Integrated production–distribution planning in two-echelon systems: a resilience view

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To link to this article: http://dx.doi.org/10.1080/00207543.2016.1213446

Published online: 25 Jul 2016.

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Global supply chains are increasingly exposed to operational and disruption risks that threaten their business continuity. This paper presents a novel two-stage scenario-based mixed stochastic-possibilistic programming model for integrated production and distribution planning problem in a two-echelon supply chain over a midterm horizon under risk. Operational risks are handled by introducing imprecise (i.e. possibilistic) parameters while disruption risks are accounted for through stochastic disruption scenarios. The proposed model accounts for the risk mitigation options and recovery of lost capacities in an integrated manner. In the first stage, the structure of the chain and proactive risk mitigation decisions are determined, while the second stage specifies the recovery plan of lost capacities in addition to production and distribution plans. Considering extra capacities in the production facilities, backup routes for transportation links and pre-positioning of emergency inventory in distribution centres are considered as feasible options to improve the resilience level of the supply chain. We propose a new indicator for optimising the resilience level of the chain based on restoration of lost capacities. For the sake of robustness, the expected worst case of the second stage’s objective function is considered by utilising the conditional value at risk (CVaR) measure. The validation and applicability of the proposed model are examined through several numerical experiments.

Keywords: production and distribution planning; supply chain resilience; two-stage scenario-based stochastic programming; possibilistic programming; conditional value at risk

1. Introduction

Over the past decades, growth in global trade has been witnessed and according to the economically well-connected world, supply chains (SCs) are exposed to multiple high-magnitude risks (Kouvelis et al. 2011). The normal set of business risks has been expanded as firms are now facing with unfamiliar events such as unexpected suppliers’ bankruptcy in the turbulent global economy and supply disruptions as a result of natural and man-made disasters. Tang (2006a) emphasised the differences between operational risks and disruption risks. Operational risks are referred to the inherent uncertainties such as uncertain customer demand, uncertain supply and uncertain cost, but disruption risks are concerned with major disruptions influencing the whole chain drastically. Given its importance, SC risk management has emerged as a topic within the domain of SC resilience.

The resilience term has been used in a wide variety of fields like supply chain management (Sheffi 2005), strategic management, (Hamel and Valikangas 2003) and safety engineering (Hollnagel, Woods, and Leveson 2007). However, across all of these fields, the concept of resilience is closely related with the capability of a system to return to a stable state after a disruption (Bhamra, Dani, and Burnard 2011). Vugrin, Warren, and Ehlen (2011) defined system resilience as the ability to reduce effectively both the magnitude and duration of the deviation from targeted system performance levels. System resilience and system reliability are used interchangeably when discussing the dependability of a system in terms of delivering desired performance over time. However, resilience refers to the ability of a system or component to bounce back from a setback whereas reliability is the ability of a system or component to perform its required functions under stated conditions for a specified period of time, or even resist failure (Schmitt and Singh 2012). Two other terms that are relevant and their distinctions should be clarified are system resilience and system robustness. A robust system can continue functioning in the presence of internal and external challenges without fundamental changes to the original system, while a resilient system can adapt to internal and external disturbances by recovering its disrupted operations while continuing to function (Levin and Luchhenco 2008). Mandal and Haigh (2014) provided a comprehensive review on supply chain resilience and identified several research issues. Nevertheless, the definition of the supply chain resilience, which best matches to our work is ‘the adaptive capability of the supply chain to get prepared for unexpected
events, respond to disruptions and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function” (Ponomarov and Holcomb 2009).

This paper addresses an integrated tactical production–distribution planning problem in a two-echelon supply chain where capacities of production facilities, transportation links and distribution centres are vulnerable to disruption risks. Also, in order to incorporate operational risks into the modelling, some production and distribution data are formulated as imprecise data. Accordingly, the considered problem accounts for both operational and disruption risks concurrently. In this regard, operational risks are handled by introducing imprecise parameters representing the possible fluctuations on production and distribution data which are formulated as possibility distributions in the form of fuzzy sets. Furthermore, disruption risks are presented through stochastic scenarios, while their impacts are shown through scenario-dependent parameters. A two-stage scenario-based mixed stochastic-possibilistic programming model is formulated to capture both stochastic and possibilistic uncertainties involved in the problem’s input data. The first stage of the model encompasses a minimisation objective function which includes the total initial cost plus the expected cost of the second stage. The second stage of the model includes two objective functions which seek for optimising the cost and resilience of the production–distribution chain under consideration over all disruption scenarios. Notably, scenario-dependent parameters depend on scenario realisation and the final solution which is immunised against all possible scenarios is not optimal in general for the individual scenarios (Birge and Louveaux 1997). Other contributions of the proposed model can be summarised as follows:

- Accounting for proactive risk mitigation decisions at pre-disruption and reactive recovery plan of lost capacities at post-disruption simultaneously.
- Considering additional capacities in production facilities, backup routes for transportation links and emergency inventory in distribution centres as resilience options.
- Measuring and maximising the resilience of the system along with a new quantitative indicator based on the available capacities as a result of post-disruption restorations.
- Considering the expected worst case of the second stage’s objective functions via the conditional value at risk (CVaR) measure, in order to ensure the robustness of the solution.

2. Literature review

There are several supply chain planning-related works under risks. Literature reviews like those of Tang and Musa (2011) or Natarajarathinam, Capar, and Narayanan (2009) have investigated the research developments and trends in managing supply chain risks. Esmaeilikia et al. (2014) reviewed a classification of the existing literature on tactical SC planning models with multiple flexibility options that can help to manage the usual operations efficiently and effectively, whilst, improving the SC resilience in response to inherent environmental uncertainties. In a recent literature review in the domain of supply chain risk management, the importance of considering disruption risks is emphasised (Ho et al. 2015), especially in production–distribution planning problems (Mula et al. 2010; Díaz-Madroñero et al. 2015). In what follows the most relevant papers are briefly reviewed followed by discussing the research gaps.

2.1 Relevant papers

In this section, we review the literature of SC risk management with focus on five characteristics including: decision level, type of risk, vulnerable part in SC, planning type and resiliency. Lim et al. (2010) studied the facility reliability problem in order to design a reliable supply chain network in the presence of random facility disruptions with the option of hardening facilities. Schmitt and Singh (2012) analysed the effects of inventory placement and backup methodologies in a multi-echelon network on reducing supply chain risk. They have demonstrated how system resilience can be improved by focusing on the supply chain network as a whole. Cao, Wan, and Lai (2013) developed a coordination mechanism for a supply chain when the production cost and demands are simultaneously disrupted. Hishamuddin, Sarker, and Essam (2012) proposed a disruption recovery model for a single stage production and inventory system, where the production is disrupted for a given period of time during the production uptime. In another work, Hishamuddin, Sarker, and Essam (2013) explored a recovery model for a two-stage production and inventory system with the possibility of disruption in transportation links. Rabbani et al. (2014) proposed a bi-objective model for the supplier selection portfolio problem that uses conditional value at risk (CVaR) criteria to control the risks of delayed and disrupted supplies via scenario analysis. Azad et al. (2014) introduced a new strategy called soft-hardening strategy for the problem of reliable stochastic supply chain network design in the presence of random disruptions in distribution centres and transportation modes. Mitra et al. (2009) formulated a resilient multi-site, multi-product and multi-period supply
chain planning problem under uncertainty using the fuzzy mathematical programming approach. Sawik (2013b) proposed a mixed integer programming approach in order to obtain a resilient supply portfolio with protected suppliers capable of supplying parts in the face of disruption events. Ishfaq (2012) discussed a logistics strategy which can improve supply chain resilience against transportation disruptions. Their strategy is based on incorporating flexibility in transportation operations through the use of multiple transportation modes. Su and Liu (2015) developed a stochastic dynamic programming formulation to characterise how dual sourcing balances the risks and opportunities, when a company bears disruption risks and correlated operational risks. Hatefi et al. (2014) offered a credibility-constrained programming model for reliable design of an integrated forward–reverse logistics network which utilises reliability concepts to deal with facility disruptions. Hatefi and Jolai (2014) proposed a robust and reliable mixed integer linear programming model for an integrated forward–reverse logistics network design, which simultaneously takes uncertain parameters and facility disruptions into account through disruption scenarios. Salehi Sadghiani, Torabi, and Sahebjamnia (2015) developed a probabilistic scenario-based robust model, alongside scenario generation and disruption profiling to design a robust and resilient retail network under operational and disruption risks. Torabi, Baghersad, and Mansouri (2015) presented a bi-objective mixed possibilistic, two-stage stochastic programming model to address supplier selection and order allocation problem to build the resilient supply base under operational and disruption risks. Torabi et al. (2016) proposed a reliable closed-loop supply chain network design model, which accounts for both partial and complete facility disruptions as well as the epistemic uncertainty in the critical input data via a novel possibilistic programming approach.

The summary of reviewed works in addition to a comparison of our work to those reviewed in the literature is presented in Table 1. It should be mentioned that resilience column in this table indicates whether any method has been developed in the related research work for optimising the resilience level (either qualitatively or quantitatively) or not.

Table 1. A summary of relevant literature.

