J Intell Manuf (2013) 24:1123–1130
DOI 10.1007/s10845-012-0640-y

An integrative supplier selection model using Taguchi loss function, TOPSIS and multi criteria goal programming

Sanjay Sharma · Srinivasan Balan

Received: 11 January 2012 / Accepted: 2 April 2012 / Published online: 12 April 2012

Abstract Some of the key factors affecting the selection of supplier are price, quality, delivery, satisfaction, and warranty degree. The present paper is an extension of previous related work to select the appropriate supplier. This paper deals with an integrative approach considering Taguchi's loss function, Technique for Order preference by similarity to ideal solution (TOPSIS) and Multi criteria goal programming. The model is split up into three phases. In the first phase, the quality losses are identified using Taguchi's loss function. In the second phase, suitable factors are identified with different weights from TOPSIS and in the third phase, a goal programming model is developed to identify the best performing supplier with the weights and the loss associates. The purpose of this paper is to integrate different criteria levels to select relatively better performing supplier. A case is also presented and finally a comparison with data envelopment analysis (DEA) is discussed.

Keywords Supplier selection · Taguchi's loss function · Technique for Order preference by similarity to ideal solution · Multi criteria goal programming

Introduction

Procurement is considered to be one of the critical activities in any industrial environment. With the increased level of outsourcing, much attention needs to be paid to the supplier selection and evaluation. Performance evaluation of the supplying firms is being recognised as one of the critical indicators (Sharma 2010; Chen et al. 2011). A wide variety of literature is available concerning supplier evaluation, factors considered, and approach adopted (Kang et al. 2010; Ozaki et al. 2011; Pang and Bai 2011; Sharma 2012). After the critical evaluation of the suppliers, the final selection takes place. For this purpose, the criteria need to be chosen carefully depending on the problem under consideration.

Supplier selection is very important to any business activity where suppliers are integrative to the business improvement processes. Supplier relations might start from the supplier evaluation, supplier selection, supplier development, and supplier empowerment. In this paper, an integrative approach is proposed to select the right supplier in order to meet the business requirements, that is, the extension of Liao and Kao (2010). Since Supplier selection process is a multi criteria decision making problem, a combination of the three techniques namely Taguchi's loss function, TOPSIS, and Goal Programming is used.

In one of the earlier work, Dickson (1966) proposed a supplier selection problem with several parameters. Out of all the criteria, the key criteria for supplier selection problem are price, quality and delivery etc. Al-Faraj et al. (1993) proposed a supplier selection model using some criteria, namely, quality, price, delivery, technical capability, performance history, warranty claim, production capacity, and financial position. The authors used Analytical hierarchy process (AHP) for selecting the supplier. A case on carton sourcing (Sharma and Dubey 2010) has also been discussed using integrated AHP and knapsack model.

Ha and Krishnan (2008) attributed the supplier selection model with many factors into consideration. The collective aggregation of these attributes for a final judgment can result in a complex problem. For these reasons, a different variety of methodologies have been developed and applied over the last years to deal with the supplier selection problem. Chan et al. (2008) apply fuzzy-AHP approach for global

S. Sharma (✉) · S. Balan
National Institute of Industrial Engineering (NITIE), Vihar Lake, Mumbai 400087, India
e-mail: s_nsit@rediffmail.com

supplier selection. Many authors proposed heuristics approach as an integrative model with MCDM problems to select the best performing decision making units (Charnes et al. 1978). Chakraborty et al. (2011) had proposed a methodology for solving the vendor selection problem using AHP and heuristics procedure. The authors had taken cost, quality, and delivery as the three criteria deciding the vendor selection problem.

Liao (2010) proposed an integrated method to solve the supplier selection problem. The author attributed the method in three phases. Delphi technique was used to identify the criteria such as Quality, price, on time delivery, and customer service. Then using Taguchi loss function and AHP, the author prioritized the best supplier and selected the best performing supplier. Use of mixed integer programming has also been made to address the supplier selection problem. For example, Kasilingam and Lee (1996) proposed a mixed integer programming approach to select the supplier. This paper addresses not only vendor selection but also the quantities which need to be ordered.

Guan et al. (2007) developed a multiple objective mixed integer stochastic programming model for the vendor selection problem (VSP) with stochastic demand under multi-products purchase. The problem is divided into three phases. The multi-objective stochastic mixed-integer programming (SMIP) model is converted into a multi-objective MIP model by transforming stochastic constraints into deterministic equivalents. Then, a weighted fuzzy multi-objectives mixed integer programming (MIP) model, which indicates decision makers' preference and objective fuzziness, is decomposed into several single-objective MIP models through the maximum satisfaction degree method.

