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Improved Acquisition for System Sustainment: Multi-sourcing Resilient Supplier Selection Under Stochastic Disruptions

23 May 2017

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Abstract

Recognizing the inevitability of large-scale disruptions, emphasis in supply chain decision making has shifted from prevention and protection to *resilience*, or the ability to withstand, adapt to, and recover in a timely manner from a disruptive event. Recent work in supply chain resilience has primarily consisted of qualitative frameworks and lessons learned after disruptions. This project addresses resilient supplier selection, a significant concern across industry and government enterprises. This work develops a supplier selection decision framework that includes (i) a multi-objective optimization formulation for multi-sourced supplier selection and (ii) a means to address uncertainty underlying the occurrence of a disruptive event through a Bayesian network-driven measure of disruption likelihood. The model accounts for several resilience strategies such as increasing supplier capacity beyond normal levels as a mitigation strategy to fortify suppliers against disruption, connecting firms to a back-up supplier as a contingency strategy that allows the supplier to adapt its loss by reconfiguring the channels for the movement of materials, and a contingency strategy of having additional recovery resources to enable suppliers to restore lost capacity more quickly.

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Introduction

In today's competitive global market, firms are more willing to delegate some of their business processes to external organizations, leveraging benefits ranging from low cost labor, improved product quality, and service innovation. A primary example of such outsourcing is purchasing components and services through global suppliers. The supplier selection problem (SSP), or the problem of choosing the appropriate supplier or set of suppliers across one or more criteria, has become a key issue due to the growth of global supply chains and strategic outsourcing. However, the disruption of a supplier's performance can halt a firm's operation and can cascade to other components of the supply chain. As such, utilizing resilient suppliers can significantly reduce the likelihood of supply chain disruption.

Supplier selection is a complex multi-criteria decision making problem that involves tangible and intangible criteria [Ho et al. 2010]. It aims to choose the best portfolio of suppliers among a set of alternatives and to optimally allocate demand among the selected suppliers to meet different procurement criteria. Traditionally, as noted by Hosseini and Barker [2016a], SSP has accounted for primary criteria (e.g., cost, quality, lead time, response rate and, more recently, green criteria (e.g., environmentally friendly transportation modes, packing, management). Interest has recently been given to the notion of resilience in supplier evaluation due to the vulnerability of global supply chains against unexpected natural and man-made disasters such as tsunamis, earthquakes, floods, fires, transport accidents, and labor strikes. In the wake of Japan's earthquake and tsunami in 2011, Toyota suspended much of its production at plants across Japan, resulting in a world-wide shortage of parts [Reuters 2016]. Many automotive companies in the UK and the US were hit the hardest in the aftermath of Japan's 2011 earthquake because of their dependence on a factory in the earthquake zone that supplied 12% of its engines [BBC News 2011]. Apple suffered from a shortage of sensors for its iPhone, as the sensors were exclusively manufactured at a Sony facility that was damaged by the Japanese tsunami [Fortune 2011]. A recent study of the exposure level of Ford Motor Company to supply chain disruptions found that the suppliers whose disruption would cause greatest damage are those from which Ford's annual purchases are relatively small [Simchi-Levi et al. 2014]. That is, there are some critical suppliers that, when disrupted, lead to significant profit losses because they are difficult to quickly replace, as shown in Figure 1. These events demonstrate that disruptive events, particularly natural disasters can pose a major threat to the incumbency of businesses from a revenue standpoint and lost productivity.

In general, the risk associated with supply chains can be classified into two categories: operational and disruption [Tang 2006]. Operational risks refer to the inherent "every day" events that occur within a supply chain, including uncertainty in transportation cost, customer demand and key personnel absence and power outage [Hosseini and Barker 2016b]. Disruption risks refer to major disruptive events such as natural disasters, man-made threats or employee strikes. These types of events, particularly natural disasters, are disruptions with low likelihood but high impact which may have short or long term negative impacts on the supply chain operations. Disruption risks are the focus of this work.

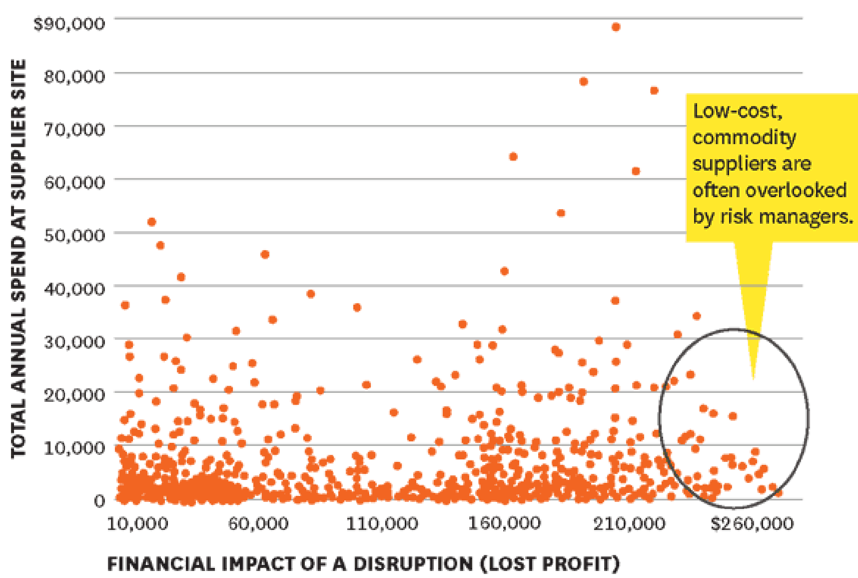

Figure 1. Impact of supplier disruption on Ford's profits [Simchi-Levi et al. 2014].

