A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0

Article *in* Production Planning & Control · May 2020

DOI: 10.1080/09537287.2020.1768450

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[Accepted in Production Planning and Control]

A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0

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Abstract

We theorize a notion of a digital supply chain (SC) twin – a computerized model that represents the network state for any given moment in real time. We explore the conditions surrounding the design and implementation of the digital twins when managing disruption risks in SCs. The proposed conceptual framework of a digital twin for SC disruption management is rooted in a combination of model-based and data-driven approaches. This combination allows uncovering the interrelations of risk data, disruption modeling, and performance assessment. The framework developed, for the first time, conceptualizes the digital SC twin and advances our understanding about *when* and *how* to integrate data analytics into manage SC disruption risks towards building a theory of a digital SC. The findings presented can also guide firms in properly maintaining data for disruption risk management and highlight potentials of transition from offline to online decision-making support. The results of this study contribute to the research and practice of SC risk management by enhancing the researchers' and decision-makers' understanding for predictive and reactive decisions by utilizing the advantages of SC visualization, historical disruption data analysis, and real-time disruption data to ensure end-to-end visibility and business continuity in global companies.

Keywords: *supply chain; resilience; Industry 4.0; disruption risk; data analytics; digital twin.*

1. Introduction

Industry 4.0 constitutes a technological framework for adoption of cyber-physical integration principles in manufacturing, logistics, and supply chains (SC). Among various perspectives (Liao et al. 2017, Strozzi et al. 2017), a particular concern has been focused on how digitalization and data analytics capabilities can be manifested in predicting future and identifying real-time events (Wamba et al. 2015, 2017, Wang et al. 2016, Papadopoulos et al. 2017, Altay et al. 2018). Some researchers point out a trend towards digital twins, i.e., computerized models that represent a physical object in real time (Negri et al. 2017, Alla et al. 2019, Frank et al. 2019, Singh et al. 2019). One of the substantive areas of data analytics and digital twin applications is SC disruption risks (Choi et al. 2017, Ivanov et al. 2019).

SC risk managers are interested in decision-making support to identify disruption scenarios, to understand the proneness to disruptions of certain parts of the network and fortify them, to monitor and recognize the disruptions in real time, and to determine the actions for the time of disruption and recovery (Oehmen et al. 2009, Wang et al. 2017, Samson and Gloet 2018, Dubey et al. 2019b, Hosseini et al. 2019). The existing optimization and simulation models provide a decision-making support for stress-testing of the existing SC designs and for the deployment of contingency and recovery plans (Ho et al. 2015, Lücker et al. 2019). These models need data on disruptions which happened in the past to construct disruption scenarios, and real-time data on disruptions to timely identify bottle-necks and to deploy the recovery policies (Ivanov et al. 2017). Recent research pointed to the new opportunities for managing SC disruption risks by data-driven approaches (Subramanian and Abdulrahman 2017, Cavalcantea et al. 2019, Dubey et al. 2019b, Ivanov et al. 2019).

Examples of SC disruptions range from the fire at the Philips microchip plant in Albuquerque, New Mexico in 2000, Hurricane Katrina in 2006, or the tsunami in Japan in 2011 to newer examples of disruptions, such as the explosion at the BASF plant in Germany in 2016, and a fire at the Meridian Magnesium Products of America factory in Eaton Rapids, Michigan in May 2018. These disasters caused a remarkable number of SC disruptions, which resulted in long delivery delays, decreases in revenues and sales, and production suspensions that affected workforce utilization. It was observed that disruption directly and indirectly impacted SC performance, lowering both stock returns and firms' competitive positioning in the markets (Hendricks and Singhal 2005, Wu and Olson 2008, Hendricks et al. 2009, Collichia et al. 2010, Marsh et al. 2011, Gunasekaran et al. 2015, Elluru et al. 2017, Ivanov 2018, Akkermans and van Wassenhove 2018,).

Although prominent scholars have acknowledged the difficulty in predicting and detecting the disruptions that vary in type and nature, and are too intermittent and irregular to be identified, estimated or forecasted well (Pettit et al. 2010, Bhattacharya et al. 2013, Ambulkar et al. 2015), relatively little consideration has been given to theory and applications of data analytics to manage the SC disruption risks. As a result, new research in data-driven decision-making on proactive, resilient SC design, including response planning activities and reactive real-time control with the deployment of recovery plans is increasingly becoming a dominant issue in managing risks in global SCs (Speier et al. 2011, Mishra et al. 2016, Dubey et al.

2019a). Moreover, operations in SCs are not only directly affected by disruption events, but indirectly affected as well. These events may propagate through a SC, causing the so-called ripple effect. This propagation can increase the severity of an event's impact (Blackhurst et al. 2005, Mizgier et al. 2012, Ivanov et al. 2014, Yildiz et al. 2016, Scheibe and Blackhurst 2018, Dolgui et al. 2018, Zhang et al. 2018). This is especially true for large scale systems, such as global SCs with multi-tier organizational networks (Dolgui et al. 2019a, Ivanov 2019a).

The quality of model-based decision-making support in resilient SC design and recovery deployment crucially depends on the availability of data and when that critical data can be acquired. Examples include, but are not limited to, data about suppliers and probabilities of route disruption, i.e., data used to build disruption scenarios for analyzing resilient SC design (Purvis et al. 2016, Yildiz et al. 2016, Gao 2018), advanced supply signal recognition (Gao et al. 2017), or real-time disruption detection data for timely deployment of recovery policies (Sheffi 2015, Bode and Macdonald 2017). Given the *online* nature of most of this data, the use of *offline* decision-making tools is somewhat restricted in its ability to uncover real needs in decision-making support in SC disruption risk management.

In light of the continuous growth of firms' capabilities in analytics, the value of data in predicting future disruptions and recovering SC operations when they is disrupted is more important than ever (Paul and Rahman 2018). Organizations are looking for ways to utilize their databases to enhance their SCs and are exploring the ways they can utilize large volumes of data to both predict risks and assess vulnerability (Choi and Lambert 2017) and improve the resilience of SC operations (Choi et al. 2017). Dubey et al. (2019b, 2018) underline that digital technologies may significantly influence agility, adaptability, and alignment and their impact on performance in SCs.

