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AN INTEGRATED D-MARCOS METHOD FOR SUPPLIER SELECTION IN AN IRON AND STEEL INDUSTRY

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Abstract: *The modern era of manufacturing has recognized the importance of a sustainable supply chain management (SCM) system in order to attain the desired level of stability and productivity for fulfillment of the customers' requirements. Selection of the most suitable set of suppliers is an integral part of SCM which can be effectively solved with the deployment of different multi-criteria decision making (MCDM) techniques. This paper endeavors to resolve the uncertainty involved in the decision making process for supplier selection with the application of D numbers. A relatively new MCDM technique in the form of measurement alternatives and ranking according to compromise solution (MARCOS) is later employed for ranking of a set of competing suppliers. This integrated approach is finally applied to choose the best performing supplier in a leading Indian iron and steel making industry based on seven selective evaluation criteria and opinions of three decision makers. It would provide more generic and unbiased results while addressing uncertainty and ambiguity involved in the supplier selection process.*

Key words: *Supplier selection; D numbers; MARCOS; Iron and steel industry.*

1. Introduction

In the modern day highly competitive manufacturing environment, a sustainable supply chain management (SCM) system has been recognized as one of the predominant issues for survival and long-term prosperity of any organization. A sustainable SCM system ensures supply of the best quality products at reduced costs to the customers, hence helping a manufacturing organization capturing its superior

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position over its competitors in the market. In case of expensive products, it focuses on quick delivery in order to minimize inventory and associated holding cost. Thus, an efficient SC should take care of a wide range of objectives keeping in mind the welfares of both the organization and its customers. The present day manufacturing organizations should focus on devising a reliable as well as flexible SC based on a proper opinionated research. In SC, an essential responsibility bestowed on the purchasing department is to identify a set of compatible suppliers based on their capabilities to fulfill the primary requirements of cost, quality, delivery, technological capability, production capacity, financial strength etc. Thus, with the adoption and advancement of SCM, supplier selection has started playing a pivotal role. The supplier selection process mainly focuses on the following tasks, i.e. a) identification of the products to be procured, b) assimilation of a list of potential suppliers, c) shortlisting of the key factors (criteria) based on which the suppliers need to be evaluated, d) formation of a team of experts/decision makers to extensively analyze and strategize this selection process, e) choosing of the most apposite supplier while disposing off the inefficient ones, and f) continuous performance evaluation of the finally sleected supplier (De Boer et al., 2001). Over the course of development, supplier selection process has undergone a gradual transition from an intuitionistic approach to a more tangible strategic one, hence characterizing its further complication (Parkhi, 2015).

It has already been well acknowledged that SCs form the backbone of most of the manufacturing industries for selection of the reliable suppliers who can provide continuous stock of quality raw materials in order to fulfill the basic objectives of productivity and profitability with economic justification to the manufacturing processes. In supplier selection process, the main challenge and mathematical complexity lies in the identification of disparate evaluation criteria with varying degrees of importance, requiring a sensible trade-off amongst them. The manufacturing sector, heavily relying on SCs to achieve its goals, finds strong dependence on the application of different multi-criteria decision making (MCDM) techniques to choose the best fit supplier from a pool of competing alternatives based on the shortlisted evaluation criteria.

The MCDM has become interesting among the researcher community over a long time, whereby, it has come across innovative methodologies to help the decision makers to weigh multiple alternatives to choose the best option, while taking into account a set of conflicting qualitative and quantitative criteria. Application of any of the MCDM techniques in supplier selection has two basic objectives, i.e. a) deriving the preferential weights (relative importance) of the considered criteria by evaluating one against the others, and b) ranking of the candidate suppliers based on the accumulative score with respect to each criterion. In this direction, an unlimited number of MCDM techniques, like analytic hierarchy process (AHP), technique of order preference similarity to the ideal solution (TOPSIS), VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), grey relational analysis (GRA), preference ranking organization method for enrichment evaluation (PROMETHEE), combinative distance-based assessment (CODAS), weighted aggregated sum product assessment (WASPAS) etc. has been deployed for solving the supplier selection problems in diverse manufacturing industries. Recently, Stević et al. (2020) proposed a new MCDM tool, called measurement of alternatives and ranking according to compromise solution (MARCOS) involving ranking of the alternatives based on a compromised solution. In this approach, the ranking procedure is based on the distance of the alternatives from the ideal and anti-ideal solutions with respect to the considered criteria and their aggregated score reflected by a utility function.

However, the biggest challenge in decision making lies in the underlying uncertainty of the decision makers while evaluating the alternatives with respect to a set of qualitative criteria based on some predefined benchmarks and linguistic judgements. A linguistic judgement cannot always be ascertained, especially when there is not a single decision maker, rather an entire team, introducing chances of biasness in the decision making process. In real life situations, it becomes difficult for the decision makers to ascertain a particular degree or rating to a specific criterion owing to their varied backgrounds and experiences. Various mathematical tools, like fuzzy set theory, intutionistic fuzzy set etc. have already been employed to deal with the uncertainty and ambiguity involved in the supplier selection process. Deng (2012) introduced another tool in the form of D numbers to successfully account for uncertainty involved in the decision making processes.

