# Constructing a Optimal Portfolio of Suppliers under Supply Disruption Risks

*P.L. Meena*[a*], *S.P. Sarmah*[b]
[a]*School of Management, New York Institute of Technology, Old Westbury, NY, USA*
[b]*Industrial and System Engineering, Indian Institute of Technology, Kharagpur, India*

## Abstract
This paper studies a problem of constructing a portfolio of suppliers (i.e., supplier selection and demand allocation) under the risks of supplier failure due to the occurrence of disruptive events. The problem is formulated as mixed integer non-linear programming (MINLP) considering different capacity, failure probability and quantity discounts for each supplier. Consideration of all these features together has made the problem realistic but at the same time complex to solve. We have used real coded genetic algorithm (RCGA) to solve the problem. The efficacy of RCGA is checked by comparing its results with BONMIN (an open source MINLP solver). The model, RCGA, and BONMIN are illustrated through a numerical study. The results show that supplier with high quantity discount and lesser gets more order quantity.

**Keywords:** Supply disruption risk, supplier selection, order allocation

### Introduction

The problem of sourcing decisions has received considerable attention from the academic community as well as practitioners in the recent times. Sourcing decision includes selection of right number of suppliers and allocation of demand (Meena and Sarmah, 2011). For an effective supply chain management, one of the key issues is the supplier selection, which consists of determining a supplier base (a set of potential suppliers to work with), the supplier(s) to procure from, and the procurement quantities from the selected suppliers (Alp and Tarkan, 2010).

There are mainly two schools of thought and they are single sourcing and multiple sourcing strategies. Single sourcing or reduced supply base has many advantages such as better coordination, cost-effectiveness, improved delivery performance, and improved buyer-suppliers relationship (Sajadieh and Eshghi, 2009). However, this strategy increases the risks of supply disruption and dependence on fewer suppliers. In the recent times, it is observed that supply chains are increasingly vulnerable to high-profile disruptive events such as earthquake, tsunami, hurricanes, terrorist attacks, etc. Moreover, there are various other events that regularly interrupt the flow of [1]supply such as strikes, bandhs, snowstorms, and traffic congestion, etc. (Meena and Sarmah, 2014). Many recent disruptive events like 9/11, the hurricane Katrina and Rita in 2005, and the recent devastating earthquake and tsunami in Japan in 2011 etc., have compelled the researchers to include the risks of these disruptive events into the procurement and supply chain management problems.

Berger *et al.* (2004) classified disruptive events in to three categories, namely (i) super-event, (ii) semi-super event, and (iii) unique event. The occurrence of a super-event completely fails all the suppliers to supply, whereas the occurrence of a semi-super event completely fails some but not all the suppliers to supply. The occurrence of a unique event completely fails a single particular supplier to supply. This paper considers the risks of super and unique events. There is a dearth of literature on the issue of determining the optimal number of suppliers and order allocation together under quantity discounts and risks of supply disruption. Here, we have made an attempt to fill up this gap in the literature by developing a mixed integer nonlinear programming (MINLP) model to solve this problem. The model considers different failure probability, capacity, quantity discounts, and compensation potential for each supplier. The compensation potential means that when a particular or set of supplier(s) fail to supply the negotiated order quantity due to the occurrence of disruptive events then the remaining supplier(s) who don't fail compensate the shortfall by supplying the extra amount at no extra cost. Inclusion of all these aspects together has made the model more realistic but at the same time more complex to solve using exact methods. Therefore, we employed real coded genetic algorithm (RCGA) to solve it. The reason behind the using RCGA is that it has been proven effective in many combinatorial problems (Goldberge, 1989; Chang and Hou, 2008). Further, we checked the efficacy of the RCGA by comparing its results with BONMIN (an open source MINLP solver).

