

Determining the Optimal Number of Cluster Suppliers under Supply Failure Risks

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Abstract— As the risk of supply disruption becomes an important concern for a purchasing company, determining the optimal number of suppliers becomes a top priority in making purchasing decisions to address the supply risk to the manufacturer's operation. Furthermore, the recently increasing co-location of dedicated supplier clusters has been observed for wider development to reduce supplier numbers, increasing geographical proximity within supply chain networks. However, previous studies only discussed the risks of supply disruption in terms of *super* and *unique* events, neglecting the probability of the occurrence of a localised *semi-super event*, which can disrupt all suppliers in a specific geographical location. The present study extends the existing models, allowing a more realistic decision-making process according to the optimal number of cluster suppliers by considering the partial loss associated with independent supply risks in specific geographical regions, which constitute the important components of the overall supply disruption risk. Model comparison and sensitive analysis are conducted on the proposed model. The results indicate that the optimal solution is significantly influenced by the supplier failure probabilities in geographical regions when the ratio of loss versus variable operational cost increases.

Keywords— *Supplier number, cluster supplier, supply failure risk, regional failure, supplier failure*

1. Introduction

Since the 1980s, many firms have increased their level of global supply chain outsourcing to gain competitive advantage. This has led managers to give more importance to the purchasing function and the decisions associated with it given that the cost of component parts represents more than 70% of the total product cost [1]. Such decisions entail the evaluation and selection of suppliers to employ. Supplier performance directly affects the capability of a firm because of its impact on quality, cost, technology, and responsiveness. Supplier selection is an important aspect of purchasing decision and management.

A prerequisite for evaluating and selecting potential

suppliers is to determine the optimal number of suppliers. In either new or repeat purchasing situations, business buyers must decide on the optimal number of suppliers to choose from. Conventionally, organisations select from a large number of suppliers based on price, but having many suppliers increases the fixed cost. With the growing need for more cooperation between manufacturers and their suppliers, organisations endeavour to reduce the number of suppliers they deal with and to establish longer-term relationships. However, considering only a few suppliers gives rise to the risk of supply disruption. Therefore, determining the optimal number of suppliers is a top priority in making purchasing decisions to address the supply risk to the manufacturer's operation. Research studies that cover the entire purchasing process have addressed the significance of pursuing the relationship between supply risks and purchasing decisions for suppliers [2,3].

The risk of supply disruption is an important concern for a purchasing company. Some recent incidents caused significant supply chain disruptions and had serious repercussions for many firms. For example, the Taiwan earthquake in September 1999 had detrimental effects on many supply chains. Sony Ericsson lost 400 million euros after their supplier's semiconductor plant caught fire in 2000. Ford closed five plants for several days when all air traffic was suspended after the September 11 incidents in 2001. The most recent earthquake in Japan on March 11, 2011 created a panic and resulted in huge losses for many suppliers, which had subsequent ripple effects through many supply chains.

According to the definitions of supply risk by Zsidisin [4], supply risk is based on individual supplier factors and market characteristics. A variety of risks associated with external disruptions of the supply process need to be taken into consideration to establish a model to deal with the problem of supplier selection and the associated decision of the number of suppliers to have. However, previous studies have neglected the supply risk of *semi-super* events, which are location-specific and disrupt all suppliers in a geographical location, while not affecting suppliers in other locations. These events may include

earthquakes, floods, typhoons, hurricanes, terrorist attack, or economic crisis and these calamities can disrupt local businesses and supply chains.

Furthermore, the recently increasing co-location of dedicated supplier clusters has been observed for wider development to reduce supplier numbers, increasing geographical proximity within supply chain networks [5,6]. A cluster is a geographic concentration of interconnected companies in a particular field. Steinle and Schiele [7] argued for the inclusion of an analysis of industry clusters when making decisions about global or local sourcing to enhance a firm's competitive advantage. Using two contrasting case studies, they concluded that a high global sourcing quota does not necessarily improve a firm's competitiveness. Rather, there may be limits to global sourcing, if a firm is unable to become a preferred customer of its strategic suppliers. Silvestre and Dalcol's [8] study verifies geographical proximity is a factor that favours innovation by the organisations within the agglomeration. The results of an empirical study, involving 10 firms located in the Campos Basin oil & gas industrial agglomeration in Brazil over 20-year span, indicate geographical proximity has a positive influence on innovation. With increasing geographical proximity within supply chain networks, the development of decision models for ordering materials from co-located cluster suppliers under the broad rubric of risk management in supply chains becomes an important problem given that geographic-specific regional failure with its associated loss is inevitable.

