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▶ **To cite this version:**

Dmitry Ivanov, Alexander Pavlov, Alexandre Dolgui, Dmitry Pavlov, Boris Sokolov. Disruption-driven supply chain (re)-planning and performance impact assessment with consideration of pro-active and recovery policies. Transportation Research Part E: Logistics and Transportation Review, 2016, Risk Management of Logistics Systems, 90, pp.7-24. 10.1016/j.tre.2015.12.007 . hal-01313260

HAL Id: hal-01313260
https://hal.science/hal-01313260

Submitted on 13 Jan 2017

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Transportation Research Part E: Logistics and Transportation Review

Volume 90, June 2016, Pages 7–24

Disruption-driven supply chain (re)-planning and performance impact assessment with consideration of pro-active and recovery policies

Dmitry Ivanov[1*], Alexander Pavlov[2], Alexandre Dolgui[3], Dmitry Pavlov[2] and Boris Sokolov[2]

[1]* Corresponding author
Prof. Dr. habil Dmitry Ivanov
Chair of International Supply Chain Management
Berlin School of Economics and Law
10825 Berlin
Germany
E-Mail: divanov@hwr-berlin.de
Tel.: +49 (0)30 308771155

[2] SPIIRAS, Saint Petersburg Institute of Automation and Informatics, Russian Academy of Sciences, Russia

[3] Ecole des Mines de Nantes, IRCCYN, UMR CNRS 6597, Nantes, France

Abstract. Supply chain planning models under disruptions are extensively studied in literature. In this paper, we consider a multi-stage supply chain (re)planning problem. We propose a new approach with an explicit connection of performance impact assessment and supply chain plan reconfiguration issues with consideration of the duration of disruptions and the costs of recovery. This approach is based on a hybrid model containing elements of system dynamics and linear programming. The supply chain structure dynamics and recovery is considered in the dynamic model while a linear programming model is used for flow balance. We transit from the classical linear programming model to maximal flow problem by excluding demand constraints. The results have several major implications. First, a method to compare different actions for supply chain resilience regarding the performance impact is suggested. Second, since the commodity flows are described in continuous time, the disruption recovery time can be described more easily. Third, service level and sales volumes can be included as resilience indicators into the performance analysis consideration. Subsequently, through numerical computations, we obtain additional managerial insights. As extensions, we study the impact of different changes in supply chain design and plans on supply chain performances. Based on these results, diverse execution scenarios can be considered and suggestions on re-planning in the case of disruptions regarding the trade-off "efficiency vs. resilience" can be developed.

Keywords: multi-stage supply chain, supply chain dynamics, supply chain planning, disruptions, recovery, structure dynamics, ripple effect, linear programming, service level, maximal flow, multi-period models.

Introduction

Supply chain (SC) planning is a referenced research problem to successfully meet customer needs while improving operations performance efficiency. SC planning (SCP) decides on directing commodity flows in the SC to efficiently balance supply and demand at the aggregate level in the medium-term planning horizon subject to a given facility location structure, capacities, customer demand, and order quantities ((Tayur et al. 1999, Amiri 2006, Hinojosa et al. 2008, Manzini and Bindi 2009, Mula et al. 2010, Dolgui and Proth, 2010, Chopra and Meindl 2012, Constantino et al. 2012).

In SCP, it is mandatory to take into account uncertainty and risks in order to provide practically relevant problem statements and decision-oriented solutions of computational models (Wu et al. 2015). Knemeyer et al. (2009), Simchi-Levi et al. (2014), Ambulkar et al. (2015) and Eckstein et al. (2015) underline crucial role of disruption events and recovery policies in the SC planning. Recent literature suggests considering *recurrent* or *operational* risks and *disruptive* risks (Chopra et al. 2007).

In 2000-14, SC disruptions (e.g., because of both natural and man-made disasters, such as on 11 March 2011 in Japan, floods in Thailand in 2011, fire in the Phillips Semiconductor plant in New Mexico, etc.) occurred in greater frequency and intensity, and thus with greater consequences (Chopra and Sodhi 2014, Simchi-Levi et al. 2014). Such *disruptive risks* represent a new challenge for SC managers who face the *ripple effect* (Ivanov et al. 2014a) subject to *structural disruptions* in the SC. The ripple effect describes the impact of a disruption on SC performance and the disruption-based scope of changes in the SC structures.

Recent studies extensively considered SCP or SCP within the SC design (SCD) decisions taking into account disruption risks (e.g., Dolgui and Louly, 2002, Xia et al. 2004, Snyder and Daskin 2005, Xiao and Yu 2006, Dolgui and Prodhon, 2007, Wilson 2007, Chauhan et al. 2009, Cui et al. 2010, Klibi et al. 2010, Chen et al. 2011, Peng et al. 2011, Kouvelis and Li 2012, Schmitt and Singh 2012, Baghalian et al. 2013, Li et al. 2013, Lim et al. 2013, Ivanov et al. 2013, 2014, Dolgui et al. 2013, Sawik 2013, Paul et al. 2014, Aloulou et al. 2014).

The scope of the disruption rippling and its performance impact depends both on robustness reserves (e.g., redundancies like inventory or capacity buffers) and speed and scale of recovery actions (Hendricks and Singhal, 2005; Sheffi and Rice 2005, Tomlin 2006, Das 2011, Bode et al. 2011, Ivanov and Sokolov 2013, Kim and Tomlin, 2013). The existing studies considered both disruptions without recovery actions and disruptions *with* recovery actions. We focus this study on the second group. The recovery options comprise facility fortification (e.g., back-up suppliers, warehouses, depots and transportation channels), inventory and capacity expansion. Contingency plans or backup planning (e.g., alternative suppliers or shipping routes) need to be developed (Knemeyer et al. 2009, Cui et al. 2010, Yang et al. 2012, Benyoucef et al. 2013, Li et al. 2013). The recovery must happen quickly to expedite stabilization and adaptation in order to ensure SC continuity and avoid long-term impact. In implementing such recovery policies, companies need a tool supported by collaboration and SC visibility solutions for assessing the impact of disruption on the SC as well as the effects from redirecting material flows (Sheffi and Rice 2005, Simchi-Levi et al. 2014, Chopra and Sodhi 2014, Gedik et al. 2015).

For example, Toyota extends its SC subject to multiple-sourcing and building new facilities on the supply side. Amazon prefers holding fast-moving items in distribution centres while slow-moving items tend to be stored centrally. Apple localized production in China but the distribu-

tion network is global. Such SC segmentation also helps to reduce disruption risk implications (Chopra and Sodhi, 2014). Samsung tends to have at least two suppliers even if the second one provides only 20% of the volume (Sodhi and Lee 2007). Online fashion retailer ASOS was badly affected by a fire in the UK warehouse in 2005 when operations were almost stopped for one month. They developed a contingency policy for such disruptions. Among others, an additional warehouse was established in Asia. This helped the company to recover within two days in June 2014 when new fire occurred in the UK warehouse.

Despite a wealth of literature on SCP with disruption considerations, most of the existing studies consider the recovery policies under the assumption that the disrupted facilities or transportation channels do not return into the SC operation during the planning horizon. There are only a few studies that incorporate SC plan reconfiguration into the performance impact assessment. To the best of our knowledge there is no published research that considers only temporary absence of some SC elements taking into account the duration of disruptions with the capacity recovery and the costs of this recovery.

In putting these aspects into a research focus, the objective of this research is to incorporate disruptions duration and capacity recovery into SCP decisions and performance impact assessment. The proposed method has been developed in a practical way with the aim to optimize the SCP and to develop a model for a multi-stage SC with structure dynamics considerations.

The remainder of this paper is organized as follows. Section 2 analyses recent literature. Section 3 considers a case-study and proposed methodology. In Section 4, the mathematical model is presented. Section 5 is devoted to the experimental calculation of optimal SC plans. In Section 6, different actions for increasing the SC resilience are analysed. Managerial insights are presented in Section 7. The paper concludes by summarizing the most important findings and outlining future research needs.

2. Literature review

Different approaches to protect and control SCs in regard to disruptions and to coping with uncertainty have been developed in recent years (Dolgui and Louly 2002, Santoso et al. 2005, Dotoli et al. 2006, Chopra et al. 2007, Schütz et al. 2009, Chauhan et al. 2009, Klibi et al. 2010, Georgiadis et al. 2011, Peng et al. 2011, Lim et al. 2010, Constantino et al. 2012, Baghalian et al. 2013). The surveys on specific aspects of these problems are presented in (Dolgui and Prodhon 2007, Dolgui et al. 2013, Alloulou et al. 2014).

In this Section, we analyse how the consideration of disruptions with recovery policies has been done in literature so far.

2.1 Mixed-integer programming

Mixed-integer programming (MIP) with application to reliable SCD and SCP has been a broad research avenue over the past ten years. The reliable location model was first introduced by Snyder and Daskin (2005). The UFL model aims at finding optimal SC design with assignments of customers to locations with the objective to minimize the sum of fixed and transportation costs in the SC. The relevant development of MIP models can be considered regarding the facility fortification. Lim et al. (2010) incorporated a totally reliable back-up supplier that can be used if a primary supplier is destroyed. The related costs are incorporated into the objective function but the fortification budget remains incapacitated. Li et al. (2013) extended this model by intro-

ducing limits on the fortification budget in a single-product case with eight distributors and up to 150 customers.

In addition, inventory considerations have been included. Chen et al. (2011) presented a joint inventory-location model under the risk of probabilistic facility disruptions. Benyoucef et al. (2013) considers SC design with unreliable suppliers. Rafiei et al. (2013) developed a comprehensive model for a problem statement with multiple products and many periods. They considered the levels of inventory, back-ordering, available machine capacity and labour levels for each source, transportation capacity at each transhipment node and available warehouse space at each destination. The problem also considered the facility fortification by taking into account the back-up supplier with reserved capacity and a back-up transhipment node that satisfied demands at higher prices without disruption facility. The solution to the model is based on a priority-based genetic algorithm.

