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SUPPLIER SELECTION FOR STEELMAKING COMPANY BY USING COMBINED GREY-MARCOS METHODS

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Abstract: *Selecting the right suppliers should saw as more than simply scanning a set of available price lists and comparing them, but rather as including a wide range of different criteria, whether qualitative or quantitative. In contemporary supply chain management, potential supplier performance is based on multiple criteria rather than considering cost as the main criterion in decision-making. This makes the process of selecting the best supplier from a group of suppliers a complex and laborious process, due to the multiplicity of criteria that must be taken into account in the evaluation process. This study aims to implement a hybrid Grey theory-MARCOS method for decision-making regarding the selection of suppliers in the Libyan Iron and Steel Company (LISCO) to help it compete. This hybrid model is divided into two phases: the first consists of determining the weights of the criteria that contribute to decision-making, which has done using the Grey theory, and the second phase consists of selecting the best supplier from among the six suppliers, which has completed using the MARCOS model. The effectiveness of the model has compared to three other methods, CODAS, TOPSIS, and VIKOR. The results showed that the proposed method effectively selected the best supplier among the six alternative suppliers.*

Key words: *MCDM, MARCOS, GREY, supplier selection, LISCO*

1. Introduction

Before the advent of multi-criteria methods, decision-making problems most often depended on a single criterion or objective function, maximizing profits or reducing costs. However, in reality, economic problems do not depend on a single objective but go beyond it. So it has been more appropriate to resort to methods with several criteria or restrictions, which are multi-criteria methods. These methods may include both quantitative and qualitative criteria, but their effect on decision-making varies from one criterion to another (Moslem and Duleba, 2018; Kiracı and Bakır, 2018). When making

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decisions, the selection of ineffective or inappropriate criteria will have negative economic impacts on the enterprise (Chatterjee and Stević, 2019).

The purchasing function has garnered much attention in supply chains due to several factors such as globalization and accelerating technological change (Erceg and Mularifović, 2019). Perhaps one of the essential activities of the purchasing function is to choose the right supplier, as it allows the company to achieve significant savings by maintaining a long-term partnership with suppliers, and thus dealing with a smaller number of these trusted suppliers. Many industrial projects suffer from numerous problems and obstacles that cause them to deviate from their specific objectives. Cost, time, and quality are the main objectives of any engineering project, and its achievement is the primary indicator for evaluating performance and ensuring the success of the project. These deviations are represented either in an overrun of the specified cost, an increase in time, or a low level of quality, where the implementing supplier plays a significant role in these deviations. The method used by many industrial companies to select the suppliers often depends on ineffective methods, where the tender is awarded to those offering the lowest price in the invitation to tender, even though the lowest price is not a sufficient indication to select the supplier that is capable of executing the contract and achieving its objectives. Methods based on the principle of multi-criteria analysis and which take into account all the criteria necessary to select the best supplier are the most appropriate for the evaluation and selection of suppliers (Durmić, 2019). Its strength lies in the fact that it applies to decision situations involving multiple criteria that it uses both qualitative and quantitative data, and that provides metrics and indicators for preference selection. From this standpoint, and because the cost of raw materials is the essential component of industrial costs in many plants, the subject of choosing between suppliers has received a great deal of attention from researchers in recent years.

Competitors in the manufacturing sector today have the challenge of providing high-quality products in addition to competitive prices. The total cost of raw materials usually constitutes the central portion of the product's final cost, which causes companies to pay more attention to supplier management (Vasiljević et al., 2018). This places the financial department a significant role in reducing products' final cost by selecting the right suppliers. Thus, selecting the best suppliers involves more than simply scanning a series from the price list, but goes beyond it to choose the right criteria to compare these suppliers. Recently, supplier evaluation and selection have received significant attention from various researchers in the literature (Badi and Ballem, 2018; Chatterjee and Stević, 2019; Mishra et al., 2019). Generally, the criteria for supplier selection are highly dependent on individual industries and companies. Therefore, different companies have different management strategies, enterprise culture, and competitiveness.

