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What it takes to design a supply chain resilient to major disruptions and recurrent interruptions

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ABSTRACT: Global supply chains are more than ever under threat of major disruptions caused by devastating natural and man-made disasters as well as recurrent interruptions caused by variations in supply and demand. This paper presents an optimization model for designing a supply chain resilient to (1) supply/demand interruptions and (2) facility disruptions whose probability of occurrence and magnitude of impact can be mitigated through fortification investments. Numerical results and managerial insights obtained from model implementation are presented. Our analysis focuses on how supply chain design decisions are influenced by facility fortification strategies, a decision maker's conservatism degree, demand fluctuations, supply capacity variations, and budgetary constraints. Finally, examining the performance of the proposed model using a Monte Carlo simulation method provides additional insights and practical implications.

KEY WORDS: *Supply Chain Network Design; Risk; Disruption; Interruption; Uncertainty; Supply and Demand Variation, Reliability; Robust Optimization*

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1. Introduction

Supply chain network design decisions form the backbone of supply chain management with direct impact on a firm's return on investment and its overall performance (Farahani et al., 2014; Zokaee et al., 2014). It concerns strategic decisions on supply chain configuration which includes determining the number, location and capacity of facilities in order to serve a predetermined, but possibly evolving, customer base. Since these decisions are by nature costly and difficult to reverse, supply chain networks are designed to last for several years and hence need to be robust to cope with future uncertainties (Jabbarzadeh et al., 2014; Snyder et al., 2007). Tang (2006) defines two types of risks facing supply chains: operational risks and disruption risks. Operational risks are caused by inherent interruptions such as uncertain customer demand, uncertain supply capacity, and uncertain procurement costs. Disruption risks are caused by major incidents such as natural and man-made disasters (e.g. earthquakes, floods, terrorist attacks, fires, etc.). Esmaeilikia et al. (2014a, b) provides a similar definition and classifies supply chain risks into those posed by major *disruptions* (rare events, but devastating impacts) and supply/demand *interruptions* (frequent occurrence, but less detrimental).

In most cases, the impact of disruptions on business performance is much larger than that of operational risks (Tang, 2006). For today's supply chains, the primary causes of increased exposure to disruptions are the lean and relentless cost-minimization practices, global reach of supply chains, and shorter product life cycles. Recent examples of natural disasters which have disrupted the performance of several supply chains include the tsunamis in the Indian Ocean (2004) and Japan (2011), the earthquakes in China (2008) and Chile (2011 and 2015), and Typhoon Haiyan in the Philippines (2013) (Fahimnia et al., 2015; Klibi et al., 2010). We have no direct control over the probability of occurrence of such disasters, and the only way to reduce the impact of these disasters is to consider the *location* of facilities or suppliers; that is, avoidance of flood-prone areas, earthquake zones, and areas exposed to high sea level rise and storm surges.

There are however disasters whose probability of occurrence and magnitude of impact can be mitigated by greater facility fortification investments. Some examples of such disasters include bushfire where prescribed burning (backburning) will prevent the occurrence, and creating firebreaks will minimize property damage. Manmade fire within factory facilities can be prevented by maintenance of electrical wiring and appliances, education on basic electrical safety principles and investment in low risk fire appliances. Also, installation of fire detection and sprinkler systems will reduce the impact of fire should it occur. Illness and injury within a workforce can be prevented by vaccination and implementation of illness and injury prevention programs (which involve hazard identification, hazard prevention and control,

education and training). Cyber-attacks can be prevented by advanced firewalls and cyber security systems. It is the disruptions caused by these disasters that this paper seeks to address.

According to a recent survey by the insurance company Zurich Financial Services Australia Ltd, 85% of Australian-based companies experienced at least one supply chain disruption during 2011. Supply chain disruptions can have substantial impacts on the both short-term and long-term performance of firms (Hendricks et al., 2009; Peng et al., 2011). Hendricks and Singhal (2005) reported that companies suffering from even smaller-scale supply chain disruptions experienced 33-40% lower stock returns relative to their industry benchmarks. These illustrations and statistics reinforce the need to consider hedging against disruption risks when designing supply chain networks, a highly complex task due to the many influencing factors including budget availability (capital investment), decision maker's risk attitude, type of network under consideration, and the probability of disruption occurrence. Given that disruptions tend to be rare events, a primary complexity in designing resilient supply chains is the lack of historical data available from past disasters. The interaction between operational risks, more importantly demand variation risks, and disruption risks can add to this complexity. For instance, under demand uncertainty, it may be more beneficial for a company to run fewer number of larger facilities taking advantage of economies of scale in purchasing (Daskin et al., 2002), while it may be more worthwhile to operate more number of smaller facilities to minimize the impact of a disruption in one facility on the overall supply chain performance (Jabbarzadeh et al., 2015 ; Snyder et al., 2006).

To address these challenges, we present a hybrid robust optimization model (applying a robust optimization approach to a stochastic model) for designing a supply chain resilient to supply/demand variations and major disruptions whose risk of occurrence and magnitude of impact can be mitigated through facility fortification investments. The objective of the proposed model is to minimize the total cost of establishing the network while maximizing the supply chain resilience. Disruption occurrence probability is expressed as a function of capital investment for facility fortification. Facilities established at lower costs receive a higher probability of failure (less reliable facilities) and those with greater capital investment are assigned a smaller disruption probability value (more reliable facilities). Obviously, for situations when the probability of a disruption is not a function of investment level, one can simply set equal probabilities for different fortification levels. The ultimate goal of the proposed model is to determine the supply chain design decisions including the number, location and type of facilities (reliable or unreliable facilities) in the presence of certain budgetary constraints. We will investigate how the proposed model is able to capture the decision-makers' risk attitude to develop tradeoff between the supply chain design costs and disruption risks.

2. Literature Review

Reviews of facility location modeling efforts have been completed by Snyder (2006), ReVelle et al. (2008), and Melo et al. (2009). The more recent review of Snyder et al. (2014) indicates that a research focus on the design of ‘resilient supply chains’ has only been a recent occurrence; becoming only about 10 years old in 2015. Snyder and Daskin (2005) were among the first to incorporate disruption risks into classical facility location problems. They present reliability models based on a P-median problem and an uncapacitated fixed-charge location problem in which facilities are subject to disruptions. Their model aims to minimize facility location costs while taking into account the expected transportation cost when an unexpected disruption occurs. Aryanezhad et al. (2010) include inventory decisions to this model and present integer programming models minimizing the sum of facility construction costs, expected inventory costs and expected customer costs under normal and disruption situations. Chen et al. (2011) propose a Lagrangian relaxation method to solve this model.

