Artificial Intelligence for Production Management and Control Towards Mass Personalization of Global Networks

Dimitris Mourtzis, Nikos Panopoulos, Panos Stavropoulos, and Nikolaos Papakostas

Abstract Companies operating in global production networks should handle the complex, uncertain, and volatile environment, making them more vulnerable to disruptions. The Mass Personalization (MPe) paradigm is already a reality and has increased the involvement of end-users in the product lifecycle. It requires responsive and flexible manufacturing operations to produce cost-effective individualized products in dynamic batch sizes at scale taking into consideration the unique preferences of each customer. Therefore, modern manufacturing and production systems and networks must be capable of responding quickly to (i) the alteration of demand and conditions in the supply chain, and (ii) the volatile customer demands. By extension, in the context of MPe, manufacturing and production systems must be capable of self-optimizing manufacturing operations in order to achieve flexible, autonomous, and error-tolerant production. On the other hand, Intelligent Manufacturing (IM) is a key concept that has evolved during the last five years and is, currently, gaining momentum thanks to the potential offered by the Industry 4.0 vision. Thus, the ability of a company to setup an effective data gathering and processing strategy, orchestrating data flows, and then draw meaningful and actionable insights from them, is critical to MPe success. As such, the technological drivers of MPe are the Big Data Sets and Artificial Intelligence (AI) among other pillar technologies of Industry 4.0. The scope of this essay is to identify and highlight the state-of-the-art on how the integration of AI and Big Data technologies and techniques will contribute towards the efficient personalization of each customer's experience under the framework of Industry 4.0 and beyond.

Keywords Mass personalization · Intelligent manufacturing · Industry 4.0 · Big data · Artificial intelligence

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Nomenclature

6LoWPAN	IPv6 Low-Power Wireless Personal Area Networks
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AI	Artificial Intelligence
AMQP	Advanced Message Queuing Protocol
AR	Augmented Reality
BA	Bat Algorithm
BBO	Biogeography Based Optimization
BFO	Bacterial Foraging Optimization
B2B	Business-To-Business
BLE	Bluetooth Low Energy
BMS	Biological Manufacturing Systems
CAx	Computer Aided Technologies
CFO	Central Force Optimization
CoAP	Constrained Application Protocol
CLSA	Clonal Selection Algorithm
CRO	Chemical Reaction Optimization
CSA	Cuckoo Search Algorithm
DE	Differential Evolution
DDS	Data Distribution Service
DL	Deep Learning
DPO	Dolphin Pod Optimization
EMO	Electromagnetism Optimization
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
FA	Firefly Algorithm
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GDP	Gross Domestic Product
GPN	Global Production Network
GSA	Gravitational Search Algorithm
HMI	Human–Machine Interface
HS	Harmony Search
IoT	Internet of Things
IIoT	Industrial Internet of Things
IM	Intelligent Manufacturing
ISA	Intelligent Search Algorithm
IT	Information Technologies
KHA	Krill Herd Algorithm
LOA	Lion Optimization Algorithm
LoRaWAN	Long Range Wide Area Network
MSA	Monkey Search Algorithm
M2M	Machine-To-Machine

MCS	Monte-Carlo-Simulation
ML	Machine Learning
MPe	Mass Personalization
NIOA	Nature Inspired Optimization Algorithm
NP	Non-deterministic Polynomial time
OIO	Optics Inspired Optimization
OS	Operating System
PFA	Paddy Field Algorithm
PSS	Product-Service System
PSO	Particle Swarm Optimization
RFD	River Formation Dynamics
SA	Simulated Annealing
SFLA	Shuffled Frog Leaping Algorithm
SOA	Spiral Optimization Algorithm
SSO	Social Spider Optimization
SCN	Supply Chain Network
SDG	Sustainable Development Goal
SME	Small and Medium sized Enterprises
TS	Tabu Search
WSN	Wireless Sensor Networks

1 Introduction

1.1 Digital Transformation

The concurrent status and structure of Smart Factories is totally different from the industrial setups of the past decades. In particular modern factories are data-driven, the equipment is embedded with multiple sensors, and each system has become a thing in the Industrial Internet of Things (IIoT) [1]. Further to that, with the implementation of cutting-edge digital technologies, human operators have been augmented along with robotic operation on the shop-floor level [2]. In more advanced factory plants, robotics are setup/capable of operating independently, also known as lights-off factory [3]. However, the majority of the manufacturing companies still operates under the mass production paradigm, as it was introduced by Henry Ford, who said that "Any customer can have a car painted any color he wants as long as it's black." [4]. Although the mass production paradigm has facilitated companies to produce larger batches minimizing the production and operation costs of their plants, the current market status is highly characterized by the demand for highly customized products and services [5]. Consequently, the integration of the nine pillars of Industry 4.0 has become mandatory for manufacturers, in a global scale. The benefits from the transition towards the Smart Factory might not be obvious. However, with the integration of technologies such as the Internet of Things (IoT), predictive maintenance, and real-time data and analytics unprecedented cost-efficiency ratios are becoming even more feasible, extending to more robust quality control, affecting positively the overall effectiveness [6]. According to recent market research, digitization, digitalization, and automation will be the key drivers for the realization and widespread adoption of the Smart Factory model, as it is projected that by the end of 2030 approximately fourteen (14) percent to global GDP (Gross Domestic Product) gains are accounted to the above-mentioned technologies [7]. To put this in perspective, these gains are equal to more than fifteen trillion US dollars (US$15 trillion) in the current value [8]. Nonetheless, the true potential of Industry 4.0 has not yet been unveiled since there are certain barriers to its implementation, which in turn affect the Sustainable Development Goals (SDGs). Therefore, it can be concluded that more extensive and proper education regarding the concepts, the frameworks and the technologies associated with Industry 4.0 are required [9]. The involved actors in Industry 4.0 technologies should be aware of data and data analytics, which are basically algorithms that combine information and simulation of processes, production lines and manufacturing systems. These algorithms are the backbone of schemes, known as architecture, with the latter being essential for the depiction of key components towards optimization of production lines and management.

With the emergence of Artificial Intelligence (AI) and its subsets, Machine Learning (ML) and Deep Learning (DL) and Digital Twins [10] new frontiers for industrial applications, such as robotics, are yet to be explored. The newest generation of machine vision (Industry 4.0: The Fourth Industrial Revolution—Guide to Industrie 4.0, 2020) powered systems can inspect products and detect potential defects with greater accuracy than any human operator. The driving vision for Industry 4.0 was the full digitization and digitalization of Industry as a whole. On the contrary, Industry 5.0, and by extension Society 5.0, will emphasize more on the human aspect of technologies. Thus, it is expected to see more developments in the field of human–machine interface (HMI). Further to that, Society 5.0 introduces several aspects relevant to AI and Production Networks. One key aspect is the integration of AI-driven automation, which leverages technologies like machine learning and robotics to enhance efficiency and intelligence in manufacturing processes. Smart factories, another aspect, envision the utilization of AI, IoT devices, data analytics, and autonomous systems to optimize production networks, improve productivity, and enable flexible and customized manufacturing. Society 5.0 also emphasizes the collaboration between humans and AI systems within production networks, aiming to enhance human capabilities through AI assistance while ensuring worker well-being and safety [11]. Regarding ergonomics, Society 5.0 recognizes the importance of designing workspaces, equipment, and tasks in a way that optimizes human performance, comfort, and safety within production networks. By integrating these aspects, Society 5.0 aims to create a harmonious and efficient ecosystem where AI and humans work together in production networks, driving innovation and productivity [12]. As per recently published literature [13–15] the main objective of Industry 5.0 is to create a new vector for human-technology collaboration (robots, cobots, IoT devices, and other cognitive systems) at and beyond production infrastructures [16]. Furthermore, according to the statement from the Japanese government (Japanese Cabinet Office) [17] that "As we move into Society 5.0, all people's lives will be more comfortable and sustainable as people are provided with only the products and services they need in the quantities and at the times they need", it is emphasized that the collaboration of cognitive systems, robots, and humans can help businesses, harmonize their production processes, and become more agile to meet market changes and requests for customization.

In [18, 19] the authors have conducted an extensive literature investigation regarding the implementation and the reference architecture of Industry 4.0 and other similar/equivalent initiatives, such as Plattform Industrie 4.0 (Austria), Manufacturing USA (USA), Industrie du Futur (France) to name a few. Despite the need for installation, maintenance, and operation of physical and static equipment, there is an increasing need for the creation and implementation of suitable communication and internet protocols.

Therefore, it can be highlighted that with the advent of Digital Transformation, there is a strong link between Mass Personalization and Artificial Intelligence (AI) in the context of Industry 4.0 [20]. Digital Transformation enables the integration of advanced technologies such as AI, Machine Learning (ML), and Deep Learning (DL) into industrial applications, particularly robotics. These technologies offer new possibilities for enhanced productivity and efficiency in manufacturing processes. For example, AI-powered machine vision systems can inspect products with greater accuracy than human operators, leading to improved quality control. Moreover, AI can enable the creation of Digital Twins, virtual replicas of physical systems, allowing for simulations and optimization of production processes [21]. The combination of Mass Personalization, which caters to the demand for customized products, and AI-driven technologies paves the way for more agile and adaptable manufacturing systems [22]. As we progress towards Industry 5.0 and Society 5.0, there will be a greater focus on human-technology collaboration and the development of human–machine interfaces (HMIs) to facilitate seamless interaction between humans and cognitive systems [23]. Thus, this essay focuses on decisions related to responsive and flexible manufacturing operations, self-optimization of manufacturing operations, and the efficient personalization of customers' experience. To sum up, the integration of AI and digital technologies is crucial for achieving the vision of Industry 4.0 and enabling the realization of Mass Personalization in manufacturing.

1.2 Global Production Networks

During the last decade manufacturing and production systems are coping to reorganize their entities towards the adoption of a decentralized network architecture. Due to the scarcity of resources, localization, and unique equipment required for highly personalized products, decentralization of manufacturing and production networks has enabled companies to maintain their competitive edge and satisfy the volatile market demand. The decentralization trend has been greatly supported by the integration of the pillar technologies introduced under the light of the ongoing Industry 4.0. Despite the utilization of cutting-edge digital technologies as a solution to complexity caused by mass personalization, for the management of global production networks, engineers are facing new challenges in redesigning management strategies [17]. In Fig. 1 the core activities that take place during the design and operation of GPNs are summarized. Concretely in the above-mentioned Fig. 1 there have been defined the key entities of a GPN, covering two aspects, the production of the goods, and the commercialization of the final products. Regarding the production of the goods, the entities involved are, (i) the GPN plants (i.e. the main factories producing the final assembly/product), (ii) the supplier plants which produce individual parts, and (iii) the recovery plants which are responsible for gathering products back from the customers/end users. Similarly, in the market side, the entities involved are in particular, (i) the distribution centers which are responsible for the delivering the goods (i.e., the finished products) to the selling points, (ii) the collection points which receive the products at the end of their lifecycle, in order to be sent to the recovery plants, and the most important entities are the customers.

The authors in [24] explore resource sharing dynamics in a production network, focusing on the anticipated increase in resource sharing demand. Using a steel manufacturing example, four scenarios with varying levels of information exchange

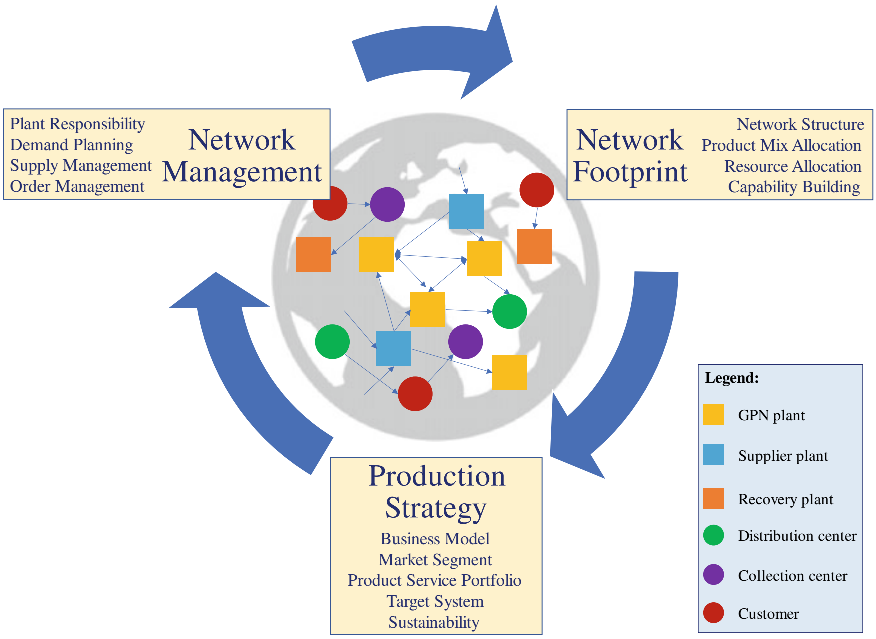

Fig. 1 Core tasks required for the design and operation of Global Production Networks

were developed. The results of this research work reveal that increased information exchange may not benefit all participating companies, as it can lead to longer cycle times for smaller companies and increased cycle time variance. Additionally, the simulation suggests that higher information exchange can result in inventory level fluctuations for shared resources. The origin of oscillatory behavior in the system was attributed to the relationships between companies and shared resources, rather than individual company or resource dynamics. Furthermore, the paper emphasizes the need for future decision-making designs to address such behavior and proposes that the findings can be applied to other production networks aiming to optimize resource utilization. The combination of discrete-event simulation and control-theoretic modeling offers a comprehensive approach to identifying fundamental dynamic properties in sharing scenarios.

1.3 Structure of the Essay

The Essay is divided into several sections that provide a structured exploration of key topics related to digital transformation, global production networks, artificial intelligence in smart factories, and efficient production management. The first section serves as an introduction, setting the stage for the subsequent discussions. It introduces the concepts of digital transformation and global production networks and outlines the essay's structure. The second section deals with the shift from traditional manufacturing to mass personalization, covering production management, smart manufacturing, decision-making challenges, complexity in manufacturing systems, and specific challenges faced in global production networks. The third section focuses on artificial intelligence in the context of smart factories, highlighting the utilization of data for knowledge generation, implementation of nature-based optimization algorithms, and AI decision-making at the network level. The fourth section introduces reference architecture model for efficient production management, encompassing an AI-assisted customized manufacturing factory, edge computing-assisted intelligent agents, digital transformation in resilient global production network frameworks, and the significance of data security. Finally, the last section offers a discussion of the main findings and an outlook for future research. Through these sections, the essay presents a comprehensive examination of the subject matter, guiding readers through the steps of understanding digital transformation, global production networks, AI in smart factories, and efficient production management. The structure of the Essay is presented in Fig. 2.