Although our primary objective is to extend the work of Liao and Kao (2010), other related literature has been discussed briefly. In this stated recent work, an inclusion of TOPSIS is especially mentioned as future research direction. Therefore, the present paper incorporates TOPSIS also in the integrated framework. Additionally DEA has been included for comparison purpose.

Proposed integrated model

Figure 1 illustrates the schematic explanation of the integrated supplier selection model. Based on the previous studies conducted to select the supplier, there are five major criteria identified and listed. For each supplier to be evaluated, the following criteria are listed namely product quality, price, delivery, service satisfaction and warranty. All the above said factors are taken into account for calculating the Taguchi's loss function. According to the characteristic features of the criteria in terms of lower the better/higher the better, the Taguchi's loss function is determined and hence the total loss incurred by each supplier is measured. With the losses calculated for the criteria, a matrix is created using pair wise comparison and weights are calculated for these factors using TOPSIS. Thus an overall weight matrix is obtained and this is taken as an input for goal program. Liao and Kao (2010) included two more factors in the selection process. These two factors are financial stability and experience period. All the mentioned factors are modelled into a goal

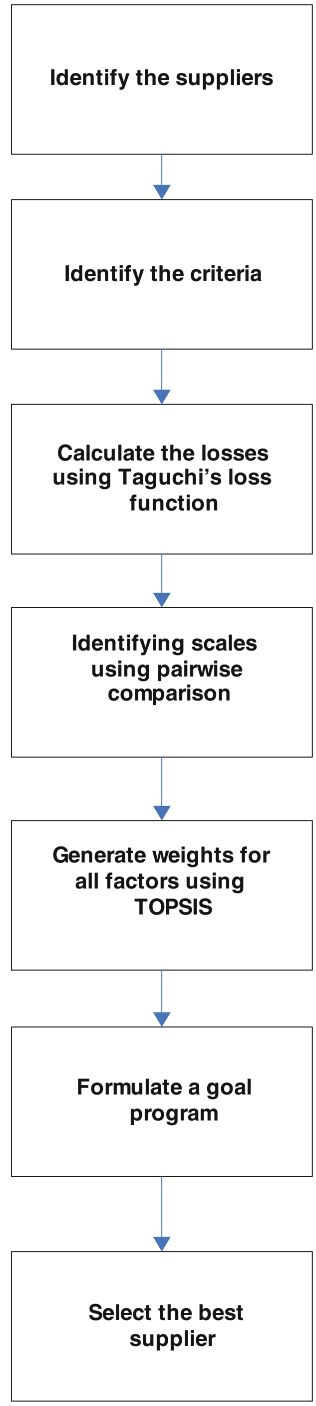

Fig. 1 Integrative supplier selection model

program to identify the best supplier. The objective function is to minimize the deviations from the mean which will incur losses.

In order to create a suitable background for using the proposed integrative supplier selection model, Taguchi loss function, TOPSIS, and multi criteria goal programming are described next.

Taguchi loss functions

According to Taguchi, Quality is minimizing the loss imparted by any product to the society after being shipped to the customer, other than any loss caused by its intrinsic function (Ross 2005). The objective is to minimize the variation from the target on both sides of the specification. The loss can be measured using a quadratic function (Taguchi et al. 1989). Taguchi's loss function is broadly classified into the three major types. These are as follows:

1. Smaller the better characteristics
2. Nominal the better characteristics
3. Larger the better characteristics

In the context of the nominal the better quality characteristics, the target will be at the centre and the two sides of the specification give the upper and lower specification limits. This can be formulated as follows:

$$L(y) = k\,(y - m)^2 \tag{1}$$

where L(y) is the loss associated with particular quality characteristics. m is the nominal value and y is the target value. k is the loss coefficient and it depends upon the specification limits and the spread $(m \pm \Delta)$ where Δ is the customer tolerance limit for the particular characteristics. Also there are other two loss functions as mentioned below which represent smaller the better and larger the better characteristics.

$$L(y) = ky^2 \tag{2}$$

$$L(y) = k/y^2 \tag{3}$$

When the deviation of a product's functional characteristic is an amount Δ from the target value m, the loss equals A (Taguchi et al. 1989). Then the Eq. (1) gives:

$$A = k\Delta^2; \text{ Or:}$$

$$k = A/\Delta^2 \tag{4}$$

where A is the average quality loss. Thus using the discussed equations, the related loss function can be calculated.

