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Supplier selection model with contingency planning for supplier failures

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A B S T R A C T
We consider the optimal allocation of demand across a set of suppliers given the risk of supplier failures. We assume items sourced are used in multiple facilities and can be purchased from multiple suppliers with different cost and reliability characteristics. Suppliers have production flexibility that allows them to deliver a contingency quantity in case other suppliers fail. Costs considered include supplier fixed costs and variable costs per unit, while failure to deliver to a demand point results in a particular financial loss. The model utilizes the decision tree approach to consider all the possible states of nature when one or more suppliers fail, as well as expand the traditional transportation problem. Unlike other supplier selection models, this model considers contingency planning in the decision process, minimizing the total network costs. This results in a base allocation to one or more of the available suppliers and a state of nature specific delivery contingency plan from the suppliers to each demand point. A numerical example, as well as sensitivity analysis, is presented to illustrate the model and provide insights.

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1. Introduction

The emergence of globalization and the extended enterprise has significantly changed the competitive environment in many industries. Initially, many companies responded by setting up manufacturing facilities in low-cost regions. Later, traditional supply sources also started to shift to the low-cost regions. However, the rising wages, tightening regulations and increasing transportation costs in the past few years have resulted in the need to redesign many supply chains (Lee, 2009).

Several observers and analysts believe that we have entered a new era, referred to as the “multi-polar world” – a world with multiple pockets of demand and supply sources, as well as sources of innovation (Foster, 2008; Lee, 2009). In this new era, globalization is no longer a one-way street where the multinational companies based in developed countries view the emerging regions only as sources of low-cost manufacturing and supply. In several emerging economies the middle class has gained critical mass and possesses sufficient disposable income to purchase a variety of consumer products. As a result, several multinational companies incorporated their facilities in the low-cost regions into their global manufacturing network and built distribution networks to reach millions of consumers in the emerging economies. More recently, leading multinationals have abandoned their stand-alone business models to pursue the “one-world strategy” by locating research/product development, manufacturing, sourcing, distribution and marketing in the most appropriate locations in the globe (Tse, 2010).

The pursuit of the “one-world strategy” has resulted in new challenges. For example, increasing supply chain risk has emerged as a major concern for both practitioners and researchers. Therefore, developing approaches to identify, assess, analyze and develop contingency plans to effectively deal with supply chain disruptions has gained significant attention (Neiger, Rotaru, & Chu-rilov, 2009). Supply chain risk management approaches generally consider supplier attributes or the supply chain structure to determine appropriate mitigation and contingency strategies (Oke & Gopalakrishnan, 2009; Trikman & McCormack, 2009). Thus, the ability to identify the suppliers that have the greatest potential for failure and the decision to increase the allocation of other suppliers (i.e., emergency production) in case of failures are critical in today’s turbulent environment.

We consider sourced items that are used in multiple facilities, referred to as demand points, and that can be purchased from multiple suppliers. For example, a smart phone manufacturer sourcing batteries could use suppliers in San Diego, Hong Kong and Shanghai to supply its manufacturing plants in Juarez, Manila,
Each supplier has different cost and reliability characteristics, and the shipping cost is unique for each source–destination combination. The model combines the characteristics of the problems studied by Berger, Gerstenfeld, and Zeng (2004) and Ruiz-Torres and Mahmoodi (2007) with the traditional transportation scenarios. In other words, our model blends decision-tree concepts with mathematical programming. However, contrary to the previous supplier selection models that do not consider contingencies in the decision process, our model provides contingency plans for each failure scenario. The context and the environment considered is critical in supply chain design given today’s sourcing strategies and relevant to companies in a variety of industries (Meixell & Gargeya, 2005).

The remainder of this paper is organized as follows. The supplier selection and order allocation literature, as well as supplier risk management literature, is reviewed in the next section. Then, we describe our proposed model and analysis approach in Section 3. This is followed by the presentation of a set of numerical examples used to illustrate the model and the associated sensitivity analyses to gain further insights in Section 4. Finally, conclusions and managerial implications, as well as directions for further research, are presented in Section 5.