While other work has analyzed supply chain resilience from a quantitative perspective [e.g., Sheffi 2005, Tang 2006, Petit et al. 2010, Carvalho et al. 2012], the *objective of this research* was to enhance supplier selection decision making under uncertainty with (i) a multi-objective optimization formulation for multi-sourced supplier selection and (ii) a means to address uncertainty underlying the occurrence of a disruptive event through a Bayesian network-driven measure of disruption likelihood.

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Background

This section provides methodological background to some components of this research, including a paradigm for resilience, recent approaches to comparing suppliers, and a particular approach for the multi-criteria comparison of discrete alternatives.

Resilience Modeling

In the last few years, the concept of *resilience* has been increasingly used to describe the behavior of systems under disruption. Resilience is a multidisciplinary concept studied across different disciplines such as sociology, ecology, engineering, and economics with applications that include disaster management, sustainable development, infrastructure restoration, emergency response, and supply chain risk management. Supply chain resilience is relatively new concept that has been defined as “the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and function” [Ponomarov and Holcomb 2009]. Melnyk et al. [2014] defined supply chain resilience as “the ability of a supply chain to both resist disruptions and recover operational capability after disruption occur”. Brandon-Jones et al. (2014) used “the ability of a supply chain to return to normal operating performance, within an acceptable period of time, after being disrupted” to define supply chain resilience. All of these definitions generally note the ability to withstand and recover timely from a disruption.

Several measures of resilience have been offered [Park et al. 2013, Hosseini et al. 2016]. In particular, this work adapts a graphical paradigm of system behavior before, during, and after a disruption is provided in Figure 2 [Henry and Ramirez-Marquez 2012, Pant et al. 2014]. The capacity of a supplier to provide supplies to a firm before, during, and after a disruption is depicted generally in Figure 2. Figure 2 highlights two important dimensions of resilience: vulnerability (or the supplier’s lack of ability to withstand the disruption) and recoverability (the supplier’s ability to return to a nominal level of capacity).

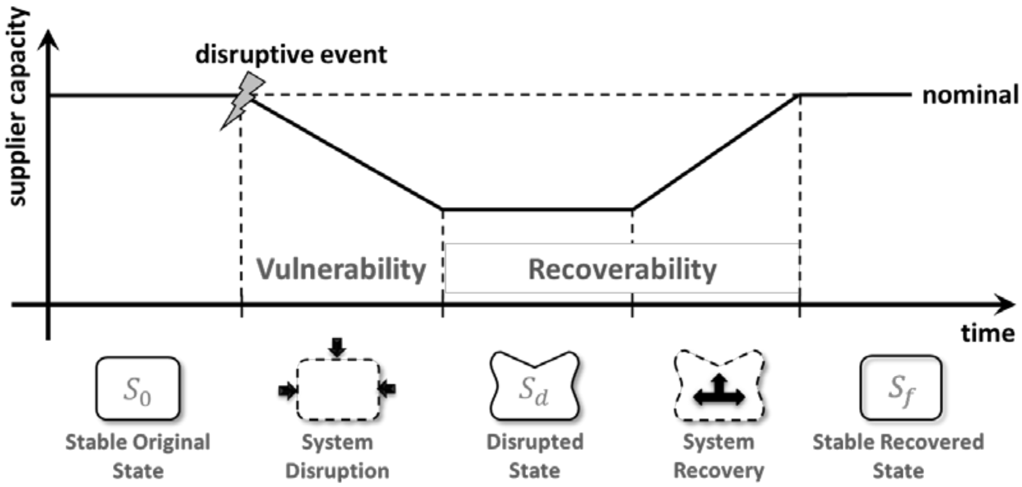

Figure 2. Depiction of a disruptive event on supplier capacity (adapted from Henry and Ramirez-Marquez [2012]).

Several practical strategies for designing a resilient supply chain can be found in the literature. Sheffi et al. [2005] argued that resilience in companies and enterprises can be built through three general ways: (i) creating redundancies throughout the supply chain (e.g., keeping extra inventory, maintain low capacity utilization, and multiple sourcing), (ii) increasing supply chain flexibility (e.g., using flexible transportation modes under disruptive event, using concurrent instead of sequential processes, aligning procurement strategies with supplier relationships), and (iii) changing corporate culture (e.g., maintaining continuous communication among informed employees, conditioning for disruptions). Christopher and Peck [2004] brought attention to the general principles that underpins resilience in supply chains, concluding that agility and flexibility are the two key dimensions of resilience. These two dimension have implications beyond process redesign to primary decisions on sourcing and the establishment of more collaborative supply chain relationships based on greater transparency of information. Torabi et al. [2015] discussed that supply chain resilience can be built based on the several proactive strategies including supplier's business continuity plans, fortification of the supplier, and contracting with backup suppliers. Rezapour et al. [2017] highlighted that three policies can be used to mitigate the disruption risk in a supply chain, including holding emergency stock, reserving back-up capacity at suppliers, and multiple-sourcing.

Most of the work in supply chain resilience is qualitative in nature, and few quantitative models that address supply chain resilience performance or examine impacts of different mitigation policies to achieve resilience in supply chains. Spiegler et al. [2012] used integral of the time absolute error, a deviation performance measure in the control engineering field, to quantify the resilience of supply chain systems, using system dynamic simulation to model the impact of disruption to inventory and ordering control systems on supply chain resilience. Datta et al. [2007] presented an agent-based computational framework to study complex multi-product, multi-country supply chain subject to demand variability and production and distribution capacity constraints with the aim of improving operational resilience. Falasca et al. [2008] introduced a simulation-based framework that captures three dimensions of supply chain resilience (complexity, density, and node criticality) into the process of supply chain design. They also developed a quantitative method for evaluating supply chain resilience by using the *resilience triangle* introduced by Bruneau et al. [2003]. Rezapour et al. [2016] introduced a non-linear model to find the most profitable supply chain networks under disruption scenarios. Miller-Hooks et al. [2012] proposed a two-stage stochastic programming model to quantify the resilience of freight transportation networks. Their stochastic model determines optimal set of preparedness and recovery actions in transportation arcs needed to achieve resilience level.