The application of data analytics methods are new in the field and allow, e.g., the geospatial spread of diseases to be predicted, emerging trends in consumer behavior during natural disasters such as hurricanes to be understood, social networks and the role of social media on public behavior to be analyzed, blockchain-based transportation control, traffic flow during catastrophic events to be managed, and the locations of relief facilities to be optimized for maximum coverage and safety (Apte et al. 2016, Morrice et al. 2016, Araz et al. 2013, Yücel et al. 2015, Oded et al. 2007, Choi et al. 2018).

With an enhancement of the existing decision-support tools by data analytics a *digital SC twin*– a computerized digital SC model that represents the network state for any given moment in real time, allowing for complete end-to-end SC visibility to improve resilience and test contingency plans – can be created. A digital twin represents the physical SC based on actual transportation, inventory, demand, and capacity data and can therefore be used for planning and real-time control decisions. SC risk managers would benefit from tools that incorporate data analytics by leveraging emerging real time data and surveillance systems, predicting future impact and reactions, optimizing strategic and logistical locational decisions for efficient contingency plan execution, and building firms' control towers (Battara et al. 2018, Salman et al. 2018).

The research reviewed shows a diversity of knowledge and findings about decision-support in SC disruption risk management (Schlüter et al. 2017). Yet, this diversity is still fragmented. Advancements gained in quantitative analysis and data-driven analytics remain only vaguely connected with each other. Despite some partial efforts to uncover the impact of data analytics on SC risk mitigation and control and the understanding of the individual contributions, left ignored, however was the interplay of data-driven technologies and SC risk management.

The objective of this conceptual study is a further development of the theoretical foundations to the theories of the SC uncertainty, structural dynamics and risk analytics (Blackhurst et al. 2005, Ivanov et al. 2010, Flynn et al. 2016, Ivanov 2018, Choi et al. 2018, Dubey et al. 2019b, Ivanov et al. 2019, Panetto et al. 2019). Our study derives methodological principles of digital SC risk analytics and combines them into a management decision-making framework utilizing the Industry 4.0 principles. This framework can be used to design a digital supply chain (SC) twin for disruption risk management. This study closes this research gap by combining the results gained from two areas, i.e., data-driven analytics and model-based decision-support in SC disruption risk management. In order to narrow the research gap, we set as our research aim the development of a management decision-making framework, i.e., an integrated decision-support system (DSS) for data analytics-driven, proactive resilient SC design and reactive real-time disruption risk management.

Our study makes substantive contributions. As an outcome of this research, we propose a conceptual-technological framework of a generalised DSS for SC disruption management comprising data-driven disruption modeling in the SC and uncovering the interrelations of risk data, disruption modeling, and performance assessment. The framework developed, for the first time, conceptualizes a unique digital SC twin framework for managing disruption risks that in turn, advances our understanding about *when* and *how* to integrate data analytics to manage SC disruption risks. Relying on offline decision-making only and ignoring accurate data on supplier and route disruptions, advanced supply signal recognition, and real-time disruption detection can result in misleading disruption scenarios for SC risk analysis and late or inefficient deployment of recovery policies.

For research methodology and logic, this study is rooted in conceptual research. To be specific, based on the literature analysis and an analysis of existing information technology applied to SC disruption risk management, we first derive generic methodological principles and a design structure of a digital twin for SC disruption risk management using information control and communication theory. This analysis allows conceptualizing a SC disruption risk modeling framework that is used to develop a digital SC twin based on a combination of model-parametric and data taxonomies. Finally, the methodological principles derived and the digital twin developed are merged into a generalized DSS structure that, for the first time, constitutes a framework integrating risk data and data-driven analytical models for SC disruption risk management building a theoretical foundation of a digital SC twin. The theoretical contribution of this study compounds the formulation of methodological principles and a conceptualization of a generalized design for digital SC twins. A decision-support system based on the digital twin principles can potentially enhance research on proactive and reactive disruption risk management strategies and contingency plans by using the advantages of SC visibility, historical disruption data analysis, and real-time disruption data to ensure business continuity in global companies.

The rest of this study is organized as follows. Section 2 analyzes state-of-the-art insights gained in optimization-simulation methods, data analytics techniques, and information technology for SC disruption risk management. Sect. 3 uncovers methodological principles of constructing the digital SC twins. Conceptualization of a digital twin design framework and its illustration through an original research are shown in Section 4. Section 5 is devoted to managerial insights and generalization of the approach developed. The results are summarized, discussed, and considered in light of future research in Section 6.

2. State of the art

2.1 Model-based disruption risk management

SC disruption risk management has gained the attention of the research community over the last two decades. As shown in recent surveys of quantitative method applications to SC disruption risks and resilience, the number of model-based studies has been increasing exponentially over the last decade (Ho et al. 2015, Ivanov et al. 2017, Dolgui et al. 2018, Dolgui et al. 2019, Ivanov and Dolgui 2019, Hosseini et al. 2019).

Analyzing literature enables the identification of several problem classes and datasets which we describe in this sessions on the basis of study by Ivanov et al. (2018). Analytical methods are applied at the SC design level and help analyzing the disruption impact on SC performance either by deactivating some structural elements, or by changing some operational parameters (e.g., capacity) and observing the resulting changes on costs or sales (Torabi et al. 2015, Yildiz et al. 2016, Ivanov et al. 2016, Rezapour et al. 2017, Sawik 2017). This analysis is helpful at the strategic decision-making level. At the same time, these models are restrictive when considering the dynamics of inventory, sourcing, or shipment control.

Dynamic simulation models allow SC behavior to be analyzed over time, a disruption's performance impact to be computed, and a resilient SC design to be recommended based on detailed and real time data and control policies subject to a variety of financial, customer, and operational performance indicators. In addition to the more detailed data of optimization models, simulation models consider additional *logical* and *randomness constraints*, such as randomness in disruptions, inventory, production, sourcing, and shipment control policies, and gradual capacity degradation and recovery. Simulation has been predominantly applied to problems in this class (Wu and Olson 2008, Schmitt and Singh 2012, Ivanov 2017, Schmitt et al. 2017, Ivanov and Rozhkov 2017, Chen et al. 2017, Trucco et al. 2017, Macdonald et al. 2018, Ivanov 2019b). Since simulation studies deal with time-dependent parameters, duration of recovery measures, and capacity degradation and recovery, they have earned an important place in academic research. Simulation has the advantage that it can extend the handling of the complex problem settings of optimization through situational behavior changes in the system over time.

