use multiple computers to either speed up the simulation of a single model by splitting it across the computers and/or to speed up experimentation by running experiments across multiple computers in parallel. This chapter discusses how DS and Simulation Analytics, as well as concepts from contemporary e-Science, can be combined to contribute to the speed problem by creating a new approach called High Speed Simulation Analytics. We present a vision of High Speed Simulation Analytics to show how this might be integrated with the future of Industry 4.0.

Keywords Big data analytics · Cyber-physical systems · Industry 4.0 · Digital twins and smart environments

S. J. E. Taylor (✉) · A. Anagnostou
Department of Computer Science, Modelling & Simulation Group,
Brunel University London, Uxbridge, Middx UB10 8JE, UK
e-mail: simon.taylor@brunel.ac.uk

A. Anagnostou
e-mail: anastasia.anagnostou@brunel.ac.uk

T. Kiss
Department of Computer Science, Centre for Parallel Computing,
University of Westminster, London W1W 6XH, UK
e-mail: t.kiss@westminster.ac.uk

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Glossary

ABS	Agent-based Simulation
APIs	Application Programming Interfaces
DES	Discrete-event Simulation
DS	Distributed Simulation
HLA	High Level Architecture
HPC	High Performance Computing
ICT	Information and Communication Technologies
IaaS	Infrastructure as a Service
i4MS	Innovation for Manufacturing SMEs
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
M&S	Modelling & Simulation
MSaaS	Modelling & Simulation as a Service
OR	Operational Research
OR/MS	Operational Research/Management Science
PADS	Parallel and Distributed Simulation
PDES	Parallel Discrete Event Simulation
PaaS	Platform as a Service
RTI	Run Time Infrastructure
SISO	Simulation Interoperability Standards Organization
SME	Small-to-Medium Enterprise
SaaS	Software as a Service

1 Introduction

Analytics can be defined as the extensive use of data, analytical techniques, models and fact-based management to drive decisions and actions [8]. Building on this Lustig introduces three types of analytics [25]: descriptive, predictive and prescriptive. Descriptive Analytics approaches analyse business performance on from a purely data perspective. Predictive Analytics techniques create explanatory and predictive models using both data and mathematics techniques to investigate and explain relationships between business outputs (outcomes) and data inputs. Prescriptive Analytics builds on this by evaluating alternative actions or decisions against a complex set of objectives and constraints.

Discrete-event simulation (DES) and Agent-based simulation (ABS) are widely used in industry to support decision making. These techniques are clearly cornerstones of Predictive and Prescriptive Analytics in that these techniques are used to create predictive models of systems that can be used to analyse what-if scenarios, perform sensitivity analytics on data and decisions and even to optimise the impact of decisions. In Industry 4.0 Simulation-based Analytics, or just Simulation Analytics, techniques have a major role to play in predictive and prescriptive decision making. For example, in these industrial cyber-physical systems, a simulation (or digital twin) might be constantly updated from the physical elements of the system and constantly runs in the "cloud" to predict and prescribe system behaviour (e.g. to balance manufacturing, to anticipate and prevent breakdowns, to plan and react to changes in customer/supplier behaviour, etc.). Further, these could create novel simulation applications (e.g. perpetual simulations that are always on and provide instant, pre-computed answers, symbiotic simulations that take real-time data and monitor real-world Key Performance Indicators (KPIs) against simulated ones to constantly improve system performance, etc.).

However, a major issue in Simulation Analytics is speed. Extensive, continuous experimentation can take a significant time, especially if many replications are required. This is compounded by detailed models as these can take a long time to simulate. Continuous data updates may also extend this time as statistical distributions within models need to be updated prior to simulation. For example, a detailed digital twin of a factory might take an hour (or more) to be updated and simulated. Each experiment might require (for example) 10 replications. One experiment there can take 10 h. The goal of experimentation might be to explore efficient manufacturing strategies (e.g. a factory might have a complex product mix with several flexible routes through the machining processes of that factory) to recommend what actions should be taken within the next planning horizon (e.g. a week). This could result in several scenarios, each with multiple parameters with many values. Arbitrarily, if we say this results in 100 experiments (each with 10 replications on a model that takes an hour to simulate) then total experimentation time would be 1000 h or around 42 days. If the planning horizon is one week then it is clearly impossible to perform the experimentation in support of this. Contemporary simulation typically uses a single computer to execute simulation. However, *Distributed Simulation* (DS) uses multiple computers to either speed up the simulation of a single model by splitting it across the computers and/or to speed up experimentation by running experiments across multiple computers in parallel. Naively, if we had, for example, 100 computers at our disposal then we could potentially speed up simulation experimentation 100 times. In the above scenario we could therefore complete the experimentation in 10 h. In reality, various computing and networking factors reduce the efficiency of an implementation. However, major speedup is still possible.

How can we achieve High Speed Simulation Analytics? To answer this question we first review advances in DS. We then discuss one aspect of DS, high speed simulation experimentation, and how a cloud computing can be used to deliver on demand speed up. Building on these concept, we then "borrow" from contemporary e-Science to present a vision of High Speed Simulation Analytics for the future.

2 Distributed Simulation

DS has contributed to major successes in the simulation of large systems in defence, computer systems design and smart urban environments. The field comes from two communities [12, 14]: the *Parallel Discrete Event Simulation* (PDES) community that focussed on how to speed up simulations using multiple processors in high performance computing systems and the *DS* community that uses PDES techniques to interconnect simulations together over a communication network. Essentially, the main goals of DS are to use parallel and distributed computing techniques and multiple computers to speed up the execution of a simulation program and/or to link together simulations to support reusability [13]. Some authors have also used DS to refer to approaches that run simulation experiments and/or replications on distributed computers in parallel with the goal of reducing the time taken to analyse a system [15].

To reflect these various influences and goals, the following "modes" of DS can be identified (Fig. 1):

- Mode A: to speed up a single simulation.
  - A model is subdivided into separate models that are simulated on different computers and interact via a communications network; speed up arises from the parallel execution of the separate simulations.
- Mode B: to link together and reuse several simulations.
  - Several simulations running on different computers are linked together to form a single simulation again with interactions between models carried out via a communications network; larger models beyond the capability of a single computer can be created. This mode enables model reuse.
- Mode C: to speed up simulation experimentation.
  - Experiments are run in parallel using multiple computers coordinated by some experimentation manager via a communication network; the parallel execution of simulation runs speeds up the experimentation thereby reducing experimentation time or increasing the number of simulation experiments possible in the same timeframe.

There are various benefits that these Modes of DS offer [5, 21, 29, 37]. For example:

Execution time. A large simulation can be slow to run. DS can be used to split the simulation across multiple computers to exploit parallel processing to speed up execution. DS may also allow simulation experimentation to be processed faster by using multiple computers.

Model composability and reuse. The development of a simulation can represent a significant investment in time and money. When building a new simulation it may be attractive to reuse a simulation as a sub-component. However, practical issues such

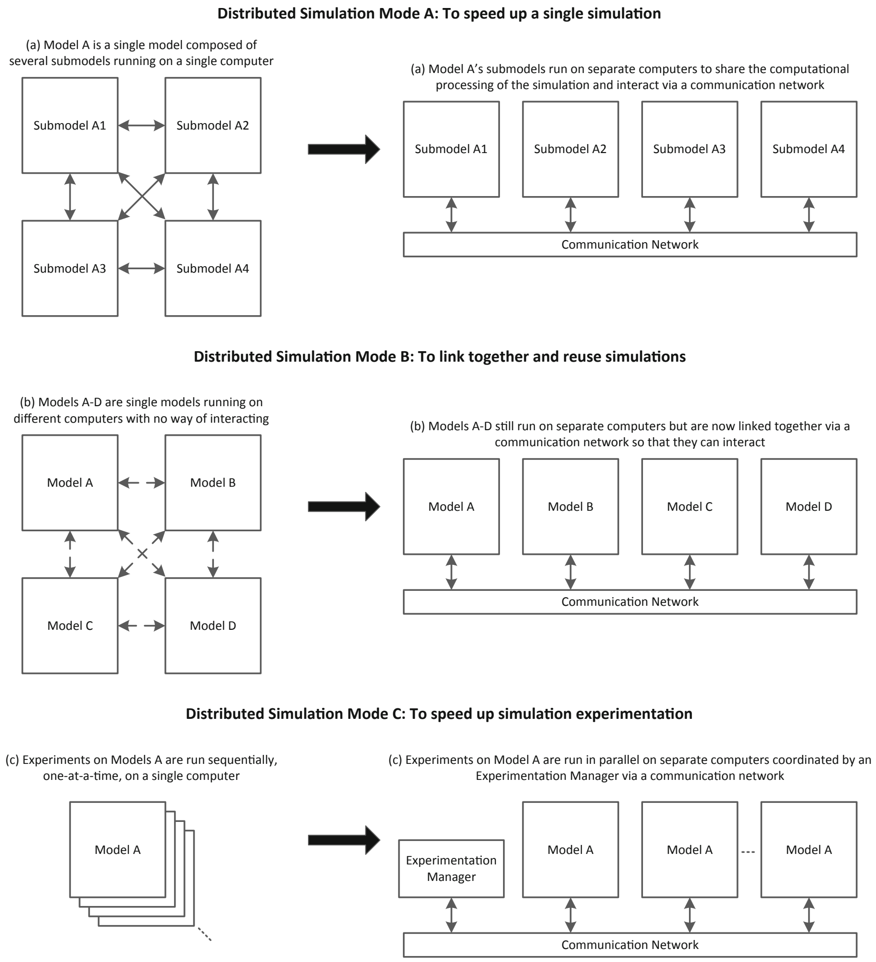

Fig. 1 Modes of distributed simulation

as variable name clashes, variable type incompatibility, global variables and different verification/validation assumptions might mean extensive recoding and testing. Further, if the simulations have been developed in different simulation packages or languages then it might not be possible to combine them at all without starting from scratch. It may be more convenient to just link the simulations together as a DS.

Ownership and Management. Following the above, if a simulation has been composed from reused simulations then it may be difficult for a simulation owner or developer to update their simulation without having to update the entire simulation. DS allows simulations to be independently managed as they are still separate.

Privacy. Creating a single simulation from other simulations could also mean that the entire details of a simulation would be revealed to the developer of the single

simulation. If a simulation contains secrets (e.g. the confidential inner workings of a factory, hospital or military system) then these would be visible to anyone running the newly composed simulation. DS preserves this separation and allows simulations to be composed from "black boxed" simulations.
Data integrity and privacy. Similar to the above problems is the issue of data integrity and privacy. If a simulation requires access to a specific database then when a new simulation is created that data may have to be copied to allow the new simulation to access it. This data may be confidential. Another issue is how can the integrity of the data be preserved (how can the copy be kept up-to-date)? DS allows data to remain with the owning simulation and therefore avoids this issue.
Hybrid simulation. There are very few commercial simulation packages that support hybrid simulations consisting of discrete-event, agent-based and/or system dynamics elements. DS allows simulations of these different types to be linked together.

Mode A and Mode B of DS can be extremely complex to implement and, unfortunately, this presents a major barrier to its use (these Modes still represent some of the most challenging research topics in general distributed systems). Exceptions are in simulation areas where modelling teams possess advanced software engineering skills and are used to developing complex software solutions (e.g. in defence and some simulation software "houses"). Some standards and reference implementations have also been created that facilitates DS development (e.g. the High Level Architecture [16] and associated interoperability issues [36]. These general standards have been adapted for process simulation used in Industry 4.0 [2].

DS Mode C, however, is conceptually simpler to implement (i.e. no complex synchronization) high speed simulation systems are beginning to emerge. Here the challenge is how to efficiently distribute and manage the execution of a series of single simulations over a range of computers. This is a common problem across many scientific disciplines and emerging solutions to DS Mode C are emerging with many borrowing techniques from scientific computing and e-Science. Early examples of these used grids of computers that already existed within an organisation (a desktop grid). More recent ones essentially use the same techniques but instead of fixed computing resources these use virtualised ones made available on a cloud. Examples of both of these include: the WINGRID desktop grid system that was used to speed up credit risk simulations in a well-known European bank [28], SakerGrid, a desktop grid and computing cluster system in use today at Saker Solutions and Sellafield PLC [20], a cluster-based high performance simulation system in use in the Ford Motor Company, a desktop grid that was used for simulations of biochemical pathways in cancer [23], and a cluster computing based grid used for a similar application [7]. Examples of cloud-based systems include an adaptation of the JADES platform to run agent-based simulations in parallel on cloud resources [31] and the CloudSME Simulation Platform is used to run simulation experiments over multiple clouds [35]. The Cloud Orchestration at the Level of Application (COLA) project[1] is developing a deadline-based auto-scaling approach for simulation experimentation on cloud with SakerCloud being the first commercial prototype [35]. Anderson et al. [3] and Yao

[1]project-cola.eu.

et al. [39] have developed Mode C DS that also run Mode A DS. Commercially, Saker Solutions have implemented the same in the DS of nuclear waste reprocessing.

In the following section, to illustrate the realisation of Mode C DS in support of High Speed Simulation Analytics, we present the CloudSME platform that arose from a major collaboration between e-Science developers and industrial simulation companies during the CloudSME project (www.cloudsme.eu).

3 Cloud-Based High Speed Simulation Experimentation

Cloud computing is attractive as it offers on-demand computing resources that can be quickly "hired" and then discarded [27]. The cost of computing resources is priced at a very attractive level. The use of these resources to power high speed simulation experimentation is therefore also very attractive. However, the complexity and variety of cloud systems and technologies can make realising these applications quite difficult and costly. Arguably, this can be prohibitive for Small and Medium-sized Enterprises (SMEs) and end user developers. Further, many cloud systems are developed for a single cloud. It is not an easy task to port from one cloud system to another.

The aim of the Cloud-based Simulation platform for Manufacturing and Engineering (CloudSME) project[2] was to create a generic approach to developing cloud-based simulation applications that enabled users to reduce implementation costs in realising commercial products and services. The project created the CloudSME Simulation Platform (CSSP) from a combination of an AppCenter, the workflow of the WS-PGRADE/gUSE [18] science gateway framework and the multi-cloud-based capabilities of the CloudBroker Platform.[3] The CSSP has been used to implement a range of commercial simulation products across a many industrial domains (see the CloudSME Website[4] for examples). To show how the CSSP has been used to for high speed simulation experimentation we now describe the Platform and a representative case study.

3.1 The CloudSME Simulation Platform

The CSSP consists of three layers:

1. **Simulation Applications Layer** that allows software vendors deploying and presenting simulation products to end-users as SaaS (Software as a Service) in a wide range of scenarios and deployment models.

[2] www.cloudsme-apps.com.

[3] www.cloudbroker.com.

[4] http://www.cloudsme-apps.com/practical-examples/.

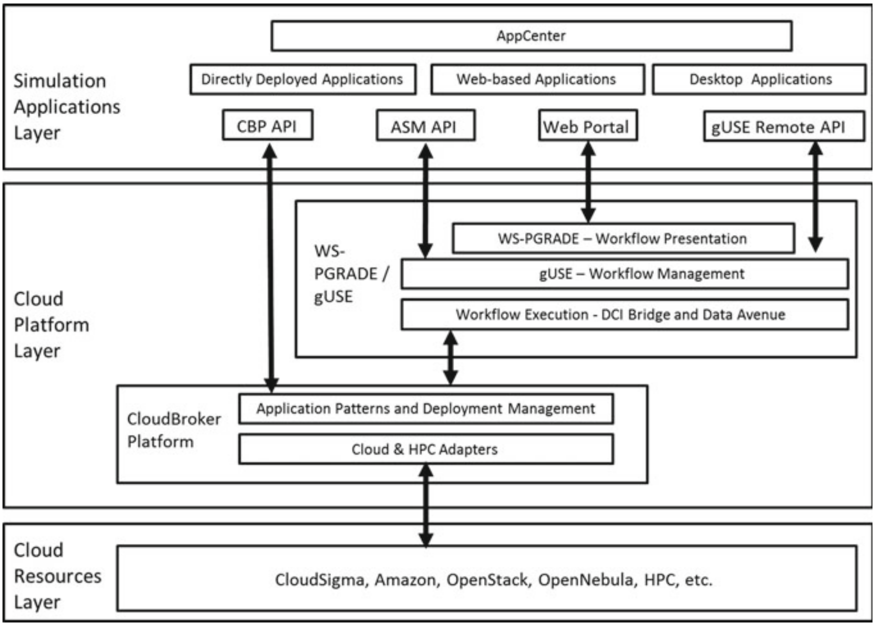

Fig. 2 The CloudSME simulation platform

2. **Cloud Platform Layer** that provides access to multiple heterogeneous cloud resources and supports the creation of complex application workflows—a PaaS (Platform as a Service) to create and execute cloud-based simulations.
3. **Cloud Resources Layer** that represents the IaaS (Infrastructure as a Service) clouds connected to the platform.

These layers are presented in detail below (Fig. 2).

3.2 Simulation Applications Layer

This contains the CloudSME AppCenter is a web-based one-stop-shop that is the "shop window" to software products and services offered by software vendors and service providers to end users via a single consistent interface. It stores information about software products in an accessible way, provides usage scenarios for the software, and offers billing functionality that includes price setting, payment integration and tracking of users' spending. It three main deployment models: Directly Deployed Applications, Web-based Applications, and Desktop Applications. The CSSP offers a wide range of Application Programming Interfaces (APIs) to support developers. To enable the development of applications that are directly deployed in the AppCenter or the extension of desktop applications with cloud support, either the CloudBroker APIs (Java Client Library API or REST API) or the gUSE Remote API can be used. Using the CloudBroker APIs bypasses WS-PGRADE/gUSE and provides direct access from the application to the multi-cloud resources supported by the CloudBroker Platform. Using the Remote API of WS-PGRADE/gUSE enables developers to execute complex application workflows linking multiple application components together. As WS-PGRADE/gUSE is integrated with the CloudBroker Platform, multi-cloud execution capabilities are still fully utilised in this scenario. In case of web-based applications, either the ASM (Application Specific Module) API of WS-PGRADE/gUSE is used that enables the rapid development of a custom portal/gateway in the form of customised Liferay Portlets or a completely custom web interface is developed by embedding either CloudBroker API or gUSE Remote API calls. Alternatively the standard web-based interface to WS-PGRADE/gUSE can also be applied to launch workflows. All APIs are described in Akos et al. [1].

3.3 Cloud Platform Layer

The middle layer of CSSP is the Cloud Platform Layer that consists of the cloud-based services from the CloudBroker Platform and the science gateway framework WS-PGRADE/gUSE. These components were developed prior to CloudSME and their first integration was implemented in the SCI-BUS (Scientific Gateway-based User Support) project [19]. During CloudSME this integration matured significantly and reached commercial production level.

3.3.1 The CloudBroker Platform

The CloudBroker Platform is a commercial PaaS that supports the management and execution of software on different cloud provider resources. The generic architecture of CloudBroker is shown in Fig. 3.

CloudBroker uses IaaS clouds from resource providers and incorporates adapters both to public and private cloud infrastructures. The platform provides access to a wide range of resources including open source (e.g. OpenStack and OpenNebula) and proprietary (e.g. Amazon and CloudSigma) clouds, and also various High Performance Computing (HPC) resources. CloudBroker supports non-interactive serial and parallel batch processing applications on both Linux and Windows operating systems. The platform itself consists of a set of modules that manage processes, applications, users, finance (accounting, billing and payment), and runtime issues (process monitoring, queuing, resources, storage and images). A scalability and fault handler layer supervises scalability requirements and failure issues. Cloud Provider Access Management oversees the connection to each Cloud technology and can control the number of virtual machines (VMs) started for a given application on a given cloud. Application “patterns” are deployed to CloudBroker in a form that allows the platform when instructed to run the application on a particular cloud and cloud

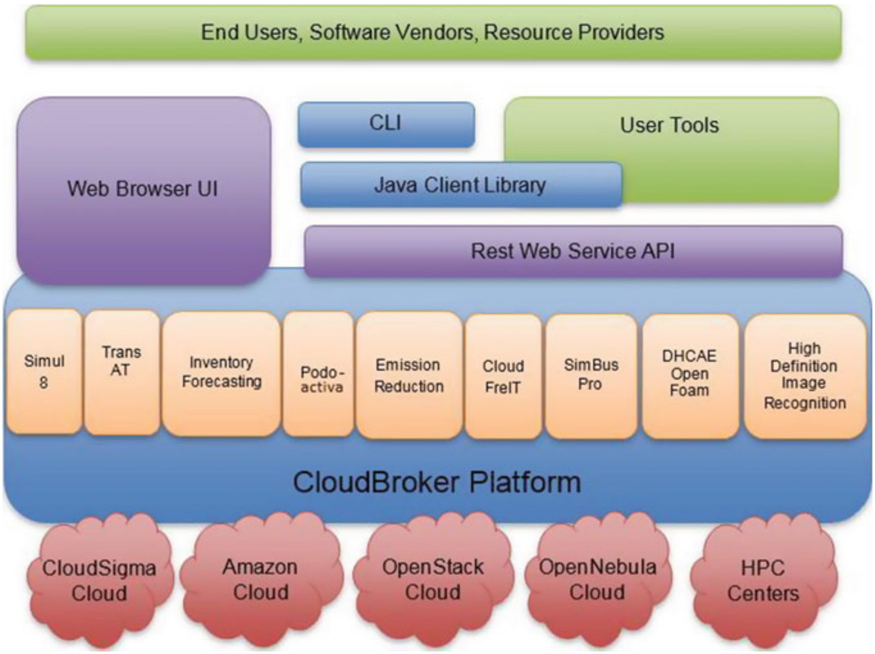

Fig. 3 CloudBroker platform architecture

instance type. Two typical patterns are direct installation (an application package and deployment script that allows the installation of the software on a cloud instance) or virtualisation (virtual machine image containing installed software that allows direct deployment to a cloud instance).

CloudBroker offers various interfaces for access. Its two main operation modes to manage and use software in the cloud are either as direct front-end, or as a back-end middleware service. For the former, the platform can be accessed directly through the Web Browser User Interface. As a back-end for advanced and automatic usage, various APIs are provided for programmatic accessibility. These include REST web service interface, Java client library and Linux shell command line interface (CLI). Via these different APIs, the CloudBroker Platform can be utilized by front-end software as middleware to allow access to applications in the cloud.

3.3.2 WS-PGRADE/gUSE

gUSE (Grid and Cloud User Support Environment) [19] is an open source scientific gateway framework providing users with easy access to cloud and grid infrastructures. gUSE provides with WS-PGRADE, a Liferay based portal to create and execute scientific workflows in various Distributed Computing Infrastructures (DCIs) includ-

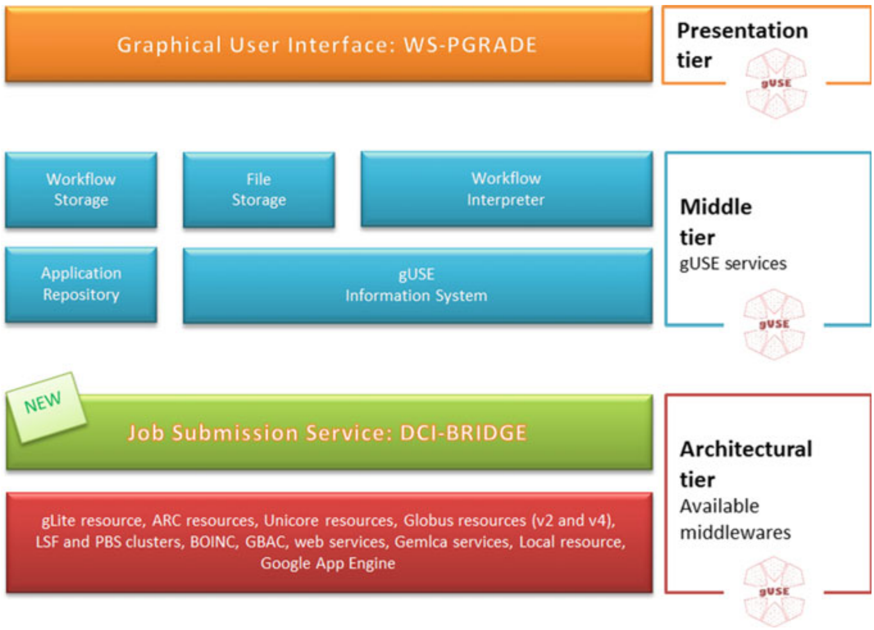

Fig. 4 Generic architecture of WS-PGRADE/gUSE

ing clusters, grids and clouds. The generic architecture of WS-PGRADE/gUSE is presented in Fig. 4.

WS-PGRADE/gUSE consists of three layers: a top presentation layer, a middle management layer, and a bottom architectural execution layer.

The presentation layer (WS-PGRADE) includes a set of Liferay portlets to create, start and control workflows, monitor their execution on various DCIs, and present results to users. WS-PGRADE has a graph editor which can be used to build workflows and specify job configurations. A WS-PGRADE workflow is a directed acyclic graph that defines the execution logic of its components. An example for a WS-PGRADE workflow is presented in Fig. 5. The large boxes are jobs, while the smaller boxes are input and output ports representing input/output files for the jobs. The execution of a job can start when all of its inputs are available. Using this logic the WS-PGRADE workflow engine automates the execution of the workflow. For example, in case of the workflow of Fig. 5 only Gen3 can start executing when the workflow is submitted. MulCross and AddPair are waiting for the result of Gen3 and can start once the output file of Gen3 is available.

The WS-PGRADE workflow concept supports multiple levels of parallelism. Each job of the workflow can in itself be a natively parallel application (e.g. using MPI). The workflow can also have parallel branches (e.g. MulCross/ColMuls and AddPair/ColAdds are in parallel branches) that can be executed in parallel of different resources. Finally, WS-PGRADE supports parameter sweep applications. Parameter

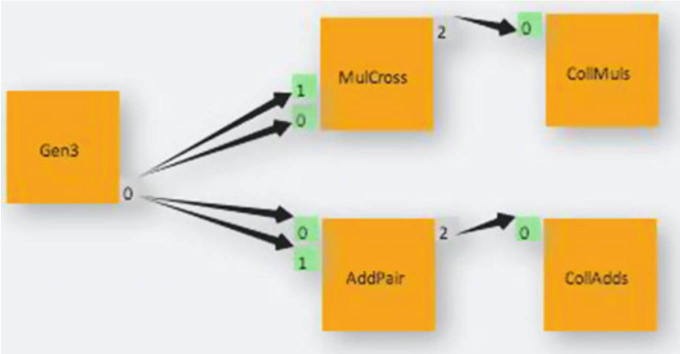

Fig. 5 Example WS-PGRADE workflow

sweep applications are simulations where the same simulation needs to be executed for multiple input data sets. This feature enables the same workflow to be submitted with multiple input data sets simultaneously.

A full description of WS-PGRADE/gUSE gateway framework is available in Kacsuk et al. [18], and Kacsuk [17] gives a complete overview of WS-PGRADE/gUSE and its applications.

3.4 Cloud Resources Layer

The bottom layer of CSSP is the Cloud Resources Layer that consists of a range of clouds and HPC resources accessible via the CloudBroker Platform. These currently include CloudSigma and Amazon public clouds, various private clouds based on either OpenStack or OpenNebula, and the HPC resources of, for example, the Cineca Galileo Cluster or the ETH Euler Cluster.

4 Case Study: High Speed Simulation Experimentation

The following case study demonstrates how the CSSP can support high speed simulation experimentation. It uses the widely used open source simulation system the Recursive Porous Agent Simulation Toolkit (REPAST). This is a cross-platform, agent-based modelling and simulation toolkit and is a Java-based simulation system that is used for developing a range of simulation applications in different fields [30]. To enable the parallel execution needed for high speed simulation experimentation it uses parameter sweeps running on multiple cloud resources via both components of the Cloud Platform Layer. CloudBroker manages deployment on multiple clouds and the parameter sweep functionality of the WS-PGRADE/gUSE workflow engine manages the execution of the simulation experiments and the parameter sweep. The deployment is first presented and then demonstrative results.

5 REPAST Deployment on the CloudSME Simulation Platform

The deployment of REPAST consists of two parts: deployment on CloudBroker and creation of the parameter sweep workflow on WS-PGRADE/gUSE.

Deployment on CloudBroker is done by creating an application package consisting of a deployment shell script, an execution shell script and the zipped REPAST environment. For each cloud deployment, CloudBroker is configured to create a virtual machine with a Linux Ubuntu OS image. Using its web interface, CloudBroker creates this virtual machine, transfers the application package to the virtual machine and then runs the deployment shell script. This installs REPAST, Java Runtime Environment and the execution shell script. When a job is started (i.e. a simulation run), the simulation model (a TAR archive consisting of the model source code and the simulation scenario) and the parameter sweep data (an XML file specifying the input parameters) are transferred to the virtual machine. The execution script then validates these inputs, extracts the model files and runs the simulation. Results are then added to a TAR archive for upload back to the Platform.

The WS-PGRADE/gUSE web interface is used to create the parameter sweep workflow. An abstract workflow graph is first created using the graph editor. From the graph, the concrete workflow is then created and configured to run the selected software on the selected cloud resources. The same abstract workflow can be used to create many concrete workflows by reconfiguring them. Once the graph is completed, it can be saved and used to create a concrete workflow where the jobs can be configured (e.g. the simulation software, the cloud and the region of the resources, and the instance type).

