

Designing Resilient Supply Chains: Capacity related Decisions and Selecting Sourcing Strategies

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Abstract

This paper focuses on the facility location problem and investigates the effectiveness of two procurement strategies, namely single and multiple sourcing, in designing resilient supply chains operating under random disruptions. Two stochastic mathematical formulations are proposed to determine sourcing and network design decisions that minimise the expected total cost. These formulations are used to address the challenges associated with selecting suppliers and establishing sourcing decisions and provide insights into how facilities' capacity can affect these decisions. The paper also includes a sensitivity analysis, which demonstrates the impact of capacity decisions on sourcing decisions and highlights the importance of considering these factors when designing facility location strategies. This article provides a valuable contribution to the field of resilient supply chain design and offers practical insights for managers looking to optimize their supply chain operations.

Keywords: Supply chain design; Mitigation strategies; Capacity utilisation; Resilience; Sourcing.

1. Introduction

The unpredictable nature of external events and an uncertain business environment, can result in supply disruptions that cause financial losses and reputational damage to the enterprise (Han et al. 2023). Terrorist attacks of September 11, 2001, Hurricane Katrina in 2005, the tsunami and earthquake that struck Japan 2011, and the 2020 COVID-19 pandemic are among events that significantly impacted supply chains (Snyder et al. 2016; Aldrichetti et al. 2021; Suryawanshi and Dutta 2022). Although the risks of these events are classified as low likelihood, they have a high impact on supply chain performance (Tang 2006). To minimize the impact of such events, resilience is promoted by practitioners (Suryawanshi and Dutta 2022) in designing SCs that can quickly adjust to disruptive changes that negatively affect performance (Wieland and Durach 2021).

Supply chain design (SCD) involves the strategic planning and optimization of supply chain activities to achieve business objectives such as cost reduction, increased efficiency, and improved customer service. SCD deals with various decision-making (DM) problems including strategic decisions such as determining the number, size, and location of facilities in a supply chain, tactical decisions such as distribution and inventory management policies, and operational decisions such as fulfilling customer demands, and transportation scheduling (Farahani et al. 2014). The most common strategic decisions consist of locating facilities in different tiers of supply chain networks, the capacities and sizes of facilities, and supplier selection, which impacts all future and operational decisions of the chain (Simchi-Levi and Kaminsky 2004).

Resilience in SCD can be attained by incorporating redundancy measures such as maintaining safety and emergency stocks, diversifying suppliers, and maintaining low capacity utilization

rates to mitigate the impact of disruptions. Scholars have explored various redundancy models as a means of creating effective mitigation strategies against the risks of disruption. Depending on whether they are implemented before or after a disruption, mitigation strategies can be classified into two subcategories: proactive and reactive (Elluru et al. 2019). Ivanov et al. (2017) highlights the importance of mitigating the risk of disruptions through the use of redundancy measures. Hosseini, Ivanov, and Dolgui (2019) have also explored the different redundancy models that can be employed to create effective mitigation strategies.

Single sourcing and Multiple sourcing are two procurement strategies that companies use to acquire the goods and services they need (Berger and Zeng 2006). Single sourcing can be defined as the procurement of all required goods or services from a single vendor by choice. The goal of single sourcing is to have only one supplier for each inventory item, with some exceptions for families of related parts. It should be noted that if an organization is forced to use a single vendor due to a monopoly, this is called sole sourcing. The term multiple sourcing refers to the procurement of an identical part or product by a purchaser from two or more vendors. In situations where only two vendors are used, this is known as dual sourcing and represents a specific type of multiple sourcing (Treleven and Schweikhart 1988; Berger and Zeng 2006). It is worth noting that in this article, we distinguish between multiple sourcing and backup suppliers (Li, Zeng, and Savachkin 2013).

Single and multiple sourcing strategies been used in addressing and solving several class of resilient SCD [\(RSCD\)](#) problems including reliable fixed-charge facility location (RFLP), logistic network design (Aldrighetti et al. 2021), and supplier selection problems (Sawik 2020; 2019). The area of interest of this paper is the application of above mentioned sourcing strategies in RFLPs [as a special class of RSCD problems](#).

RFLP is a generalized version of the traditional Fixed-Charge Facility Location Problem (FLP). FLP focuses on minimizing the total cost of fixed and transportation costs by choosing facility locations and assigning customers to them (Melo, Nickel, and Saldanha-da-Gama 2009). In contrast, the RFLP considers the possibility of one or more facilities becoming unavailable due to disruptions, and requires that demand from affected customers be redistributed to other facilities, often further away and at a higher transportation cost (Snyder 2006; Snyder et al. 2016). The aim of the RFLP is to increase the resilience and reliability of the supply chain in the face of disruptive events, and to suggest an appropriate network design (Qi, Shen, and Snyder 2010; Peng et al. 2011).

