Business Process Simulation Focusing Supply Chain Risk Management Aspects

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***Abstract* - Decision support systems refer to computable models that assist decision-makers in the identification and/or the estimation of consequences of decision alternatives. In this regard, model-driven decision support systems have been proven successfully, which use simulation models to analyze business processes and respective decision situations based on parameters and a limited amount of data. The focus of this contribution is on the opportunities of using such a business processes simulation in the field of supply chain risk management. Therefore, we present a novel approach that couples a data-based supply chain model with a consequence-driven risk simulation. Our simulation approach reverses the standard risk management cycle by identifying vulnerable parts within the supply chain – in terms of a data-based model – and subsequently backtracking possible triggering risk events instead of predicting such possible events first. The result of our approach is an easy-applicable procedure that allows companies to analyze and to improve the resilience status of their supply chains.**

Keywords - decision support systems; data-based supply chain model; consequence-driven risk simulation; resilient supply chains.

I. INTRODUCTION

Simulations can be characterized as descriptions of a real system by a model. They are particularly useful when the system under examination is complex and includes numerous interactions. Simulations offer the opportunity to run through alternative solutions in different scenarios. They make it possible to anticipate the behavior of processes at runtime and thus act as a basis for decision-making without an underlying algorithm for determining an optimal solution. Instead, by incorporating human intuition, insights into characteristics - such as bottlenecks - can be gained. Such dynamic analyses, based on different iterations and multiple variations in inputs (what-if analysis), permit human decision-makers to deepen their knowledge of the real system under study [6] [29] [35]. However, if the complexity, randomness, and variability within the system increase, the corresponding predictability under various conditions becomes more problematic.

Making good decisions depends on the available information describing the relevant aspects of the decision environment. This information can be either deterministic or subject to uncertainty [5]. In a decision situation under uncertainty, the outcome of a decision alternative is probabilistic or even unknown. In this case, the prediction of the consequences is difficult [36] and a computable model in terms of a Decision Support System (DSS) to assist decision-makers are required [8] [18]. A DSS facilitates the structuring of information to make the decision process more productive and agile as uncertainty and complexity of the decision situation can be reduced [17] [34]. Several authors have highlighted the fact that a DSS never aims to replace decision-makers; rather, the support still depends on the decision-makers with the objective of obtaining a good solution in a reduced amount of time [12] [14] [23].

There are typically three management systems included within a DSS: a data management system, a model management system, and a dialogue management system [32]. The first is targeted at structuring internal and external data, processes, information, and knowledge to develop a database as a platform for decision-making. Based on this database, the actual decision problem itself can be solved by implementing a data-based model to identify and test decision alternatives. Finally, interactive queries, reporting, and graphing functions are required to interact with the decision-makers. Particularly systems of data management are highly crucial as decision-makers never had access to more decision-relevant information than today [31]. However, this is not always beneficial as a pre-decision is needed by defining the relevant information to deal with the decision situation [11]. There are various classification schemes of DSSs available in literature. A common possibility is to describe them by their function [23] [28]. In this contribution, the focus is on model-driven DSSs using quantitative simulation models to analyze a decision situation based on parameters and a limited amount of data [28] [31].

Simulation based on a model-driven DSS reveals several opportunities: it enables an integrated view by describing the states of individual system components or even an entire system. Simulation using historical process data can support real-time business operations. From this perspective, complex business processes like supply chains, are of central importance for decision-makers. Adjustments to synchronize process steps of different supply members are often necessary. A corresponding simulation model can support the analysis of various problems for strategic, tactical, and operational questions. The application of simulation in its different methodological shapes is well established in literature of supply chain analysis [15].

In this regard, the supply chain processes must be able to accommodate changes within the environment. A DSS needs

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to be able to deal both with foreseen and unforeseen changes, even with disruptions to draw the right decisions. This means not only to avoid high costs and loss of profit but also to ensure a sufficient degree of flexibility and resilience. Supply chains are faced by lots of uncertainties, which makes risk management a key factor for success. In this paper, we consider possibilities of business process simulation to be used in supply chain risk management with the objective of creating a resilient supply chain. The rationale of our contribution is organized as follows: Sections 2 and 3 provide a summary of current developments in supply chain risk management and business processes simulation. In Section 4, we present a novel approach that facilitates the analysis of resilient supply chains based on a data-based risk simulation. The key aspects of our research are finally summarized in Section 5.

