International Journal of Industrial Engineering, 30(1), 203-231, 2023

A METHODOLOGY FOR THE BIDDERS EVALUATION AND SELECTION IN THE PUBLIC PROCUREMENT PROCESS BASED ON HETEROGENEOUS INFORMATION AND ADAPTIVE CONSENSUS APPROACHES

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The public procurement problem is a special problem of supplier selection that requires strict adherence to the principles of non-discrimination, free competition, and transparency in the contract awarding procedures. It is a very complex multi-criteria problem, which requires the engagement of several decision-makers (experts). The public procurement problem requires the usage of different types of conflicting criteria, the combination of different models (methods and techniques) of decision-making, as well as the modeling of different forms of uncertainty, inaccuracy, and subjectivity of decision-makers, which can represent a rather complex, difficult, and lengthy decision-making process. Therefore, the paper proposes a methodology for improving the tender process that focuses on heterogeneous preference structures of information (preference ordering, utility values, fuzzy (additive) preference relations, multiplicative preference relations, and linguistic preference relations) and an adaptive consensus approach for subjectively determining the weight of criteria and evaluation and selection of alternative bids. The Simple Additive Weighting (SAW) method is used for the final ranking of bidders. The proposed methodology enables obtaining a more objective and measurable value during subjective decision-making as well as minimizing the risk of unscrupulous, incompetent, and irresponsible decision-making, which is shown in the given example.

Keywords: Public Procurement; Bids Evaluation and Selection; Multi-Criteria Group Decision-Making; Heterogeneous Information; Adaptive Consensus Approaches.

(Received on July 18, 2022; Accepted on October 21, 2022)

1. INTRODUCTION

Public procurement is a very important segment of the business of public institutions. The efficiency of the procurement process directly influences the availability and quality of government-provided goods and services from private contractors. The money spent every year through public procurement amounts to about 14% of the EU's GDP, according to Sönnichsen*et al*. (2020). In the Republic of Serbia, public procurement accounts for about 8% of the GDP, Serbian Public Procurement Office (2019). Furthermore, each government, national, regional, and local public sector institution has its own preferences when it comes to criteria, methods, and models for awarding public contracts, Igarashi *et al*. (2017).

According to the legal regulation, public contracting authorities usually apply two approaches for comparing and evaluating alternative bids: Low Price (LP) and Most Economically Advantageous Tender (MEAT), which optimizes the economic benefits, seeking the highest possible quality at the best possible prices, Dotoli*et al*. (2020). In the Republic of Serbia, public contracting authorities predominantly opt for the LP approach, which accounts for about 90% of the total value of procurement, based on the Serbian Public Procurement Office (2019). According to the European Commission (2022), the MEAT approach accounts for approximately 80% of the total value of procurement in EU countries.

The key prerequisite for creating an efficient, non-discriminatory, objective, transparent, fair, and honest public procurement system is the definition of all relevant conditions and criteria in the tender documentation, taking into account the purpose and value of the procurement, Igarashi *et al*. (2017). Conducting a tender using the LP approach is much simpler, faster, and easier. However, analyses indicate that the LP approach carries some risks, as the lowest price is not always the bid that represents the best "value for money" in the long run, according to Lorentziadis (2020). Therefore, the European Commission for Public Procurement has been consistently promoting the concepts of Sustainable Public

DOI: 10.23055/ijietap.2023.30.1.8479 ISSN 1943-670X

Procurement and Green Public Procurement for several years, European Commission (2022). These concepts require that in addition to the offered price, other aspects of the bid, such as cost, environmental, social, innovation, etc., should be comprehensively considered.

In general, the selection of bidders in public procurement procedures using the MEAT approach is a multi-criteria decision-making (MCDM) problem, and the application of certain multi-criteria optimization models is a suitable tool for decision-making in the tender procedure, as given by Marcarelli &Squillante (2020). Following the subject of the procurement, the MEAT approach requires that the criteria by which the accepted bids will be compared and evaluated firstly should be selected. Then, the selected criteria should be ranked according to the order of their importance and their specific weight, i.e., point value, and should be determined, which has to be stated in the tender documentation. Also, the contracting authority is obliged to present the tender evaluation methodology in the tender documentation, which has to contain the method and the maximum number of points (ponders) that can be awarded to the tender according to the established criteria and each foreseen parameter (sub-criterion). Certainly, the decisive factor in the selection of the winner of the tender is the evaluation of the bids based on the price-quality ratio. The criterion related to the price is crucial, while the qualitative parameters are of the greatest importance, so the best bid is the one that has the highest combined value realized from all the criteria and sub-criteria, as described by Dotoli*et al*. (2020).

1.1 Literature review

The problem of supplier selection caused many research procedures that resulted in numerous scientific papers. The research focuses in two directions: (i) on criteria and (ii) on supplier evaluation methods and techniques. After reviewing the literature, it is inferred that defined numerous evaluation criteria for bidder selection. More detailed reviews of the criteria for supplier evaluation and selection can be found in the studies of Dickson (1966), Ellram (1990), Weber *et al*. (1991), Ho *et al*. (2010), Mukherjee (2016), and Cheshmberah (2020). Also, the literature presents numerous approaches that can combine several criteria to select the best possible supplier. The approaches discussed in the literature are either single assessment methods – using crisp or fuzzy values – or hybrid methods. More detailed reviews of models for supplier selection can be found in the studies: Ho *et al*. (2010), Chai *et al*. (2013), Ibáñez-Forés*et al*. (2014), Zavadskas*et al*. (2016), Simić*et al*. (2017), Liu *et al*. (2019), Chai & Ngai (2020), Çaloglu (2022).

The literature survey shows that traditional multi-criteria techniques like AHP and TOPSIS are the most frequently used for supplier evaluation and selection. However, hybrid models have represented a progressive trend during the last few years. A decision-maker or a group of decision-makers can be more confident in the results when hybrid MCDM is applied, especially in cases of increasing variety and complexity of information. Simultaneously applying different approaches can help to overcome uncertainties arising from human qualitative judgments and to bring a model closer to real-problem representation, as in Pamučar*et al*. (2021).

As for the public sector, only a few works can be found in the academic literature where innovative methodologies for the MEAT approach are proposed, which are derived from established sound business practices of supplier selection in the commercial sector. See Bobar*et al*. (2015), Nikou *et al*. (2017), Igarashi *et al*. (2017), Marcarelli &Squillante (2020), Dotoli*et al*. (2020), and Alshraideh*et al*. (2021) and Ilić*et al*. (2022), for details on the proposed methodologies based on AHP and TOPSIS techniques. In tender practice, the most common approach for the calculation of the overall performance of individual suppliers for each criterion is the normalized value of the result multiplied by the weights of the observed criteria, and it's the so-called Weighted Sum Method or Simple Additive Weighting, Mimović&Krstić (2016).

In order to make the tender selection process more transparent and objective, especially in cases where subjectivity cannot be completely excluded, such as the evaluation of procurement items according to parameters that include functional, ergonomic, and aesthetic characteristics, and also according to parameters related to the experience of the person which will be entrusted with the execution of the procurement. In that case, public contracting authorities should include an independent group of decision-makers (experts) with different skills, experience, and knowledge capable for evaluating all criteria and aspects of alternative bids, which will contribute to greater objectivity in deciding on the final selection of the most favorable bid.

In reality, the structure of decision-makers (experts) in public procurement is usually heterogeneous, and everyone can have different views, interests, and knowledge related to the problem and subject of the procurement. Dong *et al*. (2009) and Tang *et al*. (2021) suggest that each decision-maker might have significant differences in expressive abilities. They can express their own opinion in different ways by using different information formats during the determination of the weight of criteria and evaluation of alternative bids. In addition, the very context of group decision-making implies achieving a certain level of agreement and homogeneity among decision-makers, and decisions become more realistic and consistent, as explained by Zhang *et al*. (2015) and Dong *et al*. (2016).

In a complex decision-making environment, existing research has failed to effectively consider certain individual factors of decision-makers. When decision-makers choose the ideal option, they usually do not choose the best option but choose the most satisfactory option, according to Rong *et al*. (2022). For this reason, the problem of reducing subjectivity and achieving consensus or agreement among all decision-makers in group decision-making is a very interesting and important topic for numerous researchers, see Yager (2001), Dong *et al*. (2009), Erdem&Göçen (2012), Sun & Ma (2015), Chen *et al*. (2015), Zhang *et al*. (2015), Dong *et al*. (2016), Dong *et al*. (2018), Tang *et al*. (2021).

By reviewing the literature, it can be concluded that the works on public procurement did not use different information structures to express the individual preferences of decision-makers while achieving consensus.

1.2 The Aim of The Work

The aim of this paper is to expand the limited literature on procurement in the public sector and to point out the need to improve existing models for the evaluation and selection of bidders using the MEAT approach without distorting and limiting public procurement procedures. In this sense, the paper proposed a methodology in which an adaptive GDM consensus model is incorporated for determining the weight of criteria and evaluating alternative bids using different (heterogeneous) information formats. Certain MCDM methods and techniques for the final ranking of the most acceptable bid are incorporated into the proposed methodology. The proposed methodology enables obtaining a more objective and measurable value during subjective decision-making, as well as minimizing the risk of unscrupulous, incompetent, and irresponsible decision-making, which is illustrated in the given example.

1.3 The Structure of The Paper

Besides the introduction, where the problem and aim of the work are given, the paper is organized as follows. Section 2, firstly, presents the preliminary knowledge of the MEAT approach as a specific MCGDM problem in a heterogeneous and consensus context. Then, in the second part, the basic formats of preferential information structures for expressing the individual preferences of decision-makers are presented. The third part of this section focuses on the main features of consensus models in a heterogeneous context. Section 3 presents a detailed description of the proposed methodology. A numerical example is given in section 4, where the problem of decision-making in the subjective determination of criteria weights and the subjective evaluation of alternative bids according to certain qualitative criteria is considered. The results are presented for the participation of five decision-makers in the evaluation criteria (one quantitative and four qualitative), as well as for the subjective evaluation of six alternative bids according to two criteria, while the other values of alternative bids were obtained objectively based on the submitted offers. The SAW method is used for the final ranking of alternative offers. The discussion of different scenarios and managerial implicationsis given in section 5. The main conclusions and an overview of the relevant literature are given at the end of the paper.

2. BACKGROUND

2.1 MEAT approach as specific MCGDM problem

A group decision is a very important question in public procurement, where the spending of budget funds must be public. However, the legislative framework still leaves enough space for the human factor that can influence the results of the tender process. In practice, it often happens that the criteria for evaluating bids are not adequately predetermined, sufficiently clear, justified, and objective, which leads to a violation of the general principles of public procurement, Dotoli*et al*. (2020). Violation of the principles of public procurement is also manifested through a form of strategic manipulation, whereby decision-makers, on the one hand, can strategically determine the weight of criteria to obtain the desired ranking of alternative bids, Dong *et al*., (2018). On the other hand, decision-makers may, due to insufficient knowledge, experience, or interest, give their opinions dishonestly and imprecisely when evaluating alternative bids, Marcarelli &Squillante (2020). Therefore, the MEAT approach can represent a very complex multi-criteria group decision-making problem (Multi-Criteria Group Decision-Making-MCGDM) which includes the following phases: (1) identifying decision-makers (experts); (2) selecting criteria and determining weights of criteria; (3) formulating alternatives; (4) assessing the performance of alternatives against the criteria; (5) applying the MCDM technique; and (6) making the final decision.

In general, the MEAT approach, as a specific consensus MCGDM problem, gives a lot of space for research and constant search for answers to numerous questions, such as: What criteria are suitable for evaluating and ranking alternative bids under the subject of procurement? Do we objectively determine the weight of the criteria? Which information formats are suitable for use by decision-makers during the subjective assessment and evaluation of available options? Do we combine different information formats? Do we effectively determine the competence of decision-makers? Do we effectively achieve consensus or agreement among decision-makers? How to build an effective decision-making approach when determining the final ranking of alternative bids? What are the most suitable methods and techniques of multi-criteria decision-making for application in certain public procurement?

Thus, the selection set of criteria for awarding contracts, the way of determining their relative importance, and the application of adequate models (methods and techniques) for evaluating and ranking alternative bids are crucial steps that can significantly influence the final decision on choosing the best bid. Even though diversity stimulates creativity and leads to improvements in decision-making, the decision-making process itself becomes a difficult task and sometimes confusing. Therefore, to reduce subjectivity and inconsistency, the MEAT approach should be viewed in a heterogeneous and multi-criteria group context while achieving consensus among decision-makers.

In GDM, the collective decision should be supported or favored by the majority of decision-makers, and it should be a consensus solution, which is not easy to achieve given the presence of different forms of heterogeneity, as described by Morente-Molinera*et al*. (2020). Heterogeneity in the GDM problem is usually considered in three different frameworks, Li *et al*. (2018): 1) Heterogeneity in the preference representation formats. 2) Heterogeneity in the preference expression domain. 3) Heterogeneity at the importance degree of decision-makers.

Heterogeneity in GDM requires additional attention during the aggregation of individual preferences into a collective preference value in order to achieve homogeneity in group decision-making, Chen *et al*. (2015). Before unifying individual preferences, it is necessary to ensure that the individual preferences of decision-makers are not random and illogical, which could be achieved by checking of consistency level. Otherwise, a lack of consistency might lead to confusing and illogical conclusions, Li *et al*. (2019). Then, the consensus measures could be calculated, i.e., the consensus-reaching process (CRP) is carried out, Zang *et al*. (2019).

2.2 Heterogeneous preference information

In the literature, there are several different preference formats that decision-makers may use to express their individual preference information, Chen *et al*. (2015), Tang *et al*. (2021). In this paper, we have opted for the following formats of preferences: preference orderings, utility values, and reciprocal preference relations. Generally, reciprocal preference relations can be classified into two categories: numerical preference relations and linguistic preference relations, Dong *et al*. (2009). There are two well-known types of numerical preference relations: fuzzy (additive) preference relations and multiplicative preference relations.

Let $X = \{x_1, x_2, \dots, x_n\}$be a set of predefined options where x_i represents the *i*-th option$(i = 1, \dots, n)$. Let $D = \{d_1, d_2, \dots, d_k\}$ be a set of decision-makers where d_k denotes the *k*-th decision-maker ($k = 1, \dots, m$). Each decision-maker, $d_k \in D$, can express their preference information using different preference structures.

