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DEVELOPMENT OF A ROUGH-MABAC-DoE-BASED METAMODEL FOR SUPPLIER SELECTION IN AN IRON AND STEEL INDUSTRY

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Abstract: *In the context of supply chain management, supplier selection can be defined as the process by which organizations score and evaluate a range of alternative suppliers to choose the best possible one who can provide superior quality of raw materials at cheaper rate and lesser lead time. It is a decision making process with multiple trade-offs between various conflicting criteria which in turn helps the organizations identify the suitable suppliers that would establish a robust supply chain assisting in maintaining a competitive edge. The main objective of supplier selection is thus focused on reducing purchase risk, maximizing overall value to the organization, and developing closeness and long-term relationships between the suppliers and the organization. In this paper, while selecting the most suitable supplier for gearboxes in an Indian iron and steel industry, assessments of three decision makers on the performance of five candidate suppliers with respect to five evaluation criteria are first aggregated using rough numbers. The definitive distances of those rough numbers are then treated as the inputs to a 2^5 full-factorial design plan with the corresponding multi-attributivec border approximation area comparison (MABAC) scores as the output variables. Finally, a design of experiments (DoE)-based metamodel is formulated to interlink the computed MABAC scores with the considered criteria. The competing suppliers are ranked based on this rough-MABAC-DoE-based metamodel, which also easies out the computational steps when new suppliers are included in the decision making process.*

Key words: *Supplier selection; Rough numbers; MABAC; DoE; Metamodel*

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1. Introduction

In the light of present day COVID-19 pandemic situation, the importance of a robust supply chain management system has been reasserted. The goals of a supply chain have been newly oriented opting for a fair balance between the global and local networks. This has made industries in diverse sectors to reconsider their existing choices and identify the most reliable suppliers to keep their raw material supplies uninterrupted without compromising on quality, specially under uncertain environment. This problem has intensely been pronounced in the manufacturing sector which needs to keep up with its production to meet the global requirements irrespective of the prevailing situation (Vonderembse and Tracey, 1999). Iron and steel industry is one such important manufacturing sector that needs regular supplies of raw materials; therefore, a critical analysis is demanding while selecting an appropriate set of suppliers. It involves a well informed and rigorous research regarding the possible parameters based on which the candidate suppliers for a particular item should be evaluated to single out the most appropriate supplier while scraping out the unsuitable ones (Verma and Pullman, 1998). In this direction, application of any of the existing multi-criteria decision making (MCDM) techniques would be quite helpful as it has the ability to identify the most apposite supplier to provide the right quantity of material with right quality at right time and right price based on a set of conflicting evaluation criteria (Mukherjee, 2017).

The MCDM is the science which takes into account different criteria with varying degrees of importance to search out the most suitable option/course of action. The first step involves in development of the initial decision matrix exhibiting the relative performance of each of the candidate alternatives with respect to the considered criteria. In this step, there may be participation of a group of experts/decision makers, each opining and assigning performance scores to the available alternatives based on each criterion. In the second step, again based on the judgments of the decision makers, relative weights are allocated to all the criteria depending on their importance to the decision making problem under consideration. The final step involves in ranking of the set of alternatives from the best to the worst. The application potentiality of MCDM methodologies in solving complex manufacturing-related decision making problems has attracted attention of the researchers leading to the development of different innovative ranking techniques, like analytic hierarchy process (AHP) (Saaty, 1988), technique for order of preference by similarity to ideal solution (TOPSIS) (Behzadian et al., 2012), grey relational analysis (GRA) (Abdulshahed et al., 2017), multi-attributive border approximation area comparison (MABAC) (Pamučar and Ćirović, 2015), measurement of alternatives and ranking according to compromise solution (MARCOS) (Stević et al., 2020; Mahmutagić et al. 2021) etc. While all these methods have their unique mathematical foundations, their implementation in a manufacturing industry largely depends on the ease of implementation and ability to generate accurate ranking results. The MABAC is one such methodology which can provide a detailed analysis of the alternatives while partitioning them into upper, lower and border approximation areas along with identification of their relative strengths and weaknesses with respect to each of the criteria.

However, there is a major challenge associated with formulation of the decision matrix due to uncertainty/vagueness involved in human judgment. Usually, the criteria set based on which the candidate alternatives are assessed consists of both quantitative and qualitative attributes. For qualitative criteria, it becomes difficult for the team of decision makers to assign exact deterministic values. In these cases, performance scores of the alternatives with respect to the qualitative criteria are assigned based on imprecise linguistic judgments which greatly vary from one decision maker to the other. Although, it is remarkably important to account for this vagueness while solving critical decision making problems, like supplier selection, it cannot be denied that implementation of fuzzy MCDM techniques is more mathematically complex, involving choice of appropriate fuzzy membership functions affecting the final selection decision. In this direction, a lot of methodologies have already been proposed to aggregate the subjective performance scores of the alternatives. It has been noticed that application of rough numbers with uncomplicated mathematical steps can effectively resolve the problem of dealing with qualitative criteria in a decision making problem (Zhai et al., 2009). Rough numbers have efficiently been integrated with other MCDM tools, like analytic network process (ANP) and TOPSIS (Li et al., 2018), complex proportional assessment (COPRAS) (Matić et al., 2019), additive ratio assessment (ARAS) (Radović et al., 2018), AHP and MABAC (Roy et al., 2018; Pamučar et al., 2018a), best worst method (BWM) and weighted aggregated sum product assessment (WASPAS) (Stević et al., 2018; Stojić et al., 2018), BWM and simple additive weighting (SAW) (Stević et al., 2017), step-wise weight assessment ration analysis (SWARA) and WASPAS (Sremac et al., 2018), AHP and TOPSIS (Shojaei and Bolvardizadeh, 2020) etc.

In most of the MCDM techniques, the corresponding ranking results are derived based on pair-wise or relative comparisons between the candidate alternatives, which make the decision making process more tedious and time consuming. Whenever a new alternative enters into the decision making process or an existing alternative leaves the process, the entire computational procedure needs to be reinitiated from the scratch. In most of the practical situations, the set of alternatives always keeps on changing. For example, in an iron and steel industry, it has often been noticed that a new supplier may reach out, while an existing supplier may fall off the list due to poor/failing standards. Learning from the recent times of vulnerability and uncertainty, it is recommended to keep the list of participating suppliers always dynamic.