Hybrid models extend isolated analytical and simulation models through recovery policy considerations. Independent of proactive or reactive policy domination, optimization and simulation techniques can mutually enhance each other. For problems in this domain, a combination of network optimization and simulation is recommended (Vahdani et al. 2011, Ivanov et al. 2014, Paul et al. 2014, Pavlov et al. 2018). The research on the recovery stage is still new and requires further study (Bode and Macdonald 2017, Ivanov et al. 2017).

Analysis of the models in the literature reviewed enables the identification of data used in at the pre-disruption, disruption, and recovery stages. In particular, SC modeling at the pre-disruption stage requires data on suppliers' risk exposure, the risk exposure of transportation links, and alternative SC designs (Yildiz et al. 2016, Gao et al. 2018). Modeling at the disruption stage requires data about which SC elements are affected by disruption, how much capacity and inventory is still available in the SC, and a forecast for recovery (Xia et al. 2004, Govindan et al.2016, Ivanov et al. 2017). Finally, recovery and post-disruption modeling requires monitoring data about capacities and inventory, as well as real-time data about material flows in the SC (Choi et al. 2017, Schmitt et al. 2017, Ivanov et al. 2018). As such, it is crucial to consider how this data can be obtained using existing analytics and real-time control technology.

2.2 Data-driven approaches

Applications of data analytics are visible in procurement, manufacturing shop floors, promotional actions in omnichannel models, routing optimization, real-time traffic operation monitoring, and proactive safety management (Choi et al. 2018). Zhong et al. (2015) propose a big data approach to forecasting logistics trajectories using RFID-enabled production data. Sommerfeld et al. (2018) study the effects of sensor-based quality data in an automotive SC using simulation. Nguyen et al. (2018) identify areas where data analytics can be applied in SCs in the near future. These include quality control in manufacturing, dynamic vehicle routing and in-transit inventory management in logistics/transportation, and order picking and inventory control systems in warehousing. Queiroz and Wamba (2019) and Dolgui et al. (2019b) extend the discussion towards Blockchain adoption challenges in SCs.

According to Waller and Fawcett (2013) and KPMG (2017), applications of SC analytics can be classified into four areas: descriptive and diagnostic analysis, predictive simulation and prescriptive optimization, real time control, and adaptive learning. With regards to SC risk management, data-driven approaches have been recently introduced to the research agenda. Papadopoulos et al. (2017) point out that data analytics can improve SC risk management and disaster-resistance. Choi and Lambert (2017) and Choi et al. (2017) provide evidence on how data analytics can be used to improve the resilience of SC operations by utilizing firms' databases and large volumes of data to predict risks, assess vulnerability, and enhance their SCs. Ivanov et al. (2018) show that data analytics can be applied at the planning stage to identify supplier risk exposure and can help at the reactive stage to monitor and identify disruptions. They propose a framework of integrated cyber-physical SC simulation and optimization and relate this framework to system-cybernetics principles. Their results echo those in the study by Choi (2018) which presented a new practical perspective on how big data related technologies can be used for global SCs with a SoS (systems of systems) mindset.

2.3 Data-driven decision support systems and information technology

Since data analytics influences SCs, and SCs are influenced by disruption risks, it is logical to expect interrelations between data-driven technology and SC disruption risk management. As a result of the harmonization and interoperability between data and computational services, along with the facilitation of their easy discovery, the sharing and usage of data sources for risk assessment have been developed in technical systems over the last several years. For example, OpenRiskNet (ORN 2018) is an open e-infrastructure which supports data sharing, knowledge integration, and in silico analysis and modeling in toxicology risk assessment. Similar systems are still rare in SC risk management.

Simchi-Levi et al. (2015) present a SC risk management system in the automotive sector that aims to estimate supplier risk exposure, evaluate pre-disruption risk mitigation actions, and develop optimal post-disruption contingency plans, including for circumstances in which the duration of the disruption is unknown. Their risk-analysis framework integrates databases, a quantitative risk-exposure model, and an output visualization tool. The DSS developed integrates various databases, time-to-recover and time-to-survive models, and data-visualization software. The data sources include the material requirements planning system, the purchasing database, and sales-volume planning information based on a SC mapping methodology (Gusikhin and Klampfl 2012). Decision-makers in procurement and risk specialists can use this DSS to track risk exposure in real time as inventory levels fluctuate and the SC structure evolves. Park et al. (2018) proposes a visual analytic system to augment and enhance decision-making processes of SC managers. They conclude that a modern SC DSS should be able to visualize different SC structural aspects, to deliver required information on-demand and to update the visual representation via user-initiated interactions, and to support both descriptive and predictive analytic functions for managers.

When analyzing literature, information technology for SC disruption risk management can be classified into visualization, early warning systems, and real-time event-detection systems. Acquiring and sharing real-time information is of vital importance for SC recovery planning and the coordinated deployment of recovery policies (Sheffi 2015). Tracking and tracing (T&T) systems aim to identify deviations or danger of deviations in SCs, analyze those deviations and deliver actual or potential disruption alerts, and elaborate control actions in order to recover SC operability. In combination with RFID (radio-frequency identification) and mobile devices, these systems are used to provide current information about process execution (Bearzotti et al 2012). In addition, blockchain applications to SCs, the creation of information pipeline systems, and SC finance systems are becoming more and more important for enhancing the scale and scope of T&T systems (Basole and Nowak 2018, Hofmann et al. 2018, Dolgui et al. 2019b). The central idea behind these applications is to increase visibility and efficiency based on record-keeping in the SC. For example, IBM and Wal-Mart are currently researching how they can increase food SC safety controls using blockchain technology (IBM 2017).