<table>
<thead>
<tr>
<th>References</th>
<th>Decision level</th>
<th>Type of risk</th>
<th>Vulnerable part</th>
<th>Planning type</th>
<th>Resilience</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lim et al. (2010)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Facilities</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Schmitt and Singh (2012)</td>
<td>Tactical</td>
<td>Operational</td>
<td>Supply, Demand</td>
<td>Proactive</td>
<td>Yes</td>
</tr>
<tr>
<td>Cao, Wan, and Lai (2013)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Production cost, Demand</td>
<td>Reactive</td>
<td>No</td>
</tr>
<tr>
<td>Hishamuddin, Sarker, and Essam (2012)</td>
<td>Operational</td>
<td>Disruptive</td>
<td>Production capacity</td>
<td>Reactive</td>
<td>No</td>
</tr>
<tr>
<td>Hishamuddin, Sarker, and Essam (2013)</td>
<td>Operational</td>
<td>Disruptive</td>
<td>Transportation capacity</td>
<td>Reactive</td>
<td>No</td>
</tr>
<tr>
<td>Azad et al. (2014)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Distribution centres, Transportation capacity</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Mitra et al. (2009)</td>
<td>Operational</td>
<td>Disruptive</td>
<td>Production cost and capacity, Demand</td>
<td>Proactive</td>
<td>Yes</td>
</tr>
<tr>
<td>Sawik (2013b)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Supply</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Ishfaq (2012)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Transportation capacity</td>
<td>Proactive</td>
<td>Yes</td>
</tr>
<tr>
<td>Rabbani et al. (2014)</td>
<td>Tactical</td>
<td>Disruptive</td>
<td>Supply</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Su and Liu (2015)</td>
<td>Tactical</td>
<td>Disruptive</td>
<td>Supply</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Hatefi et al. (2014)</td>
<td>Strategic</td>
<td>Operational</td>
<td>Hybrid distribution-collection facilities</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Hatefi and Jolai (2014)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Demand and Facilities</td>
<td>Proactive</td>
<td>No</td>
</tr>
<tr>
<td>Sadghiani et al. (2015)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Supply</td>
<td>Proactive</td>
<td>Yes</td>
</tr>
<tr>
<td>Torabi, Baghersad, and Mansouri (2015)</td>
<td>Strategic</td>
<td>Operational</td>
<td>Transportation capacity, Supply</td>
<td>Proactive</td>
<td>Yes</td>
</tr>
<tr>
<td>Torabi et al. (2016)</td>
<td>Strategic</td>
<td>Disruptive</td>
<td>Facilitie</td>
<td>Reactive</td>
<td>No</td>
</tr>
<tr>
<td>Our work</td>
<td>Tactical</td>
<td>Operational, Disruptive</td>
<td>Transportation capacity, Backup inventories</td>
<td>Proactive</td>
<td>Yes</td>
</tr>
</tbody>
</table>
2.2 Gap analysis

Looking at the reviewed works in SC risk management and SC resilience areas as well as those characteristics considered in Table 1, it is deduced that the main body of the literature focuses on the strategic issues over a long-term planning horizon. In particular, operational risks are handled with an operational or tactical view, while handling of disruption risks requires making some strategic decisions (e.g. risk mitigation or hardening plans). Also, there have been relatively less investigations conducted in the area of handling both type of risks simultaneously. More interestingly, those research works addressing the vulnerability of production and/or distribution facilities to disruption risks are so scarce. Accordingly, accounting for both operational and disruption risks concurrently in tactical supply chain planning (SCP) problems (such as integrated production–distribution planning problems) seems to be a promising area. Also, resilience is rarely regarded as the main criterion of the developed quantitative models. It can also be seen that the most of proactive actions in the area of SC resilience are related to the strategic or tactical decision levels. Hence, it would be worthwhile to develop new SCP models integrating proactive and reactive (i.e. recovery) resilience plans while accounting for strategic and tactical decision levels simultaneously.

To address some of the aforementioned gaps, we propose a two-stage scenario-based mixed stochastic-possibilistic programming model for an integrated tactical production–distribution planning problem in which a number of risk mitigation options (i.e. proactive actions) are determined in the first stage (i.e. in the preparedness or pre-disruption phase), and post-disruption recovery decisions (i.e. reactive actions) are delimited under each disaster scenario in the second stage (i.e. in the recovery phase). The proposed model deals with both operational and disruption risks simultaneously. In this regard, operational risks are handled by introducing imprecise parameters in the form of fuzzy sets for critical parameters and disruption risks are presented through stochastic scenarios whose impacts are formulated by scenario-dependent parameters. We assume that production and distribution facilities as well as transportation links are vulnerable to disruption risks. As a result, in order to make the chain resilient, providing additional capacities in production facilities, considering backup layer (i.e. contracting with third-party logistics providers (3PLs)) for transportation links and prepositioning of emergency inventory in distribution centres (i.e. the inventory which is not used in the normal situation, but is prepared for tackling the potential shortages at post-disruption) are considered as the available proactive resilience options which are chosen in the first stage of the model. Noteworthy, inventory prepositioning is one of the well-applied proactive risk mitigation strategies in the area of supply chain resilience and humanitarian logistics (see for instance Torabi, Baghersad, and Mansouri 2015; Tofighi, Torabi, and Mansouri 2016). Also, recovery plans for disrupted capacities are delimited in the second stage of the model according to the available recovery actions. It is obvious that resilience-enhancing investments that are made prior to the occurrence of any disruptive event are important complements to effective post-event recovery actions. Accordingly, the proposed model finds an optimal balance between preparedness and recovery costs when optimising the resilience level of the whole chain. Noteworthy, in this research work, the resilience level of the whole supply chain under consideration is measured by a new indicator based on restoration of disrupted capacities using the selected proactive and reactive resilience-enhancing actions.

It is worth noting that our problem setting might be considered as a theoretical work. However, the proposed model has been inspired by the recent literatures of supply chain resilience and production–distribution planning. For instance, in a recent literature review in the domain of supply chain risk management, the importance of considering disruption risks is emphasised by Ho et al. (2015), especially, in production–distribution planning problems (Mula et al. 2010; Diaz-Madroñero et al. 2015). Also, a majority of current models regarding integrated production–distribution planning could be improved by incorporating operational and disruption risks into their formulations. Just as some real applications, the integrated production–distribution models developed by Meisel et al. (2013) and Timpe and Kallrath (2000) in chemical industry, Rizk, Martel, and D’Amours (2006, 2008) in paper industry and Meijboom and Obel (2007) in pharmaceutical industry could be revisited using the model developed in this paper while accounting for operational and disruption risks.

3. Problem description

This paper considers a two-echelon production–distribution network (Figure 1) through which a company would like to start a new project for manufacturing a set of products in different manufacturing plants (MPs) and delivering them to different customer zones through some distribution centres (DCs) and transportation links (TLs). According to the supply chain planning matrix (Stadtler 2005, 87), an integrated production–distribution planning problem is the main part of the so-called supply chain master planning (SCMP), which is typically formulated in the level of product families over a tactical (i.e. mid-term) multi-period horizon. MPs and DCs have already been installed and the company is going to dedicate its existing production capacity to a set of brand new product families while terminating the production of some out-of-date product families. The company is also trying to organise its own transportation fleet.
Due to unknown and dynamic nature of the surrounding environment, most of input data about the production and distribution of new products are imprecise. Also, capacities of MPs, TLs and DCs are vulnerable to disruption risks. Based on a scenario-based stochastic analysis of the system’s operations, the company has predicted a set of random scenarios which can threaten the chain. Each scenario is associated with a likelihood of occurrence. Disruptions range from man-made distortions (e.g. supplier’s bankruptcy, system failure, worker strikes and sanction) to natural disasters (e.g. earthquake, hurricane or flood). Risk mitigation strategies in the concerned chain include developing extra capacities for MPs and TLs, as well as prepositioning of emergency inventory in DCs. On the other hand, based on the literature (e.g. Blackhurst et al. 2005; Chen and Miller-Hooks 2012), the supply chain’s risk mitigation options in the design phase are suggested as follows:

- Investment in developing absorptive and flexible resources in order to maintain the system in operating mode during a disruption, as well as, recovering their lost capacities after a disruption.
- Developing the ability to connect each supplier node to backup nodes, when the primary supplier is not available.

Accordingly, we consider investment in absorptive resources in production and distribution facilities in order to provide recovery ability of lost capacities after a disruption. It is worth noticing that absorptive capacity is the degree to which a system can automatically absorb the impacts of system perturbations and minimise consequences with little effort. For example, if a production plant is disrupted but a large amount of collocated storage of its product is undamaged; customers can continue to be supplied by the stored quantities while the plant is recovered. This implies that such storage can enhance the absorptive capacity (Vugrin, Warren, and Ehlen 2011). Also, the proposed model allows reconfiguring the chain immediately after a disruption. As mentioned earlier, reconfiguration of the chain involves assigning a node to backup suppliers when its primary suppliers are out of service. However, there might not be transportation facilities between the node and its backup suppliers, due to consequences of disruption or lack of initial transportation links. So, our model considers a backup layer for sending products through a 3PL. It should be also noted that it is necessary to make required contract with the 3PL as a pre-disruption action. However, we do not care about investing in one or multiple third-party disaster recovery agreements in our formulation as it has already been suggested in the literature (e.g. Booty 2009).
4. Model formulation

The following assumptions are taken into account for model formulation:

- Decreased capacities of MPs, DCs and TLs should be restored completely by the last period.
- Each DC is supplied by some MPs as primary suppliers and may be supplied by other backup MPs after reconfiguration of the chain at post-disruption phase.
- Transportation of products between a DC and its primary suppliers at pre-disruption phase involves installation of TLs between them (i.e. assigning this DC to primary suppliers), while transportation of products between a DC and its backup suppliers requires contracting with at least a 3PL at pre-disruption phase.
- Transportation cost through a 3PL is much greater than transportation cost via current TLs.
- 3PL has infinite capacity for carrying products which is not decreased by any disruption.
- Each customer zone has an uncertain demand, which can be backordered in disruptive situations.
- Each random scenario might be occurred independently with a given likelihood.

Furthermore, notations used for mathematical formulation are reported in Appendix 1.