To demonstrate the performance of high speed simulation we used a well-known benchmark developed at Brunel. This is an agent-based simulation of infection disease spread [26]. The simulation consists of three types of agents that move in an environment and interact with each other. The agents represent the susceptible, infected and recovered population. The model starts an infection outbreak with an initial population of infected and susceptible agents. Infected agents move close to susceptible agents and infect them while susceptible agents move where the least infected agents are located. Infected and susceptible agents interact with each other in every simulation time unit which is a day in our simulation. Infected agents recover after a period of time and become recovered with a level of immunity. When an infected agent gets in touch with a susceptible agent, the susceptible agent becomes infected. When an infected agent gets in touch with a recovered agent, the recovered agent decreases its immunity. When the immunity level is 0, the recovered agent becomes susceptible and can be infected again. The outbreak occurs annually. When this hap-

Table 1 Cloud resources characteristics

Cloud instance	Number of vCPUs	Processor type	Memory
Amazon baseline micro (A1)	1	High Frequency Intel Xeon Processors with Turbo up to 3.3 GHz	0.5 GiB
Amazon baseline small (A2)	1	High Frequency Intel Xeon Processors with Turbo up to 3.3 GHz	1 GiB
Amazon baseline medium (A3)	2	High Frequency Intel Xeon Processors with Turbo up to 3.3 GHz	4 GiB
Amazon balanced medium (A4)	1	High Frequency Intel Xeon E5-2670 v2 at 2.6 GHz	3.75 GiB
Amazon balanced large (A5)	2	High Frequency Intel Xeon E5-2670 v2 at 2.6 GHz	7.5 GiB
UoW small (U1)	1	AMD Opteron 4122 Processor at 2.2 GHz	20 MB
UoW medium (U2)	2	AMD Opteron 4122 Processor at 2.2 GHz	40 MB
UoW large (U3)	4	AMD Opteron 4122 processor at 2.2 GHz	80 MB
UoW XL (U4)	8	AMD Opteron 4122 Processor at 2.2 GHz	160 MB

pens, the population changes to reflect the initial conditions taking into account the population dynamics of the previous year.

A series of experiments on two cloud infrastructures were performed: the Amazon EC2 commercial cloud and an academic cloud offered by the University of Westminster (UoW), UK. Cloud instances of various sizes were used as specified in Table 1. Each experiment was set up in WS-PGRADE/gUSE by quickly reconfiguring the workflow by selecting a different cloud/instance type.

Our demonstration consisted of an experiment consisting of ten runs (i.e. ten simulations with a different parameter). We conducted ten experiments. These took approximately 200 min to run on a desktop PC (i5-2500 processor at 3.30 GHz speed and 4.00 GB RAM). We ran these experiments on one, two, five and 10 instances of each cloud type. The experiments were distributed equally when run on more than one instances. Figure 6 shows the comparative runtime by instance and Table 2 shows the speedup when compared to a single PC run. The run-time is the average of five runs. From the results, we observe that Amazon EC2 instances have relatively stable performance and the academic cloud presents a larger variation. For example, five instances of U2 perform worse than two. Also, we have a considerable increase in execution time when running on 10 instances. Types U3 and U4 show similar behaviour. This is suspected to be rooted in variations in resource availability that

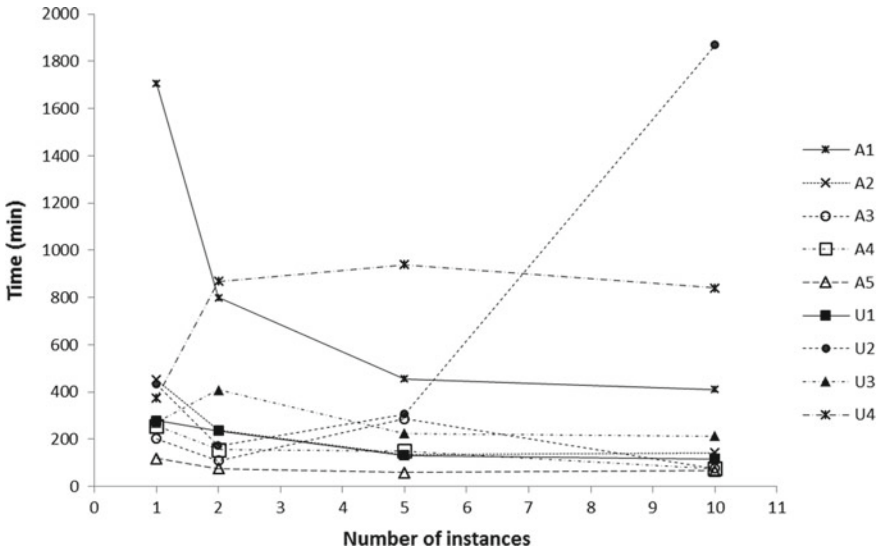

Fig. 6 Cloud-based REPAST infection model performance

Table 2 Cloud-based REPAST infection model speedup

Clouds		A1	A2	A3	A4	A5	U1	U2	U3	U4
Instances	1	0.12	0.44	0.99	0.78	1.68	0.72	0.46	0.74	0.53
	2	0.25	0.84	1.82	1.28	2.67	0.85	1.18	0.49	0.23
	5	0.44	1.49	0.70	1.32	3.39	1.53	0.66	0.89	0.21
	10	0.49	1.40	2.63	2.67	2.99	1.71	0.11	0.93	0.24

cause job requests to be queued until resources are available. Similar behaviour with less variation is shown by A3 where the execution time for five instances is increased. In terms of speedup, when running on a single instance for all cloud types in this experiment, apart from A5, the performance is slower than a desktop machine. This is expected since there is an overhead for starting up the virtual machines. Most of the larger instances, at least the commercial ones, present modest speedup. It is expected that for larger simulations there will be better considerable speedup as the longer processing time will compensate the overheads of setting up virtual instances on a cloud. Overall this shows how a user might investigate different cloud and instance types to choose which is the best for his or her needs.

6 A Vision of the Future: Towards Big Simulation Analytics

The previous sections have shown how DS and cloud computing can address high speed simulation analytics. Adding other modes of DS to this could enable high speed simulation analytics of large-scale simulations of large systems. Taking inspiration from Big Data, this move towards larger and larger systems simulations involving the analysis of diverse data suggests that we might call this emerging aspect of simulation as *Big Simulation Analytics*. We now discuss how we might realise Big Simulation Analytics.

In large scale scientific endeavours, many scientists use grid computing or e-Infrastructures, integrated collections of computers, data, applications and sensors across different organizations [11]. There are various sophisticated software systems that exist to use e-Infrastructure facilities, typically by giving "single sign-on" secure access to multiple computers across multiple administrative domains and the ability to manage the execution of jobs on those computers (e.g. WS-PGRADE/gUSE [18, 19] and the FutureGateway that has evolved from the DECIDE framework [4]). E-Infrastructure applications can be created from these by first deploying the application service on the e-Infrastructure and registering it in some form for service catalogue (see below) and then accessing the service via a science gateway (a web-based system that allow scientists to use e-Infrastructures with a simple front end that has been developed for their needs) or some kind of programming interface (usually some kind of REST interface) integrated into software that is familiar to the user (for a wide range of examples of these see www.sci-gaia.eu/community and catalog.sciencegateways.org/#/home for examples of science gateways). Software applications or services are being increasingly developed in a standard way so that they can be stored, browsed and reused from a standardized service catalogue (e.g. the EGI service catalogue (https://www.egi.eu/services/) and the INDIGO service catalogue (www.indigo-datacloud.eu)). Applications can be linked together by workflows, sequences of tasks that are translated into jobs executed on specific computing systems supported by the above software infrastructures [9, 22]. Examples of workflow systems include Pegasus [10], Kepler [24], Taverna [38], Swift [40] and WS-PGRADE/gUSE [18].

In a possible future where DS is commonly used in OR, a user might access an e-Infrastructure via a web-based science gateway, configure a workflow to execute a series of tasks and instruct those tasks to be run. As shown in Fig. 7, such a workflow might have five steps: Management, Acquisition, Composition, Experimentation and Analysis.

6.1 *Management*

In this task a user first selects a pre-defined experimentation service (e.g. direct experimentation, ranking & selection algorithm, optimization, etc.). The user then

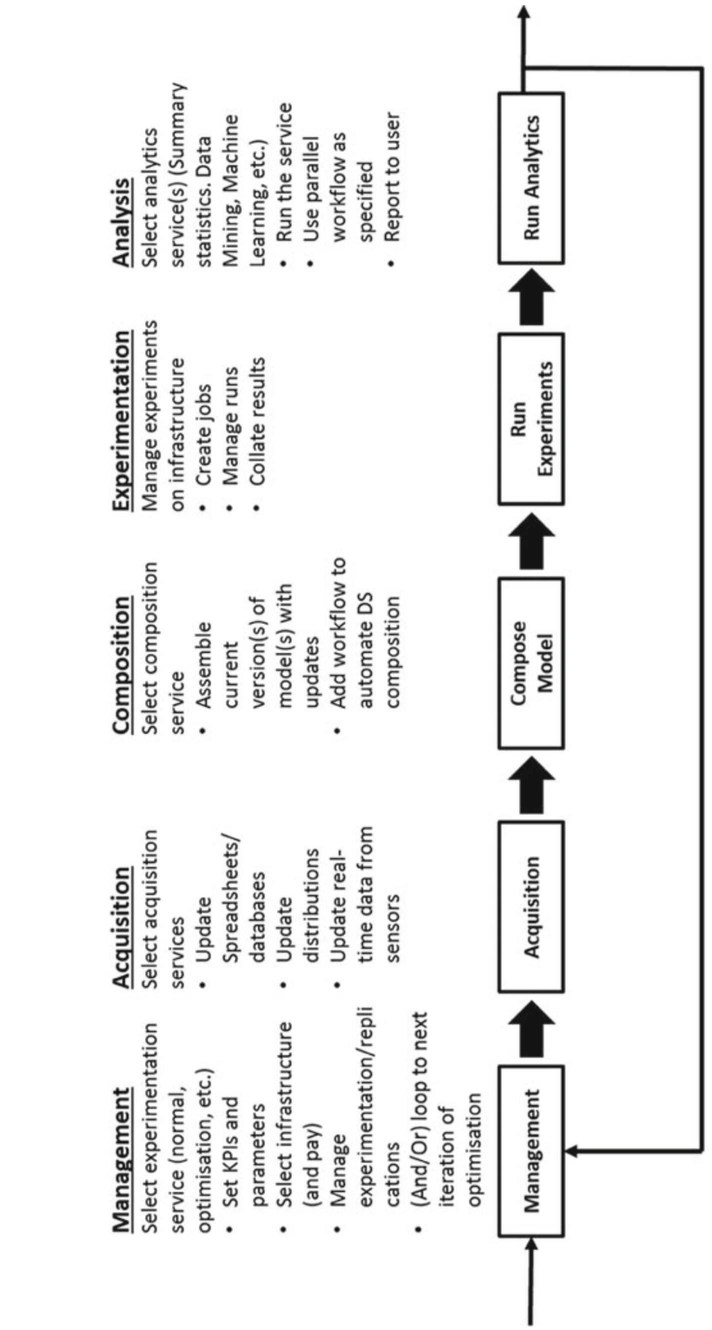

Fig. 7 A workflow for high speed simulation analytics

configures the experimentation and then selects what *infrastructure* to run on. The choice might be an internal computing resource (e.g. a cluster), different external clouds, a dedicated high performance computing facility, etc. Cost/time information might be given for each infrastructure to help the user to decide which to select. A user might also set a deadline for experimentation and then get an estimate for how much processing resources would cost (and possibly their carbon footprint). Once the infrastructure has been selected, the user then pays if necessary (or uses some pre-loaded credit), and then instructs the management task to run the experiments. The system would then manage the experiment over the selected infrastructure, reporting to user the progress of the experimentation and when it is complete.

6.2 Acquisition

Experiments configured in Management use this task to acquire relevant data sources (databases, spreadsheets, etc.), update statistical distributions, obtain the latest versions of the models and simulation software, etc. needed for experimentation. In the case of Symbiotic Simulation, Cyber-physical systems or a Digital Twin, this might involve direct data collection from the sensors in a physical system. We may assume that the selection of services in this task has been predefined and the task runs these to perform the updates.

6.3 Composition

This task simply takes the above acquired artefacts and composes the jobs to be submitted to the infrastructure. With a single simulation this task would just ready the model and its supporting components for uploading to the infrastructure. A DS would require several models to be composed (i.e. a set of federates being composed into a federation) and a supporting workflow service could be selected to automate this [6].

6.4 Experimentation

Jobs representing each run of a simulation (or possibly runs if these are quick but numerous) are submitted to a queue for the infrastructure to process. This task also manages the execution of the jobs (e.g. relaunching any failed jobs) and collates the results from each job as their results are returned from the infrastructure.

6.5 Analysis

The final step is the *Analysis* task. Users could select from a set of services that analyse the output from experimentation. This could include, for example a service that produces summary statistics or some deeper time series-based analysis. The Analysis service could itself be workflow based and run over distributed computing resources to reduce the time taken to analyse the output. Indeed, it is possible that a user could request several analyses to be performed at the same time and the results from this be brought together in some kind of hierarchical workflow. In these cases the Management task could be extended to give further cost estimates for analysis. Similar extensions could be made to reflect the on-going cost of optimization.

6.6 Conceptualisation and Example

Based on this workflow, Fig. 8 shows a possible conceptualization of an e-Science approach for DS that shows the workflow realized on an e-Infrastructure using a science gateway. This is influenced by the workflow system WS-PGRADE/gUSE and is based on recent experiences with the CloudSME project where several commercial cloud-based simulation systems using e-Infrastructure approaches were created.

Consider the following example. An enterprise is capable of manufacturing a range of widgets for a number of consumers. The manager of the enterprise in this supply chain wants to understand how the behaviour of her factory responds to changes in demand and supply over time. She has a discrete-event model of her factory and agent-based models of her suppliers and consumers (perhaps a more reasonable large supply chain model as this does not assume that other discrete-event simulations in the supply chain exist but does assume that the enterprise has detailed information about supplier/consumer behaviour over time). We assume that a management interface similar to a science gateway has been set up and a workflow has been defined in WS-PGRADE/gUSE. The manager might want to (for example) investigate the most reliable set of suppliers based on a 20% increase in consumption across her product range and to identify the most critical areas in her factory in terms of machine utilization and operator utilization (we assume that a mix of machines and operators are used in her factory to produce the widgets).

In the Management task, she sets up the experiments on her management interface (the equivalent of a science gateway) and chooses an analytics service that can correlate and cluster the simulation results. She then investigates the best available infrastructure to run the experiments within a reasonable amount of time (e.g. compares the cost of Amazon Cloud, Microsoft Azure and a High Performance Computing centre available in her region against running over a local desktop grid), makes her selection and begins the experimentation. The workflow then begins automatic execution by executing the Acquisition task. This executes in parallel to load the most recent data and model into the infrastructure. The *Composition* task then composes the DS by

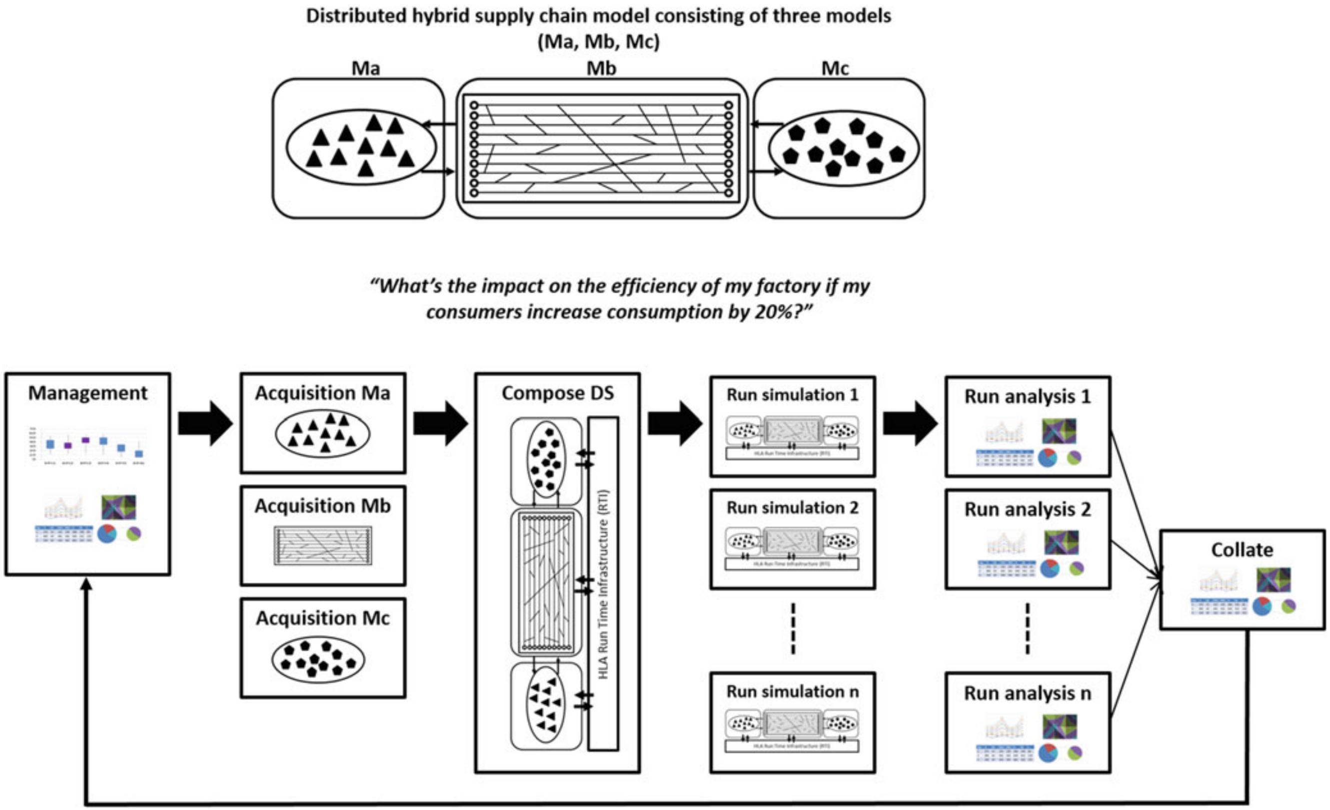

Fig. 8 An e-science vision for high speed simulation analytics

bringing together the three models with HLA standard software for time management. The *Experimentation* task would then create "jobs" based on each experiment and dispatch these through the infrastructure to (say) virtual computers running on the Amazon cloud. As results begin to come in, the infrastructure passes these onto the *Analysis* task. This task takes each set of results and, in turn, sends these jobs out for processing on the infrastructure using a clustering and classification service that runs for each job and then collates these together for display on the management interface. The manager then makes her decisions within hours rather than months. In the case of Symbiotic Simulation or Digital Twins, once set up, this process might run constantly as the system monitors and attempts to improve the performance of the system via simulation.

7 Conclusions

This article has presented the possible future of High Speed Simulation Analytics from an Industry 4.0 perspective. It has argued that the key to this is DS and high speed experimentation. A novel commercial system has been presented that demonstrates how cloud computing can be used to speed up simulation experimentation. We have then discussed how simulation analytics can borrow from e-Science and e-Infrastructures to create a vision or architecture for large-scale simulation analytics or Big Simulation Analytics. It is hope that this article has shown how the future for simulation analytics could develop and the potential functionality that emerging approaches need to urgently embrace to keep simulation relevant and at the heart of Industry 4.0. Taylor [32] develops these themes in more detail from an Operational Research perspective, and Taylor et al. [33, 34] give more detail on the CloudSME Simulation Platform and its simulation applications.

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Using Commercial Software to Create a Digital Twin

David T. Sturrock

Abstract In the manufacturing environment, the Industrial Internet of Things (IIoT) allows machines, products, and processes to communicate with each other to achieve more efficient production. With the growing move to Industry 4.0, increased digitalization is bringing its own unique challenges and concerns to manufacturing. An important component of meeting those challenges is with the use of a Digital Twin. A digital twin provides a virtual representation of a product, part, system or process that allows you to see how it will perform, sometimes even before it exists. A digital twin of the entire manufacturing facility performs in a virtual world very similar to how the entire manufacturing facility performs in the physical world. This broad definition of a digital twin may seem unattainable, but it is not—advanced discrete event simulation products and modeling techniques now make it possible. This chapter will describe the importance of a digital twin and how data-driven and data-generated models, real-time communication, and integral risk-analysis based on an advanced DES product can solve many of the challenges and help realize the benefits offered by Industry 4.0. We will illustrate by providing a brief tutorial on building a data-generated model using the Simio DES product.

Keywords Digital twin · Virtual model · Industry 4.0 · Risk reduction · Data-driven · Data-generated · Scheduling · Production control · Digital transformation · Simio

1 Introduction

We discussed earlier in Chapter "Traditional Simulation Applications in Industry 4.0", the ways that traditional DES can be used to meet the traditional factory modeling needs. We also discussed some of the challenges found in Industry 4.0

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D. T. Sturrock (✉)
Simio LLC, 504 Beaver St, Sewickley, PA 15143, USA
e-mail: dsturrock@simio.com

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implementations and how some of those challenges can be met with traditional DES products. In this chapter we will discuss Industry 4.0 challenges and opportunities that cannot generally be met with traditional DES products and discuss a relatively new solution to meet those problems. Some material in this chapter is adapted from similar material in the book *Simio and Simulation: Modeling, Analysis, Applications* [1] and is included with permission.

2 The Need for a Digital Twin

In the consumer environment the Internet of Things (IoT) provides a network of connected devices, with secure data communication, to allow them to work together cooperatively. In the manufacturing environment, the Industrial Internet of Things (IIoT) allows the machines and products within the process to communicate with each other to achieve the end goal of efficient production. With the growing move to Industry 4.0, increased digitalization is bringing its own unique challenges and concerns to manufacturing. One way of meeting those challenges is with the use of a Digital Twin.

A Digital Twin provides a virtual representation of a product, part, system or process that allows you to see how it will perform, sometimes even before it exists. Sometimes this term is applied at the device level. A digital twin of a device will perform in a virtual world very similar to how the real device performs in the physical world. An important application is a digital twin of the entire manufacturing facility that again performs in a virtual world very similar to how the entire manufacturing facility performs in the physical world. The latter, broader definition of a digital twin may seem unattainable, but it is not. Just like in the design-oriented models; our objective is not to create a 'perfect model' but rather to create a model that is 'close enough' to generate results useful in meeting our objectives. Let's explore how we can meet that goal.

According to some practitioners you can call a model a digital twin only when it is fully connected to all the other systems containing the data to enable the digital twin. A standalone simulation model will be referred to as a virtual factory model but not a digital twin until it is fully connected and runs in real-time (near real-time) mode, driven by data from the relevant ERP, MES, etc. systems. In addition to reading and processing data from external sources, it is therefore also important that you should be able to **generate models from data** to function effectively as a digital twin. This allows the model to react based on the changes in data more than just properties—items like adding a resource/machine and having that automatically created in the model and schedules by just importing the latest data.

In the current age of Industry 4.0 the exponential growth of technological developments allows us to gather, store and manipulate data like never before. Smaller sensors, cheaper memory storage and faster processors, all wirelessly connected to the network, facilitate dynamic simulation and modeling in order to project the object into the digital world. This virtual model is then able to receive operational, historical and environmental data.

Technological advancements have made the collection and sharing of large volumes of data much easier, as well as facilitating its application to the model and the processing involved in iteration through various possible scenarios to predict and drive outcomes. Of course, data security is an ever-important consideration with a Data Twin, as with any digital modeling of critical resources.

As a computerized version of a physical asset, the Digital Twin can be used for various valuable purposes. It can determine its remaining useful life, predict breakdowns, project performance and estimate financial returns. Using this data, design, manufacture and operation can be optimized in order to benefit from forecasted opportunities.

There is a three stage process to implement a useful Digital Twin:

Establish the model: More than just overlaying digital data on a physical item, the subject is simulated using 3D software. Interactions then take place with the model to communicate with it about all the relevant parameters. Data is imposed, and the model 'learns', through similarity, how it is supposed to behave.

Make the model active: By running simulations, the model continuously updates itself according to the data, both known and imposed. Taking information from other sources including history, other models, connected devices, forecasts and costs, the software runs permutations of options to provide insights, relative to risk and confidence levels.

Learn from the model: Using the resulting prescriptions and suggestions, plans can be put into action to create or manipulate the situation in the real life industry context, in order to achieve optimal outcomes in terms of utilization, in is more than just a blueprint or schematic of a device or system; it is an actual virtual representation of all the elements involved in its operation, including how these elements dynamically interact with each other and their environment. The great benefits come through monitoring these elements, improving diagnostics and prognostics, and investigating root causes of any issues in order to increase efficiencies and overall productivity.

A correctly generated Digital Twin can be used to dynamically calibrate the operational environment to positively impact every phase of the product lifecycle; through design, building and operation. For any such application, before the digital twin model is created the objectives and expectations must be well understood. Only then can a model be created at the correct fidelity to meet those objectives and provide the intended benefits. Examples of those benefits include:

- Equipment monitors its own state and can even schedule maintenance and order replacement parts when required.
- Mixed model production can be loaded and scheduled to maximize equipment usage with-out compromising delivery times.
- Fast rescheduling in the event of resource changes reduces losses by re-optimizing loading to meet important delivery dates.

3 The Role of Simulation Based Scheduling

The rise of Industry 4.0 has expedited the need for simulation of the day-to-day scheduling of complex systems with expensive and competing resources. This has extended the value of simulation beyond its traditional role of improving system design into the realms of providing faster, more efficient process management and increased performance productivity. With the latest technologies, like Risk-based Planning and Scheduling (RPS), the same model that was built for evaluating and generating the design of the system can be carried forward to become an important business tool in scheduling day to day operations in the Industry 4.0 environment.

With digitalized manufacturing, connected technologies now form the smart factory, having the ability to transmit data to help with process analysis and control during the production process. Sensors and microchips are added to machines, tools and even to the products themselves. This means that ‘smart’ products made in the Industry 4.0 factory can transmit status reports throughout their journey, from raw material to finished product.

Increased data availability throughout the manufacturing process means greater flexibility and responsiveness, making the move towards smaller batch sizes and make-to-order possible.

In order to capitalize on this adaptivity, an Industry 4.0 scheduling system needs to:

- Accurately model all elements
- Compute schedules quickly
- Provide easy visualization.

With IoT devices, big data and cloud computing as features of Industry 4.0, the scheduling system needs more than ever to bridge the gap between the physical and digital worlds.

Traditionally, there are three approaches to scheduling: manual, constraint-based and simulation.

Although labor-intensive, manual scheduling can be effective in smaller or less complex systems. But a manual approach becomes impractical in a large, highly dynamic production environment, due to the sheer volume and complexity of data.

Constraint-based scheduling involves the solution of equations that are formulated to represent all the system constraints. A mathematical model could be built of all the elements of a Smart factory; however, it would be highly complicated to populate and solve, probably taking a long time to do so. Key aspects would have to be ignored or simplified to allow for a solution which, when found, would be difficult to interpret, visualize and implement.

Often scheduling today is done for a department or section of the facility to reduce complexity both for manual and constraint-based scheduling. These localized schedules result in process buffers between section in either time or inventory or capacity.

Simulation-based scheduling stands out as the best solution for Industry 4.0 applications. Each element of the system can be modeled, and data assigned to it.

The resources, in terms of equipment, tools and workers, can be represented, as well as the materials consumed and produced in the process. In this way, the flow of jobs through the system can be simulated, showing exact resource and material usage at each stage for real-time status updates.

Decision logic can be embedded in the model, for example to select minimum changeover times, as well as custom rules added from worker experience. These equations combine to produce a range of rules that accurately model the actual flow of materials and components through the system.

This means that simulation-based scheduling software can perform calculations and permutations on all aspects of the production process. This ability, combined with the large volume of real-time data provided by the digitalized workstations, means that scheduling is fast, detailed and accurate.

Thus, the three main requirements for scheduling in Smart factories are satisfied by simulation- based scheduling software:

- Accurate modeling of all elements—a flexible model is generated from computerized information, including full representation of operating constraints as well as custom rules.
- Fast computation of schedules—calculation of schedules and scheduling alternatives, comparison and distribution is carried out quickly and precisely.
- Easily visualized—computerized simulation allows the schedule to be communicated clearly and effectively across all organizational levels.

Improved labor effectiveness is another benefit of simulation-based scheduling. The details generated enables the use of technology like Smart glass which may be one of the most significant ways of enabling the labor force—smart glass will provide employees with timely, detailed instructions. By constantly evaluating the schedule the simulation model using actual and current data will allow for the most efficient way to direct each worker using smart glass as to the next task to perform.

While such a schedule is an essential part of a smart factory, the model can play an even more integral role that just scheduling.

4 Simulation as the Digital Twin

The IT innovations of Industry 4.0 allow data collected from its digitalized component systems in the smart factory to be used to simulate the whole production line using Discrete Event Simulation software. Real time information on inventory levels, component histories, expiration dates, transport, logistics and much more can be fed into the model, developing different plans and schedules through simulation. In this way, alternative sources of supply or production deviations can be evaluated against each other while minimizing potential loss and disruption.

When change happens, be it a simple stock out or equipment breakdown or an unexpected natural disaster on a huge scale, simulation models can show how down-

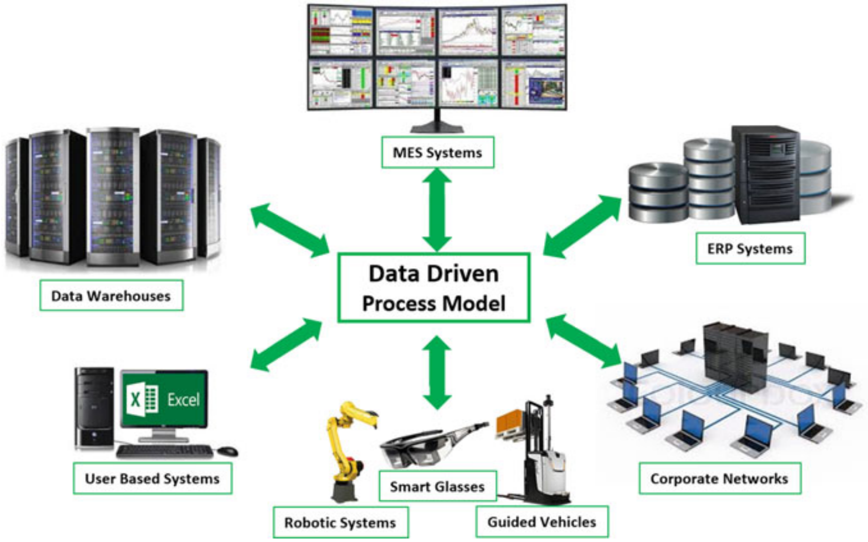

Fig. 1 Digital twin enabling the smart factory

stream services will be affected and the impact on production. Revised courses of action can then be manually or automatically assessed, and a solution implemented.