This paper aims at addressing the issue of uncertainty involved in the supplier selection process when the concerned decision makers assign relative scores to the competing suppliers with respect to different evaluation criteria, which if ignored, may result in highly ambiguous results. Though MARCOS method itself is a robust yet mathematically simple model, it still does not address the issue of uncertainty often involved in group decision making where the team of experts comes from different backgrounds and experiences. While there are alternatives, like fuzzy theory, Dempster-Shafer (D-S) theory etc. to deal with such uncertainty, they often have constraints, like elements in the frame of discernment should be mutually exclusive whereby the sum of the basic probability of mass function should be one. However, D numbers, free from such constraints, provide more generalized solutions. Thus, combining D numbers with MARCOS gives a more holistic and impactful model covering the major loopholes involved in group decision making by accounting for uncertainties using a mathematically simpler formulation. This paper thus deals with implementation of the proposed methodology for supplier selection in a fully operational large scale iron and steel industry in India which has to compete with other stalwarts to carve its own position in the global market.

The organization of this paper is as follows. Section 2 provides a brief literature review on the applications of different MCDM techniques in supplier selection. Section 3 deals with the mathematical details of D numbers and MARCOS method. Section 4 illustrates the application of the propsoed methodology for supplier selection in an Indian iron and steel industry. Finally, conclusions are drawn in Section 5 along with the future dierctions of research.

2. Literature review

The importance of supplier selection can be proved by the humungous extent of researches conducted based on the applications of various MCDM techniques under both certain and uncertain manufacturing environments. Table 1 provides a concise list of different evaluation criteria and mathematical approaches considered for resolving supplier selection problems, with a special emphasis on steel making industries.

It can be clearly noticed from Table 1 that different mathematical techniques have mainly been employed for two purposes, i.e. a) determination of weights (relative importance) to be assigned to various evaluation criteria and b) ranking of the competing suppliers. The AHP, best-worst method etc. have been deployed for criteria weight estimation, while ANP, TOPSIS, GRA, PROMETHEE, VIKOR, CODAS etc. have been augmented for supplier ranking. It is also noticed that some of those MCDM techniques have been combined with fuzzy set, intuitionistic fuzzy set, D-S theory etc. for providing more accurate solutions to supplier election problems dealing with qualitative information under group decision making environment.

For effective supplier selection, the primary task is to shortlist the appropriate set of evaluation criteria. Back in the 1960s, Dickson (1966) stressed on the dependence of supplier selection on various evaluation criteria, while enlisting an exhaustive set of criteria. However, with rapid technological advancements and involvement of global economic parameters, a shift in the criteria for supplier selection has been observed. In the 1990s, the decision makers emphasized on the introduction of more qualitative criteria in the supplier selection process making it more complicated and prone to variation due to human involvement. Stević (2017) performed a comprehensive review on various criteria and sub-criteria considered for dealing with the supplier selection problems. However, these specific sets of evaluation criteria vary from one manufacturing organization to another. With every organization thriving hard to develop the best sustainable SCM system, importance of a perfect set of evaluation criteria cannot be thus ignored. Based on the literature review, it is observed that maximum importance has been provided on price, delivery, quality and production capacity.

The extravagant research shows the importance of supplier selection in manufacturing industries. However, there has been relatively less light reflected on the uncertainty involved in the decision making process due to expensive computational steps. For industries seeking a robust decision, it has now become mandatory that the adopted technique should be both exhaustive and efficient eradicating any chance of mistake. Most of the past research works have weighed the participating decision makers equally, not accounting for their varied level of expertise and experience. Those studies have also been based on the assumption that human preference can be linearly determined. In order to overcome the drawbacks of the previously adopted techniques, in this paper, a new approach for supplier selection integrating D numbers and MARCOS method is proposed. It is numerically easier to implement, yet provides more reliable ranking results, making it attractive for the manufacturing industries. Finally, it is applied to an Indian iron and steel making industry while considering the opinions of three experts/decision makers based on five alternative suppliers and seven evaluation criteria.

3. Methods

3.1. D numbers

The D numbers are an extension of the D-S theory, accounting for uncertainty of information. It can be defined as follows (Deng, 2012; Deng et al., 2014b):

Let Ω be a finite non-empty set, D number is a mapping formulated by:

$$D:\Omega \to [0,1] \tag{1}$$

with

$$\sum_{B\subseteq\Omega} D(B) \le 1 \text{ and } D(\varphi) = 0 \tag{2}$$

where ϕ is an empty set and B is a subset of Ω.

Table 1. List of criteria and methods considered for supplier selection

Author(s)	Criteria	Method(s)
Tahriri et al. (2008)	Quality, delivery, direct cost, trust, financial position, management and organization	AHP
Gnanasekaran et al. (2010)	Quality, delivery, cost, financial position, service	Fuzzy AHP
Liu (2010)	Price, delivery, quality, relationship, financial position	Normalization
Ying-tuo and Yang (2011)	Quality of products, environmental friendship, price, development capability	Vague sets
Vimal et al. (2012)	Minimum quantity, maximum quantity, defective item, late delivery, product price, order quantity	TOPSIS
Parthiban et al. (2013)	Quality, delivery, productivity, service, cost, technological capability, application of conceptual manufacturing, environment management, human resource management, manufacturing challenges	Fuzzy logic, strength-weakness-opportunity-threat (SWOT) analysis, data envelopment analysis
Dargi et al. (2014)	Quality, price, production capacity, technical capability and facility, service and delivery, reputation, geographical location	Fuzzy analytic network process
Kar (2015a)	Product quality, delivery compliance, price, technological capability, production capability, financial strength, electronic transaction capability	AHP, fuzzy set theory, neural network
Kar (2015b)	Product quality, delivery compliance, price, technological capability, production capability, financial strength, electronic transaction capability	Delphi method, fuzzy AHP
Kamath et al. (2016)	Quality, cost, delivery, vendor relationship management	AHP
Abdulshahed et al. (2017)	Quality, direct cost, lead time, logistics service	Grey system theory
Azimifard et al. (2018)	Economic sustainability, environmental sustainability, social sustainability	AHP, TOPSIS
Badi et al. (2018)	Quality, direct cost, lead time, logistics service	CODAS
Banaeian et al. (2018)	Service level, quality, price, environmental management system	Fuzzy TOPSIS, fuzzy VIKOR, fuzzy GRA
Jain and Singh (2018)	Quality, delivery, performance history, cost	AHP, WASPAS
Kumar et al. (2018)	Cost, delivery capability, quality, performance, reputation	Fuzzy TOPSIS