4.1 First stage of the proposed model

The first stage objective function aims to minimise the design-related costs (incurred based on pre-disruption decisions) plus the expected worst-case (EW) of the second stage’s objective functions. Design-related cost (DRC), Equation (1), includes investment in equipping TLs with transportation fleet, and investment in system design improvements in order to improve system flexibility which is called as resilience-enhancing investments (REI), Equation (2). REI includes the initial investments for installing additional production capacity in the MPs, prepositioning of emergency inventory in DCs and contracting with 3PLs to make backup layer for selected TLs.

\[
DRC = \sum_j \sum_c \sum_l \sum_m \bar{n}_{ml} \omega_{ml} \sum_{jc} \]

\[
REI = \sum_j f_j w_j + \sum_k \sum_c \bar{f}_{kc} w_{kc} + \sum_c c_t z c_c
\]

Consequently, the first stage of the proposed model is as follows.

\[
\text{Min } G_0 = DRC + REI + EW
\]

ST

\[
\sum_j \sum_c \sum_l z_{mljc} \geq 1 ; \ \forall c \in C
\]

\[
\sum_m \sum_l z_{mljc} \leq 1 ; \ \forall j \in J, c \in C
\]

\[
z_{mljc} \in \{0, 1\} ; \ \forall j \in J, c \in C, m \in M, l \in L
\]

\[
w_j \geq 0 ; \ \forall j \in J
\]

\[
w_{kc} \geq 0 ; \ \forall k \in K, c \in C
\]

\[
z c_c \in \{0, 1\} ; \ \forall c \in C
\]

Equation (3) shows the objective function of the first stage which includes DRC, REI and EW. Constraint (4) guarantees that each DC is assigned to at least one primary supplier. Constraint (5) ensures that each TL is equipped by only one transportation mode with given size. Constraints (6)–(9) determine types of first stage’s decision variables.
4.2 Second stage of the proposed model

The second stage of the model includes two objective functions, i.e. the expected worst-case cost and the expected worst-case resilience. Considering the worst-case is common in the risk management literature. Pettit (2008) criticised the traditional risk management approaches for their deficiency in characterising low-probability, high-impact events (i.e. disruption risks). Unfortunately, managers tend to underestimate the impact of supply chain disruptions, deceived by their small probability of occurrence (Lim et al. 2010). Also, we have learnt from the past that the maximum loss of catastrophic events is significantly greater than the mean or median of their loss (Kelle, Schneider, and Yi 2014). Therefore, extreme risks or in other words, the worst-case must be taken into account to manage catastrophic situations (Olson and Wu 2013). Surprisingly, catastrophic risks can be mitigated significantly by a small raise in the design costs (Haines 2006). Accordingly, the worst-case scenarios are incorporated in our model via utilising two popular indices of risk measurement so-called value-at-risk (VaR) and conditional value-at-risk (CVaR) measures. The decision-maker (DM) controls the risk of high losses due to disruptions by choosing the confidence level α, where α belongs to the interval (0,1). The greater the confidence level α, the more risk averse the DM. Moreover, a risk averse DM minimises the expected worst-case exceeding VaR by minimising CVaR. The general concepts of VaR and CVaR are discussed by Uryasev (2000) and Rockafellar and Uryasev (2002). We use the following Equations (10)–(12) in our model.

\[
CVaR(x) = \min \{VaR + \frac{1}{1-\alpha} \sum_{s=1}^{S} p_s T_s^\alpha \}; \quad \text{where} \quad \sum_{s=1}^{S} p_s = 1 \tag{10}
\]

S.T.

\[
T_s^\alpha \geq g(x,s) - VaR; \quad \forall s \in S \tag{11}
\]

\[
T_s^\alpha \geq 0; \quad \forall s \in S \tag{12}
\]

where \( g(X,s) \) represents the objective function value (OFV) for the decision vector \( \lambda \) under scenario \( s \), and \( T_s^\alpha \) is the amount by which \( g(X,s) \) exceeds VaR under scenario \( s \). VaR is a decision variable that represents the acceptable OFV level which we want to minimise the number of those realisations exceeding it. With the above formulation, DM allows \( 100(1-\alpha)\% \) of the realisations of \( g(X,s) \) exceed VaR, while the mean value of them is represented by CVaR. In other words, DM is willing to accept only those decisions by which the total probability of scenarios with \( g(X,s) \) greater than VaR is not greater than \( (1-\alpha) \).

Sawik (2013a) has suggested strengthening the former model, i.e. Equations (10)–(12), by adding valid inequalities, Equations (13)–(15), to precisely determine VaR for a given confidence level. Suppose that \( \nu^s \) denotes the scenario selection variable where \( \nu^s = 1 \), if for scenario \( s \), \( g(X,s) \) is less than VaR, otherwise \( \nu^s = 0 \).

\[
M. \nu^s \geq VaR - g(x,s); \quad \forall s \in S \tag{13}
\]

\[
M. (\nu^s - 1) \leq VaR - g(x,s); \quad \forall s \in S \tag{14}
\]

\[
\sum_{s} p_s \nu^s \geq \alpha \tag{15}
\]

Equations (13) and (14) specify those scenarios with the \( g(X,s) \) less than VaR. Constraint (15) guarantees that the total probability of all such scenarios is not less than the confidence level \( \alpha \).

4.2.1 Objective 1

The first objective function of the second stage minimises the expected worst-case cost. This objective includes two main parts: the systemic impact (SI) cost and the total recovery effort (TRE) cost under each scenario. These components are defined as follows.

\[
SI_s = \sum_{k} \sum_{ij} \sum_{l} \hat{r}_{ijl} x_{ijl}^s + \sum_{k} \sum_{ij} \sum_{c} \sum_{l} \sum_{m} \hat{r}_{ijlc} m_{ijlc}^s + \sum_{k} \sum_{j} \sum_{c} \sum_{l} \hat{r}_{ijlc} y_{ijlc}^s + \sum_{k} \sum_{c} \sum_{l} \hat{b}_{iklc} q_{iklc}^s; \quad s \in S \tag{16}
\]
\[
TRE_s = \sum_j \sum_t \tilde{c}_j \tilde{p}_{jt}^s + \sum_j \sum_t \sum_m \tilde{c}_m \tilde{r}_{jtcm}^s \\
+ \sum_k \sum_j \sum_t \tilde{r}_{tk}^s + \sum_k \sum_j \sum_t \sum_m \tilde{u}_{tk}^m \\
, \quad s \in S
\]  
(17)

Constraint (16) includes production and transportation costs as well as penalty costs for unmet demand, respectively, under each scenario. Constraint (17) determines recovery cost for restoring production and transportation capacities as well as cost of replenishing the emergency inventory of DCs, respectively, under each scenario. According to Equations (10)–(15), CVaR_c as the first objective function of our model and its related constraints are presented in Equations (18)–(23), where \( G_c = SL + TRE_s \).

\[
CVaR_c = \frac{VaR_c + \sum_{s \in S} P^s T^e}{1 - \alpha}
\]  
(18)

S.T.

\[
T^e \geq G_c - VaR_c; \quad s \in S
\]  
(19)

\[
M \cdot V^e \geq VaR_c - G_c; \quad \forall s \in S
\]  
(20)

\[
M \cdot (V^e - 1) \leq 1 + VaR_c - G_c; \quad \forall s \in S
\]  
(21)

\[
\sum_s p_s V^e \geq \alpha
\]  
(22)

\[
T^e \geq 0; \quad s \in S
\]  
(23)

Constraint (19) accounts for the mount by which \( G_c \) exceeds \( VaR_c \) under scenario \( s \) via \( T^e \). As discussed earlier, constraints (20)–(22) precisely determine \( VaR_c \) for a given confidence level, and constraint (23) shows the type of variable.

4.2.2 Objective 2

The second objective function of the second stage assesses the resilience of the whole chain quantitatively. Chen and Miller-Hooks (2012) presented a resilience indicator which was defined as the expected fraction of demand that could be satisfied in post-disaster situations. With this in mind, we extend their network resilience indicator as follows. According to the SC configuration, capacities of MPs, TLs and DCs might be reduced after a disruption occurs. Hence, the proposed resilience indicator includes the following features:

- Availability of production capacity in MPs called production resilience (PR).
- Availability of transportation capacity in TLs called distribution resilience (DR).
- Availability of emergency inventory in DCs called inventory resilience (IR).

Accordingly, these resilience features are defined in Equations (24)–(26). It is noted that all of these components are calculated in terms of product/period unit.

\[
PR_s = \sum_j \sum_t (K_j + w_j - up_{jt}^s); \quad s \in S
\]  
(24)

\[
DR_s = \sum_j \sum_c \sum_m \sum_t (e_{jc} k_{m} - ut_{jt}^s); \quad s \in S
\]  
(25)

\[
IR_s = \sum_k \sum_c \sum_t (w_{ke} - ub_{kct}^s); \quad s \in S
\]  
(26)

Finally, the weighted sum of above resilience indicators is defined as the whole chain’s resilience level via Equation (27).

\[
Gr_s = ep \cdot PR_s + ed \cdot DR_s + ei \cdot IR_s; \quad s \in S
\]  
(27)
where $ep$, $ed$ and $ei$ are relative importance weights for loss of resilience in restoration of production, distribution and emergency inventory capacities, respectively. It is worthy to mention the critical properties of the proposed resilience indicator here. In each time bucket that production, distribution and inventory capacities are not restored to their normal levels, the resilience of the system is penalised. Therefore, the model would try to restore lost capacities as soon as possible. This formulation forces the whole chain to be bounced back to the normal condition as soon as possible, which makes the chain resilient. This novel compound indicator is capable of considering different weights (penalties) for resilience of each echelon according to the opinions of DMs. The second objective function (i.e. $CVaR_r$) and its related constraints are presented in Equations (28)–(33).

$$CVaR_r = VaR_r + \frac{\sum r \in S P^r Tr^r}{1 - \alpha}$$  \hspace{1cm} (28)

S.T.

$$Tr^s \geq Gr_s - VaR_r; \quad s \in S$$  \hspace{1cm} (29)

$$M \cdot vr^s \geq VaR_r - Gr_s; \quad \forall s \in S$$  \hspace{1cm} (30)

$$M \cdot (vr^s - 1) \leq 1 + VaR_r - Gr_s; \quad \forall s \in S$$  \hspace{1cm} (31)

$$\sum_s p_s vr^s \geq \alpha$$  \hspace{1cm} (32)

$$Tr^s \geq 0; \quad s \in S$$  \hspace{1cm} (33)

Constraint (29) accounts for the amount by which $Gr_s$ exceed $VaR_r$ under scenario $s$ via $Tr^s$. As discussed earlier, constraints (30)–(32) precisely determine $VaR_r$ for a given confidence level, and constraint (33) shows the type of variable.

4.2.3 Other constraints

Other constraints pertaining to the second stage of the proposed model are as follows.

