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A new decision model for weighting of experts and selecting the best sustainable supplier in project procurement problems under a grey environment

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Abstract

Project procurement is one of the essential parts of the project covering a large portion of project costs. Supplier selection is one of the significant issues in project procurement. The appropriate supplier must be selected before ordering the materials needed for the project. Hence, a new combination of COPRAS and GRA methods is presented for choosing the best project's supplier under uncertain conditions in this paper. Moreover, the weight of criteria is specified utilizing the multi-objective optimization model (MOOM). Furthermore, in group decision-making, decision-makers' importance is different because of varying education, views, and experience. Hence, determining the weights of decision-makers is inevitable. Nevertheless, decision-makers' importance is specified by a new version of a combination of COPRAS and GRA methods. To evaluate the proposed model's performance, a numerical example is solved, and the results are investigated.

Keywords: GRA-COPRAS method, grey numbers, multi-objective optimization model, project supplier selection

1- Introduction

Supplier selection is one of the crucial issues that has attracted a lot of attention. Supplier selection is an MCDM issue that can include two crucial parts. The first part is the weighting of the criteria and the second part is the supplier rankings (Büyüközkan & Çifçi, 2011). Supplier selection plays an important role in economic development. Many studies have been done in this field. Investigating the relationship between customer needs, supplier selection and order allocation, supplier selection under environmental and economic criteria, and supplier selection with uncertainty are among the studies that have been conducted (Yazdani et al., 2017; Hamdan & Cheaitou, 2017; Haeri & Rezaei, 2019).

There are many MCDM approaches to evaluate the alternatives (e.g., TOPSIS, VIKOR, DEMATEL, AHP, and COPRAS). In recent years, the COPRAS method has attracted great attention in economics, construction, and management (Chatterjee et al., 2011; Zavadskas et al., 2008). This method was first proposed by Zavadskas and Kaklauskas (1994) to determine the priority and degree of effectiveness of the alternatives.

The reasons for using COPRAS method are the simplicity of computation, needing less time for computations, the use of quantitative and qualitative criteria simultaneously, and the estimation of the importance of each option.

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This method is simple, scientific, and powerful; it does not require complicated mathematical operations (Pitchipo, 2014). Most decision-making techniques fail to provide the relative importance of distances from the best and worst solutions, while the COPRAS has this feature well (Valipour et al., 2017; Vahdani et al., 2014).

MCDM approaches are commendable means to cover the failings of traditional methods. One of the classic methods of MCDM is grey relational analysis (GRA) that can cover decision-making issues with incomplete information and analyze the relationship between qualitative and quantitative criteria (Liu, 2016; Deng, 1989). Researchers in many fields have used GRA method. For example, Wu and peng (2016) provided a way to manage a crisis in the oil industry. Zeng et al. (2017) presented an integrated method of AHP, fuzzy evaluation, and GRA for selecting enterprise resource planning systems for small and medium-sized companies. Wang et al. (2017) proposed a mathematical structure based on a hybrid AHP-GRA approach for supplier selection. Tsaur et al. (2016) examined some companies' performance by using GRA and data envelopment analysis (DEA) methods. Chen et al. (2019), Govindan et al. (2020), and Kellner & Utz (2019) used the GRA method to select the best supplier. In this paper, to simultaneously use the advantage of GRA and COPRAS methods, an integrated COPRAS-GRA method is proposed to rank the alternatives.

In many cases, there are no conclusive data for decision-making. Some types of uncertainty, such as statistics and probability, fuzzy mathematics, and grey systems, will help us solve uncertainty problems (Liu & Lin, 2006). In recent years, researchers have considered uncertainties and have conducted many studies in this regard. Some of these studies are; Mousavi et al. (2016) developed a fuzzy approach to a group decision-making problem by presenting a fuzzy VIKOR approach and a decision-making index. Mohagheghi et al. (2017) solved a predicted project cash flow problem based on interval type-2 fuzzy sets. Mousavi and Vahdani (2016) extended a new cross-docking location selection problem by using fuzzy numbers. In this paper, the grey system was used to address the uncertainties. Grey systems are advantageous because of their usability for small-sized data and incomplete information. In this system, grey numbers present uncertainty (Liu & Lin, 2006).

