Relaxed Rank Order Centroid Weighting MCDM Method With Improved Grey Relational Analysis for Subcontractor Selection: Photothermal Power Station Construction

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***Abstract*—This article addresses the problem of subcontractor selection in an uncertain decision-making environment by proposing a new hybrid method and improving a classical multicriteria decision-making (MCDM) method. First, the proposed hybrid method combines subjective and objective weighting methods to estimate the weights of criteria that are represented as grey numbers. The subjective weighting method is the PA weighting method. The objective weighting method is the rank order centroid with slacks (ROCS) weighting method used to compensate for the limitation of the rank order centroid weighting method. Second, grey relational analysis (GRA) is improved by introducing both positive and negative reference (PNR) alternatives instead of a single reference alternative as in the classical GRA. Subsequently, the proposed hybrid grey-point allocation-ROCS weighting method and the GRA-PNR evaluation method are applied to select the most suitable subcontractor for the supply of heliostats for photothermal power station construction. Sensitivity analysis is conducted to verify the robustness of the results. Finally, the technique for order preferences by similarity to an ideal solution with grey values, simple additive weighting with grey relations, and additive ratio assessment with grey criteria scores is applied to validate the participation of the selected subcontractor in the project.**

***Index Terms*—Grey relational analysis (GRA), grey system theory (GST), multicriteria decision-making (MCDM), photothermal power station, rank order centroid (ROC), subcontractor selection.**

I. Introduction

THE seventh sustainable development goal is to ensure access to affordable, reliable, sustainable, and modern energy for all [1]. Although meeting the demand for energy is not an easy requirement, the People's Republic of China (PRC) is now committed to reducing its dependence on coal and adding cleaner energy sources to its energy mix. For example, in the first half of 2021, China's photovoltaic (PV) power generation was up to 23.4% of its energy combination, which amounts to 157.64 billion kWh of generated power, [2] compared to 22 billion kWh in 2011 [3]. Undoubtedly, the seventh goal is challenging to meet, since there is an endless demand for energy, and clean energy is relatively more expensive than other hydrocarbon derivatives of energy sources. Solar electricity production from the sun is an essential green project that benefits humans because of the lack of carbon emissions during electricity generation.

Generally, the first approach for converting solar energy to electrical energy is solar panels. A solar panel is typically a sheet of flat material that holds a PV cell that converts sunlight directly into electrical energy. Additionally, solar energy can be used for heating by converging the solar rays to a single spot. The use of solar energy for heating primarily relies on concentrated solar power (CSP) and photothermal power stations. Precisely, a photothermal power station indirectly generates electrical energy through thermal energy using mirrors or lenses to focus the sun beams on a tower that directs heat energy to a steam turbine with a generator to produce electricity. For megaprojects such as a turnkey generation station, it is difficult for a single contractor to independently execute a project from start to finish without subcontractors (SCs) executing other areas of the project. Thus, there is a need for a prime contractor or general contractor (GC), such as an engineering procurement construction (EPC) contractor, to select an appropriate SC. In this article, the problem of SC selection is addressed as a multicriteria decision-making (MCDM) problem in an uncertain environment.

According to Alinezhad and Khalili [4], an MCDM problem occurs when the decision-makers (DMs) consider more than one attribute. The best alternative or ranking of the alternatives are selected by considering the weights of the criteria and the performance value of the alternative for each criterion. The objective approaches for determining the weights of the evaluation decision criteria, such as the rank-sum, rank reciprocal, and rank order centroid (ROC), rank the criteria and then transform these rankings into surrogate weights. However, these methods cannot independently incorporate the opinion of each expert in group decision-making. A workaround to overcome this problem is to

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aggregate the decision-making preferences and rank the criteria before using the surrogate weighting methods. The point allocation (PA) method is a well-understood method for most of the public, especially those who have at least a primary school level of education, because it is the method used by educational institutions to assess student performances on most examinations. Unfortunately, the reliance of the DMs on only their feelings and opinions in the PA method is a significant drawback and a common problem among other subjective methods. Therefore, an objective weighting method is considered to complement the PA method. The objective method chosen in this research is the ROC weighting method because it is 96% accurate at selecting the best alternative, as reported by Barron and Barrett [5], [6]. The 4% inaccuracy of the ROC weights is considered in this research by relaxing the estimated weights. This is achieved by relaxing the weights estimated by the ROC weighting method and representing them as grey numbers (GNs). Specifically, 8% slack is introduced, i.e., $\pm 4\%$ (4% each for the lower and upper bounds of the ROC weights to form interval GNs), to account for the limitation in the ROC weighting method. Thus, the proposed hybrid weighting method, called the grey PA ROC with slacks (grey-PA-ROCS) weighting method, is used to estimate the weights of the criteria in this research.

Furthermore, in ranking decision alternatives, comparing alternatives to ideal or optimal alternatives is the primary method to reduce the number of pairwise comparisons of alternatives. For example, the technique for order of preferences by similarity to an ideal solution (TOPSIS) compares alternatives with positive and negative ideal solutions [7], and the evaluation based on the distance from the average solution (EDAS) compares alternatives from both the positive and negative distances to the average alternative [8]. All these methods can be used to form hybrid approaches to address the limitation of uncertainty in decision-making, such as rough set theory (RST), fuzzy set theory (FST), and grey system theory (GST). Deng [9] proposed GST and developed grey relational analysis (GRA), which has been applied in various domains to solve MCDM problems. Unfortunately, the classical GRA is designed to solve MCDM problems with crisp data. While Zhang et al. [10] extended GRA to GNs, the drawback of comparing alternatives from a single reference remains today.

This article presents three contributions. First, a new hybrid method called the grey-PA-ROCS weighting method is proposed. Second, the improved GRA with GNs considering both the positive and negative reference (PNR) alternatives is proposed. Third, the hierarchical model for subcontractor selection can be adopted and modified by EPC contractors based on the project at hand. The remainder of this article is organized as follows. Section II presents the literature review, Section III presents the methodology used in weighting and selecting the best alternative, and Section IV presents the results and analysis of this research. Lastly, Section V concludes this article.

II. Literature Review

This section presents some frontiers in solar energy for electric power production, and related works with SC selection using MCDM methods. While FST is a common method for addressing uncertainty, emphasis is placed on GST in this article. A bibliometric analysis of GST from 1996 to 2010 [11] and a systematic literature review of GST from 2010 to 2020 provide a quick overview of GST [12].

A. Solar Energy and Subcontractors

The improved efficiency of solar panels is at the core of PV technology. Jelley and Smith [13] reviewed the development of CSPs for electricity production, and suggested that more research needs to be conducted to reduce the costs to make CSPs a suitable alternative in PV technology. Nespoli and Medici [14] proposed an optimization model as an unsupervised approach for computing the global horizontal irradiance from photovoltaic power measurements. Popov and Borissova [15] presented a solar–nuclear hybrid solution by transferring heated water from a solar tower to nuclear steam for electricity generation. According to Sharma et al. [16], the third generation of concentrated solar/PV cells (CPVs) has an efficiency of 38.9%, making it the best technology for harvesting electricity from the sun. Zhao et al. [17] presented carbon quantum dots with a large stroke shift to increase the luminescence efficiency of solar concentrators. Bauer et al. [18] detail the potential of molten salt storage technology, which is an alternative to using batteries, for CSPs.

The primary difference between a GC and an SC is that while a GC oversees the overall project to ensure its timeliness, quality, and cash flow, an SC is a specialist in a specific niche of a project that is expected to amount to a synergic outcome for the project. In some cases, the terms and conditions of the project force GCs to use SCs so that inexperienced contractors can be trained. In other cases, the relationship between GCs and SCs can be competitive, and can amount to transactional costs [19]. Hortal et al. [20] presented a framework for the assessment and selection of contractors to construct e-marketplaces that accommodate the bilateral evaluations between GC and SC companies. Tan et al. [21] examined the relationships between GCs and SCs, and classified their relationships as adversarial, cooperative, collaborative, and partnering, which can be profitable to both parties with a win–win principle over the long term. Ahmed et al. [22] presented contractor bidding as the winner's curse from game theory, and the results prove that SCs suffer from the winner's curse when bidding for projects. This suggests that contractors should be careful regarding their claims and orders when bidding for projects.

A number of researchers pay attention to the partnership between GCs and SCs. Kumaraswamy and Matthews [23] suggested that using a partnership principle that is built on trust can improve SC selection when GCs and SCs have mutual goals and are committed to achieving a common objective. Maturana et al. [24] presented the use of period evaluation and dialogue instances of onsite subcontractors based on lean principles and partnering practice in construction projects. Hartmann and Caerteling [25] empirically showed that neither price nor trust could be used to compromise the need for an efficient procurement mechanism. However, GCs can develop more confidence in SC performance through repeated interactions, which overall increase the level of trust and the probability of selecting SCs in subsequent jobs. Gurevich and Sacks [26] developed KanBIM that integrates the Kanban board lean management technique with building information modeling (BIM), to improve the efficiency of SC task selection in the interior workings of building apartments. In 2015, Eom et al. [27] highlighted the paradigm shift between GCs and SCs. Examples include shifts from simple qualified SCs to win–win strategies, from short-term performance improvement to long-term growth, from inaccurate and late information to open communication and information sharing, and from per-project evaluation to continued monitoring and evaluation. These paradigms are still relevant today.

The general process of solving an MCDM problem begins with criteria selection, criteria weighting estimation, and alternative assessment, respectively. El-khalek et al. [28] investigated the criteria to use out of 55 criteria and seven groups to evaluate SCs. In addition to costs and time, some important groups of criteria are the following: quality, technical and management capability, reputation, and health and safety. However, these criteria were not specific to any project. Sadeh et al. [29] investigated the feasibility of BIM for GCs and SCs, and showed that BIM has a significant role in executing a large-scale project. The feasibility of BIM amounts to different ranks for GCs and SCs. This article contributes to the literature by taking additional steps beyond reviewing the evaluation criteria for SCs while covering the full process of SC selection and applying the results to the green energy selection problem. Undoubtedly, regardless of the advances in solar technology, SCs will be needed in the construction of new power stations.

B. Decision-Making Under an Uncertain Environment

The development of a decision support system (DSS) for SCs has been explored by both researchers and engineers over the years. For example, Nielsen and Miller [30] studied the use of software for SC selection for the IRIDIUM Motorola communication satellite, and the use of DSS for blockchain platform selection [31]. The quest to simplify the assessment of SCs is still being developed. Arslan et al. [32] applied the weighted sum model (WSM) to develop a web-based interface for evaluating subcontractors. The WSM has been integrated with budget constraints to address uncertainty [33]. Blaszczyk and Blaszczyk [34] developed a DSS to tightly integrate the GC and SC work breakdown structure (WBS). Radziszewska-Zielina [35] applied ELECTRE III using a dedicated program called ConRel, a construction relationship partnering software where input data are imported from the MATLAB package using component object model technologies, to select the best subcontractor. The computation results using the ELECTRE III algorithm were exported to Excel. Garg and Garg [36] developed the ROBORANK DSS, which was implemented in MATLAB. Kannan et al. [37] combined the analytical hierarchy process (AHP) and TOPSIS methods for software package selection. Garg et al. [38] proposed the entropy-combinative distance-based assessment (CODAS-E) to select an optimal software reliability model.