2. Literature review

As the structure of today’s supply networks has become increasingly complex, managing the risks and uncertainties inherent to each supply network have received a great deal of attention. According to Tang (2006), supply network design is strategically important for supply chain risk management and that supplier order allocation is one of the three tactical plans for dealing with supply-side risks (the other two are supplier selection and supply contract). This study falls into the domain of supply network design under disruption risk with a focus on supplier order allocation. In what follows, we review the relevant recent literature.

In terms of research methods, scholars have applied a range of Operations Research techniques to arrive at optimal supply order allocation under different transportation scenarios. A comprehensive review article by Aissouei, Haoxuan, and Hassini (2007) surveys and classifies the models developed to determine the best mixture of vendors and allocate orders among them to satisfy different purchasing requirements. Since this paper’s publication, new efforts have considered more complicated supplier characteristics (e.g., price discounts by Burke, Carrillo, and Vakharia (2008), demand uncertainty (e.g., Awasthi, Chauhan, Goyal, & Proth, 2009), and costs (e.g., the interplay between transportation and inventory costs by Mendoza and Ventura (2008). In addition, integrated methods such as a combination of AHP, Fuzzy Logic, DEA, and Mixed Linear and Integer Programming have been employed to study the joint supplier selection and order allocation problem (e.g., Azadeh, Hakbaz, & Songhori, 2010; Basnet & Weintraub, 2009; Chan, Kumar, Tiwari, Lau, & Choy, 2008; Ozgen, Onut, Gulsun, Tuzkaya, & Tuzkaya, 2008; Razmi & Rafiei, 2010; Razmi, Rafiei, & Hashemi, 2009).

Recent research efforts also emphasize the impact of risks on supplier order allocation decision. An important element in this stream of research is how to model and quantify the risks in a given supply network. In this study, we consider the supply risk that stems from the inability of a supplier to deliver the required quantity to a destination point, and adopt the risk modeling methods used by Berger et al. (2004) and Ruiz-Torres and Mahmoodi (2007) to calculate the probability that a supply network may fail by utilizing a decision-tree concept. Other studies have considered various types of risks and employed different risk modeling techniques. For example, Shin, Benton, and Jun (2009) examine the supplier’s risks from two dimensions—quality and delivery performance; in particular, a probabilistic cost model in which suppliers’ quality performance is measured by inconformity of the end product measurements and delivery performance is estimated based on the suppliers’ expected delivery earliness and tardiness. Such a sourcing policy decision tool can help companies determine an optimum set of suppliers considering the risk factors. The article by Lockamy and McCormack (2010) presents a methodology for developing a risk profile for a given supplier through the creation of Bayesian networks to account for supply network risks to facilitate outsourcing decisions. The networks are used to analyze a supplier’s external, operational, and network risk probabilities, and the associated revenue impact on the organization.

Meena, Sarmah, and Sarkar (2011) address the problem of determining the number of suppliers under risks of supplier failure due to catastrophic events by considering different failure probability, capacity, and capacity specific compensation potential. The authors propose an algorithm that determines the optimal number of suppliers assuming an equal allocation among those selected under two different objective functions, minimizing the total costs subject to a target service level, and maximizing the service level subject to a budget constraint (total costs).

The study by Sawik (2011) investigates the optimal selection of supply portfolio in a make-to-order environment based on price and quality of purchased parts and delivery reliability. The problem is formulated as a single- or bi-objective mixed integer program and a value-at-risk and conditional value-at-risk approach is applied to control the risk of supply disruptions.

Our paper differs from the previous research in the following three aspects. First, we consider the supplier order allocation problem in the context of a classic transportation network with multiple supply sources and a set of separate demand points, where each supplier not only has limited capacity, but also a probability of failure to supply the required quantity. Secondly, we present a decision-tree-based method for quantifying and calculating the reliability of the entire supply network given each supplier’s probability of failure. Finally, contrary to the previous supplier selection models that do not consider contingencies in the supply network design, our approach accommodates and facilitates both decisions in network configuration and contingency planning, and provides contingency plans for each failure scenario.