Supply failure risk signifies potential loss to the organisation created by events originating in the upstream supply chain, and most firms reported that their supply chains are vulnerable to supply failures [9]. Several researchers who paid attentions on the issues associated with supply risk management have realized the importance of understanding of the costs of supplier failures. Previous studies have described the creation of decision support tools under supply failure risks that focus on individual supplier failures and missing from these models has been an assessment of the risk that all or some of a given manufacturer's targeted supply would be unavailable or that order fulfilment by all cluster suppliers in a specific geographic region would be disrupted. In this paper, we present a model that allows a more realistic decision-making process by considering both the risks of supply disruption due to the occurrence of all three types of events and the partial loss associated with independent supply risks in geographical regions, which constitute the important components of the overall risk of supply disruption. The remainder of this paper is organised as follows: Section 2 surveys the previous decision models that considered the expected losses due to supplier failure to deliver in the total cost formulation. Section 3 describes

the proposed model for determining the optimal number of cluster suppliers with consideration of the cost of maintaining a set of cluster suppliers and the expected financial loss costs associated with the risks of supply disruptions due to all three types of events. Section 4 provides a case study with model comparison and a sensitivity analysis is conducted in Section 5. Finally, Section 6 concludes the paper.

2. Literature Review

Originally, Berger et al. [10] used a decision-tree approach, which is called the BGZ model, to model the decision-making process concerning the problem of determining the optimal number of suppliers in the presence of supplier failure risks considering *super* events, which affect all suppliers, as well as *unique* events, which affect only a single supplier. The BGZ model focuses on the operating cost of working with multiple suppliers and on the financial loss caused by disasters as captured by decision trees, from which the expected total cost function is obtained and calculated by

$$ETC_{BGZ}(n) = EOC_{BGZ}(n) + ELC_{BGZ}(n)$$

where EOC denotes expected operating costs when n suppliers are used; ELC means expected loss cost incurred when a *super* event occurs with all suppliers down and if all suppliers are down even with no *super* event; and n is the number of suppliers.

Having many suppliers increases the fixed operating cost, whereas considering a few suppliers gives rise to supply disruption risks and then increases the financial loss caused by supplier failures. Therefore, the optimal number of suppliers is determined when minimizing the expected total cost.

The simplest function for the operating cost of n suppliers is used for the purpose of illustration, $EOC_{BGZ}(n) = C(n) = a + b(n)$, where $C(n)$ is a linear function of n . According to the basic decision-tree analysis by Berger et al. [10] with assumption for ease of exposition that the *unique* probability of failure is about the same for each supplier; that is, $U_1 = U_2 = \dots = U_n = U$. A loss is incurred when a *super* event occurs with a probability of P^* and if all suppliers are down even with no *super* event, with a probability of $(1 - P^*) U^n$. The expected costs of loss can be simplified to

$$ELC_{BGZ}(n) = L[P^* + (1 - P^*)U^n],$$

where L is the financial loss when all suppliers are down, P^* is the probability of *super* events occurring during the supply cycle, and $U = U_i, i = 1, 2, \dots, n$; the *unique* probability of supplier failure is about the same for each supplier. Ruiz-Torres and Mahmoodi [11] further took into account partial loss associated with the failure of any individual

supplier in the decision-making process. However, the previous studies only investigated individual supplier failures and ignored the supply risks of geographic-specific failures.