## Problem description and model development

We have considered a two-stage supply chain consisting of a single buyer and multiple suppliers, where the buyer places orders for a single item before the start of the season and takes decision regarding which of the suppliers to retain from a given set of potential suppliers, and how much to order to each selected supplier, in order to minimize the total expected cost. The expected total cost of the buyer includes purchasing, supplier management, and expected loss costs. The following assumptions are made in the development of the model.

- The demand of the item is deterministic.
- A set of pre-qualified suppliers is already determined.
- All suppliers have different capacities and failure probabilities.
- Management cost is same for every supplier and has linear relationship with number of suppliers.
- Minimum order quantity is same for all suppliers.

The following notations are used in the development of the model.

**Index**

$z$ **:** index for suppliers, $z = 1, 2, 3, ..., N$

$i$ **:** index for suppliers who fail, $i = 1, 2, 3, ..., T$

$j$ **:** index for suppliers who do not fail, $j = 1, 2, 3, ..., S$

$r$ **:** index for price breaks, $i = 1, 2, 3, ..., R$

***Notation***

| | |
|---|---|
| D = | total demand of the buyer in a given period; $d_{zr}$ = discount given by $z^{th}$ supplier in $r^{th}$ price break |
| N = | total number of potential suppliers ; n = number of selected suppliers |
| b = | per supplier management cost ; L = loss per not received unit due to supplier's failure |
| $U_z$ = | actual capacity of $z^{th}$ supplier; $Q_z$ = order quantity allocated to $z^{th}$ supplier |
| $Q_j$ = | quantity received from the supplier(s) who do not fail |
| $Q_{min}$ | minimum order quantity (certain percentage of the total demand) allocated to each selected supplier |
| $I_q$ = | increment in allocation quantity |
| $\pi^*$ | probability of the occurrence of a super-event that fails all the suppliers |
| $\pi_z$ | probability of the occurrence of the unique-events that fails the $z^{th}$ supplier |
| $y_z$ | binary decision variable where $y_z$ =1if $z^{th}$ supplier is selected else $y_z$ =0 |
| $k_j$ | compensation provided by the supplier(s) who do not fail, where $k_j = (U_z - Q_z)$ |
| $A(f_i)$ | set of suppliers who fail, $A(f_i) = \{A(f_1), A(f_2), ..., A(f_T)\}$ where, $A(f_1)$ is the set of any one supplier who fails and so on |
| $B(m_j)$ | set of suppliers who do not fail $B(m_j) = \{B(m_1), B(m_2), ..., B(m_S)\}$ where $B(m_1)$ is the set of not failed suppliers, when there is one out of n suppliers fails and so on |

**Purchasing cost**

The purchasing cost depends upon the order quantity and price of the item. In real situations, many suppliers generally offer quantity based price discount to encourage the buyer to purchase more and the purchasing cost of buyer can be formulated as follows:

$$PC(n) = C\left(\sum_{Z=1}^{N}\sum_{r=1}^{R}\left(Q_z y_z (1 - d_{zr})\right)\right) \tag{1}$$

where, $$d_{zr} = \begin{cases} d_1 & for\ Q_1 \le Q_z < Q_2 \\ d_2 & for\ Q_2 \le Q_z < Q_3 \\ d_3 & for\ Q_3 \le Q_z \end{cases} \tag{2}$$

**Supplier management cost**

The supplier management cost increases linearly as the number of supplier increases. The supplier management cost includes cost of negotiation, managing a supplier contract, and monitoring the quality etc. and one can write this cost as follows:

$$SMC(n) = b(n)\, y_z \tag{3}$$

**2.3 Expected loss cost**

The buyer may face a significant economic loss if the suppliers fail to deliver the negotiated order quantity. The minimum order quantity received by the buyer from the selected suppliers can be formulated as follows

$$min\left[ D, \left( \sum_{j=1}^{S} (Q_j) + \sum_{j=1}^{S} (k_j) \right) \right] \tag{4}$$