The above studies assume equal disruption probabilities in all facilities, an assumption that has been relaxed in some of the more recent works by Berman et al. (2007), Li and Ouyang (2010), Shen et al. (2011), and Cui et al. (2010). Berman et al. (2007) presented a nonlinear integer programming model where facilities face independent disruptions with different probabilities. Due to model intractability, a heuristic algorithm was developed to solve the problem. O’Hanley et al. (2013) proposed an efficient technique for linearizing the facility location problem with site-dependent failure probabilities to tackle the intractability issue. Cui et al. (2010) presented an exact linear formulation for this problem to consider heterogeneous facility failure probabilities utilizing the linearization method of Sherali and Alameddine (1992).

Lim et al. (2010) incorporate the facility fortification concept into a facility location model to hedge against the risk of facility disruptions. They assume that if a serving facility fails, the associated demand point is immediately assigned to its backup. The problem is formulated as a mixed integer programming model for which a Lagrangian relaxation algorithm is proposed as a solution method. Li et al. (2013) extend this model by incorporating the rate of return for fortification investment and compare the results with that of alternative investment opportunities. For instance, a firm may choose to invest in network fortification only if the rate of return exceeds a minimum acceptable rate of return. The problem is further extended and investigated by Li and Savachkin (2013) where a facility can be fortified to a certain reliability level (a partial fortification strategy). All of these studies assume unlimited facility capacity.

The aforementioned models assume that a disrupted facility is completely out of service and hence disregard the probability that the performance of a facility can only be partially affected. Jabbarzadeh et al. (2012) present a supply chain design model for a situation where a facility may be partly disrupted, but may yet be

able to fulfill a fraction of the initially assigned demand. Two solution methods based on Lagrangian relaxation and genetic algorithms are developed to solve the model. Liberatore et al. (2012) study the problem of optimally protecting a capacitated median where disasters may result in partial or complete shutdown of facilities. The proposed model optimizes protection plans when facing large area disruptions (i.e. disruptions that affect regions rather than single elements of the system). An algorithm is designed to solve the model optimally and is tested on a set of data from 2009 L'Aquila earthquake. Azad et al. (2013) formulate a capacitated location allocation model that accounts for partial disruptions considering deterministic supply chain demand. Benders decomposition is utilized to solve this computationally intractable model.

All the above models assume a risk-neutral decision maker who wishes to optimize the expected value of the objective function. Some of the most recent studies focus on risk aversion decision making through bi-level model formulation and optimizing worst-case objectives (Hernandez et al., 2014; Liberatore et al., 2011; Losada et al., 2012; Medal et al., 2014). Medal et al. (2014) investigate the minimax facility location and hardening problem seeking to minimize the maximum distance from a demand point to its closest located facility after facility disruptions. A decision maker in this case is interested in mitigation against a facility disruption scenario with the largest consequence. Likewise, Hernandez et al. (2014) apply a worst-case approach to hedge against disruptions. Using a multi-objective optimization approach, their model provides a decision maker with an option to tradeoff total weighted travelling distance before and after disruptions in a facility location problem. It allows investigating the impact that the opening of additional facilities can have on total distance travelled. Losada et al. (2012) present a bi-level mixed integer linear program for protecting an uncapacitated median type facility network against worst-case losses, taking into account the role of facility recovery time on system performance and the possibility of multiple disruptions over time. Their model differs from a typical facility protection model in that protection is not assumed to always successfully avoid facility failure, but rather to speed up recovery time post disruptions. One limitation of the worst-case approaches is that it can be highly over conservative in practical cases as the probability at which uncertain parameters reach their worst values may be very low (Snyder, 2006).

There are also studies that consider the risk preference of decision makers using scenario-based models. Peng et al. (2011) present a scenario-based modeling approach in which each scenario includes a set of facilities that can fail simultaneously. Their model aims at minimizing the total cost under normal circumstances while reducing the disruption risk using the p -robustness criterion (bounding the cost in disruption scenarios and allowing capturing risk aversion). A genetic algorithm approach is used to solve the model. Similarly, Baghalian et al. (2013) develop a scenario-based model for designing a supply chain

whose objective is to maximize profit under the risks of disruption. To address the risk-aversion attitude of a decision maker, the variance of total profit is incorporated into the model. The model is formulated using mixed integer nonlinear programming and approximated using multiple linear regressions. The limitation of a scenario-based approach is that solving such models becomes more difficult as the number of scenarios increases (Peng et al., 2011).

Our study contributes to this literature in the following ways. First, unlike the published models, our model is able to tackle multiple types of risks, including strategic disruption risks and operational supply/demand uncertainties. This allows the effective design of supply chain networks where historical risk data is limited or nonexistent. Second, we present a hybrid robust-stochastic method (i.e. applying a robust optimization approach to a stochastic model) that overcomes the limitations of the scenario-based methods (the computational overhead for managing a large number of scenarios) and the worst-case approaches (over-conservative attitude in practical cases). The approach has the flexibility of adjusting the conservativeness level of solutions while preserving the computational complexity of the nominal problem. In addition, the hybrid nature of the presented formulation facilitates the modeling of a complex situation where even the probability of random disruptions is uncertain. Third, our modeling effort takes into consideration a realistic range of assumptions (e.g. partial or complete shutdown of facilities when disruptions occur), variables (e.g. both partial and full facility fortification options) and constraints (e.g. budget and capacity constraints); representing a more realistic situation than those studied in the past (see the review of Snyder et al. (2014) for a more comprehensive review of the existing literature).

3. Model Formulation

We first present a background of robust optimization to better inform the mathematical formulation of the resilient supply chain network design. A stochastic model is then developed for supply chain network design considering the risk of disruptions. This model is then extended to incorporate uncertainties in demand, probability of disruption occurrence and capacity of facilities into the model; forming a hybrid robust-stochastic optimization formulation. The latter model aims to design a resilient supply chain network, a supply chain that is resilient to disruptions and supply/demand interruptions.