Abdullah et al. (2019)	Cost of product, quality of product, service provided, on- time delivery, technology level, environmental management system, green packaging	PROMETHEE
Jain and Singh (2019)	Economic, environmental, social	Fuzzy modified Kano model
Javad et al. (2020)	Collaborations, environmental investment and economic benefit, resource availability, green competency, environmental management initiative, research and design initiatives, green purchasing capability, regulatory obligations, pressures and market demand	Best worst method, fuzzy TOPSIS
Jain and Singh (2020)	Economic sustainability, environmental sustainability, social sustainability	Fuzzy interference system with fuzzy Kano model

The D numbers have the leverage over the D-S theory according to which all elements of set Ω need to be mutually exclusive and $\sum_{B\subseteq\Omega} D(B)=1$, i.e. the information should be complete. However, D numbers are also capable of dealing with incomplete information, i.e. when $\sum_{B\subseteq\Omega} D(B)<1$.

On considering a set $\Omega = \{b_1, b_2,...,b_i,...,b_n\}$, where $b_i \in R$ and $b_i \neq b_j$, D numbers can be represented as:

$D(\{b_1\}] = v_1, D(\{b_2\}] = v_2,...,D(\{b_i\}] = v_i,...,D(\{b_n\}] = v_n$

It can also be expressed as $D = \{(b_1,v_1), (b_2,v_2),...,(b_i,v_i),...,(b_n,v_n)\}$ where $v_i > 0$ and $\sum_{i=1}^{n} v_i \leq 1$.

There are certain properties which are important for performing different operations on D numbers.

Property 1: (Permutation invariability) (Deng et al., 2014a, 2014b) Assuming two different D numbers, i.e. $D_1 = \{(b_1,v_1),...,(b_i,v_i),...,(b_n,v_n)\}$and $D_2 = \{(b_n,v_n),...,(b_i,v_i),...,(b_1,v_1)\}$, then $D_1 \Leftrightarrow D_2$.

Property 2: (Deng, 2012; Deng et al., 2014b). If $D = \{(b_1,v_1), (b_2,v_2),...,(b_i,v_i),...,(b_n,v_n)\}$, the integrated value of D can be defined as :

$$I(D)=\sum_{i=1}^{n} b_i v_i \tag{3}$$

Property 3: (Deng, 2012; Deng et al., 2014a) Assuming two different D numbers, D_1 and D_2 such that $D_1 = \{(b_1^1,v_1^1),...,(b_i^1,v_i^1),...,(b_n^1,v_n^1)\}$ and $D_2 = \{(b_1^2,v_1^2),...,(b_j^2,v_j^2),...,(b_m^2,v_m^2)\}$, the combination of D_1 and D_2 can be expressed as $D = D_1 \oplus D_2$ which can be further defined as follows:

$$D(b) = v \tag{4}$$

where

$$b = \frac{b_i^1 + b_j^2}{2} \tag{5}$$

$$v = \left(\frac{v_i^1 + v_j^2}{2} \right) \Big/ C \tag{6}$$

$$C = \begin{cases} \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{v_i^1 + v_j^2}{2}, \\ \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{v_i^1 + v_j^2}{2} + \sum_{j=1}^{m} \frac{v_c^1 + v_j^2}{2}, \\ \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{v_i^1 + v_j^2}{2} + \sum_{i=1}^{n} \frac{v_i^1 + v_c^2}{2}, \\ \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{v_i^1 + v_j^2}{2} + \sum_{j=1}^{m} \frac{v_c^1 + v_j^2}{2} + \sum_{i=1}^{n} \frac{v_i^1 + v_c^2}{2} + \frac{v_c^1 + v_c^2}{2}, \end{cases} \tag{7}$$

$$\sum_{i=1}^{n} v_i^1 = 1 \text{ and } \sum_{j=1}^{m} v_j^1 = 1;$$

$$\sum_{i=1}^{n} v_i^1 < 1 \text{ and } \sum_{j=1}^{m} v_j^1 = 1;$$

$$\sum_{i=1}^{n} v_i^1 = 1 \text{ and } \sum_{j=1}^{m} v_j^1 < 1;$$

$$\sum_{i=1}^{n} v_i^1 < 1 \text{ and } \sum_{j=1}^{m} v_j^1 < 1;$$

where

$$v_c^1 = 1 - \sum_{i=1}^{n} v_i \text{ and } v_c^2 = 1 - \sum_{j=1}^{m} v_j^2$$

It is worthwhile to mention here that the combination operation is not associative in nature. Hence, a further operation can be formulated to combine multiple D numbers.