Other work focused particularly on supplier selection. Venkatesan and Goh [2016] proposed a multi-objective supplier selection model under disruption risks, developing a fuzzy AHP PROMETHEE to deal with the supplier selection problem. The authors then concluded that the probability of supplier’s failure affects the expected total cost more than supplier flexibility and the costs associated with losses. Rajesh and Ravi [2015] applied a combined grey methodology with AHP for resilient supplier selection, primarily considering vulnerability, risk awareness, supply chain continuity management, and collaboration. Carvalho et al. [2012] presented a discrete event simulation model to evaluate alternative supply chain scenarios for improving supply chain resilience considering two performance measures for comparing supplier alternatives: lead time and total cost. Sawik [2013] addressed the supplier selection problem under disruption risk conditions by considering fortification of suppliers as an effective strategy to reduce disruption risks. Torabi et al. [2015] developed a bi-objective mixed probabilistic, two-stage stochastic programming to address the resilient supplier selection problem.

Proposed Optimization Model

This section describes the supplier selection problem and proposed model. The notation used in the model is found in Table 3.

Likelihood of a Disruption Scenario

Prior to developing the optimization formulation for supplier selection and demand allocation, we first model the likelihood of a supplier disruption. This section proposes a probabilistic graphical model to compute this likelihood for a set I of alternative suppliers. Assume that suppliers are subject to variety of random disruption risks such as floods, earthquakes, hurricanes, and labor strikes. Let π_i denote the disruption probability of supplier i, $i = 1, \dots, m$ In the presence of a disruption, supplier i can either continue to operate or fail. Let P_s denote the probability that disruption scenario *s* is realized, where each disruption scenario $s \in S$ results in a unique subset $I_s \subset I$ of suppliers that continue to operate. The probability of realizing disruption scenario *s* can be calculated with Eq. (1).

$$P_s = \prod_{i \in I_s} (1 - \pi_i) \times \prod_{i \notin I_s} \pi_i \tag{1}$$

Table 1. Notation used in the proposed model.

Indices, sets	
i, I	Index i refers to supplier $i \in I$
t, T	Index t refers to planning period $t \in T$
s, S	Index s refers to disruption scenario $s \in S$
Parameters	
d_{ij}	Shortest distance between locations of supplier i and j
d_i	Distance between supplier i and firm
L	Smallest segregation distance between every pair of suppliers
λ_i	Expected disruption rate of supplier i
N_i	Number of disruptions that occur for supplier i in specified time period t
f_i	Unit cost of keeping additional capacity for supplier i
B_i	Cost of building secondary connection between supplier i and firm
G	Primary investment required for restorative capacity (per unit of item)
O_{it}	Order cost of supplier i in time period t
A_{it}	Amount of capacity (units) available for restoration by supplier i in time period t
Φ_i	Disruption cost incurred to supplier i
P_s	Probability of disruption scenario s
$\varepsilon, \varphi, \beta, \xi, \delta$	Weighting factors
L	Limit on suppliers allowed to a firm
D	Customer demand
c_i	Required resource to restore one unit of capacity of supplier i
E_i	Primary capacity of supplier i
ν	Penalty cost of supplying low quality products
θ_i	Expected defect rate of supplier i
τ_i^s	Fraction of capacity of supplier i available after occurrence of disruption scenario s
Δ	Threshed value of resilience cost for an extreme disruptive event
M	A very large constant
Decision variables	
z_i	1, if supplier i is assigned to the firm; 0, otherwise
r_{ij}	1, if suppliers i and j are both selected; 0, otherwise
Φ_i	Additional normal capacity of supplier i
U_i	Additional restorative capacity invested by supplier i (units per period)
Q_{it}^s	Cumulative capacity of supplier i in period t of scenario s
x_{it}^s	Proportion of customer demand that is served by supplier i in period t of scenario s
k_{it}^s	Capacity of supplier i that is restored in period t of scenario
q_t^s	Proportion of customer demand that is not met in period t of scenario s
Ω^s	Violation cost (amount of cost that exceeds resilience cost, calculated as mitigation cost + contingency cost)
w_i	Auxiliary variable
ω_i	Additional capacity provided by supplier i

Geographical Segregation

Segregating suppliers geographically is an important proactive resilience strategy that helps to reduce the risk of a supply chain disruption. Many logistics companies focus on regionalizing of their supply chains. For example, International Federation of Red Cross and Red Crescent Societies hold inventories of vital goods in four geographically segregate logistics centers to facilitate responses to humanitarian disasters [Chopra and Sodhi 2014]. In the aftermath of the Japanese earthquake and tsunami in 2011, automakers such as Toyota and Nissan tried to collaborate with suppliers that are geographically dispersed. To model this resilience strategy, an objective function represented in Eq. (2) is defined to maximize the sum of the distance between selected suppliers, thus acting to segregate suppliers. Note that *L* in Eq. (3) represents smallest segregation distance between locations of any pair of suppliers.