3.1 Background of robust optimization

Although stochastic programming methods are powerful in modeling uncertain factors (Birge and Louveaux, 2011), they usually require the availability of probability distributions of random variables (Klibi et al., 2010). Robust optimization methods have been used to tackle this drawback when there is the lack of historical data to estimate the actual distribution of uncertain parameters. They are also capable of incorporating decision-makers' risk attitude (Bental et al., 2009). Here, we explain the framework of the robust formulation introduced by Bertsimas and Sim (2003, 2004) which has been extensively adopted in the past to address supply chain uncertainty issues (Gabrel et al., 2014).

Let us consider a linear mathematical programming model as:

$$\text{Min } c_j' x_j \quad (1)$$

Subject to:

$$\sum_j a_{ij} x_j \leq b_i \quad \forall i = 1, 2, 3, \dots, m. \quad (2)$$

$$x_j \in \{0, 1\} \quad (3)$$

Here, a_{ij} denotes uncertain parameters and J_i is the set of uncertain parameters in i^{th} constraint. Bertsimas and Sim (2003, 2004) assume that each uncertain parameter a_{ij} is a random variable which takes values in interval $[\bar{a}_{ij} - \hat{a}_{ij}, \bar{a}_{ij} + \hat{a}_{ij}]$. Where \bar{a}_{ij} represents the nominal value of the uncertain

parameter and \hat{a}_{ij} is the deviation of the nominal value. Using duality theory, they prove that the robust counterpart of the uncertain linear programming model (1) to (3) can be written as:

$$\text{Min } c'_j x_j, \quad (4)$$

Subject to:

$$\sum_{j \in J} \bar{a}_{ij} x_j + Z_i \Gamma_i + \sum_{j \in J} p_{ij} \leq b_i \quad \forall i \quad (5)$$

$$Z_i + p_{ij} \geq \hat{a}_{ij} x_j \quad \forall j \in J \quad (6)$$

$$Z_i \geq 0 \quad \forall i \quad (7)$$

$$p_{ij} \geq 0 \quad \forall i, j \quad (8)$$

$$x_j \in \{0, 1\} \quad (9)$$

Z_i and p_{ij} are auxiliary variables and Γ_i is a parameter called “*uncertainty budget*”. The parameter Γ_i adjusts the uncertainty level in each row varying in interval of $[0, |J_i|]$. In other words, the robust formulation aims to protect against all cases that up to Γ_i of uncertain parameters a_{ij} are allowed to change. When Γ_i is set equal to zero, the constraints are equivalent to that of the nominal problem. Likewise, when Γ_i is set to $|J_i|$, the robust model acts with the highest level of conservatism. The role of Γ_i is thus to adjust the conservatism level of the robust formulation. Further details about robust formulation can be found in Bertsimas and Sim (2003, 2004).

3.2 Formulation of the base stochastic model

We now formulate a stochastic network design model for a supply chain under random disruptions, assuming no demand and supply uncertainties. We consider a generic supply chain network in which facilities fulfil market demands at customer locations. A disruption at any facility can cause either a complete shutdown or a reduced supply capacity. Disruption probabilities in different facilities are assumed to be independent and location specific. The facilities can be either partially or fully fortified requiring capital investments corresponding to the degree of fortification. An example of such investments is the

acquisition, installation and implementation of infection control measures to contain and prevent disease from disabling a workforce. Another example is the acquisition and installation of advanced fire protection systems to mitigate the risk of factory fires. Therefore, we assume that the probability and magnitude of a disruption in a facility can be expressed as a function of fortification degree in that facility (as is the case in many disruptions). Compliance with a full fortification degree will make a facility *reliable* (resilient to major disruptions). Partially fortified facilities still remain *unreliable* and may be affected by disruptions with a given probability. When affected by a disruption, an unreliable facility can be supplied by other reliable facilities to compensate for the reduced supply capacity so that the assigned demands can still be satisfied. For a hypothetical example with two fortification levels, Figure 1 illustrates the assignment of customers to facilities and the shipment of products between these nodes.

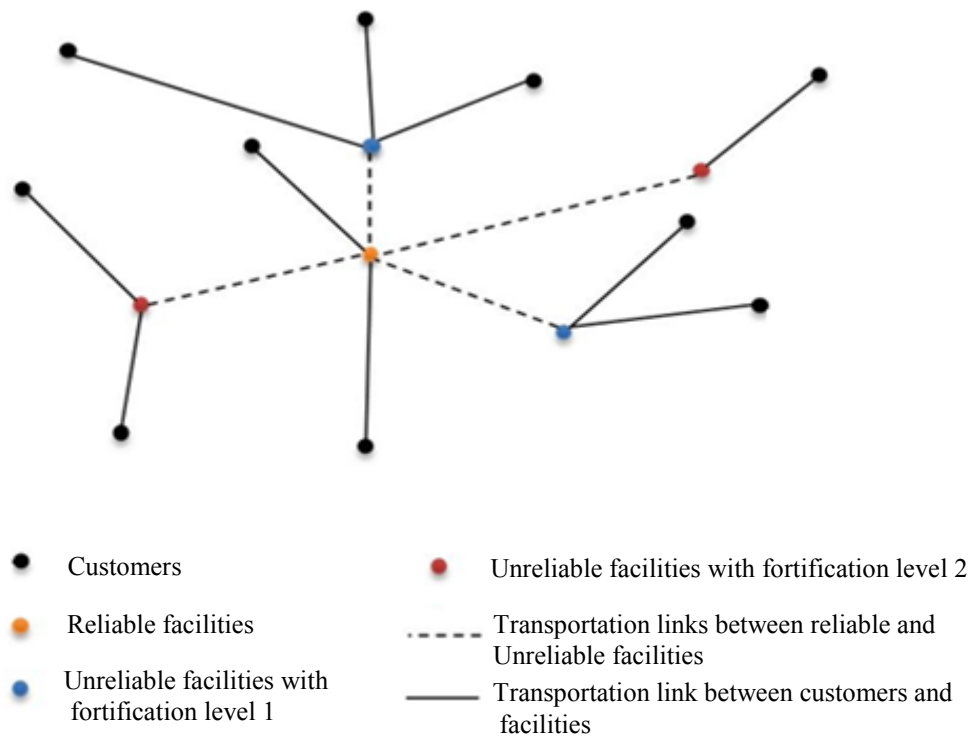


Figure 1. The assignment of customers to facilities and the shipment of products between facilities and between facilities and customers

The objective is to minimize the total cost of the supply chain in a way that customer demands are satisfied even in disruptions. In the presence of certain budgetary constraints, the proposed model aims to determine (1) the number of facilities to open, (2) the location of facilities, (3) the allocation of facilities to customers, (4) the required fortification degree of each facility, (5) the quantity of products shipped between reliable and unreliable facilities when a disruption occurs. Modeling indices, parameters and decision variables are defined below.