The choice of project procurement method is one of the factors affecting the efficiency of the project. But, the ambiguity in this choice creates extraordinary challenges for the owners. In the study of Su et al. (2019), the project procurement method (PPM) selection method is developed using interval neutrosophic set (INS), which helps decision-makers to address the uncertainty. Owusu et al. (2019) provided a measurement model to assess corruption in the project. This model has been developed to determine the vulnerability level according to the stages of corruption and their related activities in construction procurement of construction projects using a soft calculation method (i.e., fuzzy synthetic method). In the study of Pu et al. (2020), different procurement models are analyzed. Content analysis is performed to discuss the institutional and legal framework and different procurement models' features in China. To experimentally investigate the relationship between selecting other procurement models and internal features of projects, including investment, duration, mode of operation, sector, and region, a multidimensional logistic regression model has been used. Also, a survey was conducted using a questionnaire to identify important factors affecting selection preferences.

Zabeti targhi et al. (2020) have made decisions about suppliers, reviewed performance, and selected or not selected suppliers. In their study, a mathematical planning model is used to choose the supplier, and then the fuzzy analytical hierarchy process approach is used to prioritize the suppliers. Gupta et al. (2019) presented an approach based on a multi-criteria decision framework that evaluated green suppliers using an integrated fuzzy hierarchical analysis with multi-attributive border approximation area comparison (MABAC), weighted aggregated sum-product assessment (WASPAS), and TOPSIS approaches.

Determining the weight of decision-makers is very important in the decision-making procedure. There are many fields in the decision-making process; each decision-maker does not have enough expertise in all areas, so decision-makers' weights should be considered differently from each other. For this purpose, it is necessary to determine the importance of the decision-makers (Yue et al., 2009; Yue, 2011b, c; Ramanathan & Ganesh, 1994; Weiss & Rao, 1987; Yue, 2011). Many studies have been done in this field. For instance, Mirkin and Fishburn (1979) presented two approaches based on the eigenvectors method to determine group weights. Ramanathan and Ganesh (1994) developed an eigenvector approach based on their opinions to determine the group members' weight. Yue (2011c) presented an approach to weighting DMs based on the average ideal solution using the interval numbers.

Yue (2011) ranking and weighting DMs by the TOPSIS method. Yue (2012) made a decision using the TOPSIS method with interval numbers. In this study, a new GRA-based COPRAS weighting method was introduced.

One of the issues that needs to be addressed is weighing the criteria. Sometimes the weight of the criteria may not be precise and needs to be calculated. To this end, there are various methods that researchers have applied (e.g., NLP models, SWARA, QFD, BWM, MOOM) (Gitinavard et al., 2017; Valipour et al., 2017; Yazdani et al., 2017; Haeri & Rezaei, 2019; Liu et al., 2019). A multi-objective optimization model (MOOM) adapted from Liu (2019) was introduced to compute the weights of helpful criteria.

In this paper, a new GRA-COPRAS method is presented to rank the alternatives for supplier selection in project procurement. In this method, to compute weights of criteria, a MOOM method is used. To rank the alternatives in the last step, a new enhanced COPRAS index is proposed. The importance of DMs is one of the most important issues that is addressed in this paper. To deal with uncertainty, grey system theory and grey numbers are used. To investigate the applicability of the presented method, a numerical example is provided. The purpose of the example is the selection of the best supplier to project procurement. Three suppliers are compared under five criteria.

The paper is structured as follows. Prior knowledge of the uncertainty method is explained in the second section. In the third section, an extended method for ranking is described. In the fourth section, a numerical example is computed and analyzed to investigate the method's performance. Finally, in the last quarter, the results are presented in the conclusion section.

2- Preliminary knowledge of grey system

Grey systems theory was introduced in the year 1980. Specifically, in the year1982, Deng published the first research paper in this field. Probability and statistics, fuzzy mathematics, and grey system theory are three common theories and approaches for studying uncertain systems. Although each group studies different uncertainties, their common feature is generating meaningful data on deficiencies and uncertainties. Due to the differences in the type of uncertainties studied in each theory, three scientific studies have been created that each has its characteristics. Fuzzy mathematics is powerful in problems with cognitive uncertainties. Using probability and statistics, events with random uncertainty are studied using statistical patterns and historical background. Grey systems theory was developed to investigate problems with small samples and insufficient information. These issues cannot be solved using statistics and probability. Grey systems theory is looking for real problems based on a few available data (e.g., Hashemi et al., 2018; Eshghi et al., 2019; Mousavi et al., 2013, 2014, 2015). A grey system includes grey numbers. A grey number is a numeric value whose precise value is not known but a specified range and is an interval or a set of numbers (Liu & Lin, 2006).