Furthermore, company background causes a considerable difference and impacts supplier selection. Thus, the identification of supplier selection criteria mostly requires a domain expert's assessment and judgment. To select the best supplier, it is necessary to make a trade-off between these qualitative and quantitative factors (weights), some of which may conflict (Ghodsypour and O'Brien, 1998). Traditional supplier selection methods are often based on the quoted price, which ignores the significant direct and indirect costs associated with quality, delivery, and service cost of purchased materials. Uncertainty occurs because the future can never be predicted. One of the critical problems in supplier selection is to find the best supplier among several alternatives according to various criteria, such as service, cost, risk, and others. After identifying the criteria, a systematic methodology requires to integrate experts' assessments in order to find the best supplier. Various methods have been used for supplier selection (Porras-Alvarado et al., 2017).

The combined Grey theory and the Measurement of Alternatives and Ranking According to the Compromise Solution (MARCOS) method will be implemented to evaluate the suppliers of raw materials to the Libyan Iron and Steel Company (LISCO). LISCO is a large scale, a government-owned company. The company's production capacity is about 1,324,000 tons of liquid steel (Badi et al., 2017). In the last two decades, the company had almost met the demand for its products in the local market and managed to compete globally. It has started to export its products to Egypt, Tunisia, Qatar, and others. LISCO is working against the odds to rebuild the country's economy after the 2011 revolution and is doing so with a carefully considered strategy to expand its 60% iron and steel its market share in Libya. The importation of raw material is an important step to maintain and improve its market share in a competitive environment (Badi et al., 2017). The quality and cost of the final products are intimately connected to the proper selection of a sponge-iron supplier to the direct reduction, mega-scale factories.

LISCO usually imports sponge iron from India, Brazil, Canada, and Sweden. Suppliers from other countries also consider LISCO as a potential customer. Since suppliers have variable strengths and weaknesses, careful assessment and evaluation by the client are crucial before orders could be placed.

2. Research Methodology

The methodology used in this research is illustrated in Figure 1, where the weights of the criteria were determined using Grey theory. After that, suppliers were evaluated using the MARCOS technique. Finally, the results are compared with the other three multi-criteria methods.

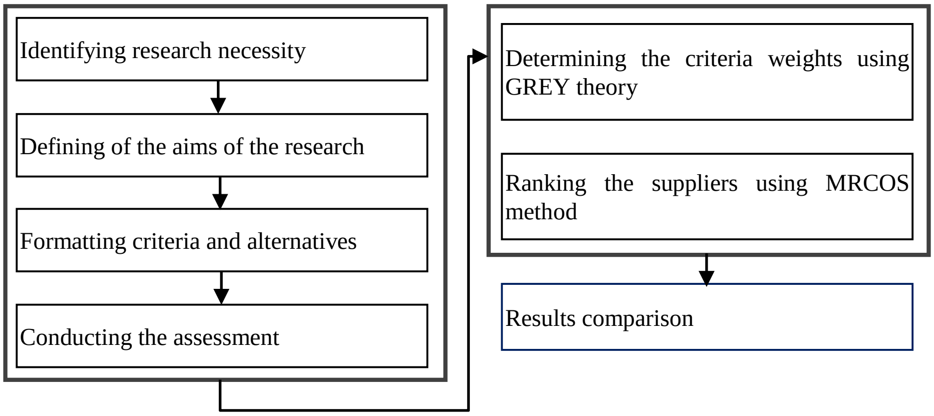

Figure 1. Methodology of the research

2.1 Grey theory

Criteria weights are often difficult to determine precisely because of uncertainty, which can be addressed by linguistic terms such as “good,” “weak,” “important” or “very important” and other similar terms. Realistic, multi-criteria decision-making applications require inaccurate, uncertain, qualitative, or ambiguous data processing. One effective method for modeling uncertainty and inaccuracy is using the Grey theory, which developed by Deng (Deng, 1982). It provides the flexibility to represent and deal with uncertainty and inaccuracy resulting from a lack of knowledge or inaccurate information. It uses a Black-Grey-White color to describe complex systems (Liu et al., 2011). The concepts of a grey system can be illustrated as in Figure 2. grey number is a kind of figure that we only know the range of values, and do not know an exact value. This number can be an interval or a general number set to represent the degree of uncertainty of information. This section describes the basics of Grey systems theory and Grey numbers in order to understand the model.