Logical constraints:

$$y^{ms}_{kjc} \leq M \cdot \sum_l z^{ml}_{jct}; \quad \forall k \in K, \quad j \in J, c \in C, t \in T, m \in M, s \in S$$  \hspace{1cm} (34)

$$r^{ms}_{kjc} \leq M \cdot \sum_l z^{ml}_{jct}; \quad \forall k \in K, \quad j \in J, c \in C, t \in T, m \in M, s \in S$$  \hspace{1cm} (35)

$$y^{bc}_{kjc} \leq M \cdot z_{c}; \quad \forall k \in K, \quad j \in J, c \in C, t \in T, s \in S$$  \hspace{1cm} (36)

$$r^{bc}_{kjc} \leq M \cdot z_{c}; \quad \forall k \in K, \quad j \in J, c \in C, t \in T, s \in S$$  \hspace{1cm} (37)

$$u^{ms}_{jct} \leq M \cdot \sum_m z^{ml}_{jct}; \quad \forall j \in J, \quad c \in C, t \in T, m \in M, l \in L, s \in S$$  \hspace{1cm} (38)

Balance constraints:

$$\sum_c \left[ \sum_m (y^{ms}_{kjc} + r^{ms}_{kjc}) + (y^{bc}_{kjc} + r^{bc}_{kjc}) \right] \leq x^{a}_{jkt}; \quad \forall k \in K, \quad j \in J, t \in T, s \in S$$  \hspace{1cm} (39)

Capacity constraints:

$$\sum_k x^{a}_{jkt} \leq up^a_{jt}; \quad \forall j \in J, t \in T, s \in S$$  \hspace{1cm} (40)
Restoration capacities due to the consequences of disruptions:

\[ \sum_k \sum_m y_{kijt}^{ms} + r_{kijt}^{ms} \leq u_{ijt}^{s}; \quad \forall j \in J, c \in C, t \in T, s \in S \]  

(41)

\[ w_{kct} y_{kct} \leq ub_{kct}^{s}; \quad \forall k \in K, c \in C, t \in T, s \in S \]  

(42)

\[ \sum_k \sum_c w_{kct} \leq \sum_j k_j; \]  

(43)

\[ \sum_k x_{kijt} \geq K_j; \quad \forall j \in J, t \in T, s \in S \]  

(44)

Demand fulfilment constraints:

\[ \tilde{D}_{kct} - \sum_j \sum_m y_{kijt}^{ms} - \sum_j y_{kct}^{s} - w_{kct} y_{kct} = q_{kct}^{s}; \quad \forall k \in K, c \in C, t \in T, s \in S \]  

(45)

Restoration capacities due to the consequences of disruptions:

\[ up_{jt}^{s} = \tilde{X}_{jt}^{s}(K_j + W_j) + \sum_{r=1}^{t-1} r_{jt}^{s}; \quad \forall j \in J, t \in T, s \in S \]  

(46)

\[ ut_{jct}^{s} = \left( \tilde{X}_{jct}^{s} \sum_m K_{mct}^{l} z_{jct}^{ml} \right) + \sum_{r=1}^{t-1} \sum_m r_{jct}^{ms} + r_{jct}^{s}; \quad \forall j \in J, c \in C, t \in T, l \in L, s \in S \]  

(47)

\[ ub_{kct}^{s} = \tilde{X}_{kct}^{s} w_{kc} + \sum_{r=1}^{t-1} \sum_m r_{kct}^{ms} + r_{kct}^{s} \]  

(48)

\[ up_{jt}^{s} \leq K_j + W_j; \quad \forall s \in S, \ j \in J, t \in T \]  

(49)

\[ ut_{jct}^{s} \leq \tilde{X}_{jct}^{s} M_{ct}^{l}; \quad \forall j \in J, c \in C, t \in T, m \in M, l \in L, s \in S \]  

(50)

\[ ub_{kct}^{s} \leq w_{kc}^{s}; \quad \forall k \in K, c \in C, t \in T, s \in S \]  

(51)

\[ up_{jt}^{s} = K_j + W_j; \quad \forall s \in S, j \in J \]  

(52)

\[ ut_{jct}^{s} = \tilde{X}_{jct}^{s} M_{ct}^{l}; \quad \forall j \in J, c \in C, m \in M, l \in L, s \in S \]  

(53)

\[ ub_{kct}^{s} = w_{kc}^{s}; \quad \forall k \in K, c \in C, s \in S \]  

(54)

Variable types:

\[ T_{ct}^{s}, T_{ct}^{s} \geq 0; \quad \forall s \in S \]  

(55)

\[ w_{kct}, ub_{kct}^{s} \geq 0; \quad \forall k \in K, c \in C, t \in T, s \in S \]  

(56)

\[ r_{jt}^{s}, up_{jt}^{s} \geq 0; \quad \forall j \in J, t \in T, s \in S \]  

(57)

\[ r_{jct}^{ms}, ut_{jct}^{s} \geq 0; \quad \forall j \in J, c \in C, t \in T, m \in M, s \in S \]  

(58)

\[ r_{jct}^{ms}, y_{jct}^{s} \geq 0; \quad \forall k \in K, j \in J, c \in C, t \in T, m \in M, s \in S \]  

(59)

\[ rb_{kct}, yb_{kct}^{s} \geq 0; \quad \forall k \in K, j \in J, c \in C, t \in T, s \in S \]  

(60)

\[ x_{kjt}^{s} \geq 0; \quad \forall k \in K, j \in J, t \in T, s \in S \]  

(61)
Constraints (34)–(37) ensure that transmission of products from one MP to a DC cannot be made unless that DC is assigned to the MP either as a primary supplier (via constraints (34) and (35)) or as a backup supplier (via constraints (36) and (37)). Constraint (38) guarantees transportation capacity is available only on installed TLs. Constraint (39) shows that the total transported amount of each product from each MP at each period and under each scenario to all DCs is limited by its production capacity. Constraints (40)–(42) control the upper bounds for production, transportation and emergency inventory capacity usage, respectively. Constraint (43) shows that the total emergency inventory cannot be greater than the total production capacity of MPs. Constraint (44) provides a lower bound for production capacity usage in each MP according to the technical limitations. Constraint (45) shows that demand of each product is fully satisfied or partially backordered under each disruption scenario. Constraints (46), (49) and (52) represent the production capacity evolution of MPs over periods. Constraint (46) illustrates the available production capacity at each MP during each period under each scenario (i.e. \( p_{jt} \)). Constraint (49) shows the available production capacity cannot be greater than the initial augmented level, and constraint (52) enforces the final level of production capacity in each MP must be equal to the initial augmented level in those scenarios that complete restoration is possible. Figure 2 clarifies what the model is representing in a specific scenario for production capacity of a given MP over time. That is, the MP has an initial capacity \( K_j \). A decision is made on investment in additional capacity, changing the total initial capacity to \( (K_j + w_j) \). During the first period, the MP operates with capacity \( (K_j + w_j) \), but at the end of first period, the MP’s production capacity is reduced to \( \ell_j(K_j + w_j) \). Restoration efforts increase this capacity by \( r_{p_{j2}} \) at the end of second period. This augmented capacity is available during the third period, and further restoration efforts increase the capacity by \( r_{p_{j2}} \) at the end of third period. This process continues with restoration efforts in each period determined by solving the model. Constraints [(47), (50), (53)] and [(48), (51), (54)] do the same restoration procedure for transportation capacity of TLs and inventory level of DCs, respectively. It is important to mention that when the restoration resources are limited, some delays in restoration process might be unavoidable. However, if required resources are available, it is desirable that restoration is to be completed as soon as possible. Constraints (52)–(54) enforce the final capacities to be restored to their initial augmented levels, but constraints (49)–(51) do not force the solution to restore all of the lost capacities as soon as possible. However, this type of early recovery is desirable in the solution. This behaviour is generated by the proposed resilience indicator. For each part of the chain, the proposed resilience indicator is penalised by the difference between the initial capacity and the available capacity at each period. Finally, constraints (55)–(61) define the types of decision variables.

### 4.3 Integration of two stages

The whole aggregated model is obtained by integrating two stages over all scenarios. We name this model as \( P(I) \), which is written as follows:

\[
P(I): \text{Objective function } = (3) \]

\[
\text{Subject to: } (4)–(9), (19)–(23) \text{ and } (29)–(61)
\]

where \( EW \) in (3) is a combination of two objectives in the second stage, i.e. Equations (18) and (28). This combination is provided by transforming the two objectives of the second stage to a single objective by utilising a multi-objective approach, which is elaborated in the next section.
5. Solution method

To solve the proposed model, a multi-step solution method is developed. In the first step, Reservation Level-driven Tchebycheff Procedure (RLTP) developed by Reeves and MacLeod (1999) is applied to convert the original bi-objective model of the second stage into an equivalent single objective model. Then, the first and the second stages of the two-stage model are aggregated over all disruption scenarios. Next, the aggregated possibilistic model is converted into an equivalent crisp model by applying the efficient possibilistic programming method developed by Jiménez et al. (2007). Finally, the equivalent crisp integrated model is solved to find the preferred compromise solution. The proposed solution approach is elaborated in the next two subsections.

5.1. The equivalent single objective model of the second stage using RLTP

There are various scalarising methods for solving bi-objective and multiple objective programmes (MOPs). It is noted that from algorithmic perspective, there is a huge difference between bi-objective and multi-objective programmes. In bi-objective programmes, it is possible to eliminate weakly efficient choices in the pay-off table and finding Pareto front (i.e. the set of non-dominated solutions) exactly, while for MOPs the efficient set could be estimated by constructing the pay-off table. Among available MOP approaches, weighted sum method (WSM), epsilon-constraint method and Tchebycheff-based approaches are frequently applied. According to the literature, WSM is not appropriate to estimate Pareto front (i.e. the set of non-dominated solutions) as it cannot guarantee yielding an efficient solution or reaching to a new efficient solution in each run of the equivalent single-objective programme (SOP). Also, through the epsilon-constraint method, the most important objective function is often optimised while the other objectives are added to the constraints. However, in real cases it might be difficult to make the DM choosing the most important objective. Furthermore, the epsilon-constraint method is unable to find non-extreme efficient solutions, which makes the correct estimation of Pareto front impossible (see for instance Torabi, Baghersad, and Mansouri 2015). Nevertheless, Tchebycheff metric-based scalarising methods are able to find both extreme and non-extreme efficient solutions in either convex or non-convex MOPs yielding to estimate a reasonable Pareto front. They are also able to find both supported and unsupported non-dominated solutions for those MOPs with a non-convex feasible region (like a mixed integer MOP). Note-worthy, unsupported non-dominated solutions are the solutions which are dominated by a convex combination of other non-dominated solutions (Demirtas and Üstün 2008). Among available Tchebycheff metric-based MOP methods, we apply RLTP, which is one of well-known interactive MOP methods for generating non-dominated solutions in an effective interaction with DM (Reeves and MacLeod 1999). It is worth noting that in an interactive MOP approach, the set of preferred non-dominated solutions is systematically reduced iteration by iteration through incorporating DM’s updated preferences at each iteration. Accordingly, as the proposed model in this paper is a mixed integer MOP (i.e. a non-convex MOP), and having an interaction with DM in the considered problem is necessary for reducing the set of preferred non-dominated solutions, RLTP method is selected to solve the formulated MOP. In what follows, a brief description of RLTP is provided.