Gedik et al. (2014) model disruptions and train re-routing actions in a coal supply chain network and assess impacts of disruptions in terms of transportation and delay costs using a two-stage mixed integer programming (MIP) model. An "interdictor" chooses a limited amount of elements to attack first on a given network, and then an "operator" dispatches trains through the residual network. The MIP model explicitly incorporates discrete unit flows of trains on the rail network with time-variant capacities. A K-th shortest path algorithm is used to enumerate all routes between points. The authors consider a real coal rail transportation network and generate scenarios to provide tactical and operational level vulnerability assessment analysis with incorporation of rerouting decisions, travel and delay costs analysis, and the frequency of interdictions of facilities for the dynamic rail system.

2.2. Stochastic programming

Stochastic programming models are often scenario-based where parameters are represented by a set of discrete scenarios with a given probability of occurrence. In standard stochastic programming models (Santoso et al. 2005, Goh et al. 2007), demand is considered as an uncertain parameter. In (Azaron et al. 2008), facility disruptions and capacity expansion costs are also considered to be uncertain. Sawik (2013) developed a stochastic programming model to integrated supplier selection, order quantity allocation and customer order scheduling in the presence of SC disruption risks.

In the study by Madadi et al. (2014), a problem of supply network design under risk of supply disruptions is considered. Tainted materials delivery disruptions are modeled as events which occur randomly and may have a random length. A mixed-integer stochastic model is proposed and solved by a meta-heuristic algorithm. Torabi et al. (2015) propose a bi-objective mixed two-stage stochastic programming model for supplier selection and order allocation problem under operational and disruption risks. The model considers several proactive strategies such as suppliers' business continuity plans, fortification of suppliers and contracting with backup suppliers. The computational results demonstrate the significant impact of considering disruptive events on the selected supply base.

2.3 Inventory management

Hishamuddin et al. (2013) presented a recovery model for a two-echelon serial SC with consideration of transportation disruption. Their model is capable to determine the optimal ordering

and production quantities during the recovery period to minimize total costs. Shao and Dong (2012) analyse an assemble-to-order system with a backup source to offer on-time delivery and compensation policy to compensate customers for waiting in each period during a disruption. The findings suggest that the backup sourcing strategy is preferred at the beginning of the supply disruption, while the compensation strategy is preferred as time elapses. Hu et al. (2013) analyse incentive mechanisms to motivate a supplier's investment in the capacity restoration. They consider the cases when the incentive is committed to *ex-ante* (prior to disruption) as well as when it is committed to *ex-post* (after disruption). The analysis indicates if the buyer offers incentives, both the buyer and supplier (weakly) prefer the ex-ante commitment over the ex-post one.

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 indicates for studied scenarios 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.

Gupta et al. (2015) study from game-theoretical perspective the implications of the contingent sourcing strategy under competition and in the presence of a possible supply disruption. The time of the occurrence of the supply disruption is uncertain and exogenous, but the procurement time of components is in the control of the firms. The results imply that supply disruption and procurement times jointly impact the firms' buying decisions, optimal order quantities and their expected profits. Subsequently, this study considers the impact endogenizing equilibrium sourcing strategies of asymmetric and symmetric firms, and of capacity reservation to mitigate disruption.

2.4 Simulation, system science and control theory

Schmitt and Singh (2012) presented a quantitative estimation of the disruption risk at production and supply capacities in a multi-echelon SC using discrete-event simulation. They also consider dual sourcing as a contingency action. The disruption risk is actioned by "weeks of recovery" as the amplification of the disruption. Carvalho et al. (2012) analysed impacts of transportation disruptions on lead-time and overall costs in an automotive SC using ARENA-based simulation.

Unnikrishnan and Figliozzi (2011) developed a scenario-based model with an adaptive routing policy. Vahdani et al. (2011) applied fuzzy program evaluation and review technique to calculate the completion time of SC operations in the case of a severe disruption. Xu et al. (2014) used AnyLogic software and modelled SC as an agent system to study the disruption at suppliers and recovery policies on the SC service level. Paul et al. (2014) analysed series of disruptions over time and presented an inventory control-based model to develop optimal recovery policies for real time disruption management for a two-stage batch production–inventory system with reliability considerations. They consider multiple disruptions and cases where new disruption may or may not affect the recovery plan of earlier disruptions.

Stochastic maximal flow models or minimal cost flow models (Lin 2001, Chou et al. 2011) and fuzzy models (Selim et al. 2008, Constantino et al. 2011) have also been applied. Chou et al. (2011) propose an algorithm for determining the system reliability with respect to the maximum flow of a network achieving a given demand. The nodes can fail randomly and the demand is assumed deterministic; no cost/profit functions are considered. In the study by Lin (2001), the goal is to determine the production quantity of a particular product for a given random demand.

The authors use a simplified supply chain that consists of plants and retailers and represent it as a deterministic bipartite graph. For solution, a heuristic scheme for determining the assignment policy is proposed. The resulting expander graphs are interesting due to the spectral properties, that is, they do not degrade by increasing the number of nodes.

Constantino et al. (2012) presented a hierarchical approach to the strategic supply chain design addressing supply planning and allowing the improvement of the manufacturing supply chain agility in terms of ability in reconfiguration to meet performance, and considering the supplier capacity constraints. The approach employs digraph modeling and integer LP to optimal supply chain design. The authors avoid stochastic models by aggregating deterministic product flows within the integer LP model.

Summarizing, the literature mainly considers three basic types of disruptive risks that should be considered by SC managers: production, supply and, transportation disruptions. Recent studies show that efficiency paradigms of lean processes, single sourcing, etc. have failed in disruption situations. Disruptions in a global SC, especially in its supply base, does immediately affect the entire SC. With the increased specialization and geographical concentration of manufacturing, disruptions in one or several nodes affect almost all the nodes and links in the SC (Kim and Tomlin 2013).

Recent literature discussed different recovery strategies:

- Back-up suppliers,
- Back-up depots and transportation channels/modes
- Inventory and capacity buffers
- Facility fortification
- Capacity expansion

Finally, recent empirical literature on SC disruptions that indicates significantly more efforts into pre-disruption stage as compared with recovery activities (Bode et al. 2011, Blackhurts et al. 2011). The rationale behind this situation may be that investments in protection are tangible and directly decrease net profits while recovery costs are anticipated.

Reaction to disruptive events can be performed depending on the severity of disruptions:

- Parametrical adaptation
- Structure adaptation

Parametrical adaptation represents the simplest case where stabilization and recovery are possible through tuning of some critical parameters like lead-time or inventory. Structure adaptation considers back-up supplier on contingency transportation plans.

Operations research along with system dynamics and control theory contain a number of useful methods that can be used for analysis and for mitigating the ripple effect. Different methods are suited to different problems. No single technique is likely to prove a panacea in this field. MIP formulations with facility fortification consider product shift to back-up suppliers if primary suppliers are disrupted. Simulation techniques consider “what-if” scenarios which can be used by SC managers in the case of disruption occurrence to quickly estimate the recovery policies and impacts on operational and financial performance.

Chopra and Sodhi (2014) and Simchi-Levi et al. (2014) point out that one has to concentrate mainly on mitigation strategies and identification of the impact of disruption on financial and operational performance regardless of what caused the disruption. In addition, a general short-

coming of existing studies, as pointed out by Cui et al. (2010) and Li et al. (2013) is that the dynamics of SC execution is not considered. The disruptions are mostly considered as static events, without taking into account their duration, stabilization/recovery policies. Other possibilities for modelling real flows are system dynamics (Villegas and Smith 2006) and control theory (Ivanov et al. 2012, Ivanov and Sokolov 2013).

While mathematical and stochastic optimization has its place at the SC design and planning stages without recovery considerations, they fail to throw much light on the dynamic behaviour of the SC. The impact of SC design and SCP on SC performance at the execution and recovery stage can be enhanced by using models based on the dynamics of the execution processes.

Summarizing, investment in SC protection can help to avoid many problems with disruptive events. However, it is impossible to avoid disruption completely. Simchi-Levi et al. (2014) underline that focus should be directed to the recovery policies regardless of what caused the disruption. Therefore, adaptation is needed to change SC plans, schedules or inventory policies in order to achieve the desired output performance (Eckstein et al. 2015).

The *contribution of this study* is a multi-objective problem formulation for SC reconfiguration model (trade-off "service level vs. costs") that includes performance impact assessment with SC re-planning in the case of structure dynamics (trade-off "efficiency vs. resilience") taking into account temporary unavailability of some SC elements and their recovery in time.

3. Problem statement and methodology

3.1 Problem statement

We investigate a multi-stage SC. Consider a referenced automotive SC design (SCD) structure subject to the study by Simchi-Levi et al. (2014) (Fig. 1).

