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FUZZY AHP - FUZZY MABAC MODEL FOR RANKING A COMBINED CONSTRUCTION MACHINE - BACKHOE LOADER

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Abstract*. The paper presents a multi-criteria decision-making (MCDM) model designed to rank combined construction machines - specifically, Backhoe Loaders - during procurement for military needs. However, the model can also be applied to construction companies. The ranking is based on criteria specifically defined for this research. The study found that most criteria relate to the structural elements of the Backhoe Loader, which is also significant for manufacturers working on improving these types of machines. The MCDM model is built on two methods: Analytic Hierarchy Process (AHP) and Multi-Attributive Border Approximation area Comparison (MABAC), both adapted using fuzzy numbers. The AHP method was modified with type 2 fuzzy numbers to calculate criteria's weight coefficients. The MABAC method, using classic triangular fuzzy numbers, is employed for ranking alternative solutions. Validation of the results involved two steps. First, a sensitivity analysis was performed by modifying the weight coefficients of the criteria. Second, a comparative analysis with other methods was performed. The validation process confirmed the stability of the obtained results.*

Keywords: *Fuzzy AHP, Fuzzy MABAC, MCDM, Backhoe loader.*

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1. INTRODUCTION

Decision-making is an integral and essential segment of the planning process, both in the implementation of tasks within companies and in certain segments of life [1]. Increasingly, the decision-making process requires the application of special methods, which significantly simplify this process [2, 3]. In this sense, numerous methods have been developed in the field of multi-criteria decision-making (MCDM) to smooth this process, and accordingly, many, most often hybrid, models are being established [4]. Given that decision-making processes are often accompanied by a series of uncertainties, MCDM methods are most often combined with various mathematical areas that have the ability to treat uncertainty, such as fuzzy, rough, grey, and other numbers [5]. The most common approach to addressing uncertainty in MCDM is the use of fuzzy numbers.

MCDM models have also gained a role in the military. A large portion of the papers focuses on different processes for selecting or ranking locations [6], resources [7], and actions [8, 9]. In other words, MCDM is an area that is recognized and highly valued for addressing decision-making challenges in the military.

A backhoe loader is a versatile construction machine designed for a wide array of construction and infrastructure tasks. It plays a significant role in both civilian and military sectors. Depending on the attachment used, these machines can be employed for soil excavation, material loading, pushing and spreading materials, lifting loads, and transporting trees. In the military, their importance is notable because they are small, agile, compact, quick, and adaptable. The tasks they perform in the army are diverse, including digging trenches, creating or removing obstacles, and building temporary military facilities related to establishing units and command posts. The multifunctionality of these machines makes them highly valuable for setting up units, including constructing trenches, roads, and shelters, as well as building shelters under harsh conditions often encountered during these activities. The specific use of a backhoe loader and the structure of engineering units in the Serbian Army determine that its primary function is land excavation and material loading. In contrast, the application in construction and other industries tends to be broader and more varied.

The selection of assets in public enterprises, including those in the military, is most often conducted through the public procurement system. Most public procurement processes focus mainly on the price of the purchased product. This approach can influence the quality of the acquired product. To avoid emphasizing only the product's price, a hybrid MCDM model was developed in this paper. This approach shifts the focus from price to other key parameters that are important when procuring a backhoe loader for the Serbian Army units. In other words, the practical goal of this study is to improve the process of equipping army units with the combined construction machine - the backhoe loader. The motivation for developing such a model stems from the lack of a standard methodology for solving this type of problem. The new model offers a proposal for standardizing this type of procurement.

The issue of selecting a backhoe loader for military and other purposes has not been discussed in the literature so far. Some papers address specific aspects related to backhoe loaders, mostly focusing on design improvements and analyses [10, 11], and their integration into particular sectors [12, 13]. However, more studies using MCDM techniques can be found when it comes to selecting other construction machines and equipment. For example, study [14] proposes a model for selecting the appropriate excavation machine for a construction site using AHP and PROMETHEE methods. In the paper of Ghorabaee et al. [15], the authors developed an MCDM model based on SWARA, CRITIC, and EDAS methods to evaluate construction equipment considering potential environmental impacts. In [16], fuzzy TOPSIS and fuzzy VIKOR methods were used to select a hydraulic excavator for open-pit mines. Hagag et al. [17] offer an overview of the literature on applying MCDM for machine selection in manufacturing and construction. Deepak et al. [18] focus on optimizing concrete pump maintenance in the construction industry using MCDM Methodologies. Additionally, in [19], an ANFIS model was introduced for loader selection. The use of AHP methods for selecting earthmoving equipment in construction projects was discussed in [20].

The AHP method has been used for solving MCDM problems for a very long time. This method has found applications in contemporary research, both in its basic form and through various modifications. Its use can be seen in works across different fields, such as human resources [21], waste management [22], construction projects [23], military science [24], industry [25], economic assessments [26], and others. Similar to the AHP method, although much younger, the MABAC method is widely applied in many fields, such as mechanical engineering [27], economics [28, 29], management [30], risk assessment [31], and more.

The literature review reveals that the problem of selecting a backhoe loader has not been thoroughly studied, creating a research gap that needs addressing. Meanwhile, applying MCDM methods in selecting construction machinery has proven to be very effective. Therefore, implementing an MCDM model to solve the backhoe loader selection problem is highly beneficial. Additionally, although this issue has been addressed for military purposes, future research on the weighting of criteria could facilitate its application in traditional construction companies.

