Simulation-based Ripple Effect Modelling in the Supply Chain

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Abstract
In light of low-frequency/high-impact disruptions, the ripple effect has recently been introduced into academic literature on supply chain management. The ripple effect in the supply chain results from disruption propagation from the initial disruption point to the supply, production and distribution networks. While optimization modelling dominates this research field, the potential of simulation modelling still remains under-explored. The objective of this study is to reveal research gaps that can be closed with the help of simulation modelling. First, recent literature on both optimization and simulation modelling is analysed. Second, a simulation model for multi-stage supply chain design with consideration of capacity disruptions and experimental results are presented in order to depict major areas of simulation application to the ripple effect modelling. Based on both literature analysis and the modelling example, managerial insights and future research areas are identified in regard to simulation modelling.
application to the ripple effect analysis in the supply chain. The paper concludes by summarizing the most important insights and outlining a future research agenda.

**Keywords**: supply chain dynamics; ripple effect; supply chain resilience; simulation; risk management; supply chain engineering

1. Introduction

Significant advancements can be observed in supply chain (SC) risk management in the last two decades (Wu et al. 2007; Tang and Musa 2012; Fahimnia et al. 2015; Ho et al. 2015; Tukamuhabwa et al. 2015; Chiu and Choi 2016; Gupta et al. 2016). Each major accident galvanizes the scientific community to renew its efforts towards disruption prevention and recovery. But whereas rapid strides have been made in the robust SC design and performance impact assessment in regard to stand-alone events, much less attention has been paid towards situations where one disruption in the SC becomes the cause of further disturbances at other SC stages.

Disruptions in SCs are characterized by different frequency and performance impact (Chopra et al. 2007; Gurnani et al. 2012; Chopra and Sodhi 2014; Simchi-Levi et al. 2014). High-frequency/low-impact disruptions are typically considered in light of the bullwhip effect and refer to demand and lead-time fluctuations (Lee et al. 1997; Chen et al. 2000; Spiegler et al. 2016). Surveys on specific aspects of SC risks in the context of a bullwhip effect are presented in Dolgui and Prodhon 2007; Klibi et al. 2010; Dolgui et al. 2013; Alloulou et al. 2014; Aglan and Lam 2015; Fahimnia et al. 2015; Ho et al. 2015; Tsai 2016).

In contrast to the well-studied bullwhip effect, low-frequency/high-impact disruptions present new challenges for SC research and managers and belong to critical company capabilities (Craighead et al. 2007; Haberman et al. 2015; Snyder et al. 2016). Knemeyer et al. (2009) underline the necessity for proactive decisions in regard to catastrophic events in the SC. In light of low-frequency/high-impact disruptions, a new term, ‘ripple effect’ has recently been introduced into academic literature (Liberatore et al. 2012; Ivanov et al 2014a, 2014b, 2015,
2016a, 2016b; Sokolov et al. 2016). To our knowledge, the study by Liberatore et al. (2012) was the first to name the ripple effect. The first study that defined the ripple effect has been the work by Ivanov et al. (2014b). According to this definition, the ‘ripple effect in the SC results from disruption propagation of an initial disruption towards other SC stages in the supply, production, and distribution networks’ (Figure 1).

Figure 1 Disruption propagation in the supply chain

The study by Sokolov et al. (2016) clearly distinguished the ripple effect from the bullwhip effect. The differences can be seen in regard to frequency of risk events, their impact on SC performance, duration and scope of recovery period, as well as in inventory dynamics (i.e. the bullwhip effect) vs structural dynamics (i.e. the ripple effect) (Figure 2).

Figure 2 Bullwhip and ripple effects
The ripple effect in the SC occurs if a disruption at a supplier or a transportation link cannot be localized and spreads out to other parts of the SC. The ripple effect can be related to the *domino effect* in process industry infrastructures (Khakzad 2015). Wierczek (2014) names disruption propagation in the SC as the *snowball effect*. 

The ripple effect is a phenomenon of disruption propagation in the SC and its impact on SC output performance (e.g. sales, on-time delivery, and total profit). The ripple effect may have much more serious consequences than the bullwhip effect. It can result in market share losses (e.g. Toyota lost its market leader position after the tsunami in 2011 and needed to redesign SC coordination mechanisms (Matsuo et al. 2015)) or company value decreases. Hendricks and Singhal (2005) quantified the negative effects of SC disruption through empirical analysis and found 33–40% lower stock returns relative to their benchmarks over a 3-year time period that started 1 year before and ended 2 years after a disruption; large negative effects on profitability; a 107% drop in operating income; 7% lower sales growth; and an 11% growth in costs, 2 years at a lower performance level after a disruption. Therefore, the ripple effect implies high commercial costs and its mitigation is of vital importance for companies.

The ripple effect is not an infrequent occurrence. In many examples given (Chopra and Sodhi 2014 and Simchi-Levi et al. 2014), SC disruptions go beyond the disrupted stage; i.e. the original disruption causes disruption propagation in the SC; at times there are still worse consequences. Reasons for the ripple effect are not difficult to find. With increasing SC complexity and consequent pressure on speed and efficiency, ever larger numbers of industries come to be distributed worldwide and are concentrated in cheek-by-jowl in industrial districts. In addition, globalized SCs depend heavily on permanent transportation infrastructure availability.