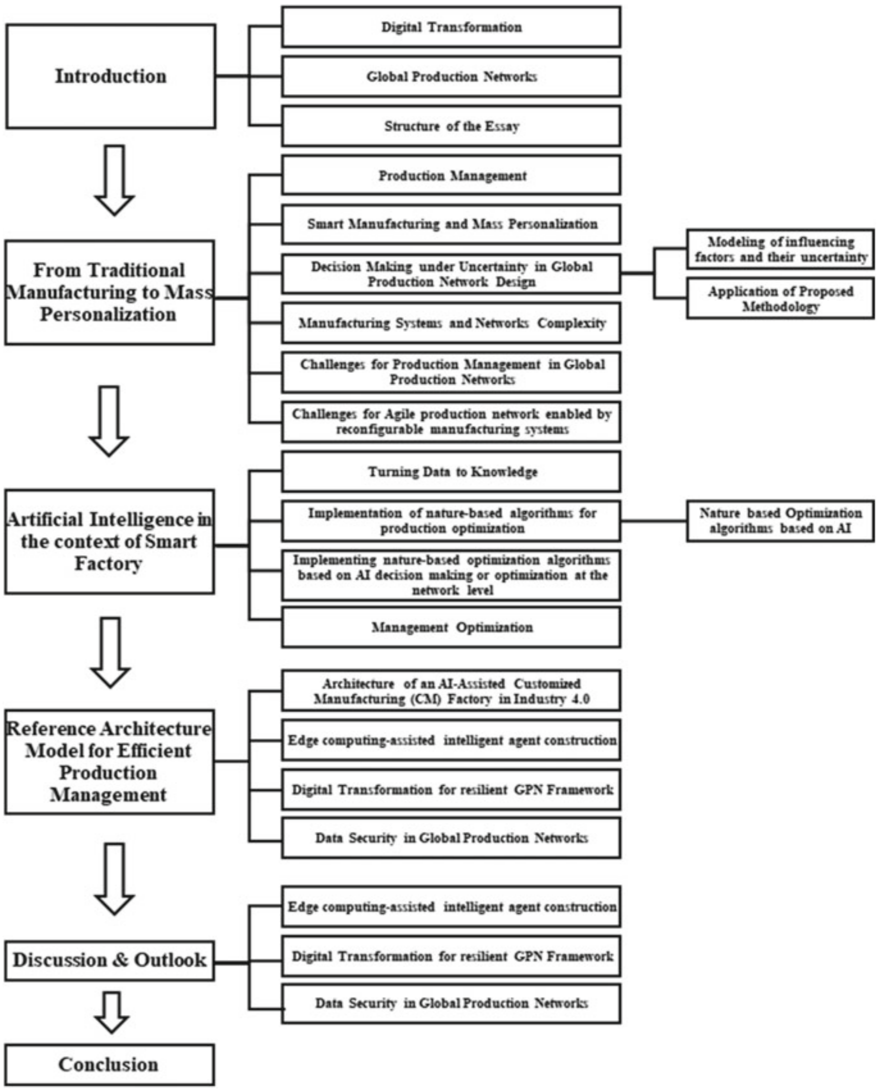

Fig. 2 Structure of the essay

2 From Traditional Manufacturing to Mass Personalization

Over the past century Manufacturing and Production paradigms have undergone several changes, ranging from the production of small batches to the mass production of goods in large volumes with minimal or no individualization prospects. Following the discussion of the previous paragraphs digitalization lies among the most influential concepts for the reshaping of Industry, and by extension of Society. The rapid development of new technologies has reshaped traditional manufacturing methods. With the arrival of the Fourth Industrial Revolution, a significant number of smart sensors capable of monitoring production in real time have been integrated into machines and manufacturing environments. These can help engineers make decisions while reducing production downtime and overall costs and improving product quality, providing engineers with continuous support throughout a series of product development phases [25]. CAx platforms and IT systems are now an essential part of standard product development processes. Mass personalization strategies typically allow potential customers to review and order individualized products, which necessitates more complex production configurations and processes [26, 27]. These strategies do not focus only on the personalization of products, but should also include personalized production and markets, since both aspects can dictate changes on the previous manufacturing level. The design and operation of production networks include decisions related to the production strategy of a company, network footprint, and network management, which can be divided into core and sub-tasks. The decision making should be done according to the principles of the Product Service System (PSS) [28, 29], but overall this decision making is highly dependent on the company, management and operational team, country, legal framework and political situation.

Since the global market has changed over the past few decades, centralized mass production appears unable to keep up with the new production demands that globalization has imposed [30]. Furthermore, according to Chryssolouris statement, "It is increasingly evident that the era of mass production is being replaced by the era of market niches. The key to creating products that can meet the demands of a diversified customer base, is a short development cycle yielding low cost and high-quality goods in sufficient quantity to meet demand" [31]. As a result, the model of an independent business that is only connected to its clients and suppliers through the delivery and acquisition of goods is no longer viable. Cooperation between businesses in Business to Business (B2B) Marketplaces and Platforms is essential [32]. The apparent gap between mass production and mass customization is a challenging issue that needs to be addressed [33]. As a result, Mourtzis et al. (2019) [34] present the cost-efficient, quick, and accurate optimal design network configurations that are dedicated to the production of highly customized products. This paper discusses an investigation into the performance and viability of centralized and decentralized production networks under heavy product customization. To evaluate the performance of automotive manufacturing networks under highly diversified product demand, discrete-event simulation models have been developed. A manufacturing network configuration must be created effectively due to the escalating demand for more product customization and the fluctuating nature of demand. Production planners, however, are impacted by the vast array of alternative design configurations because they can no longer rely on experience to plan the network. In order to achieve this, a novel platform for designing and evaluating Dynamic Manufacturing Networks has been presented in [35]. The method assesses the effectiveness and viability of centralized and decentralized production networks under the condition of high product customization. In addition, simulation models for automotive networks are created, and their effectiveness is assessed. The decision-making process then employs an exhaustive search and an intelligent search algorithm (ISA), respectively [36].

2.1 Production Management

By definition, manufacturing is a complex series of tasks and processes, demanding careful and precise management, regardless of the size of the company. Production management focuses on the utilization and allocation of resources in order to produce the final products [37]. Therefore, its importance becomes evident. Since management involves several processes within a workday, the research results presented in [38] have been compiled in the chart presented in Fig. 3, in order to highlight the most time-consuming tasks, indicating that approximately 54% of time is spent on administrative coordination and control activities.

In order to support production management, insights are required so that proper/valuable management reports can be produced. In the era of Industry 4.0, Big Data and Analytics, as technological pillars provide the necessary context in order to provide the companies' management teams with sufficient data for more in-depth reporting. However, according to recent reports [62] 53% of the managers feel that

Fig. 3 Management time distribution as a percentage of the total management within a workday

the quality of the available data is not sufficient. The above-mentioned percentage raises to eighty percent considering the lack of executive sponsorship.

Moving on to the Sustainable pillar of production networks, considerations regarding the environmental aspects of production are crucial in achieving sustainable development goals, particularly in the manufacturing sector. Sustainable Development Goals (SDGs) set by the United Nations provide a framework for addressing environmental concerns [39]. Manufacturing processes should prioritize resource efficiency, waste reduction, and pollution prevention to minimize their ecological footprint. Embracing sustainable manufacturing practices such as eco-design, clean energy adoption, and circular economy principles can contribute to SDGs such as responsible consumption and production, climate action, and sustainable cities and communities. By integrating environmental considerations into production practices, industries can move towards a more sustainable future, ensuring the well-being of both present and future generations [40]. The SDGs related to production and manufacturing, are briefly summarized as follows:

- SDG 9: Industry, Innovation, and Infrastructure—Promote sustainable industrialization and innovation.
- SDG 12: Responsible Consumption and Production—Encourage sustainable consumption and production patterns.
- SDG 13: Climate Action—Take action to combat climate change, including in manufacturing processes.
- SDG 11: Sustainable Cities and Communities—Foster sustainable industrialization within urban areas.

2.2 Smart Manufacturing and Mass Personalization

The rise of Mass Personalization necessitates manufacturing operations that can adapt to produce personalized products at scale, accommodating changing demands and conditions. However, current manufacturing systems struggle to maintain stable performance while adjusting configurations and production plans. Therefore, the authors in [41] to address these challenges propose a self-optimizing manufacturing system capable of autonomous and error-tolerant production. Moreover, they provide a systematic review of Self-Organizing Manufacturing Systems (SOMS) and propose the concept of a Self-Organizing Manufacturing Network (SOMN) as the next-generation solution for achieving Mass Personalization (see Fig. 4). The review traces the development of SOMS, highlights their limitations in achieving mass personalization, and presents the functional requirements for self-organizing manufacturing. The proposed SOMN encompasses essential technological components, such as system modeling, control architecture, peer communications, and adaptive manufacturing control, drawing upon knowledge from various disciplines.

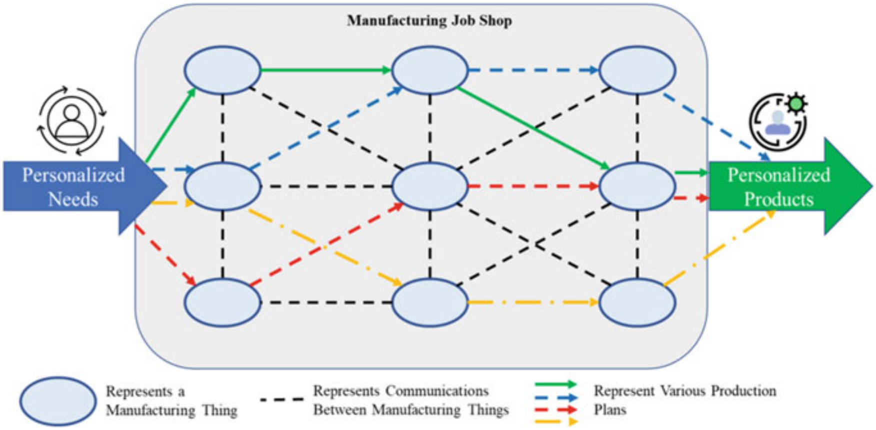

Fig. 4 Conceptual architecture of a self-organizing manufacturing system [41]

2.3 *Decision Making Under Uncertainty in Global Production Network Design*

Manufacturing companies today work in international production networks in order to manufacture their products and gain a competitive advantage [42]. Even though decisions made in the context of these complex production networks affect manufacturing companies over the long term, there is frequently a lack of integrated planning of the production network [43]. Thus, continuous network adaptive design is required to withstand the volatile environment and to be able to react to altering constraints [44]. It is imperative for companies to adapt and react to changes in their production networks so as to succeed in the face of intense competition [45]. Next, the design of production networks is closely associated with high degrees of freedom [46]. In addition, there are several influencing variables influencing the design of GPN such as volatility, production and process variables, supplier agreements, location factors and legal framework conditions [47]. The abovementioned challenges and factors, lead to complex management of GPN as stated in [44]. Reducing complexity while maintaining high decision quality is necessary to speed up design decisions for production networks because difficult-to-reverse decisions can restrict the long-term strategic options of a company [44]. There are several different quantitative and qualitative approaches for decision support in the production network design [42], which can be designed in any level of detail or aggregation, leading to a conflict of objectives between low effort and necessary accuracy [47].

The decision-making problem is always accompanied by uncertainties because of the long-term orientation and the variety of influencing factors. Therefore, for decisions involving uncertain future developments, it is necessary to take into account scenarios and their possibility of occurrence [48]. Thus, the authors in [49] presented an effort oriented and transparent decision-making process in the design of GPN and to address the necessary comprehensibility.

There are two main categories of decision-making techniques used in the design of GPN as follows: (1) qualitative, and (2) quantitative. The latter ones can be further divided to process-oriented approaches with manual selection of alternatives as well as to heuristics or optimization approaches. Furthermore, both categories can be furthered divided into stochastic and deterministic methods [50]. An overview of the body of knowledge in the field is presented in [51]. A methodical process for decision-making without an alternative selection logic is offered by quantitative, process-oriented approaches. These introduce process-based methods for the configuration of production networks through the provision of a decision support procedure [52]. Due to the incorporation of decision rules for the selection of specific results, quantitative approaches with automated decision models for network design differ from process-based approaches. More specifically, these approaches provide decision rules for the selection of specific outcomes. On the other hand, the decision field considers design alternatives and environmental condition [53–55].

Three main steps can be identified in the methodology for the support of the decision-making process in the design of global production networks. The underlying research hypothesis is that early recognition of the critical decision-influencing factors speeds up gathering information and ensures a transparent decision-making process. The first step is about the classification of factors that influence design alternatives as well as the assessment dimensions. The second step regards the stochastic modeling of influencing factors using arithmetic random walks. The third step is finally solved using a Monte-Carlo-Simulation (MCS), which is then transferred into an assessment cockpit that ranks the design alternatives according to their net present value and displays the key influencing factors as well as their aleatory and epistemic uncertainty. The process is repeated until a choice can be made [48]. The most frequently identified keywords in literature are used in [56] and are relevant to the sand cone model proposed by the authors in [38]. In order to compare the economic efficiency as the quantitative target variable of the alternatives, the qualifying targets to be met are quality, flexibility, and time. A supply chain perspective is used to define the targets along the design alternative in order to evaluate the satisfaction of customer needs in terms of quality, flexibility, and time. A design alternative is not considered in the decision-making process if it does not satisfy one of the qualifying target variables. Utilizing economic efficiency as the optimization variable, the final design alternative is chosen from the remaining alternatives. As a result, in the framework of the model proposed in [48], only financial influencing factors are presented with the design alternatives (Fig. 5).

