ARTICLE IN PRESS

Computers & Industrial Engineering xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Disruption tails and revival policies: A simulation analysis of supply chain design and production-ordering systems in the recovery and post-disruption periods

Dmitry Ivanov

Berlin School of Economics and Law, Department of Business and Economics, Professor of Supply Chain Management, 10825 Berlin, Germany

ARTICLE INFO

Keywords:
Supply chain
Disruption risk
Simulation
Production
Ordering
Network design

ABSTRACT

We study production-ordering behaviour in a supply chain (SC) with disruption risks in recovery and post-disruption periods and the influence of severe disruptions on production and distribution network design. A real-life case-study of a disruption in a SC is considered and investigated with the help of discrete-event simulation blended with network optimisation in anyLogistix. Two novel findings are presented. First, disruption-driven changes in SC behaviour may result in backlog and delayed orders, the accumulation of which in the post-disruption period we call "disruption tails". The transition of these residues into the post-disruption period causes post-disruption SC instability, resulting in further delivery delays and non-recovery of SC performance. Second, a smooth transition from the contingency policy through a special "revival policy" to normal operations mode partially mitigates the negative effects of disruption tails. The results show that isolated production and distribution network design optimisation can lead to severe decreases in performance in the event of SC disruptions. Contingent recovery policies need to be applied during the disruption period along with a revival policy in the post-disruption period to avoid disruption tails. These revival policies must be developed for the transition from the recovery to the disruption-free operations mode. A revival policy is meant to mitigate the negative impact of disruption tails and stabilise the ordering control policies and performance in the SC. Thus, recovery policies should not be limited to the disruption period only. They should also consider the post-disruption period and be included in SC design decisions. The revival policy should be included in the SC resilience framework.

1. Introduction

Design of production and distribution networks has been a prominent research avenue over the past three decades. In the supply chain (SC) framework, the tasks of production and distribution networks have been integrated. These have formed the SC design research domain (Chopra and Meindl, 2015; Dolgui and Proth, 2010). In the SC design domain, recurrent operational risks and *uncertainty* of inventory and demand have been typically analysed with the help of robust/stochastic/fuzzy optimisation or simulation models.

Tang (2006), Chopra, Reinhardt, and Mohan (2007), Klibi, Martel, and Guitouni (2010), Kumar and Tiwari (2013), Simchi-Levi et al. (2015), Sokolov, Ivanov, Dolgui, and Pavlov (2016), Choi, Govindan, Li, and Li (2017), Ivanov (2018a, 2018b), Dolgui, Ivanov, and Sokolov (2018), Lücker, Seifert, and Biçer (2018), Ivanov, Dolgui, Sokolov, and Ivanova (2017) suggest differentiating disruption risks and operational risks in the SC. Disruption risks can be caused by natural or man-made catastrophes, political crises, strikes, or legal disputes.

In regard to disruption risks, resilient production and distribution network design has become an active research avenue over the last decade (Gunasekaran, Subramanian, & Rahman, 2015; He, Alavifard, Ivanov, & Jahani, 2018; Ho, Zheng, Yildiz, & Talluri, 2015; Jain, Kumar, Soni, & Chandra, 2017; Kamalahmadi and Mellat-Parast, 2016; Losada, Scaparra, & O'Hanley, 2012; Macdonald, Zobel, Melnyk, & Griffis, 2018; Namdar, Li, Sawhney, & Pradhan, 2018; Raj et al., 2015; Rezapour, Farahani, & Pourakbar, 2017; Sawik, 2018; Simangunsong, Hendry, & Stevenson, 2012; Spiegler, Potter, Naim, & Towill, 2016; Tukamuhabwa, Stevenson, Busby, & Zorzini, 2015). Since trends of globalisation, outsourcing, efficiency principles, and specialisation have been on the rise in SC management, SC vulnerabilities, and the risks that a SC will be affected by a disturbance have correspondingly increased.

Moreover, the ripple effect has been identified in literature as a specific phenomenon in the disruption risk management framework

E-mail address: divanov@hwr-berlin.de.

https://doi.org/10.1016/j.cie.2018.10.043
Received 19 March 2018; Received in revised form 2 September 2018; Accepted 21 October 2018
0360-8352/

Please cite this article as: Ivanov, D., Computers & Industrial Engineering, https://doi.org/10.1016/j.cie.2018.10.043

(2018a, 2018b; Dolgui et al., 2018; Ivanov, 2017; Levner and Ptuskin, 2018; Liberatore, Scaparra, & Daskin, 2012; Mizgier, 2017; Pavlov, Ivanov, Dolgui, & Sokolov, 2018; Scheibe and Blackhurst, 2018). The ripple effect describes the disruption-based scope of changes in structural SC design and planning parameters and the impact of disruption propagation on SC performance. As a consequence of disruption propagation, Ivanov and Rozhkov (2017) observed post-disruption instability in the SC called 'postponed redundancy'. 'Postponed redundancy' describes the SC's delayed reaction to disruption and recovery actions as a consequence of production-ordering behaviour that occurs during the disruption period. For example, disruption-driven changes in SC behaviour may result in accumulated backlog and delayed orders. The transition of these residues into the post-disruption period destabilizes normal operations, resulting in further delivery delays and non-recovery of SC performance (Ivanov and Rozhkov, 2017).

Even if considerable advancements have been achieved in the given area, the resilient production and distribution network designs and the production-ordering systems in the SC have been mostly considered in isolation from each other. At the same time, decisions in each of these two areas are interconnected. Closing this research gap, this study considers production and distribution network design subject to disruption risk at both the proactive and reactive control stages. We study production-ordering behaviour in a SC with disruption risks in the recovery and post-disruption periods and the influence of the ripple effect on production and distribution network design. The methodology of this paper is based on a real-life case-study with real company data that is used for quantitative analysis of decisions on matching the production and distribution network design with ripple effect considerations from a disruption risk perspective. The objectives of the analysis are twofold. First, it aims to show how production and distribution network design decisions influence each other. Second, it aims to provide insights about how SC managers can enhance SC resilience by implementing proactive and reactive policies with integrated consideration of production-ordering decisions in both recovery and post-disruption periods.

The rest of this paper is organized as follows. In Section 2, a literature analysis is presented. Section 3 is devoted to the problem statement and research methodology. In Section 4, a simulation model is described. Experimental results are considered in Section 5, followed by a discussion on managerial insights in Section 6. The paper is concluded by summarizing the most important findings and outlining future research avenues in Section 7.

2. State of the art

Over the last ten years, designing resilient SCs has been a focus of research. Two policies have been developed to ensure SCs will be resilient to disruption and that effective action can be taken when disruption does occur: these policies are called *proactive* and *reactive.* An agile reconfiguration approach, which uses diagraph modelling and integer linear programming, was created by Constantino et al. (2012) to ensure the resilience of the SC by considering supplier capacity restraints. A mixed-integer programming model, which accounted for recovery costs in the objective function and included a fully reliable backup supplier, was developed by Lim, Bassamboo, Chopra, and Daskin (2013). To provide guidance for SC managers in choosing a supplier portfolio, Dupont, Bernard, Hamdi, and Masmoudi (2018) used mixed-integer linear programming, and created a model which accounts for the SC managers' risk sensitivity (i.e., risk aversion or loss aversion).

While Dupont et al. (2018) utilized deterministic demand, a stochastic programming model for guiding supplier selection and order allocation according the risk of disruption was developed by Sawik (2013). A second study by the same author contributed to the conceptualisation of using a portfolio approach for managing SC disruption (Sawik, 2017). Sawik's studies also account for the risk sensitivity of the SC manager. Khalili, Jolai, and Torabi (2017) made an analysis of the integration of production-distribution planning in the SC, and suggested a new indicator, which is based on restoring lost capacities, for SC optimisation.

Studying resilience and severe SC disruptions through *discrete-event simulation,* Carvalho, Barroso, Machado, Azevedo, and Cruz-Machado (2012) analysed how a four stage SC behaved with several alternate recovery strategies, which differed in both presence and absence of a disturbance and a mitigation strategy, and what SC performance was according to disruption dynamics. For determining lead-time rations and the total costs of the SC, an ARENA-based simulation model was created. Using "weeks of recovery" as amplification of the disruption, Schmitt and Singh (2012) calculated the risk of disruption. The authors satisfy demand in their proactive and reactive scenarios in three ways: utilizing an alternate location in the network, obtaining material or transport from other sources or routes, and maintaining reserves of inventory throughout the SC.

Giannoccaro, Nair, and Choi (2018) investigated the relationship between the scope of control (i.e., how much of its supply network a buying firm should control) and SC performance using a complex adaptive system approach. The results indicate that complexity negatively affects SC performance, with a performance decrease depending on the scope of control. Based on these findings, different control strategies to mitigate the negative influence of complexity are formulated.

Amiri-Aref, Klibi, and Babai (2018) studied a multi-period location-inventory optimization problem in a multi-echelon SC characterized by uncertain demand and multi-sourcing. The authors integrated inventory planning decisions made under a reorder point order-up-to-level (s, S) policy, with location-allocation design decisions to cope with demand uncertainty. A two-stage stochastic mathematical model that maximizes the total expected profit of the SC network is proposed. The results show the efficiency of the linear approximation of the (s, S) policy at the strategic level to produce robust design solutions under uncertainty. Further insights from this study underline the sensitivity of the design solution to the demand type and the impact of the inventory holding costs and backorder costs, especially under non-stationary processes. Paul and Rahman (2018) developed a recovery model considering sudden supply delays that affect retailers' economic order quantity model. They considered fuzzy demand and safety stock and modelled a recovery plan generation that is activated immediately after a sudden supply delay. There simulation model also considers a trade-off between backorder and lost sales costs in the recovery plan.