Disruption propagation analysis in regard to the ripple effect in the SC deserves the attention of optimization (Cui et al. 2010; Liberatore et al. 2012; Benyoucef et al. 2013; Li et al. 2013; Sawik 2016; He and Zhuang 2016) and simulation (Carvalho et al. 2012; Schmitt and Singh...

While mathematical and stochastic optimization dominates the research domain in this field, the potential of simulation modelling still remains under-explored. At the same time, simulation is a recognized approach to modelling SC and logistics dynamics (Deleris and Erhun 2005; Haasis et al. 2008; Longo and Mirabelli 2008; Tako and Robinson 2012; Meisel and Bierwirth 2014; Oliveira et al. 2016). In the last three decades, simulation applications to flexible manufacturing systems, production-inventory systems, and SCs dynamics have been extensively presented in the International Journal of Professional Research (IJPR) (Axsäter 1974; Stecke and Solberg 1981; Wu and Wysk 1989; Villegas and Smith 2006; Ivanov et al. 2016b).

The objective of this study is to reveal research gaps that can be closed with the help of simulation modelling in the field of the ripple effect in the SC. In Section 2, recent literature on simulation modelling is analysed. Section 3 derives a framework for application of the simulation research methodology to the ripple effect analysis in the SC and illustrates this on an example of anyLogistix software. In Section 4, a ‘typical’ simulation model for multistage SC design with consideration of capacity disruptions and experimental results is presented in order to depict major areas of simulation application to ripple effect modelling. Based on both literature analysis and modelling examples, managerial insights and future research directions on simulation modelling application to ripple effect analysis in the SC are derived in Section 5. Section 6 concludes the paper by summarizing the most important insights and outlining a future research agenda.

2. State-of-the-art

The need for ripple effect analysis in the SC has been recognized and systematically considered in risk analysis, performance impact and resilience assessment, and vulnerability analy-
sis. Simulation literature considers the ripple effect in the SC from five different methodical perspectives:

- system dynamics
- agent-based modelling
- discrete-event simulation
- graph theory based simulation
- optimization-based simulation

Simulation studies on the ripple effect naturally play important roles in research communities since they are able to handle time-dependent and gradual disruption duration, duration of recovery measures, capacity degradation and recovery. For complex problem settings with situational system behaviour changes in time, simulation can be even more powerful than analytical closed form analysis.

First, *system dynamics* has been applied to simulate the ripple effect in the SC. Wilson (2007) considers transportation disruptions in multistage SC in order to reveal the ripple effect impact on fulfilment rate and inventory fluctuations. The findings suggest that the highest performance impact has transportation disruptions between the Tier-1 supplier and the warehouse. Further, this study depicts the value of VMI (vendor-managed inventory) for disruption mitigation. Bueno-Salano et al. (2014) simulate a specific case of ripple effect, so-called ‘border effect’ in the Mexico–US trade that may occur if products cross land borders or arrive at seaports. The authors include three disruption duration scenarios at an international border (three, eight, and ten days in out-of-operation mode respectively) and simulate the impact of inventory increase to overcome such disruptions on total SC costs. The main finding of this study is the exponential increase of total SC costs subject to increase in disruption duration (0.1% costs increase for three days of disruption, 130% for eight days of disruption, and 472% for ten days of disruption). This is in line with results gained by Wilson (2007).
Second, *agent-based simulation* has been used to model SC disruptions and their impact on SC performance. Xu et al. (2014) model disrupted capacities at suppliers in a three-stage SC and consider recovery policies and their impact on the SC service level. The authors use AnyLogic multi-method simulation software. The authors compare performance impact with and without recovery measures for four scenarios. The results indicate the ripple effect impact on customer satisfaction depends not only on recovery measures, but also on proactive resilience planning. An interesting insight of this study is explicit identification of ‘retailer–supplier’ links that are especially sensitive to disruptions at the suppliers. Blos et al. (2015) present a framework of agent-based modelling of SC disruptions and focus on the refinement agent process.

Third, *discrete-event simulation* has been used in the area of severe SC disruptions and resilience analysis. Carvalho et al. (2012) analyse a four-stage SC based on a real case study of a Portuguese automotive SC. Focusing on the research question of how different recovery strategies influence SC performance in the case of disruptions, the authors analyse two recovery strategies and six disruption scenarios. The scenarios differ in terms of presence or absence of a disturbance and presence or absence of a mitigation strategy. The performance impact has been analysed in regard to lead-time ration and total SC costs using an ARENA-based simulation model.

Schmitt and Singh (2012) present a quantitative estimation of the disruption risk in a multi-echelon SC using discrete-event simulation. The disruption risk is measured by ‘weeks of recovery’ as an amplification of the disruption. The modelled proactive and recovery strategies include satisfying demand from an alternate location in the network, procuring material or transportation from an alternative source or route, and holding strategic inventory reserves throughout the SC. In regard to the ripple effect, this study provides two interesting results. First, increases in inventory levels of raw material and finished goods in anticipation of disruptions significantly exceed those required when only stochastic demand is considered. Sec-
ond, ‘upstream disruptions in the SC may not be felt as quickly as downstream disruptions, but their impact can be amplified, outlasting the disruptions themselves’. The authors also reveal a dependence on employment efficiency of back-up mitigation methods on the response speed.