Specifically, the above heterogeneous preference information is introduced below.

Case 1: Orderings of preferences or an ordered vector. In this case, the preferences of a decision-maker d_k about a set of options X are described as preference ordering $O^k = \{o^k(1),\dots, o^n(n)\}$ where $o^k(.)$ the permutation function is over the index set$\{i = 1,\dots, n\}$. Thus, a decision-maker gives an ordered vector of options, from the best to the worst.

Case 2: Utility values or a utility vector. In this preference structure, the decision-maker d_k gives his preferences to options as a set of n utility values $U^k = \{u^k(1),\dots, u^k(n)\}\ where\ u_j^k \in [0,1]$ represents the utility evaluation given by the decision-maker d_k to x_i. The higher value of $x_i$indicates a higher preference degree for the option x_i.

Case 3: Fuzzy (additive) numerical preference relations. In this preference structure, the decision-maker d_k gives his preferences on options X as a fuzzy preference relation $P^k = \left(p_{ij}^k\right)_{n\times n}$ where $p_{ij}^k \in [0,1]$. Every value p_{ij}^k in the matrix P^k that represents the preference degree or intensity of the preference option x_i over option x_j where $p_{ij}^k = 1/2$ indicates a difference between $x_i$and x_j $\left(x_i \sim x_j\right)$, $p_{ij}^k = 1$ indicates that x_i is absolutely preferred to x_j, and $p_{ij} > 1/2$ indicates that x_i is preferred to x_j $\left(x_i > x_j\right)$. Based on these follow $p_{ii} = 1/2 \forall i \in \{1, \dots, n\}$. The fuzzy preference relations matrix usually assumes the additive reciprocity property $p_{ij}^k + p_{ji}^k = 1, \forall i, j$.

Case 4: Multiplicative numerical preference relations. In this case, the decision-maker d_k gives his preferences on options X as a multiplicative preference relation $A^k = \left(a_{ij}^k\right)_{n\times n}$. Every value a_{ij}^k in the preference matrix A^krepresents a ratio of the preference intensity of option x_i over option x_j, i.e., it is interpreted as x_i is a_{ij}^ktimes good as x_j. The preference matrix $A^k = \left(a_{ij}^k\right)_{n\times n}$ usually assumes the multiplicative reciprocity property $a_{ij}^k \cdot a_{ji}^k = 1$ for $a_{ij}^k > 0,\ \forall i, j$.

Case 5: Linguistic preference relations. In this preference structure, the decision-maker d_k gives his preferences on options Xusing a linguistic evaluation scale $S = \{s_{-\tau}, \dots, s_{-1}, s_0, s_1, \dots, s_\tau\}$with an odd granularity and constructs the linguistic preference relation $L^k = \left(l_{ij}^k\right)_{n\times n}$. Then every value l_{ij}^k in the matrix L^k represents the linguistic preference degree or linguistic intensity of the preference option x_i over an optionx_j where $l_{ij}^k = s_\alpha \in S$. The 2-tuple linguistic representation model, which is one of the most used symbolic-based models, Herrera & Martínez (2000).

2.3 The consensus in a heterogeneous group context

As already mentioned, in GDM, there may be conflicting opinions among decision-makers with different experiences and knowledge, and therefore it would be necessary to reach a group consensus before aggregating individual preferences, Herrera-Viedma *et al*. (2002). Consensus in group decision-making requires discussion and deliberation between the group members with the aim to reach a final decision that all group members can support despite their differing opinions. Through the consensus-achieving process, their opinions can change dynamically until a desirable decision results, Pérez *et al*. (2011). In their studies, Palomares *et al*. (2014) and Pérez *et al*. (2018) present a systematic literature review on the consensus-achieving models and critically analyze their advantages and limitations. To reduce the inconsistency, researchers in the field of GDM have proposed various consensus methods based on the feedback mechanism. A detailed overview of the CRP model, with advantages and disadvantages, is given by Zhang *et al*. (2019).

When the experts provide their individual opinions by using different preference formats, before the consensus process reaches its conclusion, the unification of individual data is performed. According to Chiclana *et al*. (2008), the consistency degree is a very important indicator through which one checks the quality of the pairwise-comparison of preference relations. Transitivity is considered as the main part for defining consistency in decision-making. In particular, additive transitivity has proved to be a most popular tool among researchers for developing preference relations and consistency measures, Li *et al*. (2019). A consensus-reaching process is a dynamic and iterative group-discussion process that helps experts to bring their opinions closer before making a decision, Pérez *et al*. (2018). This process consists of several rounds where the experts discuss and change their preferences according to suggestions given by a moderator. Usually, the moderator is a person who does not participate in the discussion, but he/she helps the experts bring their preferences closer to each other. The moderator's tasks are: 1) computing the consensus measures, 2) checking the level of agreement, and 3) generating some advice for those experts that should change their opinions. In recent researches have been presented the models in which the role of the moderator is taken by the information system.

Classically, consensus means the unanimous and complete agreement regarding a collective solution. However, in reality, a full agreement is difficult to obtain and sometimes unnecessary. This has led to the use of a "soft" consensus degree. Based on the "soft" consensus degree, different consensus models have been proposed by different authors to facilitate consensus-achieving processes, see Zhang *et al*. (2019). These models are based on two soft consensus measures to guide the consensus-reaching process: similarity and proximity degrees. The former is used to measure the degree of agreement among the preference values that are provided by the individual decision-makers, while the latter is used to measure the degree of agreement among the decision-makers on the solution set of options. These soft consensus measures have usually been modeled mathematically via similarity functions. Similarity functions are defined based on the use of a metric describing the distance between decision-makers opinions or preferences. There are different types of distance measures that can be implemented in the group consensus-reaching process. For instance, the Manhattan distance, the Euclidean distance, the Dice distance, the Cosine distance, or the Jaccard distance, Del Moral *et al*. (2018). The selection process consists of two different phases: aggregation of individual preferences and exploitation of collective preferences, Herrera-Viedma*et al*. (2002).

To reach a group consensus with heterogeneous information by the group of decision-makers, in this paper, the proposed approach has the following stages: 1) the unification process where the heterogeneous preferences are transformed into one unified form; 2) the consistency process; 3) the consensus-achieving process, and; 4) the selection process.

The flow chart for determining weights of criteria, and evaluating of alternative bids with heterogeneous information given by the group of decision-makers, is illustrated in Figure 1.

To determine the weights of criteria and the value of bids by criteria, it is necessary to unify the heterogeneous preferences. After the unification process, the consistency degrees (CD) for these unify preference relations are measured. Then, the consensus-achieving (similarity) degrees (SD) and a posteriori importance degree of decision-makers are calculated. When we get the collective fuzzy preference relation, a proximity degree (PD) is computed. Both the similarity degree and proximity degree levels are utilized to control the consensus-reaching process. The approach in this paper calculates the two indexes and simultaneously compares them with the predefined thresholds during each iterative process at the same time, which makes the consensus-reaching process simpler but also with high reliability.

When the consensus levels achieve a predefined threshold, the weights of criteria and the value of bids by criteria could be calculated. Otherwise, the feedback processes started.

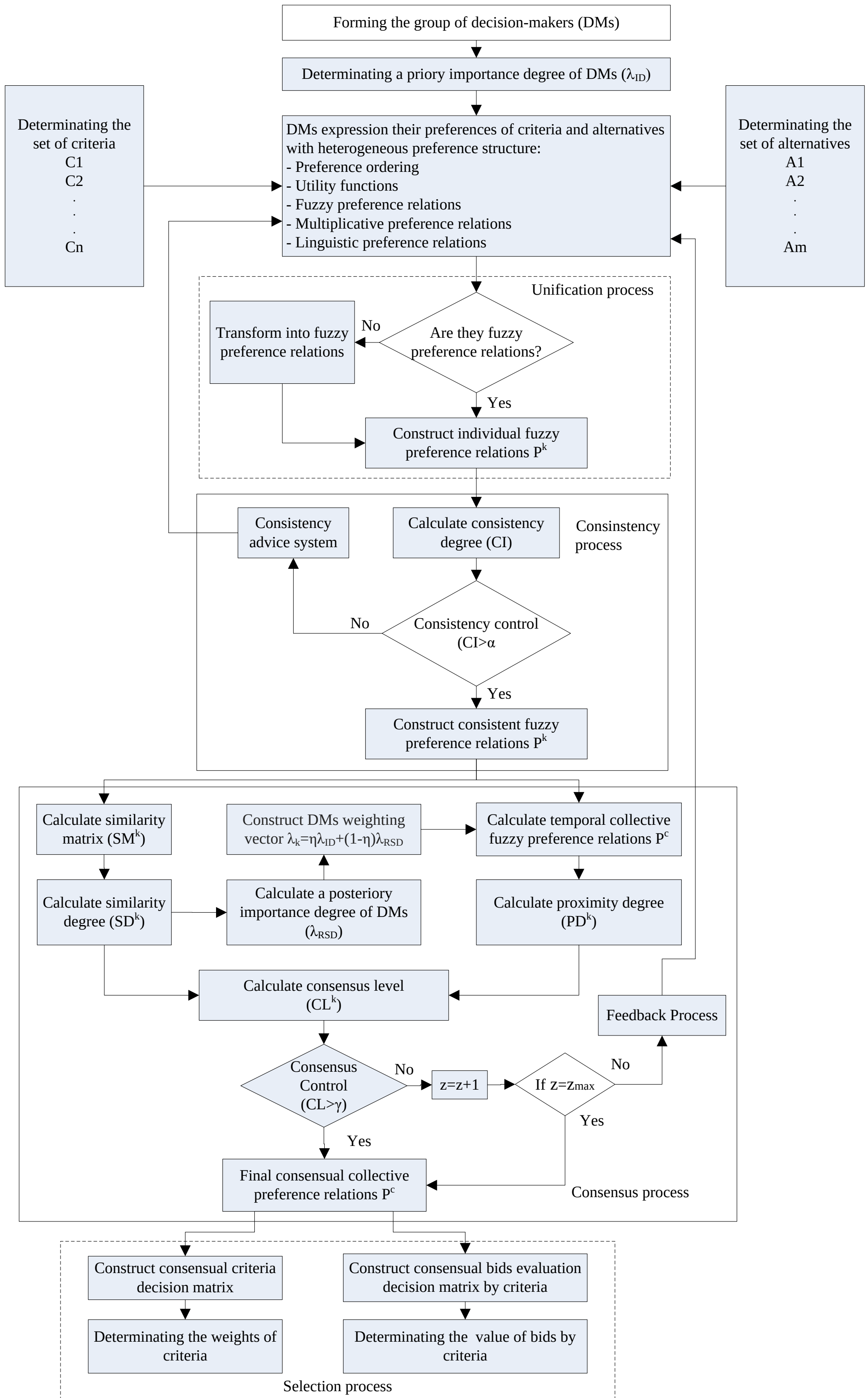

Figure 1. Flow chart of the proposed consensus approach for determining weights of criteria and evaluating bids

3. METHODOLOGY

3.1 The assumptions and notations in MEAT

The structure of the MEAT approach is shown in Figure 2.

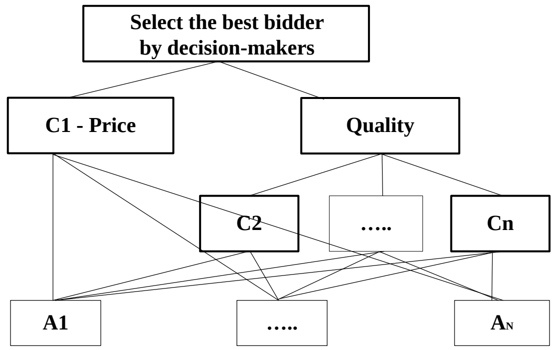

Figure 2. The general structure of the MEAT approach

To facilitate describing the proposed approach, the following assumptions and notations are used. The decision-makers are known. Let $D = \{d_1, d_2, \dots, d_k\}$ is the set of decision-makers where $(k \geq 2)$. The individual importance degree of decision-makers (λ_{ID}^k) before the decision-making process is also known. Let $\lambda_{ID} = \{\lambda_{ID}^1, \lambda_{ID}^2, \dots, \lambda_{ID}^k\}^T$ is a weight vector of decision-makers where $\lambda_{ID}^k \geq 0, (k = 1, \dots, m)$ and $\sum_{k=1}^{m} \lambda_{ID}^k = 1$. The criteria are known. Let $C = \{c_1, c_2, \dots, c_n\}$ is the set of criteria where $(n \geq 2)$. The vector of criterion weights is unknown. Let $W = \{w_1, w_2, \dots, w_n\}^T$ is the vector of criterion weights where $w_j \geq 0, (j = 1, \dots, n)$ while $\sum_{j=1}^{n} w_j = 1$ and w_j denotes the weight of the criterion C_j. The alternatives are known. Let $A = \{A_1, A_2, \dots, A_N\}$ denotes a discrete set of possible alternatives where $(N \geq 2)$.

In this paper, we assume that the criteria weights are completely unknown, where each decision-maker (expert) evaluates the criteria based on his/her knowledge and experience to obtain criteria weights. In addition, the criterion values of the alternatives according to certain qualitative criteria cannot be obtained objectively from the submitted bids, but it is necessary for the decision-makers to evaluate them subjectively.

3.2 The MEAT approach phases

Description of the MEAT approach phases is given as follows.

Phase 1: *Form a committee of decision-makers.* Identification of members of the procurement committee (group of decision-makers, experts) is an extremely important step as only competent decision-makers can effectively make eligible decisions. Incompetent decision-makers can lead to some unexpected decision results. In practice, it often happens that decision-makers (commission members) come from different departments in which they perform various duties. In that case, experts might not necessarily be perceived and treated as equally important and can be assigned by different degrees of importance. The decision-makers might use several different preference formats to express their individual preference opinions, as it is given in sub-section 2.2.

Phase 2: *Selection set of criteria and weights assignment.* One of the key steps in the implementation of a public procurement process is the establishment of the criteria on which the evaluation of bids would be based. By reviewing the literature, it is concluded that in addition to the offered price, the following criteria are most often used: quality, delivery time, service, aesthetic and functional characteristics. Therefore, the selection of bids is usually based on the relative importance of all the criteria set for awarding the contract, according to the flow chart given in Figure 1.