In this paper, an MCDM methodology integrating rough numbers, MABAC method and design of experiments (DoE) is proposed to account for the vagueness involved in the group decision making process while providing detailed analysis of the derived results at the same time. In an iron and steel industry, the relative performance of five participating suppliers is appraised by three decision makers with respect to five evaluation criteria based on a 1-9 scale. These subjective judgments of the decision makers are then aggregated to form the initial decision matrix using rough numbers. With five evaluation criteria, a 2^5 full-factorial experimental design plan is formulated along with determination of the corresponding MABAC score for each of the experimental trials. In this methodology, different evaluation criteria and MABAC scores are respectively treated as the design parameters and responses in the DoE to develop a metamodel. Based on this metamodel, the composite score of any supplier can easily be calculated in a single step, thus relieving the decision maker from complex and time-consuming computational steps. In other MCDM techniques, the concerned decision maker needs to reinitiate the entire calculation steps when a new supplier enters into or leaves out the existing list of candidate alternatives. But, in this developed metamodel, the respective score along with the rank of a new supplier can easily be estimated while putting the corresponding performance values into the model. Similarly, the relative ranking of the suppliers can quickly be updated when an existing supplier leaves the appraisal process. Simply, the computational burden would be remarkably reduced using this metamodel in the supplier selection process.

The rest of this paper is organized as follows. Section 2 reviews the recent literature dealing with the application of different MCDM techniques in solving diverse supplier selection problems. In Section 3, mathematical details of rough numbers, MABAC method and DoE are presented. Section 4 deals with a case study where the proposed rough-MABAC-DoE method is adopted for identifying the most appropriate supplier in an Indian iron and steel industry. Conclusions are drawn in Section 5 along with the future directions.

2. Literature review

The present literature is flooded with the applications of various mathematical techniques, especially MCDM tools, for identification of the suitable suppliers to fulfill the requirements of a diverse range of organizations. The supplier selection process generally starts with listing the right set of criteria based on which the competing suppliers are appraised. This criteria set obviously varies from one industry to the other depending on the requirements and end products. The process terminates with the application of a suitable methodology to single out the most appropriate supplier for a given organization. Zimmer et al. (2016) conducted an exhaustive literature survey to list down all the possible criteria that can be accounted for selection of sustainable suppliers along with diverse methodologies implemented to rank them.

Luzon and El-Sayegh (2016) adopted Delphi method along with AHP to select suppliers for oil and gas projects, while classifying the considered criteria into techno-commercial and organizational aspects. Kumar et al. (2018) designed a capital procurement decision making model by integrating fuzzy-Delphi and AHP-decision making trial and evaluation laboratory (DEMATEL) methods for selecting suppliers for a given organization. Yazdani et al. (2017) proposed an integrated quality function deployment (QFD)-MCDM-based approach for green supplier selection while considering several important evaluation criteria, like quality adaptation, price, energy and natural resource consumption, and delivery speed. While treating cost of products, quality of products, service provided, capability of delivering on time, technology level, environmental management system and green packaging as the evaluation criteria, Abdullah et al. (2018) applied preference ranking organization method for enrichment of evaluations (PROMETHEE) for solving a green supplier selection problem. Badi et al. (2018) proposed the application of combinative distance-based assessment (CODAS) method for solving a supplier selection problem for a steel making industry in Libya, which considering quality, direct cost, lead time and logistics services as the main evaluation criteria. In a group decision making environment, Badi and Ballem (2018) integrated rough-BWM with multi-attribute ideal real comparative analysis (MAIRCA) to assess the performance of pharmaceutical suppliers based on cost, quality, supplier profile, delivery and flexibility criteria. A study was conducted by Banaeian et al. (2018) to evaluate and select green suppliers for an agri-food industry while combining fuzzy set theory with VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), GRA and TOPSIS methods, and considering service level, quality, price and environmental management system as the evaluation criteria. Akcan and Güldeş (2019) applied several integrated MCDM methodologies, like AHP-TOPSIS, AHP-SAW, AHP-GRA and AHP-elimination et choice translating reality (ELECTRE) to rank suppliers based on logistics, cost, quality, flexibility and reliability criteria.

While accounting for the uncertainties involved in a group decision making process, Chattopadhyay et al. (2020) proposed the application of D-MARCOS method for solving a supplier selection problem in a steel industry with product quality, delivery compliance, price, technical capability, production capability, financial strength and electronic transaction capability as the evaluation criteria. In order to deal with both weighting of the criteria and uncertainty in group decision making, Javad et al. (2020) combined BWM with fuzzy TOPSIS to rank green suppliers in a steel company considering collaborations, environmental investments and economic benefits, resource availability, green competencies, environmental management initiatives, research and design initiatives, green purchasing capabilities, regulatory obligations, pressures and market demand as the major selection criteria. Stević et al. (2020) endeavored to prove the application potentiality of a new MCDM methodology in the form of MARCOS to assess and rank sustainable suppliers in healthcare sector with an exhaustive set of 21 criteria. Wang et al. (2020) first employed fuzzy-AHP method to determine weights of reliability, responsiveness, flexibility, cost and assets criteria, and later adopted PROMETHEE to rank the competing suppliers in a textile industry.

It has been revealed from the above-cited literature that selection of suppliers for varying organizations based on a set of conflicting evaluation criteria is really a complicated problem to solve, especially in group decision making environment involving a degree of uncertainty with respect to human judgments. To resolve this issue, several hybridized models have already been proposed. However, most of those models are computationally expensive which hinders their applications in real-time manufacturing scenario. In all those models, with the addition of a new alternative or deletion of an existing alternative from the set disrupts the entire calculation process and it needs to be reinitiated from the scratch in each occasion. Taking these drawbacks of the existing hybridized MCDM tools in solving supplier selection problems, this paper proposes to develop a DoE-based metamodel in the form of an regression equation while integrating rough numbers with the advantageous features of MABAC method. The performance scores of the alternative suppliers with respect to the evaluation criteria are aggregated using rough numbers in a group decision making environment having three participating decision makers and the competing suppliers are finally ranked from the best to the worst using the computed MABAC scores. Based on the developed metamodel, the performance score of a new supplier can easily be computed, thus relieving the concerned decision maker from lengthy repetitive calculation steps. Keeping in mind the requirements and importance of selection of suppliers, the applicability of this integrated rough-MABAC-DoE method is demonstrated here to appraise and rank five different suppliers in a leading steel manufacturer in India based on five pivotal criteria in a group decision making environment.

3. Methods

3.1. Rough numbers

One of the biggest challenges associated with group decision making is the uncertainty and vagueness involved in determining the relative weights of different criteria and performance appraisal of the candidate suppliers with respect to those criteria. In this direction, various methodologies, like fuzzy set theory, intuitionistic fuzzy set, D numbers etc. have been proposed. In this paper, the application potentiality of rough numbers in assessing the performance of the considered alternatives with regard to five evaluation criteria while solving a supplier selection problem is explored. Rough numbers have become popular due to their simplicity and adaptability while taking into account linguistic judgments of different decision makers based on boundary intervals using lower and upper limits (Zhai et al., 2008). Zhai et al. (2009) further introduced interval arithmetic to analyze and operate rough numbers.

