

Increasing supply chain resilience through efficient redundancy allocation: a risk-averse mathematical model

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Abstract: The COVID-19 pandemic has created significant uncertainty in all areas of life, including supply chains (SCs). This paper presents a new risk-averse mixed-integer nonlinear problem mathematical model for the design and planning of a two-echelon resilient SC network. Disruption events, which can partially or completely reduce the available capacity, are included in the model. The model's objective is to minimise the total costs by determining the optimal facility location and capacity, allocation flows and resilience actions for hedging against disruption risk. A solution procedure is tested through computational experiments, and managerial insights were formed based on a numerical example for several disruption configurations, with a specific case of long-term crises similar to the COVID-19 pandemic. The results showed that recovery activities are the most efficient actions to take for a short-term disruption event. Besides, proactive resilience investment in a protection system and flexibility enhancement allows the SC to handle the disruption period with a limited increase in network building costs and overcapacity.

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1. INTRODUCTION AND BACKGROUND

Enterprises worldwide are facing significant challenges from the growing competition and the destabilising effects of climate, disease and other external perils. The COVID-19 outbreak and global pandemic have immensely affected all areas of the economy and society, raising a series of completely novel decision-making settings for supply chain (SC) researchers and practitioners (Ivanov, 2020). Supply chain management (SCM) has been recognised as a critical capability to be able to navigate such risks successfully, with the aim of designing robust and resilient logistics networks to help firms maintain and enhance their competitive advantages as they encounter environmental turbulence (Hatefi and Jolai, 2014). Tang (2006) categorised SC risks into two different types: operational and disruption risk. Operational risk usually has no effect on the functionalities of the SC elements, although it affects the operational factors. On the other hand, disruption risk is related to a particular type of event that may occur that may affect the SC, such as a natural disaster (e.g. earthquake, hurricane, flood) or an intentional/ unintentional human action (e.g. war, terrorist attack, epidemic/pandemic outbreak, strike), which are marked by a low likelihood of occurrence and a high magnitude of consequence.

There is a strong and growing literature on robustness and resilience as two fundamental concepts for analysing SC performance with severe uncertainty consideration and with regard to scattered disruptive events (Ivanov and Dolgui, 2019). Proactive and reactive mitigation strategies are two types of approaches to hedging against disruption and to increasing SC resilience (Carbonara and Pellegrino, 2017). During the SC design process, the proactive approach builds robustness and accounts for possible perturbations without taking into consideration recovery actions (Paul et al., 2019). One of the most common proactive mitigation strategies is planning proactive redundancies (e.g. buffer capacities, back-

up suppliers, pre-positioned inventory, general facility fortification) at the pre-disruption stage (Ivanov and Dolgui, 2019). On the other hand, the reactive mitigation strategies aim to adjust the SC processes and structures when a disruptive event occurs. This can be done through parametrical or structural adaptations, according to the severity of the disruption (Aldrighetti et al., 2019b).

The problem of designing resilient SC networks has been widely studied in recent years (Aldrighetti et al., 2019a; Dolgui et al., 2020; Snyder et al., 2016). Location models for planning reliable systems can be broadly grouped into two main categories that can reflect the different risk attitudes of the decision maker: the risk-neutral and risk-averse models (Aldrighetti et al., 2021). The vast majority of research articles, especially in the past, have focused on risk-neutral decision models, in which facilities are assumed to fail based on pre-defined probabilities (Aldrighetti et al., 2021; Snyder et al., 2016). However, disruptions, by definition, are rare events, and they are thus difficult to predict (Ivanov and Dolgui, 2019; Snyder et al., 2016). Besides, the literature regarding the probability estimations of disruptions points out some fundamental issues: sufficient and valuable historical data may be difficult to obtain, and subjective probabilities must often be used (Aldrighetti et al., 2019a). On the other hand, the risk-averse models allow the decision maker to quantify, control and limit the risk based on his or her preferences. Risk aversion can be included in mathematical models by optimising the worst-case objectives or evaluating the risk measures, such as the p-robustness, deviations from the target, conditional value-at-risk and resilience metrics (Merzifonluoglu, 2015). The literature regarding this type of model is still scarce (Aldrighetti et al., 2021; Snyder et al., 2016). At first, from an SC manager's perspective, it is difficult to justify the investment made in disruption recovery management as today's SCs are cost-oriented and benefits can be reaped only when a disruption occurs, which has a low probability (Li et