Using anyLogistix software, a simulation of the dynamic behaviour of a SC and the impact of disruption on its performance was developed by Ivanov (2017). In this simulation, evidence of the ripple effect was seen, and strategies, both proactive and reactive, were studied. The results indicate that disruptions which occur upstream in the SC tend to cause ripple effect when there is a single source policy in place: facilities downstream of disruption risky elements of the SC should increase safety stock in order to decrease the ripple effect towards the customers. However, this stock increase should be carefully considered since when disruption risky elements are not able to perform outbound operations, then higher levels of safety stock will not mitigate the ripple effect. In addition, the simulation showed that the ripple effect impacted service level and order fulfilment more than the duration of the disruption, which indicates that dual sourcing at SC bottlenecks and keeping high inventory in facilities downstream from disruption risky elements is of greater importance that hastily investing in a fast recovery. The results of a study by Ivanov (2018a), concerning analysis of a multi-stage SC with suppliers, factory, distributions centres, and customers, show a time lag from the launch of recovery to the impact of that recovery on reducing gaps in service level. This points to the fact that proactive SC policies must be designed with the durations of disruption in mind.

Using AnyLogic to analyse a real example of a retail SC and considering product perishability, Ivanov and Rozhkov (2017) assessed how ordering and production control policies impact performance when there is a capacity disruption. The findings imply SC managers should consider the effects of 'postponed redundancy' when analysing the impact of redundant production-ordering system behaviour during the disruption on SC performance in the post-disruption period, and designing resilience into their SCs. Redundant behaviour of this kind might include redundant production or deliveries to areas downstream from the disruption, or redundant order allocation to upstream facilities which have been disrupted. In addition, the authors developed and tried out a coordinated production-ordering contingency policy during and after the SC disruption in order to decrease the negative impacts of 'postponed redundancy'. The results of a study by Trucco, Petrenj, and Birkie (2017), which analysed and simulated an Italian FMCG SC, implicate that coordinated control strategies should be developed in the event of severe SC disruptions. These findings echo those of Schmitt, Kumar, Stecke, Glover, and Ehlen (2017) and Ivanov and Rozhkov (2017).

Chen, Ponsignon, Weixlgartner, and Ehm (2017) simulated the Infineon's semiconductor SC to test its resilience. In the simulation model, four types of sites, i.e., mirror site, hot site, warm site, and cold site, are proposed to enable recovery in case of disruption. Those sites have different levels of preparedness for producing specific products. From cold site to mirror site, "the time to respond after a disruption gets faster because it is ready to use with tools and technologies, etc. Hence one may tend to demand a mirror site for their products. However the limited capacity and expensive investment upfront pose barriers to applying mirror site for all products" (Chen et al., 2017). A simulation model was developed to assess the overall impacts of disruptions and the performance trade-offs. Four disruptions scenarios, i.e., strikes, infrastructure destruction, industrial accident and long-term cyber-attack, with different disruption lengths and severity were analysed. The simulation was performed for scenarios characterized by different severity in terms of capacity disruption, ranging from 40% (i.e., long-term cyber-attack) to 100% (i.e., infrastructure disruption). The performance impact was measured by fill rate recovery time, while the financial performance was assessed according to the investment cost and Infineon cost (i.e., backorder costs, multiple costs at customer and customer of customer at long disruptions, and sales loss). The simulations in AnyLogic showed that "the mirror site has the fastest recovery at extremely high expense. A hot site could be a good alternative for mirror site, showing robust and excellent overall performance. Unexpectedly, a warm site has also satisfying results, except for short-term disruptions like strikes. Further beyond the anticipation, the cold site exhibits some achievements, especially for shortening the recovery time in long-term disruptions (e.g., infrastructure destruction)." (Chen et al., 2017).

3. Case-study, problem statement and methodology

3.1. Case-study

The case-study is based on a company that produces non-perishable products for four regional markets. Without loss of generality, a fragment of the SC considered comprises four production plants and four regional distribution centres (DCs). In each of the four regions, there is a market, a plant, and a regional DC for a single aggregated product (Fig. 1).

The former SC manager of the company decided to close the production plant in region #1 because of a decrease in demand in this region and high fixed costs (note that this region is still characterized by the highest demand among all four regions) and to supply the DC in this region from three other plants which are located quite far from this DC, but incur lower fixed costs compared to the expensive production site in region #1 (Fig. 2).

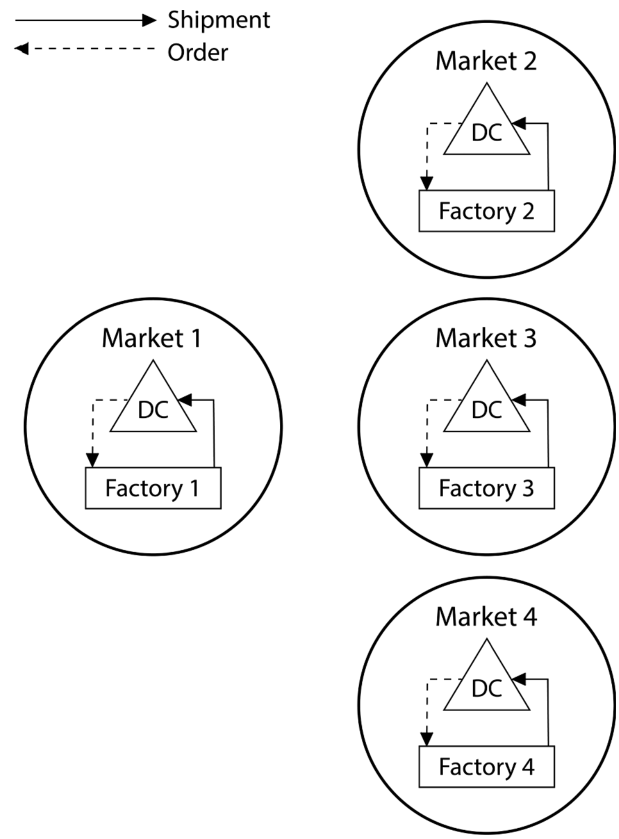


Fig. 1. Initial SC design structure.

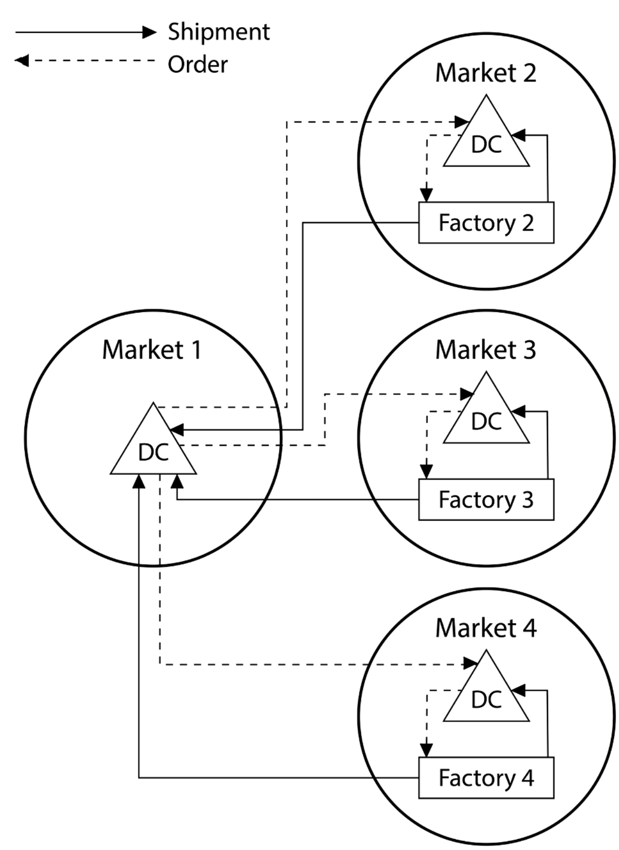


Fig. 2. SC design structure after closing the plant in region #1.

A couple of months after the plant closure, the DC in this region crashed due to construction quality problems. A huge amount of juice inventory was destroyed, and the disruption propagated into the markets. The new SC manager of this company is now responsible for reacting to this disruptive event. She first estimates the immediate impact and time-to-recovery. On the day of the DC disruption, the experts estimate that the reconstruction of the DC will take about four months. The new SC managers understand that a short-term and mid-term recovery policy is needed. She considers three options for contingent recovery policies:

- Using the capacity of another factory owned by company which produces similar products in region #1 where the DC crashed (The technological process is quite similar, but some adaptations will be needed);
- Using the capacity of other owned plants in neighbouring countries;
- Finding a subcontractor to supply market #1.