Let *U* be the universal set comprising all the objects, *X* is an arbitrary object of *U*, and *R* is a set of *n* clases $R = \{C_1,C_2,\ldots,C_n\}$ covering all the objects in *U*. If these *n* classes are ordered as $\{C_1 < C_2 <\ldots< C_n\}$, then $\forall X \in U, C_q \in R$, $1 \le q \le n$, where $R(X)$ denotes the class to which the object belongs. The lower approximation $(\underline{Apr}(C_q))$, upper approximation $(\overline{Apr}(C_q))$ and boundary region $(Bnd(C_q))$ of class C_q are given as below:

$$\overline{Apr}(C_q) = \cup\{X \in U / R(X) \ge C_q\} \tag{1}$$

$$\underline{Apr}(C_q) = \cup\{X \in U / R(X) \le C_q\} \tag{2}$$

$$Bnd(C_q) = \{X \in U / R(X) > C_q\} \cup \{X \in U / R(X) < C_q\} \tag{3}$$

Thus, the class C_q can be expressed as rough number $RN(C_q)$ with upper limit $(\overline{Lim}(C_q))$ and lower limit $(\underline{Lim}(C_q))$, defined as below (Chakraborty et al., 2020):

$$\overline{Lim}(C_q) = \frac{1}{M_U}\sum R(X) \mid X \in \overline{Apr}(C_q) \tag{4}$$

$$\underline{Lim}(C_q) = \frac{1}{M_L}\sum R(X) \mid X \in \underline{Apr}(C_q) \tag{5}$$

$$RN(C_q) = \left[\underline{Lim}(C_q), \overline{Lim}(C_q)\right] = \left[x_{ij}^L, x_{ij}^U\right] \tag{6}$$

where M_U and M_L are the number of objects in the upper and lower approximations respectively, and x_{ij}^L and x_{ij}^U are the lower and upper evaluation limits of j^{th} criterion with respect to i^{th} alternative respectively. The rough boundary interval (*RBnd*) can now be expressed as the difference between the upper and lower evaluation limits.

$$RBnd = \overline{Lim}(C_q) - \underline{Lim}(C_q) \tag{7}$$

A large value of *RBnd* symbolizes more vagueness, while, a small value represents more preciseness. It is often important to rank rough numbers to attain definitive results. Zhai et al. (2008) proposed a methodology for ranking of rough numbers. Let *RN*(*A*) and *RN*(*B*) be two rough numbers. If one rough boundary interval is not strictly bounded by the other, there may be two possibilities:

a) If $\overline{Lim}(A) > \overline{Lim}(B)$ and $\underline{Lim}(A) \geq \underline{Lim}(B)$ or
$\overline{Lim}(A) \geq \overline{Lim}(B)$ and $\underline{Lim}(A) > \underline{Lim}(B)$, then $RN(A) > RN(B)$.

b) If $\overline{Lim}(A) = \overline{Lim}(B)$ and $\overline{Lim}(A) = \overline{Lim}(B)$, then $RN(A) = RN(B)$.

However, if they are strictly bounded, they can be ranked based on their median values. Hence, the following three cases may be observed:

a) If $M(A) > M(B)$, then $RN(A) > RN(B)$
b) If $M(A) < M(B)$, then $RN(A) < RN(B)$
c) If $M(A) = M(B)$, then $RN(A) = RN(B)$

where *M*(*A*) and *M*(*B*) are the median values of rough numbers *RN*(*A*) and *RN*(*B*) respectively.

Let us assume $RN(\alpha) = [L_\alpha, U_\alpha]$ and $RN(\beta) = [L_\beta, U_\beta]$ where L_α and L_β are the lower limits, and U_α and U_β are the upper limits of the respective rough numbers. The following arithmetic rules can then be applied for interval analysis:

$$RN_\alpha + RN_\beta = [L_\alpha + L_\beta, U_\alpha + U_\beta] \tag{8}$$

$$RN_\alpha \times RN_\beta = [L_\alpha \times L_\beta, U_\alpha \times U_\beta] \tag{9}$$

$RN_\alpha \times k = [kL_\alpha, kU_\alpha]$, where k is a non-zero constant. (10)

In order to determine the distance between two rough numbers, the Euclidian distance equation is employed. Thus, $D(a,b)$ represents the Euclidian distance between two rough numbers $RN(a)$ and $RN(b)$ such that $RN(a) = [a^-, a^+]$ and $RN(b) = [b^-, b^+]$.

$$D(a,b) = \sqrt{\frac{1}{2}\left(\left(a^- - b^-\right)^2 + \left(a^+ - b^+\right)^2\right)} \tag{11}$$

This property of rough numbers is employed to calculate the distance between the considered alternative for a given criterion and geometric aggregation value for that criterion. An illustration of the same can improve the understanding. Let us assume a decision matrix X having n alternatives ($A_1, A_2, \ldots, A_i, \ldots, A_n$) and m criteria ($C_1, C_2, \ldots, C_j, \ldots, C_m$) such that using rough numbers, the performance score for i^{th} alternative against the considered set of criteria can be expressed as $A_i = \left(\left[x_{i1}^-, x_{i1}^+\right], \left[x_{i2}^-, x_{i2}^+\right], \Lambda, \left[x_{ij}^-, x_{ij}^+\right], \Lambda, \left[x_{im}^-, x_{im}^+\right]\right)$. The geometric aggregation value for j^{th} criterion is given by $RN(f_j) = \left[f_j^-, f_j^+\right]$, where

$$f_j^- = \left(\prod_{i=1}^{n} x_{ij}^- \right)^{1/n} \tag{12}$$

$$f_j^+ = \left(\prod_{i=1}^{n} x_{ij}^+ \right)^{1/n} \tag{13}$$

This helps in formation of the distance matrix $Y = [y_{ij}]_{n \times m}$ from the initial matrix X such that:

$$y_{ij} = \begin{matrix} D(x_{ij}, f_j) \text{ if } RN(x_{ij}) > RN(f_j) \\ -D(x_{ij}, f_j) \text{ if } RN(x_{ij}) < RN(f_j) \end{matrix} \quad \text{for benificial criterion} \tag{14.a}$$

$$y_{ij} = \begin{matrix} -D(x_{ij}, f_j) \text{ if } RN(x_{ij}) > RN(f_j) \\ D(x_{ij}, f_j) \text{ if } RN(x_{ij}) < RN(f_j) \end{matrix} \quad \text{for cost criterion} \tag{14.b}$$

where

$$D(x_{ij}, f_j) = \sqrt{\frac{1}{2}\left(\left(x_{ij}^- - f_j^-\right)^2 + \left(x_{ij}^+ - f_j^+\right)^2 \right)} \tag{15}$$