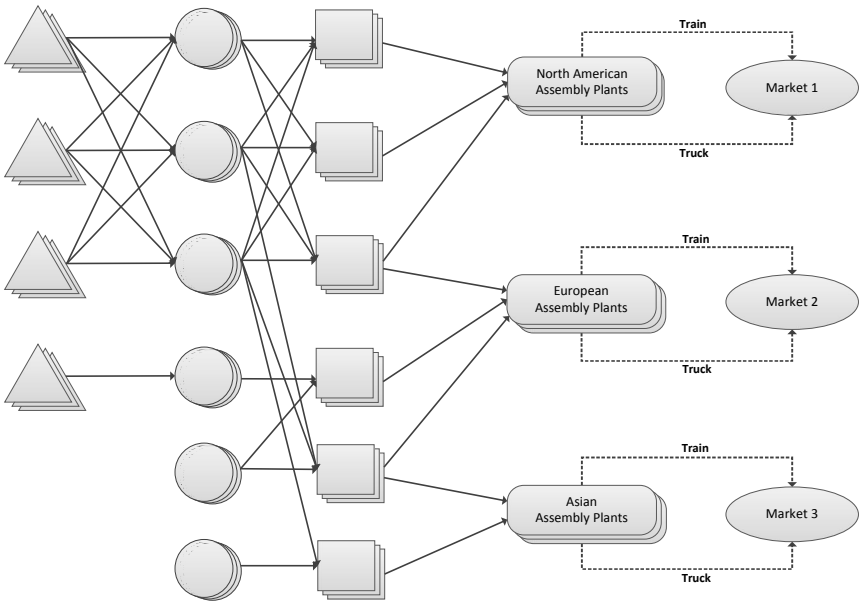


Fig. 1. SCD structure

The SC comprises Tier 3 suppliers (the triangles), Tier 2 suppliers (the circles), Tier 1 suppliers (the rectangles), assembly plants and markets. We assume that the SC displays the following characteristics: (i) SC performance depends on its ability to execute despite of perturbations; (ii) some SC elements may become unavailable due to disruptions, (iii) some SC elements recover in time and (iv) the SC experiences performance degradation if some of its elements fail.

The problem statement captures the following elements:

- Multi-stage, multi-product, multi-period SCP
- Network structure is dynamic, nodes and arc may become unavailable for different duration
- Bill-of-materials (BOM) and different processing intensities
- Reconfiguration of material flows in the case of a disruption and computation of the performance impact of the disruption taking into account optimal reconfiguration and recovery costs
- Upstream supply control in the case of disruption subject to the total SC costs minimization
- Different pro-active actions: structural and parametrical
- Sales volumes and service level as resilience indicators
- Sourcing, transportation, processing, return, fixed, inventory, and recovery costs are used for efficiency assessment and are assumed to be linear functions from the quantities.
- Multiple objective views: logistics (costs minimization), customer (service level), system (supply chain design and disruptions)
- Time duration of a disruption modelled as continuous time function in dynamic model
- Impact of disruptions on the economic performance which is simulated using a hybrid static-dynamic optimization model
- The transportation, processing, and inventory volumes are constrained by maximal capacities.
- The demands in markets may change in each period
- Inventory from previous periods may be used in the following periods
- If the processing and warehouse capacity is exceeded by the delivered quantity, unprocessed and non-stored goods are sent back subject to additional return costs (i.e., penalties)

The objective is to find the aggregate product flows to be moved from suppliers through the intermediate stages to the markets subject to maximizing the service level and minimizing the total cost under (i) constrained capacities and processing rates and (ii) SC structure dynamics for a multi-period case. It is to compute the performance impact of disruptions with consideration of the material flow reconfiguration taking into account disruption and recovery time and costs.

3.2 Methodology

The research comprises three stages:

- To develop a mathematical model
- To use this model for computing the SC plan and economic performance at the existing SC subject to disruption and recovery of SC elements
- To investigate the impact of different resilience actions on SC performance and distribution (re)planning

The preliminary analysis of the multi-stage SCP problem with uncertainty in structure dynamics has shown that it could be modelled as a stochastic maximal flow model, i.e., as maximal flow models or minimal cost flow models. However, in some aspects these methods are rather restrictive. First, existing studies have not explicitly considered possible *structure dynamics* and its impact on the flows and cost. Second, deviations or failures in the network structures and opera-

tions are *possible*, but not unrealistic or describable with some probabilistic assumptions. In addition, the SC structural states do not change permanently, but rather at some intervals. Therefore, *intervals of structural constancy* can be considered.

Another possible way to model the considered problem could be the LP/MIP-based implementation. However, structural changes in the SC and recovery in different periods do not allow direct application of LP/MIP models if disruption duration and recovery needs to be included into the analysis.

We propose to apply a hybrid approach and distribute static and dynamic parameters between a LP and a dynamic model. The dynamic model is necessary in order to describe the structure dynamics. The dynamic model contains piecewise functions in the right parts of differential equations in order to describe the facility unavailability time and recovery period in the SC can also be used to add the property of partial availability and gradual recovery of capacities. This can also be done with the help of piece-wise functions which will describe the capacities in the SC. Since the commodity flows will be described in continuous time in the dynamic model, the disruption recovery time can be described more accurately with the help of a piece-wise function that allows considering disruption durations and gradual capacity recovery. The LP model is used for solving transhipment problem within intervals of structural constancy since modelling the material flow balance in the dynamic model is not efficient. Assumed that the network elements does not change their capacities within some subintervals (structure constancy intervals), for these intervals, a multi-objective LP model with transit nodes and two side constraints is formulated. Exclusion of demand constraint allows transit from the classical LP to maximal flow problem, formulated as an LP model. The graph of structural reliability (Ivanov et al. 2014) can be used to model optimistic and pessimistic scenarios. These scenarios are used for computational experiments with the developed model.

In line with the existing research on reliable SC design, we investigate also different resilience actions such as back-up suppliers and capacity reservation regarding their impact on economic performance under disruptions.

4. Mathematical model

The model described in this Section is a generalized form of the previously developed models in (Ivanov et al. 2013, 2014). The differences to those models are as follows:

- BOM constraints are included in Eqs (3), (4), (13) and (14)
- Production processing intensities are included in the model at different stages
- Capacity degradation/recovery dynamics is described in Eqs (3) and (4)
- Recovery costs is included into the objective function (12)

4.1 Set-theoretical formulation

Let's introduce some notations and definitions:

$X_\chi(t) = \{A_{xi}(t), i \in N_\chi\}$ is the set of nodes in the SC

$E_\chi(t) = \{e_{xij}(t),\ i, j \in N_\chi\}$ is the set of arcs in the SC

$W_\chi(t) = \{w_{\chi ij}(t),\ i, j \in N_\chi\}$ is the set of operational characteristics for the transportation (if $i \neq j$) or processing at warehouse (if $i = j$)

$N^+_{\chi ik}$ is the set of node numbers for the nodes transmitting products to $A_{\chi i}$ at time interval k

$N^{-}_{\chi ik}$ is the set of node numbers for the nodes receiving products from $A_{\chi i}$ at time interval k

$\Delta_{\chi\beta} = \{\delta_{\chi}\}$ is the set of possible SC plans

$k = \{1,2,...,L_{\chi}\}$ is the number of a time interval (i.e., interval of structural constancy) in the planning horizon T=(t_0; t_f]

$\rho \in P = \{1,2,...,p\}$ is the number of an item in the SC.

χ is a number of an execution scenario

$i = \{1,2,...,n_{\chi}\}$ is the number of the delivering node in the SC, $i \in N^{-}_{\chi}$

$j = \{1,2,...,n_{\chi}\}$ is the number of the receiving node in the SC, $j \in N^{+}_{\chi}$

Elements of the set $W_{\chi}(t) = \{w_{\chi ij}(t),\ i, j \in N_{\chi}\}$ which describe transportation, processing, and warehouse operations are as follows:

$I_{\chi k}$ is the total ordered quantity from all suppliers

$V_{\chi i}(t)$ is the maximal warehouse capacity of the node $A_{\chi l}$

$\omega_{\chi ij\rho}(t)$ is the maximal transportation channel intensity for the product ρ between $A_{\chi i}$ and $A_{\chi j}$

$\psi_{\chi i\rho}(t)$ is the maximal inbound processing intensity for the product ρ in $A_{\chi l}$

$\varphi_{\chi i\rho}(t)$ is the maximal outbound processing intensity for the product ρ from $A_{\chi i}$

$c_{\chi ij\rho}(t)$ is the transportation costs intensity for the product ρ from $A_{\chi i}$ to $A_{\chi j}$

$h_{\chi i\rho}(t)$ is the inventory costs for the product ρ at the node $A_{\chi i}$

$\pi_{\chi i\rho}(t)$ is the processing costs intensity for the product ρ at the node $A_{\chi i}$

$r_{\chi i\rho}(t)$ is the return (utilization) cost for product ρ at the node $A_{\chi i}$

$\mu_{\chi ij}(t)$ is the fixed cost of the node $A_{\chi i}$ and channel from $A_{\chi i}$ to $A_{\chi j}$

f_{ik}, f_{ijk} are the fixed costs of the node $A_{\chi i}$ and channel from $A_{\chi i}$ to $A_{\chi j}$ respectively at time interval number k

b_{ik}, b_{ijk} are the recovery costs of the node $A_{\chi i}$ and channel from $A_{\chi i}$ to $A_{\chi j}$ respectively at time interval number k

Assume for each pair $<A_i\ A_j>$ that manufacturing and transportation capacities may be disrupted and the availability of the connection between two stages in the SC (i.e., tier 1 and tier 2) can be described by a given preset matrix time function of time-spatial constraints $\varepsilon_{ij}(t)$. We have $\varepsilon_{ij}(t) = 1$, if the channel between A_i and A_j is available and not disrupted within the given period of time, and $\varepsilon_{ij}(t) = 0$, otherwise. In addition, we introduce γ_{ρ} as a variable that denotes the importance of the product ρ and λ_{ρ} which is a variable that denotes the urgency of the product ρ.