2.3.1 Modeling of Influencing Factors and Their Uncertainty

Models play a crucial role in decision-making for network design by considering time-dependent factors under uncertainty. Stochastic modeling using arithmetic random walks assesses individual factors and incorporates both epistemic and

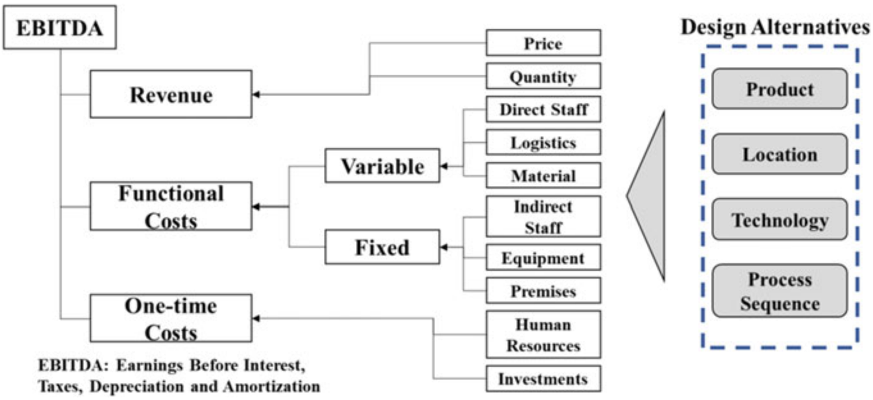

Fig. 5 Influencing factors in the context of production network design [48]

aleatory uncertainty over time. The modeling process involves four steps: specifying the epistemic uncertainty as a distribution function, incorporating aleatory uncertainty through random walks, and determining confidence intervals. The arithmetic random walk equation for an influencing factor over time depends on the selected distribution function.

$$IF(t) = \frac{X_0 + X_0 * apa * t + \sigma_e * snv1 + \sigma_\alpha * \sqrt{t} * snv2}{(1 + WACC)^t}$$

If x_0 is known, then there is no epistemic uncertainty and as a result the standard deviation of the epidemic uncertainty is $\sigma_e = 0$. The standard deviation of aleatory uncertainty is represented by σ_a while the expected annual development of the initial value is denoted as apa. The discounted interest rate, determined by the weighted average cost of capital (WACC), is applied. snv1 and "snv2" represent standard normally distributed random numbers. When influencing factors are dependent, their correlations are determined by the covariance of random variables, resulting in the expected value [48].

2.3.2 Application of Proposed Methodology

The described methodology was implemented in a real case study involving a machine tool manufacturer. The company had developed a production network with six sites in Europe over the past three decades, resulting in overcapacities that needed to be addressed. Four alternatives were derived to redesign the network structure, considering restrictions such as core competence sites and product distribution (Fig. 6). The economic efficiency of these alternatives was assessed over a 10-year period, taking into account six influencing factors. These factors included additional buy parts, machine hour rates, site base costs, logistics, implementation/divestiture

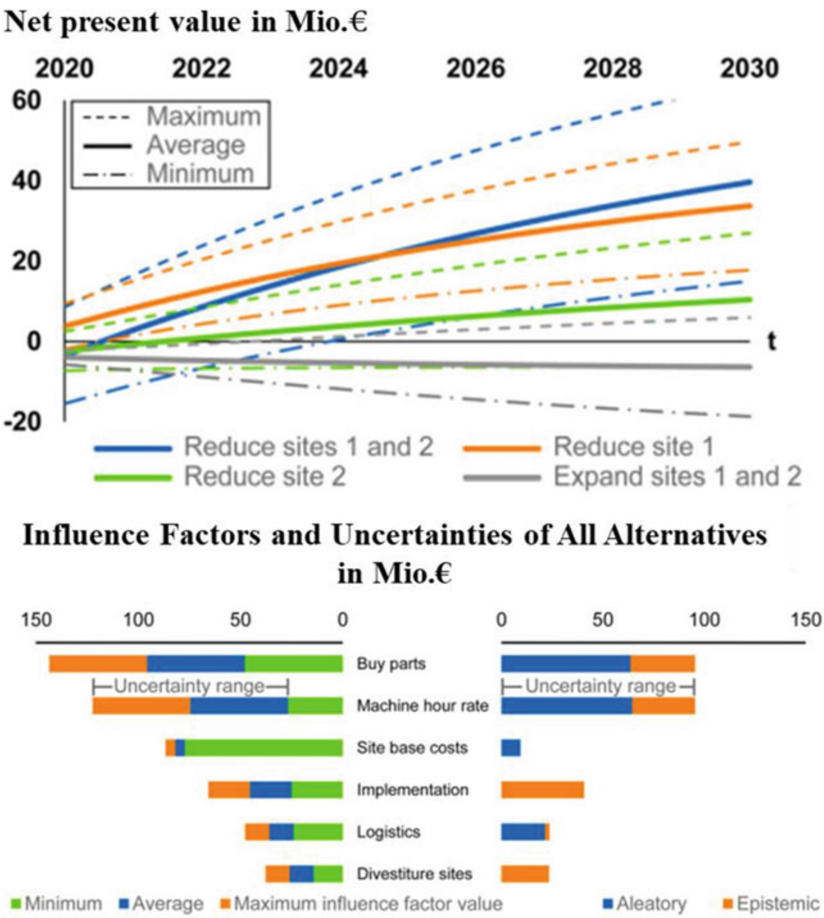

Fig. 6 Assessment cockpit of the first iteration to support decision making under uncertainty in global production network design [48]

costs, and uncertainties. The assessment revealed that the expansion of sites 1 and 2 and the reduction of site 1 were not beneficial, while reducing sites 1 and 2 showed the highest economic efficiency with a net present value of 33.7 Mio. € and a short amortization period of 1.6 years [48].

2.4 Manufacturing Systems and Networks Complexity

Manufacturing systems and networks are constantly expanding, in order to adopt a decentralized architecture. Further to that, with the implementation of the Industry 4.0 large amounts of data are constantly produced within the manufacturing environment.

Considering the market volatility it can be concluded that modern manufacturing and production activities take place in a highly dynamic environment. Consequently, complexity is useful metric for the realization of operational complexity. Following this context complexity quantification can be further divided to part, product, system and system of systems [56]. The literature also suggests that complexity of global networks can be divided to static and dynamic, following the utilization of entropy calculation methods [57]. A multi-layered methodology has been implemented for the analysis of global production networks, focusing on the plurality and diversity aspects of the networks, aiming to the assessment of the complexity for global production networks [58]. The recent global developments have unveiled that production and manufacturing systems are very prone to failure/collapse as a result of the disruption of the global supply chains. As a result, the authors in [59] following a systematic analysis of systems and networks have proposed a method for the provision of alternative solutions regarding the structure of the networks, aiming at the reduction of the effect caused by external disturbances. From a complexity point of view, the dynamic manufacturing networks (DMNs) offer a modern approach to managing risks and increasing benefits in the manufacturing sector [60]. In particular, the authors have compiled information regarding three cornerstone supply chains regarding, (i) food, (ii) textiles, and (iii) chemicals. The research work concluded that social sustainability is a factor playing a key role to the complexity of global production networks.

More specifically, challenges arise in managing GPNs due to disruptions that lead to various issues such as order modifications, quality problems, and engineering changes. The negative impact on performance can be mitigated by fostering a more extensive sharing of information among network partners. Digitalization provides numerous opportunities to enhance transparency in this regard. Nonetheless, determining the optimal level of interaction and implementing a broader information exchange poses a complex decision-making problem [61]. A disruption on either the supplier or customer side of today's tightly coupled supply chains can easily devastate the entire Supply Chain Network (SCN). The pandemic caused significant supply chain disruption, necessitating leaders to right-size their operations and embrace digital capabilities that protect supply chains from future disruptions as we transition into the post-COVID-19 reality [62]. Companies across all industries are increasing their investments in advanced technology, ranging from blockchain to artificial intelligence (AI), machine learning, and intelligent automation [63, 64]. During the COVID-19 pandemic, global supply chains were confronted with both a supply shortage and a shrinking demand, which could result in disruptions propagating forward and backward simultaneously or sequentially [65–67]. The Closed-Loop Control Systems of the Control Theory has been parallelized to a Closed-Loop Crisis Response Framework that explains the Supply Chains Disruption (see Fig. 7).

As it regards, companies across various industries and sizes organize their production through global production networks, where partners including suppliers, producers, distributors, and customers collaborate and contribute their expertise to deliver goods and services [68]. These networks are typically aligned with the strategy of a central partner and are the outcome of evolutionary decisions. Unfortunately, a

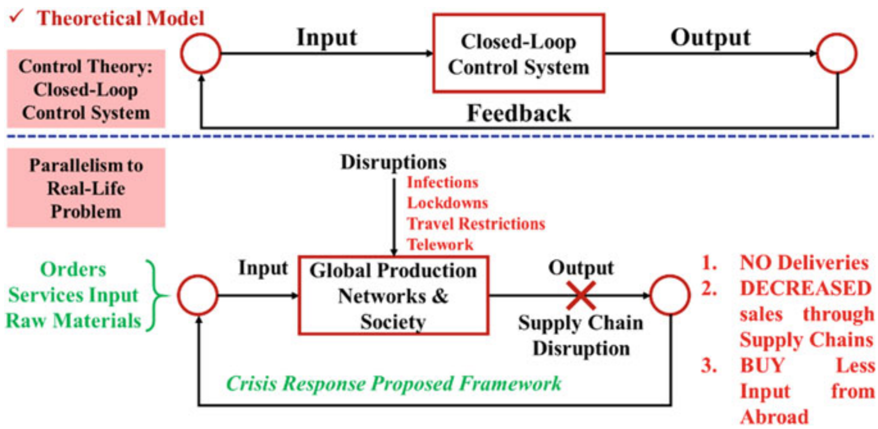

Fig. 7 Closed-loop crisis/disruption response framework [45]

prevailing mindset of insulation and silo thinking hampers transparency and collaboration within these networks. Disruptions at the operational level, caused by unforeseen events like quality issues, equipment failures, and supplier bankruptcies, have a negative impact on network performance [69]. The most affected business processes are order management, quality problem resolution, and engineering change management. The automotive industry, in particular, is more vulnerable to disruptions due to lean production and just-in-time delivery practices. To address this, the ongoing digitization and increased horizontal interlinkage among production network partners hold the promise of faster identification and resolution of disruptions [70].

The effects of a local disruption are unpredictable due to the propagating effects, which makes it challenging to plan for and manage. Risk identification is typically the first step in traditional supply chain risk management, which is followed by several risk management strategies [71, 72]. Every industrial revolution is accompanied by technological unemployment, but this is simply a characteristic of the human workforce because it is predicted that there will be an increase in the number of jobs globally [73].

2.5 Challenges for Production Management in Global Production Networks

With regards to GPNs, in the literature two generations can be identified. In particular, GPN1.0 has been developed in the 2000s [73], whereas GPN2.0 has been introduced a decade later, during the 2010s [74]. This is important, in order to familiarize with the terms as well as to clarify the differences between the two generations as they are reflected to other aspects, such as production management. Essentially, GPN1.0 was a more broad representation of the concept. On the contrary, GPN2.0 has been

Fig. 8 Key challenges and associated barriers in global production networks

presented as a more concise framework, taking into consideration the emerging challenges in the setup, management, and operation of GPNs. GPN2.0 has been developed under the framework of a theory for improving industrial organization and ensure economic development in an interconnected global economic landscape [74]. In light of the GPN2.0 framework five different types of risks have been identified, in particular (i) product quality, (ii) economic, (iii) regulatory, (iv) environmental, and (v) labor. In Fig. 8 several of the key challenges and their associated barriers regarding the operation and management of GPNs have been compiled and categorized. However, the integration of GPN2.0 framework does not necessarily guarantee the network's resiliency, which as it is discussed in the next paragraph is at high risk.

Following the recent developments of the global pandemic, it became obvious to the community, that GPNs do not possess the minimum required level of resilience. In fact, the current structure of such systems and networks has indicated that they are reluctant to sudden changes, often leading to unavoidable collapse. Dolgui and Ivanov in 2021 [74] have extensively investigated this issue from the viewpoint of the so-called ripple effect, focusing on its effects in supply chain management. The recent global pandemic has provided concrete evidence on the effect of disruptions to global production.

2.6 Challenges for Agile Production Network Enabled by Reconfigurable Manufacturing Systems

Reconfigurable manufacturing systems (RMSs) consist of machines with interchangeable modules, allowing for flexible functionality [75]. Coordinating production flows, machines, and modules requires complex decision-making algorithms

[76]. Resource sharing among collaborative manufacturing systems enhances production networks [77]. Responding to disruptions promotes network robustness [78]. Reconfigurable machines offer adaptability but fall short in emergencies. Leveraging collaborative RMSs for global network reconfiguration is a challenge [79]. More specifically, reconfiguration decisions pose challenges due to their connection with process and production planning, the roles of companies in the supply chain, and the flow of materials. The dynamic adjustment of the production network impacts collaborative machine and module sharing, which subsequently affects the production capabilities and material flow of companies. As such, the authors in [80] suggest an agile management strategy that utilizes reconfigurable manufacturing systems (RMSs) to enable a timely and flexible response to the pandemic. The approach involves iterative transformations of production networks from their pre-emergency state to achieve adaptation. Within this study, the authors consider lead-time and missed demand as crucial indicators of health risk (e.g., achieving reconfiguration with shorter lead-time could increase ventilator availability and reduce fatalities) and economic losses (e.g., inability to deliver regular commercial products due to system adaptation). As it regards the Network Interaction, the main objective of the Manufacturing System Reconfiguration (MSR) model is to align the ramp-up time and target capacity, while maximizing the capacity for commercial production based on the optimized production network target. On the other hand, the Production Network Reconfiguration (PNR) model creates a production plan within the given ramp-up time and achievable production capacity obtained from the MSR model. These two models rely on each other's inputs and calculations, and their interaction is crucial in determining the optimal solution. The PNR model aims to minimize the ramp-up time to increase production for both commercial products and critical resources. However, the feasibility of the plan must be evaluated by the MSR model to ensure that it can meet the production plan, even if it doesn't reach the target capacity. To avoid making infeasible decisions due to tight constraints during direct interaction, the MSR model initiates the iteration process with configurations that require a relatively longer ramp-up time and continues until an agreement is reached with the PNR model. The interaction process concludes when the remaining demands no longer decrease. To overcome potential challenges of getting trapped in local optima, the MSR model selectively relaxes the ramp-up time constraints to broaden the search space, thereby enhancing the robustness of the decisions.

3 Artificial Intelligence in the Context of Smart Factory

This section starts from presenting tools to transform signal-captured data to actual information and subsequently to useful knowledge. This is further supported by presenting cases from literature where some nature inspired algorithms were used for production and management optimisation, with reference architectures found in Sect. 4.