All three options cannot be activated immediately and require about three weeks to activate. The analysis must be done subject to profit maximisation, which is computed as the difference between revenue from selling goods and total costs. Total costs include fixed facility costs, transportation costs, inventory holding costs, production costs, inbound and outbound processing costs, and penalties for non-fulfillment of demand on time. The constraints include limited production capacity, limited DC storage capacity, reorder points and target inventory levels, service level, expected lead time, processing capacity at the DCs, and available paths in the SC.

3.2. Methodology

3.2.1. Selection of the methodology

Because the problem statements concerning the ripple effect deal with time-dependent settings which include dynamic inventory control, transportation control, sourcing control and production control policies, the simulation methodology for the given problem domain has earned an important role in academic research (2018b; Ivanov, 2017, 2018a). In comparison to analytical closed form analysis, simulation has the advantage that it can handle complex problem settings with situational behaviour changes in the system over time. This is inevitable in considering dynamic changes in the SC organisational and parametrical structures (Ivanov, Sokolov, & Kaeschel, 2010). In this study, we use discrete-event simulation methods. For validation, network optimisation with and without disruption consideration has been performed in CPLEX using anyLogistix optimisation and simulation software. The optimisation experiments allowed a determination of aggregate annual throughputs which are used for validation of the simulation results. The simulations in anyLogistix are run over the optimisation results and include additional, time-dependant inventory, production, transportation, and sourcing control policies which are difficult to implement at the network optimisation level.

3.2.2. Data collection

The following data (but not limited to) has been collected at the company:

- SC design: locations of SC elements (factories and DCs) and links in between them
- Demand in the markets and its uncertainty
- Parameters of SC elements (e.g., production capacities, throughputs, prices, costs)
- Operating policies of SC elements (e.g., inventory control policy, production control policy, shipment control policy, sourcing control policy).

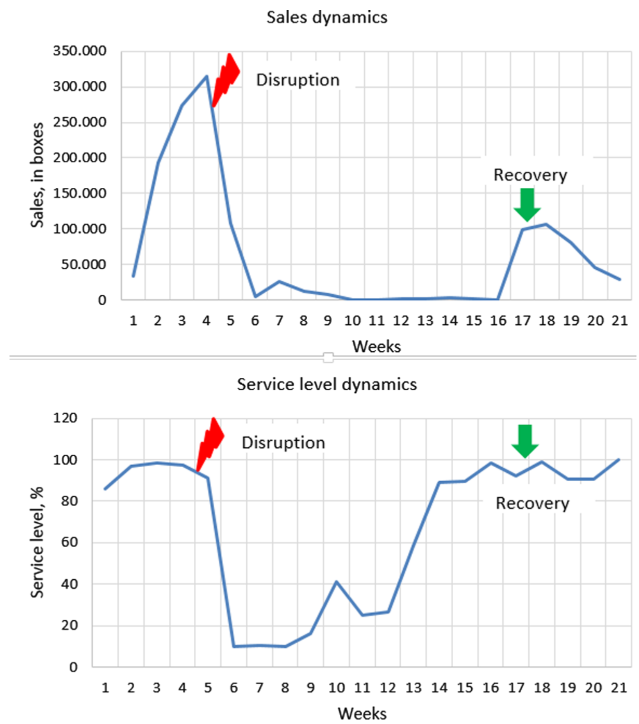


Fig. 3. Real sales and service level dynamics following the DC disruption.

This data was observed for a period of three years. Moreover, we observed the actual sales and service level data following the disruption at the DC described (Fig. 3).

Fig. 3 depicts the real sales and service level dynamics observed at a retailer that was supplied in region #1 from the disrupted DC1, following the DC1 disruption in week #4 and subject to full sales recovery in week #17. A drastic decrease can be observed in both sales and service level dynamics. It is interesting to observe that service level recovers as quickly as sales. The explanation is that the retailer adapted its ordering policy and ordered much less than usual. This effect of "postponed redundancy" reduction was previously described in literature (Ivanov and Rozhkov, 2017).

3.2.3. Experimental setting

The analysis in this study was comprised of the following experiments:

1. Simulation experiment with a DC disruption in region #1 without recovery policy.
2. Simulation experiments with four immediate recovery policies with emergency sources.

For validation, a network optimisation model has been created in CPLEX (see Appendix A). Both the network optimisation model and simulation models are implemented in anyLogistix. In addition, *analytical computations* with the help of standard inventory control models have been made. For *verification*, the following methods have been used: simulation run over network optimisation results, output data analysis in the log files and testing with the help of deterministic demand and lead time data. Moreover, replications and a warm up time with some initial inventory have been applied for *testing*. The disruptions have been scheduled in the middle of the simulation period in order to avoid the 'noise' of the simulation experiment start. Variation experiments to validate the simulation model have been performed. In particular, mean and standard deviation of demand, safety stock, and production capacity have been varied.

4. Simulation model

4.1. Control algorithms and assumptions

4.1.1. Demand generation

Demand in the markets is considered to be the aggregated demand of all customers in this region. Demand data showed that it can be considered normally distributed and characterized by a seasonal component subject to four periods. The mean and standard deviation of demand as well as the seasonal coefficients can be identified from evaluating statistical demand data over the last three years. Since the real company works on a weekly order placement basis, the demand data is considered on a weekly basis as well.

4.1.2. Inventory control

A continuous review system is applied at the DCs. Backordering is allowed so that no orders can be lost. For simplification, an average lead time from DC to the market is considered assuming that all customers within the region will be reached during this lead time. According to demand generation algorithms, orders are placed at the DCs (cf. Figs. 1 and 2). Subject to inventory-on-hand, safety stock, lead times, reorder point and the target inventory, shipments to the markets and replenishment from the factories is controlled.

4.1.3. Transportation control

Since, in reality, the company can use logistics service provider capacities along with their own fleet, no transportation capacity limitations are included. For the same reason and model simplification, no further restrictions on transportation control policies, such as minimum or maximum load or aggregation periods, are considered.

4.1.4. Production control

Each factory is considered a single stage continuous production system with fixed production time and no setups. Production capacity is limited by the unit production time. For example, a production time of 0.4 days for m^3 means a maximum daily capacity of 2.5 m^3 at a factory. No further batching rules are considered for simplification of model and result analysis.

4.1.5. Sourcing control

Multiple sourcing control with the preference “closest location” is considered. The algorithm decides where to source the demand from the paths “Markets – DCs” and “DCs – Factories” subject to closest facility location with available inventory. This holds true for both disruption-free and disrupted operation modes.

4.2. Key performance indicators

A set of key performance indicators (KPIs) has been established to analyse the simulation results. The KPIs are classified into financial, customer, and operational performance (Table 1).

Profit is equal to revenue minus the total costs (fixed facility, transportation, inventory holding, production, inbound and outbound processing, and penalties for delivery delays) (cf. Appendix A). Holding costs for inventory are computed for each day, while transport is calculated according costs per kilometer and the quantities of the shipment. When the quantity demanded is greater than the quantity of the shipment, then the total penalties are increased in proportion to the costs of the penalty. In addition, the costs for inbound and outbound processes are in proportion to the quantity of the process, while the costs for manufacturing are in relation to the number of units produced at all factories owned by the company and outsourced. The costs of daily fixed operations and site closure or opening comprise the fixed facility costs. The product unit is m^3. While the basic unit of time is one week, some parameters are calculated in days.

The probability that all orders from customers arriving in a set time interval will be delivered from on hand stock is the α service level: service level will not be impacted when a lack of stock delays deliveries. The time taken for delivery from a DC to a customer is the lead time. The ratio of orders which are delivered according to the “Expected lead time” to total orders are the measure for the ELT (expected lead time) service level. Every market has a set lead time, which is measured as the time from order placement at a DC to receipt of the goods from the DC.

Table 1
Key performance indicators.

KPI group	Performance indicators
Finance	Profit Revenue Total costs
Customer	Service level Orders on time Total number of arrived orders Delayed orders
Operations	Lead time Inventory Backlog orders Capacity usage

Arrived on time orders show the number of orders which are delivered within the expected lead time. This information updates whenever delivery of an order is made on time. Likewise, arrived on time orders show data on the quantity of orders in shipments received by the DC and factory for each day. This is also updated with each new incoming shipment, according to the set processing time of the facility. The total number of orders received by the customer is also shown in arrived orders (customers).

The sum of orders delayed and arrived on time comprise the data, which is updated with each order.

Orders which have been received but not shipped, or the current number of orders that have yet to be processed, are represented by the current backlog orders, and updated each day when new orders are received or lost, or a new shipment is sent or processed, according to the processing time of the facility. The quantity of orders which do not arrive within the expected lead time are represented by the delayed orders, and updated whenever an order is delayed or dropped.

5. Experiments

5.1. Experimental setting

5.1.1. anyLogistix

Developed by AnyLogic Company, anyLogistix is a software for simulation and optimisation. Using CPLEX as a basis, anyLogistix implements the function of optimisation in a Network Optimisation Module. anyLogistics also utilizes a simulation functionality, including agents that can be customised in AnyLogic. Using anyLogistix, one can perform stochastic, dynamic, variation, and comparison experiments related to facility location planning, multi-stage and multi-period SC design and planning, inventory control, transportation control, and sourcing analysis. SC disruptions can be modelled using events and state change diagrams.

5.1.2. Parameters

The experiments have been performed with the following parameters (Table 2).

5.2. Simulation experiment with the existing SC design without recovery policy

In the first group of experiments, the simulations with the existing SC design without a recovery policy were run. The simulation period

Table 2
Experimental settings.