Decision variables are defined as follows:

$x_{\chi ij\rho k}$ is the amount of product ρ transmitted from $A_{\chi i}$ to $A_{\chi j}$ and received at $A_{\chi j}$ at time interval number k;

$y_{\chi j\rho k}$ is the product ρ amount relating to the node $A_{\chi j}$ and to be stored at warehouse at time interval number k,

$g_{\chi j\rho k}$ is the product ρ amount relating to the node $A_{\chi j}$ and to be delivered at time interval *k*

$z_{\chi j\rho k}$ is the product ρ amount relating to the node $A_{\chi j}$ and to be returned (as caused by the missing capacity of SC nodes and channels) at time interval number *k*

$u_{\chi ij\rho}(t) \in \{0,1\}$ is the binary control variable of transportation for product ρ in the scenario Sc_{χ}

$u_{\chi ij\rho}(t) = 1$ if a transportation channel from A_{xi} to A_{xj} is selected, 0 – otherwise

$\vartheta_{\chi i\rho}(t) \in \{0,1\}$ is the 0-1 control variable of delivery to the customer $A_{\chi i}$; $\vartheta_{\chi i\rho}(t) = 1$ if a product ρ is delivered to the customer from A_{xi}, 0 – otherwise.

4.2 Dynamic model

The following *dynamic model* describes the dynamics of material flows in the SC (1)-(11):

$$J_{\chi 1} = \int_{t_0}^{t_f} \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} z_{\chi i\rho}(t)\, dt; \tag{1}$$

$$J_{\chi 2} = \int_{t_0}^{t_f} \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} \phi^{-}_{\chi i\rho}(t) \cdot \vartheta^{-}_{\chi i\rho}(t)\, dt; \tag{2}$$

$$J_{\chi 3} = \int_{t_0}^{t_f} \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} y_{\chi i\rho}(t)\, dt; \tag{3}$$

$$J_{\chi 4} = \int_{t_0}^{t_f} (\sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} \sum_{j=1}^{n_\chi} c_{\chi ij\rho}(t) \cdot u_{\chi ij\rho}(t) + \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} h_{\chi i\rho}(t) \cdot y_{\chi i\rho}(t) + \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} r_{\chi i\rho}(t) \cdot z_{\chi i\rho}(t) + \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} \pi_{\chi i\rho}(t) \cdot \vartheta^{-}_{\chi i\rho}(t) + \sum_{i=1}^{n_\chi} \sum_{j=1}^{n_\chi} \mu_{\chi ij}(t) \cdot e_{\chi ij}(t)) dt$$

(4) please split this expression into two

$$\dot{x}^{+}_{\chi i\rho}(t) = \dot{x}^{-}_{\chi i\rho}(t) + \dot{y}_{\chi i\rho}(t) + \dot{z}_{\chi i\rho}(t),\ i \in N_\chi = \{1,2,...,n_\chi\}. \tag{5}$$

$$\dot{x}^{+}_{\chi i\rho}(t) = \psi_{\chi i\rho}(t) + \phi^{+}_{\chi i\rho}(t) \cdot \vartheta^{+}_{\chi i\rho}(t) + \sum_{j=1}^{n_\chi} e_{\chi ji}(t) \cdot \omega_{\chi ji\rho}(t) \cdot u_{\chi ji\rho}(t),\ i \in N_\chi, \tag{6}$$

$$\dot{x}^{-}_{\chi i\rho}(t) = \phi^{-}_{\chi i\rho}(t) \cdot \vartheta^{-}_{\chi i\rho}(t) + \sum_{j=1}^{n_\chi} e_{\chi ij}(t) \cdot \omega_{\chi ij\rho}(t) \cdot u_{\chi ij\rho}(t),\ i \in N_\chi, \tag{7}$$

$$0 \le \sum_{\rho=1}^{p} y_{\chi i\rho}(t) \le V_{\chi i}\ \ \forall i \in N_\chi, t \in (t_0, t_f], \tag{8}$$

$$u_{\chi ij\rho}(t) \in \{0,1\},\ \vartheta^{+}_{\chi i\rho}(t), \vartheta^{-}_{\chi i\rho}(t) \in \{0,1\}\ \forall i, j \in N_\chi,\ \rho \in P, t \in (t_0, t_f], \tag{9}$$

$$z_{\chi i\rho}(t) \ge 0,\ \dot{z}_{\chi i\rho}(t) \ge 0\ \forall i \in N_\chi, \rho \in P, t \in (t_0, t_f]. \tag{10}$$

$$y_{\chi i\rho}(t_0) = z_{\chi i\rho}(t_0) = 0\ \forall i \in N_\chi, \tag{11}$$

The objective functions (1)–(3) describe minimization of return flows, throughput maximization and inventory minimization, respectively. Eq. (4) is the cost minimization objective. Eq. (5) de-

scribes the dynamics of the product ρ subject to the node $A_{\chi i}$ and ensures that the sum of the outgoing flow, inventory and return flow should equal the incoming flow.

We denote $\dot{x}^{+}_{\chi i\rho}(t)$ as actual inbound delivery (i.e., the received product flow) of the product ρ to $A_{\chi i}$, $\dot{x}^{-}_{\chi i\rho}(t)$ as actual outbound delivery of the product ρ from $A_{\chi i}$, $\dot{y}_{\chi i\rho}(t)$ as volume of stocked products ρ in the warehouse of $A_{\chi i}$, and $z_{\chi i\rho}(t)$ as unprocessed and returned volume of the product ρ from $A_{\chi i}$.

The intensity of the inbound deliveries of ρ into $A_{\chi i}$ is described in Eq. (6) that shows that the incoming flow may not exceed maximal inbound processing capacity and the capacity of the selected transportation channel.

Analogously, the intensity of the outbound deliveries of ρ from $A_{\chi i}$ is described in Eq. (7). $\psi_{\chi i\rho}(t), \omega_{\chi ij\rho}(t), \phi^{+}_{\chi i\rho}(t), \phi^{-}_{\chi i\rho}(t)$ are considered as parameters, functions $y_{\chi i\rho}(t), z_{\chi i\rho}(t), u_{\chi ij\rho}(t), \vartheta^{+}_{\chi i\rho}(t), \vartheta^{-}_{\chi i\rho}(t)$ are unknown, and controls $u_{\chi ij\rho}(t), \vartheta^{+}_{\chi i\rho}(t), \vartheta^{-}_{\chi i\rho}(t)$ uniquely define $z_{\chi i\rho}(t)$ and $y_{\chi i\rho}(t)$. Therefore, the pairs $y_{\chi i\rho}(t), z_{\chi i\rho}(t)$ can be considered as states of the SC represented through the dynamic system. Piecewise functions $e_{\chi ij}(t)$ are contained in the right parts of Eqs (6) and (7) in order to describe the *structure dynamics and disruption durations*.

Constraints are described as Eqs (8)–(11). Eq. (8) reflects the maximal warehouse capacity. Eq. (9) ensures that control variables take integer values. Eq. (10) is non-negativity constraint for the return flows. Eq. (11) shows the starting conditions, e.g., at the beginning of the planning interval, no inventory and return flows exist. Control variables $u_{\chi ij\rho}(t), \vartheta_{\chi i\rho}(t)$ are constrained by (8)–(10) and (11) are evaluated subject to (5)–(7).

Since each scenario Sc_{χ} is characterized by a number of structural states during certain intervals of structural constancy $\{St^{\chi}_{i_1,i_2,..i_k}\}$. The structure and the parameters of SC undergo changes at discrete time points $(t_0,t_1,...,t_k)$. These points divide the planning interval $(t_0,t_k]$ into sub-intervals L_{χ}, $T=\{(t_0,t_1],(t_1,t_2],...,(t_{k-1},t_k],...,(t_{L_{\chi}-1},t_{L_{\chi}}=t_f]\}$. The SC structure does not vary at each *k*-sub-interval $T_k=(t_{k-1},t_k]$ and is in the state $St^{\chi}_{i_1,i_2,..i_k}$ within this interval. The assumption on the intervals of structural constancy allows transit from the dynamic to static models.

4.3. Static model

Functions $u_{\chi ij\rho}(t), \vartheta^{+}_{\chi i\rho}(t), \vartheta^{-}_{\chi i\rho}(t)$ can be integrated and transformed to variables $u_{\chi ij\rho k}=\int_{t_{k-1}}^{t_k} u_{\chi ij\rho}(t)\,dt, \vartheta^{+}_{\chi i\rho k}=\int_{t_{k-1}}^{t_k} \vartheta^{+}_{\chi i\rho}(t)\,dt, \vartheta^{-}_{\chi i\rho k}=\int_{t_{k-1}}^{t_k} \vartheta^{-}_{\chi i\rho}(t)\,dt$. Then, the *model* (5)–(7) can be rewritten as balance equations (12)–(13) and capacity constraints (14) as follows:

$$I_{\chi i\rho k}+y_{\chi i\rho(k-1)}+\sum_{j\in N^{-}_{\chi ik}}\omega_{\chi ji\rho k}\cdot u_{\chi ji\rho k}+\phi^{+}_{\chi i\rho k}\cdot\vartheta^{+}_{\chi i\rho k}=\phi^{-}_{\chi i\rho k}\cdot\vartheta^{-}_{\chi i\rho k}+\sum_{j\in N^{+}_{\chi ik}}\omega_{\chi ij\rho k}\cdot u_{\chi ij\rho k}+y_{\chi i\rho k}+z_{\chi i\rho k}, \quad (12)$$

$$(\sum_{j\in N^{+}_{\chi ik}} x_{\chi ij\rho k} - \sum_{j\in N^{-}_{\chi ik}} x_{\chi ji\rho k}) + (y_{\chi i\rho k} - y_{\chi i\rho (k-1)}) + (g^{-}_{\chi i\rho k} - g^{+}_{\chi i\rho k}) + z_{\chi i\rho k} = I_{\chi i\rho k}. \quad (13)$$

$$0 \le x_{\chi ij\rho k} \le \omega_{\chi ij\rho k} \cdot (t_k - t_{k-1});\ 0 \le \sum_{\rho=1}^{p} y_{\chi i\rho k} \le V_{\chi i};\ 0 \le g^{-}_{\chi i\rho k} \le \phi^{-}_{\chi i\rho k} \cdot (t_k - t_{k-1});$$
$$0 \le g^{+}_{\chi i\rho k} \le \phi^{+}_{\chi i\rho k} \cdot (t_k - t_{k-1}),\ z_{\chi i\rho k} \ge 0. \quad (14)$$

The meaning of Eqs. (12)-(14) is identical to their dynamic form (5)-(11).