II. SUPPLY CHAIN RISK MANAGEMENT

Supply chains are dynamic networks of interconnected multinational firms, including relationships across a possibly large number of involved entities and integrated value-added processes [9]. Each entity refers to a specific functional stage in the supply chain, such as suppliers (e.g., raw material supplier), manufacturers, customers (e.g., wholesalers), and end customers. From the perspective of a specific entity, functional stages are either located in the upstream (supply side) or in the downstream (demand side) [4] [9] [27]. The supply chain consists of physical flows organizing the spatial-temporal transformation of goods, information flows, and financial flows, such as credits, payment schedules, and consignment arrangements [19].

In recent years, supply chains have become more interconnected and complex and they are – in particular in today’s turbulent and uncertain world –predisposed to disruptive events [7]. Every organization somehow depends on further firms, industries, and markets and even the most carefully controlled processes are only as good as the links that support them [10]. Disruptions have the potential to cause heavy short- and long-term losses in stock price, shareholder value, sales, and reputation, as well as to damage relationships between suppliers and customers [16]. The recent COVID-19 pandemic or the interruption of the Suez Channel have highlighted how crucial supply chain disruptions might be. Before a disruption occurs, its potential is described by a supply chain risk threating the movement of physical flows [37]. Basically two kinds of risks can be distinguished in this regard: internal risks, such as late deliveries, excess stock, poor forecasts, financial risks, minor accidents, and human error and external risks in terms of natural and man-made disasters (e.g., extreme weather events, wars, terrorist attacks, outbreaks of diseases, or price rises) [37].

For decades, trends, such as globalization, decentralization, outsourcing and just-in-time, have optimized supply chains mostly in the direction of being highly efficient [13]. The other side of the coin has been an increased vulnerability of supply chains towards shocks as, for example, more nodes (entities) in a logistics network increase the threat of disruptions propagating through the highly interrelated networks. Thus, even a local failure can negatively affect businesses on a global scale. The number of events causing such disruptions is growing. According to a study of McKinsey & Company [24], companies should expect supply chain disruptions lasting a month or longer to occur every 3.7 years. Logistics managers have understood the importance of resilient supply chains and, consequently, Supply Chain Risk Management (SCRM) has increasingly become a topic on their agendas. Basically, resilience is concerned with the supply chain’s ability to manage the consequences of an avoidable risk event and return to its original operations [3]. Strategies to increase resilience are related to an increased flexibility, agility, adaptability, and visibility of the supply chain [10] [25]. Examples might be postponement, strategic stock, flexible supply base, validations of make-or-buy decisions, economic supply incentives, flexible transportation, and revenue management.

But how should a SCRM be implemented and specified to improve the resilience of the logistics structures? If you open a standard textbook, you will find that supply chain risk management should follow a cyclic risk management approach in terms of identifying, analyzing, evaluating, and monitoring risks threatening the smooth functioning of the networks [e.g., 21]. Although this is relevant information, it does not translate into a direct plan of action for the managers. How can such a procedure be set into motion? Where is the starting point? What data are required? Approaching these challenges from the practical side, managers could turn to one of many commercial SCRM tools, which typically promise network transparency, provision of global real-time information (e.g., weather data) and assistance in the development of reactive emergency measures. However, they focus on very specific resilience issues like, for example, ad-hoc actions to handle a harbor strike by switching the transportation mode from ship freight to emergency air cargo. The tools do not provide what the managers who are eager to implement SCRM are looking for.

III. BUSINESS PROCESSES SIMULATION

The simulation approach maps systems with their dynamic processes for analysis purposes. It allows to anticipate the behavior of processes at runtime and to consider alternative solutions in different scenarios. System Dynamics (SD), Discrete Event Simulation (DES) and Agent-Based Modeling (AB) can be distinguished as the main simulation paradigms for modeling complex systems. Simulation tools typically allow visualization of the simulation process.

Business processes represent the backbone of the enterprise. The overarching goal of the Business Process Management (BPM) approach is the achievement of continuous improvement in organizations [30]. BPM analyses business activities and their interactions, identifying potential improvements as a support to decision makers. However, the use of simulation models for controlling business processes and related decisions (decision making) proves to be limited [1]. In practice, BPM rarely captures the dynamic characteristics of business processes, although this would provide a better understanding in the event of rapid changes by decision-makers in execution.