Table 1 RI values

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

Technique for order preference by similarity to ideal solution (TOPSIS)

Like AHP, TOPSIS is also a multi criteria decision making tool which is useful in selecting the best alternative from the set of existing alternatives. Generally for any supplier selection problem, the first step is to define the selection criteria. Then the relative weight is assigned to each criterion to evaluate the supplier performance. If there are no measures available for criteria, then the pair wise comparison will be used to identify the relationships. According to Saaty (1980), a nine point likert scale will be used to perform this task. Then the quality of the criteria matrix is checked using consistency ratio. The value of random index (RI) is taken from the data shown in the Table 1 which depends upon the matrix size (Saaty 1980). The value of consistent ratio (CR) should be <0.1 to continue the calculations. After the criteria matrix is ready with the pair wise data, the two artificial alternatives are hypothesized namely Ideal and anti ideal alternatives. Ideal alternative is the one which has the best level for all attributes considered. Anti ideal alternative is the one which has the worst attribute values. TOPSIS selects the alternative that is the closest to the ideal solution and farthest from anti ideal alternative (Tsai et al. 2008).

TOPSIS assumes that there are m alternatives (options) and n attributes (criteria). Assuming that there are scores of each option with respect to each criterion, the following procedure will be adopted for finding the weights.

Let x_{ij} be the score of option i with respect to criterion j. Then there will be a matrix $X = (x_{ij})$, i.e., mxn matrix. Let J be the set of benefit attributes or criteria (more is better) which represents ideal alternative, and J' be the set of negative attributes or criteria (less is better) which represents anti ideal alternative. The following steps illustrate the usage of TOPSIS to select the supplier (Lu et al. 2007).
Step1: Construct normalized decision matrix

This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across criteria. Normalize scores or data as follows:

$$r_{ij} = x_{ij}/\ \mathrm{SQRT}\ (\Sigma x_{ij}^2) \quad \text{for } i = 1, \ldots, m;\ j = 1, \ldots, n \tag{5}$$

Step 2: Construct the weighted normalized decision matrix

Assume that we have a set of weights for each criteria w_j for j = 1,…n. Where w_j is the weight of the i^{th} attribute or criterion, and $\Sigma w_j = 1$ for all j. Weights are highly dependent upon the type of the multiple criteria decision making problem where the researcher tries to investigate the criteria ranking with his experience and expertise in the field. Multiply each column of the normalized decision matrix by its associated weight. Let the new matrix be v_{ij}. Therefore the value of v_{ij} is obtained using the Eq. (6).

$$v_{ij} = w_j r_{ij} \tag{6}$$

Step 3: Determine the ideal and negative ideal solutions

As mentioned earlier, ideal solutions are those which will be close to the optimum and best selection and anti ideal solutions are those which are farthest from the alternatives (Hwang and Yoon 1981). Ideal solution is given below,

$$A^* = \left\{v_1^*, \ldots, v_n^*\right\}, \text{ where}$$
$$v_j^* = \{\max\left(v_{ij}\right) \quad \text{if } j \in J; \min\left(v_{ij}\right) \quad \text{if } j \in J'\} \quad \text{for all i} \tag{7}$$

Similarly negative ideal solution is given by,

$$A' = \left\{v_1', \ldots, v_n'\right\}, \text{ where}$$
$$v_j' = \{\min\left(v_{ij}\right) \quad \text{if } j \in J; \max(v_{ij}) \text{ if } j \in J'\} \text{ for all i} \tag{8}$$

Step 4: Calculate the separation measures for each alternative

The separation for the ideal alternative is,

$$S_i^* = \left[\sum\left(v_j^* - v_{ij}\right)^2\right]^{1/2} \quad \text{for all} \quad i = 1, \ldots, m \text{ and } j = 1 \text{ to } n \tag{9}$$

Similarly, the separation for the negative ideal alternative is,

$$S_i' = \left[\sum\left(v_j' - v_{ij}\right)^2\right]^{1/2} \quad \text{for all} \quad i = 1, \ldots, m \text{ and } j = 1 \text{ to } n \tag{10}$$

Step 5: Calculate the relative closeness to the ideal solution C_i^* using Eq. (9) and (10)

$$C_i^* = S_i'/(S_i^* + S_i'), \quad \text{where} \quad 0 < C_i^* < 1 \tag{11}$$

Thus the best alternative can be selected with C_i^* closest to 1 (Athawale and Chakraborty 2010). If in case, where the weights are to be measured for each alternative, then the values of C_i^* will be taken for fixing up the weightage for each criterion. Thus the weightage will be calculated and taken further for formulating a goal program.