The benefits of using simulation to schedule and reduce risk in an Industry 4.0 environment include assuring consistent production where costs are controlled, and quality is maintained under any set of circumstances.

By leveraging scheduling, highly data-driven simulation models can also fill the role of a Digital Twin. Figure 1 illustrates how a simulation model can sit at the core of a smart factory. It can communicate with all the critical sub-systems, collect planning and real-time execution information, automatically create a short-term schedule, and distribute the components and results of that schedule back to each sub-system for further action. Advanced simulation-based scheduling software is uniquely suited for such an application due to its ability to communicate in batch or real-time with any sub-system, model the complex behavior required to represent the factory, execute sophisticated techniques to generate a suitably 'optimal' schedule, report that schedule back to stakeholders for execution, then wait for a deviation from plan to be reported which could cause a repeat of the process. This fills an important gap left in most smart factory plans.

5 Tough Problems in Planning and Scheduling

Planning and scheduling are often discussed together because they are related applications. *Planning* is the "big-picture" analysis—how much can or should be made, when, where, and how, and what materials and resources will be required to make it? Planning is typically done on an aggregate view of the capacity assuming infinite material. *Scheduling* is concerned with the operational details—given the current production situation, actual capacities, resource availabilities, and work in progress (WIP), what priorities, sequencing, and tactical decisions will result in best meeting the important goals? Where planning is required days, weeks or months ahead of execution, scheduling is often done only minutes, hours, or days ahead. In many applications, planning and scheduling tasks are done separately. In fact, it is not unusual for only one to be done while the other may be ignored.

One simple type of planning is based on lead times. For example, if averages have historically indicated that most parts of a certain type are "normally" shipped 3 weeks after order release, it will be assumed that—regardless of other factors—when we want to produce one, we should allow 3 weeks. This often does not adequately account for resource utilization. If you have more parts in process than "normal," the lead times may be optimistic.

Another simple type of planning uses a magnetic board, white board, or a spreadsheet to manually create a Gantt chart to show how parts move through the system and how resources are utilized. This can be a very labor-intensive operation, and the quality of the resulting plans may be highly variable, depending on the complexity of the system and the experience level of the planners.

A third planning option is a purpose-built system—a system that is designed and developed using custom algorithms usually expressed in a programming language. These are highly customized to a particular domain and a particular system. Although they have the potential to perform quite well, they often have a very high cost and implementation time and low opportunity for reuse because of the level of customization.

One of the most popular general techniques is *Advanced Planning and Scheduling* (APS). APS is a process that allocates production capacity, resources, and materials optimally to meet production demand. There are a number of APS products on the market designed to integrate detailed production scheduling into the overall Enterprise Resource Planning (ERP) solution, but these solutions have some widely recognized shortcomings. For the most part the ERP system and day-to-day production remain disconnected largely due to two limitations that impede their success: Complexity and Variation.

Complexity. The first limitation is the inability to effectively deal with indeterminately complex systems. Although purpose-built systems can potentially represent any system, the cost and time required to create a detailed, custom-built system often prevents it from being a practical solution. Techniques such as those discussed above tend to work well if the system is very close to a standard benchmark implementation, but to the extent the system varies from that benchmark, the tool may lack enough detail to provide an adequate solution. Critical situations that are not handled include complex material handing (e.g., cranes, robotic equipment, transporters, workers), specialized operations and resource allocations (e.g., changeovers, sequence dependent setups, operators), and experience-based decision logic and operating rules (e.g., order priorities, work selection rules, buffering, order sequence).

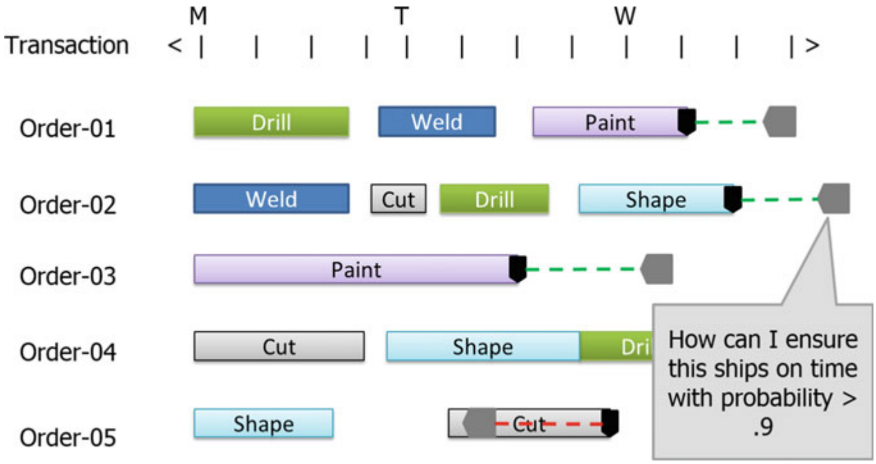

Fig. 2 Typical Gantt chart produced in planning

Variation. A second limitation is the inability to effectively deal with variation within the system. All processing times must be known, and all other variability is typically ignored. For example, unpredictable downtimes and machine failures aren't explicitly accounted for; problems with workers and materials never occur, and other negative events don't happen. The resulting plan is by nature overly optimistic. Figure 2 illustrates a typical scheduling output in the form of a Gantt chart where the green dashed line indicates the slack between the (black) planned completion date and the (gray) due date. Unfortunately, it is difficult to determine if the planned slack is enough. It is common that what starts off as a feasible schedule turns infeasible over time as variation and unplanned events degrade performance. It is normal to have large discrepancies between predicted schedules and actual performance. To protect against delays, the scheduler must buffer with some combination of extra time, inventory, or capacity; all these add cost to the system.

The problem of generating a schedule that is feasible given a limited set of capacitated resources (e.g. workers, machines, transportation devices) is typically referred to as Finite Capacity Scheduling(FCS).

There are two basic approaches to Finite Capacity Scheduling. The first approach is a mathematical optimization approach in which the system is defined by a set of mathematical relationships expressed as constraints. An algorithmic Solver is then used to find a solution to the mathematical model that satisfies the constraints while striving to meet an objective such as minimizing the number of tardy jobs. Unfortunately, these mathematical models fall into a class of problems referred to as NP-Hard for which there are no known efficient algorithms for finding an optimal solution. Hence, in practice, heuristic solvers must be used that are intended to find a "good" solution as opposed to an optimal solution to the scheduling problem. Two well-known examples of commercial products that use this approach are the ILOG product family (CPLEX) from IBM, and APO-PP/DS from SAP.

The mathematical approach to scheduling has well-known shortcomings. Representing the system by a set of mathematical constraints is a very complex and expensive process, and the mathematical model is difficult to maintain over time as the system changes. In addition, there may be many important constraints in the real system that cannot be accurately modeled using the mathematical constraints and must be ignored. The resulting schedules may satisfy the mathematical model but are not feasible in the real system. Finally, the solvers used to generate a solution to the mathematical model often take many hours to produce a good candidate schedule. Hence these schedules are often run overnight or over the weekend. The resulting schedules typically have a short useful life because they are quickly outdated as unplanned events occur (e.g. a machine breaks down, material arrives late, workers call in sick).

This section was not intended as a thorough treatment, but rather a quick overview of a few concepts and common problems. For more in-depth coverage we recommend *Factory Physics* [2].

6 Simulation-Based Scheduling

As an alternative to the mathematical approach discussed above, another approach to Finite Capacity Scheduling is based on using a simulation model to capture the limited resources in the system. The concept of using simulation tools as a planning and scheduling aid has been around for decades. This author used simulation to develop a steel-making scheduling system in the early 1980s. In scheduling applications, we initialize the simulation model to the current state of the system and simulate the flow of the actual planned work through the model. To generate the schedule, we must eliminate all variation and unplanned events when executing the simulation.

Simulation-based scheduling generates a heuristic solution—but can do so in a fraction of the time required by the optimization approach. The quality of the simulation-based schedule is determined based on the decision logic that allocates limited resources to activities within the model. For example, when a resource such as a machine goes idle, a rule within the model is used to select the next entity for processing. This rule might be a simple static ranking rule such as the highest priority job, or a more complex dynamic selection rule such as a rule that minimizes a sequence dependent setup time, or a rule that selects the job based on urgency by picking the job with the smallest value of the time remaining until the due date, divided by the work time remaining (critical ratio).

Many of the simulation-based scheduling systems have been developed around a data-driven pre-existing, or “canned,” job shop model of the system. For example, the system is viewed as a collection of workstations, where each workstation is broken into a setup, processing, and teardown phase, and each job that moves through the system follows a specific routing from workstation to workstation. The software is configured using data to describe the workstations, materials, and jobs. If the application is a good match for the canned model, it may provide a good solution; if

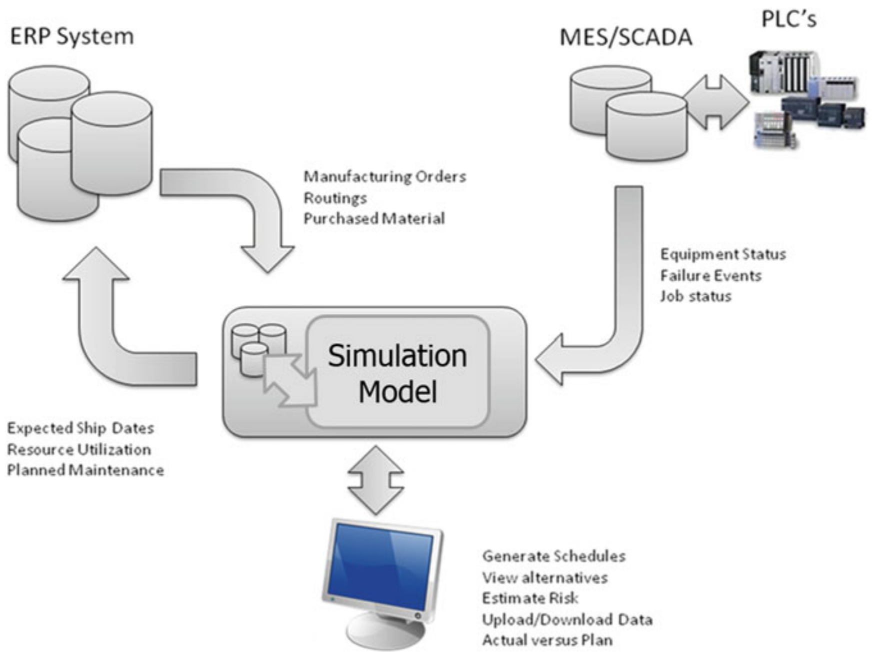

Fig. 3 Architecture of a typical simulation-based scheduling system

not, there is limited opportunity to customize the model to your needs. You may be forced to ignore critical constraints that exist in the real system but are not included in the canned model.

It is also possible to use a general purpose discrete event simulation (DES) product for Finite Capacity Scheduling. Figure 3 illustrates a typical architecture for using a DES engine at the core of a planning and scheduling system. The advantages of this approach include:

- It is flexible. A general-purpose tool can model any important aspects of the system, just like in a model built for system design.
- It is scalable. Again, similar to simulations for design, it can (and should) be done iteratively. You can solve part of the problem and then start using the solution. Iteratively add model breadth and depth as needed until the model provides the schedule accuracy you desire.
- It can leverage previous work. Since the system model required for scheduling is very similar to that which is needed (and hopefully was already used) to fine tune your design, you can extend the use of that design model for planning and scheduling.
- It can operate stochastically. Just as design models use stochastic analysis to evaluate system configuration, a planning model can stochastically evaluate work rules

and other operational characteristics of a scheduling system. This can result in a "smarter" scheduling system that makes better decisions from the start.

- It can be deterministic. You can disable the stochastic capabilities while you generate a deterministic schedule. This will still result in an optimistic schedule as discussed above, but because of the high level of detail possible, this will tend to be more accurate than a schedule based on other tools. And you can evaluate how optimistic it is (see next point).
- It can evaluate risk. It can use the built-in stochastic capability to run AFTER the deterministic plan has been generated. By again turning on the variation—all the bad things that are likely to happen—and running multiple replications against that plan, you can evaluate how likely you are to achieve important performance targets. You can use this information to objectively adjust the schedule to manage the risk in the most cost effective way.
- It supports any desired performance measures. The model can collect key information about performance targets at any time during model execution, so you can measure the viability and risk of a schedule in any way that is meaningful to you.

However, there are also some unique challenges in trying to use a general purpose DES product for scheduling, since they have not been specifically designed for that purpose. Some of the issues that might occur include the following:

- Scheduling Results: A general purpose DES typically presents summary statistics on key system parameters such as throughput and utilization. Although these are still relevant, the main focus in scheduling applications is on individual jobs (entities) and resources, often presented in the form of a Gantt chart or detailed tracking logs. This level of detail is typically not automatically recorded in a general purpose DES product.
- Model Initialization: In design applications of simulation we often start the model empty and idle and then discard the initial portion of the simulation to eliminate bias. In scheduling applications, it is critical that we are able to initialize the model to the current state of the system—including jobs that are in process and at different points in their routing through the system. This is not easily done with most DES products.
- Controlling Randomness: Our DES model typically contains random times (e.g. processing times) and events (e.g. machine breakdowns). During generation of a plan, we want to be able to use the expected times and turn off all random events. However, once the plan is generated, we would like to include variation in the model to evaluate the risk with the plan. A typical DES product is not designed to support both modes of operation.
- Interfacing to Enterprise Data: The information that is required to drive a planning or scheduling model typically resides in the company's ERP system or databases. In either case, the information typically involves complex data relations between multiple data tables. Most DES products are not designed to interface to or work with relational data sources.

- Updating Status: The planning and scheduling model must continually adjust to changes that take place in the actual system e.g. machine breakdowns. This requires an interactive interface for entering status changes.
- Scheduling User Interface: A typical DES product has a user interface that is designed to support the building and running of design models. In scheduling and planning applications, a specialized user interface is required by the staff that employs an existing model (developed by someone else) to generate plans and evaluate risk across a set of potential operational decisions (e.g. adding overtime or expediting material shipments).

A new approach, Risk-based Planning and Scheduling (RPS), is designed to overcome these shortcomings to fully capitalize on the significant advantages of a simulation approach.

7 Risk-Based Planning and Scheduling

Risk-based Planning and Scheduling (RPS) is a technology that combines deterministic and stochastic simulation to bring the full power of traditional DES to operational planning and scheduling applications [3]. The technical background for RPS is more fully described in *Deliver On Your Promise: How Simulation-Based Scheduling Will Change Your Business* [4]. RPS extends traditional APS to fully account for the variation that is present in nearly every production system and provides the necessary information to the scheduler to allow the upfront mitigation of risk and uncertainty. RPS makes dual use of the underlying simulation model. The simulation model can be built at any level of detail and can incorporate all the random variation that is present in the real system.

RPS begins by generating a deterministic schedule by executing the simulation model with randomness disabled (deterministic mode). This is roughly equivalent to the deterministic schedule produced by an APS solution but can account for much greater detail when necessary.

However, RPS then uses the same simulation model with randomness enabled (stochastic) to replicate the schedule execution multiple times (employing multiple processers when available), and record statistics on the schedule performance across replications. The recorded performance measures include the likelihood of meeting a target (such as a due date), the expected milestone completion date (typically later than the planned date based on the underlying variation in the system), as well as optimistic and pessimistic completion times (percentile estimates, also based on variation). Contrast Fig. 2 with the RPS analysis presented in Fig. 4. Here the risk analysis has identified that even though Order-02 appears to have adequate slack, there is a relatively low likelihood (47%) that it will complete on time after considering the risk associated with that particular order, and the resources and materials it requires. Having an objective measure of risk while still in the plan

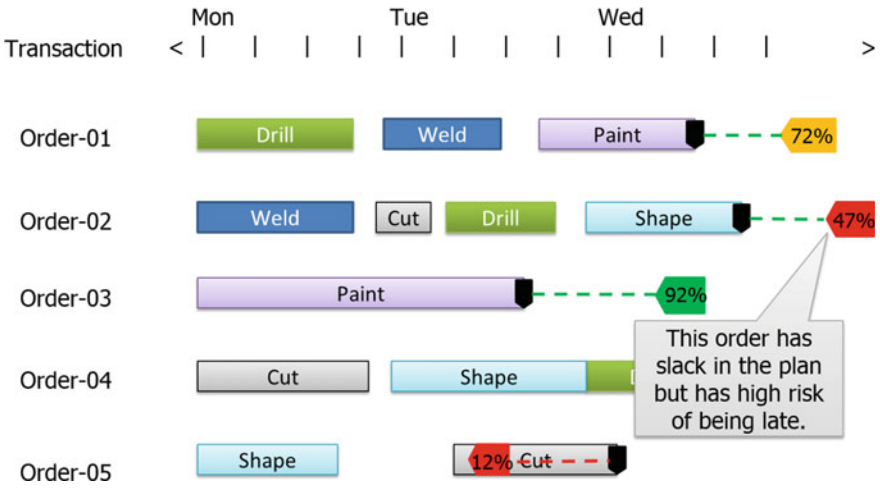

Fig. 4 Gantt chart identifying high-risk order

development phase provides the opportunity to mitigate risk in the most effective way.

RPS uses a simulation-based approach to scheduling that is built around a purpose-built simulation model of the system. The key advantage of this is that the full modeling power of the simulation software is available to fully capture the constraints in your system. You can model your system using the complete simulation toolkit. You can use custom objects for modeling complex systems (if your simulation software provides that capability). You can include moving material devices, such as forklift trucks or AGVs (along with the congestion that occurs on their travel paths), as well as complex material handling devices such as cranes and conveyors. You can also accurately model complex workstations such as ovens and machining centers with tool changers.

RPS imposes no restrictions on the type and number of constraints included in the model. You no longer must assume away critical constraints in your production system. You can generate both the deterministic plan and associated risk analysis using a model that fully captures the realities of your complex production and supply chain. You can also use the same model that is developed for evaluating changes to your facility design to drive an RPS installation which means a single model can be used to drive improvements to your facility design as well as to your day-to-day operations.

RPS implemented as a Digital Twin can be used as a continuous improvement platform to continuously review operational strategies and perform what-if analysis while generating the daily schedule. It can be used off-line to test things like the introduction of a new part to be produced or new machine/line to be installed. When you update the model to reflect the new reality or decision rules it then can be promoted to be the live operational model to immediately affect the schedule based on the changes without having to re-implement the software or make costly updates or changes.

The same model can be extended into the planning horizon to ensure better alignment between the master plan and the detail factory schedule to ensure better supply chain performance. The same model will run for 3 to 6 weeks for planning and 1 to 3 weeks for scheduling and perhaps 1 or 2 days for the detail production schedule for execution. This will then ensure material availability as procurement will be based on the correct requirement dates. This more accurate information can then be used to update the ERP system, for example feeding updates back to SAP.

RPS can even be linked to optimization programs like OptQuest. You can set corporate KPIs and run automatic experiments to find the best configuration for things such as buffer sizes, resource schedules, dispatching rules, etc. to effectively run the factory and then schedule accordingly.

Let's end this chapter by using Simio to build and analyze a system similar to what we did in Chapter "Traditional Simulation Applications in Industry 4.0", Traditional Simulation Applications in Industry 4.0, but this time we will follow a data driven approach, such as you might use if you were building a digital twin of an existing system and you could use data that already existed in an MES system like Wonderware or an ERP system like SAP. For this example, we will assume that that data is stored in a B2MML-compliant format and we will start our model-building effort by importing that data.

8 Modelling Data First Approach to Scheduling

In Sect. 5 of Chapter "Traditional Simulation Applications in Industry 4.0", we practiced building a partially data-driven model with the model first approach. Another approach to building a model is to create it from existing data. This data generated approach is appropriate when you have an existing system and the model configuration data already exists in Enterprise resource planning (ERP) (e.g., SAP), MES (e.g., Wonderware), spreadsheets, or elsewhere. A significant benefit of this approach is that you can create a base working model much faster. Now that we have a bit more modeling and scheduling background, let's build a model from a common data standard (B2MML) and then explore how we might enhance that model.

> B2MML is an XML implementation of the ANSI/ISA-95 family of standards (ISA-95), known internationally as IEC/ISO 62264. B2MML consists of a set of XML schemas [...] that implement the data models in the ISA-95 standard. Companies [...] may use B2MML to integrate business systems such as ERP and supply chain management systems with manufacturing systems such as control systems and manufacturing execution systems. [5]

The system we are modeling has two machines to choose from for each of four operations as illustrated in Fig. 5. Each product will have its own routing through the machines. We will start by using some built-in tools to setup the data tables and configure the model with predefined objects that will be used by the imported data.

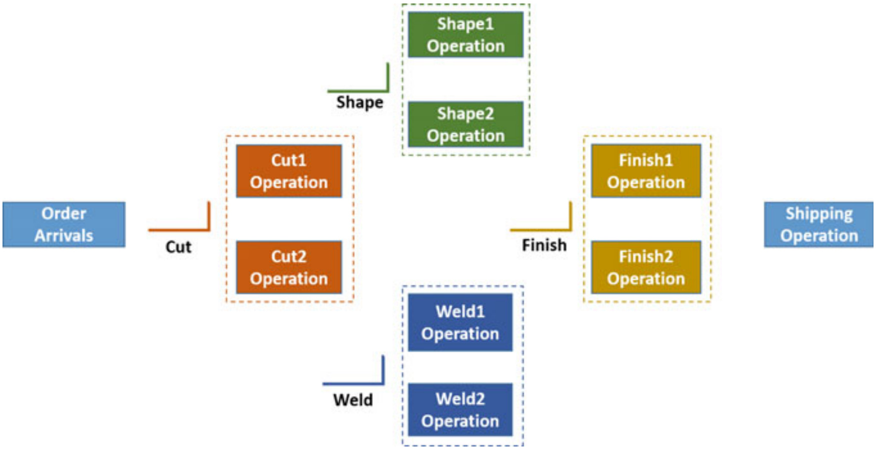

Fig. 5 Overview of data-generated model

Then we will import a set of B2MML data files to populate our tables. We will also import some dashboard reports and table reports to help us analyze the data.

8.1 *Configuring the Model for Data Import*

Simio B2MML compliant tables include: Resources, Routing Destinations, Materials, Material Lots, Manufacturing Orders, Routings, Bill Of Materials, Work In Process, and Manufacturing Orders Output. We will be creating all of these tables and importing all except the last one. But before we can import them, we will configure the model for their use. To do this we will go to the Schema ribbon on the Data tab and press the Scheduling button to the right as illustrated in Fig. 6. After indicating Yes, to continue, you next select whether your routings are based on products (e.g., all products that are the same have the same routing) or orders (e.g., each order has its own independent routing). We will select the Product Based Routing Type for this example. This will create the set of data tables with the B2MML-compliant data schemas and add additional objects to your model that are customized to work with the B2MML data.

Fig. 6 Configuring model for B2MML data import

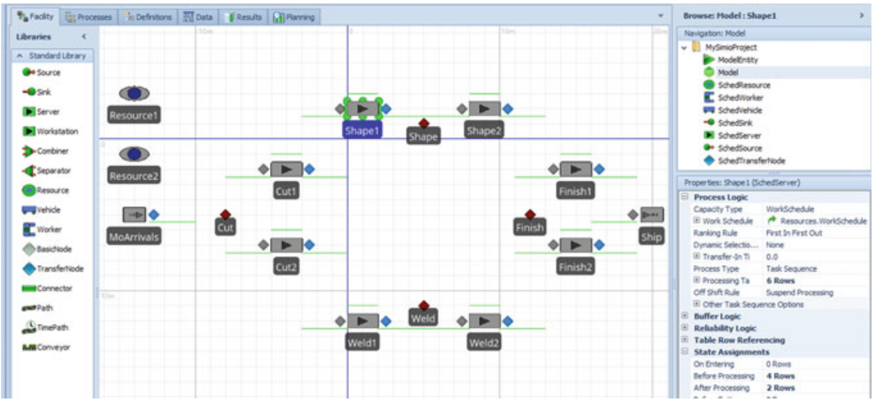

Fig. 7 Model after importing B2MML data

8.2 Data Import

We are now ready to import the data. Select the Resources table. Choose the Create Binding option on the Content ribbon, select CSV, and select the file named Resources.csv from the folder named DataFirstModelDataFiles found in the student downloads files. Then click the Import Table button on the Content ribbon. If you navigate to the Facility view, you will see that the resources have been added to the model.

Navigate back to the Data tab. Repeat the above process with each of the seven other tables, binding each to its associated CSV file, then importing it. After completing the imports, if you navigate back to the Facility view, you will see our completed model. The navigation view of Fig. 7 illustrates the custom objects that were added to this model when you clicked the Configure Scheduling Resources button. If you select the Shape1 object, you can see in the Properties window on the right that it is a SchedServer custom object and that many of the properties like the Work Schedule, Processing Tasks, and Assignments have been preconfigured to draw data directly from the tables. If the properties seem familiar, it is because SchedServer was actually derived from (and almost identical to) the Server object in the Standard Library.

8.3 Running and Analyzing the Model

Our model has been completely built and configured using the data files! You can now run the model interactively and see the animation. Before we can use this model for scheduling we must go to the Run ribbon Advanced Options and select Enable Interactive Logging. Note that each custom object we used already has its option set

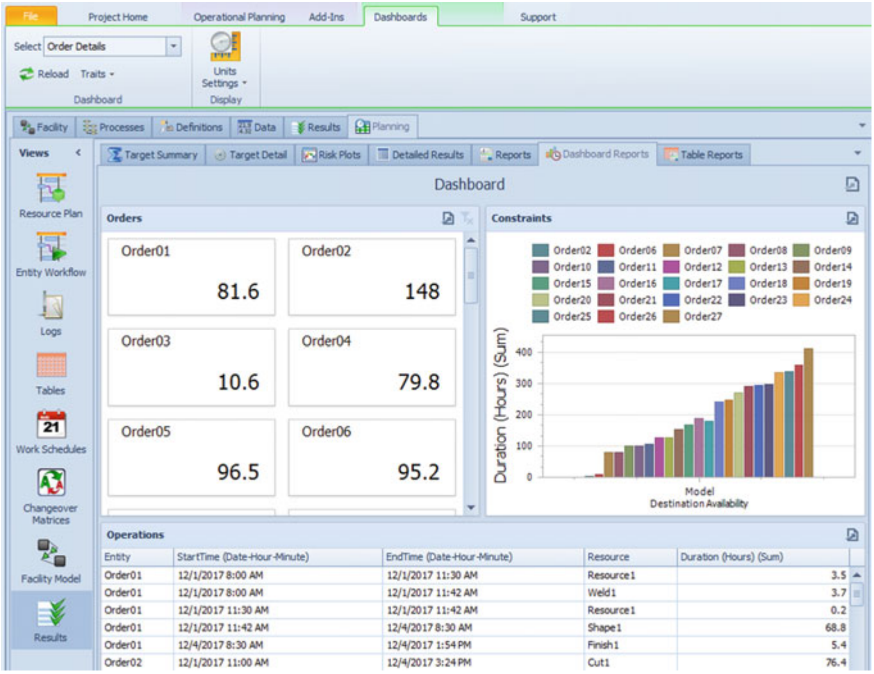

Fig. 8 Order details dashboard report

to log its own resource usage. Now you can go to the Planning tab and click the Create Plan button to generate the Gantt charts and other analysis previously discussed.

Let's import some predefined dashboards that were designed to work with this data schema. These dashboards are saved as XML files and can be found in the same folder as the CSV files. The three dashboards provide material details, order details, and a dispatch list for use by operators. To import these dashboards, go to the Dashboard Reports window of the Results tab (*not* the Results window under Planning) and select the Dashboards ribbon. Select the Import button and select the Dispatch List.xml file from the same folder used above. Repeat this process with the Materials.xml file and the Order Details.xml file. If you go back to the Planning tab—Results window—Dashboard Reports sub-tab, you can now select any of the three reports for display. Figure 8 illustrates the Order Details dashboard report.

Finally, lets add a couple traditional reports. To import these reports, go to the Table Reports window of the Results tab (again, *not* the Results window under Planning) and select the Table Reports ribbon. Select the Import button for ManufacturingOrdersOutput and select the Dispatch List Report.repx file from the same folder used above. Repeat this process Importing for ManufacturingOrders with the OrderDetails.repx file. Importing these two files has now defined the reports for use in the Planning tab. If you go back to the Planning tab—Results window—Table

Dispatch List Report

Scheduled Resource

Cut1

Order Id	Scheduled Quantity	Scheduled Start Time	Scheduled End Time
Order04	10	12/1/2017 8:00:06 AM	12/1/2017 11:00:06 AM
Order02	10	12/1/2017 11:00:08 AM	12/4/2017 3:24:08 PM
Order08	10	12/4/2017 3:24:11 PM	12/5/2017 10:48:11 AM
Order09	10	12/5/2017 10:48:14 AM	12/5/2017 4:12:14 PM
Order11	10	12/5/2017 4:12:17 PM	12/6/2017 3:06:17 PM
Order13	10	12/6/2017 3:06:20 PM	12/8/2017 9:06:20 AM
Order15	10	12/8/2017 9:06:22 AM	12/8/2017 4:06:22 PM
Order17	10	12/8/2017 4:06:25 PM	12/11/2017 2:06:25 PM
Order19	10	12/11/2017 2:06:28 PM	12/13/2017 8:30:28 AM
Order21	10	12/13/2017 8:30:31 AM	12/13/2017 4:24:31 PM
Order23	10	12/13/2017 4:24:34 PM	12/15/2017 10:24:34 AM
Order25	10	12/15/2017 10:24:36 AM	12/18/2017 8:24:36 AM
Order27	10	12/18/2017 8:24:39 AM	12/18/2017 3:24:39 PM

Fig. 9 Dispatch list report for Cut1 resource

Reports sub-tab, you can now select either of the two new custom reports for display. Figure 9 illustrates the Dispatch List report for the Cut1 resource.

