




A GREY COMBINED COMPROMISE SOLUTION (COCOSO-G) METHOD FOR SUPPLIER SELECTION IN CONSTRUCTION MANAGEMENT

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Abstract. This study investigates an extended version of the combined compromise solution method with grey numbers, named CoCoSo-G for short, to measure the performance of suppliers in a construction company in Madrid. Seven criteria from a relevant previous study are the basis for assessing the performance of suppliers, while ten suppliers are composing our decision matrix. To initiate the decision-making process, we invite experts to aid us in the qualitative evaluation of the suppliers using grey interval values. Two weighting methods, including the DEMATEL (Decision Making Trial and Evaluation Laboratory) and BWM (best worst method) are used to achieve the importance of supplier criteria in a combined manner. The DEMATEL method is used to realise the best and worst criteria, and the BWM is used to sort the criteria according to a linear programming formulation. The CoCoSo-G method used to release the score of each supplier and rank them. We compare the results obtained by the CoCoSo-G with those obtained by the Complex Proportional Assessment method. It is evident that offering grey values for supplier qualification, using the combined weighting tool and proposing the new CoCoSo-G approach facilitate the evaluation process while indicating trustable outcomes.

Keywords: multi-criteria decision-making, supplier selection, grey values, Combined Compromise Solution method, CoCoSo, CoCoSo-G, Best-Worst method.

Introduction

Supply chain management (SCM) is an essential term in many sectors and industries with different levels of influence and integration. Manufacturing and automobile industries, retail trade, agriculture and service industry in terms of implementing supply chain concepts and practices dedicated a remarkable consideration. Notably, the manufacturing industry initiated to develop SCM for many years. However, the construction industry delays due to variables like distinct organisational structure and its nature. A client in this sector focuses on the final product, his/her investment but not necessarily the physical dimensions like the way of supplying, type of materials and contractors (Akintoye, McIntosh, & Fitzgerald, 2000; Christopher, 2016; Dadhich, Genovese, Kumar, & Acquaye, 2015).

It is essential that controlling the process, quality and performance of suppliers is the most challenging topic in supply chain studies (Hosseini, Martek, Chileshe, Zavadskas, & Arashpour, 2018). Supply chain in construction management includes the control, monitoring, and execute the process of supply until end-user delivery. It starts from the compelling needs of the clients, takes the general contractor as the core enterprise, links subcontractors, suppliers and clients into a fully functional chain structure mode by controlling information flow, logistics and capital flow, starting from bidding to construction, completion acceptance and after-sales service. As an essential part of the construction supply chain, suppliers have a significant impact on the quality of construction projects. Hence, selecting suitable suppliers is crucial for

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construction contractors. It not only helps to speed up the process of material procurement, improve flexibility and product quality, but also can significantly reduce the cost of material procurement and improve the competitiveness of enterprises (Tamošaitienė, Zavadskas, Šileikaitė, & Turskis, 2017).

Due to the particularity of the construction industry, the supply chain has the following characteristics in construction management (Vrijhoef & Koskela, 2000):

- It is a converging supply chain that assembles all the materials needed at a construction site for assembly and processing, thereby providing a single product;
- It is a temporary supply chain that produces one-off construction projects by repeatedly configuring new project organisations;
- It is a make-to-order supply chain that each project creates a new product;
- It is a complex supply chain that includes many stages of construction, a large number of participants, a large scale of development, a long-lasting construction cycle, and many uncertain factors.

These characteristics reveal that contractors need to consider many developmental factors to select suppliers according to frequent changes in customer needs, and the selection process of suppliers is repetitive, which forms systemic multi-criteria decision-making (MCDM) problem under ambiguous and uncertain environments.

Deciding for various sectors is to decode a complex and multi-variable problem in different conditions and dimensions, probably with incorrect information. Each decision-maker supposes that taking a wrong decision or making a mistake during the process of problem formulation undoubtedly causes the failure of the system and encourages a bad management practice. The consequences of disruption of such a system involve ill-managed decision-making formulations that widely affect the future of the organisation and disperse inappropriate social image in the community. Decision-makers have to ensure that accurate decision-making formulation in all levels of the company structure is adopted and implemented. In service or product based companies, the act of supplying all the requirements, conditions and materials contains a big responsibility that the core management function has to consider. Securing the entire supply network to provide the necessary construction materials, equipment, infrastructure, human resource, and environmental protection guarantee is the operation of procurement and supply chain sector. Project developers and their clients make thousands of small and large-scale decisions every day. However, how the optimal result can happen is a highly demanded topic that needs a joined cooperation of academics, industrial owners, investors and stakeholders. The substantial element of this paper is to respond to this concern of top managers as fast. One of the concrete and well-formulated decision approaches in situations like this is to apply MCDM methods.

MCDM is a growing field of decision-making theory for a wide range of experts (Liu & Liao, 2017; Liao, Tang,

Li, & Lev, 2019b). Zionts (1979) introduced two classes of methods, namely continuous and discrete approaches, based on the nature of the considered alternatives. Continuous MCDM methods refer to us as multi-objective decision-making (MODM) methods and help to find the optimal quantitative value. Discrete MCDM methods refer to us as multi-attribute decision-making (MADM) methods. They represent techniques that contain a finite number of discrete alternatives and a set of criteria and help decision-makers to rank, or select the best choice among investigated alternative solutions. MADM approaches refer to the decision-makers as weighting methods and ranking methods (Zavadskas & Turskis, 2011). Since the 1980s, scientists introduced many ways and proposed new insights about how to improve decision-making quality. The most widely applied tools include ELECTRE (ELimination Et Choice Translating REALity), PROMETHEE (preference ranking organization method for enrichment evaluation), TOPSIS (technique for preference by similarity to the ideal solution), VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), COPRAS (Complex proportional assessment), and MABAC (MultiAttributive Border Approximation Area Comparison) (Zavadskas, Turskis, & Kildienė, 2014). Similar to that, several tools were invented for weight processing (Zavadskas & Podvezko, 2016). For instance, DEMATEL (Yazdani, Chatterjee, Zavadskas, & Zolfani, 2017) and best worst method (Rezaei, Kothadiya, Tavasszy, & Kroesen, 2018; Mi, Tang, Liao, Shen, & Lev, 2019; Mi & Liao, 2019) are criteria weighting approaches. During years, scientists understood that incorrect information and somehow, the lack of information transforms MCDM problems into such classification types as fuzzy, grey, and stochastic. One of the new methods is the Combined Compromise Solution (CoCoSo) method (Yazdani, Zarate, Zavadskas, & Turskis, 2018) that is capable of being extended by those classifications.

An MCDM decision problem composes by a matrix with two dimensions of criteria and alternatives. This matrix is achieved by the amount of data and information from a dataset or experts relevant to the problem. In the majority of MCDM problems, providing deterministic measurements to express the preferences of experts is very difficult due to limited time, the complexity and dimensions of the decision problem. In decision-making environments, it is probable to face kind of conditions while lacking information (Liang, Zhang, Wu, Sheng, & Wang, 2018). According to uncertain theories, a system whose private information is wholly known is called a white system.

On the contrary, a system is defined as a black system if one cannot obtain any information and characteristics of the system. Grey space is expressed as a system defined between the white and black systems (Zavadskas, Kaklauskas, Turskis, & Tamošaitienė, 2008). The grey system is a useful tool to solve problems in many fields, such as economics, agriculture, geography, weather forecasting, natural disasters, and science. In general, in a grey system scoring, decision experts assign random variables

depending upper and lower bounds they choose. However, it is possible that several decision-makers perhaps do not agree on similar limits and therefore, they fail to reach consensus on the evaluation information. Due to that, scientists introduced random variables in the form of extended grey numbers (EGNs). Suppose that experts must evaluate the company innovation capacity by an interval of $[0, 50]$. Then, one expert offers a range of $[20, 25]$, while another one offers $[28, 30]$. Then according to the EGN theory, the aggregated field will be $[20, 25] \cup [28, 30]$ (Zhou, Wang & Zhang, 2019).

The idea of the BWM is to first select the best and worst criteria according to the opinions of experts. Although, it might be determined, however, this is somehow a confusing task for experts. To fill this gap, we offer them a second method to guide them in selecting the best and worst options. This latter method is DEMATEL, which can filter sudden mistake or unintentional bias of experts and present best-worst factors conveniently and reliably. The utilisation of DEMATEL method can be incorporated in the further BWM pairwise assessment effectively. Furthermore, the application of the CoCoSo method is useful in several areas like supply chain, construction sector and engineering fields. Rather than this, it can be extended by grey variables and solve uncertain decision problems in which experts are required to deal with less quantitative information about the candidate suppliers.