Multi criteria goal programming

The goal programming (GP) is one of the multi criteria decision making (MCDM) techniques used to solve MCDM problems. GP was first introduced by Charnes and Cooper (1961); Aouni and Kettani (2001) listed the developments happened in the past 40 years in the area of multi criteria decision making and multi objective programming. The authors described some of the future applications of GP in different MCDM.

There are many different types of methods available in GP. They are Lexicographic GP, Weighted GP and MINMAX GP, Reference point method, Compromise programming, etc. (Romero 2001). Since there will be multiple objective functions, the idea is to allocate proper weights to all goal criteria and prioritize the goals to yield the optimal solution. The purpose of GP is to minimize the unwanted deviations between the achievement of goals and their aspiration levels. Tamiz et al. (1998) reviewed modelling techniques such as detection and restoration of Pareto efficiency, normalisation, redundancy checking, and non-standard utility function modelling. The connection between GP and other multi objective-programming techniques as well as a utility interpretation of GP are also examined.

The oldest form of Goal programming is represented below (Liao 2009).

Minimize

$$\sum_{i=1}^{n}\left(|f_i(X) - g_i|\right) \tag{12}$$

Subject to $X \in F$ and F is a feasible set; where $f_i(X)$ is the linear function of the ith goal, g_i is the aspiration level of the ith goal.

Ignizio (1976) proposed a mathematical model for GP which details the model to minimize the unwanted deviation variables each weighted according to the importance. The model is represented as follows:

Minimize

$$\sum_{i=1}^{n}(\propto_i d_i + \beta_i k_i) \tag{13}$$

subject to,

$$f_i(X) + d_i - k_i = g_i \quad \text{for all} \quad i = 1, 2, \ldots n$$
$$d_i,\ k_i >= 0 \quad \text{for all} \quad i = 1, 2 \ldots n$$
$$X \in F$$

where $\propto_i$ = positive deviation which are preferential purpose, β_i = negative deviation which are normalizing purpose, d_i = Max $[0, g_i - f_i(X)]$ under achievement, k_i = Max $[0, f_i(X) - g_i]$ over achievement

Chang (2007) proposed a method which allows the decision makers to set different aspiration levels for smaller the better and larger the better characteristics. Chang (2008) described two alternative types of formulations for MCGP objective function. The two cases illustrate the types of Taguchi loss functions characteristics called as Smaller the better and larger the better. The following equations detail the modelling part which is illustrated below:

Minimize

$$\sum_{i=1}^{n} \left(w_i \left(d_{ii} + d_{ij}\right) + \alpha_i \left(e_{ii} + e_{ij}\right)\right) \tag{14}$$

subject to,

$$\begin{aligned}
&f_i(X) - d_{ii} + d_{ij} = y_i \quad \text{for all} \quad i = 1, 2, \ldots n \\
&y_i - e_{ii} + e_{ij} = g_{i,max}, \quad \text{for all} \quad i = 1, 2 \ldots .n \\
&g_{i,min} \le y_i \le g_{i,max} \\
&d_{ii},\ d_{ij},\ e_{ii},\ e_{ij} >= 0 \quad \text{for all} \quad i = 1, 2 \ldots n
\end{aligned}$$

$X \in F$, F is a feasible set, X unrestricted in sign where, d_{ii}, d_{ij} are positive and negative deviations attached to goals $f_i(X) - y_i$, e_{ii}, e_{ij} are positive and negative deviation attached to $y_i - g_{i,max}$, $\propto_i$ is the weight attached to the sum of the deviation of $y_i - g_{i,max}$.