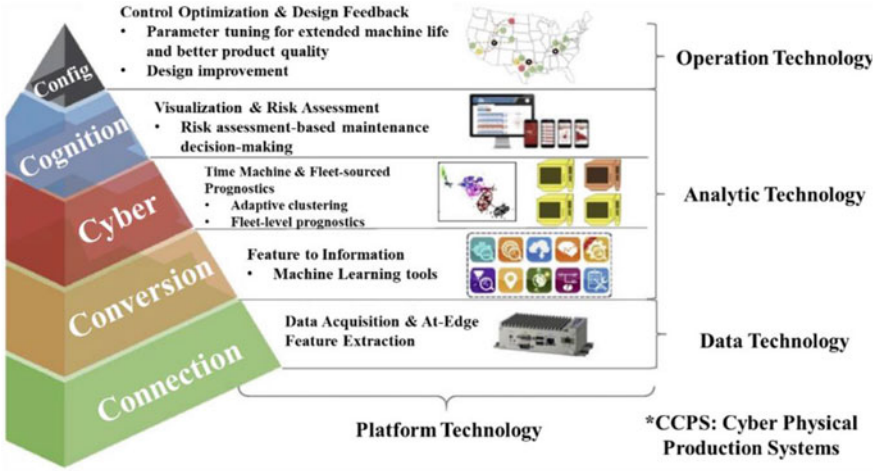

Fig. 9 From Automation Pyramid to Digital Transformation with Industry 4.0 [82]

3.1 Turning Data to Knowledge

Chen et al. in 2022 [81] in their research work have investigated data-driven approaches for constructing dynamic content for efficient knowledge management. Industrial AI plays a crucial role in creating intelligent and resilient industrial systems that possess fault tolerance, self-organization, and on-demand capabilities. It is a systematic discipline that focuses on the development, validation, and deployment of machine learning algorithms specifically designed for industrial applications, ensuring sustainable performance. The core concept revolves around delivering manufacturing services to end users by effectively coordinating distributed manufacturing resources through the integration of AI methodologies. Figure 9 provides a visual representation of how the four enabling technologies of industrial AI can be better understood within the context of the IMS 5C-CPPS architecture. This architectural framework offers a comprehensive and step-by-step strategy, encompassing data collection, processing, analysis, and ultimately generating value [82].

3.2 Implementation of Nature-Based Algorithms for Production Optimization

Optimization is a broad topic, which covers all the technologies, techniques and algorithmic approaches for enabling engineers to enhance a plethora of manufacturing and production activities. The most prevailing approaches until recently were (i) deterministic, and (ii) meta-heuristic. However, the recent technological advances

Fig. 10 The bi-directional systematic approach to identify the potential impact of biological transformation of manufacturing

imposed by Industry 4.0 and its pillar technologies, advanced computational capabilities in combination with AI have enabled engineers to design and implement algorithms based on principles and concepts of nature. Therefore, in Fig. 10 an attempt has been made for comparing core Biology concepts versus Manufacturing concepts. Therefore, in the center part of the Fig. 10, bio-inspired approaches/algorithms are illustrated [83].

Nature-based algorithms also defined as "Bio-localization in Manufacturing" can be realized as the imitation of nature-based algorithms for solving engineering problems. Briefly, some examples are mentioned, falling under the category of swarm algorithms. Such algorithms are imitating the behavior of groups of animals and particles in order to optimize a mathematically modelled problem. Concretely such mathematical models are structured in a way that they are expressed as minimization or maximization problems. The implementation of any kind of AI requires a training process for the computerized system before it can provide suggestions/predictions and perform any kind of data analysis. Consequently, the need for implementing optimization methods becomes mandatory. On the other hand, nature's optimization mechanisms, follow the "Open Adaptation" paradigm. Concretely, Open Adaptation does not require the strict setup of the above-mentioned parameters, thus entailing an advanced level of intelligence versus the evolutionary intelligence of modern computational systems [84]. By extension, it is necessary for engineers to reverse engineer nature's algorithmic approaches, before proceeding with application in manufacturing systems.

In the context of continuous production systems, The authors in [85] introduce a new algorithm simulating the behavior of the Siberian Tiger, and which operates in two stages, namely (i) the attacking stage, and (ii) the chase phase. The algorithm has been tested in a variety of engineering applications indicating promising results in comparison with similar optimization algorithms. On the contrary, Trojovská et al. in 2022 [86] have developed an algorithm which mimics the behavioral patterns of zebras, including the foraging and defense actions. Following the validation of the algorithm in common engineering problem, its superiority over traditional heuristic algorithms is proved. Finally, in [87] the authors have proposed a bio-inspired meta-heuristic algorithm inspired by the hunting behavior of the Tasmanian devil. Through testing the proposed algorithm outperforms the common algorithms in terms of exploration abilities and quality of results.

In the previous paragraph, a handful of cutting-edge bio-inspired algorithms have been presented. Undeniably, this does not cover the entirety of the algorithms. However, this discussion provides concrete evidence, that engineers should investigate the working principles of natural activities throughout its species, in order to develop robust optimization models. Furthermore, it can also be concluded that AI is not a revolutionary technological field. Instead the technological advances have unveiled its potential.

It can be concluded that natural systems are extremely complex systems that have significant effort and stages of development, adaptation, and optimization. A potential strategy for the effective decoding of the natural systems would be the creation of parallels as we delve deeper into their structure. Engineers could concentrate on modeling natural systems as engineering systems or translating natural processes into engineering/system processes. For example, the logic of immune systems may help in the creation of crisis management plans. The robustness and resilience of systems, which have been extensively studied over the past two years, could specifically imitate the principles of immune systems in order to detect volatile behaviors, detect and recover from external disturbances, and consequently to reschedule the operation of the production network in order to minimize undesirable effects. Further to that, similar to how humans use collective systems, nature uses smaller communities as collective systems (e.g., insects). The development of scheduling techniques, such as job-shop scheduling, can benefit from these social insect societies and their operating principles, and their contribution may even extend to the planning and organization of entire manufacturing networks. Ultimately, nature could be considered as a black box that engineers have not yet fully decoded. However, there are a few crucial issues that demand discussion and further study. First, engineering has traditionally relied on highly structured systems that, in some cases, are not flexible or adaptable to disturbances. These systems are also centralized and have all of their components overly defined, which reduces the degrees of freedom. On the other hand, natural systems, operate in an abstract manner. A pioneer new concept for manufacturing systems entitled "Biological Manufacturing Systems (BMS)" [88]. As a result, it is necessary to implement appropriate frameworks that give lower production levels access to decision-making tools and/or functionalities while providing adequate information about facility and network operations to the higher production levels. Consequently, holonic approaches have therefore been developed, realizing individual production entities as holons or agents, dispersed throughout the production network, capable of cooperating with other holons, but also autonomous.

Currently, more computational resources are needed due to the enormous amount of data generated daily from manufacturing facilities and the growing complexity of the digital/virtual models used to describe physical production networks. Therefore, complex calculations can be carried out more easily due to continuously connected device networks.

Recapping the context of this Section, engineers at a global scale have focused their efforts on the design, development, implementation, and improvement of bio-inspired algorithms. These category of algorithms in combination with the increasing computational resources/power, facilitates the design of more detailed/realistic models for manufacturing and production systems. However, despite the efforts for creating robust simulation frameworks, it remains unclear which type of algorithm to utilize, and what are the criteria for selecting an algorithm.

3.2.1 Nature Based Optimization Algorithms Based on AI

Nature-based optimization algorithms based on AI have found significant applications in production control at the operational level. These algorithms leverage concepts inspired by natural systems to optimize various aspects of production processes. Genetic Algorithms (GA) can be employed to optimize production scheduling, resource allocation, and inventory management, considering multiple objectives and constraints. Particle Swarm Optimization (PSO) can aid in production line balancing, minimizing cycle times, and improving throughput. Ant Colony Optimization (ACO) algorithms can optimize routing and scheduling in transportation and logistics, reducing delivery times and costs. These nature-based optimization algorithms (Fig. 11) provide efficient and effective solutions for production control, enabling organizations to achieve higher productivity, reduced costs, and improved overall operational efficiency [89]. Some key applications are summarized in Table 1. The Abbreviations are included in Nomenclature List.

3.3 Implementing Nature-Based Optimization Algorithms Based on AI Decision Making or Optimization at the Network Level

While various Nature-Inspired Optimization Algorithms (NIOAs) exhibit their own unique approaches, they generally adhere to a set of overarching principles. This section explores the shared concepts employed in NIOAs.

- **Exploration:** NIOAs focus on exploration, aiming to uncover unknown areas within the vast search space of NP-Hard optimization problems. This approach reduces time complexity by probing potential solution areas, helping to avoid sub-optimal solutions. The amount of emphasis placed on exploration directly

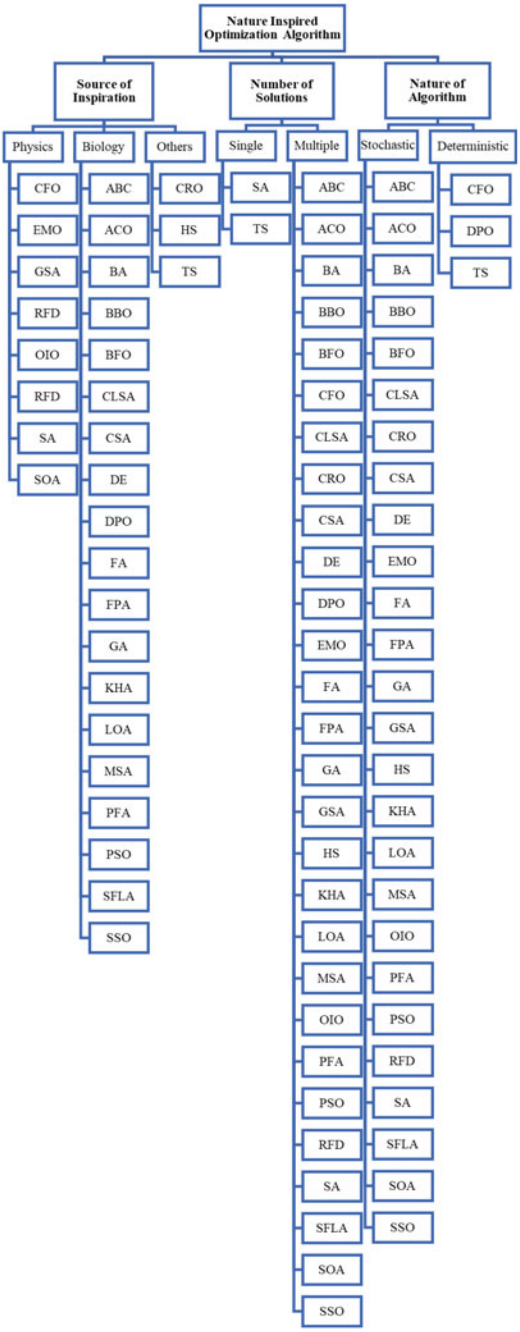

Fig. 11 Classification hierarchy of nature inspired optimization algorithms [89]

Table 1 Nature based Optimization algorithms based on AI that are used on production control level (Decision Making & Optimization)

Nature-based optimization algorithm	Description	Application in production control	References
Genetic algorithm	Concepts of mutation, crossover, and selection to iteratively search for the optimal solution	Production scheduling, resource allocation, and facility layout optimization	[90]
Particle swarm optimization	Nature-inspired algorithm that simulates the movement and cooperation of particles in a search space to find the optimal solution	Job shop scheduling, inventory management, and production planning	[91]
Ant colony optimization	Nature-inspired algorithm that uses pheromone trails to guide the search for the optimal solution	Routing and scheduling of material handling systems, vehicle routing, and supply chain optimization	[92]
Artificial bee colony algorithm	Mimics the foraging behavior of honeybee colonies, where bees explore the search space and communicate to find the best solution	Job scheduling, task allocation, and resource optimization in manufacturing environments	[93]
Firefly algorithm	Nature-inspired optimization algorithm that utilizes the attractiveness between fireflies to guide the search for optimal solutions	Production planning, facility layout design, and job shop scheduling	[94]
Grey wolf optimizer	Nature-inspired optimization algorithm that simulates the hunting behavior of grey wolves to search for the best solution in optimization problems	Production scheduling, workforce planning, and supply chain optimization	[95]
Cuckoo Search Algorithm (CSA)	Nature-inspired optimization algorithm that imitates the behavior of cuckoo birds to discover optimal solutions by replacing poorer solutions in the search space	Production control systems to optimize scheduling, resource allocation, and task assignment, improving efficiency and minimizing production costs	[96]

impacts an algorithm's performance, with well-executed exploration, particularly in the initial iterations, significantly improving algorithmic performance [97]

- **Exploitation:** In Nature-Inspired Optimization Algorithms (NIOAs), exploration involves searching for unknowns, while exploitation utilizes local knowledge to improve solutions. The exploitation process aims to find better solutions within a specific region of the search space, building upon existing best solutions. Balancing exploration and exploitation is crucial for achieving global optima, and the effectiveness of NIOAs relies on the coordination between these two processes [Yang X et. al., 2014].

- **Encoding:** NIOAs mimic complex natural phenomena that are difficult to replicate, requiring solutions to be represented in a specific format. This representation, known as encoding, transforms a solution into a problem-specific form, such as binary strings, ordered sets, unordered sets, or permutations, depending on the problem requirements. For instance, genetic algorithms commonly use binary string representations for the population of individuals [98].
- **Generation of New Solutions:** Algorithms generate solutions in two ways: (1) randomly at the start, and (2) through algorithmic operators during optimization. Generated solutions must adhere to encoding techniques and remain within the feasible search space. Accepted solutions with improved values contribute to generating better solutions in subsequent stages [89].
- **Elitism:** NIOAs are iterative algorithms that generate new solutions in each iteration, which may or may not be better than existing ones. Elitism is employed to preserve high-quality solutions separately, allowing them to potentially contribute to generating new solutions. The advantage of using elitism is that solution quality can improve with increasing iterations [89].
- **Stopping Criteria:** In real-world problems where the optimal solution is unknown, a significant number of iterations are required to approach it, necessitating the definition of appropriate stopping criteria. Literature proposes various techniques to address this issue, including setting maximum iterations and monitoring changes in the best solution over iterations. Careful consideration should be given to the selection of a specific criterion as it can impact the algorithm's performance [99].
- **Interpretation of result:** NIOAs are stochastic algorithms that select solutions randomly from the search space, leading to potential local optima. Different algorithms may yield varying results even with the same parameters, making correct interpretation crucial. Guaranteeing the best solution is impossible as the entire search space is not considered. To address this, a common approach is to run the algorithm multiple times, compare results, and select the best outcome [89].
- **Objective function:** The objective function is a fundamental component within the realm of optimization, serving as a representation of the function that requires optimization. Once a solution is generated, it becomes imperative for the algorithm to assess its efficacy. The quality of a solution is determined by its associated objective function value, which may manifest as a formal mathematical function or take on a different form based on the specific problem at hand. This objective function plays a crucial role in facilitating decision-making processes within the algorithm, influencing judgments regarding the selection of solutions to carry forward into subsequent iterations and determining the applicability of specific operators to individual solutions [89].