The structure of the study is as below displayed: Section 1 gives a history and review of the methods involved in the study containing the supplier selection in the construction sector. Section 2 introduces some materials, equations and arithmetic operations. Section 3 applies the decision model to solve decision-making problems in construction management. Section 4 provides a case study on a construction management decision-making problem, and the last section presents conclusions.

1. Study background

Many scholars have studied the critical role of supply chain management in the construction industry. For example, Vrijhoef and Koskela (2000) introduced four purposes of supply chain management in construction industry. Love, Irani, and Edwards (2004) proposed a seamless SCM model for integrating the design and production processes of construction projects. V. Kumar, V. Kumar, Rao, and Veeramalla (2019) studied the critical factors related to improving product quality and competitiveness of construction enterprises in SCM. Wu and Barnes (2016) presented a combined model for green partner selection through Analytic Network process (ANP) and multi-objective programming in a construction supply chain. Tsai, Lin, Lee, Chang, and Hsu (2013) utilized a three-type decision-making model using ANP, DEMATEL and goal programming to measure the consistency of construction projects, sort them according to green objectives. Chatterjee, Zavadskas, Tamošaitienė, Adhikary, and Kar (2018)

proposed a hybrid model consisting of ANP, MABAC, and fuzzy order preference for construction project risk evaluation. In India, Raut and Mahajan (2015) worked on a fuzzy quality function deployment and (AHP) approach for preference to determine the best residential housing project. Another group of investigators constructed a decision-making platform including AHP and GRA to rate suppliers of a resilient construction supply chain. In their evaluation, to obtain the required date, they implemented building information modeling and a geographic information system (T. K. Wang, Zhang, Chong, & X. Wang, 2017). Seth, Nemani, Pokharel, and Al Sayed (2018) demonstrated the efficiency of MCDM in construction projects primarily in supplier evaluation.

Contemporary economics demands to design and produce sustainable products with both international and local perspectives (Hashemkhani Zolfani, Zavadskas, & Turskis, 2013). Stakeholders, when implementing long-time requiring plans, act in a dynamically changing environment. All the impacting factors changes (Kalibatas & Turskis, 2008) and in advice could not be accurately determined. Moreover, in some cases, project managers need to change technologies and select among feasible options (Zavadskas, Turskis, Volvačiovas, & Kildiene, 2013; Štreimikienė, Šliogerienė, & Turskis, 2016). Selection among active working suppliers in the market highly depend on the place of introducing project (Peldschus, Zavadskas, Turskis, & Tamosaitiene, 2010), possessing equipment, and devices (Sivilevičius, Zavadskas, & Turskis, 2008), personnel qualification (Keršulienė & Turskis, 2011), and innovation capabilities (Kumar, Kaviani, Hafezalkotob, & Zavadskas, 2017). One of the essential decisions in the supply chain for contractors is to select suppliers, and the usual decision-aiding methods in contemporary economics are related to MCDM (Zavadskas, Turskis, & Antucheviciene, 2015). At present, various MCDM methods for the evaluation and selection of suppliers in the construction industry have been developed, such as the Simple Multi-Attribute Rating Technique Exploiting Ranking (SMARTER) method (Schramm & Morais, 2012), triangular fuzzy AHP method (Guan, Zhang, & Wu, 2013), AHP-ER (Evidential Reasoning) method (Polat & Eray, 2015), EDAS method (Keshavarz Ghorabae, Zavadskas, Amiri, & Turskis, 2016), AHP and fuzzy AHP method (Plebankiewicz & Kubek, 2016), fuzzy AHP-TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method (Polat, Eray, & Bingol, 2017), AHP-GRA (grey relational analysis) method (Wang et al., 2017). However, none of those mentioned above studies assumed integration of the DEMATEL and BWM methods, which is a new system to determine weights of attributes.

The CoCoSo method introduced Yazdani et al. (2018). At present, this method has been extended to some uncertain context to solve decision-making problems in various fields. For instance, Wen, Liao, Zavadskas, and Al-BaIrakati (2019) extended the CoCoSo method to hesi-

tant linguistic fuzzy context and applied the hesitant fuzzy linguistic CoCoSo method to select third-party logistics service providers for financial institutions. Also, Hashemkhani Zolfani, Chatterjee and Yazdani (2019) integrated the CoCoSo method with the BWM to form a hybrid MADM model for sustainable supplier selection.

Deng (1982) initially proposed Grey theory. After that, Yang (2007) advanced the extended grey numbers, which combines discrete grey numbers with interval grey numbers. Compared with the fuzzy set theory, the grey theory can deal with the fuzzy situation more flexible (Turskis & Zavadskas, 2010). Thus, it has been developed to solve fuzzy and complex decision-making problems with many MCDM methods. Zhou et al. (2019) employed the extended grey numbers and a conjunction of SMAA (stochastic multi-criteria acceptability analysis) and ELECTRE III to select cleaning services companies for urban industrial waste. Qian, Liu, and Fang (2018) combined the general grey numbers with regret theory and EDAS (evaluation based on distance from average solution) method to solve the selection problem of new product investment for companies. K. Chen, P. Chen, Yang, and Jin (2019) integrated interval grey numbers with AHP to construct a grey clustering evaluation model for evaluating the flight safety of the airline. Chalekaee, Turskis, Khanzadi, Ghodrati Amiri, and Keršulienė (2019) advanced a hybrid MCDM method which integrates grey numbers with the SWARA (Stepwise Weight Assessment Ratio Analysis), TOPSIS, ARAS (Additive Ratio Assessment) and Geometric Mean techniques to improve the problem-solving model.

The DEMATEL method was presented by Gabus and Fontela (1972) to capture complex relationships among various criteria. Due to the gradual fuzzification and uncertainty of information, Hsu, Kuo, Chen, and Hu (2013) used the DEMATEL method to derive the importance and causal relationships among the criteria of evaluating suppliers in green chain management. B. Chang, C. W. Chang, and Wu (2011) developed a fuzzy DEMATEL method to find essential criteria in selecting suppliers. Govindan, Khodaverdi, and Vafadarnikjoo (2015) integrated the DEMATEL method with intuitionistic fuzzy sets for coping with the importance and causal relationships between practices and the performances in green supply chain management. Abdullah, Zulkifli, Liao, Herrera-Viedma, and Al-Barakati (2019) introduced a combination of the DEMATEL method, interval-valued intuitionistic fuzzy numbers and Choquet integral for sustainable solid waste management.

Also, the BWM (Rezaei, 2015) derives the weights of criteria with fewer pairwise comparisons and higher consistency than the AHP method. Guo and Zhao (2017) extended the BWM to the fuzzy environment to enhance the applicability of this method. Mou, Xu, and Liao (2016) presented an intuitionistic fuzzy multiplicative extension of the Best-Worst method for evaluating the severity of pulmonary emphysema. Aboutorab, Saberi, Asadabadi, Hussain, and Chang (2018) integrated the BWM and Z-numbers to solve a supplier development problem. A.

Hafezalkotob, A. Hafezalkotob, Liao, and Herrera (2019) proposed the group interval BWM and combined the interval MULTIMOORA (multi-objective optimization based on ratio analysis with multiplication form) method to address engineering selection problem. Liao, Mi, Yu, and Luo (2019a) developed the hesitant fuzzy linguistic BWM for hospital performance evaluation. Brunelli and Rezaei (2019) introduced a new metric into the BWM to make it more mathematically reasonable. A. J. Liu, Ji, Lu, and H. Y. Liu (2019) extended the BWM to interval-valued Pythagorean hesitant fuzzy context to form a novel multi-criteria group decision-making method for selecting third-party reverse logistics suppliers. Mi et al. (2019) made a systematic literature review of the BWM and its applications.

From the literature mentioned above review, we can see that combining the CoCoSo method with grey theory can further enhance the applicability of the CoCoSo method in the uncertain decision-making environment. Furthermore, the DEMATEL method and BWM, as two prevalent methods of weight determination, have been employed by many scholars to determine the weights of criteria. However, some of the researches have expertly combined the two ways to determine the weights of criteria with high reliability. Therefore, this paper proposes to apply a novel grey extension of the CoCoSo method (CoCoSo-G) to find the best supplier for the construction contractor based on the combination of the DEMATEL and BWM (to determine the criteria weights) techniques. This study complements and addresses practical decision-making in the area of SCM, specifically in the construction sector. Section 4 describes the case study in detail. We propose a combined decision-making platform to evaluate suppliers of a construction Company to aid its functions and operations. The following information expresses the objectives of the study:

- An implemented hybrid weight determination method based on the DEMATEL and BWM effectively synthesises the advantages of the two ways and enhances the reliability of the derived weights of criteria.
- A combination of the CoCoSo method with extended grey numbers is established to form a CoCoSo-G way to solve decision-making problems in an uncertain environment.
- We implement the proposed method to select the best supplier for the construction company and promote the application and effectiveness of the proposed method.