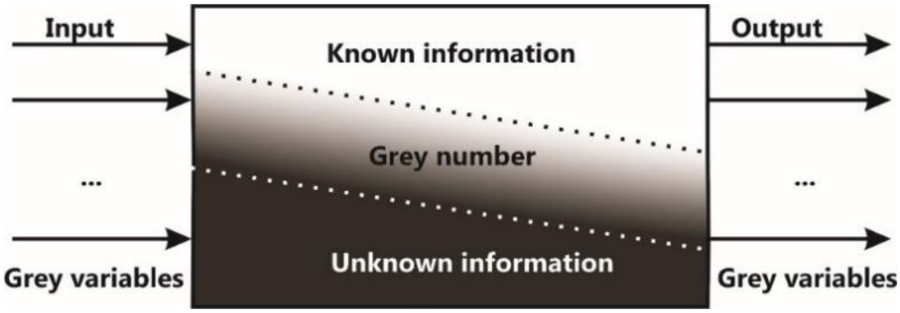

Figure 2. The concept of Grey System (Badi et al., 2018b; Abdulshahed et al., 2017b)

Let X is the universal set. Then a Grey set G of X is defined by its two mappings $\overline{\mu}_G(X)$ and $\underline{\mu}_G(X)$: $\overline{\mu}_G(X): X \longrightarrow [0,1]$ and $\underline{\mu}_G(X): X \longrightarrow [0,1]$ such that $\overline{\mu}_G(X) \geq \underline{\mu}_G(X), \times \in X$. Since the lower limit $\otimes G = [\underline{G}, \infty)$ and upper limit $\otimes G = (-\infty, \overline{G}]$ can possibly be estimated, G is defined as an interval grey number $\otimes G = [\underline{G}, \overline{G}]$ where $\underline{G} > \overline{G}$. Let t be the information, $\overline{G}$ the upper, $\underline{G}$ the lower limit then $\underline{G} \leq t \leq \overline{G}$ if $\underline{G} = \overline{G}$ then $\otimes G$ is a white number with a crisp value which shows the existence of full knowledge. On the contrary, a black number is a grey number one known nothing about it (Liu et al., 2012).

The arithmetic of grey numbers is similar to interval value (Liu et al., 2012, Li et al., 2007) and the operation rules of general grey numbers can defines as operation rules of real numbers (Liu et al., 2012; Badi et al., 2019). Addition: $\otimes G_1 + \otimes G_2 = [\underline{G_1} + \underline{G_2}, \overline{G}_1 + \overline{G}_2]$

Subtraction: $\otimes G_1 - \otimes G_2 = [\underline{G_1} - \overline{G}_2, \overline{G}_1 - \underline{G_2}]$

Multiplication: $\otimes G_1 \times \otimes G_2 = [min(\underline{G_1}\underline{G_2}, \underline{G_1}\overline{G}_2, \overline{G}_1\underline{G_2}, \overline{G}_1\,\overline{G}_2), max(\underline{G_1}\underline{G_2}, \underline{G_1}\overline{G}_2, \overline{G}_1\underline{G_2}, \overline{G}_1\,\overline{G}_2)]$

Division: $\otimes G_1 \div \otimes G_2 = [\underline{G_1}, \overline{G}_1] \times \left[\frac{1}{\underline{G_2}}, \frac{1}{\underline{G_2}}\right]$

Length of grey number: $L(\otimes G) = [\overline{G} - \underline{G}]$

Comparison of grey numbers: the possibility degree of two grey number expressing as:

$$P\{\otimes G_1 \leq \otimes G_2\} = \frac{max\left(0, L^* - max(0, \overline{G}_1 - \underline{G_2})\right)}{L^*}$$

Where $L^* = L(\otimes G_1) + L(\otimes G_2)$

According to this comparison of two grey numbers, there may be four distinct outcomes:

If $\otimes G_1 = \otimes G_2$ then $P\{\otimes G_1 \leq \otimes G_2\} = 0.5$ if $P\{\otimes G_1 > \otimes G_2\}$ then $P\{\otimes G_1 \leq \otimes G_2\} = 1$

If $\otimes G_1 < \otimes G_2$ then $\{\otimes G_1 \leq \otimes G_2\} = 0$
If $P\{\otimes G_1 \leq \otimes G_2\} > 0.5$ then $\otimes G_2 > \otimes G_1$
Otherwise if $P\{\otimes G_1 \leq \otimes G_2\} < 0.5$ then $\otimes G_2 < \otimes G_1$
Attribute weight W_j can be calculated as follows (Li et al., 2007):

$$\otimes W_j = \frac{1}{K}\left[\otimes W_j^1 + \otimes W_j^2 + \cdots + \otimes W_j^K\right] \quad (1)$$

$$\otimes W_j^K = \left[\underline{W}_j^K, \underline{W}_j^K\right] \quad (2)$$

3.2 The Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) method

The MARCOS method is based on defining the relationship between alternatives and reference values (ideal and anti-ideal alternatives) (Stević et al., 2020). Decision-making preferences are defined based on utility functions. A utility function is the position of an alternative concerning the ideal and anti-ideal solutions (Stanković et al., 2020). The best alternative is that closest to the ideal point and farthest from the anti-ideal point. The MARCOS method is implemented through the following steps (Puška et al., 2020):

Step 1. The formation of the initial decision matrix.

Step 2. The formation of an extended initial matrix. This step defines the ideal and anti-ideal solutions. The ideal solution is an alternative with the best alternative for specific criteria, whereas the anti-ideal solution is the worst alternative. This is based on the following equations:

$$AAI = \min_j x_{ij} \quad if \;\; j \in B \;\; and \;\; AAI = \max_j x_{ij} \quad if \;\; j \in C \quad (3)$$

$$AI = \max_j x_{ij} \quad if \;\; j \in B \;\; and \;\; AAI = \min_j x_{ij} \quad if \;\; j \in C \quad (4)$$

where B stands for the criteria to be maximized, and C stands for the criteria to be minimized.

Step 3. The normalization of the extended initial matrix. Normalization is performed by using the following equations:

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \;\; if \; j \in C \quad (5)$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \;\; if \; j \in B \quad (6)$$

where the elements x_{ij} and x_{ai} represent the elements of the initial decision matrix.

Step 4. The determination of a weighted matrix. Aggravation is performed by multiplying normalized matrix values by corresponding weights.

Step 5. The calculation of the utility degree of the alternatives Ki. The utility degree is determined by applying the following equations:

$$K_i^- = \frac{S_i}{S_{aai}} \quad (7)$$

$$K_i^+ = \frac{S_i}{S_{ai}} \quad (8)$$

where S_i ($i=1,2,..,m$) represents the sum of the elements of a weighted matrix

$$S_i = \sum_{i=1}^{n} v_{ij} \quad (9)$$

Step 6. The formation of the utility function of the alternatives $f(K_i)$. The utility function is calculated by using the following equation:

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \quad (10)$$

where $f(K_i^-)$ is the utility function versus the anti-ideal solution, while $f(K_i^+)$ is the utility function versus the ideal solution. The utility functions are calculated using the following equations:

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \quad (11)$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{12}$$

Step 7. Ranking the alternatives. A rank is formed based on the final value of the utility function. The alternative should have the most significant value of the utility function.

3. Case study

The proposed model has been applied to evaluate the LISCO's suppliers. LISCO is one of the largest national companies in Libya. In order to maintain its competitive advantage, the import of raw materials is an important step that should be managed carefully. The quality and cost of the finished products are intimately related to the appropriate selection of sponge iron suppliers. LISCO imports sponge iron from several countries, the most potential of which is Brazil. The data used in this paper was based on the two models used in (Badi et al., 2018a) and (Abdulshahed et al., 2017a), which aimed to choose the best suppliers for LISCO. Four different criteria which are considered: Quality (in points) Direct Cost (in $), Lead time (in days), Logistics services (in points). Quality and logistics services criteria are defined as benefit criteria, while the cost and lead time are cost criteria. Table 1 shows the details of these criteria. There are six suppliers.

