Towards designing a robust supply chain network; A multi objective optimization approach

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Abstract

In this paper, we propose a proactive approach to design a robust supply chain network. The purpose of this model is supplier selection with the objective of minimizing the total cost and maximizing the supply chain visibility while considering the probability of suppliers' failure. The model is based on double souring, considering second-tier suppliers. We calculate the visibility of suppliers and sub-suppliers and select the suppliers with higher visibility. By using numerical examples, we show that selecting suppliers with higher visibility lowers the probability of both suppliers' failure.

Keywords: Supply chain risk, Supplier selection, Optimization approach,

Introduction

From the literature, it becomes apparent that the main consideration in supply chain risk management is the visibility of the risk (Yu and Goh, 2014). (Harland et al., 2003) examined the supply chains and reported that less than half of the risk was visible to the focal company.

One key question arising from the two Asian disasters and the extant literature that needs an answer is: how to choose the parts supplier in order to minimize the supply risk/disruptions due to the supply chain and how to invoke as high a visibility as possible without exceeding the production or total budget (Yu and Goh, 2014). According to (Enslow, 2006) about 79% of the large companies surveyed globally cited the lack of Supply Chain Visibility (SCV) as their top concern. (Ouyang, 2007) further shows that SCV implementation can enhance supply chain stability and mitigate the bullwhip effect. Visibility ensures confidence into the Supply Chain (SC) and prevents overreactions, unnecessary interventions and ineffective decisions in a risk event situation (Christopher and Lee, 2004).

The motivation of this study is the disruption in SC of Toyota after the Great East Japan Earthquake in March 2011. For two weeks after the earthquake, the entire Toyota plants in Japan stopped completely. However, most of Toyota assembly plants in Japan located in Nagoya and Kyushu regions and were not damaged by the earthquake. The problems were lack of parts, or not even knowing which parts would be missing when it resumed production. In other words, the lack of visibility in the downstream supply chain was one of the main problems. It is reported that it took one week for Toyota to list 500 suppliers from 200 locations. Moreover, the usual mitigation tactic of having multiple sourcing had not been taken into account (Matsuo, 2015).

Supply chain visibility

We read nine papers related to SCV and divided them into two categories of conceptual-empirical studies (five papers), and mathematical studies (four papers). Among these, only two papers considered visibility and risk simultaneously.

Barratt and Oke (2007) reviewed the existing papers in SCV. Caridi et al. (2014) assessed the value of an improvement in SCV. Brusset (2016) and Lee et al. (2014) did empirical studies in supply chain visibility. Vilko et al. (2016) discussed theoretically the SCV.

Among the papers who applied mathematical programming, Silva et al. (2017) did the simulation to study SCV. Caridi et al. (2010) studied the quantitative measures of visibility in supply networks. While only one paper (Yu and Goh, 2014) considered the Supply Chain Risk and SCV simultaneously. After that, Nooraie and Parast (2015) studied the stochastic version of the model presented by (Yu and Goh 2014) considering demand as stochastic.

Caridi et al. (2010) mentioned that in any case, there is no single definition for SCV. They mentioned that in general there are three ways to define visibility. First way is defining visibility as the ‘‘ability to access/share information across the supply chain’’. In the second way of definition, visibility’s level in SC is determined by the extent to which the shared information is accurate, trusted, timely, useful, and in a readily usable format. Third way defines visibility as the importance of exchanging useful information between partners. In a nutshell, SCV is related to the information in the SC network. Thus, depending on the need and considered dimensions of SC network, SCV can be defined exclusively in each model of SC network.

In our study, we follow the first approach which is “visibility as the ability to access or share information across the supply chain to define the SCV. However, as the author's highlight, this index is specific to retail and refers to a supply chain consisting of only two members, i.e. supplier and retailer, and thus not being suitable to assess the visibility level in more complex supply chains. Moreover, most authors either focus on simplified supply chains like two-level supply chain, which are far from the complexity of real environments or provide only ‘‘partial’’ measures, which do not consider the different dimensions of visibility (Caridi et al., 2010).

In this model, we consider two-sides visibility: visibility of supplier and visibility of sub-supplier.