The *objectives* (1)–(4) can be rewritten as follows:

$$J_{\chi 1} = \sum_{\rho=1}^{p} \gamma_\rho \sum_{i=1}^{n_\chi} \sum_{k=1}^{L_\chi} z_{\chi i\rho k}; \quad (15)$$

$$J_{\chi 2} = \sum_{\rho=1}^{p} \lambda_\rho \sum_{i=1}^{n_\chi} \sum_{k=1}^{L_\chi} g^{-}_{\chi i\rho k}; \quad (16)$$

$$J_{\chi 3} = \sum_{\rho=1}^{p} \gamma_p \sum_{i=1}^{n_\chi} \sum_{k=1}^{L_\chi} y_{\chi i\rho k}; \quad (17)$$

$$J_{\chi 4} = \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} \sum_{j=1}^{n_\chi} c_{ij\rho} \sum_{k=1}^{L_\chi} x_{\chi ij\rho k} + \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} h_{i\rho} \sum_{k=1}^{L_\chi} y_{\chi i\rho k} + \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} \pi_{i\rho} \sum_{k=1}^{L_\chi} g^{-}_{\chi i\rho k} +$$
$$+ \sum_{\rho=1}^{p} \sum_{i=1}^{n_\chi} r_{i\rho} \sum_{k=1}^{L_\chi} z_{\chi i\rho k} + \sum_{k=1}^{L_\chi} \sum_{\substack{i=1,n_\chi \\ N^{+}_{\chi ik} \cup N^{-}_{\chi ik} \neq \varnothing}} f_{ik} + \sum_{k=1}^{L_\chi} \sum_{i=1}^{n_\chi} \sum_{j\in N^{-}_{\chi ik}} f_{ijk} + \sum_{k=2}^{L_\chi} \sum_{\substack{i=1,n_\chi \\ N^{+}_{\chi i(k-1)} \cup N^{-}_{\chi i(k-1)} = \varnothing \\ N^{+}_{\chi ik} \cup N^{-}_{\chi ik} \neq \varnothing}} b_{ik} + \sum_{k=2}^{L_\chi} \sum_{i=1}^{n_\chi} \sum_{\substack{j\in N^{-}_{\chi ik} \\ j\notin N^{-}_{\chi i(k-1)}}} b_{ijk} \quad (18)$$

respectively.

The search for optimal SC plan $\Delta^{*}_{\chi\beta} \subseteq \Delta_{\chi\beta}$ is performed under preference relations (e.g., weights) based on the following criteria:

$J_{\chi 1}(\delta_\chi) \to \min$

$J_{\chi 2}(\delta_\chi) \to \max$

$J_{\chi 3}(\delta_\chi) \to \min$

$J_{\chi 4}(\delta_\chi) \to \min$

We use the successive concessions method for multi-objective decision-making.

Since $J_{\chi 1} = I - J_{\chi 2} - J_{\chi 3}$, then $J_{\chi 1}(\delta_\chi) \to \min\limits_{\delta_\chi \in \Delta_{\chi\beta}}$ causes maximization of $J_{\chi 2}(\delta_\chi) + J_{\chi 3}(\delta_\chi)$. On the other hand, $J_{\chi 2}(\delta_\chi) \to \max\limits_{\delta_\chi \in \Delta_{\chi\beta}}$ reduces stocked quantities. By setting $J_{\chi 2}(\delta_\chi) \to \max\limits_{\delta_\chi \in \Delta_{\chi\beta}}$ as the objective with highest priority, the model will calculate the solution for maximal flow and push inventory to the final customer (as requested by service level strategy), even if this may result in higher transportation costs. So the rational precedence relation in the considered settings would

be $J_{\chi 1} \succ J_{\chi 2} \succ J_{\chi 4}$. This sequence is therefore the basic rule for using the successive concessions method.

Since the set $\Delta_{\chi\beta} = \{\delta_\chi\}$ is convex and polyhedral, and objective functions are linear, the following scalar objective can be built based on the additive convolution:

$$J_{рез}(\delta_\chi) = \alpha_3\alpha_2 J_{\chi 2}(\delta_\chi) - \alpha_3\alpha_1 J_{\chi 1}(\delta_\chi) - \alpha_4 J_{\chi 4}(\delta_\chi) \to \max, \quad (19)$$

where $\alpha_1 + \alpha_2 = 1$, $\alpha_1, \alpha_2 \geq 0$ are priority coefficients for $J_{\chi 1}, J_{\chi 2}$ and $\alpha_3 + \alpha_4 = 1$, $\alpha_3, \alpha_4 \geq 0$ are priority coefficients between the group $\{J_{\chi 1}, J_{\chi 2}\}$ and $J_{\chi 4}$. With the suggested convolution, the Pareto set points can be gained with the help of varying the coefficients α (one possible solution is presented in Eg. (19)). The coordination of the planning results of static and dynamic models is carried out through the variables x_{ijk}, y_{jl}, and g_{jl} (aggregate amount of products) of the static models and the corresponding variables $x_{ijk}(t)$, $y_{jk}(t)$, and $g_{jk}(t)$ from the dynamic model, where vector **u** is optimal control vector, i.e., the optimal SC plan.

5. Experimental results

This section describes an example of the practical application and managerial insights. Since the developed model is an LP model with transit nodes and two-side constraints, it can be solved with the simplex method with consecutive plan improvement techniques implemented in any LP solver. The model includes $m \times k$ equations and $\left(\sum_{l=1}^{k} f_l + 3 \times m \times k\right)$ unknown variables, where m is the number of nodes in the SC; k is the number of time intervals; f_l is the number of variables characterizing amounts of received (transmitted) products at the *l*-interval. Since the modified simplex method is used in the computational procedure, we avoid extensive numerical experiments. However, we note that the computational complexity increases subject to the number of different types of products and intensity-depended costs of production and transportation.

5.1 Computing the SC plans and economic performance for the existing SC

Consider a part of an SC in automotive industry that is composed of two Tier 2 suppliers (nodes #1 and #2), one Tier 1supplier (node #3), two assembly plants (nodes #5 and #6), and two markets (nodes #8 and #9) (see Fig. 2).

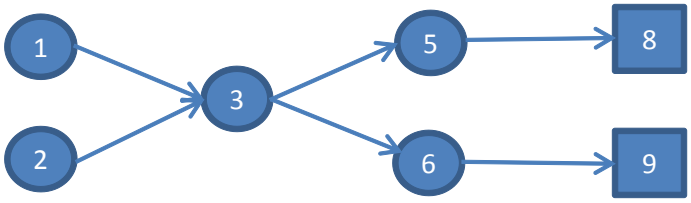


Fig. 2. Current structure of the supply chain

For computational experiments, the following data set has been used:

- Consider six periods

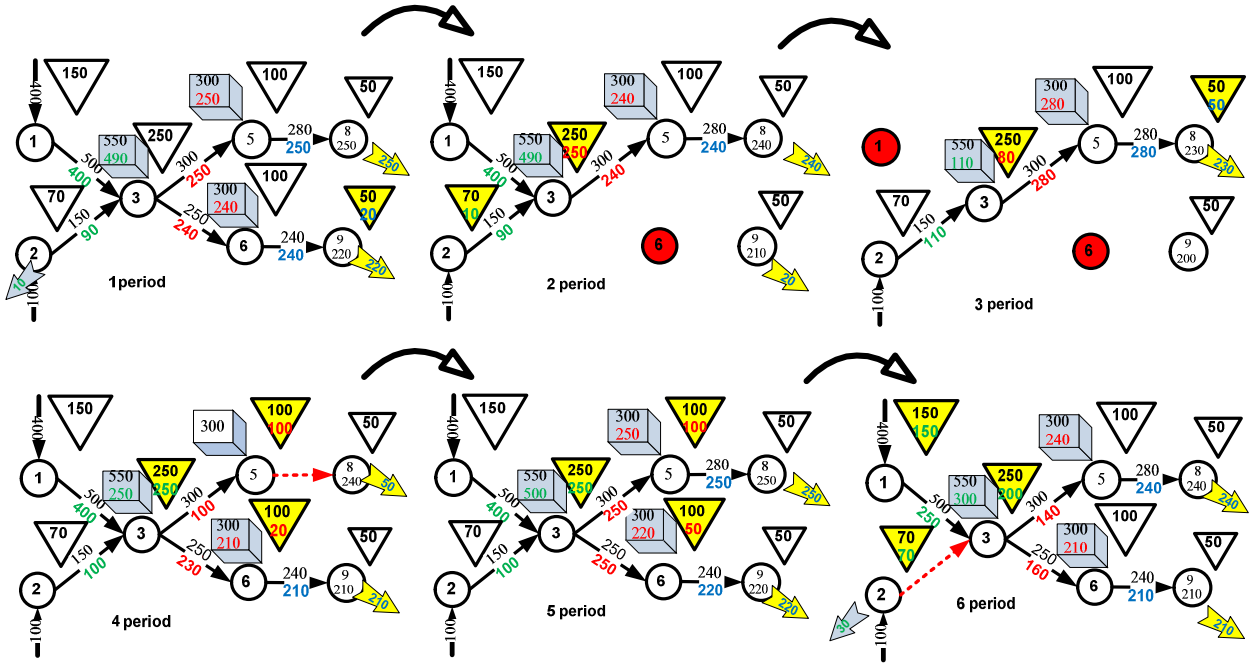
- Demand is known from Sales & Operations Planning and set up at 250-240-230-240-250-240 units in market #8 and 220-210-200-210-220-210 units in market #9 in each period respectively.
- The supplier #1 is the main Tier 2 supplier that delivers 400 units in each period
- The supplier #2 is the secondary Tier 2 supplier that delivers 100 units in each period
- Without loss of generality we consider the BOM factor as 1:1 for all stages
- The processing intensities are as follows: node #3 - 550 units, nodes #5 and 6 – 300 units respectively, channel 1→3- 500 units, channel 2→3=150 units, channel 3→5=300 units, channel 3→6=250 units, channel 5→8=280 units, channel 6→9=240 units
- The warehouse capacities are as follows: node #1=150 units, node #2=70 units, node #3=250 units, nodes #5 and 6 = 100 units, nodes #8 and 9 = 50 units
- The price for each final product in each market is $65
- Upstream SC costs is $25 per unit (i.e., the costs on the upstream SC stages prior to the Tier 2 stage)
- Transportation costs is $4 for each arc
- Processing costs is $2 per unit
- Inventory holding costs is $2 per unit in each period
- Return flow costs is $15 per unit
- Total fixed cost is composed of a firm part (proportionally to the number of SC elements) and the operating part (proportionally to the design capacity): $200 for each node and channel and $5 for each unit of processing or transportation capacity
- Recovery costs is $1 for each unit of disrupted capacity in each period