$$GS = \max \sum_{i=1}^{n} \sum_{j=i+1}^{n} z_i z_j d_{ij} \tag{2}$$

The constraint in Eq. (3) is written for the location of each pair of potential suppliers, effectively placing an upper bound on *L* equal to d_{ij} only if both suppliers *i* and *j* are selected, since $(1 - z_i)$ and $(1 - z_j)$ will be both zero. However, if either supplier *i* or *j* is not selected, then either $(1 - z_i)$ or $(1 - z_j)$, or both, will have a value of 1. In such a case the upper bound on *L* in Eq. (3) will be large, equal to either $d_{ij}(1 + M)$ or $d_{ij}(1 + 2M)$, where M is a large value. Therefore, only the distance between pairs of supplier locations that are selected will have a limiting effect on *L*. Note that the number of constraints associated with Eq. (3) is $n(n-1)/2$.

$$L \le d_{ij}\left(1 + M(1 - z_i) + M\left(1 - z_j\right)\right) \quad \forall i, j \in n |\ i < j \tag{3}$$

The objective function in Eq. (2) is nonlinear because of multiplication of binary variables $z_i z_j$, which can be linearized by introducing a new auxiliary binary variable r_{ij}. The proposition of linearization and related proof are discussed below.

Proposition 1. The non-linear term in objective function of Eq. (2) can be linearized with $r_{ij} = z_i z_j$ under the following sets of constraints:

$$r_{ij} \le z_i \qquad \forall i, j \in n |\ i < j \tag{4}$$

$$r_{ij} \le z_j \qquad \forall i, j \in n |\ i < j \tag{5}$$

$$r_{ij} \ge z_i + z_j - 1 \qquad \forall i, j \in n |\ i < j \tag{6}$$

Proof. This can be shown for all four cases that can arise.
Case (i): $z_i = z_j = 0$, $\forall i, j \in n|\ i < j$. In this case $r_{ij} \le 0, r_{ij} \le 1$ and $r_{ij} \ge 0$ which turns in $r_{ij} = 0$.
Cases (ii) and (iii): $z_i = 1,\ z_j = 0$ or $z_i = 0,\ z_j = 1$.These cases are similar to case (i).
Case (iv): $z_i = z_j = 1$. In this case, $r_{ij} \ge 1, r_{ij} \le 1$ which turns in $r_{ij} = 1$.

Disruption Cost

The reliability of a supplier can be viewed as a proactive strategy for choosing resilient suppliers. Manufacturers prefer to collaborate with highly reliable suppliers so they can reduce the chance of disruption on their production. As such, reliability is considered in the proposed model, accounting for the following assumptions:

- Suppliers fail due to random external and internal disruptive events, which are described probabilistically.
- The disruption time for each supplier follows an exponential distribution with a known disruption rate.
- The disruption cost of each supplier is known.

The objective function of the proposed model minimizes the total cost of supplier's disruption (failure). Considering y_i as the number of disruptions including external and internal disruptions of supplier *i* in time period *H*. Let λ_i denote the expected disruption rate of supplier *i* within time period *H*, N_i denote the number of disruptions that occur into supplier *i* in specified time period *H*, and Φ_i denote the disruption cost imposed to supplier *i*. As such, the disruption cost (DC) of suppliers is calculated with Eq. (7).

$$\text{DC} = \sum_{i=1}^{n} z_i y_i \, \Phi_i \tag{7}$$

In this model, the time between supplier disruptions is assumed to follow an exponential distribution. Therefore, the number of disruptions for each supplier follows a Poisson distribution. As such, the probability of N_i disruptions for supplier *i* is calculated with Eq. (8).

$$P(y_i = N_i) = \frac{(\lambda_i c_i H)^{N_i} \exp(\lambda_i c_i H)}{N_i!} \tag{8}$$

Due to the stochastic nature of a supplier disruption, a chance constraint programming (CPP) approach is used. The core assumption in CPP models is that the stochastic constraints will hold at least α proportion of time, where α is a suitable safety margin by the decision maker. Based on the concept of CPP, the stochastic variable y_i is replaced with N_i as a new deterministic variable, and the chance constraint in Eq. (9) is added to the model to ensure that the number of disruptions for supplier *i* never exceed N_i in at least α of time.

$$P(y_i \leq N_i) \geq \alpha \tag{9}$$

Integrating Eqs. (8) and (9), is rewritten in Eq. (10).

$$\sum_{k=0}^{N_i} \frac{(\lambda_i c_i H)^k \exp(\lambda_i c_i H)}{k!} \geq \alpha \tag{10}$$

An additional integer constraint in Eq. (11) is added.

$$N_i \text{ is integer} \quad \forall i \tag{11}$$

The TDC in Eq. (7) is nonlinear because of the product of z_i and N_i. To manage this difficulty, a new auxiliary variable w_i is shown in Eq. (12). The proposition of linearization and related proof are provided subsequently.

$$w_i = z_i N_i \tag{12}$$

Proposition 2. The nonlinear term in objective function of Eq. (7) can be linearized with $w_i = z_i N_i$ under the following constraints of Eq. (13).

$$w_i \geq N_i - (1 - z_i)M \tag{13}$$

Proof. This can be shown for the possible cases explained below:
Case (i): z_i is a binary variable, and N_i is an integer variable. Let M be a large positive number. If z_i takes 0, the above constraint becomes $w_i \geq -M$, because of the minimization form of the objective function, w_i takes 0.
Case (ii): If z_i takes 1, the constraint (13) becomes $w_i \geq N_i$, and because of the same argument (minimization form), w_i will equal to N_i.

The only difficulty remains in the CCP model is the nonlinearity of Eq. (10).

Proposition 3. The nonlinear constraint (10) is linearized by introducing Eq. (14).

$$N_i \geq F^{-1}(\lambda_i c_i H, \alpha) \tag{14}$$

Proof. The left hand side of Eq. (10) is the cumulative Poisson distribution with parameter λ_i. Considering the inverse form of the cumulative Poisson distribution, the Eq. (10) then can be rewritten as Eq. (14). Note that in Eq. (14), F^{-1} is the inverse of cumulative Poisson distribution function.