The expected loss incurred by the buyer due to the failure of supplier(s) to supply the negotiated order quantity can be written as

$$L\left( D - \min\left[ D, \left( \sum_{j=1}^{S} (Q_j) + \sum_{j=1}^{S} (k_j) \right) \right] \right) \tag{5}$$

When all the suppliers fail to deliver the negotiated order quantity due to the occurrence of super-event then the expected loss faced by the buyer is $(L \times D \times \pi^*)$. The expected total loss cost for $n$ suppliers can be written as follows

$$ETL(n) = (L \times D \times \pi^*) + L(SF1 + SF2 + SF3 + ... + SFn) \tag{6}$$

where, SF1, SF2, SF3, and SFn are as follows:

$$\begin{aligned}
SF1 &= \sum \left[ \prod_{i \in A(f_1)} (\pi_i) \times \prod_{j \in B(m_1)} (1 - \pi_j) \right] \times \left[ D - \min\left( D, \sum_{j \in B(m_1)} (Q_j + k_j) \right) \right] \\
SF2 &= \sum \left[ \prod_{i \in A(f_2)} (\pi_i) \times \prod_{j \in B(m_2)} (1 - \pi_j) \right] \times \left[ D - \min\left( D, \sum_{j \in B(m_2)} (Q_j + k_j) \right) \right] \\
SF3 &= \sum \left[ \prod_{i \in A(f_3)} (\pi_i) \times \prod_{j \in B(m_3)} (1 - \pi_j) \right] \times \left[ D - \min\left( D, \sum_{j \in B(m_3)} (Q_j + k_j) \right) \right] \\
SFn &= \sum \left[ \prod_{i \in A(f_T)} (\pi_i) \right] \times D
\end{aligned} \tag{7}$$

**Expected total cost**

The expected total cost is the sum of purchasing, supplier's management and expected total loss costs. Therefore, for a given $n$ number of suppliers, it can be written as

$$ETC(n) = PC(n) + SMC(n) + ETL(n) \tag{8}$$

The objective of the buyer is to minimize the expected total cost and it can be written as

$$\text{Min. } ETC(n) \tag{9}$$

Subject to

$$\sum_{z=1}^{N}(Q_z) = D \tag{10}$$

$$Q_{\min} \le Q_z \le U_z \tag{11}$$

Constraint (10) ensures that sum of the allocated order quantity must be equal to total demand. Constraint (11) indicates the minimum and maximum order quantity for each supplier.

### Solution methodology

Here, first we have employed real coded genetic algorithm (RCGA) to solve the problem as it is a powerful global search algorithm inspired by evolution theory. Genetic algorithm has gained huge popularity for its easy implementation and successful application for different optimization problem (Gen and Cheng, 2000). Later, BONMIN (Basic Open-source Nonlinear Mixed Integer) (Bonami *et al.*, 2008) was used test the performance of RCGA to solve the problem. The procedure of GA is explained below:

Generate an *initial population*,
Evaluate *fitness* of individual in the *population*,
**repeat:**
    Select *parents* from the *population*,
    Recombine (mate) parents to produce children,
    Evaluate *fitness* of the *children*,
    Replace some or all of the *population* by the *children*,
**until** a satisfactory solution have been found

We refer the readers to Meena and Sarmah (2014) for more detail regarding RCGA and BONMIN.

### Numerical illustration

We have conducted a numerical experiment to demonstrate the proposed model and methods to solve the problem. The RCGA and BONMIN are implemented in MATLAB 7.5. All tests have been carried out on a Lenovo PC (with Intel Core 2 Duo processor@ 1.66 GHz with 1.49 GB of RAM, running on Windows XP). The following values of different parameters are considered for the numerical experiment: The buyer demand D=200 units, base price of item offered by all suppliers C= 5 monetary unit (mu)/unit, management cost per supplier b= 5 mu, loss per not obtained unit due to supplier failure L=10 mu, super-event probability $\pi^*$=0.01, minimum allocated order quantity and incremental order quantity $Q_{min}=I_q=0.10D$. The capacity, failure probability, price break quantity, and discount percentage of suppliers are given in Table 1.

