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ORIGINAL ARTICLE

An integrated Taguchi loss function–fuzzy cognitive map–MCGP with utility function approach for supplier selection problem

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Abstract

Due to the effects of supplier evaluation and selection problem on the quality of products and companies' business activities, supplier selection is considered as a strategic issue in organizations' development plans. The purpose of this study is to provide an integrated framework for supplier selection problem regarding to the loss of criteria deviation from specification limits, causal relationships between criteria and the preferences of decision makers (DMs) in the supplier selection problem. Thus, in the first step, the loss of each criterion is calculated using Taguchi loss function (TLF), then fuzzy cognitive map (FCM) and hybrid learning algorithm are applied to determine criteria weights. Finally, considering outputs of TLF and FCM methods, multi-choice goal programming with utility function (MCGP-U) is used to select an optimal supplier and to increase the DMs' expected utility values, simultaneously. The results of implementation of proposed framework based on the extended MCGP-U model on an active company in paint and coating industry show that delivery time criterion has the most effect and priority on suppliers' evaluations. Also among six qualified suppliers, a supplier with the least total loss value and the most utility values is selected as the optimal supplier for the under consideration company.

Keywords Supplier selection · Taguchi loss function · Fuzzy cognitive map · Multi-choice goal programming with utility function

Abbreviations

GP	Goal programming
MCGP	Multi-choice goal programming
MCGP-U	Multi-choice goal programming with utility function
TLF	Taguchi loss function
LLUF	Left linear utility function
RLUF	Right linear utility function
FCM	Fuzzy cognitive map
NHL–DE	Nonlinear Hebbian learning–differential evolution
DMs	Decision makers
MCDM	Multi-criteria decision making
MODM	Multi-objective decision making
ANP	Analytic network process
AHP	Analytic hierarchy process

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1 Introduction

The issue of purchasing and supplier selection (outsourcing) has a great impact on a supply chain since the main processes of supply chain and firm's development consist of the price of purchasing raw materials and providing parts from several vendors. Indeed, supplier selection problem is recognized as a critical issue in supply chain management (SCM) due to its impact on profitability, cash flows and consequently maintaining strategically competitive aspect of companies [1]. Therefore, evaluation and selection of the optimal supplier is considered to be a strategic issue in firm's business and development plans and in the last two decades, great attention has been paid to supplier selection issue [2]. Supplier selection is a multi-criteria decision-making (MCDM) problem [3]. The selection process mainly involves providing an effective framework to compare and evaluate a number of suppliers through a set of common and conflicting criteria [4]. Basically, two major issues should be considered in the supplier selection problem. First, the selection of a set of appropriate criteria based on their degree of importance in decision-making process in which the supplier's performance is evaluated and reflected regarding the goals of the firm and second, the selection of an appropriate evaluating methodology which selects an optimal supplier based on the various and sometimes conflicting evaluation criteria.

Regarding the criteria selection issue, an effective criteria selection framework has a great importance on suppliers' evaluations. Enterprises inclination to respond to the firm's requirements, customer satisfaction and foster competitiveness leads to selection of suppliers' performance evaluation criteria based on the mentioned features [5]. In other words, correct selection of a set of criteria and determining their relative weights based on the strategic and performance objectives of the purchasing department allows accurate feedback and credibility over the purchasing decisions [6].

Different sets of quantitative and qualitative evaluation criteria have been proposed in literatures. For instance, Dickson [7] proposed 23 qualitative and quantitative criteria such as quality, price, delivery time, services and so on. After that, researchers considered different criteria derived from Dickson's proposed criteria to measure the supplier's performance. Generally, quality, price, services and delivery time are the most decisive criteria considered in the supplier selection problems since in practice, most of the firm's profits depend on the purchasing price and total satisfactory rate through high-quality products and the subsequent services [8, 9]. As mentioned before, selected criteria's conformity with the goals of companies is a vital step and can influence the supplier selection process. However, in most of the supplier selection literatures, in criteria selection process, their impact on achieving aspired goals of organizations, criteria's degree of importance and their impact on each other such as, dependency, causal relationships and relationship structure, have not been investigated accurately.

Generally, the impact of the criteria on each other, importance degree and their impact on the objective function could be considered as weights of criteria in MCDM techniques. For instance, analytic network process (ANP) method can consider interrelations among criteria. However, the weaknesses of this method lies in identifying causal relationships between criteria and its high dependency on experts which leads to the low efficiency of this method in the supplier selection problems [10]. Also, according to Govindan et al. [11], analytic hierarchy process (AHP) is the most used technique in determining the importance degree and the weights of criteria. But like ANP, AHP is subjected to some shortcomings and in a compound set of criteria with various causal relationships between elements, it is hard for decision makers (DMs) to make a good decision by using simple weighing methods [10].

Therefore, to overcome the shortcomings of ANP, AHP and the other MCDM techniques, this study has focused on the criteria weighing using fuzzy cognitive map (FCM). FCM is capable of depicting all causal relationships among criteria and effectively weighing the criteria according to the causal relationships and dependency among criteria. FCMs have many applications in decision analysis and are applied in different fields such as strategic marketing planning for industrial firms [12], renewables local planning [13], assessment and decision support in the emergency department [14], integrated environmental assessment [15], airport risks management [16], design of an energy management system [17], risk assessment of production processes [18], estimating system outputs [19] and supplier selection problems [10]. In Xiao et al. [10] study, FCM is applied to assess the weights of risk criteria of suppliers. In fact, the total risk value of suppliers is obtained based on the FCM and fuzzy sets.

In addition to the above complexity in the criteria selection, the situations in which the evaluation criteria are intangible, are difficult to be quantified economically, and are involved with features of "the larger/more is better," "the nominal is the best" and "the smaller/less is better" have been considered in a narrow of literature. In order to include such criteria in supplier selection problems, Taguchi loss function (TLF) is applied in some researches. Taguchi proposed a quadratic function to reduce any losses occur when a characteristic value deviates from specification limit systemically. In recent decade, some researches considered intangibility of criteria and loss function in the suppliers' evaluations. Pi and Low [20] measured the efficiency of suppliers using loss function first. In Pi and Low [20] study, total loss of each supplier is calculated by measuring the loss of deviation of criteria from specification limits. Also, Pi and Low [21] transferred the quality losses to variables for decision making by AHP. Sivakumar et al. [22] proposed the AHP and loss function to measure the loss of outsourcing vendor performance for pertinent benefit and risk factors. Also, Liao and Kao [23] considered two "the smaller/less is better" price and delivery time indexes and three "the larger/more is better" warranty degree, product quality and service satisfaction indexes to calculate the loss of criteria and used obtained values in multi-choice goal programming (MCGP) for decision making. In this study, TLF is applied to consider the losses occurred when criteria values deviate from target values and also the inclusion of criteria with intangible features in the supplier selection problem. Moreover, the TLF converts the different values to a common value of quality loss which makes the evaluations and comparisons more meaningful and easy [24].

Second important issue in the supplier selection problem is to choose an appropriate and flexible methodology for evaluating suppliers' efficiencies and selecting the best supplier among them. The early versions of supplier selection methods considered a single model to select optimum supplier such as data envelopment analysis, ANP, AHP, goal programming, neural network, factor analysis, fuzzy set theory and etc. Single models' deficiencies and limitations have led to the application of combined models in researches. In fact, combined models take the advantages of individual single models and cover the deficiency of single models. Combined models include integration of two or more single models such as case based reasoning (CBR) and neural network, AHP and loss function, fuzzy set theory and AHP [4]. Among existing approaches of evaluating suppliers, goal programming (GP) is one of the most popular methods which has been applied in many supplier selection problems [25, 26]. The aim of GP is to minimize unwanted deviations of achieved goal and aspirations level [27]. The inherent flexibility of GP in solving multi-objective decision making (MODM) and MCDM problems has led to introducing and using various types of GP such as lexicographic GP, robust and fuzzy GP, intuitionistic fuzzy GP, weighted GP and extended GP [28–32]. However, in real-world problems, due to the lack of information, it is difficult for a DM to set a specific aspiration level for a goal. To solve this shortage, MCGP was proposed by Chang [33]. MCGP allows DMs to set multi-aspiration levels for their goals. This feature of MCGP has made this model applicable in various problems such as supplier selection [8, 23, 34]. Liao and Kao [23] used MCGP to set multiple aspirations for decision criteria to solve a supplier selection problem. Liao and Kao [8] in their study proposed integrated fuzzy techniques for order preference by similarity to ideal solution (TOPSIS) and MCGP approach to solve the supplier selection problem. The advantage of their method was that it allowed DMs to set multiple aspiration levels for supplier selection problems. Also, Chang et al. [35] proposed an integrated MCGP and multi-segment goal programming to deal with supplier selection problem.

Although MCGP compensates the GP's drawback in setting multi-aspiration levels for goals but considers no preferences of DMs in its structure. Therefore, Chang [27] proposed a new multi-choice goal programming with utility function (MCGP-U) to consider the DMs preferences in MODM problems. The contribution of MCGP-U is to help DMs assign goals with considering their utilities to solve practical real-world decision and management problems [27]. In the supplier selection problem, Jadidi et al. [34] considered preference in the supplier selection model and proposed a new MCGP which provides DMs with more control over their preference. Also, in this study, MCGP-U is applied to select the best supplier with increasing the utility values of DMs.

In this study, a novel framework for supplier selection has been proposed. In order to solve supplier selection problem an integrated framework of TLF, FCM and MCGP-U model is presented. First, the loss of deviation of criteria from specification limits is calculated using the TLF. Then, FCM is applied to determine the weights of criteria and specify the priority of criteria in the supplier selection problem. Finally, after obtaining the results of the last two phases, MCGP-U model is used to select the optimal supplier and maximize the DMs' expected utility. The contribution of this study is to consider causal relationships between criteria, the inclusion of intangibility of some criteria in supplier evaluations. Furthermore, it considers the utility values of DMs simultaneously which has never been undertaken before. In the previous studies, just a part of the proposed approach is applied to select the optimum supplier. For instance, in Liao and Kao [23], causal relationships between criteria and utility function are not considered or in Pi and Low [20]; only loss function is considered to select best supplier. Since the proposed approach is an integration of various methods and factors, it has enabled DMs to evaluate suppliers more reliably and precisely. Additionally, the shortcomings of using each method individually are covered. Moreover, DMs can benefit from each method's individual advantages simultaneously.