Vulnerability and Recoverability Impact

Discussed previously, a disruptive event may reduce the capacity of supplier as illustrated in Figure 2. The recovery of a disrupted supplier requires the allocation of resources. Different recovery strategies may require a different level of recovery cost, as depicted in Figure 5. In addition to recovery strategies, it may also be possible to make investments in the system to reduce the magnitude of the disruptive effect, as depicted in Figure 6. In general, a supplier’s resilience cost is comprised of (i) the mitigation cost to reduce vulnerability and (ii) the contingency cost to enhance recoverability. Across different disruption scenarios, the total resilience cost will vary, resulting in a probability distribution of total impact. A conceptual version of such a distribution is illustrated in Figure 7.

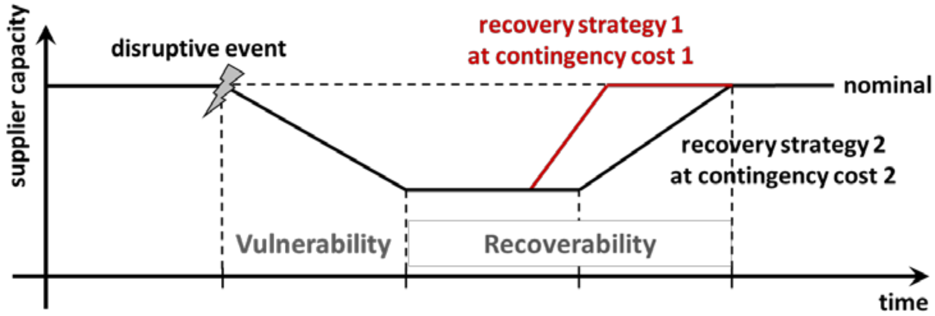

Figure 3. Two different recovery strategies with two different recovery costs.

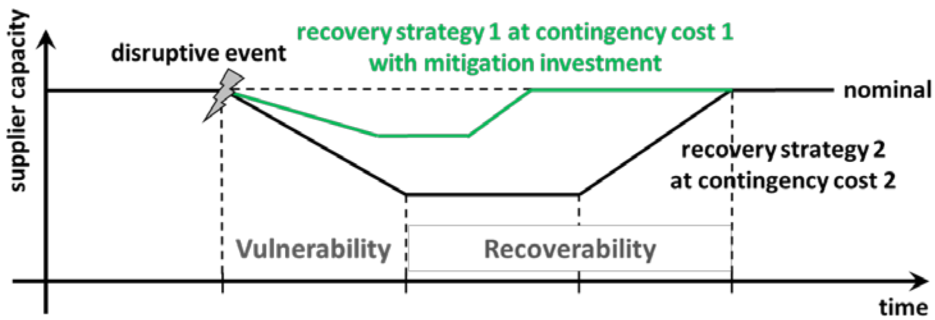

Figure 4. Comparison of two different recovery actions, one with pre-investment (recovery action 2), and other without pre-investment (recovery action 1).

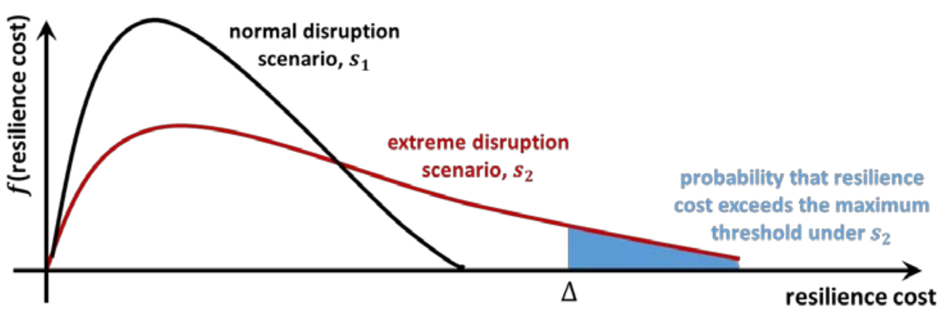

Figure 5. Probability distribution of resilience cost under different scenarios.

The purpose of considering the resilience cost is to find a set of investment and operational decisions that shift this distribution to the left. Doing so results in a smaller and flatter tail, where extreme costs are found. Variable Ω^s is introduced to emphasize large resilience cost values found in the upper tail of cost distributions for extreme disruption scenarios, as depicted in Figure 5. This mechanism is implemented with an input parameter Δ that represents the threshold value on total resilience cost. If total resilience cost exceeds the threshold value Δ in scenario *s*, then Ω^s is defined as the amount of the difference. The values of Ω^s are then penalized in the objective function with nonnegative weights, βP^s. This weighting factor includes the probability of disruption for extreme scenarios, P^s, and a relative weighting term, β. The combination of input parameters Δ and β makes the tuning of the model possible for the extreme outcomes by determining how heavily β is weighted and which outcomes are considered to be extreme using Δ.

To reduce (i) the chance of supplier inoperability and (ii) supplier resilience cost, three resilience strategies are taken into account:

- Expansion of supplier capacity: Increasing supplier capacity beyond normal levels is a mitigation strategy to fortify suppliers against disruption.
- Back-up supplier: Connecting firms to a back-up supplier is a contingency strategy that allows the supplier to adapt its loss by reconfiguring the channels for the movement of materials.
- Resource investment for faster supplier recovery: A contingency strategy of having additional recovery resources will enable suppliers to restore lost capacity more quickly.

Integrating the modeling approaches above with these resilience enhancement strategies result in the proposed optimization formulation discussed subsequently.

