Digital Supply Chain Twins: Managing the Ripple Effect, Resilience, and Disruption Risks by Data-Driven Optimization, Simulation, and Visibility

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Abstract The quality of model-based decision-making support strongly depends on the data, its completeness, fullness, validity, consistency, and timely availability. These requirements on data are of a special importance in supply chain (SC) risk management for predicting disruptions and reacting to them. Digital technology, Industry 4.0, Blockchain, and real-time data analytics have a potential to achieve a new quality in decision-making support when managing severe disruptions, resilience, and the Ripple effect. A combination of simulation, optimization, and data analytics constitutes a digital twin: a new data-driven vision of managing the disruption risks in SC. A digital SC twin is a model that can represent the network state for any given moment in time and allow for complete end-to-end SC visibility to improve resilience and test contingency plans. This chapter proposes an SC risk analytics framework and explains the concept of digital SC twins. It analyses perspectives and future transformations to be expected in transition toward cyber-physical SCs. It demonstrates a vision of how digital technologies and smart operations can help integrate resilience and lean thinking into a *resileanness* framework "Low-Certainty-Need" (LCN) SC.

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1 Introduction

Digital technologies catalyze the development of new paradigms, principles, and models in supply chain management (SCM). The Internet of Things (IoT), cyber-physical systems, and smart, connected products, facilitate the development of digital supply chains (SC) and smart operations (Fazili et al. 2017; Liao et al. 2017; Qu et al. 2017; Strozzi et al. 2017; Tran-Dang et al. 2017; Yang et al. 2017; Minner et al. 2018; Panetto et al. 2019). Recent surveys by Addo-Tenkorang and Helo (2016), Oesterreich and Teuteberg (2016), Gunasekaran et al. (2016, 2017, 2018), Nguyen et al. (2018), Moghaddam and Nof (2018), Choi et al. (2018), Ben-Daya et al. (2018) proposed classifications of different digital technologies and discussed their potential impacts on SCM. Such digital technologies include big data analytics, advanced manufacturing technologies with sensors, decentralized agent-driven control, advanced robotics, augmented reality, advanced tracking and tracing technologies, and additive manufacturing.

The increasing interest in the digital data applications to SCM is not surprising. The quality of model-based decision-making support strongly depends on the data, its completeness, fullness, validity, consistency, and timely availability. These requirements on data are of a special importance in SC risk management for predicting disruptions and reacting to them (Ivanov 2018b). Digital technology, Industry 4.0, Blockchain, and real-time data analytics have a potential to achieve a new quality in decision-making support when managing severe disruptions, resilience, and the Ripple effect (Frazzon et al. 2018, Ivanov et al. 2017, 2019a).

A combination of simulation, optimization, and data analytics constitutes a digital twin: a new data-driven vision of managing the disruption risks in SC. A digital SC twin is a model that can represent the network state for any given moment in time and allow for complete end-to-end SC visibility to improve resilience and test contingency plans (Ivanov 2018c). This chapter proposes an SC risk analytics framework and explains the concept of digital SC twins. It analyses perspectives and future transformations to be expected in transition toward cyber-physical SCs. It demonstrates a vision of how digital technologies and smart operations can help integrate resilience and lean thinking into a *resileanness* framework "Low-Certainty-Need" (LCN) SC (Ivanov and Dolgui 2019).

The investigation of the interrelations between digital technology and SC risks is still at a preliminary the beginning stage of its development and requires new conceptual frameworks and taxonomies (Ivanov et al. 2019a). This chapter seeks to move the discussion forward and develop a framework for a detailed analysis of SC digital technology and disruption risk effects manifested at times in *structural dynamics* (Ivanov et al. 2010) and the *ripple effect* (Ivanov et al. 2014a, b, 2016; Sokolov et al. 2016; Elluru et al. 2017; Dolgui et al. 2018; Ivanov and Rozhkov 2017; Pavlov et al. 2018; He et al. 2018; Ivanov 2018a, b; Dolgui et al. 2019a; Pavlov et al. 2019). Despite initial efforts to unearth new insights about the impact of digital technologies on SC risks (Tupa et al. 2017; Ivanov et al. 2017; Papadopoulos et al. 2017; Schlüter et al. 2017; Ivanov et al. 2019a; Baryannis et al. 2018; Dolgui et al. 2019b, c; Dubey et al. 2019), the understanding of individual and interactive contributions on specific SC disruption risk management and ripple effects remains limited. This study closes this research gap by a combinatorial examination of the results gained from two isolated areas, i.e., the SC digitalization and managing the disruption risks in the SC. In particular, the focus of this chapter is directed on the data-driven decision-support systems to improve SC resilience and manage the ripple effect and disruption risks.

This chapter does not pretend to be encyclopedic and rather highlights the research that examines the relationships between SC digitalization and SC disruptions risks. The objective is to identify the perspectives of digital SC twins that can be leveraged to direct future research in exploring how digital technologies affect ripple effect and performance of the SCs, and how they can be used to manage the disruption risks and to improve resilience. More specifically, this study seeks to answer the following questions:

- What relationships exist between big data analytics, Industry 4.0, additive manufacturing, Blockchain, and advanced trace and tracking systems and SC disruption risks?
- How digitalization can contribute to enhancing ripple effect mitigation and analysis?;
- What digital technology-based extensions are needed in applications of quantitative analysis to ripple effect in the SC to emerge with digital supply chain twins?

2 Digital Supply Chain Technologies

Digitalization means using digitized data and digital technologies not only to improve processes, functions, and activities, but also to change processes to achieve a certain benefit. The objective is to enhance revenue streams and create new business opportunities (Hagberg et al. 2016). Digitalization of operations aims to improve production and SC capability and flexibility through real-time communication and intelligent, high-resolution data systems (Reddy et al. 2016). Digitalization is a continuing transformation toward a digital supply chain, and progressively changes most enterprise processes.