The rest of the present study is organized as follows: In Sect. 2, methods of TLF, FCM and MCGP-U are introduced. In Sect. 3, an integrated framework to solve supplier selection problem is proposed. A case study of a company in paint and coating industry has been investigated in Sect. 4. The results of implementation of the proposed framework on the case study are presented in Sect. 5 and finally, the summary and conclusion of the study is presented in Sect. 6.

2 Methods

The aim of present study is to propose an integrated framework for the supplier selection problem based on the three methods of TLF, FCM and MCGP-U. The TLF method measures the loss of deviation of evaluation criteria from the target values. Moreover, FCM considers causal relationships between criteria and determines the weight of each criterion based on the direct and indirect relation of criterion under evaluation on the objective "supplier evaluation" concept. Finally, the outputs of first two methods have been transferred to variables for decision making using MCGP model with considering DMs' preferences in the decision process. In the following, three used methods in this framework have been introduced.

2.1 Taguchi loss function

Quality costs are the imposed costs incurring to ensure that whether responses quality are complying with the specified quality standards. In the most cases, due to the existence of intangible quality costs, i.e., customer's satisfaction, TLF was introduced as an effective method to assess such costs. The original idea of the TLF is to reduce variability of response quality value from the target value [20]. In other words, the TLF was defined as a loss occurs when parameters' quality values deviate from the target values or specification limits. Thereby, loss will be zero when measured quality value and the target value are the same. Taguchi measured the occurred loss by introducing quadratic loss function. Quadratic loss function reduces variability near the target value systematically [36]. Taguchi defined three types of loss functions: (1) "the nominal is the best," (2) "the larger/more is better" and (3) "the smaller/less is better" functions. First one related to situations in which deviation allowed in both directions of target value. In this function, target value can be the center of two upper and lower specification limits and is formulated as Eq. (1).

$$L(y) = K(y - T)^2 \quad (1)$$

where L is the cost occurs due to the quality deviation from the target value, T is target value, y is the performance or quality characteristics, and K is the quality loss coefficient which depends on the cost of the production process structure. Costumer's acceptable range of specification limits can be $(T \pm \Delta)$ where Δ represents the customer's tolerance (shown in Fig. 1).

As shown in Fig. 1, losses near target values and specification limits are in its minimum and maximum levels, respectively. The other two loss functions are related to situations in which deviation is only allowed in one direction called one-sided maximum and minimum for "the larger/more is better" and "the smaller/less is better" characteristics, respectively (shown in Figs. 2, 3). Equations (2) and (3) formulate the aforementioned loss functions, respectively.

$$L(y) = k/y^2 \quad k = A/\Delta \quad (2)$$

$$L(y) = ky^2 \quad k = A/\Delta \quad (3)$$

where A is average loss; other variables are defined in "the nominal the best" function formulation.

2.2 Fuzzy cognitive map

In the real world, factors may have complex relationships with other factors. Many of them are influencing and meanwhile, many of them are affecting each other. FCM is an appropriate technique to map these relations. FCM is a soft computing tool considering relationships between components of a "mental vision" to calculate the "impact potency" of causal relationships in numerical intervals [− 1,1] or [0,1] [37]. The main components of FCMs are nodes with weighted interconnection arcs between nodes. In fact, the nodes represent concepts that describe the system, the arcs represent causal relationships between concepts and symbols on the arcs determine the types of causality between concepts [38]. To depict a FCM, experts' opinions and time-series data are required. In the calculation-based FCM, time-series data are used as input of FCM and neural networks logic is applied to assess weights and relationships of concepts. In fact, knowledge, experience and scenario contribute to depict a desirable FCM. In Fig. 4, a general schematic of FCM with component has been presented.

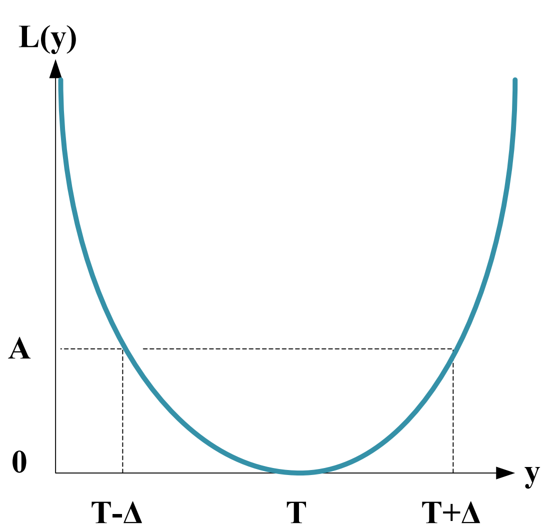

Fig. 1 Nominal is the best function

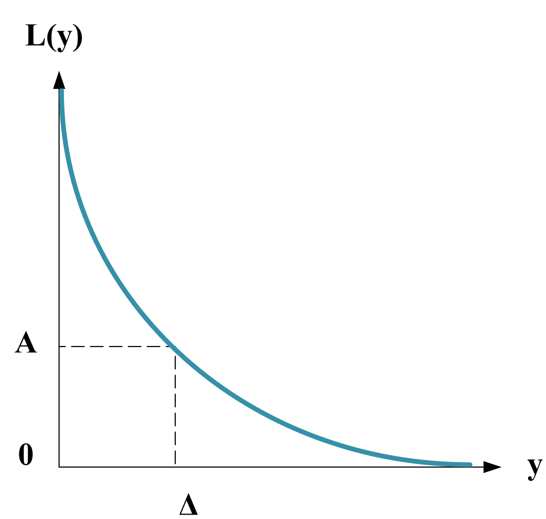

Fig. 2 Larger/more is better function

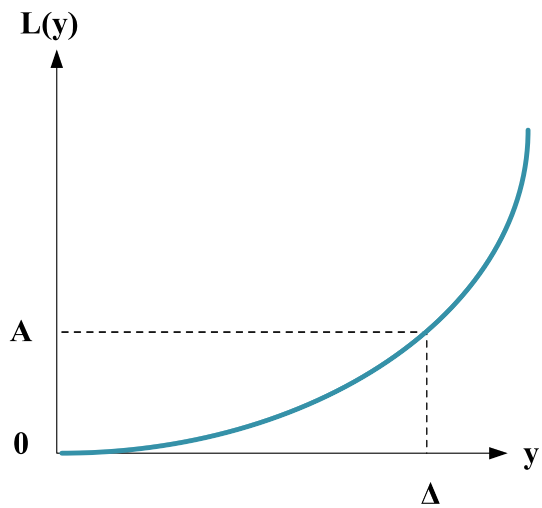

Fig. 3 Smaller/less is better function

In Fig. 4, C_i represents nodes and concepts of the system which are interconnected with weighted arcs. Two concepts *Ci* and *Cj* are connected with a weight of w_{ij} which indicates the degree of causality and relationships between them. So $w_{ij} > 0$ indicate a positive causality, $w_{ij} < 0$ represent a negative causality and $w_{ij} = 0$ shows a no relationship between two concepts. To explain a FCM, six steps should be done as follows:

- *Step 1* Determination of affecting concepts on the system and relationships between them.
- *Step 2* Weighing these relationships regarding to the experts' opinions.
- *Step 3* Selection of appropriate calculation method and transformation functions.
- *Step 4* Releasing the concept with relationship to interact with each other
- *Step 5* measuring the interaction value of concepts in each cycle.
- *Step 6* Continuing this trend until terminating conditions occur.

In the FCM technique, estimation of the weights of concepts is an essential issue. In recent years, learning algorithms is used to increase the accuracy of weight estimation, map convergence and reducing dependency on experts' opinions. Learning algorithms classified to three Hebbian algorithms, population-based learning algorithms and hybrid learning algorithms [39]. According to the data of this study which are based to the expert's opinions, hybrid learning algorithm would be the best option. Since the hybrid learning algorithms are combinations of the other two learning algorithms and are suitable to adjust the weights of concepts with the combination of time-series and experts' opinions data, simultaneously.

Moreover, among various hybrid learning algorithms, nonlinear Hebbian learning–differential evolution (NHL–DE) algorithm is used in this study, since this algorithm updates the nonzero weights in different iterations and maintains the relationships between concepts which are defined in the original map [40]. The pseudocode of nonlinear Hebbian learning (first stage of NHL–DE) and differential evolution (second stage of NHL–DE) is presented in Fig. 5. In the presented pseudocode, $A^{(0)}$ is the initial state matrix of the system, $W^{(0)}$ is the initial weights matrix of causal relationships of concepts, $A_i^{(k-1)}$, $A_i^{(k)}$ and $A_i^{(k+1)}$ are the values of concept C_i at iterations $k-1$, k and $k+1$, $A_j^{(k)}$ is the values of concept C_j at iteration k, $w_{ij}^{(k-1)}$

Fig. 4 A fuzzy cognitive map

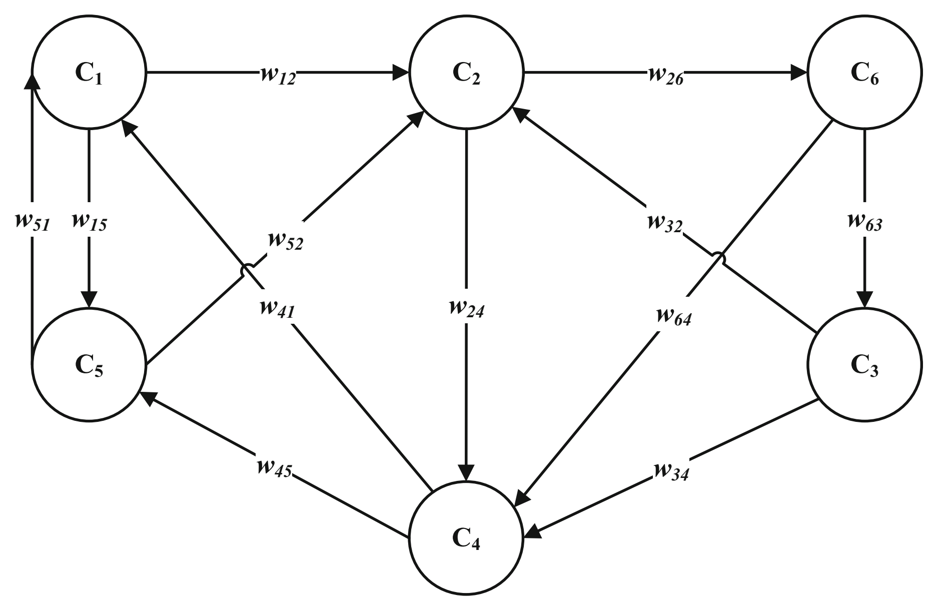

Fig. 5 Nonlinear Hebbian learning–differential evolution algorithm

Procedure 1: Nonlinear Hebbian learning algorithm

Step A1. Read input concept state A^0 and initial weight matrix W^0.