This paper offers several original contributions: 1) it defines specific criteria that are important when choosing a backhoe loader; 2) it performs the calculation of weighting criteria for the defined criteria; 3) it demonstrates models practical use in ranking alternatives; 4) it shows the quality of implementing the AHP and MABAC methods for addressing modern challenges.

2. Description of the Methods Applied

2.1 Model Description

The main goal of the model is to assist decision makers in selecting the best available alternative. This goal also guides the application of certain MCDM methods [32]. The model presented in this paper primarily consists of two methods: the AHP method enhanced by applying interval, type 2, fuzzy numbers (F2AHP), and the MABAC method, which is fuzzified using type 1 fuzzy numbers (FMABAC). The F2AHP method is used to establish the weight coefficients of the criteria, whereas the ranking of alternatives is carried out using the FMABAC. As evident, different fuzzy approaches are used for fuzzification, reflecting varying degrees of uncertainty in defining the criteria's weight coefficients and ranking the alternatives. The phases of the F2AHP-FMABAC model are illustrated in Fig. 1.

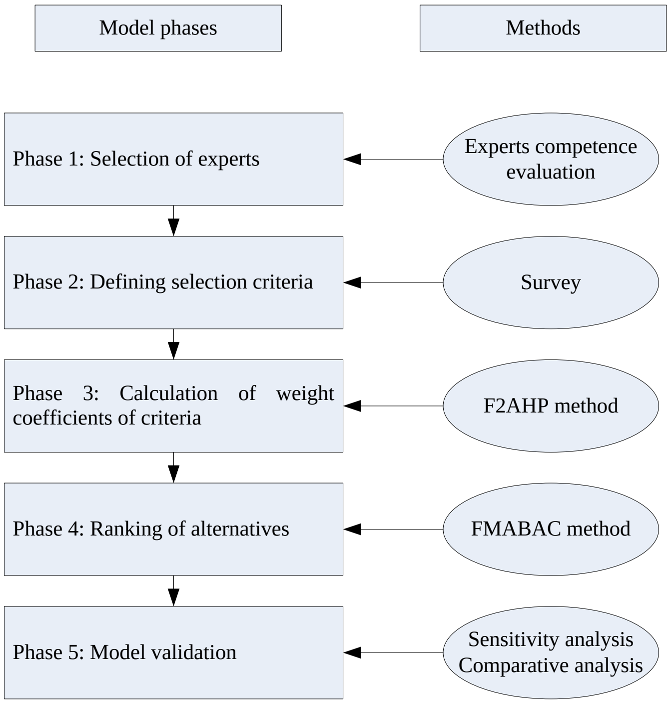

Fig. 1 F2AHP-FMABAC model

As presented in Fig. 1, the model executed in 5 phases:

- Phase 1: During this phase, the selection and evaluation of experts' competence are conducted. The competence of experts can be measured using some well-known methods for calculating expert competence [33]. The competence coefficient (k) ranges from 0 to 1, where a coefficient of k=1 indicates a highly competent expert, and lower values indicate less competence. Of course, the minimum competence level depends on the available experts. In this research, only experts with a minimum competence coefficient of 0.5 are considered.

- Phase 2: At this phase, the key criteria are determined through surveys and consultations with experts who influence the selection of the backhoe loader.

- Phase 3: In the third phase, criteria are compared in pairs, and the criteria weight coefficients are calculated using the AHP method, which is fuzzified by interval fuzzy numbers.

- Phase 4: In the fourth, the optimal alternative is identified through the application of fuzzy MABAC.

- Phase 5: During this phase, the model was validated through sensitivity analysis and comparative analysis.

This paper focuses on presenting the decision-making model itself. In the next section, basic information on fuzzy numbers of types 1 and 2 will be provided, along with a description of the F2AHP and the FMABAC method. The phases related to selecting and evaluating experts' competencies and identifying key criteria are not specifically explained, as they are part of a standard procedure.

2.2 Fuzzy Numbers Type 1 and Type 2

The foundation of fuzzy logic was established by Lotfi Zadeh [34]. It proved to be a highly effective tool for describing uncertainties, which are very common in decision-making processes [35, 36]. Essentially, using fuzzy logic allows spoken language and human knowledge to be translated into mathematical terms across various areas, which can then be processed in different ways using fuzzy arithmetic [37, 38]. This paper uses fuzzy numbers type 1 and type 2.

Type 1 fuzzy numbers represent the beginning of fuzzy logic but are still widely used today [39, 40]. Figure 2 shows triangular fuzzy Type 1 numbers, which are used during the fuzzification process of the MABAC method.

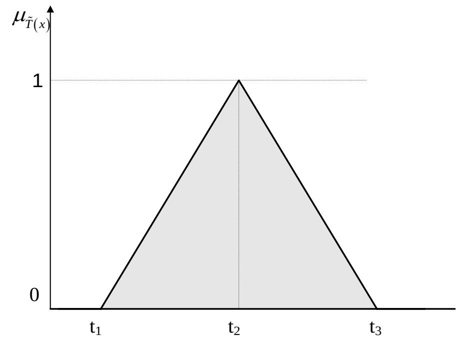

Fig. 2 Triangular fuzzy number

With the further development of fuzzy logic, the question arises if fuzzy numbers, which describe uncertainty, explain why there was no uncertainty in the membership function defining fuzzy numbers. This was followed by the extension of type 1 fuzzy numbers to include interval fuzzy numbers, known as type 2. In this case, the membership function is also presented as uncertain, as shown in Fig. 3.