Suppose there are \( K \) objectives. First, the number of solutions (\( P \geq K \)) for presenting to the DM at each iteration is defined. Next, a reference vector called \( z^{**} \) for each objective is defined as:

\[
    z_i^{**} = \max_{x \in S} [f_i(x) : x \in S] + \varepsilon_i; \quad i = 1, \ldots, K
\]

where \( \varepsilon_i \) is a small positive scalar associated with \( i \)th objective and \( S \) is the primary solution space of the model. Let \( RL_i \) be the reservation level for the \( i \)th objective which is set as \( RL_i = -\infty \) for the first iteration. Next, a group of \( 2P \) dispersed weight vectors (i.e. \( A = [\lambda \in \mathbb{R}^P : \lambda_i \in (0,1) \text{ and } \sum_i \lambda_i = 1] \)) is generated. Afterwards, the respective Tchebycheff programme for each weight vector (i.e. model (63)–(66)) is solved:

\[
    \text{Min } |RLTP - \rho \sum_i z_i|
\]

s.t. \( RLTP \geq \lambda_i(z_i^{**} - z_i) \); \quad i = 1, \ldots, K

\[
    f_i(x) = z_i; \quad i = 1, \ldots, K
\]

\[
    z_i \geq RL_i; \quad i = 1, \ldots, K
\]

\[
    x \in S
\]
where $\rho$ is a small positive scalar (often something between 0.0001 and 0.01). The $P$ most dispersed objective vectors obtained from the former model are presented to the DM. If DM prefers to continue the search process, he/she must partition the current solutions into the more preferred and less preferred clusters. Also, $RL$s should be revised by DM to reduce the objective space for which they must be set less than or equal to the worst value for that objective among the current more preferred solutions. Yet, at least one $RL$ must be set greater than an objective value of current less preferred solutions in order to reduce the objective space. After that, procedure returns back to the step of preparing $2P$ new dispersed weight vectors again. The algorithm stops whenever DM is satisfied with the provided solution.

It is important to mention that RLTP fits to the case of this paper as an interactive procedure is needed for making trade-off between cost and resilience of the chain through an interaction with DM. By applying RLTP, $P(I)$ is rewritten as follows:

$$P(I) : \text{Min } G_0 = DRC + REI + (RLTP - \rho \cdot \{CVaRc + CVaRr\})$$

S.T.

(4)–(9), (19)–(23) and (29)–(61)

$$RLTP \geq \lambda_1 \cdot \{CVaRc - \text{BestValue}(CVaRc)\}$$

$$RLTP \geq \lambda_2 \cdot \{CVaRr - \text{BestValue}(CVaRc)\}$$

$$CVaRc \leq RL1$$

$$CVaRr \leq RL2$$

5.2. Finding the equivalent crisp model

Several methods relying on the possibility theory (Zadeh 1999) have been developed in the literature for handling possibilistic mathematical models. In this paper, a possibilistic programming method proposed by Jiménez et al. (2007) is applied to deal with the impreciseness of parameters and transforming the original possibilistic model into its crisp counterpart. In this regard, without loss of generality, we assume that each imprecise parameter is formulated as a triangular possibility distribution in the form of a triangular fuzzy number. For example, imprecise parameter $\tilde{n}$ is characterised by three prominent values $n^o$, $n^m$ and $n^p$ denoting the most pessimistic, the most likely and the most optimistic values of $\tilde{n}$. In this way, $\tilde{n}$ is denoted by $\tilde{n} = (n^p, n^m, n^o)$ whose membership function is defined as:

$$\mu_{\tilde{n}}(x) = \begin{cases} f_\theta(x) = \frac{x - n^p}{n^m - n^p} & \text{if } n^p \leq x \leq n^m \\ 1 & \text{if } x = n^m \\ g_\theta(x) = \frac{x - n^m}{n^o - n^m} & \text{if } n^m \leq x \leq n^o \\ 0 & \text{if } x \leq n^o \text{ or } x \geq n^o \end{cases}$$

(72)

Also, the expected interval (EI) and expected value (EV) of $\tilde{n}$ are defined as (Jiménez et al. 2007):

$$EI(\tilde{n}) = [E_1^n, E_2^n] = \left[ \int_0^1 f^{-1}_\theta(x) \, dx, \int_0^1 g^{-1}_\theta(x) \, dx \right] = \left[ \frac{1}{2} (n^p + n^m), \frac{1}{2} (n^m + n^o) \right]$$

$$EV(\tilde{n}) = \frac{E_1^n + E_2^n}{2} = \frac{n^p + 2n^m + n^o}{4}$$

(73) (74)

Without loss of generality, for any pair of fuzzy numbers like $\tilde{a}$ and $\tilde{b}$, the degree in which $\tilde{a}$ is bigger than $\tilde{b}$ is defined as (Jiménez 1996):

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 0 & \text{if } E_2^a - E_1^b < 0, \\ \frac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_1^b)} & \text{if } 0 \in [E_1^a - E_2^b, E_2^a - E_1^b], \\ 1 & \text{if } E_1^a - E_2^b > 0 \end{cases}$$

(75)

In other words, $\tilde{a}$ is bigger than or equal to $\tilde{b}$ at least at degree $\alpha$ if we have $\mu_M(\tilde{a}, \tilde{b}) \geq \alpha$, which is represented by $\tilde{a} \geq_{\alpha} \tilde{b}$. Now, consider the following possibilistic linear programming model:
\[
\min z = \bar{c}'x
\]

S.T.
\[
\tilde{a}_i x \geq \tilde{b}_i, i = 1, \ldots , l
\]
\[
\tilde{a}_i x = \tilde{b}_i, i = l + 1, \ldots , m
\]
\[
x \in \mathbb{R}^p
\]

For a given decision vector \((x \in \mathbb{R}^n)\), constraints (77) are feasible in degree of \(\alpha\) (or \(\alpha\)-feasible) if we have (Jiménez et al. 2007):
\[
\min_{i=1, \ldots , l} \{\mu_M(\tilde{a}_i x, \tilde{b}_i)\} = \alpha
\]

In other words, according to Equation (75), \(\tilde{a}_i x \geq \tilde{b}_i\) is equivalent to:
\[
\frac{E_{\tilde{a}_i}^x - E_{\tilde{b}_i}^x}{E_{\tilde{a}_i}^x + E_{\tilde{b}_i}^x - E_{\tilde{a}_i}^x} \geq \alpha; \quad i = 1, \ldots , l
\]

Or:
\[
[(1 - \alpha)E_{\tilde{a}_i}^x + \alpha E_{\tilde{b}_i}^x]x \geq \alpha E_{\tilde{b}_i}^x + (1 - \alpha)E_{\tilde{a}_i}^x; \quad i = 1, \ldots , l
\]

Also, for equality constraints (78) we know \(\tilde{a}_i x = \tilde{b}_i\) is equal to \(\tilde{a}_i x \geq \gamma \tilde{b}_i\) and \(\tilde{a}_i x \leq \gamma \tilde{b}_i\). Therefore, the crisp equivalent constraints could be written as follow:
\[
\begin{cases}
(1 - \alpha)E_{\tilde{a}_i}^x + \frac{\alpha}{2}E_{\tilde{b}_i}^x \geq \gamma E_{\tilde{b}_i}^x + (1 - \alpha)E_{\tilde{a}_i}^x; \quad i = l + 1, \ldots , m
\end{cases}
\]

Finally, imprecise parameters in the possibilistic objective function are transformed to their crisp counterparts by applying the expected value term, i.e. Equation (74). Hence, the original possibilistic model (76)–(79) is transformed into its \(\alpha\)-parametric crisp counterpart as follows:
\[
\min z = EV(\tilde{c})x
\]

S.T.
\[
(82) \text{ and } (83)
\]
\[
x \in \mathbb{R}^p
\]

By applying the above-mentioned method in this subsection, the imprecise data in \(P(l)\) can be handled and the equivalent crisp model is provided.

6. Numerical experiments

We explore properties of the considered problem and show the usefulness of the proposed model in this section. It should be mentioned that the proposed model has been inspired by a real-life case in precision machinery and transmission components industry (i.e. the works of Liang and Cheng (2009) or Liang (2011)), which is also possible to be observed in other supply chains. Furthermore, to the best of our knowledge, there is no similar model in the literature addressing a tactical supply chain problem under disruption risks, which can be compared with the one proposed in this paper. Therefore, we generate a number of random numerical examples whose computational results are used to show the applicability and usefulness of the proposed model in practice. Nevertheless, exploring some real applications of the proposed model in future works could approve its applicability and effectiveness in different contexts, which is in our research agenda.

Required fuzzy triangular parameters are produced based on the LH method (Lai and Hwang 1992). In this regard, the most likely value \((n^m)\) for each fuzzy parameter is randomly generated based on a specific uniform distribution. Then, the most pessimistic \((n^p)\) and the most optimistic \((n^o)\) values of the fuzzy parameter \((ii)\) are calculated as \((n^p = 0.8n^m)\) and \((n^o = 1.2n^m)\), respectively. Feasibility degrees of possibilistic constraints for all test problems are set to 0.8. The crisp equivalent model is coded in GAMS 23.5/CPLEX 12.2 optimisation package. All of experiments are
done on a laptop with Intel Core i7 processor running at 2 GHz with 4 GB RAM. Furthermore, required parameters of RLTP for all numerical experiments are shown in Table 2.