Parameter	Values
Mean basis weekly demand in the market 1, in m^3	6000
Mean basis weekly demand in the markets 2–4, in m^3	4000
Order placement interval, in weeks	1
Number of periods	4
Period length, in months	3
Seasonal demand coefficients for four periods	0.75 – 1.25 – 1.0 – 1.0
Standard deviation of weekly demand, in m^3	25% from the mean
Expected lead time in the markets, in days	3
Lead time in between two SC stages within a region, in days	1
Mean lead time in between two SC stages from different regions, in days	4
Standard deviation lead time between two SC stages from different regions, in days	2
Reorder point at the DC1, the factories and emergency plants, in m^3	10,000
Target inventory level at the DC1, the factories and emergency plants, in m^3	20,000
Safety stock at the DC1, in m^3	6000
Reorder point at the DCs 2–4, in m^3	7000
Target inventory level at the DCs 2–4, in m^3	14,000
Initial inventory at the DCs 2–4 and factories, in m^3	10,000
Initial inventory at the DC1, in m^3	20,000
DC maximum storage capacity, in m^3	30,000
Production time for product unit, in days, in m^3	0.001
Maximum production capacity at own factory, in m^3 per period	90,000
Maximum production capacity at emergency sources, in m^3 per period	10,000
Unit price, in $ for m^3	2000
Fixed facility costs, in $ per day	50,000
Transportation costs, in $ per km, per m^3	0.3
Inventory holding costs at DCs and factories, in $ per day	10
Production costs at own factories, per product unit (m^3), in $	250
Emergency manufacturing costs at subcontractor and milk producer, per product unit (m^3), in $	500
Inbound processing costs at the DC, in $, per m^3	150
Outbound processing costs at the DC, in $, per m^3	100
Penalty for demand non-fulfillment, in $, per m^3	5000
Recovery time after a disruption, in months	4
Time between the disruption and activating the contingency policy such as subcontractor, milk producer capacity, and own factories abroad, in days	20
Mean lead time to the market 1in the disruption period, in days	8
Standard deviation lead time to the market 1 in the disruption period, in days	2

was one year, whereby DC1 disruption has been scheduled on April 1 and lasts until August 1. The simulation results are presented in Fig. 4.

Post-disruption instability in the SC has been observed as a consequence of the production-ordering behaviour during the disruption period. Service level reduction, backlog, and delayed orders can be observed in Fig. 4 as consequences of the DC disruption that lasts from day #91 until day #210. Because of the high number of delayed and backlog orders built up during the disruption period, the service level cannot recover to 100% even after the disruption recovery. The bottom diagrams in Fig. 4 provide another explanation for this effect: the inventory dynamics at the DCs experience backlogs. The existing capacity is not sufficient to recover and return to a normal inventory system operation. In addition, the left-hand diagram in the bottom part of the dashboard in Fig. 4 shows that the number of backlog orders (the blue line) and the delayed orders (the red line) continue increasing even after DC1 recovers. Disruption also influences the lead time which fluctuates during the disruption period and even after the capacity recovery. The explanation of these behaviours is the effect of so called ‘postponed redundancy’ (Ivanov and Rozhkov, 2017), i.e., the impact at the post-disruption stage of the delayed and backlog orders accumulated during the disruption period. The limited capacity in the SC prevents compensation for this residue from the disruption period. Within the capacity limits, the SC needs to serve both the delays/backlog from the disruption period and new incoming orders which results in new delays and backlogs.

5.3. Recovery policy experiments

Simulation experiments have been conducted with three recovery policies, i.e.:

- back-up contractors
- capacity flexibility (capacities of the own plant in the same region)
- using capacity of other owned plants in neighbouring countries.

These emergency sources operate according to the following logic. No initial inventory is available. Two days after the DC1 disruption, the emergency sources start producing for market 1. The first deliveries to market 1 arrive about 18–20 days after the disruption date.

In line with the study by Ivanov (2018a), we assume a time lag between disruption and activation of the contingency policies, such as subcontractor, owned factory capacity in region 1, and owned factories abroad. The emergency sources therefore operate according to the following logic: No initial inventory is available. Two days after the DC1 disruption, the emergency sources start producing for market 1. First deliveries to market 1 arrive about 18–20 days after the disruption date.

The simulation experiments were run for all six combinations (all backups are activated, different pairs of the backups are activated, and the backups are activated individually). The better results in terms of financial performance were achieved when all backups were activated. These results are presented in Fig. 5.

It can be observed in Fig. 5 that the recovery policy positively influences all performance indicators. Increases in profit and service levels as well as a reduction in backlog and lead time variability can be observed. The inventory system performs stably (note that the diagram does not represent inventory at the emergency sources in order to make the results in Figs. 4 and 5 comparable).

Table 3 compares the SC performance in the disrupted modes with and without recovery policies.

A comparison of Figs. 4 and 5 leads to the conclusion that the recovery policy helps to achieve better financial performance and higher service levels. An interesting insight can be observed from the “Inventory-Backlog” diagram that depicts the DC inventories: the recovery policy with backup sources stabilises the inventory control system during the time of disruption, which happens in the period with higher demand (cf. Table 2). Lead time variation has also been reduced.

5.4. Sensitivity analysis

Finally, we ran the same experiments in the disruption mode without a recovery policy subject to higher standard deviation of demand, and therefore, higher safety stocks. The new data is shown in Table 4.

The results are presented in Fig. 6.

In comparing Fig. 6 with Fig. 4, a higher service level and lower lead time variation can be observed. At the same time, the higher inventory carrying costs result in profit reduction.

Table 5 compares SC performance in the disrupted modes with and without recovery policies subject to the initial and changed datasets.

Table 5 provides evidence that higher demand variability is favourable for service level, lead time, and inventory system stabilisation. However, it comes at the cost of higher inventory, which decreases profits. This effect of the *mutual impact of the demand variability and SC resilience* has been observed for the first time in this experiment.

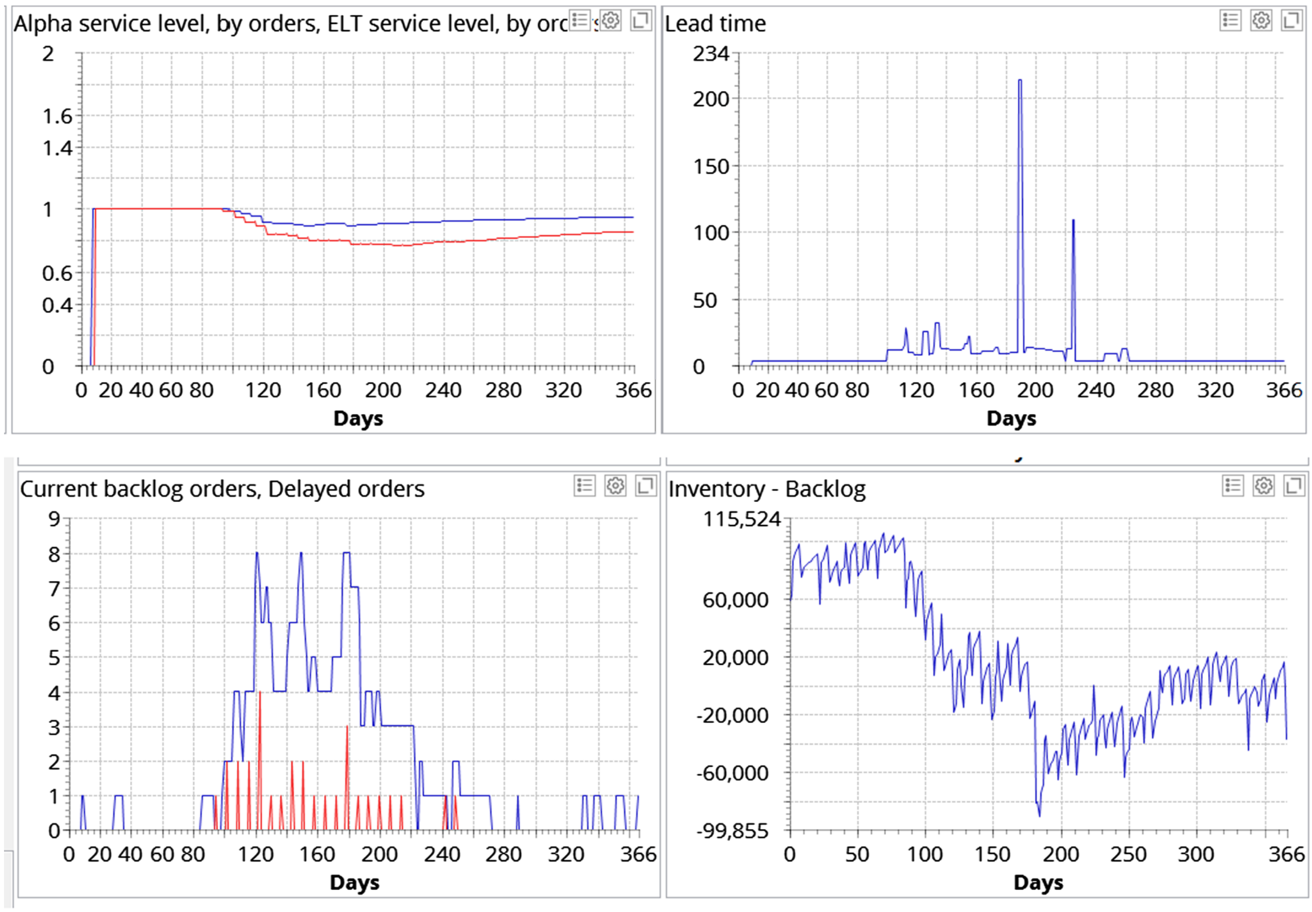


Fig. 4. Supply chain performance in the case of DC disruption and without a recovery policy.