Several classes of mathematical models have been presented to address and solve RFLPs in the literature (Hosseini, Ivanov, and Dolgui 2019; Ivanov et al. 2017; Aldrighetti et al. 2021). Snyder et al. (2016) categorised these models into four sub categories: probabilistic non-linear terms or implicit functions (IF), reliable backup (RB), scenario-based (SB), and robust optimisation (RO) models. IF models are based on implicitly calculating the probability that a customer will be served by each facility, which requires an assumption of independent disruptions (M. Lu, Ran, and Shen 2015). RB models assumes that each customer is backed up by a reliable facility under all disruption scenarios (Azad et al. 2013; M. Lu, Ran, and Shen 2015). In SB models the failure of facilities are defined as explicit scenarios with their occurrence probabilities calculated based on the known probability of occurrence of local, regional or global disruption events (Shen, Zhan, and Zhang 2011). In RO models, parameters are uncertain and no information about probabilities are known. Similar to SB methods, RO models have been successfully applied to model proactive, reactive, and SC design quality strategies (An et al. 2014; Hernandez et al. 2014; M. Lu, Ran, and Shen 2015; Cheng, Adulyasak, and Rousseau 2021). The main advantage of RO models is that they do not rely on probability distributions or the generation of scenarios (Cheng, Adulyasak, and Rousseau 2021).

Taking into account the capacity constraint for facilities, RFLP can be categorised into two groups: uncapacitated and capacitated problems. Reliable uncapacitated FLP (RUFLP) assumes that each facility has an unbounded capacity while in reliable capacitated FLP (RCFLP) the capacities are limited. RUFLP has been the focus of many researchers and has been studied well in the literature (Snyder et al. 2016; Hosseini, Ivanov, and Dolgui 2019; Aldrichetti et al. 2021). The single-sourcing strategy has been the dominant approach in modelling RUFLPs. A few researchers also addressed RCFLP. Aydin and Murat (2013) proposed a scenario-based formulation for CRFLP as a two-stage stochastic program. They applied a single sourcing strategy to satisfy the demand of customers in such a way that either the entire demand of a customer is provided by one of the open facilities, or it is subject to a penalty cost as a lost sale. Albareda-Sambola et al. (2017) proposed an IF-based mathematical formulation for the problem for a version of CRFLP with single sourcing strategy in which capacity constraints on the facilities were stated as hard constraints for the scenario where no failures occurred, but relatively small violations were allowed if they did. Azad and Hassini (2019) studied CRFLP with the aim of investigating different mitigation strategies including multiple sourcing. A SB mixed-integer linear programming model was presented and several sensitivity analysis including *benefit of considering multimitigation strategies, exploring the impact of the lost capacity of the opened facilities on the disruption cost, the impact of disruption probability on the number and residual capacity of opened facilities* were performed. More recently, Cheng, Adulyasak, and Rousseau (2021) studied capacitated fixed-charge location problem (CFLP) in which customers are subject to demand uncertainty and facilities may experience disruption risks. Considering multiple sourcing strategy, they adopt a two-stage robust optimization (RO) scheme to model the problem and apply a column-and-constraint-generation (C&CG) algorithm based on a decomposition scheme.

The above literature review reveals that there are a few numbers of studies that implement multiple sourcing strategies as a resilience mitigation strategy to solve CRFLPs. However, based on our current knowledge, no published study has investigated the efficiency of these two categories of sourcing strategies on the resilience of supply chains from the perspective of capacity utilization. Thus, the aim of this research is to fill this research gap, by developing stochastic mathematical models for CRFLP that aim to minimize the expected total cost of the supply chain when considering single sourcing and multiple sourcing strategies as procurement approaches, with a focus on enhancing the resilience of the entire supply chain. Additionally, a sensitivity analysis is conducted to investigate how capacity decisions impact sourcing decisions and resilience levels.

The remainder of this paper is organized as follows: first, in Section 2, the problem under study is defined. Afterwards, in Section 3, mathematical formulations for the problem are proposed. In Section 4, we discuss the performance of the mathematical formulations in solving an experimental problem instance. Finally, conclusions and descriptions of future works will follow in section 5.

2. Problem definition

The problem we address in this paper is a capacitated version of the RFLP. The CRFLP involves locating a set of facilities in potential locations to cover the demand of known customers. In this problem, each facility has a predetermined capacity that cannot be exceeded. The objective of our study is to minimize the total cost of the supply chain, which includes the cost of designing the supply chain, the expected shipment costs, and the penalty costs that are incurred when a disruption occurs. We assume that facilities are at risk of failing due to disruptions caused by natural disasters, terrorist attacks, or labour strikes, meaning that the service such facilities provide to their customers may be interrupted at some point during the planning period. In such cases, the demand points that were initially assigned to the disrupted facility must be

reassigned to another operational facility. If this is not possible, the demand points are subjected to a penalty cost.

This problem involves two strategies: single sourcing and multiple sourcing. In the single sourcing strategy, a customer's entire demand is fulfilled either by one facility or incurs a penalty cost in the form of lost sales. On the other hand, in the multi-source strategy, products can be partially or fully supplied to customers from multiple facilities. However, unfulfilled demands are still penalized in this strategy.

3. Mathematical formulation

SB models are attractive due to their straightforward structure, simplicity and their ability to model dependence among random parameters (M. Lu, Ran, and Shen 2015). SBs allow the explicit modeling of uncertain parameters, which can lead to more realistic and robust solutions (Sabouhi et al. 2020). In this section, we present two mathematical formulations to model single-sourcing versus multiple sourcing strategies in RFLPs. The proposed models are developed based on the two-stage SB approach proposed by (Shen, Zhan, and Zhang 2011). Given a finite set of scenarios, each specifying a set of operational facilities, the first stage decisions, which determine the value of the scenario-independent supply chain design variables, are taken before the realisation of disruption scenarios. These decisions are made about which facilities to open. Once a disruption occurs, the second-stage decisions involve either assigning each client (demand point) to an operational facility or incurring a penalty for non-assignment. To implement single-source and multi-source strategies, two sets of scenario-dependent assignment variables have been defined. Binary variables are used to represent the single-source strategy, while continuous variables are used for the multi-source strategy in this model. Subsection 3.1 introduce the notations. Besides, the models related to single and multi-source strategies are presented in subsections 3.2 and 3.3, respectively.

