

# Chapter 17

## Allocation of Order Amongst Available Suppliers Using Multi-objective Genetic Algorithm



Azharuddin Shaikh, Poonam Mishra and Isha Talati

**Abstract** In a supply chain, procurement of items is done on the basis of individual performance, whereas the performance of supply chain can be improved by using scientific techniques. In this chapter, we discuss the manufacturer's problem of procuring several items from the available suppliers; where, supplies from each supplier are constrained. The manufacturer needs to determine which item is to be procured from which supplier and in what quantity. The allocation of order amongst suppliers is done on the basis of multiple criteria such as unit price, quality, supply capacity, delivery time, and unit transportation cost. To demonstrate the scenario, we formulate the mathematical model, which leads to a multi-objective optimization problem. The optimization is done using multi-objective genetic algorithm, which gives a set of Pareto-optimal solutions, then we utilize 3D-RadVis technique to get the best solution. To validate the model, numerical example is presented.

**Keywords** Multi-objective Genetic Algorithm · Order allocation · Supplier selection · 3D-RadVis

### 17.1 Introduction

In supply chain activities, organizations of all shapes and sizes are outsourcing different activities to enhance their performance. Amongst these activities, selection of supply partner plays a vital role for their efficient functioning. Several criterion should be considered for selecting the supply partners. For a manufacturing firm, if the suppliers are chosen cleverly, it could lead to an effective supply network. The

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supplier selection can be done more effectively by employing the scientific techniques. The area of selecting supplier has gained ample attention and several researchers have given their contribution for creating a sustainable supply network. Timmerman [23] formulated linear weighting models to study vendor performance evaluation. Weber and Current [27] were the first to use multi-objective programming for selecting vendors under multiple criteria. In their model, different constraints affected the number of vendors to be employed. This problem was solved by [26] with data envelopment analysis (DEA) tool. Amin and Zhang [1] studied supplier selection model in an integrated closed-loop supply chain. Shaw et al. [21] used fuzzy AHP and fuzzy multi-objective linear programming for supplier selection in developing a low carbon supply chain. Seifbarghy and Esfandiari [20] established multi-objective supplier selection model with transportation cost. A supplier pre-selection model was formulated by [3] for platform-based products. Izadikhah et al. [10] used DEA approach to study supplier's sustainability in the presence of dual-role factor and volume discounts. Later, [11] extended the same work by considering volume discount and negative data.

Genetic algorithm (GA) is one of the commonly used heuristic search techniques that mimics the evolutionary process of nature [5]. It is inspired by Darwin's theory of "Survival of fittest" and is one of the emerging areas of artificial intelligence. It is a calculus-free optimization method with least possibility of getting stuck at local optima. Genetic algorithm starts with a random set of solution called population. This method runs iteratively and in every iteration, population is updated by means of three basic genetic operators, i.e., selection/reproduction, crossover, and mutation. The process is continuously repeated until the desired accuracy is attained and each of this iteration is called generation. The fundamental perception of this algorithm was anticipated by Prof. J. H. Holland of the University of Michigan [7]. Thereafter, this field evolved with the contribution given by number of researchers. One can find the details on the development of this area in the books of [4, 5, 13, 18] and others. [19] used genetic algorithm in machine learning. After that, many researchers utilized GA to solve their optimization problem. Srinivasan and Deb [22] employed nondominated GA to solve their multi-objective optimization problem. Murata et al. [14] scheduled flow shop using multi-objective GA. Parks and Miller [16] did the selection of breeding using multi-objective GA. Basnet and Weintraub [2] formulated supplier selection under bi-criteria and solved it using multi-objective GA. For an overview of evolutionary algorithms for many-objective optimization problems, one can refer to [25].

In multi-objective programming (MOP), the goal is to optimize all the objective functions simultaneously. A single solution may not be optimal for all the objectives simultaneously when objectives are complex in nature. In that case, we get a Pareto-optimal solution set which means the MOP has number of optimal solutions. From this set of solution, we select an appropriate optimal solution. To visualize this set of solution in terms of quality, shape, and distribution of solution set, different methods exists in available literature. [15] used self-organizing map to reveal visualization and data mining of Pareto solutions. For population-based multi-objective algorithms, [17] proposed heatmap visualization. In case of evolutionary multi-objective

optimization, refer [24] for a review on visualization of pareto front approximations. For many-objective optimization, [6] gave the performance metric for visualization; while [12] explained how to use parallel coordinates for understanding the solution set. Finally, [8, 9] gave 3D-RadVis technique for reading and measuring the performance of solution set.