Step B1. Repeat for each iteration k.

Step C1. Calculate $A_i^{(k+1)}$ according to follow equation:

$$A_i^{(k+1)} = f\left(A_i^{(k)} + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^{(k)}.w_{ij}^{(k)} \right)$$

Step D1. Update the weight w_{ij}^{k} according to follow equation:

$$w_{ij}^{(k)} = \gamma.w_{ij}^{(k-1)} + \eta\, A_i^{(k-1)} \left(A_j^{(k-1)} - sgn\left(w_{ij}^{(k-1)}\right) w_{ij}^{(k-1)} A_i^{(k-1)} \right)$$

Step E1. Calculate the termination functions.

Step F1. Until the termination condition are met.

Step G1. Return the final weights $W_{NHL}^{(k+1)}$ to the Procedure 2.

Procedure 2: Differential evolution algorithm

Step A2. Initialize the DE population in the neighborhood of $W_{NHL}^{(k+1)}$ and within the suggested weight constraints.

Step B2. Repeat for each input concept state (k).

Step C2. For $i=1$ to NP (number of population) do step D2 to step G2.

Repeat D2 to F2 for each population.

Step D2. Mutation $W_i^{(k)}$ to obtain mutation vector.

Step E2. Crossover mutation vector to obtain trial vector.

Step F2. If $F(\text{Trial\_Vector}) \leq F(W_i^{(k)})$, accept Trial_Vector for the next generation.

Step G2. Until the termination condition are met.

and $w_{ij}^{(k)}$ are updated weight between concepts C_i and C_j at iterations $k-1$ and k, η and γ are learning rates, $W_{\mathrm{NHL}}^{(k+1)}$ represents the final weights matrix of causal relationships of concepts in the first stage, $W_i^{(k)}$ represents the state matrix of concept C_i at iteration k, sgn is sign function, NP is the number of population and f is a transformation function, provided that the product of two matrixes is more than the amount defined for variables, that returns the resulting values to defined ranges. In this study, according to the concept values, which are between interval [0,1], the most appropriate transfer function is sigmoid function. Also, the termination conditions of FCM calculations include: 1. a stable state, that is, until $A_i^{(k)}$ and $A_i^{(k+1)}$ is equal or have a little difference, 2. exhibiting limit cycle behavior, i.e., the concept values fall in a loop of numerical values under a specific time period, 3. indicating a chaotic behavior, i.e., the concept values obtain a variety of numerical values in a non-deterministic, random way [38].

2.3 Multi-choice goal programming with utility function

Goal programming (GP) is an extension of linear programming to solve MCDM and MODM problems which was first introduced by Charnes and Cooper [41]. GP requires that DMs determine an aspiration level for each objective regarding to the evaluation criteria, then tries to minimize deviations of the achieved goals and aspiration level [27]. GP formulated as follow:

$$\begin{aligned} &\min \sum_{i=1}^{n} d_i^+ + d_i^- \\ &\text{s.t:} \\ &\quad f_i(x) - d_i^+ + d_i^- = g_i, \qquad i = 1,2,\ldots,n \\ &\quad d_i^+, d_i^- \geq 0, \qquad i = 1,2,\ldots,n \\ &\quad x \in F \end{aligned} \tag{4}$$

where $f_i(x)$ is the linear function of ith objective. d_i^+ and d_i^- are allowable positive and negative deviations of ith goal. g_i is aspiration value of ith goal and F is a feasible set.

In most real cases, restrictions to determine an aspiration level for each objective, such as uncertainty in decision problems or lack of information, led to propose of MCGP by Chang [33]. The MCGP allows DM to set a multiple aspiration levels for each objective instead of one and helps avoiding underestimation of decisions made by DM [23]. The MCGP can be divided in two “the more is better” and “the less is better” types. Two types can be modeled as follows:

$$\begin{aligned} &\min \sum_{i=1}^{n} [w_i(d_i^+ + d_i^-) + \alpha_i(e_i^+ + e_i^-)] \\ &\text{s.t:} \\ &\quad f_i(x) - d_i^+ + d_i^- = y_i, \qquad i = 1,2,\ldots,n \\ &\quad y_i - e_i^+ + e_i^- = g_{i,\max} \text{ or } g_{i,\min}, \qquad i = 1,2,\ldots,n \\ &\quad g_{i,\min} \leq y_i \leq g_{i,\max}, \qquad i = 1,2,\ldots,n \\ &\quad d_i^+, d_i^-, e_i^+, e_i^- \geq 0, \qquad i = 1,2,\ldots,n \\ &\quad x \in F \end{aligned} \tag{5}$$

where w_i and α_i are the weights attached to $d_i^{+,-}$ and $e_i^{+,-}$. e_i^+, e_i^- are positive and negative deviations of $|g_{i,\max} - y_i|$ or $|y_i - g_{i,\min}|$. $g_{i,\max}$ and $g_{i,\min}$ are the upper and lower bound of y_i. y_i is the continues variable between interval values $g_{i,\min}$ and $g_{i,\max}$. Other variables are the same as those in Model (4).

Although Model (5) resolves GP's shortage in definition of multiple goals for an objective, it considers no preferences of DMs in decision-making evaluations. Utility function is an important method to responses to the DM's preferences. Utility function defines in U: $X \rightarrow R$ form where X is a set of feasible values and R is a set of real number. The utility function assigns a real number for each preference. MCGP with utility function is an effective MODM method to response real-world problem, was first proposed by Chang [27]. The purpose of MCGP-U is to address MODM problems with considering DMs' preferences and maximizing expected utility of DMs. Four forms of utility functions have been proposed in the previous researches including convex, concave, s shaped and reverse s shaped. Chang [27] for the sake of simplicity combined two linear and s-shaped utility functions in MCGP model. In this study, linear utility function is implemented in the MCGP model. Linear utility functions can be stated in Eqs. (6) and (7).

$$u_i(y_i) = \begin{cases} 1, & \text{if } y_i \leq g_{i,\min} \\ \dfrac{g_{i,\max} - y_i}{g_{i,\max} - g_{i,\min}}, & \text{if } g_{i,\min} \leq y_i \leq g_{i,\max} \\ 0, & \text{if } y_i \geq g_{i,\max} \end{cases} \tag{6}$$

$$u_i(y_i) = \begin{cases} 1, & \text{if } y_i \geq g_{i,\max} \\ \dfrac{y_i - g_{i,\min}}{g_{i,\max} - g_{i,\min}}, & \text{if } g_{i,\min} \leq y_i \leq g_{i,\max} \\ 0, & \text{if } y_i \leq g_{i,\min} \end{cases} \tag{7}$$

where $g_{i,\min}$ and $g_{i,\max}$ are the lower and upper bounds of ith objective, respectively. The other variables are defined as before. Equation (6) relates to cases in which lower values are preferred and is named left linear utility function (LLUF) (shown in Fig. 6). As shown in Fig. 6, DMs in order to increase utility value of $u_i(y_i)$ should produce y_i value close to $g_{i,\min}$ value as much as possible. Equation (7) refers to situations in which higher values are preferred and is named right linear utility function (RLUF) (shown in Fig. 7). Also in RLUF, DMs in order to increase utility value of $u_i(y_i)$ should produce y_i value close to $g_{i,\max}$ value as much as possible. In the following, the formulations of MCGP with considering LLUF and RLUF are stated in Eqs. (8) and (9), respectively.

$$\begin{aligned} &\min \sum_{i=1}^{n} \left[w_i \left(d_i^+ + d_i^- \right) + \beta_i f_i^- \right] \\ &\text{s.t:} \\ &f_i(x) - d_i^+ + d_i^- = y_i, && i = 1, 2, \ldots, n \\ &g_{i,\min} \leq y_i \leq g_{i,\max}, && i = 1, 2, \ldots, n \\ &\lambda_i \leq \frac{g_{i,\max} - y_i}{g_{i,\max} - g_{i,\min}}, && i = 1, 2, \ldots, n \\ &\lambda_i + f_i^- = 1, && i = 1, 2, \ldots, n \\ &d_i^+, d_i^-, f_i^-, \lambda_i \geq 0, && i = 1, 2, \ldots, n \\ &x \in F \end{aligned} \tag{8}$$

$$\begin{aligned} &\min \sum_{i=1}^{n} \left[w_i \left(d_i^+ + d_i^- \right) + \beta_i f_i^- \right] \\ &\text{s.t:} \\ &f_i(x) - d_i^+ + d_i^- = y_i, && i = 1, 2, \ldots, n \\ &g_{i,\min} \leq y_i \leq g_{i,\max}, && i = 1, 2, \ldots, n \\ &\lambda_i \leq \frac{y_i - g_{i,\min}}{g_{i,\max} - g_{i,\min}}, && i = 1, 2, \ldots, n \\ &\lambda_i + f_i^- = 1, && i = 1, 2, \ldots, n \\ &d_i^+, d_i^-, f_i^-, \lambda_i \geq 0, && i = 1, 2, \ldots, n \\ &x \in F \end{aligned} \tag{9}$$

where w_i and β_i are the weights attached to the deviation values d_i and f_i^- respectively. λ_i is the utility value and f_i^- is the normalized deviation of $g_{i,\min}$. The other variables are defined as before.