Property 4: (Deng et al., 2014a) If $D_1, D_2, \ldots, D_n$ are n D numbers, μ_j is an order variable for each D_j, indicated by the tuple $<\mu_j, D_j>$, then the function f_D represents the combination operation of multiple D numbers,

$$f_D(D_1, D_2, \ldots, D_n) = [\ldots[D_{\lambda_1} \oplus D_{\lambda_2}] \oplus \ldots \oplus D_{\lambda_n}] \tag{8}$$

where D_{λ_1} is equal to D_j in the tuple $<\mu_j, D_j>$ in which the value of μ_j is the least.

3.2. MARCOS method

It is a recently developed MCDM technique used for ranking of the candidate alternatives (Stević et al., 2020). Consideration of the reference ideal and anti-ideal solutions at the initial stages of analysis makes it advantageous over the other ranking techniques. In this method, each alternative receives a particular value of utility function depending on its relation with the ideal and anti-ideal solutions. Preference is provided to those alternatives which are closest to the ideal solution and farthest from the anti-ideal solution. Its computation starts with the formation of a decision matrix showing the performance of the alternatives with respect to different criteria. In this matrix, the ideal solution (having maximum values for benefit criteria and minimum values for cost criteria) and anti-ideal solution (with maximum values for cost criteria and minimum values for benefit criteria) are defined. The initial matrix is normalized with respect to the reference value and the corresponding weighted normalized matrix is derived by multiplying all the elements of the normalized matrix with the weight coefficients of the considered criteria. This matrix is finally employed to evaluate the utility degree for each of the alternatives based on which they are subsequently ranked.

3.3. D-MARCOS method

It has already been mentioned that this paper deals with integration of D numbers with MARCOS method for selection of the most apposite supplier in an Indian iron and steel making industry while taking into account the uncertainty prevalent in human judgement to make the decision more robust. For its successful implementation, a set of n criteria is recognized along with determination of their weights (relative importance) using a suitable criteria weight measurement technique. A versatile team of r experts is then formulated where each expert is assigned a weight $\lambda_k > 0$ (i = 1,2,…,r) such that $\sum_{i=1}^{r} \lambda_k = 1$ based on his/her level of experience and expertise. The procedural steps of D-MARCOS method are presented as below:

Step 1: In this step, the evaluation matrices for all the participating experts are formulated. Due to different backgrounds and variation in human judgements, there exists certain extent of uncertainty while evaluating the alternatives with respect to each of the criteria, which can be taken care of by the implementation of D numbers.

For k^{th} expert, the performance score assigned to i^{th} alternative against j^{th} criterion is represented by D number d_{ij}^k. Hence, the decision matrix with m alternatives and n criteria for k^{th} expert is represented as below:

$$T_k^{'} = \begin{array}{c} A_1^k \\ A_2^k \\ \vdots \\ A_m^k \end{array} \begin{bmatrix} d_{11}^k & d_{12}^k & \cdots & d_{1n}^k \\ d_{21}^k & d_{22}^k & \cdots & d_{2n}^k \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1}^k & d_{m2}^k & \ldots & d_{mn}^k \end{bmatrix} \tag{9}$$

Step 2: The aggregated decision matrix for all the experts in the team is now computed based on the properties of D numbers, keeping in mind the weight assigned to each expert. If there are two matrices evaluated by experts E_1 and E_2:

$$T_1^{'} = \begin{array}{c} A_1^1 \\ A_2^1 \\ \vdots \\ A_m^1 \end{array} \begin{bmatrix} d_{11}^1 & d_{12}^1 & \cdots & d_{1n}^1 \\ d_{21}^1 & d_{22}^1 & \cdots & d_{2n}^1 \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1}^1 & d_{m2}^1 & \ldots & d_{mn}^1 \end{bmatrix}, \quad T_2^{'} = \begin{array}{c} A_1^2 \\ A_2^2 \\ \vdots \\ A_m^2 \end{array} \begin{bmatrix} d_{11}^2 & d_{12}^2 & \cdots & d_{1n}^2 \\ d_{21}^2 & d_{22}^2 & \cdots & d_{2n}^2 \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1}^2 & d_{m2}^2 & \ldots & d_{mn}^2 \end{bmatrix}$$

then the aggregated decision matrix is presented as follows:

$$T' = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \ldots & d_{mn} \end{bmatrix} \tag{10}$$

Such that $d_{ij} = d_{ij}^1 \oplus d_{ij}^2$, where $1 \le i \le m$ and $1 \le j \le n$. For more than two experts in the decision making team, the aggregated decision matrix is developed using Eq. (8).

Step 3: In order to rank the candidate alternatives applying MARCOS method, a consolidated $m \times n$ matrix is formulated, integrating each of the D numbers assigned to a particular alternative against each criterion.

$$X = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{11}$$

where $x_{ij} = I(d_{ij})$.

Step 4: All the considered evaluation criteria are now grouped into two categories, i.e. benefit (larger-the-better) (represented by B) and cost (smaller-the-better) (denoted by C).