The cloud-based analytics platform SupplyOn Industry 4.0 Sensor Clouds makes it possible to control a SC in real-time, plan and adjust processes using up-to-date information (SupplyOn 2018). The data analysis capabilities allow quick identification of all orders where lead time was exceeded, further enabling quick identification of questionable transports. Resilience360 at DHL enables comprehensive disruption risk management by mapping the SC end-to-end, building risk profiles, and identifying critical hotspots in order to initiate mitigation activities and deliver alerts, in near-real time, about incidents that could disrupt the SC (DHL 2018). RiskMethods software aims to support proactive SC risk management. It contains the modules "Risk Radar", "Impact Analyzer", and "Action Planner", which allow for risk monitoring, performance impact assessment, and the planning of mitigation actions (RM 2018). GEOCOM (2018) developed a risk management and business continuity tool that combines modules of property assets, procurement, transportation, and dynamic SC risk management. The results of SC redesign can be reported to ERP systems and quantified through KPIs (key performance indicators), such as revenues, sales, on-time-delivery, etc. The EventWatch tool from SC risk management software Resilinc classifies and analyzes risk data, such as extreme weather, factory fire, force majeure, earthquake, power outage, mergers and acquisitions, and business sales. In the first half of 2018, they identified 1,069 disruption events (Resilinc 2018).

3. Derivation of methodological principles of data-driven DSS for SC disruption risk management

The analysis of literature and the practical examples enable us to formulate several methodological principles of data-driven DSS and information technology for SC disruption risk management. We relate the derivation of these principles to information control theory, i.e., to system and cybernetics principles following the approach of considering SCs as Systems of Systems (SoS) as developed by Choi (2018) and along the SC system-cybernetics frameworks developed by Ivanov and Sokolov (2013) and Ivanov et al. (2018).

The studies on SC disruption risks frequently refer to "loss of control" (Christopher and Peck 2004) and "communication" (Sheffi 2015). Cybernetics is the science of information control and communication (Wiener 1948, Ashby 1956). As such, cybernetics principles cannot be disregarded when considering SC disruption risk modeling. Moreover, cybernetics poses open system context analysis. An open system (Mesarovic and Takahara 1975, Casti et al. 1979) is a system that has interactions with the environments and evolves based on these interactions. The major characteristics of *open systems* are control, self-adaptation, and self-organization (von Bertallanfy 1969, Gao et al. 2016). Previous studies on cybernetics principles in the SC domain (Wang 2008, Tejeida et al. 2010, Ivanov and Sokolov 2010, 2013, Ivanov et al. 2014, Choi 2018) identify three major principles applicable to the information control and risk management.

The *first* principle is requisite variety. Ashby (1956) uses *variety as a measure of the number of possible system states* that can be differentiated from each other. Ashby's law of requisite variety states that: "A controller has requisite variety when he has the capacity to maintain the outcomes of a process within targets, if and only if he has the capacity to produce responses to all those disturbances that influence the process". According to this principle, situational variety should be balanced by the response variety of the controller following Ashby's (1956) statement: *"Only variety absorbs variety".* The *second* principle is Beer's Viable System Model (VSM) (Beer 1966, 1981). Generally, viability is the ability to keep system identity in a changing environment. A cybernetic viable system is predominantly concerned with striking a balance between management, operations, and the environment. VSM includes requirements for variety, dynamics, and communication. In this setting, the principles of *homeostasis* play a crucial role, whereby homeostatic behavior is dependent on requisite variety. The *third* principle is related to second-order cybernetics (Maruyama 1963, von Foerster 1974), which is concerned with proactive planning and control. Second-order cybernetics aims to simultaneously model the environment and control an object in this environment. This principle is closely related to adaptive and feedback control with online data updates.

With these systemic foundations in mind, we now formulate methodological principles of data-driven DSS for SC disruption risk management.

Principle 1: Decision-making support is considered a Viable System Model comprised of pre-disruption, disruption, and post-disruption stages.

According to literature, decisions in SC risk management are frequently brought into correspondence with disruption profiles, which contain the stages of pre-disruption (preparedness), disruption (response), and post-disruption (recovery and stabilization). Optimization and simulation models enable robust SC design, resilience analysis, stress-testing of different alternative SC designs, and simulation of contingent recovery policies. These are only a few examples of the numerous possible areas of application. As such, we suggest using this three stage classification as the major structure within which decision-making support is provided by digital SC twin.

Principle 2: Integration of physical and cyber data sources with online SC modeling

Decision-making support models can be enriched with data from physical sources (e.g., ERP, RFID, sensors) and cyber sources (e.g., blockchain, supplier collaboration portals, and risk data). For example, historical risk data about previous disruptions or geographical data about regional risks may help in the construction of realistic scenarios for SC resilience assessment. Real-time data from RFID and sensors can help to provide capacity and parametric inventory inputs to simulation and optimization models for SC recovery simulations, considering available resources in the non-disrupted SC. As such, the integration of physical and cyber data sources with SC modeling is considered the second principle of constituting a digital SC twin.

Principle 3: Supply chain models as an integration of physical and cyber networks.

In data-driven DSS, SC models become broader and represent both the physical SC and its cyber system. Therefore, the third principle of the digital twin design is consideration of SC models as an integration of physical and cyber networks in terms of second-order cybernetics.

Principle 4: Data-driven supply chain risk analytics systems support the use of data for learning and disruption pattern recognition.

The learning component is one new quality data analytics can add to digital SC twins. Learning from real disruptions and the respective SC behaviors provides a basis for identification of disruption and reaction patterns which can be used to improve both quantitative models and the design of experiments in which they are used.

Summarizing the four principles stated above, data-driven SC risk analytics systems in the form of digital twins could support decision-making in historical data-based analysis of SC resilience, predictive optimization, and simulation of alternative SC designs and contingent operational policies, real-time recovery control, and use of data for learning and disruption pattern recognition.

4. Digital supply chain twin: A framework of a decision-support system for disruption risk management

This section presents a digital SC framework as a DSS for SC disruption risk management based on the literature analysis in Sects. 2.1-2.2, the examples of information technology used for SC disruption risk management in Sect. 2.3, and the methodological principles described in Sect. 3.

4.1. Data-driven disruption modeling framework

Data-driven disruption modeling provides a basis for proactive, resilient SC design in anticipation of disruptions and structural-parametrical adaptation in the event of disruptions. The modeling combines simulation, optimization, and data analytics to create a *digital SC twin* and thereby manage disruption risks.