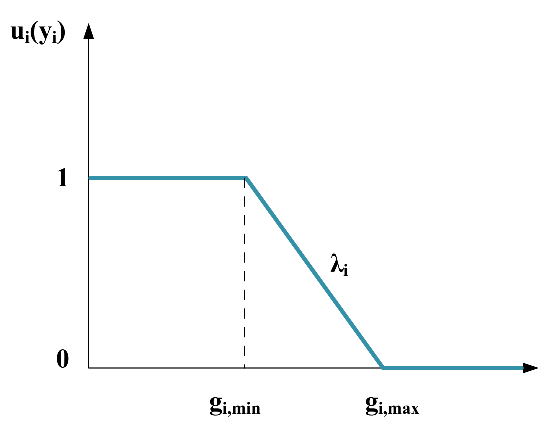

Fig. 6 Left linear utility function

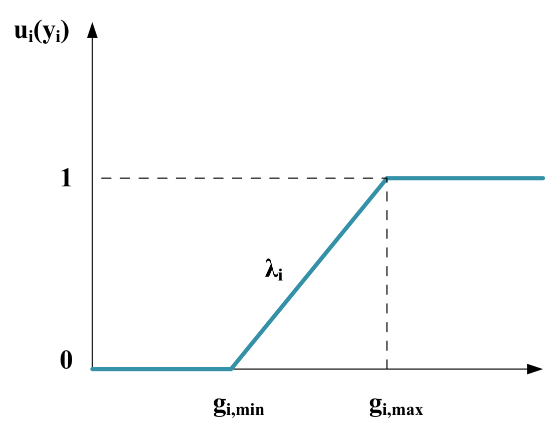

Fig. 7 Right linear utility function

Since the MCGP-U model is linear, so it can be solved using linear programming packages. Ability of measuring the utility values of DMs makes this model as an important technique in management and decision-making problems. However, incommensurability is a major issue in MCGP model. Incommensurability occurs when deviational variables with different units sum up directly and causing some unintentional bias toward the objectives with large magnitude [42]. So normalization and scaling methods must be done. However, Gass [43] mentioned that the selection of appropriate weights does not appear to cause GP problem formulation too much difficulty, as their problems tend to have few goals (< 100) and there usually are explicit reasons for the scale, weights and trade-offs between the goals. So Gass [43] incorporated the weights derived of AHP to GP model directly. Gass [43] stated that normalizing weights is simply part of whole weight that is absorbed by pairwise comparison weighing. Also, some researchers incorporated preferential weights derived of interactive MCDM methods directly to GP model. However, in this study, considering causal relationships of criteria, the FCM is used to determine the weights of criteria and priority of the goals.

3 Proposed framework

As mentioned before, the purpose of this study is to provide an integrated framework to evaluate and select suppliers based on the three methods of loss function, FCM and MCGP-U. Proposed approach includes three significant features. First, considers the imposed loss of deviations of intangible evaluation criteria values from specification limits by applying the TLF, second, determines the weights and priority of evaluation criteria based on the causal relationships between criteria and finally, the preferences of the DMs are considered in the supplier selection evaluations using MCGP-U. In the first step of the proposed framework, after eliciting the evaluation criteria from the recorded documents in the purchasing and suppliers' management department, regarding to the specified limits which have been assigned by the experts team of corporation, and according to the characteristic features of the criteria in terms of "the smaller/less the better" or "the larger/more the better," the TLF is used and consequently the loss coefficient and loss of each criteria for each supplier is assessed.

In the second phase, to determine the weights of supplier evaluation criteria, by considering the causal relationships, the FCM method is applied. In this step, criteria of supplier evaluation are assumed as concepts of FCM. In addition to these criteria, a node named "supplier evaluation" is considered as a target concept of the study. Then, according to the opinions of the experts, the causal relationships between concepts are determined and weighted. Thus, an initial weight matrix of causal relationships of concepts with elements between interval [− 1,1] is composed. This matrix is the main input of learning algorithm. Now, a scenario technique is used to measure the weight of each criterion, so that in each scenario, it is assumed that only one criterion is effective on the suppliers' evaluation process. In other words, in the calculations of the FCM for each scenario, only value of concept associated with the mentioned criterion has a value of 1 (active node). Then, the learning algorithm is executed according to the each defined scenario and initial weights matrix of causal relationships of concepts. The amount of output per target node caused by the implementation of each scenario (after acquiring a FCM to a stable structure) indicates the weight of each evaluation criterion. In fact, these weights are derived of direct and indirect effect of under evaluation criteria on the target concept of "supplier evaluation."

After determining the loss of each criterion and weights of evaluation criteria, total loss of each supplier is calculated. Total loss can be seen as a helpful method in decision making and in Pi and Low [20] study was considered as the only requirement to select the optimum supplier. However, the proposed approach in this study has improved the decision-making process, which is based on the both total loss values and utility values of DMs. Indeed, the proposed approach makes a trade-off between minimizing the total loss and maximizing the utility values of DMs, simultaneously. In other words, best supplier necessarily may not lead to the least total loss; however, the loss values are the significant factors in selecting the best supplier. The last step is implementing of the MCGP-U method as a decision-making alternative to select the optimal and best supplier. The MCGP-U model has been used in this step based on Eqs. (8) and (9) with respect to the utility feathers in terms of the less/more is better.

To implement MCGP-U method, first, the parameters of MCGP-U should be assigned. The parameters include deviations weights in objective function, upper and lower aspiration levels for goals, suppliers coefficients in each constraint and utility functions in constraints. Briefly, the weights of deviations (goals) in the objective function are determined by using FCMs. Also aspiration levels for each goal are assigned based on the DMs' opinions for the goals. Indeed, preferences of the DMs stated as aspiration levels of the model. In addition to that, the coefficients of variables (suppliers) in each constraint are the loss values of each supplier at the related criterion. Finally, based on the criteria characteristics (the smaller/less is better or the larger/more is better) an appropriate utility function (RLUF or LLUF) will be defined. For the sake of simplicity, linear utility function has been used in this study. In summary, the objective function of MCGP-U model tries to decrease the positive deviations for "the smaller/less is better" goals and negative deviations for "the larger/more is better" goals and increasing the excepted utility values of DMs by selecting an optimal supplier at the same time. As mentioned in Sect. 2 in the most cases of management problems, especially supplier selection problem, the utility values of objectives are more important than benefit of objectives and reaching to the goal. By implementing MCGP-U, a DM can increase expected utility of each objective. At last, model is solved using LINGO 16.0.33 software and the best supplier/s is selected. Detailed schematic view of the proposed framework is presented in Fig. 8.

4 Case study

In this section in order to illustrate the capability of the proposed framework to solve the real-world problem and to observe the results of proposed framework, the case study of U.A.CH has been investigated. U.A.CH manufacturing company started its activity in production of paint and coating industry, using advanced machinery and production lines with quality management systems, in an area of 4000 m^2 in the city of Urmia since 2010. The U.A.CH due to the high-quality production, innovation, extra value creation, efficiency and sustainable participation in markets is one of the premier brands in the paint and coating industry in the West Azerbaijan province of Iran and even some neighbor countries. Products of this company include 2250 tons plastic paint, 3150 tons traffic paint, 900 tons of oil paint and 3220 tons filling spray paint capacity each year. According to the production capacity, with a total capacity of 9500 tons, the U.A.CH Company is the second largest producer in producing a variety of colors in the West Azerbaijan province. The company's central laboratory is associated with the national organization of standard and industrial research; therefore, laboratory services needed by industries, especially the paint industry in the nationwide, could be provided. Also, research and development department of the company with the help of committed employers and broad set of facilities plays a significant role in promotion of quality and meets the customers updated needs. "Resins" and "Titanium dioxide" are the company's major required raw materials for the production of paint. "Resin" is liquid like adhesive, causes the paint adhesion and "Titanium dioxide" specifies color shades.

In the mentioned company, according to the outsourcing policy, raw material of "Resin" is considered as a product for study. According to records in the U.A.CH purchasing and suppliers' management department, company plans to purchase needed "Resin" from six qualified suppliers. After determination of the criteria used to evaluate suppliers based on information recorded in the purchasing and suppliers' management department and approved by the expert team, the proposed framework in Sect. 3 has been implemented. It should be noted that, in current situation, the company is able to meet its raw material needs from a supplier. However, due to the varying demands of market, limited capacity of suppliers and also uncertainty in working with only a supplier, the company to meet its raw material needs and to put the production in a secure and sustainable position, has inclination to select up to three suppliers. Therefore, different scenarios regarding to the number of suppliers (selecting up to three suppliers) are considered in the suppliers' evaluations.

According to information obtained, 11 criteria and goals to evaluate suppliers in the company of U.A.CH are selected. Criteria are selected according to the both recorded documents of suppliers at the purchasing and suppliers' management department and also the importance degree of criteria for the company's management. In the following 11 criteria are briefly explained. Briefly, price, quality and delivery time are the most significant criteria used in the researches to evaluate suppliers [8, 23]. In other words, on time delivery of the high-quality product with lower price, not only considered as competitive aspects of the firms but also are crucial factors in success of the organizations. On the other hand, customer's satisfaction criterion to keep current market share is important for producers. Environmental management system is a set of supplier's management actions to identify and to evaluate the effects of suppliers' activities on the environment to improve the environmental activities' efficiencies. This criterion can help both suppliers and buyers to meet the environmental protection agency's obligations, and consequently saving energy and material consumption. Also, research and development of new product is a crucial factor in company's survival. In industries with rapid development, manufacturers need to develop new design and increase their production continuously. Continuous changes in technologies, presence of competitors in the markets and customers changing priorities, make the development of the new products inevitable and important on buyer's perspective.