6.1. Data generation and model validation

In order to validate the proposed model, five test problems are solved whose characteristics are presented in Tables B1 and B2 of Appendix 2. As there might be partial disruptions in capacities of MPs, DCs and TLs under each disruption scenario, the number of potential disruption scenarios can be infinite. However, the literature of supply chain risk management accentuates that the number of scenarios should be reduced to a manageable list (Pettit 2008; Olson and Wu 2013). Shapiro (2007) suggested sampling as a technique to tackle the problem of infinite scenarios in risk management. Each risk is characterised by two dimensions: likelihood and severity. Risk filtering models based on likelihood and severity are addressed by Haimes (2004). Different combinations of likelihood and severity build up the Risk Matrix which addresses different regions for prioritising disruption risk scenarios from high priority to low priority (U.S. Department of Defense 2000). In this regard, each disruption scenario that is located in the high-priority region based on its likelihood and consequences should be added to the list of critical scenarios. As Peng et al. (2011) discussed, the disruption probability of more than two unrelated facilities at the same time has sufficiently low probability that it is not worth planning for them. Hence, our presumption is that in each scenario only one part of the chain is disrupted (i.e. production capacity of a MP or transmission capacity of a TL or emergency inventory in a DC). Table B3 of Appendix 2 clarifies the likelihood and consequences of considered scenarios. The last scenario for each test problem is considered as ‘No disruption’ (i.e. normal situation) scenario. It should be mentioned that in all instances we assume that in all scenarios, lost capacities could be restored completely at the end of planning horizon (i.e. sr = S), and 3PL can carry products from all MPs to all of DCs (i.e. j_e = j, ∀e ∈ C). Table 3 reports the normalised objective function value of model P(I) and required computational time for each test problem.

6.2. Verifying the robustness and resilience

In order to verify the robustness of the proposed model, we introduce another version of the basic model, called P(II). As mentioned before, P(I) is the model that takes into account the worst-case scenarios by applying CVaR, while in P(II), CVaR and its respective constraints are excluded from the second stage of the model. Instead of CVaR and considering the worst-case scenarios, P(II) includes the expected values of the objective functions of the second stage as follows:

\[
P(II) : \text{Min } G1 = DRC + REI \text{ + RLTP} - \rho \cdot \sum_s p_s \cdot (Gcs + Grs)
\]

S.T.

\[
4) - 9), (34) - (54), (56) - (61) and (68)-(71).
\]

We consider another instance whose characteristics are shown in Tables B4–B6 of Appendix 2. The obtained results of P(I) and P(II) are summarised in Table 4. In Table 4, the normalised objective function values of P(I) and P(II), as well as, the objective value of each goal in the second stage are shown for 10 non-dominated solutions under considered values for \( \lambda_1 \) and \( \lambda_2 \). As Table 4 shows, the objective value for P(I) is greater than P(II), and this behaviour might be originated from the fact that P(I) focuses on the worst-case scenarios and makes a more conservative solution than P(II). Indeed, P(I) which utilises CVaR as the risk measurement makes the system prepared with more risk mitigation options to be able to stand against worst-case disruption scenarios, nevertheless, costs are pushed up in such a system.

Figure 3 shows the behaviour of P(I) and P(II) under different confidence levels for the first non-dominated solution as reported in Table 4. This figure shows that reducing the confidence level in P(I) results in closeness of P(I) and P(II). This result could be justified by the fact that, P(I) accounts for the worst-case scenarios via CVaR measure, whilst P(II) considers the expected loss under all scenarios. In this regard, the lower values of confidence level in P(I) imply

<table>
<thead>
<tr>
<th>( \rho )</th>
<th>Weight of the first objective function of the second stage (( \lambda_1 ))</th>
<th>Weight of the second objective function of the second stage (( 1 - \lambda_1 ))</th>
<th>The number of presented non-dominated solutions at each iteration</th>
<th>Number of iterations</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>Uniform (0,1)</td>
<td>( 1 - \lambda_1 )</td>
<td>10</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 2. Parameters of RLTP.
the lower attention of the DM to the worst-cases (i.e. equal importance of all scenarios which is somehow the same approach in \( P(II) \)).

As mentioned in the definition of constraints (20)–(22) and (30)–(32), a major advantage of \( P(I) \) in comparison with \( P(II) \) is the identification of disruption scenarios with extreme consequences that overpass acceptable thresholds (i.e. \( \text{Var}_c \) and \( \text{Var}_r \)), via constraints (20)–(22) and (30)–(32). The obtained results for the considered case in this section show scenarios 1, 6 and 10 are destructive disruption scenarios as their \( TC \) are positive values. Figures 4 and 5 show the first and the second objective function values of the second stage of the model, i.e. \( \text{CVaR}_c \) and \( \text{CVaR}_r \) in \( P(I) \), as well, \( E(G_c) \) and \( E(G_r) \) in \( P(II) \), respectively. Alongside, these figures highlight those destructive disruption scenarios (i.e. scenarios 1, 6 and 10) as their \( TC \) are positive values. As a matter of fact, in \( P(I) \), \( \text{Var} \) and \( \text{CVaR} \) are minimised simultaneously, where \( \text{CVaR} \) accounts for high-magnitude scenarios in which their losses exceed \( \text{Var} \). However, \( P(II) \) minimises the expected loss of all scenarios.

Table 5 shows the resulted configuration of production–distribution chain for the considered case in addition to risk mitigation decisions in the first non-dominated solution of \( P(I) \). The second column of Table 5 reports the primary supplier of each DC, and the other four columns present risk mitigation decisions. As the results show, the second, the fifth and the sixth DCs use backup suppliers and backup logistics services; whereas, emergency inventory of both products is prepared in the first, the third and the seventh DCs. In the fourth and eighth DCs, emergency inventory of the second

<table>
<thead>
<tr>
<th>Table 3. Results of test problems.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test problem No.</td>
</tr>
<tr>
<td>Normalised objective function value</td>
</tr>
<tr>
<td>CPU time (seconds)</td>
</tr>
</tbody>
</table>

![Figure 3. Comparing the behaviour of \( P(I) \) and \( P(II) \) under different confidence levels for the first non-dominated solution.](image)

Table 4. The obtained results of the considered instance.

<table>
<thead>
<tr>
<th>Non-dominated solution No.</th>
<th>( \lambda_1 )</th>
<th>( \lambda_2 )</th>
<th>( \text{CVaR}_c )</th>
<th>( \text{CVaR}_r )</th>
<th>NOFV</th>
<th>( E(G_c) )</th>
<th>( E(G_r) )</th>
<th>NOFV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45</td>
<td>0.55</td>
<td>273,272,870.52</td>
<td>7,461,269.46</td>
<td>40.77</td>
<td>132,539,820.8</td>
<td>2,955,162.179</td>
<td>8.108</td>
</tr>
<tr>
<td>2</td>
<td>0.38</td>
<td>0.62</td>
<td>277,437,900.48</td>
<td>7,368,226.36</td>
<td>42.03</td>
<td>134,559,898.15</td>
<td>2,918,310.88</td>
<td>9.23</td>
</tr>
<tr>
<td>3</td>
<td>0.70</td>
<td>0.30</td>
<td>258,054,007.97</td>
<td>7,801,245.43</td>
<td>41.32</td>
<td>125,158,534.47</td>
<td>3,089,815.42</td>
<td>9.27</td>
</tr>
<tr>
<td>4</td>
<td>0.42</td>
<td>0.58</td>
<td>275,094,689.65</td>
<td>7,420,571.62</td>
<td>39.09</td>
<td>133,423,419.65</td>
<td>2,939,043.11</td>
<td>10.17</td>
</tr>
<tr>
<td>5</td>
<td>0.02</td>
<td>0.98</td>
<td>299,472,942.41</td>
<td>6,875,982.95</td>
<td>40.30</td>
<td>145,247,093.35</td>
<td>2,723,349.54</td>
<td>9.98</td>
</tr>
<tr>
<td>6</td>
<td>0.50</td>
<td>0.50</td>
<td>270,236,505.29</td>
<td>7,529,099.18</td>
<td>40.56</td>
<td>131,067,156.16</td>
<td>2,982,027.29</td>
<td>6.25</td>
</tr>
<tr>
<td>7</td>
<td>0.33</td>
<td>0.67</td>
<td>280,560,147.06</td>
<td>7,298,478.12</td>
<td>39.80</td>
<td>136,074,216.06</td>
<td>2,890,685.91</td>
<td>7.54</td>
</tr>
<tr>
<td>8</td>
<td>0.80</td>
<td>0.20</td>
<td>252,073,546.54</td>
<td>7,934,843.67</td>
<td>39.80</td>
<td>122,257,956.43</td>
<td>3,142,729.27</td>
<td>6.18</td>
</tr>
<tr>
<td>9</td>
<td>0.76</td>
<td>0.24</td>
<td>254,295,643.69</td>
<td>7,885,203.98</td>
<td>38.81</td>
<td>123,335,693.70</td>
<td>3,123,068.63</td>
<td>6.56</td>
</tr>
<tr>
<td>10</td>
<td>0.60</td>
<td>0.40</td>
<td>264,163,774.83</td>
<td>7,664,758.63</td>
<td>39.74</td>
<td>128,121,826.81</td>
<td>3,035,757.51</td>
<td>10.49</td>
</tr>
</tbody>
</table>

Note: N: Normalised, OFV: Objective Function Value.
product and the first product is stored, respectively. Also, the resulted initial production capacity and additive production capacity of MPs (which is the other risk mitigation decision) are reported in Figure 6.