3.1. Notations

3.1.1. Parameters

- I : number of facilities;
- J : number of customers;
- S : number of scenarios;
- h_j : demand of customer j ;
- d_{ij} : transportation cost per unit of demand served from i to j ;
- c_j : regular capacity of facility i ;
- o_{is} : binary parameter which equals 1 if facility i is operative in scenario s ; 0, otherwise;
- r_j : penalty cost, associate with costumer j ;
- f_i : fixed cost of opening facility i .

3.1.2. Decision variables

3.1.2.1. Variables used in both models

- $Y_i \in \{0, 1\}$: binary variable; if facility i is open;
- T_c : Total cost of designing the supply chain;

3.1.2.2. Variables used in modelling single sourcing strategy

- $X_{ijs} \in \{0, 1\}$: binary assignment variable; $X_{ijs} = 1$, if customer i is assigned to facility j under scenario s ; $X_{ijs} = 0$, otherwise;
- $Z_{js} \in \{0, 1\}$: binary unsatisfied demand variables: $Z_{js} = 1$ if demand of customer j is not satisfied in scenario s ; $Z_{js} = 0$, otherwise.

3.1.2.3. Variables used in modelling multiple sourcing strategy

- $X_{ijs} \geq 0$; continuous assignment variable; the number of products shipped from facility i to customer j under scenario s ;
- $Z_{js} \in \{0, 1\}$: continuous unsatisfied demand variables: the unsatisfied demand of customer j in scenario s .

3.2. Single sourcing model

3.2.1. Objective function

$$\text{Min. } T_c \quad (\text{S-1})$$

3.2.2. Constraints

$$T_c = \sum_{i=1}^I f_i \cdot Y_i + \sum_{s=1}^S P_s \left[\sum_{i=1}^I \sum_{j=1}^J h_j \cdot d_{ij} \cdot x_{ijs} + \sum_{j=1}^J h_j \cdot Z_{js} \right] \quad (\text{S-2})$$

$$\sum_{i=1}^I X_{ijs} + Z_{js} = 1, \quad 1 \leq j \leq J, \quad 1 \leq s \leq S \quad (\text{S-3})$$

$$\sum_{j=1}^J h_j \cdot X_{ijs} \leq c_i \cdot Y_i \cdot o_{is}, \quad 1 \leq i \leq I, \quad 1 \leq s \leq S \quad (\text{S-4})$$

Objective function (S-1) minimises the total cost of designing the supply chain. Constraint (S-2) calculates the total cost of designing the supply chain including fixed facility location costs and expected shipment and unsatisfied demand penalty costs. Constraints (S-3) enforce that the demand of each customer j under scenario s must be satisfied by a facility (i) or be calculated as an unsatisfied demand. Constraints (S-4) require, in each scenario, the total amount of products shipped from a facility to the customers does not exceed its assigned capacities.

3.3. Multiple sourcing model

3.2.1. Objective function

$$\text{Min. } T_c \quad (\text{M-1})$$

3.2.2. Constraints

$$T_c = \sum_{i=1}^I f_i \cdot Y_i + \sum_{s=1}^S P_s \cdot \left[\sum_{i=1}^I \sum_{j=1}^J d_{ij} \cdot x_{ijs} + \sum_{j=1}^J Z_{js} \right] \quad (\text{M-2})$$

$$\sum_{i=1}^I X_{ijs} + Z_{js} = h_j, \quad 1 \leq j \leq J, \quad 1 \leq s \leq S \quad (\text{M-3})$$

$$\sum_{j=1}^J X_{ijs} \leq c_i \cdot Y_i \cdot o_{is}, \quad 1 \leq i \leq I, \quad 1 \leq s \leq S \quad (\text{M-4})$$

Again the objective function (M-1) minimises the total cost of designing the supply chain. Constraint (M-2) calculates the total cost of designing the supply chain including fixed facility location costs and expected shipment and unsatisfied demand penalty costs. Constraints (M-3) enforce that the demand of each customer j under scenario s must be satisfied by a facility (i) or be calculated as an unsatisfied demand. Constraints (M-4) require, in each scenario, the total amount of products shipped from a facility to the customers does not exceed its assigned capacities.

4. Computational experiments

In this section, we introduce an illustrative example as a case study to perform a set of sensitivity analyses to investigate the performance of the presented models with binary and continuous assignment variables. Table 1 provides a data set as the experimental instance with six customers and five candidate locations. We solved this problem by coding the proposed mathematical formulations in Java, using IBM ILOG Cplex 22.1 as the MIP solver.

To investigate the performance of the single and multiple sourcing strategies, we solved the given problem instance with three different levels of facilities' capacity: small, medium, and large. Furthermore, two different levels of unitary shipment costs are considered including: low, and high.