3.2. Rough MABAC

MABAC is a newly developed and widely accepted MCDM technique (Pamučar and Ćirović, 2015) which primarily ranks a set of alternatives based on their distances from the border approximation area for each criterion. However, it has been modified from time to time to develop more purposeful hybrid models. In this paper, MABAC is integrated with rough numbers which is further fed into a DoE model to provide a generalized metamodel for evaluation and ranking of a set of suppliers. Considering a decision problem having n alternatives ($A_1, A_2, \ldots, A_i, \ldots, A_n$) and m criteria (C_1, $C_2, \ldots, C_j, \ldots, C_m$), the procedural steps of rough MABAC method are enumerated as below (Chakraborty et al., 2020):

Step 1: The decision matrix X is constructed using rough numbers while taking into account the judgments of a team of experts/decision makers in assessing the relative performance of the suppliers with regard to the evaluation criteria:

$$X = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{bmatrix} RN(x_{11}) & RN(x_{12}) & \cdots & RN(x_{1m}) \\ RN(x_{21}) & RN(x_{22}) & \cdots & RN(x_{2m}) \\ \vdots & \vdots & \vdots & \vdots \\ RN(x_{n1}) & RN(x_{n2}) & \ldots & RN(x_{nm}) \end{bmatrix}$$
$$= \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{bmatrix} [x_{11}^-, x_{11}^+] & [x_{12}^-, x_{12}^+] & \cdots & [x_{1m}^-, x_{1m}^+] \\ [x_{21}^-, x_{21}^+] & [x_{22}^-, x_{22}^+] & \cdots & [x_{2m}^-, x_{2m}^+] \\ \vdots & \vdots & \vdots & \vdots \\ [x_{n1}^-, x_{n1}^+] & [x_{n1}^-, x_{n1}^+] & \ldots & [x_{nm}^-, x_{nm}^+] \end{bmatrix} \tag{16}$$

where $RN(x_{ij}) = [x_{ij}^-, x_{ij}^+]$.

Step 2: Depending on the type of the criterion, the initial decision matrix X is normalized to obtain the corersponding normalized decision matrix $N = \left[n_{ij}^{-}, n_{ij}^{+}\right]_{n\times m}$.

$$RN(n_{ij}) = \begin{Bmatrix} \left[\dfrac{x_{ij}^{-} - x_{j}^{-}}{x_{j}^{+} - x_{j}^{-}}, \dfrac{x_{ij}^{+} - x_{j}^{-}}{x_{j}^{+} - x_{j}^{-}}\right]; \text{if } j \in B, \\ \left[\dfrac{x_{ij}^{+} - x_{j}^{+}}{x_{j}^{-} - x_{j}^{+}}, \dfrac{x_{ij}^{-} - x_{j}^{+}}{x_{j}^{-} - x_{j}^{+}}\right]; \text{if } j \in C, \end{Bmatrix} \tag{17}$$

where $x_{j}^{+} = \max_{i}(x_{ij}^{+}), x_{j}^{-} = \min_{i}(x_{ij}^{-}), B$ is the set of beneficial criteria and C is the set of cost criteria.

Step 3: Determine the weight assigned to each criterion $W = (w_1, w_2,\ldots,w_j,\ldots,w_m)$ such that $\sum_{j=1}^{m} w_j = 1$. The weighted normalized decision matrix $Y = \left[y_{ij}^{-}, y_{ij}^{+}\right]_{n\times m}$ is now calculated using Eq. (18).

$$y_{ij}^{-} = \left(n_{ij}^{-} + 1\right)w_j;\; y_{ij}^{+} = \left(n_{ij}^{+} + 1\right)w_j,\; i = 1,2,\ldots n;\; j = 1,2,\ldots,m \tag{18}$$

Step 4: The border approximation area (BAA) matrix is derived based on geometric aggregation of the rough numbers.

$$Q = \left[RN(q_1) \quad RN(q_2) \quad \Lambda \quad RN(q_m)\right]$$

$$\begin{aligned} q_{j}^{-} &= \left(\prod_{i=1}^{n} y_{ij}^{-}\right)^{1/n},\; j = 1,2,\ldots,m \\ q_{j}^{+} &= \left(\prod_{i=1}^{n} y_{ij}^{+}\right)^{1/n},\; j = 1,2,\ldots,m \end{aligned} \tag{19}$$

Step 5: The Eucledian distance of an alternative from the BAA is evaluated based on the difference between the border approximation area and the weighted normalized matrix, and is represented by the matrix $K = \left[RN(k_{ij})\right]_{n\times m}$.

$$k_{ij} = D(y_{ij}, q_j) = \sqrt{\frac{1}{2}\left(\left(y_{ij}^{-} - q_{j}^{-}\right)^2 + \left(y_{ij}^{+} - q_{j}^{+}\right)^2\right)} \text{ if } RN(y_{ij}) > RN(q_j) \tag{20}$$

$$k_{ij} = -D(y_{ij}, q_j) = -\sqrt{\frac{1}{2}\left(\left(y_{ij}^{-} - q_{j}^{-}\right)^2 + \left(y_{ij}^{+} - q_{j}^{+}\right)^2\right)} \text{ if } RN(y_{ij}) < RN(q_j)$$

Step 6: The considered alternatives are finally ranked in descending order of S_i values.

$$S_i = \sum_{j=1}^{m} k_{ij} \quad (i = 1,2,\Lambda\ ,n) \tag{21}$$

3.3 Design of experiments

The DoE is a statistical methodology to help in determining the influence of independent factors/variables as well as effect of their interactions on the system response (dependent variable). Each of these factors can operate at different levels and hence, several experiments need to be performed to study the effects of factor level variations on the system under consideration. It has already established itself as a helpful tool for engineers and decision makers to develop strong mathematical metamodels based on experimental results. A full-factorial design proves to be exhaustive as it includes all the possible combinations for the factors at each of their corresponding levels. However, implementation of a full-factorial design plan is computationally expensive and time consuming. In these cases, a suitable subset of factor level combinations is selected resulting in a fractional factorial experiment design plan. In this paper, a two-level full-factorial experimental design plan is adopted to visualize how the considered evaluation criteria influence the MABAC scores for alternative suppliers. The metamodel linking the dependant variable (MABAC score) with *m* independent variables (criteria) is expressed as below:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \Lambda + \beta_m x_{im} + \varepsilon \tag{22}$$

where Y is the response variable (MABAC score), β_0 is the y-intercept coefficient, β_1-β_m are the effect coefficients for m criteria, x_1-x_m are the input variables and ε is the error term. The main effect of each input variable is presumed to be independent of the other variables. In this metamodel, interaction effects can also be considered to explore the presence of interactions between the input variables.