- ***Sub-supplier visibility (vss_i):***

Sub-supplier visibility or downstream SCV indicates the visibility level of the downstream supply chain members of the supplier. It is measured by the level of information disclosure from the supplier.

By considering sub-supplier visibility, we aim to fill the gap of previous model (Khojasteh.G and irohara, 2018). In the previous model, they proposed a model based on double souring, where the two selected suppliers cannot share the same sub supplier. Clearly, we need to know the sub-suppliers as much as possible to avoid selection of suppliers which share the same sub-supplier. Therefore, we must know more information about the sub-suppliers which is called sub-suppliers’ visibility. Since considering visibility is just with the aim of knowing if the suppliers share the same sub-supplier or not, we limit the sub-supplier visibility’s scope to unique minimum information about sub-suppliers. Hereby, we limit the information of sub-suppliers to the name and their location. We assume that each sub-supplier, as a focal company can have more than one plant. To validate our assumption, we refer to (Berger et al., 2004) who mentioned that to avoid the risk, firms are considering multiple locations. So, only knowing the name of sub-supplier is not enough. We assume that by knowing name and location of the sub-suppliers, it will be clear if the candidate suppliers share a common sub-supplier or not. For quantifying sub-suppliers' visibility, we follow the quantification method of Tse and Tan (2012) and write it as follow:

$$vss_i = \sum_{q\in Q} \sum_{u\in U} \beta_u x_{iqu} \qquad (1)$$

$$Where$$

$$x_{iqu} \in \{0,1\} \quad \forall\, u \in U,\ \forall\, q \in Q,\ \forall\, i \in I$$

$$\sum_{u\in U} \beta_u = 1 \quad 0 < \beta_u \le 1$$

In equation (1), vss_i is the visibility of sub-suppliers of supplier i. It is measured by the level of information disclosure from the supplier. U is the information set about sub-suppliers that manufacturer requests the supplier i to provide; u is the specific information about sub-suppliers that manufacturer requests; x_{iqu} is the status of disclosure of sub-supplier q information u by supplier i; and β_u reflects the importance of information u to the supplier visibility vss_i.

- ***Supplier Visibility (vi):***

For quantifying the visibility of the suppliers, we follow the methodology that Caridi et al. (2010) proposed. In consistent with the literature review, they defined visibility in terms of access to useful information. Therefore, it is considered that each supplier is characterized by a set of information which may be shared with the manufacturer. In other words, visibility is measured on the basis of the amount and quality of the information which the manufacturer knows, compared to the total information that could be exchanged. For diagnostic purposes, four different types of information flows are considered (Bracchi et al., 2001): transactions (e.g. order confirmation, ASN—Advance Shipping Notice), status information (e.g. stock level, residual shelf-life), master data (e.g. bill of materials, commercial information), and operational plans (e.g. distribution plan, production plan).

The judgement about the exchanged information is based on three qualitative scales: one for measuring the quantity of the exchanged information, two for measuring its quality, in terms of both freshness and accuracy. The scales have four ordered response levels, from *1* (low rate) to *4* (best rate). Quantity and quality judgements are collected for each information flow (i.e. transactions/events, status information, master data, operational plans) and for each supplier. The procedure to evaluate the visibility is as follow, where:

x ∈{q,a,f}, q=quantity, a=accuracy, f=freshness
y ∈{t,s,m,o}, t=transactions, s=status, m=master data, o=operational plan

The collected judgements are then combined—using the geometric mean—to have a synthetic evaluation of the visibility that the focal company has on each node. The geometric mean, which is obtained multiplying a set of n numbers and then nth rooting the result—was chosen since it proved to better represent the phenomenon. Equation (2) depicts the visibility quantification. Equations (3 and 4) represents the how to calculate quantity of visibility and quality (accuracy and freshness) of visibility, respectively. Here, *j* represents the judgement.

$$v_i = \sqrt{V_{Quantity_i} . VIS_{Quality_i}} \qquad (2)$$

$$V_{Quantity_i} = \sqrt[4]{j_{i,q,t} \cdot j_{i,q,s} \cdot j_{i,q,m} \cdot j_{i,q,o}} \qquad (3)$$

$$V_{Quality_i} = \sqrt{\sqrt[4]{j_{i,a,t} \cdot j_{i,a,s} \cdot j_{i,a,m} \cdot j_{i,a,o}} \cdot \sqrt[4]{j_{i,f,t} \cdot j_{i,f,s} \cdot j_{i,f,m} \cdot j_{i,f,o}}} \qquad (4)$$

Model description

The existing model (Khojasteh.G and Irohara, 2018) had the single objective of minimizing the total cost. However, the current model upgrades the previous model with integrating the supply chain visibility as the second objective function. Authors believe that without considering downstream SCV, the previous model does not have its maximum functionality.