SC selection has been addressed in the domain of supply chain management. Lee et al. [39] considered improving production efficiency as a scheduling problem with time and budget constraints in a make-to-order environment. Palha et al. [40] addressed the SC problem as a supply chain problem and integrated the robust ordinal regression with UTADIS (UTilités Additives DIScriminantes) to categorize activities that can be outsourced to SCs in the construction of a brewery in Brazil. Haoues et al. [41] addressed the problem of SC selection as a cost minimization strategy by formulating the problem as mixed-integer programming that balances the trade-off between two echelons of the supply chain. Ren et al. [42] presented a supply chain scheduling problem in which jobs are outsourced to SCs to maximize the production of a manufacturing company. Khemiri et al. [43] applied the fuzzy TOPSIS method to evaluate a supply chain when procurement is cut across multiple SCs to minimize risk.

After the criteria for evaluating the alternatives are selected, there is a need to determine the relative importance of the criteria, which can be described as weighting in MCDM. There are two distinct classifications of weighting methods. First, subjective weighting methods are based on the opinions and intuition of DMs. For instance, the PA weighting method is among the simplest approaches used to express different levels of criteria importance. PA was applied to evaluate human resource information systems [44]. Second, objective weighting methods consider the facts associated with the criteria and then assign surrogate weights. ROC weights was employed to evaluate the business environment in Africa by simply ranking the evaluation criteria and transforming the ranking to ROC weights, which are crisp values [45]. Shujie [46] applied the entropy weighting method for the SC selection weighting problem.

FST has been used to address uncertainty in SC selection. Guray et al. [47] presented a Choquet integral fuzzy model for SC selection in a turnkey project by considering economic, social, and environmental factors. Trapezoidal fuzzy linguistic variables were used to measure the SC performance. Ulubeyli and Kazaz [48] developed CoMoS, an SC selection model that can manage a large number of criteria with an interactive input system and storage and reporting data. The case presented was a Turkish GC who had to select the best SC among six other Russian SCs in the construction of a multistorey building complex. Ghorabaee et al. [49] presented the application of the EDAS method with interval type-2 fuzzy sets. Abbasianjahromi et al. [50] applied the Kano model for marketing decisions to classify the evaluation criteria, and used the AHP to determine the weights of the criteria. The fuzzy TOPSIS method was applied to rank the subcontractors. Afshar et al. [51] applied a type-2 fuzzy method with Shannon entropy weights, and TOPSIS for the selection of an SC among four contractors to pour concrete in the construction of an elementary school in Iran.

GST has been applied with other uncertainty measuring approaches. Zhai et al. [52] combined RST and GRA to evaluate different design concepts in product development. Lin et al. [53] combined cased-based reasoning with RST and GRA to develop a business failure forecasting model. Lin et al. [54] combined FST and evidential reasoning with GST to conduct

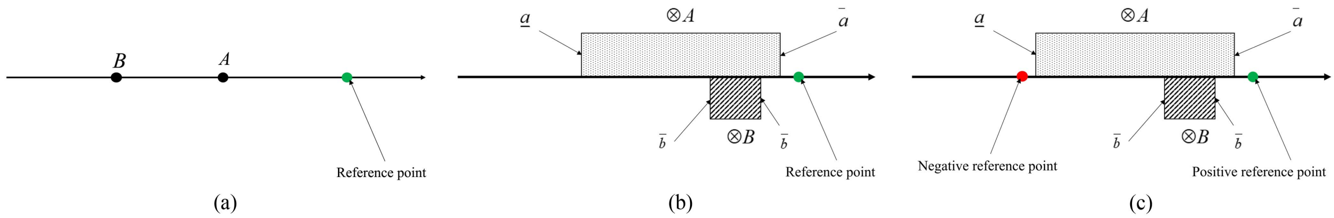


Fig. 1. GRA with positive and negative references in comparison with GRA with GNs. (a) Classical GRA. (b) GRA with GNs. (c) Improved GRA.

failure mode and effects analysis to identify components that have high probabilities of failing. Memon et al. [55] combined GST with uncertainty theory to address supplier selection problems in group decision-making. Although Bai et al. [56] applied the fuzzy c-mean and Vlsekriterijumska Optimizacijia I Kompromisno Resenje (VIKOR) in segmenting multicriteria green suppliers, Kumar and Gupta [57] applied the best–worst method (BWM) and VIKOR methods to evaluate the green performance of five Indian airports. Then, Kannan et al. [58] applied GRA in conjunction with the BWM and VIKOR with Monte Carlo simulation to select the best potential solar site location. Li and Zhao [59] applied FST to compensate for the limitation of classical GRA and VIKOR. The hybrid fuzzy GRA-VIKOR method was used to evaluate the performance of a thermal power station. Although GST can address uncertainty in decision-making, combining other approaches for managing uncertainty, such as Monte–Carlo simulation, RST, uncertainty theory, FST, and evidential reasoning, confirms that there is room to improve the GRA method.

GST has equally been applied in SC selection under uncertainty. Chen et al. [60] improved grey correlational analysis by integrating the AHP and quality function deployment (QFD) to determine the best-fit SC for a housing construction project in Beijing. Biong [61] applied multiple regression analyses in the contingent price effects of SCs in plumbing services, and the results suggested that the supplier's reputation is the most important criterion for evaluation. Lin et al. [62] presented a dynamic MCDM model using TOPSIS with GNs that considers the current and past performances of alternatives. In addition, they [63] re-emphasized the importance of TOPSIS with GNs using the Minkowski distance to measure the distance between two GNs. Sheikh et al. [64] combined the relative importance index (RII) and GRA to select the most appropriate contractor. The RII was used to rank the factors, which can be considered the evaluation criteria with their respective levels of importance. Interestingly, classical GRA was designed to evaluate crisp values, as shown in Fig. 1(a). Zhang et al. [10] extended GRA to interval GNs, as shown in Fig. 1(b). For example, Esangbedo and Bai [65] applied GRA with interval GNs in scaling foreign service premium allowance of expatriates. However, there is a problem that exists with using a single reference alternative when using GNs. For example, consider two alternatives $\otimes A$ and $\otimes B$ that are evaluated with a reference alternative, represented as a green point in Fig. 1(b). From Fig. 1(b), we can assume that alternative $\otimes A$ is better than alternative $\otimes A$, based on a single point of reference. Surprisingly, when a second reference point is introduced, shown as a red point in Fig. 1(c), it is evident that alternative $\otimes B$ is better than $\otimes A$, since it is further from the negative reference alternative. A practical example of this is the battery discharge time of two different battery technologies.

Among the various applications of the ROC weighting method, to the best of our knowledge, this would be the first application to consider the relaxation of ROC weights by introducing some slack, and representing it as GNs. More importantly, this article extends the literature on GRA by using PNRs as an MCDM evaluation method. Overall, this article fills the gap in the literature by addressing the subcontractor selection problem using improved weighting and evaluation methods based on the GST. To reiterate, this article incorporates uncertainty in using the ROC weights, and improves on the limitation of classical GRA.

III. Methodology

This section presents the evaluation criteria that are considered in evaluating the alternatives with the weighting and evaluation methods. The works of Pal et al. [66] and El-khalek et al. [28] capture a number of the criteria for SC evaluation, and these criteria were also considered. We also reviewed the literature and consulted the chief executive officer (CEO) of an EPC company who has decades of experience in bidding for contracts and sitting on a panel that evaluates the tenders of SCs.

A. Evaluation Criteria

In this research, the evaluation criteria consisted of five first-level and 27 second-level indicators, as shown in Fig. 2. The following are the criteria that were chosen to evaluate SCs to participate in the construction of a photothermal power station.

1) Technical Strength (C_1): Workmanship standard (C_{1-1}) is the skill to which the technical staff complete construction work, and in most cases, it is accumulated through the years of experience the organization has accumulated [50], [67]. *Project engineering scope* (C_{1-2}) is used to determine the scale of the project that SCs can handle, which may be represented by the availability of equipment [20]. *Green construction* (C_{1-3}) is a form of waste management and attitude toward sustainable practice by an SC [67]. *Operating a quality system* (C_{1-4}) considers the completed construction projects of the SC by investigating the procedure used to maintain top quality [23]. *Construction technique* (C_{1-5}) evaluates the conventional and unconventional approaches that an SC uses during construction [20].

2) Quotation Rationality (C_2): Budget and conditions (C_{2-1}) reflect the plan and expected costs [23]. *Completion of*

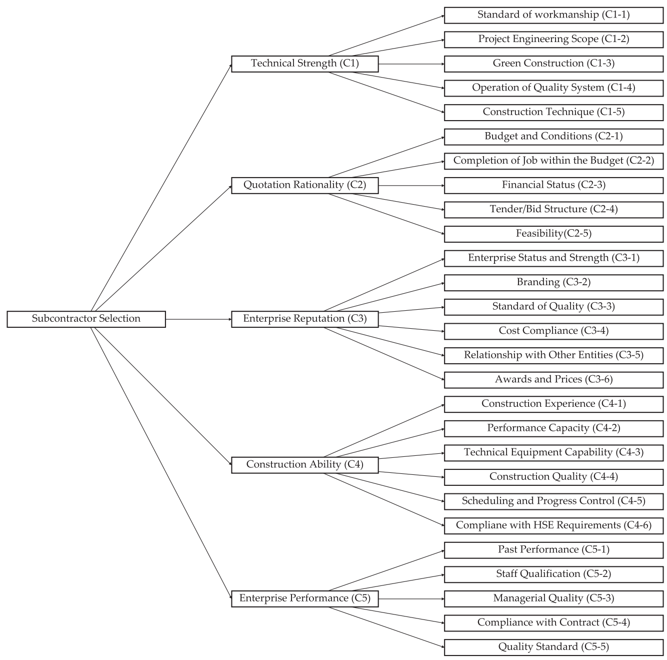


Fig. 2. Evaluation criteria for subcontractor selection.

jobs within the budgets (C_{2-2}) captures the past cost control performance of an SC. *Financial status* (C_{2-3}) is the financial capability of an enterprise, and reflects the financial stability, bank credit, and profitability/liquidity/autonomy of the enterprise [20], [50]. In other words, financial status reflects the financial capacity of an SC [67]. *Tender/bid structure* (C_{2-4}) includes the tender price and trust [25], [50], [67]. *Feasibility* (C_{2-5}) measures the perceived possibility of an SC being able to deliver on the required result needed by the GC.

3) Enterprise Reputation (C_3): Enterprise status and strength (C_{3-1}) is the impression of the SC according to past and current events. *Branding* (C_{3-2}) is the perceived image that would be created when an GC associates with an SC. In most cases, a non-negative image is acceptable. *Cost compliance* (C_{3-4}) the ability to keep to the agreed costs, and regulatory requirements are also considered [20]. *Quality standards* (C_{3-3}) measure the awareness of the required codes that have been set for the delivery of the required result and consider how the past jobs completed by an SC hold up. *Relationships with other entities* (C_{3-5}) includes relationships with clients, which include claims, litigation, governments, and local authorities [20], [23], [67]. *Awards and prizes* (C_{3-6}) considers the outstanding recognition that the SC has accrued over the years, which may include speed, innovation, and participation in government projects.