Table 1: Input data

	Customer						$f(\pounds)$
	$D(\pounds)$						
Facility	1	2	3	4	5	6	
1	2	3	4	3	2	2	5000
2	1	2	5	3	2	1	7000
3	3	2	6	5	4	3	6000
4	1	1	2	1	3	4	6000
5	4	3	4	1	2	3	7000
h (Unit)	2000	1500	1000	2000	2000	1500	
r (£)	20	25	22	24	25	20	

The small level of capacity limit is calculated by dividing the total demand of customers by the number of facilities. The medium and large capacity limits were set to 2 and 5 times of the small capacity level, respectively. Thus, the small, medium, and large capacity levels of all facilities are considered as 2000, 4000, and 10000 product units, respectively.

The table 1 already includes the high level of shipment costs. At the low level, the cost of shipment of products from facilities to customers are five percent of the shipment cost (D) presented in the table 1.

Since we have five candidate locations to open facilities, 32 different disruption scenarios (i.e. 2^5) are possible. We solved the problem introduced in Table 1 under all these disruption scenarios.

4.1. Shipment costs and facilities' capacity limits

In this subsection, we solve the problem instance introduced in Table 1 by setting the capacity of facilities to three different levels: 2000, 4000, and 10000 product units. We analyse the efficiency of the models with binary and continuous shipment variables being used to model single versus multiple sourcing strategies in terms of supply chain design cost, expected shipment and penalty costs, and total supply chain costs. The results of this analysis are reported in Table 2. In this table in order to compare the solutions generated by two models, the improving rate (Imp(%)) of reported costs when using the model with continuous assignment variables instead of one with binary assignment variables are calculated as $[100 * (\text{Binary solution} - \text{Continuous solution}) / \text{Binary solution}]$.

Reviewing the values of *Imp*(%) in table 2 reveals that, by setting the capacity of facilities to tighter ones i.e. at low or medium levels, the model implementing the multi-source strategy results in a lower total supply chain cost, as compared to the model which implements single sourcing strategy. However, when the capacity of facilities increases to a large level, The same results were found.

When comparing the expected costs of shipping of products and the expected penalty costs for two models, the binary model yielded lower shipping costs than the continuous model, but the cost of lost sales was apparently increased. This is because the continuous model was able to meet a greater amount of customer demand, resulting in higher shipping costs in the model's output. However, the cost of lost sales was reduced to an acceptable level, which was not the case in the binary model.

Table 2: The comparison between the solutions generated by binary and continuous models

Capacity	Unitary Shipment cost	Models	Costs (£)			
			Fixed facility location costs (£)	Expected shipment costs (£)	Expected penalty cost (£)	Total cost (£)
Small	Low	Binary	12500	376.5	23700	36576
		Continuous	12500	388.5	21750	34638
		Imp (%)	0	-3.19	8.23	5.29
	High	Binary	12500	6555	24300	43355
		Continuous	12500	7530	21990	42020
		Imp (%)	0	-14.87	9.51	3.08
Medium	Low	Binary	20000	514.5	12960	33474
		Continuous	20000	533.5	11400	31932
		Imp(%)	0	-3.69	12.04	4.61
	High	Binary	15000	7440	20640	43080
		Continuous	15000	7980	18660	41640
		Imp(%)	0	-7.26	9.59	3.34
Large	Low	Binary	25000	576	14400	39976
		Continuous	25000	576	14400	39976
		Imp (%)	0	0	0	0
	High	Binary	12500	7920	28800	49220
		Continuous	12500	7920	28800	49220
		Imp(%)	0	0	0	0

B: Binary; C: Continuous; Imp: improving rate.

Figures 1 and 2 compare the different supply chain costs taking into account different levels of unitary shipment costs. In these charts, each line is named with a triple, which indicates: *the capacity level, the shipment cost level, and the type model used to solve the problem*, respectively. Comparing the graphs in Figures 1 and 2 shows that an increase in unitary shipment costs affects the total supply chain design. On one hand, for all scenarios, increasing shipment costs from low to high levels resulted in significant increases in both the total expected shipment and penalty costs. On the other hand, when facility capacities are set to medium and large levels, the fixed cost of locating facilities decreased. These findings demonstrates 1) As the shipment unitary costs rise, the ability to meet customer demands decreases. 2) when the capacity of facilities increases relative to total demand, opening a smaller number of facilities is more cost-effective if the cost of transporting materials also increases, and 3) The model's performance was relatively better when applying the multiple sourcing strategy.

4.2. Capacity utilisation

In this subsection, we analyse the performance of the two proposed models in utilizing the facilities' capacities. We do this by analysing the solutions generated by two presented models, taking into account the number of open facilities, the total available capacity of opened facilities, the total expected utilized capacity, the total expected unused capacity, and the total expected lost sale of all facilities over all scenarios. The results are reported in Table 3.

Note that the values reported in Table 3 for the total expected utilized capacity, the total expected unused capacity, and the total expected lost sale are calculated using equations (B-1), (B-2), and (B-3) for binary model, and using equations (C-1), (C-2), and (C-3) for continuous model, respectively.