This section reviews recent literature in four elements identified in recent surveys on digitalization applications to SCM, i.e.,

- Big data analytics
- Industry 4.0
- Additive manufacturing
- Advanced tracking and tracing technologies, Blockchain.

In each of these groups, we describe the respective technology and its recent applications to SCM.

2.1 Big Data Analytics and Artificial Intelligence

Big data analytics (BDA) and artificial intelligence (AI) bring a completely new potential benefit to data-driven SC risk management. Big data has been characterized in the literature by 5Vs: volume, variety, velocity, veracity, and value (Wamba et al. 2015, 2017). Veracity and value are particularly important since data analysis shows the real value of big data.

Big data analytics (BDA) is based on knowledge extraction from vast amounts of data, facilitating data-driven decision-making. The more the data from the actual production process is recorded, the more important it becomes to evaluate this data volume with the help of BDA applications. ERP systems are generally not suited to this task. One challenge is that internal and external data from smart, networking products are frequently unstructured. The resulting solution is a repository that stores different data streams in their original formats. From there, the data can be reformatted and examined with descriptive, diagnostic, predictive, and prescriptive data analytics tools.

Descriptive analysis records the condition, the environment, and the functioning of the products. Diagnostic analysis analyses the reasons for reduced product performance or failure. Predictive analysis recognizes patterns that signal upcoming events. Prescriptive analytics identifies measures to solve issues and improve outcomes (Porter and Heppelmann 2015).

Analytics employs mathematical and statistical tools to collect, store, accumulate, and analyze big data volumes. The applications themselves are not new, but it is the combination with big data that brings new added value and competitive advantage. What is new is the rapid pace at which data can be captured in real time. This, in turn, extends the type and richness of data sets, and offers an unprecedented opportunity for investigation. Additionally, the nature of the investigation has changed. Technological tools are continuously supplied with data, and become more intelligent by using self-learning algorithms. For example, predictive analytics involves self-learning algorithms that identify and analyze relationships among variables, and develop outcomes such as buyer behavior forecasts. Active human involvement is not required in this process As a result, BDA becomes an active participant in the investigation process, and can create new knowledge about unknown or buried patterns and effects. Large-scale investigations detect such patterns, turning volume data into precise insights (Sanders 2016).

BDA has undoubtedly been the most elaborated area of digital technology application to SCM over the last decade. Johnson et al. (2016) and Simchi-Levi and Wu (2018) analyzed the application of BDA to retail. Nguyen et al. (2018) noted that optimization is the most popular approach in prescriptive analytics application to logistics and transportation area. Retailers strive to grow revenue, margins, and market share. Price optimization models calculate the variance of demand with price changes, and combine this information with relevant cost and inventory data to recommend prices that could maximize revenue and profits. BDA applications to SCM can also be seen in procurement processes, manufacturing shop floors, promotion actions in the omnichannel model, routing optimization, real-time traffic operation monitoring, and proactive safety management (Addo-Tenkorang and Helo 2016; Gunasekaran et al. 2016, 2017; Nguyen et al. 2018; Zhong et al. 2017). Nguyen et al. (2018) identified some additional areas where BDA can be applied to SCM in the near future. These areas include quality control in manufacturing, dynamic vehicle routing, in-transit inventory management in logistics/transportation, and order picking and inventory control systems in warehousing. Niesen et al. (2016) and Papadopoulos et al. (2017) observed that BDA can help improve SC risk management and disaster resistance. Baryannis et al. (2018) summarized recent AI applications to SC risk management and identified some future research directions in risk identification, assessment, and response. Priori et al. (2018) applied machine learning to the dynamic selection of replenishment policies according to SC environmental dynamics. Cavalcantea et al. (2019) developed a supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing.

2.2 Industry 4.0

The intelligent networking of machines and processes with the help of digital technologies is creating autonomous, Internet-linked, self-regulating production systems, popularly termed as Industry 4.0. Industry 4.0 seeks to visualize and predict the performance of processes, plants, SCs, and product properties on the basis of information available in real time (Ivanov et al. 2019b). For this purpose, smart sensors are applied to capture and communicate information and requirements comprehensively to any recipient in real time. Production models are implemented in the form of so-called cyber-physical production systems. Such cyber-physical production systems collect data via production-integrated sensors and measurement systems in real time, store and evaluate data, and interact actively with the physical, human, and digital world. Intra and external connectivity are provided by IoT via digital communication devices.

Industry 4.0 is a global phenomenon. There is no unique or circumscribed set of technologies or practices that define Industry 4.0. Most research considers factory concepts that share attributes of smart networking (Strozzi et al. 2017). The vision of Industry 4.0 is that the product to be manufactured carries all the relevant information about its production requirements. In addition, integrated production installations become self-organized through the collaboration of production machines, transport equipment, tools, and logistical components that can communicate with each other and exchange data via embedded systems. Digital technologies enable flexible decision-making by providing real-time data in all areas of the SC (Bonfour 2016, p.20). Digitalization and Industry 4.0 offers information and coordination based competitive advantage, generates new employment opportunities, and increases visibility and control in supply chains. However, it requires long-term commitment, and guarantees about data security (Porter and Heppelmann 2015).

Industrial robots are a part of Industry 4.0, found mainly in series production and warehousing applications. Robots perform high precision tasks independently as also support employees in their work, by handing over tools, for example. Their use accelerates, facilitates, and simplifies production activities. Unlike conventional industrial robots, which require time-consuming training, flexible robots learn quickly from people. They communicate with one another via the cloud, and support optimal production planning. In practice, however, questions still remain on several issues such as the ownership of cloud data among SC partners, or machine intercommunication protocols (Andelfinger and Hänisch 2017).