Optimization Formulation

This section proposes a stochastic multi-objective optimization model for supplier selection and demand allocation. The first objective function, *GS*, ensures geographical segregation among suppliers by maximizing the distances between all pairs of supplier locations. The second objective function, *TC* in Eq. (16), minimizes the total cost of supplier selection. Eq. (16) consists of, respectively, (i) the cost of initial capacity carried by suppliers, (ii) the cost of making backup connections between suppliers and customers, (iii) the additional restorative capacity invested by suppliers, (iv) the order cost of suppliers, (v) the disruption costs incurred by the suppliers, (vi) transportation costs, (vii) the penalty costs associated with the proportion of customer demand that is unmet, (viii) the restoration costs of suppliers, (ix) the capacity holding costs of suppliers, (x) a penalty for scenarios whose resilience cost exceeds the maximum threshold, and finally (xi) the total defect rate.

$$GS = \max \sum_{i=1}^{n} \sum_{j=i+1}^{n} r_{ij} d_{ij} \tag{15}$$

$$\begin{aligned} TC = \min \sum_{i=1}^{n} f_i\, \omega_i + \sum_{i=1}^{n} B_i z_i + \sum_{i=1}^{n} G_i U_i + \sum_{i=1}^{n} z_i \sum_{t=1}^{T} O_{it} + \sum_{i=1}^{n} w_i\, \Phi_i \\ + \sum_{s=1}^{S} P^s \left[\varepsilon \sum_{i=1}^{n} Dd_i \sum_{t=1}^{T} x_{it}^s + \varphi D \sum_{t=1}^{T} q_t^s + \delta \sum_{i=1}^{n} c_i \sum_{t=1}^{T} k_{it}^s \right] \\ + \sum_{s=1}^{S} P^s \left[\xi \sum_{i=1}^{n} \sum_{t=1}^{T} (E_i + \omega_i - Q_{it}^s) + \beta \Omega^s + \nu \sum_{i=1}^{n} \sum_{t=1}^{T} \theta_i\, x_{it}^s \right] \end{aligned} \tag{16}$$

Subject to

$$L \leq d_{ij} \left(1 + M(1 - z_i) + M\left(1 - z_j\right)\right) \quad \forall i, j \in n |\; i < j \tag{17}$$

$$r_{ij} \leq z_i \qquad \forall i, j \in n |\; i < j \tag{18}$$

$$r_{ij} \leq z_j \qquad \forall i, j \in n |\; i < j \tag{19}$$

$$r_{ij} \geq z_i + z_j - 1 \qquad \forall i, j \in n |\; i < j \tag{20}$$

$$w_i \geq N_i - (1 - z_i)M \quad \forall i \tag{21}$$

$$N_i \geq F^{-1}(\lambda_i c_i H, \alpha) \qquad \forall i \tag{22}$$

$$\sum_{i=1}^{n} z_i \leq L \tag{23}$$

$$z_{i^*} = 1 \tag{24}$$

$$c_i k_{it}^s \leq A_{it} + U_i \qquad \forall i, t, s \tag{25}$$

$$Q_{it}^s = \tau_i^s (E_i + \omega_i) + \sum_{\psi=1}^{t-1} k_{i\psi}^s \qquad \forall i, t, s \tag{26}$$

$$Q_{it}^s \leq E_i + \omega_i \qquad \forall i, t < T, s \tag{27}$$

$$Q_{iT}^s = E_i + \omega_i \qquad \forall i, s \tag{28}$$

$$x_{it}^s - z_i \leq 0 \qquad \forall i, t, s \tag{29}$$

$$\sum_{i=1}^{n} x_{it}^{s} + q_{t}^{s} = 1 \qquad \forall t, s \tag{30}$$

$$D x_{it}^{s} \leq Q_{it}^{s} \qquad \forall i, t, s \tag{31}$$

$$\varepsilon \sum_{i=1}^{n} D d_i \sum_{t=1}^{T} x_{it}^{s} + \varphi D \sum_{t=1}^{T} q_{t}^{s} + \sum_{i=1}^{n} c_i \sum_{t=1}^{T} k_{it}^{s} - \Delta \leq \Omega^{s} \qquad \forall s \tag{32}$$

$$z_i \in \{0,1\} \qquad \forall i \tag{33}$$

$$r_{ij} \in \{0,1\} \qquad \forall i, j \in n |\ i < j \tag{34}$$

$$w_i, N_i, \text{are integer} \qquad \forall i \tag{35}$$

$$U_i \text{ is integer} \qquad \forall i \tag{36}$$

$$f_i, q_t^s, x_{it}^s, Q_{it}^s, r_{it}^s, \Omega^s \geq 0 \qquad \forall i, t, s \tag{37}$$

Constraints (17)-(22) are discussed in Section 4 with Eqs. (3) through (6) and Eqs. (13) and (14). Constraint (23) specifies that a firm can be connected up to L suppliers. Constraint (24) determines that the primary connection as given, decisions in the model must be made only for secondary or backup connections. Constraint (25) specifies the restoration capacity limitation in terms of units/period for each supplier. Constraints (26)-(28) represent capacity evolution of suppliers over time in each disruption scenario. Constraint (29) ensures that produce movement from supplier *i* to the customer can be done when a connection is made between supplier *i* and customer. Constraint (30) quantifies the amount of unmet demand when customer is not fully served by suppliers. Constraint (31) ensures that the product shipped to the customer for supplier *i* is not more than its available capacity. Constraint (32) ensures that extreme scenarios that produce high resilience costs are penalized. Constraints (33)-(37) define the type of decision variables.