## Computational results of RCGA and BONMIN

We ran the programs of both methods (i.e., RCGA and BONMIN) for 100 iterations to get more accuracy in results. For solving the problem with RCGA, we first determined the optimal values for its parameters (e.g. population size, crossover probability, mutation probability and generation) for all problems and the values are given in Table 2. The results of both methods for supplier selection and order allocation are given in Table 2. The optimal solution (i.e., optimal number of suppliers and respective order allocations) are presented in Table 2 for different values of demand. The results reveal that as the demand increases, the optimal number of suppliers also increases.

Further, the buyer allocates maximum order quantity to the supplier who provides high discounts compared and has lesser failure probability. It indicates that the allocation of order quantity mainly depends on the cost of supplier's rather than its failure probability. Another interesting finding we observed that, instead of getting small discount from many suppliers, it is better to allocate more demand to low cost supplier(s) and get more discounts and keep less risky but more costly supplier(s) as backup for emergency. It is observed from the results that RCGA produces better quality solution compared to BONMIN and also consumes lesser cpu time.

## Conclusions and scope for future work

This paper studies a problem of supplier selection and order demand allocation under quantity discounts and supply disruption risks. The problem is NP-Hard in nature and very difficult to solve with existing exact method. Therefore, RCGA approach was employed to solve it. Further, RCGA results were compared with BONMIN to check its efficacy to solve the problem. The results show that the demand allocation mostly depends on the cost of the supplier's rather than its failure probability. Also it is found that supplier(s) with high quantity discounts and lower failure risks get more order quantity compared to the other suppliers. Numerical results show that the RCGA approach finds better quality solution as compared to BONMIN in lesser cpu time. The interesting area for future research may be extension of current model for multi-items and multi-period settings.

*Table 1 - Capacity, unique-events probability, and discount percentage of each supplier*

| Supplier no. | Supplier capacity (units) | Unique-events probability ($\pi_z$) | Price break quantity (units) | | | Associated discount $d_{zr}$ (%) | | |
|---|---|---|---|---|---|---|---|---|
| S1 | 70 | 0.05 | 25 | 35 | 45 | 15 | 25 | 31 |
| S2 | 85 | 0.09 | 28 | 38 | 47 | 12 | 19 | 29 |
| S3 | 90 | 0.13 | 30 | 40 | 50 | 09 | 18 | 33 |
| S4 | 95 | 0.07 | 33 | 45 | 55 | 14 | 19 | 25 |
| S5 | 105 | 0.06 | 35 | 50 | 60 | 10 | 15 | 27 |
| S6 | 110 | 0.10 | 37 | 55 | 65 | 17 | 21 | 30 |
| S7 | 115 | 0.11 | 40 | 60 | 70 | 18 | 23 | 35 |

*Table 2 - Comparison of the results of the proposed heuristic procedure, RCGA and BONMIN*