al., 2020). In addition, the inclusion of these criteria or measures/constraints leads to an increase in computational complexity (Snoeck et al., 2019). From our point of view, considering the strategic nature of the aforementioned decision-making process, risk aversion can allow managers to evaluate several scenarios, from nominal to worst-case, and to test their SC performance for different disruption configurations.

This study aims to develop a new decision model for building resilient SCs in response to major disruption events. A combination of several resilience actions, i.e. additional capacity, proactive protection systems and recovery actions, have been considered with the objective to analyse the effectiveness of adopting proactive and reactive mitigation strategies to efficiently plan for redundancies and recovery actions. The resultant mixed-integer nonlinear formulation also incorporates risk aversion of decision makers in two ways. Firstly, the scenario generation procedure is based on considering only scenarios with at least one disruption event at an opened facility. Secondly, the decision maker can increase his or her risk-averse attitude by varying the number of possible events that can happen in a scenario. Our study's contribution to the literature is twofold: it increases the body of knowledge in terms of the risk-averse SC network design mathematical model and it provides a deeper understanding of how to plan for redundancies and recovery actions for enhancing SC resilience in several disruption scenarios. To the best of our knowledge, this is the first study that tried to match these modelling features with a complete resilience actions plan and that obtained a good solution within a reasonable computational time.

The organisation of this paper is as follow: section 2 presents the mathematical model, and its formulation is described. Section 3 proposes a solution approach that is tested through computational experiments and a numerical example in section 4. Finally, section 5 contains conclusions and future research directions.

2. MATHEMATICAL MODEL

In this section, we present our formulation of a two-echelon SC network design consisting of facilities and customer zones. Facilities are capacitated based on predefined capacity levels Q_i . It is assumed that customer zones are predetermined and fixed and each customer zone can be supplied by multiple facilities. The demand of each client zone needs to be completely satisfied, otherwise, the system will incur in a penalty cost. A periodic-based scenario modelling is adopted to include dynamics of different time periods along with a number of discrete scenarios, which account for disruption risks. All facilities are subject to possible disruption events that may reduce the installed capacity by percentage θ . To mitigate disruption effects, facilities can proactively increase their installed capacity and customers could be reassigned based on availabilities. In addition, two resilient specific investments are included, as described here below.

- *Investing in protection systems*: facilities can be reinforced through investment in protection systems. These could be seen as specific disruption-resistant features (e.g. water sprinkler against fire, earthquake-resistant racking) or, as

recent trends have shown, more flexible systems that can allow switching or adapting the business and operability based on the needs and dynamics that changed during the disruption (McKinsey, 2020). In this context, flexibility can be achieved by increasing component commonalities, postponements, risk-pooling strategies or by setting up more flexible production systems and industry 4.0 technologies (Andriolo et al., 2015). This resilience investment is expressed as a percentage of the standard facility establishment costs through a set of protection level p . Each level allows a reduction of β_p in the disruption magnitude, and the new disrupted capacity will be $\theta \cdot \beta_p$. It is worth noting that even with the highest protection level, facilities cannot become completely infallible.

- *Planning recovery activities to restore the lost capacity*: Disruption events have a duration dur . After such time periods, there is the possibility invest money in resources and to recover the lost capacity until the nominal installed capacity at period 0 (see Fig. 1) (Ivanov, 2021a).