For the considered case in this section, as shown in the third row and third column of Table B6, the initial production capacity of the second MP is completely disrupted at the beginning of planning horizon (since $E_2^3$ is 0). Then, restoration is done gradually during next periods until the last period in which the production capacity is recovered completely. Figure 7 shows the recovery procedure of production capacity in a disrupted MP for the first non-dominated solution of $P(I)$. This figure inspires a well-known triangle called Resilience Triangle in the resilience literature (see for instance Torabi, Baghersad, and Mansouri 2015). It is used to illustrate and measure the loss of functionality of a system over time due to disruptions, as well as, the pattern of recovery and the amount of time it takes for the system to return to the normal performance level (Falasca, Zobel, and Cook 2008). Two dimensions of this triangle show the severity of disruption and recovery state of the system. Hence, the smaller the size of this triangle, the more resilient the system is (Ta, Goodchild, and Pitera 2009). It should be reminded that the proposed resilience indicator as the second objective function of the second stage of the model becomes worsen by the difference between the initial capacity and the available capacity at each period, which in turn, implies smaller size of Resilience Triangle is desirable.
6.3 Verifying the effect of resilience-enhancing investments

As mentioned in Section 3, the proposed model considers three resilience-enhancing investment options (i.e. extending capacities in MPs, considering backup layer for TLs and prepositioning of emergency inventory in DCs). In this section, the effect of these options is verified using an instance whose characteristics are shown in Table B7 and Table B8 of Appendix 2. Required parameters are generated based on random distributions shown in Table B5 of Appendix 2. We consider the following five policies:

1. Applying all options.
2. Applying only extending capacities in MPs.
3. Applying only emergency inventory in DCs.
4. Applying only backup layer for TLs.
5. Applying no option.

We ran \( P(I) \) for these policies and the obtained results for the initial cost of the first stage, incurred cost of the second stage and the total cost are shown in Figure 8. This figure shows although the first policy imposes the highest initial...
cost, but total cost is kept at the lowest level in comparison with other polices. This result is similar to the results of Snyder and Daskin (2006) and Salehi Sadghiani et al. (2015), where they have declared by a little increase in initial cost (i.e. investing on resilience-enhancing options), significant improvements in total cost can be achieved. For example, consider comparison of the third and the fifth policies. A small increase in initial cost by %17.3 (i.e. from 141,357,640.4 to 165,894,713.8) reduces incurred cost and total cost by 36.7 and 28.9% (i.e. from 830,418,690.9 to 525,071,798.3 and from 971,776,331.3 to 690,966,512.1), respectively. Consequently, Figure 8 shows the advantages of the proposed model which considers all resilience-enhancing options (i.e. the first policy).

7. Conclusion
This paper addresses an integrated tactical production–distribution planning problem in a two-echelon supply chain, while active capacity levels of production facilities, transportation links and distribution centres are vulnerable to various operational and disruption risks. In order to handle operational and disruption risks concurrently, a two-stage scenario-based mixed stochastic-possibilistic programming model is presented. Additional capacities in production facilities, backup layer for transportation links and prepositioning of emergency inventory in distribution centres are considered as the available risk mitigation (i.e. resilience-enhancing) options. Furthermore, the recovery plan of lost capacities is determined by the proposed model. A new indicator is developed for optimising the resilience of the chain quantitatively based on available capacities provided by required restorations. The expected worst case of the second stage objective function is considered, utilising the conditional value at risk (CVaR), in order to make robust decisions. The developed two-stage scenario-based mixed stochastic-possibilistic programming model is then converted to its crisp counterpart for which RLTP method is used to generate Pareto-optimal (compromise) solutions. A number of numerical experiments are conducted from which some useful managerial insights are drawn.

Despite the consideration of the mentioned issues, our research has some limitations that should be addressed in future works. We assumed that disruptions could occur independently in different parts of the production–distribution chain; however, in real-world situations, there might be interdependencies between some disruptions (for example, a fire after an earthquake). Accordingly, accounting for multiple concurrent disruptions at some parts of the chain under each scenario, and developing an appropriate resilience assessment index for this situation would be worthwhile. Extending the proposed model by including the supply network (for instance, see Torabi, Baghersad, and Mansouri 2015) could be a promising direction for further research. Other possible avenues for future research include:

- Developing other quantitative resilience measures for the considered problem.
- Incorporating other risk mitigation options like insurance of facilities into the formulation.
- Applying the scenario planning and clustering approaches in order to reduce the number of disruption scenarios to a reasonable range.
- Developing exact or meta-heuristic algorithms for handling large-scale instances.
- Exploring applications of the presented work in various manufacturing supply chains to promote its applicability and effectiveness in different contexts.

Disclosure statement
No potential conflict of interest was reported by the authors.

References


Appendix 1.
Notations used for mathematical modelling are reported as follows:

Sets
\( j \in J \) Set of MPs
\( c \in C \) Set Of DCs
\( j_c \in j \) Set of MPs that 3PLs can transport products from them to \( DC_c \)
\( s \in S \) Set of disruption scenarios
\( sr \subseteq S \) Set of disruption scenarios through which lost capacities could be restored completely until the end of planning horizon
\( t \in T \) Set of planning periods
\( k \in K \) Set of products
\( m \in M \) Set of transportation modes
\( l \in L \) Set of transportation capacity levels

Parameters
\( c_{f_j} \) Unit cost of restoring production capacity of \( MP_j \) ($/unit of product)
\( c_{m} \) Unit cost of restoring transportation capacity of mode \( m \) ($/unit of product)
\( f_{j} \) Unit cost of preparing initial additional production capacity in \( MP_j \) ($/unit of product)
\( f \) Unit cost of preparing emergency inventory of product \( k \) in \( DC_c \) ($/unit of product)
\( c_{e} \) Contracting cost with 3PL for preparation of backup TLs for \( DC_c \) ($)
\( t_{r_{j_{cm}}} \) Unit cost of transporting product \( k \) by mode \( m \) from \( MP_j \) to \( DC_c \) ($/unit of product)
\( t_{b} \) Unit cost of transporting product \( k \) by 3PL from \( MP_j \) to \( DC_c \) ($/unit of product)
\( K_i \) Initial production capacity of \( MP_j \) in each period (unit of product)
\( K_{l_{j}} \) Lower bound for production capacity usage of \( MP_j \) in each period (unit of product)
\( K_{m_{j}} \) Transmission capacity of transportation mode \( m \) with size \( l \) in each period (unit of product)
\( D \) Demand of product \( k \) at \( DC_c \) in period \( t \)
\( p_s \) Probability occurrence of scenario \( s \)
\( \tilde{\xi}_s^{f_{j}} \) Fraction of production capacity in \( MP_j \) that remains available immediately after the realisation of scenario \( s \)
\( \tilde{\xi}_s^{e_{cm}} \) Fraction of transmission capacity of TL\(_{j_{cm}}\), with mode \( m \), that remains available immediately after the realisation of scenario \( s \)
\( \tilde{\xi}_s^{e_{cm}} \) Fraction of emergency inventory of product \( k \) in \( DC_c \) that remains available immediately after the realisation of scenario \( s \)
\( M \) A big number
\( n_{i_{cm}}^{m_{l}} \) Installation cost of making a TL with mode \( m \) and size \( l \) between \( MP_j \) and \( DC_c \) ($)
\( B \) Backorder cost of product \( k \) in \( DC_c \) ($/unit of product)
\( k_{j_{cm}} \) Unit production cost of product \( k \) in \( MP_j \) ($/unit of product)
\( e_{p} \) Relative importance for loss of resilience in restoration of production capacity ($)
\( e_{d} \) Relative importance for loss of resilience in restoration of distribution capacity ($)
\( e_{l} \) Relative importance for loss of resilience in restoration of emergency inventory capacity ($)

Decision variables
\( w_{j} \) Additional initial production capacity in \( MP_j \) (unit of product)
\( w_{b_{j_{cm}}} \) Emergency inventory of product \( k \) in \( DC_c \)
\( w_{y_{l_{j_{cm}}}^{s_{t}}} \) Backup inventory of product \( k \) in \( DC_c \) that is used in period \( t \) under scenario \( s \)
\( z_{c} \) 1 if contract with 3PL is made for transporting products from backup MPs to \( DC_c \); otherwise = 0
\( z_{m_{jl}} \) 1 if TL\(_{j_{cm}}\) is equipped by transportation mode \( m \) and size \( l \); otherwise = 0
\( r_{f_j}^{p_{s}} \) Production capacity of \( MP_j \) that is restored in period \( t \) under scenario \( s \) (unit of product)
\( r_{t_{m_{jl}}} \) Transportation capacity of TL\(_{j_{cm}}\) with mode \( m \) that is restored in period \( t \) under scenario \( s \) (unit of product)
\( r_{x_{l_{j_{cm}}}^{s_{t}}} \) Amount of emergency inventory that is transported from \( MP_j \) to \( DC_c \) by internal TL\(_{j_{cm}}\) with mode \( m \) in period \( t \) under scenario \( s \)
\( r_{b_{j_{cm}}}^{s_{t}} \) Amount of emergency inventory that is transported from \( MP_j \) to \( DC_c \) by 3PL provider in period \( t \) under scenario \( s \)
\( u_{p_{s}} \) Production capacity of \( MP_j \) that is available in period \( t \) under scenario \( s \) (unit of product)
\( u_{t_{m_{jl}}} \) Transportation capacity of TL\(_{j_{cm}}\) that is available in period \( t \) under scenario \( s \) (unit of product)
\( u_{f_{j_{cm}}} \) Emergency inventory level of product \( k \) in \( DC_c \) that is available in period \( t \) under scenario \( s \)
\( x_{f_{j_{cm}}}^{s_{t}} \) Amount of product \( k \) produced at \( MP_j \) in period \( t \) under scenario \( s \)

(Continued)
Appendix 2.

Table B1. The main characteristics of the test problems in Section 6.1.