4) Construction Ability (C_4): Construction experience (C_{4-1}) is the cumulative period that the SC has spent performing similar or related construction jobs that can reflect the skill of the SC. *Performance capacity* (C_{4-2}) is the maximum volume of jobs the SC can handle and deliver satisfactory results from. *Technical equipment capability* (C_{4-3}) is the amount of equipment at the disposal of the SC to conduct the job once a contract is awarded [50]. *Construction quality* (C_{4-4}) is how well an SC performed on a previous job, based on inspected projects and recommendations. *Scheduling and progress control* (C_{4-5}) [24] is the timing of the job as given in the plan from start to finish. Previous jobs are equally considered during the assessment. *Compliance with HSE requirements* (C_{4-6}) is how well an SC follows health and safety policy and makes provisions for it in their proposal [20], [50]. This can be deduced according to the current project of an SC and a visit to the SC's facilities[49], [68], [69], [70].

5) Enterprise Performance (C_5): Past performances (C_{5-1}) depict how well an SC has performed on previously assigned contracts.[20], [67] *Staff qualifications* (C_{5-2}) are the education the staff have received after participating in training, or taking and passing a course, and paper qualifications are not disregarded. *Managerial quality* (C_{5-3}) is the ability of an SC to effectively run a project [20], [50], [67]. *Compliance with contracts* (C_{5-4}) is the extent to which an SC adhered to the contracts of previous jobs. *Quality standards* (C_{5-5}) are the quality assurance policy, which may include guarantees and insurance coverage [20], [23].

B. MCDM Weighting Methods

The proposed grey-PA-ROCS weighting method consists of two independent group decision-making weighting methods that are extended to GNs. These two methods are aggregated to form the hybrid weighting method used in this research.

1) Grey Point Allocation Method: The grey PA assigns points to the criteria and scales the points to one unit as the weights of the criteria. Points ranging from 0 to 10 or percentages are commonly used. In this research, the percentage points, i.e., 0% to 100%, are used. The grey-PA method procedures are as follows.

1) Collate criteria points. The DMs (v) answer the questionnaire and give percentage scores, i.e., from 0 to 100 points. The DMs (v) score the criteria as percentages (0%–100%).
2) Normalize the points assigned by each of the DMs. The property of criteria weights is that they represent the ratio of the importance of one criterion over another. To clearly reflect this property as given by the DMs, the points are normalized using (1).

$$x_p(v) = \frac{DM_v(h)}{\max\limits_{1\leq h\leq s} DM_v(h) - \min\limits_{1\leq h\leq s} DM_v(h)} \tag{1}$$

where h is the criteria index and s is the last criterion scored by the vth DM.
3) Compute the local weight of each DM. The percentage scores for each branch in the hierarchy are scaled to unity value using the following.

a) The first-level criteria are computed using (2)

$$x'_p(v) = \frac{x_p(v)}{\sum_{p=1}^{\rho} x_p(v)} \tag{2}$$

where x is the criterion with an index of p, and ρ is the index for the last first-level criterion.

b) The second-level criteria are computed using (3)

$$x'_{p-q}(v) = \frac{x_{p-q}(v)}{\sum_{q=1}^{\sigma} x_{p-q}(v)} \tag{3}$$

where x is the criterion with an index of q, and σ is the index for the last second-level criterion.
Thus, $\sum_{p=1}^{\rho} x'_p(v) = 1$ and $\sum_{q=1}^{\sigma} x'_{p-q}(v) = 1$.

4) Compute the local grey weights. The local grey weights are determined by taking the minimum and maximum weights given by the DMs for each criterion to represent the lower and upper bounds of the GNs, respectively, and scaled so that the summation of the upper bound is a unit value, as given in (4) and (5), respectively.

$$\otimes w_p^{\alpha} = \left[\underline{d_p^{\alpha}}, \overline{d_p^{\alpha}}\right] = \frac{\left[\min\limits_{1\le p\le \rho} w_p(v), \max\limits_{1\le v\le \vartheta} w_p(v)\right]}{\left(\sum_{p=1}^{\rho} \max\limits_{1\le v\le \vartheta} x_p(v)\right)} \tag{4}$$

$$\otimes w_{p-q}^{\alpha} = \left[\underline{d_{p-q}^{\alpha}}, \overline{d_{p-q}^{\alpha}}\right] = \frac{\left[\min\limits_{1\le v\le \vartheta} w_{p-q}(v), \max\limits_{1\le v\le \vartheta} w_{p-q}(v)\right]}{\left(\sum_{q=1}^{\sigma} \max\limits_{1\le v\le \vartheta} x_{p-q}(v)\right)}. \tag{5}$$

The use of the PA method to obtain data from DMs allows one to rank the criteria that can be used in computing the ROC weights. However, these points increase the probability of two or more criteria having equal points, i.e., the two criteria are ranked equally.

2) Grey Rank Order Centroid With Slacks Method: It is difficult to argue that there is an MCDM weighting method that is 100% accurate; otherwise, there would be no need for further research. In the 1980s, there was equal early usage of ROC weights by other authors [5], [6]. ROC weights are obtained from the mean of the corresponding coordinates of the defining vertices. The grey ROC method is based on reducing the rigidity of the ROC weights by introducing a slack value of $\pm\varepsilon\%$ represented as GNs. This is called the grey-ROCS weighting method in this article. The steps for computing the grey-ROCS weights are as follows.

1) Collate the scores of the criteria.
2) Rank the data obtained for the DMs for the set of criteria.
3) Compute the ROC weights. They are computed using (6). An example of the ROC weights for one to six criteria is given in Table I.

$$w_i(ROC) = \frac{1}{n}\sum_{n}^{j=1}\frac{1}{j} \tag{6}$$

where j is the rankings of the nth criteria.

4) Compute the local ranking. This is used to scale the ROC weights to address the situation of equal ranking of the criteria. For a set of criteria that are unequally ranked, the ROC weights are the same as the scaled ROC weights, as shown in Fig. 3(a). The scaled ROC weights are computed using (7) and (8) for the first- and second-level criteria.

$$x'_p(v) = \frac{x_p(v)}{\sum_{p=1}^{\rho} x_p(v)} \tag{7}$$

where x is the criterion with an index of p, and ρ is the index for the last first-level criterion.

$$x'_{p-q}(v) = \frac{x_{p-q}(v)}{\sum_{q=1}^{\sigma} x_{p-q}(v)}. \tag{8}$$

where x is the criterion with an index of q, and σ is the index for the last second-level criterion.
$\sum_{p=1}^{\rho} x'_p(v) = 1$ and $\sum_{q=1}^{\sigma} x'_{p-q}(v) = 1$.

5) Introduce the slack value. The slack value is the relaxation of the scaled ROC value to obtain a grey value, as shown

TABLE I
ROC WEIGHTS FOR ONE CRITERION TO SIX CRITERIA

Rankings (j)/ Criteria (n)	1	2	3	4	5	6
1	1	0.7500	0.6111	0.5208	0.4567	0.4083
2		0.2500	0.2778	0.2708	0.2567	0.2417
3			0.1111	0.1458	0.1567	0.1583
4				0.0625	0.0900	0.1028
5					0.0400	0.0611
6						0.0278

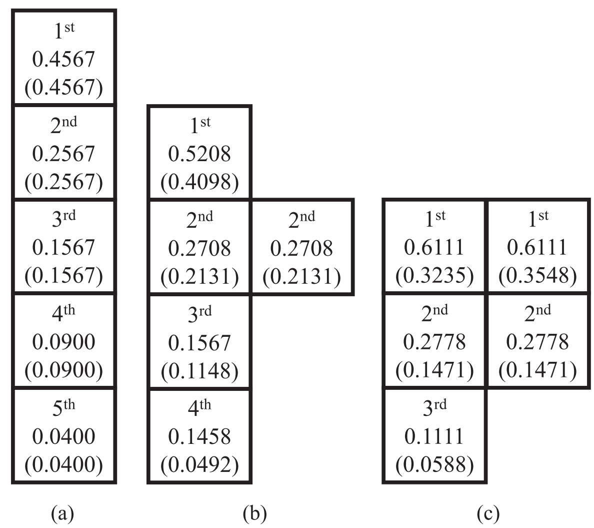


Fig. 3. Five criteria rankings using the ROC weighting method (scaled weights). (a) ROC weights for five ranks. (b) ROC weights for four ranks. (c) ROC weights for three ranks.

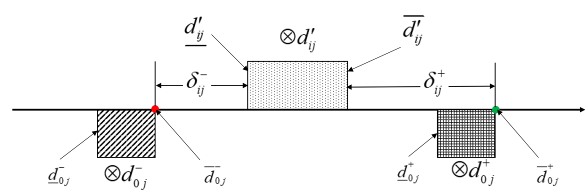


Fig. 4. Distance of a GN from positive and negative references.

in (9).

$$\otimes x^{\varepsilon}(v) = [-\varepsilon\% \times x, \varepsilon\% \times x] \tag{9}$$

where $\pm\varepsilon\%$ is the slack value. Thus, $\otimes d_p^{\epsilon}(v)$ and $\otimes d_{p-q}^{\epsilon}(v)$ can be obtained.

6) Compute the local grey weights. These are the weights of every branch of the hierarchy of the criteria in which the summation of the weight in that branch is a unit value. The local weights for the first- and second-level criteria are computed using (10) and (11), respectively.

$$\otimes w_p^{\beta} = \left[\underline{w_p^{\beta}}, \overline{w_p^{\beta}}\right] = \frac{\left[\min_{1\le v\le\vartheta} \underline{d_p^{\varepsilon}}(v), \max_{1\le v\le\vartheta} \overline{d_p^{\varepsilon}}(v)\right]}{\left(\sum_{p=1}^{\rho} \max_{1\le v\le\vartheta} \overline{d_p^{\varepsilon}}(v)\right)} \tag{10}$$

$$\begin{aligned}\otimes w_{p-q}^{\beta} &= \left[\underline{w_{p-q}^{\beta}}, \overline{d_{p-q}^{\beta}}\right] \\ &= \frac{\left[\min_{1\le v\le\vartheta} \underline{d_{p-q}^{\varepsilon}}(v), \max_{1\le v\le\vartheta} \overline{d_{p-q}^{\varepsilon}}(v)\right]}{\left(\sum_{q=1}^{\sigma} \max_{1\le v\le\vartheta} \overline{d_{p-q}^{\varepsilon}}(v)\right)}.\end{aligned} \tag{11}$$

3) Grey-PA-ROCS Weighting Method: This method aggregates the grey-PA weights and the grey-ROCS weights presented in Sections III-B1 and III-B2. First, the minimum and maximum possible bounds for each criterion are used to determine the grey weights of the criteria. Next, they are scaled to obtain the local and global weights, as given in in the steps below.