Technical capabilities and laboratory facilities are directly in a relation with the quality criterion; thus, it can be considered as a criterion in supplier's evaluation. In the other hand, due to the possibility of imposing additional cost of transportation to the buyers based on the content of the contract, it is better to select a supplier with better geographical position and appropriate availability to the company. Services provided when the product did not meet the expected expectations and inappropriate service can

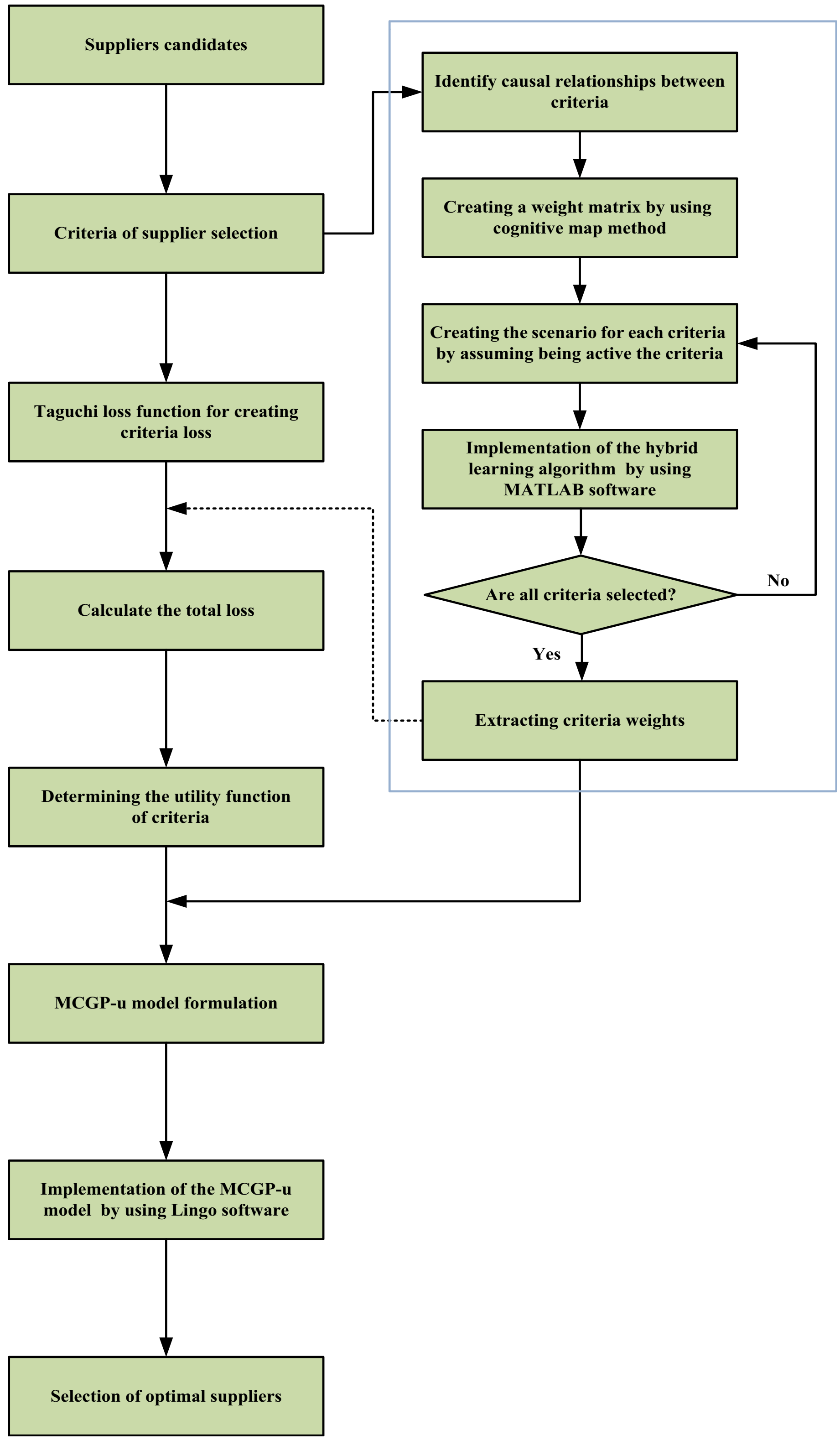

Fig. 8 Proposed framework for suppliers' evaluation in this study

affect DMs' decisions. Financial stability of the company to provide the capital needed to producing order of customers lead to considering this criterion in the evaluations. At last, suppliers' experience as an index to ensure buyers in terms of commitment to produce high-quality products with on time delivery is important. The values and relative values of criteria for each supplier and the specification limits for nine criteria have been presented in Table 1. For two criteria of the financial stability and experience, specification limits and quality loss coefficients (K) are not considered. However, the financial stability and experience of suppliers are considered important attributes for company's management and thus be included in the analysis. Moreover, specification limits are set based on the experts' opinions and company's policy, which are to improve the average loss for the next year and are expressed as the utility intervals in Table 2.

For better understanding Table 1 contexts, some of the values and specification limits are interpreted. For instance, concerning to the sales price criterion (the smaller/less is better), experts set the lowest offering price (100 thousand Tomans) as the target value of zero and upper specification limit is set as 15% which is the allowable deviation from target value. It means that loss will be zero for a supplier offering the lowest price and will be 100% for the supplier who offers the price 15% more (115 thousand Tomans) than the lowest price. For delivery time criterion (the smaller/less is better) DMs set, the specification limit of three working days, which indicates that 100% loss will be occurred if the suppliers delivery delay is three working days. About service criterion (the larger/more is better), DMs set the specification limit of 60%. Indeed, at the point of 60% service, loss will be 100% and loss will be zero at 100% service level. Geographical location (the smaller/less is better) specification limits like sales price is set based on the lowest distance (300 km is set as target value of zero) and upper specification limit is set at 20% more than the lowest distance. In the upper specification limit of geographical location, loss will be 100%. Other criteria definitions and values could be interpreted like these mentioned criteria. It should be noted that for experience and financial stability, loss coefficients and specification limits are not considered. However, these two criteria are important for the management and are considered in the evaluations to have a supplier selection problem with the combination of different criteria features.

5 Analysis of the results

In this section, the proposed framework presented in Fig. 8 has been conducted in the case study and the results are presented. In the first step of the proposed framework, the evaluation criteria based on the both recorded document in the purchasing and suppliers' management department and importance degree of criteria for company's management have been selected and are presented in Table 1. As it can be seen in Table 1, some of the criteria are difficult to quantify from the cost point of view. In this study, for example, to quantify some criteria like services, the Monczka and Trecha's [44] proposed method is used to quantify such criteria. Values and relative values of criteria are indicated in Table 1. Also, as mentioned before, the upper and lower specification limits are set based on the experts' decisions and are presented in Table 1.

Now, by utilizing the TLF and according to the specification limits, the loss of each criterion can be calculated. The loss value of each criterion is applicable in both calculating the total loss of suppliers and as coefficients of the suppliers in the MCGP-U model. For "the smaller/less is better" characteristics, loss will be zero in lower specification limits and 100% loss will occur in upper specification limits. As mentioned before, for instance, concerning to delivery time loss will be 100%, if the supplier's delivery delay is three working days and loss will be zero for receiving orders without delay. On the contrary, for "the larger/more is better" characteristics, loss will be zero in upper specification limits and will be 100% in lower specification limits. For example, loss will be zero if customer's satisfaction relative value is 100% and 100% loss will be occurring if customer satisfaction is in 80% specification limit. Table 2 completely presents the characteristic features, and calculated average loss coefficient from Eqs. (2) and (3) for each criterion. In addition to that, no loss is considered for the two criteria of financial stability and experience. However, as mentioned before, because of the financial stability and experience of suppliers' importance for company's management, these two criteria are included in the analysis. By considering these two criteria in the analysis, the problem is now comprised of nine criteria with quality loss coefficient (k) and two criteria without quality loss coefficient feature. Table 3 shows the calculated loss values of criteria for each supplier. Also the calculation of obtaining K is explained in Table 3.

At this point, the comparison of suppliers is impossible, unless the weighted sum of loss values (Total Loss) for each supplier is calculated. Calculating the total loss value for each supplier can be considered as a helpful tool in the supplier selection problem. However, total loss values may not lead to the best supplier in this problem necessarily. Since the best supplier should minimize the total loss and maximize the utility values of DMs simultaneously. Hence, by selecting the best supplier based on only the total loss value, the utility values and preferences of DMs are ignored. Consequently, there is need to use an extra model to consider both loss of criteria and preferences of DMs, simultaneously.