The following notations are defined for formulating the mathematical model:

Indexes :

i index of suppliers

j index of manufacturers

q index of sub suppliers

Parameters:

p_i Unit purchasing cost of supplier i

h_i Setup cost of supplier i

v_i Visibility of supplier i

vss_i Visibility of sub - suppliers of supplier i

c_i Capacity of supplier i

d_j Demand of manufacturer j

M Big number

$$s_{iq} \; : \begin{cases} =1, & \text{if } q \text{ is the sub - supplier of supplier } i, \\ =0, & \text{Otherwise;} \end{cases}$$

pd_j Percentage of demand of manufacturer j

Decision variables :

y_{ij} Quantity to be transferred from supplier i to manufacturer j

$$a_{ij} \; : \begin{cases} =1, & \text{if supplier } i \text{ is selected for manufacturer } j, \\ =0, & \text{Otherwise;} \end{cases}$$

$$f_1 : Min\,\text{cost} \sum_{i\in I}\sum_{j\in J} p_i y_{ij} + \sum_{i\in I}\sum_{j\in J} h_i y_{ij} \tag{5}$$

$$f_2 : MaxVisibility \sum_{i\in I}\sum_{j\in J} v_i y_{ij} + \sum_{i\in I}\sum_{j\in J} vss_i y_{ij} \tag{6}$$

subject to

$$y_{ij} \ge 0 \qquad \forall i \in I, \forall j \in J \tag{7}$$

$$\sum_j y_{ij} \le c_i \qquad \forall i \in I \tag{8}$$

$$\sum_i y_{ij} \ge d_j \qquad \forall j \in J \tag{9}$$

$$\sum_i a_{ij} \ge 2 \qquad \forall j \in J \tag{10}$$

$$\sum_i a_{ij} * s_{iq} \le 1 \qquad \forall j \in J, \forall q \in Q \tag{11}$$

$$y_{ij} \ge a_{ij} \qquad \forall i \in I, \forall j \in J \tag{12}$$

$$y_{ij} \le M * a_{ij} \qquad \forall i \in I, \forall j \in J \tag{13}$$

$$y_{ij} \ge pd_j * d_j * a_{ij} \qquad \forall i \in I, \forall j \in J \tag{14}$$

Equation (5) is minimizing the total cost which is from the previous model (Khojasteh.G and Irohara, 2018). Equation (6) is maximizing visibility, including suppliers' visibility and sub-supplier's visibility. Constraint (7) is the non-negativity of the integer decision variable. Constraint (8) serves as the capacity constraint for each supplier. Constraint (9) specifies that for each manufacturer, the total number of supplies to be received should be more than its demand. Constraint (10) specifies the concept of double sourcing. Constraint (11) prevents the selection from the suppliers which have the same sub-suppliers. Constraint (12 and 13) defines the relation between binary and integer decision variables. Constraint (14) specifies the minimum number of order from each supplier which should be a certain portion (percentage) of demand.

Normalization of objective functions

We solve the model using Gurobi Optimizer Version 6.5.0 mathematical programming solution software. All experiments were run on a personal computer with an Intel (R) Core (TM) i7-6700 CPU (3.40 GHz) and 16.0 GB of RAM. All the runs solved in few second.

The mathematical programming model that we proposed is a multi-objective optimization problem. In order to solve it in Gurobi solver, we need to convert it to a single objective optimization problem. Besides, one of the objective functions is minimizing, even though the other is maximizing. Therefore, we transform the max objective function $(f_2(x))$ into equivalent minimization problems $(-(f_2(x)))$.