1) Aggregate the grey-PA and grey-ROCS weights. This is the union of both the grey-PA and grey-ROCS weights using (12) and (13) for first- and second-level criteria.

$$\begin{aligned}\otimes r_p &= \otimes w_p^{\alpha} \cup \otimes w_p^{\beta} \\ &= \left[\min\left(\underline{w_p^{\alpha}}, \underline{w_p^{\beta}}\right), \max\left(\overline{w_p^{\alpha}}, \overline{w_p^{\beta}}\right)\right]\end{aligned} \tag{12}$$

and

$$\begin{aligned}\otimes r_{p-q} &= \otimes w_{p-q}^{\alpha} \cup \otimes w_{p-q}^{\beta} \\ &= \left[\min\left(\underline{w_{p-q}^{\alpha}}, \underline{w_{p-q}^{\beta}}\right), \max\left(\overline{w_{p-q}^{\alpha}}, \overline{w_{p-q}^{\beta}}\right)\right]\end{aligned} \tag{13}$$

2) Compute the local weights. These are the grey weights for each branch that are scaled to a unit using (14) and (15).

$$\otimes w_p^{\gamma} = \left[\underline{w_p^{\gamma}}, \overline{w_p^{\gamma}}\right] = \left[\underline{r_p}, \overline{r_p}\right]\left(\sum_{p=1}^{\rho} \max_{1\le v\le\vartheta} \overline{r_p}(v)\right)^{-1} \tag{14}$$

$$\begin{aligned}\otimes w_{p-q}^{\gamma} &= \left[\underline{w_{p-q}^{\gamma}}, \overline{w_{p-q}^{\gamma}}\right] \\ &= \left[\underline{r_{p-q}}, \overline{r_{p-q}}\right]\left(\sum_{q=1}^{\sigma} \max_{1\le v\le\vartheta} \overline{r_{p-q}}\right)^{-1}.\end{aligned} \tag{15}$$

3) Compute the global weights. These are the effective grey weights, which are the fractional contributions of the first-level criteria to their respective second-level criteria; and they are computed using (16).

$$\otimes W_j = \otimes w_{p-q} = \otimes w_p^{\gamma} \times \otimes w_{p-q}^{\gamma}. \tag{16}$$

Thus, $\sum_{j=1}^{n} \underline{W_j} = 1$.

C. MCDM Evaluation Method

Traditional GRA is recalled, and then the procedure for applying the GRA-PNR is presented.

1) Classical Grey Relational Analysis: Classical GRA was proposed by Deng [9]. Alternatives are ranked using the grey relational grade after computing the weighted normalized decision matrix using (17).

$$r_i^- = \frac{1}{n}\sum_{j=1}^{n} \gamma_{ij} \tag{17}$$

where the grey relational coefficient is $\gamma_{ij} = \frac{\min_{1\le i\le m}\min_{1\le j\le n}\delta_{ij} + \zeta \max_{1\le i\le m}\max_{1\le j\le n}\delta_{ij}}{\delta_{ij} + \zeta \max_{1\le i\le m}\max_{1\le j\le n}\delta_{ij}}$, δ_{ij} is the difference between the reference alternative and the evaluated alternative, and ζ is the grey relational grade. [71] presented the primary methods of GST with the application of GRA.

2) GRA With Positive and Negative References: GRA with PNRs (GRA-PNR) is an improved GRA method proposed in this article. Unlike classical GRA, which uses crisp data and a single reference alternative, GRA-PNR uses GNs to account for the uncertainty in the evaluation, and uses two reference alternatives. First, the positive reference alternative (PRA) is the ideal alternative. Second, the negative reference alternative is the nonideal alternative. The main principle is that the alternative closest to the PRA is the worst, and that the alternative farthest away from the negative reference alternative is the best.

It should be noted that the positive reference comparison is between the upper bound performance values of the alternatives and the upper bound of the reference alternative. The negative reference comparison is between the lower bound performance values of the alternatives and the upper bound of the negative reference alternative. The steps for the GRA-PNR are as follows.

1) Formulate the criteria hierarchical model and determine the performance values for the alternatives. See Fig. 2.
2) Formulate the grey decision matrix. This is achieved by extracting the element of the grey decision matrix from the decision table, as given in (18).

$$D = \begin{pmatrix} \otimes d_{1,1} & \otimes d_{1,2} & \cdots & \otimes d_{1,n} \\ \otimes d_{2,1} & \otimes d_{2,2} & \cdots & \otimes d_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes d_{m,1} & \otimes d_{m,2} & \cdots & \otimes d_{m,n} \end{pmatrix} \tag{18}$$

where $\otimes d_{ij} = [\underline{d}_{ij}, \overline{d}_{ij}]$ is the GN of the j^{th} criterion of the ith alternative, for which $1 \le i \le m$ and $1 \le j \le n$, where m and n are the numbers of the alternatives and the criteria, respectively.

3) Normalize the grey decision matrix. The normalized grey decision matrix $\otimes D'$ is calculated, with the standardized element $[\underline{d'}_{ij}, \overline{d'}_{ij}] = \left[\frac{\underline{d}_{ij}}{\|d_j\|}, \frac{\overline{d}_{ij}}{\|d_j\|}\right]$ and $\|d_j\| = \max_{1\leq i\leq m} \overline{d}_{ij}$ [10].

$$D' = \begin{pmatrix} \otimes d'_{1,1} & \otimes d'_{1,2} & \cdots & \otimes d'_{1,n} \\ \otimes d'_{2,1} & \otimes d'_{2,2} & \cdots & \otimes d'_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes d'_{m,1} & \otimes d'_{m,2} & \cdots & \otimes d'_{m,n} \end{pmatrix}. \tag{19}$$

4) Compute the weighted normalized decision matrix. Given that the grey weight is $\otimes W = (\otimes w_1 \otimes w_2 \cdots \otimes w_m)^T$, then the weighted normalized decision matrix is

$$D^* = \begin{pmatrix} \otimes d^*_{1,1} & \otimes d^*_{1,2} & \cdots & \otimes d^*_{1,n} \\ \otimes d^*_{2,1} & \otimes d^*_{2,2} & \cdots & \otimes d^*_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \otimes d^*_{m,1} & \otimes d^*_{m,2} & \cdots & \otimes d^*_{m,n} \end{pmatrix} \tag{20}$$

where

$$\otimes d^*_{ij} = \otimes d'_{ij} \times \otimes w_{ij}.$$

The series of the weighted normalized alternative is

$$D^*_1 = \left\{\otimes d^*_{1,1}, \otimes d^*_{1,2}, \ldots, \otimes d^*_{1,n}\right\}$$
$$D^*_2 = \left\{\otimes d^*_{2,1}, \otimes d^*_{2,2}, \ldots, \otimes d^*_{2,n}\right\}$$
$$\vdots$$
$$D^*_m = \left\{\otimes d^*_{m,1}, \otimes d^*_{m,2}, \ldots, \otimes d^*_{m,n}\right\}.$$

5) Determine the weighted positive and negative ideal reference alternatives. The PRA is the best obtainable alternative based on the performances of the alternatives on every criterion (also called the optimal alternative [72]). Conversely, the negative reference alternative is the worse obtainable alternative based on the performances of the alternatives on every criteria.

a) The PRA is calculated using (21)

$$D^+_0 = \left\{\otimes d^+_{01}, \otimes d^+_{02}, \ldots, \otimes d^+_{0n}\right\} \tag{21}$$

where

$$\otimes d^+_{0j} = \left[\max_{1\leq i\leq m} \underline{d^+_{ij}}, \max_{1\leq i\leq m} \overline{d^+_{ij}}\right].$$

b) The NRA is calculated using (22)

$$D^-_0 = \left\{\otimes d^-_{01}, \otimes d^-_{02}, \ldots, \otimes d^-_{0n}\right\} \tag{22}$$

where

$$\otimes d^-_{0j} = \left[\min_{1\leq i\leq m} \underline{d^-_{ij}}, \min_{1\leq i\leq m} \overline{d^-_{ij}}\right].$$

6) Obtain the differences between the PNR and the weighted normalized decision matrix. Based on the highlighted limitation of classical GRA in Fig. 1, we propose measuring the alternatives using the PNR numbers with PNR points, indicated with red and green dots, respectively, in Fig. 4. In other words, the reference points in Fig. 4 imply how close the alternative is to the highest possible value of the positive ideal alternative, and how far away the alternative is from the highest possible negative ideal alternative to the worst possible value for an alternative for all criteria.

a) The difference between the normalized weighted PRA and all alternatives is

$$\Delta^+ = \begin{pmatrix} \delta^+_{1,1} & \delta^+_{1,2} & \cdots & \delta^+_{1,n} \\ \delta^+_{2,1} & \delta^+_{2,2} & \cdots & \delta^+_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta^+_{m,1} & \delta^+_{m,2} & \cdots & \delta^+_{m,n} \end{pmatrix} \tag{23}$$

where $\delta^+_{ij} = \overline{d^+_{0j}} - \overline{d^*_{ij}}$.

b) The difference between the alternatives and weighted normalized negative reference alternative is NRA, given as

$$\Delta^- = \begin{pmatrix} \delta^-_{1,1} & \delta^-_{1,2} & \cdots & \delta^-_{1,n} \\ \delta^-_{2,1} & \delta^-_{2,2} & \cdots & \delta^-_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta^-_{m,1} & \delta^-_{m,2} & \cdots & \delta^-_{m,n} \end{pmatrix} \tag{24}$$

where $\delta^-_{ij} = \underline{d^*_{ij}} - \overline{d^-_{0j}}$.

7) Calculate the positive and negative grey relational grades. The grey relational coefficient is used to calculate the grey relation grades using (25) and (26)

a) Positive grey relational grades

$$r^+_i = \frac{1}{n}\sum_{j=1}^{n} \gamma^+_{ij} \tag{25}$$

where the grey relational coefficient is

$$\gamma^+_{ij} = \frac{\min\limits_{1\leq i\leq m} \min\limits_{1\leq j\leq n} \delta^+_{ij} + \zeta \max\limits_{1\leq i\leq m} \max\limits_{1\leq j\leq n} \delta^+_{ij}}{\delta^+_{ij} + \zeta \max\limits_{1\leq i\leq m} \max\limits_{1\leq j\leq n} \delta^+_{ij}}.$$

b) Negative grey relational grades

$$r^-_i = \frac{1}{n}\sum_{j=1}^{n} \gamma^-_{ij} \tag{26}$$

where the grey relational coefficient is

$$\gamma^-_{ij} = \frac{\min\limits_{1\leq i\leq m} \min\limits_{1\leq j\leq n} \delta^-_{ij} + \zeta \max\limits_{1\leq i\leq m} \max\limits_{1\leq j\leq n} \delta^-_{ij}}{\delta^-_{ij} + \zeta \max\limits_{1\leq i\leq m} \max\limits_{1\leq j\leq n} \delta^-_{ij}}.$$

The distinguishing grey coefficient, $\zeta = 0.5$, is used [9].

8) Obtain the ranking scores. The positive and negative grey relational grades are aggregated and ranked. This seeks to balance the positive and negative grey relational grades by balancing the PNR points using (27). Then, the alternatives are ranked from the highest to the lowest, where the best alternative has the highest-ranked score.

$$V_i = r^-_i (1 - \lambda) + r^+_i \lambda \tag{27}$$

where λ is the reference coefficient of the grey relational grades.

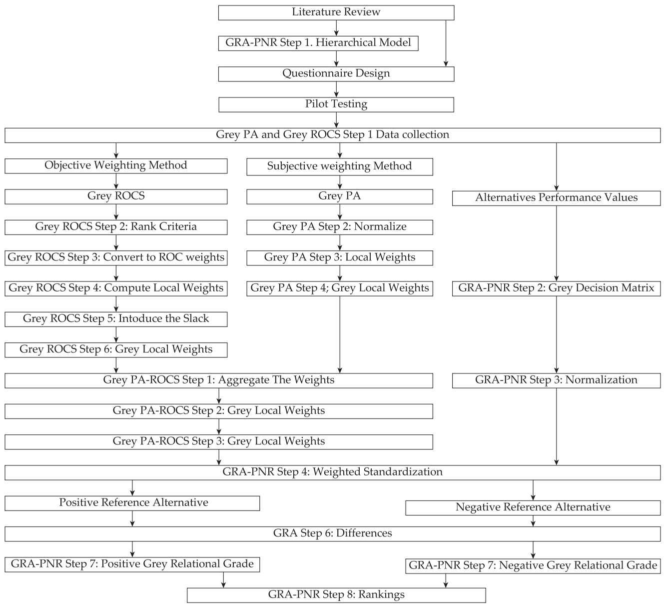


Fig. 5. Flowchart of the research procedures.