3. Proposed Model

Our model determines the optimal number of suppliers while taking into consideration the independent supplier failures in geographical regions, including the loss incurred by all suppliers that are down as well as the partial loss when not all suppliers fail to deliver due to *super*, *semi-super*, and *unique* events. Considering that a total of n suppliers, of which n_k suppliers are at location k of total K locations, are to be selected, i.e., $\sum_{k=1}^K n_k = n$, and:

P^* probability of occurrence of a *super* event causing all suppliers to fail;

P_k^{**} the probability of a localised *semi-super* event causing all suppliers at location k , ($k = 1, \dots, K$), to fail;

U_{ik} the probability of a *unique* event causing supplier i , ($i=1, \dots, n_k$), at location k to fail;

n_k number of suppliers at location k ;

K number of locations,

L the financial loss when all suppliers are down.

The objective is to determine the optimal number of suppliers by minimizing the expected total costs. In this study, the Expected Total Costs (ETC) is the sum of the Expected Operating Costs (EOC), and the Expected Loss Costs (ELC), i.e.,

$$ETC(n) = EOC(n) + ELC(n)$$

The same operating cost function of working with multiple suppliers is adopted from the works of Berger et al. [10]. However, an extended approach on the formulations of the ELC was made in the decision-making process with the consideration of the independent supplier failures in geographical regions.

The total ELC is the sum of the partial loss of some down suppliers and the financial loss incurred by all down suppliers. We first consider the partial loss of some suppliers that are down due to the occurrence of *super*, *semi-super*, and *unique* events. The partial loss costs are determined by the probabilities of those possible outcomes where at least one supplier does not fail during a cycle and the associated financial loss. However, it adds a new level of complexity to supplier number decisions when also considering the partial loss associated with the independent supplier failures in geographical regions. Therefore, in the following subsections, formal formulations of the probabilities of partial suppliers that are down and the associated financial loss are presented to

handle multiple locations with multiple suppliers for most practitioners.

3.1 Probabilities of Partial Suppliers Down

To determine the partial loss associated with the independent supplier failures in a problem of K locations with n_k suppliers at location k , we defined a probability factor of regional failure of the locations in X ,

$$F_X = (1 - P^*) \prod_k^X P_k^{**} \prod_k^{R-X} (1 - P_k^{**})$$

where P_k^{**} is the probability of *semi-super* events at location k , X represents the set of all possible combinations of the K locations in a given set R , and \bar{X} represents the set of all possible combinations of X .

Let $P_{X, [j, n]}$ be the probability that there are j suppliers that are down out of a total of n suppliers in a given set N upon condition that the locations in X are down:

$$P_{X, [j, n]} = \begin{cases} 0, & \text{if } n_X > j \\ \sum_{E \in \bar{E}} \left[\prod_{s \in E} U_s \prod_{s \in (W-E)} (1 - U_s) \right] & \text{otherwise} \end{cases}$$

where W populating the suppliers in all locations except those in X and E represents the set of all possible combinations of $(j - n_X)$ suppliers in W , \bar{E} represents the set of all possible combinations of E sets, n_X is the number of suppliers in the locations of set X , and U_s is the probability of *unique* events happening to the supplier s .

Therefore, for a problem of K locations with n_k suppliers at location k , the probability of j suppliers being down out of the total n suppliers, represented by $P_{[j, n]}$, can be obtained by

$$P_{[j, n]} = \sum_{X \in \bar{X}} F_X P_{X, [j, n]}$$

For example, To obtain $P_{[3, 4]}$, for two suppliers in each of the two locations, we must consider all possible combinations of locations: $X = \{\}$, $X = \{A\}$, $X = \{B\}$, $X = \{A, B\}$; $\bar{X} = \{\{\}, \{A\}, \{B\}, \{A, B\}\}$. The corresponding F_X and $P_{X, [j, n]}$ for the locations that are down in each X were calculated as follows:

For no down location ($X = \{\}$, $n_X = 0$),

$$F_{\{\}} \times P_{\{\}, [3, 4]} = (1 - P^*) (1 - P_A^{**}) (1 - P_B^{**}) \times [U_{1A} U_{2A} U_{1B} (1 - U_{2B}) + U_{1A} U_{2A} (1 - U_{1B}) U_{2B} + U_{1A} (1 - U_{2A}) U_{1B} U_{2B} + (1 - U_{1A}) U_{2A} U_{1B} U_{2B}]$$