3. Model description

This section provides a formal presentation of the problem and the proposed model. There are s possible suppliers, \( S = \{1, \ldots, s\} \) and \( n \) demand points that consume the material being procured,
Each demand point \( k \) has a required demand in units, \( d_k \), and failure to deliver a demand point results in a per unit financial loss, \( l_k \). Let \( a_h \) be the number of units allocated to supplier \( h \). Each supplier has maximum capacity (\( m_h \)) and a flexibility factor (\( b_h \)). The maximum capacity limits the number of units that a supplier can produce per cycle, while the flexibility factor is used to model the ability of the supplier to deliver more than its allocation when other suppliers fail. Note that the flexibility factor is a reasonable assumption, as many suppliers design their manufacturing capacity in a certain range rather than in a fixed quantity. For example, if \( a_h = 50 \), \( b_h = 40\% \), and \( m_h = 100 \), the supplier could produce up to 70 units (50 \( \times \) 1.4) in a cycle, if other suppliers fail. However, if \( m_h = 60 \), then the supplier could produce up to 60 units.

There is a per-unit cost to transport from supplier \( h \) to demand point \( k \), \( t_{gh} \). Each supplier \( h \) is characterized by a probability of failure (i.e., \( p_h \)) that represents a supplier shutdown (e.g., equipment failure, quality problem and lack of raw materials). Each supplier \( h \) is characterized by two costs; a variable cost per unit, \( c_h \), and a fixed cost, \( f_h \), which represent the cost of maintaining the supplier. Furthermore, let \( e_h \) be the premium charged by supplier \( h \) when delivering units above their baseline allocation. The number of possible states of nature (SN) that the model considers, given that there are \( s \) possible suppliers and each supplier can either deliver or fail to deliver, is \( 2^s \). Let \( v \) be the number of states of nature, \( V = \{1, \ldots, v\} \). For a state of nature \( g \), let \( w_{gh} = 1 \) if supplier \( h \) will deliver, and let \( w_{gh} = 0 \) if it fails to deliver.

Each state of nature has a separate set of flow quantities from the suppliers in \( S \) to the demand points in \( D \). Therefore, the amount of material that flows from each supplier to each demand point is particular to each state of nature. Let \( q_{ghk} \) be the number of units that flow from supplier \( h \) to demand point \( k \) for the state of nature \( g \). Let \( q_{ghk} \) represent the number of units not delivered to a demand point \( k \) for the state of nature \( g \). A list of the notation and symbols used throughout the paper is summarized below:

- **Decision variables**
  - \( z_h \): A binary variable; 1 if supplier \( h \) is active, 0 otherwise.
  - \( a_h \): Allocation of demand to supplier \( h \) in number of units.
  - \( q_{ghk} \): Quantity flowing from supplier \( h \) to demand point \( k \) during the state of nature \( g \).

- **Input parameters**
  - \( p_h \): Probability that supplier \( h \) will not deliver (supplier failure).
  - \( m_h \): Maximum output capacity for supplier \( h \).
  - \( b_h \): Flexibility factor for supplier \( h \).
  - \( c_h \): Variable cost per unit for supplier \( h \).
  - \( f_h \): Fixed management cost for supplier \( h \).
  - \( e_h \): Variable premium cost per unit for supplier \( h \).
  - \( d_k \): Demand in units for demand point \( k \).
  - \( t_{hk} \): Transportation cost per unit from supplier \( h \) to demand point \( k \).
  - \( l_k \): Loss cost per unit for failure to deliver to demand point \( k \).
  - \( u_{gh} \): Unsatisfied demand (in units) for demand point \( k \) during the state of nature \( g \).
  - \( w_{gh} \): Binary variable related to the delivery condition of supplier \( h \) during the state of nature \( g \); 1 if the supplier is delivering, 0 if it fails to deliver.

The model considers all the possible states of nature combinations given \( s \) suppliers. Each state of nature has a probability \( r_g \) determined as:

\[
 r_g = \prod_{h \in S} (1 - w_{gh}) p_h + w_{gh} (1 - p_h) \tag{1}
\]

An example of how \( r_g \) is calculated is shown in Fig. 2.