Table 1. Qualitative criteria for supplier evaluation.

Evaluation criteria	Description	Measuring principle	Criteria status
Quality (C_1)	Poor quality materials are found during incoming inspection	Total number of rejected items in each batch	Benefit-criteria
Direct cost (C_2)	Direct cost of the material	Reasonable direct cost	Cost-criteria
Lead time (C_3)	The supplier capability to timely meet the demand	This can be measured by percentage of demand meet in each period	Cost-criteria
Logistics Service (C_4)	Logistics service used by suppler and transportation time	This can be analysed by percentage of demand meet in each period	Benefit-criteria

The first stage is to determine the criteria weights. Four experts have been invited to participate in the determination of the importance of each criterion for the evaluation of suppliers. The linguistic variables can be expressed in grey numbers by a scale shown in Table 2 (Abdulshahed et al., 2017a). The suppliers were rated for their performances of attributes on grey scales shown in Table 3.

Table 2. The importance of grey number for the weights of the criteria.

Importance	Abbreviation	Scale of grey number $\otimes W$
Very Low	VL	[0.0, 0.1]
Low	L	[0.1, 0.3]
Medium Low	ML	[0.3, 0.4]
Medium	M	[0.4, 0.5]
Medium High	MH	[0.5, 0.6]
High	H	[0.6, 0.9]
Very High	VH	[0.9, 1.0]

Table 3. Linguistic assessment and the associated grey values.

Performance	Abbreviation	Scale of grey number $\otimes W$
Very Poor	VP	[0.0, 0.1]
Poor	P	[0.1, 0.3]
Medium Poor	MP	[0.3, 0.4]
Fair	F	[0.4, 0.5]
Medium Good	MG	[0.5, 0.6]
Good	G	[0.6, 0.9]
Very Good	VG	[0.9, 1.0]

Collect the evaluation of the experts' attributes by using linguistic variables, as shown in Table 4. Next, the attributes can be weighted using equation 1.

Table 4. The linguistic assessment of the attributes by experts.

C_i	Expert #1	Expert #2	Expert #3	Expert #4	$\otimes W$		Whitening degree
C_1	VH	H	H	H	0.67	0.92	0.80
C_2	H	VH	VH	H	0.75	0.95	0.85
C_3	MH	H	H	MH	0.55	0.75	0.65
C_4	M	M	MH	MH	0.45	0.55	0.50

After the criteria weights were calculated, the suppliers are ranked using the MARCOS method. Based on the data collected (Badi et al., 2018a), an initial decision matrix was prepared (Table 5).

Table 5. The initial decision matrix

Weights of criteria	0.80	0.85	0.65	0.50
Alternatives Suppliers	Quality	Direct Costs ($)	Lead Time (Days)	Logistics service
S1	45	3,600	45	0.9
S2	25	3,800	60	0.8
S3	23	3,100	35	0.9
S4	14	3,400	50	0.7

S5	15	3,300	40	0.8
S6	28	3,000	30	0.6
MAX	**45**	**3,800**	**60**	**0.9**

The next step is to normalize the data to be uninformed. For this purpose, a simple linear normalization (Equation 5) was applied to the MARCOS method. The maximum value of the criteria is determined, as required for all criteria to be maximized. The normalization of the initial decision matrix is step 3 of the MARCOS method (Table 6).

Table 6. The normalized decision matrix

Alternatives	Quality	Direct Costs ($)	Lead Time (Days)	Logistics Service
S1	1.000	1.056	1.333	1.000
S2	0.556	1.000	1.000	0.889
S3	0.511	1.226	1.714	1.000
S4	0.311	1.118	1.200	0.778
S5	0.333	1.152	1.500	0.889
S6	0.622	1.267	2.000	0.667

The fourth step after the normalization of the initial matrix is the calculation of the aggregated values using the weighting coefficients. The fifth step is to calculate the utility degree. In order to perform this step, it was first necessary to determine the ideal and anti-ideal solutions. The ideal solution represents the maximum value of a specific criterion, whereas anti-ideal values represent the minimum value of a specific criterion. Then, the values for the individual alternatives and the ideal and anti-ideal solutions were summed up, and the utility degrees were calculated (Equations 7 and 8).