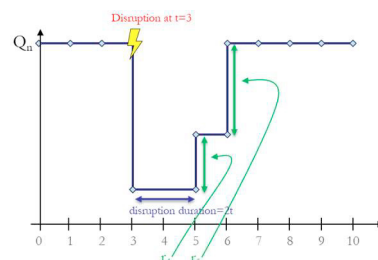


Fig. 1. Graphical explanation of recovery activities.

Below are the other main assumptions.

- There is no disruption at any site at time period 0.
- A disruption at time period t decreases the capacity in the same period t .
- A recovery action planned at period t will be fulfilled in the next period. Therefore, recovery costs are registered at period t but the capacity will become available in time period $t+1$ (see Fig. 1).
- Last available period for making recovery actions is period $T-1$.

The goal of the proposed model is to determine the optimal facility location and capacity, number of facilities, investment in protection systems, quantity of product flows between facilities and customer zones and recovery actions for reacting to disruption occurrence.

2.1 Notation

Sets and indices

- I : set of facilities, indexed by i
- J : set of customers, indexed by j
- L : set of capacity levels, indexed by l
- P : set of protection levels, indexed by p
- T : set of time periods, indexed by t
- S : set of scenarios, indexed by s

Parameters

- a_{it}^s : 1 if facility i is disrupted at time period t in scenario s ; 0 otherwise
- Cc_i : unitary cost of capacity for facility i
- Ch : holding costs

- Ci_i : fixed cost of opening facility i
- Ct : transportation costs per unit of product and distance
- d_{ij} : distance between facility i and customer j
- D_j : periodic demand of customer j
- dur : disruption duration
- Q_l : facility's capacity at level l
- φ : penalty applied for missing unit of demand
- P_s : probability associated to scenario s
- θ : disrupted capacity as a percentage of nominal capacity
- β_p : percentage reduction of disrupted capacity after investing in protection systems at level p
- ε_p : percentage of capacity costs invested in protection system at protection level p

Variables

- Qn_i : nominal capacity installed at facility i
- Qp_i : capacity protected against disruption at facility i
- q_{it}^s : available capacity at facility i at time period t in scenario s
- qd_{it}^s : lost capacity due to disruption at facility i at time period t in scenario s
- qr_{it}^s : capacity recovered at facility i at time period t in scenario s

Decision variables

- y_{il} : 1 if facility i is opened with capacity level l ; 0 otherwise
- w_{ilp} : 1 if facility i opened with capacity level l is reinforced with protection level p ; 0 otherwise
- r_{ilt}^s : 1 if capacity level Q_l is recovered at facility i at time period t in scenario s ; 0 otherwise
- x_{ijt}^s : product flows between facility i and customer j at time period t in scenario s
- u_{jt}^s : lost demand of customer j at time period t in scenario s

2.2 Formulation

$$\begin{aligned} \min \text{TotalCosts} = & \sum_i \sum_l (C_{i_l} + C_{c_i} \cdot Q_l) \cdot y_{il} + \sum_i \sum_l \left[C_{c_i} \cdot Q_l \cdot \sum_p (\varepsilon_p \cdot w_{ilp}) \right] \\ & + \sum_s P_s \left[\sum_t \sum_i \sum_j (Ct \cdot d_{ij} + Ch) \cdot x_{ijt}^s + \sum_t \sum_j \varphi \cdot u_{jt}^s \right] \\ & + \sum_t \sum_i \left[C_{c_i} \cdot (1 - t/r) + Ch \right] \cdot qd_{it}^s + \sum_t \sum_i C_{c_i} \cdot \sum_l Q_l \cdot \theta \cdot r_{ilt}^s \end{aligned} \quad (1)$$

$$\sum_l y_{il} \leq 1 \quad \forall i \in I \quad (2)$$

$$\sum_l \sum_p w_{ilp} \leq 1 \quad \forall i \in I \quad (3)$$

$$Q_l \cdot \sum_p w_{ilp} \leq Q_l \cdot y_{il} \quad \forall i \in I, \forall l \in L \quad (4)$$