Step 5: The consolidated matrix is extended by defining two additional rows, indicating the ideal (AI) and anti-ideal (AAI) solutions. The anti-ideal solution reflects the worst alternative, whereas, the ideal solution reflects the best possible alternative.

$$X' = \begin{array}{c} \\ \mathrm{AAI} \\ \mathrm{A}_1 \\ \mathrm{A}_2 \\ \vdots \\ \mathrm{A}_m \\ \mathrm{AI} \end{array} \begin{array}{c} \begin{array}{cccc} \mathrm{C}_1 & \mathrm{C}_2 & \cdots & \mathrm{C}_\mathrm{n} \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \\ x_{a1} & x_{a2} & \cdots & x_{an} \end{bmatrix} \end{array} \tag{12}$$

where

$$AAI = \min_i x_{ij} \text{ if } j \in B \text{ and } \max_i x_{ij} \text{ if } j \in C \tag{13}$$

$$AI = \max_i x_{ij} \text{ if } j \in B \text{ and } \min_i x_{ij} \text{ if } j \in C \tag{14}$$

Step 6: The X' matrix is then normalized to form another matrix N of $(m + 2) \times n$ dimension, i.e. $N = \lfloor n_{ij} \rfloor_{(m+2)\times n}$, based on the following equations:

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \text{ if } j \in B \text{ (for benefit criterion)} \tag{15}$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \text{ if } j \in \mathrm{C} \text{ (for cost criterion)} \tag{16}$$

Step 7: The final weighted matrix $Y = \lfloor y_{ij} \rfloor_{(m+2)\times n}$ is obtained while multiplying the elements of the normalized matrix by the corresponding criteria weights.

$$y_{ij} = n_{ij} \times w_j \tag{17}$$

where n_{ij} is an element of matrix N and w_j is the weight assigned to j^{th} criterion.

Step 8: The positive and negative degrees of utility for each alternative with respect to the ideal and anti-ideal solutions are respectively determined using the following equations:

$$K_i^+ = \frac{T_i}{T_{ai}} \tag{18}$$

$$K_i^- = \frac{T_i}{T_{aai}} \tag{19}$$

where

$$T_i = \sum\nolimits_{j=1}^{n} y_{ij} \quad (i = 1,2...,m) \tag{20}$$

Step 9: The utility function hence used to evaluate the compromise of each alternative with respect to the ideal and anti-ideal solutions can be defined as follows:

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{21}$$

where the utility function with respect to the ideal and anti-ideal solutions can be respectively defined using the following equations:

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{22}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{23}$$

Step 10: The final ranking order of the alternatives can be obtained while assigning the best rank to the alternative having the highest utility function value.

4. Application of D-MARCOS method for supplier selection

As mentioned earlier, this paper deals with the application of D-MARCOS method for selecting the most apposite supplier for an iron and steel making industry. The steel industry being considered here is located in an industrial town of West Bengal, India and procures the requisite materials from various organizations across the globe. It is a leading producer of steel with annual production of around 2.4 million tonnes of crude steel. It came into existence in the year of 1959 and has been growing ever since. Although some of its primary raw materials are arranged from its own captive mines or from the parent organization, there are a lot of other materials need to be acquired from other suppliers. It is a gigantic unit which houses a large number of equipments and machineries, requiring huge indenting volume. Apart from the semi-finished products, its product basket consists of structural, merchant and railway items. In this plant, there is large number of furnaces and reheating units continuously in action, involving huge refractory consumption. These refractory materials are mostly procured from the external suppliers. This unit needs to be managed to stand the test of time while satisfying its clients across the globe. The importance of SC in such a big unit thus cannot be ignored. There is a dedicated team continuously working to evaluate its wide range of suppliers and choosing the most eligible ones.

Based on the humongous set of criteria available in the literature for iron and steel industry (Kar, 2015b), seven most important criteria are shortlisted for evaluation of the competing suppliers engaged in supply of refractory materials to the considered plant. Table 2 provides the list of those criteria which are again weighed by the participating experts using the best-worst method (Rezaei, 2015). It is worthwhile to mention here that amongst the criteria, delivery compliance (C_2) and price (C_3) are the cost criteria always preferred with their minimum values. It is also noticed from Table

2 that product quality (C_1) and delivery compliance (C_2) are the two most important criteria for this supplier selection, whereas, electronic transaction capability (C_7) is the least important criterion. Table 3 represents details of the five major suppliers among whom the most competent one needs to be identified using D-MARCOS method. These five suppliers are now appraised by a team consisting of three decision makers from the steel melting unit, materials management and finance department having more than 15 years of industrial experience. Based on their varying expertise and knowledge, they are assigned weights with 0.4, 0.35 and 0.25 respectively. They are asked to assess the relative performance of the considered suppliers with respect to each criterion using a 1-9 scale, where 1-2 represent the least scores, 8-9 mark the highest scores, 4-6 denote medium scores, and 3 and 7 are intermediate scores.

Table 2. List of the criteria for supplier selection

Criterion	Description	Weight
Product quality (C_1)	It takes into account worth of a product in compliance to a particular threshold value for minimum assured life and guaranteed performance.	0.312
Delivery compliance (C_2)	It accounts for the time within which delivery is met. Scheduled delivery of materials is much needed to ensure proper inventory level such that production never gets disrupted due to unavailability of resources.	0.223
Price (C_3)	It is the monetary value of an item to be paid by the organization to the concerned supplier.	0.208
Technological capability (C_4)	With the advancements of cutting edge technology, product and service must be proficient enough to meet various requirements of the organization even beyond maintaining the delivery schedule. It deals with the compatibility of a supplier to upkeep with the advanced technology.	0.125
Production capability (C_5)	It primarily deals with the ability of a supplier to deliver the required quantity of material at the specified time keeping in mind the fluctuating requirements. It is often graded with respect to standard certifications.	0.114
Financial strength (C_6)	It stresses on the overall financial stability of a supplier with respect to changing market scenario. It is ranked based on a particular supplier's annual turnover.	0.009
Electronic transaction capability (C_7)	With technological advancements, electronic transaction capability is a much needed sophistication for a supplier to ensure online payment with reduction of other additional costs.	0.006