Similarly for smaller the better characteristics,

Minimize

$$\sum_{i=1}^{n} \left(w_i \left(d_{ii} + d_{ij}\right) + \alpha_i \left(e_{ii} + e_{ij}\right)\right) \tag{15}$$

subject to,

$$\begin{aligned}
&f_i(X) - d_{ii} + d_{ij} = y_i \quad \text{for all} \quad i = 1, 2, \ldots n \\
&y_i - e_{ii} + e_{ij} = g_{i,min}, \quad \text{for all} \quad i = 1, 2 \ldots .n \\
&g_{i,min} \le y_i \le g_{i,max} \\
&d_{ii},\ d_{ij},\ e_{ii},\ e_{ij} >= 0 \quad \text{for all} \quad i = 1, 2 \ldots n
\end{aligned}$$

$X \in F$, F is a feasible set, X unrestricted in sign where, d_{ii}, d_{ij} are positive and negative deviations attached to goals $f_i(X) - y_i$, w_i are the weights associated with each criteria's in the objective function, e_{ii}, e_{ij} are positive and negative deviation attached to $y_i - g_{i,min}$, $\propto_i$ is the weight attached to the sum of the deviation of $y_i - g_{i,min}$.

Thus considering all the criteria, an integrative Taguchi loss function, TOPSIS and MCGP model is formulated to solve the supplier selection problem. The section 3 illustrates the methodology with a suitable case.

Case description

A company has a huge product segments and varieties to position it in the heavy commercial vehicles which include bus, truck, marine diesel engine, and haulage vehicles. The company offers a wide range of products for different customer requirements. Over 40 % of the total production of company takes place at one of their plants. This plant manufactures a wide range of vehicles and has the production facilities for important aggregates such as Engines, Gear Box, Axles and other key in-house components.

Supplier selection is a key multi criteria decision making problem which requires several criteria to be evaluated to identify the key supplier. Over 90 % of the parts are bought out for final assembly. Since it is an assembly process which takes place in the said plant, the right kind of parts must reach the station on time as per the requirements. In order to understand the application of the proposed model in this paper, let us take the example of diesel injection pump subassembly in which the supplier's part is vital in terms of cost, quality, delivery, warranty and financial strength. The company's policy is to develop a vendor base committed to continuous improvement in order to meet the desired standards in terms of these criteria. As discussed before, the idea is to convert all the selection criteria into loss functions and also find out the weightages for each criterion to meet the required targets and minimize the deviations.

The following weightages are given concerning diesel pump subassembly which is based on a case for automotive industry where the manufacturer ranks the criteria for their products; Product quality—50 %, price—20 %, delivery—15 %, service satisfaction—10 %, and warranty degree—5 %. The main purpose of the proposed integrated model can be summarized in the following aspects:

1. It converts all the criteria into Taguchi loss function.
2. In order to find the normalized scores for the evaluation of weightages for each criterion, the TOPSIS is considered which uses simple steps to implement in a scientific way.
3. The right supplier is identified by converting the problem into a goal programming model after minimizing the deviations for all the relevant variables such that the loss is minimized and kept in the optimum levels of criteria.

In the process of supplier selection, several authors used many parameters to select the right supplier. Pi and Low (2005) used four key parameters, namely, quality, price, on time delivery and service. In this paper, there are five different criteria selected to determine the suppliers which include product quality, price, delivery time, service satisfaction and warranty degree. As discussed before, experience and financial stability of the suppliers are also considered and included in the goal program. Input parameters are similar to that used by Liao and Kao (2010).

According to the Taguchi's loss function, the target range for product quality will be zero defects and a maximum of 2 % to indicate the deviation from the target value. Hence zero loss will occur at target value and maximum 100 % loss will occur at 2 % level. In the case of price, zero loss will be for those suppliers who offer product at the lowest price and a maximum of 15 % increase in the price is given the upper specification limit. Thus 100 % loss will be given at 15 % increase in the price. With regards to the delivery time, the targeted delivery time is 0 days and is given zero loss and a maximum delivery delay up to 3 days is taken as 100 % loss.

Similarly, the service satisfaction level is given 100 % loss at 60 % service level and zero loss incurred at 100 % service level. For warranty policy on different suppliers, zero loss will be incurred at 100 % warranty and 100 % loss will be incurred at 85 %. Thus the specification ranges from 100 to 85 %. The specific financial criteria in terms of experience time have been considered as 5, 9, 8, 10, and 12 years, and the financial stability in million $ are 7, 10, 14, 11, and 6 respectively for different suppliers namely x1, x2, x3, x4, and x5.