2. The materials, equations and arithmetic operations

This section devotes to the combined weighting process using DEMATEL and BWM. As stated before, in many cases, experts would not be able to indicate which criterion is best or worst directly. Decision-makers might need a pre-evaluation before applying the BWM practically and

operationally to offer them a viewpoint. The DEMATEL designs cause and effect groups and provide the most preferred and least essential criteria for similar decision-making problems. Then, with higher confidence, experts can count on the best and worst items for further processing with the BWM.

2.1. The decision making trial and evaluation laboratory (DEMATEL) method

The method of decision-making trial and evaluation laboratory consists of the following seven steps (Ranjan, Chatterjee, & Chakraborty, 2016; Yazdani et al., 2017; Kaur, Sidhu, Awasthi, Chauhan, & Goyal, 2018). It presumes a system restraining a set of components (or factors, criteria) $C = \{C_1, C_2, \dots, C_n\}$, with pair-wise relations that can be assessed. It is useful for decision-criteria weighting. The operative procedure to reach the weight of criterion is as follows.

Step 1: Generation of the direct-relation matrix (A) by scores

At first, the decision makers (DM) indicates the relationships between the sets of pairwise criteria that signify the direct effect that the i^{th} criterion exerts on the j^{th} criterion, as specified by an integer score ranging a scale of (0–7), representing no influence as 0, and very strong influence as 7. Based on these assessments, a direct-relation matrix (A) is obtained in the form of an $n \times n$ matrix, in which the individual element (a_{ij}) denotes the degree to which the i^{th} criterion affects the j^{th} criterion and n denotes the total number of criteria.

$$A = \begin{bmatrix} 0 & a_{12} & \dots & a_{1j} & \dots & a_{1n} \\ a_{21} & 0 & \dots & a_{2j} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nj} & \dots & 0 \end{bmatrix} \tag{1}$$

Step 2: Forming a normalised direct-relation matrix (X)

After generating the direct-relation matrix (A), the normalised matrix (X) is achieved by

$$X = kA, \tag{2}$$

where

$$k = \frac{1}{\max_{1 \leq i \leq n} \left(\sum_{j=1}^n a_{ij} \right)}, i, j=1, 2, \dots, n. \tag{3}$$

Each element in the matrix X ranges from 0 to 1.

Step 3: Computing the total-relation matrix (T)

Since $T = X + X^2 + X^3 + \dots + X^k = X(I + X + X^2 + \dots + X^{k-1})[(I - X)((I - X)^{-1}] = X(I - X^k)(I - X)^{-1}$. Then, $T = X(I - X)^{-1}T$, when $k \rightarrow \infty, X^k = [0]_{n \times n}$. Thus, the total-relation matrix $T = [t_{ij}]_{n \times n}$ is obtained by

$$T = X(I - X)^{-1}, \tag{4}$$

where I denotes the identity matrix. Each element t_{ij} of this matrix symbolises the indirect influences that the i^{th}

criterion imparts on the j^{th} criterion, and the matrix T reveals the total relationship between each pair of decision variables.

Step 4: Determining the sums of rows and columns of matrix T

In the total-relation matrix T , the sum of rows and sum of columns are represented by vectors D and R , as derived by Eqns (5) and (6), respectively.

$$D_i = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1} = [t_i]_{n \times 1}, i=1, 2, \dots, n; \tag{5}$$

$$R_j = \left[\sum_{i=1}^n t_{ij} \right]_{1 \times n} = [t_j]_{1 \times n}, j=1, 2, \dots, n. \tag{6}$$

From the last step, we need to sum each element of D and R vector, and then two vectors can be estimated as $(D + R)$ and $(D - R)$ for each decision criterion. The weights of DEMATEL are the normalised vector of $(D + R)$ where the highest value of $(D + R)$ means the most important criteria. For more details about the DEMATEL method, readers can refer to Ranjan et al. (2016), Yazdani et al. (2017) and Kaur et al. (2018).

2.2. The Best-Worst method

BWM (Rezaei, 2015) is one of the recent MCDM approaches in the weighting process. It acts based on linear programming. It has received considerable attention in various fields (Van de Kaa, Scholten, Rezaei, & Milchram, 2017; Chitsaz & Azarnivand, 2017; Mi et al., 2019). The idea behind the BWM allows decision-makers to run an operable model in complex decision environments (Rezaei, Nispeling, Sarkis, & Tavasszy, 2016; Rezaei, Wang, & Tavasszy, 2015; Ahmadi, Kusi-Sarpong, & Rezaei, 2017; Gupta, 2018). The steps below are processed to obtain the weights of decision criteria:

Step 1: The decision-maker determine a set of decision criteria: $\{c_1, c_2, \dots, c_n\}$. Then, each expert must select the best and worst criteria. We suppose that the best criterion is the most desirable and the worst criterion is the least important one among others.

Step 2: The expert performs pairwise comparisons between the best criterion and other criteria using a scale from 1 to 9 (1: *equally important*, and 9: *extremely more critical*). The comparison outcome is described as a Best-to-another vector: $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$, where a_{Bj} represents the preference of the best criterion B over the j^{th} criterion and $a_{BB} = 1$.

Step 3: Same as the last step, again the expert is asked for making pairwise comparisons, however in this step, between the other criteria and the worst criterion. An other-to-worst vector expresses the comparison results: $A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$, where a_{jw} represents the preference of the j^{th} criterion over the worst criterion W and $a_{WW} = 1$.

Step 4: Calculating the optimal weights: $(W_1^*, W_2^*, \dots, W_n^*)$.

For the pairs of $\frac{W_B}{W_j}$ and $\frac{W_j}{W_W}$, the optimal weights should meet the requirement that $\frac{W_B}{W_j} = a_{Bj}$ and $\frac{W_j}{W_W} = a_{jW}$. To satisfy such conditions, the maximum absolute differences $\left| \frac{W_B}{W_j} - a_{Bj} \right|$ and $\left| \frac{W_j}{W_W} - a_{jW} \right|$ for all criteria are minimised. Besides, taking into consideration the non-negativity characteristic and sum condition of the weights, the following model can be formulated:

$$\text{Min max}_j \left\{ \left| \frac{W_B}{W_j} - a_{Bj} \right|, \left| \frac{W_j}{W_W} - a_{jW} \right| \right\}$$

$$\text{s. t.: } \sum_j W_j = 1, W_j \geq 0 \text{ for all } j. \tag{7}$$

The model can be transformed as:

$$\begin{aligned} &\text{min } \xi \\ &\text{s.t.: } \left| \frac{W_B}{W_j} - a_{Bj} \right| \leq \xi, \text{ for all } j; \\ &\quad \left| \frac{W_j}{W_W} - a_{jW} \right| \leq \xi, \text{ for all } j; \\ &\quad \sum_j W_j = 1, W_j \geq 0 \text{ for all } j. \end{aligned} \tag{8}$$

After finding the results, we should calculate the consistency ratio (CR) of comparisons as follows:

$$CR = \frac{\xi^*}{CI}, \tag{9}$$

where the corresponding consistency index (CI) can be seen in Table 1. It can be seen that the smaller ξ^* is, the lower the CR value is, and the more consistent the vectors are.

Table 1. The consistency index of BWM

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency index	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Shortly, BWM is used to clarify the importance of decision criteria. Rather than the AHP, ANP, SWARA or other weighting tools, It has an advantage that achieves the criteria weights under a linear model. It advances the quality of the results and guarantees reliable results. Besides, BWM comparing other MCDM tools needs fewer pairwise comparisons. One of the benefits of BWM is that it can be combined with other techniques easily. In this paper, we use an innovative manner of weighting, it is said, to prevent the hesitation of finding the best and worst criteria in BWM, the DEMATEL is proposed to determine the best and worst items (Rezaei, 2015).

2.3. Concepts and mathematical relations of grey sets

This section provides several definitions, requirements and functions for grey approach and its aggregation into an MCDM approach.

A grey number is defined as a number whose exact value is unknown, but with a known range. Usually, a grey number is represented as a closed interval or as a set of numbers.