Sets:

K : Set of customers

J : Set of potential locations for unreliable facilities

M : Set of potential locations for reliable facilities

I : Set of potential locations for facilities ($I = J \cup M$)

N : Set of fortification levels for unreliable facilities

Parameters:

D_k : Demand of customer k ($\forall k \in K$)

B : Budget available for establishing facilities

f_{jn}^U : Fixed cost of locating an unreliable facility at location j with fortification level n

f_m^R : Fixed cost of locating a reliable facility at location m ($\forall m \in M$)

o_{jk} : Unit transportation cost from unreliable facility at location j to customer k ($\forall j \in J, \forall k \in K$)

l_{mk} : Unit transportation cost from reliable facility at location m to customer k ($\forall m \in M, \forall k \in K$)

C_{mj} : Unit transportation cost from reliable facility at location m to unreliable facility at location j ($\forall m \in M, \forall j \in J$)

CU_j : Capacity of unreliable facility at location j under normal circumstances ($\forall j \in J$)

CR_m : Capacity of reliable facility at location m ($\forall m \in M$)

q_{jn} : Disruption probability in unreliable facility at location j with fortification level n ($\forall j \in J, \forall n \in N$)

α_{jn} : Percentage of total capacity lose when a disruption occurs in unreliable facility at location j with fortification level n

Decision variables:

T_{mj} : Quantity of products shipped from reliable facility at location m to unreliable facility at location j

$(\forall m \in M, \forall j \in J)$

$Y_{jn} = \begin{cases} 1 & \text{If unreliable facility } j \text{ is opened with fortification level } n \\ 0 & \text{Otherwise} \end{cases} \quad (\forall j \in J, \forall n \in N)$

$X_m = \begin{cases} 1 & \text{If reliable facility } m \text{ is opened} \\ 0 & \text{Otherwise} \end{cases} \quad (\forall m \in M)$

$U_{jk} = \begin{cases} 1 & \text{If customer } k \text{ is assigned to unreliable facility } j \\ 0 & \text{Otherwise} \end{cases} \quad (\forall j \in J, \forall k \in K)$

$R_{mk} = \begin{cases} 1 & \text{If customer } k \text{ is assigned to reliable facility } m \\ 0 & \text{Otherwise} \end{cases} \quad (\forall m \in M, \forall k \in K)$

The stochastic supply chain network design model can now be developed by incorporating the impact of fortification levels of facilities on the probability of disruptions as well as the associated capacity and budget constraints into the model of Azad et al. (2013). The model is formulated as follows (note: uncertainties in demand, probability of disruption occurrence and capacity of facilities will be incorporated into the model in a later stage):

$$\begin{aligned} \text{Min: } & \sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m + \sum_{j \in J} \sum_{k \in K} o_{jk} D_k U_{jk} + \sum_{m \in M} \sum_{k \in K} l_{mk} D_k R_{mk} \\ & + \sum_{j \in J} \sum_{n \in N} q_{jn} Y_{jn} \left(\sum_{m \in M} T_{mj} C_{mj} \right) \end{aligned} \quad (10)$$

Subject to:

$$\sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m \leq B \quad (11)$$

$$\sum_{m \in M} X_m \geq 1 \quad (12)$$

$$X_i + \sum_{n \in N} Y_{in} \leq 1 \quad \forall i \in I \quad (13)$$

$$R_{mk} \leq X_m \quad \forall m \in M, k \in K \quad (14)$$

$$\sum_{k \in K} D_k U_{jk} \leq \sum_{n \in N} C U_j Y_{jn} \quad \forall j \in J \quad (15)$$

$$\sum_{m \in M} T_{mj} + \left(1 - \sum_{n \in N} a_{jn} Y_{jn}\right) C U_j \geq \sum_{k \in K} D_k U_{jk} \quad \forall j \in J \quad (16)$$

$$\sum_{j \in J} T_{mj} + \sum_{k \in K} D_k R_{mk} \leq C R_m X_m \quad \forall m \in M \quad (17)$$

$$\sum_{j \in J} U_{jk} + \sum_{m \in M} R_{mk} = 1 \quad \forall k \in K \quad (18)$$

$$X_m \in \{0, 1\} \quad \forall m \in M \quad (19)$$

$$Y_{jn} \in \{0, 1\} \quad \forall j \in J, \forall n \in N \quad (20)$$

$$R_{mk} \in \{0, 1\} \quad \forall m \in M, \forall k \in K \quad (21)$$

$$U_{jk} \in \{0, 1\} \quad \forall j \in J, \forall k \in K \quad (22)$$

$$T_{mj} \geq 0 \quad \forall m \in M, \forall j \in J \quad (23)$$

The objective function (10) minimizes the expected total cost including the costs of locating reliable and unreliable facilities with different fortification levels, transportation costs for shipment of products from facilities to customers, and expected transportation costs for shipment of products from reliable facilities to unreliable facilities when disruptions occur. Constraint (11) expresses the total budget limitation. Constraint (12) enforces that at least one reliable facility must be opened to guarantee demand satisfaction when all unreliable facilities are disrupted. Constraint (13) ensures that only one facility can be opened at each location. For this constraint, we set $X_i = 0$ for $i \notin M$ and $Y_{in} = 0$ for $i \notin J$. Constraint (14) ensures that customers can only be assigned to open facilities. Constraint (15) expresses the capacity restriction of unreliable facilities. Constraint (16) guaranties that demand assigned to each unreliable facility is satisfied. Constraint (17) expresses the capacity limit of reliable facilities. Constraint (18) enforces that each customer is assigned to a facility. Constraints (19) to (23) define the domains of the decisions variables.