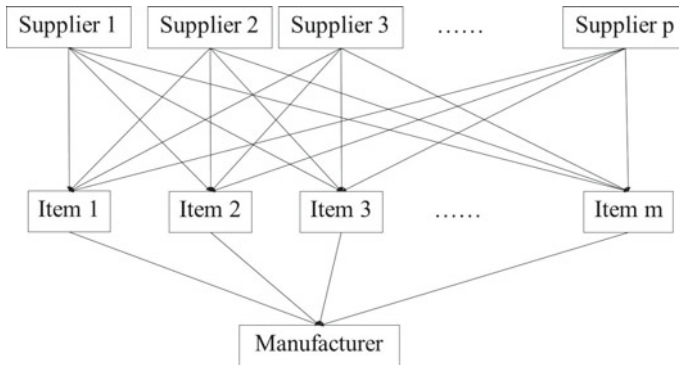
In this chapter, we propose an approach to solve manufacturer problem of selecting supplier and allocating the order. After the mathematical modeling, a Pareto-optimal solution set is obtained by employing multi-objective GA. Next, based on literature survey, it has been found that three-dimensional radial coordinate visualization (3D-RadVis) technique is not used by any researcher working on supplier selection. This method maps the multi-objective function (with  $M$ -objectives) to a three-dimensional radial coordinate plot. Therefore, we use this technique to get the best solution from the Pareto-optimal solution set. The benefit of using this method is it reserves relative location and distribution of solution set preserving the convergence trend of optimization process without affecting the shape of pareto front. Further, the paper is arranged in the subsequent manner. In Sect. 17.2, notations and assumptions are given that are used to formulate mathematical model along with the description of problem. In Sect. 17.3, the mathematical model under given assumption is formulated. Multi-objective genetic algorithm (MOGA) and 3D-RadVis visualization technique are discussed in Sect. 17.4. In Sect. 17.5, numerical example is presented which is optimized by using (MOGA) and 3D-RadVis visualization technique. Then, conclusion and references concludes the paper.

## 17.2 Notations and Assumptions

We use the following notations and assumptions for the proposed model:

### Notations

|                      |  |
|----------------------|--|
| $i = 1, 2, \dots, m$ | Index of Item  |
| $j = 1, 2, \dots, p$ | Index of Supplier  |
| $D_i$                | Demand of $i$ th item  |
| $P_i$                | Manufacturer's processing cost for $i$ th item                         |
| $MIC_i$              | Manufacturer's inventory carrying cost for $i$ th item                 |
| $x_{ij}$             | Order quantity of $i$ th item from $j$ th supplier (decision variable) |
| $P_{ij}$             | Unit purchase cost of $i$ th item from $j$ th supplier                 |
| $O_{ij}$             | Unit transportation cost of $i$ th item from $j$ th supplier           |
| $q_{ij}$             | Defective quality of $i$ th item from $j$ th supplier                  |
| $Q_{ai}$             | Quality acceptable for $i$ th item                                     |
| $l_{ij}$             | Late delivery of $i$ th item from $j$ th supplier                      |
| $L_{ai}$             | Late delivery acceptable for $i$ th item                               |
| $C_{ij}$             | Capacity of $j$ th supplier to supply $i$ th item                      |
| $TC$                 | Manufacturer total cost  |



**Fig. 17.1** Supply chain with single manufacturer and multiple suppliers

### Assumptions

1. Demand of each item is known.
2. Supply capacity from each supplier is limited.
3. Supplier selection is done on the basis of quality, cost, delivery performance, and transportation cost.
4. Allocation of order is to be done in such a way that the demand of each item ( $i$ ) is satisfied.

### Problem

Here, we discuss the manufacturer's problem of procuring ( $m$ ) items from the ( $p$ ) available suppliers; where, supplies from each supplier is constrained. The objective is to determine which item is to be procured from which supplier and in what quantity. The allocation of order amongst suppliers is done on the basis of multiple criteria such as unit price, quality, supply capacity, delivery time, and unit transportation cost. The pictorial representation of this supply chain is shown in Fig. 17.1.

Next, we formulate the problem mathematically with an objective of minimizing four functions under given constraints. This multi-objective function is then optimized using MOGA which gives a Pareto-optimal solution set. Next, we utilize 3D-RadVis technique on this solution set to get the best solution.