While this was obviously a small example, it illustrates the potential for building entire models from existing data sources such as B2MML, Wonderware MES, and SAP ERP systems. This approach can provide an initial functioning model with relatively low effort. Then the model can be enhanced with extra detail and logic to provide better solutions. This is a very powerful approach!.

9 Additional Information and Examples

If you installed Simio so that you can follow along with the examples, you already have additional resources at hand to learn more. The Simio software includes the e-book *Planning and Scheduling with Simio: An Introduction to Simio Enterprise Edition*. You can find this on the Books button on the Support ribbon. This is an excellent place to continue your exploration of simulation-based scheduling. This book covers the standard data schemas and many of the general scheduling concepts and how each of those is addressed in Simio.

The Simio software also includes the e-book *Deliver on Your Promise: How Simulation-Based Scheduling will Change Your Business* [4]. This book is great for managers who want a better understanding of the complex process of scheduling. This provides more details on some of the topics discussed in this chapter as well as describes a few case studies. You are encouraged to share this pdf (or the printed version available on-line) with managers who are looking to solve their scheduling problems.

The Simio software includes three scheduling examples that are each thoroughly documented in accompanying pdf files. These files are located under the Examples button on the Support ribbon:

- Scheduling Discrete Part Production
- Scheduling Bicycle Assembly
- Scheduling Batch Beverage Production.

10 Summary

In Chapter "Traditional Simulation Applications in Industry 4.0", we discussed ways that traditional DES could be used to meet some smart factory modeling needs and we illustrated with a model using Simio. While many DES products can fulfill important aspects of that role, there are many challenges remaining. In this chapter, we discussed some of those remaining Industry 4.0 challenges and opportunities.

We discussed the concept of a digital twin and how it addresses many of those challenges. Then we continued by examining how modern simulation software can be used to create a digital twin of the entire factory. We looked at some of the tough problems in planning and scheduling and the weaknesses of common approaches—weaknesses that often prevent realizing an effective solution. We discussed how simulation can be used to overcome many of these problems, especially using data-driven and data-generated models.

We continued with a discussion of how Simio's patented Risk-based Planning and Scheduling (RPS) provides a unique solution. Then we ended by creating a simple data-generated model, from a set of B2MML-compatible data files. Finally, we have provided resources for additional learning opportunities.

Combining traditional simulation, RPS, and optimization together you could follow modeling phases like the following

(1) Build the DES model to assess the design.
(2) Use that model to optimize system configuration.
(3) Add details and heuristics to prepare the model for scheduling use.
(4) Use the model to optimize heuristics and tune the system to achieve best results overall.
(5) Use the model to generate a proven, feasible schedule.
(6) Use variability analysis (RPS) to evaluate risk and assess the schedule robustness.
(7) Optimize short-term options to improve robustness and effectiveness at the lowest cost.

All of these can take place using a single tool and a single model. And the 3D animation supports and encourages stakeholder buy-in at each phase. A well-designed model is the simplest model that meets the objectives for each phase. Then, rather than having a static tool that can only be changed by "the experts", the model animation and graphical logic definition make it easy to understand, and incrementally change as needed over its lifespan adapting to refined heuristics and system changes.

There are many advantages to using simulation in Industry 4.0 applications, and new applications are being discovered every day particularly relating to designing, assessing, and implementing digital twins.

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Virtual Simulation Model of the New Boeing Sheffield Facility

Ruby Wai Chung Hughes

Abstract In October 2018, The Boeing Company opened their first production facility in Europe. Located in Sheffield in the United Kingdom, the factory will become an Industry 4.0 flagship facility for Boeing; with robust IT infrastructure and a fully connected virtual simulation model working between its digital and physical systems—a "digital twin" factory. With the vision of developing a digital twin factory, the Boeing Information Technology and Data Analytics team collaborated with the University of Sheffield Advanced Management Research Centre's (AMRC) Manufacturing Intelligence (MI) team led by Dr Ruby Hughes to set out a strategic plan to simulate the current factory concept, de-risk the introduction of new technologies, monitor factory performance in real-time, and feedback optimal decisions back to the physical environment based on the latest factory situation data. This chapter presents the key elements within the first stage of the strategy plan—simulate—and discusses the approach of linking the simulation model to physical systems to achieve the creation of a digital twin factory.

Keywords Discrete event simulation · Digital twin · Optimisation · Smart factory

1 Introduction

In October 2018, The Boeing Company opened their first production facility in Europe. Located in Sheffield in the United Kingdom, the factory will become an Industry 4.0 flagship facility for Boeing; with robust IT infrastructure and a fully connected virtual simulation model working between its digital and physical systems—a "digital twin" factory.

With the vision of developing a digital twin factory, the Boeing Information Technology and Data Analytics team collaborated with the University of Sheffield Advanced Management Research Centre's (AMRC) Manufacturing Intelligence (MI) team, led by Dr. Ruby Hughes, to set out a strategic plan to *simulate* the current

R. W. C. Hughes (✉)
Advanced Manufacturing Research Centre, University of Sheffield, Sheffield, UK
e-mail: r.hughes@amrc.co.uk

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factory concept, *de-risk* the introduction of new technologies, *monitor* factory performance in real-time, and *feedback* optimal decisions back to the physical environment based on the latest factory situation data.

This strategic approach supported Boeing in designing factory flows, validating resource requirements, evaluating impacts for implementing advanced technologies and monitoring uncertainties within the production environment. It will also eventually allow the company to support agile decision-making at Boeing Sheffield based on real-time scenarios.

This chapter presents the key elements within the first stage of the strategy plan—*simulate*—and discusses the approach of linking the simulation model to physical systems to achieve the creation of a digital twin factory.

Discrete Event Simulation (DES) is selected to simulate the facility based on its (1) capability to model complex systems and the discrete-events of manufacturing processes; (2) flexibility to model what-if scenarios and to run analytic experiments; and (3) its compatibility for connecting physical devices and systems to obtain real-time system data.

Tim Underwood, Manufacturing Engineer for Boeing Research and Technology, stated: "Using DES gave Boeing a holistic view of the factory floor operations that will take place in the new factory, before construction was even complete." Indeed, the simulation model created in this project has already validated the opportunities Boeing has to increase productivity by up to 50%.

2 Background Information

Boeing Sheffield will make more than 100 different high-tech actuation system components for the company's Next Generation 737, 737 MAX and 767 aircraft, from raw materials sourced in the UK. These components will be transported to the Boeing Commercial Airplanes (BCA) facility in Portland, Oregon, in the United States for assembly into trailing edge actuation systems [1].

The new 6200 m^2 facility in Sheffield includes a machining shop floor and office space. The shop floor includes three work centres: a housings cell, a complex shafts and discs cell, and a simple shafts and discs cell.

The first stage of the project was to create a virtual simulation model using DES to examine the potential capabilities of the factory and to validate opportunities for increasing productivity.

3 Virtual Simulation Model Development

The virtual simulation model as shown in Fig. 1 was created in Siemens Tecnomatix Plant Simulation, a DES software package allowing events and what-if scenarios to be run without interrupting existing production systems or processes.

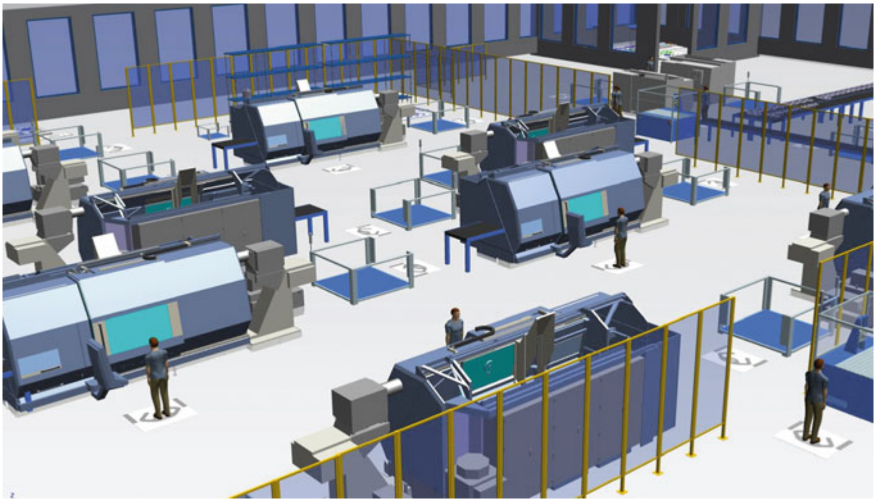

Fig. 1 One of the machine work cells within the virtual simulation model of Boeing Sheffield

3.1 Data Collection

Even before Boeing Sheffield was operational, the Information Technology and Data Analytics team at Boeing had sight of the full concept of how each of the components will be manufactured and how long each of the operations would take through the machining centres.

This conceptual data became the backbone of the virtual simulation model. Table 1 highlights the model data requirements for the DES simulation.

Table 1 Data requirement table for creating virtual simulation model

Process and time information	– Process flow diagram of the key processes/operations – Process data (process time, setup time, number of machines in each process, batch sizes and buffer sizes) – Calendar data (shift pattern, holiday information, and preventive maintenance information) – CAD factory layout/machines in 3D shape
Resource information	– Machine data (number of machines, mean time to failure, mean time to repair and resource data) – Operator data (shift patterns and skill/experience required) – Transport system required for material handlings
Demand information	– Volume, due date, priority and demand pattern – Product variances and quantity for assembly

In literature, the data collection phase is always highlighted as a time-consuming and expensive process within Modelling and Simulation (M&S) [2], even though this challenge could soon be unravelled by the Industry 4.0 capabilities of linking a simulation model to physical systems, for example a manufacturing execution system (MES), machine controllers and component tracking system etc. Until then, data collection is still a critical step for developing an accurate simulation model of a system.

As Boeing Sheffield was not yet operational when this project commenced, capturing real production data was impossible. The AMRC MI team worked closely with the team at Boeing Sheffield (including manufacturing engineers and decision-makers) to identify and collect the required data. This approach has proven to be very effective as long as the model data requirement is communicated well in advanced with the key stakeholders.

3.2 Virtual Simulation Development

The modelling phase included two key stages within this project, the first to create two-dimensional layouts of the factory floors and add in data for machines, processes, production sequences and materials; allowing a simulation model to be created which mimicked production flow on the new workshop floor at Boeing Sheffield.

Figure 2 shows the factory flow simulation model in 2D. The 2D factory simulation allowed the team to validate the number of machines for the workshop floor, to check if adequate workforce and resources are allocated in the right place and at the right time and look at any bottlenecks in production to validate production targets against intended operations.

The second stage of the modelling work included further developing the 2D factory simulation into a virtual simulation model (Fig. 3). The term virtual simulation or virtual factory has been defined in multiple ways in manufacturing research, including as a high-fidelity simulation, a virtual organisation, a virtual reality representation and an emulation facility [2]. This project utilises the virtual simulation definition as a high-fidelity simulation of a manufacturing facility in two levels. First is the effort on modelling the factory assets in three-dimensional shapes, such as the machines that are included within the virtual simulation model as a true representation of the actual machines that are going to be invested within the new factory. Second is the level of detail on modelling the primary production processes of each of the components that is going to be manufactured within the new factory. For instance, within the virtual simulation each of the components is identifiable with a dedicated component number and different cycle times and setup times, and each of the component groups has different quantity requirements which make the simulation more representable and accurate.

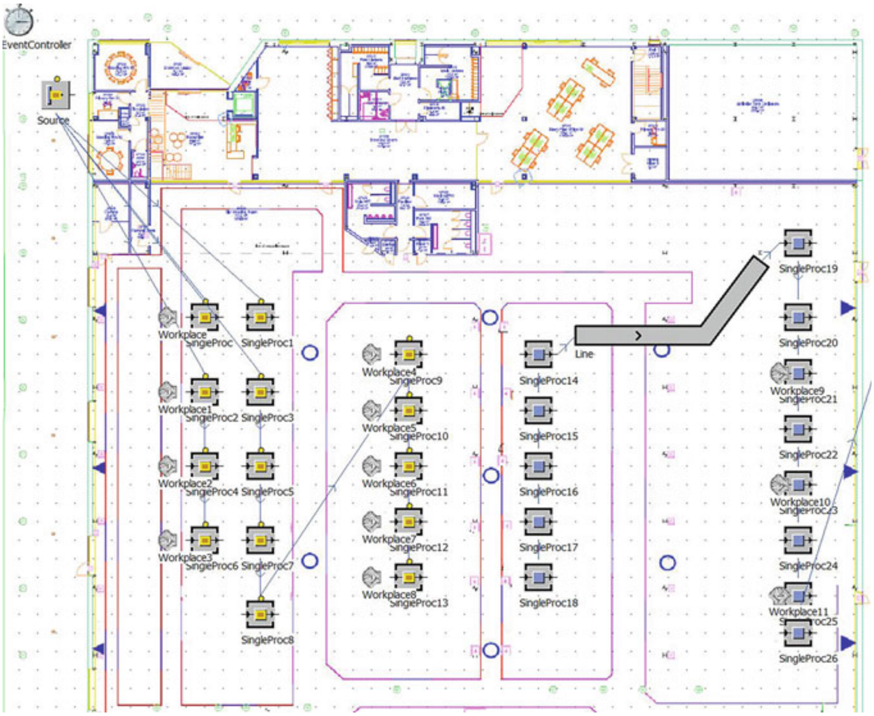

Fig. 2 Factory flow simulation model in 2D

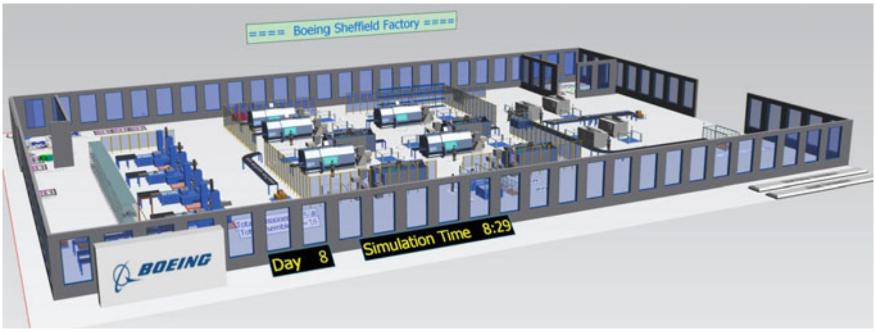

Fig. 3 Full view of the virtual simulation model of Boeing Sheffield created in Siemens Tecnomatix Plant Simulation software

Setting up the virtual simulation at the appropriate levels of detail has the advantage of allowing decision-makers to examine the as-is scenario and supports a deeper understanding of the consequences of different strategies and decisions as what-if scenario analyses. Indeed, the setup of a high-fidelity simulation would also support the transition from off-line virtual simulation to a digital twin factory model.

3.3 Validation Process

A validated virtual simulation model is a fundamental step and a backbone of a digital twin factory. So it is key that the model reflects true factory performance and this depends on the variety of data measurements that are available during a project.

This project used the key performance indicators (KPI) including throughput targets of each machining cells as the key measurement. A dashboard system was created as shown in the top section of Fig. 4. This system links in real-time to the virtual simulation model so the latest simulation results can be displayed simultaneously via the dashboard. Currently, the dashboard system has the ability to display simulation throughputs vs actual throughput targets and the utilisation rates of each of the machine centres.

The KPI results from the virtual simulation model have been validated against Boeing Sheffield data, and the team was amazed at the accuracy of the simulation results. These results gave Boeing the confidence of using the simulation model to support the team to understand future factory capabilities; with the model showing the opportunities Boeing has to increase productivity by up to 50% at the new factory.

4 Next Step Towards the Digital Twin Factory

The virtual simulation model validated the impact of Boeing Sheffield's planned production processes and showed where they had further production capacity and to assist with future optimisation of production schedules.

In future phases of the project, the simulation model will provide new opportunities for Boeing to validate operational changes, technology introduction, identify opportunities to further increase throughput and introduce real-time factory monitoring.

Linking the virtual simulation model to Boeing's production data in real-time, for instance material delivery time, machine states, machine maintenance and process scheduling will provide continuing benefits such as:

- Improving the model's accuracy
- Real-time monitoring of factory performance
- Apply optimisation to the physical environment based on the latest factory situation.

AMRC

Dashboard system to monitor factory key performance indicators remotely.

"Going forward the technology will give us the ability to link the virtual simulation to the workshop floor to establish a digital twin for Boeing Sheffield." Gary Hilton, Boeing.

"Through the collaboration with the AMRC, we have been able to look at whether we had invested in the right number of machines for the workshop floor, to check we had the adequate workforce and resources availability to support operations and look at any bottle-necks in production to validate our targets against our intended operations."

Gary Hilton, Chief IT Engineer for Vertical Integration at Boeing, said: "Going forward the technology will give us the ability to link the virtual simulation to the workshop floor to establish a digital twin for Boeing Sheffield. This will enable us to discern in real-time how processes within the facility are operating and monitor the workshop floor for any issues that are occurring, or plan resources around future targets."

The AMRC is further developing its DES research to link to artificial intelligence (AI) solving complex real-world problems in shorter experimental time.

The methodology developed is suited to applications across many such as aerospace, automotive, defence and healthcare; where increases in productivity and reduced resource usage are critical to maintain productivity levels.

Technical Fellow and Head of Manufacturing Intelligence Group, Dr Ruby Hughes, said this also includes SMEs working in those sectors where low-risk validation and what-if analysis can be a major benefit: "With the expertise in house at the AMRC, the simulation model development time is fairly short, making this kind of technology accessible to any business who can access these capabilities through working with us."

Fig. 4 AMRC case study document which highlights the key benefits of virtual simulation [3]

Additionally, the team will adopt on-going research in artificial intelligence (AI) algorithms to enable more accurate and shorter experimental time to solve complex real-world problems in near future.

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Use of a Simulation Environment and Metaheuristic Algorithm for Human Resource Management in a Cyber-Physical System

Hankun Zhang, Borut Buchmeister, Shifeng Liu and Robert Ojstersek

Abstract At the time of Industry 4.0 and the emergence of collaborative workplaces based on the cooperation of robots (machines) and humans, the number of human workplaces in the Industry 4.0 production system is crucial. In this chapter, we present the use of the evolutionary computation methods that use the input data of a real production system and transfer it through the five-stage Cyber-Physical System architecture into the simulation environment in order to determine the optimal number of workers. By using these methods, we confirm the hypothesis of the importance of correctly determining the number of workers in the manufacturing process in Industry 4.0. Number of workers' determination has a key influence on the product flow time, machine utilization and cost-effectiveness of a production system. Research results show the importance and effectiveness of combining evolutionary computation methods and simulation modelling for the purpose of implementing the advanced approaches of Industry 4.0. The demonstrated approach of combining evolutionary computing, simulation environments and methods of Industry 4.0 can be used from mass customization to mass production systems for the purpose of single-criteria or multi-criteria optimization.

Keywords Simulation modelling · Evolutionary computation · Cyber-physical system · Heuristic Kalman Algorithm · Human resource management

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H. Zhang · S. Liu
School of Economics and Management, Beijing Jiaotong University, Beijing 100044, People's Republic of China
e-mail: zhanghankun@bjtu.edu.cn

S. Liu
e-mail: shfliu@bjtu.edu.cn

B. Buchmeister · R. Ojstersek (✉)
Faculty of Mechanical Engineering, University of Maribor,
Smetanova 17, Maribor 2000, Slovenia
e-mail: robert.ojstersek@um.si

B. Buchmeister
e-mail: borut.buchmeister@um.si

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1 Introduction

The globalised world of Industry 4.0 is focused on mass customization [31], dynamic response to product demand, and real-time optimization of the manufacturing environment. Human Resource Management (HRM) is a very important aspect [3, 13]. HRM methods are, in Industry 4.0, considered as one of the primary sources for appropriate work skills, capabilities, and behaviours to achieve production system goals. In these cases, they have a significant value in the manufacturing environment. Research work done in past was focused mainly on development of human expertise in-depth knowledge. Now scientists are developing methods of Artificial Intelligence (AI) and Evolutionary Computation (EC) to solve different problems. In our case, we have introduced HRM as the main objective to optimise with AI for Job Shop Scheduling Problems (JSSP) [32, 45]. Our research work proposed a new evolutionary algorithm combined with discrete system simulation to optimise the number of workers on a factory production line. In this chapter, we present the use of simulation environment in production systems, supported by the concept of Industry 4.0, and a metaheuristic algorithm for the Minimum Number of Workers' (MNW) determination. The fundamental research work was first presented by Zhang et al. [45]. The MNW determination problem is a complex problem, due mainly to the following features:

– Possible variation of the workstation capacity during the time period.
– Legal constraints on the capacity and its evolution.
– Different skills must be considered for an operator, especially in production systems involving Industry 4.0.
– Individual company expectations.

Research work presented in this chapter is limited to an HRM problem just for MNW determination in a production system supported by Industry 4.0. The main research contribution is a newly proposed metaheuristic algorithm and its simulation testing on a real-world production system to achieved appropriate MNW determination. We proposed an improved estimation method of the Heuristic Kalman Algorithm (HKA) [24] for the purpose of HRM optimization. The research problem is based on the need to increase the productivity of the existing production system. The problem can be essentially solved by employing new workers in the existing production system or by automating the existing production system by applying the concept of Industry 4.0. In the second case, the productivity of the production system increases, and the number of workers can be reduced or unchanged. In the following research work presented in this chapter, we want to present how important it is to correctly determine the number of workers (MNW), when the concept of Industry 4.0 is introduced into exiting production system. Use of the main Industry 4.0 architecture model (CPS model) leads to an increase in productivity with a uniform workers' workload and the economic viability of workers for the enterprise. The presented research work is based on applying the 5C CPS architectural model, metaheuristic algorithm and simulation environments in order to determine the optimal number of workers in the production process supported by the concept of Industry 4.0. All proposed methods are based on the Cyber-physical system [26], which is 5C (connection, conversion, cyber, cognition, and configuration) level cloud architecture (first connection, second conversion, third cyber, fourth cognition, and fifth configuration) based technologies. It refers to a modern manufacturing system that offers an information-transparent environment to facilitate asset management, HRM, provide flexibility, and maintain productivity.

The chapter is structured as follows: in Sect. 2, the literature review is presented in four research areas (simulation modelling, 5C CPS architecture in Industry 4.0, HRM, and Heuristic Kalman Algorithm). This section is followed by Sect. 3, in which the presentation of the 5C CPS architectural model, which is generally presented as one of the constituent concepts of Industry 4.0. In the continuation of this section, the model apply a real-world production system model, which serves as a reference model throughout the whole chapter. Section 4 presents the method of evolutionary computation called HKA, which was developed during the first development phase of our project: Implementation of HKA for the purpose of production systems' single-objective optimization. In Sect. 5, we present an Improved HKA (IHKA) method, and its results are tested and displayed on benchmark test data, followed by the implementation of the IHKA for the purpose of MNW determination. At the beginning of this section, we give some general basic knowledge and mathematical modelling in the field of HMR and MNW determination. The following is a description of the solution coding and the experimental part carried out in a real-world production system. Section 6 represents a simulation modelling of the production system in which we want to optimize a single-objective MNW parameter. The whole section is based on a real-world example, the implementation of IHKA and simulation modelling on the 5C CPS architectural model. Section 7 presents conclusions and further research work.

2 Literature Review

In a time of rapid development of companies that meet in the global market with the introduction of the Industry 4.0 concept based on mass personalization of customised products, simulation methods are very important. The introduction of simulation methods for the purpose of production systems' modelling and analysing was first presented by Emery [10], Askin and Standridge [4], who defined the basic simulation methods. These methods were improved and represented on application cases by Law and Kelton [19]. In order to optimise production, researchers use a wide range of software environments to analyse and optimise production processes [17, 29]. Due to the wide range of different simulation methods, their advantages and disadvantages, it is essential that the correct choice of simulation methods be made with respect to the optimization problem's characteristics [7]. The simulation methods are divided into two groups: Continuous simulation, in which the simulation tracks the system dynamics continuously over time. On the other hand, we have event-based simulation, also called an activity-based simulation, in which time is broken up into small slices and the system state is updated according to the set of activities happening in the time slice. Because discrete-event simulations do not have to simulate every time slice, they can, typically, run much faster than the corresponding continuous simulation [11]. Practical examples of discrete systems' simulation are presented in solving scheduling problems using linear programming [14], layout and material flow optimization in a digital factory [8], and on production optimization [25]. The mentioned authors present various simulation methods and approaches, and, in doing so, they discuss a problems that arise with the application of simulation methods. In the already existing and newly proposed production processes, the use of simulation methods is particularly important in the implementation of the Industry 4.0 concept [5]. In designing production processes, authors suggest the introduction of AI and EC [43, 44], which imply the concepts of the Internet of Things (IoT), Cloud Computing, Cyber-Physical Systems (CPS) and Big Data in Industry 4.0. In most cases, the authors use the CPS model as a reference architectural model for dynamically variable production processes [36]. Several dimensional approaches are proposed for the design of advanced mechatronic systems in production processes [30], which differ essentially from Product Service Systems (PSS), especially in the processing efficiency of a Big Data calculation [22]. The established architecture, the CPS model, in relation to the implementation of Artificial Intelligence and simulation methods at all five architectural stages, is presented below with reference to the cited research work [20]. When implementing the concept of Industry 4.0 and its associated CPS architecture, the Human Resource Management (HRM) aspect is particularly important. The regularity of labour load planning affects the flexibility, productivity and efficiency of the production process significantly [12]. The HRM area has been well researched in the past production systems [13]. In the current time of Industry 4.0, based on the CPS architectural model, the appropriate treatment of HRM is more and more important [3, 34]. When discussing HRM in Industry 4.0, we also talk about collaborative workspaces that are occurring increasingly in production systems. They will have a significant impact on the setting up and organising of jobs in the future [47]. Recently, in this field of research, we can find the proposals of new methods related to a holistic HRM based on the support of robotised and automated production processes [15]. Researchers use modern approaches of AI to determine the Near Optimum (NO) solution [45] when introducing new methods proposed for the purpose of HRM optimization. The importance of HRM in the production planning and scheduling [32] and the introduction of Artificial Intelligence methods [1, 9, 35] present new research challenges for the future. Recently, research results [18, 38] demonstrated the benefits of heuristic and metaheuristic methods for the purpose of optimising production processes. Due to the complexity of the optimization problems, the solutions mentioned refer to NP-hard or strongly NP-hard problems. In solving strongly NP-hard problems, researchers use either hybrid Artificial Intelligence methods based on combining the positive properties of individual evolutionary computing methods, or solving multi-objective optimization problems [23, 46]. Particularly deeply explored is the field of Planning and Scheduling, from service activities [42] to production systems [37]. The authors implement

Artificial Intelligence algorithms to benchmark examples [28], as well as to real-world examples [33]. The high efficiency of modern Artificial Intelligence methods are reflected in the implementation of the Kalman Filter approach for the purpose of multiprocessor evolutionary computation and obtaining estimated solutions [21]. The advantage of using Heuristic Kalman Algorithm is based on ease of use and real-world application implementation [27, 39]. The Heuristic Kalman algorithm can act as an estimator of single-objective problems, as well as a multi-objective problem estimator [16]. The authors [26] first used it for the purpose of production systems single-objective optimization. Based on the obtained NO results, researchers were expanded, and improved their algorithm in the further development phase for optimising multi-objective real-world problems [24].

2.1 5C CPS Architecture

A general model of 5C CPS architecture is presented in Fig. 1. It represents the five-level architecture, which is defined as a modern mechanism for monitoring and controlling production systems [20]. It offers an information environment for optimising and designing the following parameters: Human Resources Management, flexibility and productivity sustainability. In the following section, we present an application example of using an evolutionary algorithm and simulation environment, which refers to all five levels of the architectural model.

The first level of the architectural model is a smart communication level that relates to Plug & Play applications and open-source communication protocols to sensor networks. The second level of data-to-information conversion level allows intelligent evolutionary algorithms' optimization of the expected objective to obtain

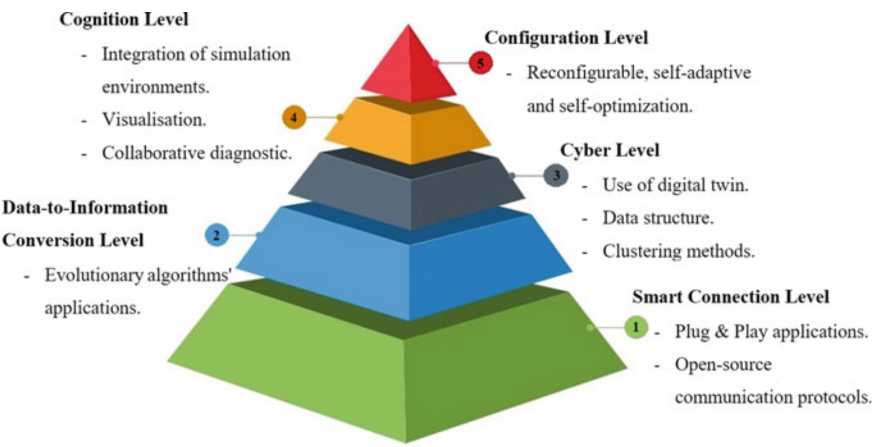


Fig. 1 The 5C CPS architecture

optimal solutions. The third level, or the cyber level, allows the use of a digital twin between the basic components in completed blocks, the data-time structure, and the use of the clustering in data structures. The fourth level, or cognition level, enables the integration of simulation environments with real-world data sets, visualization for the user, and machine interface in collaborative diagnostic and decision models. The highest, fifth level, or so-called configuration level, refers to reconfigurable, self-adaptive and self-optimization of the proposed evolutionary algorithms and simulation models. This architectural model shares similarity to the Internet of Things, but this model represents a higher-level integration degree of physical and digital elements.