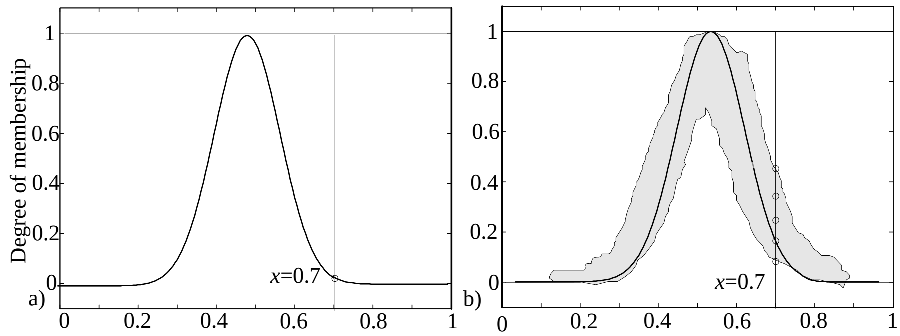

Fig. 3 Membership function type -1 (a) and type-2 (b)

Triangular interval fuzzy numbers are used to fuzzify the AHP method, as shown in Fig. 4.

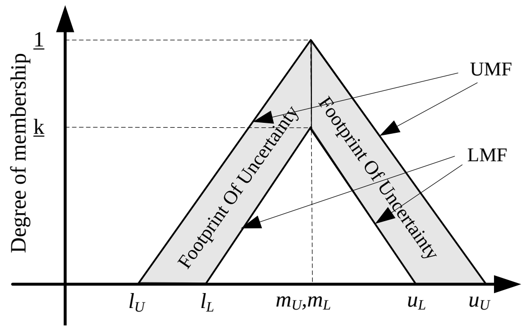

Fig. 4 Triangular fuzzy number type 2

In interval fuzzy numbers, there are two membership functions describing uncertainty, which are not included in fuzzy numbers type 1: upper membership functions (UMF) and lower membership functions (LMF). More information about fuzzy numbers type 2 can be found in [41, 42, 43].

2.3 The AHP method fuzzification

The AHP was developed by Thomas Saaty [44]. The standard for this method is Saaty's scale, used for comparing criteria or alternatives two at a time [45]. Although many alternative scales have been created, Saaty's scale remains the most widely used [46]. The widespread use of AHP has led to many modifications, one of the most common being its fuzzification. This process usually involves fuzzifying Saaty's scale. Currently, there are various methods to fuzzifying Saaty's scale, which can generally be categorized into two types: sharp and soft fuzzification. Sharp fuzzification involves establishing the confidence interval of Saaty's scale values before conducting pairwise comparisons [47, 48, 49]. Some studies utilize the principle of Saaty's scale but with fewer comparison options, such as a six-point scale [50, 51] or a five-point scale [52, 53]. Fuzzification is usually performed using a triangular fuzzy number T = (t_1, t_2, t_3) = (x-1, x, x+1), where x represents a standard value from Saaty's scale. In the papers [54, 55, 56], Saaty's scale is fuzzified using the fuzzy number T = (x-δ, x, x+δ), where δ is taken from the interval $0.5 \le \delta \le 2$. Further analysis shows that some papers also use fuzzifications by applying other types of fuzzy numbers (Gauss curve, trapezoidal, and the like), as well as interval fuzzy numbers [57, 58]. However, most papers primarily use triangular fuzzy numbers.

The second group of fuzzification is "soft" fuzzification of Saaty's scale. Here, the confidence interval is defined with fuzzy numbers after the pairwise comparison based on a new parameter - the degree of uncertainty (β). One type of such fuzzification is presented in the papers [59, 60]. In the aforementioned papers, the degree of uncertainty related to the accuracy of all comparisons in the table is defined at the level of Saaty's scale. It ranges from 0 to 1, where 1 indicates that the decision-makers are confident in the pairwise comparisons they performed, and vice versa. Based on the level of uncertainty, fuzzy numbers are calculated. This method works well for group decision making, but for individual decision making, the results compared to the classic AHP method are not significantly different. The second approach of the so-called "soft" fuzzification was developed based on the previous one, with the difference that the decision-makers define the degree of certainty (γ) for each comparison they make [61]. The degree of certainty ranges from 0 to 1, where the value 1 indicates a high degree of certainty, and vice versa.

As the previous two fuzzifications are further developed, the question arises whether other factors might influence the final calculation of the weight coefficients of the criteria or alternatives. Clearly, the question arises whether all decision-makers, including experts, are equally capable of making decisions. In that regard, a new approach has been developed that uses the level of competence of decision makers (k_e), where $e \in (1,2, \ldots K)$, and K represents the total number of experts or decision makers.

On the other hand, considering that the process of defining the degree of conviction (γ) cannot be completely precise, interval fuzzy numbers are chosen to better handle the uncertainty. The general form of the fuzzy number shown in the fuzzification is (Fig. 4):

$$\tilde{T} = \left(l_U, l_L, m, u_L, u_U\right) \tag{1}$$

where $m_U = m_L = m$.

The expressions used for calculating the interval fuzzy number $\tilde{T}$ are presented in Table 1 [62].