IV. Results and Analysis

An EPC contractor preparing a bid for the construction of a photothermal power station is to select a subcontractor that would supply and install the heliostats for a solar tower. More information about the EPC contractor is not given, to maintain the anonymity of the company. The criteria for assessing the subcontractors were drawn from the literature and the working experiences of the EPC company, which included numerous calls for tenders and sitting on a panel for the evaluation of the tenders' bids. The chosen sample of subcontractors was biased and based on the previous relationship and interaction with the EPC contractor. However, the assessment of these SCs was a blind assessment process to reduce the human biases in the PA process, simply because of knowing the names of the SCs. Detailed information on the EPC contractor and the six SCs were kept anonymous. A flowchart of the selection process is given in Fig. 5, and the methods applied in the evaluation are given in Section III.

A. Criteria Weighting Based on Grey-PA-ROCS

The primary criteria for assessing the SCs are given in Fig. 2. Four DMs, which included a full professor in project management and the chief executive officer (CEO), the vice president, and an engineering manager in the EPC company, were asked to allocate percentage scores to the criteria by answering the questionnaire. It should be noted that a scoresheet can be used to collate the points given by the DMs. The data obtained are used in computing the grey-PA and grey-ROCS weights, and are aggregated to form the grey-PA-ROCS weights.

1) Application of the Grey-PA Weighting Method: After the percentage scores were normalized, the effective weights of the second-level criteria were computed. Based on Section III-B1, the steps used to obtain the grey-PA weights are as follows.

TABLE II
Raw Weights Given by the DMs (%)

Criteria	Index (h)	DM_1	DM_2	DM_3	DM_4
C_1	1	88	90	90	95
C_2	2	85	95	89	85
C_3	3	90	85	80	85
C_4	4	92	95	92	95
C_5	5	90	90	95	85
C_{1-1}	6	85	80	89	80
C_{1-2}	7	75	80	91	60
C_{1-3}	8	80	75	92	90
C_{1-4}	9	95	90	87	80
C_{1-5}	10	90	80	88	95
C_{2-1}	11	90	80	88	85
C_{2-2}	12	95	75	85	90
C_{2-3}	13	90	85	83	70
C_{2-4}	14	75	90	81	80
C_{2-5}	15	85	85	80	90
C_{3-1}	16	95	90	79	90
C_{3-2}	17	90	80	90	90
C_{3-3}	18	90	85	89	95
C_{3-4}	19	85	95	92	80
C_{3-5}	20	80	70	93	85
C_{3-6}	21	80	85	89	85
C_{4-1}	22	90	80	88	95
C_{4-2}	23	88	95	81	90
C_{4-3}	24	95	90	91	90
C_{4-4}	25	90	90	87	95
C_{4-5}	26	75	95	89	85
C_{4-6}	27	75	95	92	80
C_{5-1}	28	85	80	90	95
C_{5-2}	29	80	85	89	80
C_{5-3}	30	90	95	85	80
C_{5-4}	31	84	100	92	85
C_{5-5}	32	75	90	87	90

a) Collate the criteria points. The DMs' percentage scores are obtained from the questionnaire and collected as given in Table II.

b) Normalize the raw data. Since percentages are benefit rates, the more points there are, the higher the level of importance of the criteria. The raw data are normalized using (1).

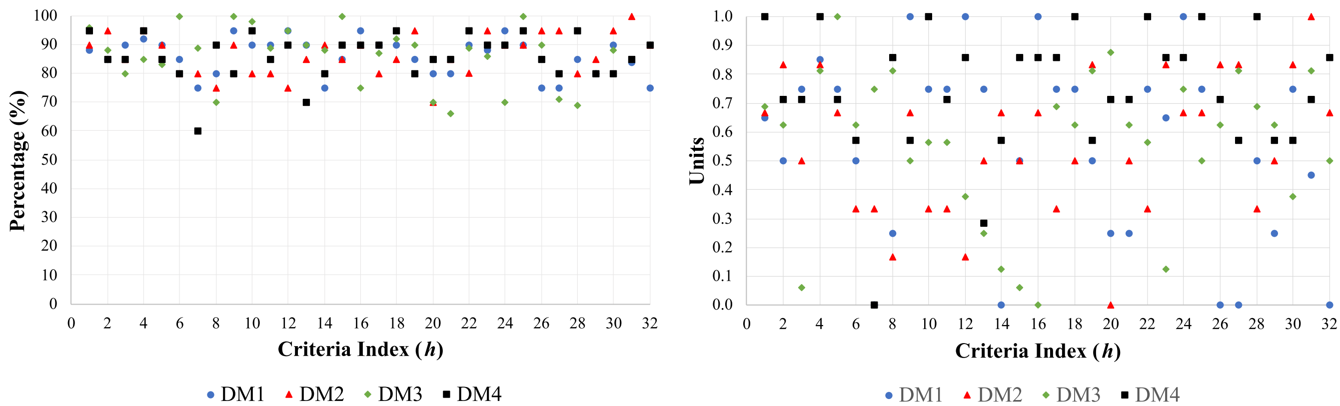
$$x_1(1) = \frac{DM_1(1)}{\max\limits_{1\leq h\leq 32} DM_1(h) - \min\limits_{1\leq h\leq 32} DM_4(h)} = 0.65. \tag{28}$$

Similarly,

$$x_{5-5}(32) = \frac{DM_4(32)}{\max\limits_{1\leq h\leq 32} DM_4(32) - \min\limits_{1\leq h\leq 32} DM_4(32)} = 0.8571. \tag{29}$$

The impact of normalization is shown in Fig. 6. Specifically, Fig. 6(a) indicates that the scores assigned by the DMs are skewed toward the third and fourth percentiles, which is generally the case because of the Chinese educational grading system, where 60% is the cut-off mark between pass and fail. Conversely, Fig. 6(b) shows the use of the full range of the scale for weighting, based on the DMs' preferences.

c) Compute the local weight of each DM. The local weights for the first and second levels are given as (2) and (3),



(a) (b)

Fig. 6. Scatter plots of DMs' weights. (a) Raw data obtained. (b) Normalized data obtained.

TABLE III
PA WEIGHTS

Criteria	Local				Local grey-PA
	DM_1	DM_2	DM_3	DM_4	
C_1	0.1857	0.1905	0.2157	0.2414	[0.1471, 0.1912]
C_2	0.1429	0.2381	0.1961	0.1724	[0.1132, 0.1886]
C_3	0.2143	0.1429	0.0196	0.1724	[0.0155, 0.1697]
C_4	0.2429	0.2381	0.2549	0.2414	[0.1886, 0.2019]
C_5	0.2143	0.1905	0.3137	0.1724	[0.1366, 0.2485]
C_{1-1}	0.2000	0.1818	0.1923	0.1905	[0.1084, 0.1439]
C_{1-2}	0.0000	0.1818	0.2308	0.0000	[0, 0.1558]
C_{1-3}	0.1000	0.0909	0.2500	0.2857	[0.0542, 0.2159]
C_{1-4}	0.4000	0.3636	0.1538	0.1905	[0.1039, 0.2325]
C_{1-5}	0.3000	0.1818	0.1731	0.3333	[0.1084, 0.2519]
⋮	⋮	⋮	⋮	⋮	⋮
C_{5-5}	0.0000	0.2000	0.1667	0.2308	[0, 0.1465]

TABLE IV
CRITERIA RANKING BASED ON DMs

Criteria	DM_1	DM_2	DM_3	DM_4
C_1	3rd	2rd	3rd	1st
C_2	4th	1st	4th	2rd
C_3	2rd	3rd	5th	2rd
C_4	1st	1st	2rd	1st
C_5	2rd	2rd	1st	2rd
C_{1-1}	3rd	3rd	3rd	3rd
C_{1-2}	5th	3rd	2rd	4th
C_{1-3}	4th	5th	1st	2rd
C_{1-4}	1st	1st	5th	3rd
C_{1-5}	2rd	3rd	4th	1st
⋮	⋮	⋮	⋮	⋮
C_{5-5}	5th	3rd	4th	2rd

respectively. For example, the local weight of the *technical strength* (C_1) given by the first DM (DM_1) is

$$x'_p(1) = \frac{x_p(1)}{\sum_{p=1}^{5} x_p(1)} = \frac{0.65}{17.6} = 0.1857. \tag{30}$$

Similarly, the local weight of *quality standards* (C_{5-5}) by the fourth DM (DM_4) is

$$x'_{5-5}(4) = \frac{x_{5-5}(4)}{\sum_{q=1}^{5} x_{5-5}(4)} = \frac{0.8571}{3.7143} = 0.2308. \tag{31}$$

The detailed computed results are given in Table III.

d) Calculate the local grey weights. The local grey weights are computed using (32) and (38). The local grey weight of *technical strength* (C_1) is

$$\otimes w_1^{\alpha} = \left[\underline{w_1^{\alpha}}, \overline{w_1^{\alpha}}\right] = \frac{\left[\min\limits_{1\le p\le 5} d_p(1), \max\limits_{1\le p\le 5} d_p(1)\right]}{\left(\sum_{p=1}^{5} \max\limits_{1\le p\le 5} x_p(1)\right)}$$
$$= [0.1857, 0.2414] \times 1.2624 = [0.1471, 0.1912]. \tag{32}$$

See Table III for the other results.

2) *Application of the Grey-ROCS Weight Method:* Based on the procedure presented in Section III-B2, the grey ROC weights with slacks are computed as follows.

a) Collate the scores of the criteria. This is the same as the first step in Section IV-A1, and the results are presented in Table II.

b) Rank the data obtained for the DMs for the set of criteria. The ranking of the raw data obtained is given in Table IV.

c) Compute the ROC weights. These weights are computed using (6), and can be directly obtained from Table I.

d) Compute the local weights. The scaled ROC weights are computed using (7) and (8) for the first- and second-level criteria, respectively. The *technical strength* C_1 for DM_1, DM_2, and DM_3 are directly represented in Fig. 3(b), (c), and (a), respectively. See Table IV for the rankings derived from Table II.

$$x'_1(v) = \frac{x_1(v)}{\sum_{p=1}^{\rho} x_1(v)} = \frac{0.1458}{1.2708} = 0.1148 \tag{33}$$

$$x'_{5-5}(v) = \frac{x_{5-5}(v)}{\sum_{q=1}^{\sigma} x_{5-5}(v)} = \frac{0.2708}{1.0625} = 0.2549. \tag{34}$$

Thus, $\sum_{p=1}^{\rho} x'_p(v) = 1$ and $\sum_{q=1}^{\sigma} x'_{p-q}(v) = 1$.