There are several types of grey numbers; use the grey number with both a lower bound and upper bound is called an interval grey number, denoted as $\otimes A = [A^L, A^U]$. The operation between two grey numbers are defined as follows,$\otimes A_1$ and $\otimes A_2$ are two grey numbers.

$$\otimes A_1 + \otimes A_2 = [\mathrm{A}_1^L + \mathrm{A}_2^L, \mathrm{A}_1^U + \mathrm{A}_2^U] \tag{1}$$

$$\otimes A_1 + \otimes A_2 = [\mathrm{A}_1^L - \mathrm{A}_2^U, \mathrm{A}_2^U - \mathrm{A}_1^L] \tag{2}$$

$$\otimes A_1 \times \otimes A_2 = [\min(\mathrm{A}_1^L\mathrm{A}_2^L\ , \mathrm{A}_1^L\mathrm{A}_2^U, \mathrm{A}_1^U\mathrm{A}_2^L, \mathrm{A}_1^U\mathrm{A}_2^U), \max(\mathrm{A}_1^L\mathrm{A}_2^L\ , \mathrm{A}_1^L\mathrm{A}_2^U, \mathrm{A}_1^U\mathrm{A}_2^L, \mathrm{A}_1^U\mathrm{A}_2^U)] \tag{3}$$

$$\otimes A_1 \div \otimes A_2 = [\mathrm{A}_1^L, \mathrm{A}_1^U\ ] \times [\frac{1}{\mathrm{A}_2^U}, \frac{1}{\mathrm{A}_2^L}] \tag{4}$$

$$K \otimes \mathrm{A} = [\mathrm{k}A^L, \mathrm{k}A^U] \tag{5}$$

3- The proposed approach

In this section, a new decision-making method under grey uncertainty is proposed to project the supplier selection problem. The proposed method saves the uncertainty of data until the last step. In this method, after collecting and normalizing DMs' ideas, the importance of each DM is computed, and the obtained weights are used to aggregate the decision matrices. Then, a combined COPRAS and GRA method is used to rank the alternatives. To calculate the criteria's weights, a new MOOM model under a grey environment is introduced. In the last step, a new grey ranking index is presented. The stages of the proposed method are visualized in figure 1. The process of the method is as follows:

Step1. The judgment of DMs is collected, and the decision matrices are formed as:

$$\otimes \mathrm{D}_k = (\otimes \mathrm{D}_{ij}^k)_{m\times n} = \begin{pmatrix} \otimes D_{11}^k & \dots & \otimes D_{1n}^k \\ \vdots & \ddots & \vdots \\ \otimes D_{m1}^k & \dots & \otimes D_{mn}^k \end{pmatrix} \tag{6}$$

Where: $\otimes \mathrm{D}_k$ means the grey decision matrix, $1 \leq k \leq K$, represents the number of DMs, $1 \leq i \leq m$, presents the number of alternatives and, $1 \leq j \leq n$, denotes the number of criteria.

Step 2. The decision matrices are normalized by equations. (7-9):

$$\otimes \mathrm{R}_k = \begin{pmatrix} \otimes R_{11}^k & \dots & \otimes R_{1n}^k \\ \vdots & \ddots & \vdots \\ \otimes R_{m1}^k & \dots & \otimes R_{mn}^k \end{pmatrix} \tag{7}$$

$$R_{ij}^{kL} = \frac{d_{ij}^{kL}}{\max_i\{d_{ij}^{kU}\}}, \; R_{ij}^{kU} = \frac{d_{ij}^{kU}}{\max_i\{d_{ij}^{kU}\}} \qquad \text{For benefit criteria} \tag{8}$$

$$R_{ij}^{kL} = \frac{\min_i\{d_{ij}^{kL}\}}{d_{ij}^{kU}}, \; R_{ij}^{kU} = \frac{\min_i\{d_{ij}^{kL}\}}{d_{ij}^{kL}} \qquad \text{For cost criteria} \tag{9}$$

Step3. The importance of each DM is computed by the COPRAS-GRA method as follows:

Step 3-1. The average, positive, and negative ideals (R_{ij}^* and R_{ij}^-) are specified from the normal decision matrix by using the following:

$$\otimes R_{ij}^* = \frac{1}{t}\sum_k r_{ij}^{kT}, T\epsilon[L,U] \tag{10}$$

$$\otimes R_{ij}^- = \begin{cases} \otimes R_{ij}^{lT} = \min_k\{\otimes R_{ij}^{kT} \mid \otimes R_{ij}^{kT} \leq \otimes R_{ij}^*\} & (11) \\ \otimes R_{ij}^{rT} = \max_k\{\otimes R_{ij}^{kT} \mid \otimes R_{ij}^{kT} \geq \otimes R_{ij}^*\} & (12) \end{cases}, \; T\epsilon[L,U]$$