$$\sum_t x_{ijt}^s + u_{jt}^s = D_j \quad \forall j \in J, \forall t \in T, \forall s \in S \quad (5)$$

$$\sum_j x_{ijt}^s \leq q_{it}^s \quad \forall i \in I, \forall t \in T, \forall s \in S \quad (6)$$

$$Qp_i = \sum_l Q_l \cdot \sum_p w_{ilp} \beta_p \quad \forall i \in I \quad (7)$$

$$Qn_i = \sum_l Q_l y_{il} \quad \forall i \in I \quad (8)$$

$$q_{i0}^s = Qn_i \quad \forall i \in I, \forall s \in S \quad (9)$$

$$qd_{i0}^s = 0 \quad \forall i \in I, \forall s \in S \quad (10)$$

$$qr_{i0}^s = 0 \quad \forall i \in I, \forall s \in S \quad (11)$$

$$q_{it}^s = q_{it-1}^s - qd_{it}^s + qr_{it-1}^s \quad \forall i \in I, \forall t \in T, t > 0, \forall s \in S \quad (12)$$

$$qd_{it}^s = (q_{it-1}^s - Qp_i) \theta a_{it}^s \quad \forall i \in I, \forall t \in T, t > 0, \forall s \in S \quad (13)$$

$$qr_{it-1}^s = \sum_l Q_l \cdot \theta \cdot r_{ilt}^s \quad \forall i \in I, \forall l \in L, t > (t_{dis} + dur), \forall s \in S \quad (14)$$

$$\sum_l r_{ilt}^s \leq 1 \quad \forall i \in I, \forall t \in T, \forall s \in S \quad (15)$$

$$qr_{it}^s \leq Qn_i - q_{it}^s \quad \forall i \in I, \forall t \in T, \forall s \in S \quad (16)$$

$$qr_{it}^s = 0 \quad \forall i \in I, \forall s \in S \quad (17)$$

$$y_{il} \in \{0,1\} \quad \forall i \in I, \forall l \in L \quad (18)$$

$$w_{ilp} \in \{0,1\} \quad \forall i \in I, \forall l \in L, \forall p \in P \quad (19)$$

$$x_{ijt}^s \in \mathbb{N}, \quad x_{ijt}^s \geq 0 \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \quad (20)$$

$$u_{jt}^s \in \mathbb{N}, \quad u_{jt}^s \geq 0 \quad \forall j \in J, \forall t \in T, \forall s \in S \quad (21)$$

$$r_{ilt}^s \in \{0,1\} \quad \forall i \in I, \forall j \in J, \forall t \in T, \forall s \in S \quad (22)$$

The resulting Mixed-Integer Non-Linear Problem (MINLP) is written in equations (1)-(23). Objective function (1) seeks to minimise the total expected cost. The first two terms of the expression represent investment costs for building new facilities and provide protection systems against disruption events. In terms of operational costs, the third and fourth terms are transportation and holding costs and penalty costs for not meeting the demand, respectively. The fifth term represents the damages inflicted by the disruption to the facilities (i.e. capacity) and the inventory. Finally, the last term represents the recovery costs for restoring capacity after a disruption occurrence.

Constraints (2) ensure that if a facility is established, only one capacity level must be selected. Similarly, constraints (3) guarantee that facilities can be protected at only one level of protection. Constraints (4) are necessary for applying the protection investment to the right capacity level selected for each facility. Equation (5) specifies that the demand needs to be completely covered. Constraints (6) restrict the facility flow to the available capacity. Equations (7) and (8) are the protected and nominal capacity definitions, respectively. Constraints (9)–(11) represent the available, disrupted and recovered capacity at the first time period ($t = 0$) at each scenario. Equations (12)–(14) are the capacity definitions for the rest of the time periods. Constraints (15) guarantee that only one level of capacity can be recovered in each time period. Relations (16) and (17) define the maximum recoverable capacity per period and state that at the last period, no recovery activities are allowed. Finally, constraints (18)–(22) define the nature of the decision variables.