Phase 3: *Formulating alternatives (bids).* The committee for public procurement, after the expiration of the specified time for submission of bids, reviews the submitted bids and performs their check in terms of meeting the conditions of the tender documentation. Only bids that meet the mandatory requirements will be subject to rating. The bids that fail to meet mandatory requirements and evaluation criteria will be declared as non-responsive. If only one bidder fulfills the conditions of the tender documentation, it goes to Phase 6.

Phase 4: *Assessing the performance of alternative bids according to the criteria.* It is generally known that in MCDM problems, each alternative can be described by a set of quantitative and qualitative criteria. These criteria usually have different units of measurement and different optimization directions. Concerning the required direction of optimization, criteria can be classified as benefit type (higher is better) and cost type (lower is better). Evaluation criteria can also be classified as subjective and objective. Subjective criteria have a qualitative nature, i.e., performance ratings of these criteria are expressed by qualitative values, often using fuzzy numbers, linguistic variables, orders, etc. In contrast, objective criteria have a quantitative nature, i.e., the performance ratings of these criteria are rather expressed using quantitative values (real numbers), which is why the performance ratings of these criteria can be much more precisely determined. The determination of the value of bids is identical to the procedure in Phase 2.

Phase 5: *Applying the MCDM method*. The committee for public procurement performs the procedure of selecting the most favorable bidder from the set of submitted bids, following the defined criteria and the selected MCDM method. The main differences between MCDM methods lie in (a) the normalization procedure for comparing all performance ratings measured using non-commensurable units on a common scale and (b) the aggregation procedure for combining the normalized decision matrix and weight vector for obtaining an overall preference value for each alternative. Due to these structural differences, the ranking outcome produced by these methods might not always be consistent for a given decision matrix and weight vector, Yeh & Chang (2008). In literature, there are numerous procedures for normalization; see Zavadskas&Turskis (2008). In this paper, the SAW method is used.

Phase 6: *Making the final decision.* The committee for public procurement, after conducting the tender selection procedure, prepares a report on the professional evaluation of all bids that constitutes the explanation of the selection of the most favorable bid or the decision to suspend the procedure if the conditions for awarding the contract are not fulfilled. The final result of each procurement process is the signing of a contract with the selected bidder or more of them.

Phase 2 and Phase 4 represent the most important activities in the work of the selection committee. If the Public Procurement Commission, in Phase 2, incorrectly determines the importance of the criteria and, in Phase 4, incorrectly evaluates the submitted bids, which will lead to the wrong choice of the most favorable bid. Phase 5 is also important because the final ranking of the bids might depend on the applied MCDM method. Therefore, in practice, special attention should be paid to these phases.

3.3 The algorithm

Input: The established set of criteria $C = \{C_1, C_2, \dots, C_n\}$, the established set of alternatives $A = \{A_1, A_2, \dots, A_N\}$, the established importance experts' weight vector λ_{ID}^{k}, the established consistency threshold α the established consensus threshold γ and the established maximum number of iterations $z_{\max}$, the original preference information O^k, U^k, P^k, A^k and L^k about of criteria and alternatives (bids). ***Output:*** The weight vector of criteria $W = \{w_1, w_2, \dots, w_n\}$ with the established consensus level γ. The performances of alternatives are $A = \{A_1, A_2, \dots, A_N\}$ against the criteria with the established consensus level γ. The rank of alternatives is $A = \{A_1, A_2, \dots, A_N\}$.

Step 1: Unification process.

In this paper, the unification of the data is performed in the fuzzy preference relations by using an adequate transformation function to construct the fuzzy preference matrix $P^k = \left(p_{ij}^{k}\right)_{n\times n}$.

(i) Consolidation of the decision-makers d_k heterogeneous preference information into the fuzzy preference relation

$$p_{ij}^{k} = \left\{\begin{array}{ll} p_{ij}^{k}\left(o^k(i), o^k(j)\right) = \frac{1}{2}\left(1 + \frac{o^k(j) - o^k(i)}{n-1}\right), \dots & d_k \in O^k \\ p_{ij}^{k}\left(u_i^k, u_j^k\right) = \frac{\left(u_i^k\right)^2}{\left(u_i^k\right)^2 + \left(u_j^k\right)^2}, \dots\dots & d_k \in U^k \\ p_{ij}^{k} = p_{ij}^{k}, \dots\dots & d_k \in P^k \\ p_{ij}^{k}\left(a_{ij}^{k}\right) = \frac{1}{2}\left(1 + \log_9 a_{ij}^{k}\right), \dots\dots & d_k \in A^k \\ p_{ij}^{k}\left(l_{ij}^{k}\right) = \frac{1}{2} + \frac{\Delta\left(l_{ij}^{k}\right)}{2\tau}, \dots\dots & d_k \in L^k \end{array}\right\} \tag{1}$$

(ii) Create the decision-makers d_k individual fuzzy preference matrix $P^k = \left(p_{ij}^{k}\right)_{n\times n}$.

Step 2: Consistency process.

The mathematical formulation of this additive transitivity was given by Tanino (1984). The additive preference relation $P = \left(p_{ij}\right)_{n\times n}$ is additive consistent if and only if the following additive transitivity is satisfied:

$$(p_{ij} - 0.5) + (p_{jl} - 0.5) = (p_{il} - 0.5), \forall i,j,l \in \{1,\dots,n\} \quad (2)$$

Because additive transitivity implies additive reciprocity ($p_{il} + p_{li} = 1, \forall_{i,j}$), it can be rewritten as:

$$p_{il} = p_{ij} + p_{jl} - 0.5, \text{ for } \forall i,j,l \in \{1,\dots,n\} \quad (3)$$

The steps of the consistency process are follows.

(i) Calculate the consistency index CI^k of the decision-maker d_k. We use a method for calculating the consistency index that satisfies additive consistency, Li *et al*. (2019), i.e.,

$$CI^k = 1 - \frac{2}{3n(n-1)(n-2)} \sum_{i,j,l=1; i \neq j \neq l}^{n} \left| p_{ij} + p_{jl} - p_{il} - 0.5 \right| \quad (4)$$

Clearly stand that $CI^k \in [0,1]$. When $CI^k = 1$, the additive preference relation $P^{(k)}$ is fully consistent; otherwise, the lower CI^k the more inconsistent is $P^{(k)}$.

(ii) System of consistency control and advice. If $CI^k < \alpha$, then activate consistency advice system, Chiclana *et al.* (2008). If a decision-maker is not consistent enough, that decision-maker will receive appropriate recommendations on the changes to his/her preference values to increase his/her global consistency to an acceptable/agreed threshold α level one. If all decision-makers are consistent, i.e., $CI^k \geq \alpha$, then the consensus-reaching process is applied.

(iii) Construct the consistency matrix $P^k = \left(p_{ij}^k\right)_{n \times n}$ for the decision-maker d_k.

Step 3: Consensus process.

The consensus control process is used to decide when the feedback mechanism should be applied to advise the decision-makers or when the consensus-reaching process has to come to an end. Consensus measures will be defined at the three different levels of a preference relation: the pairs of options, the options, and the whole set of options (see Taghavi *et al*. (2017)). The steps of this consensus model are given as follows.

(i) Calculate similarity degrees. Calculate the similarity degree between decision-makers d_k and d_h $(k < h)$ on the pair of options (x_i, x_j), and construct the similarity (agreement) matrix $SM_{ij}^{(kh)} = \left(sm_{ij}^{(kh)}\right)_{n \times n}$. The agreement matrix can be constructed as follows:

$$sm_{ij}^{(kh)} = 1 - \left|p_{ij}^k - p_{ij}^h\right| \text{ where } k = 1,\dots,m-1 \text{ and } h = k+1,\dots,m. \quad (5)$$

The $sm_{ij}^{(kh)} \in [0,1]$ is a similarity degree between decision-makers d_k and d_h in their preference values p_{ij}^k and p_{ij}^h. Obviously, $sm_{ij}^{(kh)}$ have the following properties:

1) $sm_{ij}^{(kh)} = sm_{ij}^{(hk)}$;
2) $sm_{ij}^{(kh)} = 1$ If and only if $p_{ij}^k = p_{ij}^h$, i.e., p_{ij}^k and p_{ij}^h is identical (completely similar);
3) $sm_{ij}^{(kh)} = 0$ If and only if p_{ij}^k and p_{ij}^h is completely dissimilar.

(ii) Calculate the average similarity degree of agreement for each decision-maker. Once we obtain the similarity matrix, we compute the average similarity degree of agreement for the decision-maker d_k with the rest of the group of decision-makers at the following three different levels:

Level 1. The average degree of similarity between options. The similarity degree of a decision-maker d_k on the pair of options (x_i, x_j) to the rest of the decision-makers in the group is calculated as:

$$SPA_{ij}^{(k)} = \frac{1}{m-1} \sum_{k=1,k \neq h}^{m} SM_{ij}^{(kh)}; \tag{6}$$

Level 2. The average degree of similarity on option. The similarity degree of a decision-maker d_k on an optionx_i to the rest of the decision-makers in the group is calculated as:

$$SA_i^{(k)} = \frac{1}{n-1} \sum_{j=1,j \neq i}^{n} SPA_{ij}^{(k)}; \tag{7}$$

Level 3. The average degree of similarity on the preference relation. The similarity degree of a decision-maker d_k on the whole set of options X to the rest of the decision-makers in the group is calculated as follows:

$$SD^{(k)} = \frac{1}{n} \sum_{i=1}^{n} SA_i^{(k)}. \tag{8}$$

(iii) Calculate the Relative Degree of Agreement for each decision-maker (A posterior expert's weight). After calculating the average degree of agreement for all decision-makers based on the similarity degrees computed above, could be calculated the relative similarity degree of the decision-maker (expert):

$$RSD^{(k)} = \frac{SD^{(k)}}{\sum_{k=1}^{K} SD^{(k)}}. \tag{9}$$

Obviously, these relative importance degrees could be different to the particular importance weights the decision-makers in the group are assigned before they provide their information on the set of options X.

Let $\lambda_{RSD}^k = RSD^{(k)}$ be a posterior the weight of the decision-maker d_k, and $\sum_{k=1}^{m} \lambda_{RSD}^k = 1$.

(iv) Calculate the experts' weight vector.

Let $\lambda_{ID} = \{\lambda_{ID}^1, \lambda_{ID}^2, \dots, \lambda_{ID}^m\}^T$ is a prior weight vector of decision-makers where $\lambda_{ID}^k \geq 0$, $(k = 1, \dots, m)$, and $\sum_{k=1}^{m} \lambda_{ID}^k = 1$.

An expert's weight vector is a linear combination of a prior weight (λ_{ID}^k) of the decision-maker d_k and a posterior the weight (λ_{RSD}^k) of the decision-maker d_k:

$$\lambda_k = \eta \cdot \lambda_{ID}^k + (1-\eta) \cdot \lambda_{RSD}^k, (k = 1, \dots, m), \eta \in [0,1]. \tag{10}$$

When $\eta = 0$, it means that the group of decision-makers is considered to be homogeneous. If $\eta > 0.5$, then the decision-maker's prior importance degree (λ_{ID}^k) values are higher than their posterior degrees (λ_{RSD}^k).

(v) Determine the collective fuzzy preference relationship. The collective fuzzy preference relationship is defined as:

$$p_{ij}^{(c)} = WA\left(p_{ij}^{(1)}, p_{ij}^{(2)}, \dots, p_{ij}^{(m)}\right) = \sum_{k=1}^{m} \lambda_k p_{ij}^{(k)}, \tag{11}$$

where $\lambda_k \in [0,1]$ is the weight of the decision-makers $d_k \in D$ and $\sum_{k=1}^{m} \lambda_k = 1$.

(vi) Determining the proximity degree.

Once the collective preference relation $P^{(c)}$ is obtained, we compute the proximity measures for each decision-maker at the three different levels of a relation:

Level 1. The proximity degree on pairs of options. The proximity degree of a decision-maker d_k to the group on the pair of options(x_i, x_j) is:

$$PPA_{ij}^{k} = 1 - \left|p_{ij}^{k} - p_{ij}^{c}\right|; \tag{12}$$

Level 2. The proximity degree on options. The proximity degree of a decision-maker d_k to the group on the option x_i is:

$$PA_{i}^{k} = \frac{1}{n-1}\sum_{j=1, j\neq i}^{n} PPA_{ij}^{k}; \tag{13}$$

Level 3. Proximity degree on the preference relation. The proximity degree of a decision-maker d_k to the group on the set of options X is:

$$PD^{k} = \frac{1}{n}\sum_{i=1}^{n} PA_{i}^{k}. \tag{14}$$

(vii) Calculate the consensus levels.

Consensus levels (CL) are defined as a linear combination of similarity degree with proximity degree, and all would be defined at the three different levels of a preference relation: the pairs of options, the options, and the whole set of options.

Level 1. Consensus level on the pairs of options (CLPA). The consensus level of a decision-maker d_k on the pair of options (x_i, x_j) is:

$$CLPA_{ij}^{k} = \psi \cdot SPA_{ij}^{k} + (1-\psi) \cdot PPA_{ij}^{k}; \tag{15}$$

Level 2. Consensus level on the options (CLA). The consensus level of a decision-maker d_k on the option x_i is:

$$CLA_{i}^{k} = \psi \cdot SA_{i}^{k} + (1-\psi) \cdot PA_{i}^{k}; \tag{16}$$

Level 3. Consensus level on the relation (CL). The consensus level (CL) of a decision-maker d_k on the set of options X is:

$$CL^{k} = \psi \cdot SD^{k} + (1-\psi) \cdot PD^{k}. \tag{17}$$

With $\psi \in [0,1]$ a parameter to control the weights of both similarity and proximity criteria. Unless there are specific reasons to prefer one index to the other one, the value to be assumed for the weighting parameter ψ should be 0.5.

(viii) Control the consensus level.