2.3 Additive Manufacturing

Additive manufacturing technology is a design-driven manufacturing process in which components are produced from material layers on the basis of 3D data sets and a virtual blueprint. "3D printing" is often used as a synonym. The use of different materials and the elimination of previously required special tools are an advantage. Furthermore, the rapid design and manufacturing process allows considerable time savings compared to conventional product development cycles (Zhang and Jung 2018, pp. 3–5). Great freedom of design, low material waste, and the feasibility of economically manufactured, individualized products make additive manufacturing attractive for many industries. The method is currently used primarily in rapid prototyping, but increasingly so in series production too (Li et al. 2017). Khajavi et al. (2014), Holmström and Gutowski (2017), Feldmann and Pumpe (2017), Li et al. (2017) described the applications of additive manufacturing to operations and SCM. Those applications reach from spare part logistics to redesigning global SC production and sourcing strategy. The core of additive manufacturing applications to SCM is the usage of 3D printers at different stages in the SC to increase manufacturing flexibility, achieve shorter lead times, increase product individualization, and reduce inventory. However, mass production volumes are not commercially possible yet.

2.4 Blockchain and Advanced Tracking and Tracing Technologies

Capturing and sharing information in real time is critical to detecting faults and their extent, as well as in planning SC recovery (Sheffi 2015). Tracking and tracing (T&T) systems aim at timely identification of deviations or danger of deviations in SCs, analysis of such deviations, alerts about disruptions that have occurred or may occur, and elaborating control actions to recover SC operability.

T&T systems combine with radio-frequency identification (RFID) and mobile devices to provide current information about process execution (Bearzotti et al. 2012). T&T systems and feedback control can be supported by RFID technology (Dolgui and Proth, 2010) and SC event management systems (Ivanov et al. 2013), effectively communicating disruptions to the SC tiers and helping revise initial schedules (Dolgui and Proth 2010; Zelbst et al. 2012). A critical issue is detecting disruptions and their scope in real time. Embedding SC visualization and identification technology is crucial for this, in practice.

In addition, emerging Blockchain applications in SCs promise enhanced scale and scope of T&T systems together with creation of information pipeline systems and SC finance applications (Hofmann et al. 2018). The central idea is to increase visibility and efficiency based on dispersed, tamper-proof, and verifiable record-keeping in the SC.

For example, IBM and Walmart are researching how to increase food SC safety control using Blockchain technology (IBM 2017). Recently, the applications of Blockchain technology have begun to revolutionize different aspects of SC and operations management for development of real time SC capabilities (Ivanov et al. 2019a; Kshetri 2018; Saberi et al. 2018). The central idea is to increase visibility and efficiency based on record-keeping in the SC. Blockchain applications to SCs become more and more important to enhance the scale and scope of digital processes along with creation of information pipeline systems and SC finance applications (Hofmann et al. 2018). A Blockchain is a decentralized database that exists as copies in a network of computers (Crosby et al. 2016). It is a chain of blocks, because the data and information stored is captured in blocks.

Regulatory processes (e.g., customs) can be expedited using Blockchain by improving confidence in documentations. This, in turn, can result in reductions in wastage, risk, and insurance premiums. The list of all transactions is stored as copies throughout all further evolvements on numerous computers (a network of even hundreds of computers).

These and further recent examples of Blockchain technology applications to SCs (Ivanov et al. 2019a; Saberi et al. 2018) support the new proposition that competition is not between the SCs, but rather between the information services and analytics algorithms behind the SCs. As such, SCs will no more be understood as a rigid physical system with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services in supply, manufacturing, logistics, and sales which will result in the dynamic allocation of processes and dynamic SC structures forming a cyber-physical SC.

In practice, new cloud-based analytics platforms such as SupplyOn Industry 4.0 Sensor Clouds make it possible to control the SC in real time, and plan and adjust processes using up-to-date information. By simply clicking on a container type, the graphs indicate whether there has been a violation of the defined temperature or humidity limits along the time axis. The data analysis in this chart allows a quick identification of all orders where the lead time was exceeded, allowing for a quick identification of questionable transports.

Summarizing, the following SC digitalization framework can be presented (Fig. 1).

BDA, additive manufacturing, Industry 4.0, and advanced tracking and tracing technologies can be considered as digital enablers of the four major SC processes in the SCOR model, i.e., plan, source, make and deliver, respectively. A digital version of the SCOR model would therefore consist of digital planning, digital manufacturing,

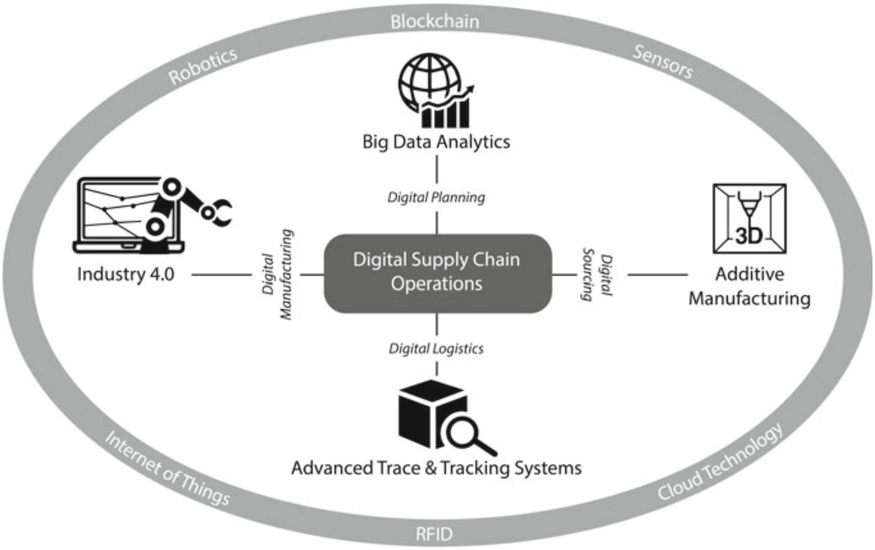

Fig. 1 Digitalization framework of supply chain risk management (Ivanov et al. 2019a)