Table 3. List of the shortlisted suppliers

Supplier	Description
S_1	An almost new organization with presence in different countries is well preferred by the steel industries due to its capability to deliver functional refractory at reasonably low price.
S_2	It was established in early 70s as an MSME and proceeded towards adapting better technology of late, but has already succeeded in carving its name amongst the top suppliers of refractory materials.
S_3	It started its journey in early 70s and has become a well-known supplier of regular refractory materials. With the introduction of state-of-the-art technology, it has also collaborated with other international manufacturers to sustain through the competitive race.
S_4	It was established in 80s with modern technology and management. It has always been adaptive to the latest technologies grabbing the steel industry's attention.
S_5	Established in late 90s, it grossly depends on outsourcing of materials with high variation in product quality and hence, is supposed to be a risky supplier.

Tables 4-6 respectively show the corresponding evaluation matrices developed by the participating decision makers (DM_1, DM_2 and DM_3) while assessing the performance of each of the five suppliers with respect to each criterion in terms of D numbers. For example, in Table 4, using the 1-9 scale, DM_1 assigns scores 7 and 8 with 50% assurance in each case while appraising supplier S_1 with respect to criterion C_1. Similarly, in Table 5, DM_2 is 80% confident to assign a score of 6 to supplier S_1 with respect to criterion C_1. The DM_2 is in a dilemma (20% chance) while appraising supplier S_1 with respect to criterion C_1, i.e. in 20% cases, DM_2 is not assured to provide any score to supplier S_1 against C_1. In Table 6, DM_3 is 100% assured to assign a score of 6 to supplier S_1 against criterion C_1. Now, based on the individual evaluation matrices by the three decision makers and using properties (2)-(4) of D numbers, the aggregated D number scores are computed in Table 7.

It is observed that the scores assigned to supplier S1 with respect to criterion C_1 by DM_1, DM_2 and DM_3 are respectively $D_1 = \{(7, 0.5), (8, 0.5)\}$, $D_2 = \{(6,0.8)\}$ and $D_3 = \{(6,1)\}$. Therefore, the aggregated score for supplier S_1 against criterion C_1 is derived as: $D = (D_1 \oplus (D_2 \oplus D_3)) = \{(6.5, 0.35), (7, 0.35)\}$.

Table 4. Evaluation matrix by DM_1

Supplier	Criteria						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
S_1	{(7,0.5),(8,0.5)}	{(2,0.5),(3,0.5)}	{(1,1)}	{(7,1)}	{(8,0.2),(7,0.8)}	{(8,1)}	{(7,1)}
S_2	{(8,1)}	{(3,1)}	{(5,1)}	{(7,0.2),(8,0.8)}	{(7,1)}	{(8,1)}	{(7,0.8),(8,0.2)}
S_3	{(7,0.8),(8,0.2)}	{(1,0.8)(2,0.2)}	{(3,0.5),(4,0.5)}	{(9,1)}	{(9,1)}	{(7,0.6),(8,0.4)}	{(7,1)}
S_4	{(6,0.5),(7,0.5)}	{(3,0.8)}	{(4,1)}	{(8,1)}	{(8,1)}	{(9,1)}	{(8,1)}
S_5	{(7,0.5)}	{(2,1)}	{(3,0.2),(4,0.8)}	{(8,0.4),(7,0.6)}	{(7,0.8),(8,0.2)}	{(7,0.8),(8,0.2)}	{(9,1)}

Table 5. Evaluation matrix by DM_2

Supplier	Criteria						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
S_1	{(6,0.8}	{(2,1)}	{(1,1)}	{(7,0.6),(6,0.4)}	{(7,1)}	{(7,1)}	{6,1)}
S_2	{(7,1)}	{(2,0.7),(3,0.3)}	{(4,1)}	{(9,1)}	{(8,1)}	{(7,0.6),(8,0.4)}	{(8,1)}
S_3	{(7,1)}	{(1,1)}	{(3,0.7),(2,0.3)}	{(8,1)}	{(9,0.8),(8,0.2)}	{(8,0.7),(7,0.3)}	{(7,1)}
S_4	{(6,0.3),(7,0.7)}	{(2,1)}	{(4,0.7),(5,0.3)}	{(8,0.5),(7,0.5)}	{(8,0.8),(9,0.2)}	{(9,1)}	{(8,0.5),(7,0.5)}
S_5	{(6,0.8)}	{(2,0.9)}	{(3,0.6),(4,0.4)}	{(7,0.2),(6,0.8)}	{(7,1)}	{(7,1}	{(9,1)}

Table 6. Evaluation matrix by DM_3

Supplier	Criteria						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
S_1	{(6,1)}	{(2,1)}	{(1,1)}	{(7,0.6),(8,0.4)}	{(8,1)}	{(7,1)}	{(7,1)}
S_2	{(8,1)}	{(2,0.5),(3,0.5)}	{(5,1)}	{(9,0.6),(8,0.4)}	{(8,1)}	{(7,0.5),(8,0.5)}	{(9,1)}
S_3	{(7,0.7)}	{(1,1)}	{(3,0.4),(4,0.6)}	{(9,0.3),(8,0.7)}	{(9,1)}	{(8,1)}	{(9,1)}
S_4	{(7,0.6),(8,0.4)}	{(3,1)}	{(4,0.6)}	{(8,1)}	{(8,0.8),(9,0.2)}	{(8,1)}	{(8,1)}
S_5	{(6,0.7),(7,0.3)}	{(1,0.3),(2,0.7)}	{(3,0.8),(4,0.2)}	{(7,1)}	{(7,1)}	{(7,0.8),(8,0.2)}	{(9,1)