The model formulation (10)-(23) is nonlinear by the term $\sum_{j \in J} \sum_{n \in N} q_{jn} Y_{jn} \left(\sum_{m \in M} T_{mj} C_{mj} \right)$ in objective function (10). This formulation can be linearized using a new auxiliary variable named H_{jmm} and a new constraint (25) as follows.

$$\text{Min} : \sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m + \sum_{j \in J} \sum_{k \in K} o_{jk} D_k U_{jk} + \sum_{m \in M} \sum_{k \in K} l_{mk} D_k R_{mk} + \sum_{j \in J} \sum_{m \in M} \sum_{n \in N} q_{jn} C_{mj} H_{jmm} \quad (24)$$

Subject to:

Constraints (11) to (23)

$$H_{jnm} \geq T_{mj} + M(Y_{jn} - 1) \quad \forall j \in J, m \in M, n \in N \quad (25)$$

$$H_{jnm} \geq 0 \quad \forall j \in J, \forall k \in K \quad (26)$$

Where M is a big number and the auxiliary H_{jnm} is defined as follows.

$$H_{jnm} = Y_{jn} T_{mj} \quad \forall m \in M, j \in J, n \in N \quad (27)$$

Constraint (25) ensures that products cannot be transported from a reliable facility to an unreliable facility that is not yet established. Bringing the objective function (24) into the constraints and defining a new variable λ , the above model can be rewritten as:

$$\text{Min} : \lambda \quad (28)$$

Subject to:

Constraints (11) to (23) and (25) and (26)

$$\begin{aligned} & \sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m + \sum_{j \in J} \sum_{k \in K} o_{jk} D_k U_{jk} + \sum_{m \in M} \sum_{k \in K} l_{mk} D_k R_{mk} + \\ & \sum_{j \in J} \sum_{m \in M} \sum_{n \in N} q_{jn} C_{mj} H_{jnm} \leq \lambda \end{aligned} \quad (29)$$

$$\lambda \geq 0 \quad (30)$$

3.3 Formulation of the hybrid robust-stochastic model

We now extend the stochastic model presented in Section 3.2 to include uncertainties in demand, supply capacity and probability of disruption occurrence, forming a robust-stochastic optimization model. We first look at demand uncertainty in Section 3.3.1 and will then incorporate uncertainty in the likelihood of disruption occurrence and uncertainty in capacity of facilities in Section 3.3.2.

3.3.1 Formulating demand uncertainty

We utilize the robust optimization approach discussed in Section 2 to formulate demand uncertainty. The uncertain parameter D_k takes the values within the range of $[\bar{D}_k - \hat{D}_k, \bar{D}_k + \hat{D}_k]$ corresponding to all

customers. Also, budget uncertainty Γ^D (conservatism degree) is considered for customer demands taking values between zero and the number of customers. As discussed in Section 2, the robust model can be written as follows.

$$\text{Min} : \lambda \quad (31)$$

Subject to:

Constraints (11) to (14), (18) to (23), (25) and (26)

$$\sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m + \sum_{j \in J} \sum_{k \in K} o_{jk} \bar{D}_k U_{jk} + \sum_{m \in M} \sum_{k \in K} l_{mk} \bar{D}_k R_{mk} + \sum_{j \in J} \sum_{m \in M} \sum_{n \in N} q_{jn} C_{mj} H_{jnm} \quad (32)$$

$$\sum_{k \in K} p_k^1 + \sum_{k \in K} p_k^2 + Z^0 \Gamma^D + Z^1 \Gamma^D \leq \lambda$$

$$Z^0 + p_k^1 \geq o_{jk} \hat{D}_k U_{jk} \quad \forall j \in J, k \in K \quad (33)$$

$$Z^1 + p_k^2 \geq l_{mk} \hat{D}_k R_{mk} \quad \forall j \in J, k \in K \quad (34)$$

$$\sum_{k \in K} \bar{D}_k U_{jk} + \sum_{k \in K} p_k^3 + Z_j^2 \Gamma^D \leq \sum_{n \in N} C U_j Y_{jn} \quad \forall j \in J \quad (35)$$

$$Z_j^2 + p_k^3 \geq \hat{D}_k U_{jk} \quad \forall j \in J, k \in K \quad (36)$$

$$\sum_{m \in M} T_{mj} + \left(1 - \sum_{n \in N} a_{jn} Y_{jn}\right) C U_j \geq \sum_{k \in K} \bar{D}_k U_{jk} + \sum_{k \in K} p_k^4 + Z_j^3 \Gamma^D \quad \forall j \in J \quad (37)$$

$$p_k^4 + Z_j^3 \geq \hat{D}_k U_{jk} \quad \forall j \in J, k \in K \quad (38)$$

$$\sum_{j \in J} T_{mj} + \sum_{k \in K} \bar{D}_k R_{mk} + \sum_{k \in K} p_k^5 + Z_j^4 \Gamma^D \leq C R_m X_m \quad \forall m \in M \quad (39)$$

$$p_k^5 + Z_j^4 \geq \hat{D}_k U_{jk} \quad \forall j \in J, k \in K \quad (40)$$

$$p_k^1, p_k^2, p_k^3, p_k^4, p_k^5, Z_j^0, Z_j^1, Z_j^2, Z_j^3, Z_j^4 \geq 0 \quad \forall j \in J, k \in K. \quad (41)$$

Where variables $p_k^1, p_k^2, p_k^3, p_k^4, p_k^5, Z_j^0, Z_j^1, Z_j^2, Z_j^3, Z_j^4$ are auxiliary variables.

3.3.2 Formulating supply uncertainty

We now formulate uncertainty in supply capacity of facilities (a_{jn}) and uncertainty in the probability of disruption occurrence (q_{jn}). Consider uncertain parameters q_{jn} and a_{jn} that can take values within intervals

$[\bar{q}_{jn} - \hat{q}_{jn}, \bar{q}_{jn} + \hat{q}_{jn}]$ and $[\bar{a}_{jn} - \hat{a}_{jn}, \bar{a}_{jn} + \hat{a}_{jn}]$, respectively. Here, Γ^q denotes the uncertainty budget for the probability of disruption occurrence ranging between zero and the number of facilities multiplied by number of fortification levels. Also, the uncertainty budget for capacity of facilities is denoted by Γ^a which takes values between zero and the number of fortification levels. Therefore, the robust optimization model including the uncertainties in demand, probability of a disruption occurrence and capacity of facilities can be formulated as follows.

$$\text{Min} : \lambda \quad (42)$$

Subject to:

Constraints (11) to (14), (18) to (23), (25), (26), (33) to (36), and (38) to (41)

$$\sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m + \sum_{j \in J} \sum_{k \in K} o_{jk} \bar{D}_k U_{jk} + \sum_{m \in M} \sum_{k \in K} l_{mk} \bar{D}_k R_{mk} + \quad (43)$$

$$\sum_{j \in J} \sum_{m \in M} \sum_{n \in N} \bar{q}_{jn} C_{mj} H_{jnm} + \sum_{j \in J} \sum_{n \in N} p_{jn}^6 + \sum_{k \in K} p_k^1 + \sum_{k \in K} p_k^2 + Z^0 \Gamma^D + Z^1 \Gamma^D + Z^5 \Gamma^q \leq \lambda$$

$$Z^5 + p_{jn}^6 \geq \hat{q}_{jn} H_{jnm} \quad \forall j \in J, n \in N, m \in M \quad (44)$$

$$\sum_{m \in M} T_{mj} + \left(1 - \sum_{n \in N} \bar{a}_{jn} Y_{jn}\right) CU_j \geq \sum_{k \in K} \bar{D}_k U_{jk} + \sum_{n \in N} p_{jn}^7 + \sum_{k \in K} p_k^4 + Z_j^3 \Gamma^D + Z_j^6 \Gamma^a \quad \forall j \in J \quad (45)$$

$$Z_j^6 + p_{jn}^7 \geq \hat{a}_{jn} CU_j Y_{jn} \quad \forall j \in J, \forall n \in N \quad (46)$$

$$Z^5, Z_j^6, p_{jn}^6, p_{jn}^7 \geq 0 \quad \forall j \in J, \forall n \in N \quad (47)$$

Where variables $Z^5, Z_j^6, p_{jn}^6, p_{jn}^7$ are axillary variables.

Considering constraint (43), the above model can be rewritten as follows:

$$\text{Min} : \sum_{j \in J} \sum_{n \in N} f_{jn}^U Y_{jn} + \sum_{m \in M} f_m^R X_m + \sum_{j \in J} \sum_{k \in K} o_{jk} \bar{D}_k U_{jk} + \sum_{m \in M} \sum_{k \in K} l_{mk} \bar{D}_k R_{mk} + \quad (48)$$

$$\sum_{j \in J} \sum_{m \in M} \sum_{n \in N} \bar{q}_{jn} C_{mj} H_{jnm} + \sum_{j \in J} \sum_{n \in N} p_{jn}^6 + \sum_{k \in K} p_k^1 + \sum_{k \in K} p_k^2 + Z^0 \Gamma^D + Z^1 \Gamma^D + Z^5 \Gamma^q$$

Subject to:

Constraints (11) to (14), (18) to (23), (25), (26), (33) to (36), (38) to (41), and (44) to (47).

4. Computational Experiments and Practical Implications

4.1 *Experimental design*

The application of the proposed model is investigated for 21-node, 32-node and 49-node datasets presented in Daskin (1995). For the 21-node and 32-node datasets, the nodes represent the state capitals of the lower 21 and 32 United States. The 49-node dataset consists of the 48 state capitals of the United States plus Washington, DC. The same datasets have been used in some other studies of Snyder and Daskin (2005), Snyder et al. (2007), Aryanezhad et al. (2010), Qi et al. (2010) and Jabbarzadeh et al. (2012). The computational experiments for these data sets are completed using a branch and bound algorithm coded in GAMS 24.1 on a laptop with Intel Core i2 CPU, 2.53GHz and 3GB of RAM. We also need larger datasets to evaluate the performance of the proposed Lagrangian relaxation method. For this purpose, we develop and adopt three larger datasets: 88-node, 100-node and 150-node datasets. The 88-node dataset includes the 49-node dataset, plus the 50 largest cities in the United States, minus duplicates. The 150-node dataset includes the 150 largest cities in the United States based on 1990 census data (Daskin, 1995). The 100-node dataset is comprised of random data, adopted from Snyder and Daskin (2005).

For the 100-node dataset, the values of all parameters are obtained similar to Snyder and Daskin (2005). For the other datasets, the nominal demand is obtained by dividing the population data given in Daskin (1995) by 1,000. Three levels of fortification—full, moderate and low—are considered for facilities, denoted as FF, FM and FL, respectively. The fixed cost of establishing a reliable (i.e. fully fortified facilities) facility is obtained by dividing the fixed facility cost by 10. The fixed costs of locating unreliable facilities with moderate and low fortification levels are set equal to 32% and 20% of establishing a reliable facility. Unit transportation cost from facilities to customers is assumed to be 50% of the great-circle distance between facilities and customers. Unit shipment cost from reliable facilities to unreliable facilities is equal to 10% of the great-circle distance between them. The available budget for establishing all facilities is \$200,000. The values of the other parameters are given in Table 1. Computational experiments are conducted considering 5% variability in uncertain parameters from the nominal values.

Table 1. Input parameters for all datasets

	Capacity under normal circumstance			Probability of disruption occurrence		Percentage disrupted capacity	
	FF	FM	FL	FM	FL	FM	FL
21-Node	1,600	1,400	1,400	0.85	0.95	0.55	0.75
32-Node	2,000	1,500	1,500	0.85	0.90	0.3	0.60
49-Node	2,600	1,900	1,900	0.9	0.95	0.4	0.75
88-Node	2,000	1,500	1,500	0.9	0.95	0.25	0.5
100-Node	2,600	1,900	1,900	0.85	0.95	0.3	0.7
150-Node	2,600	1,900	1,900	0.9	0.95	0.3	0.6

4.2 Model implementation and initial observations

Initial numerical results are shown in Tables 2-4 providing the optimal location of facilities as well as the optimal assignment of customers to facilities corresponding to different conservatism degrees for the three datasets. From these initial findings, one can see that the optimal location of facilities, especially the reliable facilities, is almost analogous at different conservatism degrees. Reliable facilities tend to be opened at sites 5 and 7 regardless of the conservatism degree chosen. One possible reason for this can be the more convenient proximity of these facilities to customers and other facilities resulting in a lower transportation cost between nodes. Likewise, in all instances, site 4 is a preferred location to open a facility with low fortification level. An important insight from these observations can be that small changes in supply chain topology (changes in location of a small fraction of facilities) can help protecting the network against some of the potential risks.