For only location A down ($X = \{A\}$, $n_X = 2$),

$$F_{\{A\}} \times P_{\{A\}, [3, 4]} = (1 - P^*) P_A^{**} (1 - P_B^{**}) \times [U_{1B} (1 - U_{2B}) + U_{2B} (1 - U_{1B})]$$

For only location B down ($X = \{B\}$, $n_X = 2$),

$$F_{\{B\}} \times P_{\{B\},\{3,4\}} = (1 - P^*) P_B^{**} (1 - P_A^{**}) \times [U_{1A}(1 - U_{2A}) + U_{2A}(1 - U_{1A})]$$

For both locations A and B down ($X = \{A, B\}$, $n_X = 4$),

$$F_{\{A,B\}} \times P_{\{A,B\},\{3,4\}} = (1 - P^*) P_A^{**} P_B^{**} \times 0$$

Therefore, the probability of three suppliers down is $P_{\{3,4\}}$

$$\begin{aligned} = & F_{\{1\}} \times P_{\{1\},\{3,4\}} + F_{\{A\}} \times P_{\{A\},\{3,4\}} + F_{\{B\}} \times P_{\{B\},\{3,4\}} + F_{\{A,B\}} \times P_{\{A,B\},\{3,4\}} \\ = & (1 - P^*) (1 - P_A^{**}) (1 - P_B^{**}) \times [U_{1A} U_{2A} U_{1B} (1 - U_{2B}) + U_{1A} U_{2A} (1 - U_{1B}) U_{2B} \\ & + U_{1A} (1 - U_{2A}) U_{1B} U_{2B} + (1 - U_{1A}) U_{2A} U_{1B} U_{2B}] + \\ & (1 - P^*) P_A^{**} (1 - P_B^{**}) \times [U_{1B} (1 - U_{2B}) + U_{2B} (1 - U_{1B})] + \\ & (1 - P^*) P_B^{**} (1 - P_A^{**}) \times [U_{1A} (1 - U_{2A}) + U_{2A} (1 - U_{1A})] \end{aligned}$$

Thus, the probability calculations for $n > 2$ or $K > 2$ can be performed accordingly.

3.2 The Partial Loss Function

Ruiz-Torres and Mahmoodi [11] determined the optimal number of suppliers with considering the partial loss associated with the failure of any individual supplier in the decision-making process, which proposed the additional financial loss that is associated with the j th supplier who fails ($A_{[j,n]}$) and based on a percentage of the total loss:

$$A_{[j,n]} = \frac{j^m L}{\sum_{i=1}^n [i^m]}, \quad 0 \leq m \leq \infty$$

where m represents the ability of the organisation to mitigate failure from a partial set of suppliers. The sum of all partial losses was also proposed to be equal to the loss of all suppliers that are down:

$$L = \sum_{i=1}^n A_{[i,n]}$$

For example, let $L = \$300$, and $n = 3$, if $m = 1$, the loss of one supplier results in cost of \$50, the loss of the second supplier costs an additional \$100, therefore a cumulative loss of \$150, and finally, the cumulative loss when all suppliers are down equals \$300 or L . As m increases, so does the ability of the organisation to mitigate the effects of a supplier failure through other suppliers. This effect is assumed as in most cases with multiple sourcing, the loss of a partial set of supplies can be mitigated by the remaining suppliers.

3.3 Partial Loss of Some Suppliers Down

The partial lost costs of some suppliers being down are obtained from the probabilities of the possible outcomes where at least one supplier does not fail during a cycle and of the associated financial loss. For a problem of K locations with n_k suppliers at location k , the partial loss

costs of j suppliers down out of the total n suppliers are defined as

$$\sum_{j=1}^{n-1} P_{[j,n]} T_{[j,n]} \quad (1)$$

where $T_{[j,n]}$ represent the financial loss per j suppliers that are down out of the total n suppliers, i.e., $T_{[j,n]} = \sum_{i=1}^j A_{[i,n]}$, and $T_{[n,n]} = L$.