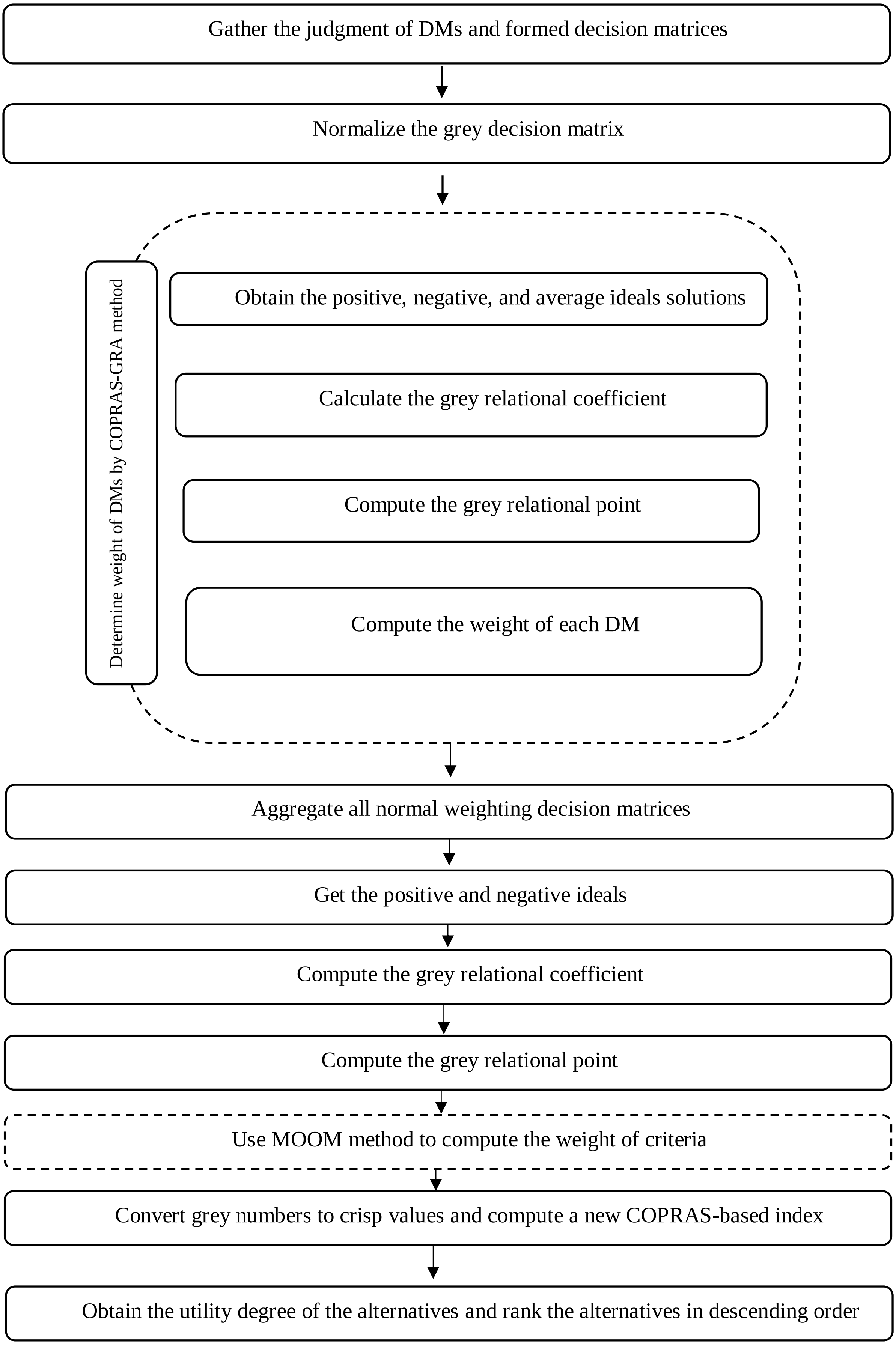

Fig 1. Visual representation of the proposed method

Step 3-2. The grey relational coefficients are calculated below:

$$\gamma^{*}\left(\otimes R^{*}_{ij},\otimes R^{kT}_{ij}\right)=\frac{\delta^{*}_{min}+\vartheta\delta^{*}_{max}}{\delta^{k}_{ij}+\vartheta\delta^{*}_{max}} \qquad \text{Where} \quad {\delta_{ij}}^{*}=\left|\left(r^{L*}_{ij}-r^{Lk}_{ij}\right)+\left(r^{U*}_{ij}-r^{Uk}_{ij}\right)\right| \tag{13}$$