For analysis, the management considers two scenarios (Table 1).

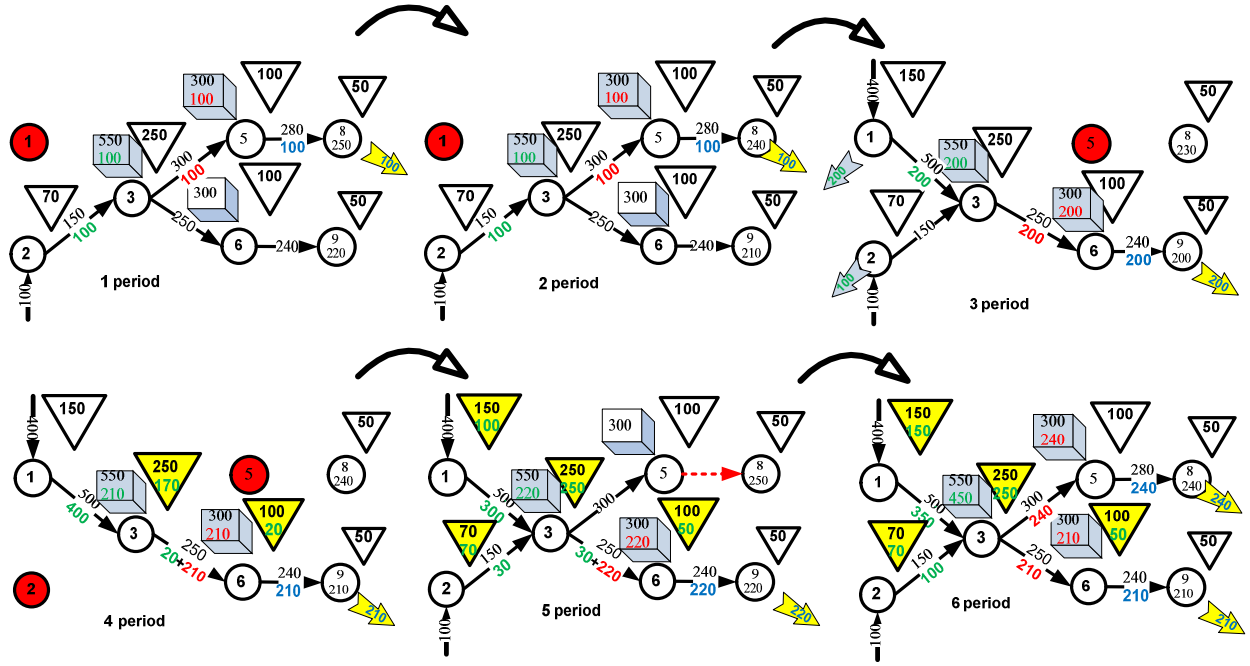
Table 1 Optimistic and pessimistic scenarios

Period	1	2	3	4	5	6
Disrupted elements in the optimistic scenario	-	6	6,1	5→8	-	2→3
Disrupted elements in the pessimistic scenario	1	1	4	4,2	5→8	-

In Fig. 3, results of optimal planning subject to the given data set and highest priority of the service level component in the goal function (Eqs. (1)–(3) and (15)–(17)) for the optimistic and pessimistic scenarios are presented.



(a) Optimistic scenario



(b) Pessimistic scenario

Fig. 3. Planning results for the initial SC

The production and shipment quantities are marked green, red and blue, according to the type of product in BOM. The yellow triangles show the storage capacities and their actual utilization. The grey rectangles depict the manufacturing design and utilized processing capacity respectively. The numbers on the arc represent the design transportation capacities and their actual utilization. The red nodes and channels are disrupted. The yellow arrows at nodes #8 and #9 depict the delivered volume of goods. The grey arrows depict the return flows. The results are presented in Table 2.

Table 2 SC reconfiguration plan for the optimistic scenario

Node / Arc						**Inventory / Shipment quantity**						**Manufacturing / sales quantity**					
k=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6	*k*=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6	*k*=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6
1	1	-	1	1	1						150	400	400		400	400	400
2	2	2	2	2	2		10				70	90	100	100	100	100	70
3	3	3	3	3	3		250	80	250		200	490	490	110	250	500	300
5	5	5	5	5	5				100	100		250	240			250	240
6	-	-	6	6	6				20	50		240		280	210	220	210
8	8	8	8	8	8			50				250	230	230	50	250	240
9	9	9	9	9	9	20						220			210	220	210
1→3	1→3	-	1→3	1→3	1→3	400	400		400	400	250						
2→3	2→3	2→3	2→3	2→3	-	90	90	110	100	100	140						
3→5	3→5	3→5	3→5	3→5	3→5	250	240	280	100	250	160						
3→6	-	-	3→6	3→6	3→6	240			230	250	240						
5→8	5→8	5→8	-	5→8	5→8	250	240	280		250	210						
6→9	-	-	6→9	6→9	6→9	240			210	220							

In Table 3, the performance impact with consideration of the reconfiguration plan is presented. Running the developed planning model on the assumption of the highest priority of the service level component in the goal function, the optimal solution for the optimistic scenario leads to delivering 2,140 units which is equivalent to a service level of 78.7%, subject to the estimated demand of 2,720 units in six periods. For the pessimistic scenario, optimal solution delivers 1,280 units, i.e. the service level is of 47.1%.

Table 3. Performance impact with consideration of the reconfiguration plan

№	***Performance indicators***	***Optimistic scenario***							***Pessimistic scenario***						
		1	2	3	4	5	6	***$***	1	2	3	4	5	6	***$***
1	Revenue	470	260	230	260	470	450	**139100**	100	100	200	210	220	450	**83200**
2	Transportation costs	1470	970	670	1040	1470	1000	**26480**	300	300	600	830	800	1350	**16720**
3	Inventory holding costs	20	260	130	370	400	420	**3200**	0	0	0	190	470	520	**2360**
4	Return costs	10	0	0	0	0	30	**600**	0	0	300	0	0	0	**4500**
5	Fixed costs							**12200**							**12200**
6	Upstream costs	500	500	100	500	500	500	**65000**	100	100	500	400	500	500	**52500**
7	Recovery costs	0	790	1290	280	0	150	**2510**	500	500	880	1030	280	0	**3190**
8	Processing costs	980	730	390	460	970	750	**8560**	200	200	400	420	440	900	**5120**
9	Total costs							**118550**							**96590**
10	**Profit**							**20550**							**-13390**

In the optimistic scenario, the SC still remains profitable, in the pessimistic scenario the losses of $13,390 arise. In comparison to the ideal case (no disruptions), in both optimistic and pessimistic scenarios the service level decreases to 78.7% and 47.1%, respectively. Moreover, the profits would decrease to $20,500 and $-13,390 as compared to $42,720, in the ideal case.

5.2. Analysis of different resilience actions

In both cases considered in Sect. 5.1, the profits and service level (i.e., sales volume) significantly decrease. This is the starting point for the SC managers to develop actions to increase the SC resilience. The central trade-off in this analysis is the question of *efficiency vs resilience*. In the next step, the developed model is applied to analysis of different actions for a possible resilience increase (measured through the service level and sales volumes) subject to this trade-off.

The management considers some structural and parametrical resilience increase actions (Fig. 4):

- The supplier #2 is used as a back-up supplier, i.e., it delivers under normal conditions 100 units in each period and can extend the quantity to 400 units if necessary
- Back-up Tier 1 suppler #4 that can be used in the case of disruptions in node #3
- Back-up assembly capacity #7 that can be used in the case of disruptions in nodes #5 and #6

- Alternative transportation channels
- Increase in warehouse storage and processing capacity
- Increase in transportation channel capacity
- Increase in order quantities from the Tier 2 suppliers #1 and #2.

Each of these actions could increase the resilience and have positive impact on the service level. However, the costs would also increase.