If the consensus degrees are greater than or equal to a predefined threshold $\gamma \in [0,1]$, then the collective preference relation is considered consensus. Otherwise, the decision-makers with a consensus degree below the threshold are asked to reevaluate their preferences until the consensus degree reaches the acceptable level or up to a specified number of negotiation rounds $z_{\max}$. A feedback mechanism is used to achieve this. It is important to note that the effectiveness of the feedback mechanism is affected by the value of the group consensus threshold used to identify inconsistent experts. However, group consensus thresholds are different for different decision-making scenarios, and in practice, the consensus threshold may be different for different situations, as explained by Sun *et al*. (2021). In this paper, we assumed that $\gamma = 0.85$.

(ix) Feedback mechanism.

If $CL^k < \gamma$, then activate the feedback mechanism and let the next round ($z = z + 1$) begin. The feedback mechanism generates personalized recommendation rules, which will not only tell the conflicting experts which preference values they should change but also provide them with consensus advice to revisit their evaluation in light of this extra information. It consists of two steps: firstly, the identification of the preference values that should be changed; and secondly, the generation of advice on the direction-value of the required change.

(1) To identify the preferential values to be changed, first, it is necessary to identify the decision-makers with consensus levels below the threshold value. For the identified decision-makers, the options below the consensus level are identified. If necessary, we identify the fuzzy preference values that need to be changed for the decision-makers and their identified options. Mathematically, these steps are modeled as follows:

Step 1. The set of decision-makers with consensus levels below the threshold value γ is identified:

$$ECH = \{k|CL^k < \gamma\}; \tag{18}$$

Step 2. For the decision-makers identified in step 1, those options with a consensus level below γ are identified:

$$ACH = \{(k,i)|k \in ECH \wedge CLA_i^k < \gamma\}; \tag{19}$$

Step 3. Finally, the fuzzy preference values for the decision-makers and options identified in steps 1 and 2 that need to be changed are identified:

$$PACH = \{(k,i,j)|(k,i) \in ACH \wedge CLPA_{ij}^k < \gamma\}. \tag{20}$$

(2) The generation of advice aims at giving adjustment suggestions to help the decision-makers improve the consensus level. A lot of feedback adjustment methods have been proposed by Dong & Zhang (2014) and Tang et al. (2021). The feedback adjustment rules are composed of three key components: (i) calculate the standardized collective preference vector $w_i^{c*}$for the optionx_i, (ii) converting the standardized collective preference vector w_i^{c*}into the type of preference data expressed by each individual, (iii) the individuals adjust to their preferences based on the original preference information and transformed preference information. With the consideration of the heterogeneous preference structures, the detailed feedback adjustment rules are introduced as follows.

Let the original preference information O^k, U^k, P^k, A^k and L^k about the option x_i.Let the collective preference information P^con the option x_i. The collective preference vector w_i^con the option x_i is calculated by:

$$w_i^c = \frac{1}{n}(p_{i1}^c + p_{i2}^c + \cdots + p_{in}^c),\ i = 1, \ldots, n. \tag{21}$$

Normalizing $w^c = (w_1^c, w_2^c, \ldots, w_n^c)^T$yields the standardized collective preference vector $w^{c*} = (w_1^{c*}, w_2^{c*}, \ldots, w_n^{c*})^T$ where

$$w_i^{c*} = \frac{w_i^c}{\sum w_i^c}. \tag{22}$$

Case 1:$d_k \in D^O$. In this case, the collective preference vector is transformed into a preference ordering $O^{c,k} = \left(o_1^{c,k}, o_2^{c,k}, \ldots, o_n^{c,k}\right)^T$. If w_i^{c*} is the t-th most significant in $\{w_1^{c*}, w_2^{c*}, \ldots, w_n^{c*}\}$, then

$$o_i^{c,k} = t. \tag{23}$$

Let $O^k = (o_1^k, o_2^k, \ldots, o_n^k)^T$ be as earlier. Let $\overline{O^k} = \left(\overline{o_1^k}, \overline{o_2^k}, \ldots, \overline{o_n^k}\right)^T$ be the adjusted preference order provided by the decision-maker d_k where $\overline{o_i^k} \in \left[\min\left(o_i^k, o_i^{c,k}\right), \max\left(o_i^k, o_i^{c,k}\right)\right]$.

Case 2:$d_k \in D^U$. In this case, the collective preference vector is transformed into a utility preference vector. Let $U^k = (u_1^k, u_2^k, \ldots, u_n^k)^T$ be as earlier. Let $U^{c,k} = \left(u_1^{c,k}, u_2^{c,k}, \ldots, u_n^{c,k}\right)^T$ be the transformed utility vector where

$$u_i^{c,k} = w_i^{c*} \sum_{i=1}^{n} u_i^k. \tag{24}$$

Let $\overline{U^k} = \left(\overline{u_1^k}, \overline{u_2^k}, \ldots, \overline{u_n^k}\right)^T$ be adjusted utility preference vector where $\overline{u_i^k} \in \left[\min\left(u_i^k, u_i^{c,k}\right), \max\left(u_i^k, u_i^{c,k}\right)\right]$.

Case 3: $d_k \in D^P$. In this case, the collective preference vector is transformed into an additive preference relation. Let $P^k = \left(p_{ij}^k\right)_{n\times n}$ be as earlier. Let $P^{c,k} = \left(p_{ij}^{c,k}\right)_{n\times n}$ be a transformed additive preference relation where

$$p_{ij}^{c,5} = \frac{w_i^{c*}}{w_i^{c*} + w_j^{c*}}. \tag{25}$$

Let $\overline{P^k} = \left(\overline{p_{ij}^k}\right)_{n\times n}$ be the adjusted fuzzy (additive) preference relation where

$$\overline{p_{ij}^k} = \begin{cases} \overline{p_{ij}^k} \in \left[\min\left(p_{ij}^k, p_{ij}^{c,k}\right), \max\left(p_{ij}^k, p_{ij}^{c,k}\right)\right], & i < j \\ \overline{p_{ij}^k} = 0.5, & i = j \\ \overline{p_{ij}^k} = 1 - \overline{p_{ji}^k}, & i > j \end{cases}. \tag{26}$$

Case 4: $d_k \in D^A$. In this case, the collective preference vector is transformed into a multiplicative preference relation. Let $A^k = \left(a_{ij}^k\right)_{n\times n}$ be as earlier. Let $A^c = \left(a_{ij}^{c,k}\right)_{n\times n}$ be a transformed multiplicative preference relation where

$$a_{ij}^{c,k} = \frac{w_i^{c*}}{w_j^{c*}} \tag{27}$$

Let $\overline{A^k} = \left(\overline{a_{ij}^k}\right)_{n\times n}$ be the adjusted multiplicative preference relation where

$$\overline{a_{ij}^k} = \begin{cases} \overline{a_{ij}^k} \in \left[\min\left(a_{ij}^k, a_{ij}^{c,k}\right), \max\left(a_{ij}^k, a_{ij}^{c,k}\right)\right], & i < j \\ \overline{a_{ij}^k} = 1, & i = j \\ \overline{a_{ij}^k} = \dfrac{1}{\overline{a_{ji}^k}}, & i > j \end{cases} \tag{28}$$

Case 5: $d_k \in D^L$. In this case, the collective preference vector is transformed into a linguistic preference relation. Let $L^{c,k} = \left(l_{ij}^{c,k}\right)_{n\times n}$ be the transformed linguistic preference relation. According to the 2-tuple linguistic representation model, we obtain the values $\Delta^{-1}\left(l_{ij}^{c,k}\right)$ as follows:

$$\Delta^{-1}\left(l_{ij}^{c,k}\right) = 2\tau \frac{w_i^{c*}}{w_i^{c*} + w_j^{c*}} - \tau. \tag{29}$$

Then, we encode the values of $\Delta^{-1}\left(l_{ij}^{c,k}\right)$ into $l_{ij}^{c,k}$ as follows:

$$l_{ij}^{c,k} = \Delta\left(\Delta^{-1}\left(l_{ij}^{c,k}\right)\right) = \left(l_{ij}^{c,k}, \alpha_{ij}^{c,k}\right). \tag{30}$$

Furthermore, let $\overline{L^k} = \left(\overline{l_{ij}^k}\right)_{n\times n}$ be the adjusted linguistic preference relation where

$$\overline{l_{ij}^k} = \begin{cases} \overline{l_{ij}^k} \in \left[\min\left(l_{ij}^k, l_{ij}^{c,k}\right), \max\left(l_{ij}^k, l_{ij}^{c,k}\right)\right], & i < j \\ \overline{l_{ij}^k} = s_0, & i = j \\ \overline{l_{ij}^k} = \Delta\left(\tau - \Delta^{-1}\left(\overline{l_{ji}^k}\right)\right), & i > j \end{cases} \tag{31}$$

Step 4: Selection process.

The selection process consists, involves two different phases, Herrera-Viedma*et al*. (2002): aggregation of individual preferences and exploitation of collective preferences.

(i) Phase of aggregation. This phase defines a collective preference relation $P^c = \left(p_{ij}^c\right)$, obtained using the aggregation of all individual fuzzy preference relations $\{P^1, P^2, \dots, P^m\}$, and indicates the global preference between every pair of options according to the majority of DM opinions as follows:

$$p_{ij}^{(c)} = WA\left(p_{ij}^{(1)}, p_{ij}^{(2)}, \dots, p_{ij}^{(m)}\right) = \sum_{k=1}^{m} \lambda_k p_{ij}^{(k)}\ , \tag{32}$$

where $\lambda_k \in [0,1]$ is the weight of the decision-makers $d_k \in D$ and $\sum_{k=1}^{m} \lambda_k = 1$.

(ii) Exploitation phase. In this phase, from the collective matrix $p_{ij}^{(c)}$ the final values of the considered options are obtained by using the expression Xu (2001):

$$v_i = \frac{1}{n(n-1)}\left(\sum_{j=1}^{n} p_{ij} + \frac{n}{2} - 1\right), i = 1, \dots, n. \tag{33}$$

Step 5: MCDM process.

In this process, alternative bids are ranked using the MCDM method specified in the tender documentation. In general, MCDM methods in essence, involve two key procedures: normalization and aggregation. In this paper, we used the Simple Additive Weighting (SAW) method, which is usually used to evaluate bids in public procurement procedures.

(i) Normalization procedure. The vector normalization procedure implies that all criteria (attributes) have the same unit length of the vector. This procedure divides the performance ratings of each criterion (attribute) in the decision matrix by its norm. The SAW method uses the normalization procedure of linear scale transformation (max). The normalized performance ratings r_{ij} of x_{ij} in the decision matrix are calculated as

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{x_j^{max} \text{if is a benefit criteria}} \\ \dfrac{x_j^{min}}{x_{ij} \text{ if is a cost criteria}} \end{cases} \tag{34}$$

(ii) Aggregation procedure.

The basic logic of the SAW method is to obtain a weighted sum of the performance ratings of each alternative overall criteria (attributes). With a normalized decision matrix r_{ij} and a weight vector w_j, the overall preference value of each alternative V_i is obtained by

$$V_i = \sum_{j=1}^{m} r_{ij} w_j, i = 1, \dots, n. \tag{35}$$

The greater the value V_i, the more preferred the alternative A_i.

4. NUMERICAL EXAMPLE

In this section, a numerical example of bidder selection is considered to illustrate the proposed method.

4.1 Form a committee of decision-makers

The public contracting authority formed a commission for the implementation of the tender for the procurement of laboratory equipment at the University of Defense. Professional assistance for the evaluation of criteria and alternative bids is provided by a group of experts with m=5 members, $D = \{d_1, d_2, \dots, d_5\}$. The weights of the experts are given by $\lambda_{ID} = \{0.2,\ 0.2,\ 0.2,\ 0.2,\ 0.2\}$.

4.2 Selection set of criteria and weights assignment

The public contracting authority defined that the tender procedure is conducted based on the MEAT approach, that is, based on price and quality where the price criterion C1 (purchase price, import taxes, transport, and assembly costs) is assigned 40 weightings, and the quality criterion 60 weightings. The Public Procurement Commission has chosen n=4 qualitative sub-criteria (attributes): C2 - warranty period, C3 - functional, ergonomic, and aesthetic characteristics, C4 - service (post-warranty maintenance - servicing, technical assistance, training), C5 - delivery time thus), Figure 3.

The selection of criteria was made in accordance with the long-term operational practice in the Republic of Serbia, which is in accordance with scientific research in the subject area, which can be seen in more detail in Dickson (1966), Ellram (1990), Weber *et al*. (1991), Ho *et al*. (2010), Mukherjee (2016), Cheshmberah (2020), as well as by the proposed criteria given in the Law on Public Procurement in the Republic of Serbia.

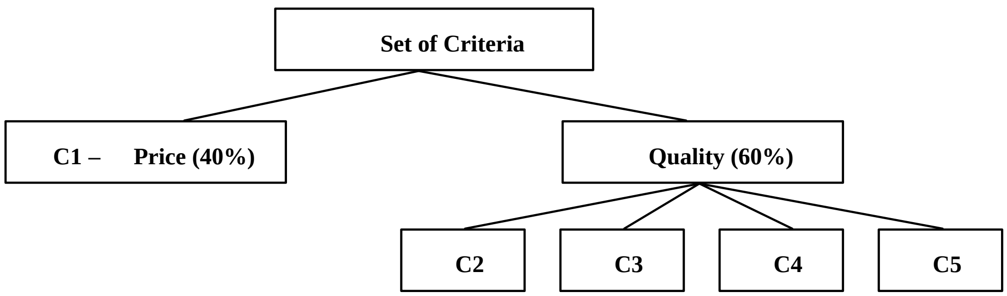

Figure 3. Structure of the criteria and sub-criteria (attributes)

The first task is to determine the weight of the qualitative sub-criteria $C = \{c_2, c_3, c_4, c_5\}$, i.e., the number of criteria is n = 4. The number of decision-makers (experts) is m = 5, $D = \{d_1, d_2, \dots, d_5\}$. The initial vector of expert weighting coefficients is $\lambda_{ID} = \{0.2,\ 0.2,\ 0.2,\ 0.2,\ 0.2\}$. The consistency threshold is $\alpha = 0.9$. The consensus threshold $\gamma = 0.85$. Maximum number of iterations $z_{\max} = 5$.