Table 7. Aggregated decision matrix for the supplier selection problem

Supplier	Criteria						
	C_1	C_2	C_3	C_4	C_5	C_6	C_7
S_1	{(6.5,0.35), (7,0.35)}	{(2,0.5), (2.5,0.5)}	{(1,1)}	{(7,0.375), (6.75,0.3125), (7.25,0.3125)}	{(7.75,0.4), (7.25,0.6)}	{(7.5,1)}	{(6.75,1)}
S_2	{(7.75,1)}	{(2.5,0.325), (2.75,0.375), (3,0.3)}	{(4.75,1)}	{(8,0.18325), (8.5,0.33325), (8.25,0.3165), (7.75,0.1665)}	{(7.5,1)}	{(8.25,0.375), (7.5,0.31875), (8,0.30625)}	{(7.75,0.6), (8.25,0.4)}
S_3	{(7,0.3425), (7.5,0.1925)}	{(1,0.6), (1.5,0.4)}	{(3,0.2), (3.5,0.2), (3.25,0.3), (3.75,0.165), (2.75,0.135)}	{(8.5,0.522), (8.75,0.477)}	{(9,0.5333), (8.75,0.4666)}	{(7.5,0.29), (8,0.24), (7.25,0.26), (7.75,0.21)}	{(7.5,1)}
S_4	{(6.25,0.145), (6.75,0.3), (7.25,0.155), (7,0.2), (6.5,0.2)}	{(2.75,0.6)}	{(4,0.33125), (4.25,0.30625)}	{(8,0.5), (7.75,0.5)}	{(8.25,0.375), (8.5,0.275), (8,0.35)}	{(8.75,1)}	{(8,0.5), (7.75,0.5)}
S_5	{(6.5,0.175), (6.75,0.155)}	{(1.75,0.325), (2,0.35)}	{(3,0.275), (4,0.19), (3.5,0.3), (3.75,0.26), (3.25,0.14)}	{(7.5,0.2), (7,0.25), (6.75,0.3), (7.25,0.25)}	{(7,0.6), (7.5,0.4)}	{(7.5,0.2), (7,0.35), (7.75,0.15), (7.25,0.3)}	{(9,1)}

It is worthwhile to mention here that in this supplier selection problem, the participating decision makers have been assigned weights with 0.4, 0.35 and 0.25 respectively depending on their varying experience and expertise. Thus, the combination operation for D numbers is first performed between DM_2 and DM_3 with minimum weights, and then the corresponding D number for DM_1 is taken into consideration for the combination operation. Now, based on the developed aggregated decision matrix in terms of D numbers, the corresponding consolidated matrix X is formulated using Eq. (3).

For instance: x_{11} = ((6.5×0.35) + (7×0.35)) = 4.72.

In the similar direction, DM_1, DM_2 and DM_3 respectively evaluate the performance of supplier S_2 against criterion C_4 as D1 = {(7,0.2), (8,0.8)}, D2 = {(9,1)}and D3 = {(9,0.6),(8,0.4)} in terms of D numbers. The aggregated score for supplier S2 with respect to criterion C4 is calculated as:

$D=(D_1 \oplus (D_2 \oplus D_3))$ = {(8.0, 0.18325), (8.5, 0.33325), (8.25, 0.3165), (7.75, 0.1665)}

Thus, the value of element x_{24} in the consolidated matrix becomes:

$$x_{24} = ((8 \times 0.18325) + (8.5 \times 0.33325) + (8.25 \times 0.3165) + (7.75 \times 0.1665)) = 8.2$$

$$X = \begin{bmatrix} 4.72 & 2.25 & 1 & 7 & 7.45 & 7.5 & 6.75 \\ 7.75 & 2.74 & 4.75 & 8.2 & 7.5 & 7.93 & 7.95 \\ 3.84 & 1.20 & 3.26 & 8.61 & 8.88 & 7.60 & 7.5 \\ 6.75 & 1.65 & 2.63 & 7.87 & 8.23 & 8.76 & 7.87 \\ 2.18 & 1.27 & 4.06 & 7.09 & 7.2 & 7.29 & 9 \end{bmatrix}$$

Based on the procedural steps of D-MARCOS method, another matrix X' (extended matrix) is formulated from the consolidated matrix by defining two additional rows, indicating the ideal (AI) and anti-ideal (AAI) solutions at the bottom and top of the consolidated matrix respectively.

$$X = \begin{array}{c} \\ AAI \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ AI \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{bmatrix} 2.18 & 2.74 & 4.75 & 7 & 7.2 & 7.29 & 6.75 \\ 4.72 & 2.25 & 1 & 7 & 7.45 & 7.5 & 6.75 \\ 7.75 & 2.74 & 4.75 & 8.2 & 7.5 & 7.93 & 7.95 \\ 3.84 & 1.20 & 3.26 & 8.61 & 8.88 & 7.60 & 7.5 \\ 6.75 & 1.65 & 2.63 & 7.87 & 8.23 & 8.76 & 7.87 \\ 2.18 & 1.27 & 4.06 & 7.09 & 7.2 & 7.29 & 9 \\ 7.75 & 1.20 & 1 & 8.61 & 8.88 & 8.76 & 9 \end{bmatrix} \end{array}$$