A careful comparison between the impacts that the number of customers and demand scale can have on facility location decisions can provide additional insights. Tables 2-4 indicates that the location of reliable facilities is less sensitive to changes in the number of customers served (comparing the location results for the three datasets). In other words, adjustment in location of unreliable facilities is used to deal with different demand sizes. The model is clearly taking advantage of the lower cost of opening unreliable facilities to cope with variations in the number of customers served. This is a good example of a situation where various facility fortification strategies can be used for effective demand fulfillment in different network sizes.

Table 2. Initial model outputs for the 21-node dataset

Conservatism Degrees			Location of Facilities			Number of Assigned Customers		
Γ^D	Γ^q	Γ^a	FF	FM	FL	FF	FM	FL
0	0	0	7	5,6	3,4,15	2	11	8
5	10	0	7	5, 6	3, 4, 9, 10, 15	2	9	10
10	20	1	5	3,6	4, 7, 9, 10, 15	5	8	8
15	30	1	5	6,17	4, 7, 9, 10,15	5	7	9
18	36	2	5	6,17	4, 7, 9, 10, 12, 15	5	7	9
21	42	2	5	4,6,17	4,7, 9, 12, 15	5	11	5

Table 3. Initial model outputs for the 32-node dataset

Conservatism Degrees			Location of Facilities			Number of Assigned Customers		
Γ^D	Γ^q	Γ^a	FF	FM	FL	FF	FM	FL
0	0	0	7	5	3, 4, 9,18 ,28 ,30 ,32	3	4	25
5	10	0	7	5	3, 4, 9,18 ,28 ,30 ,32	3	5	24
8	16	0	5	-	3, 4,7, 9,18 ,28 ,30 ,32	5	-	27
12	24	1	5	-	3, 4,7, 9,18 ,28 ,30 ,32	5	-	27
17	34	1	5	9	3, 4, 7, 18, 28, 30	5	5	22
21	42	1	5	17	4, 7,9, 18, 28, 30, 32	5	3	21
25	50	2	5	17	4,7,9,10,18,28,30,32	5	3	21
29	58	2	5	6	4,7,9,12,17,18,28,30	2	4	26
32	64	2	5	9,17	4,7,12,15,18,28	2	8	22

Table 4. Initial model outputs for the 49-node dataset

Conservatism Degrees			Location of Facilities			Number of Assigned Customers		
Γ^D	Γ^q	Γ^a	FF	FM	FL	FF	FM	FL
0	0	0	7	5,46	3,4,15,18,29,30,33	7	13	22
5	10	0	7	5,46	3,4,15,18,29,30,33	7	13	22
10	20	0	7	5,46	3,4,15,18,29,30,33	8	13	21
20	40	1	7	5,46	3,4,15,18,29,30,33	7	13	22
25	50	1	7	5,46	3,4,12,15,18,29,30,33	5	11	33
30	60	1	7	5,46	3,4,12,15,18,29,30,33	7	10	32
40	80	2	5	46	3,4,7,15,28,30,33,34	6	8	35
45	90	2	5	46	3,4,7,12,15,28,30,33,34	3	8	38
49	98	2	5	46	3,4,7,12,15,28,30,33,34	2	8	39

5.3 Analysis on the impact of a decision maker's conservatism degree

We now complete an experiment to investigate how the choice of conservatism degree can influence the overall supply chain cost and model runtime. The results are shown in Tables 5-7 for the concerned datasets. Not surprisingly, a greater conservatism degree results in a higher total supply chain cost to hedge the network against the potential risks and uncertainties. What is interesting is that in no occasion does the cost increase by more than 9%, indicating that considerable resilience improvements can be achieved with only insignificant increases in costs.

The total cost and cost difference values in Tables 5-7 show that the supply chain cost is not linearly increased as conservatism degree gets larger. For example, from Table 5, a 8.9% cost increase occurs to improve the supply resilience from the conservative level of $\Gamma^D = 0$ and $\Gamma^q = 0$ to $\Gamma^D = 5$ and $\Gamma^q = 10$; while only 0.9% cost difference is enough to move from $\Gamma^D = 5$ and $\Gamma^q = 10$ to $\Gamma^D = 10$ and $\Gamma^q = 20$. Another interesting observation is that in all datasets the greatest cost increase occurs in the second row, implying that the initial efforts to build resilience into the supply chain network are more costly. Note that the total cost at $\Gamma^D = 0$, $\Gamma^q = 0$ and $\Gamma^a = 0$ is obtained from the objective value of the stochastic model disregarding the supply chain resilience in the face of supply and demand variations as described in Section 3. The last columns of Tables 5-7 provide the model runtimes.

Table 5. Supply chain cost and model runtime at various conservatism degrees for the 21-node dataset

Γ^D	Γ^q	Γ^a	Total Cost (\$)	Cost Difference (%)	Runtime (Seconds)
0	0	0	266459	0.0	3.2
5	10	0	290078	8.9	10
10	20	1	292757	0.9	17
15	30	1	298763	2.1	23
18	36	2	301572	0.9	11
21	42	2	307879	2.1	10

Table 6. Supply chain cost and model runtime at various conservatism degrees for the 32-node dataset

Γ^D	Γ^q	Γ^a	Total Cost (\$)	Cost Difference (%)	Runtime (Seconds)
0	0	0	289838	0.0	2
5	10	0	312003	7.6	50
8	16	0	316459	1.4	56
12	24	1	319550	1.0	62
17	34	1	320947	0.4	67
21	42	1	321988	0.3	78
25	50	2	324640	1.0	69
29	58	2	332697	2.5	62
32	64	2	338583	1.8	78

Table 7. Supply chain cost and model runtime at various conservatism degrees for the 49-node dataset

Γ^D	Γ^q	Γ^a	Total Cost (\$)	Cost Difference (%)	Runtime (Seconds)
0	0	0	314381	0.0	7
5	10	0	319798	2.0	33
10	20	0	327184	2.0	38
20	40	1	330139	0.9	42
25	50	1	331896	0.5	67
30	60	1	335101	1.0	72
40	80	2	336124	1.0	78
45	90	2	342110	1.8	265
49	98	2	348829	2.0	394

5.4 Analysis on the impacts of demand and supply uncertainties

For the 49-node dataset, Table 8 shows how demand and supply variations can influence the total supply chain cost at different conservatism degrees. What is obvious from this data is that demand variation can have greater impact on the strategic supply chain cost when compared to supply uncertainty. In some scenarios when $\Gamma^D \geq 30$, demand variations can even result in infeasibility implying failure to satisfy customer demand and hence product shortage and lost sales. A practical implication from this finding would be for the risk managers to place the primary focus on developing more accurate demand forecasts, rather than a focus on capacity adjustments, to avoid stockout and potential reputational damage.