digital sourcing, and digital logistics. IoT, cloud technology, robots, and sensors form the technical guts of a digital SC. This classification will be further used in the paper for analysis of digitalization impacts on severe SC risks and the ripple effect. For each of the areas, Fig. 1 suggests possible applications of digital technology with regards to SC disruption risks. For example, additive manufacturing can reduce supply risk by creating the opportunity to replace missing materials with the 3D printed components. BDA can be used at the planning stage to identify supplier risk exposure. T&T systems can help at the reactive stage to monitor and identify disruptions. At the same time, it needs to be noted that digital technologies may have multiple applications, which are not restricted to a particular SCOR process.

3 Impact of Digital Technologies on the Ripple Effect

3.1 Linking the Digital Supply Chain and Disruption Risks

Following the study by Ivanov et al. (2019a), Table 1 summarizes the major drivers of digital technology applications to SCM, the respective enablers, opportunities and challenges for SCM, as well as the impact on disruption risk management and the ripple effect

Table 1 Major digital technology applications to SCM and the impact on disruption risk management and ripple effect

Digitalization application to SCM	Enablers	Opportunities and benefits	Challenges in SCM	Impact on disruption risk management and ripple effect
Predictive analytics	Big data	Increase in promotion action quality Better demand forecasts Increase in supply chain visibility Better customer experience promotions	Data transparency and safety Coordination complexity increase in cross-channel logistics	Reduction in demand risks Reduction in information disruption risks and better quality of contingency plan activation Higher time risks because coordination complexity increases
Industry 4.0	IoT, smart products, robotics, augmented and virtual reality	Customized production system at the costs of mass production Individualized products and higher market flexibility Risk diversification Higher responsiveness Shorter lead times and better capacity utilization	Radical changes in SC and manufacturing process organization Reduction in number of SC layers New locations close to the markets Re-qualification of employees, redesign of facility layouts Data security Increase in design and control complexity	Higher information risks Higher exposure to external risks, including unauthorized access Reduction in time and demand risks
3D printing	Additive manufacturing	Flexibility increase, Product variety, Shorter lead time Efficiency increase in MRO inventory control		Reduction in demand risks Higher exposure to external risks Higher supply risks if disruption happens in the upstream SC since no intermediate inventory in between the stages
Advanced T&T technologies	RFID, sensors, Blockchain	Real-time identification Real-time material flow tracing Increase in data quality	Increase investments in ICT Data security	Reduction in information disruption risks and better quality of contingency plan activation Reductions in supply and time risks due to real-time coordination if activating contingency policies

Specifically, digitalization's impact on the ripple effect, that is, the magnitude and reach (upstream and downstream) of a disruption in a part of the SC is elaborated in Table 2.

It can be observed in Tables 1 and 2 that digitalization technologies generally have a positive impact on the ripple effect, but may create a few challenges for ripple effect mitigation and control. BDA, Industry 4.0, and additive manufacturing, have mixed influences on the ripple effect, while advanced T&T systems have a positive impact.

Structuring analysis in terms of the supply chain operations reference (SCOR) model, *sourcing and production* activities involving additive manufacturing and Industry 4.0 imply higher exposure to external risks and ripple effect. This could be due to an increase in complexity and probable reduction in time and demand risks due to higher flexibility and shorter lead times. Higher supply risks can be encountered if a disruption happens in the upstream SC since there is no intermediate inventory in between the stages. *Delivery* process risks in the SC are alleviated by big data analytics due to better SC visibility and forecast accuracy, reduction in information disruption risks, and better quality of contingency plan activation. For integrated SC *planning*, reductions in supply and time risks can be achieved by using advanced T&T systems that enable real-time coordination and timely activation of contingency policies.

At the proactive stage, SCs are typically protected from disruptions by employing risk mitigation inventory, capacity reservations, and backup sources. This is expensive, especially if no disruption happens. Blockchain could help reduce these inefficiencies if we are able to create a record of activities and data needed for recovery in terms of synchronized contingency plans. Additive manufacturing can reduce the need for risk mitigation inventory and capacity reservations as well as for the backup contingent suppliers. The decentralized control principles in Industry 4.0 systems make it possible to diversify the risks and reduce the need for structural SC redundancy, using manufacturing flexibility.

At the reactive stage, if a disruption happens, the contingency plans from proactive stage can be deployed faster and implemented effectively if SC visibility were increased. BDA and advanced T&T systems in general, and Blockchain technology in particular, can help us to trace the roots of disruptions, to observe disruption propagation (i.e., the ripple effect), to select short-term stabilization actions based on a clear understanding of what capacities and inventories are available (emergency planning), to develop a mid-term recovery policy and to analyze the long-term performance impact of the ripple effect. Additive manufacturing has the potential to reduce disruption propagation in the SC, since the number of SC layers and the resulting complexity would be reduced.