One of the common approaches to solve multi-objective optimization is the weighted sum method. The weighted sum method allows the multi-objective optimization problem to be solved as a single-objective mathematical optimization problem. This single objective function is the sum of objective functions f_i multiplied by weighting coefficients α_i. While, the weights for each objective function are assigned by the decision maker based on an intrinsic knowledge of the problem. The weighted sum method is formulated as:

$$\sum_{i=1}^{u} \alpha_i f_i(x) \quad \text{where } \alpha_i \geq 0, \forall i = 1,\ldots,u \text{ and } \sum_{i=1}^{u} \alpha_i = 1 \tag{15}$$

We normalize objective functions (5) and (6) using a linear normalization technique to allow inter-criterion comparison. The idea is to normalize by the differences of optimal function values in the Utopia and Nadir points that give us the length of the intervals where the optimal objective functions vary within the Pareto optimal set (Mausser, 2006). To assign the same magnitude to each objective function, all objective functions after normalization will be bounded by spans below:

$$0 \leq \frac{f_i(x) - z_i^U}{z_i^N - z_i^U} \leq 1 \quad \text{for cost criterion;} \qquad 0 \leq \frac{z_i^U - f_i(x)}{z_i^U - z_i^N} \leq 1 \quad \text{for benefit criterion.}$$

When considering the cost criterion, the ideal objective vector z^U, called the Utopia point, is not normally feasible because of the conflicting nature of the individual objectives. However, it can be obtained by minimizing each of the objective functions individually subject to the original constraints. The Utopia point provides the lower bounds of the Pareto optimal set for the cost criterion. The upper bounds of the Pareto optimal set are obtained from the components of a Nadir point z^N. These are defined as the anti-ideal solution. Conversely, for the benefit criterion, normalization can be performed by maximizing the objective functions for the Utopia point, and simultaneously minimizing for the Nadir point. Therefore, objective functions (5) and (6) can be formulated as a single linear minimization objective function (6) (Manopiniwes and Irohara, 2017).

$$\text{minimize} \quad \alpha\left(\frac{(5) - z_1^U}{z_1^N - z_1^U}\right) + (1-\alpha)\left(\frac{z_2^U - (6)}{z_2^N - z_2^U}\right) \tag{16}$$

In equation (16), the formulation notes the following definitions:

Z_1^U is a Utopia point with Min $f_i(x)$ for the cost criteria and Max $f_i(x)$ for the benefit criteria.

Z_1^N is a Nadir point with Max $f_i(x)$ for the cost criteria and Min $f_i(x)$ for the benefit criteria.

Numerical examples

We examined the proposed model by using the numerical example. For the new parameter (v_i), we use the dataset from Caridi et al. (2010) who applied real case studies. The information needed to evaluate visibility indexes was gathered by means of one or two direct interviews, lasting about three hours each. Instead, for the sub-supplier visibility (vss_i), we use the weights 0.7 and 0.3 for the information about the location and the name of sub-suppliers, respectively.

U={location, name} of sub-suppliers

$u1$: location β_1=0.7
$u2$: name β_2=0.3

The double objective function selects two suppliers for each manufacturer with the maximum visibility and minimum total cost, with the restriction of having the common point of failure- the same sub-suppliers. Therefore, this model lessens disruption risks by selection the suppliers which do not expose to the same kind of risk. Moreover, as the literature shows, visibility is one of the key reasons in risk avoidance (Yu and Goh, 2014). By selecting the suppliers with high visibility, the disruption probability in SC will be less. Besides, by selecting the supplier with high visibility in their sub-suppliers, we guarantee the higher performance of the previous model (Khojasteh.G and Irohara, 2018).

To illustrate the applicability of our proposed model numerically, we calculate the suppliers' failure probability. For supplier failure probability, we follow the formulation of Berger et al, (2004). They noted that if there is a single supplier, the probability of this supplier being down is S_1 while if there are two suppliers, the probability that both will be unable to deliver is $S_1 S_2$. Besides, we assume that each supplier's failure probability comes from two reasons. One reason is downstream suppliers, which in this case is sub-suppliers. The other reason can be from other causes which is out of scope to discuss here. We set a random number for the second reason.

Figure 1 illustrates the importance of addition visibility in model B. As Figure 1 shows, without considering visibility, the two suppliers A and B will be selected. However, on the right-hand side of the same image, it is shown that two suppliers might share the same sub-supplier which due to the lack of visibility, we won't be aware of it. Model C improve this decision and will not select the two suppliers A and B of Figure 1 together.