## 17.3 Mathematical Model

In the proposed model, our aim is to meet the requirement of manufacturer at a minimal cost. Along with this objective there are certain constraints which are to be taken into consideration.

First, we consider the cost bared by manufacturer, which are as follows: The **purchase cost** of required item  $i$  is given by the sum of product of quantity ordered from  $j$ th supplier and selling price of  $i$ th item from supplier  $j$ . Therefore, the purchase cost for all items is

$$PC = \sum_i \sum_j x_{ij} P_{ij} \quad (17.1)$$

Next, the **processing cost** for all items is given by

$$PRC = \sum_i x_i P_i \quad (17.2)$$

where,  $x_i = \sum_j x_{ij}$

The **holding cost** for manufacturer is

$$HC = \sum_i x_i MIC_i \quad (17.3)$$

Finally, the **transportation cost** of item  $i$  is given by the sum of quantity ordered from supplier  $j$  times the unit transportation charge of item  $i$  from supplier  $j$ . Therefore, the transportation cost for all items is

$$TRC = \sum_i \sum_j x_{ij} O_{ij} \quad (17.4)$$

Hence, the manufacturer's total cost is given by

$$TC = PC + PRC + HC + TRC \quad (17.5)$$

The next task is to frame the multi-objective function along with the constraints involved for procuring the items.

The two objective functions of minimizing purchase cost (say  $f_1$ ) and transportation cost (say  $f_2$ ) have already been discussed in (17.1) and (17.4). Whereas, the other two objective of minimizing the defective quality and late delivery is given by (17.6) and (17.7).

$$f_3 = \sum_i \sum_j x_{ij} q_{ij}; \text{ Defective quality} \quad (17.6)$$

$$f_4 = \sum_i \sum_j x_{ij} l_{ij}; \text{ Late delivery} \quad (17.7)$$

Further, the constrained involved are

1. The supplied item ( $i$ ) from the available suppliers should be adequate to meet the manufacturer demand. That is

$$\sum_j x_{ij} \geq D_i \tag{17.8}$$

2. The quantity of item ( $i$ ) obtained from available supplier ( $j$ ) should be less than or equal to supply capacity of supplier ( $j$ ). That is

$$x_{ij} \leq C_{ij} \tag{17.9}$$

3. The aggregate defective quality of item ( $i$ ) ordered should be less than or equal to acceptable quality of manufacturer. That is

$$\sum_j x_{ij}q_{ij} \leq Q_{ai}D_i \tag{17.10}$$

4. The aggregate late delivery time of item ( $i$ ) ordered should be less than or equal to acceptable delivery time of manufacturer. That is

$$\sum_j x_{ij}l_{ij} \leq L_{ai}D_i \tag{17.11}$$

**Multi-objective Function**

Hence, the goal is to allocate order such that the manufacturer gets good quality of material in lesser delivery time with minimum purchase cost and transportation cost. So, the manufacturer has the following multi-objective function with certain constraints:

Minimize,

$$\begin{aligned} f_1 &= \sum_i \sum_j x_{ij}P_{ij}; \text{ Purchase cost} \\ f_2 &= \sum_i \sum_j x_{ij}O_{ij}; \text{ Transportation cost} \\ f_3 &= \sum_i \sum_j x_{ij}q_{ij}; \text{ Defective quality} \\ f_4 &= \sum_i \sum_j x_{ij}l_{ij}; \text{ Late delivery} \end{aligned} \tag{17.12}$$

Subject to,

$$\begin{aligned} \sum_j x_{ij} &\geq D_i; && \text{Demand constraint} \\ x_{ij} &\leq C_{ij}; && \text{Supplier capacity constraint} \\ \sum_j x_{ij}q_{ij} &\leq Q_{ai}D_i; && \text{Acceptable quality constraint} \\ \sum_j x_{ij}l_{ij} &\leq L_{ai}D_i; && \text{Acceptable late delivery constraint} \end{aligned}$$

## 17.4 Algorithm

### 17.4.1 Multi-objective Genetic Algorithm

Generally, a multi-objective optimization problem is represented as

$$\begin{aligned} \min (\bar{f}(\bar{x})) &= (f_1(\bar{x}), f_2(\bar{x}), \dots, f_n(\bar{x})) \\ \text{subject to, } \bar{c}(\bar{x}) &\leq 0 \end{aligned}$$

where  $f_i : R_n \rightarrow R_m$  is the list of objective function;  $\bar{c}(\bar{x})$  is the list of constraints and  $\bar{x} \in S$  (feasible region).