Lewis et al. (2013) analyse the disruption risks at ports of entry with the help of closure likelihood and duration which are modelled using a completely observed, exogenous Markov chain. They developed a periodic review inventory control model that for studied scenarios indicates that operating margins may decrease 10% for reasonably long port-of-entry closures or eliminated completely without contingency plans, and that expected holding and penalty costs may increase 20% for anticipated increases in port-of-entry utilization.

Hishamuddin et al. (2015) simulate a three-echelon inventory system in the SC with multiple sourcing and consider both supply and transportation disruptions. They include disruption duration, recovery costs, and a random disruption generator in the model. The most important finding of this study is that back-order quantity and recovery duration have strong positive correlations with total SC costs as compared to the importance of lost sales. This study contributes to the body of knowledge on the ripple effect in SCs by revealing the fact that disruptions between the supplier and manufacturer imply higher average SC costs as compared to disruptions between the producer and distributor. At the same time, the authors reveal that both performance impacts of recovery duration and disruption location are quite similar for both supply and transportation disruptions. This result is in line with the study by Yu et al. (2009).

Fourth, graph-theoretical simulation studies need to be named. Li et al. (2006) use directed acyclic networks and the shortest path method to model an SC and consider disruptions on sub-graphs in the networks. The authors evaluate the time lags between the disruptions in the upstream and the consequences of these disruptions in the downstream SC. In addition, performance impact is studied in regard to SC costs. Petri nets have been applied to analyse dis-
ruption propagation through the SC and to evaluate the performance impact of the disruptions (Wu et al. 2007). Tuncel and Alpan (2010) extend the body of knowledge by incorporating multiple disruption scenarios (disruptions in demand, transportation, and quality). In addition, this study also considers recovery actions and the performance impact of such mitigation strategies. Zegordi and Davarzani (2012) apply coloured Petri nets in order to improve the visualization abilities of simulation models. The study by Lin et al. (2014) concentrates on the reliability assessment for a multi-state SC with multiple suppliers as the probability to satisfy market demand within the budget and production capacity limitations. They develop an algorithm in terms of minimal paths to evaluate network reliability along with a numerical example regarding auto-glass. Garvey et al. (2015) build upon minimal paths analysis and suggest using a Bayesian network to analyse risk propagation in the SC. This is an interesting research avenue since Bayesian networks have been applied to domino effect analysis in chemical industry infrastructures (Khakzad 2015).

Kim et al. (2015) apply graph theory to analyse the impact of SC structure on resilience. This study reveals that the network structure significantly determines the likelihood of disruption. Sokolov et al. (2016) quantify the ripple effect in the SC with the help of selected indicators from graph theory subject to disruption propagation in a multistage distribution network. Han and Shin (2016) assess the SC structural robustness considering disruption propagation in a connected graph. They perform quantitative assessment of the structural robustness on random networks compared with the probability of network disruption due to random risk. Tang et al. (2016) develop a time-varied cascading failure model and analyse the ripple effect on failed loads propagation in the SC. They present the SC as an interdependent structure of an undirected cyber network and a directed physical network, two layers that constitute an SC. The authors develop robustness measures and analyse the SC collapse situations. Lin et al. (2016) evaluate the reliability of a multistage SC as the probability that the SC can successfully deliver a sufficient amount of the commodity to meet market demand via several
transit stations under the delivery time threshold and time windows. System reliability is treated as a delivery performance index and evaluated in terms of minimal paths.

Fifth, optimization-based simulation studies can be identified. Benyoucef et al. (2013) consider a two-period SC design model in which selected suppliers are reliable in the first period and can fail in the second period. The corresponding facility location/supplier reliability problem is formulated as a non-linear stochastic programming problem. The authors use a Monte Carlo approach in combination with Lagrangian relaxation. Lim et al. (2013) turned away from probability estimation issues and faced the trade-off of under- vs overestimation of disruption probabilities. Simulation results provide the evidence that underestimation of disruptions may have a significantly higher impact on the total SC costs as compared to overestimation. Such analysis has been performed on the basis of a stylized continuous location model.

Lee et al. (2014) simulate supply forecasts during SC disruptions. Ivanov et al. (2014a) use a hybrid optimization-control model for simulation of SC recovery policies for multiple disruptions in different periods in a multistage SC. The approach developed allows simultaneous performance impact analysis of SC disruptions and recovery policies simulation. Schmitt et al. (2015) investigate effects of demand uncertainty and disrupted supply. In contrast to classical results on risk pooling in multistage inventory systems, the authors find that decentralized inventory system performs better for deterministic demand and stochastic supply. For the case of stochastic demand and supply, they also recommend using a decentralized inventory system if the decision maker is risk averse.