Results

Following the conventional procedure, it is possible to evaluate:

(i) Average loss coefficient and range values
(ii) Characteristics and relative values of suppliers
(iii) Supplier characteristic Taguchi loss

In the TOPSIS calculation, the largest Eigen value λ_{max} is 5.1504. Using Eq. (11), the corresponding weights are 0.665, 0.390, 0.357, 0.322, and 0.368 for product quality, price, delivery, service satisfaction and warranty degree respectively and are shown in the Table 2 (Saaty 2008). The Weightage given for TOPSIS analysis is based on a sample for automotive industry where the manufacturer ranks the criteria for their products. As mentioned before, in the present case, the weightages for each criterion is as follows; Product quality—50 %, price—20 %, delivery—15 %, service satisfaction—10 %, and warranty degree—5 %. In order to validate the model, the consistency index is obtained using λ_{max} and found to be 0.0376. For the order 5, the RI value = 1.12 for a matrix size of 5 (Saaty 1980). The calculated CR value is equal to 0.033.

All the above mentioned weights and loss associated with each Taguchi's loss function are incorporated into the multi criteria goal programming model to select the best supplier. Using (14) and (15), the MCGP is formulated and the results are obtained. In order to compare the proposed approach with a well known methodology, i.e., the data envelopment analysis (DEA), a brief discussion is also made in section "Comparison of the proposed model with DEA".

Based on the above model formulation, the problem is solved using LINGO 12.0 on an Intel ®CORE™ i3 CPU @ 2.27 GHz based personal computer. The optimal solution is as follows:

The supplier x5 is obtained as the best supplier, i.e.,

$x1 = x2 = x3 = x4 = 0, x5 = 1$

$y1 = 225400, y2 = 2352, y3 = 1.43, y4 = 24.50,$

$y5 = 17.78, y6 = 12, y7 = 6$

Comparison of the proposed model with DEA

In Data envelopment analysis (DEA) literature, any entity whose efficiency is being evaluated is usually referred to as "Decision Making Unit (DMU)". DEA is a technique used to measure and compare the efficiencies of various DMUs by taking their ratios of weighted sum of outputs to inputs. This technique was first proposed by Charnes et al. (1978) when they provided a linear programming formulation to measure the productive efficiency (CCR Efficiency) of a DMU relative to a set of referent DMUs. To measure the technical efficiency and the returns to scale, the CCR model can be modified via addition of convexity constraint. Banker et al. (1984) introduced a new separate variable which makes it possible for operations when these are conducted in regions of increasing, constant or decreasing return to scale. DEA is receiving importance as a tool for evaluating the performance of manufacturing and service operations in terms of multi criteria decision making. Weber (1996) used DEA for supplier selection and determined the best performing suppliers. The model can be illustrated as both primal and dual model of the fractional DEA programming.

The value of objective function reveals the efficiency frontiers of each supplier. In order to find out whether the efficiencies are real benchmark and to yield the better supplier relatively, the primal model is to be converted into a dual model to get the Farrell's efficiency which is the same efficiency of primal but the dual variables lambdas give the impact of relatively best supplier to the underperforming supplier. The output is measured by Farrell efficiency where the objective is to minimize it. Pareto Koopmans efficiency was proposed by Charnes et al. (1978) where it illustrates that the Farrell's efficiency (Farrell 1957) will be in frontier efficiency only when the slack variables will be zero. If the slack variables are greater than 0, then that particular DMU is not efficient even if the efficiency reaches maximum, i.e., 1. This is called as Pareto Koopmans efficiency.

Liu et al. (2000) have taken the three inputs, namely, price, delivery & distance, and two outputs, i.e., supply variety and quality. Ramanathan (2007) used one output which is the total costs and the three inputs, namely, quality, technology and service. The above model uses 5 criteria as inputs and taking unit item as output; the above problem can be modelled using MS Excel based DEA model (Ramanathan 2007; Talluri 2000) and the efficiencies can be figured out using the dual model. The results are indicated below:

Farrell's efficiency of all the suppliers is 1 except for supplier 1 whose efficiency is 0.966. This shows that the supplier selection problem is not meeting its objective of selecting a relatively better supplier among the existing list. Thus DEA in those situations might fail to select the best supplier among the efficient suppliers 2, 3, 4, and 5.