In order to calculate total loss, weighted sum of loss values is measured which are more reliable and real than measuring only the sum of loss values. So determination of the weight of each criterion is critical in the evaluations of total loss and then using in MCGP-U model to assess suppliers. Indeed, the weights calculated in this section also determine the priority of the goals in the proposed MCGP-

Table 1 Criteria values, relative values and specification limits

Evaluation criteria	Supplier 1		Supplier 2		Supplier 3		Supplier 4		Supplier 5		Supplier 6		Specification limits
	Value	Relative value	Value	Relative value	Value	Relative value	Value	Relative value	Value	Relative value	Value	Relative value	
Sales price (SP)	109 TT	9%	100 TT	0%	107 TT	7%	104 TT	4%	113 TT	13%	110 TT	10%	[0,15%]
Delivery time (DT)	2 days	2 days	3 days	3 days	1 day	1 day	0 day	0 day	1 day	1 day	2 days	2 days	[0,3 days]
Quality (Q)	98.8%	98.8%	98.2%	98.2%	98%	98%	99.5%	99.5%	99.1%	99.1%	97.6%	97.6%	[97,100%]
Customer satisfaction (CS)	85%	85%	82%	82%	88%	88%	80%	80%	91%	91%	83%	83%	[80,100%]
Environmental management systems (EMS)	93%	93%	90%	90%	88%	88%	90%	90%	95%	95%	85%	85%	[85,100%]
Research and development (R&D)	89%	89%	73%	73%	80%	80%	86%	86%	90%	90%	78%	78%	[75,100%]
Technical capabilities and laboratory facilities (TC&LF)	73%	73%	92%	92%	77%	77%	83%	83%	89%	89%	95%	95%	[70,100%]
Service (S)	90%	90%	68%	68%	75%	75%	84%	84%	92%	92%	95%	95%	[60,100%]
Geographical location (GL)	345 km	15%	330 km	10%	300 km	0	345 km	15%	321 km	7%	333 km	11%	[0,20%]
Financial stability (F)	14 BT	14 BT	7 BT	7 BT	8 BT	8 BT	11 BT	11 BT	12 BT	12 BT	9 BT	9 BT	–
Experience (E)	10 years	10 years	6 years	6 years	10 years	10 years	9 years	9 years	8 years	8 years	11 years	11 years	–

TT thousand Tomans, *BT* billion Tomans

Table 2 Criteria characteristic features and utility limits

Evaluation criteria	Criteria characteristics	K	Utility intervals to improve average loss	Expected loss ranges
Sales price (SP)	Less is better	444.40[a]	[1.5,3%]	[431.06,437.73]
Delivery time (DT)	Less is better	1.11	[2,5%]	[1.05,1.08]
Quality (Q)	More is better	9.40[b]	[5,8%]	[8.64,8.93]
Customer satisfaction (CS)	More is better	6.40	[0.5,3.5%]	[6.24,6.36]
Environmental management systems (EMS)	More is better	7.20	[3,5%]	[6.84,6.98]
Research and development (R&D)	More is better	5.60	[4,7%]	[5.20,5.37]
Technical capabilities and laboratory facilities (TC&LF)	More is better	4.90	[2.5,5.5%]	[4.63,4.77]
Service (S)	More is better	3.60	[2,4%]	[3.45,3.52]
Geographical location (GL)	Less is better	250	[0.5,2.5%]	[243.75,248.75]
Financial stability (F)	–	–	–	–
Experience (E)	–	–	–	–

[a] $L(Y_1) = k \cdot Y_1^2$ (for the smaller/less is better characteristics) where $L = 10$ (Taguchi loss at the upper specification limit) and $Y_1 = 0.15$ (upper specification limit set by the DM). Thus $k = 10/(0.15)^2 = 444.40$

[b] $L(X_1) = K/X_1^2$ (for the larger/more is better characteristics) where $L = 10$ (Taguchi loss at the lower specification limit) and $X_1 = 0.97$ (lower specification limit set by the DM). Thus $k = 10 * (0.97)^2 = 9.40$

Table 3 Loss values of the criteria for each supplier

Evaluation criteria	Supplier 1	Supplier 2	Supplier 3	Supplier 4	Supplier 5	Supplier 6
Sales price (SP)	3.59[a]	0	2.18	0.71	7.51	4.45
Delivery time (DT)	4.44	9.99	1.11	0	1.11	4.44
Quality (Q)	9.62[b]	9.74	9.78	9.49	9.57	9.86
Customer satisfaction (CS)	8.85	9.51	8.26	10	7.73	9.29
Environmental management systems (EMS)	8.32	8.88	9.29	8.88	7.97	9.96
Research and development (R&D)	7.06	10.50	8.75	7.57	6.91	9.20
Technical capabilities and laboratory facilities (TC&LF)	9.19	5.79	8.26	7.11	6.18	5.42
Service (S)	4.45	7.78	6.40	5.10	4.25	3.99
Geographical location (GL)	5.62	2.5	0	5.62	1.22	3.02
Financial stability (F)	–	–	–	–	–	–
Experience (E)	–	–	–	–	–	–
Total loss[c]	35.45	38.79	30.98	30.81	29.83	34.52

[a] $L(Y_1) = k.Y_1^2$ (for the smaller/less is better characteristics) where $k = 444.4$ (Taguchi loss coefficient for the sales price criterion) and $Y_1 = 0.09$ (the relative value of the sales price criterion for supplier 1).Thus $L = 444.4 * (0.09)^2 = 3.59$

[b] $L(X_1) = K/X_1^2$ (for the larger/more is better characteristics) where $k = 9.40$ (Taguchi loss coefficient for the quality criterion) and $X_1 = 0.988$ (the relative value of the quality criterion for supplier 1). Thus $L = \frac{9.40}{(0.988)^2} = 9.62$

[c] Total loss $= \sum_i w_i l_i$, where w_i is the weight of criterion i obtained from FCM and l_i is loss value of criterion i

U model. As mentioned before, in fact, due to the causal relationships between criteria and considering experts' opinions, it is difficult to assess the weights with simple MCDM techniques such as AHP. To deal with above complexity, an appropriate system with considering causal relationships between criteria to observe the effects of criteria on the evaluation of supplier concept can be a solution.

In this study, the weights are determined according to the causal relationships between criteria using the FCM method. Since each criterion may have indirect effect on supplier evaluation concept as well as direct effect. The FCM drawing requires to identify the concepts and determine the causal relationships between these concepts and weighing them, which are determined by proficient experts in the field of study [37, 40]. Therefore, the experience of the Cross Functional Team (including individuals

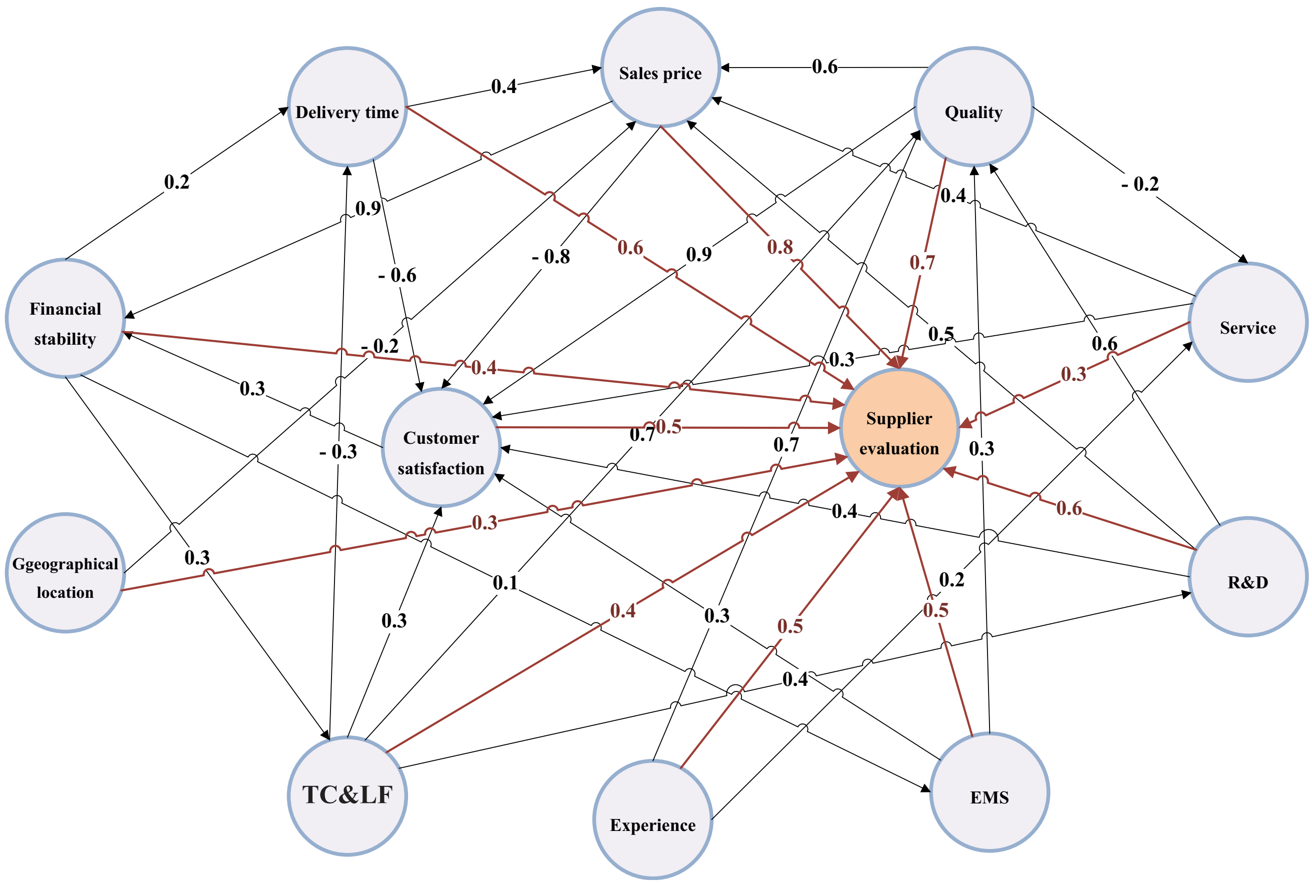

Fig. 9 Cognitive map of supplier evaluation criteria of the case study

belonging to the sectors and organizational levels that involved in the problem of company) has been used to determine the concepts of the FCM and the weights of the causal relationships between concepts. After initial weighing the relationships by experts' team, the final weight of each causal relationship between the concepts is calculated based on the agreement between the experts. Figure 9 clearly presents the initial weights of causal relationships considering experts' opinions. Depending on the types of the concepts' effects on each other, weights can take values between [− 1,1]. So that, if an increase/decrease in effect of a criterion leads to an increase/decrease in effect of another criterion, the weight of the causal relationship between these two criteria is considered to be more than zero (direct relationship) and if an increase/decrease in effect of a criterion leads to a decrease/increase in effect of another criterion, the weight of the causal relationship between these two criteria is considered to be less than zero (reverse relationship). At last, the weight of causal relationship between two criteria is zero, if criteria have no effects on each other.