In the digital SC twin, *model-based decision-making support* enables simulation of the SC's dynamic behavior in the event of disruption. In addition, before a disruption occurs, potential impacts on SC performance can be evaluated, and then recovery policies can be optimized. *Data analytics* is used at the proactive stage for building realistic disruption scenarios based on risk data about historical disruptions and other data (e.g., supplier reliability data from ERP systems) during the SC design phase. At the reactive stage, data analytics is used for disruption identification in real-time using process feedback data, e.g., from sensors, T&T, and RFID. The goal of using data analytics this way is to embed real-time disruption data into a reactive simulation model for recovery policy simulation and optimization. Data analytics can also be used to create a data-driven learning system at the proactive stage, helping to generate adequate disruption scenarios for resilient SC design and planning. In addition, the data analytics component of the digital SC twin enables observation and monitoring functions to be integrated into SC disruption management, closing the loop "plan-monitor-adjust-control".

According to the principles described above, the following modeling framework for resilient SC design and recovery planning, which contains the conceptually integrated data, can be proposed (Fig. 1).

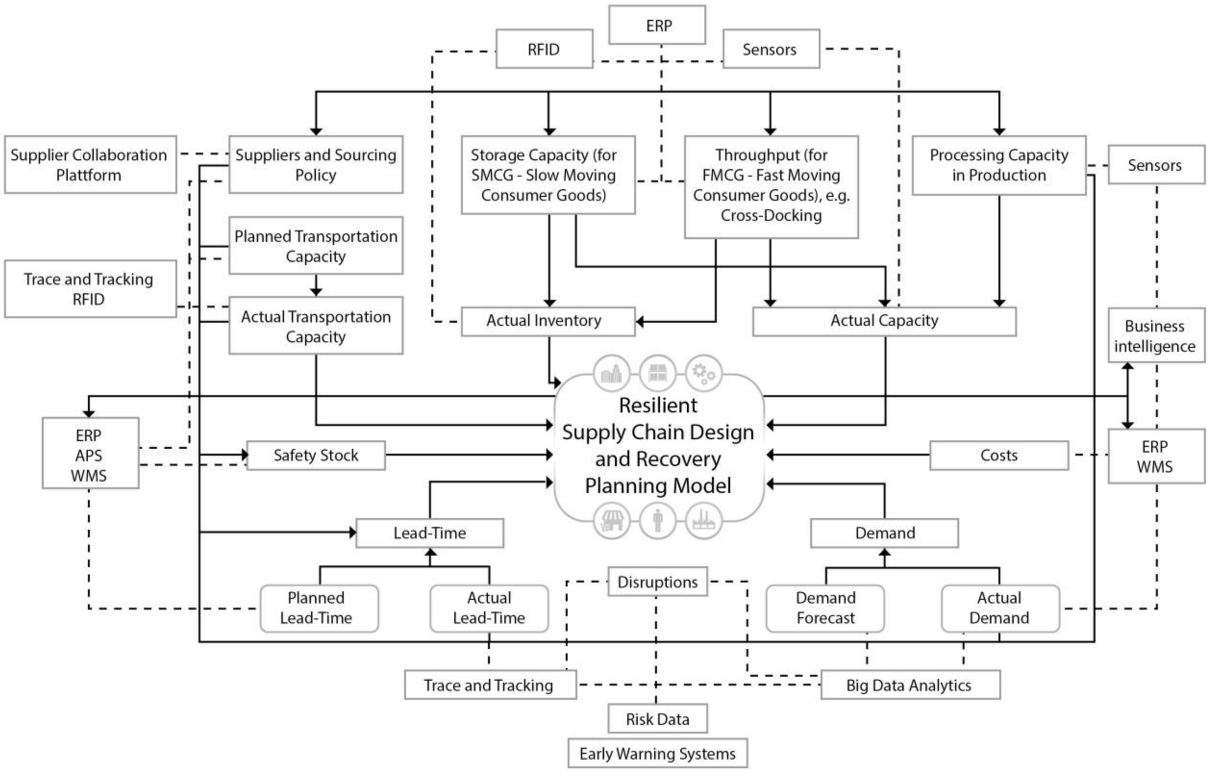

Fig. 1. Data structure in supply chain disruption risk modeling framework

Fig. 1 brings different data sources, the respective information systems, and the parameters of models for resilient SC design and recovery planning into correspondence. Data used to design resilient SCs and resilience recovery was shown in the analysis of the models in the studies described in Sect. 2. Data-driven support can be classified as external and internal information control loops. External support is mainly concerned with disruption data, both anticipated and actual, aggregated through a firm's own historical data and partner risk data, early warning systems, and T&T systems. Internal support encompasses the use of sensors and RFID to update SC data, such as capacity and inventory.

4.2. Digital supply chain twin: Example

We illustrate the digital SC twin principles from Sect. 3 and data-driven disruption modeling framework from Fig. 1 on example of a digital SC twin developed with the use of anyLogistix software which is a tool for model-based decision-making support in SCs (Fig. 2).