In this paper, a two-level full-factorial design plan is adopted with 2^5 combinations, where only the minimum and maximum intervals for each factor (criterion) are considered to develop the corresponding factorial design. The related distance values of these intervals are subsequently treated as the inputs and MABAC scores as the outputs to the DoE for development of the required metamodel.

4. Development of a rough-MABAC-DoE-based metamodel

It has already been noticed that the manufacturing industries often face problems while indentifying the best alternative/course of action amid a set of conflicting criteria. This paper proposes a new methodology for evaluation and ranking of competing suppliers based on a developed metamodel in an Indian iron and steel industry. The existing MCDM techniques suffer from a major drawback, i.e. when a new alternative is introduced in the decision making problem, the entire computational process needs to be reinitiated from the scratch to derive the ranking of the candidate alternatives, which often constrains their applications in real-time situations. In the proposed method, once the rough-MABAC-DoE-based metamodel is formulated, the concerned decision maker can easily estimate the corresponding MABAC score for a new supplier based on its performance and position it in the revised ranking list. The application potentiality of this method is illustrated as a case study in an Indian iron and steel industry with an annual production of around 2.4 million tonnes of crude steel. Like any other industry operating at such a large scale, it also houses a large number of machineries which need to be maintained from time to time for uninterrupted production. This creates requirement for large varieties of gearboxes to be procured from the suppliers across the globe. At this stage, it becomes essential to choose the most apposite supplier who can deliver the right quality of gearboxes at right quantity, right price and right time. It is worthwhile to mention here that while selecting the most suitable supplier for a manufacturing industry, the set of evaluation criteria usually varies depending on the item/product to be purchased. In a group decision making environment, assessment of the candidate suppliers with respect to the considered criteria also varies from one decision maker to the other depending on the experience and expertise of each of the participating decision makers. To deal with this problem, i.e. selection of suppliers for providing gearboxes in the iron and steel industry, the opinions of three decision makers (DM_1, DM_2 and DM_3) are sought. These decision makers have been respectively selected from the finance, materials management and mechanical technical bureau of the organization having 15, 20 and 15 years of job experience. Tables 1 and 2 exhibit the list of evaluation criteria and candidate suppliers considered for this supplier selection problem. For having replications in the experimental design plan while developing the corresponding metamodel, two sets of criteria weights are chosen based on the judgments of the decision makers. In this direction, other subjective techniques for criteria weight measurement, like BWM (Rezaei, 2015), full consistency method (FUCOM) (Pamučar et al., 2018b; Durmić et al. 2020), level based weight assessment (LBWA) (Žižović and Pamučar, 2019) etc. can also be applied. These criteria weights are so selected that their summation must be always one. Amongst these criteria, delivery compliance and price are non-beneficial (cost) attributes requiring their lower values, whereas, higher values are desired for the remaining three beneficial criteria.

Table 1. Description of the evaluation criteria

Criterion	Description	Weight	
Product quality (C_1)	It accounts for credibility of the product with respect to its expected performance and quality.	0.318	0.300
Delivery compliance (C_2)	It considers the time taken to fulfill an order once it has been placed even in uncertain situations. Meeting the delivery schedule is extremely important to maintain uninterrupted production of the end products.	0.226	0.240
Price (C_3)	It is the monetary value of an item that the organization has to pay to the supplier against its delivery.	0.206	0.200
Technological capability (C_4)	It deals with the capability of a supplier to remain updated with the state-of-the-art technologies to fulfil the requirements of the modern day manufacturing organizations.	0.132	0.138
Production capability (C_5)	It focuses on the competence of a supplier to provide the required quality and quantity of products, especially in times of fluctuating demands.	0.118	0.122

In order to single out the most suitable supplier for the identified product, the decision makers now appraise the performance of each of the candidate suppliers with respect to five evaluation criteria, while assigning scores based on a 1-9 scale, where 1-2 indicate poor performance, 3-7 denote moderate performance and 8-9 signify satisfactory performance. This performance appraisal process by the three participating suppliers is exhibited through Tables 3-5 in the form of evaluation matrixes. From Table 3, it can be revealed that DM_1 assesses the performance of supplier S_1 with respect to criteria C_1 = 4 (moderate), C_2 = 3 (moderate), C_3 = 2 (poor), C_4 = 6 (moderate) and C_5 = 8 (satisfactory). Rough numbers are now employed to aggregate the individual judgments of the three decision makers. For example, the set of performance ratings for supplier S_1 with respect to criterion C_1 as evaluated by the three decision makers is expressed as x_{11} = {4, 6, 7}. Based on Eqs. (4)-(6), this set of subjective linguistic information is converted into the corresponding rough numbers as below:

For element x_{11} = {4, 6, 7}

$$\underline{Lim}(4) = 4.00, \overline{Lim}(4) = \frac{1}{3}(4+6+7) = 5.67,$$

$$\underline{Lim}(6) = \frac{1}{2}(4+6) = 5.00, \overline{Lim}(6) = \frac{1}{2}(6+7) = 6.50$$

$$\underline{Lim}(7) = \frac{1}{3}(4+6+7) = 5.67, \overline{Lim}(7) = 7.00$$

$$RN(x_{11}^1) = [4.00, 5.67], RN(x_{11}^2) = [5.00, 6.50], RN(x_{11}^3) = [5.67, 7.00]$$

$$x_{11}^L = \frac{4.00+5.00+5.67}{3} = 4.88,\ x_{11}^U = \frac{5.67+6.50+7.00}{3} = 6.39$$

Table 2. List of the candidate suppliers

Supplier	Description
S_1	While this supplier proves to be a cheaper alternative with reputable delivery compliance, it does not appear to be the most suitable option under emergency situations.
S_2	It is a public sector organization situated in the eastern India. While it is reputed for its technological strength and reliability, there are situations when it fails to meet the supply deadlines.
S_3	This organization manufacturing premium gearboxes has customers all over the country. However, there is a substantial tradeoff with respect to robustness of its supply chains and adaption to changing technological scenario.
S_4	It is a reputed organization established in the southern India, always adhering to the specified delivery schedules while supplying gearboxes of perfect quality. However, it offers higher price for its products as compared to other suppliers.
S_5	It is a relatively new organization, yet to capture its reputation in the market and stabilize its delivery modes.