Scenario-based formulations generally lead to a solution that may not be tractable due to the huge number of scenarios involved. Besides, evaluating and using discrete probabilities for disruption events can be difficult due to the lack of available data, and can lead to results that are not representative of reality. As such, in our model, we adopted a risk-averse attitude in two ways. Firstly, all the scenarios included in (1) need to consider at least one disruption at an opened facility. Based on this assumption, the parameter $n_{dis} = \sum_t \sum_i a_{it}^s$ represent the number of disruption event that are modelled in scenario s . On the other hand, the parameter $n_{ad} = \sum_t \sum_i (a_{it}^s \cdot \sum_l y_{il})$ represents the number of disruption event that impact on an actual opened facility and/or selected primary supplier. Based on this formulation, equation (23) defines the weight associated with scenario s where N represents the maximum number of disruption events that can happen in a scenario. Finally, we define the scenarios' probability as in (24). The weights' formulation, that assume a null value for scenarios with no disruption at opened facilities,

allows a risk-averse formulation and to reduce the tested scenario set.

$$weight_s = \begin{cases} N + 1 - n_{ad_s} & \text{if } n_{ad_s} = n_{dis_s} \\ 0 & \text{otherwise} \end{cases} \quad (23)$$

$$P_s = \frac{weight_s}{\sum_s weight_s} \quad (24)$$

3. SOLUTION PROCEDURE

In this section, we are going to address how to cope with the complexity of the problem presented earlier. The MINLP formulation proposed in equations (1)–(24) is nonlinear due to the scenario probability formulation (equation (23)–(24)), which is multiplied by an integer variable in the operational costs' term. We therefore propose a two-stage solution approach. In the first stage, we consider only one disruption-free scenario. The objective function is composed of investment costs for building new facilities, transportation and holding costs and penalty costs for not meeting the demand (equation (25)).

$$\min \text{SubP} = \sum_i \sum_t (C_{it} + C_{ci} \cdot Q_i) \cdot y_{it} + \sum_t \left[\sum_i \sum_j (C_{tj} \cdot d_{ij} + C_h) \cdot x_{ijt}^0 + \sum_j \varphi \cdot w_{jt}^0 \right] \quad (25)$$

Through an optimiser (i.e. CPLEX), the first-stage mathematical model is solved, and the opened facilities' indices are extracted. The second-stage objective function then introduces a disruption effect, and it is represented by equation (1). Here, we force the opened facilities resulting from the first stage, and through an optimiser, we solve the complete mathematical model. It is worth underlining that only the locations of facilities are forced: in fact, optimal capacities are calculated through the second stage. This two-stage process is applied iteratively in a procedure composed of the four blocks presented in Fig. 2 (different combinations of the same number of facilities are obtained through additional constraints in the optimization model).

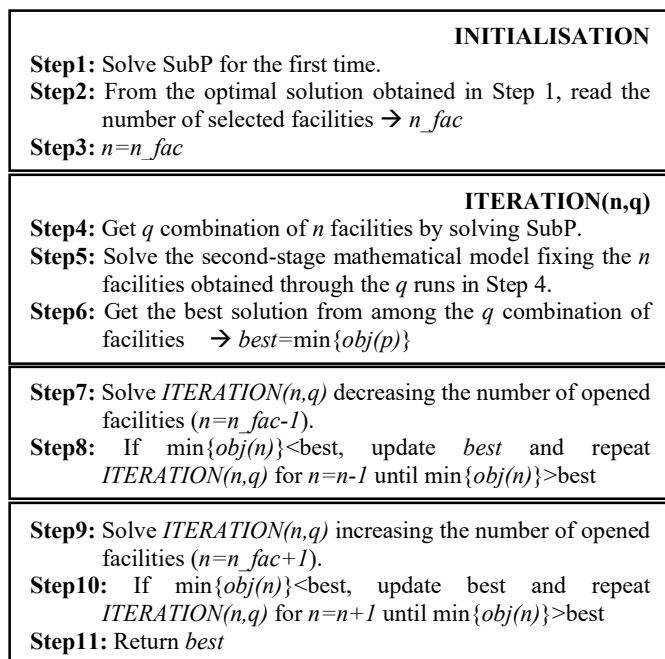


Fig. 2. Solution procedure.