Table 1 Fuzzified values of Saaty's scale

Definition	Standard values	Interval fuzzy number
The same importance	1	(1,1,1,1,1)
Weak dominance	3	$\left(3\gamma_{ji}^2, 3\gamma_{ji}, 3, \left(2-\gamma_{ji}\right)3, \left(2-\gamma_{ji}^2\right)3\right)$
Strong dominance	5	$\left(5\gamma_{ji}^2, 5\gamma_{ji}, 5, \left(2-\gamma_{ji}\right)5, \left(2-\gamma_{ji}^2\right)5\right)$
Very strong dominance	7	$\left(7\gamma_{ji}^2, 7\gamma_{ji}, 7, \left(2-\gamma_{ji}\right)7, \left(2-\gamma_{ji}^2\right)7\right)$
Absolute dominance	9	$\left(9\gamma_{ji}^2, 9\gamma_{ji}, 9, \left(2-\gamma_{ji}\right)9, \left(2-\gamma_{ji}^2\right)9\right)$
In between values	2, 4, 6, 8	$\left(x\gamma_{ji}^2, x\gamma_{ji}, x, \left(2-\gamma_{ji}\right)x, \left(2-\gamma_{ji}^2\right)x\right)$; $x = 2,4,6,8$

Fuzzy number $\tilde{T} = \left(l_U, l_L, m, u_L, u_U\right)$, $x \in [1,9]$ must meet the following conditions:

$$l_U = \begin{cases} x\gamma_{ji}^2, & \forall\ 1 \le x\gamma_{ji}^2 \le x \\ 1, & \forall\ x\gamma_{ji}^2 < 1 \end{cases}, \ x \in [1,9] \tag{2}$$

$$l_L = \begin{cases} x\gamma_{ji}, & \forall\ 1 \le x\gamma_{ji} \le x \\ 1, & \forall\ x\gamma_{ji} < 1 \end{cases}, x \in [1,9] \tag{3}$$

$$m = x, \forall\, x \in [1,9] \tag{4}$$

$$u_L = \left(2-\gamma_{ji}\right)x, \forall x \in [1,9] \tag{5}$$

$$u_U = \left(2-\gamma_{ji}^2\right)x, \forall x \in [1,9] \tag{6}$$

Based on the provided expressions, the example is shown in Fig. 5. The comparison used as an example is "4 - the value between weak and strong dominance", with an expert competence $k = 0.75$, and different levels of certainty $\gamma \in [1, 0.6, 0.4]$.

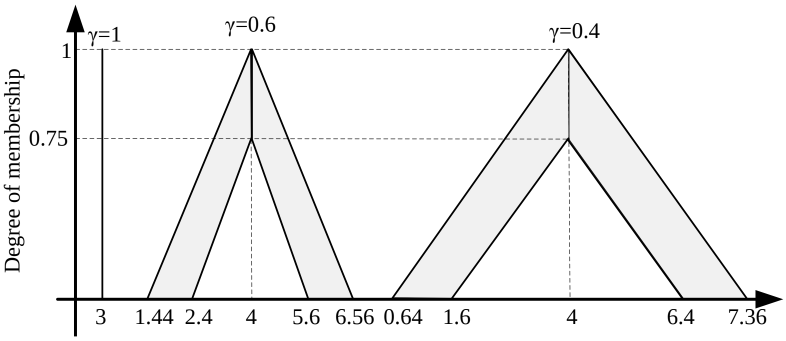

Fig. 5 Example of a comparison from Saaty's scale using interval fuzzy numbers

The expressions for calculating the inverse interval fuzzy number $\tilde{T}^{-1} = \left(1/u_U, 1/u_L, 1/m, 1/l_L, 1/l_U\right)$ are shown in Table 2.

Table 2 Inverse fuzzified values of Saaty's scale

Definition	Inverse value	Interval fuzzy number
The same importance	1	(1,1,1,1,1)
Weak dominance	1/3	$\left(1/(2-\gamma_{ji}^2)3, 1/(2-\gamma_{ji})3, 1/3, 1/3\gamma_{ji}, 1/3\gamma_{ji}^2\right)$
Strong dominance	1/5	$\left(1/(2-\gamma_{ji}^2)5, 1/(2-\gamma_{ji})5, 1/5, 1/5\gamma_{ji}, 1/5\gamma_{ji}^2\right)$
Very strong dominance	1/7	$\left(1/(2-\gamma_{ji}^2)7, 1/(2-\gamma_{ji})7, 1/7, 1/7\gamma_{ji}, 1/7\gamma_{ji}^2\right)$
Absolute dominance	1/9	$\left(1/(2-\gamma_{ji}^2)9, 1/(2-\gamma_{ji})9, 1/9, 1/9\gamma_{ji}, 1/9\gamma_{ji}^2\right)$
In between values	1/2, 1/4, 1/6, 1/8	$\left(1/(2-\gamma_{ji}^2)x, 1/(2-\gamma_{ji})x, 1/x, 1/x\gamma_{ji}, 1/x\gamma_{ji}^2\right)$; $x = 2,4,6,8$