Decision-makers (experts) approached the evaluation with qualitative sub-criteria, using different information structures to express their preferences, according to the following:

The decision-maker d_1 uses the preference ordering $O^{(1)}$ to express preference information on C, i.e.,

$$O^{(1)} = (1,\quad 2,\quad 3,\quad 4).$$

The decision-maker d_2 uses the utility function $U^{(2)}$ to express preference information on C, i.e.,

$$U^{(2)} = (0.08,\quad 0.60,\quad 0.70,\quad 0.55).$$

The decision-maker d_3 uses the additive (fuzzy) preference relation $P^{(3)}$ to express preference information on C, i.e.,

$$P^{(3)} = \begin{bmatrix} 0.50 & 0.60 & 0.80 & 0.90 \\ 0.40 & 0.50 & 0.70 & 0.80 \\ 0.20 & 0.30 & 0.50 & 0.60 \\ 0.10 & 0.20 & 0.40 & 0.50 \end{bmatrix}.$$

The decision-maker d_4 uses the multiplicative preference relation $A^{(4)}$ to express preference information on C, i.e.,

$$A^{(4)} = \begin{bmatrix} 1 & 3 & 5 & 7 \\ 1/3 & 1 & 2 & 4 \\ 1/5 & 1/2 & 1 & 2 \\ 1/7 & 1/4 & 1/2 & 1 \end{bmatrix}$$

The decision-maker d_5 uses linguistic preference relations $L^{(5)}$ to express preference information on C. Here, the term set used by the decision-maker is granularity $\tau = 3$, i.e., $S = \{s_{-3}, s_{-2}, s_{-1}, s_0, s_1, s_2, s_3\}$. Then, $L^{(5)}$ is given as follows:

$$L^{(5)} = \begin{bmatrix} s_0 & s_2 & s_1 & s_3 \\ s_{-2} & s_0 & s_{-1} & s_2 \\ s_{-1} & s_1 & s_0 & s_3 \\ s_{-3} & s_{-2} & s_{-3} & s_0 \end{bmatrix}$$

Step 1: Unification process.

Based on Formula (1), the unification data is entered into the fuzzy preference relation and constructed into the individual fuzzy preference matrix, i.e.,

$$P^{(1)} = \begin{bmatrix} 0.5000 & 0.6667 & 0.8333 & 1.0000 \\ 0.3333 & 0.5000 & 0.6667 & 0.8333 \\ 0.1667 & 0.3333 & 0.5000 & 0.6667 \\ 0.0000 & 0.1667 & 0.3333 & 0.5000 \end{bmatrix}$$

$$P^{(2)} = \begin{bmatrix} 0.5000 & 0.6400 & 0.5664 & 0.6790 \\ 0.3600 & 0.5000 & 0.4235 & 0.5434 \\ 0.4336 & 0.5765 & 0.5000 & 0.6183 \\ 0.3210 & 0.4566 & 0.3817 & 0.5000 \end{bmatrix}$$

$$P^{(3)} = \begin{bmatrix} 0.5000 & 0.6000 & 0.8000 & 0.9000 \\ 0.4000 & 0.5000 & 0.7000 & 0.8000 \\ 0.2000 & 0.3000 & 0.5000 & 0.6000 \\ 0.1000 & 0.2000 & 0.4000 & 0.5000 \end{bmatrix}$$

$$P^{(4)} = \begin{bmatrix} 0.5000 & 0.7500 & 0.8662 & 0.9428 \\ 0.2500 & 0.5000 & 0.6577 & 0.8155 \\ 0.1338 & 0.3423 & 0.5000 & 0.6577 \\ 0.0572 & 0.1845 & 0.3423 & 0.5000 \end{bmatrix}$$

$$P^{(5)} = \begin{bmatrix} 0.5000 & 0.8333 & 0.6667 & 1.0000 \\ 0.1667 & 0.5000 & 0.3333 & 0.8333 \\ 0.3333 & 0.6667 & 0.5000 & 1.0000 \\ 0.0000 & 0.1667 & 0.0000 & 0.5000 \end{bmatrix}$$

Step 2: Consistency process.

Using Eq. (4), we calculate the consistency index CI^k for each decision-maker d_k, which amounts to $CI^k = \{1.0 \quad 0.9976 \quad 1.0 \quad 0.9591 \quad 0.9444\}$. All matrices are consistent due to a consistency index greater than 0.90.

Step 3:Consensus-building procedure.

The implementation of the consensus process deals with a consensus measure and feedback adjustment.

1) Computing Consensus Measures

Based on Eq. (5), Eq. (6), Eq. (7), and Eq. (8), we calculate the similarity degrees $SD^k = \{0.8859 \quad 0.7984 \quad 0.8741 \quad 0.8822 \quad 0.8055\}$.

Using Eq. (9), we calculate a posterior experts' weight vector based on the Relative Degree of Agreement for each expert $\lambda_{RSD}^k = \{0.2086 \quad 0.1880 \quad 0.2059 \quad 0.2078 \quad 0.1897\}$.

Using Eq. (10), we calculate the experts' weight vector as a linear combination of a prior weight (λ_{ID}^k) of expert d_k and a posterior the weight(λ_{RSD}^k) of expert d_k where $\eta = 0.5$, is $\lambda_k = \{0.2043 \quad 0.1940 \quad 0.2029 \quad 0.2039 \quad 0.1949\}$.

Using Eq. (11), we calculate the collective fuzzy preference matrix:

$$P^{(c)} = \begin{bmatrix} 0.5000 & 0.6974 & 0.7490 & 0.9058 \\ 0.3026 & 0.5000 & 0.5595 & 0.7667 \\ 0.2510 & 0.4405 & 0.5000 & 0.7069 \\ 0.0942 & 0.2333 & 0.2931 & 0.5000 \end{bmatrix}$$

Based on Eq. (12), Eq. (13), and Eq. (14), we calculate the proximity degree PD^k,

$$PD^k = \{0.9294 \quad 0.8476 \quad 0.9275 \quad 0.9328 \quad 0.8503\}.$$

2) Managing the Consensus State

In this paper, we took the consensus threshold to be $\gamma = 0.85$. Based on Eq. (15), Eq. (16), and Eq. (17), we calculate the consensus level. The value of the weighting parameter $\psi$is 0.5. The consensus level is:

$$CL^k = \{0.9077 \quad 0.8230 \quad 0.9008 \quad 0.9075 \quad 0.8279\}.$$

If $CL^k < \gamma$, then activate the feedback mechanism and let the next round ($z = z + 1$).

Given that decision-makers d_2 and d_5 do not meet the defined consensus threshold, the feedback mechanism is activated.

3) Mechanism of Feedback

Based on Eq. (18), Eq. (19), and Eq. (20), the proposed feedback adjustment rules are used to improve consensus levels among decision-makers. Decision-makers d_2 and d_5 are advised to change their preferences according to the following.

Firstly, based on Eq. (21), calculate the collective preference vector w^c:

$$w^c = (0.7131, 0.5322, 0.4746, \ 0.2802)^T.$$

Then, according to Eq. (22), $w^c$is transformed into the standardized collective preference vector, i.e.w^{c*}:

$$w^{c*} = (0.3565, 0.2661, 0.2373, 0.1401)^T.$$

Since $d_2 \in D^U$, using Eq. (24) transforms w^{c*} into the preference information described by the utility function associated with d_2. Then is $U^{c,2} = (0.9448, 0.7051, 0.6288, 0.3712)^T$.

Let $SUG^{(k)} = \left(sug_1^k, sug_2^k, \ldots, sug_4^k\right)^T$ $(k = 2)$ denote the adjusted suggestion for the decision-maker d_2 where $sug_i^{(k)} = \left[\min\left(u_i^k, u_i^{c,k}\right), \max\left(u_i^k, u_i^{c,k}\right)\right]$. $SUG^{(2)}$ is as

$$SUG^{(2)} = (|0.80, 0.9448|, |0.60, 0.7051|, |0.6288, 0.70|, |0.3712, 0.55|).$$

When constructing $\overline{U^k} = \left(\overline{u_1^k}, \overline{u_2^k}, \ldots, \overline{u_n^k}\right)^T$ $(k = 2)$, we suggest that $\overline{u^k} \in sug_{i^{(k)}}$.

Without loss of generality, the adjusted utility function is $\overline{U^{(2)}} = (0.85 \quad 0.60 \quad 0.70 \quad 0.50)$.

Since $d_5 \in D^L$, using Eq. (29) transforms w^{c*}into the preference information described by the linguistic preference relations, associated with d_5. Then is

$$L^{(c,5)} = \begin{bmatrix} (s_0,0.00) & (s_1,0.44) & (s_2,-0.40) & (s_1,0.30) \\ (s_2,-0.44) & (s_0,0.00) & (s_1,0.17) & (s_1,-0.07) \\ (s_1,0.40) & (s_2,-0.17) & (s_0,0.00) & (s_1,-0.23) \\ (s_2,-0.30) & (s_2,0.07) & (s_2,0.23) & (s_0,0.00) \end{bmatrix}$$

Let $SUG^{(k)} = \left(sug_1^k, sug_2^k, \ldots, sug_4^k\right)^T$ $(k = 5)$ denote the adjusted suggestion for the decision-maker d_5 where $sug_i^{(k)} = \left[\min\left(l_{ij}^k, l_{ij}^{c,k}\right), \max\left(l_{ij}^k, l_{ij}^{c,k}\right)\right]$. $SUG^{(5)}$ is as follows:

$$SUG^{(5)} = \begin{bmatrix} |(s_0,0.00),(s_0,0.00)| & |(s_1,0.44)(s_2,0.00)| & |(s_1,0.00),(s_2,-0.40)| & |(s_1,0.30),(s_3,0.00)| \\ |(s_{-2},0.00),(s_2,-0.44)| & |(s_0,0.00),(s_0,0.00)| & |(s_{-1},0.00),(s_1,0.17)| & |(s_1,-0.07),(s_2,0.00)| \\ |(s_{-1},0.00),(s_1,0.40)| & |(s_2,-0.17),(s_1,0.00)| & |(s_0,0.00),(s_0,0.00)| & |(s_1,-0.23),(s_3,0.00)| \\ |(s_{-3},-0.00),(s_2,-0.30)| & |(s_{-2},0.00),(s_2,0.07)| & |(s_{-3},0.00),(s_2,0.23)| & |(s_0,0.00),(s_0,0.00)| \end{bmatrix}$$

When constructing $\overline{L^k} = \left(\overline{l_1^k}, \overline{l_2^k}, \ldots, \overline{l_n^k}\right)^T$ $(k = 2)$, we suggest that $\overline{l^k} \in sug_{i^{(k)}}$.

Without loss of generality, the adjusted linguistic preference relations are

$$\overline{L^{(5)}} = \begin{bmatrix} (s_0,0.00) & (s_1,0.50) & (s_1,0.00) & (s_2,0.50) \\ (s_{-2},0.50) & (s_0,0.00) & (s_0,0.00) & (s_1,0.50) \\ (s_{-1},0.00) & (s_0,0.00) & (s_0,0.00) & (s_2,0.00) \\ (s_{-3},0.50) & (s_{-2},0.50) & (s_{-2},0.00) & (s_0,0.00) \end{bmatrix}$$

Finally, the consensus level is

$$\overline{CL^k} = \{0.9221 \quad 0.8648 \quad 0.9179 \quad 0.9231 \quad 0.9052\}.$$

Thus, an acceptable consensus has been reached, i.e.,

$$\overline{CL^k} > 0.85.$$

Step 4: Selection process.

In the Aggregation phase, the collective preference relation is calculated by Eq. (32):

$$P^{(c)} = \begin{bmatrix} 0.5000 & 0.6869 & 0.7537 & 0.9015 \\ 0.3131 & 0.5000 & 0.5909 & 0.7589 \\ 0.2463 & 0.4091 & 0.5000 & 0.6838 \\ 0.0985 & 0.2411 & 0.3162 & 0.5000 \end{bmatrix}$$

Next, in the Exploitation phase, we obtain the collective preference vectors by Eq (33), as $v_i = (0.3202 \quad 0.2636 \quad 0.2366 \quad 0.1797)$. Based on this value the final weights (ponders) for qualitative criteria are calculated as $w_j = v_i \cdot 60$.

The final distribution of weights by criteria is given in Table 1.

Table 1. Criteria, sub-criteria (attributes), and weights

Criteria (weights)	Sub-criteria (attributes) (weights)		Final weights (ponders)
Price (40%)	C1	Price in monetary units	40
Quality (60%)	C2	Warranty period	20
	C3	Aesthetics	15
	C4	Service	15
	C5	Delivery time	10

The final qualitative weights values are shown in table 1. It could be seen that the warranty period has the greatest value and, at the same time, the greatest importance for the customer. Aesthetic features and service support have the same and, at the same time, slightly less importance compared to the warranty period, while the delivery time has the least weight. This means, according to experts, that there is no rush in the actual procurement. It is important to emphasise that the weight coefficients were obtained by the consensus of experts. The weight values of the criteria may differ for the specific procurement item when the delivery time may have the highest value in the case of urgent procurement.

4.3 Formulating alternatives (bids)

At this stage, the public procurement commission first determines the timeliness and completeness of submitted bids. Six bids, A1, A2, A3, A4, A5, and A6, who met the conditions of the tender, responded to the tender. The commission separated the offered price, warranty period, and delivery time of the procurement item from the received bids and formed the initial decision matrix (Table 2).