Table 2 Pair wise comparison for different criteria

	Product quality	Price	Delivery time	Service satisfaction	Warranty degree	Weights
Product quality	1.00	2.00	3.00	3.80	2.50	0.665
Price	0.50	1.00	2.50	2.70	1.80	0.390
Delivery time	0.33	0.40	1.00	0.50	0.80	0.357
Service satisfaction	0.26	0.37	2.00	1.00	1.70	0.322
Warranty degree	0.40	0.56	1.25	0.59	1.00	0.368

The above method illustrates the usage of DEA as a multi criteria decision making tool. The method proceeds to find out the maximum efficiency for each supplier which should lie on the frontiers. If the number of suppliers is relatively less, then in most of the scenarios the value of efficiency will be maximal for all the suppliers. Thus the researcher/ practitioner might not know which supplier is to be selected and who is relatively better than the other suppliers which is the purpose of the analysis. But, as far as the proposed integrated approach is concerned, the GP model will select a supplier based on the objective function to minimize the deviations which is illustrated in terms of all the selection criteria. Thus the integrated Taguchi loss function, TOPSIS and GP method will be superior enough to select a supplier even if the number of suppliers are relatively less and will also be efficient in computation.

Conclusion

Supplier selection is a key decision making problem which involves both qualitative and quantitative assessment of multiple criteria under consideration. This paper proposes an integrative approach to solve the supplier selection problem using Taguchi loss function, TOPSIS and GP. Ramanathan (2007) illustrated the use of both quantitative and qualitative types of data for selecting the supplier. Many authors used AHP as an integrative approach along with Taguchi's loss function. Although different methods propose for selecting the suppliers, every method will be limited by its own methodology. However, the proposed method is expected to select relatively better supplier because of an integration of TOPSIS with other methods. A brief discussion is also made for the comparison of present approach with DEA.

Apart from the supplier selection problem, this methodology can be used in many different fields like facility selection, warehouse location, different strategies to market the products, production planning and scheduling when data are measurable. If the data required for modelling is not measurable, then as per the Likert scale proposed by Saaty (1980), the pairwise comparison matrix will be formed using the 1-9 scale and the problem can be solved in a shorter span of time. The future scope of MCDM problems also lies in tools such as Fuzzy GP and DEA. Although DEA has been included briefly for comparison purpose, however these methods may be considered in detail for future research and development.

References

Al-Faraj, T. N., Alidi, A. S., & Al-Zayer, J. A. (1993). Vendors selection via a spreadsheet analytical hierarchy process. *Computers and Industrial Engineering, 25*(1-4), 65–68.

Aouni, B., & Kettani, O. (2001). Goal programming model: A glorious history and a promising future. *European Journal of Operational Research, 133*(2), 225–231.

Athawale, V. M., & Chakraborty, S. (2010). A TOPSIS method based approach to Machine tool selection. In *International conference on Industrial engineering and operations management*, Dhaka.

Banker, R. D, Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078–1092.

Chakraborty, T., Ghosh, T., & Dan, P. K. (2011). Application of analytical hierarchy process and heuristic algorithm in solving vendor selection problem. *Business Intelligence Journal, 4*(1), 167–177.

Chan, F. T. S., Kumar, N., Tiwari, M. K., Lau, H. C. W., & Choy, K. L. (2008). Global supplier selection: A fuzzy-AHP approach. *International Journal of Production Research, 46*(14), 3825–3857.

Chang, C. T. (2007). Multi choice goal programming. *Omega The International Journal of Management Science, 35*(4), 389–396.

Chang, C. (2008). Revised multi choice goal programming. *Applied Mathematical Modelling Volume, 32*(12), 2587–2595.

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of the decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Charnes, A., & Cooper, W. W. (1961). *Management models and industrial application of linear programming*. New York: Wiley.

Chen, Y.-S., Cheng, C.-H., & Lai, C.-J. (2011). Extracting performance rules of suppliers in the manufacturing industry: An empirical study. *Joural of Intelligent Manufacturing*. doi:10.1007/s10845-011-0530-8.

Dickson, G. W. (1966). An analysis of vendor selection systems and decisions. *Journal of Purchasing, 2*(1), 5–17.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of Royal Statistical Society, A, 120*(III), 253–290.

Guan, Z., Jin, Z., & Zou, B. (2007). A multi-objective mixed-integer stochastic programming model for the vendor selection problem under multi-product purchases. *Information and Management Sciences, 18*(3), 241–252.

Ha, S. H., & Krishnan, R. (2008). A hybrid approach to supplier selection for the maintenance of a competitive supply chain. *Expert Systems with Applications, 34*(2), 1303–1311.