Inverse fuzzy number $\tilde{T}^{-1} = \left(1/u_U, 1/u_L, 1/m, 1/l_L, 1/l_U\right)$, $x \in [1,9]$ must satisfy the following conditions:

$$1/l_U = \begin{cases} 1/x\gamma_{ji}^2, & \forall\ 1/x \leq 1/x\gamma_{ji}^2 < 1 \\ 1, & \forall\ 1/x\gamma_{ji}^2 \geq 1 \end{cases}, \ x \in [1,9] \tag{7}$$

$$1/l_L = \begin{cases} 1/x\gamma_{ji}, & \forall\ 1/x \leq 1/x\gamma_{ji} < 1 \\ 1, & \forall\ 1/x\gamma_{ji} \geq 1 \end{cases}, x \in [1,9] \tag{8}$$

$$m = 1/x, \forall\ x \in [1,9] \tag{9}$$

$$1/u_L = 1/\left(2-\gamma_{ji}\right)x, \forall x \in [1,9] \tag{10}$$

$$1/u_U = 1/\left(2-\gamma_{ji}^2\right)x, \forall x \in [1,9] \tag{11}$$

In the next section, the standard AHP process is followed to determine the weight vector w. Once the weight vectors are obtained, defuzzification of $\tilde{w}$ is carried out using the method described in [58]:

$$w = \frac{\dfrac{(u_U - l_U)+(m_U - l_U)}{3} + l_U + k\left[\dfrac{(u_L - l_L)+(m_L - l_L)}{3} + l_L\right]}{2} \tag{12}$$

When discussing the degree of certainty (γ), it could be set in two ways: 1) as a percentage or 2) with fuzzy linguistic descriptors. In this paper, fuzzy linguistic descriptors are used, as shown in Fig. 6.

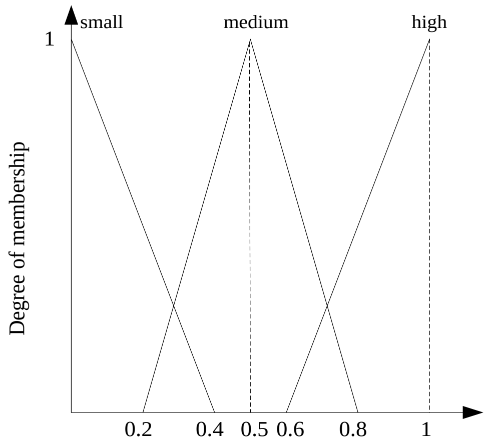

Fig. 6 Fuzzy linguistic descriptors for the evaluation of the degree of certainty

2.4 Fuzzy MABAC

The MABAC was first presented in 2015 by Pamučar and Ćirović [63]. This approach is based on calculating the border approximation area and the distance of alternatives from this area. Although it is a relatively recent approach, it has been cited in many papers. The fundamental steps of the FMABAC are outlined in Table 3.

Table 3 Presentation of the FMABAC method steps

Step number	Step name
Step 1	Forming of the initial decision matrix ($\tilde{X}$).
Step 2	Normalization of the initial matrix elements ($\tilde{N}$)
Step 3	Calculation of the weighted matrix ($\tilde{V}$) elements
Step 4	Determination of the approximate border area matrix ($\tilde{G}$).
Step 5	Calculation of the matrix elements of alternatives distance from the border approximate area ($\tilde{Q}$)
Step 6	Defuzzification of the obtained values
Step 7	Ranking of alternatives

A more detailed presentation of the FMABAC method can be found in [64].

3. Results

3.1 Criteria Description and Definition of Weight Coefficients

Developing criteria for ranking backhoe loaders involves two steps. First, a review of the existing literature was conducted to identify an initial set of criteria. From this analysis, 11 criteria were established. These criteria were then presented to experts, who had the option to add, refine, modify, or remove any criteria they found unnecessary. At the conclusion of this process, the experts identified six criteria that will be used to rank the alternatives. The criteria are outlined as follows:

C1 - *Digging depth* is a segment that directly depends on the design of the backhoe loader, such as the excavator arm and its capabilities. The potential for greater digging depth broadens the backhoe loader's range of capabilities and increases its suitability for more tasks. The value of the alternatives based on this criterion is given in meters.

C2 - *Capacity of the loading tool* (loading bucket) is a fundamental parameter for calculating the loader's performance, indicating how many cubic meters of material a backhoe loader can load per unit of time. The values of the alternatives based on this criterion are presented in cubic meters.

C3 – *Capacity of the standard digging tool* (excavator bucket) is the key parameter when calculating excavator performance, indicating how many cubic meters backhoe loaders can dig in a given amount of time. The value of alternatives based on this criterion is measured in cubic meters.

C4 – *Constructional features* criterion covers various construction segments of the backhoe loader, which experts believe should not be considered separate criteria because their individual impact is minimal. When combined into one criterion, their influence increases. This includes factors such as the comfort provided to the operator, the training time needed for the tool, the variety and replaceability of working tools, engine power, speed, unloading height, and more.

C5 - *Backhoe loader price* criterion reflects the market value of the machine. The unit of measure for this criterion is €.

C6 – Maintenance costs. This criterion considers various factors that influence maintenance expenses, such as the length of the warranty period, parts availability, reliability, and the accessibility and speed of service for routine maintenance and repairs. The criterion is especially important because experience so far shows that resources continue to be used extensively after the warranty expires.

According to the previously described criteria, four numerical (C1, C2, C3, and C5) and two linguistic (C4 and C6) criteria stand out. The criteria C1, C2, C3, and C4 are benefit-type, while C5 and C6 are cost-type criteria. To describe the linguistic criteria, fuzzy linguistic descriptors were used, as shown in Fig. 7.