| Demand | | 100 | 150 | 200 | 250 | 300 | 350 | 400 | 450 |
|---|---|---|---|---|---|---|---|---|---|
| RCGA results | Selected Suppliers | [S1,S2,S5] | [S1,S3,S4] | [S3,S5,S7] | [S1,S3,S6,S7] | [S3,S5,S6, S7] | [S1,S3,S5, S6, S7] | [S1,S2, S3, S5,S6,S7] | [S1,S2,S3,S4, S5,S6,S7] |
| | Allocated order quantity | [40,40,20] | [45,60,45] | [60,60,80] | [50,50,75,75] | [60,60,90,90] | [70,70,70, 70,70] | [40,40,80, 80, 80, 80] | [45,90,45, 90,90,90] |
| | Min. ETC | 469.21 | 611.25 | 776.2 | 965.4 | 1167.0 | 1360.0 | 1574.1 | 1776.9 |
| | Max. ETC | 471.06 | 615.90 | 787.43 | 965.4 | 1167.0 | 1360.0 | 1574.1 | 1776.9 |
| | Avg. ETC | 469.46 | 612.29 | 779.3 | 965.4 | 1167.0 | 1360.0 | 1574.1 | 1776.9 |
| | S.D. ETC | 0.3515 | 2.3 | 26.08 | 1.44E-26 | 5.74E-26 | 0 | 5.74E-26 | 0 |
| | CPU time (s.) | 9.20 | 9.44 | 9.96 | 13.45 | 17.53 | 21.61 | 39.18 | 37.43 |
| BONMIN results | Selected Suppliers | [S1,S3,S4, S6, S7] | [S1,S3,S4, S6, S7] | [S1,S2,S4, S5] | [S1,S2,S3, S6,S7] | [S1,S2,S3, S4,S5,S6,S7] | [S1,S2,S3, S4,S5,S6,S7] | [S1,S2,S3, S4,S5,S6,S7] | [S1,S2,S3, S4,S5,S6,S7] |
| | Allocated order quantity | [10,40,20, 10,20] | [15,60,30, 15,30] | [20,80,20, 80] | [25,50,50, 25,75,25] | [30,30,30,90, 30,60,30] | [35,35,35, 35,70,70,70] | [40,80,40,80, 40,40, 80] | [45,45,90,45, 45,90] |
| | Min. ETC | 549.04 | 741.17 | 862.78 | 1068.8 | 1390.9 | 1464.1 | 1654.4 | 1795.3 |
| | Max. ETC | 564.0 | 756.01 | 1039.0 | 1215.1 | 1390.9 | 1488.6 | 1654.4 | 1795.3 |
| | Avg. ETC | 562.5 | 753.04 | 968.62 | 1184.2 | 1390.9 | 1479.5 | 1654.4 | 1795.3 |
| | S.D. ETC | 20.84 | 37.12 | 156.64 | 1225.7 | 1.34E-24 | 102.5 | 5.35E-26 | 1.34E-24 |
| | CPU time (s.) | 83.77 | 82.33 | 72.89 | 63.7 | 63.32 | 67.72 | 43.43 | 38.8 |

## References


Meena, P.L., Sarmah, S.P. & Sarkar, A. (2011) Sourcing decisions under risks of catastrophic event disruptions. Transportation Research Part E, 47(6): 1058–1074.

Alp, O., & Tarkan, T. (2010). Tales of a so(u)rcerer : optimal sourcing decisions under alternative capacitated suppliers and general cost structures. In. BETA publicatie.

Sajadieh, M.S., & Eshghi, K. (2009). Sole versus dual sourcing under order dependent lead times and prices. Computers and Operations Research, 36, 3272-3280.

Meena, P.L. & Sarmah, S.P. (2014). Mitigating the Risks of Supply Disruption under Stochastic Demand, *International Journal of Management Science and Engineering Management.* 9(3): 157-168.

Berger, P.D., Gerstenfeld, A., & Zeng, A. Z. (2004). How many suppliers are best? A decision-analysis approach. Omega, 32, 9-15.

Goldberg, D.E. (1989). Genetic Algorithms in Search, Optimization and Machine Learning: Addison-Wesley Longman Publishing Co., Inc.

Chang, Y.H., & Hou, Y.C. (2008). Dynamic programming decision path encoding of genetic algorithms for production allocation problems. Computers and Industrial Engineering, 54, 53-65.

Gen, M., & Cheng, R. (2000). Genetic Algorithms and Engineering Optimization. New York: Willey.

Bonami, P., Biegler, L. T., Conn, A. R., Cornuéjols, G., Grossmann, I. E., Laird, C. D., Lee, J., Lodi, A., Margot, F., Sawaya, N., & Wächter, A. (2008). An algorithmic framework for convex mixed integer nonlinear programs. Discrete Optimization, 5, 186-204.