Figure 1: The comparison between results generated by the binary model

$$\sum_{i=1}^I c_i \cdot Y_i - \sum_{i=1}^I \sum_{s=1}^S P_s \cdot \left(c_i \cdot Y_i \cdot o_{is} - \sum_{j=1}^J h_j \cdot X_{ijs} \right) \quad (\text{B-1})$$

$$\sum_{i=1}^I \sum_{s=1}^S P_s \cdot \left(c_i \cdot Y_i \cdot o_{is} - \sum_{j=1}^J h_j \cdot X_{ijs} \right) \quad (B-2)$$

$$\sum_{s=1}^S P_s \cdot \left[\sum_{j=1}^J h_j \cdot Z_{js} \right] \quad (B-3)$$

$$\sum_{i=1}^I c_i \cdot Y_i - \sum_{i=1}^I \sum_{s=1}^S P_s \cdot \left(c_i \cdot Y_i \cdot o_{is} - \sum_{j=1}^J X_{ijs} \right) \quad (C-1)$$

$$\sum_{i=1}^I \sum_{s=1}^S P_s \cdot \left(c_i \cdot Y_i \cdot o_{is} - \sum_{j=1}^J X_{ijs} \right) \quad (C-2)$$

$$\sum_{s=1}^S P_s \cdot \left[\sum_{j=1}^J Z_{js} \right] \quad (C-3)$$

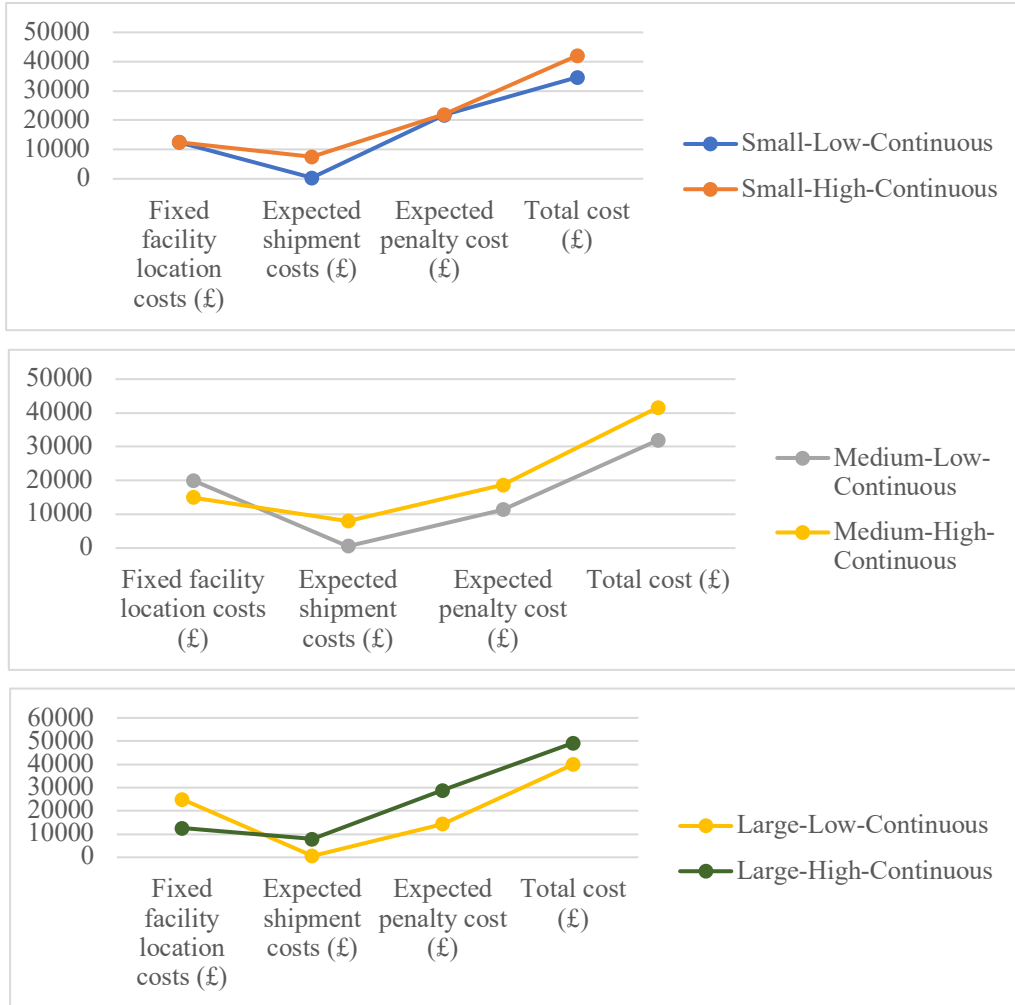


Figure 2: The comparison between results generated by the continuous model

To compare the results generated by the binary and continuous models, we first examined the solutions generated by each model for various levels of capacities and unit shipment costs. We

did this by analysing the solutions generated by each model separately, rather than comparing them directly against each other. Table 3 highlights the comparison between the number of open facilities reported in both the binary and continuous models. The results show that as the capacity of the facilities increases, there is a decrease in the number of open facilities. However, there is an increase in the total available capacity of the opened facilities, as well as the expected utilized capacity and expected unused capacity. When it comes to the expected lost sale, our findings show that increasing the capacity of facilities from small to medium leads to a decrease in the expected lost sale for both the binary and continuous models. However, as the capacity of facilities further increases from medium to large levels, the expected lost sale increases instead. This indicates that increasing facility capacity may not always result in a decrease in expected lost sale, and that there may be an optimal capacity level that minimizes lost sales. In addition to comparing the solutions generated by the binary and continuous models separately, we also computed an improvement percentage measure. This measure was based on the solutions generated by the continuous model, and it compared them to the solutions generated by the binary model to determine the extent of improvement achieved by the continuous model over the binary one. This measure (Imp(%)) is calculated as $[100 * (\text{Binary solution} - \text{Continuous solution}) / \text{Binary solution}]$ for all measures, except for the Expected utilized capacity, which has been calculated as $[100 * (\text{Continuous solution} - \text{Binary solution}) / \text{Continuous solution}]$.