In MOP, the aim is to optimize all the objective functions simultaneously. A single solution may not optimize all objectives simultaneously when objectives are complex in nature. In that case, we get a Pareto-optimal solution set, which means the MOP has number of optimal solutions. The solution obtained are such that one cannot further optimize any of the objective without affecting at least one of the other objective values. This Pareto-optimal solution set is termed as Pareto-optimal front.

Genetic algorithm (GA) is one of the commonly used heuristic search techniques that mimics the evolutionary process of nature. It is inspired by Darwin's theory of "Survival of fittest" and is one of the emerging area of artificial intelligence. It is a calculus free optimization method. GA starts with a random set of solution called population. This method runs iteratively and in every iteration population is updated by means of three basic genetic operators, i.e., selection/reproduction, crossover, and mutation giving successfully a better and better solution. The process is continuously repeated until the desired accuracy is attained and each of this iteration is called generation.

Here, to minimize the objective functions given in (17.12) subject to the given constraints, we use the algorithm given below:

1. For the involved parameters, allot numerical values except for the decision variables ( $x_{ij}$ ).
2. Start with an initial population of 50 for five or less decision variables else with 200.
3. Evaluate the fitness value for each individual of this population and rank the individual on the basis of fitness score.
4. From the population, individuals with good fitness score will enter the mating pool.
5. Next for reproduction, perform stochastic uniform crossover with 0.8 fraction value and considering two elites at each generation.
6. For the new generation obtained repeat from Step 3.
7. Repeat the algorithm till the desired accuracy of ( $10^{-4}$ ) is attained.

### 17.4.2 3D-RadVis Visualization Technique

In multi-objective optimization problem, imagining Pareto-optimal solution or non-dominated solutions is not an easy task. For the obtained solutions, an effective visualization technique is required to study their distribution, position, range and shape. The commonly used existing methods fails to show the shape of pareto front. Therefore, in this chapter we use three-dimensional radial coordinate visualization (3D-RadVis). This method maps the multi-objective function (with  $M$ -objectives) to a three-dimensional radial coordinate plot. Therefore, we use this technique to get the best solution from the Pareto- optimal solution set. The benefit of using this method is it reserves relative position and distribution of solution set preserving the convergence trend of optimization process without affecting the shape of pareto front. References [8, 9] for detailed explanation of this method. Next, the algorithm to obtain 3D-RadVis plot is listed below. For  $N$  Pareto-optimal, the solution of  $M$  objectives is

1. Compute

$$x = \frac{\sum_{j=1}^M f_{i,j}^{Norm} \cos(\theta_j)}{\sum_{j=1}^M f_{i,j}^{Norm}}; y = \frac{\sum_{j=1}^M f_{i,j}^{Norm} \sin(\theta_j)}{\sum_{j=1}^M f_{i,j}^{Norm}}$$

$$\text{where } f_i^{Norm} = \frac{f_i(x) - \min(f_i(x))}{\max(f_i(x)) - \min(f_i(x))}$$

2.  $px = x + 1$  and  $py = y + 1$
3. Find normal vector perpendicular to the extreme point  $n = norm(z)$ ; where  $z$  is hyperplane.
4. Calculate  $c = n \cdot z_1$
5. For  $i = 1$  to  $n$  find  $d = \frac{abs(f_i - n \cdot c)}{\|n\|}$
6. Finally, we convert 3D-RadVis  $R = [x, y, d]$

## 17.5 Numerical Example

*Example 1* To provide managerial insight, let us consider a manufacturer's problem of procuring two items from three suppliers with the available data  $D_1 = 50$  units,  $D_2 = 80$  units,  $Q_{a1} = 5\%$ ,  $Q_{a2} = 8\%$ ,  $L_{a1} = 3\%$ ,  $L_{a2} = 5\%$ ,  $P_1 = 10$  (\$/unit),  $P_2 = 5$  (\$/unit),  $MIC_1 = 2$  (\$/unit), and  $MIC_2 = 3$  (\$/unit) other details of the suppliers is given in Table 17.1.