In this way, all the performance assessment scores assigned by the three decision makers are aggregated using rough numbers to formulate the corresponding combined evaluation matrix, as shown in Table 6. In this table, the beneficial and cost criteria are also identified along with their best and worst rough intervals. For example, with respect to product quality, S_3 performs the best, S_1 ensures the best delivery compliance at the lowest price, S_2 has the highest technological capability and S_4 exhibits the highest production capability.

Table 3. Evaluation matrix by DM_1

Criteria / Supplier	C_1	C_2	C_3	C_4	C_5
S_1	4	3	2	6	8
S_2	7	2	4	7	4
S_3	8	3	2	5	6
S_4	6	4	4	8	9
S_5	7	5	3	6	5

Table 4. Evaluation matrix by DM_2

Criteria / Supplier	C_1	C_2	C_3	C_4	C_5
S_1	6	2	3	7	5
S_2	7	3	3	8	6
S_3	8	4	2	6	7
S_4	7	2	4	5	8
S_5	7	4	2	6	7

Table 5. Evaluation matrix by DM_3

Criteria / Supplier	C_1	C_2	C_3	C_4	C_5
S_1	7	2	3	8	6
S_2	8	4	2	7	7
S_3	7	3	4	6	6
S_4	8	2	3	7	8
S_5	6	3	4	5	5

Table 6. Aggregated evaluation matrix

Criteria / Supplier	C_1	C_2	C_3	C_4	C_5
S_1	[4.88,6.39]	[2.11,2.55]	[2.44,2.88]	[6.50,7.50]	[5.61,7.11]
S_2	[7.11,7.55]	[2.5,3.50]	[2.5,3.5]	[7.11.7.55]	[4.88,6.39]
S_3	[7.44,7.88]	[3.11,3.55]	[2.22,3.11]	[5.44,5.88]	[6.11,6.55]
S_4	[6.50,7.50]	[2.22,3.11]	[3.44,3.88]	[5.88,7.38]	[8.11,8.55]
S_5	[6.44,6.88]	[3.50,4.50]	[2.50,3.50]	[5.44,5.88]	[5.22,6.11]
Min/Max	Max	Min	Min	Max	Max
Best	[7.44,7.88]	[2.11,2.55]	[2.44,2.88]	[7.11,7.55]	[8.11,8.55]
Worst	[4.88,6.39]	[3.50,4.50]	[3.44,3.88]	[5.44,5.88]	[4.88,6.39]

In order to develop the corresponding metamodel, five supplier selection criteria are treated as the input variables, whereas, the computed MABAC score is the output variable. To represent the two-level combinations for these five input variables, a 2^5 full-factorial design plan having 32 experiments is proposed in Table 7 while considering only the worst and best rough intervals of each input variable in the experiment plan. Now, employing Eqs. (12)-(15), the corresponding value of definitive distance for each of the rough intervals is computed, as shown in Table 8.

For example, in case of criterion C_1, the geometric aggregation is given as: $RN(f_1)=\left[f_1^-,f_1^+\right]$ where $f_1^- = (4.88\times 7.11\times 7.44\times 6.50\times 6.44)^{1/5} = 6.41$ and $f_1^+ = (6.39\times 7.55\times 7.88\times 7.50\times 6.88)^{1/5} = 7.22.$

Table 7. 2^5 full factorial design plan with rough intervals of the considered criteria

Experiment	Factor level				
No.	C_1	C_2	C_3	C_4	C_5
1	[7.44,7.88]	[2.11,2.55]	[2.44,2.88]	[7.11,7.55]	[8.11,8.55]
2	[4.88,6.39]	[2.11,2.55]	[2.44,2.88]	[7.11,7.55]	[8.11,8.55]
3	[7.44,7.88]	[3.50,4.50]	[2.44,2.88]	[7.11,7.55]	[8.11,8.55]
4	[4.88,6.39]	[3.50,4.50]	[2.44,2.88]	[7.11,7.55]	[8.11,8.55]
5	[7.44,7.88]	[2.11,2.55]	[3.44,3.88]	[7.11,7.55]	[8.11,8.55]
6	[4.88,6.39]	[2.11,2.55]	[3.44,3.88]	[7.11,7.55]	[8.11,8.55]
7	[7.44,7.88]	[3.50,4.50]	[3.44,3.88]	[7.11,7.55]	[8.11,8.55]
8	[4.88,6.39]	[3.50,4.50]	[3.44,3.88]	[7.11,7.55]	[8.11,8.55]
9	[7.44,7.88]	[2.11,2.55]	[2.44,2.88]	[5.44,5.88]	[8.11,8.55]
10	[4.88,6.39]	[2.11,2.55]	[2.44,2.88]	[5.44,5.88]	[8.11,8.55]
11	[7.44,7.88]	[3.50,4.50]	[2.44,2.88]	[5.44,5.88]	[8.11,8.55]
12	[4.88,6.39]	[3.50,4.50]	[2.44,2.88]	[5.44,5.88]	[8.11,8.55]
13	[7.44,7.88]	[2.11,2.55]	[3.44,3.88]	[5.44,5.88]	[8.11,8.55]
14	[4.88,6.39]	[2.11,2.55]	[3.44,3.88]	[5.44,5.88]	[8.11,8.55]
15	[7.44,7.88]	[3.50,4.50]	[3.44,3.88]	[5.44,5.88]	[8.11,8.55]
16	[4.88,6.39]	[3.50,4.50]	[3.44,3.88]	[5.44,5.88]	[8.11,8.55]
17	[7.44,7.88]	[2.11,2.55]	[2.44,2.88]	[7.11,7.55]	[4.88,6.39]
18	[4.88,6.39]	[2.11,2.55]	[2.44,2.88]	[7.11,7.55]	[4.88,6.39]
19	[7.44,7.88]	[3.50,4.50]	[2.44,2.88]	[7.11,7.55]	[4.88,6.39]
20	[4.88,6.39]	[3.50,4.50]	[2.44,2.88]	[7.11,7.55]	[4.88,6.39]
21	[7.44,7.88]	[2.11,2.55]	[3.44,3.88]	[7.11,7.55]	[4.88,6.39]
22	[4.88,6.39]	[2.11,2.55]	[3.44,3.88]	[7.11,7.55]	[4.88,6.39]
23	[7.44,7.88]	[3.50,4.50]	[3.44,3.88]	[7.11,7.55]	[4.88,6.39]
24	[4.88,6.39]	[3.50,4.50]	[3.44,3.88]	[7.11,7.55]	[4.88,6.39]
25	[7.44,7.88]	[2.11,2.55]	[2.44,2.88]	[5.44,5.88]	[4.88,6.39]
26	[4.88,6.39]	[2.11,2.55]	[2.44,2.88]	[5.44,5.88]	[4.88,6.39]
27	[7.44,7.88]	[3.50,4.50]	[2.44,2.88]	[5.44,5.88]]	[4.88,6.39]
28	[4.88,6.39]	[3.50,4.50]	[2.44,2.88]	[5.44,5.88]	[4.88,6.39]
29	[7.44,7.88]	[2.11,2.55]	[3.44,3.88]	[5.44,5.88]	[4.88,6.39]
30	[4.88,6.39]	[2.11,2.55]	[3.44,3.88]	[5.44,5.88]	[4.88,6.39]
31	[7.44,7.88]	[3.50,4.50]	[3.44,3.88]	[5.44,5.88]	[4.88,6.39]
32	[4.88,6.39]	[3.50,4.50]	[3.44,3.88]	[5.44,5.88]	[4.88,6.39]