ITERATION(n,q) represents the core of this solution procedure: n is derived directly from the initialisation process;

on the other hand, q needs to be properly tuned to find a trade-off between the optimal value and the computational time.

4. RESULTS AND DISCUSSION

In this section, we present the instances, discuss our numerical tests, analyse the influence of the parameters and present some insights. The algorithm is coded in the Python programming language and is run on a PC with a 3.6 GHz Intel Core i7-4790 Processor and 8 GB memory. The MINLP and subproblem (SubP) are solved using CPLEX 12.1. For all the mathematical tests, as has already been done by Cheng et al. (2018) and Hatefi and Jolai (2014), considering that disruption risk is associated with rare events, we assume that at most two disruption events can happen per scenario ($N=2$).

4.1 Computational Experiments

Table 1. Computational experiments

I	J	q	OF	S	Obj	gap	iter	CT
N=1								
5	13	1	4	4	6.5666E+06	na	3	0.21
		3	3	3	6.5018E+06	0.99%	2	0.10
		5	3	3	6.5018E+06	-	2	0.10
24	36	1	10	10	2.3097E+06	na	1	12.1
		3	10	10	2.3097E+06	-	1	24.2
		5	10	10	2.3097E+06	-	1	36.3
42	84	1	8	8	1.6882E+06	na	1	413.1
		3	8	8	1.6879E+06	0.02%	3	6070
		5	8	8	1.6879E+06	-	3	7284
N=2								
5	13	1	4	10	6.6562E+06	na	3	0.30
		3	4	10	6.6562E+06	-	7	0.72
		5	4	10	6.6562E+06	-	11	2.38
24	36	1	10	55	2.3166E+06	na	1	357.3
		3	10	55	2.3166E+06	-	1	714.8
		5	10	55	2.3166E+06	-	1	1072
42	84	1	8	36	1.7105E+06	na	1	3681.6
		3	8	36	1.7033E+06	0.42%	3	6207
		5	8	36	1.7033E+06	-	3	16097

OF: number of opened facilities; Gap: relative gap with objective function obtained in the previous iteration; iter: iteration number where best solution is obtained; CT: computational time [s]

In this section, we present the conduct and results of the computational experiments that we carried out to determine the efficacy of the previously introduced solution procedure, and to tune the parameters. We randomly generated three instances of different sizes, where, for brevity, we reported only the number of possible facility locations and the customer zones to serve. Table 1 presents the computation results. Each generated dataset was tested for three different levels of q (numbers of combination of n facilities successively forced in the second stage: 1, 3 and 5). The column *gap* presents the relative gap between the actual objective function value and the one obtained in the previous run with a lower q . As we can see from the table, $q = 3$ seems to reach the best values both for $N = 1$ and $N = 2$. In addition, in all the tested instances, good results were obtained within a reasonable computational time. Therefore, we can assert that the proposed procedure can be considered appropriate for the analysed problem.

4.2 Numerical Example

We apply our model to a numerical example composed of 48 customer zones with randomly generated demand, and 21 possible location for facilities with 15 capacity level (the highest capacity level allows one facility to cover all the demands). We first tested the efficacy of the resilience

investment included in our formulation by comparing our model with a shorter formulation removing investment in protection systems and recovery actions (called *No Resilience Action*). Disruption are modelled as always starting at the second time period ($t=1$). Secondly, we performed sensitivity analysis to develop managerial insight and to show the behaviour of the location decisions and the objective function with respect to a change in the disruption magnitude, disruption duration and risk aversion of the decision maker.