Now, based on the type of the considered criterion and employing Eqs. (15)-(16), the related normalized decision matrix is obtained.

$$N = \begin{array}{c} \\ AAI \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ AI \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{bmatrix} 0.28 & 0.44 & 0.21 & 0.81 & 0.81 & 0.83 & 0.75 \\ 0.61 & 0.53 & 1 & 0.81 & 0.84 & 0.86 & 0.75 \\ 1 & 0.44 & 0.21 & 0.95 & 0.84 & 0.90 & 0.88 \\ 0.49 & 1 & 0.31 & 1 & 1 & 0.87 & 0.83 \\ 0.87 & 0.73 & 0.38 & 0.91 & 0.93 & 1 & 0.87 \\ 0.28 & 0.94 & 0.41 & 0.82 & 0.81 & 0.83 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \end{array}$$

The weighted normalized decision matrix is then computed by multiplying each element of the normalized matrix with the corresponding criteria weights.

$$Y = \begin{array}{c} \\ AAI \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ AI \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 \end{array} \\ \begin{bmatrix} 0.0874 & 0.0981 & 0.0436 & 0.1013 & 0.0923 & 0.0074 & 0.0045 \\ 0.1903 & 0.1182 & 0.2080 & 0.1013 & 0.0958 & 0.0078 & 0.0045 \\ 0.3120 & 0.0981 & 0.0436 & 0.1188 & 0.0958 & 0.0081 & 0.0053 \\ 0.1529 & 0.2230 & 0.0645 & 0.1250 & 0.1140 & 0.0078 & 0.0050 \\ 0.2714 & 0.1628 & 0.0790 & 0.1138 & 0.1060 & 0.0090 & 0.0052 \\ 0.0874 & 0.2096 & 0.0853 & 0.1025 & 0.0923 & 0.0074 & 0.0060 \\ 0.3120 & 0.2230 & 0.2080 & 0.1250 & 0.1140 & 0.0090 & 0.0060 \end{bmatrix} \end{array}$$

Using Eqs. (18)-(23), the positive and negative degrees of utility, and value of the utility function for all the competing suppliers are estimated, as shown in Table 8. The detailed computational steps for determining the utility function value for supplier S_1 are explained as below:

For ideal solution:

T_{ai} = 0.3120 + 0.2230 + 0.2080 + 0.1250 + 0.1140 + 0.0090 + 0.0060 = 0.9970

For anti-ideal solution:

T_{ai} = 0.0874 + 0.0981 + 0.0436 + 0.1013 + 0.0923 + 0.0074 + 0.0045 = 0.4346

For supplier S_1:

T_1 = 0.1903 + 0.1182 + 0.2080 + 0.1013 + 0.0958 + 0.0078 + 0.0045 = 0.7259

$$K_1^+ = \frac{0.7259}{0.9970} = 0.7281 \; ; \; K_1^- = \frac{0.7259}{0.4346} = 1.6702 \, ;$$

$$f(K_1^+) = \frac{1.6702}{1.6702 + 0.7281} = 0.696410; \; f(K_1^-) = \frac{0.7281}{1.6702 + 0.7281} = 0.303590$$

$$f(K_1) = \frac{0.7281 + 1.6702}{1 + \frac{1 - 0.696410}{0.696410} + \frac{1 - 0.303590}{0.303590}} = 0.643001$$

In order to identify the most apposite supplier for providing refractory materials to the considered iron and steel making industry, they are now ranked based on the computed values of utility function. It is observed that supplier S_4 with the maximum utility value of 0.661829 is ranked first, closely followed by supplier S_1. The performance of suppliers S_2 and S_3 is almost similar. On the other hand, supplier S_5 would be considered with least preference.

Table 8. Estimation of utility functions for the candidate suppliers

Supplier	T_i	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Rank
S_1	0.7259	1.6702	0.7281	0.303590	0.696410	0.643001	2
S_2	0.6817	1.5686	0.6838	0.303587	0.696412	0.603879	4
S_3	0.6922	1.5927	0.6943	0.303585	0.696414	0.613154	3
S_4	0.7472	1.7193	0.7494	0.303560	0.696439	0.661829	1
S_5	0.5905	1.3587	0.5923	0.303588	0.696412	0.523066	5

5. Conclusions

This paper proposes integration of D numbers with MARCOS method for effective selection of suppliers for refractory materials in an iron and steel industry in India. For this purpose, the relative performance of five competing suppliers is evaluated with respect to seven conflicting criteria using D numbers based on the opinions of three decision makers with varying knowledge and expertise. The MARCOS method is later employed for ranking of the considered suppliers. It has already been acknowledged that accounting for uncertainty involved in supplier selection process for effective SCM system development is an important task in today's manufacturing environment. Although there are several approaches, like fuzzy set theory, D-S theory etc. to deal with uncertainty in decision making processes, the concept of D numbers supersedes the others with respect to its ability to provide more robust and flexible results while taking into consideration varied opinions of individual decision makers who can evaluate the relative performance of the participating suppliers with varying degrees of uncertainty. Thus, this integrated MCDM tool can be efficiently adopted in other domains of decision making, like selection of optimal maintenance strategy, plant layout, inventory control policy, machine tool etc. in uncertain manufacturing environment.

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