Based on Eq. (14), as [7.44,7.88] > [6.41,7.22], the definitive distance for the best interval of C_1 can be estimated as $D=\sqrt{\frac{1}{2}\left((7.44-6.41)^2+(7.88-7.22)^2\right)}=0.865$. Similarly, as [4.88,6.39] < [6.41,7.22], the definitive distance for the worst interval of C_1 can be calculated as $D=-\sqrt{\frac{1}{2}\left((4.88-6.41)^2+(6.39-7.22)^2\right)}=-1.231.$

Table 8. Definitive distance matrix along with the MABAC scores

Experiment No.	C_1	C_2	C_3	C_4	C_5	MABAC score	
						1	2
1	0.865	0.696	0.355	0.928	1.960	0.345	0.345
2	-1.231	0.696	0.355	0.928	1.960	0.124	0.135
3	0.865	-0.998	0.355	0.928	1.960	0.184	0.174
4	-1.231	-0.998	0.355	0.928	1.960	-0.037	-0.036
5	0.865	0.696	-0.704	0.928	1.960	0.215	0.220
6	-1.231	0.696	-0.704	0.928	1.960	-0.006	0.010
7	0.865	-0.998	-0.704	0.928	1.960	0.054	0.049
8	-1.231	-0.998	-0.704	0.928	1.960	-0.167	-0.161
9	0.865	0.696	0.355	-0.771	1.960	0.239	0.235
10	-1.231	0.696	0.355	-0.771	1.960	0.018	0.025
11	0.865	-0.998	0.355	-0.771	1.960	0.078	0.064
12	-1.231	-0.998	0.355	-0.771	1.960	-0.143	-0.146
13	0.865	0.696	-0.704	-0.771	1.960	0.109	0.110
14	-1.231	0.696	-0.704	-0.771	1.960	-0.112	-0.100
15	0.865	-0.998	-0.704	-0.771	1.960	-0.052	-0.061
16	-1.231	-0.998	-0.704	-0.771	1.960	-0.273	-0.271
17	0.865	0.696	0.355	0.928	-0.797	0.256	0.254
18	-1.231	0.696	0.355	0.928	-0.797	0.035	0.044
19	0.865	-0.998	0.355	0.928	-0.797	0.095	0.083
20	-1.231	-0.998	0.355	0.928	-0.797	-0.126	-0.127
21	0.865	0.696	-0.704	0.928	-0.797	0.126	0.129
22	-1.231	0.696	-0.704	0.928	-0.797	-0.095	-0.081
23	0.865	-0.998	-0.704	0.928	-0.797	-0.035	-0.042
24	-1.231	-0.998	-0.704	0.928	-0.797	-0.256	-0.252
25	0.865	0.696	0.355	-0.771	-0.797	0.150	0.144
26	-1.231	0.696	0.355	-0.771	-0.797	-0.071	-0.066
27	0.865	-0.998	0.355	-0.771	-0.797	-0.011	-0.027
28	-1.231	-0.998	0.355	-0.771	-0.797	-0.232	-0.237
29	0.865	0.696	-0.704	-0.771	-0.797	0.020	0.019
30	-1.231	0.696	-0.704	-0.771	-0.797	-0.201	-0.191
31	0.865	-0.998	-0.704	-0.771	-0.797	-0.141	-0.152
32	-1.231	-0.998	-0.704	-0.771	-0.797	-0.362	-0.362

Based on the procedural steps of MABAC method, the corresponding scores are computed for all the experimental trials using two different criteria weight sets. Thus, for each combination of factor levels, two MABAC scores are calculated at two replications. Assignment of different criteria weight sets results in different MABAC scores. This experimental design plan with definitive distance values as the inputs and MABAC scores as the responses is now analyzed using MINITAB (R17) software which results in subsequent development of the corresponding metamodal and analysis of variance (ANOVA) table. This metamodel in the following form can not only account for the main effects of different factors, but can also highlight the existent interactions among them.

$$Y = \beta_0 + \sum_{i=1}^{5} \beta_i x_i + \sum_{i} \sum_{j_{i<j}} \beta_{ij} x_i x_j + \sum_{i} \sum_{j} \sum_{k_{i<j<k}} \beta_{ijk} x_i x_j x_k + \sum_{i} \sum_{j} \sum_{k} \sum_{l_{i,j<k<l}} \beta_{ijkl} x_i x_j x_k x_l + \beta_{12345} x_1 x_2 x_3 x_4 x_5 \tag{23}$$

where Y is the MABAC score, β_0 is the intercept coefficient or overall mean response, β_i is the main or first-order effect of factor i, β_{ij} is the two-factor interaction between factors i and j ($i \neq j$), β_{ijk} is the three-factor interaction between i, j and k ($i \neq j \neq k$), β_{ijkl} is the four-factor interaction between i, j, k and l ($i \neq j \neq k \neq l$), and β_{12345} is the five-factor interaction between all the factors.