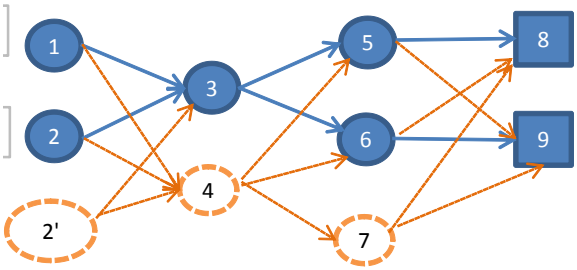


Fig. 4. Possible extensions to SC structure

The task is to identify experimentally the action (or a combination of actions) that ensures the best balance "*efficiency vs service level*" through the SC (re)planning. For experiments, the following assumptions have been made regarding processing and transportation intensities of new elements: new transportation channels - 120% of the processing intensity of the outgoing node; node #4 – 250 units in each period, node #7 – 150 units in each period. In Table 3, the planning results are summarized.

Table 4 Performance impact of different resilience policies in the optimistic scenario

Indicator	**Node #2 and channel 2→3**	**Node #4 and channels 4→5 and 4→6**	**Node #7 and channels 7→8 and 7→9**	**Channels 6→8 and 5→9**	**Actions 1+2**	**Actions 3+5**	**Actions 4+6**
	Action 1	*Action 2*	*Action 3*	*Action 4*	*Action 5*	*Action 6*	*Action 7*
Revenue	139100	139100	151450	160550	139100	160550	176800
Transportation costs	28280	26600	24320	29640	28880	33400	32800
Inventory holding costs	2680	3260	1300	920	3600	4080	3940
Return costs	22350	150	450	450	20100	14100	10350
Fixed costs	13100	15200	12350	12600	16300	18400	18800
Upstream costs	110000	65000	65000	65000	110000	110000	110000
Recovery costs	2510	3310	2510	2990	3310	3310	3310
Processing costs	8560	8560	9320	9880	8560	9880	10880
Total costs	187480	122080	115250	121480	190750	193170	190080
Profit	**-48380**	**17020**	**36200**	**39070**	**-51650**	**-32620**	**-13280**

It can be observed that structural changes significantly impact the performance and resilience. The most significant contribution to resilience increase is the action #7 where 100% service level can be achieved despite the disruptions. Obviously, this is one of the most expensive actions as well. In this particular case, action #7 results in a negative profit. The highest profit can be achieved using actions #3 and #4 which can be considered for SC re-design. In the optimistic scenario, for action #3, the service level increases by 8.9%, and the profit rises by 76.2% as

compared to the initial SC design. For action #4, the service level increases by 15.4% and the profit rises by 90.1%. As an example, the SC reconfiguration plan for action #4 is presented in Fig. 5.

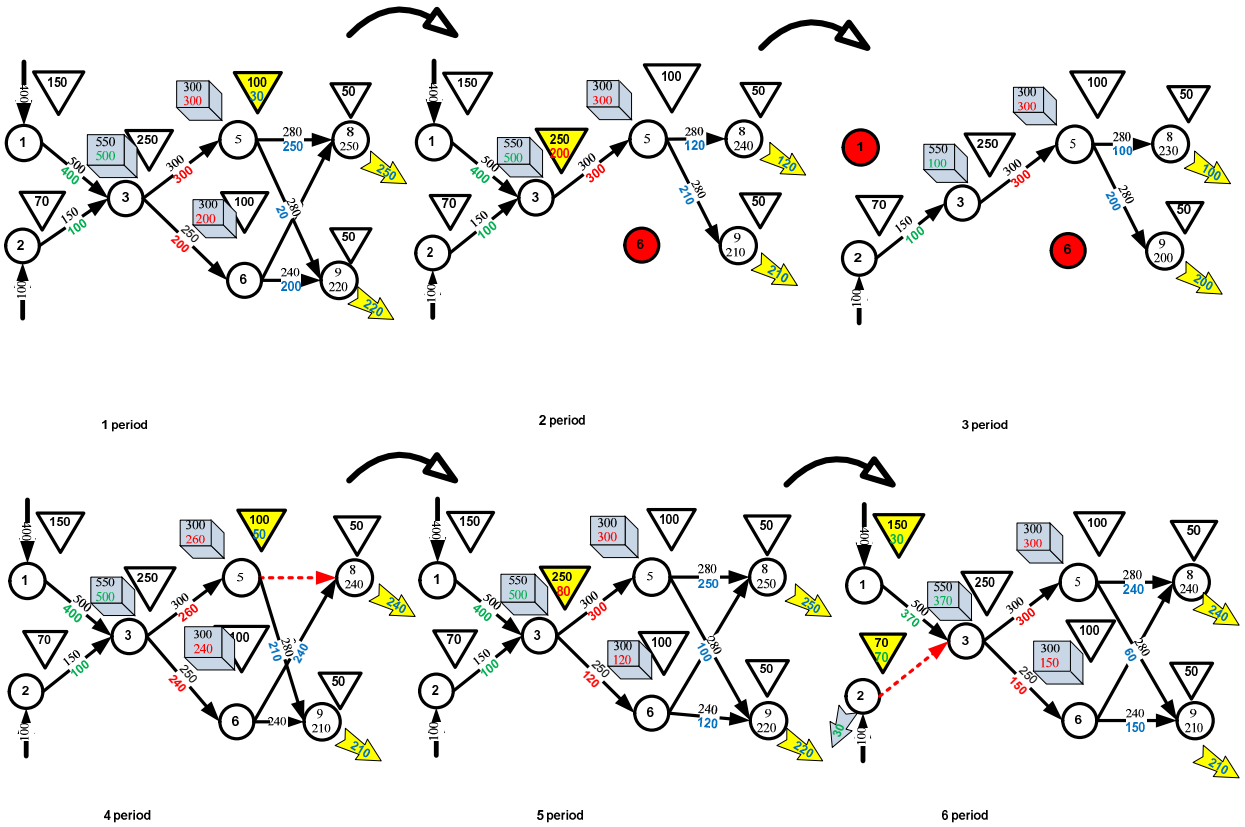


Fig. 5. Planning results for the re-designed SC (action #4)

In Fig. 6, SC costs for seven structural resilience actions are presented. In Fig. 7, the resilience and efficiency views of different structural actions are depicted.

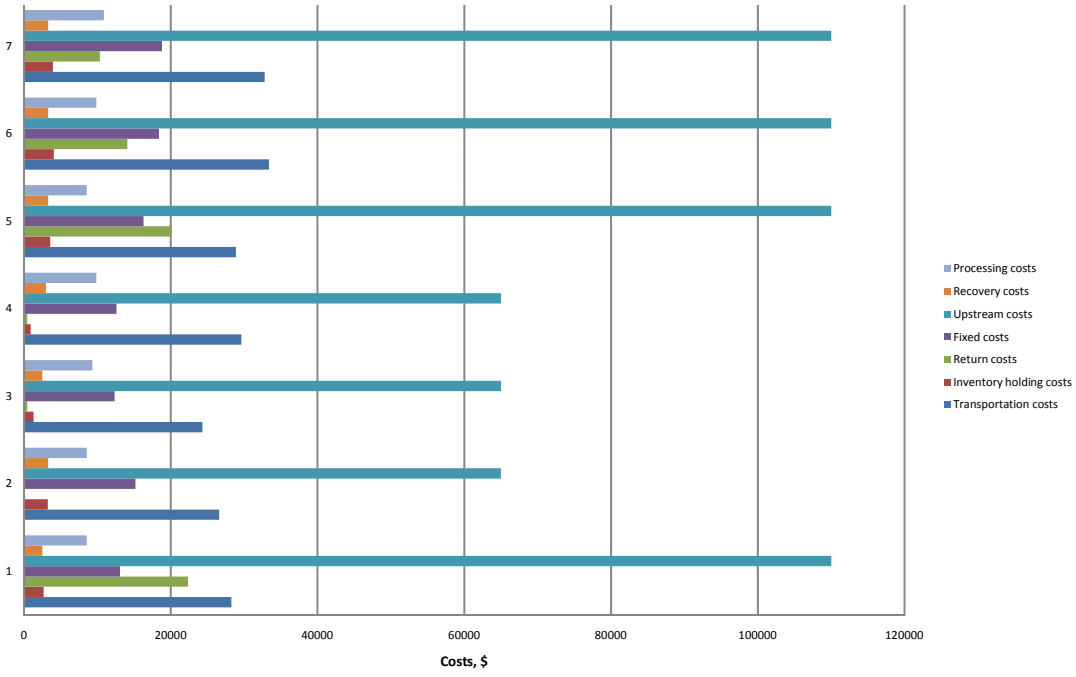


Fig. 6 Impact of different resilience policies on SC efficiency

Analogously, pessimistic scenario can be investigated.

In Fig. 7, performance impact of structural resilience actions for optimistic and pessimistic scenarios is presented.

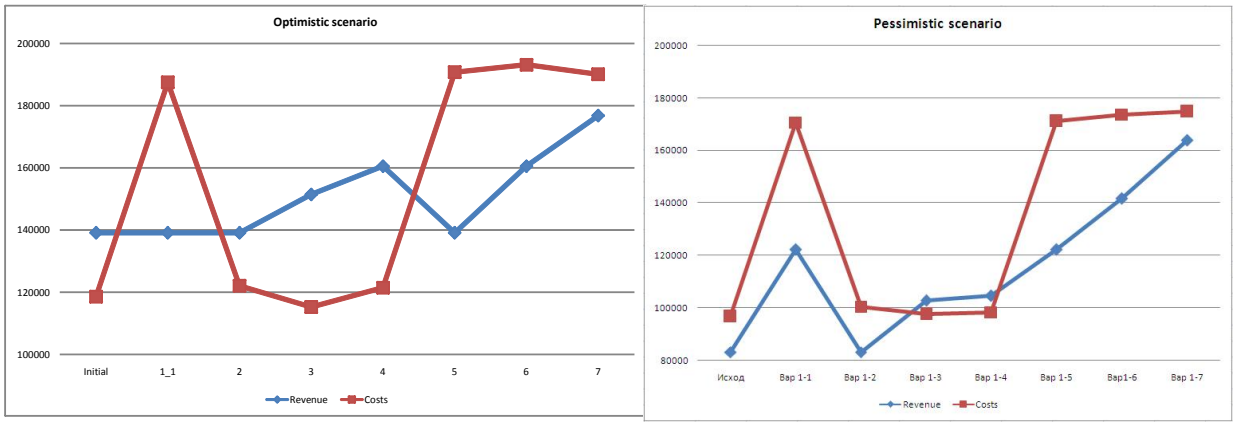


Fig. 7. Impact of different resilience policies on SC resilience and efficiency

It can be observed that structural changes differently impact the performance and resilience in the optimistic and pessimistic scenarios. The most significant contributions to the resilience increase in both scenarios are the actions #6 and #7. However, the profits are negative in these cases. The highest profit can be achieved using actions #3 and #4 which can be considered for SC re-design. Even in the pessimistic scenario, actions #3 and #4 achieves profits.