Chavez et al. (2016) consider transportation disruption within a multi-objective stochastic optimization model in regard to freight costs and lead-time minimization. The authors analyse a special case of products, e.g. perishable goods. Hasani and Khosrojerdi (2016) develop a non-linear mixed-integer programming model and use it to simulate resilience strategies to mitigate the risk of correlated disruptions. Ivanov et al. (2016a) extend performance impact assessment and SC plan reconfiguration with consideration of the duration of disruptions and
the costs of recovery. They analyse seven proactive SC structures, compute recovery policies to redirect material flows in the case of two disruption scenarios, and assess the performance impact for both service level and costs with the help of an SC (re)planning model containing elements of control theory and linear programming. This study reveals the impact of different parametrical and structural resilience measures on SC service level and efficiency.

3. Simulation research framework on studying the ripple effect in the supply chain

In this section, we derive a framework for application of the simulation research methodology in the SC to the ripple effect analysis on the basis of literature analysis and subsequently illustrate it by an example on anyLogistix software.

3.1. Simulation framework

Analysis of literature allows summarizing of the following framework for investigating the ripple effect in the SC with the help of simulation research methodology (Figure 3).

<table>
<thead>
<tr>
<th>Structural dynamics</th>
<th>Disruption randomness</th>
<th>Recovery randomness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operational parameter dynamics</td>
<td>Inventory dynamics</td>
<td>Production dynamics</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Shipment dynamics</td>
</tr>
<tr>
<td>Performance impact dynamics</td>
<td>Sales dynamics</td>
<td>Service level dynamics</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Costs dynamics</td>
</tr>
</tbody>
</table>

Figure 3 Framework for investigating the ripple effect on the SC with the help of simulation research methodology

Let us consider in detail the content of the different levels in the framework for investigating the ripple effect on the SC with the help of simulation research methodology.

3.1.1. Structural dynamics level
Randomness in disruptions. The first stage is to decide how to model the disruptions. Realistic estimations are important here in regard to frequency and duration of disruptions. For example, survey [10] in 426 organizations found that 74% of firms had experienced more than one SC disruption, with 6–20 disruptions per year for 15% of companies.

One possible option is to work with homogenous or heterogeneous probabilities of disruptions at different SC elements. The second option is to perform a preliminary analysis and to derive the most critical elements in the SC in regard to the ripple effect impact on the SC performance. For these critical elements random or scheduled disruption events can be modelled with a probability distribution in regard to their duration.

Randomness in recovery. The ripple effect impact on the SC performance depends both on the severity of disruptions and the speed and scale of recovery actions. Recovery can be modelled in two basic ways. The simplest way is to schedule different periods of the capacity restorations and assign some recovery costs whereas the quickest recovery may imply the highest recovery cost. The second way is to programme individual recovery policies and to define the rules of recovery policy activation in dependence on the occurrence time, expected duration, and the severity of the disruption in regard to both local disturbances and the ripple effect propagation and impact on the SC performance.

3.1.2. Operational parameter dynamics level

Inventory, supply, production and transportation dynamics belong to major SC processes which are influenced by disruptions and recoveries and which, in turn, influence SC behaviour and ripple effect severity. At this stage, inventory control policies, back-ordering rules, production batching and scheduling algorithms as well as shipment rules and policies need to be defined and balanced with each other for both normal and disrupted modes. Some preliminary analysis may be helpful in this area in regard to safety stocks, reorder points, etc.

3.1.3. Performance impact dynamics level
The direct impact of the ripple effect is reflected in the changes of key performance indicators (KPI). Revenue, sales, service level, fill rate and costs are typically considered in this setting. A number of issues need to be addressed in this area. First is to decide either planned performance needs to be fully recovered or changes to KPI targets are acceptable. Next is to decide whether the planned KPI targets need to be recovered as soon as possible or at the end of the planning horizon. Final step is to decide how to aggregate the individual performance impacts of the ripple effect at different nodes and arcs in the network.

3.2 Modelling approach

Consider an example of simulating the ripple effect in software. Software anyLogistix (2016) has been used and exhibits the following data structure (Figure 4).

Figure 4. Simulation model data structure (based on Popkov 2015)

AnyLogistix is a multi-method software with a focus on SC optimization, network design and simulation analysis. It empowers the user with the tools for modelling complex SCs with a greater level of detail and its comprehensive optimization. With anyLogistix, it becomes possible to model SC behaviour in dynamics and observe how changes in design, ordering and transportation policies affect it.
The simulation environment (Figure 4) exhibits the following characteristics. It is a discrete-event simulation model of which each structural model object is an agent in AnyLogic simulation software. In block ‘demand’, customers are created and demand forecasts are set up based on either historical data or periodic demand. In the block ‘Ordering’, sourcing policies from distribution centres (DCs) to customers (e.g. single or multiple sourcing) and inventory control policies (e.g. $s,S$ or $r,q$) at DCs are set up and matched logically with demand forecasts. Similarly, in block ‘production’, sourcing policies from factories to DCs and inventory policies at factories are set up and matched logically with production policy with the possibility of using a BOM (bill of materials). In block ‘transportation’, vehicle types and path data are set up. Path data define parameters for shipments in the SC. By decreasing capacities at different points in time and for different durations, performance impacts are observed for different scenarios.