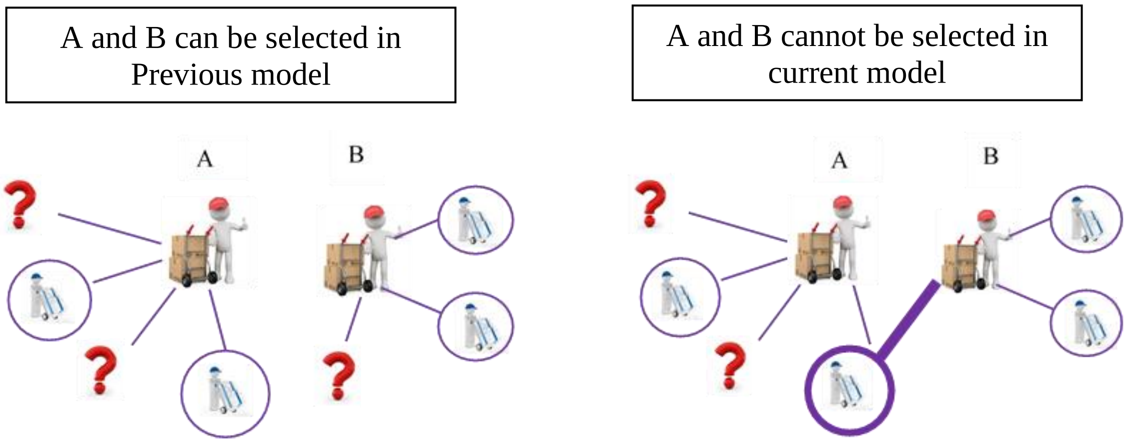
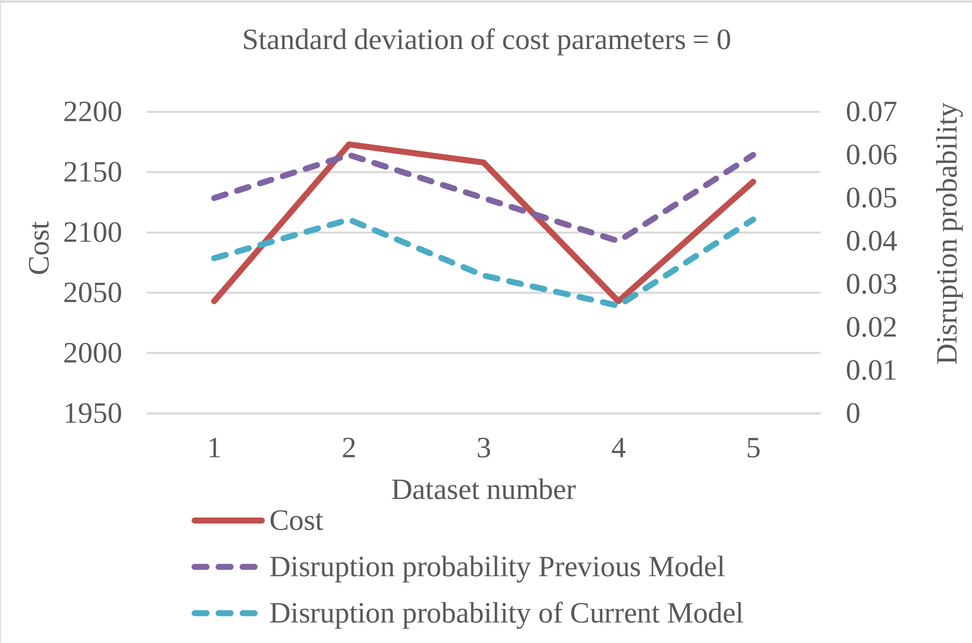


Figure 1. Illustration of necessity of considering visibility

We tried *5* datasets both with previous model and the current model. In each dataset, we consider *5* candidate suppliers. Depending on the SC network structure, the sub-suppliers can be shared by suppliers. For example, if number of sub-suppliers is *5* and number of sub-suppliers for each supplier is *3*, in *70%* of cases, the two selected suppliers will share the same sub-supplier. In the previous model, the shared sub-supplier could be hidden. In the current model, since we consider the visibility of sub-suppliers as well, the model will select the two suppliers with higher visibility on their sub-supplier and therefore the possibility that they share the same sub-supplier will decrease. Figure 2 shows the numerical example results of 5 datasets and compares the values of previous and current models.