5.5. Revival policy experiments

Simulation experiments have been conducted subject to the following three settings:

- without the contingent recovery policy
- with the contingent recovery policy, which implies the installation of additional links in the SC from the factories to the market 1 (cf Fig. 1 and Section 3.1). These links are activated after the DC1 disruption and function until DC1 recovers
- with the contingent recovery policy and an additional revival policy.

The revival policy includes such emergency sources as backup contractors, capacity flexibility (capacities of own plant in region 1), and using capacity of other owned plants in neighbouring countries. It extends the recovery policy by using the additional capacities of subcontractors even in the post-disruption period until the production-ordering system stabilises.

A transportation order aggregation period of five days with an LTL (less-than-truckload) control policy has been considered to enlarge the scope of the investigation as compared to the cases with no further restrictions on transportation policies in Sections 5.1–5.4.

The results are shown in Fig. 7.

Fig. 7 depicts the dynamics of order fulfillment following the disruption on day #91 and lasting until the DC1 recovery on day #213. Delayed and backlogged orders occur when there is no contingent recovery policy in place and when there is such a policy in place, but disruption tails still appear in the post-disruption period. The revival policy helps to improve service levels and reduce the impacts of the disruption tail in terms of delayed and backlogged orders in the post-recovery period.

When observing Fig. 7, a reduction in the number of delayed orders during the disruption period and an elimination of delayed orders after the disruption recovery can be observed with the transition from no contingent recovery policy, the introduction of a recovery policy, to the usage of the revival policy. The revival policy stabilises the order fulfillment dynamics, resulting in a positive effect on service level. The *delayed orders accumulated over the disruption period do not influence SC operations and performance since new contracting plants compensate for this with the help of additional production capacity. This allows the SC to recover faster as compared to the usage of a recovery policy only*. This observation provides evidence of *disruption tail mitigation with the help of a revival policy based on a production capacity increase in the post-disruption period.* It indicates the necessity of considering not only contingent recovery policies, but also *revival policies in the SC* which may align normal operation policy and deactivation of the contingency policies. On this basis, we recommend including revival policy in the SC resilience framework (Fig. 8).

The disruption profile delineated in the work by Sheffi and Rice (2005) includes eight phases: preparation actions, the disruptive event, the first response, the initial impact, the full impact, the recovery preparations, and the recovery and long term impact. Our experimental results suggest the inclusion of revival policy into the SC resilience framework if performance cannot be recovered fully after capacity recovery. The revival policy extends the SC resilience framework during the transition from recovery to post-disruption. The rationale for inclusion of a revival policy into the SC resilience framework is the fact that an immediate transition from the contingency plan during the disruption and recovery period to the normal operations mode may by complicated by disruption tails. In addition, for the companies

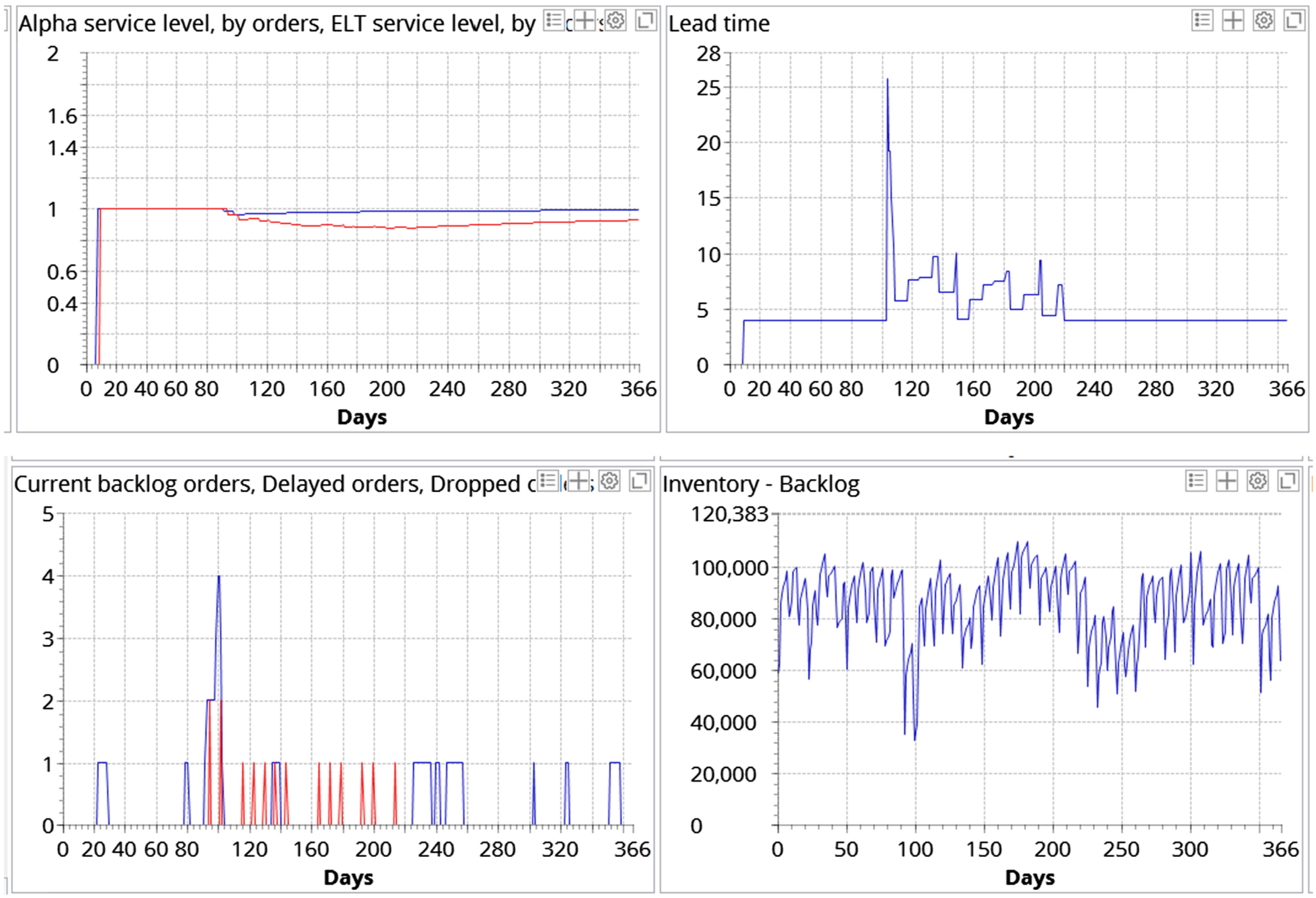


Fig. 5. Simulation results with recovery policies.

Table 3
SC performance in the disrupted modes with and without recovery policies.

Performance indicators	Disrupted mode with recovery	Disrupted mode without recovery
Profit, $	932,678,806.11	883,226,509,94
Service level α (at the end of the year), %	99	94
Service level ELT (at the end of the year), %	93	88
Inventory – Backlog, in m^3	72,827.75	−28,727.55

Table 4
Experimental settings for the sensitivity analysis.

Parameter	Values
Standard deviation of weekly demand, in m^3	50% from the mean
Reorder point at the DC1, in m^3	20,000
Target inventory level at the DC1, in m^3	40,000
Safety stock at the DCs, in m^3	12,000
Reorder point at the DCs 2–4, in m^3	14,000
Target inventory level at the DCs 2–4, in m^3	28,000
Initial inventory at the DCs 2–4 and factories, in m^3	20,000
Initial inventory at the DC1, in m^3	40,000

operating with forecast recovery dates, the inertness of decisions on activation and deactivation of contingency plans frequently leads to disruption tails. Disruption tails represent residue from the disruption period, such as backlog and delayed orders, which may influence SC operations and performance in the post-disruption mode. The revival policy intends to mitigate the negative impact of these disruption tails and stabilise the SC control policies and long term performance.

6. Managerial insights

In this study, we analysed the impact of disruption risk and the ripple effect on the design of production and distribution networks in the SC. As an example, we took a real-life case-study of a severe disruption at a DC. Using simulation and optimisation, we compared SC performance in the disruption-free mode and the disrupted SC with and without contingency plans. We also analysed the impact of demand variability on SC performance in terms of profits, service levels, and lead time.

The findings suggest that isolated production and distribution network design optimisation can lead to severe performance decreases in the event of disruptions in the SC. First, post-disruption instability in the SC, referred to as 'disruption tails', was observed as a consequence of production-ordering behaviour during the disruption period. Dependencies between the amount of backlog during the disruption period, the SC capacities, and inventory dynamics control were observed. If a large backlog is built up during the period of disruption and existing capacity is not sufficient to recover and return to normal inventory system operation, the full restoration of the SC becomes impossible. In this setting, when backups do not fully replace capacity during the disruption period, the development of contingency inventory control policies can be considered. These policies would apply to the period of disruption, and the period of transition to recovery with the aim of reducing backlog and the number of delayed orders and adjusting to disrupted SC capacities. Recovery policies should not be limited in scope to the disruption period only, but should include consideration of the post-disruption period.