Table 3: The comparison between the solutions generated by binary and continuous models in terms of facilities' capacity utilisation

Capacity	Unitary Shipment cost	Models	Number of Open facilities	Total available capacity (U)	Expected utilised capacity (U)	Expected unused capacity (U)	Expected lost sale (U)
Small	Low	Binary	5	10000	9092.5	907.5	3600
		Continuous	5	10000	9248.6	751.4	3405
		Imp (%)	0	0	1.72	17.20	5.42
	High	Binary	5	10000	9089.7	910.3	3690
		Continuous	5	10000	9247.7	752.3	3435
		Imp (%)	0	0	1.74	17.36	6.91
Medium	Low	Binary	4	16000	14514	1486	1950
		Continuous	4	16000	14760	1240	1770
		Imp(%)	0	0	1.69	16.55	9.23
	High	Binary	3	12000	10899	1101	3060
		Continuous	3	12000	11087	913	2820
		Imp(%)	0	0	1.72	17.07	7.84
Large	Low	Binary	2	20000	18091	1909	2040
		Continuous	2	20000	18091	1909	2040
		Imp (%)	0	0	0	0	0
	High	Binary	1	10000	9227.5	772.5	4080
		Continuous	1	10000	9227.5	772.5	4080
		Imp(%)	0	0	0	0	0

Upon reviewing the Imp(%) values, it is apparent that the multiple-sourcing strategy outperforms the single-sourcing strategy in terms of capacity utilization and reducing lost sales, particularly when the capacity of the facilities is set to small and medium levels. However, as the capacity of facilities increases and approaches a model without capacity constraints, the results of the two strategies become comparable and the advantage of the multi-source strategy diminishes.

4.3. The optimal capacity level

In this section, we compare the binary and continuous models' results to determine the best facility capacity among those provided (i.e., small, medium, and large) previously. The graphs presented in Figure 3 show the supply chain costs related to the example presented in Table 1 for different levels of facility capacity. In this figure, each chart is displayed as a pair representing the model and the unitary shipment cost, respectively.

By examining the graphs presented in figure 3, it can be found that the total cost of the supply chain reaches its minimum value when the capacity of the facilities is equal to the average limit of 4000 units, as reveals by all the graphs. With a smaller difference, the better supply chain is then associated with facilities whose capacity is set to the small level. However, the highest cost, which is significantly different from other solutions, is associated with the supply chain when the capacity of facilities is to large capacity level.