TABLE V
GREY RANK ORDER CENTROIDS WITH SLACK WEIGHTS

Criteria	Local weights				Local grey weights
	DM_1	DM_2	DM_3	DM_4	
C_1	0.1148	0.1471	0.1567	0.3333	[0.061, 0.192]
C_2	0.0492	0.3235	0.0900	0.1111	[0.0261, 0.1863]
C_3	0.2131	0.0588	0.0400	0.1111	[0.0213, 0.1227]
C_4	0.4098	0.3235	0.2567	0.3333	[0.1364, 0.236]
C_5	0.2131	0.1471	0.4567	0.1111	[0.0591, 0.263]
C_{1-1}	0.1567	0.1621	0.1567	0.1273	[0.0434, 0.1109]
C_{1-2}	0.0400	0.1621	0.2567	0.0545	[0.0111, 0.1052]
C_{1-3}	0.0900	0.0414	0.4567	0.2364	[0.0147, 0.206]
C_{1-4}	0.4567	0.4724	0.0400	0.1273	[0.0151, 0.1817]
C_{1-5}	0.2567	0.1621	0.0900	0.4545	[0.034, 0.3962]
⋮	⋮	⋮	⋮	⋮	⋮
C_{5-5}	0.0400	0.1567	0.0900	0.2549	[0.0147, 0.0767]

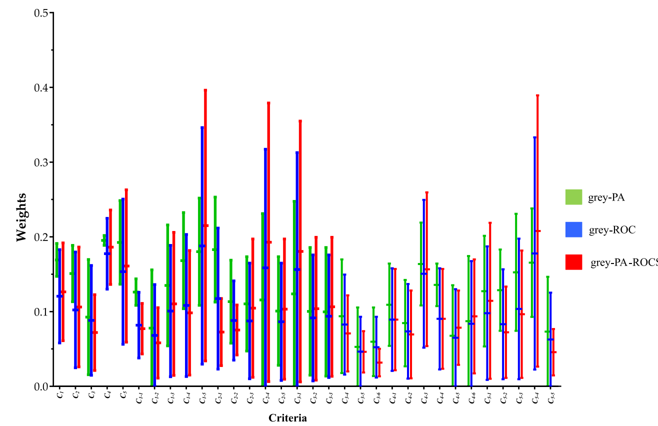


Fig. 7. Local grey weights.

e) Introduce the slack value. This is computed using (9). In this article, a slack value of ± 4 is used to compensate for the 96% accuracy of the ROC weights to select the best alternatives, which was measured as the hit rate after 10 000 trials, as given by Barron and Barrett [6]. The following is for *technical strength* (C_1) by the fourth DM (DM_4).

$$\begin{aligned}\otimes x_1^{\varepsilon}(1) &= [-4\% \times 0.1148, 4\% \times 0.1148] \\ &= [0.96 \times 0.1148, 1.04 \times 0.1148] \\ &= [0.1102, 0.1193]. \end{aligned} \tag{35}$$

Similarly,

$$\begin{aligned}\otimes x_{5-5}^{\varepsilon}(4) &= [0.96 \times 0.2549, 1.04 \times 0.2549] \\ &= [0.0272, 0.0295]. \end{aligned} \tag{36}$$

f) Compute the local grey weights.

$$\begin{aligned}\otimes w_1^{\beta} = \left[\underline{w_1^{\beta}}, \overline{w_1^{\beta}}\right] &= [0.1102, 0.3467] \times 1.8059^{-1} \\ &= [0.0610, 0.1920] \end{aligned} \tag{37}$$

$$\begin{aligned}\otimes w_{5-5}^{\beta} = \left[\underline{w_{5-5}^{\beta}}, \overline{w_1^{\beta}}\right] &= [0.0082, 0.0427] \times 0.5572^{-1} \\ &= [0.0147, 0.0767]. \end{aligned} \tag{38}$$

Other results that are omitted are given in Table V.

3) Application of the Grey-PA-ROCS Weighting Method:

a) Aggregate the grey-PA and grey-ROCS weights. This is the union of both the grey-PA and grey-ROCS weights using (12) and (13).

$$\otimes r_p = \otimes w_p^{\alpha} \cup \otimes w_p^{\beta} = [0.0610, 0.1920] \tag{39}$$

... and

$$\otimes r_{5-5} = \otimes w_{5-5}^{\alpha} \cup \otimes w_{5-5}^{\beta} = [0.0000, 0.1465]. \tag{40}$$

b) Compute the local weights. These weights were obtained using (14) and (15).

$$\otimes x_p^{\gamma} = \left[\underline{x_1^{\gamma}}, \overline{x_1^{\gamma}}\right] = [0.0581, 0.1829] \tag{41}$$

... and

$$\otimes x_{p-q}^{\gamma} = \left[\underline{x_{p-q}^{\gamma}}, \overline{x_1^{\gamma}}\right] = [0.0000, 0.1254]. \tag{42}$$

c) Compute the global weights.

$$\otimes W_1 = \otimes x_1^{\gamma} \times \otimes x_{1-1}^{\gamma} = [0.0022, 0.0230]] \tag{43}$$

$$\otimes W_{27} = \otimes x_5^{\gamma} \times \otimes x_{5-5}^{\gamma} = [0.0000, 0.0314]. \tag{44}$$

Therefore, the grey-PA-ROCS weights are

$$\otimes W_j = \big([0.0022, 0.023]\ [0, 0.0249] \cdots [0, 0.0314]\big)^T \tag{45}$$

The complete effective grey-PA-ROCS weights are given in the third column of Table VI, and Fig. 7 shows the grey effective weights of the criteria.

B. SC Selection Using GRA-PNR

Because of the significant amount of time required to critically reflect on each of the six SCs, two of the DMs, which are the top management, selected four people to assess the six SCs and grade them. It should be noted that during the assessment, the names and logos of the SCs were removed from the bidding documents of the SCs to reduce the biases during the scoring process. Thus, there were four individuals who provided scores for the six SCs. A common research approach is to find the averages of the scores provided by these individuals, which are crisp numbers, as the performance values. However, we consider the uncertainty in the assessment by representing these performance values as GNs. First, the scores provided by each scorer are normalized to force the points to range from zero to one, since the minimum points given by the six scores are 60%. Next, the minimum and maximum values of the normalized scores for each alternative are used as the grey performance values, as shown in Table VI. Based on the steps presented in Section III-C2, the best SC is selected as follows.

1) Formulate the criteria hierarchical model and determine the performance values for the alternatives. The hierarchical model for the assessment of the SCs is given in Fig. 2.

TABLE VI
GREY PERFORMANCE VALUES OF THE SCs

Criteria	Index (j)	Weight ($\otimes W_j$)	A_1	A_1	A_2	A_3	A_4	A_5
C_{1-1}	1	[0.0022, 0.023]	[80, 95]	[60, 80]	[70, 85]	[75, 88]	[65, 85]	[65, 86]
C_{1-2}	2	[0, 0.0249]	[85, 90]	[65, 81]	[70, 90]	[75, 85]	[65, 90]	[64, 90]
C_{1-3}	3	[0.0007, 0.0345]	[80, 100]	[60, 90]	[70, 95]	[75, 86]	[65, 95]	[64, 90]
C_{1-4}	4	[0.0008, 0.0372]	[75, 95]	[60, 75]	[71, 90]	[75, 83]	[66, 82]	[63, 85]
C_{1-5}	5	[0.0017, 0.0633]	[79, 98]	[50, 74]	[70, 85]	[75, 79]	[67, 80]	[65, 88]
C_{2-1}	6	[0.0006, 0.0381]	[85, 98]	[65, 95]	[72, 95]	[75, 95]	[65, 95]	[65, 95]
C_{2-2}	7	[0.0009, 0.0254]	[85, 98]	[65, 81]	[70, 85]	[75, 90]	[65, 90]	[65, 85]
C_{2-3}	8	[0.0003, 0.0296]	[85, 95]	[60, 90]	[70, 90]	[76, 92]	[65, 90]	[63, 90]
C_{2-4}	9	[0, 0.057]	[80, 95]	[65, 81]	[70, 90]	[74, 90]	[65, 90]	[63, 91]
C_{2-5}	10	[0.0002, 0.0296]	[80, 97]	[65, 79]	[73, 90]	[60, 95]	[66, 85]	[64, 90]
C_{3-1}	11	[0, 0.0506]	[75, 95]	[60, 80]	[70, 95]	[75, 85]	[67, 85]	[63, 85]
C_{3-2}	12	[0.0001, 0.0284]	[80, 90]	[65, 85]	[70, 95]	[75, 83]	[65, 90]	[65, 90]
C_{3-3}	13	[0.0002, 0.0284]	[80, 98]	[65, 90]	[70, 85]	[75, 80]	[64, 85]	[65, 87]
C_{3-4}	14	[0.0002, 0.0242]	[70, 90]	[40, 70]	[65, 80]	[60, 90]	[65, 80]	[60, 85]
C_{3-5}	15	[0, 0.0151]	[75, 95]	[60, 75]	[70, 78]	[75, 85]	[65, 90]	[60, 90]
C_{3-6}	16	[0.0002, 0.0151]	[80, 96]	[60, 70]	[70, 80]	[70, 88]	[65, 85]	[65, 85]
C_{4-1}	17	[0.0027, 0.0355]	[80, 98]	[60, 78]	[70, 82]	[75, 90]	[65, 85]	[60, 90]
C_{4-2}	18	[0.0013, 0.0308]	[75, 95]	[60, 70]	[70, 85]	[76, 90]	[65, 85]	[65, 88]
C_{4-3}	19	[0.0067, 0.0561]	[80, 95]	[65, 75]	[70, 85]	[75, 87]	[65, 90]	[65, 90]
C_{4-4}	20	[0.0029, 0.0355]	[80, 93]	[40, 85]	[60, 80]	[40, 82]	[66, 81]	[65, 85]
C_{4-5}	21	[0, 0.0293]	[70, 96]	[65, 88]	[70, 85]	[75, 95]	[66, 89]	[60, 88]
C_{4-6}	22	[0, 0.0377]	[85, 96]	[65, 70]	[70, 90]	[74, 90]	[66, 85]	[65, 85]
C_{5-1}	23	[0.0005, 0.0469]	[80, 95]	[60, 90]	[72, 87]	[70, 93]	[65, 85]	[65, 86]
C_{5-2}	24	[0.0005, 0.0393]	[75, 97]	[60, 75]	[70, 85]	[74, 87]	[66, 90]	[65, 85]
C_{5-3}	25	[0.0005, 0.0495]	[80, 96]	[65, 85]	[72, 90]	[74, 83]	[67, 85]	[65, 90]
C_{5-4}	26	[0.0013, 0.0835]	[75, 89]	[64, 80]	[70, 88]	[75, 87]	[66, 90]	[64, 87]
C_{5-5}	27	[0, 0.0314]	[70, 95]	[60, 95]	[70, 90]	[71, 95]	[66, 95]	[60, 95]

2) Formulate the grey decision matrix. The decision matrix is built from Table VI using (18)

$$\otimes D' = \begin{array}{c} \begin{pmatrix} [80,95] & [85,90] & \cdots & [70,95] \\ [60,80] & [65,81] & \cdots & [60,95] \\ [70,85] & [70,90] & \cdots & [70,90] \\ [75,88] & [75,85] & \cdots & [71,95] \\ [65,85] & [65,90] & \cdots & [66,95] \\ [65,86] & [64,90] & \cdots & [60,95] \end{pmatrix} \end{array} \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{array} \tag{46}$$

where $\otimes d_{ij} = [\underline{d}_{ij}, \overline{d}_{ij}]$ is the GN of the *j*th criterion of the *i*th alternative, for which $1 \leq i \leq 6$ and $1 \leq j \leq 27$, where *m* and *n* are the numbers of the alternatives and the criteria, respectively.