One of the important factors in double sourcing and its role in increasing the cost is the standard deviation of cost parameter of suppliers. When the standard deviation of unit purchasing cost (p_i) and setup cost (h_i) is close to zero, by changing the selected suppliers the total cost will not vary. In figure 1, we considered two cases when the standard deviation of cost parameters of suppliers is zero and when the standard deviation is a positive number. In the lower part of figure 2, we assign the standard deviation to 5.



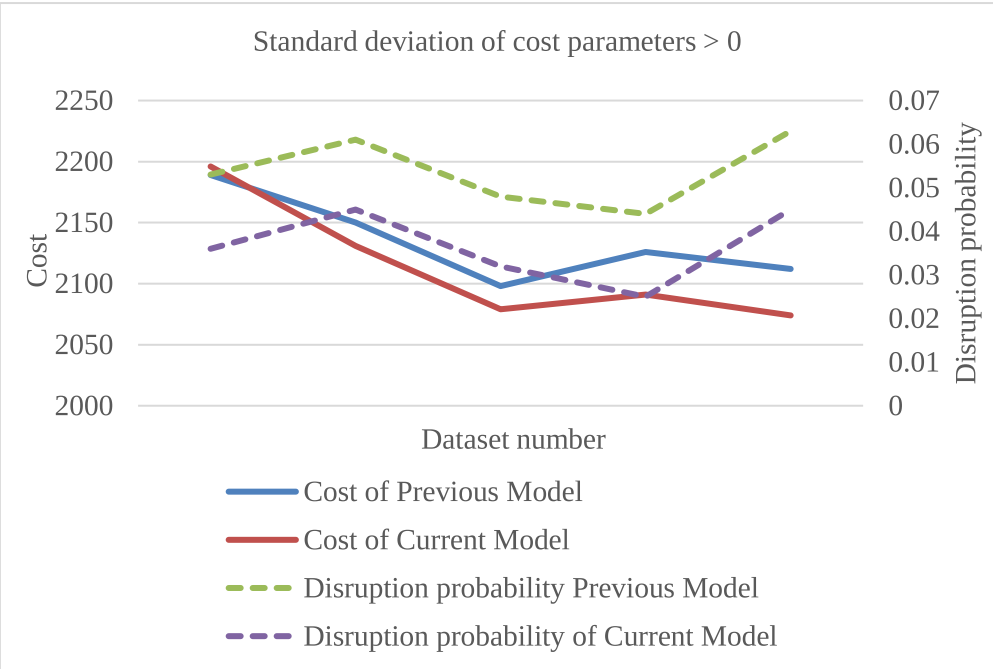


Figure. 2 Comparison the results of previous and current model

As figure 2 shows, when the standard deviation between cost parameters is close to zero, the total cost of current model will be the same as previous model. However, the disruption probability of suppliers will be lower in the current model. Moreover, the chart in the lower part of figure 2 also shows that the current model lowers the disruption probability. However, when the standard deviation of cost parameters is more than zero, the total cost fluctuates. Therefore, there is not a certain tendency in cost difference between previous and the current model.

Conclusion

In this paper, we proposed a new mathematical programming model to complete an existing model (Khojasteh.G and Irohara 2018). The aim of the previous model was selecting two suppliers for each manufacturer while the selected suppliers could not share the same sub-supplier. The model aimed to avoid the suppliers' failure when a sub-supplier is down. In this model, we proposed to add SCV as the second objective function to complete the previous model.

We considered suppliers' visibility and the sub-supplier visibility. In numerical examples, we showed that by selecting the supplier with high visibility in their sub-suppliers, we guarantee the higher performance of the previous model which is lower disruption probability of suppliers.

We are certainly aware of the limitations of our models. The datasets we used are not all from a real case, and therefore the findings from experimental results are not astonishing. As a future study, we will try the currently proposed model with real data sets.

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