Table 2. Initial decision matrix

Alternatives	Criteria				
	C1 [Price]	C2 [Warranty period]	C3 [Aesthetics]	C4 [Service]	C5 [Delivery time]
A1	13,601,596.00	60			45
A2	13,808,741.00	36			60
A3	12,991,000.00	48			45
A4	12,995,855.00	36			60
A5	13,051,374.00	48			45
A6	13,222,359.00	60			45
Type	min	max	max	max	min
wj (ponders)	40	20	15	15	10

4.4 Assessing the performance of alternative bids according to the criteria

In this phase, the subjective evaluation of alternative bids is carried out according to certain qualitative criteria. Given that alternative bids according to criteria C3 and C4 are evaluated subjectively, the public procurement commission hired a group of experts who approached the subjective evaluation of the bids according to the following:

Subjective evaluation of alternatives according to C3 criteria

The number of decision-makers (experts) is m = 5, $D = \{d_1, d_2, \dots, d_5\}$.
The number of alternative bids is N = 6, $A = \{A_1, A_2, A_3, A_4, A_5, A_6\}$.
The initial vector of expert weighting coefficients is $\lambda_{ID} = \{0.2,\ 0.2,\ 0.2,\ 0.2,\ 0.2\}$.
The consistency threshold is $\alpha = 0.9$.
The consensus threshold $\gamma = 0.85$.
Maximum number of iterations $z_{\max} = 5$.,
The initial input preferences are given as follow.
The decision-maker $d_1$uses the preference ordering $O^{(1)}$ to express preference information on A, i.e.,

$$O^{(1)} = (3,\quad 1,\quad 5,\quad 2,\quad 6,\quad 4).$$

The decision-maker $d_2$uses the utility function $U^{(2)}$ to express preference information on A, i.e.,

$$U^{(2)} = (0.75,\quad 0.90,\quad 0.60,\quad 0.50,\quad 0.45,\quad 0.40).$$

The decision-maker $d_3$uses the additive (fuzzy) preference relation $P^{(3)}$ to express preference information on A, i.e.,

$$P^{(3)} = \begin{bmatrix} 0.50 & 0.60 & 0.40 & 0.50 & 0.70 & 0.90 \\ 0.40 & 0.50 & 0.30 & 0.80 & 0.60 & 0.70 \\ 0.60 & 0.70 & 0.50 & 1.00 & 0.80 & 0.90 \\ 0.50 & 0.20 & 0.00 & 0.50 & 0.30 & 0.40 \\ 0.30 & 0.40 & 0.20 & 0.70 & 0.50 & 0.60 \\ 0.10 & 0.30 & 0.10 & 0.60 & 0.40 & 0.50 \end{bmatrix}$$

The decision-maker $d_4$uses the multiplicative preference relation $A^{(4)}$ to express preference information on A, i.e.,

$$A^{(4)} = \begin{bmatrix} 1 & 2 & 3 & 5 & 7 & 9 \\ 1/2 & 1 & 2 & 3 & 4 & 6 \\ 1/3 & 1/2 & 1 & 4 & 5 & 8 \\ 1/5 & 1/3 & 1/4 & 1 & 2 & 3 \\ 1/7 & 1/4 & 1/5 & 1/2 & 1 & 4 \\ 1/9 & 1/6 & 1/8 & 1/3 & 1/4 & 1 \end{bmatrix}$$

To express preference information A, the decision-maker d_5 employs linguistic preference relations $L^{(5)}$.Here, the term set used by the decision-maker is granularity $\tau = 4$, i.e., $S = \{s_{-4}, s_{-3}, s_{-2}, s_{-1}, s_0, s_1, s_2, s_3, s_4\}$. Then, $L^{(5)}$is given as follows:

$$L^{(5)} = \begin{bmatrix} s_0 & s_{-1} & s_{-2} & s_2 & s_1 & s_3 \\ s_1 & s_0 & s_1 & s_2 & s_2 & s_4 \\ s_2 & s_{-1} & s_0 & s_3 & s_1 & s_2 \\ s_{-2} & s_{-2} & s_{-3} & s_0 & s_{-1} & s_0 \\ s_{-1} & s_{-2} & s_{-1} & s_1 & s_0 & s_1 \\ s_{-3} & s_{-4} & s_{-2} & s_0 & s_{-1} & s_0 \end{bmatrix}$$

Step 1: Unification process

Based on Formulas (1), the unification of data is performed into the fuzzy preference relation and constructs the individual fuzzy preference matrix, i.e.,

$$P^{(1)} = \begin{bmatrix} 0.5000 & 0.3000 & 0.7000 & 0.4000 & 0.800 & 0.6000 \\ 0.7000 & 0.5000 & 0.9000 & 0.6000 & 1.0000 & 0.8000 \\ 0.3000 & 0.1000 & 0.5000 & 0.2000 & 0.6000 & 0.4000 \\ 0.6000 & 0.4000 & 0.8000 & 0.5000 & 0.9000 & 0.7000 \\ 0.2000 & 0.0000 & 0.4000 & 0.1000 & 0.5000 & 0.3000 \\ 0.4000 & 0.2000 & 0.6000 & 0.3000 & 0.7000 & 0.5000 \end{bmatrix}$$

$$P^{(2)} = \begin{bmatrix} 0.5000 & 0.4098 & 0.6098 & 0.6923 & 0.7353 & 0.7785 \\ 0.5902 & 0.5000 & 0.6923 & 0.7642 & 0.8000 & 0.8351 \\ 0.3902 & 0.3077 & 0.5000 & 0.5902 & 0.6400 & 0.6923 \\ 0.3077 & 0.2258 & 0.4098 & 0.5000 & 0.5525 & 0.6098 \\ 0.2647 & 0.2000 & 0.3600 & 0.4475 & 0.5000 & 0.5586 \\ 0.2215 & 0.1649 & 0.3077 & 0.3902 & 0.4414 & 0.5000 \end{bmatrix}$$

$$P^{(3)} = \begin{bmatrix} 0.5000 & 0.6000 & 0.4000 & 0.5000 & 0.7000 & 0.9000 \\ 0.4000 & 0.5000 & 0.3000 & 0.8000 & 0.6000 & 0.7000 \\ 0.6000 & 0.7000 & 0.5000 & 1.0000 & 0.8000 & 0.9000 \\ 0.5000 & 0.2000 & 0.0000 & 0.5000 & 0.3000 & 0.4000 \\ 0.3000 & 0.4000 & 0.2000 & 0.7000 & 0.5000 & 0.6000 \\ 0.1000 & 0.3000 & 0.1000 & 0.6000 & 0.4000 & 0.5000 \end{bmatrix}$$

$$P^{(4)} = \begin{bmatrix} 0.5000 & 0.6577 & 0.7500 & 0.8662 & 0.9428 & 1.0000 \\ 0.3423 & 0.5000 & 0.6577 & 0.7500 & 0.8155 & 0.9077 \\ 0.2500 & 0.3423 & 0.5000 & 0.8155 & 0.8662 & 0.9732 \\ 0.1338 & 0.2500 & 0.1845 & 0.5000 & 0.6577 & 0.7500 \\ 0.0572 & 0.1845 & 0.1338 & 0.3423 & 0.5000 & 0.8155 \\ 0.0000 & 0.0923 & 0.0268 & 0.2500 & 0.1845 & 0.5000 \end{bmatrix}$$

$$P^{(5)} = \begin{bmatrix} 0.5000 & 0.3750 & 0.2500 & 0.7500 & 0.6250 & 0.8750 \\ 0.6250 & 0.5000 & 0.6250 & 0.7500 & 0.7500 & 1.0000 \\ 0.7500 & 0.3750 & 0.5000 & 0.8750 & 0.6250 & 0.7500 \\ 0.2500 & 0.2500 & 0.1250 & 0.5000 & 0.3750 & 0.5000 \\ 0.3750 & 0.2500 & 0.3750 & 0.6250 & 0.5000 & 0.6250 \\ 0.1250 & 0.0000 & 0.2500 & 0.5000 & 0.3750 & 0.5000 \end{bmatrix}$$

Step 2: Consistency process.

Using Eq. (4), we calculate the consistency index CI^k for each decision-maker d_k, which amounts are $CI^k = \{1.0 \quad 0.9875 \quad 0.9333 \quad 0.9017 \quad 0.9167\}$. All matrices are consistent due to a consistency index greater than 0.90.

Step 3: Consensus-building procedure.

The implementation of the consensus process deals with a consensus measure and feedback adjustment.

1) Developing Consensus Measures

Based on Eq. (5), Eq. (6), Eq. (7), and Eq. (8), we calculate the similarity degrees $SD^k = \{0.7246 \quad 0.8403 \quad 0.7785 \quad 0.7883 \quad 0.8176\}$.

Using Eq. (9), we calculate a posterior expert's weight vector, based on the Relative Degree of Agreement for each expert

$$\lambda_{RSD}^{k} = \{0.1835 \quad 0.2128 \quad 0.1971 \quad 0.1996 \quad 0.2070\}.$$

Using Eq. (10), we calculate the experts' weight vector as a linear combination of a prior weight (λ_{ID}^{k}) of expert d_k and a posterior the weight (λ_{RSD}^{k}) of expert d_k where $\eta = 0.5$.

$$\lambda_k = \{0.1917 \quad 0.2064 \quad 0.1986 \quad 0.1998 \quad 0.2035\}.$$

Using Eq. (11), we calculate the collective fuzzy preference matrix

$$P^{(c)} = \begin{bmatrix} 0.5000 & 0.4690 & 0.5402 & 0.6446 & 0.7597 & 0.8323 \\ 0.5310 & 0.5000 & 0.6336 & 0.7341 & 0.7915 & 0.8496 \\ 0.4598 & 0.3664 & 0.5000 & 0.6997 & 0.7063 & 0.7454 \\ 0.3554 & 0.2659 & 0.3003 & 0.5000 & 0.5539 & 0.5911 \\ 0.2403 & 0.2085 & 0.2937 & 0.4461 & 0.5000 & 0.5821 \\ 0.1677 & 0.1504 & 0.2504 & 0.4089 & 0.4179 & 0.5000 \end{bmatrix}$$

Based on Eq. (12), Eq. (13), and Eq. (14), we calculate the proximity degree $PD^k = \{0.7871, \quad 0.9574, \quad 0.8470, \quad 0.8605, \quad 0.9028\}$.

2) Managing the Consensus State

In this paper, we took the consensus threshold to be $\gamma = 0.85$. Based on Eq. (15), Eq. (16), Eq. (17), we calculate the consensus level. The value of the weighting parameter ψ is 0.5. The consensus level is: $CL^k = \{0.7559, \quad 0.8988, \quad 0.8127, \quad 0.8244, \quad 0.8602\}$.

If $CL^k < \gamma$, then activate the feedback mechanism and let the next round $(z = z + 1)$begin.

Given that the decision-makers d1, d3, and d4 do not meet the defined consensus threshold, the feedback mechanism is activated.

3) Mechanism of Feedback

Based on Eq. (18), Eq. (19), and Eq. (20), the proposed feedback adjustment rules are used to improve consensus levels among decision-makers. Decision-makers d_1, d_3, and d_5 are advised to change their preferences according to the following:

Firstly, based on Eq. (21), calculate the collective preference vector w^c : $w^c = (0.6243 \quad 0.6733 \quad 0.5796 \quad 0.4278 \quad 0.3784 \quad 0.3166)^T$.

Then, according to Eq. (22), w^c is transformed into the standardized collective preference vector, i.e., w^{c*}: $w^{c*} = (0.2081 \quad 0.2244 \quad 0.1932 \quad 0.1426 \quad 0.1261 \quad 0.1055)^T$.

Since $d_1 \in D^O$, using Eq. (23) transforms w^{c*}into the preference information described by the preference orderings, associated with d_1. Then $O^{c,1} = (2 \quad 1 \quad 3 \quad 4 \quad 5 \quad 6)^T$.

Let $SUG^{(k)} = \left(sug_1^k, sug_2^k, \ldots, sug_4^k\right)^T$ $(k = 1)$ denote the adjusted suggestion for the decision-maker d_1 where $sug_i^{(k)} = \left[\min\left(o_i^k, o_i^{c,k}\right), \max\left(o_i^k, o_i^{c,k}\right)\right]$. $SUG^{(1)}$ is as follows:

$$SUG^{(1)} = (|2,3|, |1,1|, |3,5|, |2,4|, |5,6|, |4,6|)$$

When constructing $\overline{O^k} = \left(\overline{o_1^k}, \overline{o_2^k}, \ldots, \overline{o_n^k}\right)^T$ $(k = 1)$, we suggest that $\overline{o^k} \in sug_{i^{(k)}}$.

Without loss of generality, the adjusted preference orderings are $\overline{O^{(1)}} = (2, \quad 1, \quad 4, \quad 3, \quad 6, \quad 5)$.

Since $d_3 \in D^P$, using Eq. (25) transforms w^{c*}into the preference information described by the fuzzy preference relations, associated with d_3. Then is

$$P^{(c,3)} = \begin{bmatrix} 0.5000 & 0.4811 & 0.5186 & 0.5934 & 0.6226 & 0.6635 \\ 0.5189 & 0.5000 & 0.5374 & 0.6115 & 0.6402 & 0.6802 \\ 0.4814 & 0.4626 & 0.5000 & 0.5754 & 0.6050 & 0.6467 \\ 0.4066 & 0.3885 & 0.4246 & 0.5000 & 0.5306 & 0.5747 \\ 0.3774 & 0.3598 & 0.3950 & 0.4694 & 0.5000 & 0.5445 \\ 0.3365 & 0.3198 & 0.3533 & 0.4253 & 0.4555 & 0.5000 \end{bmatrix}.$$

Let $SUG^{(k)} = \left(sug_1^k, sug_2^k, \ldots, sug_4^k\right)^T$ $(k = 3)$ denote the adjusted suggestion for the decision-maker d_3 where $sug_i^{(k)} = \left[\min\left(p_{ij}^k, p_{ij}^{c,k}\right), \max\left(p_{ij}^k, p_{ij}^{c,k}\right)\right]$. Based on Eq. (26), $SUG^{(3)}$ is as follows:

$$SUG^{(3)} = \begin{bmatrix} |0.5000,0.5000| & |0.4811,0.6000| & |0.4000,0.5186| & |0.5000,0.5934| & |0.6226,0.7000| & |0.6635,0.9000| \\ |0.4000,0.5189| & |0.5000,0.5000| & |0.3000,0.5374| & |0.6115,0.8000| & |0.6000,0.6402| & |0.6802,0.7000| \\ |0.4814,0.6000| & |0.4626,0.7000| & |0.5000,0.5000| & |0.5754,1.0000| & |0.6050,0.8000| & |0.6467,0.9000| \\ |0.4066,0.5000| & |0.2000,0.3885| & |0.0000,0.4246| & |0.5000,0.5000| & |0.3000,0.5306| & |0.4000,0.5747| \\ |0.3000,0.3774| & |0.3598,0.4000| & |0.2000,0.3950| & |0.4694,0.7000| & |0.5000,0.5000| & |0.5445,0.6000| \\ |0.1000,0.3365| & |0.3000,0.3198| & |0.1000,0.3533| & |0.4253,0.6000| & |0.4000,0.4555| & |0.5000,0.5000| \end{bmatrix}$$

When constructing $\overline{P^k} = \left(\overline{p_1^k}, \overline{p_2^k}, \ldots, \overline{p_n^k}\right)^T$ $(k = 3)$, we suggest that $\overline{p^k} \in sug_{i^{(k)}}$.