Solution Approach

The solution procedure to solve the proposed stochastic multi-objective model involves the augmented ε-constraint method to deal with the multiple objectives of geographical segregation and total cost.

Augmented ε-constraint Method

To solve the proposed resilient supplier selection model, we apply an extension of the ε-constraint method by which the two objective functions are converted to the single objective counterpart. In the ε-constraint method, one of the objective functions is chosen as the main objective function while the other functions are added to the constraints. For the bi-objective optimization formulation proposed in this paper, the ε-constraint method is illustrated in Eq. (43).

$$\begin{aligned} \min \quad & TC(x,z) \\ \text{s.t.} \quad & GS(z) \geq \varepsilon \\ & x,z \in S \end{aligned} \tag{43}$$

In this way, the main objective function is optimized individually, and the value of other objective functions is calculated at this optimal point. The efficient solutions of bi-objective model can be obtained by parametrical variation in the right hand side (ε_1) of constrained objective function [Mavrotas 2009]. The range of ε_2 can be calculated by optimizing the constrained objective RE separately subject to the feasible set S and establishing the pay-off table [Torabi et al. 2016]. Then, by dividing the range of constrained objective $GS(r)$ to q equal intervals for ε_2 can be calculated with Eq. (44).

$$r = GS^{\max} - GS^{\min}; \quad \varepsilon_2^l = GS^{\max} - \frac{r}{q} \times l \qquad l = 0, \dots, q-1 \tag{44}$$

The ε-constraint is a popular approach to deal with bi-objective models, but it has some drawbacks. For example, this method does not guarantee optimality of solutions (i.e., reaching to weakly efficient solutions). Mavrotas [2009] discussed some other drawbacks and introduced an improved version of ε-constraint, called augmented ε-constraint approach. The formulation of this method for the proposed bi-objective model is illustrated in Eq. (45), where Υ is a small number usually between 10^{-6} to 10^{-3}, s_2 is slack variable for second objective function, and the efficient solution for each ε vector results from incorporating the augmented term $\Upsilon \times s_2$.

$$
\begin{aligned}
\min \quad & TC(x,z) + (\Upsilon \times s_2) \\
\text{s.t.} \quad & GS(z) - s_2 = \varepsilon_2 \\
& x, z \in S, s_2 \in R^+
\end{aligned}
\tag{45}
$$

Illustration and Computational Results

In this section, the proposed epsilon constraint model with sensitivity analysis capability is applied on a case study with 10 instances entitling 10 suppliers selection scenarios (i.e., the first chosen supplier, z_{i^*}), with 9 supplier candidates that are located randomly in a Cartesian coordinate system. To generate these instance, we vary problem characteristics by specifying the cost parameters from random distribution according to the model limitations. The fraction of remained capacity f supplier i after the occurrence of disruptive scenario s, τ_i^s, is calculated from $\tau_i^s = \rho_s \theta_i$. Here ρ_s is a parameter used to determine the effect of scenario on the expected defect each supplier. We note that our choice of the threshold value of resilience cost changes the upped bound of the model in the given time limit. Figure 8 illustrates the trajectory of the two objective categories, minimizing supplier selection and restoration costs and maximizing selected suppliers distance, over the course of an optimization run. On average, each of the instances was computed in less than 10 seconds. The results provide sufficient information to choose the optimal supplier selection policy when trying to decrease the cost. Note that the points above the line are dominated by points on the Pareto front.

In this respect, a question arising from the result is how the uncertainty of key parameters (e.g., demand and threshold value of resilience cost), change the behavior of the model and consequently decision making policies. When the model's condition changes during the uncertainties, decision makers lack the capability to select the best answer, but rather to avoid the least desirable decision. Therefore, analyzing the sensitivity of the optimal model on the uncertainty/errors minimizes the undesirable quality of decisions.

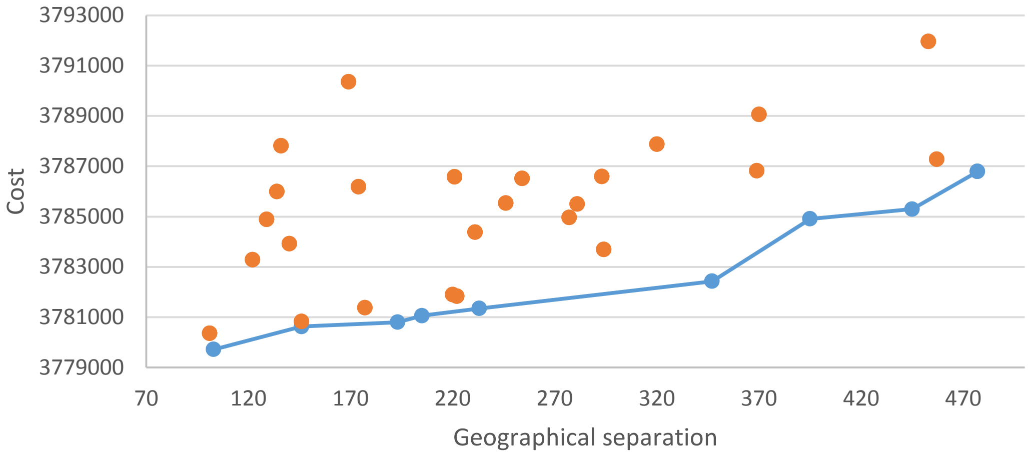

Figure 6. Pareto-optimal frontier for different pairs of selected suppliers.

We analyze how the uncertainty of demand, D, and threshold value of resilience cost, Δ, affect the trajectory of two objective functions and their interaction. Figure 9 illustrates the sensitivity of the bi-objective model to changes in demand. Higher demand values lead to more expensive supplier selection and restoration decision. For lower value of objective function one, the uncertainty of demand does not result in a wide range of the second objective function values. On the other hand, when higher selected suppliers distance is required, the model shows obvious sensitivity on the uncertainty of demand in higher values.