Structural dynamics in the SC is modelled using events of which appearance and duration may be random, scheduled or triggered by other events. Operational parameter dynamics is the key advantage of using simulation for the ripple effect analysis since real complexities can be considered and analysed. A KPI dashboard can be customized on the basis of more than 200 KPI that cover the large range of monetary (e.g. revenue and costs), time (e.g. lead time), quantity-based (e.g. delayed orders) or ratio (e.g. service level or on-time delivery) KPI.

4. Experiments

4.1 Problem statement

We consider a four-stage SC that comprises a manufacturer in Austria, a central distribution centre (CDC) in France, two regional distribution centres (RDC) in the Czech Republic and in Germany, and ten customers in different European cities (Figure 5).
A single sourcing strategy is used for deliveries from DCs to customers. The SC design structure is shown in Figure 6.

The developed simulation model is designed to be as simple as possible in order to derive insights for a broad audience. This model is used for depicting ‘typical’ simulation features in SC disruption analysis. We include the following parameters in the problem statement:

- A one-year period is considered.
- All DCs use (s,S)-inventory control policy.
- LTL (less-than-truckload) shipments are allowed.
- Transportation costs are computed subject to product weight and shipment distance (real routes are used subject to average truck speeds).
• Inbound and outbound processing costs are known.
• Fixed facility and inventory holding costs are known.
• Production costs and end product price are known.
• Production time for each product unit is fixed.
• Periodic demand data is used.

The problem consists of the ripple effect analysis in the SC. In particular, we are interested to analyse how disruptions in the upstream SC influence the plans, processes and performance of the downstream SC elements. Second, the objective is to quantify the impact of different capacity disruptions at CDCs and RDCs on overall financial, customer and operational performance in the SC and analyse the disruption propagation that causes performance impact. The following KPI are included in the analysis. For financial SC performance, total sales (i.e. revenue at the CDC and RDCs) and total costs (i.e. the sum of production, transportation and inventory costs) will be analysed. For customer performance, we consider β-service level (i.e. percentage of total sales in regard to maximum possible sales, i.e. to customer demand during the lead time) and total sales (i.e. delivered products to customers). On the operational performance side, transportation costs (i.e. shipment costs from factory to CDC, from CDC to RDCs, and from RDCs to customers) and inventory holding costs will be computed

4.2. Input data

The example in this section is based on our work with a distribution network. For all experiments, the following data were used:

• A one-year period is considered.
• All DCs use (s=40,S=200)-inventory control policy (note: these parameters are not optimal and are used as they have been seen in the practical example).
• Demand and lead time are subject to triangular distribution.
• LTL shipments are allowed.
- Transportation costs are computed as 0.01 x weight x distance (real routes are used subject to average truck speed of 70 km/h).
- Inbound and outbound processing costs at DCs are $2 each per product unit.
- Fixed facility costs are $2 per day.
- Inventory holding costs are $0.1 per day per unit.
- Production costs are $30 per unit and price is $100 per unit.
- Production time is fixed at 0.1 day per unit.
- The following demand data has been used for the experiments (Table 1).

Table 1 Demand data

<table>
<thead>
<tr>
<th>Customer</th>
<th>Triangular lead-time distribution</th>
<th>Triangular demand distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Min</td>
</tr>
<tr>
<td>Spain</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Germany 2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Poland</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>UK</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Germany 1</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Italy 2</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Denmark</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>France</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Italy 1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Austria</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

The experimental part comprises consideration of the following disruption and reconfiguration scenarios (Table 2)

Table 2 Disruptions and reconfiguration scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Disruption</th>
<th>Recovery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>Full disruption of CDC on 1 March and 50% capacity disruption at RDC 1 on 1 August</td>
<td>50% CDC capacity recovery on 1 April and full CDC capacity recovery on 31 May</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>Full disruption of CDC on 1 May</td>
<td>Full CDC capacity recovery on 1 July</td>
</tr>
</tbody>
</table>
Note that the scenarios in Table 2 are consciously selected without a high randomness degree in order to make the results and their analyses more depictive. For testing, 500 replications with a duration of 12,000 periods (weeks) with a warming up time of 50 periods have been applied for a wide range of randomness in disruptions and recovery actions.

For sensitivity analysis, optimization experiments have been performed, the results of which have been used for testing system behaviour in a number of scenarios. In some cases, embedded an anyLogistix optimizer has been used to find optimal parameter values.

For verification, the following methods have been used: simulation run monitoring, output data analysis in the log files, and testing with the help of deterministic data.

4.3 Sensitivity analysis

First, we test the sensitivity of the model to S-parameter of the inventory control policy that depends on DC capacities. We perform experiments for cases without disruptions for three data sets: S=200 for all DCs, S=100 for all DCs, and S=200 for CDC and S=100 for RDCs. Financial and customer performance impacts are shown in Figures 7 and 8.

![Comparison Diagram](image)

Figure 7. Financial performance impact in sensitivity analysis
It can be observed from Figures 7 and 8 that changes in DC capacities directly influence both financial and customer performance.