Table 8. Supply chain cost at various conservatism degrees when facing demand and supply variations

Demand Uncertainty			Supply Uncertainty			
Conservatism Degree		Total Cost	Conservatism Degree		Total Cost	
Γ^D	5% Demand Variability	10% Demand Variability	Γ^q	Γ^a	5% Supply Variability	10% Supply Variability
0	309270	309270	0	0	309270	309270
5	319006	330153	10	0	309797	310060
10	322863	352176	20	0	309797	310060
20	325791	357042	40	1	312663	319319
25	330941	376643	50	1	312663	319319
30	334773	Infeasible	60	1	312663	319319
40	336124	Infeasible	80	2	314010	332212
45	342110	Infeasible	90	2	314010	332212
49	348829	Infeasible	98	2	314010	332212

5.5 Analysis on the impact of budgetary constraints

For the largest dataset, Figure 2 illustrates how the total cost is influenced by the budget availability at different conservatism degrees. Interesting insights can be obtained from this graph. First, regardless of the decision maker's conservatism degree, initial budget availability results in significant total cost reductions. This is evidenced by the steepness of all three curves at the left end. However, greater cost responses to the initial budget injections can be observed at the higher conservatism degrees (a steeper curve for a higher conservatism degree). Second, the minimum required budget for the design of the supply chain is set higher at a larger conservatism degree. The required supply chain design budget is \$50,000 at the conservatism level $\Gamma^D = 0$, $\Gamma^q = 0$ and $\Gamma^a = 0$; while at-least \$75,000 of initial budget is required to design a network at higher conservatism levels. Third, while these results confirm that budget availability can play a key role in building resilience into a supply chain network, excessive budget injections do not necessarily result in reduced total costs. That is to say that the total cost remains unchanged (i.e. no additional improvements) after certain budget injections. As could be expected, this budget unresponsiveness is reached at smaller dollar values for lower conservatism degrees.

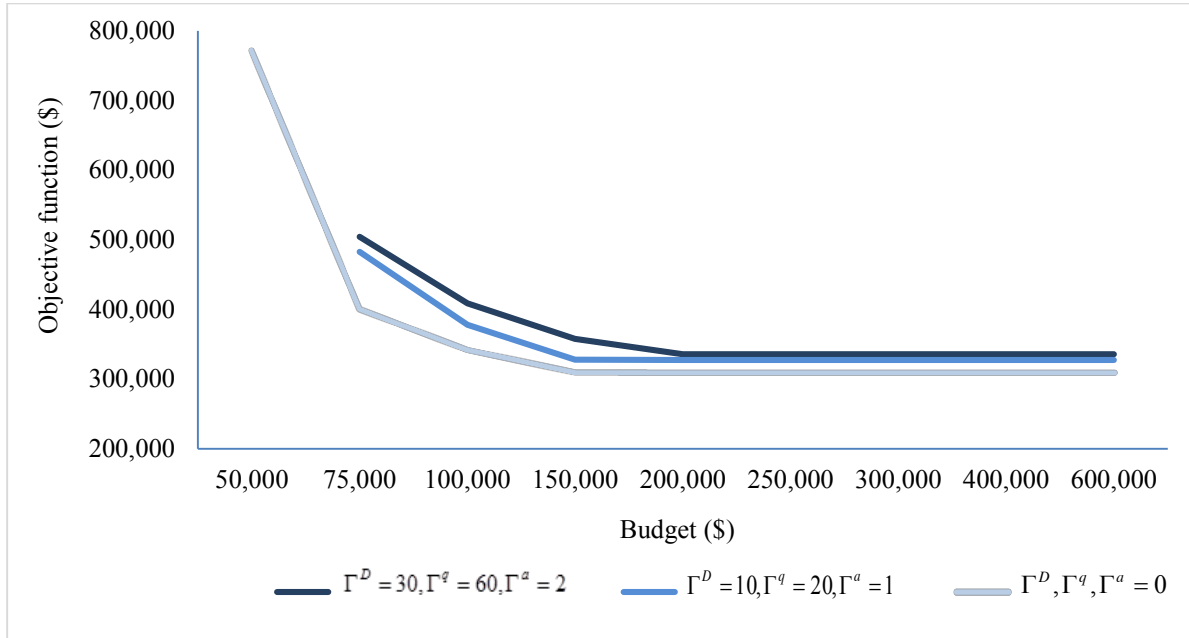


Figure 2. The impact of initial budget on the total supply chain cost

6. Conclusions

Today's supply chains are more difficult to design and manage. The increasing frequency and intensity of natural and man-made disasters from one hand, and systemic volatilities such as demand fluctuations and supply uncertainties from the other hand pose serious risks to global supply chains. Supply chain resilience is hence more critical to supply chain profitability and competitiveness than ever before. This paper presented an optimization model that can be used to design a supply chain resilient to (1) supply/demand interruptions and (2) facility disruptions whose probability of occurrence and magnitude of impact can be mitigated through fortification investments. The proposed robust-stochastic optimization model can also be utilized for reconfiguration of existing supply chains by assessing the affected operations and injecting more resilience into the network.

Our interpretation of the numerical results from several experiments arrived at some interesting practical implications and managerial insights. For example, from multiple viewpoints we found that supply chain resilience can be enhanced to a large extent by only slight changes in supply chain configuration and insignificant increase in supply chain costs. Our analyses also showed how facility fortification strategies can help address demand fluctuations. Another interesting finding is that initial capital investment plays a

key role in developing a resilient supply chain and reducing the strategic supply chain costs, whilst excessive budget injections may not necessarily result in conforming supply chain cost reductions.

The investigation of the influence of disruptions and interruptions on supply chain design decisions is gaining increasing importance. The development and availability of new decision tools and risk mitigation strategies can help address many of these concerns facing supply chain practitioners. Given the multiple contributions of this work, we set the stage for additional and important future modeling efforts and practical investigations in this critical research area. For example, the proposed model can be extended to incorporate the interdependency between supply chain disruptions/interruptions in different facilities and their impacts on supply chain decisions. Another direction for future research can be the inclusion and analysis of customer responsiveness and agility elements such as service time and delivery lead-time which are the critical performance metrics in fast-paced business environments.

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