Definition 1. Let Z be a grey value. If $\forall \tilde{z} \in Z$ and $\tilde{z} = [a, b]$, then \tilde{z} is recognised as an interval grey number, while a and b are the upper and lower limits (boundaries) of \tilde{z} and $a, b \in R$.

Definition 2. Suppose that $\tilde{z}_1 = [a, b]$ and $\tilde{z}_2 = [c, d]$ are two interval grey numbers, and $\lambda > 0, \lambda \in R$. Then, the operations below are defined (Liu, Dang, Fang, & Xie, 2010; Zhou et al., 2019):

- 1) $\tilde{z}_1 + \tilde{z}_2 = [a + c, b + d]$;
- 2) $-\tilde{z}_1 = [-b, -a]$;
- 3) $\tilde{z}_1 - \tilde{z}_2 = [a - d, b - c]$;
- 4) $\lambda \tilde{z}_1 = [\lambda a, \lambda b]$.

Grey numbers, in general, refer to continuous grey numbers in an interval, while those values from a finite number or a set of numbers are called discrete grey numbers. A combined approach for both continuous and discrete grey numbers provided a new definition for grey numbers (Yang, 2007; Zhou et al., 2019).

Definition 3 (Yang, 2007). Suppose that Z is a grey number. If $Z = \bigcup_{i=1}^n [a_i, b_i]$, then we call Z as an extended grey number (EGN). We assume Z as a union of a set of closed or open intervals, while n is an integer and $0 < n < \infty$, while $a_i, b_i \in R$, and $b_{i-1} < a_i \leq b_i < a_{i+1}$.

Theorem 1. If Z is an EGN, then, the following properties are correct:

- (1) $Z = [a_1, b_n]$ is a continues EGN if and only if $a_i \leq b_{i-1} (\forall i > 1)$ or $n = 1$;
- (2) $Z = \{a_1, a_2, \dots, a_n\}$ is a discrete EGN if and only if $a_i = b_i$;
- (3) Z is a mixed EGN if only part of its intervals integrates to crisp numbers and the others keep as intervals.

Definition 4 (Zhou et al., 2019) For two EGNs $Z_1 = \bigcup_{i=1}^n [a_i, b_i]$ and $Z_2 = \bigcup_{j=1}^m [c_j, d_j]$, let $a_i \leq b_i (i = 1, 2, \dots, n)$, $c_i \leq d_i (j = 1, 2, \dots, m)$, $\lambda \geq 0$ and $\lambda \in R$. Then, the arithmetic operations are:

- 1) $Z_1 + Z_2 = \bigcup_{i=1}^n \bigcup_{j=1}^m [a_i + c_j, b_i + d_j]$;
- 2) $-Z_1 = \bigcup_{i=1}^n [-b_i, -a_i]$;
- 3) $Z_1 - Z_2 = \bigcup_{i=1}^n \bigcup_{j=1}^m [a_i - d_j, b_i - c_j]$;

- 4) $\frac{Z_1}{Z_1} = \bigcup_{i=1}^n \bigcup_{j=1}^m \left[\min \left\{ \frac{a_i}{c_j}, \frac{a_i}{d_j}, \frac{b_i}{c_j}, \frac{b_i}{d_j} \right\}, \max \left\{ \frac{a_i}{c_j}, \frac{a_i}{d_j}, \frac{b_i}{c_j}, \frac{b_i}{d_j} \right\} \right]$
while $c_j \neq 0, d_j \neq 0$ and $(j = 1, 2, \dots, m)$;
- 5) $Z_1 * Z_2 = \bigcup_{i=1}^n \bigcup_{j=1}^m \left[\min \{ a_i c_j, a_i d_j, b_i c_j, b_i d_j \}, \max \{ a_i c_j, a_i d_j, b_i c_j, b_i d_j \} \right]$;
- 6) $\lambda Z_1 = \bigcup_{i=1}^n [\lambda a_i, \lambda b_i]$;
- 7) $Z_1^\lambda = \bigcup_{i=1}^n [\min (a_i^\lambda, b_i^\lambda), \max (a_i^\lambda, b_i^\lambda)]$.

Definition 5. The length of a grey value like $Z = [a, b]$ is measured as: $L(Z) = [b - a]$.

Definition 6. For two grey numbers $Z_1 = [a, b]$ and $Z_2 = [c, d]$ while $a < b$ and $c < d$, the possibility degree $P\{Z_1 \leq Z_2\} = \frac{\text{Max}(0, L^* - \text{Max}(0, b - c))}{L^*}$, where $L^* = L(Z_1) + L(Z_2)$.

- For the position relation between two grey values,
- 1) if $P\{Z_1 \geq Z_2\} < 0,5$ then $Z_1 < Z_2$, which means that Z_1 is smaller than Z_2 ;
 - 2) if $P\{Z_1 \geq Z_2\} = 0,5$ then $Z_1 = Z_2$, which implies that Z_1 is equal to Z_2 ;
 - 3) if $P\{Z_1 \geq Z_2\} > 0,5$ then $Z_1 > Z_2$, which means that Z_1 is more significant than Z_2 .

2.4. A grey combined compromise solution (CoCoSo-G) method

The CoCoSo method (Yazdani et al., 2018) has been utilised widely in applications, and its usability is increasing. After the introduction of grey numbers, it is the time to implement the grey theory for the CoCoSo method. An extended grey CoCoSo (CoCoSo-G) method to solve MCDM problems uses the following steps:

Step 1: Set the alternatives and criteria for the proposed decision problem.

Step 2: Prepare the decision matrix X :

$$X = \begin{bmatrix} \bigcup [a_{11}, b_{11}] & \bigcup [a_{12}, b_{12}] & \dots & \bigcup [a_{1m}, b_{1m}] \\ \bigcup [a_{21}, b_{21}] & \bigcup [a_{22}, b_{22}] & \dots & \bigcup [a_{2m}, b_{2m}] \\ \vdots & \vdots & \dots & \vdots \\ \bigcup [a_{n1}, b_{n1}] & \bigcup [a_{n2}, b_{n2}] & \dots & \bigcup [a_{nm}, b_{nm}] \end{bmatrix}, \tag{10}$$

where a_{ij} represents the lower limit, while b_{ij} the upper limit, for $i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

Step 3: Develop the normalised matrix based on compromise normalisation equations:

$$r = \bigcup [c_{ij}, d_{ij}] = \frac{\bigcup [a_{ij}, b_{ij}] - \min_i \bigcup [a_{ij}, b_{ij}]}{\max_i \bigcup [a_{ij}, b_{ij}] - \min_i \bigcup [a_{ij}, b_{ij}]}$$

for the benefit criterion; (11)

$$r = \bigcup [c_{ij}, d_{ij}] = \frac{\max_i \bigcup [a_{ij}, b_{ij}] - \bigcup [a_{ij}, b_{ij}]}{\max_i \bigcup [a_{ij}, b_{ij}] - \min_i \bigcup [a_{ij}, b_{ij}]}$$

for the cost criterion. (12)

Step 4: Obtain the weighted normalised matrix and sum of power weight of comparability sequences for each alternative as S_i and P_i , respectively:

$$S_i = \sum_{j=1}^n \left(w_j \bigcup [c_{ij}, d_{ij}] \right); \tag{13}$$

$$P_i = \sum_{j=1}^n \left(\bigcup [c_{ij}, d_{ij}]^{w_j} \right). \tag{14}$$

Step 5: Compute the relative weights of alternatives using the following aggregation strategies. In this step, three appraisal score strategies are used to generate the relative weights of other options, which are derived by Eqns (13), (14), and (15):

$$H_{ia} = [h_{1ij}, h_{2ij}] = \frac{P_i + S_i}{\sum_{i=1}^m (P_i + S_i)}; \tag{15}$$

$$L_{ia} = [l_{1ij}, l_{2ij}] = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}; \tag{16}$$

$$M_{ia} = [m_{1ij}, m_{2ij}] = \frac{\lambda S_i + (1 - \lambda)(P_i)}{\lambda \max_i S_i + (1 - \lambda) \left(\max_i P_i \right)},$$

for $0 \leq \lambda \leq 1$. (17)

In Eqn (15), decision-makers chose λ (usually $\lambda = 0.5$). However, the flexibility and stability of the proposed CoCoSo can rely on different values of λ . The final ranking of the alternatives based on the CoCoSo-G method is determined based on K values (as more significant as better):

$$K_i = (H_{ia} * L_{ia} * M_{ia})^{\frac{1}{3}} + \frac{1}{3}(H_{ia} + L_{ia} + M_{ia}). \tag{18}$$

Step 6: To compare various K values, we propose two different strategies and check their similarity and coronation to get a finally acceptable list of ranked alternatives. The first strategy comes from Turskis and Zavadskas (2010), where they proposed a ranking index for grey numbers. For example, if $K_i = [s_i, t_i]$ is a vector of alternative scores with grey values, while s and t are bigger than zero, then one can transform the grey values to crisp values. In this way, we find the maximum among all the elements of matrix K . We normalise the data based on the maximum value. Then, the score for each alternative can be obtained using

$$K = (t_i - s_i) / t_i, \tag{19}$$

where K is the crisp value for the assumed grey number. The score obtained by Eqn (19) is called the CoCoSo score.