In the next section, we present a real-world example of 5C CPS architecture integrated into a production system in which, at the connection level, we proposed smart communication and data transfer for the real-world simulation model, which is implemented in fourth level of cognition. The second level of conversion integrates the IHKA for MNW estimation and optimization. The Cyber level includes improved solution clustering of algorithm solutions. As said before, the cognition level integrates the simulation model with the mathematical model of IHKA. In the final, fifth configuration level, we proposed self-adjusted solutions for the purpose of near optimal HRM configuration.

2.2 Applied 5C CPS Architecture

The following is an introduction of the implementation of the CPS model in the case of advanced single-objective production systems' optimization methods. In the left column of Table 1, we can see five levels of the above-described 5C CPS architectural model and, presented in the right-hand column, is the architectural definition of the real production system.

1. *Smart communication level*: The input data of the real production system are captured through the analytical tools and advanced sensors systems presented in Table 3. The main constraint is that the production system must support Industry 4.0 methodology regarding individual machine sensors and data connectivity. It should be noted that the quality of the captured and processed input data has a significant impact on all the following architectural levels.
2. *Data to information conversion level*: In our case, we use the Heuristic Kalman Algorithm (HKA) [26] to evaluate the optimal solutions of the single-objective (MNW determination) production system optimization. Using the estimation method of the HKA, we can predict the optimal or almost optimal (near-optimum, NO) solutions of several production system criteria (flow rates, utilization of workplaces and machines, number of finished products in the simulation period, and MNW problem).
3. *Cyber level*: The characteristic of HKA is that, when assessing the NO solution, a negative noise (error) occurs, which contributes to the relative error of the

Table 1 Applied 5C CPS model

Architecture level	Production system implementation
Smart connection level	Input data of a real-world production system, suitable for the simulation model (all machines in production systems support Industry 4.0 methodology)
Data-to-information conversion level	Use of input data collected from a production system needed for mathematical and simulation modelling (evaluation algorithm computing)
Cyber level	Use of single-objective methods to determine optimal solutions (production system HRM and MNW determination)
Cognition level	Building a simulation model with the goal of single or multi-objective production system optimization
Configuration level	Use of self-adaptive methods with the goal of determining optimal solutions in a real-time environment

estimated value [45]. To this end, we use the method of clustering that allows us to use only the best solutions. At cyber architecture level, we proposed the Improved Heuristic Kalman Algorithm (IHKA) to obtain the best solutions.

4. *Cognitive level*: Based on all previously collected production system data and built mathematical models, the construction of the simulation model follows. The simulation model captures all production system real-world characteristics, followed by the optimal solution decision. Depending on the complexity of the production system and the built-in simulation model, we can choose to implement simulation scenarios [25], which allow us detailed simulation modelling according to the previously predicted production system characteristics.
5. *Configuration level*: The obtained solutions from the simulation experiments and mathematical model calculation depend on the function of the time variable, which, in general, means that the mentioned solutions change according to the time. To this end, we propose the introduction of self-adaptive decision-making methods for determining NO IHKA solutions.

3 Heuristic Kalman Algorithm

The Heuristic Kalman Algorithm (HKA), as a Kalman filtering based heuristic approach, only requires the user to set three parameters [38, 39]. The search heuristic of the HKA is entirely different from other population-based stochastic optimization algorithms, in that it considers the optimization problem explicitly as a measurement process designed to give an estimate of the optimum. During the measurement process, HKA develops a specific procedure based on the Kalman estimator to improve the quality of the estimate obtained. HKA needs initialising the Gaussian distribu-

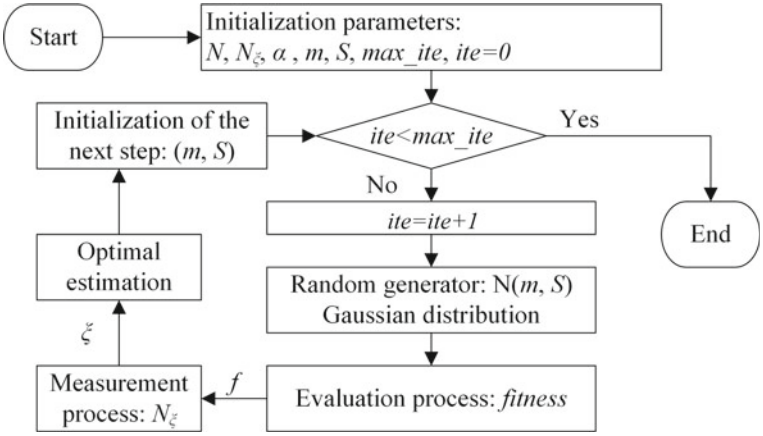


Fig. 2 The flowchart of the HKA

tion, selecting the user-defined parameters, and introducing the stopping rule for practical implementation [18]. During the HKA optimization process, first, the solutions are generated by the Gaussian distribution that is parametrised by a given mean vector with a given variance–covariance matrix, followed by the measurement procedure, and, finally, the optimum estimator of the parameters is introduced for the next generation. Figure 2 shows the flowchart of HKA [38, 39].

4 Improved Heuristic Kalman Algorithm

Experiments show that HKA is so convergent that it is easy to fall into the local minimum. This chapter proposes a new improved estimation method of the Heuristic Kalman Algorithm, the IHKA. In the IHKA, a mutation operation is introduced after the solutions are generated by the Gaussian distribution, then a function is introduced that handles the boundary constraint, and, finally, a random number is introduced in the updating formula of the standard deviation vector of the Gaussian generator. The general pseudo-code of the IHKA is shown in Algorithm 1 [24].

Algorithm 1 The general pseudo-code of the IHKA.

Step 0 Initialization. Set the size of the population Ns, the number of dimensions of the actual problem Nd, the number of top individuals under consideration N_{ξ}, the slowdown coefficient α, the mutation parameter β the maximum block size of the random $Bsize$ and the maximum number of iterations *max_ite*. Initialise the mean vector m and the variance–covariance vector S.

$$m = \left[\frac{lu(1,1)+lu(2,1)}{2}, \cdots, \frac{lu(1,j)+lu(2,j)}{2}, \cdots, \frac{lu(1,Nd)+lu(2,Nd)}{2}\right]^T$$

$$S = \left[\left(\frac{lu(2,1)-lu(1,1)}{6}\right)^2, \cdots, \left(\frac{lu(2,j)-lu(1,j)}{6}\right), \cdots, \left(\frac{lu(2,Nd)-lu(1,Nd)}{6}\right)^2\right]^T$$

Where *lu(1, j)* (respectively, *lu(2, j)*) is the j^{th} lower bound (respectively, upper bound) of the problem.

Step 1 Iteration.

For *ite* = 1: *max_ite*

Step 1.1 Random generator. Generate a population *x* with *Ns* individuals by a Gaussian distribution parametrised by *m* and *S*:

x = *mvnrnd*(*mvnrnd*(*m, diag*(*S*)*, Ns*)

where *mvnrnd*(.) is a function that generates random vectors from the multivariate normal distribution and *diag*(.) is a function that generates diagonal matrices or diagonals of a matrix.

Step 1.2 For each individual in the population

for *i* = 1: *Ns*

Step 1.2.1 Mutation operator by Algorithm 2.

x (*i*, :) = *mutate*(*x*(*i*, :)*, Nd, β, Bsize, ite, max_ite*)

Step 1.2.2 Handling the constraints of the problem (see Equation (1)):

x (*i*, :) = *handleCons*(*x*(*i*, :)*, Gbx, Nd, lu*)

where *Gbx* is the global best position

Step 1.2.3 Evaluate fitness. Calculate the individual fitness *f(i)* in *x* (*i*, :).

end

Step 1.3 Update the global best position.

Step 1.4 Choose process. Choose the top N_{ξ} individuals according to *f*.

Step 1.5 Measurement process. Compute the measurement ξ and the variance vector V.

$\xi = \frac{1}{N_\xi}\sum_{k=1}^{N_\xi} x_k$, $V = \frac{1}{N_\xi}\left[\sum_{k=1}^{N_\xi}\left(x_{k,1} - \xi_1\right)^2, \cdots, \sum_{k=1}^{N_\xi}\left(x_{k,j} - \xi_j\right)^2, \cdots, \sum_{k=1}^{N_\xi}\left(x_{k,Nd} - \xi_{Nd}\right)^2\right]^T$

Step 1.6 Optimal estimation. Compute the posterior estimation the mean vector m_pe and the variance–covariance vector S_pe.

$L = S./(S+V)$, $W = (S - L.*S)^{0.5}$, $m\_pe = m + L.*(\xi - m)$, $\tau = min(1, mean(\sqrt{V})^2)$

$a = \alpha\tau / (\tau + max(W))$, $S\_pe = (S^{0.5} + ar_z.*(W - S^{0.5}))^2$

where a is the slowdown factor, r_z is a random number vector generated by Logistic chaotic map, $mean(.)$ is a function that calculates the average or mean value and the symbol $./$ (respectively, $.*$) stands for a component-wise divide (respectively, product).

Step 1.7 Initialise the next step.

$m = m\_pe$, $S = S\_pe$

end

Mutation operator:

In order to improve the performance of the HKA in combinatorial optimization problems, which is likely to fall into a local optimum for the fast convergence speed, a mutation operation is introduced after the population is generated. In IHKA, a mutation parameter is set to control the decreasing speed of the mutation probability [46]. As the number of iterations increases, the probability of mutation operation decreases, that is, the effect of the mutation operator decreases [46]. In the mutation function *mutate*, inspired by Zhang et al. [45], this paper introduces four mutation operators with random size; insert operator, random size move backward operator, random size swap operator, and 2-opt operator. It should be noted that the solution is based on the sort to decode, so the mutation operation is also based on the sorted individual. When mutating, a mutation operator is selected from them randomly, then two positions are selected from the current mutated individual. After the mutation block size is determined, the mutation operation is finally executed. Algorithm 2 shows the general pseudo-code of the mutation function *mutate*.

Algorithm 2 The general pseudo-code of the $mutate$.

Input: The individual before mutation *xi*, the number of dimensions of the actual problem *Nd*, the mutation parameter *β*, the maximum block size of the random operator *Bsize*, the current iteration *ite* and the maximum number of iterations *max_ite*.
Output: the new individual after mutation *xi*.
Step 1 Calculate the current mutation probability.
$e = exp(-\beta * ite/max\_ite)$
Step 2 Determine whether to mutate.
if *rand* < *e*
    Step 2.1 Select a neighbourhood structure randomly.
    ri = *randi* (4)
    Step 2.2 Select two different positions randomly, and the first selected position needs to be smaller than the second one:
    Step 2.3 *SI* = *sort*(*randperm*(*Nd,* 2)).
    Step 2.4 Determine the random operator block size.
    rs = *randi*(*min*([*SI*(2) – *SI*(1), *Nd* – *SI*(2) + 1*, Bsize*]))
    Step 2.5 Sort the individual.
    [*xiS, xiI*] = *sort*(*xi*)
    Step 2.6 Mutation operator.
    switch *ri*
    case 1
        Step 2.6.1 Random insert operation.
        $xi(xiI(SI(2){:}SI(2) + rs - 1)) = xiS(SI(1){:}SI(1) + rs - 1)$
        $xi(xiI(SI(1){:}SI(2) - 1)) = xiS(SI(1) + rs{:}SI(2) + rs - 1)$
    case 2
        Step 2.6.2 Random move backward operation.
        $xi(xiI(SI(1){:}SI(1) + rs - 1)) = xiS(SI(2){:}SI(2) + rs - 1)$
        $xi(xiI(SI(1) + rs{:}SI(2) + rs - 1)) = xiS(SI(1){:}SI(2) - 1)$
    case 3
        Step 2.6.3 Random swap operation.
        $xi(xiI(SI(1){:}SI(1) + rs - 1)) = xiS(SI(2){:}SI(2) + rs - 1)$
        $xi(xiI(SI(2){:}SI(2) + rs - 1)) = xiS(SI(1){:}SI(1) + rs - 1)$

otherwise
Step 2.6.4 The 2-opt.
$xi(xiI(SI(2){:}-1{:}SI(1))) = xi(xiI(SI(1){:}SI(2)))$
end
end

Handling of the constraints:

In IHKA, a handling constraints function is introduced to handle the boundary constraints and increases the abundance of the population. If the value of a dimension exceeds the constraint boundary, it is replaced by random generation with a fifty percent probability. There is 25% probability to assign to the corresponding dimension value of the global optimal solution. Otherwise, it is replaced by the minimum or maximum boundary value corresponding to less than the minimum, or greater than the maximum, boundary value, respectively.

$$x_{i,j} = \begin{cases} lu_{1,j} + \left(lu_{2,j} - lu_{1,j}\right)rand, & r < 0.5 \\ Gbx_j, & 0.5 \leq r < 0.75 \\ lu_{1,j}, & r \geq 0.75 \wedge x_{i,j} < lu_{1,j} \\ lu_{2,j}, & r \geq 0.75 \wedge x_{i,j} > lu_{2,j} \end{cases} \tag{1}$$

where $x_{i,j}$ represents the *j*th dimension of the *i*th individual in the population x exceeds the value range, $rand$ is a function that generates a uniformly distributed random number in the interval $(0, 1)$, and r is a random number generated by $rand$.

Random coefficient:

In order to improve the convergence performance of the HKA, a random number is introduced in the updating formula of the Standard Deviation vector of the Gaussian generator. Inspired by literature [37], the random number is generated by the Logistic chaotic map.

4.1 IHKA Test

The Travelling Salesman Problem (TSP), as one of the most famous combinatorial optimization problems, is selected as the benchmark problem to test the performance of IHKA. We select wi29 [41], dj38 [41], eil51 [40] and eil76 [40] as the benchmark instances. Their optimal tours have lengths 27601.17, 6659.43, 429.98 and 545.39, respectively. In this chapter, algorithms were implemented in MATLAB and simulated in version R2017b. For each instance, algorithms are run independently 30 times. Figure 3 shows the IHKA and HKA convergence for the 4 TSP benchmark instances. The computational statistics of the IHKA and HKA for the fitness of the 4-benchmark instances are shown in Table 2 and in Fig. 3. As can be seen from,

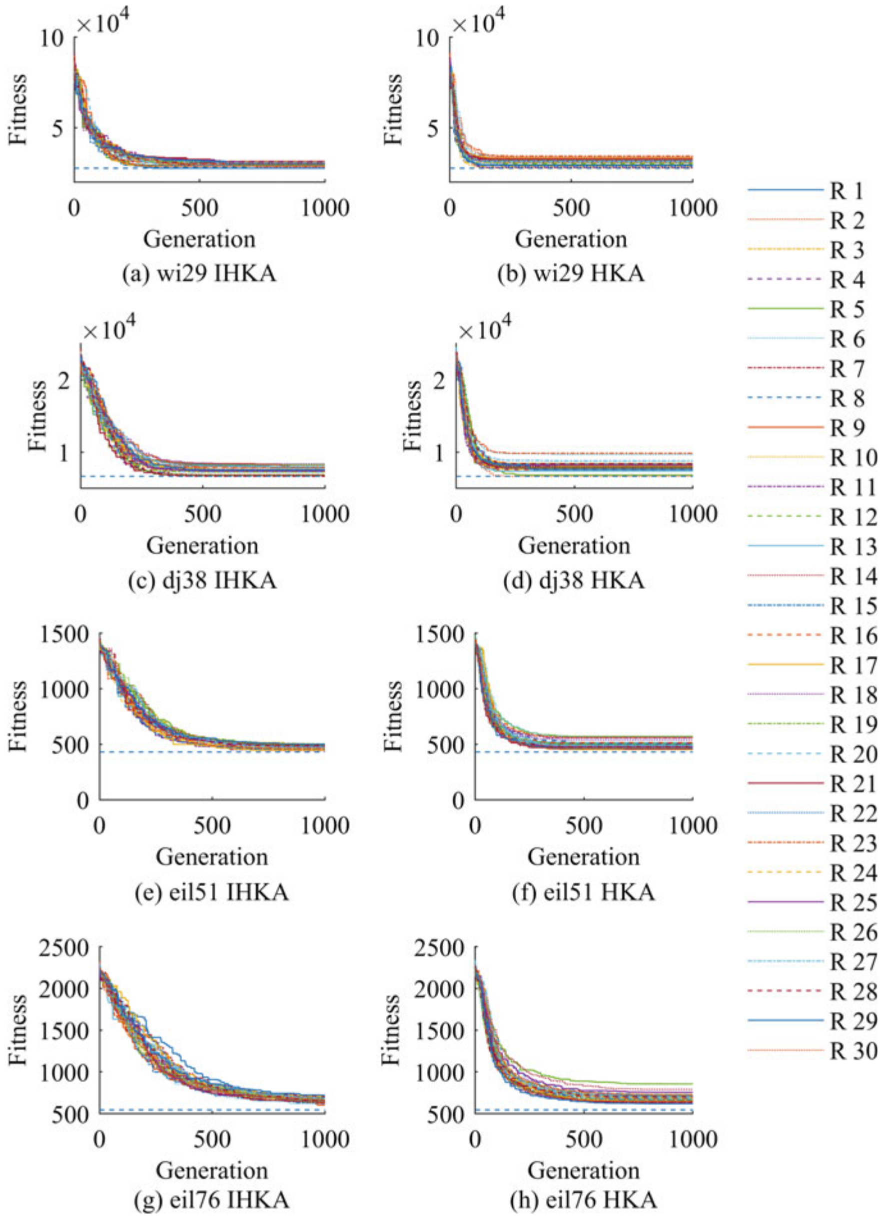


Fig. 3 The IHKA and HKA convergences of the best solutions for the benchmark instances (the horizontal dotted line is the length of the optimal tours for each instance and the “R” in the legend is an abbreviation for runtime)

Table 2 Computational statistics of the IHKA and HKA on the fitness for the benchmark instances

TSP	Algorithm	Min	Max	Mean	Standard deviation
wi29	IHKA	27,601.20	31,406.20	29,815.70	1056.77
	HKA	27,601.20	34,307.20	31,277.90	1743.08
dj38	IHKA	6659.43	8350.67	7494.76	464.09
	HKA	6659.43	9842.75	8047.69	648.52
eil51	IHKA	442.25	502.73	477.91	18.25
	HKA	451.98	570.28	496.61	33.66
eil76	IHKA	602.39	721.30	663.59	28.91
	HKA	619.35	856.57	691.71	51.00

both IHKA and HKA can tend to converge to the global optimal in the 4 benchmark instances. In the same benchmark instances, the convergence speed of IHKA is obviously lower than HKA, which reduces the possibility of falling into a local minimum. As the dimension of the problem increases, their speed of convergence decreases significantly. Table 2 shows that the robustness of IHKA is significantly better than HKA in all four selected benchmark instances. For the 30 independent runs, the mean and standard error of the IHKA is smaller than that of the HKA in all selected benchmark instances.

5 IHKA Applied in MNW

Human Resource Management, especially MNW determination, is a critical task in Industry 4.0 production systems. We must allocate workers appropriately due to two resources:

- *Technical resources*: Are smart manufacturing equipment supported by the Industry 4.0 production line where the workload per operation is calculated based on production systems' planning and scheduling tasks. In this case, we must assign the human resources carefully with regard to the machine specific constraints and demounts (utilization, workflow, control time, maintenance time, etc.).
- *Human resources*: Are critical where they are assigned simultaneously to a job considering the same level technical resources. Specific qualifications, skills, capabilities, behaviour, attitude and technical knowledge are required from the workers.

Regarding the above described technical and human resources, HRM in Industry 4.0 is based on [20]:

- *Staffing*: The right candidate for every job must be selected using extensive recruitment and selection methods, where the potential of the candidate is very important.

- *Training*: Manufacturing or service companies in Industry 4.0 must design their own training programmes to enhance the innovative capability and knowledge of employees.
- *Compensation*: The contribution of the employees to the company should be a ratio between performance, working achievements and reward. With an appropriate ratio, we can enhance innovation and the learning curve of the company.
- *Job design*: In a mass personalization production, system, the job design must be flexible regarding tasks and responsibilities of the employees. High flexibility of all employees can help the company to adjust quickly to the customers' demounts.

5.1 MNW Mathematical Model

The following is a mathematical model of HRM for determining MNW. The mathematical model was proposed by Becker and Scholl [6], and modified by Alghazi [2]. The presented mathematical model is adapted according to the 5C CPS architectural model and real-world production system characteristics.

Notation:

c	cycle time
t	time
j	potential worker
i	machine station
N	number of task indexed $h, l = 1, 2, 3, \ldots, N$
F_h	the set of feasible stations that task h is assignable to
F_l	the set of feasible stations that task l is assignable to
O_l	the set of immediate predecessors of task l
s_h	starting time of task h
s_l	starting time of task l
t_h^f	lateness for task h
t_h^s	earliness for task h.

Variables:

$$x_{ijh} = \begin{cases} 1, & \text{if task } h \text{ is assigned to station } i \text{ and worker } j \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$x_{ijl} = \begin{cases} 1, & \text{if task } l \text{ is assigned to station } i \text{ and worker } j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$y_{ij} = \begin{cases} 1, & \text{if potential worker } j \text{ at machine station } i \text{ is assigned} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$v_{hl} = \begin{cases} 1, & \text{if task } h \text{ is executed before task } l \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$v_{lh} = \begin{cases} 1, & \text{if task } l \text{ is executed before task } h \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

The main objective to minimise is $\mathrm{MNW} = \sum_i \sum_j y_{ij}$, Eqs. (7–12):

– Just one task can be assigned to an individual worker.

$$\sum_{i \in FS_h} \sum_j x_{ijh} = 1, \quad \forall h \tag{7}$$

– Cycle time assigned to a worker.

$$\sum_h x_{ijh} \leq c y_{ij}, \quad \forall (i \in F_h, j) \tag{8}$$

– Individual task station time, each task assigned to a worker should be scheduled between the workers' machine centre star and finish times.

$$\begin{cases} s_h \geq \sum\limits_{i \in F_h} \sum\limits_j S_i x_{ijh} \\ s_h \leq \sum\limits_{i \in FS_h} \sum\limits_j (S_i + c) x_{ijh} \end{cases}, \forall h \tag{9}$$

– Individual task can only start when the existing task is finished.

$$s_h \leq s_l, \quad \forall h, l \in O_l \tag{10}$$

– Task assigned to worker must be executed before the next task can start.

$$\begin{aligned} & v_{hl} + v_{lh} \geqslant x_{ijh} + x_{ijl} - 1, \quad \forall j, h \neq l \wedge i \in F_h \cap F_l \\ & s_h + t_h \leqslant s_l + (1 - v_{hl})\left(t_h^f - t_h^s\right), \quad \forall h \neq l \end{aligned} \tag{11}$$

– Generalised MNW calculation regarding the upper equations.

$$\mathrm{MNW} = \frac{\sum t_h}{c} \tag{12}$$

The described mathematical model was implemented in the next section, where we represent the solution of using evolutionary computing, IHKA for solving the HRM problem with MNW determination in a real-world Industry 4.0 production system.

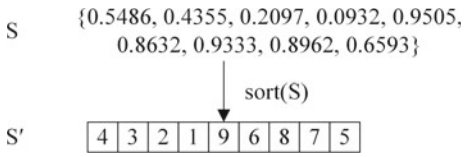


Fig. 4 The example of the solution coding

5.2 Solution Coding

In this chapter, the machines for the workers to check are represented by the index of the order in the production lines (see the 'No.' column in Table 3). The number of dimensions is set to $Nd = machinesNum + workersNum - 1$ to encode the workers into the coding, where *machinesNum* and *workersNum* are the number of machines and the number of workers in the problem, respectively [45]. It means that if the number of workers is more than 1, one or more decision $workersNum - 1$ variables are used as separators, which are greater than *machinesNum* [45]. The value range of the *j*th dimension of an individual is an open interval (0, 1). In order to solve the combinatorial optimization problem by IHKA, this chapter introduces the relative position indexing [23] to transform the optimised solution into the discrete domain. We sort the original solution to get the machines for each worker to check and the order in which they check the machines. In Fig. 4, we sort the S to get S', the decision variable 9 is serviced as a separator, the S' can be decoded as worker 1 checks the machines, and its sequence is (4, 3, 2, 1), and worker 2 checks the machines, and its sequence is (6, 8, 7, 5).

Table 3 The data of the production lines in the manufacturing enterprise E

No.	Name	Position (x, y)	Checking time (min)	No.	Name	Position (x, y)	Checking time (min)
1	A	(0, 1.5)	15	9	A′	(3, 28)	15
2	B	(0, 4.8)	17	10	B′	(3, 26)	17
3	C	(0, 9.1)	17	11	C′	(3, 22)	17
4	D	(0, 13.5)	24	12	D′	(3, 16.5)	24
5	E	(0, 16.5)	55	13	E′	(3, 13.5)	55
6	F	(0, 22)	28	14	F′	(3, 9.1)	28
7	G	(0, 26)	17	15	G′	(3, 4.8)	17
8	H	(0, 28)	17	16	H′	(3, 1.5)	17

5.3 Computational Experiment

A manufacturing enterprise E in Slovenia has two automated production lines with the same machines, but the order of the machines on these two production lines is opposite. During the operation of these two production lines, workers are required to check the machines on them. Table 3 shows the data of these two production lines in the manufacturing enterprise E [45]. According to the Zhang et al. [45], the minimum checking time for a worker and two workers is 380.75 and 190.36 min, respectively.

5.4 Experimental Results

For comparison, three well-known meta-heuristic algorithms, the Particle Swarm Optimization (PSO) proposed by Eberhart and Kennedy [9] and improved by Shi and Eberhart [35], the Multi-Phase Particle Swarm Optimization (MPPSO) proposed by Al-Kazemi [1], and the Bare Bones Particle Swarm Optimization (BBPSO) proposed by Kennedy [18], were selected to assess the performance of IHKA.

For all algorithms in this chapter, the size of the population $Ns = 100$, and the maximum number of iterations is set to $max\_ite = 1000$. According to the literatures [28, 38] and experiments, the parameter for the IHKA is set as $N_\xi = 10$, $\alpha = 0.9$, $\beta = 5$ and $Bsize = \left[\frac{Nd}{5} + 0.5\right]$. The parameter for the PSO is set as $c_1 = 2.8$, $c_2 = 1.3$ and $w = 0.729$ [33]. The parameter for the MPPSO is set as $ph = 2$, $pcf = 5$, $g = 2$, $sllu = [1, min(10, Nd)]$ and $VC = 10$ [1].

Figure 5 and 6 shows the convergence of 5 algorithms for the MNW with 1 and 2 workers, respectively. The statistical analysis of the 5 algorithms for the MNW with 1 and 2 workers are shown in (a) and (b) of Fig. 7, respectively. The computational statistics of the 5 algorithms on the fitness for the MNW with 1 and 2 workers are shown in Tables 4 and 5, respectively. The proposed IHKA performed well in the MNW with 1 worker. In the MNW with 1 worker, the success rate of the improved algorithm to find the optimal value is 100%. However, the success rate of the improved algorithm to find the optimal value is very low in the MNW with 2 workers. However, the improved HKA performs better than the original HKA in both the MNW with 1 and 2 workers.

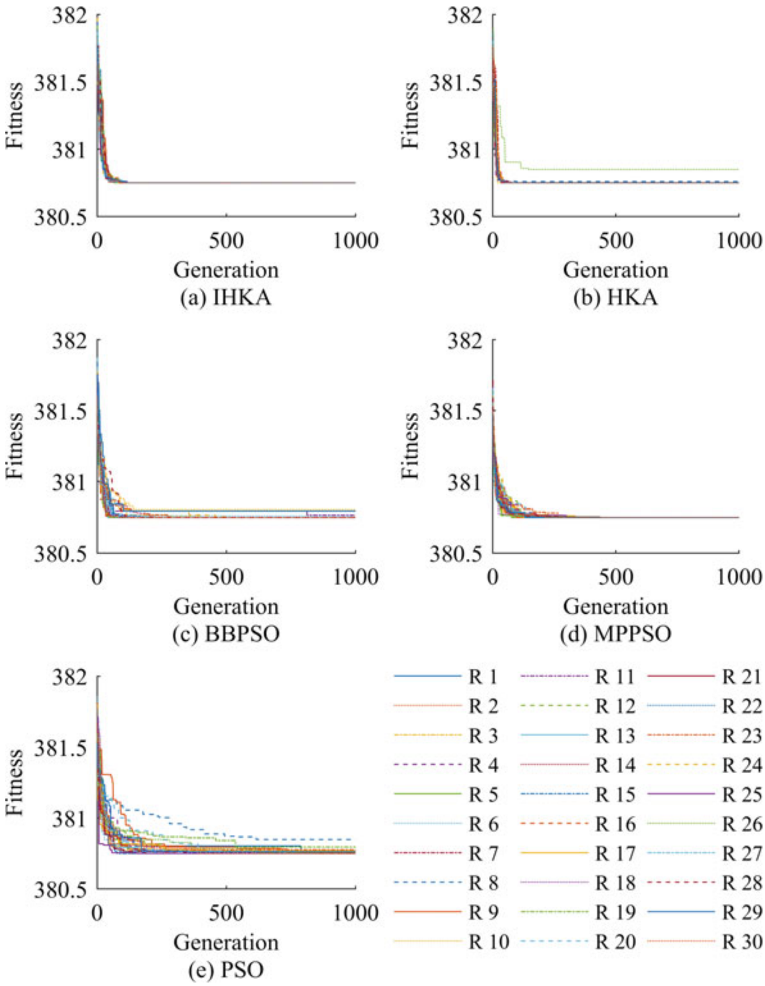


Fig. 5 The convergence rates of the five algorithms convergences for the MNW with 1 worker (the "R" in the legend is an abbreviation for runtime)

The MPPSO performs the best in both the MNW with 1 and 2 workers, while the BBPSO performs the second. In the MNW with 1 worker, the IHKA and MPPSO perform the same, they are the best among the 5 algorithms. The performance of the PSO is the worst among the 5 algorithms for the MNW with 1 worker. However, both improved HKA and original HKA perform worst among the 5 algorithms in the MNW with 2 workers. The MPPSO and PSO are performing better among the 5 algorithms in the MNW with 2 workers. Therefore, the improved HKA improves the performance of the original HKA, but still needs further improvement to increase its performance.