Table 7. The weighted normalized decision matrix and the negative-ideal solution

Alternatives	Quality	Direct Costs ($)	Lead Time (Days)	Logistics Service	Sum
S1	0.800	0.897	0.867	0.500	3.064
S2	0.444	0.850	0.650	0.444	2.389
S3	0.409	1.042	1.114	0.500	3.065
S4	0.249	0.950	0.780	0.389	2.368
S5	0.267	0.979	0.975	0.444	2.665
S6	0.498	1.077	1.300	0.333	3.208
Ideal	0.800	1.077	1.300	0.500	3.677
Anti-Ideal	0.249	0.850	0.650	0.333	2.082

The sixth step of the MARCOS method was to form the utility function of the alternatives. The utility function was calculated by using Equation 10. To calculate the utility function of the alternatives, it was necessary to calculate the utility function concerning the ideal and anti-ideal solutions. The inclusion of these values generated the final value for the alternatives (Table 8) and determined the ranking of the suppliers.

Table 8. The relative assessment matrix and the assessment scores of alternatives

Supplier	K_i^-	K_i^+	F(ki)	Rank
S1	1.471	0.833	0.692	3
S2	1.147	0.650	0.539	5
S3	1.472	0.834	0.692	2
S4	1.137	0.644	0.535	6
S5	1.280	0.725	0.602	4
S6	1.541	0.872	0.724	1

As can be seen from Table (8), S6 is the best supplier concerning the assessment of the MRCOS method. Besides, a comparative analysis has been conducted to demonstrate the validity and stability of the MRCOS method. Three different multi-criteria methods are used, which are the Combinative Distance-based Assessment (CODAS) model, Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), and VIšekriterijumsko KOmpromisno Rangiranje (VIKOR) method. Figure 2 shows the results obtained by these methods.

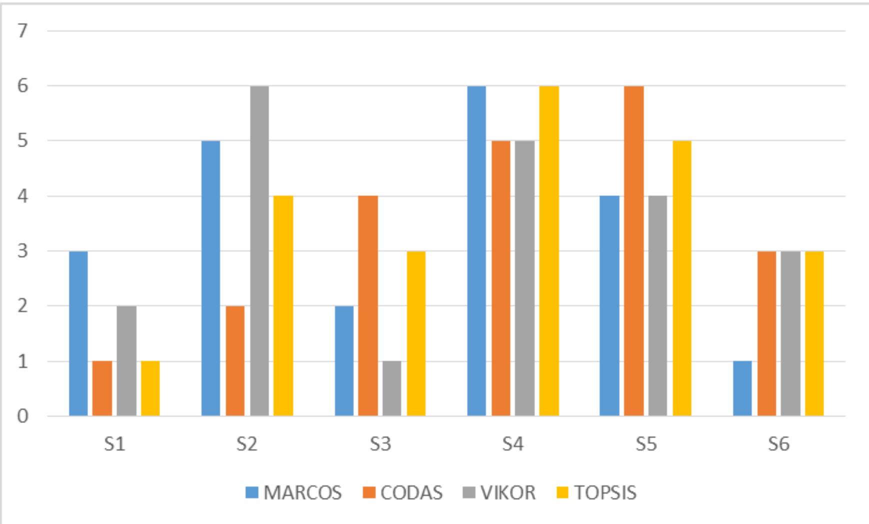

Figure 2. Results comparison

4. Conclusion

It is well known that MCDM techniques are gaining popularity in solving supplier evaluation and selection problems. This paper provides a supporting tool for multi-criteria decision-making to evaluate suppliers using hybrid Grey-MARCOS methods. Grey theory has been used to weigh criteria, which is an appropriate method for dealing with uncertainty. Suppliers have been ranked using the MARCOS method. Therefore, in the future, this method can be used to deal with uncertainty in multi-criteria decision-making problems such as project selection, manufacturing systems, staff selection, and many other areas related to management decisions. Furthermore, the MARCOS method can be used in the future for other applications of MCDM.

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