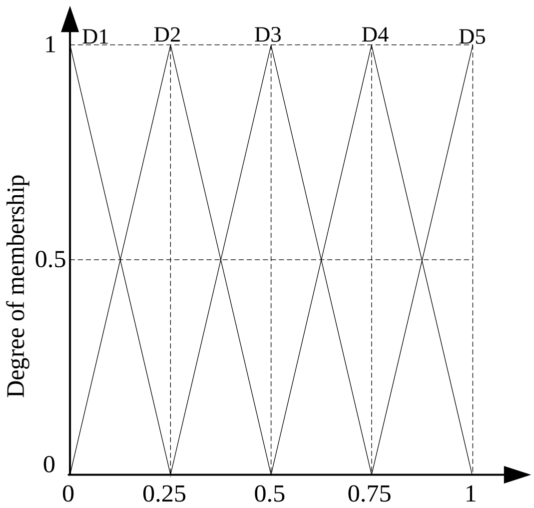

Fig. 7 Overview of fuzzy linguistic descriptors

As noted in Fig. 7, linguistic criteria are described with five fuzzy descriptors (D1 to D5). The significance of each linguistic descriptor relative to the criterion is given in Table 4.

As previously mentioned, the F2AHP was used to evaluate the criteria weight coefficients. Each expert individually compared the criteria in pairs, applying Saaty's scale, and determined the degree of certainty for each comparison using fuzzy linguistic descriptors, as shown in Fig. 6. The initial decision-making matrix for the first expert is presented in Table 5 - numbers outside the brackets represent the comparison of two criteria, while the values inside the brackets indicate the degree of certainty in the statement.

Table 4 Description of fuzzy linguistic descriptors by criteria

Linguistic descriptor	C4	C6
D1	Very bad	Very small
D2	Bad	Small
D3	Average	Average
D4	Good	High
D5	Very good	Very high

Table 5 Initial decision-making matrix for expert 1 for defining the criteria weight coefficients

	C1	C2	C3	C4	C5	C6
C1	1	2 (H)	6 (M)	7 (S)	5 (M)	1 (M)
C2	1/2(H)	1	4 (H)	5 (M)	2(H)	1/2 (VH)
C3	1/6 (M)	1/4 (H)	1	3 (H)	1/3 (S)	1/5 (M)
C4	1/7 (S)	1/5 (M)	1/3 (H)	1	1/2 (M)	1/5 (M)
C5	1/5 (M)	1/2 (H)	3 (S)	2 (M)	1	1/5 (S)
C6	1 (M)	2 (VH)	5 (M)	5 (M)	5 (S)	1

(CR=0.06<0.10)

Furthermore, the quantification of fuzzy linguistic descriptors, as shown in Fig. 6, is performed based on the degree of certainty when comparing criteria in pairs. Defuzzification of these values is carried out using the following expression [65]:

$$A=((t_3-t_1)+(t_2-t_1))/3+t_1 \tag{13}$$

Using Eq. (13), the values given in Table 6 are obtained.

Table 6 Defuzzified values of the degree of certainty

Descriptor name	Value after defuzzification
Small (S)	0.13
Medium (M)	0.5
High (H)	0.87
Very high (VH)	1

The next step is to fuzzify the initial decision-making matrix using the expressions from Tables 1 and 2. An example calculation is provided for comparing criteria C1 and C2, where the relation between the two criteria is defined as two, the certainty is indicated by the fuzzy linguistic descriptor "high," and the coefficient of competence k equals 0.5.

$$l_U = 2*0.87^2 = 1.51$$

$$l_L = 2*0.87 = 1.74$$

$$m = 2$$

$$u_L = (2-0.87)*2 = 2.26$$

$$u_U = (2-0.87^2)*2 = 2.49$$

In Table 7, the fuzzified initial decision-making matrix for expert 1 is provided:

Table 7 Fuzzified initial decision-making matrix for the expert 1

	C1	C2	...	C6
C1	(1,1,1,1,1)	(1.51, 1.74, 2, 2.26, 2.49)	...	(1,1,1,1,1)
C2	(0.4, 0.44, 0.5, 0.57, 0.66)	(1,1,1,1,1)	...	(0.5, 0.5, 0.5, 0.5,0.5)
C3	0.1,0.11,0.17,0.33, 0.67)	(0.2, 0.22, 0.25, 0.29, 0.33)	...	(0.11, 0.13, 0.20, 0.4, 0.8)
C4	(0.07, 0.08, 0.14, 1,1)	(0.11, 0.13, 0.2, 0.4, 0.8)	...	(0.11, 0.13, 0.20, 0.4, 0.8)
C5	(0.11, 0.13, 0.2, 0.4, 0.8)	(0.4, 0.44, 0.5, 0.57, 0.66)	...	(0.1, 0.11, 0.2, 1,1)
C6	(1,1,1,1,1)	(2,2,2,2,2)	...	(1,1,1,1,1)

Additionally, the classic steps of the AHP method are executed using standard fuzzy arithmetic. Finally, fuzzy weight coefficients for each criterion, calculated separately for each expert, are defuzzified using Eq. (12). The weight coefficients of the first expert are displayed in Table 8.

Table 8 Weight coefficients of the criteria for expert 1

Criterion	Classic AHP method (w_i)	F2AHP (w_i)
C_1	0.328	0.300
C_2	0.177	0.181
C_3	0.061	0.076
C_4	0.040	0.059
C_5	0.088	0.103
C_6	0.305	0.282

In Table 8, in addition to the F2AHP method, the criteria weight coefficients obtained by applying the classic AHP are also shown. As noted in the table, there are differences between the results obtained. The value range using the AHP method extends from 0.040 to 0.328, while in the application of the F2AHP, it is significantly lower, ranging from 0.059 to 0.300. Based on this, the expected conclusion is that using the F2AHP, the results - specifically, the weight coefficients of the criteria - are similar but not identical. The ranking of criteria has been maintained, indicating that pairwise comparison remains the most valued approach. However, by examining the ratio of the weight coefficients, it is clear that they are not the same for both methods. This suggests that in some other applications, the criteria rank may differ when applying the AHP versus the F2AHP. The same conclusions can be drawn from the results provided by other experts.