Table 2 Contribution of digital technologies to ripple effect control in the SC

Reasons for ripple effect in the SC	Countermeasures	Digital technologies impact on ripple effects
Single sourcing	Multiple/Dual sourcing/Backup suppliers	Additive manufacturing tends to reduce the number of SC layers and suppliers—mitigates ripple effect Advanced T&T systems allow better SC coordination in real time—mitigates ripple effect Industry 4.0 increases sourcing coordination complexity—may delay detection and response to ripple effects BDA increase the quality of procurement processes—mitigates ripple effects
Low inventory	Risk mitigation inventory	Additive manufacturing tends to reduce the inventory in the SC—enhances ripple effects Advanced T&T systems allow inventory control in real time—mitigates ripple effects
Inflexible capacity	Postponement	Industry 4.0 and additive manufacturing increase demand and production flexibility—mitigates ripple effects
SC complexity	Global SC contingency plans	Advanced T&T systems allow better SC coordination in real time and faster contingency plan activation—mitigates ripple effects Industry 4.0 increases the SC coordination complexity—enhances ripple effects BDA contributes to an increase in supply chain visibility—mitigates ripple effects
Multistage SCs	Supplier segmentation according to disruption risks	Additive manufacturing tends to reduce the number of SC layers and suppliers—mitigates ripple effects Industry 4.0 increases the SC complexity—connectivity enhances ripple effect Advanced T&T systems allow better SC coordination in real time and faster contingency plan activation—mitigates ripple effects

Fig. 3 Low-certainty-need supply chain framework (Ivanov and Dolgui 2018)

4 Supply Chain Resileanness: Low-Certainty-Need (LCN) Framework

4.1 Conceptual Framework

The LCN SC framework (Ivanov and Dolgui 2018) suggests approaching SC disruption risk and the ripple effect field from another perspective. Rather than opposing the efficiency and resilience, we suggest considering their mutual intersections to enhance each other based on synergetic effects in terms of SC *resileanness*.

Major costs of disruption management are seen in disruption prediction, protective redundancy, and reactive capabilities as a result of a higher need for certainty and the resulting higher redundancy and recovery efforts. As such, we suggest studying these areas from the perspective of efficiency and resilience complementarity (Fig. 3).

According to Fig. 3, structural complexity, process inflexibility and non-flexible usage of resources, and insufficient parametric redundancy increase uncertainty and disruption risk propagation in the SC. The ultimate objective of the LCN SC design is to develop the ability to operate according to planned performance regardless of environmental changes. As such, the LCN SC design possess two critical capabilities, i.e.,

- low need for uncertainty consideration in planning decisions and
- low need for recovery coordination efforts.

Structural variety, process flexibility, and parametrical redundancy ensure disruption resistance and recovery resource allocation and allow for SC operation in a broad range of environmental states. This means that planning activities in the LCN SCs do not heavily rely on uncertainty prediction and proactive protection investments. Similarly, recovery coordination efforts are reduced to a minimum. Note that the LCN SC design does not necessarily imply higher costs, but rather seeks for an efficient combination of lean and resilient elements.

Let us discuss the principles of implementing the LCN SC framework in practice using digital technology.

4.2 Process and Resource Utilization Flexibility

Process and resource utilization *flexibility* means in a wider sense an establishment of universal, very flexible workstations such as those postulated in Industry 4.0 systems. Similar, the usage of universal materials can be considered with regards to recovery flexibility in the SC. Additive manufacturing technology can also positively influence product and process flexibility resulting in a combination of efficiency and resilience. Additive manufacturing can reduce the need for backup contingency suppliers. The decentralized control principles in Industry 4.0 systems make it possible to diversify the risks with the help of manufacturing flexibility increases. New research directions can be seen with regards to the impact of the digitalization on the SC design resilience (Ivanov et al. 2019a). For example, Big Data analytics and advanced Trace &Tracking systems in general, and Blockchain technology in particular, can help to trace the roots of disruptions, to observe disruption propagation (i.e., the ripple effect), to select short-term stabilization actions based on a clear understanding of what capacities and inventories are available (emergency planning), to develop a mid-term recovery policy, and to analyze the long-term performance impact of the ripple effect. Additive manufacturing has the potential to reduce disruption propagation in the SC since the number of SC layers and the resulting complexity would be reduced.

4.3 Non-expensive Parametric Redundancy

Non-expensive parametric redundancy targets the efficient reservations of capacity, inventory, and lead time. More specifically, those reservations need to be considered not as a non-used redundancy, but rather for use in normal operation modes as well. Network redundancy optimization can be viewed as a new research topic in this area. Another aspect of parametric redundancy is its efficient allocation. A new research direction extending the existing value-stream mapping techniques toward the SC resilience can be considered. Efficient redundancy can be implemented by using additive manufacturing that helps to reduce the need for risk mitigation inventory and capacity reservations. Finally, new material classification schemes need to be developed subject to material criticality and risk exposure in terms of the efficient and resilience SC design.

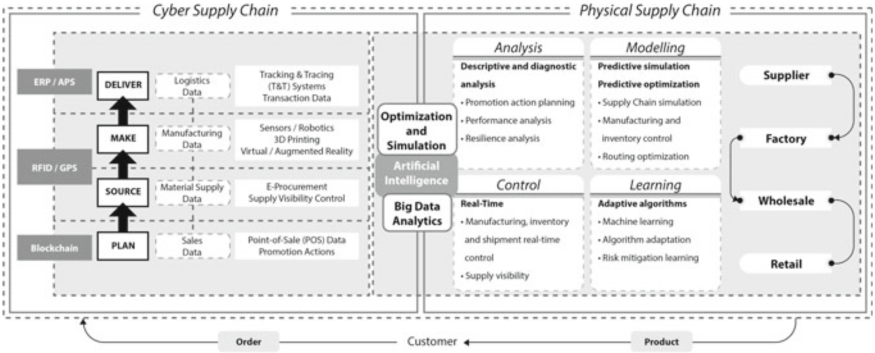

Fig. 4 Service and material flow coordination in the cyber-physical supply chain

5 Digital Supply Chain Twin: Data-Driven Optimization and Simulation to Manage the Disruption Risks

5.1 Supply Chains as Cyber-Physical Systems

Today and looking at the near future, the SC will be as good as the digital technology behind it. *The recent examples of digital technology applications to SCs allow for the new proposition that the competition is not between SCs, but rather between SC services and the analytics algorithms behind the SCs.* The services may be ordered in packages or as individual modules (Fig. 4).