The second strategy is to make the ideal alternative set like a referential alternative (*comparing reference*). For example, while we have the alternative set as

$A = \{A_1, A_2, \dots, A_m\}$, the ideal reference can be stated as:

$$A^{\max} = \left\{ \max_{1 \leq i \leq m} s_i, \max_{1 \leq i \leq m} t_i \right\}. \quad (20)$$

Then, using Eqn (21), we calculate the grey possibility degree between the comparing alternative set and reference alternatives obtained by Eqn (33).

Rank the order of alternatives in the following condition: when $P\{A_i \leq A^{\max}\}$ is smaller, the ranking order of A_i is better; otherwise, the ranking order is worse. According to the above procedures, the ranking orders of all alternatives are obtained, and the best option among a set of feasible options is detected.

3. Application of the proposed model in the construction supply chain

Figure 1 illustrates a systemic procedure for the implementation of the proposed method. As the flowchart reflects, we design a three-phase decision-making structure to aid construction executives in their supply process and encounter the updated list of suppliers. The phases are interpreted in the following manner.

Phase 1 – Recognition of the decision problem, existing information or data, experts background, problem dimensions, how to configure the model. In this case, realising existing suppliers, the related criteria and assuring the experts can rate suppliers’ performance and suppliers’ criteria. Section 4 extensively discuss this phase.

Phase 2 – The model recognition and formulation. This phase insists on several tasks like analysing the supplier criteria, evaluation and ranks them. The role of DEMATEL and BWM techniques is to handle this task. At first, the DEMATEL is conducted to distinguish the ideal and nadir decision criteria. The function of DEMATEL lets us confirm this. The output of DEMATEL allows experts to

have a global view and facilitate the BWM procedure for experts. After that, the unique structure of the BWM can release the list of the rated criteria, the weights score and the consistency index. At the ultimate stage of this phase, the CoCoSo-G method is directed while it generates the performance score of each supplier and the corresponding priority.

Phase 3 – Test and examine that the obtained results are confidential. We compare the results with other grey MCDM method like the Complex Proportional Assessment (COPRAS). It certifies how experts can rely on the outcomes of the study and whether the proposed approach can be improved or used for future projects.

4. Case study description, decision model implementation and results

4.1. Problem definition of the case study

Maintaining the supply chain as reliable is related to several factors. Contracting and collaborating to professional suppliers is one of those factors. In another side, the importance of the supply chain management in construction projects is strategic, and supplier performance has a direct influence on the stability and advancement of this supply chain (Vrijhoef & Koskela, 2000; Wu & Barnes, 2016).

The idea behind this case study is to implement the proposed grey extension of the CoCoSo-G method in a supplier selection problem in a construction company in Madrid called DOVHER Arquitectura. The company since 1990 was dedicated on more than 50 construction projects including building, reforming and designing construction and architecture projects in Madrid, Salamanca and Zamora in Spain. Recently, with the new roles made by the ministry of industry, construction firms should ensure the material, supply operations, mainly evaluate and

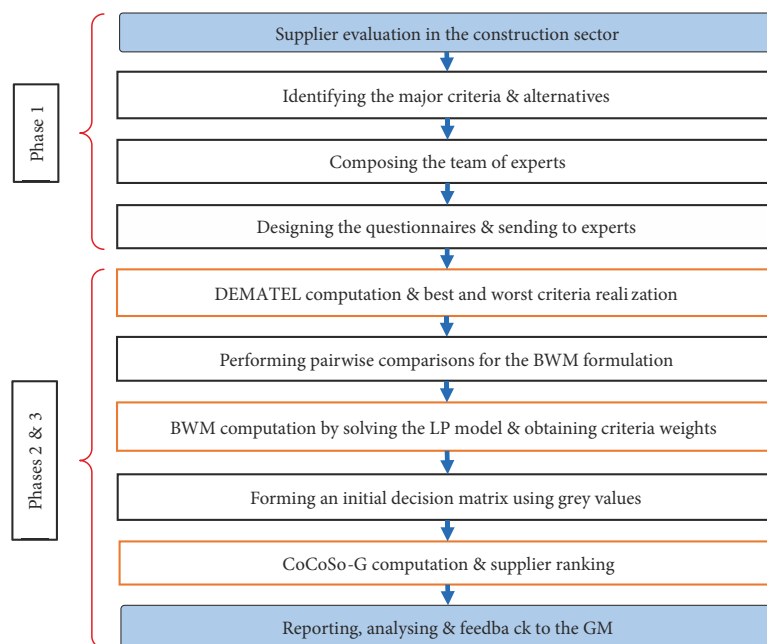


Figure 1. The proposed decision-making process for supplier evaluation

guarantee the purchasing process. It certifies the constant and periodic evaluation of suppliers and several partners. The government passed a law in which small and big companies are obliged to approve the supply process through the regular programs of evaluation. In this manner, permission for starting a construction project is very dependent on that certification. The company works with almost 20 official suppliers who provide the main requirements such as foundation, consulting and geometrical measurement, electricity equipment and raw materials such as wood, cement and iron for construction projects. However, based on the interviews and meetings with the general manager (GM), we decide to implement the evaluation model for ten suppliers (S_1-S_{10}). As the supplier selection is usually an internal organisational process, for the initial qualitative evaluation, the experts (decision makers) are responsible for filling the questionnaires. The evaluation team designs the survey for supplier performance rating using grey variables. The evaluation team includes experts of DOVHER such as the GM of the company, an architect (with more than ten years of experience) and an assistant in procurement activities. We sent the questionnaire, and the experts returned their opinions within three days. The team appointed a reunion and discussed the suppliers' performance.

To use a multiple attribute decision matrix for supplier evaluation, we need a set of decision criteria. For this reason, the evaluation team agreed to use this list as design (C_1), GHG pollution (C_2), delivery and flexibility (C_3), responsiveness and communication (C_4), financial condition (C_5), the offered price (C_6) and environmental management system (C_7) (Yazdani, Chatterjee, Pamucar, & Abad, 2019). The weight of each decision criterion can be determined using a combined version of DEMATEL-BWM.

4.2. DEMATEL solution

The first step of the DEMATEL process is to carry out pairwise comparisons among seven criteria by requesting experts to rate them using a scale of (0–7). A zero value means there is no influence while a value of 7 directs the maximum relation. We have distributed the questionnaires between 7 experts. Table 2 pictures the total decision maker opinions. In this table, (ex. 1, ex. 2, ex. 3,..., ex. 7) releases the opinion of each expert. Experts compare the criteria independently. For example, expert 1 measures the relation between C_5 and C_7 and the value is announced as 2, but this value for expert 7 is equal to 7. In the next step, we aggregate the opinions of all experts, and Table 3 tabulates the geometric average of them. We now use this as the initial matrix for DEMATEL processing.

Afterwards, the normalization is performed using Eqns (2) and (3). In the following step, the total-relation matrix for the assumed criteria is obtained. Eqn (4) in Step 3 of the DEMATEL forms Table 4 (matrix T) as the entire relationship gathered by experts concerning the supplier criteria. The essential outputs of Table 4 are the sum of each row (we call it vector D) and each column (we call it vector R). Then, to gain the weight of each decision criterion, Eqns (5) and (6) should be used. With these equations, we can generate the $(D + R)$ and $(D - R)$ columns, as shown in Table 5. It is the first view of criteria weights. Our results in Table 5 obtained by the DEMATEL show that C_5 (a financial condition with the score of 0.16379) and C_2 (GHG pollution with the value of 0.1324) are the most favorite and most undesirable factors, respectively. As has been described, the normalized values of $(D + R)$ column give us the importance or weights of decision criteria.