Second, we observed that for markets with higher demand variability, SC resilience is higher in terms of longer survival time after the disruption (expressed in terms of service level and sales during the disruption period). This can be explained by higher safety stocks which are typically held in the SC in the event of highly variable demands.

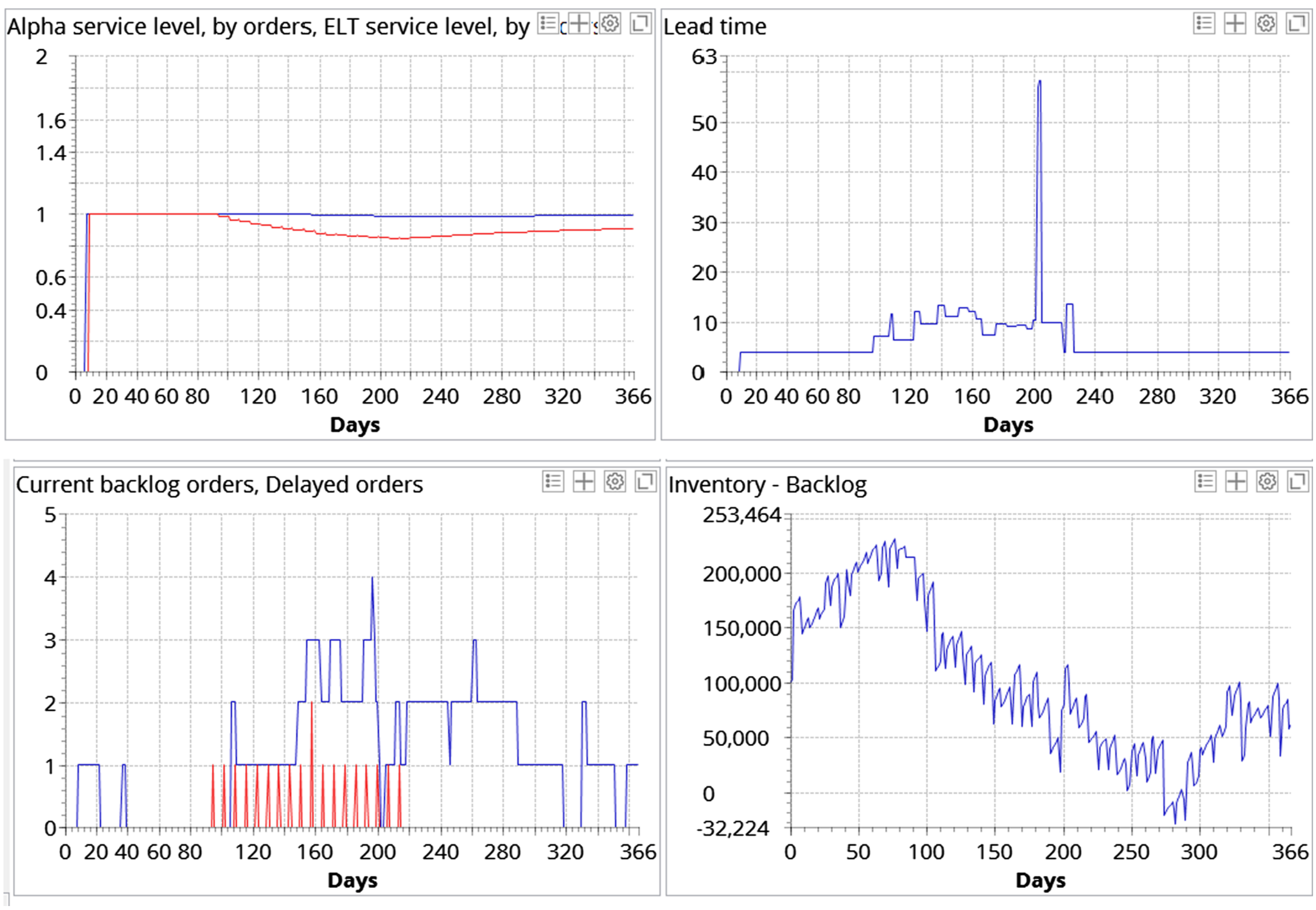


Fig. 6. Simulation results for markets with higher demand variability and without recovery policy.

However, this observation holds true only in the case of inventory diversification at different DCs in the SC. This effect of the *mutual impact of the degree of demand variation degree and SC resilience* was observed for the first time in this experiment.

We point out the necessity for specific policies for the transition period, so called “revival policies”. An immediate deactivation of the contingency plans after capacity recovery may result in the destabilisation of the inventory system and backlog. In many settings, recovery policies must be run for certain periods of time, even after disruption recovery, in order to ensure smooth revival of the control systems. Specific changes in SC behaviour during the disruption period may result in backlog and changed production, ordering, and inventory control policies. This residue could bleed over into the post-disruption period, destabilising the normal operations mode that is typically in place after recovery: immediate deactivation of the contingency plan and switching to a ‘normal’ operation plan after recovery can be inefficient. This observation indicates the necessity of considering not only recovery, but also revival policies for the SC.

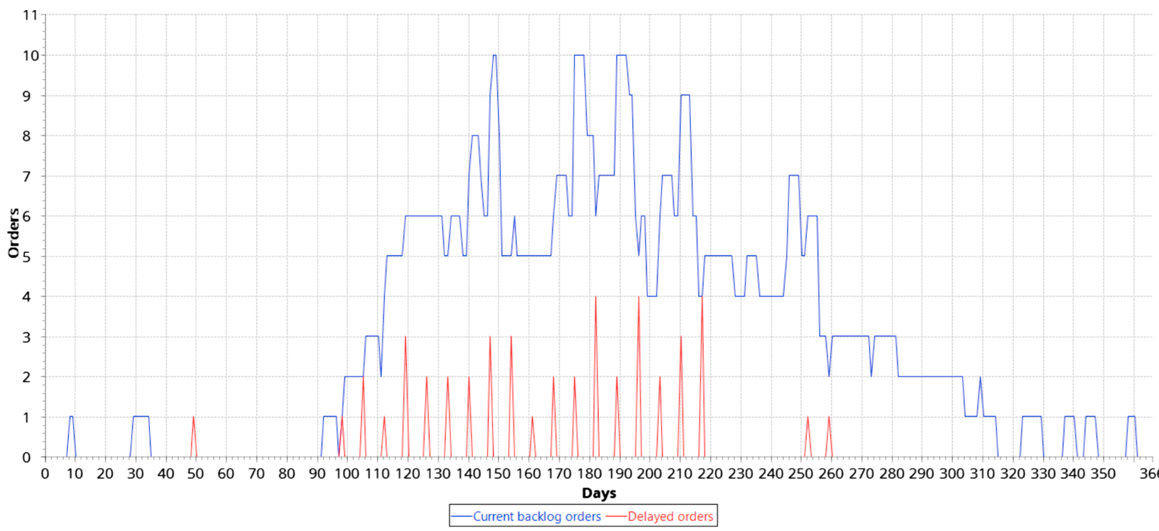
7. Conclusion

We studied the influence of disruption risk on production and distribution network design. A real-life case-study of a disruption at a DC was considered and investigated with the help of discrete-event simulation blended with network optimisation in anyLogistix. The findings suggest that isolated production and distribution network design optimisation can lead to severe performance decreases in the case of disruptions in the SC. It is therefore argued that considerations of production-ordering dynamics with disruptions must be taken into account in production-distribution network design.

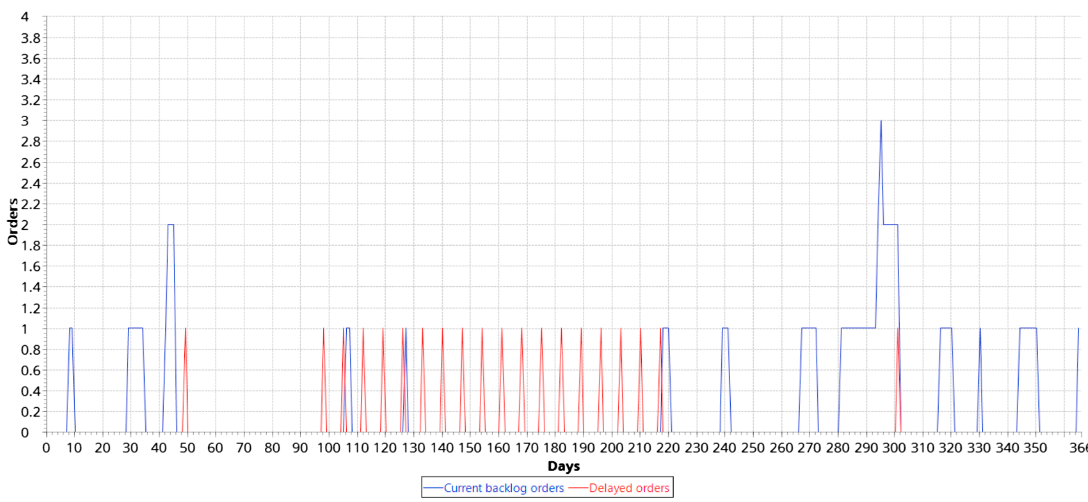
Two specific findings have been observed. First, when a high backlog accumulates during the disruption period and there is limited SC capacity, the inventory control system is prevented from returning to normalcy even after full capacity is recovered. Second, immediate deactivation of contingency plans after capacity recovery results in the destabilisation of the inventory system and backlog. This observation indicates the necessity of considering not only recovery, but also revival policies in the SC. Contingent recovery policies need to be applied

Table 5
SC performance comparison.