3.4 Management Optimization

Liu in 2023 [100] has proposed a supply chain management model targeting at the more robust control of uncertainties and ensuring that the supply chain operation adheres to the latest environmental regulations, for small and medium sized enterprises (SMEs). The proposed model is based on the implementation of a tabu search algorithm, which imitates the functioning of the human memory. What is worth noting, is the influence of this supply chain model in the decision-making processes. Concretely, the framework can support managers into making more environmentally friendly decisions, without compromising the company's economic growth.

The aspect of genetic algorithms implementation in supply chain management is investigated by Santos et al. in 2022 [88]. More specifically, the authors have proposed a framework based on the utilization of a genetic optimization for resource replenishment for dynamic industries, which have a plethora of product codes, thus having complex resource requirements. Due to the complexity of the manufacturing system and the corresponding complexity of the model, simulations are resource intensive in terms of computational power, which depending on the time horizon, might be acceptable. Supply chain management has been investigated by Chong et al. in 2022 [100], who have developed a Deep Reinforcement Learning model for the optimization of supply chains, considering aspects such as service level, inventory-to-sales ratio, and sell-through rate.

4 Reference Architecture Model for Efficient Production Management

4.1 Architecture of an AI-Assisted Customized Manufacturing (CM) Factory in Industry 4.0

Taking into consideration the information presented in Sect. 3 and the technological advancements of Industry 4.0, new frameworks for intelligent manufacturing are constantly being developed as can be summarized from the literature. In that context, in this Section, an architecture is presented and discussed for enhancing interconnectivity of the various manufacturing assets as well as for integrating AI techniques, for the provision of improved customization functionalities. The added value of the proposed architecture is the integration of ML elements/functionalities, such as knowledge graphs, artificial neural networks, and advanced HMI functionalities, in order to improve cornerstone metrics of the manufacturing network, such as, efficiency, scalability, sustainability, and flexibility. The core activities of the architecture take place at the Cloud Layer (see Fig. 12, center part), which hosts the AI functionalities. However, since devices and embedded systems are constantly being improved following the trends of micro-electronics, the integration of Edge

Computing is mandatory. By extension, with Edge Computing, the computational burden can be shifted from the Cloud to the Edge (local node layer), thus further minimizing the network traffic. Furthermore, Edge Computing facilitates achieving true real-time reaction from the computational systems. Consequently, for critically fast reactions/decisions, the Edge Computing functionalities are recalled. On the contrary, for decisions requiring more time, for efficient data processing, Cloud functionalities/services are recalled. Concretely, the framework presented in Fig. 12, is based on the interconnection and of three layers, in particular (i) the smart interaction, (ii) the smart devices, and (iii) smart services. More specifically, in this proposed AI-assisted Cognitive Manufacturing (AIaCM) framework, several components are identified, namely smart devices, smart interaction, the AI layer, and smart manufacturing services. The framework is explained in detail as follows:

Smart devices: This component encompasses robots, conveyors, and other controlled platforms that form the physical layer of the AIaCM system. Automatic control systems govern the operation of these devices, and real-time performance is crucial. Machine Learning (ML) algorithms, implemented on low-power devices like FPGAs, can enable real-time processing. Interconnections between physical devices are established through edge computing servers.

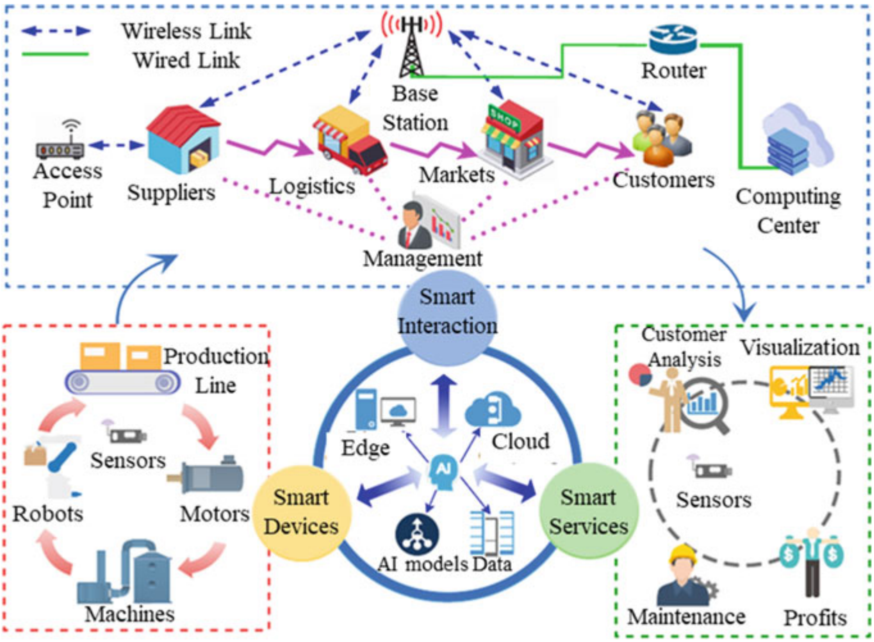

Fig. 12 Smart customization framework based on the utilization cloud, edge computing and artificial intelligence [101]

Smart interaction: Serving as a bridge between the device layer, AI layer, and services layer, this component consists of two modules. The first module comprises network devices like switches and routers, forming the network layer. The second module encompasses dynamic elements such as network protocols, information interaction, and data storage, facilitating connections between manufacturing processes. AI techniques, such as Recurrent Neural Networks (RNN) or Reservoir Computing (RC), are applied for tasks like wireless channel prediction and network optimization.

The AI layer: Algorithms running on computing platforms like edge or cloud servers form the AI layer. This environment incorporates cloud and edge computing servers equipped with frameworks like MapReduce, Hadoop, and Spark. AI algorithms are deployed at different levels, with cloud servers used for tasks like training deep learning models, while edge computing servers handle simpler algorithms for specific manufacturing operations.

Smart manufacturing services: This component encompasses various services, including data visualization, system maintenance, predictions, and market analysis. For instance, a recommender system can provide detailed information on CM products, while performance metrics of production lines, market trends, and supply chain efficiency contribute to comprehensive decision-making [101].

Next, having discussed the physical layer, which incorporates the machines and the sensing systems, the discussion of the smart interaction layer follows. This layer/module of the proposed architecture encapsulates the network infrastructure required for the wired and wireless communication of the sub-systems with the Cloud Computing framework. In this layer, there are two types of components used, in particular, the physical equipment which is static/fixed, and the digital assets, which are dynamic. The digital assets include the necessary communication protocols (IEEE 804.15.4, IEEE 802.15.4, DDS, AMQP, CoAP etc.), information interactions, and the information exchange (e.g. data storage). In this layer, ML algorithms can also be implemented in order to facilitate network optimization, improve network security, and reduce network traffic.

The closed-loop system is completed by the smart services layer/module, which encapsulates the functionalities and services provided to the human operators for facilitating the advanced HMI. Through the services provided, the engineers are capable of constantly monitoring the status of the manufacturing assets and making proper decisions. Further to that, engineers are capable of visualizing data and consequently planning ahead maintenance and repair operations. Among the list of provided services are the market analysis tools, which enable the company to capture the volatile market trends and demands. By extension, with proper adjustment of the manufacturing activities, the company is more capable of adapting to the concurrent circumstances, which leads to improved flexibility and sustainability. This methodology could be demonstrated in an example, however due to highly subjective decision-making of technologies for a case-specific implementation, the selection of technologies will depend on the agent of the decision making, the company's priorities, any legal framework and/or political aspects. Infrastructure is also important such as sensor type and data format, which can dictate the selection of technologies for the specific case.

4.2 Edge Computing-Assisted Intelligent Agent Construction

The production of big data, with increasing volume, variety, and speed, is one of the most important outcomes of IoT development. The modern range of mass customization, which entails satisfying the needs of individualized consumer markets, is built on the analysis of this data. Because of this, it is crucial to analyze this data in order to enhance decision-making and knowledge repositories. Tao et al. [1] presented a conceptual framework and typical application scenarios for big data in smart manufacturing [102]. For the quantification of complexity, many approaches based on heuristics, statistics, and probabilities have been also developed. Decentralized decision-making and real-time response to unexpected developments are two important factors influencing the flexibility required by a production chain to meet market demand. The global market landscape has shifted in recent decades, and hierarchical mass production appears to be incapable of meeting the changing demand requirements imposed by globalization [5].

In parallel, the advancements in intelligent edge and intelligent cloud have given manufacturing companies a great deal more autonomy. The edge device and the public cloud provider merge to form a new hybrid that allows suppliers, manufacturers, and industrial customers to collaborate effectively. The manufacturing operations management domain and its activities are described in ISO standard IEC 62,264 [103] following a real case from the management systems of a production line. This description makes it possible to integrate the manufacturing operations and control domain with the enterprise domain. This standard serves as a guideline for increasing interface uniformity and consistency while lowering the risk, cost, and errors associated with the implementation of these interfaces. Thus, the authors in [80] have proposed an edge-enabled manufacturing management platform. In this platform, the control domain and the manufacturing operations are executed by edge computing and the enterprise domain is handled by cloud computing. As depicted in Fig. 13, services and manufacturing activities such as maintenance, quality control and inventory management will be assisted by intelligent edge.

Since cloud computing, edge computing, and local computing paradigms have their unique set of advantages and disadvantages, they should be combined to maximize their effectiveness. Simultaneously, the corresponding AI algorithms should be redesigned to match the corresponding computing paradigm. Next, cloud intelligence is responsible for producing comprehensive, time intensive analysis and decisions. On the other hand, edge and local node intelligence present high applicability to time-aware environments. Intelligent manufacturing systems combine AI technologies to create smart manufacturing devices, intelligent information interaction, and intelligent manufacturing services. Figure 14 depicts an AI-assisted Cloud Manufacturing framework with smart devices, smart interaction, AI layer, and smart services. Manufacturing devices in the customized production paradigm should be capable of rapid restructuring and reuse for small batches of personalized products. However, achieving elastic and rapid control over massive manufacturing devices is challenging. The agent-based system was considered as a solution to this challenge.

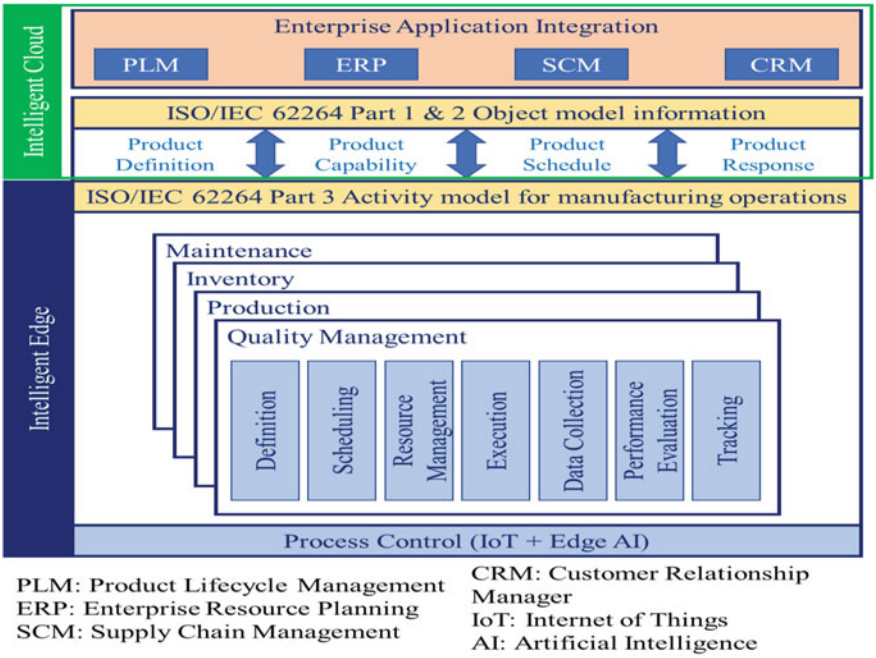

Fig. 13 Edge computing-assisted intelligent agent construction Architecture

Agents can operate autonomously and continuously in a collaborative system. A multi-agent system can be built to perform autonomous actions. Although a single agent has sensing, computing, and reasoning capabilities, it can only perform relatively simple tasks on its own. Smart manufacturing may entail complex tasks, such as image-based personalized product recognition, which is expected from emerging multi-agent systems applied in an Additive Manufacturing application [104]. A variety of decentralized manufacturing agents are connected to edge computing servers via high-speed industrial networks, as shown in Fig. 14. The device layer, agent layer, edge computing layer, and AI layer are all part of the edge computing assisted manufacturing agents.

The complexity of the product, particularly in highly personalized markets, affects the overall performance of the production systems. Moreover, production scheduling is a vital component of a decision-making process to address the challenge of high flexibility [105]. Therefore, a knowledge-enriched short-term job shop scheduling mechanism was proposed in [106]. The proposed framework was implemented into a mobile application for an actual milling machine. The operating principle focuses on the short-term scheduling of machine shop resources through an intelligent algorithm creating and comparing alternate resource allocations to tasks. In addition, a collection of mobile apps built to facilitate consumer integration in the service design phase and subsequently in the network design phase. The applicability of the mobile application is tested by customizing accessories and car aesthetics.