Table 2. Initial experts' comparison for DEMATEL

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_1	(0,0,0,0,0,0)	(2,2,2,1,1,2,3)	(3,2,0,3,3,1,2)	(5,4,0,1,5,1,5)	(3,3,3,3,4,2,3)	(6,3,0,5,3,3,2)	(0,7,2,3,6,3,1)
C_2	(2,2,3,3,5,2,3)	(0,0,0,0,0,0,0)	(1,1,1,1,1,4,3)	(3,3,3,3,3,5,4)	(1,5,1,1,1,3,1)	(0,3,3,1,0,3,1)	(3,3,3,2,3,2,1)
C_3	(1,3,4,2,4,1,4)	(3,0,1,5,2,3,1)	(0,0,0,0,0,0,0)	(2,2,3,4,3,2,2)	(3,3,4,5,3,6,4)	(4,4,4,0,4,0,4)	(5,0,2,5,5,4,5)
C_4	(4,4,2,1,6,1,3)	(4,2,5,0,2,1,5)	(3,4,2,3,4,3,4)	(0,0,0,0,0,0,0)	(4,4,5,6,3,4,4)	(0,2,1,1,1,1,4)	(2,1,0,0,0,0,1)
C_5	(5,1,2,1,0,0,2)	(3,2,3,2,4,2,5)	(1,3,5,0,1,4,3)	(5,2,4,1,1,4,4)	(0,0,0,0,0,0,0)	(3,3,6,4,1,2,3)	(2,0,6,1,3,0,7)
C_6	(3,1,3,4,2,5,1)	(4,5,4,3,3,2,4)	(0,2,1,2,0,2,7)	(3,2,3,3,2,3,2)	(3,3,5,6,5,3,3)	(0,0,0,0,0,0,0)	(2,2,4,6,1,2,5)
C_7	(2,5,1,4,2,1,0)	(0,1,0,3,5,4,3)	(1,5,0,1,1,3,2)	(4,0,2,0,1,1,2)	(5,4,3,7,6,4,3)	(1,5,3,3,3,2,4)	(0,0,0,0,0,0,0)

Table 3. The aggregated decision matrix for all decision criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
C_1	0	1.8571	2	3	3	3.1429	3.1429
C_2	2.8571	0	1.7143	3.4286	1.8571	1.5714	2.4286
C_3	2.7143	2.1429	0	2.5714	4	2.8571	3.7143
C_4	3	2.7143	3.2857	0	4.2857	1.4286	0.5714
C_5	1.5714	3	2.4286	3	0	3.1429	2.7143
C_6	2.7143	3.5714	2	2.5714	4	0	3.1429
C_7	2.1429	2.2857	1.8571	1.4286	4.5714	3	0

Table 4. The total-relation matrix for supplier criteria assessment

X	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	D
C ₁	0.2878	0.3866	0.3494	0.4319	0.5289	0.4245	0.4283	2.8373
C ₂	0.3669	0.2622	0.3033	0.4069	0.4295	0.3226	0.3572	2.4487
C ₃	0.4267	0.4277	0.2909	0.4476	0.6054	0.4463	0.4824	3.1269
C ₄	0.3954	0.4011	0.3857	0.3015	0.5482	0.3463	0.321	2.6992
C ₅	0.3529	0.4233	0.3599	0.4272	0.3976	0.4155	0.4061	2.7824
C ₆	0	0	0	0	1	0	0.456	3.097
C ₇	0.361	0.389	0.329	0.361	0.562	0.407	0	2.7
R	2.616	2.767	2.391	2.823	3.668	2.686	2.742	

Table 5. The realisation of the best and worst criteria and cause & effect groups

	D + R	D - R	Weights	Group	Rank
C ₁	5.4529	0.2218	0.13845	CAUSE	5
C ₂	5.2155	-0.3181	0.13242	EFFECT	7
C ₃	5.5175	0.7364	0.14009	CAUSE	4
C ₄	5.5226	-0.1242	0.14022	EFFECT	3
C ₅	6.4501	-0.8853	0.16377	EFFECT	1
C ₆	5.7836	0.4112	0.14685	CAUSE	2
C ₇	5.4426	-0.0417	0.13819	EFFECT	6

4.3. BWM modelling & criteria weight computation

The DEMATEL method perceives that C₅ and C₂ are the best and worst criteria. Similar to the DEMATEL, we need to ask again experts to present their pairwise judgments over criteria. There is a difference between the previous method and the current one. Here we need experts to reveal their preference (using the scale of 1–9) of the best item to each of other criteria, and in the same way, the preferences of all criteria over the worst criterion. The results of this task are shown in Table 6 (in the second and third columns).

Based on the second and third columns of Table 6, we build a linear programming model as illustrated below (for details about how to build such a model, please refer to Section 2.2). Finally, we solve the linear programming (LP) model (it can be done by LINGO, or Excel) and the required weights for all the decision criteria are produced as the fourth column of Table 6. The consistency ratio derived from the model approves that the achieved weights

are consistent and reliable. Figure 2 explains the visual comparison and values of the seven decision criteria for the supplier evaluation system.

$$\begin{aligned}
 &\min \xi \\
 &\text{s.t.} \\
 &\left| \frac{W_5}{W_1} - 5 \right| \leq \xi, \left| \frac{W_5}{W_2} - 7 \right| \leq \xi, \left| \frac{W_5}{W_3} - 4 \right| \leq \xi, \left| \frac{W_5}{W_4} - 3 \right| \leq \xi, \left| \frac{W_5}{W_6} - 3 \right| \leq \xi, \\
 &\left| \frac{W_5}{W_7} - 6 \right| \leq \xi, \left| \frac{W_2}{W_1} - 3 \right| \leq \xi, \left| \frac{W_2}{W_3} - 4 \right| \leq \xi, \left| \frac{W_2}{W_4} - 5 \right| \leq \xi, \left| \frac{W_2}{W_5} - 7 \right| \leq \xi, \\
 &\left| \frac{W_2}{W_6} - 5 \right| \leq \xi, \left| \frac{W_2}{W_7} - 2 \right| \leq \xi, \\
 &\sum_{j=1}^7 W_j = 1, W_j \geq 0 \text{ for all } j
 \end{aligned}$$

Table 6. The weights of decision criteria by BWM

	Best (C ₅) to Others	Others to Worst (C ₂)	Weights	Consistency Ratio
C ₁	5	3	0.0899	0.0705
C ₂	7	1	0.0441	
C ₃	4	4	0.1124	
C ₄	3	5	0.1498	
C ₅	1	7	0.379	
C ₆	3	5	0.1498	
C ₇	6	2	0.0749	

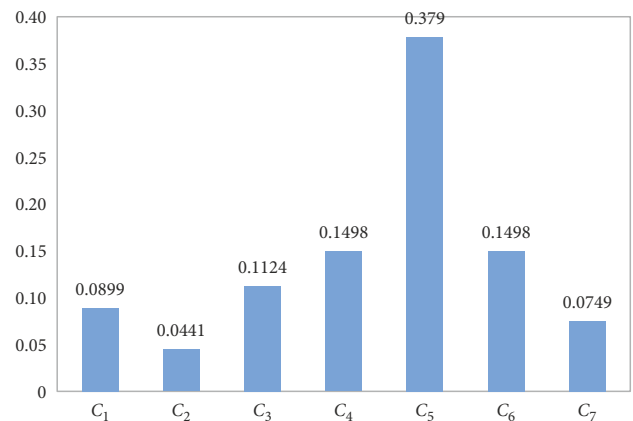


Figure 2. The BWM method weights

4.4. Implementation of the CoCoSo-G for supplier evaluation

In our proposed supplier evaluation and selection program, several matrixes must be provided to reach the optimal list of suppliers and their score. One of the matrixes is the weight vector that has been produced by the BWM. The second matrix concerning the supplier evaluation is demonstrated by the G-CoCoSo method. To reach to the second matrix, the team should design the performance rating of each candidate supplier concerning the criteria. Seven experts similar to DEMATEL must manage this action. However, in contrast to the last sections, the main

table for the supplier evaluation is developed using grey interval variables. The scale for assessment includes numbers between intervals of 1 to 100. It means 1 is a very low value for the corresponding criterion, while 100 is the strongest one. Once again, the experts contribute and offer the complete comparison of each among the deciding factors. As for this case, C_2 and C_6 are cost-oriented, and their lower values are in favor. The performance matrix of suppliers produced by expert 1 and 7 are shown in Table 7 and 8, respectively. The aggregated average matrix of all respondents is seen in Table 9. It is equal to the matrix mentioned in Eqn (10). Given to this matrix,

Table 7. The grey measurement of supplier performance regarding decision factors (Expert 1)