Without loss of generality, the adjusted fuzzy preference relations are

$$\overline{P^{(3)}} = \begin{bmatrix} 0.5000 & 0.5500 & 0.4500 & 0.5500 & 0.7000 & 0.9000 \\ 0.4500 & 0.5000 & 0.4500 & 0.8000 & 0.6000 & 0.7000 \\ 0.5500 & 0.5500 & 0.5000 & 0.8000 & 0.7000 & 0.8000 \\ 0.4500 & 0.2000 & 0.2000 & 0.5000 & 0.4500 & 0.5000 \\ 0.3000 & 0.4000 & 0.3000 & 0.5500 & 0.5000 & 0.6000 \\ 0.1000 & 0.3000 & 0.2000 & 0.5000 & 0.4000 & 0.5000 \end{bmatrix}$$

Since $d_4 \in D^A$, using Eq. (27) transforms w^{c*} into the preference information described by the multiplicative preference relations, associated with d_4. Then is

$$P^{(c,3)} = \begin{bmatrix} 1.0000 & 0.9272 & 1.0771 & 1.4594 & 1.6496 & 1.9719 \\ 1.0785 & 1.0000 & 1.1617 & 1.5740 & 1.7792 & 2.1268 \\ 0.9284 & 0.8608 & 1.0000 & 1.3549 & 1.5315 & 1.8307 \\ 0.6852 & 0.6353 & 0.7381 & 1.0000 & 1.1303 & 1.3512 \\ 0.6062 & 0.5621 & 0.6530 & 0.8847 & 1.0000 & 1.1954 \\ 0.5071 & 0.4702 & 0.5462 & 0.7401 & 0.8366 & 1.0000 \end{bmatrix}.$$

Let $SUG^{(k)} = \left(sug_1^k, sug_2^k, \ldots, sug_4^k\right)^T$ $(k = 4)$ denote the adjusted suggestion for the decision-maker d_4 where $sug_i^{(k)} = \left[\min\left(a_{ij}^k, a_{ij}^{c,k}\right), \max\left(a_{ij}^k, a_{ij}^{c,k}\right)\right]$. Based on Eq. (28), $SUG^{(4)}$ is as follows:

$$SUG^{(4)} = \begin{bmatrix} |1.0000,1.0000| & |0.9272,2.0000| & |1.0771,3.0000| & |1.4594,5.0000| & |1.6496,7.0000| & |1.9719,9.0000| \\ |0.5000,1.0785| & |1.0000,1.0000| & |1.1617,2.0000| & |1.5740,3.0000| & |1.7792,4.0000| & |2.1268,6.0000| \\ |0.3333,0.9284| & |0.5000,0.8608| & |1.0000,1.0000| & |1.3549,4.0000| & |1.5315,5.0000| & |1.8307,8.0000| \\ |0.2000,0.6852| & |0.3333,0.6353| & |0.2500,0.7381| & |1.0000,1.0000| & |1.1303,2.0000| & |1.3512,3.0000| \\ |0.1429,0.6062| & |0.2500,0.5621| & |0.2000,0.6530| & |0.5000,0.8847| & |1.0000,1.0000| & |1.1954,4.0000| \\ |0.1111,0.5071| & |0.1667,0.4702| & |0.1250,0.5462| & |0.3333,0.7401| & |0.2500,0.8366| & |1.0000,1.0000| \end{bmatrix}$$

When constructing $\overline{A^k} = \left(\overline{a_1^k}, \overline{a_2^k}, \ldots, \overline{a_n^k}\right)^T$ $(k = 4)$, we suggest that $\overline{a^k} \in sug_{i^{(k)}}$.

Without loss of generality, the adjusted fuzzy preference relations are

$$\overline{A^{(4)}} = \begin{bmatrix} 1 & 1 & 2 & 3 & 5 & 7 \\ 1 & 1 & 2 & 3 & 4 & 6 \\ 1/2 & 1/2 & 1 & 4 & 5 & 6 \\ 1/3 & 1/3 & 1/4 & 1 & 2 & 3 \\ 1/5 & 1/4 & 1/5 & 1/2 & 1 & 4 \\ 1/7 & 1/6 & 1/6 & 1/3 & 1/4 & 1 \end{bmatrix}$$

Finally, the consensus level is calculated as $\overline{CL^k} = \{0.8512, \quad 0.9208, \quad 0.8787, \quad 0.8810, \quad 0.8822\}$.

An acceptable consensus has been reached, i.e., $\overline{CL^k} > 0.85$

Step 4: Selection process.

In the Aggregation phase, based on Eq. (32), the collective preference relation is calculated,

$$P^{(c)} = \begin{bmatrix} 0.5000 & 0.4469 & 0.5333 & 0.6688 & 0.7648 & 0.8592 \\ 0.5531 & 0.5000 & 0.6448 & 0.7530 & 0.7926 & 0.8685 \\ 0.4667 & 0.3552 & 0.5000 & 0.6966 & 0.7060 & 0.7503 \\ 0.3312 & 0.2470 & 0.3034 & 0.5000 & 0.5663 & 0.6117 \\ 0.2352 & 0.2074 & 0.2940 & 0.4337 & 0.5000 & 0.6003 \\ 0.1408 & 0.1315 & 0.2497 & 0.3883 & 0.3997 & 0.5000 \end{bmatrix}$$

Next, in the Exploitation phase, based on Eq. (33), we obtain the collective preference vectors as $v_i = (0.1924,\ \ 0.2037,\ \ 0.1835,\ \ 0.1520,\ \ 0.1424,\ \ 0.1270)$.

According to the same principle, a subjective evaluation of alternatives was carried out according to criterion C4. The final values of the decision matrix are shown in Table 3.

Table 3. Final values of the decision matrix

Alternatives	Criteria				
	C1 (RS dinar)	C2 (month)	C3 (value of subjective assessment)	C4 (value of subjective assessment)	C5 (day)
A1	13,601,596.00	60	0.1924	0.1735	45
A2	13,808,741.00	36	0.2037	0.2011	60
A3	12,991,000.00	48	0.1825	0.1818	45
A4	12,995,855.00	36	0.1520	0.1459	60
A5	13,051,374.00	48	0.1424	0.1453	45
A6	13,222,359.00	60	0.1270	0.1220	45
Type	min	max	max	max	min
wj (ponders)	40	20	15	15	10

4.5 Applying the MCDM method

By applying the SAW method, we rank the bids. Firstly, we use Eq. (34) to normalize the decision matrix, whose normalization results are presented in Table 4.

Table 4. Normalized values of the decision matrix

Alternatives	Criteria (normalized values)				
	C1 (RS dinar)	C2 (month)	C3 (value of subjective assessment)	C4 (value of subjective assessment)	C5 (day)
A1	0.9551	1.0000	0.9445	0.8628	1.0000
A2	0.9408	0.6000	1.0000	1.0000	0.7500
A3	1.0000	0.8000	0.8959	0.9040	1.0000
A4	0.9996	0.6000	0.7462	0.7255	0.7500
A5	0.9954	0.8000	0.6991	0.7225	1.0000
A6	0.9825	1.0000	0.6235	0.6067	1.0000
wj (ponders)	40	20	15	15	10

Secondly, based on Eq. (35), an aggregation procedure is performed to combine the normalized decision matrix and the weight vector to obtain the total preference value for each alternative bid. The final ranking of bids is presented in Table 5.

Table 5. Final ranking of bids

Alternatives	The total preference value (Vi)	Final rank
A1	95.31	1
A2	87.13	5
A3	93.00	2
A4	81.56	6
A5	87.14	4
A6	87.75	3

Based on the final results of the decision matrix, given in table 3, the normalized results, given in table 4, and the applied SAW method for the final ranking of accepted bids, the results of which are given in table 5, the following can be concluded. The highest-ranked bid is A1. Then follow A3, A6, A5, and A2. While the worst-ranked bid is A4. The best-ranked bid is not the cheapest, but the qualitative values of the criteria played a decisive role. This confirmed the recommendation that the best bid in the procurement process is the one with the best price-quality ratio.

4.6 The final decision making

In this phase, the public procurement commission prepares a report on the expert evaluation of all bids and an explanation of the decision on the selection of the most favorable bid. The final result of this phase is the signing of the contract with the selected bidder A1.

5. DISCUSSION AND MANAGERIAL IMPLICATIONS

5.1 Discussion and results

In previous works, for the evaluation of the bids in public procurement, homogeneous preferential structures of information were used to express the opinions of decision-makers. However, in this one, the focus has been on different preferential structures of information in order to allow decision-makers greater flexibility in expressing individual opinions in the most convenient way. This enabled a greater reduction of subjectivism in decision-making.

In table 6, several scenarios are shown, which are based on a differently defined relationship between the value of the price and the quality of the criteria.

Table 6. Ranking of bids in different scenarios (price-quality ratio)

Scenario	**Price (%)**	**Quality(%)**	**Bidders Rank**
1	10	90	A1>A3>A2>A6>A5>A4
2	20	80	A1>A3>A2>A6>A5>A4
3	30	70	A1>A3>A2>A6>A5>A4
4	***40***	***60***	***A1>A3>A6>A5>A2>A4***
5	50	50	A1>A3>A6>A5>A2>A4
6	60	40	A1>A3>A5>A6>A2>A4
7	70	30	A3>A1>A5>A6>A4>A2
8	80	20	A3>A5>A1>A6>A4>A2
9	90	10	A3>A5>A4>A6>A1>A2

In the numerical example presented in this paper, scenario number 4 was taken when the price-quality ratio was 40%-60%. Then the optimal bidder was A1.

With an increase in the value of the quantitative criterion (price) by over 60%, there is a change in the ranking so that the most favorable offer is A3. In those cases, the choice of the most favorable offer goes in favor of the cheapest offer, which can be seen in the table where the worst-ranked offer is also the most expensive.

On the other hand, the higher the value of qualitative criteria (over 40%), the optimal choice of the offer is based on quality, and in those cases, the optimal bidder is A1.

It should be noted that the final ranking depends on the decision-makers and their weighting coefficients. In this paper, the weighting coefficients of the decision-makers are identical because the assumption was that they all have the same experience and competencies for the considered procurement subject. If there were differences in the competencies of the decision-makers, their initial weight coefficients would be different, which might affect the final ranking of the bids.

Table 7 discusses several scenarios where decision-makers do not have the same weighting coefficients assigned based on individual competencies.

In relation to the base scenario, which is shown in the numerical example, it is observed that the first three ranked bids (A1, A3 and A6) and the last ranked bid A4 do not change rank. It could be concluded that the proposed methodology does not allow any form of strategic manipulation by individual decision-makers. Also, the consensus approach prevents unscrupulous work and unfair bidder evaluation by individual decision-makers.

Based on the obtained results and considered scenarios, the initial assumption in the paper has been confirmed that by applying heterogeneity in the evaluation of offers and the consensus approach in decision-making, greater convenience of applying the MEAT approach in practice is enabled.

Table 7. Ranking of bids in the scenario with changing weights of decision-makers

Scenario	Weights of decision-makers (λ_{ID})					Bidders Rank
Base scenario	***0.20***	***0.20***	***0.20***	***0.20***	***0.20***	***A1>A3>A6>A5>A2>A4***
1	0.30	0.20	0.20	0.20	0.10	A1>A3>A6>A2>A5>A4
2	0.10	0.30	0.20	0.20	0.20	A1>A3>A6>A5>A2>A4
3	0.20	0.10	0.30	0.20	0.20	A1>A3>A6>A5>A2>A4
4	0.20	0.20	0.10	0.30	0.20	A1>A3>A6>A2>A5>A4
5	0.20	0.20	0.20	0.10	0.30	A1>A3>A6>A5>A2>A4
6	0.40	0.15	0.15	0.15	0.15	A1>A3>A6>A2>A5>A4
7	0.15	0.40	0.15	0.15	0.15	A1>A3>A6>A5>A2>A4
8	0.15	0.15	0.40	0.15	0.15	A1>A3>A6>A5>A2>A4
9	0.15	0.15	0.15	0.40	0.15	A1>A3>A6>A5>A2>A4
10	0.15	0.15	0.15	0.15	0.40	A1>A3>A6>A5>A2>A4

5.2 Managerial implications

In the public procurement procedure, using the MEAT approach, it is difficult to determine the weighting coefficients of the criteria. Also, the evaluation of alternative bids, according to certain qualitative criteria, requires the subjective assessment of the decision-maker, which can be of crucial importance for the selection of the most favorable bid.

With the aim of greater application of the MEAT approach in practice, the proposed methodology in this work offers for public contracting authorities and decision-makers an application solution in which different information is incorporated for the subjective assessment of available options while achieving consensus. The presented methodology can be widely applied in theory and practice in various areas where the subjective opinion of the decision-maker plays a key role.

In cases of subjective evaluation of criteria, at different hierarchical levels, the proposed methodology enables the harmonization of the needs of different users and their priorities. Also, based on the proposed methodology, there is a possibility of self-evaluation of the supplier according to the tender criteria, with the aim of future performance on the market.

Special attention is drawn to the defense and security sectors, where numerous problems are solved on the basis of expert assessments, given the frequent lack of complete information and rapid changes in the security environment. That is why it is very often necessary to apply a consensus approach in decision-making, especially in the procurement of armaments and military equipment.

It is especially important to apply consensus when procuring unique assets and services for numerous public services at the same time, which, in addition to savings, also achieves interoperability and procurement security, which reduces the possibility of corruption in the public sector.

The proposed model can be implemented in a software application to enable decision-makers who are unfamiliar with the field of multi-criteria group decision-making to make decisions in a unique way by applying different heterogeneous information in the context of consensus. This would, in addition to standardizing the procedure, enable an objective assessment while reducing the effort and time invested.

6. CONCLUSIONS

Public procurement is one of the key areas in which the public and private sectors enter into significant financial interaction, so public procurement is considered one of the most critical economic activities. The purpose of regulating the public procurement system, apart from the implementation of the basic principle of economic and efficient use of public funds ("value for money"), is certainly also to fight corruption. Therefore, the development of the public procurement system is a constant process that must be directed towards the introduction of new decision-making elements that will ensure that the public procurement system rests on the principles of transparency, equal treatment, free market competition, and non-discrimination. In this sense, it is expected that the further development of the public procurement system in the Republic of Serbia will also bring a new solution to the award of contracts; that is, the contract will be awarded to the most economically favorable bid based on price or costs using the cost efficiency approach or based on the best price-quality ratio.