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making method and applications*. New York: Springer.

Ignizio, J. P. (1976). *Goal programming and extensions*. Lexington, MA: Lexington books.

Kang, H.-Y., Lee, A. H. I., & Yang, C.-Y. (2010). A fuzzy ANP model for supplier selection as applied to IC packaging. *Joural of Intelligent Manufacturing*. doi:10.1007/s10845-010-0448-6.

Kasilingam, R. G., & Lee, C. P. (1996). Selection of vendors—a mixed integer programming approach. *Computers and Industrial Engineering, 31*(1/2), 347–350.

Liao, C. N., & Kao, H.-P. (2010). Supplier selection model using Taguchi Loss function, analytical hierarchy process and multi choice goal programming. *Computers & Industrial Engineering, 58*(4), 571–577.

Liao, C. N. (2010). Supplier selection project using an integrated Delphi, AHP and Taguchi loss function. *Probstat Forum, 3*, 118–134.

Liao, C. N. (2009). Formulating the multi segment goal programming. *Computers and Industrial Engineering, 56*(1), 138–141.

Liu, J., Ding, F. Y., & Lall, V. (2000). Using data envelopment analysis to compare suppliers for supplier selection and performance improvement. *Supply Chain Management: An International Journal, 5*(3), 143–150.

Lu, J., Zhang, G., Ruan, D., & Wu, F. (2007). *Multi-objective group decision making: methods, software and applications with fuzzy set techniques*. ISBN-13 978-1-86094-793-3, ISBN-10 1-86094-793-X. Imperial College Press, London.

Ozaki, T., Lo, M.-C., Kinoshita, E., & Tzeng G.-H. (2011). Decision-making for the best selection of suppliers by using minor ANP. *Joural of Intelligent Manufacturing*. doi:10.1007/s10845-011-0563-z.

Pang, B., & Bai, S. (2011). An integrated fuzzy synthetic evaluation approach for supplier selection based on analytic network process. *Joural of Intelligent Manufacturing*. doi:10.1007/s10845-011-0551-3.

Pi, W., & Low, C. (2005). Supplier evaluation and selection using Taguchi loss functions. *International Journal of Advanced Manufacturing Technology, 26*(1-2), 155–160.

Ramanathan, R. (2007). Supplier selection problem: Integrating DEA with the approaches of total cost of ownership and AHP. *Supply Chain Management—An International Journal, 12*(4), 258–261.

Romero, C. (2001). Extended lexicographic goal programming: A unifying approach. *Omega: The International Journal of Management Science, 29*(1), 63–71.

Ross, P. J. (2005). *Taguchi Techniques for Quality Engineering*. New Delhi: Tata McGraw Hill Edition.

Saaty, T. L. (2008). Relative measurement and its generalization in decision making. Why pairwise comparisons are central in mathematics for the measurement of intangible factors. The Analytic hierarchy/network process. *Statistics and Operations Research, 102*(2), 251–318.

Saaty, T. L. (1980). *The analytic hierarchy process*. New York: McGraw Hill edition.

Sharma, S. (2010). Policies concerning decisions related to quality level. *International Journal of Production Economics, 125*(1), 146–152.

Sharma, S. (2012). Development of supplier relationship including cost of defectives in the cyclic production. *Production Planning & Control: The Management of Operations*. doi:10.1080/09537287.2012.666866.

Sharma, S., & Dubey, D. (2010). Multiple sourcing decisions using integrated AHP and knapsack model: A case on carton sourcing. *International Journal of Advanced Manufacturing Technology, 51*(9-12), 1171–1178.

Taguchi, G., Elsayed, A., & Hsiang, C. T. (1989). *Quality Engineering in production systems*. Tokyo: Mc Graw Hill Book company.

Talluri, S. (2000) Data envelopment analysis: Models and extensions. *Decision Line*, 8–11.

Tamiz, M., Jones, D., & Romero, C. (1998). Goal programming for decision making: An overview of the current state of the art. *European Journal of Operational Research, 111*(3), 569–581.

Tsai, H. Y., Huang, B. H., & Wang, A. S. (2008). Performance evaluation model of property-liability insurance companies in Taiwan-application of analysis network process. *Journal of Information and Optimization Sciences, 29*(6), 1045–1065.

Weber, C. A. (1996). A data envelopment analysis approach to measuring vendor performance. *Supply Chain Management—An International Journal, 1*(1), 28–39.