There are four costs that are state of nature dependent: flow or transportation costs (\( f_{cg} \)), base variable costs (\( v_{cg} \)), premium variable costs (\( p_{cg} \)), and loss costs (\( l_{cg} \)). The flow costs are based on the number of units that flow between each source-demand point combination. The base variable costs consider all the units that are sourced from a particular supplier under a state of nature, including those that are part of the supplier’s original allocation and those that are produced due to other supplier failures. The premium variable costs consider those units sourced by a supplier above its baseline allocation. The loss costs consider the number of units not delivered to a demand point, given the particular flow decisions for that state of nature. The flow costs, base variable costs, premium variable costs and loss costs for the state of nature \( g \) are determined as:

\[
 f_{cg} = \sum_{h \in S \cap N} t_{gh} q_{ghk} \tag{2}
\]

\[
 v_{cg} = \sum_{h \in S \cap N} c_h q_{ghk} \tag{3}
\]

\[
 p_{cg} = \sum_{h \in S \cap N} e_h w_{gh} \left( \sum_{k \in N} q_{ghk} - a_h \right) \tag{4}
\]

\[
 l_{cg} = \sum_{h \in N} u_{gh} l_k \tag{5}
\]

The only cost that does not depend on the state of nature is the supplier management fixed costs (\( sc \)), determined as:

\[
 sc = \sum_{h \in S} z_{gh} \tag{6}
\]

The total costs (\( tc \)) for this model are determined as:

\[
 tc = sc + \sum_{g \in V} r_g (f_{cg} + v_{cg} + p_{cg} + l_{cg}) \tag{7}
\]

The complete optimization model can be written as:

Minimize \( tc = sc + \sum_{g \in V} r_g (f_{cg} + v_{cg} + p_{cg} + l_{cg}) \tag{8} \)

Subject to:

\[
 \sum_{k \in N} q_{ghk} \leq m_h w_{gh} \tag{C1}
\]

\[
 a_h (1 + b_h) \leq m_h w_{gh} \tag{C2}
\]

\[
 \sum_{k \in N} q_{ghk} \leq a_h (1 + b_h) \tag{C3}
\]

\[
 \sum_{k \in N} q_{ghk} \geq a_h w_{gh} \tag{C4}
\]

\[
 a_h \leq z_{gh} m_h \tag{C5}
\]

\[
 \sum_{h \in S} q_{ghk} = u_{gh} + d_k \tag{C6}
\]

\[
 \sum_{h \in S} a_h = \sum_{k \in N} d_k \tag{C7}
\]

\[
 z_h = \{0, 1\}; \ q_{ghk} \geq 0; \ u_{gh} \geq 0; \ a_h \geq 0 \tag{C8}
\]
Note that in the constraints C1 to C8, $g \in V$, $h \in S$, $k \in N$, and constraints C6 and C7 are standard in classic transportation problems, while the others consider supplier failures and flexible capacities. In addition, constraint C1 ensures that outflow from a supplier does not exceed its capacity; constraint C2 ensures that the allocation to a supplier modified by the flexibility factor does not exceed its capacity; constraint C3 ensures that outflow from a supplier cannot exceed the modified allocation capacity; constraint C4 indicates that outflow from a supplier must be at least equal to the allocation if the supplier delivers; while constraint C5 is used to determine the active suppliers based on an allocation greater than zero.

The complexity of the model is defined by $2^g \times n \times s$ binary variables and by $s$ binary variables. Given in practice the number of suppliers is relatively small, the number of binary variables would also be small, and therefore the problem is readily solvable by commercial mathematical programming software.

4. Numerical examples and sensitivity analyses

A numerical example is presented to illustrate the model and provide further insights. The example is loosely based on the observations of a global manufacturer of appliances. There are three demand points (i.e., manufacturing/assembly plants), and five, first-tier suppliers with significant geographical dispersion.

The supplier information is provided in Table 1, while the flow costs and demand information are summarized in Table 2.

The proposed model was implemented on Excel® in combination with Frontline’s premium Solver (Frontline Systems, 2011) and Visual Basic for Applications. The Excel/Solver/Visual Basic tool found a solution for the described problem (and all additional instances discussed later on in this section) in less than five seconds using a personal computer with a Pentium V processor.