For the final definition of weight coefficients, it is required to convert the existing weight coefficients set into a single value, which is known in the literature as an aggregated weight coefficient. The calculation of this coefficient can be performed in several ways; in this paper, it is done by applying the following synthesis of individual expert decisions using the Geometric Mean Method (GMM) [66].

Table 9 shows the final aggregated weight coefficients for the criteria used to select backhoe loaders.

Table 9 Aggregated (final) weight coefficients of the criteria

Criterion	F2AHP (w_i)
C1	0.295
C2	0.184
C3	0.082
C4	0.069
C5	0.104
C6	0.266

3.2 Selection of backhoe loaders

There are many manufacturers of backhoe loaders on the market, and almost all of them have developed several different models. Six alternatives were identified for selecting backhoe loaders. The assessment of these alternatives based on each criterion (initial decision-making matrix) is presented in Table 10.

Table 10 Initial decision-making matrix ($\tilde{X}$)

	C1	C2	…	C4	C5	C6
A1	(4.04,4.24,4.24)	(0.96,1.2,1.26)	…	D5	(89000,91000,94000)	D2
A2	(4.14,4.44,4.44)	(0.8,1.1.05)	…	D4	(72000,75000,79000)	D3
A3	(4.14,4.44,4.44)	(1.04,1.3,1.37)	…	D3	(76000,79000,88000)	D5
A4	(4.7,4.8,5.7)	(0.8,1.1.05)	…	D3	(84000,89000,98000)	D4
A5	(4.6,5.6,5.6)	(1.01,1.26,1.33)	…	D3	(98000,102000,107000)	D4
A6	(5.2,5.8,5.8)	(0.8,1,1.05)	…	D4	(102000,104000,111000)	D5

Next, the quantification of linguistic descriptors or the fuzzification of the initial decision-making matrix was performed, as demonstrated in Table 11.

Table 11 Fuzzified initial decision-making matrix

	C1	...	C4	C5	C6
A1	(4.04,4.24,4.24)	...	(0.75,1,1)	(89000,91000,94000)	(0,0.25,0.5)
A2	(4.14,4.44,4.44)	...	(0.5,0.75,1)	(72000,75000,79000)	(0.25,0.5,0.75)
A3	(4.14,4.44,4.44)	...	(0.25,0.5,0.75)	(76000,79000,88000)	(0.75,1,1)
A4	(4.7,4.8,5.7)	...	(0.25,0.5,0.75)	(84000,89000,98000)	(0.5,0.75,1)
A5	(4.6,5.6,5.6)	...	((0.25,0.5,0.75)	(98000,102000,107000)	(0.75,1,1)
A6	(5.2,5.8,5.8)	...	(0.5,0.75,1)	(102000,104000,111000)	(0.75,1,1)

The steps of the FMABAC method, shown in [64], are further applied. Finally, the criteria functions of the alternatives are calculated, and ranking is performed based on them, as shown in Table 12.

Table 12 Rank of alternatives

	$\tilde{S}_i$	$def.\tilde{S}_i$	Rank
A1	(-0.252,0.089,0.385)	0.074	1
A2	(-0.337,0.011,0.33)	0.001	5
A3	(-0.362,-0.042,0.285)	-0.039	6
A4	(-0.345,0,0.479)	0.045	2
A5	(-0.356,0.062,0.389)	0.032	4
A6	(-0.3,0.045,0.364)	0.036	3

4. MODEL VALIDATION

4.1 Sensitivity Analysis

Sensitivity analysis has become an essential component of models based on MCDM [67, 68]. The most common method involves sensitivity analysis by adjusting the criteria weight coefficients [69, 70], which is also used here. Since this study highlights two criteria with higher weight coefficients (C1 and C6), the analysis was conducted for both. For each criterion, nine scenarios of weight coefficient changes were tested, where the weight of criteria C1 and C6 was reduced by 10%, with the remaining weight redistributed among the other criteria. The weight coefficients for each scenario when reducing criterion C1 are shown in Fig. 8.

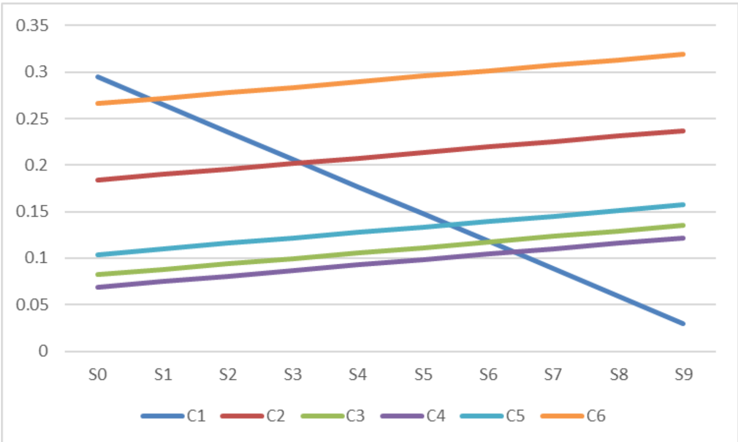

Fig. 8 Weight coefficient in different scenarios when reducing the weight coefficient of criterion C1

Scenarios for lowering the weighting coefficient of criterion C6 are shown in a similar manner (Fig. 9).