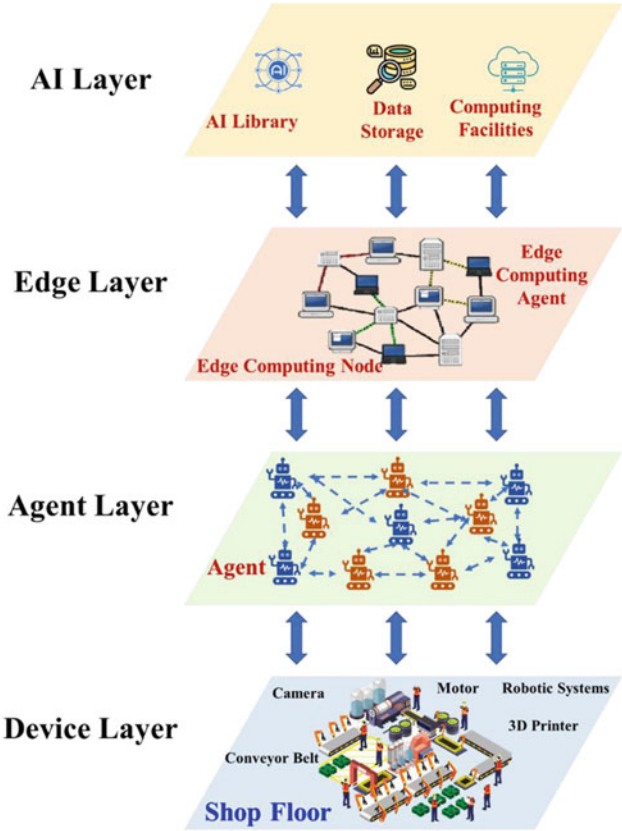

Fig. 14 Edge computing-assisted manufacturing devices

Next, a framework consisting of a mobile application supported by Augmented Reality (AR) technology and a production network design tool supported by a smart search algorithm is presented in [107]. In the product design phase, the proposed framework aims to integrate client ideas. Therefore, the customer contributes to the design of the production network. The results of the proposed research work were validated with a real-life application in the white-goods industry. Furthermore, production is based on routine tasks in many manufacturing plants, which can cause workload-related disorders. As a result, job rotation provides a widely accepted and adopted solution to that issue. However, due to the physical limitations of human operators, careful planning is a critical requirement for the avoidance of production bottlenecks. As such, the manager/engineer is responsible for the task allocation among the available employees. To that end, a web-based tool has been designed and developed in order to create job rotation schedules. The tool presented in [108] can calculate a range of alternative solutions that are continuously being evaluated and the most valuable solution is chosen, based primarily on the repetitiveness score and, secondly, on minimizing the distance of travel as a result of the constant work rotation. In the specific application, the focus was on assembling five trucks, with specific number of tasks, operators and workplaces involved.

Similarly, the authors in [109] present a novel production network model that utilizes a federation-based approach, enabling local factory agents to collaborate and share manufacturing assets. The goal is to enhance resource utilization and service levels. Using a real industrial data set, a cloud-based distributed framework was created for a limited number of factories. Building upon this concept, the framework was then scaled up significantly and modeled globally using AnyLogic's agent-based simulation. This simulation aimed to evaluate how the expansion of the federation impacts cooperation, service level variations, and local resource utilization. More specifically, the approach that is employed is based on the decentralized control concept of Industry 4.0. In this framework, there are various agents with different objectives, such as financial, manufacturing, and supply chain optimization. These agents can make independent decisions and have the ability to select preferred partners for collaboration. A Collaboration Platform (CP) acts as a facilitator, operating as a market where agents can offer or request resource capacities. The platform assists in finding suitable matches for capacity requests. Since agents may have diverse preferences, the goal is not to provide a single optimal solution, but rather to offer feasible alternatives, similar to flight search applications that suggest different flights based on search conditions. Therefore, the agents have the final stage in making decisions.

More specifically, the authors adopted the decentralized control paradigm of Industry 4.0. There is a system of diverse agents that make decisions independently and aim to optimize different key performance indicators (KPIs) such as financial metrics (e.g., total cost), manufacturing metrics (e.g., Overall Equipment Effectiveness), and supply chain metrics (e.g., service level, fill rate). These agents also have preferences regarding the partners they choose for collaboration. To facilitate cooperation among the agents, a Collaboration Platform (CP) that acts as a marketplace for resource capacities has been developed (as shown in Fig. 15). Agents can offer their available capacities or request capacities when they have excess or shortages respectively. The platform helps to find suitable offers for each request. Given the complexity of the agents' preferences, the goal of matching requests and offers is not to provide a single optimal solution, but to offer feasible alternatives, similar to flight search applications that suggest alternative flights based on different search conditions.

The matching mechanism involves a basic model where the platform stores incoming offers and attempts to find alternative proposals for requesting agents to choose from. The selection considers the agents' specific optimization requirements and strategies. A capacity request is described by parameters such as the resource, required quantity, release date, and due date. Capacity offers include details like the resource, earliest start, latest finish, minimum accepted time, resource speed, and resource utilization price. The minimum accepted time sets a lower limit for requests, preventing lending capacity for durations less than a shift. Transportation time and price between the offering and requesting agents can be calculated for each request

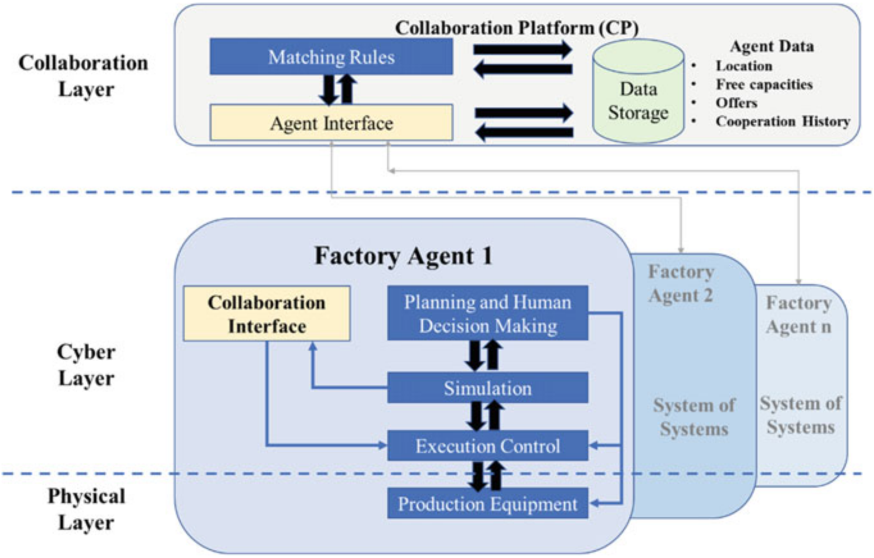

Fig. 15 Layers and components of the CP model

or offer. The decision variables include whether an offer is selected, as well as start and end times for production on a specific resource. Derived variables simplify the model by representing production time and produced quantity. Relaxing constraints are introduced through additional parameters. The optimization problem is formulated using mathematical programming techniques, including the simplex algorithm, with appropriate equations and a "big number" (M) to solve linear problems.

$$min \sum (T_i P_i + 2A_i T P_i) \tag{1}$$

$$(R - R_i)A_i = 0(\forall i) \tag{2}$$

$$L_i \le s_i \le e_i \le U_i \tag{3}$$

$$Q - \varepsilon_1 \le \sum Q_i(\forall i) \tag{4}$$

$$(L - \varepsilon_2 + \mathrm{TT}_i)A_i \le s_i(\forall i) \tag{5}$$

$$e_i + TT_i \le U + \varepsilon_3 + 1(1 - A_i)M(\forall i) \tag{6}$$

$$MA_i \ge T_i \ge m_i A_i(\forall i) \tag{7}$$

where,

A_i ($0 \leq A_i \leq 1$) indicates whether offer i is selected or not.

s_i gives the start of the production on resource R_i,

e_i gives the end of the production on resource R_i,

$T_i = e_i - s_i$ is the production time,

$Q_i = T_i S_i$ is the produced quantity on resource R_i.

In order to allow non-exact matches, three additional parameters are used for relaxing the constraints: ε_1, ε_2, $\varepsilon_3 > 0$.

Equation (1) represents the requirement to minimize the overall cost associated with production and transportation. When an offer *i* is not chosen, denoted by $A_i = 0$, the transportation cost is not considered in the objective function. Additionally, in this scenario, the production time is zero according to Eq. (7), implying zero production cost as well. Equation (2) specifies that only the appropriate resource can be matched. Equation (3) ensures that the production time is non-negative and falls within the given interval. Equation (4) states that the total quantity produced covers the requested amount, considering the permitted shortage. Equation (5) formulates the condition that sufficient time exists for transportation between the release and start time, allowing for a tolerance e2. Similarly, Eq. (6) expresses that there is enough time for delivery after production, considering the deadline and allowing for a maximum tardiness of ε_3. Finally, Eq. (7) guarantees that the production time is either zero or exceeds the minimum offered amount, such as a shift or a day.

4.3 Digital Transformation for Resilient GPN Framework

Corporations that neglected to follow the trends of new technologies in areas such as Entrepreneurial Resource Planning (ERP) software, end-to-end business solutions, or even basic websites, were caught off guard when the COVID-19 pandemic swept the world and forced a sudden increase in digital transformation efforts. Companies were forced to turn to e-commerce as physical stores were shut down by government mandates. Those who adapted to the changes brought by the pandemic and technology had the advantage over those who did not [111]. The key to successful digital transformation lies in a clear vision, a roadmap, and a focus on the four key areas of technology, data, process, and organizational change capability, all working together. The COVID-19 pandemic also highlighted the importance of having a flexible and agile supply chain, with real-time data playing a critical role in decision making. The six stages of digital transformation include Business as Usual, Present and Active, Formalized, Strategic, Converged, and Innovative and Adaptive [110]. Organizations can become more agile and better able to sustain profitability

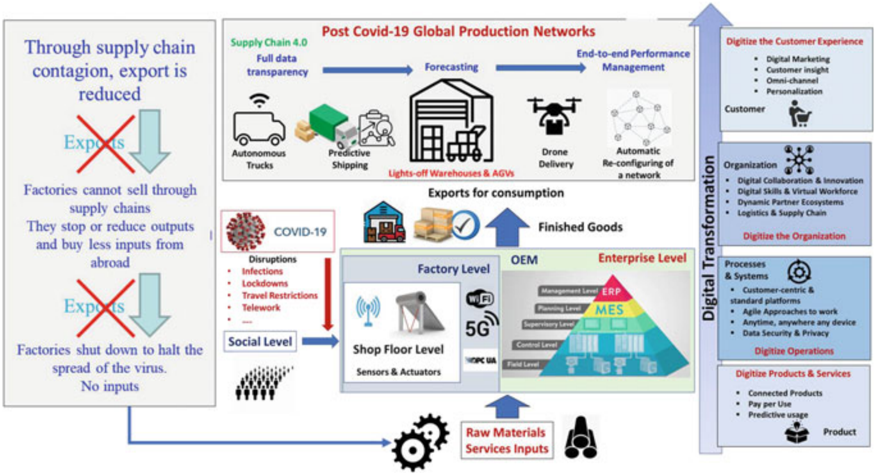

Fig. 16 Framework for Digital Resilient Cloud-Based Supply Chains [39]

by automating and standardizing processes and allowing for flexible work arrangements for employees. Agile practices in IT have allowed for faster product development and organizational transformation, enabling businesses to keep pace with the rapid changes in the market. Based on the above-mentioned challenges, the digital transformation in action framework is presented in Fig. 16. More specifically, to enhance their agility, responsiveness to market changes, and overall profitability, organizations are embracing automation, standardization, and global sourcing of processes. The ability to anticipate and swiftly adapt to evolving market dynamics is increasingly crucial for maintaining competitiveness. Agile methodologies have proven successful in the realm of IT, facilitating accelerated product development and organizational change. With the rapid pace of new product and software development, businesses must align their transformation efforts accordingly to effectively navigate continuous and abrupt shifts. Furthermore, empowering employees with flexible and device-independent work options is vital. Considering these challenges, the implementation of the digital transformation in action framework is warranted.

4.4 Data Security in Global Production Networks

The utilization of large-scale data in factory operations has led to increased concerns about data security [112, 113]. In the past, the manufacturing industry has been cautious about leveraging data due to fears of cyberattacks. High-profile incidents like Stuxnet and traditional attacks like phishing have amplified these concerns, particularly in light of stricter government regulations surrounding data distribution and usage. IT professionals are particularly worried about the age, obsolescence, and

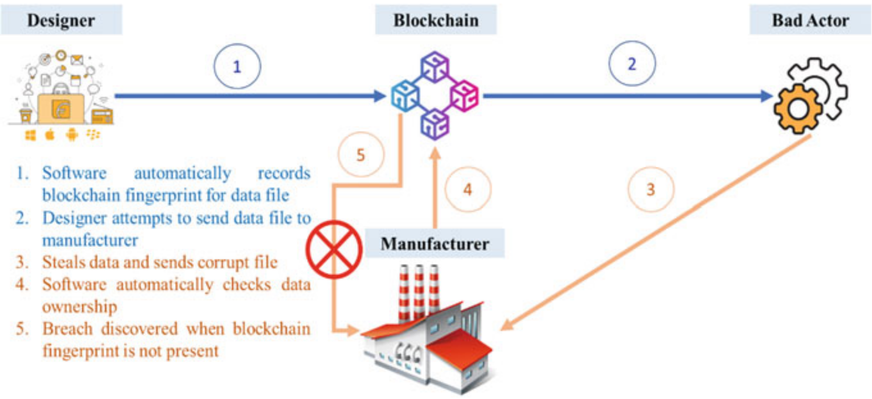

Fig. 17 Example of using blockchain to identify breach in transmission of data file to a manufacturer, adapted from [116]

diversity of operating systems and control technologies in manufacturing, as these factors have created numerous vulnerable points that could be targeted by malicious individuals [114].

Blockchain is a decentralized system or database that consists of a growing list of records known as "blocks". These blocks are managed by anonymous peers who follow a protocol that allows for transaction verification without revealing the participants. The blockchain is designed to be resistant to manipulation, providing trust despite transaction anonymity. An example in Fig. 17 demonstrates how blockchain can facilitate secure data transfer, such as sharing a part model from a designer to a manufacturer. By utilizing the blockchain, the manufacturer can verify the integrity of the data, confirming its source and ensuring a smooth transaction. Hedberg et al. [115] have proposed a reference information model that utilizes blockchain for traceability of product and manufacturing data, further developing this concept.

5 Discussion and Outlook

In this manuscript, we have aimed to shed light on the current status of Global Production Networks (GPNs) and their limitations as a robust solution for advancing global production activities. While GPNs still face challenges in terms of reliability and resilience, the inevitable shift towards Industry 5.0 and Society 5.0, along with the growing demand for highly personalized products and services, will undoubtedly drive the adoption of GPNs. This results in the need for a holistic framework for their application, that can implement all technologies, using objective metrics, to support the decision making of AI and Big data integration for mass personalization. This framework, though, should be human-centric and will therefore require. Therefore, more suitable education frameworks for the preparation of the next generation of engineers or other disciplines, for them to support and execute the technological implementation is required.