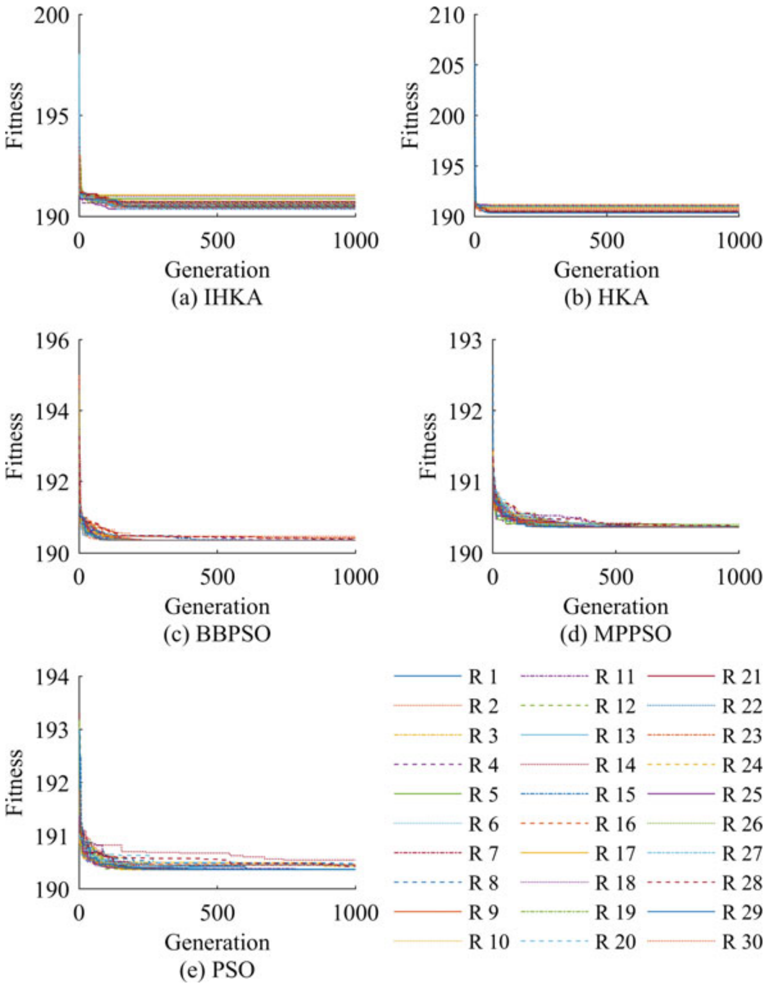
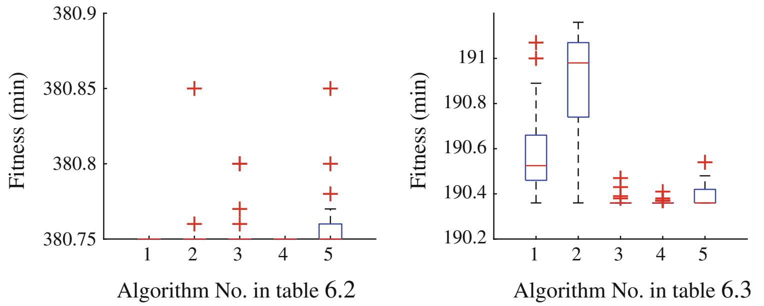


Fig. 6 The convergence rates of the five algorithms convergences for the MNW with 2 workers (the "R" in the legend is an abbreviation for runtime)



(a) The MNW with 1 worker (b) The MNW with 2 workers

Fig. 7 The statistical analysis of the five algorithms for the MNW with 1 and 2 workers

Table 4 Computational statistics of the five algorithms on the fitness for the MNW with 1 worker

No.	Name	Min	Max	Mean	Standard deviation	Success rate (%)
1	IHKA	380.75	380.75	380.75	0	100
2	HKA	380.75	380.85	380.75	0.02	93.33
3	BBPSO	380.75	380.80	380.76	0.01	86.67
4	MPPSO	380.75	380.75	380.75	0	100
5	PSO	380.75	380.85	380.76	0.02	50

Table 5 Computational statistics of the five algorithms on the fitness for the MNW with 2 workers

No.	Name	Min	Max	Mean	Standard deviation	Success rate (%)
1	IHKA	190.36	191.07	190.59	0.18	6.67
2	HKA	190.36	191.16	190.88	0.24	3.33
3	BBPSO	190.36	190.47	190.37	0.02	86.67
4	MPPSO	190.36	190.41	190.37	0.01	83.33
5	PSO	190.36	190.54	190.39	0.05	63.33

6 Simulation Modelling

Simulation modelling in 5C CPS architecture is the process of creating a smart digital model of the physical model to estimate its performance and behaviour in a real-world production system. A smart digital simulation model can estimate and analyse a wide range of production system parameters by applying a software environment. In our case, we use Simio, simulation and scheduling software for the purpose of production system optimization and MNW determination. Then we propose data exchange and results' calculation between the mentioned optimization methods of IHKA for the purpose of MNW determination. We have implemented the real-world simulation model, which integrate analysis and design solution for production system, created in the simulation environment Simio [17]. The simulation model shown in Fig. 8

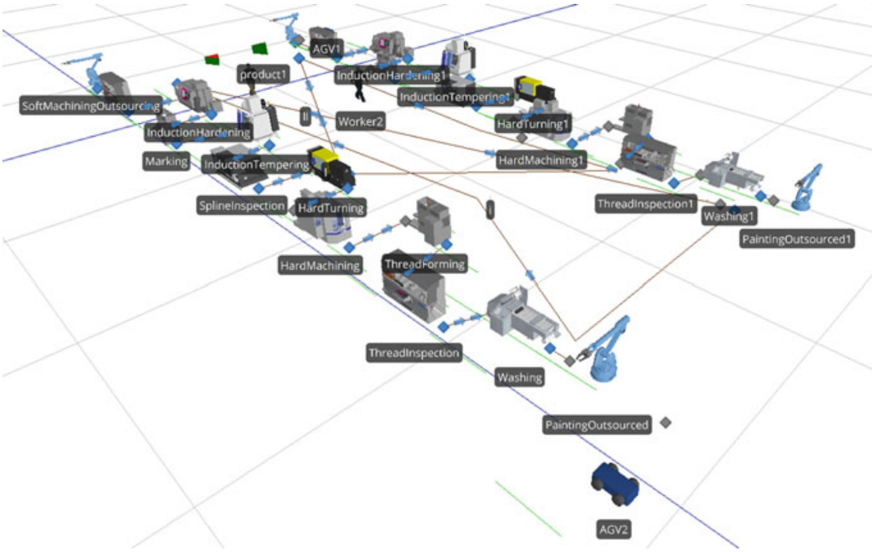


Fig. 8 The production system model in Simio

presents a real-world model of factory line E. The simulation model consists of all the necessary real-world data from a real production line: The number of the machine centre (machine centre parameters: Utilization, Overall Equipment Efficiency (*OEE*) and machine piece's capacity), distances, times and number of workers, which was calculated by IHKA.

The experiment was carried out in a manufacturing enterprise based in Slovenia, in the European Union. The production system has two automated, Industry 4.0 supported production lines, which still needs workers to check the machines in the automated production lines while they are running. In this case, the number of workers must be determined. Therefore, at the pre-determined number of workers, it is possible to optimise the number of machines for each worker to check and their checking sequence of the machines. Once the optimal solution is obtained at the pre-determined number of the workers, the maximum time required among all workers (the time of the critical worker) to complete the check of the machines, denoted as *best_fitness*, can be determined, and the comparison can be made with the working time in one shift. If $best\_fitness \leq shift\_time$, the pre-determined number of workers is sufficient. Otherwise, it is not enough. In order to determine the optimal number of workers, we can reduce or increase the number of workers, then the new *best_fitness* *i* is obtained for the next comparison.

The real-world simulation, the model consists of ten machine centres that perform the operations listed in Table 6. We can also see the individual operation duration, Overall Equipment Effectiveness (*OEE*) and individual machine piece's capacity. Operations 0 and 11 are underlined due to outsourcing; their parameters are not

Table 6 Real-world production system parameters

Number of operations	Operation	Duration (s)	*OEE*	Capacity (parts)
0	*Soft machining outsourced*	/	/	/
1	Spline and thread rolling	15	85%	1630
2	Induction hardening	17	85%	1630
3	Marking	15	85%	1630
4	Induction tempering	17	85%	1630
5	Spline inspection	17	85%	1630
6	Hard turning	24	85%	1020
7	Combine hard machining	55	85%	890
8	Thread forming	28	85%	870
9	Thread inspection	17	85%	870
10	Washing	17	85%	1440
11	*Painting outsourced*	/	/	/

available, but the contract with an external supplier guarantees that they are always available.

Performing the processed operations is carried out in the above sequence, the transport of the product between machine centres is carried out using a conveyor belt. Its speed is 0.1 m/s. Two workers, who are responsible for the smooth operation of the machine centres, operate the production line and the work pieces' quality control at control points. An Automated Guided Vehicle (AGV) ensures the access to semi-finished products and the removal of finished products automatically. The AGV speed is 1.11 m/s, the speed of the AGVs is limited electronically. Semi-finished products that arrive at the processing line are already pre-treated at the external supplier, also the finished products require external corrosion protection. The entire production system is fully automated (production and logistics), just the operation of Quality Control (which is not performed on all products, just on randomly picked products) is made by workers, Fig. 9. In the further step, we propose machine vision operation at Quality Control for more robust, consistent and reliable Quality Control operation.

In the results received by IHKA, the E production line only needs one worker to complete all the machines' check in one shift. However, in the simulation of the Simio software, the *shift_time* is a constant value for one eight hour working shift, calculated in Eq. (13). *Shift_time* exclude three brakes, one 30 min lunch break and two shorter 15 and 10 min rest brakes. The OEE of the machines is 85%, that is, the effective working time of the machines in one shift is set as:

$$\begin{aligned} shift\_time &= 8 * 60 - 30 - (15 + 10) \\ &= 425 \text{ min} \end{aligned} \tag{13}$$

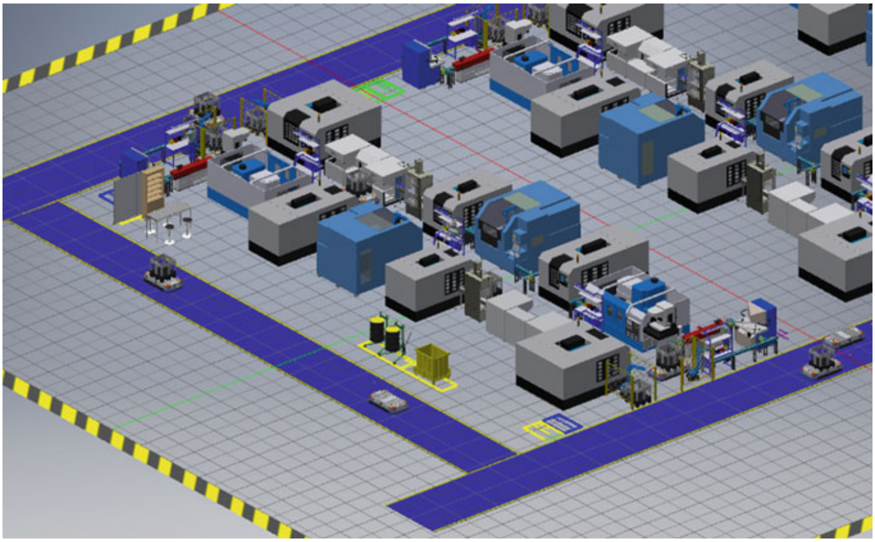


Fig. 9 The three dimensional view of production system model

$$
\begin{aligned}
machine\_time &= shift\_time \cdot \mathrm{OEE} \\
&= shift\_time \cdot 85\% \\
&= 361.25 \text{ min}
\end{aligned} \tag{14}
$$

The effective working time of the machines is 361.25 min in one shift. In this case, one worker is not enough to complete all the machine checking in one shift. The real-world simulation model takes into account also the tools' changing time, maintenance time and randomly occurring emergency situations that happen during the production lines' operation. Results from the simulation model recommend the presence of two workers to check the machines and perform Quality Control in one shift. The simulation results confirm the IHKA calculated optimal times for performing the control check of the production system in amount of 380.75 min in the case of one worker and 190.36 min in the case of controlling two workers. In this case, when *machine_time* is 361.25, one worker is not capable of quality performing controlling tasks in the production system, that is why we need two workers as is it calculated by the IHKA.

7 Conclusions

In this chapter, we have presented the Industry 4.0 5C CPS architectural model, which was applied successfully to the five-level architecture implemented with simulation modelling and Evolutionary Computation. We demonstrated a methodology of 5C CPS architecture and practical approach for the transfer of theoretical knowledge to the real-world production system. Then, we presented the HKA evolutionary method for the purpose of determining single-criteria optimization and extended it to the IHKA. The IHKA is proposed and applied successfully to solve the MNW problem. Based on the original HKA, a mutation operation is introduced after the solutions are generated by the Gaussian distribution, a function that handles the boundary constraint is introduced, and, finally, a random number is introduced in the updating formula of the standard deviation vector of the Gaussian generator, to improve the performance of the algorithm. In the mutation operation, four operators with random size insert operator, random size move backward operator, random size swap operator, and 2-opt operators were introduced. A random number generated by the Logistic chaotic map is introduced in the updating formula of the standard deviation vector of the Gaussian generator. The discrete continuous mapping encoding system, based on the relative position indexing, is introduced for the MNW. The IHKA is tested on 4 selected TSP benchmark instances. From the 4 selected TSP benchmark instances, it can see that the improved HKA improves the performance of the original HKA. In solving the MNW problem; three algorithms were selected for comparison, a quantitative analysis method based on statistical analysis, and a qualitative method based on convergence figures, were used to clarify the performance of the IHKA. Although the improved HKA performs better than the original HKA in both MNW with 1 and 2 workers, especially in the MNW with 1 worker, but performs poorly in the MNW with 2 workers, it still needs further improvement to increase its performance. The optimization results of the IHKA algorithm were transferred to the simulation environment, where the correctness was simulated of the obtained NO solutions. The results confirm the correspondence between the proposed methods of Evolutionary Computing (IHKA) and simulation modelling (Simio). In this case, we have combined advanced knowledge of simulation modelling and evolution computing for the purpose of single-objective MNW optimization in Industry 4.0.

Further research work will be based on the implementation of collaborative workplaces in Industry 4.0 manufacturing systems. Here, the main question arises related to the impact of productivity, efficiency and, at the ultimate stage, workers social inclusion in collaborative workplaces. Their determination, eligibility and productivity could be determined with simulation modelling. In this case, simulation modelling will be very important in the phase of inclusion of collaborative workplaces in real-world production systems. However, in decision-making methods, we should not forget the need for the integration of evolutionary computational algorithms for the purpose of determining NO solutions regarding collaborative work places. Our further research work will be based on the optimal number determination and the setting of collaborative workplaces in the production systems using EC methods and simulation environments. For the laboratory simulation testing, we will introduce methods of virtual and augmented reality, which will combine EC algorithms and simulation models for collaborative workplaces optimization.

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Smart Combat Simulations in Terms of Industry 4.0

M. Fatih Hocaoğlu and İbrahim Genç

Abstract The military Command, Control, Computer, Communication, Intelligence, Surveillance, and Reconnaissance (C4ISR) concepts and those of Industry 4.0 (I4.0) have lots in common. The analysis of defense systems is described by showing the corresponds of the three basic concepts of I4.0 in defense systems. These are connections between cyber-physical systems and automated weapon systems, between Internet of the things and shared tactical picture and sensory data, and between smart factories and computer in the C4ISR concept. The main motivation of this study is to make a conceptual association between C4ISR and I4.0 technologies and an intelligent analysis and run-time decision making mechanism as an intersection of both technologies is exemplified with a smart war effectiveness analysis system which is designed as an intelligent agent for a land-based air defense system.

Keywords AdSiF · Agent driven simulation · Execution time analysis · Model driven simulation · Post-data analysis · Simulation management

1 Introduction

Last few years, everybody talks about I4.0 and there are as many different explanations of its meaning as there are titles for it (Industrial Internet of Things, The Fourth Industrial Revolution (4IR), etc.). The study aims to give answer to the questions; is there any reflection of I4.0 in military domain? and "Is I4.0 a naming convention already known, or is it an age of technology that is yet to be created by concepts and technologies?"

M. F. Hocaoğlu (✉) · İbrahim Genç
Faculty of Engineering and Natural Sciences, İstanbul Medeniyet University, İstanbul, Turkey
e-mail: mfatih.hocaoglu@medeniyet.edu.tr; hocaoglu@agenabst.com

İbrahim Genç
e-mail: ibrahim.genc@medeniyet.edu.tr; genc@agenabst.com

Agena Information and Defense Technologies LLC, 34912 İstanbul, Turkey

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The steam engine has become a highly represented concept and object associated with the first industrial revolution and it was electric for the second one. Maybe it is not a wrong analogy to consider cyber-physical-systems for I4.0. A cyber physical system (CPS) refers to the network of IT/software components and mechanical and electronic parts that communicate via a data infrastructure such as the Internet. Internet of things and internet of services (IoS) are two main concepts often associated with CPS.

In this chapter, a smart war effectiveness analysis system is designed for a land-based air defense system and an analogy is built between missile defense system and I4.0 concepts by using an agent-based simulation solution. The analysis of defense systems is described by showing the corresponds of the three basic concepts of I4.0 in defense systems. These are connections between cyber-physical systems and automated weapon systems, between internet of the things and shared tactical picture and sensory data, and between smart factories and computer in C4ISR concept. From this perspective, the I4.0 concepts come to life under C4ISR concept for defense systems. As seen from the definition while the main idea of I4.0 concept is the interconnectivity of production machinery, machined products and semi-finished products and all other systems and subsystems of an industrial enterprise (including ERP, sales systems, etc.), C4ISR concept aims to establish a fully connected and smart warfare environment with reasoning capability. From this perspective, the connectivity between command and control (C2) entities and the entities managed by C2 structures that make whole defense system a smart infrastructure are taken into consideration. Especially last years, an increasing autonomy in defense applications and the tactical internet effort. The autonomous systems are seen in robotics and sensory systems. The autonomous systems, which stand potentially to transform the way in which warfare is conducted. Advances in sensors, robotics and computing are permitting the development of a whole new class of systems, which offer a wide range of military benefits including the ability to operate without personnel on board the platform, novel human-machine teaming concepts, and "swarm" operating methods [1]. Current studies try to find a balance between human and machine cognition, and it seems it will be not so easy because of lack the robustness and flexibility of human intelligence in autonomous systems.

From the viewpoint of communication; it has a key role as it defines interconnections and information flow of the whole system in both of the concepts, C4ISR and I4.0, and this is the most important similarity of the two concepts. In military, good or bad communication effects the result of a combat to a victory or to a defeat and beside technical capabilities, different tactics are planned and executed in order to maintain good communication lines since too many factors exist such as, weather, topography, enemy's counter measures like jamming and almost none of these is under control of the user. In the industry, instant and real time communication of CPSs with each other, with humans and networked sensory system is required and timing constraints are so tight for real time automation that is why the I4.0 concept had to wait for big advances in communication technologies although users have much more control on the facility layout, environmental conditions compared to C4ISR applications. Considering both similarities and differences, communication units of I4.0 and C4ISR in the era of IoT and IoS are conceptually alignable.

Simulation of a defense system and its reasoning software establish a set of criteria and the way of satisfying all these criteria are shown. The criteria set consists of interoperability, virtualization, decentralization, real time running capability, service-orientation, modularity and reconfigurability. A simulation and software architecture based on an agent-based solution is one of the most proper choices. Simulation has a long-standing tradition within artificial intelligence methods often applied as a computational capability of CPS. We know that CPS expose the characteristics of intelligent, adaptive, and autonomous systems, operating in complex environments, often in collaboration with other systems and humans. CPS bring a new hybrid simulation definition by combining discrete event, system Dynamics, agents, and modeling paradigms [2]. A detailed literature review showing the importance of CPS in the simulation world and how it defines a new hybrid simulation concept are given in [3]. Simulation is also used as an environment for development and testing. In the test purpose, CPS provide necessary stimuli in synchronized form to test all aspects of cyber and physical interactions [3].

An analysis opportunity during simulation execution with a rule-based reasoning capability (first order logic) is defined. The solution is capable of analyzing warfare in run time and making decision depending on performance measurement calculated during execution. This allows modelers to prepare scenarios that are directed in run time.

The chapter is organized as follows. The fundamental concept of I4.0 and C4ISR concepts are explained in Sects. 2 and in Sect. 3, respectively, as preparation section for Sect. 4 that shed light on the analogy between two concepts. Because of the importance both online analysis and communication between entities, intelligent analysis concept and communication technologies are explained from the perspective of both concepts. By a case study the analogy is exemplified. The chapter ends with a discussion of results obtained from this comparison.

2 The Fundamental Concepts of I4.0

In this section, while the fundamental concepts of I4.0 are given, the concepts are explained so that it allows us to bridge between C4ISR concepts and I4.0 concepts.

The Internet of Things is the technological vision of integrating objects of all kinds, devices and people in a universal digital network. The objects have a unique identifier and are located or move in an ‘intelligent’ environment [4]. Internet of Things allows “things” and “object” as RFID, sensors, mobile phones integrate into unique links, which can work together with other objects to achieve a common goal. In a combat environment, sensors and communication devices detect and distribute intelligence and status information of friendly forces and own entities. In the Internet of Services envisioned, services and functions are represented as software components and made available by providers via the Internet (cloud). In the Internet of Services, cloud-based development and service platforms from a variety of market players provide the simple option of developing and offering web-compatible services.

CPS are generally defined as systems with integrated physical and computational capabilities that can interact with humans through variety of modalities [5]. Autonomy that is one of the important characteristics is expected from CPS and an autonomous system collaborates with humans and with other system component. A collaborative system, in other words, during collaboration, has to be interoperable, i.e. able to exchange data and utilize service calls, but also composable, i.e. provide a consistent interpretation of truth [6].

A combat simulation is seen as a military activity achieved by many participants that are highly connected with each other and they consist of autonomous components. They interchange information with each other, expect each other to do specific tasks to succeed a common goal such as defending a territory and/or a set of assets. In a Combat Simulation system, entities such as land-based defense systems, sensors, weapon systems, and platforms share their positional information, their status and intelligence they have with C4ISR systems that they are connected and C4ISR systems provide fused data, targets identified, a set of directives to make their missions realized. In some systems, the computer that is one of the components of C4ISR system simulates the current combat scene for a close future to direct the scenario mission plans or to change the force deployments and to give any other similar combat management decisions. As seen, a combat simulation has similar task with a I4.0 system such as sharing information/intelligence, expecting the close future using simulation and asking any component something do.

In the I4.0 world, smart factories are defined as factories and machinery to assist people to fulfill their tasks. There are several other terms used interchangeably: a U-Factory (ubiquitous factory) [7], a factory-of-things [8], a real-time factory [9], or an intelligent factory of the future [10]. Scholars refer to smart factory (SF) as a technology [11], an approach [8, 9], or a paradigm [7]. This objective is fed on the basis of information obtained online, so is every moment possible to ascertain the status of the device, the position and the like.

Semantic technologies find the appropriate services. Among other things, this is aided by a new Internet standard known as USDL (Unified Service Description Language), which enables the description of services and a context sensitive language. Similar to this, in C4ISR domain a specific language called Battlefield Management Language (BML) is developed [12, 13]. BML refers to the general approach of utilizing a digitized form of military information in support of the unambiguous exchange across C2, simulation and robotic systems. Lately, BML is extended to coalition level operations and C-BML refers to the branch of BML that specifically addresses needs associated with coalition operations. The term "SISO C-BML" is used in this document to refer to the SISO C-BML standards effort [14].

3 C4ISR Concept

C4ISR defines systems, procedures, and techniques that are used to collect and disseminate information. This includes intelligence collection and dissemination networks, command and control networks, and systems that provide the common operational/tactical picture. C4ISR also includes information assurance products and services, as well as communications standards that support the secure exchange of information by C4ISR systems (digital, voice, and video data to appropriate levels of command). The concept is started as a Command and Control system and it is evolved up to C4ISR. The dramatic improvements are seen in communication and intelligent decision making. After development of sensory systems and so do surveillance systems, the data sharing and intelligent decision making have got more and more important ever, because of there are more information to evaluate and to share.

A C4ISR process follows observe, orient, decide, and act cycle (OODA). OODA is started by a threat detection or by a mission to be succeeded. The OODA idea has been documented in detail by Boyd [15]. It is applied at the operational level during military campaigns. It is now also often applied to understand commercial operations and learning processes. The approach explains how agility can overcome raw power in dealing with human opponents.

I4.0 is established on Industry 3.0, on its robotic technologies and automated production facilities. Similar to this, C2 and Platform Centric Warfare evolved to C4ISR and Network Centric Warfare, respectively. It is not a big claim the fact that future tactical command and control (C2) will undoubtedly be affected by a shift toward network centric warfare (NCW), a concept of operations that relies on sophisticated information and communication technologies for enabling real-time collaboration and heightened shared situational awareness among geographically-distributed entities [16].

4 Analogy Between I4.0 and C4ISR

In parallel or may be some time earlier, similar concepts and similar goals are being developed in military domain under the concepts of C4ISR and Network Centric Warfare. Both I4.0 and C4ISR are being fed by the same motivation: sharing data, enhancing them, providing intelligent decision-making support, and integrating companies in all sense.

Within the next paragraphs, we are compiling some similar characteristics between C4ISR and I4.0.

- While the main purpose of a smart factory that is one of the key features of I4.0, is to produce a set of products with the lowest cost and the highest productivity, a C4ISR systems aims to defense areas and assets with the lowest defense cost and the highest security. The concept of smart factory is defined as a manufacturing cyber-physical system that integrates physical objects such as machines, conveyers, and products with information systems such as MES (manufacturing execution system) and ERP (Enterprise Resource Planning) to implement flexible and agile production [17]. In this sense the property of a smart factory has similar

Table 1 Characteristics common to I4.0 and C4ISR

	I4.0	C4ISR
Interoperability	Machines, devices, sensors and people that connect and communicate with one another	Military items, weapon systems, devices, sensors (radars, optical sensors and Microwave radars, etc.) and even soldiers
Information transparency	The systems create a virtual copy of the physical world through sensor data in order to contextualize information	Detections and orders are stored in C2 databases and knowledge bases, detections are fused to create a tactical picture. A tactical picture is a contextualized battlefield environment
Technical assistance	Both (i) the ability of the systems to support humans in making decisions and solving problems *and* (ii) the ability to assist humans with tasks that are too difficult or unsafe for humans	The computer concept of C4ISR is related with automated decision making with reasoning capability to support C2 systems, and a C2 system allows human decision makers to interact with it by providing interfaces
Decentralized decision-making	The ability of cyber-physical systems to make simple decisions on their own and become as autonomous as possible	Autonomous C2 is a C2 architecture and it allows sub C4ISR systems to make their own decisions based on existing rule-bases and detections
Virtualization	Virtualization is able to monitor the physical processes through CPS. Sensor data obtained are connected to the virtual enterprise model and simulation models. This creates a copy of the physical world in a virtual environment. The virtual environment is the opportunity to simulate the processes	In real time, virtualization provides capability to predict close future by simulating warfare. Each real-world entity is virtualized in simulation environment and the simulation is used as a decision support system instrument

(continued)

characteristics of a C4ISR system and what they must have is shown in Tables 1 and 2.

- All items in Table 2 are broke down until C4ISR and I4.0 components. As seen in the table, the requirements are supported different subcomponent of each of them.

Table 1 (continued)

	I4.0	C4ISR
Capacities in real time	Control systems are essential to collect and analyze data in real time. On the basis of the information gathered can respond in real time, for example to malfunction or shifting production to another device	Real time data collection is very vital for a battlefield environment to be able to create a true tactical picture and to enhance awareness
Service-orientation	Services companies, CPS and people are available through IoS and thus they can be offered to other parties. They can be internal or external. It is possible, for example, to access those services through web services	It is possible to provide communication and coordination for the same mission of the battalions, platoons, and any other military unit using web services, or secure internet-based services. Sharing detections and fusing data collected from different sources are succeeded by IoS
Modularity and reconfigurability	Modular systems are able to flexibly adapt to changing requirements. Modular systems are therefore easily editable for seasonal fluctuations or changes in the product characteristics. One example of modularity is plug and play feature. The system must also be capable of automatic configuration changes	In a battlefield environment, since tactical environment changes frequently, to be able to give fast response to changes requires the system to be modular, and reconfigurable. Being reconfigurable also means including different defense doctrines, different C2 architecture, and interfaces to other systems even C4ISR systems of other forces

A smart factory incorporates industrial network, cloud, and supervisory control terminals, with smart-floor objects such as machines, conveyors, and products [17].