As an initial condition let’s assume there is no contingency planning in place; therefore shipments from suppliers to demand points do not change if suppliers fail. This further implies there will be no emergency production. In this environment, the best solution is an allocation to two suppliers: 1500 units to $s[4]$, and 900 units to $s[5]$. Given two suppliers are selected there are only four possible SN: (i) all suppliers deliver; (ii) only $s[4]$ delivers; (iii) only $s[5]$ delivers; and (iv) both $s[4]$ and $s[5]$ fail. Fig. 2 presents the decision tree with the corresponding values for the delivery condition variables in $w_{gh}$, the non-zero probability components of $v_g$, and the resulting probabilities per state of nature. The resulting flow quantities, probabilities, and costs for each state of nature are displayed in Fig. 3. The expected total costs are $72,827.


Fig. 4 presents five SN (those with 0 or 1 supplier failing), while Fig. 5 presents the six SN with two suppliers failing. The remaining four SN are not presented for the sake of brevity and given the total probability for these four states is only 0.02%. For each state of nature the figure includes the probability, costs, and units not delivered. Also, in all cases where one or more suppliers failed, all “operational suppliers” produced to their maximum flexibility. In other words, when supplier $s[2]$ failed, $s[3]$, $s[4]$, and $s[5]$ produced 56, 336, and 141 extra units, respectively (allocation + flexibility factor).

The expected total cost for this plan is $60,247 with a reduction of about 17% (compared to $72,827 of the previous solution). As observed in Fig. 4, the current set of plans is able to meet the demand requirements in most states of nature with a single supplier failure. In only one of the four states of nature with one supplier failing the demand is not satisfied (when $s[4]$ fails), although when two suppliers fail (see Fig. 5) the demand can never be fully satisfied. While not shown, it is obvious that the demand cannot be met when three suppliers fail, and no deliveries occur when all suppliers fail.

4.1. Sensitivity analysis of supplier $s[1]$

This section focuses on how the characteristics of supplier $s[1]$, in particular its reliability and flexibility characteristics, affect the resulting solutions. Fig. 6 illustrates the baseline configuration with $p_{d[1]} = 9\%$, 6\%, 1\%, 0.5\% and 0.1\%, noting that in the original configuration $p_{d[1]} = 10\%$ (note that the baseline configuration is the same for $p_{s[1]} = 6\%$ and $p_{s[1]} = 1\%$). As the reliability of supplier $s[1]$ improves, its baseline assignment increases (as expected).
At $p_{s1} = 6\%$ it replaces suppliers $s[3]$ in the supplier set, and as its reliability increases its allocation increases. It is important to note that even when it becomes the most reliable supplier, the demand allocation is still distributed across multiple suppliers. Also, as its reliability increases the number of arcs decreases (from 6 to 5 as $p_{s1}$ changes from $6\%$ to $0.5\%$), and the number of suppliers

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Fig. 3. Optimal solution with no contingency planning.

Fig. 4. Solution based on the proposed model (states of nature with 0 or 1 supplier failure).
decreases (from four to three suppliers; supplier s[5] no longer receives an allocation when \( p_{s[1]} = 0.1\% \)). The second parameter investigated in the sensitivity analysis for s[1] was the flexibility factor, focusing on its interaction with the failure probability. Figs. 7 and 8 present the effect of this parameter on the allocation to supplier s[1] and the total cost. The effect here is interesting as the allocation to supplier s[1] and the total cost are clearly related to the interaction of flexibility and reliability, but in different tendencies. When supplier s[1] was unreliable (\( p_{s[1]} = 9\% \) or 6\%) having more flexibility resulted in being included in the selected supplier set. At \( p_{s[1]} = 9\% \) this supplier received an allocation of 0 units until its flexibility reached 30%; on the other hand, whith this supplier was slightly more reliable (\( p_{s[1]} = 6\% \)), it received a similar allocation when its flexibility level reached the 15\% level. This is explained by s[1] being able to provide a larger number of units in contingency situations at the lowest premium cost, reducing the expected loss costs. This example provides insights into the interaction between flexibility and reliability.