3) Normalize the grey decision matrix. The normalized grey decision matrix is computed using (19).

$$D' = \begin{pmatrix} [0.5714, 1] & [0.8077, 1] & \cdots & [0.2857, 1] \\ [0, 0.5714] & [0.0385, 0.6538] & \cdots & [0, 1] \\ [0.2857, 0.7143] & [0.2308, 1] & \cdots & [0.2857, 0.8571] \\ [0.4286, 0.8] & [0.4231, 0.8077] & \cdots & [0.3143, 1] \\ [0.1429, 0.7143] & [0.0385, 1] & \cdots & [0.1714, 1] \\ [0.1429, 0.7429] & [0, 1] & \cdots & [0, 1] \end{pmatrix}. \tag{47}$$

4) Compute the weighted normalized decision matrix. This is obtained using (45) and the grey weights in Table VI, i.e.,

$$\otimes W_j = \left([0.0022, 0.023] \; [0, 0.0249] \; \cdots \; [0, 0.0314] \right)^{\mathrm{T}}. \tag{48}$$

Then, the weighted normalized decision matrix is

$$D^* = \begin{pmatrix} [0.0013, 0.023] & [0, 0.0249] & \cdots & [0, 0.0314] \\ [0, 0.0131] & [0, 0.0163] & \cdots & [0, 0.0314] \\ [0.0006, 0.0164] & [0, 0.0249] & \cdots & [0, 0.0269] \\ [0.0009, 0.0184] & [0, 0.0201] & \cdots & [0, 0.0314] \\ [0.0003, 0.0164] & [0, 0.0249] & \cdots & [0, 0.0314] \\ [0.0003, 0.0171] & [0, 0.0249] & \cdots & [0, 0.0314] \end{pmatrix}. \tag{49}$$

The series is given as follows:

$$\begin{aligned} \otimes D_1' &= \{[0, 0.0131] \; [0, 0.0163] \cdots [0, 0.0314]\} \\ \otimes D_2' &= \{[0.0006, 0.0164] \; [0, 0.0249] \cdots [0, 0.0269]\} \\ \otimes D_3' &= \{[0.0006, 0.0164] \; [0, 0.0249] \cdots [0, 0.0269]\} \\ \otimes D_4' &= \{[0.0009, 0.0184] \; [0, 0.0201] \cdots [0, 0.0314]\} \\ \otimes D_5' &= \{[0.0003, 0.0164] \; [0, 0.0249] \cdots [0, 0.0314]\} \\ \otimes D_6' &= \{[0.0003, 0.0171] \; [0, 0.0249] \cdots [0, 0.0314]\}. \end{aligned} \tag{50}$$

5) Determine the weighted positive and negative ideal reference alternative. The PRA (D_0^+) and negative reference alternative D_0^- are determined using (21) and (22), respectively.

$$\otimes D^+ = \{[0.0131, 0.023] \; [0.0201, 0.0249] \cdots [0.0099, 0.0314]\} \tag{51}$$

which has positive reference points of: $D^+ = \{\, 0.0201, \; 0.0269, \; \ldots, \; 0.0314 \,\}$ and

$$\otimes D^- = \{\, [0, 0.0131] \; [0, 0.0163] \cdots [0, 0.0269] \,\}. \tag{52}$$

The negative reference point is $D^- = \{0.0131,\ 0.0163,\ \ldots,\ 0.0269\}$

6) Obtain the differences between the PNR and the weighted normalized decision matrix.
   a) The differences between the normalized weighted PRA and all alternatives are

$$\Delta^+ = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ 0.0099 & 0.0086 & \cdots & 0 \\ 0.0066 & 0 & \cdots & 0.0045 \\ 0.0046 & 0.0048 & \cdots & 0 \\ 0.0066 & 0 & \cdots & 0 \\ 0.0059 & 0 & \cdots & 0 \end{pmatrix}. \quad (53)$$

   b) The differences between the alternatives and the weighted normalized negative reference alternative (NRA) are

$$\Delta^- = \begin{pmatrix} -0.0119 & -0.0163 & \cdots & -0.0269 \\ -0.0131 & -0.0163 & \cdots & -0.0269 \\ -0.0125 & -0.0163 & \cdots & -0.0269 \\ -0.0122 & -0.0163 & \cdots & -0.0269 \\ -0.0128 & -0.0163 & \cdots & -0.0269 \\ -0.0128 & -0.0163 & \cdots & -0.0269 \end{pmatrix}. \quad (54)$$

7) Calculate the positive and negative grey relational grades. The positive grey relational grade r_i^+ and the negative grey relational grade r_i^- with a grey relational coefficient of 0.5 $\zeta = 0.5$ are calculated using (25) and (26), respectively.
   a) Positive grey relational grades:

$$r_i^+ = \frac{1}{27}\sum_{j=1}^{27} \gamma_{ij}^+ \quad (55)$$

$$r_i^+ = [0.9871\ 0.5997\ 0.7314\ 0.7343\ 0.7267\ 0.7351]^{\mathrm{T}}. \quad (56)$$

   b) Negative grey relational grades:

$$r_i^- = \frac{1}{27}\sum_{j=1}^{27} \gamma_{ij}^- \quad (57)$$

$$r_i^- = [0.4154\ 0.4247\ 0.4203\ 0.4191\ 0.4222\ 0.4228]^{\mathrm{T}}. \quad (58)$$

8) Obtain the ranking scores. The ranking scores are computed using (27). The results are a column matrix based on (27) with $\lambda = 0.5$

$$\begin{aligned} V_i &= [0.7013\ 0.5122\ 0.5758\ 0.5767\ 0.5745\ 0.5789]^{\mathrm{T}} \\ &\approx \left(1^{\text{st}}\ 6^{\text{th}}\ 4^{\text{th}}\ 3^{\text{rd}}\ 5^{\text{th}}\ 2^{\text{nd}}\right)^{\mathrm{T}}. \end{aligned} \quad (59)$$

   After sorting the SCs based on V_i, the ranking of SCs as an inequality can be written as $A_1 > A_6 > A_4 > A_3 > A_5 > A_2$.

Therefore, we can infer that the best alternative is the first alternative, which is based on the DMs' preferences, because A_1 is in the first position, A_6 is in the second position, A_4 is in the third position, A_3 is in the fourth position, A_5 is in the fifth position, and A_2 is in the sixth position.

C. Discussion

In this section, we focus on the aspects of weighting and ranking, with the managerial implication based on this study.

From the weight of the criteria based on the DMs' preferences, the most important criterion is *compliance with contracts* (C_{5-4}). Indeed, if an SC does not abide by the terms and conditions of a contract, this would affect other areas of the construction project, which would eventually lead to avoidable disputes and penalties that could cause the GC to suffer losses. *Technical equipment capability* (C_{4-3}) is equally among the important criteria, since it is a proxy to understand the quality and speed at which the construction work would occur. *Construction techniques* (C_{1-5}) go beyond conventional techniques in the construction industry, and innovative approaches should benefit both the GC and SC. Conversely, the least important criterion is *relationships with other entities* (C_{3-5}), suggesting that the DMs are primarily concerned about their immediate relationships, i.e., the relationship between the GC and SC.

The managerial implications of the weights are examined. First, the GC assigned more weight to *compliance with contracts* (C_{5-4}) based on the DMs' preferences. This implies that compliance with contracts can be strengthened by using management tools such as the WBS. The WBS would assist in reducing the work into smaller manageable portions, which breaks the deliverable into phases. Commonly, all critical documents should be collated, the key staff should be identified, a hierarchical structure for the project should be developed, a detailed description of the elements in the hierarchy should be provided, and a Gantt chart should be constructed for job scheduling. Conversely, *relationships with other entities* (C_{3-5}) is the least important. The contract that binds a GC and an SC should not be neglected. For example, a GC can face litigation challenges that can be raised by a competitor if there are legal gaps that the SC creates that directly exposes the GC. Thus, none of the evaluation criteria is unimportant.

Moreover, decision-making has the objective of selecting the most appropriate alternative, which does not exclude choosing weighting and evaluation methods for situations under uncertainty. This uncertainty may be in the form of risk, and risk distribution is one of the reasons for using SCs since it allows experts to conduct jobs according to their specialties, instead of half-baked in-house solutions. Since all contracts are legal instruments, they may equally consider using external legal services. For example, poor construction of the project may lead to litigation (C_{1-1}), a construction project that exceeds the budget (C_{2-2}), an SC consistent record of uncompleted projects has an increased chance of not treating the GC in a similar way (C_{3-5}), and an SC that does not comply with HSE requirement can drag the GC into ligation (C_{4-6}); without any doubt, there should be no breach of contract in these examples (C_{5-2}). The overall implication is that the GC should pay attention to uncertainty, which includes legal risk.

D. Methods and Results Validation

There are several MCDM methods that can be used to select the best alternative. We used three methods to validate the best alternative, namely, TOPSIS with grey values (TOPSIS-G), simple additive weighting with grey relations (SAW-G), and additive ratio assessment with grey criteria scores (ARAS-G). The TOPSIS-G method is selected since it shares the assessment principle based on the positive and negative ideal alternatives. In addition, SAW-G is based on the WSM, also called the simple additive weighting (SAW) method, which is one of the simple approaches for solving an MCDM problem. The ARAS-G method is relatively simple to compute and is less computationally complex. Finally, sensitivity analysis is presented to assign the range to which the ranking changes as the evaluation score changes from an evaluation that is solely based on the PRA, to one that is based on the negative reference alternative.

1) Evaluation Using TOPSIS With Grey Values: This is an extension of the TOPSIS method to GST by Lin [62], using the following steps.

1) Formulate the grey decision matrix using (46).
2) Normalize the grey decision matrix using (47).
3) Obtain the weighted normalized grey decision matrix using (49).
4) Determine the positive and negative ideal solutions.

a) The positive ideal solution is

$$D^+ = \{d_1^+, d_2^+, \ldots, d_{27}^+\} = \{0.023, 0.0249, 0.0345, \ldots, 0.0314\} \quad (60)$$

where
$d_j^+ = \left\{ \left(\max_{1\le i\le 5} \overline{d_{ij}^*} | j \in J \right), \left(min_{1\le i\le 5} \underline{d}_{ij}^* | j \in J \right) | i \in n \right\}$.

b) The negative ideal solution is

$$D^- = \{d_1^-, d_2^-, \ldots, d_{27}^-\} = \{0, 0, \ldots, 0\} \quad (61)$$

where
$d_j^- = \left\{ \left(\min_{1\le i\le 5} \underline{d}_{ij}^* | j \in J \right), \left(max_{1\le i\le 5} \overline{d_{ij}^*} | j \in J \right) | i \in n \right\}$.

5) Calculate the separation from the ideal solution to obtain the positive and negative distances using (62) and (63), respectively.

a) The positive ideal points are

$$D^+ = \left(D_1^+ \; D_2^+ \; D_3^+ \; D_4^+ \; D_5^+ \; D_6^+ \right)^{\mathrm{T}} = (0.7647\ 0.7401\ 0.7449\ 0.7355\ 0.7401\ 0.7411)^{\mathrm{T}} \quad (62)$$

where $d_{ij}^+ = \sqrt{\left(\frac{1}{2} \sum_{i=1}^{n} \left(|\underline{d_{ij}^*} - d_j^+|^2 + |\overline{d_{ij}^*} - d_j^+|^2 \right) \right)}$ is the Euclidean distance, and the aggregated criteria are $D_i^+ = d_{i1}^+ + d_{i2}^+ + \cdots + d_{i27}^+$.

b) The negative ideal points are

$$D^- = \left(D_1^- \; D_2^- \; D_3^- \; D_4^- \; D_5^- \; D_6^- \right)^{\mathrm{T}} = (0.7016\ 0.4182\ 0.5610\ 0.5541\ 0.5527\ 0.5666)^{\mathrm{T}} \quad (63)$$

where $D_i^- = \sqrt{\left(\frac{1}{2} \sum_{i=1}^{n} \left(|\underline{d_{ij}^*} - d_j^-|^2 + |\overline{d_{ij}^*} - d_j^-|^2 \right) \right)}$ is the Euclidean distance, and the aggregated criteria are $D_i^- = d_{i1}^- + d_{i2}^- + \cdots + d_{i27}^-$.