4.4 Simulation results

The experiments were performed subject to a no-disruption case and two disruption scenarios (cf. Table 2). The financial and customer performance impact analysis is shown in Figures 9–14.

Figure 9 Financial performance impact comparison in regard to scenario 1

It can be observed from Figure 9 that disruption at the CDC (100% in March and 50% in April) significantly impacts total sales ($3,135,000 in the no-disruption scenario and $2,650,000 in disruption scenario 1), revenue at DCs ($3,300,000 against $2,795,000 in disruption scenario 1), and profit ($1,539,320 against $1,125,760 in disruption scenario 1). Figure 10 depicts inventory dynamics for the disruption period from March to April.
Figure 10 Inventory dynamics in the disruption period

The ripple effect can be observed from Figure 10. Disruption in the CDC results in delivery interruption to RDC 1 and RDC 2 (we can observe shrinking inventory quantities in Figure 10 at both RDCs and no new replenishments). Therefore disruption propagation from CDC to customers can be observed. At the same time, the disruption at RDC 1 in summer does not affect SC financial performance (cf. Figure 9). No ripple effect is caused by this disruption since deliveries to customers can be continued as planned. This can indicate that the capacity of RDC 1 is excessive and can be reduced without influencing overall SC performance.

Insight 1: Ripple effect enhances the performance impact of disruptions. Upstream disruptions are more likely to result in the ripple effect in the case of single source policy. A
safety stock increase can be recommended at the facilities downstream of the disruption-risky SC elements. Higher inventory levels in downstream SC dampen the ripple effect propagation towards the customers. At the same time, safety stock increase at disruption-risky facilities should be considered carefully since if these facilities are not able to perform outbound operations (e.g. fire or strike) the increased safety stock is not useful for dampening the ripple effect.

Figure 11 Financial performance impact comparison in regard to scenarios 1 and scenario 2
Figure 11 extends the analysis from Figure 9 and includes financial performance impact in regard to both scenario 1 and scenario 2. It can be observed from Figure 11 that disruptions in scenario 1 have higher performance impact than disruptions in scenario 2. Figure 11 presents changes in financial performance KPI that can be expected in the case of considered disruption scenarios.

Figure 12 Customer performance impact comparison in regard to scenarios 1 and 2
In Figure 12, customer performance impact on the example of service level comparison in regard to no-disruption scenario (#1), scenario 1 (#2) and scenario 2 (#3) is presented. Fig-
Figure 10 illustrates that service level decreases in comparison with a no-disruption scenario (81.9%) to 69.2% in scenario 1 and 76.2% in scenario 2.

Figure 13 Financial performance impact analysis for March

Insight 2: The ripple effect has higher impact on service level and order fulfilment than disruption duration. This implies that dual sourcing at SC bottlenecks and large inventory holding points downstream of disruption-risky facilities is more important than hasty investments in quick recovery.

While Figures 9‒13 depict annual performance impact, let us consider in more detail the periods when disruptions happened. Figure 13 presents financial performance impact analysis for March when CDC was supposed to be disrupted 100%. It can be observed from Figure 13 that total sales, revenue, and profit significantly decrease. The only positive effect is that the total costs also decrease since the CDC is out of operation.

Figure 14 Recovery impact on monthly performance in April

In Figure 14, we compare the performance impact for March–April in regard to recovery actions. In particular, we are interested in revealing the performance impact of recovery strategies. It can
be observed from Figure 14 that KPI increase as compared to the no-recovery case: total sales increase from $275,000 to $345,000 ($830,000 in the no-disruption scenario), total revenue increases from $405,000 to $475,000 ($995,000 in the no-disruption scenario), and total profit increases from $353,784 to $416,739 ($782,576 in the no-disruption scenario). Having an estimation of recovery costs, a decision maker can simulate different recovery options and analyse both the recovery costs and performance impact with and without recovery.

**Insight 3:** Speed of recovery needs to be balanced with recovery costs and performance impact of recovery. Speed of gradual capacity recovery depends on the severity of the disruption-driven performance decrease and ripple effect intensity.

### 5. Managerial insights and future research avenues on simulation application to ripple effect modelling and decision-making support in supply chain disruption management

#### 5.1. Managerial insights

It can be observed from the literature review and experiments that optimization and simulation studies on SC dynamics and disruptions differ from each other regarding problem statements, complexities and analysis objectives (Figure 15).