In terms of future developments in production management, the integration of blockchain technology holds significant promise. Although still in its early stages within the management sector, blockchain adoption can bring about greater transparency, alignment, agility, and adaptability. Moreover, blockchain offers inherent benefits such as enhanced security, trust, and authenticity. Further research is needed to explore the full potential of blockchain integration in production management and uncover its impact on optimizing supply chain processes and facilitating seamless collaboration among global partners.

While the integration of Artificial Intelligence (AI) technologies and techniques in manufacturing aspects has shown considerable support for human operators and decision-makers, ethical considerations must not be overlooked. Trusting the decisions made by AI systems and establishing ethical boundaries become critical aspects. Recent studies comparing human behavior and AI behavior in moral decision-making scenarios highlight both areas of agreement and divergence. Understanding the extent to which AI can be trusted and establishing ethical guidelines will be vital for the responsible deployment of AI systems in decision-making contexts [90]. Similarly, in the domain of human resource management, the utilization of AI for decision-making purposes presents challenges related to the potential de-skilling of HR professionals. Research should focus on finding alternative approaches to mitigate the loss of control and explore the long-term outcomes in terms of the professional expertise and commercial approach of HR practitioners as AI technologies become more prevalent.

In conclusion, the future of global production management holds immense potential with the inevitable adoption of GPNs and the integration of technologies such as blockchain and AI. By addressing the limitations of current systems, fostering education frameworks, and establishing ethical guidelines, we can create a more robust, efficient, and responsible production management ecosystem. Continued research and collaboration across academia and industry will play a pivotal role in realizing the full benefits of these advancements and driving the future success of global production networks.

5.1 Challenges and Trends

Decision-making in the design and operation of production networks is confronted by several significant challenges, including uncertainty, complexity, sustainability, and disruptive innovation. It is crucial for decision-makers to acknowledge and address these challenges.

Uncertainty poses a formidable obstacle, as it involves predicting the development of influencing factors. Unforeseen internal and external events can occur, altering the impact of these factors and the behavior of the production network. This makes it difficult to account for all possible eventualities. Market demand uncertainty is particularly prominent and represents a primary challenge for global production [117].

Complexity is another challenge, characterized by the vast number and diversity of elements and relationships within influencing factors and the production network itself. It encompasses the variability in the passage of time, as expressed by the various behavioral possibilities of the elements and the fluctuation in the effects observed between these elements [118].

In addition to uncertainty and complexity, sustainability is a broad and increasingly critical long-term challenge. It necessitates that production network partners fulfill the needs of present stakeholders, including customers and partners, without compromising the ecosystem's ability to meet future needs and those of future generations [119].

Furthermore, the management of production networks faces significant challenges due to technological advancements and organizational transformations. One such challenge arises from the emergence of disruptive innovations, characterized by novel technological advancements such as 3D printing, Internet of Things (IoT), and biotechnology. These innovations redefine performance metrics, consumer expectations, and introduce radical changes in functionality, technical standards, and ownership structures. In the present era, digitalization stands as a prominent challenge, driven by the digitization of instruments, devices, and machinery. This transformation brings forth complex implications for industries, including concerns regarding the loss of control over customer relationships, the necessity of digital engagement with suppliers and customers, intensified competition, and the potential commoditization of hardware products [120].

5.2 Research Gaps

Based on the literature survey conducted, several research gaps emerge in the context of AU-based Global Production Networks (GPNs) in the era of mass personalization, including the effective integration of AI, scalability and flexibility challenges, data security and privacy concerns, human–machine interaction dynamics, and sustainability and ethical considerations. More details are summarized as follows:

- Integration of Artificial Intelligence (AI): One research gap in the context of AU-based Global Production Networks (GPNs) is the exploration of how AI technologies can be effectively integrated to support mass personalization. This includes investigating AI algorithms and approaches that can optimize production processes, enable adaptive manufacturing, and enhance decision-making in GPNs.
- Scalability and Flexibility: Another research gap lies in understanding how AU-based GPNs can effectively scale and adapt to meet the demands of mass personalization. This involves examining strategies for dynamically configuring and reconfiguring production networks to accommodate varying product specifications, customization requirements, and market dynamics.

- Data Security and Privacy: The protection of sensitive data within AU-based GPNs is a critical research area. Investigating robust security measures, privacy-preserving techniques, and mechanisms for secure data exchange and collaboration in the era of mass personalization is essential to ensure trust and mitigate risks associated with data breaches and unauthorized access.
- Human–Machine Interaction: With the increasing role of automation and AI in GPNs, there is a need to study the impact of human–machine interaction on productivity, job roles, and employee well-being. Research should explore how humans can effectively collaborate and work alongside autonomous systems in AU-based GPNs, considering factors such as skill requirements, training needs, and the potential for human error in complex decision-making processes.
- Sustainability and Ethical Considerations: As GPNs embrace mass personalization, it is crucial to address sustainability and ethical aspects. Research should focus on developing sustainable manufacturing practices, such as eco-friendly materials, energy-efficient processes, and waste reduction strategies. Additionally, ethical considerations related to the use of AI, data privacy, and social implications of automation in GPNs need to be explored to ensure responsible and socially conscious production practices.

5.3 Future Trends

It becomes necessary to address the ability of the network footprint to respond to changes and disturbances, thereby minimizing the hysteresis effect and effectively managing the inherent uncertainty and complexity in Global Production Networks (GPNs). To ensure an appropriate alignment between real-world network footprints and production strategies, the core task of production strategy can benefit from the utilization of straightforward frameworks and tools. These frameworks and tools must consider the intangible advantages associated with global production. Furthermore, when designing the network footprint for the core task, the significance of adaptability within the footprint becomes crucial.

The potential for increased transparency and standardization warrants thorough examination, particularly in light of the digitalization that is shaping the requirements within network management. Research endeavors should focus on exploring the potential of digitalization and its associated new business models for effective network management through real-world applications. Overcoming concerns related to privacy and cybersecurity is imperative in this regard. Additionally, the development of algorithms for automated decision-making, negotiation, and balancing of interests is necessary. By concentrating research efforts, the practical relevance of GPNs can be further enhanced. However, it is crucial for research to remain cognizant of future drivers of globalization, such as the circular economy, resource accessibility, and sustainability (refer to Fig. 1). Depending on the increasing significance of these drivers, research should be directed towards addressing their implications.

Only through a combined focus on research needs and the examination of globalization drivers can we gain a comprehensive understanding, clarification, and predictive capabilities pertaining to GPNs within our globalized world [60].

6 Conclusion

Global production networks (GPNs) represent a pivotal organizational form that plays a significant role in today's global trade, exhibiting continuous evolutionary growth. However, the design and operation of GPNs often face practical challenges due to inefficient structures. This keynote paper provides a comprehensive summary of technical and scientific aspects pertaining to global production within the CIRP community and beyond. Drawing from industrial examples, the paper presents a framework for designing and operating GPNs, which encompasses essential planning tasks, influential factors, challenges, enablers, and decision support systems. Through a meticulous analysis of the current state-of-the-art in production strategy formation, network footprint design, and operational network management, the paper identifies three key trends that necessitate future research. The first trend emphasizes the importance of defining and maintaining alignment between production strategy and footprint design while considering the intangible benefits of global production. The second trend highlights the need to address adaptability in footprint design and provide theoretical support for emerging network and factory phenotypes. The third trend underscores the exploration of the potential offered by digitalization and novel collaboration models in network management. By embracing these trends, the paper envisions the transformation of historically rigid production networks into efficient networks with focused and resilient footprints.

References

1. Tao F, Qi Q, Liu A, Kusiak A (2018) Data-driven smart manufacturing. J Manuf Syst 48:157–169
2. Liu X, Zheng L, Wang Y, Yang W, Jiang Z, Wang B, Tao F, Li Y (2022) Human-centric collaborative assembly system for large-scale space deployable mechanism driven by Digital Twins and wearable AR devices. J Manuf Syst 65:720–742
3. Lee J, Siahpour S, Jia X, Brown P (2022) Introduction to resilient manufacturing systems. Manuf Lett 32:24–27
4. Ford H, Crowther S (1922) My life and work. Binker North
5. Mourtzis, D (2021) Design and operation of production networks for mass personalization in the era of cloud technology pp 1–393
6. Tolio T, Bernard A, Colledani M, Kara S, Seliger G, Duflou J, Battaia O, Takata S (2017) Design, management and control of demanufacturing and remanufacturing systems. CIRP Ann 66(2):585–609
7. Smart Factory Market Size, Share & Segment by Component (Industrial Robots, Machine Vision, Sensors, Industrial 3D Printing) by solution (SCADA, PLC, DCS, MES, PLM, ERP,

HMI, PAM) by industry (process industries and discrete industries) by regions, and global forecast 2023–2030. https://www.snsinsider.com/reports/smart-factory-market-1391
8. Geissbauer R, Lübben E, Schrauf S, Pillsbury S (2018) How industry leaders build integrated operations ecosystems to deliver end-to-end customer solutions. Glob Digit Oper
9. Upadhyay A, Balodi KC, Naz F, Di Nardo M, Jraisat L (2023) Implementing industry 4.0 in the manufacturing sector: circular economy as a societal solution. Comput Ind Eng 109072
10. Stavropoulos P, Mourtzis D (2022) Digital twins in industry 4.0. In: Design and operation of production networks for mass personalization in the era of cloud technology. Elsevier, pp 277–316
11. Shiroishi Y, Uchiyama K, Suzuki N (2019) Better actions for society 5.0: using AI for evidence-based policy making that keeps humans in the loop. Computer 52(11):73–78
12. Gladden ME (2019) Who will be the members of Society 5.0? Towards an anthropology of technologically posthumanized future societies. Soc Sci 8(5):148
13. Leng J, Sha W, Wang B, Zheng P, Zhuang C, Liu Q, Wuest T, Mourtzis D, Wang L (2022) Industry 5.0: prospect and retrospect. J Manuf Syst 65:279–295
14. Mourtzis D, Angelopoulos J, Panopoulos N (2022) A literature review of the challenges and opportunities of the transition from industry 4.0 to society 5.0. Energies 15(17):6276
15. Huang S, Wang B, Li X, Zheng P, Mourtzis D, Wang L (2022) Industry 5.0 and society 5.0—comparison, complementation and co-evolution. J Manuf Syst 64:424–428
16. Demir KA, Döven G, Sezen B (2019) Industry 5.0 and human-robot co-working. Procedia Comput Sci 158:688–695
17. Fukuyama M (2018) Society 5.0: aiming for a new human-centered society. Jpn Spotlight 27(5):47–50
18. Aceto G, Persico V, Pescapé A (2019) A survey on information and communication technologies for industry 4.0: state-of-the-art, taxonomies, perspectives, and challenges. IEEE Commun Surv Tutor 21(4):3467–3501
19. Mourtzis D, Doukas M (2013) Decentralized manufacturing systems review: challenges and outlook. In: Robust manufacturing control: proceedings of the CIRP sponsored conference RoMaC 2012, Bremen, Germany, 18th–20th June 2012. Springer, Berlin, pp 355–369
20. Chryssolouris G, Alexopoulos K, Arkouli Z (2023) Artificial intelligence in manufacturing systems. In: A perspective on artificial intelligence in manufacturing. studies in systems, decision and control, vol 436. Springer, Cham
21. Bergs T, Biermann D, Erkorkmaz K, M'Saoubi R (2023) Digital twins for cutting processes. CIRP Ann. Accessed 2023 May 27.
22. Hermann E (2022) Artificial intelligence and mass personalization of communication content—an ethical and literacy perspective. New Media Soc 24(5):1258–1277
23. Mourtzis D, Angelopoulos J, Panopoulos N (2023) The future of the human–machine interface (HMI) in society 5.0. Future Internet 15(5):162
24. Freitag M, Becker T, Duffie NA (2015) Dynamics of resource sharing in production networks. CIRP Ann 64(1):435–438
25. Aheleroff S, Mostashiri N, Xu X, Zhong RY (2021) Mass personalisation as a service in industry 4.0: a resilient response case study. Adv Eng Inform 50:101438
26. Aheleroff S, Philip R, Zhong RY, Xu X (2019) The degree of mass personalisation under industry 4.0. Procedia CIRP 81:1394–1399
27. Belkadi F, Boli N, Usatorre L, Maleki E, Alexopoulos K, Bernard A, Mourtzis D (2020) A knowledge-based collaborative platform for PSS design and production. CIRP J Manuf Sci Technol 29:220–231
28. Mourtzis D, Fotia S, Boli N, Pittaro P (2018) Product-service system (PSS) complexity metrics within mass customization and Industry 4.0 environment. Int J Adv Manuf Technol 97:91–103
29. Moser E, Verhaelen B, Haefner B, Lanza G (2021) Configuration and optimization of migration planning in global production networks. CIRP J Manuf Sci Technol 35:803–818
30. Chryssolouris G (2013) Manufacturing systems: theory and practice. Springer Science & Business Media