Suppliers	C_1		C_2		C_3		C_4		C_5		C_6		C_7	
S_1	20	25	32	35	42	45	50	55	60	65	70	75	80	85
S_2	20	28	42	48	60	70	82	90	45	50	20	25	40	45
S_3	12	23	30	40	50	55	73	76	65	70	15	20	22	28
S_4	20	30	40	50	60	70	50	55	81	85	70	75	20	25
S_5	5	10	40	45	25	28	35	40	45	50	55	60	12	15
S_6	40	45	50	55	20	25	70	75	80	85	90	95	20	30
S_7	40	50	30	35	80	87	35	45	40	45	64	67	83	90
S_8	30	40	50	60	32	37	55	65	75	80	30	40	50	55
S_9	30	45	40	45	45	60	32	35	20	25	10	20	50	60
S_{10}	70	80	30	35	52	55	70	80	90	95	20	35	45	50

Table 8. The grey measurement of supplier performance (Expert 7)

Suppliers	C_1		C_2		C_3		C_4		C_5		C_6		C_7	
S_1	20	25	34	67	25	49	27	34	6	19	18	42	41	55
S_2	20	30	82	84	22	53	69	73	42	64	11	18	3	14
S_3	10	34	8	29	32	54	79	83	29	42	7	19	23	38
S_4	64	69	75	79	70	75	27	44	28	46	38	51	77	85
S_5	19	22	30	40	50	55	70	85	65	70	15	20	34	45
S_6	32	40	30	43	62	69	50	55	70	85	70	75	20	29
S_7	15	27	43	45	25	28	32	57	45	50	55	60	18	25
S_8	42	52	50	55	20	28	70	75	65	85	30	54	20	30
S_9	18	32	43	63	94	98	65	79	44	63	43	49	51	61
S_{10}	74	79	61	83	18	39	40	58	38	42	54	66	3	14

Table 9. The aggregated grey measurement for suppliers

Supplier	C_1		C_2		C_3		C_4		C_5		C_6		C_7	
S_1	31.71	36.71	44.29	52.29	44.57	51.86	48.86	54.29	60.57	67	64	71.86	70.71	78.71
S_2	26.43	32.71	46.29	52.29	50.29	61.71	65	72.14	58.86	67.57	44.86	54.57	36.57	44.86
S_3	19.29	32.14	25.86	35.71	31.71	39.14	52.14	58	51.43	59	28.71	34.86	35.14	42.43
S_4	34.29	42.71	44.43	52.71	57.14	62.86	57.14	67.57	64.71	70.43	49.71	58.57	32.43	41
S_5	37.71	47.71	55.86	64.71	46.86	52.43	44.86	52	52.29	59.29	43.71	50.29	42.86	53.43
S_6	47.57	54.29	50.14	58.29	49.14	56.57	63.86	70	47.43	57.43	63.71	73.29	44.29	54.29
S_7	24.71	35	42.57	47.43	59.14	64.57	40.71	50.71	50.14	55.43	63.29	71.14	73.86	79.71
S_8	27.29	41.57	44	55.57	47.86	58.14	47.71	59.29	54.43	64	46.86	56.29	36	43.71
S_9	50.57	62.29	48.29	57.71	67	75.14	48.71	55.86	27.86	35.57	24.29	38.43	43.43	54.43
S_{10}	58.43	71.14	45.57	57	48.71	55.71	51.71	61.86	42.14	48	33.86	48.43	52.14	60.43

the normalized supplier matrix can be computed using Eqns (11) and (12) for benefit and cost criteria. The normalized decision table is obtained in Table 10. Following the process of supplier’s evaluation, the weights extracted in the last section must be integrated. The G-CoCoSo contains a unique structure that presents the weighted normalized decision matrix and weighted power matrix together. For this, Eqns (13) and (14) are formulated and the relevant matrixes are approached in Tables 11 and 12. The sum of each row in Tables 11 and 12, indicates S_i and

P_i , in order and we denote them in Table 13. At this moment, the two previous matrices must be aggregated, and the relative weights (score) for suppliers are grasped. To head for that function, the G-CoCoSo deploys three different formulations (15, 16 and 17). As a result, Table 14 is composed and H_{ia} , L_{ia} and M_{ia} for the ten suppliers can be exhibited. At the final stage, we measure the grey values of K_i under Eqn (18) for every supplier. It yields the overall comparative performance score for suppliers and determines the priority of them.

Table 10. The normalized grey decision matrix

Suppliers	C ₁		C ₂		C ₃		C ₄		C ₅		C ₆		C ₇	
S ₁	0.24	0.336	0.474	0.68	0.296	0.464	0.259	0.432	0.768	0.919	0.81	0.971	0.81	0.979
S ₂	0.138	0.259	0.526	0.68	0.428	0.691	0.773	1	0.728	0.933	0.42	0.618	0.088	0.263
S ₃	0	0.248	0	0.254	0	0.171	0.364	0.55	0.554	0.732	0.09	0.216	0.057	0.211
S ₄	0.289	0.452	0.478	0.691	0.586	0.717	0.523	0.855	0.866	1	0.519	0.7	0	0.181
S ₅	0.355	0.548	0.772	1	0.349	0.477	0.132	0.359	0.574	0.738	0.397	0.531	0.221	0.444
S ₆	0.545	0.675	0.625	0.835	0.401	0.572	0.736	0.932	0.46	0.695	0.805	1	0.251	0.462
S ₇	0.105	0.303	0.43	0.555	0.632	0.757	0	0.318	0.523	0.648	0.796	0.956	0.876	1
S ₈	0.154	0.43	0.467	0.765	0.372	0.609	0.223	0.591	0.624	0.849	0.461	0.653	0.076	0.239
S ₉	0.603	0.829	0.577	0.82	0.813	1	0.255	0.482	0	0.181	0	0.289	0.233	0.465
S ₁₀	0.755	1	0.507	0.801	0.391	0.553	0.35	0.673	0.336	0.473	0.195	0.493	0.417	0.592

Table 11. The weighted normalized decision matrix for suppliers

Suppliers	C ₁		C ₂		C ₃		C ₄		C ₅		C ₆		C ₇	
S ₁	0.022	0.03	0.021	0.03	0.033	0.052	0.039	0.065	0.291	0.348	0.121	0.145	0.061	0.073
S ₂	0.012	0.023	0.023	0.03	0.048	0.078	0.116	0.15	0.276	0.354	0.063	0.093	0.007	0.02
S ₃	0	0.014	0	0.011	0	0.019	0.054	0.082	0.21	0.277	0.014	0.032	0.004	0.016
S ₄	0.026	0.041	0.021	0.03	0.066	0.081	0.078	0.128	0.328	0.379	0.078	0.105	0	0.014
S ₅	0.032	0.049	0.034	0.044	0.039	0.054	0.02	0.054	0.217	0.28	0.059	0.08	0.017	0.033
S ₆	0.049	0.061	0.028	0.037	0.045	0.064	0.11	0.14	0.174	0.263	0.121	0.15	0.019	0.035
S ₇	0.009	0.027	0.019	0.024	0.071	0.085	0	0.048	0.198	0.245	0.119	0.143	0.066	0.075
S ₈	0.014	0.039	0.021	0.034	0.042	0.068	0.033	0.089	0.237	0.322	0.069	0.098	0.006	0.018
S ₉	0.054	0.075	0.025	0.036	0.091	0.112	0.038	0.072	0	0.069	0	0.043	0.017	0.035
S ₁₀	0.068	0.09	0.022	0.035	0.044	0.062	0.052	0.101	0.127	0.179	0.029	0.074	0.031	0.044

Table 12. The normalized weighted power matrix for suppliers

Suppliers	C ₁		C ₂		C ₃		C ₄		C ₅		C ₆		C ₇	
S ₁	0.867	0.897	0.914	0.955	0.803	0.871	0.817	0.882	0.936	0.979	0.975	0.996	0.983	0.998
S ₂	0.820	0.874	0.926	0.955	0.858	0.936	0.962	1	0.924	0.983	0.901	0.944	0.823	0.899
S ₃	0	0.87	0	0.848	0	0.728	0.859	0.914	0.863	0.925	0.749	0.832	0.796	0.883
S ₄	0.883	0.924	0.915	0.957	0.908	0.942	0.907	0.977	0.965	1	0.924	0.958	0	0.872
S ₅	0.902	0.942	0.969	1	0.827	0.875	0.738	0.858	0.87	0.927	0.895	0.927	0.886	0.937
S ₆	0.941	0.961	0.945	0.979	0.848	0.904	0.955	0.989	0.823	0.913	0.974	1	0.895	0.94
S ₇	0.798	0.887	0.904	0.932	0.921	0.951	0	0.842	0.851	0.897	0.973	0.995	0.989	1
S ₈	0.83	0.919	0.913	0.968	0.837	0.914	0.798	0.924	0.889	0.96	0.911	0.950	0.813	0.892
S ₉	0.951	0.981	0.936	0.976	0.963	1	0.814	0.896	0	0.652	0	0.861	0.89	0.941
S ₁₀	0.972	1	0.922	0.974	0.845	0.899	0.854	0.942	0.761	0.829	0.822	0.919	0.932	0.959