3.4 Loss of All Suppliers Down

The financial loss of all suppliers at all locations was formulated for the occurrence of either a *super* event, a *semi-super* event, or a *unique* event,

$$L \times P^* + L \times P_{[n,n]} \quad (2)$$

where P_k^{**} is the probability of a localised *semi-super* event causing all suppliers at location k ($k = 1, \dots, K$) to fail, U_{ik} is the probability of a *unique* event causing supplier i ($i = 1, \dots, n_k$) at location k to fail, n_k is the number of suppliers at location k , and K is the number of locations. The last item in Eq. (2) represents a combining effect of some *semi-super* events at some locations and *unique* events at the other ones.

3.5 Expected Costs of Loss

The total ELC is the sum of the partial loss of some suppliers down, as represented in Eq. (1), and the financial loss incurred by all suppliers fail, as represented in Eq. (2).

$$\begin{aligned} \text{ELC} &= L \times P^* + L \times P_{[n,n]} + \sum_{j=1}^{n-1} P_{[j,n]} T_{[j,n]} \\ &= L \times P^* + \sum_{j=1}^n P_{[j,n]} T_{[j,n]} \quad (3) \end{aligned}$$

The formal equations make the proposed model more generalisable, and spreadsheets are allowed to be used to solve a problem. The problem of determining the optimal number of suppliers is combinatorial in nature when the partial loss incurred by the supplier failures in geographical regions was considered in the formulations and finding a solution to the problem became computationally cumbersome. As proposed by Sarkar and Mohapatra [12], an elegant method was used to make the solution of the proposed model computationally simple. The solution procedures start with the generation of truncated tables for selecting n suppliers from different k ($k = 1, 2, \dots, K$) locations, and each cell represents the corresponding values of n and n_k (the number of suppliers selected from the k location). The step-by-step procedures find the minimum of all costs in each column with three

calculation loops to complete each table column, each table, and all the tables. If the most recently calculated total cost associated with the present column is more than the previous cost for the same column, then stop the loop to reduce the solution space. The final solution to the problem is then obtained when all the truncated tables are completed.

4. Model Comparison

In this section, we compare the behaviour of the existing and proposed formulations by assuming the parameters similar to those used by Ruiz-Torres and Mahmoodi [11]. The baseline values for the fixed cost of operating/supplier (a), the variable cost of operating/supplier (b), the incurred loss if all suppliers are down (L), the mitigation capability (m), the *super* event probability (P^*), and the *unique* event probability (U_{jk}) of supplier j at location k are as follows:

$$a = 50$$

$$b = 10$$

$$L = 4300$$

$$m = 1.5$$

$$P^* = 0.001$$

$$U_{jA} = U_{jB} = U_{jC} = U = 0.05 \quad (j = 1, 2, 3)$$

The EOC= $C(n) = a + b(n)$ is defined as in the BGZ model, while the expected cost of loss considering the independent supplier failures in geographical regions in Eq. (3) is defined for a problem of multiple locations with multiple suppliers. Now, we take an illustrative example of three locations with three suppliers in each location. The procedure to search for the best solution is similar, and Excel-based spreadsheets can be used.

Table 1 presents the ETC associated with alternative decisions when n suppliers are selected from three locations. The variables n_A , n_B , and n_C represent the number of suppliers chosen from locations A, B, and C, respectively, and the probabilities of *semi-super* events at three locations are assumed to be identical ($=P^{**}$). As shown in Table 1, the impact of supplier distribution at specific locations is significant. The dispersed suppliers in different locations can reduce the financial loss associated with the supply risks in geographical regions. The loss of (1, 1, 1) distribution of (n_A , n_B , n_C) is lower than that of (2, 1, 0) or (3, 0, 0) for the alternative decision of three suppliers. In addition, when six suppliers are chosen from three locations, the more dispersed (2, 2, 2) has a lower expected total cost than the (3, 3, 0) or (3, 2, 1) distribution. This is attributed to the fact that the more locations are dispersed by n suppliers at K locations, the less is the probability of n down suppliers and so is the expected cost of loss. The behaviour is further explored in Figure 1 (baseline values and $P^{**} = 0.1$), and it illustrates how the supplier distribution at different locations can affect the financial loss caused by supply failures when

the partial loss associated with the independent supply risks in geographical regions are taken into consideration. The reduction in the expected cost of loss is much significant as the number of suppliers is three or six for the high dispersion of suppliers at different locations, and this behaviour influences the determination of the optimal number of suppliers.