In Fig. 9, causal relationships between 11 criteria and concept of "supplier evaluation" are indicated. The arcs between criteria presents the causal relationships between them and the values on the arcs shows the initial weights of criteria on each other. NHL–DE hybrid learning algorithm was run in MATLAB R2013a (8.1.0.604) software for each scenario and the weights of criteria are obtained and are summarized in Table 4. According to the FCM results, delivery time criterion with the weight of 0.743 has the most effect on the supplier evaluations. Also, research and development and financial stability are on the second and the third priorities with the weights of 0.728 and 0.711, respectively. On the other hand, the criterion of environmental management system has the least impact on the supplier evaluations with the weight of 0.441. After obtaining the criteria weights, now, calculation of each supplier total loss is possible.

The total loss of suppliers which have been shown in Table 3 can be considered as an extra tool in supplier selection decision making. According to the total loss values, supplier 5 has the least total loss and is optimal for the company in terms of total loss. In other words, selecting the supplier 5 as a supplier for next year leads to the lower loss for the company. However, it is not obvious that whether supplier 5 could lead to increase the utility values

Table 4 Weights assigned to each criterion by hybrid learning algorithm based on the FCM

Evaluation criteria	Initial weights	Final weights	Priority
Sales price (SP)	0.8	0.581	8
Delivery time (DT)	0.6	0.743	1
Quality (Q)	0.7	0.446	10
Customer satisfaction (CS)	0.5	0.615	6
Environmental management systems (EMS)	0.5	0.441	11
Research and development (R&D)	0.6	0.728	2
Technical capabilities and laboratory facilities (TC&LF)	0.4	0.631	5
Service (S)	0.7	0.590	7
Geographical location (GL)	0.3	0.552	9
Financial stability (F)	0.4	0.711	3
Experience (E)	0.5	0.695	4

of DMs too. So, in the last step of supplier selection problem of this study, MCGP-U model is used to evaluate suppliers and increase the expected utility values of DMs, simultaneously. The proposed model to select the optimal supplier makes a trade-off between minimizing the imposed loss of selecting supplier on the one hand and maximizing the utility values of DMs on the other hand. The MCGP-U model used in this study is presented in Appendix. Also, the preferences of DMs have been presented as intervals in Table 2. MCGP-U model's objective considers positive and negative deviations from goals, DMs' utility values and priorities of goals (weights) at the same time. Also constraints of MCGP-U model consist of the company's goals and utility functions. According to the records, management team established 11 goals which are demonstrated in Appendix. The coefficients of goals are the loss values of criteria deviation from specification limit for each supplier and the aspiration levels for goals are the experts expected intervals to improve the average loss for the next year.

After setting parameters of MCGP-U model, the model is solved using LINGO 16.0.33 extended version and supplier 5 selected as the optimal supplier to provide "Resin" for the company $(S_5 = 1, S_1 = S_2 = S_3 = S_4 = S_6 = 0)$. It should be noted that the purpose of the proposed model, in the first scenario, is to select only one supplier and since supplier variables are binary variables (0 or 1); therefore, the value of the supplier 5 is equal to 1 and for other suppliers will be zero to satisfy the Eq. (55) in Appendix. As it is obvious in the results, the supplier 5 has the best performance (the least loss value) in the criteria of research and development, customer satisfaction and environmental management systems which have the 2nd, 6th and 11th priorities with the weights of 0.728, 0.615 and 0.441, respectively. Also, the supplier 5 has the second best performance in the criteria of delivery time, financial stability and quality which have the 1st, 3rd and 10th priorities for DMs, respectively. Due to the high performance of the supplier 5 in mentioned criteria and the priority weights of these criteria, so it was expected that the supplier 5 to be selected as the optimal supplier. On the other hand, although the supplier 5 has the weakest performance in the sales price criterion, due to the low impact of this criterion on the evaluation, the supplier 5 will remain the optimal supplier of in this study. Also this result is comparable to the results presented in Table 3. Since the optimal supplier both increases the DMs' utility values and decreases the loss imposed to the company, simultaneously, among all suppliers, the supplier 5 has this feature. In other words, among these six suppliers, supplier 5 with the total loss value of 29.83 has the least total loss value and increases DMs utility values at the same time. All variable values are presented in Table 5.

As it obtained from Table 5 obviously, all criteria were satisfied fully expect financial stability and experience. For the fully satisfied goals, the value of λ is equal to 1 and consequently the values of f^- are 0, which confirms that the DMs expected aspiration levels have been met. However, the utility values for the financial stability and the experience criteria are 0.40 and 0.72, respectively which shows that only a part of preference of DMs is satisfied and expected aspiration levels for these two criteria are not completely satisfied. It should be noted that the utility function for these two criteria was RLUF, since the larger values of these two criteria was desirable for DMs.

As mentioned in Sect. 4, company in order to meet its varying demand for raw material and to put the production in a secure and sustainable position tends to evaluate up to three suppliers, so different scenarios based on the number of selected suppliers are considered. First scenario is to select a supplier which was evaluated and analyzed before. The second scenario is to select two suppliers for the contract of outsourcing raw material. In this scenario, model is solved using LINGO 16.0.33 software and suppliers 5 and 4 are the selected suppliers $(S_4 = S_5 = 1\ , S_1 = S_2 = S_3 = S_6 = 0)$. Also, the results of implementing second scenario

Table 5 Variable values obtained from implementing MCGP-U model for three scenarios

Evaluation criteria	$\sum_{n=1}^{6} S_n = 1$			$\sum_{n=1}^{6} S_n = 2$			$\sum_{n=1}^{6} S_n = 3$		
	λ_i	f_i^-	y_i	λ_i	f_i^-	y_i	λ_i	f_i^-	y_i
Sales price (SP)	1	0	431.06	1	0	431.06	1	0	431.06
Delivery time (DT)	1	0	1.05	1	0	1.05	1	0	1.05
Quality (Q)	1	0	9.77	1	0	9.77	1	0	9.77
Customer satisfaction (CS)	1	0	6.24	1	0	6.24	1	0	6.24
Environmental management systems (EMS)	1	0	6.84	1	0	6.84	1	0	6.84
Research and development (R&D)	1	0	5.20	1	0	5.20	1	0	5.20
Technical capabilities and laboratory facilities (TC&LF)	1	0	4.63	1	0	4.63	1	0	4.63
Service (S)	1	0	3.45	1	0	3.45	1	0	3.45
Geographical position	1	0	243.75	1	0	243.75	1	0	243.75
Financial stability (F)	0.72	0.28	12	1	0	14	1	0	14
Experience (E)	0.40	0.60	8	1	0	11	1	0	11
Selected suppliers	S_5			S_4, S_5			S_4, S_5, S_6		

are presented in Table 5. Like the first scenario, model tries to make a trade-off between decreasing total loss and increasing utility values of DMs. So as it can be seen, the supplier 4 which has the second least total loss value is selected as the second supplier besides the supplier 5 to provide the needed raw material for the company if needed. Also all utility values are maximized in this scenario which is one of the main purposes of this study. Third scenario is to select three suppliers. According to the last two scenarios, it seems that supplier 3 is selected due to its low total loss value besides suppliers 4 and 5. But after calculations, suppliers 4, 5 and 6 selected as optimal suppliers ($S_4 = S_5 = S_6 = 1$, $S_1 = S_2 = S_3 = 0$). Indeed, the set of suppliers 4, 5 and 6 can better increase the utility values for DMs and as it can be seen in Table 5, utility values are fully satisfied. The result verifies that suppliers with the low values of total loss necessarily may not lead to increase the utility values of DMs and be selected as optimal suppliers. Also, this model could be solved by conventional MCGP, but conventional MCGP is unable to calculate the utility values of model and this may be a major issue in the management and decision-making problems. Since utility values for DM may be more valuable than benefit of the achieving goal.

Generally, the main reason of using MCGP-U in this study is to consider the preferences of DMs in the supplier selection problem. However, the loss values of deviations of criteria from specification limits for each supplier and the priority of goals and criteria according to the causal relationships are also considered. The privilege of the proposed integrated framework is to enable DMs to benefit from each method's individual advantage simultaneously. The TLF provides DMs a common value of quality loss which makes the comparisons of alternatives much easier and meaningful [24]. Additionally, the priority of criteria and goals is important for management in the real-world problems. Hence, determination of each goal weight is a critical issue. In the most of the previous studies, MCGP and GP models goals' weights are assigned based on the traditional MCDM techniques such as AHP and ANP. For example, among the MCDM techniques, the nearest method that is able to consider the interactions between the criteria and options is ANP method. However, this technique shortcoming in applying in the problems with high numbers of criteria, lack of being intelligent, high dependency to the experts' opinions and the inability to consider relations from higher levels to lower levels led to apply FCM approach to assign the weights of criteria. The FCM strengths in considering causal relationships of concepts, increasing the reliability of results due to use of learning algorithms, being intelligent and lower dependency to the experts' opinions make this method superior than other techniques in determining the weights of criteria in researches [16, 39] and in this study, to determine the criteria and goals weights, FCM is applied which has never undertaken before. Therefore, the weaknesses of the previous studies in assigning the weights of criteria are covered and make the results more reliable and valid.

6 Summary and conclusion

In the high competitive raw material and finished product markets, decision making to select the best supplier is critical issue that most managers are concerned with. The purpose of this study was to propose an integrated framework to help DMs to select an optimal supplier with considering some of required features of such problem. The integrated framework was proposed in three main phases. In the first phase, after selection of evaluation criteria according to the recorded document in purchasing and suppliers' management department and specification limits determined by experts' opinions, the loss of each criterion for all suppliers was calculated using the TLF. Indeed, the TLF was used to minimize the loss imposed of deviation of criteria value from specification limit. On the other hand, since the criteria can affect each other directly or indirectly, it is essential to obtain the real weight of each criterion for next phase computations by considering causal relationships between criteria and inclusion of expert's opinions simultaneously. Thus, in the second phase of the proposed framework, FCM and NHL–DE hybrid learning algorithm were used to analyze the relationships and interactions of criteria with each other. In other words, the results of this phase determined the weights of criteria and priority of the goals, more realistic and reliable.