The design of business processes both within a company and across company boarders leads from the as-is analysis to the definition of a to-be model and its implementation, which is increasingly characterized using IT solutions in the context of digital transformation. Business process modeling acts as an essential vehicle in this regard and, thus, Business Process Modeling Notation (BPMN) has emerged as a de facto standard. In principle, an extension of the BPMN modeling language for simulation purposes is possible, as shown by the Business Process Simulation Interchange Standard (BPSim). However, there is still a need for research in this context, for example to develop a fully elaborated resource model [20]. By extending such a solution, simulation can be integrated into the business process management concept.

Simulation has been used in the supply chain sector for a long time. The focus is mostly on efficiency aspects and less on risks and resilience. However, basically triggered by global trends and corresponding uncertainties, it is indispensable that a holistic management of supply chains is required which additionally respects risk aspects [26]. Such a holistic management enables logistics managers to adjust their planning individually by steering and trading-off the degrees of efficiency and resilience within their supply chains.

IV. Business Process Simulation for Supply Chain Risk Management

The objective of our research is to develop a practical SCRM approach that supports decision-makers in simulating the current (as-is) and future (to-be) resilience status of their strategic supply chain processes.

Our approach suggests combining a data-based supply chain model with a consequence-driven risk simulation. In fact, we translate the data available within a company, which describe the strategic supply chain processes in terms of physical flows of goods into a data-based representation of the supply chain. This data-based model provides a platform for decision-making in resilient supply chain design. Firstly, companies can directly identify and analyze vulnerable parts of the supply chains as well as the consequences of specific risk events. Secondly, the suitability of logistics strategies (decision alternatives) to improve the current resilience status can be simulated within the model. Thereby, the consequence-driven risk simulation reverses the standard risk management cycle by identifying vulnerable parts within the supply chain (model) and subsequently backtracking possible triggering risk events instead of predicting such possible events first.

Our approach switches the focus from an efficient to a resilient supply chain management (see Section 2) and provides decision support for supply chain risk managers. The main rationales behind the two core components – data-based supply chain model and consequence-driven risk simulation – are described in the forthcoming paragraphs. The formulation of the steps included within these components as well as their exemplary application is work-in-progress and not the focus of this paper.

Data-based supply chain model

The data-based supply chain model includes all physical flows of the network under consideration for a certain reference time (e.g., 12 months) from the perspective of the company. It is the objective of the company to define the scope of the analysis in terms of geographic regions of entities, material groups, and organizational entities. From an analytical point of view, a supply chain is defined as a network of nodes and edges. Each node refers to each one entity of the supply chain, such as suppliers, customers, or company-specific facilities (e.g., factories, warehouses). An edge defines a single physical flow in terms of a delivery, which arises over time between each one sender (point of origin) and receiver (point of consumption) location.

The necessary company data to develop the model refers to transaction and master data, which can be gathered out of the data warehouse of a company. In this regard, one major benefit of our approach becomes obvious: instead of investing in external tools to analyze and improve the supply chain, we suggest applying the data which is already available. Our approach, thus, ensures that SCRM can be conducted incidentally by the companies themselves, which, in turn, implies low cost, as well as high practicability and acceptance.

The relevant systems defining the data warehouse are widespread and might refer to Enterprise Resource Planning (ERP) systems, excel, or Structured Query Language (SQL) files. Our approach does not focus on the origin of the data but on the necessarily required information (as possible parameters in the consequence-driven risk simulation) within the transaction and master data to represent the physical flows. In fact, the data-based model captures transaction data in terms of delivery positions and master data in terms of material data and entity data:

- Delivery positions: each single physical flow in the network refers to a delivery of a certain material across each one sender and receiver location. Such a material-specific flow is called delivery position; several delivery positions can be part of a shipment (e.g., truck load), which, in turn, includes various materials. Delivery positions provide the basis of the data-based supply chain model as they include all spatial information regarding the entities and temporal information regarding the physical flows. Sender, receiver, and material must be identifiable in an unambiguous manner – which implies that each of them is specified by a unique ID. Via this ID, further in-depth information can be captured out of the entity and material master data (see below). Moreover, delivery positions should provide information regarding the sending date (start of delivery from the sender location), receiving date (end of delivery at the receiver location), material quantity (number of parts to be delivered), and transportation mode (e.g., road transport, air cargo).
- Entity and material data: entities included within the supply chain might be suppliers, customers, or company-specific facilities, such as factories or warehouses. Master data should be used to pull further entity-specific information per delivery position via a sender ID or a receiver ID referring to an entity ID. Such further information refers to the entity type (e.g., supplier), entity country, entity city, and

entity geo-information of latitude and longitude. As the objective of our approach is to analyze resilience from a strategic perspective, the aggregation level of geoformation referring to a city is seen as sufficient. Optionally, further details, such as addresses, can be used to further detail the supply chain. Material-specific information per delivery position should be captured from the material master data. Via the unique material ID, such information might be the material description, material weight [kg], material volume [m^3], material price [e.g., EUR] and material product group.

TABLE I. NECESSARY INFORMATION OF THE DATA-BASED MODEL

Data category (source)	Dataset	Description
Delivery positions (transaction data)	Sender ID	Unique identification of sending location
	Receiver ID	Unique identification of receiving location
	Material ID	Unique identification of delivered material
	Quantity	Number of materials delivered
	Transportation mode	Road transport, air freight etc.
	Sending date	Date to which the delivery has started
	Receiving date	Date to which the delivery has finished
Entity data (master data)	Entity ID	Unique identification of entity
	Entity type	Characteristic, e.g., supplier or customer
	Entity country	Country of the entity location
	Entity city	City of the entity location
	Entity latitude	Geo-information of the entity location
	Entity longitude	Geo-information of the entity location
Material data (master data)	Material ID	Unique identification of material
	Material weight	Weight [kg] of one piece of the material
	Material volume	Volume [m^3] of one piece of the material
	Material price	Price [e.g., EUR] of one piece of the material
	Product group	Material category

Table I summarizes the necessary information (parameters) of a single physical delivery to be gathered out of the transaction and master data. The arrows in the table highlight connections between transaction and master data. In fact, entity-specific information of a delivery position can be captured by via a unique entity ID (referencing to the sender ID or receiver ID given in the delivery position); material-specific information can be captured by a unique material ID (referencing to the material ID given in the delivery position).

It becomes obvious that the data-based supply chain model consists of a database where each single dataset refers to a delivery position specifying each one material-specific physical flow in the network. Based on this data, further information can be included to the database, such as information regarding the considered part of the supply chain (e.g., an inbound flow between a supplier and a company-specific entity, an intra-company flow across company-specific entities, or an outbound flow between a company-specific entity and a customer), distance [km], which can be easily included by using open-access web tools (distance calculators), or further calculations, such as the total delivery weight (material weight * quantity), delivery volume (material volume * quantity) and total price (material price * quantity).

In summary, each physical flow in the data-based supply chain model provides sender-specific, receiver-specific, material-specific, and transport-specific information. An exemplary representation of this data is given in Figure 1. For two nodes of the supply chain, A and B, the model includes two datasets with the respective information for the physical flows 1 to n.