Table 13. The computed values for S_i and P_i per supplier

Suppliers	S_i		P_i	
S_1	0.5879	0.7443	6.2957	6.578
S_2	0.5449	0.7466	6.2141	6.5893
S_3	0.2822	0.4521	3.2669	5.9999
S_4	0.5971	0.7772	5.5029	6.6292
S_5	0.4183	0.5934	6.0877	6.4653
S_6	0.5456	0.7492	6.3829	6.687
S_7	0.4827	0.6481	5.4354	6.5042
S_8	0.4209	0.6668	5.9906	6.5277
S_9	0.2266	0.4421	4.5546	6.3087
S_{10}	0.3744	0.5857	6.1086	6.5217

Table 14. Computing the relative weights of the alternatives

	H_{ia}		L_{ia}		M_{ia}	
S_1	0.0967	0.1214	4.5221	5.2988	0.9222	0.981
S_2	0.0949	0.1216	4.3071	5.3124	0.9055	0.9828
S_3	0.0498	0.107	2.2455	3.8322	0.4755	0.8644
S_4	0.0857	0.1228	4.32	5.4595	0.8172	0.9923
S_5	0.0914	0.117	3.7099	4.598	0.8716	0.9457
S_6	0.0973	0.1233	4.3621	5.3536	0.9282	0.9962
S_7	0.0831	0.1186	3.7942	4.8515	0.7929	0.9582
S_8	0.09	0.1193	3.6913	4.9413	0.859	0.9639
S_9	0.0671	0.1119	2.3942	3.8822	0.6405	0.9044
S_{10}	0.091	0.1178	3.5222	4.5813	0.8685	0.9522

Table 15. The final ranking of suppliers for G-CoCoSo

Suppliers	K_i		CoCoSo Score (CS)	Rank	Ref. comparison (RC)	Rank	SCC (CS, RC)	COPRAS ranking	SCC (COPRAS, RC)
S_1	2.5857	2.9915	0.1356	10	0.5412	10	0.77	9	0.87
S_2	2.4872	2.9985	0.1705	8	0.5831	7		4	
S_3	1.2997	2.3088	0.437	1	1	1		1	
S_4	2.4122	3.0644	0.2129	5	0.5767	8		7	
S_5	2.2236	2.6853	0.1719	7	0.8941	4		5	
S_6	2.5289	3.0273	0.1646	9	0.5481	9		10	
S_7	2.1867	2.796	0.2179	4	0.8067	5		8	
S_8	2.2052	2.8363	0.2225	3	0.7742	6		6	
S_9	1.5026	2.3653	0.3647	2	1	2		2	
S_{10}	2.1469	2.6848	0.2003	6	0.9025	3		3	

Based on this measure, we convert the grey values using Eqn (19). The corresponding vector (score) is seen in Table 15. The second manner to find the supplier score is using reference comparison shown as Eqn (20) and transforming them to crisp values. This permits us to rank suppliers and compare the two methods as well. Table 15 declares the final ranking of each supplier. The results of both rankings announce that S_3 is the most preferred supplier, while S_9 the second important supplier. It also reports that S_1 is known as the least important supplier. To

find out how the results are similar, the Spearman correlation value is used that is between -1.0 (an absolute negative correlation) and 1.0 (an absolute positive correlation). Accordingly, it can be classified as follows:

- $1 \rightarrow$ "Absolute";
- $0.8-0.999 \rightarrow$ "Very strong";
- $0.6-0.79 \rightarrow$ "Strong";
- $0.4-0.59 \rightarrow$ "Moderate";
- $0.2-0.39 \rightarrow$ "Weak";
- Correlation $< 0.19 \rightarrow$ "Very weak".

According to our results, the Spearman correlation coefficient (77%) shows a strong agreement and similarity between the two rankings.

To assure the obtained results from the proposed decision-making framework is applicable and can be acquired in further applications, we implement a grey COPRAS model. Zavadskas et al. (2008) released a COPRAS method with grey interval data in building wall structure evaluation. By executing the COPRAS, we identified that still Supplier 3 (S_3) is the best supplier, while S_9 is the second valued supplier according to the model and experts opinion. The correlation coefficient between the ranking deduced by the COPRAS and that obtained by the G-CoCoSo is a value of 0.87 that is a very strong similarity. In total, we agree on the list of preferred suppliers as this; S_3 and S_9 are the first and second place preferred suppliers, while we are quite sure that S_1 and S_6 are the worst suppliers. The company can keep working with 3rd and 9th suppliers by proposing better conditions, long term contract, incentives, and improving barriers in future communication. In the same way, the other mentioned supplier must be given a fixed period to increase their quality, meet the buyer requirements or finding the substitution for them.

Conclusions

A significant part of construction projects success is related to the coherence, reliability and performance of its supply chain. Managers and investors in this sector do not want to fail due to unstructured material supply and incapable suppliers. The role of suppliers in many industries and businesses is inevitable and small firms in such sectors must rely on a strong supply network and trustable suppliers. A reliable supplier does not even benefit the buyer; it causes the dynamism of the economy. Therefore, planning and programming for constant performance evaluation of suppliers is a knowledgeable recommendation to the body of industries, particularly construction management system.

In this paper, we studied the impact of a supplier performance evaluation in a construction-based firm. The lack of an efficient supplier causes unrecoverable costs and disadvantages that lead to enhanced risky conditions. To this objective, we proposed a decision-making structure concerning multiple attributes using qualitative and grey interval values. We established the decision structure in a real-world case to check the feedback and benchmark it as a registered program for the firm. The construction firm was based in Madrid and was served its requirements and materials from various contractors, suppliers and agencies. Joint with a team of experts from the case company, we planned a supplier evaluation using seven criteria, seven respondents (experts or decision makers) and a list of ten suppliers. The two weighting tools, as the DEMATEL and BWM supported us in the criteria weighting process. The DEMATEL introduced the best and worst criteria using its step-by-step formulas. The method is a useful instrument in many applications. The DEMATEL adopted pairwise

influence among decision criteria. With the DEMATEL results, we found out that financial condition was the most critical attribute while delivery was the worst item. The obtained information from the DEMATEL is as inputs of the BWM. In the next process, we conveyed the BWM to seek the importance (weights) of decision criteria by a linear program model. Then, these weights enabled us to look for the rest of the computations as implementing the CoCoSo-G and realised the supplier overall performance score.

Other construction companies could take benefit from the proposed approach in long terms plans and reduce the probable vulnerabilities encountered with their construction supply chains. The highlighted point of this investigation was the operations of DEMATEL and BWM for the first time in the context of multi-criteria decision analysis. It is an improvement for the BWM because usually, decision experts confront with confusion on how to choose best and worst factors. That is why we combined the DEMATEL to increase the reliability of the BWM outcomes. Many studies present the grey extensions of MCDM tools. However, no paper addressed the CoCoSo-G, and again for the first time, we proposed it here. We compared the CoCoSo performance with the other well-known method as COPRAS and figured out that they generated almost similar priority for suppliers, specifically in 1th and 2nd places and worst ones. It approved our approach in modelling an integrated and interval-valued decision making perspective in the context of supplier selection problem.

It is essential to consider the connection between the study results and the effectiveness reality of all suppliers. In the future, we should find the compromising behaviour of suppliers in the market with the construction companies. Also, since experts' opinions could change the results of suppliers, it is interesting to consider the sensitivity analysis and the rank inverse problem in the future.

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Author contributions

Morteza Yazdani, Zhi Wen and Huchang Liao conceived the study and were responsible for the design and development of the data analysis. Morteza Yazdani was responsible for data collection and analysis. Morteza Yazdani, Zhi Wen and Huchang Liao were responsible for data interpretation. Morteza Yazdani, Zhi Wen and Huchang Liao wrote the first draft of the article. Audrius Banaitis and Zenonas Turskis revised the paper.

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