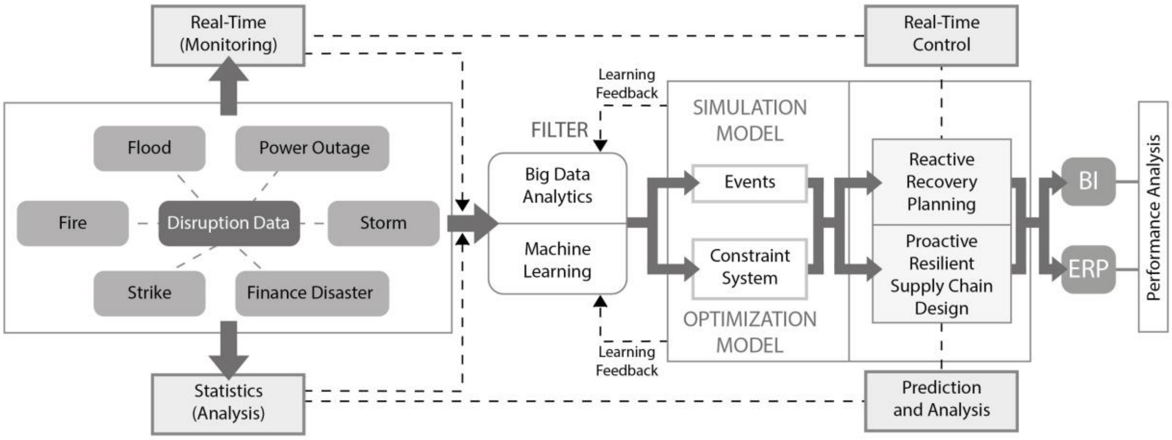

Fig. 2. Digital supply chain twin for managing disruption risks

The combination of anyLogistix and data analytics is based on a mapping of the risk data with geographical locations in the SC structure as previously discussed in Ivanov et al. (2019). This mapping is considered at the resilient SC design and resilience recovery stages. At the resilient SC design stage, the DSS developed uses disruption risk data to assess supplier and transportation disruption risks, predicting possible SC interruptions. This data is used for computing of alternative supply network topologies and back-up routes with assessment of estimated times of arrival in anyLogistix. In the dynamic mode, simulation is applied using real-time data to analyze the disruption impact on SC performance and alternative SC designs that contain non-disrupted network nodes and arcs depending on real-time inventory, demand, and capacity data. Furthermore, the interaction of data analytics and simulation-optimization tools is not limited to updating model data. Considering the output of simulation modeling, simulation results can be transferred to an ERP system or a business intelligence (BI) tool in order to analyze the performance impact of disruptions. Additionally, the simulation models can activate some BI algorithms. For example, if service level decreases to a certain level in the SC's simulation model, the digital twin might activate a BI algorithm to search for the cause of that problem and the necessary data updated to resolve the problem.

Fig. 3 demonstrates three major areas of SC disruption risk management covered in the digital twin proposed, i.e., disruption identification, disruption modeling, and disruption impact assessment.

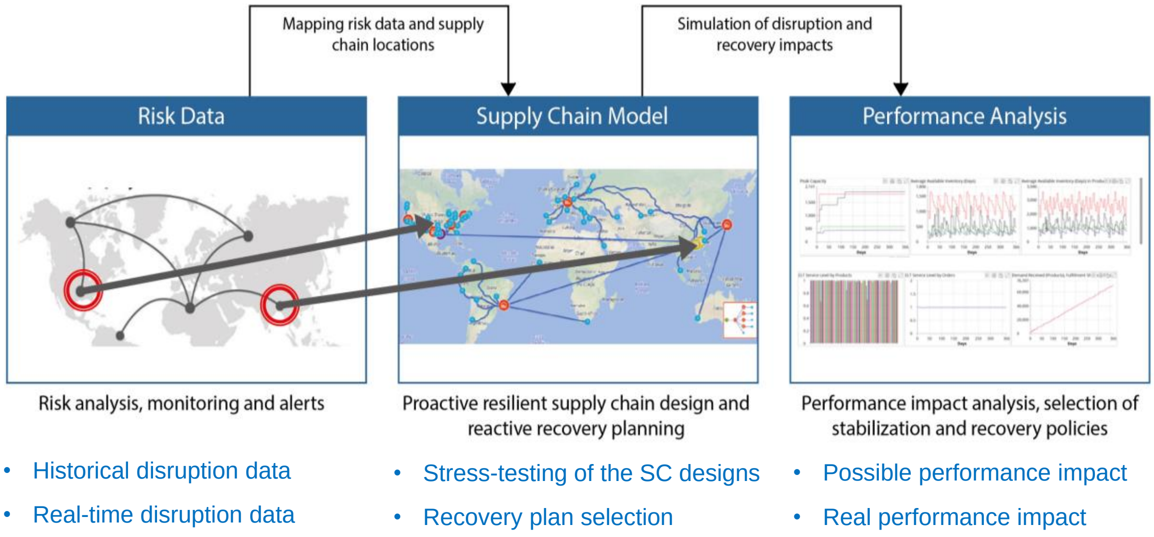

Fig. 3. Interrelations between risk data, modeling, and performance analysis (images used are from anyLogistix™ software)

Fig. 3 shows the mapping of risk data identification, the locational SC model in anyLogistix, and performance impact analysis in external tools, such as BI or ERP. Multiple experiments with different risk data, SC structures, and disruption scenarios have been performed, which allowed synthesis in the following multi-step analysis procedure.

Step 1. At the proactive risk analysis stage, historical risk data from external databases (e.g., natural disaster events in the past and geographical regional risk assessments) and internal sources (e.g., ERP data about supplier reliability performance) are collected. Using this data, the disruption scenarios for SC resilience analysis are setup in the simulation-optimization model. Technically, the function of data pre-processing is used in anyLogistix to transfer the incoming disruption data into the risk events in the simulation model. In addition, the parameters of network optimization and simulation models (e.g., capacities available) are set up subject to possible supply unavailability, capacity degradation, and natural disaster events. The resulting multiple disruption scenarios are investigated using optimization and simulation models to stress-test the existing and alternative SC designs.

Step 2. Next, a disruption example close to a real natural disaster is considered, e.g., the Typhoon Mangkhut in Hong Kong in September 2018 that closed down harbor and airport operations for many days. The risk analytics system is used to search for relevant disruption data (e.g., at a global logistics hub) that might affect SC resilience given the facility locations in the SC simulation model. Then the system gathers data about the forecasted disruption duration. The simulation is subsequently run with the existing SC design to observe the impact of such a disruption duration on SC performance.

Step 3. The recovery policies, such as alternative SC designs, that could be used in the period of disruption are simulated. Data collected from different sources in real-time are used to update model parameters, such as capacity, inventory, and lead times in terms of production and shipment capacities and inventory availability in the SC. This data is used to run the simulation of the recovery policies.

Step 4. The output of the experiments with the recovery policies is transferred to an ERP system or a BI tool to analyze the performance impact of the disruptions and the KPIs affected. Technically, the function of data post-processing is used in anyLogistix to transfer the simulation modeling outcomes into an external performance evaluation tool.

5. Implications to building a theory of supply chain risk analytics

In this section, we summarize and generalize the lessons learned from the conceptual and experimental integration of risk data and the model-based decision-making support tool in order to develop implications to building a theory of SC risk analytics. The *first* theoretical implication of this research is that the data-driven analytics and model-based methods represent a vision of a future DSS in SC disruption risk management. Based on the literature analysis in Sect. 2, the derived principles of data-driven DSS for SC risk management in Sect. 3, and the example of the digital twin presented in Sect. 4, we now conceptualize a generalized framework of a digital twin to manage SC disruptions (Fig. 4).