<table>
<thead>
<tr>
<th>Optimization</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC structure with back-ups</td>
<td>Randomness in disruption and recovery policies</td>
</tr>
<tr>
<td>Discrete number of periods</td>
<td>Real-time analysis</td>
</tr>
<tr>
<td>Demand (distribution) in periods</td>
<td>Real problem complexity</td>
</tr>
<tr>
<td>Production capacities in periods</td>
<td>Inventory control policies</td>
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<tr>
<td>Beginning and ending inventory in periods</td>
<td>Dynamic recovery policies</td>
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<tr>
<td>Production quantities in periods</td>
<td>Gradual capacity degradation and recovery</td>
</tr>
<tr>
<td>Sourcing quantities in periods</td>
<td>Impact of changes in sourcing, transportation and production policies on the ripple effect and operational parameter dynamics in time</td>
</tr>
<tr>
<td>Shipment quantities in periods</td>
<td>Multiple performance impact dimensions including financial, service level, and operational performance in time</td>
</tr>
<tr>
<td>Backorder quantities in periods</td>
<td></td>
</tr>
<tr>
<td>Production, shipment, setup, holding, delay, lost sales, fixed, processing, ordering, backordering costs</td>
<td></td>
</tr>
<tr>
<td>Disruption duration, in periods</td>
<td></td>
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<tr>
<td>Recovery duration, in periods</td>
<td></td>
</tr>
<tr>
<td>Individual impact on service level, costs, lost sales at the end of planning horizon</td>
<td></td>
</tr>
</tbody>
</table>

Multiple performance impact dimensions including financial, service level, and operational performance in time
Optimization studies empower decision makers to determine the performance impact and resilient SC redesign policies within rigorous analytical solutions. These studies consider a large variety of parameters, variables and objectives. However, in many cases simulation can enlarge the scope of a ripple effect investigation.

In optimization studies, performance impact analysis has been typically performed in regard to disrupted elements assuming that other elements are not affected by that disruption and continue operation in the planned mode (apart from a few studies, e.g. Losada et al. 2012; Liberatore et al. 2012; Lee et al. 2014; Ivanov et al. 2016a). Optimization studies typically reduce real complexity in order to obtain feasible solutions in a reasonable time. By nature, randomness and time-related aspects of disruptions and recovery actions are difficult to represent within closed forms of mathematical equations.

State-of-the-art simulation research reveals correlations between proactive strategies (backup vendors, inventory levels and control policies, and capacity buffers and flexibility), performance impact, disruption duration, disruption location, disruption propagation and recovery dynamics. Some of the important findings in optimization and simulation studies on the ripple effect are summarized in Figure 16, based on studies by Carvalho et al. (2012); Schmitt and Singh (2012); Bueno-Salano et al. (2014); Ivanov et al. (2014, 2016a); Xu et al. (2014); Hishamuddin et al. (2015) and in the experiment with the simulation model in Section 4 of this paper.
Figure 16. State-of-the-art insights on the ripple effect in the supply chain

First, simulation literature provides evidence that disruption duration and propagation impact SC performance. Second, proactive strategies such as backup facilities and inventory have positive impacts in regard to both performance and prevention of disruption propagation.
Third, speed of recovery plays an important role in mitigating the performance impact of disruptions. Fourth, SC resilience increase implies significant cost increases in the SC.

However, even in simulation studies disruption duration has been typically modelled without explicit integration with dynamic recovery time and costs. The performance analysis of the use of supplier failure probabilities dominates the research domain. At the same time, another important question of disruption propagation and SC design survivability with regard to both service level and costs is still at the early stage of investigations. The role of recovery policies needs to be analysed in more detail.

The expected managerial results of the ripple effect analysis in the SC are to provide new insights in regard to the following questions:

- When does one failure trigger an adjacent set of failures?
- Which SC structures are particularly sensitive to the ripple/domino effect?
- What are the typical ripple effect scenarios and what is the most efficient way to react in each of these scenarios?

In light of the reflections considered, some directions for simulation application to the ripple effect modelling in the SC can be derived. The possibility of changing parameters dynamically during the experiment and of observing the performance impact of these changes in real time allows the closing of some research gaps, e.g.:

- considering disruption propagation in the SC
- considering dynamic recovery policies
- considering gradual capacity degradation and recovery
- considering multiple performance impact dimensions including financial, service level and operational performance.

Simulation analysis is therefore of vital importance for SC operations planners and dispatchers at tactical and operative decision-making levels while optimization methods provide rigorous decision-making support for SC executives at the strategic level. By making changes to
the simulated SC, one expects to gain understanding of the dynamics of the physical SC. Simulation is an ideal tool for further analysing the performance of a proposed SC design derived from an optimization model. Simulation-based optimization can be considered in this regard as a technique that can integrate decision making at strategic and tactical–operative levels.

5.2 Future research avenues

5.2.1 General use of simulation for ripple effect modelling in the SC

The ripple effect is a phenomenon of disruption propagations in the SC and their impact on SC performance (e.g. sales, on-time delivery, total profit). With the help of optimization and simulation approaches, the current research generates new knowledge for the influence of disruption propagation on output SC performance considering disruption location, duration, propagation and recovery policies.

It is natural to use simulation to further study disruption propagations and the ripple effect on the SC. Existing studies considered time and length of disruptions and recovery policies. In future, sensitivity analysis of output SC performance in regard to both parametrical and structural resilience levers (i.e. different capacity levels, inventory control policies, dual sourcing and backup facilities) need to be performed. Such analysis can allow revealing and substantiating major proactive and reactive decision-making support processes and models in regard to disruption severity, recovery policies, and resilience levers in light of their singular and combinatorial performance impacts with consideration of disruption propagation in the SC. The expected results of this research are to provide new insights on how to estimate the impact of possible disruptions on performance in the proactive stage, to estimate the impact of real disruptions on performance at the execution stage, and to generate efficient and effective stabilization and recovery measures.