$$\delta^{*}_{min}=\min_{i}\delta^{*}_{ij} \qquad \forall i,j,$$

$$\delta^{*}_{max}=\max_{i}\delta^{*}_{ij} \qquad \forall i,j.$$

$$\gamma^{l}\left(\otimes R^{lT}_{ij},\otimes R^{kT}_{ij}\right)=\frac{\delta^{l}_{min}+\vartheta\delta^{l}_{max}}{\delta^{k}_{ij}+\vartheta\delta^{l}_{max}} \qquad {\delta_{ij}}^{l}=\left|\left(r^{Ll}_{ij}-r^{Lk}_{ij}\right)+\left(r^{Ul}_{ij}-r^{Uk}_{ij}\right)\right| \tag{14}$$

$$\delta^{l}_{min}=\min_{i}\delta^{l}_{ij} \qquad \forall i,j,$$

$$\delta^{l}_{max}=\max_{i}\delta^{l}_{ij} \qquad \forall i,j.$$

$$\gamma^{r}\left(\otimes R^{rT}_{ij},\otimes R^{kT}_{ij}\right)=\frac{\delta^{r}_{min}+\vartheta\delta^{r}_{max}}{\delta^{k}_{ij}+\vartheta\delta^{r}_{max}} \qquad {\delta_{ij}}^{r}=\left|\left(r^{Lr}_{ij}-r^{Lk}_{ij}\right)+\left(r^{Ur}_{ij}-r^{Uk}_{ij}\right)\right| \tag{15}$$

$$\delta^{r}_{min}=\min_{i}\delta^{r}_{ij} \qquad \forall i,j$$

$$\delta^{r}_{max}=\max_{i}\delta^{r}_{ij} \qquad \forall i,j.$$

$$\text{And} \quad \vartheta\epsilon[0,1]$$

Step 3-3. The grey relation points are obtained via the following equations:

$$\Gamma^{*}_{k}=\sum_{j}\gamma^{*}\left(\otimes R^{*}_{ij},\otimes R^{kT}_{ij}\right) \tag{16}$$

$$\Gamma^{l}_{k}=\sum_{j}\gamma^{l}\left(\otimes R^{lT}_{ij},\otimes R^{kT}_{ij}\right) \tag{17}$$

$$\Gamma^{r}_{k}=\sum_{j}\gamma^{r}\left(\otimes R^{rT}_{ij},\otimes R^{kT}_{ij}\right) \tag{18}$$

Step 3-4. The final value of each DM is determined by Eq. (19):

$$C^{T}_{k}=\frac{\Gamma^{*}_{k}}{\sum_{k}\Gamma^{*}_{k}}+(1-\frac{\Gamma^{l}_{k}}{\sum_{k}\Gamma^{l}_{k}})+(1-\frac{\Gamma^{r}_{k}}{\sum_{k}\Gamma^{r}_{k}}) \tag{19}$$

Step 3-5. The final weight of each DM is specified thorough Eq. (20):

$$\lambda_{k}=\frac{C_{k}}{\sum_{k}C_{k}} \tag{20}$$

Step 4. All normal decision matrices are integrated by using DMs' importance as:

$$\otimes G_{ij}=\sum_{k}\lambda_{k}*\otimes R_{k} \tag{21}$$

Step 5. Get positive and negative ideals ($\otimes G^{+}$and $\otimes G^{-}$) by using Eqs. (22) and (23):

$$\otimes G^{+} = \max_{i} \otimes G_{ij} = \left\{ \max_{i} g_{ij}^{L}, \max_{i} g_{ij}^{U} \right\} \tag{22}$$

$$\otimes G^{-} = \min_{i} \otimes G_{ij} = \left\{ \min_{i} g_{ij}^{L}, \min_{i} g_{ij}^{U} \right\} \tag{23}$$

Step 6. The grey relational coefficients are computed to use the advantage of the GRA method:

$$\gamma^{*}{}_{\left(\otimes R_{ij}^{*}, \otimes R_{ij}^{kT}\right)} = \frac{\delta_{min}^{*} + \vartheta \delta_{max}^{*}}{\delta_{ij}^{k} + \vartheta \delta_{max}^{*}} \qquad \text{Where} \qquad \delta_{ij}{}^{+} = |\left(g_{j}^{L+} - g_{ij}^{L}\right) + \left(g_{j}^{U+} - g_{ij}^{U}\right)| \tag{24}$$