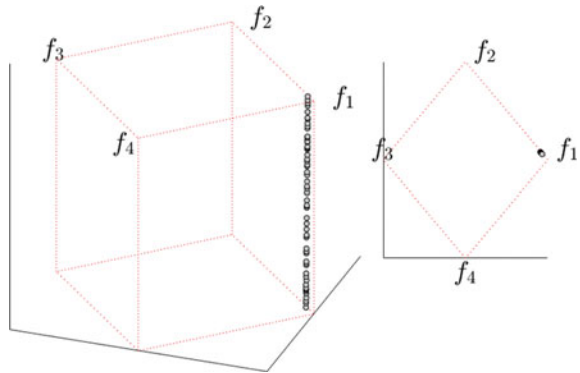
We use the MOGA to acquire a Pareto-optimal solution set, the solution set obtained is given in Table 17.2. Next, 3D-RadVis technique is applied to this solution set and values of  $R = [x, y, d]$  is also shown in Table 17.2. For the obtained solution, 3D-RadVis plot is shown in Fig. 17.2, while normalized 3D-RadVis plot is shown in



**Table 17.1** Supplier Information

| Supplier's                    | Supplier 1 |      | Supplier 2 |     | Supplier 3 |      |
|-------------------------------|------------|------|------------|-----|------------|------|
| Items                         | 1          | 2    | 1          | 2   | 1          | 2    |
| Price (\$)                    | 8          | 20   | 10         | 15  | 9          | 18   |
| Unit transportation cost (\$) | 0.8        | 1    | 1.2        | 1.2 | 0.5        | 1.5  |
| Supplier capacity             | 40         | 100  | 30         | 50  | 50         | 70   |
| Quality (%)                   | 7          | 3    | 4          | 4   | 6          | 5    |
| Late delivery per unit time   | 0.01       | 0.05 | 0.02       | 0.1 | 0.025      | 0.07 |

**Fig. 17.2** 3D-RadVis plot



**Fig. 17.3** Normalized 3D-RadVis plot

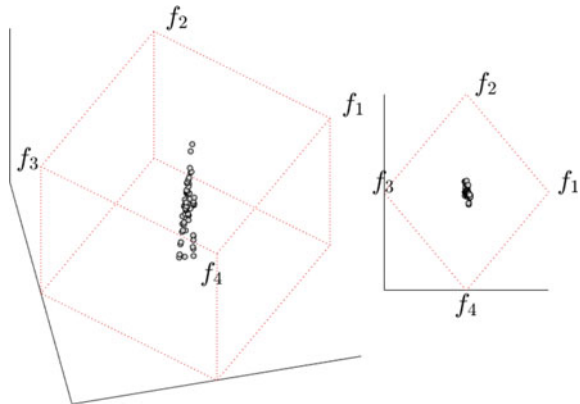


Fig. 17.3. Hence, after using this technique, the optimal order allocated among the available suppliers is highlighted in Table 17.2. Therefore, the manufacturer's total cost is \$3288.32 corresponding to this solution.