At the next reliability level (\( p_{s[1]} = 1\% \)), supplier s[1] has an allocation even with 0 flexibility. As the flexibility increased, its allocation increased. However, as its flexibility increased beyond the 20\% level, its allocation started to decrease. Note that after the 20\% flexibility level was reached its “flexible capacity” (allocation + flexibility factor) stayed constant at about 260 units. This indicates that 20\% flexibility level is the “best flexibility level” for this supplier and that at this reliability level the number of suppliers used remains constant at 4. We observe that loss costs are minimized when suppliers reach a “best flexibility level” based on the probability of the different SN with failures, particularly those SN with higher probabilities.

When \( p_{s[1]} = 0.5\% \), the allocation to supplier s[1] starts at 900 at the 0 flexibility level (it is the supplier with the highest allocation), its allocation increases to 1524 units at 5% flexibility, and then decreases from this point on until it reaches the 35\% flexibility level, where it increases again. As in the \( p_{s[1]} = 1\% \) level, the allocation decreases but the flexible capacity (baseline allocation \* flexibility rate) remains constant at about 200 units (flexibility from 15% to 30%). At 35\% flexibility, the solution changes from 4 active suppliers to 3, thus the “best flexibility level” for a supplier is based on the number of suppliers in the active set.

The final level of reliability (\( p_{s[1]} = 0.1\% \)) provides further interesting insights. Under this condition, supplier s[1] becomes the sole source for the network when it has no flexibility (or 5\%), and as its flexibility increased it received a smaller allocation. It is interesting to note that as the flexibility of s[1], \( b_{s[1]} \) increased, the number of active suppliers changed: 1 supplier at \( b_{s[1]} = 0\% \) and 5\%, 4 suppliers at \( b_{s[1]} = 10\% \), 3 suppliers at \( b_{s[1]} = 15\% \) to 35\%, and 2 suppliers at \( b_{s[1]} = 40\% \), and supplier s[1] was an active supplier in all cases. When \( p_{s[1]} = 0.1\% \) the loss and premium costs are a very small percentage of the total costs, thus the optimal decision is closely related to balancing fixed and transportation costs.

4.2. Sensitivity analysis: simultaneous change for all suppliers

As a second set of experiments we consider a modification to all of the supplier’s characterization. We assume all the suppliers now have a flexibility of 5\% and consider three reliability levels. The first level (base) is the same as the initial case (illustrated in Table 1), the second called high has double the failure probabilities for each supplier than the base level, and the low level where all suppliers have half the failure probabilities than the base case: (high level: \( p_{s[1]} = 20\% \), \( p_{s[2]} = 8\% \), \( p_{s[3]} = 14\% \), \( p_{s[4]} = 4\% \), \( p_{s[5]} = 6\% \); low level: \( p_{s[1]} = 5\% \), \( p_{s[2]} = 2\% \), \( p_{s[3]} = 3.5\% \), \( p_{s[4]} = 1\% \), \( p_{s[5]} = 1.5\%)\).

The allocation to suppliers in the base failure case (with all suppliers at 5\% flexibility) is 114, 1386, and 900 for s[2], s[4] and s[5], respectively, and resulting in a total expected cost of $71,759. When we compare this solution to the original one (each supplier having independent flexibilities, presented in Figs. 4 and 5), the cost has increased by about 19\%, thus the benefit of flexible suppliers is clearly measurable. Besides the increase in cost, the change in flexibility resulted in a reduction in the number of active suppliers

![Fig. 5. Solution based on the proposed model (states of nature with 2 suppliers failing).](image-url)
(from 4 to 3) and in less dispersed distribution as supplier s[4]
now receives a significantly larger allocation, while supplier s[2]
receives a significantly smaller allocation.

The allocation to the suppliers when we consider the higher
failure probability values is 114, 114, 1429 and 743 for s[2], s[3],
s[4] and s[5], respectively, with a total expected cost of $91,869.
This significant increase in total cost is expected as less reliable
suppliers will result in an increased expected loss costs. Compared
to the base case with 5% flexibility, the number of suppliers in-
creases with 157 units assigned to s[5] being allocated to s[3]
and s[4]. This result (i.e., the number of suppliers increases as their
reliability decreases) is consistent with the results of Ruiz-Torres
and Mahmoodi (2007) and Sawik (2011). When comparing this
solution to the original one, note that while the supplier set is
the same, the allocation with less flexibility has a much higher le-
vel of dispersion with suppliers s[2] and s[3] receiving relatively
small allocations.