Table 1. Decision alternatives when n suppliers are selected from three locations

n	n_A	n_B	n_C	ETC							
				BGZ	PLSD	P^{**}					
						0.01	0.03	0.05	0.07	0.1	
2	2	0	0	123	195	236	320	403	487	612	
2	1	1	0	123	195	212	248	285	325	389	
3	3	0	0	123	171	213	297	381	466	592	
3	2	1	0	123	171	191	233	276	321	392	
3	1	1	1	123	171	182	205	230	256	300	
4	3	1	0	133	167	189	235	283	333	410	
4	2	2	0	133	167	184	221	260	301	365	
4	2	1	1	133	167	179	206	236	267	318	
5	3	2	0	143	169	187	225	265	307	374	
5	3	1	1	143	169	184	217	252	288	347	
5	2	2	1	143	169	180	206	234	264	314	
6	3	3	0	153	174	190	225	262	301	363	
6	3	2	1	153	174	188	219	251	285	340	
6	2	2	2	153	174	185	206	226	246	275	
7	3	3	1	163	178	192	225	264	309	387	
7	3	2	2	163	178	192	226	265	309	385	

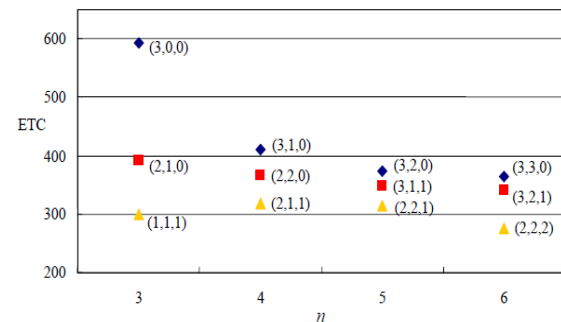


Figure 1. Expected total cost of different supplier distributions at three locations

5. Analysis

The optimal number of suppliers (n^*) varied with the assumed parameters used in the models. Hence, a sensitivity analysis is conducted to see the effect of change in the values of similar parameters on the optimal solution. As concluded by previous studies [6,7], the ratio L/b (the loss versus variable operational cost ratio), U , and m are useful variables in the analysis of the behaviour of the models, while the effect of varying P^* , *super* event probability, is not noticeable on the supplier decision, which is also confirmed by our results, as shown in Table 2.

Table 2. Effect of variation of P^{**} on the optimal number of suppliers

P^{**}	BGZ	PLSD	P^{**}			
			0.01	0.05	0.1	0.2
0.001	3	4	4	6	6	6
0.01	3	4	4	6	6	6
0.05	2	4	4	6	6	6
0.1	2	4	4	6	6	6
0.2	2	4	4	6	6	6

The optimal numbers of suppliers as functions of P^{**} , U , L/b , and m within reasonable ranges are summarised in Table 3. As P^{**} , U , or L/b increases, the optimal number of suppliers increases regardless of the m value. However, the degree of increase is dictated by the value of m . As concluded in Ruiz-Torres and Mahmoodi [7], n^* varies in very small ranges at the lowest value of m . As the value of m decreases from $m \sim \infty$ to $m = 0.15$, the optimal number of suppliers increases, then stays flat, and decreases.

Table 3. Optimal number of suppliers as a function of P^{**} , U , L/b , and m .