However, since structural changes cannot be implemented in short-term period, the management also considers the following parametrical measures:

Action 1. Increase in storage capacities and intensities in production and transportation by 10%
Action 2. Increase in storage capacities and intensities in production and transportation by 25%
Action 3. Increase in order quantities for Tier 2 suppliers by 10%
Action 4. Increase in order quantities for Tier 2 suppliers by 20%
Action 5. Actions 1+3
Action 6. Actions 2+4

The modelling results are summarized in Table 5 and Fig. 8.

Table 5 Performance impact of different resilience policies for parametrical actions

№	Performance indicators	Optimistic scenario							Pessimistic scenario						
		Initial	1	2	3	4	5	6	Initial	1	2	3	4	5	6
1	Revenue	139100	140075	140530	139100	139100	140985	142610	83200	83200	83200	85800	88400	85800	88400
2	Transportation costs	26480	26580	26548	26680	27720	27128	29324	16840	16444	16608	18280	18920	18004	19120
3	Inventory holding costs	3200	3204	3182	2920	3440	3402	3606	2400	2320	2888	2840	2660	2840	3320
4	Return costs	600	345	195	3900	6000	2760	4935	4350	4500	3510	5250	7650	5250	6000
5	Fixed costs	12200	13160	14585	12200	12200	13160	14585	12200	13160	14585	12200	12200	13160	14585
6	Upstream costs	65000	65000	65000	71750	78500	71750	78500	52500	52500	52500	58000	63500	58000	63500
7	Recovery costs	2510	2761	3136	2510	2510	2761	3136	1530	3509	3987	3190	3190	3509	3987
8	Processing costs	8560	8660	8648	8560	8560	8676	8776	5120	5120	5120	5280	5440	5280	5440
9	Total costs	118550	119710	121294	128520	138930	129637	142862	94940	97553	99198	105040	113560	106043	115952
10	**Profit**	20550	20365	19236	10580	170	11348	-252	-11740	-14353	-15998	-19240	-25160	-20243	-27552

The impact of different resilience policies on SC economic performance for parametrical actions in graphical form is reported in Fig. 8.

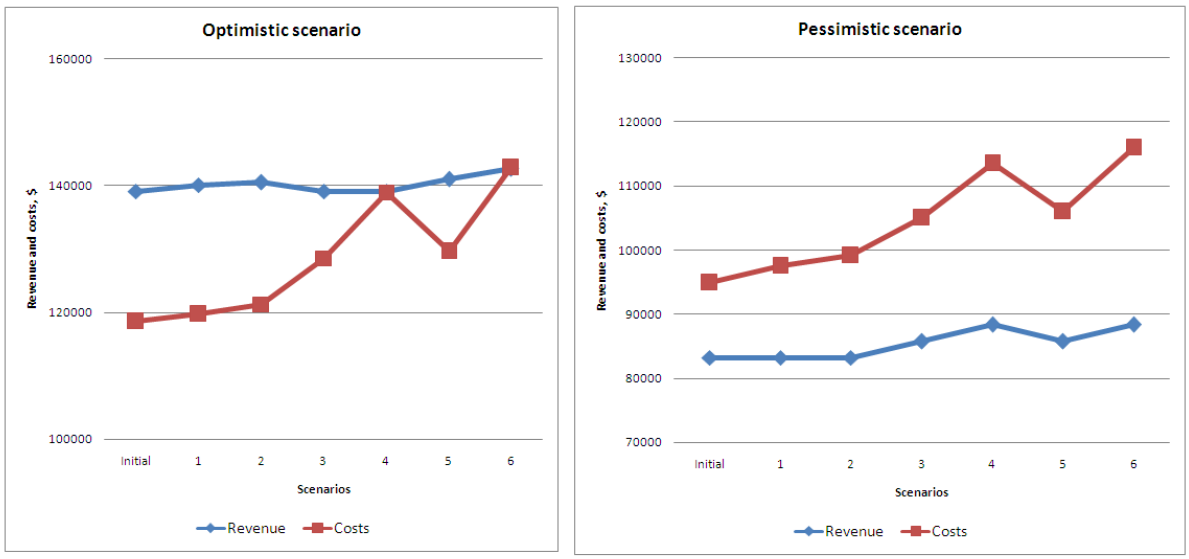


Fig. 8. Performance impact of different resilience policies for parametrical actions

It can be observed from Table 5 and Figure 8 that parametrical actions help to improve the SC resilience measured in service level and sales volumes. The most significant contribution to resilience increase is the action #6 in both scenarios. Obviously, this is the most expensive action. In this particular case, action #6 results in negative profits in both scenarios. Actions #1 and #2 can be considered for SC re-planning. In the optimistic scenario, for action #1, the service level increases by 0.7% and the profit declines by 0.9%. For action #2, the service level increases by 1.02% and the profit declines by 6.4%.

6. Managerial Insights

Disruption risks may result into ripple effect and structure dynamics in the SC. It is to notice that the scope of the rippling and its performance impact depend both on robustness reserves (e.g., redundancies like inventory or capacity buffers) and speed and scale of recovery actions (Knemeyer et al. 2009, Ivanov and Sokolov 2013, Hu et al. 2013, Kim and Tomlin, 2013, Pettit et al. 2013). In many practical settings, companies need analysis tools to estimate both the SC efficiency and SC resilience. For SC resilience, the impacts of recovery actions subject to different disruptions and performance indicators need to be estimated.

The results of this study contribute to support decisions in these practical problems. The developed model can help the SC risk managers to identify how the existing SCD is resilient for different disruption scenarios. The model also considers recovery strategies (i.e., reconfiguration) that can be used by SC managers and translated into the SCD and SCP changes.

With the use of the developed approach, SC managers can compare different possible SCDs regarding their resilience (measured through the sales volumes or service level) using the proposed model. Since the computation includes the recovery actions, the developed model can help to identify opportunities to reduce disruption and recovery costs by SC re-design and re-planning.

The proposed model analyses effective ways to recover and re-allocate resources and flows after a disruption. It also considers disruption durations and operative reactions to disruptions. Such a model can be used by SC risk specialists to analyse the performance impact of different resilience and recovery actions and adjust mitigation and recovery policies with regard to critical SCD elements and SCP parameters.

7. Conclusions

SC planning models known in literature have been extensively considered in the light of severe disruptions. Taking into account the gap between practical needs and the literature, we developed a multi-objective formulation for the SC reconfiguration model (trade-off "service level vs. costs") that offers performance impact assessment with SC re-planning in the case of structure dynamics (trade-off "efficiency vs. resilience") taking into account temporary unavailability of some SC elements and their recovery in time. Therefore, this study extends the existing models to multi-stage SC (re)planning problem by an explicit connection of performance impact assessment and SC plan reconfiguration with consideration of the duration of disruptions and the costs of recovery.

The approach is based on a hybrid model containing elements of system dynamics and linear programming. The SC structure dynamics and recovery is considered in the dynamic model while a linear programming model is used for the flow balance. We pass from a standard linear programming model to a maximal flow problem by excluding demand constraints.

The results have some major implications. First, it suggests a method to compare different actions for supply chain resilience regarding the performance impact. Second, since the commodity flows are described in continuous time in the dynamic models, the disruption recovery time can be described more accurately. Third, this offers the possibility to include a service level and sales volumes as resilience indicators into the performance consideration.

Subsequently, through numerical computations, we obtain additional managerial insights. The developed model can provide the SC risk, sales, production and purchasing managers with the analytical tool of how to identify the SC resilience and the impact of recovery strategies in order to compare different possible SCDs regarding their resilience and efficiency. This extends the existing theoretical knowledge and practical applications which can be used by SC managers to apply robust methods to SC design and planning in the case of disruption occurrence to estimate the recovery policies and impacts on operational and financial performance.

Finally, some extensions of this model in future can be considered. First, the possibility of addressing decision components of different time horizons and levels of detail arises from a combination of a static LP and dynamic OPC models. This combination can result in a hybrid multi-period production-routing model that can be investigated in detail in the future research.

Second, additional restrictions, e.g., total recovery budget with time value or other optimization objectives, e.g., minimizing delivery times, can be included in a future analysis. On-line adaptation can be an additional possible future research direction. Here different adaptation options (e.g., flow re-direction, capacity adjustment, and structure adjustment) and their costs can be compared. In addition, a comparison between investments in robustness vs. costs of adaptation can be made.

Some limitations of the proposed approach belong to its centralized planning focus. However, for the considered case-study the proposed model has been successfully validated and practically tested on different examples. In future, an extrapolation of other case-studies with different numbers of intervals of structural constancy and other SC structures may reveal some additional insights in the application of the proposed model. Additional research into dynamic and inverse models is needed. Cumulative impacts of different structural and parametrical actions can be investigated.

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