Eventually, in the last phase of integrated framework, the MCGP-U model was employed. The proposed framework considers the output of first two phases and DMs' preferences as inputs of MCGP-U model. In fact, each criterion's loss impacts the linear function of goals to reach the less average loss aspiration level and weights can determine the priority and weights of the goals. The output of last phase was the optimal supplier with the least total loss value and maximum utility values. The MCGP-U model allows DMs to set their preferences in form of utility function. The result of the proposed framework was conducted in an active company in paint and coating industry. The result showed that the supplier 5 selected as the optimal supplier to contract and will provide the demanded "Resin". Moreover, to meet the varying demands of market and to put production in a secure and sustainable position, up to three suppliers are evaluated in three various scenarios. The results of scenarios confirmed the model capability in selecting the best supplier based on the two features of total loss values and the preferences of DMs.

The proposed integrated framework is applicable to a variety of supplier selection problems in various industries based on the conventional criteria and other criteria appropriate to the nature of the industry. Furthermore, the proposed framework can be beneficial for many decision-making problems such as portfolio selection, transportation problems, location problems. Also, linguistic preference relations can be used to define the relationships between concepts of FCM in future research.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

$$\begin{aligned}\operatorname{Min} Z = {} & 0.581\left(d_1^+ + f_1^-\right) + 0.743\left(d_2^+ + f_2^-\right) \\ & + 0.446\left(d_3^+ + f_3^-\right) + 0.615\left(d_4^+ + f_4^-\right) \\ & + 0.441\left(d_5^+ + f_5^-\right) + 0.728\left(d_6^+ + f_6^-\right) \\ & + 0.631\left(d_7^+ + f_7^-\right) + 0.590\left(d_8^+ + f_8^-\right) \\ & + 0.552\left(d_9^+ + f_9^-\right) + 0.711\left(d_{10}^- + f_{10}^-\right) \\ & + 0.695\left(d_{11}^- + f_{11}^-\right)\end{aligned} \tag{10}$$

Equation (10) is the objective function of proposed model and minimizes the deviations of goals from aspiration levels to satisfy the utility values of DM. The calculated weights are multiplied to the goals indicate the priority of goals based on the causal relationships between goals.

$$\begin{aligned}& 3.59(S_1) + 2.18(S_3) + 0.71(S_4) + 7.51(S_5) + 4.45(S_6) \\ & \quad - d_1^+ + d_1^- = y_1\end{aligned} \tag{11}$$

Equation (11) represents the sales price criterion goal (the less is better goal). It should be noted that, the goal is to decrease the loss, so the less is better for such goals. Coefficients are the loss values of suppliers for the sales price criterion.

$$431.06 \le y_1 \le 437.73 \tag{12}$$

Equation (12) represents the y bound for the sales price criterion.

$$\lambda_1 \le \frac{437.73 - y_1}{6.67} \tag{13}$$

Equation (13) represents LLUF (for the less is better).

$$\lambda_1 + f_1^- = 1 \tag{14}$$

Equation (14) represents the high value of 1 for utility values. In cases that utility value is not perfect, it can take value in [0,1].

$$\begin{aligned}& 4.44(S_1) + 9.99(S_2) + 1.11(S_3) + 1.11(S_5) + 4.44(S_6) \\ & - d_2^+ + d_2^- = y_2\end{aligned} \tag{15}$$

Equation (15) represents the delivery time goal function (the less is better goal).

$$1.05 \leq y_2 \leq 1.08 \tag{16}$$

Equation (16) represents the y bound for the delivery time criterion.

$$\lambda_2 \leq \frac{1.08 - y_2}{0.03} \tag{17}$$

Equation (17) represents LLUF (for the less is better).

$$\lambda_2 + f_2^- = 1 \tag{18}$$

Equation (18) represents the high value of 1 for utility values.

$$9.62(S_1) + 9.74(S_2) + 9.78(S_3) + 9.49(S_4) + 9.57(S_5) + 9.86(S_6) - d_3^+ + d_3^- = y_3 \tag{19}$$

Equation (19) represents the quality goal function (the less is better goal).

$$8.84 \leq y_3 \leq 8.93 \tag{20}$$

Equation (20) represents the y bound for the quality criterion.

$$\lambda_3 \leq \frac{8.93 - y_3}{0.29} \tag{21}$$

Equation (21) represents LLUF (for the less is better).

$$\lambda_3 + f_3^- = 1 \tag{22}$$

Equation (22) represents the high value of 1 for utility values.

$$8.85(S_1) + 9.51(S_2) + 8.26(S_3) + 10.00(S_4) + 7.73(S_5) + 9.29(S_6) - d_4^+ + d_4^- = y_4 \tag{23}$$

Equation (23) represents the customer satisfaction goal function (the less is better goal).

$$6.24 \leq y_4 \leq 6.36 \tag{24}$$

Equation (24) represents the y bound for the customer satisfaction criterion.

$$\lambda_4 \leq \frac{6.36 - y_4}{0.12} \tag{25}$$

Equation (25) represents LLUF (for the less is better).

$$\lambda_4 + f_4^- = 1 \tag{26}$$

Equation (26) represents the high value of 1 for utility values.

$$8.32(S_1) + 8.88(S_2) + 9.29(S_3) + 8.88(S_4) + 7.97(S_5) + 9.96(S_6) - d_5^- + d_5^- = y_5 \tag{27}$$

Equation (27) represents the environment management systems goal function (the less is better goal).

$$6.84 \leq y_5 \leq 6.98 \tag{28}$$

Equation (28) represents the y bound for the environment management systems criterion.

$$\lambda_5 \leq \frac{6.98 - y_5}{0.14} \tag{29}$$

Equation (29) represents LLUF (for the less is better).

$$\lambda_5 + f_5^- = 1 \tag{30}$$

Equation (30) represents the high value of 1 for utility values.

$$7.06(S_1) + 10.50(S_2) + 8.75(S_3) + 7.57(S_4) + 6.91(S_5) + 9.20(S_6) - d_6^+ + d_6^- = y_6 \tag{31}$$

Equation (31) represents the research and development goal function (the less is better goal).

$$5.20 \leq y_6 \leq 5.37 \tag{32}$$

Equation (32) represents the y bound for the research and development criterion.

$$\lambda_6 \leq \frac{5.37 - y_6}{0.17} \tag{33}$$

Equation (33) represents LLUF (for the less is better).

$$\lambda_6 + f_6^- = 1 \tag{34}$$

Equation (34) represents the high value of 1 for utility values.

$$9.19(S_1) + 5.79(S_2) + 8.26(S_3) + 7.11(S_4) + 6.18(S_5) + 5.42(S_6) - d_7^+ + d_7^- = y_7 \tag{35}$$

Equation (35) represents the technical capabilities and laboratory facilities goal function (the less is better goal).

$$4.63 \leq y_7 \leq 4.77 \tag{36}$$

Equation (36) represents the y bound for the technical capabilities and laboratory facilities criterion.

$$\lambda_7 \leq \frac{4.77 - y_7}{0.14} \tag{37}$$

Equation (37) represents LLUF (for the less is better).

$$\lambda_7 + f_7^- = 1 \quad (38)$$

Equation (38) represents the high value of 1 for utility values.

$$4.45(S_1) + 7.78(S_2) + 6.40(S_3) + 5.10(S_4) + 4.25(S_5) + 3.99(S_6) - d_8^+ + d_8^- = y_8 \quad (39)$$

Equation (39) represents the services goal function (the less is better goal).

$$3.45 \le y_8 \le 3.52 \quad (40)$$

Equation (40) represents the y bound for the services criterion.

$$\lambda_8 \le \frac{3.52 - y_8}{0.07} \quad (41)$$

Equation (41) represents LLUF (for the less is better).

$$\lambda_8 + f_8^- = 1 \quad (42)$$

Equation (42) represents the high value of 1 for utility values.

$$5.62(S_1) + 2.50(S_2) + 5.62(S_4) + 1.22(S_5) + 3.02(S_6) - d_9^+ + d_9^- = y_9 \quad (43)$$

Equation (43) represents the geographical location goal function (the less is better goal).

$$243.75 \le y_9 \le 248.75 \quad (44)$$

Equation (44) represents the y bound for the geographical location criterion.

$$\lambda_9 \le \frac{248.75 - y_9}{5} \quad (45)$$

Equation (45) represents LLUF (for the less is better).

$$\lambda_9 + f_9^- = 1 \quad (46)$$

Equation (46) represents the high value of 1 for utility values.

$$14(S_1) + 7(S_2) + 8(S_3) + 11(S_4) + 12(S_5) + 9(S_6) - d_{10}^+ + d_{10}^- = y_{10} \quad (47)$$

Equation (47) represents the financial stability goal function (the more is better goal). Coefficients are the financial stability values of suppliers.

$$7 \le y_{10} \le 14 \quad (48)$$

Equation (48) represents the y bound for the financial stability criterion.

$$\lambda_{10} \le \frac{y_{10} - 7}{7} \quad (49)$$

Equation (49) represents RLUF (for the more is better).

$$\lambda_{10} + f_{10}^- = 1 \quad (50)$$

Equation (50) represents the high value of 1 for utility values.

$$10(S_1) + 6(S_2) + 10(S_3) + 9(S_4) + 8(S_5) + 11(S_6) - d_{11}^+ + d_{11}^- = y_{11} \quad (51)$$

Equation (51) represents the experience goal function (the more is better goal). Coefficients are the experience values of suppliers.

$$6 \le y_{11} \le 11 \quad (52)$$

Equation (52) represents the y bound for the experience criterion.

$$\lambda_{11} \le \frac{y_{11} - 6}{5} \quad (53)$$

Equation (53) represents RLUF (for the more is better).

$$\lambda_{11} + f_{11}^- = 1 \quad (54)$$

Equation (54) represents the high value of 1 for utility values.

$$S_1 + S_2 + S_3 + S_4 + S_5 + S_6 = 1 \quad (55)$$

Equation (55) shows that a supplier selection constraint.

$$\begin{aligned} &S_i \in \{0, 1\}, \quad i = 1, \ldots, 6 \\ &\lambda_j, y_j, d_j^+, d_j^-, f_j^- \ge 0, \quad j = 1, \ldots, 11 \end{aligned} \quad (56)$$

Equation (56) specifies variable types of the model.

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