Table 9. Estimated effects and coefficients

Term	Effect	Coefficient	SE of coefficient	t-value	p-value
Constant		**-0.00597**	**0.00283**	**-2.11**	**0.043**
C_1	**0.21044**	**0.10522**	**0.00283**	**37.12**	**0.000**
C_2	**0.17106**	**0.08553**	**0.00283**	**30.18**	**0.000**
C_3	**0.12244**	**0.06122**	**0.00283**	**21.60**	**0.000**
C_4	**0.11306**	**0.05653**	**0.00283**	**19.94**	**0.000**
C_5	**0.08494**	**0.04247**	**0.00283**	**14.98**	**0.000**
$C_1 \times C_2$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_1 \times C_3$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_4$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_1 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_2 \times C_3$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_2 \times C_4$	0.00506	0.00253	0.00283	0.89	0.379
$C_2 \times C_5$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_3 \times C_4$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_3 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_4 \times C_5$	-0.0×0506	-0.00253	0.00283	-0.89	0.379
$C_1 \times C_2 \times C_3$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_2 \times C_4$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_1 \times C_2 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_3 \times C_4$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_3 \times C_5$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_1 \times C_4 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_2 \times C_3 \times C_4$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_2 \times C_3 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_2 \times C_4 \times C_5$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_3 \times C_4 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_2 \times C_3 \times C_4$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_2 \times C_3 \times C_5$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_1 \times C_2 \times C_4 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_3 \times C_4 \times C_5$	-0.00506	-0.00253	0.00283	-0.89	0.379
$C_2 \times C_3 \times C_4 \times C_5$	0.00506	0.00253	0.00283	0.89	0.379
$C_1 \times C_2 \times C_3 \times C_4 \times C_5$	-0.00506	-0.00253	0.00283	-0.89	0.379

Table 9 shows the effects and coefficients of different factors along with their varied levels of interactions, while Table 10 exhibits the derived ANOVA results based on the calculated MABAC scores. These ANOVA results provide a summary of the main effects and interactions between various factors. In table 9, the *p*-values help in identifying statistically significant factors and interaction effects. Terms with *p*-value less than or equal to 0.05 are considered to be statistically significant, whereas, those with *p*-value greater than 0.05 can be neglected while developing the corresponding metamodeal. In this table, the column 'Term' depicts the main effects and all the possible interactions among the factors. The 'Effect' column shows the relative strength of a particular factor or interaction. The β coefficients and their standard errors (SE) are provided in the third and fourth columns respectively. The last two columns highlight the calculated *t*- and *p*-values. In Tables 9-10, the rows of all the significant factors ($p \leq 0.05$) are shown in bold face. Based on the derived results, it can be concluded that all the two-way, three-way, four-way and five-way interactions are statistically insignificant, whereas, all the main effects due to criteria C_1, C_2, C_3, C_4 and C_5 have independently significant contributions in calculating the MABAC score. Thus, the metamodel for obtaining the MABAC score for a given supplier based on the evaluation criteria can be expressed as below:

$$Y = -0.00597 + 0.10522\times C_1 + 0.08553\times C_2 + 0.06122\times C_3 + 0.05653\times C_4 + 0.04247\times C_5 \tag{24}$$

In Table 10, the R^2 value is the square of correlation coefficient indicating the percentage of variation explained by the developed metamodel out of the total variation. On the other hand, the value of R^2(adj) represents the proportion of variation in the target variable contributed by the statistically significant terms. It can be concluded that 99.07% of the variation in the dependant variable Y (MABAC score) can be explained by the variation of the independent variables in this metamodel. Extremely high values of both R^2 and R^2(adj) as 99.07% and 98.16% respectively thus confirm the acceptance of the developed metamodel in exhibiting the relationship between MABAC score and supplier selection criteria.

Table 10. ANOVA results

Source	DoF	Adj. SS	Adj. MS	*t*-value	*p*-value
Linear	**5**	**1.73656**	**0.347311**	**675.46**	**0.000**
2-way interaction	10	0.00410	0.000410	0.80	0.632
3-way interaction	10	0.00410	0.000410	0.80	0.632
4-way interaction	5	0.00205	0.000410	0.80	0.560
5-way interaction	1	0.00041	0.000410	0.80	0.379
Error	32	0.01645	0.000514		
Total	63	1.76367			
R^2 = 99.07%, R^2(adj) = 98.16%					

Now, based on this model, the corresponding MABAC scores for the five alternative suppliers are determined as Y_1 = -0.0301, Y_2 = 0.0746, Y_3 = 0.0175, Y_4 = 0.1100 and Y_5 = -0.1990 (where Y_i is the MABAC score for i^{th} supplier). When these MABAC scores are arranged in descending order, a complete ranking of the competing suppliers from the best to the worst can be derived. Thus, S_4 emerges out as the most competent supplier for providing gearboxes to the iron and steel industry under consideration, followed by suppliers S_2 and S_3. In the derived ranking list of the suppliers, S_5 performs the worst. In Table 11, the rankings of the considered suppliers derived using rough-MABAC-DoE-based metamodel are contrasted with those obtained using rough-TOPSIS, rough-EDAS, rough-ARAS and rough-WASPAS-DoE-based metamodels. It can be revealed that except rough-EDAS, the ranking of the most favoured supplier (S_4) matches for all the remaining rough-MCDM-DoE-based metamodels. High Spearman's rank correlation coefficients (r_s) prove the application potentiality of rough-MABAC-DoE-based metamodel in solving supplier selection problems.

Table 11. Comparison of rankings of the suppliers using different rough MCDM methods

Supplier	MABAC	TOPSIS	EDAS	ARAS	WASPAS
S_1	4	5	5	5	5
S_2	2	2	1	2	2
S_3	3	3	3	3	3
S_4	1	1	2	1	1
S_5	5	4	4	4	4
r_s	-	0.90	0.80	0.90	0.90

4. Conclusions

This paper proposes a novel approach to solve a supplier selection problem in an Indian iron and steel industry while integrating rough numbers with MABAC method and DoE leading to the development of a metamodel. Its application starts with aggregation of the relative performance scores of five competing suppliers using rough numbers considering the uncertainty involved in the decision making process. Based on the worst and best rough number intervals, a 2^5 full-factorial experimental design plan is formulated with subsequent conversion of those rough intervals into the corresponding definitive distances. Using two different criteria weight sets as the replications, the related MABAC scores are computed for all the experiment trials. Finally, a metamodel is developed interlinking the MABAC scores and supplier evaluation criteria, which is finally employed to rank the competing suppliers. Its main advantage lies on easy computation of the performance score (in terms of MABAC score) for a new supplier to be included in the decision making process, thus relieving the decision maker from reinitiating the entire calculation from the scratch. Besides its application in iron and steel industry, it can also be efficiently employed in other sectors, like healthcare, tourism, food, textile etc. The possibility of similar hybridization with other MCDM techniques, like MARICA, MARCOS, combined compromise solution (CoCoSo) etc. for solving supplier selection problems can be explored as the future scope of this paper. Two sets of criteria weights are considered here based on the opinions of the decision makers, helping in replication of the MABAC scores. Other subjective methods, like BWM, FUCOM or LBWA can also be applied for estimating the corresponding criteria weights. The main limitation of the proposed approach is that its computational complexity would monotonically increase for high-dimensional decision making problems having large number of evaluation criteria.

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