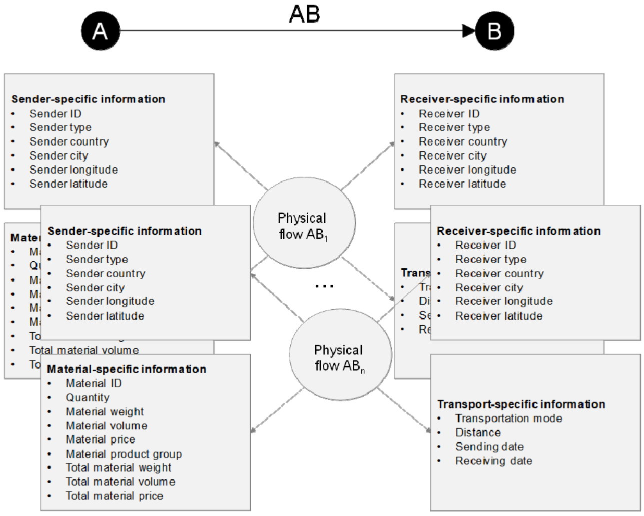

Figure 1. Included data per physical flow

Consequence-driven risk simulation

The data-based model provides the ingredients for simulations by changing the values of the parameters, which leads to a modified structure and, thus, performance of the supply chain. It can be used to evaluate the current and future resilience status of the supply chain under consideration. This is because the model allows to directly explore the effects of risk events facing the supply chain as well as logistics strategies to hedge against the negative consequences of such events. In difference to standard approaches of risk management, we propose a procedure that reverses the traditional contents of risk identification, risk analysis and assessment, and risk mitigation (see Figure 2). In fact, we believe that rather than answering to the question “what is happening to the supply chain if a certain risk event enters?”, the rationale of SCRM should be: “what are the most vulnerable parts in the network that lead to the highest consequences and how can they be mitigated?”.

Therefore, our simulation procedure starts with the identification of the most business-critical and, thus, vulnerable parts of the supply chain, which might be the nodes or edges of the network. For instance, the most vulnerable parts might be the top sending and receiving nodes (e.g., nodes with high frequencies of deliveries, a high value of materials), most exclusive material-specific sender and receiver locations, or top materials (e.g., annual value of deliveries). The data-based model thereby provides a platform to rapidly identify and analyze those vulnerable parts.

Based on the identified vulnerable parts, we suggest simulating effects in the supply chain when the business processes behind the vulnerable parts change (e.g., total weight or value per supplier, outbound flows of warehouses). Therefore, forecasts are implemented, which affect the parameter values, e.g., price increases of certain materials or disruptions of certain regions, sender and/or receiver

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locations. By modifying the parameter values, worst-case consequences can be revealed when business-critical or vulnerable parts fail.

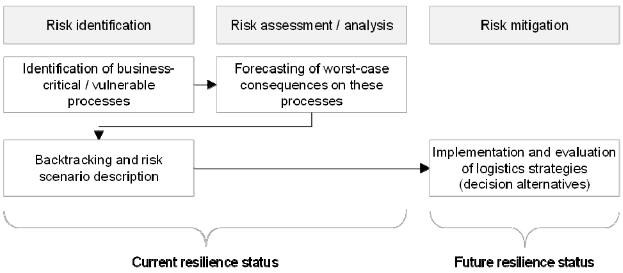

Figure 2. Procedure of consequence-driven risk simulation

Rather than it is the objective of standard risk management, the identification of risk events triggering disruptions is the third step of our procedure. In fact, the scenarios and narrative descriptions are developed leading to the parameter changes, which have been simulated in the previous step. Such scenarios might refer to geographic issues (e.g., natural disasters), political events (e.g., tariffs), drops in demand, or further events, such as disruptions of key entities as warehouses due to strike events.

Finally, the data-based model can be again used to simulate logistics strategies that hedge against the failures of the most crucial parts. These logistics strategies might be, for example, multiple sourcing strategies, additional entities in the network (e.g., further warehouses in certain areas), adapted frequencies in supplies, or further redundancies, such as larger inventories. Again, consequences of the logistics strategies must be translated into several parameters of the data-based model, such as further supplier locations for a previously single-sourcing material. In this way, the effects in the supply chain can be evaluated and the targeted future resilience status can be compared with the previously analyzed current resilience status.

V. CONCLUSION

In this paper, we have discussed the relevance of using business processes simulation in supply chain management and, in fact, for the creation of resilient supply chains. Therefore, we have presented the rationale of a novel approach, which consists of two core components: data-based supply chain model and consequence-driven risk simulation. We have outlined the basic rationale behind the two core components and, in fact, how a data-based model and simulation procedure can be used for business processes management in SCRM. The two core components include various steps.

The specific steps of our approach refer to the determination of framework conditions, data gathering, data structuring, data modelling, and the application of standardized key resilience indicators to identify vulnerable parts and to analyze the consequences of risk events. Our future research objective is to develop an easily implementable "cooking recipe" for our SCRM approach by providing in-depth descriptions of those steps for the logistics managers. In this contribution, we have exemplarily outlined the result of the step of data structuring in terms of a clear definition and links of the necessary data to stretch the logistics network (see Table 1). The specification of all further steps is work-in-progress.