6) Compute the similarities to the positive ideal solution. The similarities of the SC to the positive ideal alternative are computed using (64)

$$T = (0.4785\ 0.3610\ 0.4296\ 0.4297\ 0.4275\ 0.4333)^{\mathrm{T}} \approx \left(1^{\text{st}}\ 6^{\text{th}}\ 4^{\text{th}}\ 3^{\text{rd}}\ 5^{\text{th}}\ 2^{\text{rd}} \right)^{\mathrm{T}} \quad (64)$$

where $T_i = \frac{D_i^-}{D_i^- + D_i^+}$.

$\therefore, A_1 > A_6 > A_4 > A_3 > A_5 > A_2$.

2) Evaluation Using SAW With Grey Relations: The classical SAW method is extended to GST by Zavadskas et al. [73], and is called SAW-G. The main idea of SAW-G is to compute the weighted grey decision matrix and to aggregate the criteria for the alternative, and the weighted values of the alternatives are ranked. The steps used are as follows.

1) Determine the evaluation criteria, as given in Section III-A.
2) Formulate the grey decision matrix using (46).
3) Normalize the grey decision matrix using (47).
4) Obtain the criteria weights, W, using (45).
5) Aggregate the weighted normalized decision matrix using (49).
6) Calculate the optimality criteria, L_i, using (65).

$$L_i = \frac{1}{n} \sum_{j=1}^{m} \frac{\underline{d_{ij}^*} + \overline{d_{ij}^*}}{2} \quad (65)$$

$$L_i = (0.0191\ 0.0115\ 0.0153\ 0.0152\ 0.0150\ 0.0154)^{\mathrm{T}} \approx \left(1^{\text{st}}\ 6^{\text{th}}\ 3^{\text{rd}}\ 4^{\text{th}}\ 5^{\text{th}}\ 2^{\text{nd}} \right)^{\mathrm{T}}. \quad (66)$$

$\therefore, A_1 > A_6 > A_3 > A_4 > A_5 > A_2$.

3) Evaluation Using ARAS With Grey Criteria Scores: Additive ratio assessment (ARAS) was developed by Zavadskas [74] and was further extended to GST [75]. The procedure of ARAS-G used in this section are those presented by Turskis and Zavadskas [75] in different stages.

1) Formulate the grey decision-making matrix using (46).
2) Normalize the initial values of all the criteria using (47).
3) Compute the normalized-weighted matrix using (49).
4) Determine the values of the optimal function using (67).

$$\otimes S_i = \sum_{i=1}^{n} \otimes \hat{x}_{ij}; i = 0, m = \left([0.0134, 0.992]\ [0, 0.5914] \cdots [0.0028, 0.8013] \right)^{\mathrm{T}}. \quad (67)$$

5) Obtain the crisp value based on the center of the area, using (68).

$$S_i = \frac{1}{2}(\underline{S_i} + \overline{S_i})$$

TABLE VII
RANKINGS CORRELATION—KENDALL'S-τ (SPEARMAN'S-ρ)

Methods	GRA-PNR	TOPSIS-G	SAW-G	ARAS-G
GRA-PNR	1	1	0.867	0.867
TOPSIS-G	(1)	1	0.867	0.867
SAW-G	(0.943)	(0.943)	1	1
ARAS-G	(0.943)	(0.943)	(1)	1

$$= \left(0.5027\ 0.2957\ 0.3998\ 0.3958\ 0.3926\ 0.4021\right)^{\mathrm{T}}. \tag{68}$$

6) Compute the degree of utility of the alternative.

$$\begin{aligned} K_i &= \frac{S_i}{S_0} \\ &= \left(1.0000\ 0.5883\ 0.7954\ 0.7874\ 0.7811\ 0.7999\right)^{\mathrm{T}} \\ &= \left(1^{\mathrm{st}}\ 6^{\mathrm{th}}\ 3^{\mathrm{rd}}\ 4^{\mathrm{th}}\ 5^{\mathrm{th}}\ 2^{\mathrm{nd}}\right)^{\mathrm{T}}. \end{aligned} \tag{69}$$

$\therefore, A_1 > A_6 > A_3 > A_4 > A_5 > A_2$.

It is not uncommon for different MCDM evaluation methods to rank alternatives differently. More importantly, there is a strong correlation among the GRA-PNR, TOPSIS-G, SAW-G, and ARAS-G, as shown in Table VII, using both Kendall's Tau and Spearman's Rho rank correlation coefficients.

However, it is interesting to observe that GRA-PNR and TOPSIS-G both consider ideal and nonideal alternatives to have the same rankings. Additionally, SAW-G and ARAS-G have the same rankings. The primary difference in the ranking among the four evaluation methods is the switch between the ranking of the third SC (A_3) and fourth SC (A_4). Since all four evaluation methods rank the fifth SC (A_5) and second SC (A_2) poorly, these SCs should be excluded from further consideration. More importantly, the first SC (A_1) is ranked as the best SC for all evaluations, and the sixth (A_6) that is ranked as the second position by all evaluation methods can serve as a good backup SC for future projects.

The MCDM methods based on the GST have their advantages and disadvantages. First, the advantage of the TOPSIS-G is that it provides a fundamental ranking with rational and logical mathematics by entirely using the allocated information that may be dependent, but with discrete alternatives based on the closeness to the ideal alternative. However, the cons of the TOPSIS-G are that it does not consider the priority weights of the decision parameters, and a strong deviation of one criteria can affects the results. Sadly, the TOPSIS-G does not consider the relative importance of distance. Second, the strength of the SAW-G is intuitively simple to compute, and it is well suited for single-dimension MCDM problems that account for all of the criteria. However, all of the criteria must be positive, and generally, weights are assigned arbitrarily. Thus, the MCDM weighting method is combined with SAW-G as a hybrid method. Third, on the one hand, the ARAS-G has an advantage, in that different units of measurement in the criteria and the optimization direction are assessed. On the other hand, there is the disadvantage of weight, which can be arbitrarily assigned. Finally, the GRA-PNR inherits the benefits of the tradition-GRA, which includes easily computed and relatively usable results for the problem of incomplete information [71], with a drawback of additional computational steps. All four methods do not check for the consistency of the DMs' points. Users should implement the GRA-PNR when they have a chance of making incorrect decisions using the traditional GRA, since its consideration of both PNRs is more superior.

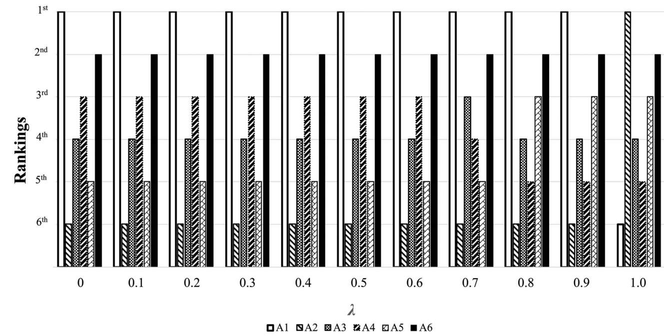


Fig. 8. Reference coefficient sensitivity analysis.

E. Sensitivity Analysis

Another requirement to certify the robustness of the ranking in selecting the best alternative is to conduct sensitivity analysis. The objective of the sensitivity analysis is to see how the rankings of the SC would be impacted by the score coefficient. Specifically, sensitivity analysis of the ranking of the score coefficients is conducted in a step-wise approach from 0 to 1, using an interval of 0.1. When $\lambda = 0$, it is the ranking based only on the negative reference point, and when $\lambda = 1$, it is the classical GRA. So, $\lambda = 0.5$, as given in (59), equally combines the ranking of both the positive reference point and the negative reference point. The rankings of the sensitivity analysis are presented in Fig. 8. One ranking that stands out is that of the sixth SC A_6, which remains in the second position, regardless of whether the positive reference point or the negative reference point is considered.

Primarily, the best alternative, A_1, remains the best alternative for a significant range (from $0 \sim 0.9$), then A_1 becomes the least preferred when using the classical GRA; i.e., vice versa when $\lambda = 0$. However, the rankings of the third SC A_3 were predominantly the fourth position, and then rose to the third position at $\lambda = 0.7$. As λ increases, A_4 decreases. Undoubtedly, based on the proposed method and the sensitivity analysis results, the first SC (A_1) is the best alternative. The validity of the GRA-PNA is checked to ensure that the proposed method does not diverge from already established MCDM methods in the literature.

V. CONCLUSION

The demand for electricity will continue to increase, since the utilization of solar energy to perform work commonly does not produce any pollution as waste. However, not all electrical energy solutions are clean. For example, when the energy cycle is examined, an electric car whose battery is charged by electricity from a coal-fired power station can be considered a coal-powered car. Thus, the government should push toward achieving a net-zero carbon solution that encompasses the seventh sustainable development goal.

The conversion for evaluating alternatives and for selecting the best alternative for an MCDM problem begins with choosing the evaluation standard, i.e., the evaluation criteria. Next, the weighting and evaluation methods are used in the assessment while accounting for uncertainties. One primary symptom of a poor decision is ignoring uncertainty [76]. So, this article accounted for uncertainties by addressing the selection of SCs as group decision-making, and represented the DMs' preferences and the performance values of the alternatives as GNs. Explicitly, this article presented two new hybrid methods. First, the grey-PA-ROCS weighting method was used to estimate the weights of the criteria based on the DMs' preference. Second, the GRA-PNR method was used to select the best SC, by considering how close the alternatives were to the ideal alternative, and how far away they were from the nonideal alternative. This new approach reduces the possibility that the best alternative has an equal chance of performing poorly. Sensitivity analysis was conducted to demonstrate the stability of the results. Moreover, TOPSIS-G, SAW-G, and ARAS-G were used to verify the results. The best alternative A_1 is the same for all of the MCDM evaluation methods presented in this research.

Unfortunately, one limitation of this research is that the performance values of the alternatives are subjective. In some cases, it may be possible to use an objective approach to determine the performance values. For instance, *finance status* (C_{2-5}) can be directly represented using monetary values, i.e., in a flat currency such as the Chinese yuan (CNY) or the United States dollar (USD). Another example is counting the number of paper qualifications as *staff qualifications* (C_{5-2}).

Further research can be conducted by formulating this problem as a multiobjective optimization problem with the conflicting objectives of minimizing costs and time, or as a bilevel optimization problem, where the GC is the leader and the SCs are the followers. Moreover, research can be done to reduce the complexity of the proposed method to increase the cost-to-benefit ratio of applying it. Although TOPSIS-G, SAW-G, and ARAS-G were used to validate this research, further research could comprehensively compare the obtained results from other existing methodologies such as DBA [77], TOPSIS [78], BWM [79], the matrix method [80], complex proportional assessment, and level-based weight assessment [81]. Lastly, greater applicability of this research, with its implications, can be explored in areas such as transportation, agriculture, and petroleum.

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