Examples of SC and operations analytics applications include logistics and SC control with real-time data, inventory control, and management using sensing data, dynamic resource allocation in Industry 4.0 customized assembly systems, improving forecasting models using Big data, machine learning techniques for process control, SC visibility, and risk control, optimizing systems based on predictive information (e.g., predictive maintenance), combining optimization and machine learning algorithms, and simulation-based modeling and optimization for stochastic systems.

Success in SC competition will become more and more dependent on analytics algorithms in combination with optimization and simulation modeling. Initially intended for process automation, business analytics techniques now disrupt markets and business models and have a significant impact on SCM development. *As such, new disruptive SC business models will arise where SCs will be understood not as rigid physical systems with a fixed and static allocation of some processes to some firms. Instead, different physical firms will offer services of supply, manufacturing, logistics, and sales which will result in a dynamic allocation of processes and dynamic SC structures.* Recent literature documented the possibility of modeling such integrated service-material flow SCs (Ivanov et al. 2014c).

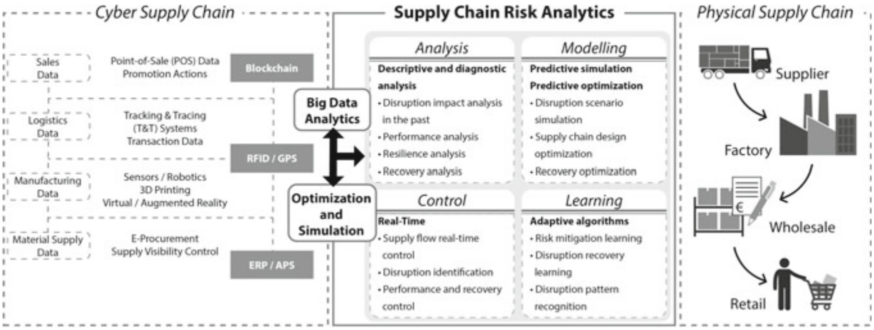

Fig. 5 Digital supply chain risk analytics framework

5.2 *Supply Chain Digital Twins*

Dunke et al. (2018) underline that digitalization and Industry 4.0 may significantly influence the optimization techniques in the SC domain as well as disruption propagation impacts on SC performance. With the help of optimization and simulation approaches, current research generates new knowledge about the influence of disruption propagation on SC output performance considering disruption location, duration and propagation, and recovery policies. New digital technologies create new challenges for the application of quantitative analysis techniques to SC ripple effect analysis and open new ways and problem statements for these applications.

In the past decades, simulation and optimization have played significant roles in solving complex problems. Successful examples include production planning and scheduling, SC design, and routing optimization, to name a few. However, many problems remain challenging because of their complexity and large scale, and/or uncertainty and stochastic nature. In addition, the major application of optimization and simulation methods in the last decades was seen in decision support, meaning that decision makers were to manually provide the model input and interpret the model output. On the other hand, the rapid rise of business analytics provides exciting opportunities for Operations Research and the reexamination of these hard optimization problems, as well as newly emerging problems (Fig. 5).

Sourcing, manufacturing, logistics, and sales data are distributed among very different systems, such as ERP, RFID, sensors, and Blockchain. Big data analytics integrates this data to information used by AI algorithms in the cyber SC and managers in the physical SC. As such, a new generation of simulation and optimization models is arising. The pervasive adoption of analytics and its integration with Operations Research shows that simulation and optimization are key, not only in the modeling of physical SC systems, but also in the modeling of cyber SC systems and learning from them.

An example of a decision-support system that combines a simulation, optimization, and data analytics is shown in Fig. 6.

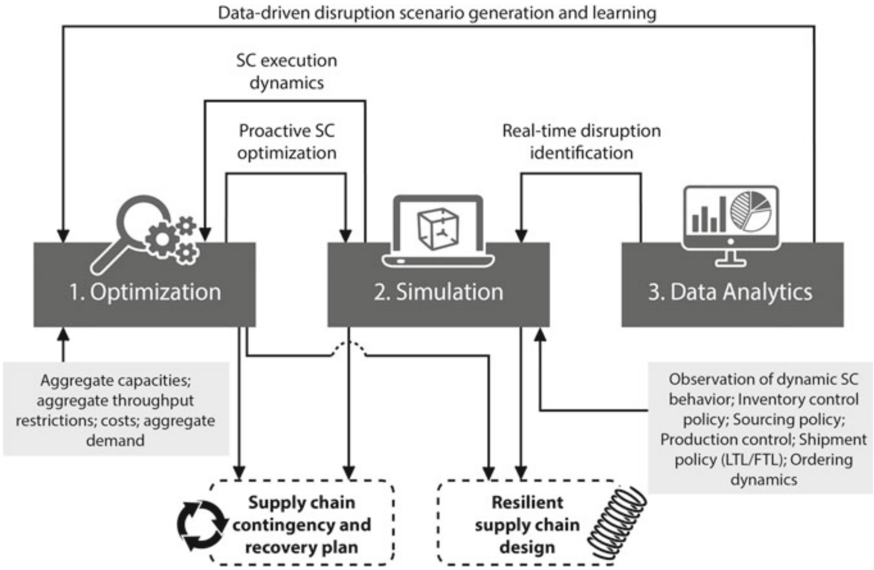

Fig. 6 Concept of a decision-support system for supply chain risk analytics (Ivanov et al. 2019a)