Particularly the steps of data modelling and the application of the key resilience indicators include various mathematical formulations (e.g., delivery-specific volumes and weights, percentages of disrupted entities in the network). Those formulations are highly crucial aspects of our "cooking recipe" and will be therefore addressed as the next step of our future research. Moreover, an adequate graphical presentation of the decision support results (e.g., as-is versus to-be scenarios) as well as sensitivity analyses will be highly crucial.

The quality of simulation results strongly depends on the quality of the input data. Business process simulation models are intended to use real-life data sources for gathering relevant data. The process mining approach, which is not discussed further in this article, can make an important contribution to the creation of conceptual models by generating process models from event logs. Process mining enables automated control flow discovery (process model discovery), performance analysis (process bottlenecks), conformance checking (process guidelines vs. actual practices), enhancement (diagnostics), and resource organizational structure (collaboration) [2]. A limitation of contemporary process mining techniques can be seen in the fact that they tend to focus on distinct process instances and not on the multi-case setting of BPS [22]. To utilize a multi-case context in business process Simulation, approaches, such as the Multi-Event-Log from Celonis, can be applied [33].

REFERENCES

[1] W. M. P. van der Aalst, "Process Mining and Simulation: A Match made in Heaven!," SpringSim-SCSC, 2018 July 9-12, Bordeaux, 2018.

[2] W. Abhohamad, A. Ramy, and A. Arisha, "A Hybrid Process-Mining Approach for Simulation Modeling," in: Proceedings of the 2017 Winter Simulation Conference, W. Chan, A. D´Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E. Page (editors), pp. 1527-1538, 2017.

[3] V. Anbumozhi, F. Kimura, and S. M. Thangavelu, Supply Chain Resilience. Singapore: Springer Singapore, 2020.

[4] D. Arnold, H. Isermann, A. Kuhn, H. Tempelmeier, and K. Furmans, Handbuch Logistik, Berlin: Springer, 2008.

[5] V. Bertsch, Uncertainty Handling in Multi-Attribute Decision Support for Industrial Risk Management, Universitätsverlag Karlsruhe, 2008.

[6] S. Bisogno, and A. Calabrese, "Combining modelling and simulation approaches," in: Business Process Management Journal, 22 (1), pp. 56-74, 2015, DOI 10.1108/BPMJ-02-2015-0021.

[7] C. Bode, and S. M. Wagner, "Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions," in: Journal of Operations Management 36 (1), pp. 215–228, 2015, DOI: 10.1016/j.jom.2014.12.004.

[8] F. Burstein, and C. W. Holsapple, Handbook on Decision Support Systems 1 - Basic themes, Springer-Verlag Berlin Heidelberg, 2008.

[9] M. Christopher, Logistics and Supply Chain Management, Financial Times/ Prentice Hall, 2011.

[10] M. Christopher, H. Peck, “Building the Resilient Supply Chain,” in: The International Journal of Logistics Management, 15 (2), pp.1–14, 2004.

[11] S. Djamasbi, “Does positive affect influence the effective usage of a Decision Support System?” Decision Support Systems, 43 (4), pp.1707–1717, 2007.

[12] M. C. Er, “Decision Support Systems: A summary, problems, and future trends,” in: Decision Support Systems, 4 (3), pp. 355–363, 1988.

[13] A. Ghadge, S. Dani, M. Chester, and R. Kalawsky, “A systems approach for modelling supply chain risks," in: Supply Chain Management: An International Journal, Vol. 18 (5), pp. 523-538, 2013.

[14] D. J. Hall, “Decision Makers and Their Need for Support,” in: F. Burstein, and C. W. Holsapple (editors), Handbook on Decision Support Systems 1, Springer Berlin Heidelberg, pp. 83–102, 2008.

[15] I. Heckmann, Towards Supply Chain Risk Analytics, SpringerGabler, Wiesbaden, 2016.

[16] K. B. Hendricks, and V. R. Singhal, „The effect of supply chain glitches on shareholder wealth,” in: Journal of Operations Management 21 (5), pp. 501–522, 2003, DOI: 10.1016/j.jom.2003.02.003.

[17] C. W. Holsapple, “Decisions and Knowledge,” in: F. Burstein, and C. W. Holsapple (editors), Handbook on Decision Support Systems 1, Springer Berlin Heidelberg, pp. 21–53, Arnott & Pervan, 2008.