L/b	P^{**}	U	m				
			7	1.5	0.7	0.4	0.15
100	0.01	0.01	2	2	1	1	1
		0.03	2	2	2	1	1
		0.05	2	2	2	2	1
	0.05	0.01	2	2	2	2	1
		0.03	2	3	3	2	1
		0.05	2	3	3	2	1
	0.1	0.01	3	3	3	3	1
		0.03	3	3	3	3	2
		0.05	3	3	3	3	2
300	0.01	0.01	2	2	2	2	1
		0.03	2	3	3	3	2
		0.05	3	3	4	3	2
	0.05	0.01	3	3	3	3	2
		0.03	3	3	3	3	3
		0.05	3	3	3	3	3
	0.1	0.01	3	3	6	6	6
		0.03	3	6	6	6	6
		0.05	3	6	6	6	6

Figure 2 shows that the optimal number of suppliers increases as P^{**} , the probability of semi-super events, increases for the four cases of U and L/b , where the case with the highest values of U and L/b results in the highest value of n^* . Generally, when both P^{**} and L/b are high, for example, in the case of $L/b = 430$ and $P^{**} > 0.03$, the optimal number of suppliers tends to stay flat at (1, 1, 1) or (2, 2, 2) over a wide range of P^{**} . This can be attributed to the fact that, as shown in Figure 1, the reduction in the expected cost of loss at (2, 2, 2) with six suppliers is much significant than that at (2, 1, 1) with four suppliers or at (2, 2, 1) with five suppliers, offsetting the gains from the increase in the cost of multiple suppliers. Hence, we propose that the level of $L/b < 200$ represent low loss

versus operational cost ratio, the level of $200 \leq L/b \leq 400$ represent intermediate loss versus operational cost ratio, and the level of $L/b > 400$ represent relatively high loss versus operational cost ratio. The 0.005 and 0.02 levels of variable U represent the high reliability suppliers, the 0.02 and 0.04 levels represent medium reliability suppliers, and the 0.04 and 0.06 levels represent relatively low reliability suppliers.

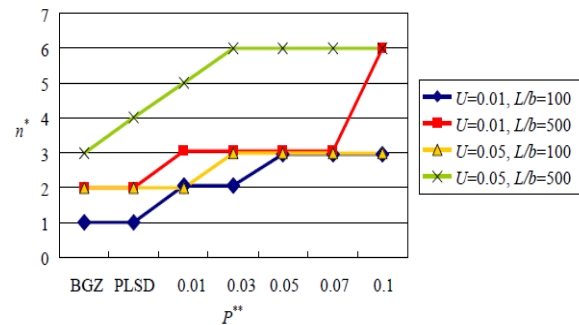


Figure 2. Optimal number of suppliers as a function of P^{**} , U , and L/b

The effect of the partial loss associated with the independent supplier failures in geographical regions is further explored in Figure 3, which is similar to the behaviour discussed in Ruiz-Torres and Mahmoodi [7] without the consideration of the supply failure at individual locations. However, the optimal number of suppliers stayed flat at the supplier distribution (1, 1, 1) or (2, 2, 2) when both P^{**} and L/b were high, as noted in Figure 2. Moreover, Figure 3 shows that the optimal solution of this behaviour is specific only for intermediate mitigation ability. Hence, we propose that $m = 0.15$ represent low mitigation ability, $m = 0.4 \sim 1.5$ represent medium mitigation ability, and $m = 7$ represent relatively high mitigation ability. The level of $0 \leq P^{**} < 0.03$ represents a safe area, the level of $0.03 \leq P^{**} \leq 0.07$ represents an intermediate risk area, and the level of $0.07 < P^{**} \leq 1$ represents a risky area. Then we can develop a decision-tree model of summarising and simplifying the results to assist managers in their decision-making.