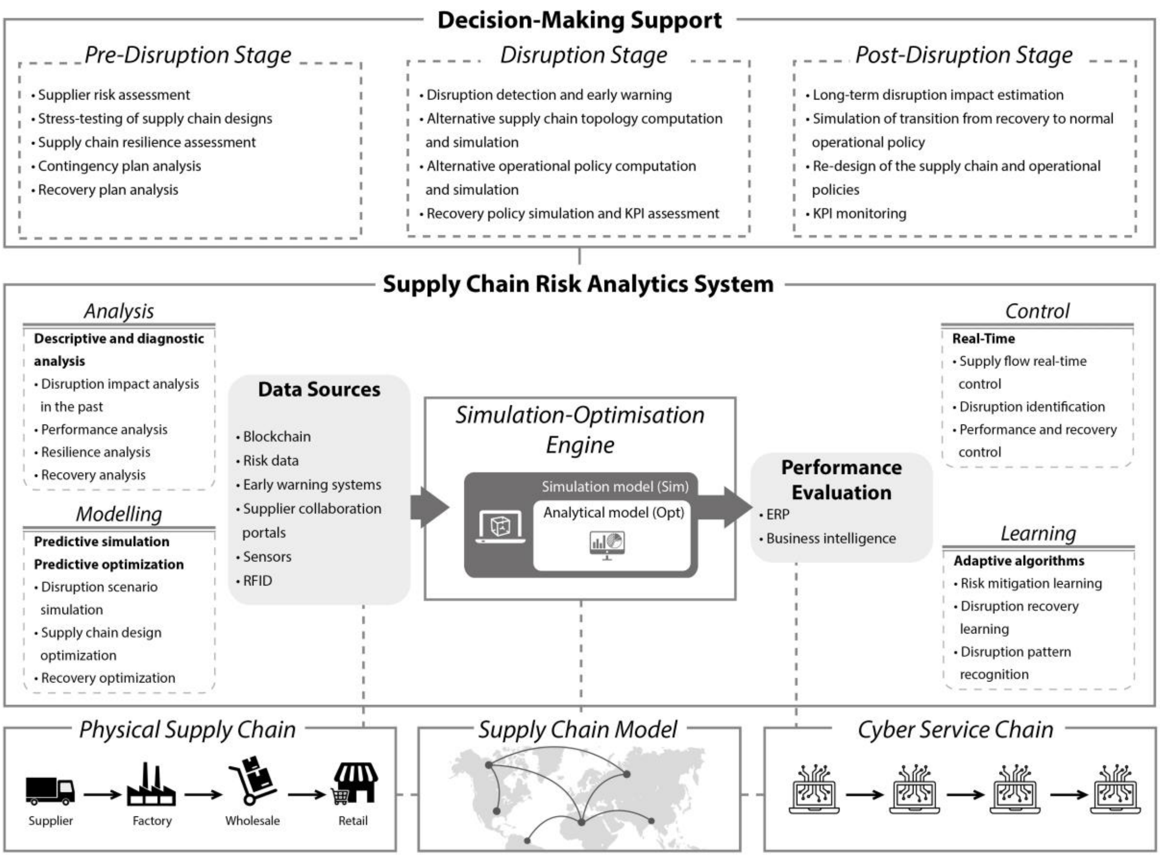

Fig. 4. Generalized framework of a digital twin for SC disruption management

Going from the bottom up, we start the analysis of Fig. 4 with the cyber-physical SC model. The firms in the physical SC and their IT generate data on sourcing, manufacturing, and logistics in cyber space that can be used for risk estimation and inclusion. SC model serves to integrate the physical and cyber components and is considered to be a central element in the SC risk analytics system aims to integrate the physical and cyber systems (cf. SoS) with the simulation-optimization engine. The computerized SC model is used by artificial intelligence algorithms in the cyber SC and managers in the physical SC. As such, the generalized framework of DSS for SC disruption risk management can be viewed as a cyber-physical system that integrates real *physical processes* and virtual computational *services*. In other words, a *digital twin* of the physical SC exists in the data space in the form of a cyber service chain.

The *second* theoretical implication of this research is that a combination of simulation and optimization with data analytics constitutes a new level of technologies to create a digital SC twin – a model that always represents the *current state* of the network. A digital twin gives analysts the possibility of experimenting with the SC's computer prototype to test what-if scenarios and quantify the effects of changes. Digital twins make use of data from physical SC in real-time – including information from online risk databases, IoT sensors, track and trace systems (T&T), and RFID. These monitoring technologies allow identification of critical hotspots and delivery of alerts in near-real time about incidents that could disrupt the SC. Then, this real-time disruption data can be embedded into a simulation model, along with third-party real-time data about natural, financial, or political risks. Machine learning algorithms are used to reduce noise levels and identify relevant disruption information (Cavalcantea et al. 2019).

In this setting, the cyber part of the model will represent the current state of the SC, with real-time transportation, inventory, demand, and capacity data. For example, if there is a strike at an international logistics hub, this disruption can be identified by an online risk data monitoring tool and transmitted to a simulation tool as a disruptive event. With this, simulation in a digital twin will support the identification and forecasting of disruption propagation and the quantification of its impact. On the other hand, simulation will provide for efficient recovery policy testing to adapt contingency plans according to each situation – for example, reconsidering alternative network topologies and back-up routes on-the-fly.

The *third* theoretical implication of this research is that the application of cyber-physical solutions can help to combine simulation and analytics to create a digital twin and thereby increase SC resilience through faster and more reliable recognition of potential external and internal disruptions and disturbances, and through the minimization or avoidance of their negative consequences. Real-time data analytics can help to trace the causes of disruptions, observe disruption propagation, select short-term stabilization actions based on a clear understanding of what capacities and inventories are available (emergency planning), develop a mid-term recovery policy, and analyze the long-term performance impact. Interacting with other SC tools, a digital twin provides a control tower for end-to-end SC visibility. As such, the digital SC can enable dynamic sensing capability and further helps to enhance robustness.

Finally, data analytics can be used as data-driven *learning* system at the proactive stage, helping to generate adequate disruption scenarios for resilient SC design and planning. Decision-makers in property, procurement, logistics, and SC risk management can use the framework developed for asset risk assessments, supplier risk analysis, locational and transportation decisions, and real-time risk control.