[18] C. A. Hooker, “Introduction to Philosophy of Complex Systems: A: Part A: Towards a framework for complex systems,” in: C. A. Hooker et al. (editors), Philosophy of Complex Systems, Volume 10 (Handbook of the Philosophy of Science), Elsevier B.V., pp. 3–90, 2011.

[19] P. R. Kleindorfer, and L. van Wassenhove, “Managing risk in the global supply chain,” in: The INSEAD-Wharton Alliance on Globalizing. Cambridge University Press, UK, 2004.

[20] R. Laue, and C. Müller, „The Business Process Simulation Standard (BPSim): Chances and Limits,” in: Proceedings 30th European Conference on Modelling and Simulation (ECMS), T. Claus, F. Herrmann, M. Manitz, and O. Rose (editors), pp. 1-6, 2016, ISBN: 978-0-9932440-2-5.

[21] T. Liebetruth, Prozessmanagement in Einkauf und Logistik: Instrumente und Methoden für das Supply Chain Process Management, Springer Gabler, 2020.

[22] N. Martin, B. Depaire, and A. Caris, “The Use of Process Mining in a Business Process Simulation Context: Overview and Challenges,” IEEE Symposium on Computational Intelligence and Data Mining (CIDM), Orlando, FL (USA), pp. 1-8, 2014, ISBN: 978-1-4799-4518-4.

[23] A. Mattiussi, M. Rosano, and P. Simeoni, “A decision support system for sustainable energy supply combining multi-objective and multi-attribute analysis: An Australian case study,” in: Decision Support Systems, 57, pp.150–159, 2014.

[24] McKinsey & Company. Corona und andere Krisen: Lieferketten werden sich global dramatisch verändern, online: https://www.mckinsey.de/news/presse/2020-08-06-global-value-chains [retrieved: September, 2021]

[25] S. A. Melnyk, C. Zobel, S. E. Griffis, and J. R. Macdonald, Understanding Supply Chain Resilience, Supply Chain Management Review, 2014.

[26] D. Neiger, M. Churilov, M. zur Muehlen, and M. Rosemann, Integrating Risks in Business Process Models with Value Focused Process Engineering, Proc. European Conf. Information Systems (ECIS ’06), 2006.

[27] H.-C. Pfohl, „Logistiksysteme - Betriebswirtschaftliche Grundlagen,“ in: R. Jünemann, and H.-C. Pfohl (editors), Springer-Verlag Berlin Heidelberg, 2010.

[28] D. J. Power, “Decision Support Systems: A Historical Overview,” in F. Burstein, and C. W. Holsapple (editors), Handbook on Decision Support System 1. Springer Berlin Heidelberg, pp. 121–140, 2008.

[29] S. Robinson, Simulation: The Practice of Model Development and Use, John Wiley & Sons, 2014.

[30] M. Rosemann, and J. vom Brocke, The Six Core Elements of Business Process Management, Springer, Berlin, Heidelberg, 2015.

[31] F. Schätter, Decision support system for a reactive management of disaster-caused supply chain disturbances., Karlsruhe, Deutschland, 2016.

[32] J. P. Shim, et al., “Past, present, and future of decision support technology,” in: Decision Support Systems, 33(2), pp. 111–126, 2002.

[33] B. Shlakeski, Business Process Mining through the lens of “Multi-Event Log” approach. Master Thesis, Pforzheim University of Applied Sciences, 2021.

[34] R. S. Sojda, 2007, “Empirical evaluation of decision support systems: needs, definitions, potential methods, and an example pertaining to waterfowl management,” in: Environmental Modelling & Software, 22(2), pp. 269–277, 2007.

[35] C. Vallejo, D. Romero, and A. Molina, “Enterprise integration engineering reference framework and toolbox,” in: International Journal of Production Research, Vol. 50 No. 6, pp. 1489-1511, 2012.

[36] R. Vahidov, G. E. Kersten, “Decision station: situation decision support systems,” in: Decision Support Systems, 38(2), pp. 283–303, 2004.

[37] C. Waters, and J. Donald, Supply chain risk management. Vulnerability and resilience in logistics, 2nd ed. London, Philadelphia: Kogan Page, 2011.