- Although, current military structures are not supporting self-organization, it would be the best way to improve but as a vision, a C4ISR system aims to have as a vision a wide area network, a cloud to share raw information and status information about entities, computers to make decisions automatically, and a set of networked smart autonomous objects such as solders equipped with wearable computers, weapons that share their status and being able to be controlled remote decision makes, sensors, guided missiles that are capable of filtering false alarms and countermeasure systems. This kind of self-organized systems, both C4ISR systems and smart factories, leverage the feed-back and coordination by the central coordinator in order to achieve high efficiency. Thus, the smart factory is characterized by a self-organized

Table 2 Relations between principles and components

	C4ISR						I4.0			
	C2	Computer	Comm	I	S	R	CPS	IoT	IoS	SF
Interoperability	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
Information transparency	✔	✔	✔							
Virtualization	✔			✔	✔	✔	✔	–	–	✔
Decentralization	✔	✔					✔	–	–	✔
Real time capability	✔	✔	✔				–	–	–	✔
Service-oriented	✔	✔					–	–	✔	–
Modularity and reconfigurability		✔					–	–	✔	–

multi-agent system assisted with big data-based feedback and coordination and so is C4ISR vision m. For this purpose, Network Enabled Capability (NEC) as a high priority alliance goal. NATO is in the process of developing a maturity model related to improving force capability and transformation. Achieving this goal clearly depends on the development of an appropriate approach to NATO Consultation, Command, and Control and the identification of a corresponding Command and Control (C2) Maturity Model [18].

- In both systems, each smart entity is seen as an agent and having many of them in the same environment bring multi-agent coordination problem. A C4ISR system offers a solution by C2 architectures. It offers three types of C2 architectures. These are central C2 architecture, coordinated C2 architecture and autonomous C2. In coordinated C2 architecture, a negotiation on what decision to be given is done as is done in I4.0. Both use new technologies in multi-agent systems such as internet of things, wireless sensor networks, big data, cloud computing, embedded systems and mobile devices.

As mentioned earlier, while a threat detection or a mission trigs a C4ISR system to follow its process, an I4.0 system is trigged in similar way. Either it is a new product idea to reach new customers, or a potential market to take part in as a mission or it is both. Table 3 shows for what purposes the technologies are used.

As seen in Table 1, the examples show that components must be able to interact with each other which requires them to be interoperable and transparent. Technical assistance both in a C4ISR system and a I4.0 system is needed to be able to give robust decisions and decisions are given in decentralized way. We know that command and control systems have centralized, decentralized, and autonomous architectures and regarding with the architecture, information sources differentiate used in decision making. Virtualization is required to be able to create a synthetic, virtual environment using sensory data because the whole decision making, and simulation processes use

Table 3 Purposes and technologies

Technology	I4.0	C4ISR
IoT	Machines and products, semi-finished products	All military assets (communication devices, computers as a decision-making tool, weapon systems including ammunitions especially fire and forget smart missiles, sensory systems, platforms, and soldiers
Wireless sensor network	Quality control, product counters and work in process measurement for planning, product flow control	Situational awareness (being aware of both situations of friendly forces and enemy forces, in general to be able to depict a correct tactical picture)
Big data	Data flowing from the production line and from the companies integrated in both horizontally and vertically	Detections, inferred data, decisions, and orders
Cloud computing	Data warehouses, vendor information, analysis on market information	Data fusion (inferring new information, target identification and localization), data warehouses
Embedded systems	Industrial and intelligent robot technologies	Weapon systems capable of target tracking,
Mobile devices	Hand terminals, readers, AGVs (automated guided vehicles)	Wearable computers, hand terminals, unmanned aerial vehicles (UAVs) with sensors

the virtualized information. Both C4ISR systems and I4.0 systems have interaction with real components and this makes real time execution mandatory. Picking detections/information from sensors and asking to actuators (real system components) to do something and, waiting for a result are some basic examples. The task asked from a component can be achieved using web services or any cloud-based function. To be able to react changing requirements and missions to be achieved, having reconfigurable and modular components have big importance. Table 1 enumerates and compares the concepts of I4.0 and C4ISR to show the similarities.

4.1 Principles and Components

The main idea of this section is to show that while the components providing the functionalities for the I4.0 and the C4SIR domain are different, they are based on similar concepts aiming at the same principles.

In C4ISR systems, the concepts that build C4ISR must be interoperable to be able to work together. This is also valid for I4.0. Because both has to build a whole system.

The main rule in information transparency is the rule the knowledge is given to the person who needs to know. The rule is also valid for I4.0 because of the commercial confidence.

Virtualization consists of a dual world representation. Each virtual counterpart of a real system has the information that the real system has. In C4ISR case, each C2 entity has information of the entities that are connected with and if the C4ISR scenario has an analysis agent, the agent collects the information from the entities to analyze and makes decisions to drive the entities. In addition to this, the dual world representation also keeps each information with old ones as time labeled information. This allows modelers to be able to make more robust decision since it is possible to use the information with earlier values. In I4.0, CPS and SF have virtual counterparts in an online analysis or a control system and in a C4ISR system, sensory data and command control systems that evaluate sensory data have their virtual components or their data representation to convey their information in a networked environment.

Decentralization is related with distributed computing and decision making. In C4ISR systems, depending on C2 architecture decision making can be a process both decentralized and/or centralized. While coordinated C2 and autonomous C2 is decentralized decision making, central C2 collects all data in one center, makes decision and distributes orders to the companies. In a smart factory, autonomous machines that behave as synchronized multi-agents are examples of decentralization. Because the fact that the whole system is a system that is vertically and horizontally integrated, each sub component has their own decentralized decision-making units. In a sub system, CPSs and SF components are decentralized components.

Real time data processing is vital for C4ISR systems to be able to process information picked up from sensors and to keep intelligence up to date. That is why C2, Computer, communication and SF should support real-time processing or even faster than real-time.

Service orientation is an architectural preference. In both the literature and practical implementations, for I4.0 and C4ISR systems, a layered architecture that a service or a function are placed at each layer is suggested [19]. Both systems, internally or externally provide services being accessed via internet, intranet and web services.

Modularity, reconfigurability, and extendibility are important for the concepts of computer and IoS. A modular system is able to flexibly adapt to changing requirements and conditions to extend or change its modules. A modular system is therefore adaptive for seasonal fluctuations in I4.0 case and changing battlefield conditions in a C4ISR system. In addition to all, modularity, reconfigurability, and extendibility are important to be able to follow technological developments and to adapt them.

Table 2 shows how important horizontal and vertical integrations are in I4.0 and network centric warfare in C4ISR concept.

The principles, concepts and components are supported by technologies. The technologies being used both in C4ISR and in I4.0 support the concepts and the principles. Further necessary to have modular, reusable technologies with well-defined generic design, being able to use the same technology for different purpose shows how well interactions there are between C4ISR and I4.0. IoT, wireless communication, big data analysis, cloud computing, embedded systems, and mobile devices take important roles in both C4ISR and I4.0. In Table 3, what roles are taken in I4.0 and C4ISR by using what kind of devices and for what purposes are shown.

Big data analytics provides automation, historical data analysis, anomaly detection, predictive analysis, behavioral trends and patterns of life. The automation gives automatically correlated data based on explicit and implicit relationships within that data. Predictive analytics provides ability to process C4ISR datasets to determine likely events, actions, or behaviors in smart factory case, it provides opportunity for predictive maintenance. Predictive analytics are supported by historical analysis that is the ability to look across accumulated sets of data over time to uncover important trends or insights from past events, and anomaly detection that is quick discovery of unexpected events, actions, or behaviors that deviate from known trends. Since it is possible to consider each agent as a Belief, Desire, Intention agent (BDI agent) in a smart factory and in a C4ISR system, it is possible to execute actor-centric behavior models to produce likely actor intentions and actions. To be able to produce behavioral characteristics of customers, vendors and competitors in I4.0 and enemy behaviors in C4ISR system.

Big data analytics provides quicker turnaround from processing and exploitation to produce actionable information for C4ISR systems and I4.0 smart factories so that it results alerts, warnings and indications.

Cloud computing provides Software as a Service (SaaS), Platform as a Service (PaaS), Infrastructure as a Service (IaaS), and Data Storage as a Service (dSaaS). SaaS provides managed software applications to the end user and Service Oriented Architecture (SOA) framework that can deliver enhancements for software applications to communicate with each other. PaaS is a production and development environments as a service. It provides clients build applications that run on the provider's infrastructure. I4.0 connects different smart factories in a single computational environment and also it supports horizontal and vertical integration. IaaS consists of servers, software, data center space, and network equipment abstracted from end user and also resources dynamically allocated. In C4ISR, dynamic resources allocation is achieved by implementing a mission, and it is a kind of counterpart of a production plan in a smart factory. Clearly, dSaaS provides data storage space as a service to the end user via a common network. Both a C4ISR system and a smart factory store data with a separation seen in confidentiality and volume. A smart factory stores commercially classified data but in C4ISR case, mostly, they are military level classified.

In C4ISR systems, there are numerous entities and sensors, wide area networks, and decision-making entities. If it is compared with a smart factory, we talk about mostly a bigger system. The situation brings a new service need called "Content Distribution Management" (CDM). CDM is a set of approaches and techniques for efficiently delivering network content, reducing the load on origin servers, and improving overall network performance. CDM involves caching and distributing content by placing it on content servers, which are located near users and can scale with changes in demand. Its benefits can be realized on both afloat-to-ashore and ashore-to-afloat data traffic. Solutions in this space address problems associated with: (i) Inefficient use of bandwidth, that is, sending the same redundant data multiple times generates unnecessary traffic, (ii) latency, that is, the greater the physical distance between users and data, the greater the latency and (iii) hits that are surges of network traffic can result in Denial of Service at the host [20].

5 Communication Concepts in C4ISR and I4.0

Communication is the third 'C' of C4ISR and it comes just after command and control concepts. It has a key role as it defines interconnections and information flow of the whole system. Since C4ISR is a military concept, it is normal to be in that order. These can be deduced from the famous book of military world, On War. After explaining that a victory is more than number of dead or winning of a battle, the writer expresses the importance of communication but also that its priority is lower than winning a battle: "A turning movement can only be justified by general superiority or by having better lines of communication or retreat than the enemy's [21]" and "For an attack on the lines of communication takes effect only very slowly, while victory on the field of battle bears fruit immediately [22]". At the same time, Clausewitz explains lines of communication as roads for ordnance support and roads of retreat too. Considering there were not today's technical communication devices in the 19th age and almost all communication were done by messengers through roads, communication and other support functions used the same lines.

Please note that communication is still in higher importance than surveillance and reconnaissance, as the concept starts from C2 and extends to C3I, C4I and finally C4ISR [23].

On the other side I4.0 is highly related to information and communication technologies (ICT) and Internet of things (IoT) [24]. In fact, I4.0 become possible in part by serious advances in technology on interconnecting IoT and Cyber-Physical Systems (CPSs) on both wide and local scale for industrial applications and automation [25].

In this section, at first, communication concept in C4ISR architecture is explained. Then, in the Sect. 2, its counterpart in I4.0 is given. Finally, a comparison of these two approaches is summarized at the end of the section.

5.1 Communication Entities in C4ISR

Since the purpose of proposing C4ISR concept is to provide a standard architecture to assure the system-wide characteristics are achieved throughout the whole project life-cycle [26], it defines three different views, namely, Operational Architecture View, Systems Architecture View and Technical Architecture View [23]. For a complete representation of the system it would be better to use all these three views as integrated although the views provide different perspectives on the same architecture, it expected that there will be some amount of redundancy of system characteristics. Similarly, in all these three views, the communication naturally has a place but in different ways.

In the operational architecture view; beside operational elements, i.e., nodes, their tasks and activities performed at each node, connectivity and information flow among these elements are described. Here, the information and information path are parts of the communication functions and the view defines information types, timing properties of information exchanges, source and target tasks/activities so that interoperability in- and inter-systems is ensured. By given an operational node connectivity description, the source and destination of information flow, the characteristics of the data or information, such as its content, type (e.g., text, voice, image and its format), amount properties, and bandwidth, security and timing requirements for communication interoperability are all defined. However, note that, in an operational view, nodes do not have to be real physical entities.

In the systems architecture view; systems and the interconnections between these systems are described. From the communication viewpoint this might be the most familiar description for communication and/or network engineers since it consists of nodes and their locations, physical connections, network elements, circuits and some other entities such as platforms, sensors and weapon systems as information transmitters or receivers. Beside physical nodes and their communication setups, some performance parameters of the communication systems/devices are also defined in this view such as robustness, availability, communications capacity requirements and security protection need. In a system interface description, interfaces may simply be represented with a pathway or network depicted graphically as a line or in a matrix form. Please note that, systems or components do not have to have only one interfaces but often they have multiples and the description consists all of them. Another description method in systems architecture views is the systems communication description and it represents the specific communications systems pathways or networks and their configurations details including communications elements and services. These may include cable ends on ocean shores, a satellite and its ground stations, relays, amplifiers or repeaters in a communication channel, network switches or routers. The presentation should describe all related attributes such as radio frequency, waveform, bandwidth, coding, packet or waveform encryption methods [23].

Technical architecture view does also define performance parameters but in different approach, namely, by defining the standards and rules that system implementation and system operation must meet. These rules and standards, preferably in a minimal complete set, manage the interactions, interfaces, relationships and interdependence of system elements,

The ultimate aim of the C4ISR architecture is to ensure the information capabilities of a warfighter to be compatible or plug&play in a global environment such as joint forces operations, surface-based air defense, air task order or in planning tools of such operational tasks.

Although in C4ISR approach, these views are required to handle the all systems from sensors, information processing systems, communications systems, and weaponry which produce, convey, process or receive information to achieve their goals, we concentrate on communication elements and their models for a simulation throughout this section.

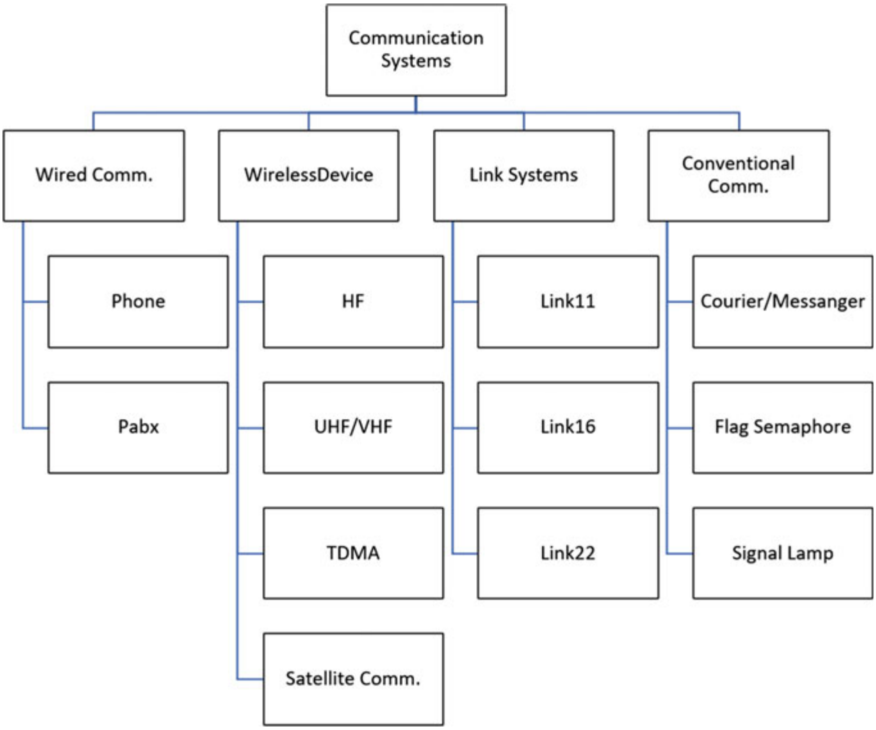

Fig. 1 Hierarchical structure of communication models

5.1.1 Common Communication Entities' Models in Combat Simulations

Some communication models used in C4ISR combat simulations are shortly explained below. These are the models of entities which are commonly used in simulations of tactical battlefield and they are hierarchically depicted in Fig. 1. Here are models not only technological but also some conventional communication methods and tools such as couriers in army and semaphore flags or signal lamps in navy as military tactics use every possible way to convey the message to its destination. However, these models are left out of scope of this section since the I4.0 communication model counterparts are all high-tech devices.

Battlefield communication systems are mostly wireless devices. Therefore, propagation models are the main part of the model in order to discriminate whether a message is received correctly by the receiver or not or it is received with an error in the content. There exist, in the literature, well-understood and accepted propagation models for wireless communication. These are mainly based on well-known Friis transmission equation [27]. Friis transmission equation models the radio wave propagation in the free space but it does not explain environmental losses, multipath and diffraction effects. This equation answers the question of what is the signal strength at the receiver when a transmitter emits. Since Friis equation only describes the free space transmission, to operate the simulation with higher fidelity, it is necessary to consider multipath effects, diffraction effects, surface wave propagation and environmental losses should be modeled when required [27, 28].

Environmental conditions in the battlefield might cause significant losses in transmission and effect the communication health. Even though rain loss is negligible below 1 GHz frequencies, the attenuation should be calculated at higher frequencies [29].

Snow loss is also negligible for dry snow as the same amount of ice causes much less attenuation compared to water [30]. When snow is wet, the attenuation substantially increases and, in such cases, the same approach as in rain can be used (ibid.). However, if an exact value of attenuation is required, it can be looked up from curves [31] or can be calculated from the snow loss formula (ibid.).

5.2 Communication in I4.0

It is well known that I4.0 is highly related to information and communication technologies (ICT) and Internet of things (IoT) [24]. Main goals of I4.0 are maximizing efficiency and productivity with the help of automatization [32]. Cyber-physical systems (CPSs) have a big role in I4.0 and in one definition, CPSs are defined as systems of agents which are in intensive connection with the surrounding world, providing and using data available on the environment and also on the Internet [33]. They, as a kind of agents, monitor physical processes and make decentralized decisions [34]. Moreover, making decentralized decision in an industrial manufacturing area requires instant and real time communication of CPSs with each other, with humans and networked sensory system.

The key technologies of I4.0 can be stated as mobile computing, cloud computing, big data, and the IoT [24]. In fact, I4.0 become possible in part by serious advances in technology interconnecting IoT and CPSs on both wide and local scale for industrial applications and automation [25]. Please note that recent automation applications are generally distributed systems and they are highly dependent on information flow and its reliability. Even though IoT and CPSs are not totally new concepts, they have not intensely involved in industrial communication area up to recent advances on communication. Internet based communication is the infrastructure for these concepts however it is far to meeting the requirements of automation domain such as determinism, reliability and efficiency in communication. While new advances as Ethernet TSN (time sensitive networking) offer hard real time capabilities for real time automation, telecom industry also works on 5G networks to meet the requirements of automation.

The new capabilities of the communication technology can be seen as an important game changer especially when follow the technology in time; starting from fieldbus systems such as MODBUS, PROFIBUS and CAN (Controller Area Network) [35] and then Ethernet based systems, namely, PROFINET or EtherCAT [36, 37]. The next step is development of wireless networks which make the systems free of cabling and supply great mobility for all components of the automation systems. Almost all wireless networks work based on common wireless network standards such as 802.11 or 802.15 and real-time working or reliability problems are still valid for all these [38, 39]. Please note that computer networks used in automation, even they are cabled, suffers the same problems about timeliness [40, 41].

It is known that agent-based distributed manufacturing execution systems are already introduced [42] but whole and efficient interconnection of units in automation systems on both wide and local area is made possible by the advances in communication technology [43]. In fact, the agent concept is very familiar for simulation society. One of the fundamental definitions of agent states that an agent continuously performs the actions; perception of the environment, action to affect the environment and reasoning [44]. However, it is necessary to add interaction to these activities given in that early definition of agent, especially after multi agent systems are introduced. Since CPSs are agent like structures, it is so convenient to model and simulate I4.0 systems using agent development environments such as AdSiF (Agent driven Simulation Framework). The example given in Sect. 8 is developed using AdSiF to show the conceptual similarity.

Actually, from the communication viewpoint, modeling communication networks of I4.0 is not different from a regular computer communication network and available modeling and simulation techniques can be used according to the specific system properties and problem scope [45]. In the following subsection, some communication modeling and simulation approaches for I4.0 are given.

5.2.1 Common Communication Models in I4.0 Simulations

It is obvious that, for different purposes, different tools or different levels of fidelity of models are required. If it is only intended to simulate the communication network, there are some available tools and languages in the literature and in the market. Network Simulator 2 is to study the dynamic behavior of a communication network and it includes too many network protocols [46]. Another tool, OPNET, is developed to analyze the performance of a network and it includes wireless systems' analysis [47]. OMNeT, which supplies a programming feature, is an open source simulation package for discrete event simulations of computer networks [48]. On the other hand, if the simulation of a whole I4.0 system is intended, the communication entities are a part of a simulation application and its model library, so all these models should be able to be used within the I4.0 system-wide simulation environment.

Computer communication networks specific simulation tools are good for design and testing networks to check whether they meet the requirements or not. They can also be used to specify the parameters' values of the communication models which are used in I4.0 simulation applications.

Since the communication in I4.0 systems are mainly machine to machine, it can be examined in computer communication concept. In computer communication networks simulations, discrete event simulation methods are commonly used and either trace driven or stochastic approaches are taken under these methods [49]. Trace driven method is superior to the latter mainly in terms of credibility and detail. It is also better in randomness, i.e., more deterministic so that it represents the real operating conditions better. Fidelity level of the model is higher. However, these methods generally require much more computational time because of model detail and complexity in order to ensure the fidelity. On the other hand, only one trace corresponds to a very specific time interval and it does not represent whole system behavior. Therefore, too many tracings are necessary for a total coverage of the system behavior in time [50]. Stochastic modeling is useful to design and analyse computer and communication systems [51, 52] and these methods in modeling communication systems are very common such as Markov chains, Queuing Networks and Petri Nets [53].

Since the computer communication networks is designed in layers [54], the communication society models each layer separately. However, since it is so low level for such an application domain, physical layer can be omitted. For the other layers, main approach is preferred as stochastic modeling based on some parameters or performance metrics and these parameters and metrics are defined in the following paragraphs for each network layer.

For the modeling of link layer communication systems, the model parameters are defined as throughput, channel capacity, bit error rate (BER) and packet error rate (PER). Beyond these, if the communication device is a wireless device, spectral efficiency (b/s)/(Hz/m^2), received signal strength, access point transition time (duration of the handover), Jain's index (2015 Muhammed) and SNR (signal to noise ratio) can also be added to model parameters where Jain's index represents the measure of fairness in access to wireless medium when multiple devices attempt to access it. SNR is also applicable to the cabled communication. However, while it includes all interferences in wireless communication, in cable it consists of background noise only.

For the modeling of communication entities in TCP/IP layer (network and transport layers), the model parameters are defined as propagation delay in the network access layer and this can be taken as fixed for the lowest fidelity level. Researches show that higher traffic load requires higher model detail [55].

When it comes to internet layer, networks are modeled as a graph with weighted links and these links also have some other model parameters such as delay and bandwidth. In this layer, topology is important and it defines the interconnections of entities. Routing, subnet traffic control, frame fragmentation, logical-physical address mapping and subnet usage accounting are done in Internet layer and the operations of the subnet is controlled and which physical path the data takes is decided here. The model of Internet layer may represent the path selection method of the real system and it determines best path to destination in terms of hop count, bandwidth of the links, round trip time etc. so that delay of each communication can be computed properly in simulation.

Two different methods exist for modeling of communication in transport layer. The one is direct modeling, and models in this method reproduce protocols and interactions. Parameters of these models can be defined as throughput, end-to-end delay, jitter etc. The other is a kind of performance modeling and it is based on stochastic processes.

Workload modeling is a modeling method of the transport and the application layer and it defines traffic model of the protocols since every protocol has its own overheads over the message. A very well-known example is TCP versus UDP where each protocol has different additional information for each message package. Workload model, also known as traffic model, is a critical part of the modeling in order to obtain a model with enough fidelity level [56]. Throughput with the behavior of the protocol, end-to-end delay, and jitter can be defined as model parameters.

As shortly mentioned above, some more detailed model should be considered for wireless communication devices so that parameters' set is extended as it includes the following model parameters; expected transmission count (etx), expected transmission time (ett), number of retransmissions needed, time to be correctly transferred; metric of interference and channel switching; exclusive expected transmission time; interference aware routing metric. If necessary, signal level modeling and simulation can be done for analyzing coverage properties and signal levels for every point the scene. Propagation model is exactly the same as in C4ISR wireless communication models, but multipath effects and diffraction models should be considered in detail since I4.0 scenes include factory settings, indoor spaces, walls, corners, and dense obstacles such as buildings, trees and machinery.

5.3 A Comparison Summary Between C4ISR and I4.0

C4ISR is a military concept aiming to design, develop and deploy interoperable and cost-effective systems. "War is nothing but a duel on a larger scale" [21] and it requires a condensation of all factors and assuring the communications with home is one of the necessities (ibid). A vulnerability of lines of communication leads to serious consequences like losing coordination among units and losing control of garrisons on forces. In strategical level you have to defend your line of communication while in tactical level, the communication is more technical concept including the devices used, the method selected, the success rate of message delivery, the duration of conveying messages etc. Therefore, in C4ISR combat simulations, communication models are designed to analyze and reveal the answers to these questions for different scenarios contain of different communication devices with different configurations on different geographical locations under different environmental conditions. Developers and users consider several parameters such as communication speed, used bands width, error rate, accessibility range, latency, robustness under environmental conditions defined in the scenario, e.g., rain, snow, fog, geographical forms and terrain elevations, time of day, day of year. It should be also noted that the communication entities are mostly moving ones and distances are long.

In I4.0, since the concept is based on five major features –one of which is automatic data exchange and communication [24]—and industrial wireless networks (IWNs) are among the key technologies enabling the deployment of I4.0 [57], communication entities have important role in I4.0 simulation applications. The assumption of good communication conditions exists and the requirements on communication in I4.0 applications such as high bit rate and low delay/latency comes from the current status of communication technology. As compared to a battlefield, the environment for an I4.0 application is much more in control as system is designed to meet these requirements; all data, in time, in everywhere. Although propagation models frequently used in C4ISR simulations are still valid in I4.0 applications, they are not used too often since the problem is generally focused on optimization of production, cost and/or efficiency etc. Moreover, since the communication in I4.0 is computer communication type, i.e. machine to machine networks or IoT, problem is addressed as network modeling instead of tracking electromagnetic waves over free space.

Along with the technological improvements, the higher aggregated models use different models for communication mentioned above especially in the military community, e.g. network centric warfare, and the network components plays a more pivotal role as well. Therefore, communication units of I4.0 and C4ISR in the era of IoT and IoS are conceptually more and more alignable.

6 Agent Architecture and Decision Making in Distributed Systems

Today, advanced CPS use simulation to predict future developments based on real time observations that are interpolated. They use these predictions for their decision processes that are not only reactive, but deliberate, just like smart agents are doing it.

One of the components of the agent-based solution is an online analysis and decision-making component. Basically, it undertakes collecting data from the components (CPSs) it monitors, analyzing data online, and making decisions to manage a combat simulation environment or a smart factory.

A special agent is developed for this purpose. Basically, it is situated in a combat simulation environment or an I4.0 based production system and even it is used as an intelligent analysis agent embedded in a real system.

6.1 Agent Architecture

As a necessity of being an agent, the analysis agent invokes its behaviors by event interactions and/or conditional activation. An event sent by any entity in the simulation/real system (C4ISR or I4.0) and it requests a behavior consisting of a set of functions. Conditionally, any change in the environment can be defined as a behavior activation condition. This makes the agent reactive and also the agent aims to keep

C4ISR system and/or I4.0 system performance high and this is proactiveness of the agent.

The functions that are invoked by the agent are defined in plugin architecture and open architecture. This allows modelers to define new functions, even in run time. The Model View Controller (MVC) architecture is also supported to keep modularity and extendibility. In Fig. 2, the agent interface (View) is designed as an e-table, and analysis functions are defined as plugin libraries (Model). The rule base and inference engine are used to make decision to drive simulation scenarios and/or the systems by ordering what to do based on the rules and inferences. The whole data being used are collected by sensors from the systems (from CPSs, machines, weapon systems, ammunitions etc.) and they are kept in matrix form to analyze. The analysis functions are defined in the form of matrix cells as well.