**Table 17.2** Pareto-optimal front for available suppliers

|    | $x_{11}$ | $x_{12}$ | $x_{13}$ | $x_{21}$ | $x_{22}$ | $x_{23}$ | $x$    | $y$    | $d$     |
|----|----------|----------|----------|----------|----------|----------|--------|--------|---------|
| 1  | 4        | 30       | 16       | 2        | 8        | 70       | 0.9114 | 0.0758 | 5.5800  |
| 2  | 6        | 28       | 17       | 72       | 8        | 0        | 0.9309 | 0.0562 | 57.2450 |
| 3  | 20       | 30       | 0        | 2        | 8        | 70       | 0.9088 | 0.0785 | 0.0000  |
| 4  | 7        | 29       | 15       | 74       | 6        | 0        | 0.9309 | 0.0564 | 62.8450 |
| 5  | 6        | 30       | 15       | 74       | 6        | 0        | 0.9308 | 0.0565 | 64.0350 |
| 6  | 7        | 28       | 16       | 73       | 7        | 1        | 0.9308 | 0.0564 | 61.1950 |
| 7  | 5        | 30       | 15       | 9        | 10       | 61       | 0.9135 | 0.0737 | 12.9250 |
| 8  | 10       | 29       | 12       | 35       | 8        | 38       | 0.9200 | 0.0672 | 31.1100 |
| 9  | 6        | 28       | 17       | 50       | 7        | 23       | 0.9250 | 0.0622 | 51.6100 |
| 10 | 9        | 28       | 13       | 55       | 8        | 17       | 0.9257 | 0.0615 | 43.3100 |
| 11 | 7        | 29       | 14       | 52       | 8        | 21       | 0.9252 | 0.0620 | 48.0450 |
| 12 | 7        | 28       | 16       | 59       | 8        | 13       | 0.9273 | 0.0598 | 50.3350 |
| 13 | 7        | 28       | 16       | 74       | 6        | 0        | 0.9311 | 0.0561 | 62.0050 |
| 14 | 19       | 30       | 1        | 6        | 8        | 66       | 0.9101 | 0.0772 | 4.9300  |
| 15 | 6        | 30       | 15       | 72       | 6        | 1        | 0.9304 | 0.0568 | 62.9000 |
| 16 | 3        | 29       | 18       | 3        | 8        | 69       | 0.9122 | 0.0750 | 5.4100  |
| 17 | 6        | 28       | 16       | 39       | 7        | 34       | 0.9218 | 0.0653 | 34.8250 |
| 18 | 9        | 28       | 13       | 48       | 7        | 26       | 0.9237 | 0.0635 | 42.8150 |
| 19 | 6        | 29       | 15       | 71       | 7        | 3        | 0.9301 | 0.0572 | 61.9250 |
| 20 | 5        | 28       | 17       | 56       | 8        | 17       | 0.9267 | 0.0605 | 50.1600 |
| 21 | 5        | 27       | 17       | 57       | 7        | 16       | 0.9270 | 0.0601 | 54.2800 |
| 22 | 1        | 25       | 23       | 3        | 8        | 69       | 0.9133 | 0.0737 | 4.3050  |
| 23 | 5        | 28       | 17       | 46       | 7        | 27       | 0.9240 | 0.0632 | 40.1500 |
| 24 | 7        | 28       | 16       | 66       | 8        | 7        | 0.9290 | 0.0581 | 57.5450 |
| 25 | 7        | 28       | 14       | 43       | 8        | 30       | 0.9226 | 0.0645 | 38.1600 |
| 26 | 7        | 28       | 16       | 59       | 8        | 13       | 0.9271 | 0.0600 | 48.8100 |
| 27 | 17       | 30       | 4        | 15       | 8        | 57       | 0.9133 | 0.0740 | 13.3850 |
| 28 | 0        | 25       | 25       | 2        | 8        | 70       | 0.9134 | 0.0736 | 3.0100  |
| 29 | 6        | 28       | 16       | 62       | 8        | 11       | 0.9281 | 0.0590 | 51.8600 |
| 30 | 19       | 30       | 1        | 4        | 8        | 68       | 0.9095 | 0.0778 | 1.9650  |
| 31 | 6        | 27       | 16       | 53       | 8        | 20       | 0.9257 | 0.0615 | 48.6000 |
| 32 | 5        | 30       | 15       | 14       | 10       | 57       | 0.9149 | 0.0723 | 17.0550 |
| 33 | 11       | 29       | 11       | 26       | 7        | 47       | 0.9175 | 0.0698 | 25.4900 |
| 34 | 7        | 29       | 14       | 64       | 7        | 9        | 0.9281 | 0.0592 | 55.8150 |
| 35 | 7        | 28       | 15       | 56       | 8        | 16       | 0.9263 | 0.0609 | 46.2850 |
| 36 | 6        | 28       | 16       | 31       | 8        | 41       | 0.9198 | 0.0674 | 30.3850 |
| 37 | 6        | 27       | 17       | 61       | 8        | 12       | 0.9281 | 0.0590 | 51.8300 |
| 38 | 10       | 29       | 11       | 28       | 8        | 44       | 0.9182 | 0.0690 | 27.2200 |

(continued)