4.2.1 Model comparison

The proposed formulation allows significant savings in terms of SC network design cost. As can be seen in Table 2, the investment in protection systems and the ability to recover lost capacity may prevent an increase of overcapacity and/or of the number of facilities, which may result in a total cost reduction of up to 8% considering two highly impactful events per scenario.

4.2.2 Managerial insights

Disruption magnitude and duration play crucial roles in determining the best risk mitigation strategy to apply. For short-term disruption, carrying out recovery actions is the most efficient way to overcome interruption effects and to increase SC resilience. In this context, the SC can manage to lose capacity independently from the amount as it will be able to restore such capacity if necessary. Assuming that the disruption duration is constant, as the disruption magnitude increases, it will be increasingly more essential to carry out recovery actions to efficiently maintain the operability of the system.

On the other hand, the longer the disruption duration, the less recovery actions can help mitigate the effect of the disruption. If a facility becomes unavailable for an extended period, the system can try to increase its reliability in two ways: by investing in robustness (i.e. increasing capacity) or by

investing in a protection system and maintaining a lower level of installed capacity, which is less subject to interruptions (in terms of disruption magnitude). In our numerical example, investing in a protection system ('complete formulation') outperforms the overcapacity case ('no resilience action') for all the disruption magnitude and duration values tested. In general, for long-lasting disruptions, SCs ask for a huge increase in SC resilience, independently from the disruption magnitude. As we can see in Table 2, flexibility and protection system investment increase is mainly driven by disruption duration increase. In addition, an interesting result is obtained from the scenario with $g=1$ and $dis=9$ (half the total considered time periods). In this situation, our formulation has been found to be more efficient in reducing the capacity installed and in investing in protection systems and flexibility. Therefore, assuming a disruption scenario similar to COVID-19, where companies can be subjected to a long and unexpected halt in their operations, flexibility investment may be seen as a winning strategy to reduce the economic impact of the disruption and to maintain their operations and sustain their business or enter other markets based on the needs during the pandemic. In this context, flexibility can be achieved by using more adaptable manufacturing systems or risk-pooling strategies, postponement and component commonalities. Therefore, protection and flexibility investment can be seen as an effective and efficient way to increase the resilience of SCs. On the other hand, overcapacity is generally less suggested because it initially increases the complexity of the network, resulting in greater difficulty managing the flows (Ivanov, 2021b). In addition, if overcapacity is not smartly employed during 'normal' periods (Ivanov and Dolgui, 2020), managers and investors may have difficulty accepting it.

5. CONCLUSION

In this paper, we present a new risk-averse mixed-integer nonlinear problem mathematical model for the design and