$$\delta_{min}^{+} = \min_{i} \delta_{ij}^{+} \qquad \forall i, j,$$

$$\delta_{max}^{+} = \max_{i} \delta_{ij}^{+} \qquad \forall i, j.$$

$$\gamma^{-}{}_{\left(\otimes R_{ij}^{lT}, \otimes R_{ij}^{kT}\right)} = \frac{\delta_{min}^{-} + \vartheta \delta_{max}^{-}}{\delta_{ij} + \vartheta \delta_{max}^{-}} \qquad \delta_{ij}{}^{-} = |\left(g_{j}^{L-} - g_{ij}^{L}\right) + \left(g_{j}^{U-} - g_{ij}^{U}\right)| \tag{25}$$

$$\delta_{min}^{-} = \min_{i} \delta_{ij}^{-} \qquad \forall i, j$$

$$\delta_{max}^{-} = \max_{i} \delta_{ij}^{-} \qquad \forall i, j.$$

Step 7. The grey relational points are calculated employing equations (26) and (27) as follows:

$$\otimes \Gamma_{i}^{+} = \sum_{j} \otimes W_{j} \, \gamma^{+}{}_{\left(\otimes R_{ij}^{+}, \otimes R_{ij}^{T}\right)} \tag{26}$$

$$\otimes \Gamma_{i}^{-} = \sum_{j} \otimes W_{j} \, \gamma^{-}{}_{\left(\otimes R_{ij}^{-T}, \otimes R_{ij}^{T}\right)} \tag{27}$$

$\otimes w_{j}$ is the weight of each criterion calculated by the MOOM method.

Step 7-1. The multi-objective model to achieve the weights of criteria is applied by using the following:

$$\begin{aligned} & max \, \Gamma_{i}^{+} = (\gamma_{1}^{+}, \gamma_{2}^{+}, \dots, \gamma_{m}^{+}) \,) \\ & s.t. \\ & 0 \leq \; w_{j}^{+} \leq 1 \,, \qquad j = 1,2, \dots, n \\ & w_{j}^{+} \in \Delta \end{aligned} \tag{28}$$

$$\begin{aligned}&max\,\Gamma_i^- = (\gamma_1^-, \gamma_2^-, \dots, \gamma_m^-)\,)\\&s.t.\\&0 \le\ w_j^- \le 1\,, \qquad j = 1,2,\dots,n\\&w_j^- \in\ \Delta\end{aligned} \tag{29}$$

Step 7-2. The multi-objective model is replaced by the single-objective model below:

$$\begin{aligned}&\textbf{max}\ \ \mu\\&\qquad s.t:\\&\gamma^+ \ge \mu \qquad\qquad i = 1,2,\dots,m\\&0 \le\ w_j^+ \le 1 \quad j = 1,2,\dots,n\\&w_j^+ \in\ \Delta\end{aligned} \tag{30}$$

$$\begin{aligned}&\textbf{max}\ \ \mu\\&\qquad s.t:\\&\gamma^- \ge \mu \qquad\qquad i = 1,2,\dots,m\\&0 \le\ w_j^- \le 1 \qquad j = 1,2,\dots,n\\&w_j^- \in\ \Delta\end{aligned} \tag{31}$$

Where $\otimes w_j = \left[w_j^-, w_j^+\right]$.

Step 8. To compute the ranking index, equation (34) is applied that introduced a new COPRAS index. To this end, firstly, the average of the lower and upper bound of grey numbers are gathered, and then the Q_i is computed.

$$\Gamma_i^- = \frac{(\otimes\Gamma_i^{L-} + \otimes\Gamma_i^{U-})}{2} \tag{32}$$

$$\Gamma_i^+ = \frac{(\otimes\Gamma_i^{L+} + \otimes\Gamma_i^{U+})}{2} \tag{33}$$

$$Q_i = \alpha\left(1 - \frac{\Gamma_i^-}{\sum_i \Gamma_i^-}\right) + (1-\alpha)\left(\frac{\Gamma_i^+}{\sum_i \Gamma_i^+}\right) \tag{34}$$

$\alpha\epsilon[0,1]$

Step 9. The utility degree of each alternative is computed by using the following. Notably, the alternatives are ranked in decreasing order of U_i.

$$U_i = \frac{Q_i}{Q_{max}} \times 100 \qquad\qquad ,\ \ Q_{max} =\ \max_i Q_i \tag{35}$$

4- Application example

In this section, to determine the proposed method's procedure, an adopted numerical example from literature is presented (Memon et al., 2015). In this paper to project supplier selection, we assumed that three suppliers ($i=3$) evaluated under five criteria ($j=5$), quality (Q), delivery (Sl), logistics services (Ls), sustainability factor (Sf), and risk factor (R). For this purpose, introduced linguistic variables and DMs views on suppliers' evaluation are illustrated in tables 1, 2, and 3. Then, decision matrices are constructed in table 4. Afterward, the normalized decision matrices are computed by step 2, and the results are demonstrated in table 5. In table 6, the obtained average, positive, and negative ideals solutions are depicted. By sub-steps 3-2 and 3-3, the grey relational coefficient and grey relational point are obtained. In the last step of this section, the weight of each DM is calculated that displayed in table 7.