In summary, with the results of this study, we contribute to the theory and practice of SC disruption risk management by enhancing the researchers' and decision-makers' understanding of the value and use of data for predictive and reactive decisions. The developed principles and a generalized framework of a digital SC twin contribute to the theory building of the digital SC and SC risk analytics. More specifically, the development of adaptive SC management theory (Ivanov and Sokolov 2010), SC resilience (Blackhurst et al. 2011, Ivanov 2018, Pettit et al. 2019), organizational theory (Altay et al. 2018, Dubey et al. 2019a,b) as well as SC uncertainty theory (Flynn et al. 2016) can be furthered with the results of this study. Adaptation in supply chains is as vital for firms as adaptation mechanisms are for living organisms. Adaptation mechanisms continuously monitor, anticipate and adjust to dynamic environments. Similarly, organizations are also exposed to, and affected by changes in environmental and operational factors. The digital twin constitutes a technological framework for adoption of cyber-physical integration principles in manufacturing, logistics, and SCs. In addition, such systems evolve through adaptation and reconfiguration of their structures, i.e. through *structural dynamics* (Ivanov 2018). The theoretical implications of our study to the research areas of digital SCs and risk analytics can be considered in light of two dimensions. The first dimension is the change in traditional manufacturing and SC designs, and the resulting change in their management. Our approach supports the service-oriented SCs which are based on cyber-physical principles. The second dimension is the visibility. Big data applications and Blockchain allows to address central objectives of data analytics to increase visibility, response time, and efficiency in the SC. Similarly advances in sensor technology and IoT have enabled heightened awareness and visibility in the supply chain. Organizations are exploring ways to utilize large volumes of data to both predict risks and assess vulnerability. Our approach can be of value when developing theoretical foundations in this areas. To the practical end, the system developed can be utilized for asset risk assessments, supplier risk analysis, locational and transportation decisions, and real-time risk control. These decision-makers can use the system proposed to define proactive and reactive resilience strategies and contingency plans by applying the advantages of SC visualization, historical disruption data analysis, and real-time disruption data to ensure business continuity in global companies.

6. Conclusion

A combination of model-driven and data-driven decision-making support became a visible research trend in the last years. The quality of model-based decision-making support strongly depends on the data, its completeness, fullness, validity, consistency, and timely availability. These data requirements are of special importance in SC risk management for predicting disruptions and reacting to them. Industry 4.0 in general and digital technology in particular give rise to data analytics applications to achieve a new quality of decision-making support when managing severe disruptions. The combination of simulation, optimization, and data analytics constitutes a digital twin: a new data-driven framework of managing disruption risks in the SC. A digital SC twin is a model that represents the network state for any given moment in time and allows for complete end-to-end SC visibility to improve resilience and test contingency plans.

This study focused on creating a generic structure of a digital SC twin for managing disruption risks, i.e., a DSS for data-driven modeling of proactive resilient SC designs and reactive real-time disruption risk management. With the results of this study, we contribute to both the theory and practice of decision-making support in SC disruption risk management by enhancing decision-makers' understanding of the value and use of harnessing a firm's own risk data and that of their partners for predictive and reactive decision-making.

First, the methodological principles of data-driven DSS and information technology for SC disruption risk management were derived using system-cybernetic analysis. Future DSS in SC disruption risk management will extensively utilize data-driven technologies and be united by three basic principles of system-cybernetic research to form SC risk analytics decision-support and learning frameworks. A combination of these three principles builds a framework of future digital SC twins for managing disruptions, i.e., DSS for SC disruption risk management which utilizes integrated disruption risk modeling with simulation, optimization, and analytics components to support situational forecasting, predictive simulation, prescriptive optimization, and adaptive learning based on a transition from offline to online simulation and optimization.

To prove the implementation feasibility of these principle in different contextual settings, a DSS for disruption risk management and business continuity in the SC was developed and tested. In addition, the framework of a generalized DSS was proposed. At the SC design stage and in the pre-disruption mode, the system should allow visualization of SC risks, assessment of supplier disruption risks, prediction of possible supply interruptions, and computation of alternative supply network topologies and back-up routes with assessment of estimated times of arrival. In the dynamic mode, the system should be applied using real-time data to simulate disruption impacts on the SC and alternative SC designs that contain non-disrupted network nodes and arcs depending on real-time inventory, demand, and capacity data. The SC redesign results can be reported to ERP systems and quantified by means of KPIs, such as revenues, sales, on-time-delivery, etc.

The methodological principles and generalized design of the digital SC twin proposed in this study can potentially enhance research on proactive and reactive resilient strategies and contingency plans by using the advantages of SC visualization, historical disruption data analysis, and real-time disruption data to ensure business continuity in global companies. The findings presented can also guide a firm in properly maintaining data for model-based decision-making support. Ignoring accurate data on supplier and route disruption probabilities, advanced supply signal recognition, and real-time disruption detection can result in misleading disruption scenarios for SC design resilience and late deployment of recovery policies.

When generalizing the insights gained in this study, the following directions can be observed. Ivanov et al. (2018) proposed that in the future competition will occur not between SCs, but rather between the information services and analytics algorithms behind the SCs. This is also true for SC disruption risk management. Examples of SC and operations risk analytics applications include logistics and SC control with real-time data, inventory control, and management using sensing data, dynamic resource allocation, improving recovery forecasting models using big data, SC visibility and risk control, optimizing systems based on predictive information, and combining optimization and machine learning algorithms. Success in SC disruption risk management will become more and more dependent on data analytics in combination with optimization and simulation modeling.

Our study has a few limitations. First, a discussion of technical requirements on data processing capacities remained outside of the scope of this paper. Second, the detailed technical analysis of disruption data filtering, e.g., using machine learning techniques would make this study more comprehensive, however, going beyond of the scope of the paper.

A number of future research directions for extending these applications with the help of data driven techniques can be identified with regards to applications to SC disruption risk management. Detailed, technical analysis of the proposed technologies and how they can be integrated with each other could extend the content of this study. The speed and scope of SC digitalization comprise a trend whereby the success of SC risk management will be more and more dependent on SC risk analytics. As such, a promising future research avenue is the development and testing of different manufacturing and logistics cloud platforms from the positions of both efficiency and resilience. Finally, the understanding of organizational changes in the new decision-making settings with an increased role of artificial intelligence algorithms belong to the crucial research areas helping to underpin the theoretical foundations of the new emerging field of a digital SC.

Acknowledgement

The author thanks two anonymous reviewers for their invaluable comments that greatly contributed to the improvement of the manuscript.

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