Table 2. Numerical examples

N	g	dis	Total Cost	Gap	Investment Cost	Gap	Operational Cost	Gap	Opened facilities	Installed capacity	Protection levels	Recovery actions
<i>No disruption</i>			1.728E+06	-	4.995E+05	-	1.228E+06	-	7	7136	-	-
<i>Complete Formulation</i>												
1	0.2	1	1.735E+06	0.41%	4.995E+05	-	1.236E+06	0.65%	7	7136	-	1.204E+04
		5	1.737E+06	0.52%	4.995E+05	-	1.237E+06	0.73%	7	7136	-	1.204E+04
		9	1.738E+06	0.58%	4.995E+05	-	1.238E+06	0.81%	7	7136	-	7.760E+03
	0.6	1	1.765E+06	2.14%	5.044E+05	0.98%	1.260E+06	2.61%	7	7136	1	7.814E+04
		5	1.783E+06	3.18%	5.070E+05	1.50%	1.276E+06	3.91%	7	7582	-	7.359E+04
		9	1.798E+06	4.05%	5.070E+05	1.50%	1.291E+06	5.13%	7	7582	-	6.717E+04
	1	1	1.806E+06	4.51%	5.237E+05	4.84%	1.283E+06	4.48%	7	7582	2	1.664E+05
		5	1.848E+06	6.94%	5.794E+05	16.00%	1.268E+06	3.26%	8	7582	4	1.588E+05
		9	1.874E+06	8.45%	6.065E+05	21.42%	1.268E+06	3.26%	8	7582	11	1.111E+05
2	0.2	1	1.740E+06	0.69%	4.995E+05	-	1.240E+06	0.98%	7	7136	-	8.840E+04
		5	1.742E+06	0.81%	4.995E+05	-	1.243E+06	1.22%	7	7136	-	9.188E+04
		9	1.744E+06	0.93%	4.995E+05	-	1.245E+06	1.38%	7	7136	-	6.458E+04
	0.6	1	1.798E+06	4.05%	5.263E+05	5.37%	1.271E+06	3.50%	7	8028	1	5.301E+05
		5	1.822E+06	5.44%	5.743E+05	14.97%	1.248E+06	1.63%	8	8028	1	5.513E+05
		9	1.841E+06	6.54%	5.825E+05	16.62%	1.259E+06	2.52%	8	7582	5	4.212E+05
	1	1	1.870E+06	8.22%	5.597E+05	12.05%	1.310E+06	6.68%	7	8474	6	1.030E+06
		5	1.909E+06	10.47%	6.569E+05	31.51%	1.252E+06	1.95%	8	7582	18	7.279E+05
		9	1.919E+06	11.05%	6.458E+05	29.29%	1.273E+06	3.66%	7	7136	26	1.748E+05
<i>No Resilience Actions</i>												
1	0.2	na	1.739E+06	0.64%	4.995E+05	-	1.239E+06	0.90%	7	7136	na	na
	0.6	na	1.812E+06	4.86%	5.693E+05	13.97%	1.242E+06	1.14%	8	8028	na	na
	1	na	1.919E+06	11.05%	6.743E+05	34.99%	1.244E+06	1.30%	10	8028	na	na
2	0.2	na	1.746E+06	1.04%	4.995E+05	-	1.246E+06	1.47%	7	7136	na	na
	0.6	na	1.861E+06	7.70%	5.867E+05	17.46%	1.275E+06	3.83%	8	8920	na	na
	1	na	2.014E+06	16.55%	7.308E+05	46.31%	1.283E+06	4.48%	11	9366	na	na

planning of a resilient two-echelon logistics network. Disruption events are included, and they could partially or completely reduce available capacity. On the other hand, proactive and reactive resilience actions could be planned to hedge against disruption risk: facilities could be reinforced through a protection system and flexibility investment, and recovery actions are allowed for restoring lost capacity. The model objective minimises the total SC design cost with the goal to determine the facility location and capacity, allocation flows and resilience actions to hedge against disruption risk. The risk aversion of the decision makers is included in two ways. Firstly, the scenario generation procedure is based on considering only scenarios with at least one disruption event at an opened facility where scenarios' weight is based on the number of events. Secondly, decision maker could increase the risk-attitude by varying the number of possible events that can happen in a scenario. To deal with the nonlinearity of the proposed formulation, a two-stage solution procedure is proposed and tuned through computational experiments. Several scenarios are tested with different disruption duration and magnitude. The results highlighted that recovery activities resulted in the most efficient action to employ for short-term disruption event. On the other hand, proactive resilience investment as protection systems and flexibility enhancement allows SC to handle disruption period with a limited increase in network building costs and overcapacity.

For the managerial implications of the study results, the proposed approach has a high potential to be applied in real-world situations as it can evaluate event uncertainties better than the risk-neutral approaches can. Besides, managers can choose their risk level by increasing parameter N and evaluating different SC configurations in several scenarios. Future research should concentrate on increasing the number of echelons included in the mathematical model to determine how to efficiently allocate redundancies on more complex networks considering disruption propagation (Li et al., 2020). In addition, it may be helpful to consider multiple objective functions and to integrate resilience metrics into the best-results evaluation.

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