5.2.2 Disruptions and perishable products

In literature, inventory is typically considered as an SC resilience driver. In perishable product SCs, inventory management exhibits some specific properties due to limited storage length
and short expiration periods. The major distinguishing features in an SC with perishable products that may affect resilience are the risks of goods write-off and customer segmentation according to product freshness requirements. Constraints on product perishability typically result in safety stock reductions and transportation frequency increase. On the contrary, consideration of the production capacity disruption risks may lead to safety stock increase. Limited capacities of suppliers can be included in the analysis. On the customer side with typically vulnerable demand, different requirements on product freshness and penalties for product unavailability or freshness decrease can be encountered. In addition, batching issues play an important role in perishable product SCs. In this setting, a broad research avenue can be seen.

5.2.3 Agent-based simulation: collaboration resilience drivers

While discrete event and optimization-based simulation have their focus rather on SC re-engineering resilience principles such as redundancy and flexibility, agent-based modelling can be applied to a broader scope of SC resilience principles. These principles may include collaboration (trust and information sharing) and an SC risk management culture (e.g. leadership and risk-averse behaviour). In this setting, agent-based modelling can be seen as a suitable method to enhance the existing simulation impact on SC ripple effect research in regard to non-engineering SC resilience principles.

5.2.4 Ripple effect visualization

This is quite an obvious simulation feature for visualizing the processes, one which surprisingly has not been extensively used in literature for modelling the ripple effect in the SC. In this setting, simulation models can enhance existing tools on SC agility and visibility in regard to disruption velocity.

5.2.5 Interdisciplinary contributions

Finally, the ripple effect can be encountered not only in SCs. Therefore, specific analysis can be conducted in regard to state-of-the-art in financial management where the ripple effect has been extensively developed over the last decades. Special attention can also be paid to the
works on the so-called domino effect in the processing industry. According to Khakzad (2015), the domino effect is a ‘low frequency high consequence chain of accidents, where a primary accident […] spreads to adjacent units, causing secondary accidents the total consequences of which could be much severer than that of the primary accident’. As such, the domino effect seems to be quite similar to the ripple effect in the SC, so that the engineering contributions on the domino effect are worth studying in detail.

6. Conclusion

Simulation modelling methods allow us to consider details and specific traits of the SC elements. This allows not only for visualizing network operations but also for tracing every process inside. In addition, using simulation allows us to observe the impact of different disruptions and recovery policies in time and consider gradual capacity degradation and recovery. This study focused on low-frequency/high-impact disruptions in the four-stage SC in light of the ripple effect. The ripple effect in the SC results from disruption propagation from the initial disruption point into the supply, production and distribution networks. The objective of the study was to reveal research gaps that can be closed with the help of simulation modelling. First, recent literature on the simulation modelling of the ripple effect was analysed. Second, a simulation model for multistage SC design with consideration of capacity disruptions and experimental results were presented.

With the help of simulation approaches, the research can generate new knowledge on the influence of disruption propagation on output SC performance considering disruption duration and recovery policies. Sensitivity analysis of output SC performance in regard to both parametrical and structural resilience levers (i.e. different capacity levels, inventory control policies, dual sourcing and backup facilities) allows for revealing and substantiating major proactive and reactive decision-making support processes and models in regard to disruption severity, recovery policies, and resilience levers in light of their singular and combinatorial performance impacts with consideration of disruption propagation in the SC.
Further, observations from the literature review acknowledge the conclusion that while optimization modelling dominated the research field of SC disruption management, the potential of simulation modelling still remains under-explored. This potential lies in the dynamic analysis of both proactive strategies and recovery contingency plans.

In light of these reflections, some directions for simulation application to ripple effect modelling in the SC can be derived. First, the possibility of changing parameters dynamically during the experiment and observing the performance impact of these changes in real time has to be acknowledged. Second, simulation models allow consideration of disruption propagation in the SC (e.g. by analysing inventory dynamics), considering dynamic recovery policies and utilizing gradual capacity degradation and recovery in time.

In an example of a four-stage SC simulation model implemented in anyLogistix multi-method simulation software, we developed a case study on ripple effect analysis in the SC using simulation. Three scenarios (a no-disruption scenario and two disruption scenarios) have been modelled and evaluated in regard to SC financial, customer and operational performance. The experimental results can be used by SC managers to analyse the performance impact of different disruptions, disruption propagation in the SC (i.e. the ripple effect), and recovery policies in regard to their dynamics, duration, performance impact and costs.

Future research on simulation-based ripple effect modelling is multifaceted. The model presented may include extensions in both the conceptual aspect and on the technical side. In the conceptual, more detailed scenarios and KPI schemes can be explored. On the technical side, the model presented can be extended in regard to both parameter structure and customization of sourcing and inventory policies in AnyLogic.

In general, future research directions on the simulation application to ripple effect modelling in the SC can imply disruption analysis for SCs with deteriorating products, agent-based simulation of non-engineering drivers of SC resilience, ripple effect visualization, and usage of methodical tools for domino effect analysis.
7. Literature