Table 1. Scale for evaluating alternatives against criteria

Linguistic variable	L	U
VP	0	1
P	1	3
MP	3	4
F	4	6
MG	6	7
G	7	9
VG	9	10

Table 2. Criteria weighing scale

Linguistic variable	L	U
VL	0	0.1
L	0.1	0.3
ML	0.3	0.4
M	0.4	0.6
MH	0.6	0.7
H	0.7	0.9
VH	0.9	1

Table 3. Experts' opinions on supplier selection criteria

Alternative	Criteria	Decision Maker			
		DM_1	DM_2	DM_3	DM_4
S_1	QL	G	MG	F	MG
	SL	G	G	MG	G
	LS	G	MG	VG	VG
	SF	F	VG	F	MG
	R	G	MG	G	G
S_2	QL	F	MG	MG	F
	SL	MG	MG	G	G
	LS	MG	F	F	F
	SF	F	F	MG	F
	R	G	MG	F	MG
S_3	QL	G	MG	MG	G
	SL	G	MG	F	G
	LS	VG	VG	G	VG
	SF	MG	G	MG	VG
	R	MG	F	F	F

Table 4. Decision matrix

Alternative	Criteria	DM1		DM2		DM3		DM4	
S_1	Q	7	9	6	7	4	6	6	7
	S	7	9	7	9	6	7	7	9
	L	7	9	6	7	9	10	9	10
	SF	4	6	9	10	4	6	6	7
	R	7	9	6	7	7	9	7	9
S_2	Q	4	6	6	7	6	7	4	6
	S	6	7	6	7	7	9	7	9
	L	6	7	4	6	4	6	4	6
	SF	4	6	4	6	6	7	4	6
	R	7	9	6	7	4	6	6	7
S_3	Q	7	9	6	7	6	7	7	9
	S	7	9	6	7	4	6	7	9
	L	9	10	9	10	7	9	9	10
	SF	6	7	7	9	6	7	9	10
	R	6	7	4	6	4	6	4	6

Table 5. Normalized decision matrix

Alternatives	Criteria	$\otimes \mathrm{R}_k$							
		DM1		DM2		DM3		DM4	
S_1	Q	0.777778	1	0.8571429	1	0.571428571	0.857143	0.666667	0.777778
	S	0.777778	1	0.7777778	1	0.666666667	0.777778	0.777778	1
	L	0.7	0.9	0.6	0.7	0.9	1	0.9	1
	SF	0.571429	0.85714	0.9	1	0.571428571	0.857143	0.6	0.7
	R	0.666667	0.85714	0.5714286	0.666666667	0.444444444	0.571429	0.444444	0.571429
S_2	Q	0.444444	0.66667	0.8571429	1	0.857142857	1	0.444444	0.666667
	S	0.666667	0.77778	0.6666667	0.777777778	0.777777778	1	0.777778	1
	L	0.6	0.7	0.4	0.6	0.4	0.6	0.4	0.6
	SF	0.571429	0.85714	0.4	0.6	0.857142857	1	0.4	0.6
	R	0.666667	0.85714	0.5714286	0.666666667	0.666666667	0.571429	0.571429	0.666667
S_3	Q	0.777778	1	0.8571429	1	0.857142857	1	0.777778	1
	S	0.777778	1	0.6666667	0.777777778	0.444444444	0.666667	0.777778	1
	L	0.9	1	0.9	1	0.7	0.9	0.9	1
	SF	0.857143	1	0.7	0.9	0.857142857	1	0.9	1
	R	0.857143	1	0.6666667	1	0.666666667	1	0.666667	1

Table 6. Positive and Negative ideals

Alternatives	Criteria	$\otimes R_{ij}^{*}$		$\otimes R_{ij}^{l}$		$\otimes R_{ij}^{r}$	
S_1	Q	0.718254	0.90873	0.5714286	0.777777778	0.857142857	1
	S	0.75	0.94444	0.6666667	0.777777778	0.777777778	1
	L	0.775	0.9	0.6	0.7	0.9	1
	SF	0.660714	0.85357	0.5714286	0.7	0.9	1
	R	0.531746	0.66667	0.4444444	0.5714286	0.666666667	0.85714
S_2	Q	0.650794	0.83333	0.4444444	0.6666667	0.857142857	1
	S	0.722222	0.88889	0.6666667	0.7777778	0.777777778	1
	L	0.45	0.625	0.4	0.6	0.6	0.7
	SF	0.557143	0.76429	0.4	0.6	0.857142857	1
	R	0.619048	0.69048	0.571429	0.5714286	0.666666667	0.85714
S_3	Q	0.81746	1	0.777778	1	0.857142857	1
	S	0.666667	0.8611	0.444444	0.6666667	0.777777778	1
	L	0.85	0.975	0.7	0.9	0.9	1
	SF	0.828571	0.975	0.7	0.9	0.9	1
	R	0.714286	1	0.6666667	1	0.857142857	1