In the procurement process, a key issue is the choice of the criteria and the models for evaluation and scoring of alternative bids. A review of the procurement literature indicated that there is no single, widely accepted approach to supplier selection that can fit every case. In general, the purchasers may adopt different selection criteria and different methods for evaluation and selecting bids each time a procurement need arises. While each bid evaluation process may differ based on the methodology and criteria contained within the specific tender documents, the key to a successful evaluation is to maintain an impartial, fair, consistent, accurate, transparent, and confidential evaluation process.

The proposed methodology tries to enrich the methods of selecting potential suppliers in public procurement, that is, it enables combining mathematics with experience, using flexibly a combination of well-established group decision-making tools in a multi-criteria context. Practitioners can conclude that the proposed methodology can be extended to other aspects of decision-making as well.

Future research will be focused on the application of different information structures for expressing the opinions of decision-makers (experts), such as numeric, linguistic, multi-granular linguistic domains, unbalanced linguistic domains, expression domains based on interval numbers, hesitant fuzzy sets, intuitionistic fuzzy sets, Pythagorean fuzzy sets, and Fermatean fuzzy sets, for determining the weight of criteria and subjective evaluation of alternative bids.

Given that there is no best multi-criteria decision-making method, future research will be focused on the comparative analysis of multi-criteria decision-making methods and the search for hybrid consensus models that best suit specific cases. Also, future research should be focused on the development of methodologies for the procurement of certain types of goods and services, which would later be confirmed by appropriate normative acts.

It is necessary to point out that the aforementioned guidelines are directed towards the development and improvement of e-procurement, which is the trend and the future of the modern information age.

ACKNOWLEDGEMENT

The work stemmed from the Model of Logistics Support Planning System (VA–TT-1/20-22) Project, Military Academy, University of Defense in Belgrade.

REFERENCES

Alshraideh, M., Ababneh, S., Gunay, E. E., and Al-Araidah, O. (2021). A Fuzzy-TOPSIS Model for Maintenance Outsourcing Considering The Quality of Submitted Tender Documents. *EksploatacjaI Niezawodność*, 23(3).

Bobar, V., Mandić, K., Delibašić, B., and Suknović, M. (2015). An Integrated Fuzzy Approach to Bidder Selection in Public Procurement: Serbian Government Case Study. *Acta PolytechnicaHungarica*, 12(2): 193-211.

ÇalogluBüyükselçuk, E., Tozan, H., and Vayvay, Özalp. (2022). A Multi-Criteria Decision-Making Approach for Greenovative Supplier Selection. *International Journal of Industrial Engineering: Theory, Applications, and Practice*, 29(2). DOI: https://doi.org/10.23055/ijietap.2022.29.2.7511

Chai, J. and Ngai, E. W. (2020). Decision-Making Techniques in Supplier Selection: Recent Accomplishments and What Lies Ahead. *Expert Systems with Applications*, 140.

Chai, J., Liu, J. N., and Ngai, E. W. (2013). Application of Decision-Making Techniques in Supplier Selection: A Systematic Review of Literature. *Expert Systems with Applications*, 40(10): 3872-3885.

Chen. X., Zhang, H. J. and Dong, Y.C. (2015). The Fusion Process with Heterogeneous Preference Structures in Group Decision Making: A Survey, Inform. *Fusion*, 24: 72–83.

Cheshmberah, M. (2020). Developing An Integrated Framework for Supplier Evaluation Based on Relevant Attributes and Performance Measures. *Logistics and Sustainable Transport*, 11(1): 101-113.

Chiclana, F., Mata, F., Martinez, L., Herrera-Viedma, E., and Alonso, S.. (2008). Integration of A Consistency Control Module Within A Consensus Model. *International Journal of Uncertainty Fuzziness and Knowledge-Based Systems*, 16(1): 35–53.

Del Moral, M. J., Chiclana, F., Tapia, J. M., and Herrera-Viedma, E. (2018). A Comparative Study on Consensus Measures in Group Decision Making. *International Journal of Intelligent Systems*, 33(8): 1624-1638.

Dickson, G. W. (1966). An Analysis of Vendor Selection: Systems and Decisions. *Journal of Purchasing*, 1(2): 5-17.
Dong, Y. C., Liu, Y. T., Liang, H. M., Chiclana, F., and Herrera-Viedma, E. (2018). Strategic Weight Manipulation in Multiple Attribute Decision Making. *Omega*, 75: 154-164.

Dong, Y. and Zhang, H. (2014). Multiperson Decision Making with Different Preference Representation Structures: A Direct Consensus Framework and Its Properties. *Knowledge-Based Systems*, 58: 45-57.

Dong, Y. C., Xu, Y. F., and Yu, S. (2009). Linguistic Multiperson Decision Making Based on The Use of Multiple Preference Relations. *Fuzzy Set. Syst*.,160: 603–623.

Dong, Y. C., Zhang, H. J., and Herrera-Viedma, E. (2016). Consensus Reaching Model in The Complex and Dynamic MAGDM Problem. *Knowledge-Based Systems*, 106: 206-219.

Dotoli, M., Epicoco, N., and Falagario, M. (2020). Multi-Criteria Decision Making Techniques for The Management of Public Procurement Tenders: A Case Study. *Applied Soft Computing*, 88.

Ellram, Lisa M. (1990). The Supplier Selection Decision in Strategic Partnerships. *Journal of Purchasing and Materials Management*, 26(4): 8-14.

Erdem, A. S. and Göçen E. (2012). Development of A Decision Support System for Supplier Evaluation and Order Allocation. *Expert Systems with Applications*, 39(5): 4927–4937.

European Commission. (2022). Single Market Scoreboard. Public Procurement. Retrieved on 26 June 2022 from Https://Single-Market-Scoreboard.Ec.Europa.Eu/Policy_Areas/Public-Procurement_En.

Herrera, F. and Martínez, L. (2000). An Approach for Combining Linguistic and Numerical Information Based on The 2-Tuples Fuzzy Linguistic Representation Model in Decision-Making. Int. J. *Uncertainty Fuzziness Knowl.-Based Syst*, 8(5): 539–562.

Herrera-Viedma, E., Herrera, F. and Chiclana, F. (2002). A Consensus Model for Multiperson Decision Making with Different Preference Structures. *IEEE Transactions on Systems, Man and Cybernetics Part A: Systems and Humans*, 32(3): 394– 402.

Ho, W., Xu, X., and Dey, P. K. (2010). Multi-Criteria Decision Making Approaches for Supplier Evaluation and Selection: A Literature Review. *European Journal of Operational Research*, 202(1): 16-24.

Ibáñez-Forés, V., Bovea, M. D., and Pérez -Belis, V. (2014). A Holistic Review of Applied Methodologies for Assessing and Selecting The Optimal Technological Alternative from A Sustainability Perspective. *Journal of Cleaner Production*, 70: 259–281.

Igarashi, M., De Boer, L., and Pfuhlr, G. (2017). Analyzing Buyer Behavior When Selecting Green Criteria in Public Procurement. *Journal of Public Procurement*, 17(2): 141–186.

Ilić, M. D. (2022). Logistics Support of The Serbian Armed Forces (Supply and Maintenance Through Public Procurement). *VojnotehničkiGlasnik/Military Technical Courier*, 70(2): 475-490. DOI: https://doi.org/10.5937/vojtehg70-35171.

Li, C.C., Dong, Y., Xu, Y., Chiclana, F., Herrera-Viedma, E., and Herrera, F. (2019). An Overview on Managing Additive Consistency of Reciprocal Preference Relations for Consistency-Driven Decision Making and Fusion: Taxonomy and Future Directions. *Information Fusion*, 52: 143-156.

Li, G., Kou G., and Peng, Y. (2018). A Group Decision Making Model for Integrating Heterogeneous Information. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 48(6): 982-992.

Liu, Y., Eckert, C., Yannou-Le Bris, G., and Petit, G. (2019). A Fuzzy Decision Tool to Evaluate The Sustainable Performance of Suppliers in An Agrifood Value Chain. *Computers and Industrial Engineering*, 127: 196-212.

Lorentziadis, P. L. (2020). Competitive Bidding in Asymmetric Multidimensional Public Procurement. *European Journal of Operational Research*, 282(1): 211-220.

Marcarelli, G., and Squillante, M. (2020). A Group-AHP-Based Approach for Selecting The Best Public Tender. *Soft Computing*, 24(18):13717-13724.

Mimović, P., and Krstić, A. (2016). Application of Multi-Criteria Analysis in The Public Procurement Process Optimization. *Economic Themes*, 54(1): 103-128.

Morente-Molinera, J. A., Wu, X., Morfeq, A., Al-Hmouz, R., and Herrera-Viedma, E. (2020). A Novel Multi-Criteria Group Decision-Making Method for Heterogeneous and Dynamic Contexts Using Multi-Granular Fuzzy Linguistic Modelling and Consensus Measures. *Information Fusion*, 53: 240-250.

Mukherjee, K. (2016). Supplier Selection Criteria and Methods: Past, Present and Future. *International Journal of Operational Research*, 27(1-2): 356-373.

Nikou, C., Moschuris, S. J., and Filiopoulos, I. (2017). An Integrated Model for Supplier Selection in The Public Procurement Sector of Defence. *International Review of Administrative Sciences*, 83(1_Suppl): 78-98.

Palomares, I., Estrella, F. J., Martínez, L., and Herrera, F. (2014). Consensus Under A Fuzzy Context: Taxonomy, Analysis Framework AFRYCA and Experimental Case of Study. *Information Fusion*, 20: 252-271.

Pamučar, D. S., and Dimitrijević, S. R. (2021). Multiple-Criteria Model for Optimal Anti Tank Ground Missile Weapon System Procurement. VojnotehničkiGlasnik/Military Technical Courier, 69(4): 792-827. DOI: https://doi.org/10.5937/vojtehg69-32117.

Pérez, I. J., Cabrerizo, F. J., Alonso, S., Dong, Y. C., Chiclana, F., and Herrera-Viedma, E. (2018). On Dynamic Consensus Processes in Group Decision Making Problems. *Information Sciences*, 459: 20-35.

Perez, I.J., Cabrerizo, F.J. and Herrera-Viedma, E. (2011). Group Decision Making Problems in A Linguistic and Dynamic Context. *Expert Systems with Applications*, 38(3): 1675-1688.

Rong L, Wang L, Liu P. (2022), Supermarket Fresh Food Suppliers Evaluation and Selection with Multigranularity Unbalanced Hesitant Fuzzy Linguistic Information Based on Prospect Theory and Evidential Theory. *Int J Intell Syst*., 37: 1931-1971. Doi:10.1002/Int.22761.

Serbian Public Procurement Office, Reports (2019). Retrieved on 26 June 2022 from https://www.ujn.gov.rs/en/reports/public-procurement-office-reports/.

Simić, D., Kovačević, I., Svirčević, V., and Simić, S. (2017). 50 Years of Fuzzy Set Theory and Models for Supplier Assessment and Selection: A Literature Review. *Journal of Applied Logic*, 24: 85–96.

Sönnichsen, S. D. and Clement, J. (2020). Review of Green and Sustainable Public Procurement: Towards Circular Public Procurement. *Journal of Cleaner Production*, 245: 118901.

Sun, B.Z. and Ma, W.M. (2015). An Approach to Consensus Measurement of Linguistic Preference Relations in Multi-Attribute Group Decision Making and Application. *Omega*, 51: 83-92.

Sun, Q., Wu, J., Chiclana, F., Fujita, H., and Herrera-Viedma, E. (2021). A Dynamic Feedback Mechanism with Attitudinal Consensus Threshold for Minimum Adjustment Cost in Group Decision Making. *IEEE Transactions on Fuzzy Systems*, 30(5): 1287-1301.

Taghavi, A., Eslami, E., Cabrerizo, F. J., and Herrera-Viedma, E. (2017). Analyzing Feedback Mechanisms in Group Decision Making Problems. *In Advances in Fuzzy Logic and Technology*, 371-382. Springer, Cham.

Tang, H., Wan, S., Li, C. C., Liang, H., and Dong, Y. (2021). Consensus Reaching Process in The Two-Rank Group Decision-Making with Heterogeneous Preference Information. *International Journal of Computational Intelligence Systems*, 14(1): 758-768.

Tanino, T. (1984). Fuzzy Preference Orderings in Group Decision Making. *Fuzzy Sets and Systems*, 12: 117–131.

Weber, C.A., Current, J.R., Benton, W.C., (1991). Vendor Selection Criteria and Methods. *European Journal of Operational Research*, 50(1): 2–18.

Xu, Z.S., (2001). Algorithm for Priority of Fuzzy Complementary Judgment Matrix. *J Syst Eng*., 16(4): 311–314.

Yager, R.R. (2001). Penalizing Strategic Preference Manipulation in Multi-Agent Decision Making. *IEEE Transactions on Fuzzy Systems*, 9(3): 393–403.

Yeh, C. H., and Chang, Y. H. (2008). Validating Multiattribute Decision Making Methods for Supporting Group Decisions. *In 2008 IEEE Conference on Cybernetics and Intelligent Systems*, 878-883.

Zavadskas, E. K. and Turskis, Z. (2008). A New Logarithmic Normalization Method in Games Theory. *Informatica*, 19(2): 303-314.

Zavadskas, E. K., Govindan, K., Antucheviciene, J., and Turskis, Z. (2016). Hybrid Multiple Criteria Decision-Making Methods: A Review of Applications for Sustainability Issues. *EkonomskaIstraživanja*, 29(1): 857-887.

Zhang, H., Dong, Y., Chiclana, F., and Yu, S. (2019). Consensus Efficiency in Group Decision Making: A Comprehensive Comparative Study and Its Optimal Design. *European Journal of Operational Research*, 275(2): 580-598.

Zhang, X., Xu, Z., and Wang, H. (2015). Heterogeneous Multiple Criteria Group Decision Making with Incomplete Weight Information: A Deviation Modeling Approach. *Information Fusion*, *25*: 49-62.