<table>
<thead>
<tr>
<th>Problem No.</th>
<th>MPs</th>
<th>DCs</th>
<th>Disruption scenarios</th>
<th>Planning periods</th>
<th>Product types</th>
<th>Transportation modes</th>
<th>Transportation capacity levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>6</td>
<td>7</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>8</td>
<td>9</td>
<td>6</td>
<td>6</td>
<td>4</td>
<td>3</td>
</tr>
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<td>4</td>
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<td>11</td>
<td>11</td>
<td>7</td>
<td>7</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>13</td>
<td>13</td>
<td>8</td>
<td>9</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

Table B2. The uniform distributions used to generate the centre of symmetric fuzzy parameters and crisp parameters in Section 6.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Random distribution</th>
<th>Parameter</th>
<th>Random distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \bar{c}_j )</td>
<td>Uniform(5,8)</td>
<td>( K_{ji} )</td>
<td>0.6. ( K_{ji} )</td>
</tr>
<tr>
<td>( \bar{c}_m )</td>
<td>Uniform(17,29)</td>
<td>( \bar{D} )</td>
<td>Uniform(1000,1200)</td>
</tr>
<tr>
<td>( \bar{f}_j )</td>
<td>Uniform(20,25)</td>
<td>( k_{ji} )</td>
<td>Uniform(500,600)</td>
</tr>
<tr>
<td>( f )</td>
<td>Uniform(12,17)</td>
<td>( \bar{r}_{ml} )</td>
<td>Uniform(5,60)</td>
</tr>
<tr>
<td>( k_t )</td>
<td>Uniform(1000,1500)</td>
<td>( \beta )</td>
<td>Uniform(5,6)</td>
</tr>
<tr>
<td>( k_{jc} )</td>
<td>Uniform(3,8)</td>
<td>( p_{ji} )</td>
<td>Uniform(5,6)</td>
</tr>
<tr>
<td>( tr_{bc} )</td>
<td>Uniform(80,100)</td>
<td>( ep )</td>
<td>Uniform(15,25)</td>
</tr>
<tr>
<td>( K_{ik} )</td>
<td>4000.k</td>
<td>( ed )</td>
<td>Uniform(10,32)</td>
</tr>
<tr>
<td>( K_{ij} )</td>
<td>0.5. ( K_{ij} )</td>
<td>( ei )</td>
<td>Uniform(10,15)</td>
</tr>
</tbody>
</table>
Table B3. Likelihood and consequences of disruption scenarios in test problems of Section 6.1.

<table>
<thead>
<tr>
<th>Disruption scenarios</th>
<th>Problem No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L</td>
<td>C</td>
<td>L</td>
<td>C</td>
<td>L</td>
<td>C</td>
</tr>
<tr>
<td>1</td>
<td>0.05</td>
<td>$\tilde{L}_{1}^1 = 0$</td>
<td>0.05</td>
<td>$\tilde{L}_{2}^1 = 0$</td>
<td>0.06</td>
<td>$\tilde{L}_{1,4}^1 = 0.01$</td>
</tr>
<tr>
<td>2</td>
<td>0.03</td>
<td>$\tilde{L}_{2,2,1}^2 = 0$</td>
<td>0.06</td>
<td>$\tilde{L}_{2,6}^2 = 0$</td>
<td>0.01</td>
<td>$\tilde{L}_{2,2}^2 = 0$</td>
</tr>
<tr>
<td>3</td>
<td>0.07</td>
<td>$\tilde{L}_{1,4,2}^3 = 0.10$</td>
<td>0.04</td>
<td>$\tilde{L}_{3,4,2}^3 = 0.10$</td>
<td>0.03</td>
<td>$\tilde{L}_{4,4}^3 = 0$</td>
</tr>
<tr>
<td>4</td>
<td>0.02</td>
<td>$\tilde{L}_{2,1,4}^4 = 0.05$</td>
<td>0.05</td>
<td>$\tilde{L}_{4}^4 = 0.2$</td>
<td>0.03</td>
<td>$\tilde{L}_{3,7,2}^4 = 0.04$</td>
</tr>
<tr>
<td>5</td>
<td>0.83</td>
<td>ND</td>
<td>0.04</td>
<td>$\tilde{L}_{4,1}^5 = 0$</td>
<td>0.07</td>
<td>$\tilde{L}_{5,2}^5 = 0$</td>
</tr>
<tr>
<td>6</td>
<td>–</td>
<td>–</td>
<td>0.72</td>
<td>ND</td>
<td>0.04</td>
<td>$\tilde{L}<em>{3,5}^6 = 0, \tilde{L}</em>{1,6,1}^6 = 0.05$</td>
</tr>
<tr>
<td>7</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.07</td>
<td>$\tilde{L}_{6,5}^7 = 0$</td>
</tr>
<tr>
<td>8</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.63</td>
<td>ND</td>
</tr>
<tr>
<td>9</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>10</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>11</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>12</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>13</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

ND: No Disruption, L: Likelihood, C: Consequences.

Table B4. The main characteristics of the test problems in Section 6.2.

<table>
<thead>
<tr>
<th>MP</th>
<th>DC</th>
<th>Disruption scenarios</th>
<th>Planning periods</th>
<th>Product types</th>
<th>Transportation modes</th>
<th>Transportation capacity levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>8</td>
<td>14</td>
<td>12</td>
<td>2</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

Table B5. The uniform distribution used to generate the centre of symmetric fuzzy parameters and crisp parameters in Section 6.2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Random distribution</th>
<th>Parameter</th>
<th>Random distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{c}_j$</td>
<td>Uniform(500,900)</td>
<td>$k_{m}^j$</td>
<td>Uniform(100,000,200,000), L</td>
</tr>
<tr>
<td>$\tilde{c}_m$</td>
<td>Uniform(19,26)</td>
<td>$D$</td>
<td>Uniform(75,000,85,000)</td>
</tr>
<tr>
<td>$f_j$</td>
<td>Uniform(20,202)</td>
<td>$\alpha$</td>
<td>0.9</td>
</tr>
<tr>
<td>$f$</td>
<td>Uniform(12,17)</td>
<td>$\tilde{z}_{m}^{wi}$</td>
<td>Uniform(500,000,1,000,000)</td>
</tr>
<tr>
<td>$c_{t}$</td>
<td>Uniform(500,000,700,000)</td>
<td>$B$</td>
<td>Uniform(5, 60)</td>
</tr>
<tr>
<td>$\tilde{m}$</td>
<td>Uniform(10,16)</td>
<td>$p_i$</td>
<td>Uniform(3,5)</td>
</tr>
<tr>
<td>$tr_{kc}$</td>
<td>Uniform(80,100)</td>
<td>$ep$</td>
<td>Uniform(15,25)</td>
</tr>
<tr>
<td>$K_i$</td>
<td>Uniform(300,000,400,000)</td>
<td>$ed$</td>
<td>Uniform(10,32)</td>
</tr>
<tr>
<td>$KL_i$</td>
<td>300,000</td>
<td>$ei$</td>
<td>Uniform(10,15)</td>
</tr>
</tbody>
</table>
Table B6. Likelihood and consequences of disruption scenarios in test problems of Section 6.2.

<table>
<thead>
<tr>
<th>Disruption scenarios</th>
<th>L</th>
<th>C</th>
<th>Disruption scenarios</th>
<th>L</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.02</td>
<td>$\bar{\lambda}_1 = \bar{\lambda}_1 = \bar{\lambda}_4 = \bar{\lambda}_6 = 0$</td>
<td>8</td>
<td>0.05</td>
<td>$\bar{\lambda}_4 = \bar{\lambda}_3, 7, 4 = 0$</td>
</tr>
<tr>
<td>2</td>
<td>0.06</td>
<td>$\bar{\lambda}<em>2 = \bar{\lambda}</em>{12} = \bar{\lambda}_{12} = 0$</td>
<td>9</td>
<td>0.03</td>
<td>$\bar{\lambda}_{4, 63} = 0$</td>
</tr>
<tr>
<td>3</td>
<td>0.05</td>
<td>$\bar{\lambda}<em>3 = \bar{\lambda}</em>{2, 1} = 0$</td>
<td>10</td>
<td>0.04</td>
<td>$\bar{\lambda}<em>{4} = \bar{\lambda}</em>{40} = 0$</td>
</tr>
<tr>
<td>4</td>
<td>0.05</td>
<td>$\bar{\lambda}<em>4 = \bar{\lambda}</em>{15, 4} = 0$</td>
<td>11</td>
<td>0.08</td>
<td>$\bar{\lambda}_{11} = 0$</td>
</tr>
<tr>
<td>5</td>
<td>0.08</td>
<td>$\bar{\lambda}<em>5 = \bar{\lambda}</em>{2, 4} = 0$</td>
<td>12</td>
<td>0.03</td>
<td>$\bar{\lambda}<em>5 = \bar{\lambda}</em>{12} = 0$</td>
</tr>
<tr>
<td>6</td>
<td>0.02</td>
<td>$\bar{\lambda}_6 = \bar{\lambda}_6 = 0$</td>
<td>13</td>
<td>0.08</td>
<td>$\bar{\lambda}<em>1 = \bar{\lambda}</em>{13} = 0$</td>
</tr>
<tr>
<td>7</td>
<td>0.12</td>
<td>$\bar{\lambda}<em>7 = \bar{\lambda}</em>{2, 5, 3} = 0.25$</td>
<td>14</td>
<td>0.29</td>
<td>ND</td>
</tr>
</tbody>
</table>

ND: No Disruption, L: Likelihood, C: Consequences.

Table B7. The main characteristics of the test problems in Section 6.3.

<table>
<thead>
<tr>
<th>MPs</th>
<th>DCs</th>
<th>Disruption scenarios</th>
<th>Planning periods</th>
<th>Product types</th>
<th>Transportation modes</th>
<th>Transportation capacity levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>8</td>
<td>9</td>
<td>6</td>
<td>6</td>
<td>4</td>
<td>3</td>
</tr>
</tbody>
</table>

Table B8. Likelihood and consequences of disruption scenarios in test problems of Section 6.3.

<table>
<thead>
<tr>
<th>Disruption scenarios</th>
<th>L</th>
<th>C</th>
<th>Disruption scenarios</th>
<th>L</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.05</td>
<td>$\bar{\lambda}_1 = 0$</td>
<td>6</td>
<td>0.08</td>
<td>$\bar{\lambda}_6 = 0$</td>
</tr>
<tr>
<td>2</td>
<td>0.02</td>
<td>$\bar{\lambda}_2 = 0$</td>
<td>7</td>
<td>0.06</td>
<td>$\bar{\lambda}_4 = 0$</td>
</tr>
<tr>
<td>3</td>
<td>0.03</td>
<td>$\bar{\lambda}<em>3 = \bar{\lambda}</em>{44} = 0$</td>
<td>8</td>
<td>0.07</td>
<td>$\bar{\lambda}_8 = 0$</td>
</tr>
<tr>
<td>4</td>
<td>0.03</td>
<td>$\bar{\lambda}<em>4 = \bar{\lambda}</em>{72} = 0$</td>
<td>9</td>
<td>0.60</td>
<td>ND</td>
</tr>
<tr>
<td>5</td>
<td>0.06</td>
<td>$\bar{\lambda}_5 = 0$</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

ND: No Disruption, L: Likelihood, C: Consequences.