The decision-support system for SC risk analytics aims at proactive, resilient SC design in anticipation of disruptions and structural–parametrical adaptation in the case of disruptions. *The decision-support system is based on a concept that combines simulation, optimization, and data analytics.* The simulation–optimization part of the system is intended to provide proactive, resilient SC optimization and simulation of SC dynamic behavior in the event of possible disruptions or disruption scenarios. In addition, this supports reactive, predictive simulation of disruption impacts on SC performance and of recovery policies which are subsequently optimized in a prescriptive manner using an analytical model. The data analytics part of the system is applied to disruption identification in real time using process feedback data, e.g., from sensors and RFID. In addition, this aims at automated data input of disruption data into the reactive simulation model for recovery policy simulation and optimization. Finally, data analytics is used as data-driven learning system at the proactive stage, helping to generate adequate disruption scenarios for resilient SC design and planning.

At the proactive level, mathematical programming models produce notable insights for managers and can be applied where the probability of disruption can be roughly estimated. On the one hand, big data analytics and advanced trace and tracking systems may help in predicting disruptions and providing more accurate data to build sophisticated disruption scenarios for resilient SC design analysis. Digital technologies open new problems for resilient SC design. For example, additive manufacturing changes SC designs whereby new resilient sourcing problems may arise. This area can further be enhanced using collaborative purchasing platforms.

At the reactive level and with regards to mitigation strategies and identifying disruption impact on finance and operational performance, digital technologies can be extensively used to obtain real-time information on the scope and scale of disruptions, their propagation in the SC and to simulate possible recovery strategies. In addition, at the reactive level, adaptation is necessary for achieving desired output performance by ensuring the possibility of changing SC plans and inventory policies. Adaptation processes in ripple effect control can be supported by feedback and adaptive control methods using decentralized agent techniques with the help of digital technologies (Levalle and Nof 2017). Visualizing these processes through virtual reality-supported simulation has not yet been done extensively to model the ripple effect in the supply chain. For this, simulation models, along with new digital technologies, can improve tools which are already used in developing SC agility and visibility in terms of disruption velocity.

A combination of simulation and optimization can extend the scope of both. Combining the methods enables:

- Network optimization to minimize total SC cost.
- Dynamic analysis of ordering, production, inventory, and sourcing control policies using simulation.

Simulation is a newer tool and especially powerful when combined with optimization. More SC managers are now adopting the practice of using these techniques together.

What can a typical SC simulation-optimization model include, and what factors can it account for when working on risk analysis?

Network design and geographical information

Network design, with regard to the geographical location of sites, is the core of most SC simulation models. GIS maps are used in simulation models to locate the sites, and calculate distances, routes, and travel times along real roads. In addition to geospatial calculations, they provide visualization and transparency in a model.

Operational parameters

Inventory control policies, back-order rules, production batching, and scheduling algorithms, as well as shipment rules and policies, need to be defined in the model and balanced against each other for both normal and disrupted operation modes. Modern SC simulation tools enable visual modeling of these policies and do not require programming skills.

Disruptions and recovery

The duration of random or scheduled disruption events can be modeled with the probability distribution. As to recovery, analysts can set individual recovery policies for different sites and define the rules of policy activation depending on when the event occurs, the expected duration, and the severity of the disruption.

Performance impact

The direct impact of the ripple effect is reflected in changes to KPIs. Revenue, sales, service level, fill rate, and costs are typically calculated. Unlike analytical models

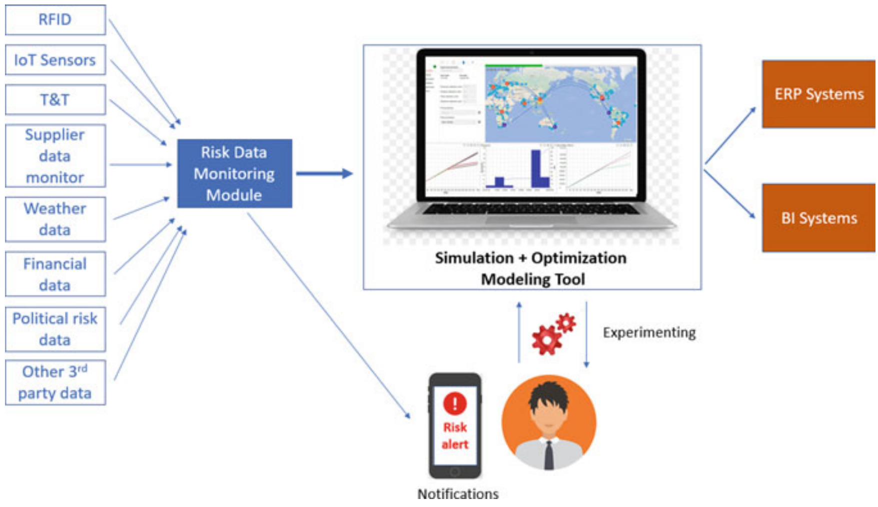

Fig. 7 Supply chain digital twin (Ivanov 2018c)

that usually focus on a particular metric (e.g., costs/profit), simulation enables the simultaneous measurement of all metrics in the same model. Their values can be checked at any chosen moment of the time period modeled. This way, disruption duration can be modeled, performance impact measured, and mitigation policies evaluated for efficiency.

A simulation model that considers all of these factors can be the basis for building a successful *digital twin* of a physical SC that can be used for complex analysis of SC risks, the development of contingency plans, and more efficient operational management.