31. Mourtzis D, Angelopoulos J, Panopoulos N (2021) A survey of digital B2B platforms and marketplaces for purchasing industrial product service systems: a conceptual framework. Procedia CIRP 97:331–336
32. ElMaraghy H, Monostori L, Schuh G, ElMaraghy W (2021) Evolution and future of manufacturing systems. CIRP Ann 70(2):635–658
33. Mourtzis D, Zogopoulos V, Vlachou K (2019) Frugal innovation and its application in manufacturing networks. Manuf Lett 20:27–29
34. Mourtzis D, 62264 N, Mavrikios D, Makris S, Alexopoulos K (2015) The role of simulation in digital manufacturing: applications and outlook. Int J Comput Integr Manuf 28(1):3–24
35. Mourtzis D, Panopoulos N, Angelopoulos J (2022) Production management guided by industrial internet of things and adaptive scheduling in smart factories. In: Design and operation of production networks for mass personalization in the era of cloud technology. Elsevier, pp 117–152
36. Lanza G, Treber S (2019) Transparency increase in global production networks based on multi-method simulation and metamodeling techniques. CIRP Ann 68(1):439–442
37. Kolbjørnsrud V, Amico R, Thomas RJ (2016) How artificial intelligence will redefine management. Harv Bus Rev 2(1):3–10
38. Bailey J, Weber T, Horton R, Zorn M (2022) Developing insightful management reporting | Standardise management reporting to support strategy execution. https://www2.deloitte.com/content/dam/Deloitte/ch/Documents/finance-transformation/ch-en-developing-insightful-management-reporting.pdf
39. United Nations. Department of Economic and Social Affairs (2022) The sustainable development goals: report 2022. UN. https://unstats.un.org/sdgs/report/2022/
40. Moldavska A, Welo T (2019) A Holistic approach to corporate sustainability assessment: Incorporating sustainable development goals into sustainable manufacturing performance evaluation. J Manuf Syst 50:53–68
41. Qin Z, Lu Y (2021) Self-organizing manufacturing network: a paradigm towards smart manufacturing in mass personalization. J Manuf Syst 60:35–47
42. Schuh G, Prote JP, Dany S (2017) Reference process for the continuous design of production networks. In: 2017 IEEE international conference on industrial engineering and engineering management (IEEM). IEEE, pp 446–449
43. Ferdows K, Vereecke A, De Meyer A (2016) Delayering the global production network into congruent subnetworks. J Oper Manag 41:63–74
44. Moser E, Stricker N, Lanza G (2016) Risk efficient migration strategies for global production networks. Procedia CIRP 57:104–109
45. Ferdows K (2018) Keeping up with growing complexity of managing global operations. Int J Oper Prod Manag
46. Mourtzis D, Doukas M (2014) Design and planning of manufacturing networks for mass customisation and personalisation: challenges and outlook. Procedia Cirp 19:1–13
47. Benfer M, Ziegler M, Gützlaff A, Fränken B, Cremer S, Prote JP, Schuh G (2019) Determination of the abstraction level in production network models. Procedia CIRP 81:198–203
48. Schuh G, Gützlaff A, Schollemann A (2022) Reduction of planning efforts for decision making under uncertainty in global production network design. CIRP Ann 71(1):385–388
49. Krebs P, Reinhart G (2012) Evaluation of interconnected production sites taking into account multidimensional uncertainties. Prod Eng Res Devel 6:587–601
50. Cheng Y, Farooq S, Johansen J (2015) International manufacturing network: past, present, and future. Int J Oper Prod Manag
51. Lanza G, Ude J (2010) Multidimensional evaluation of value added networks. CIRP Ann 59(1):489–492
52. Hochdörffer J, Buergin J, Vlachou E, Zogopoulos V, Lanza G, Mourtzis D (2018) Holistic approach for integrating customers in the design, planning, and control of global production networks. CIRP J Manuf Sci Technol 23:98–107

53. Schuh G, Potente T, Varandani R, Schmitz T (2014) Global footprint design based on genetic algorithms–an "Industry 4.0" perspective. CIRP Ann 63(1):433–436
54. Koberstein A, Lukas E, Naumann M (2013) Integrated strategic planning of global production networks and financial hedging under uncertain demands and exchange rates. BuR-Bus Res 6(2)
55. Angelis J (2015) Strategic management of global manufacturing networks
56. Mourtzis D, Fotia S, Boli N, Vlachou E (2019) Modelling and quantification of industry 4.0 manufacturing complexity based on information theory: a robotics case study. Int J Prod Res 57(22):6908–6921
57. Schuh G, Potente T, Varandani RM, Schmitz T (2013) Methodology for the assessment of structural complexity in global production networks. Procedia CIRP 7:67–72
58. Peukert S, Hörger M, Lanza G (2023) Fostering robustness in production networks in an increasingly disruption-prone world. CIRP J Manuf Sci Technol 41:413–429
59. Najjar M, Yasin MM (2021) The management of global multi-tier sustainable supply chains: a complexity theory perspective. Int J Prod Res 1–18
60. Lanza G, Ferdows K, Kara S, Mourtzis D, Schuh G, Váncza J, Wang L, Wiendahl HP (2019) Global production networks: design and operation. CIRP Ann 68(2):823–841
61. Lanza G, Treber S (2019) Transparency increase in global production networks based on multi-method simulation and metamodeling techniques. CIRP Ann 68(1):439–442
62. Zhong RY, Xu X, Klotz E, Newman ST (2017) Intelligent manufacturing in the context of industry 4.0: a review. Engineering 3(5):616–630
63. Mourtzis D, Angelopoulos J, Panopoulos N (2022) Industry 4.0 and smart manufacturing. In: Reference module in materials science and materials engineering. Elsevier
64. Ivanov D (2020) Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transp Res Part E: Logist Transp Rev 136:101922
65. Ivanov D (2022) Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. Ann Oper Res 319(1):1411–1431
66. Ivanov D, Dolgui A, Sokolov B (2019) The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. Int J Prod Res 57(3):829–846
67. Mourtzis D, Panopoulos N (2022) Digital transformation process towards resilient production systems and networks. In: Dolgui A, Ivanov D, Sokolov B (eds) Supply network dynamics and control. Springer series in supply chain management, vol 20. Springer, Cham
68. Lanza G, Moser R (2014) Multi-objective optimization of global manufacturing networks taking into account multi-dimensional uncertainty. CIRP Ann – Manuf Technol 63(1):397–400
69. Singhal P, Agarwal G, Mittal ML (2011) Supply chain risk management: review, classification and future research directions. Int J Bus Sci Appl Manag (IJBSAM) 6(3):15–42
70. Thun JH, Hoenig D (2011) An empirical analysis of supply chain risk management in the German automotive industry. Int J Prod Econ 131(1):242–249
71. Baghersad M, Zobel CW (2021) Assessing the extended impacts of supply chain disruptions on firms: an empirical study. Int J Prod Econ 231:107862
72. Peters MA (2019) Technological unemployment: Educating for the fourth industrial revolution. In: The Chinese dream: educating the future. Routledge, pp 99–107
73. Yeung HWC (2018) The logic of production networks. The new Oxford handbook of economic geography 1:382–406
74. Dolgui A, Ivanov D (2021) Ripple effect and supply chain disruption management: new trends and research directions. Int J Prod Res 59(1):102–109
75. Koren Y, Heisel U, Jovane F, Moriwaki T, Pritschow G, Ulsoy G, Van Brussel H (1999) Reconfigurable manufacturing system. CIRP Ann 48(2):527–540
76. Epureanu BI, Li X, Nassehi A, Koren Y (2020) Self-repair of smart manufacturing systems by deep reinforcement learning. CIRP Ann 69(1):421–424
77. Ma A, Nassehi A, Snider C (2019) Anarchic manufacturing. Int J Prod Res 57(8):2514–2530

78. Putnik GD, Škulj G, Varela L, Butala P (2015) Simulation study of large production network robustness in uncertain environment. CIRP Ann 64(1):439–442
79. Tsutsumi D, Gyulai D, Kovács A, Tipary B, Ueno Y, Nonaka Y, Monostori L (2018) Towards joint optimization of product design, process planning and production planning in multi-product assembly. CIRP Ann 67(1):441–446
80. Epureanu BI, Li X, Nassehi A, Koren Y (2021) An agile production network enabled by reconfigurable manufacturing systems. CIRP Ann 70(1):403–406
81. Chen Y, Luo H, Chen J, Guo Y (2022) Building data-driven dynamic capabilities to arrest knowledge hiding: a knowledge management perspective. J Bus Res 139:1138–1154
82. Lee J, Singh J, Azamfar M (2019) Industrial artificial intelligence. arXiv:1908.02150
83. Yang XS (2020) Nature-inspired optimization algorithms. Academic Press
84. Igiri CP, Bhargava D, Ekwomadu T, Kasali F, Isong B (2022) Bio-inspired ant lion optimizer for a constrained petroleum product scheduling. IEEE Access 10:94986–94997
85. Trojovský P, Dehghani M, Hanuš P (2022) Siberian tiger optimization: a new bio-inspired metaheuristic algorithm for solving engineering optimization problems. IEEE Access 10:132396–132431
86. Trojovská E, Dehghani M, Trojovský P (2022) Zebra optimization algorithm: a new bio-inspired optimization algorithm for solving optimization algorithm. IEEE Access 10:49445–49473
87. Liu B (2023) Integration of novel uncertainty model construction of green supply chain management for small and medium-sized enterprises using artificial intelligence. Optik 273:170411
88. Santos JA, Sousa JM, Vieira SM, Ferreira AF (2022) Many-objective optimization of a three-echelon supply chain: a case study in the pharmaceutical industry. Comput Ind Eng 173:108729
89. Kumar A, Nadeem M, Banka H (2023) Nature inspired optimization algorithms: a comprehensive overview. Evol Syst 14:141–156
90. Ponticelli GS, Guarino S, Tagliaferri V, Giannini O (2019) An optimized fuzzy-genetic algorithm for metal foam manufacturing process control. Int J Adv Manuf Technol 101:603–614
91. Zou J, Chang Q, Ou X, Arinez J, Xiao G (2019) Resilient adaptive control based on renewal particle swarm optimization to improve production system energy efficiency. J Manuf Syst 50:135–145
92. Silva CA, Sousa JMC, Runkler TA, Da Costa JS (2009) Distributed supply chain management using ant colony optimization. Eur J Oper Res 199(2):349–358
93. Xu X, Hao J, Zheng Y (2020) Multi-objective artificial bee colony algorithm for multi-stage resource leveling problem in sharing logistics network. Comput Ind Eng 142:106338
94. Elkhechafi M, Benmamoun Z, Hachimi H, Amine A, Elkettani Y (2018) Firefly algorithm for supply chain optimization. Lobachevskii J Math 39:355–367
95. Sadeghi AH, Bani EA, Fallahi A, Handfield R (2023) Grey wolf optimizer and whale optimization algorithm for stochastic inventory management of reusable products in a two-level supply chain. IEEE Access 11:40278–40297
96. Shehab M, Khader AT, Al-Betar MA (2017) A survey on applications and variants of the cuckoo search algorithm. Appl Soft Comput 61:1041–1059
97. Yang X-S, Deb S, Fong S (2014) Metaheuristic algorithms: optimal balance of intensification and diversification. Appl Math Inf Sci 8(3):977
98. Talbi E-G (2009) Metaheuristics: from design to implementation, vol 74. Wiley, Amsterdam
99. Fernández-Vargas JA, Bonilla-Petriciolet A, Rangaiah GP, Fateen S-EK (2016) Performance analysis of stopping criteria of population-based metaheuristics for global optimization in phase equilibrium calculations and modeling. Fluid Phase Equilib 427:104–125
100. Chong JW, Kim W, Hong JS (2022) Optimization of apparel supply chain using deep reinforcement learning. IEEE Access 10:100367–100375
101. Wan J, Li X, Dai H-N, Kusiak A, Martínez-García M, Li D (2021) Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. Proc IEEE 109(4):377–398. Accessed 4 Apr 2021

102. Bein W, Pickl S, Tao F (2019) Data analytics and optimization for decision support. Bus Inf Syst Eng 61:255–256
103. Dotsenko S, Fesenko H, Illiashenko O, Kharchenko V, Moiseenko V, Yermolenko L (2020) Integration of security, functional and ecology safety management systems: concept and industrial case. In: 2020 IEEE 11th international conference on dependable systems, services and technologies (DESSERT). IEEE, pp 470–474
104. Papakostas N, Newell A, George A (2020) An agent-based decision support platform for additive manufacturing applications. Appl Sci 10(14):4953
105. Duffuaa S, Kolus A, Al-Turki U, El-Khalifa A (2020) An integrated model of production scheduling, maintenance and quality for a single machine. Comput Ind Eng 1(142):106239
106. Mourtzis D, Zogopoulos V, Xanthi F (2019) Augmented reality application to support the assembly of highly customized products and to adapt to production re-scheduling. Int J Adv Manuf Technol 105:3899–3910
107. Dutta P, Choi TM, Somani S, Butala R (2020) Blockchain technology in supply chain operations: applications, challenges and research opportunities. Transp Res Part E: Logist Transp Rev 142:102067
108. Zhang Z, Chen Z, Xu L (2022) Artificial intelligence and moral dilemmas: perception of ethical decision-making in AI. J Exp Soc Psychol 101:104327
109. Kádár B, Egri P, Pedone G, Chida T (2018) Smart, simulation-based resource sharing in federated production networks. CIRP Ann 67(1):503–506
110. Rodgers W, Murray JM, Stefanidis A, Degbey WY, Tarba SY (2023) An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. Hum Resour Manag Rev 33(1):100925
111. Charlwood A, Guenole N (2022) Can HR adapt to the paradoxes of artificial intelligence? Hum Resour Manag J 32(4):729–742
112. Esposito C, Castiglione A, Martini B, Choo K-KR (2016) Cloud manufacturing: security, privacy, and forensic concerns. IEEE Cloud Comput 3(4):16–22
113. Gao R, Wang L, Teti R, Dornfeld D, Kumara S, Mori M, Helu M (2015) Cloud-enabled prognosis for manufacturing. CIRP Ann 64(2):749–772
114. Helu M, Hedberg T (2020) Connecting, deploying, and using the smart manufacturing systems test bed. NIST advanced manufacturing series 200–2. National Institute of Standards and Technology
115. Hedberg TD, Krima S, Camelio JA (2019) Method for enabling a root of trust in support of product-data certification and traceability. J Comput Inf Sci Eng. 19(4). https://doi.org/10.1115/1.4042839
116. National Institute of Standards and Technology (2018) FIPS general information
117. Váncza J, Monostori L, Lutters D, Kumara SR, Tseng M, Valckenaers P, Van Brussel H (2011) Cooperative and responsive manufacturing enterprises. CIRP Ann 60(2):797–820
118. Schuh G, Monostori L, Csáji BC, Döring S (2008) Complexity-based modeling of reconfigurable collaborations in production industry. CIRP Ann 57(1):445–450
119. Kates RW, Clark WC, Corell R, Hall JM, Jaeger CC, Lowe I, McCarthy JJ, Schellnhuber HJ, Bolin B, Dickson NM, Faucheux S, Gallopin GC, Grübler A, Huntley B, Jäger J, Jodha NS, Kasperson RE, Mabogunje A, Matson P, Mooney H, Moore B 3rd, O'Riordan T, Svedlin U. (2021) Environment and development. Sustainability science. Science. 27;292(5517):641–642 (2001 Apr)
120. Monostori L, Kádár B, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, Sauer O, Schuh G, Sihn W, Ueda K (2016) Cyber-physical systems in manufacturing. CIRP Ann 65(2):621–641