6.2 *Analysis Libraries*

The analysis functions are independent from conceptual model. Moreover, this makes the libraries domain independent and reusable, it also provides a standard language

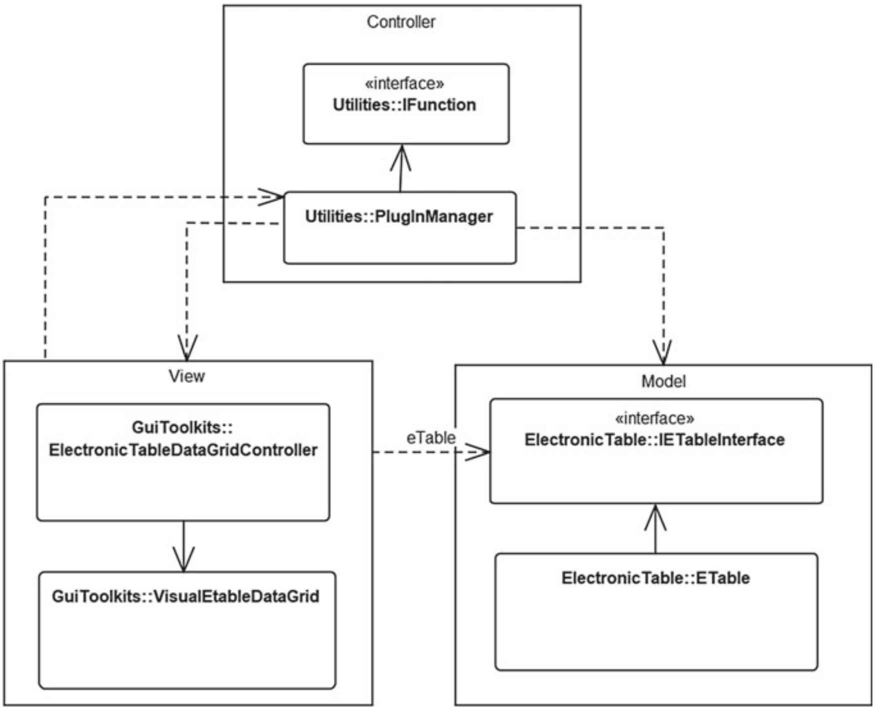

Fig. 2 The agent architecture

to acquire the system and each component over the same concepts such as behaviors, states, events and custom data fields. For example, acquiring crashed number of flights is to ask how many entities are in the crashed state and it also is the same thing asking how many machines in broken state in a production facility.

The analyzing agent has an analysis library and because it has open architecture, it is possible to extend it without any software dependency. Some commonly used analysis functions are given as a built-in library. The analysis functions are categorized under two headlines;

- Query Functions
  - Behavior query: the queries result time of phases of entity behaviors such as behavior activation time, behavior cancel time, behavior suspension time, behavior finish time, and behavior reactivation time. In addition to these, it allows analysts to query what events are processed and what state transitions are done.
  - State query: Similar to behavior query, the query result state transition times.
  - Attribute/Function query: entity attribute values and function values calculated during execution are saved as time labeled. Queries are designed independently from their context.
  - Complex queries: composed queries can be written using logical and mathematical operators.
- Statistical Functions consists of measures of central tendency (mean $(\bar{X})$, standard variation (σ), variance (σ^2), range (R), variability coefficient $(\frac{\bar{X}}{\sigma})$, confidence intervals, statistically meaningful tests, and randomness tests.

7 Case Study: Air Defense Example

7.1 The Scenario Ratio

The air defense simulation scenario is chosen to give a brief representation for C4ISR concept, because air defense consists of reactive defense units such as land-based missile defense systems and proactive components such as opponents aiming a set of specific high value assets. The example also shows the communication network established between C2 systems and sensors and consist of the technologies given in Table 3 such as wireless communication devices, radars as sensors, mobile devices such as unmanned aerial vehicles (UAVs) used to extend line of sight communication range, and big data analysis to fuse sensory data and infer results. The simulation components and agents are modeled using an agent and simulation development and execution environment called Agent driven Simulation Framework (AdSiF) [58, 59]. AdSiF provides a complete simulation environment and it support different simulation purposes such as analysis, real time execution, testing, and experimentation [60]. That is why AdSiF is chosen to simulate the example. The scenario is developed for analysts and decision makers. In the scenario, similar to a I4.0 systems, information is collected using sensors from battle environment, there is at least a mission to achieve, a set of components being driven to achieves the mission. While I4.0 systems produces industrial products and provide services, in C4ISR systems and especially in the example given, an area is being defended and defense success level is used as a performance criteria for the defense service.

7.2 The Scenario Design and Execution

The air defense scenario includes a series of land-based air defense systems, fighter aircraft, ships, sensory systems (surveillance and tracker radars), commanders, missiles, free-fall bombs, UAVs and a set of communication devices. Each missile has its own seeker to follow the target that it has engaged. A land-based defense system consists of launchers with a set of missiles, radars or any other types of sensors, and a command and control (C2) unit, which is an intelligent agent with a set of communication devices connected with sensors and other C2 units. Surveillance radars detect targets, send their detections to C2 units to which they are connected with communication devices, the C2 units evaluate the threats, select a defense system and missile type for the engagement, and give the engagement order to the selected defense system. A set of relays is carried by UAVs over the defense zone to extend line-of-sight for the line-of-sight based communication devices. The UAVs follow paths that are given them. This cycle is known as a C4ISR cycle (or OODA cycle). A C2 unit may manage more than one defense system. A surveillance radar detects a threat in its line of sight and in its look angle, it analyzes the threat and sends detection information using wireless devices (Communication and intelligence). As soon as the C2 unit receives any threat information, it registers the threat to a threat list and starts a threat evaluation process (C2, decision making) [59]. The scenario deployment is seen in Fig. 3. As seen in the figure, blue side aircraft aim on drop bombs to the red target sensor systems (in the figure, the middle phase of the course of action is seen and Red forces and Blue Forces are tagged by R and B, respectively). Red land-based air defense systems detect and engage the blue aircraft. The deployment of the surveillance radars and the land based air defense systems are depicted in the figure. To detect blue aircraft sooner, a surveillance mission is achieved by red aircraft.

In the example, the simulation is started by a centralized C2 structure. Commander-1 controls other commanders, picks detections from the commanders ranked below it, evaluates the targets and gives a decision on who engages which target using which weapon system. When Commander-1 is passivated, it breaks the relations that it has with the commanders at lower ranks (the relation commands) (Reconfiguration). As defined in the relation programming declaration, the commanders change their behavior list to an autonomous C2 structure. Then they evaluate targets themselves and give their own decisions (Decentralization).

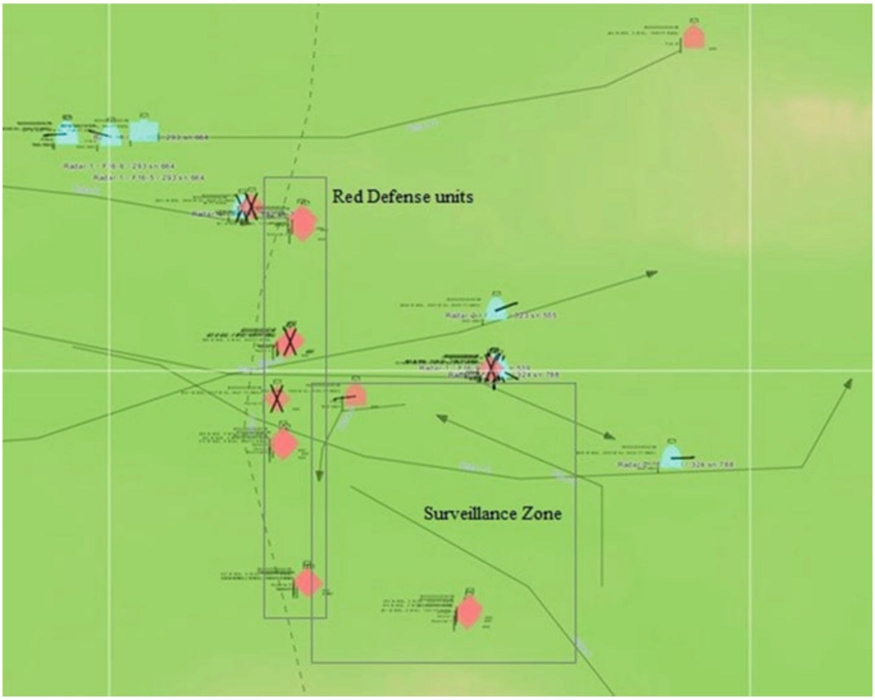

Fig. 3 Scenario force deployment

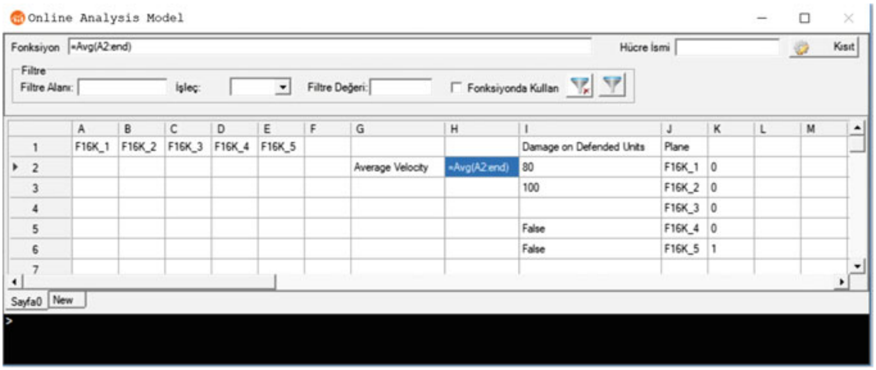

Fig. 4 Function declarations

In run time, the online analysis agent collects data generated by the simulation models during execution. As seen in Fig. 4, the function declared on the agent graphical user interface makes its calculations on the fly. The conditions defined using both the data being monitored and the functions being calculated are associated with behaviors to activate, to cancel, to suspend, or to reactivate.

As seen in Fig. 4, the cell I2 includes damage level of the defended units and I3 includes the targeted damage level. I5 is defined as GreaterEqual(I2:I3) (it means I2≥I3) and it means target is dead. The constraint in I5 is defined as a engagement termination condition, anytime it turns true the behavior engagement termination is activated. The cells between K2 and K6 represent the fighter status and zero means it is still active and one means it is deactivated. The sum function defined in the cell K7 (Sum(K2:K6)) calculates how many fighters are deactivated. When it is equal to total number of enemy aircraft it is used as a mission termination condition (Or(I5:I6)).

In this example, communication between military groups is similar to communication between companies horizontally and vertically integrated in I4.0 and also taking a target into consideration or leaving it to any other partner is a type of negotiation. Decision making is based on rule-based evaluation and online in both systems. Similar way, targeting an opponent in an air defense is similar to targeting a consumer group in a manufacturing environment. It is possible to qualify ads as weapons and customers as targets.

Regarding with technology, smart missiles, UAVs and soldiers, who share their situation and states, are seen as IoTs in the combat area. The sensors share their detection by sensing cues with each other by defining a network. Although the example is not big enough, still the data fusion achieved by the commanders is related with big data and data mining. The principles, concepts and components given in Table 2 are seen in the example.

Furthermore, the example proves that the things a combat simulation consist of are highly similar with the things an I4.0 system consists of. If we want to simulate a factory, we need machines to produce products, a set of sensors to pick information up from the facility, communication devices and network to send information and to share, respectively, work on the big amount of data. The simulation also virtualize factory to be able to manage the production and it also has a mission producing products with low cost and delivering them timely.

8 Results and Discussions

In this study, a conceptual bridging is done between the concepts of military C4ISR and civil I4.0. The comparison shows that data sharing, fusing data received from different sources, distributed decision, automated decision making, integration of systems, and handling big amount of data are common points for both C4ISR and I4.0.

In addition to the fact that a defense system and an I4.0 system have a common criteria set consists of interoperability, virtualization, decentralization, real time running capability, service-orientation, modularity and reconfigurability, they also have a similar analysis and a requirement real-time, on-the-fly analysis. From the viewpoint of communication, although I4.0 is introduced after the communication technology stepped into new age with fast and reliable understructure and protocols, communication has indefeasibly been used for centuries in military and conceptualized in C4ISR definition. As another step, reliability studies of military communications under EMP weapons are directly applicable to I4 vulnerabilities to solar storms which are new type of disasters of information and technology age [61, 62]. The aim is the same in both areas, to convey the message fast, in time and without any deterioration as agents are required to do the same in multiagent systems, social agents or distributed artificial intelligence.

Having common technologies, common goals, online decision making, online analysis, and a similar architectural view draw some common solution and intelligent agents are the prominent one. An intelligent agent gives an architectural view, a reasoning mechanism, reactive and proactive behavioral aspects. From this perspective, it seems that agent technologies will be an essential part of both C4ISR systems and I4.0 systems.

Two new technologies that I4.0 and C4ISR meet at are cloud technology and big data analysis. Both technologies are related with storing and processing huge amount of data and using them for decision making as both technologies do.

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Simulation for the Better: The Future in Industry 4.0

Murat M. Gunal

Abstract Simulation help achieve the better in the industry in many ways. It reduces the waste in time and resources and increase efficiency in manufacturing. It also helps increase productivity and the revenue. Simulation has also significant role in the design of products. Furthermore, as the complexity in technology increase, skilled workers required by the industry can be trained by using simulation. Additionally, work safety issues are more important than it was in the past with the emergence of autonomous machines in manufacturing. The data will help create smartness and intelligence in manufacturing and simulation help data analytics in comprehension and knowledge extraction. This chapter is the concluding chapter of this book and summarizes the role of simulation in Industry 4.0. There are explicit and implicit imposed roles of simulation which are summarized in terms of technologies composed of Cyber-Physical Systems (CPS) and smart factory. In conclusion, as this book makes it clear with evidences, simulation is at the heart of Industry 4.0 and the main driver of the new industrial revolution.

Keywords Simulation · Industry 4.0 · Digital twin · CPS · Smart factory

1 Introduction

Industry 4.0 is expected to alter the way we do manufacturing and business. As in the previous industrial revolutions, it impacts the human life in many ways. More people can access to products which are cheaper and customized. The industry has adapted itself and manufacturing technologies have been developed accordingly to increase the speed in "time-to-market" and product customization.

Simulation mirrors real-world physical phenomenon on computers by virtual models. Using models, any changes in systems can be tried safely and with significantly less cost. Mcginnis and Rose [3] present the history of simulation and give

M. M. Gunal (✉)
Barbaros Naval Science and Engineering Institute, National Defense University, Turkish Naval Academy, Tuzla, Istanbul, Turkey
e-mail: m_gunal@hotmail.com

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a perspective on the use of simulation in manufacturing. Although we see many successful applications of simulation in manufacturing, the literature review in Chapter "Industry 4.0, Digitisation in Manufacturing, and Simulation: A Review of the Literature" reveals that most of the recent studies in the new era is written without a specific industrial focus. This suggests that concepts in Industry 4.0 are forming and specific studies will come soon. There are tremendous opportunities for research community. We also note that automotive sector is already using technologies of smart factories. The review also revealed that number of studies in the literature which depicts "simulation and manufacturing" are declining, however inversely, CPS is increasing.

Simulation is an enabler of Industry 4.0 and there are "to do"s for everyone in simulation community. For example, simulation software vendors must adapt their software to answer the changes in manufacturing environment, such as collaborative workforce and robot scheduling, advanced queue management. For symbiotic simulation, the vendors must make their software able to communicate with real systems in order to create "digital twin". A simulation must be able to update the simulation state based on the data read from a real system. In symbiotic simulation, there is feed-back loop in the decision problem in which variables in the model are updated and simulation continues with updated variables.

In this chapter, benefits of simulation are presented in the next section. The role of simulation in Industry 4.0 is summarized in the following sections. The presentation is done in two parts; first, technologies in Industry 4.0 are evaluated from simulation point of view, and second, the reasons why simulation is the driver of Industry 4.0 is discussed.

2 Benefits of Simulation in Industry 4.0

As a technology-oriented revolution, Industry 4.0 uses computer simulation and related technologies in many ways. Simulation facilitates CPS and smart factory and the following benefits of simulation emerge.

2.1 Reduced Waste in Time and Resources, Increased Efficiency

Simulation will enable optimum configurations in processes and "optimum" decisions in CPS. Smart factory concept is a by-product of CPS. In smart factories, machines communicate with each other and synchronize the processes. An up-stream machine can inform other machines about the status of the job being processed. These machines can then regulate themselves for the upcoming jobs, or switch between jobs.

The job-shop scheduling is done by connected and smart machines. Note that the connectedness makes the machine scheduling possible with embedded algorithms.

Reduction in work-in-progress (WIP) inventory through better information exchange in value-chain is another benefit of simulation. When the machines in manufacturing systems synchronise, the WIP reduces significantly. Simulation takes part in tuning the synchronisation parameters. Alternative scenarios which can be run in a simulation model, or in a digital twin, help observe the effects of changing system parameters such as routing conditions, machine processing times, production speed.

2.2 Increased Revenue and Productivity

Reduction in costs increases revenues, as well as productivity, in manufacturing. Robots, and autonomous machines, have significant role in increasing revenue and productivity. Robots are being used in manufacturing more often and taking over the tasks humans do before. Increased use of robots also increase productivity since robots can do recurrent tasks better than humans. We see different type of industrial robots which can also collaborate. A robot arm can hand over the part being processed to another robot arm for the next stage of manufacturing. Collaborated robots are the future of robotics.

Simulation is being used in robotics for development and testing. There are robot design and simulation tools in the market and these tools help designers to use right parts in robots. Before producing robots, simulation software can test their motion in 6 degrees of freedom fidelity level. Simulation tools also help design collaborated robotic systems for machine parks in factories. Note that all these efforts are included in a digital twin and a part of smart factory.

Increasing revenue and productivity is also possible with vertical and horizontal system integrations. For vertical integration, machines in the factory are linked, meaning that they are aware of what states other machines are in. For horizontal integration, a factory is aware of its suppliers and customers. Information linkage between machines and between suppliers are critical for optimum use of resources. Factory simulations, digital twins, and supply chain simulations can help increase revenue and productivity.

2.3 Individualisation in Demand for Products

In this century, the demand for products has changed significantly. The demand comes in almost batches of size one. This means that manufacturing systems are likely to produce many types of products, or custom products with individual preferences. It is difficult to satisfy this type of demand with current manufacturing systems since customisation in mass production is not possible. A product is designed, its production stages are determined, related moulds are made, casting is done, components are produced, and the final product is assembled.

The traditional manufacturing systems benefit from “economy of scale” principle, that is, with capital investment, the manufacturer assumes a certain amount of product is to be sold to pass the break-even point. The investment is allocated to machinery, to do certain tasks in production process, and more importantly to the moulds, to make the product “custom”. The traditional systems are bulky and can hardly satisfy contemporary customer expectations.

In the new era, additive manufacturing is introduced as a revolutionary alternative to traditional manufacturing. With 3D printers, many “custom” products can be produced. The virtue of 3D printers is that they work without a mould and therefore they do not require capital investment. The mould in 3D printers is essentially the 3D design of the product. As of 2019, although the materials that can be used in 3D printers are limited, in the future, there will be more materials that 3D printers can use, including composite materials.

Simulation exists in custom production and additive manufacturing in two ways; in the design of products, and in the 3D printing process. CAD software is used to design products and simulation software support the design by testing its compatibility and dynamics. For the printing process, all 3D printers simulate the printing job first to have error-free printed products or parts.

2.4 Increase in Skilled Workers

Augmented Reality (AR) and Virtual Reality (VR) help humans increase their knowledge about systems, and hence, reduce human related errors. With AR, complex machines and processes are displayed in a simplified way.

Although smart factory ideal is about fully automated robotic factories with no, or less human workers, this ideal seems far away for now. Humans will still exist in factories for a while. However, it is true that manufacturing needs highly skilled workers today than it needed in the past. Complex machines in manufacturing systems are challenging for humans when extra ordinary things, such as failures or breakdowns, occur.

AR help simplify the complexity in manufacturing. The simplification increases understandability. Human operators can see the world differently with AR, in terms of explanations and status of parts, sections, and links of a machine.

AR and VR are simulations of machines and parts of CPS. AR is used as an online and embedded simulation since it works in real-time and with real objects. The VR requires special spaces but is more effective in learning.

2.5 Increased Work-Safety

Humans are still required on factory shop floors and therefore they are open to dangers of the work environment. Moving sections of machines, robot arms, high temperature on surfaces, chemical substances, visible and infrared lights are some of the causes of hazards at work.

Simulation is ideal for training people for work-safety. With AR and VR, workers can be trained before they work on shop floors in factories. The training can be for general safety rules or for specific machine usage. For example, forklift simulators can train drivers to make them aware of possible dangers.

2.6 New Opportunities with Data

IoT devices provide data from manufacturing systems which we cannot collect any data before. This will open a new world. IoT devices are embedded systems which transfers data collected from sensor systems and to central repositories. This creates big amounts of data. For example, if we measure the temperature of the mould in a plastic injection machine in every 2 s with a temperature sensor and transfer this bit of data via an IoT device on the machine, then we will have 14,400 measurements in every 8-h shift. If we scale this up to whole factory and reciprocate for the other types of data we need, the amount will be huge. Obviously, we collect such data for a purpose, e.g. real-time monitoring of the heat on machines.

We can use IoT devices to tag and monitor many things in factories. The more data we collect the more use of data will emerge, or the visa-versa. The data is used to make inference, and feed the “digital twin”. Simulation models, and a digital twin, requires data from systems that is being represented. The IoT will provide the data and smart algorithms will make inferences from the data and simulation models will predict or inform about the future.

3 The Role of Simulation in Industry 4.0

The new industrial revolution is related to the use of advanced technologies in manufacturing. According to Rüssmann et al. [5], there are nine technologies identified within Industry 4.0; big data analytics, autonomous robots, horizontal and vertical integration, industrial IoT, cyber-security, the Cloud, additive manufacturing, augmented reality, and simulation. It is certainly difficult to create a final list of related technologies as new ones emerge on the way. The literature review in Chapter “Industry 4.0, Digitisation in Manufacturing, and Simulation: A Review of the Literature”, however, revealed that creating Cyber-Physical Systems (CPS) and smart factory is the common goal in Industry 4.0. CPS is the general concept which aims at creating

Technologies of Industry 4.0		SIMULATION	Digital Twin
Cyber-Physical Systems (CPS) Smart Factory	Robotics and Autonomous Machines	✓	✓
	Advanced Visualisation (AR/VR/MR)	✓	✓
	Industrial IoT and Sensor Technologies	✓	✓
	The Cloud and Data Analytics	✓	✓
	Additive Manufacturing Product Design	✓	✓
	Vertical & Horizontal Integration of Systems	✓	✓

Fig. 1 The link between simulation and technologies of Industry 4.0

link between systems in physical and cyber worlds. This requires machines capable of conducting physical tasks, controlled by and reporting actions to a software. This software is also called "Digital Twin". Once CPS are created, the software can take "smart" actions to better manage factories. Kagerman et al. [2] mentions that the smartness is not only about factories but also about services the factories are linked to. These are smart mobility, logistics, buildings, grids, and products. These services are to be linked to CPS through Internet of Things and Services.

A digital twin is a simulation model of the system it is representing. A digital twin can be built for a machine, a process, or a whole factory. A digital twin creates the "smartness" in the system. Algorithms which optimize the processes and the decisions are embedded into a digital twin. It can also learn from the past experiences with historical data which is generally collected from sensors and sent to the cloud via IoT devices.

Simulation and digital twins are used in Industry 4.0 technologies listed in Fig. 1. These technologies are related to CPS and Smart Factory concepts and it is evident from the figure that all of them require simulation. Simulation is at the heart of Industry 4.0.

We see extensive use of simulation in robotics and autonomous machines. Simulation is used in the design of these systems. The way these systems behave is simulated in virtual environments in order to understand their effects on the whole system. Digital twins are generally used for controlling autonomous systems and assuring that they operate in desired limits. Interaction of robots, and autonomous machines, are provided by way of digital twins.

Advanced visualisation technologies including AR, VR, and MR mean simulation. As it is evident from the definition of simulation in Chapter "Simulation and the Fourth Industrial Revolution", simulation mimics the reality on computer and AR, VR and MR deliver the imitation through advance visualisation technologies and devices. These are hand-held and head mounted display devices which can interact with real world. We must note that 3D models and their dynamics have significant role and therefore the people will continue to ponder mathematics and algorithms behind them. Digital twins utilise these advanced visualisation technologies in creating better human-machine interaction experiences.

IoT and sensors are important components of CPS since data collection and systems monitoring are possible with these technologies. Simulation is used to set up and tune the IoT and sensor devices. Furthermore, digital twins are used in designing these systems and in integrating with other systems. We note that complete connectivity in machines would be possible with 5G technology and we will require advanced simulation techniques to study this technology.

Today, we live in a world full of data. Data, which is available electronically, is collected on purpose to create value. Simulation is used to build models of value creation in manufacturing. "Smartness" in factories can be achieved by learning machines which utilise past information. The cloud provides the medium to store, manage, process, and create inference, and data analytics help the cloud with optimised and smart algorithms. Digital twins benefit from the cloud and data analytics in terms of being aware of the past, learning from the experiences, and acting rationally.

Additive Manufacturing (AM) revolutionizes the conventional production cycle in which moulds exists physically. In AM, in a way, moulds are virtual, since products are designed using CAD software and can directly be "printed" in 3D printers. Mass production in AM might not be possible today, however advancements in material technology will make it happen soon. Simulation is applicable in AM in two ways; first, in the design phase, a product is modelled using CAD software and is simulated for its dynamics. This eases the design-prototype-test cycle significantly. Secondly, before the product is manufactured in 3D printers, the printing process is simulated on computers so that inefficiencies and waste are diminished.

Integration of composing systems in smart factories are essential for creating optimised decisions. Vertical integration is to link the machines in production and making them aware of each other. Integrating machines in processes eliminates possible bottlenecks. Horizontal integration is to link the entities outside the factory such as suppliers, customers, and competitors. To some extent, this integration is possible and required. Destructive consequences of the famous "bull whip effect" in supply chains is alleviated with horizontal system integration. Simulation help achieve the two types of integration in terms of design, test and evaluation.

4 Simulation as a Driver of Industry 4.0

CPS and Smart Factory are in fact the two most important terms in Industry 4.0. By creating CPS, factories are able to link physical and virtual worlds. A smart factory is a natural product of CPS. Once the physical processes are digitised, data is collected, analysed, and synthesized. Decisions made in cyber-world by algorithms lead machines in physical world. The whole process is more difficult than it is said since many technologies, as evaluated in this book, are involved in.

CPS and Smart Factory are driven by Simulation, as picturized in Fig. 2. In almost every component of CPS, simulation is used to create value in designing, experimentation, evaluation, or training. The use of simulation is explicit in some technologies in Industry 4.0, such as digital twin, AR/VR, additive manufacturing, systems integration, and is implicit in others, such as robotics, IoT, and analytics. In anyway, simulation is used in associated technologies.

Simulation methodologies in Fig. 2 are the drivers of simulation. With these methodologies, CPS and smart factories are managed better. Discrete Event Simulation (DES) was invented more than 70 years ago and is still the main methodology to simulate systems that needs to be understood and improved. System Dynamics (SD) was invented and developed by Forrester [1] in 1960s and is still applicable in the industry. In fact, the dynamics of Industry 4.0 enabled manufacturing systems can be better understood with the concepts in SD. Agent Based Simulation (ABS) is relatively newer simulation methodology since it waited for the developments in Object-Oriented software. In ABS, simulated entities called "agents" can be programmed as self-deciding entities in a virtual environment. Agents interact with each other, and behaviours emerge as a result of interaction, just like in the real world. ABS is particularly useful to model autonomous systems. Hybrid simulation

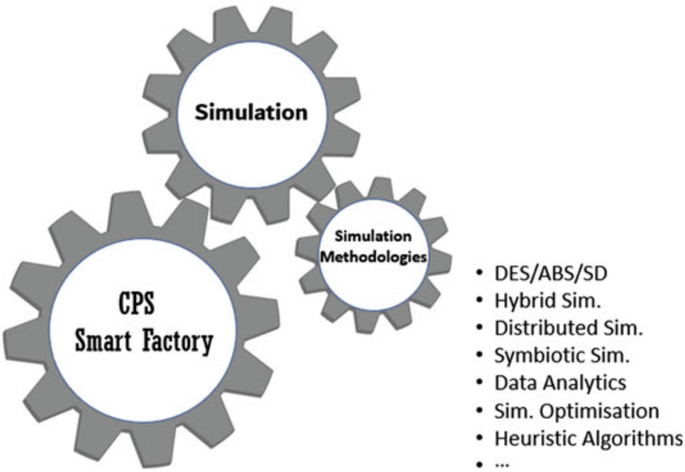

Fig. 2 Simulation as a driver of CPS and smart factory

is also a new concept which benefits from DES, ABS, and SD. Hybrid models can better tackle the complexity in the industry and can handle different level of detail required in different systems [4]. Distributed simulation has also significant role in the new era, as discussed in Chapter "Distributed Simulation of Supply Chains in the Industry 4.0 Era: A State of the Art Field Overview".

One of the driving methodologies of simulation is symbiotic simulation. As discussed in Chapter "Symbiotic Simulation System (S3) for Industry 4.0", Symbiotic Simulation (S2) is "a tool designed to support decision-making at the operational management level by making use of real-time or near-real-time data which are fed into the simulation at runtime". This terminology has been developed before the Industry 4.0, with different names such as "co-simulation", "online simulation", and "real-time simulation". All these terms echo "digital twin" concept, suggestion once again the significance and routes of simulation in Industry 4.0.

Data analytics is a growing area of research and development. Simulation is both the user and creator of data analytics. As discussed in Chapter "High Speed Simulation Analytics", we need high-speed analytics and simulation to accomplish.

Smart factories can only be called "smart" if their operations are optimized. Simulation optimisation and heuristic algorithms help optimize machine operations as well as whole factory operations.

Finally, this book conveyed the message that the role of simulation is prominent in Industry 4.0. We are hoping that the book helps contribute to the industry and research community. We recalled that the "simulation" door is opened to "Industrial Revolutions" avenue and that will never be closed.

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Correction to: Product Delivery and Simulation for Industry 4.0

Oliverio Cruz-Mejía, Alberto Márquez and Mario M. Monsreal-Barrera

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In the original version of the book, the co-author's misspellt name "Monsreal-Berrera" has been changed to read as "Monsreal-Barrera" in Chapter "5".

The erratum chapter have been updated with the change.

The updated version of this book can be found at
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