**Table 17.2** (continued)

|    | $x_{11}$ | $x_{12}$ | $x_{13}$ | $x_{21}$ | $x_{22}$ | $x_{23}$ | $x$    | $y$    | $d$     |
|----|----------|----------|----------|----------|----------|----------|--------|--------|---------|
| 39 | 17       | 30       | 3        | 9        | 8        | 63       | 0.9112 | 0.0761 | 9.3450  |
| 40 | 8        | 29       | 14       | 54       | 7        | 19       | 0.9256 | 0.0616 | 48.5600 |
| 41 | 7        | 28       | 15       | 36       | 7        | 37       | 0.9208 | 0.0664 | 32.6100 |
| 42 | 12       | 29       | 9        | 44       | 7        | 29       | 0.9223 | 0.0650 | 36.7200 |
| 43 | 11       | 29       | 11       | 42       | 8        | 30       | 0.9220 | 0.0652 | 34.8700 |
| 44 | 13       | 30       | 7        | 10       | 8        | 62       | 0.9123 | 0.0750 | 10.3650 |
| 45 | 16       | 30       | 4        | 12       | 7        | 61       | 0.9125 | 0.0748 | 16.9350 |
| 46 | 7        | 28       | 15       | 60       | 7        | 13       | 0.9274 | 0.0597 | 51.5850 |
| 47 | 5        | 30       | 15       | 16       | 10       | 55       | 0.9154 | 0.0718 | 17.9300 |
| 48 | 7        | 28       | 15       | 60       | 8        | 12       | 0.9274 | 0.0597 | 50.1700 |
| 49 | 7        | 29       | 14       | 20       | 7        | 52       | 0.9165 | 0.0708 | 21.8500 |
| 50 | 4        | 27       | 19       | 42       | 8        | 31       | 0.9232 | 0.0640 | 36.0800 |
| 51 | 6        | 28       | 16       | 68       | 8        | 5        | 0.9295 | 0.0577 | 59.3050 |
| 52 | 13       | 30       | 7        | 36       | 7        | 37       | 0.9196 | 0.0677 | 30.9000 |
| 53 | 12       | 29       | 10       | 24       | 7        | 49       | 0.9168 | 0.0705 | 23.7950 |
| 54 | 9        | 29       | 12       | 51       | 7        | 22       | 0.9243 | 0.0629 | 44.8900 |
| 55 | 6        | 28       | 17       | 40       | 8        | 34       | 0.9222 | 0.0649 | 40.2900 |
| 56 | 5        | 30       | 15       | 13       | 10       | 58       | 0.9145 | 0.0727 | 16.4650 |
| 57 | 5        | 30       | 15       | 2        | 8        | 70       | 0.9114 | 0.0759 | 5.5350  |
| 58 | 12       | 29       | 9        | 22       | 7        | 51       | 0.9159 | 0.0713 | 21.2800 |
| 59 | 13       | 28       | 9        | 2        | 8        | 70       | 0.9105 | 0.0767 | 1.3400  |
| 60 | 12       | 29       | 9        | 23       | 8        | 50       | 0.9162 | 0.0710 | 22.0050 |
| 61 | 5        | 30       | 16       | 11       | 10       | 60       | 0.9140 | 0.0732 | 13.9800 |
| 62 | 7        | 29       | 14       | 44       | 8        | 29       | 0.9230 | 0.0642 | 41.0100 |
| 63 | 6        | 29       | 15       | 45       | 8        | 28       | 0.9234 | 0.0638 | 44.3300 |
| 64 | 19       | 30       | 1        | 7        | 8        | 65       | 0.9104 | 0.0769 | 5.9000  |
| 65 | 7        | 29       | 15       | 51       | 8        | 22       | 0.9248 | 0.0624 | 50.5700 |
| 66 | 6        | 28       | 16       | 64       | 8        | 8        | 0.9286 | 0.0585 | 54.9050 |
| 67 | 6        | 28       | 16       | 52       | 8        | 20       | 0.9256 | 0.0616 | 47.9800 |
| 68 | 7        | 29       | 14       | 52       | 8        | 21       | 0.9252 | 0.0620 | 48.4400 |
| 69 | 1        | 25       | 24       | 8        | 8        | 64       | 0.9149 | 0.0722 | 8.3400  |
| 70 | 20       | 30       | 0        | 3        | 7        | 70       | 0.9092 | 0.0782 | 6.8650  |

## 17.6 Conclusion

This chapter discusses the manufacturer problem of allocating order among available suppliers. The selection criteria depends on quality of items delivered, delivery time taken, unit cost, and transportation cost. This scenario is modeled mathematically

and it leads to multi-objective optimization problem with certain constraints. Using hypothetical data, we acquire a Pareto-optimal solution set by employing heuristic search algorithm called MOGA. Finally, we get the best solution for the manufacturer by using 3D-RadVis method.

Further, this research work can be extended by incorporating some more selection criterion. Quantity discounts is also in fashion, so discount on purchased quantity from supplier if order is above threshold quantity can also be considered. One can also have more number of manufacturing units with finite production capacity and then there could be two MOP, i.e., (1) allocating order among suppliers and (2) allocating lot size among available plants. In a similar manner, one can incorporate distributors and retailer selection.

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