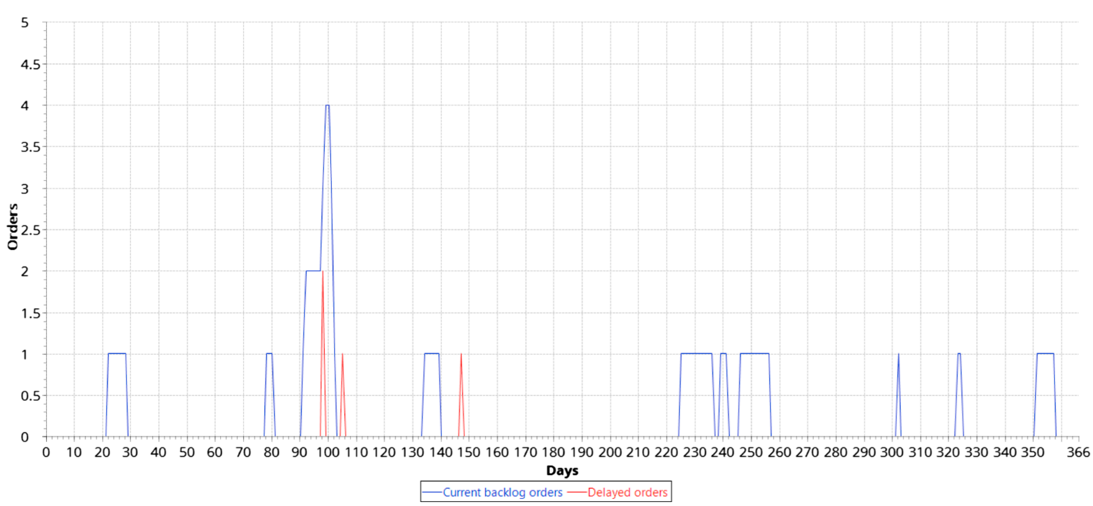
Performance indicators	Disrupted mode with recovery	Disrupted mode without recovery	Disrupted mode without recovery and with higher demand variability and safety stocks
Profit, $	932,678,806.11	883,226,509,94	737,701,705.81
Service level α (at the end of the year), %	99	94	99
Service level ELT (at the end of the year), %	93	88	91
Inventory – Backlog, in m^3	72,827.75	−28,727.55	60.950,31



a) Order fulfillment dynamics without contingency and revival policy



b) Order fulfillment dynamics with contingency policy



c) Order fulfillment dynamics with contingency and revival policy

Fig. 7. Order fulfillment dynamics.

during the disruption period and revival policies in the post-disruption period in order to avoid disruption tails. These revival policies need to be developed for the transition from recovery to a disruption-free operation mode. The recovery should also consider the post-disruption period and be included in SC design decisions. The revival policy should also be included in the SC resilience framework.

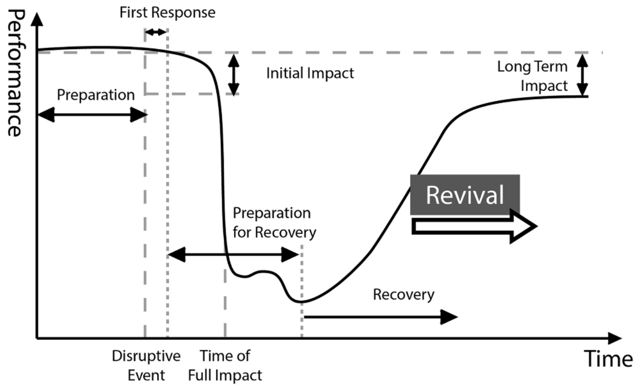


Fig. 8. The place of the revival policy in the supply chain resilience framework (extended from Sheffi and Rice (2005)).

The findings of this study open new avenues for future research. First, the interrelations between demand variability, safety stock, and recovery policies need to be studied in more detail: the interrelation of time for activating a recovery policy (i.e., time gap between the disruption occurring and a backup facility starting to supply), reorder point adjustment, and safety stock control at the DCs.

Second, a detailed analysis is needed for the mutual interrelations between disruption duration, backlogs, and SC capacities. More specifically, the development of contingent inventory control policies can be considered with the aim of reducing backlogs and adjusting to SC capacities during and after the disruption period. Third, revival policies require closer attention. The SC transition from a disrupted to a recovered state is connected with a number of specific issues. Specific indicators must be developed to analyse when the SC can be considered recovered. An immediate deactivation of the contingency plan and switching to a 'normal' operation plan after recovery can be inefficient. Specific revival policies for this transition period can be a promising research avenue in the future.

Concerning the limitations of this study, it needs to be pointed out that the findings are based upon a contextual case-study simulation analysis which restricts insight generalization. At the same time, the SC design structures and ordering policies considered are standard and encountered in different industries. As such, the findings of this study are generalizable and applicable to other cases, too. Further research can include analysis of other industries and datasets. Moreover, analytical studies are needed to provide more generalisable theoretical results and practical recommendations.

Acknowledgment

The author is grateful to associate editor and two anonymous reviewers for their invaluable comments that immensely helped to improve the manuscript.

Appendix A. . Optimisation model

Indices	
f	Actual demand index
α	α-service level
r	Period index, $r \in [1; T]$)
ST	Standard deviation index
λ	Market number, $\lambda \in [1; \Lambda]$
i	Production facility number, $i \in [1; H]$
j	Distribution centre number, $j \in [1; G]$)
t	Running time index
T	Length of the planning horizon
Parameters	
T	Number of planning periods in planning horizon
G	Number of DCs
H	Number of factories
Λ	Number of markets
D	Mean weekly demand in a r-period, in units
q	Mean basis demand, in units
k	Seasonal demand coefficient in a r-period
δ^{ST}	Weekly demand standard deviation in a r-period
K	Maximum production capacity per day, in units
B	Maximum storage capacity at the DCs per day, in units
L^{in}	Maximum inbound processing capacity at the DCs per day, in units
L^{out}	Maximum outbound processing capacity at the DCs per day, in units
ξ	Capacity reduction coefficient, in units
c_h	Unit inventory holding costs per day, in $
c_{tr}	Unit transportation costs per delivery, in $
c_{fix}	Fixed site costs, in $ per day
c_{man}	Own manufacturing costs, in $ per unit
c_{sub}	Subcontracting manufacturing costs, in $ per unit
c_{in}	Inbound processing costs, in $ per unit
c_{out}	Outbound processing costs, in $ per unit
c_{down}	Penalty for demand non-fulfillment, in $ per unit
p	Unit price, in $
Variables	
P	Production quantity at the factory, in units per day

S	Selling quantity in the markets, in units
X^{in}	Processed inbound quantity at the DC, in units per day
X^{out}	Processed outbound quantity at the DC, in units per day
Q	Shipment quantities in between the factory, DC, and the markets, in units per day
H	Total inventory holding costs, in \$
T	Total transportation costs, in \$
W	Total processing costs, in \$
F	Total fixed costs, in \$
M	Total manufacturing costs, in \$
U	Total penalty for delayed delivery, in \$
TC	Total costs, in \$
y	Inventory in a r-period, in units
d	Distance, in km (computed based on real routes)

Objective function

$$max \quad Profit = Revenue - TC = (p \cdot S) - (H + T + W + U + M + F), \quad where \tag{1}$$

$$\underbrace{H = \sum_{t=1}^{T}\sum_{j=1}^{G} c_h \cdot y_{jt}^{g}}_{Total\ inventory\ holding\ costs}$$

$$\underbrace{T = \sum_{j=1}^{G}\sum_{i=1}^{N} c_{tr} \cdot d_{ij} \cdot Q_{ij} + \sum_{i=1}^{N}\sum_{\lambda=1}^{\Lambda} c_{tr} \cdot d_{\lambda i} \cdot Q_{i\lambda}}_{Total\ transportation\ costs}$$

$$\underbrace{W = \sum_{j=1}^{G}(c_{in} + c_{out}) \quad Total\ processing\ costs}$$

$$\underbrace{F = \sum_{j=1}^{G} c_{fix} + \sum_{i=1}^{N} c_{fix}}_{Total\ fixed\ costs}$$

$$\underbrace{F = \sum_{i=1}^{N} c_{sub} \cdot P_i + \sum_{i=1}^{N} c_{man} \cdot P_i}_{Total\ manufacturing\ costs}$$

$$\underbrace{U = \sum_{\lambda=1}^{\Lambda} c_{down}}_{Total\ penalty\ costs}$$

Demand constraints

$Q_{j\lambda t} \geq d_{t\lambda}$

$D_r = k \cdot q_\lambda$

$D_{fr} = D_r \cdot \sigma_r^{ST}$

Shipment constraints

$Q_{ijt} \leq X_t^{out}$

$Q_{\lambda jt} \leq y_{jt}$

Capacity constraints

$P_{it} \leq K_{it} \cdot \xi$

Constraints on inventory holding and processing at the DCs

$y_j \leq B_j \cdot \xi$

$X_{t+1}^{out} \leq L^{out}$

$X_{t+1}^{in} \leq L^{in}$

References

Amiri-Aref, M., Klibi, W., & Babai, M. Z. (2018). The multi-sourcing location inventory problem with stochastic demand. *European Journal of Operational Research, 266*(1), 72–87.

Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S., & Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering, 62*(1), 329–341.

Chen, Y., Ponsignon, T., Weixlgartner, R., & Ehm, H. (2017). Simulating recovery strategies to enhance the resilience of a semiconductor networks. In W. K. V. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, & E. Page (Eds.). *Proceedings of the 2017 winter simulation conference*.

Choi, T. M., Govindan, K., Li, X., & Li, Y. (2017). Innovative supply chain optimization models with multiple uncertainty factors. *Annals of Operations Research, 257*(1–2), 1–14.

Chopra, S., & Meindl, P. (2015). *Supply chain management – Strategy, planning and operation* (6th ed.). Harlow: Pearson Education.

Chopra, S., Reinhardt, G., & Mohan, U. (2007). The importance of decoupling recurrent and disruption risks in a supply chain. *Naval Research Logistics, 54*(5), 544–555.

Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: An analysis and recent literature. *International Journal of Production Research, 56*(1–2), 414–430.

Dolgui, A., & Proth, J. M. (2010). *Supply chain engineering: Useful methods and techniques.* London: Springer.

Dupont, L., Bernard, C., Hamdi, F., & Masmoudi, F. (2018). Supplier selection under risk of delivery failure: A decision-support model considering managers' risk sensitivity. *International Journal of Production Research, 56*(3), 1054–1069.

Giannoccaro, I., Nair, A., & Choi, T. (2018). The impact of control and complexity on supply network performance: An empirically informed investigation using NK simulation analysis. *Decision Science, 49*(4), 625–659.

Gunasekaran, A., Subramanian, H., & Rahman, S. (2015). Supply chain resilience: Role of complexities and strategies. *International Journal of Production Research, 53*(22), 6809–6819.

He, J., Alavifard, F., Ivanov, D., & Jahani, H. (2018). A Real-Option Approach to Mitigate Disruption Risk in the Supply Chain. *Omega: The International Journal of Management Science* (published online).

Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. *International Journal of Production Research, 53*(16), 5031–5069.

Ivanov, D. (2017). Simulation-based ripple effect modelling in the supply chain. *International Journal of Production Research, 55*(7), 2083–2101.

Ivanov, D. (2018b). *Structural dynamics and resilience in supply chain risk management.* New York: Springer.

Ivanov, D. (2018a). Revealing interfaces of supply chain resilience and sustainability: A simulation study. *International Journal of Production Research, 56*(10), 3507–3523.

Ivanov, D., Dolgui, A., Sokolov, B., & Ivanova, M. (2017). Literature review on disruption recovery in the supply chain. *International Journal of Production Research, 55*(20), 6158–6174.

Ivanov, D., & Rozhkov, M. (2017). Coordination of production and ordering policies under capacity disruption and product write-off risk: An analytical study with real-data based simulations of a fast moving consumer goods company. *Annals of Operations Research* (published online).

Ivanov, D., Sokolov, B., & Kaeschel, J. (2010). A multi-structural framework for adaptive supply chain planning and operations with structure dynamics considerations. *European Journal of Operational Research, 200*, 409–420.

Jain, V., Kumar, S., Soni, U., & Chandra, C. (2017). Supply chain resilience: Model development and empirical analysis. *International Journal of Production Research, 55*(22), 6779–6800.

Kamalahmadi, M., & Mellat-Parast, M. (2016). Developing a resilient supply chain through supplier flexibility and reliability assessment. *International Journal of Production Research, 54*(1), 302–321.

Khalili, S. M., Jolai, F., & Torabi, S. A. (2017). Integrated production–distribution planning in two-echelon systems: A resilience view. *International Journal of Production Research, 55*(4), 1040–1064.

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: A critical review. *European Journal of Operational Research, 203*(2), 283–293.

Kumar, S. K., & Tiwari, M. K. (2013). Supply chain system design integrated with risk pooling. *Computers & Industrial Engineering, 64*, 580–588.

Levner, E., & Ptuskin, A. (2018). Entropy-based model for the ripple effect: Managing environmental risks in supply chains. *International Journal of Production Research, 56*(7), 2539–2551.

Liberatore, F., Scaparra, M. P., & Daskin, M. S. (2012). Hedging against disruptions with ripple effects in location analysis. *Omega, 40*(2012), 21–30.

Lim, M. K., Bassamboo, A., Chopra, S., & Daskin, M. S. (2013). Facility location decisions with random disruptions and imperfect estimation. *Manufacturing and Service Operations Management, 15*(2), 239–249.

Losada, C., Scaparra, M. P., & O'Hanley, J. R. (2012). Optimizing system resilience: A facility protection model with recovery time. *European Journal of Operational Research, 217*, 519–530.

Lücker, F., Seifert, R. W., & Biçer, I. (2018). Roles of inventory and reserve capacity in mitigating supply chain disruption risk. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2018.1504173.

Macdonald, J. R., Zobel, C. W., Melnyk, S. A., & Griffis, S. E. (2018). Supply chain risk and resilience: Theory building through structured experiments and simulation. *International Journal of Production Research, 56*(12), 4337–4355.

Mizgier, K. J. (2017). Global sensitivity analysis and aggregation of risk in multi-product supply chain networks. *International Journal of Production Research, 55*(1), 130–144.

Namdar, J., Li, X., Sawhney, R., & Pradhan, N. (2018). Supply chain resilience for single and multiple sourcing in the presence of disruption risks. *International Journal of Production Research, 56*(6), 2339–2360.

Paul, S., & Rahman, S. (2018). A quantitative and simulation model for managing sudden supply delay with fuzzy demand and safety stock. *International Journal of Production Research, 56*(13), 4377–4395.

Pavlov, A., Ivanov, D., Dolgui, A., & Sokolov, B. (2018). Hybrid fuzzy-probabilistic approach to supply chain resilience assessment. *IEEE Transactions on Engineering Management, 65*(2), 303–315.

Raj, R., Wang, J. W., Nayak, A., Tiwari, M. K., Han, B., Liu, C. L., & Zhang, W. J. (2015). Measuring the resilience of supply chain systems using a survival model. *IEEE Systems Journal, 9*(2), 377–381.

Rezapour, S., Farahani, R., & Pourakbar, M. (2017). Resilient supply chain network design under competition: A case study. *European Journal of Operational Research, 259*(3), 1017–1035.

Sawik, T. (2013). Integrated selection of suppliers and scheduling of customer orders in the presence of supply chain disruption risks. *International Journal of Production Research, 51*(23–24), 7006–7022.

Sawik, T. (2017). A portfolio approach to supply chain disruption management. *International Journal of Production Research, 55*(7), 1970–1991.

Sawik, T. (2018). Two-period vs. multi-period model for supply chain disruption management. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2018.1504246.

Scheibe, K. P., & Blackhurst, J. (2018). Supply chain disruption propagation: A systemic risk and normal accident theory perspective. *International Journal of Production Research, 56*(1–2), 43–59.

Schmitt, T. G., Kumar, S., Stecke, K. E., Glover, F. W., & Ehlen, M. A. (2017). Mitigating disruptions in a multi-echelon supply chain using adaptive ordering. *Omega, 68*, 185–198.

Schmitt, A. J., & Singh, M. (2012). A quantitative analysis of disruption risk in a multi-echelon supply chain. *International Journal of Production Economics, 139*(1), 23–32.

Sheffi, Y., & Rice, J. B. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review, 47*(1) September.

Simangunsong, E., Hendry, L. C., & Stevenson, M. (2012). Supply-chain uncertainty: A review and theoretical foundation for future research. *International Journal of Production Research, 50*(16), 4493–4523.

Simchi-Levi, D., Schmidt, W., Wei, Y., Zhang, P. Y., Combs, K., Ge, Y., ... Zhang, D. (2015). Identifying risks and mitigating disruptions in the automotive supply chain. *Interfaces, 45*(5), 375–390.

Sokolov, B., Ivanov, D., Dolgui, A., & Pavlov, A. (2016). Structural quantification of the ripple effect in the supply chain. *International Journal of Production Research, 54*(1), 152–169.

Spiegler, V. L. M., Potter, A. T., Naim, M. M., & Towill, D. R. (2016). The value of nonlinear control theory in investigating the underlying dynamics and resilience of a grocery supply chain. *International Journal of Production Research, 54*(1), 265–286.

Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics, 103*, 451–488.

Trucco, P., Petrenj, B., & Birkie, S. E. (2017). Assessing supply chain resilience upon critical infrastructure disruptions: A multilevel simulation modelling approach. In Y. Khojasteh (Ed.). *Supply chain risk management* (pp. 311–334). Singapore: Springer.

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production Research, 53*(18), 5592–5623.