Table 7. The weight of each DM

DM	C_k	λ_k	Rank
1	1.76607	0.2523	1
2	1.74465	0.24924	3
3	1.75081	0.25012	2
4	1.73847	0.24835	4

Now, the weights of each DM are used to aggregate the decision matrices. In table 8, the weighted normalized decision matrices are aggregated according to DMs importance. The grey relational coefficient and the grey relational point from steps 6 and 7 are obtained. Computing the grey relational point requires the criteria weights. For this purpose, the MOOM model is presented in sub-steps 7-1 and 7-2 depicted in table 9. Table 10 shows the derived ranking results from steps 8 and 9.

Table 8. The aggregated normal weighted matrix

Alternatives	Criteria	$\otimes G_{ij}$	
S_1	Q	0.7183	0.9091
	S	0.7499	0.9444
	L	0.7748	0.9
	SF	0.6605	0.8537
	R	0.5322	0.6672
S_2	Q	0.6505	0.8331
	S	0.6485	0.8886
	L	0.4505	0.6252
	SF	0.5576	0.7649
	R	0.6193	0.6909
S_3	Q	0.8174	1
	S	0.6667	0.8613
	L	0.84998	0.9749
	SF	0.8286	0.9751
	R	0.7147	1

Table 9. The weight of criteria

Criteria	$\otimes W_j$	
Q	0.7	0.8
S	0.9	1
L	0.8	1
SF	0.7	0.9
R	0.7	0.8

Table10. The ranking result of the GRA-COPRAS method

Alternatives	Q_i	U_i	Rank
S1	0.4252	87.9524	2
S2	0.3413	70.5818	3
S3	0.4835	100	1

As can be seen in Table 10, the rankings are as follows:

$$S_2 > S_3 > S_1$$

The COPRAS has been regarded as one of the multi-criteria decision-making methods in recent years. In this method, the comparable options are ranked according to the positive and negative ideals (Zavadskas et al., 2008). The GRA method can be considered impressively the complex inter-relationships among criteria. It takes the correlation of reference sequence and analogical sequence, ranks the alternatives based on the correlation, and makes the right decisions (Chen, 2019). Furthermore, the GRA method ranks alternatives based on the various criteria by using a global preference relation (Kahraman and Karaşan, 2018). It is subsumed as a recognized multi-criteria decision-making (MCDM) method and has been applied in many problems in recent years (Baudry et al., 2018).

In this paper, an integrated COPRAS method based on GRA is developed to take advantage of both methods simultaneously. To evaluate the introduced method results, a comparison with the other well-known MCDM methods is performed. Table 11 shows the obtained results of well-known MCDM methods and introduced method. The same rankings illustrate that the reliability and validity of the proposed method. To better express the uncertainty of practical situations, the proposed method is extended under the grey environment. In other words, the introduced method will be able to cope with the uncertain and ambiguous data.

Table 11. The result of different MCDM methods

Alternative	TOPSIS	GRA-TOPSIS	GRA-COPRAS	Rank
S_1	0.4593	0.5047	87.9524	2
S_2	0.0664	0.3466	70.5818	3
S_3	0.9083	0.62972	100	1

5- Conclusion

In this paper, a GRA based on the COPRAS method under grey system theory was presented to project supplier selection. Before alternatives evaluation, the importance of each DM was obtained by using a new developed COPRAS-GRA method. Moreover, for computing the criteria weights, a MOOM was used. After this, a new version of the COPRAS-GRA method was extended for rankings of alternatives. In this method, the advantage of the GRA and COPRAS methods were combined by using a new index. To investigate the applicability of the introduced method, a numerical example was solved, and the result of this example was compared with other well-known MCDM methods. The same results showed the proper performance of this method. Based on what is presented in this study, suggestions have been made to develop and complement further studies. As a suggestion for future studies, the model presented in this paper can be shown in a decision support system. This method can also be applied in various fields of management and engineering (e.g., transportation system, human resource management, factory location selection, project procurement system selection, and project portfolio selection).

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