The allocation at the low failure level is 1429 and 971 for sup-
pliers s[4] and s[5], respectively, with a total expected cost of
$61,451. As expected, more reliable suppliers result in lower total
expected costs, as expected loss costs are much lower. Compared
to the base case with 5% flexibility, the number of suppliers decrease with most of s[2]'s allocation shifted to s[5]. Thus, it is
shown that increases in reliability can offset flexibility losses,
and as in previous studies, increases in reliability result in fewer
suppliers.

5. Discussion and managerial implications

Global sourcing strategies have enabled many organizations to
take advantage of resources and production capacities available
in different parts of the world. With numerous perceivable benefits
come various pitfalls and challenges when managing such global
supply chains, one of which is coping with supplier risks and devel-
op contingency plans when supplier failures are noticeably present
or readily measurable.

This paper focuses on determining the optimal supply alloca-
tion and contingency planning in supply networks with multiple
sources and a set of separate demand points, which are frequently
observed in today’s global supply chains. The capacity of each sup-
plier, demand quantity at each demand point, and the per-unit

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Fig. 6. Baseline configurations as the reliability of supplier s[1] is changed.

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transportation cost of each supply-demand combination are assumed to be known. The optimal supply allocation decision aiming at minimizing the total transportation costs can be solved as the classic transportation problem, where each supplier is assumed to be completely reliable. This research expands the traditional transportation model by taking each supplier’s failure probability and flexible capacity, as well as more complicated cost structures into consideration. Our model blends decision-tree concepts with mathematical programming and provides guidelines for multiple decisions, including the allocation quantities that best utilize available suppliers’ flexible capacities, the number of suppliers needed to best satisfy the demand quantities, and provides a balance between each supplier’s reliability and its flexibility. Unlike other supplier selection models, our model considers contingency planning in the decision process, minimizing the total network costs. This results in a base allocation to one or more of the available suppliers and a state of nature specific delivery contingency plan from the suppliers to each demand point.

While the results of this study are limited by our particular experimental settings, they provide several insights and important managerial implications. First, it is demonstrated that having contingency plans reduces the total costs (compared to having no contingency plans). While this is intuitive, our model provides the practicing managers the ability to quantify the effect of not having contingency plans. Furthermore, it is clear that not accounting for contingencies could result in the selection of the “wrong” set of suppliers.

Second, as suppliers become more reliable, the total costs, as well as the number of suppliers decrease. This is consistent with the results of Ruiz-Torres and Mahmoodi (2007) and Sawik (2011). Furthermore, as the reliability of a certain supplier improves, its baseline assignment increases. Thus, it is worthwhile to source from fewer, reliable suppliers rather than from a larger set of unreliable suppliers.

Third, as the suppliers’ flexibility increases, the total costs decrease, regardless of the reliability of the suppliers. Therefore, the benefits of flexible suppliers are measurable, aiding practicing managers to make appropriate decisions. Furthermore, the reduction in suppliers’ flexibility can result in a decrease in the number of active suppliers and in a more dispersed distribution as the most reliable suppliers receive a significantly larger allocation, while the less reliable suppliers receive smaller allocations (or are removed from the active set). Finally, our experiments demonstrate that improved reliability can offset flexibility losses and result in fewer suppliers, thus strategies that balance the flexibility and reliability of the suppliers may provide desirable results.

Although our model takes supplier risk and failure and associated costs into consideration when designing a global supply network, it has a few major limitations. First, the network structure is comprised of direct supply–demand links only and does not consider intermediary points. Second, our model does not capture the dynamic nature of the supply network since all the input parameters and supplier characteristics are assumed to be deterministic. Lastly, real data, cases and practices should be used to verify the results and implications of this research.

This work can be extended based on the aforementioned limitations. Specifically, investigating a more complicated network structure (e.g., supply chains with intermediary points) would be of much interest. Also, more diverse supplier performance attributes, such as lead time and quality, can be included in each supplier’s performance metric, in addition to reliability and flexibility considered in this study.

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