A *digital SC twin* can support decision-making about the physical SC on the basis of data. At each point of time, the digital twin mirrors the physical SC: the actual transportation, inventory, demand, and capacity data and can be used for planning and real-time control decisions. The combination of simulation, optimization, and data analytics constitutes a full stack of technologies which can be used to create an SC digital twin—a model that always represents the state of the network in real time (Fig. 7).

As stated, a digital twin reflects the current state of an SC, with the actual transportation, inventory, demand, and capacity data. For example, if there is a strike at an international logistics hub, this disruption can be spotted by a risk data monitoring tool and transmitted to the simulation model as a disruptive event. Then, simulation in the digital twin can help forecast possible disruption propagation and quantify its impact. In addition, simulation enables efficient testing of recovery policies and the adaptation of contingency plans—for example, alternative network topologies and backup routes can be reconsidered on the fly. These screenshots are taken from any Logistix™ software and show the map-based model animation and the model-building editor.

The output data from a digital twin simulation can be transferred to an ERP system or a business intelligence (BI) tool to analyze the performance impact of the disruptions. Additionally, a simulation model can activate BI algorithms. For example, if the service level in a simulation model decreases to a certain level, the digital twin might activate a BI algorithm to search for the cause of the problem. Interacting with other SCM tools, a digital twin provides a control tower for end-to-end SC visibility.

6 Conclusions

The impact of digitalization and Industry 4.0 on the ripple effect in the SC has been studied in this chapter. Despite some partial efforts to uncover new insights in the impact of digital technologies on SC risks, the understanding of the individual contribution and the interplay of different digital technologies on specific SC disruption risk management and ripple effect is still vague. This study contributes to the body of knowledge in the field by combining the results gained from two isolated areas, i.e., the impact of digitalization on SCM, and managing the ripple effect in the SC.

Digitalization is expected to increasingly penetrate industry in the coming years, greatly changing operating and business systems, and the economy. Such potential offers new approaches to SC risk management that bring both opportunities and challenges. The fusion of the digital world with industrial processes is the so-called digital transformation. In addition to internal and cross-company processes in production and logistics, this also applies to the products and services offered to customers that need to be refined through the use of digital technologies. This chapter explained digital technologies can be used in managing SC disruption risks and the ripple effect.

The trend toward the application of digital technologies goes beyond the manufacturing company. The supplier network, the customer network, and the logistics service providers must also install and develop digital technologies to make the entire SC in nonstop delivery flexible. For this reason, the focus must be on risk management for every SC actor in the event of more frequent incidents such as natural catastrophes or supplier disruptions. The sources and handling process of risks need to be understood to facilitate the successful application of digital technologies. Digital technologies can potentially offer SCs enormous benefits in terms of transparency, visibility, cost reduction, efficiency, and resilience. However, there is still great uncertainty about the application and acceptance of the technologies, as many technologies are still in development, and industry standards are not yet established.

More specifically, this study found that at the *proactive* stage, digital technologies increase demand responsiveness and capacity flexibility. This may have a positive impact on reductions in risk mitigation inventory in ripple effect control. In addition, shorter lead times due to additive manufacturing enhance the impact of digitalization on inventory control. Industry 4.0 and additive manufacturing with the support of

BDA and T&T technologies facilitate a new quality of proactive planning of risk management infrastructure and increase the ability to reconfigure resources at the recovery stage. At the *reactive* stage, Blockchain, T&T technologies, and BDA allow a principally new quality of data coordination and SC visibility when simulating and activating recovery policies.

In terms of the SCOR model, *sourcing and production* activities can be adversely affected by additive manufacturing and Industry 4.0, which carry higher exposure to external risks and ripple effect. A plausible explanation is the increase in complexity and the reduction in time and demand risks that occur, driven in turn by greater flexibility and shorter lead times. Higher supply risks can be encountered if a disruption happens in the upstream SC, since there is no intermediate inventory in between the stages. The risks in the *delivery* processes are influenced by big data analytics with regards to a reduction in demand risks due to better SC visibility and forecast accuracy, reduction in information disruption risks and better quality of contingency plan activation. Reductions in supply and time risks in integrated SC *planning* can be achieved by using Blockchain and advanced T&T systems that provide real-time coordination while activating contingency policies. Designing a resilient SC can be influenced by higher information risks, higher exposure to external risks and a reduction in time and demand risks on the basis of Industry 4.0 technology and additive manufacturing.

A number of directions for simulation and optimization applications to SCM have been identified for digital technology application. BDA and advanced T&T systems may help in predicting disruptions and providing more accurate data to build sophisticated disruption scenarios for resilient SC design analysis. Digital technologies can be used extensively to obtain real-time information on the scope and scale of disruptions, their propagation in the SC, and to simulate possible recovery strategies. In addition, at the reactive level, adaptation is necessary for achieving the desired output performance by ensuring the possibility of changing SC plans and inventory policies. Adaptation processes in ripple effect control can be supported by feedback and adaptive control methods using decentralized agent techniques with the help of digital technologies. Visualizing these processes through virtual reality-supported simulation has not yet been done extensively to model the ripple effect in the SC.

Future decision-support systems will extensively utilize digital technologies and the digital SC twin, i.e., a computerized model of an SC updated with actual data in real time.

Notwithstanding the rapid developments in SCs and their digital twins, a number of questions arise:

- Is the SC as resilient as the digital technology behind it?
- If yes, what will provide the most competitive advantage in the future: physical SCs or their digital twins?
- Will SC resilience be managed by human, artificial intelligence, or a hybrid of both?
- What will be the role of future SC risk managers?

There is much research and practical potential with regards to the questions stated above. These can hopefully motivate new insightful developments in research on the ripple effect and disruption risk.

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