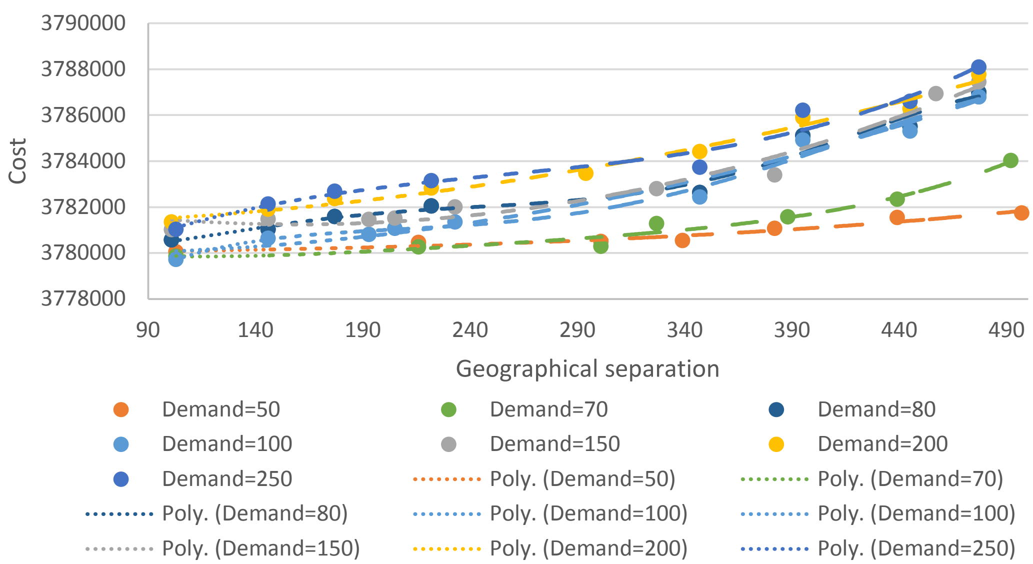

Figure 7. Non-dominated solutions showing the sensitivity of model on the uncertainty of demand.

In Figure 10 we analyze the sensitivity of the model on the variation of threshold value of resilience cost, $\Delta = \{100,300,500,700,1000,1300\}$. When the threshold decreases, the portion of supplier selection and restoration showed in the cost objective function increases with a fixed rate, 260 approximately. Therefore, optimal investment on resilience cost threshold can be identified based on decision making policies used by the managers.

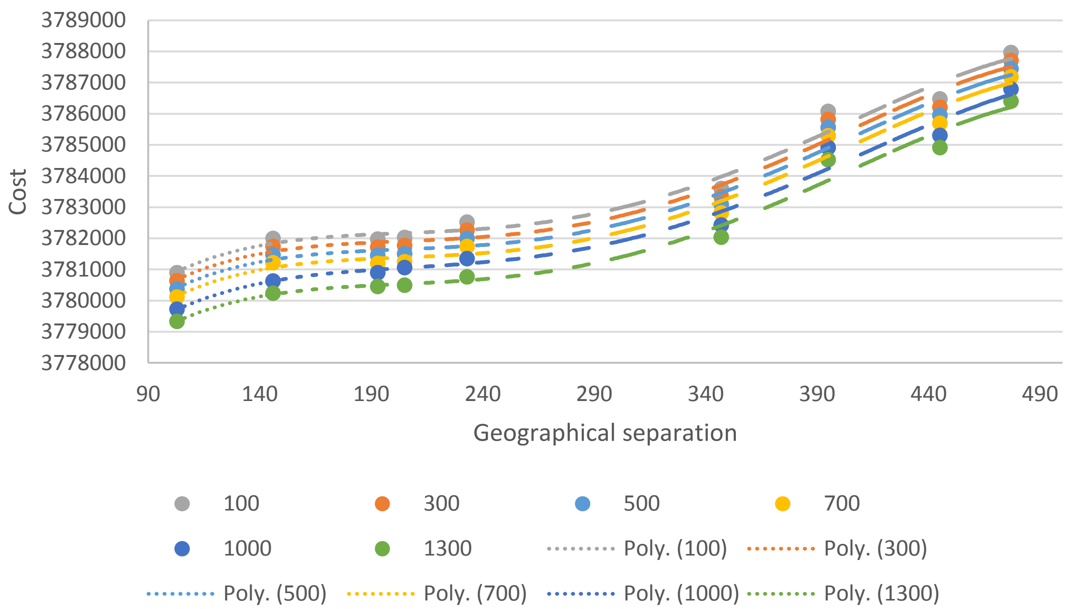

Figure 8. Non-dominated solutions showing the sensitivity of model to parameter variation.

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Conclusions

The study provided an optimization formulation for supplier selection and demand allocation. The formulation (i) captures multiple objectives of supplier segregation distance and cost associated with implementing resilience building strategies and (ii) captures the uncertainty associated with disruptive events that may affect suppliers.

The model accounts for several resilience strategies from mitigation (i.e., fortify suppliers against disruption) and contingency (i.e., connecting firms to a back-up supplier, having additional recovery resources to enable suppliers to restore lost capacity more quickly). Uncertainty associated with supplier disruption with P_s could be captured with a Bayesian network formulation. The investigators are continuing to explore the usefulness of Bayesian networks in modeling resilience in an on-going NPS Acquisition Program project.

Research Output

Given the change of date for the 2017 Acquisition Research Symposium, a conference paper was not submitted, though one is planned for 2018. A larger scale work is still ongoing, and a manuscript will be submitted in coming months.

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