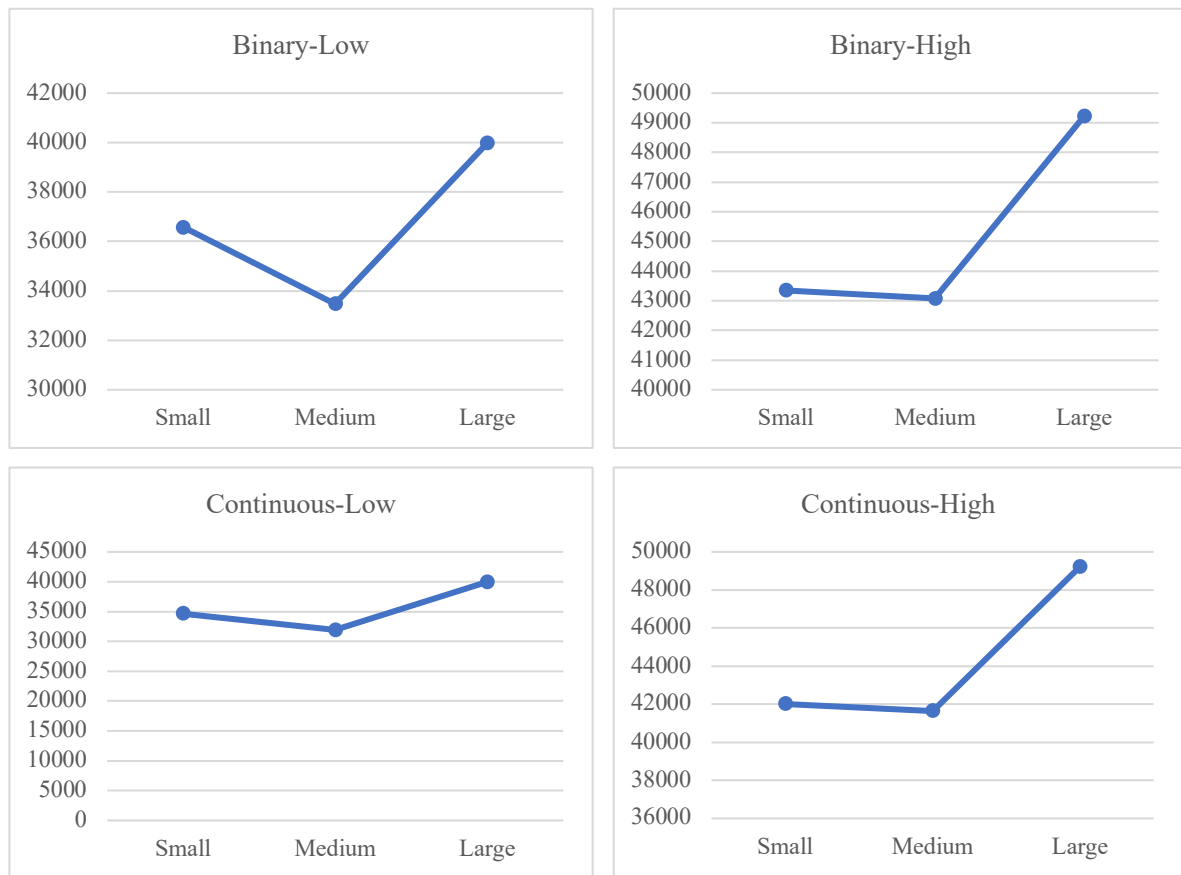


Figure 3: The comparison of the total cost of the supply chain for different capacity levels.

5. Conclusion

In this paper, a capacitated version of reliable fixed-charge facility location problems is addressed. Two mathematical formulation based on the two-stage SB approach are proposed to implement the single sourcing versus multiple sourcing strategy. In the sensitivity analysis, a numerical example was used to evaluate the impact of varying facility capacities and shipment costs on the models' performance. It is observed that in situations where the capacity of facilities is small or medium, a model with multiple sourcing tends to outperform a single sourcing model. This is because in such situations, the demand may exceed the capacity of a single facility, and having multiple sourcing options allows for the distribution of the demand among different facilities, which can lead to better utilization of resources and improved efficiency. our analysis also showed that larger capacity levels are not always the best solution.

Therefore, it is crucial to conduct a thorough cost analysis to identify the optimal capacity levels that minimize costs and maximize efficiency.

In the future, we will investigate the application of multiple sourcing strategies in IF models. Applying multiple sourcing strategies in IF models is more challenging than in SB models, as the expected failure cost may not be linear. Future research can benefit from conducting empirical studies and testing the proposed formulations on real-world.

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Disclosure statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

- Aldrichetti, Riccardo, Daria Battini, Dmitry Ivanov, and Ilenia Zennaro. 2021. "Costs of Resilience and Disruptions in Supply Chain Network Design Models: A Review and Future Research Directions." *International Journal of Production Economics* 235 (May). <https://doi.org/10.1016/j.ijpe.2021.108103>.
- An, Yu, Bo Zeng, Yu Zhang, and Long Zhao. 2014. "Reliable P-Median Facility Location Problem: Two-Stage Robust Models and Algorithms." *Transportation Research Part B: Methodological* 64: 54–72. <https://doi.org/10.1016/j.trb.2014.02.005>.
- Azad, Nader, Georgios K.D. Saharidis, Hamid Davoudpour, Hooman Malekly, and Seyed Alireza Yektamaram. 2013. "Strategies for Protecting Supply Chain Networks against Facility and Transportation Disruptions: An Improved Benders Decomposition Approach." *Annals of Operations Research* 210 (1): 125–63. <https://doi.org/10.1007/s10479-012-1146-x>.
- Berger, P. D., and A. Z. Zeng. 2006. "Single versus Multiple Sourcing in the Presence of Risks." *Journal of the Operational Research Society* 57 (3): 250–61. <https://doi.org/10.1057/palgrave.jors.2601982>.
- Cheng, Chun, Yossiri Adulyasak, and Louis Martin Rousseau. 2021. "Robust Facility Location under Demand Uncertainty and Facility Disruptions." *Omega (United Kingdom)* 103 (September). <https://doi.org/10.1016/j.omega.2021.102429>.
- Elluru, Sahitya, Hardik Gupta, Harpreet Kaur, and Surya Prakash Singh. 2019. "Proactive and Reactive Models for Disaster Resilient Supply Chain." *Annals of Operations Research* 283 (1–2): 199–224. <https://doi.org/10.1007/s10479-017-2681-2>.
- Farahani, Reza Zanjirani, Shabnam Rezapour, Tammy Drezner, and Samira Fallah. 2014. "Competitive Supply Chain Network Design: An Overview of Classifications, Models, Solution Techniques and Applications." *Omega (United Kingdom)*. <https://doi.org/10.1016/j.omega.2013.08.006>.
- Han, Bing, Ying Zhang, Song Wang, and Yongshin Park. 2023. "The Efficient and Stable Planning for Interrupted Supply Chain with Dual-Sourcing Strategy: A Robust Optimization Approach Considering Decision Maker's Risk Attitude." *Omega (United Kingdom)* 115 (February). <https://doi.org/10.1016/j.omega.2022.102775>.
- Hernandez, Ivan, Jose Emmanuel Ramirez-Marquez, Chase Rainwater, Edward Pohl, and Hugh Medal. 2014. "Robust Facility Location: Hedging against Failures." *Reliability Engineering and System Safety* 123: 73–80. <https://doi.org/10.1016/j.ress.2013.10.006>.
- Hosseini, Seyedmohsen, Dmitry Ivanov, and Alexandre Dolgui. 2019. "Review of Quantitative Methods for Supply Chain Resilience Analysis." *Transportation Research Part E*:

- Ivanov, Dmitry, Alexandre Dolgui, Boris Sokolov, and Marina Ivanova. 2017. “Literature Review on Disruption Recovery in the Supply Chain*.” *International Journal of Production Research* 55 (20): 6158–74. <https://doi.org/10.1080/00207543.2017.1330572>.
- Li, Qingwei, Bo Zeng, and Alex Savachkin. 2013. “Reliable Facility Location Design under Disruptions.” *Computers and Operations Research* 40 (4): 901–9. <https://doi.org/10.1016/j.cor.2012.11.012>.
- Lu, Mengshi, Lun Ran, and Zuo Jun Max Shen. 2015. “Reliable Facility Location Design under Uncertain Correlated Disruptions.” *Manufacturing and Service Operations Management* 17 (4): 445–55. <https://doi.org/10.1287/msom.2015.0541>.
- Lu, Xiaohan, and Chun Cheng. 2021. “Locating Facilities with Resiliency to Capacity Failures and Correlated Demand Uncertainty.” *Transportation Research Part E: Logistics and Transportation Review* 153 (September). <https://doi.org/10.1016/j.tre.2021.102444>.
- Melo, M. T., S. Nickel, and F. Saldanha-da-Gama. 2009. “Facility Location and Supply Chain Management - A Review.” *European Journal of Operational Research* 196 (2): 401–12. <https://doi.org/10.1016/j.ejor.2008.05.007>.
- Peng, Peng, Lawrence V. Snyder, Andrew Lim, and Zuli Liu. 2011. “Reliable Logistics Networks Design with Facility Disruptions.” *Transportation Research Part B: Methodological* 45 (8): 1190–1211. <https://doi.org/10.1016/j.trb.2011.05.022>.
- Qi, Lian, Zuo Jun Max Shen, and Lawrence V. Snyder. 2010. “The Effect of Supply Disruptions on Supply Chain Design Decisions.” *Transportation Science* 44 (2): 274–89. <https://doi.org/10.1287/trsc.1100.0320>.
- Sabouhi, Fatemeh, Mohammad Saeed Jabalameli, Armin Jabbarzadeh, and Behnam Fahimnia. 2020. “A Multi-Cut L-Shaped Method for Resilient and Responsive Supply Chain Network Design.” *International Journal of Production Research*, 7353–81. <https://doi.org/10.1080/00207543.2020.1779369>.
- Sawik, Tadeusz. 2019. “Two-Period vs. Multi-Period Model for Supply Chain Disruption Management.” *International Journal of Production Research* 57 (14): 4502–18. <https://doi.org/10.1080/00207543.2018.1504246>.
- Sawik, Tadeusz. 2020. “A Two-Period Model for Selection of Resilient Multi-Tier Supply Portfolio.” *International Journal of Production Research* 58 (19): 6043–60. <https://doi.org/10.1080/00207543.2019.1665204>.
- Shen, Zuo Jun Max, Roger Lezhou Zhan, and Jiawei Zhang. 2011. “The Reliable Facility Location Problem: Formulations, Heuristics, and Approximation Algorithms.” *INFORMS Journal on Computing* 23 (3): 470–82. <https://doi.org/10.1287/ijoc.1100.0414>.
- Simchi-Levi, David, and Philip Kaminsky. 2004. *Managing the Supply Chain: Definitive Guide*. Boston: Irvin McGraw-Hill.
- Snyder, Lawrence V. 2006. “Facility Location under Uncertainty: A Review.” *IIE Transactions (Institute of Industrial Engineers)*. <https://doi.org/10.1080/07408170500216480>.
- Snyder, Lawrence V., Zümbül Atan, Peng Peng, Ying Rong, Amanda J. Schmitt, and Burcu Sinsoysal. 2016. “OR/MS Models for Supply Chain Disruptions: A Review.” *IIE Transactions (Institute of Industrial Engineers)*. Taylor and Francis Ltd. <https://doi.org/10.1080/0740817X.2015.1067735>.
- Suryawanshi, Pravin, and Pankaj Dutta. 2022. “Optimization Models for Supply Chains under Risk, Uncertainty, and Resilience: A State-of-the-Art Review and Future Research Directions.” *Transportation Research Part E: Logistics and Transportation Review* 157 (January). <https://doi.org/10.1016/j.tre.2021.102553>.
- Tang, Christopher S. 2006. “Perspectives in Supply Chain Risk Management.” *International Journal of Production Economics*. <https://doi.org/10.1016/j.ijpe.2005.12.006>.

- Treleven, Mark, and Sharon Bergman Schweikhart. 1988. "A RISK/BENEFIT ANALYSIS OF SOURCING STRATEGIES: SINGLE VS. MULTIPLE SOURCING." *JOURNAL OF OPERATIONS MANAGEMENT*. Vol. 7.
- Wieland, Andreas, and Christian F. Durach. 2021. "Two Perspectives on Supply Chain Resilience." *Journal of Business Logistics* 42 (3): 315–22. <https://doi.org/10.1111/jbl.12271>.