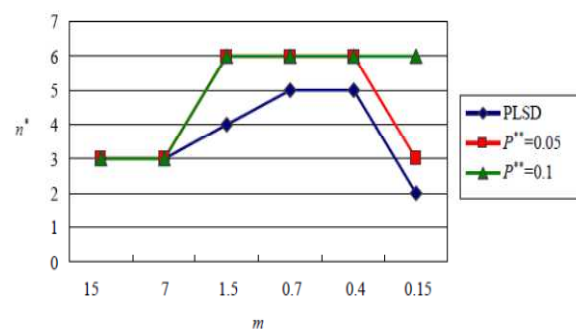


Figure 3. Optimal number of suppliers as a function of m and P^{**}

A decision-tree model for determining the optimal number of suppliers, as shown in Figure 4, is recommended to summarise and simplify the results in Table 3 based on all parameters represented by three levels: *high*, *medium*, and relatively *low*. In practice, suppliers of an organisation are classified by items being purchased. It is the criticality of a purchased item that determines the resulting impact of a supply disruption on the financial loss. Hence, the decision-making process demonstrated in Figure 4 begins from the determination of the financial loss when all suppliers are down and the variable operating cost during a cycle, which is dependent on all suppliers of an item. Regional supply risks or the probability of a localised *semi-super* event is the next decision factor. The optimal number of suppliers is then determined according to the reliability of suppliers and the organisation mitigation ability for failure from some suppliers. For example, in the case of medium or high *L/b* and when all suppliers are located in a risky area, as shown in Figure 4, the optimal number of suppliers is three for high organisation mitigation ability; otherwise, the optimal solution becomes six if the organisation mitigation ability is medium or relatively low. Figure 5 is a supplement of Figure 4 because the resulting n^* varies in a wider range in the case of a medium or high *L/b* and a safe area and is more sensitive to the different levels of mitigation ability and supplier reliability.

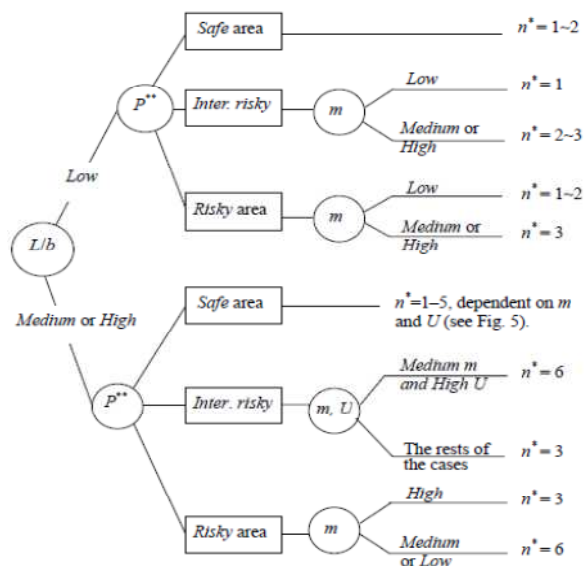


Figure 4. Decision tree for the summary of the results

		Mitigation ability		
		High	Medium	Low
Supplier reliability	High	2	2-3	1
	Medium	2	3	2
	Low	3	3-5	2-3

Figure 5. Supplement of Figure 4 for suppliers at safe area under Medium or High *L/b*

6. Conclusion

Determining the optimal number of suppliers constitutes an important part of purchasing decision in the context of supply disruption risk and has gained the interest of researchers to model the decision-making process. The present research extends the existing models to illustrate how the supplier distribution at different locations can affect the financial loss caused by supply failures when the partial loss associated with the independent supply risks in geographical regions is taken into consideration.

In practice, suppliers of an organisation are classified by items being purchased. It is the criticality of a purchased item that determines the resulting impact of a supply disruption on the financial loss. The decision-making process begins from the determination of the financial loss when all suppliers are down and the variable operating cost during a cycle, which is dependent on all suppliers of an item. The proposed model demonstrates that regional supply risks or the probability of a localised *semi-super* event is the next decision factor. The optimal number of suppliers must be determined according to the reliability of suppliers and the organisation mitigation ability for failure from some suppliers.

The proposed model illustrates how supplier distribution at particular locations can reduce the financial loss caused by supplier failures, consequently changing the optimal number of suppliers. It adds a new level of generalisation in practices and thus helps purchasing managers to better deal with supplier number decisions in the context of supply risks. The proposed model will continue to be explored to determine the supplier order allocations in the context of supply risks. However, other factors may have to be considered, such as the combination of probabilities and savings.

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