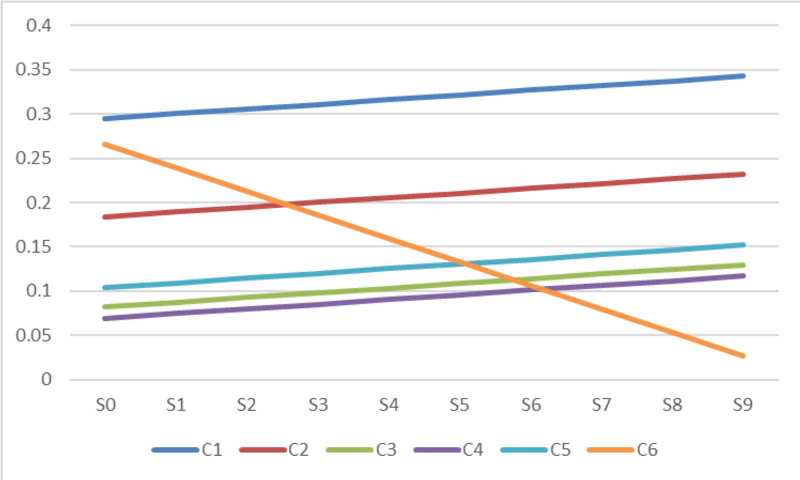

Fig. 9 Weight coefficient in different scenarios when reducing the weight coefficient of criterion C6

The ranking of alternatives in the sensitivity analysis when decreasing the weight coefficient C1 is shown in Fig. 10. It can be observed that the top-ranked alternative remains consistently A1, but there are notable shifts in the ranking of the other criteria. These changes are expected for two reasons. First, criterion C1 has an extremely high weight coefficient, so larger shifts in rank are likely when the weight of C1 changes significantly. Second, the criterion function values for alternatives A4, A5, and A6 are very close, so even minor changes in the weight coefficient can cause rank changes. A similar pattern occurs when analyzing the changes in the weight coefficients for criterion C6 (Fig. 11). In this case, alternative A6 moves to the first rank after the second scenario and remains there until the end. Meanwhile, alternative A1 drops from the first position to finally rank at number 5. This decline for A1 is due to its evaluation based on criterion C6.

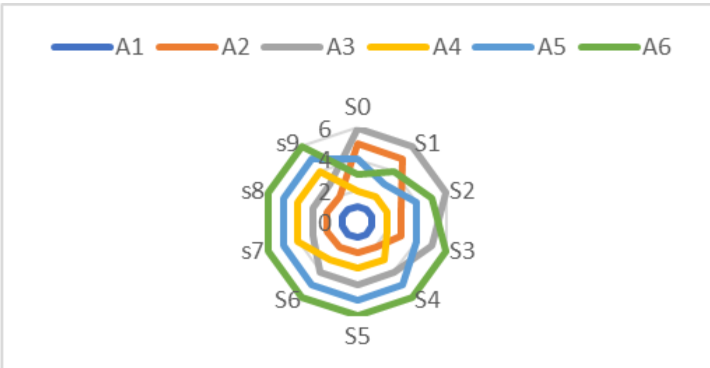

Fig. 10 Ranking of alternatives by applying different scenarios when reducing the weight coefficient of criterion C1

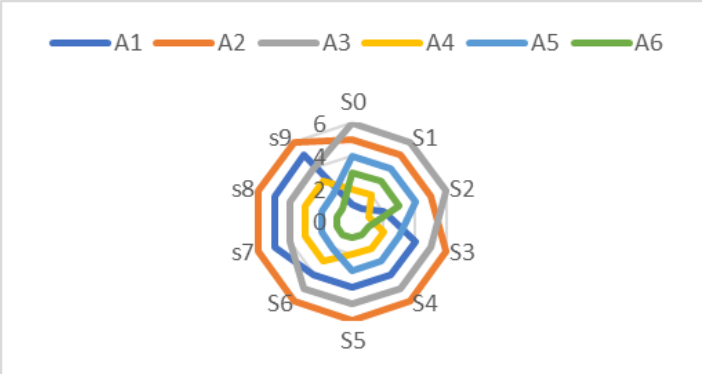

Fig. 11 Ranking of alternatives based on different scenarios when reducing the weight coefficient of criterion C6

Although the results are fairly stable and expected, it is useful to verify and analyze them using a correlation coefficient. In this case, Spearman's rank correlation coefficient (S_{rcc}) was used. The values of S_{rcc} for the analysis when reducing the weight coefficient of criterion C1 are shown in Fig. 12. It can be seen that the values of S_{rcc} from S1 to S3 are high and approach an ideal correlation. In this part, the weight of criterion C1 is reduced by up to 30%. As we move forward, the weight coefficient of criterion C1 decreases from 40% to 60% (S4 to S6), and S_{rcc} drops accordingly, but overall, the results stay satisfactory. Finally, with a substantial reduction in criterion C1 (70% to 90%), there is a notable decline in S_{rcc} when comparing the initial scenario (S0) and scenario S1 with scenarios S7 to S9. This outcome is expected, considering that the weight coefficient of criterion C1 is 0.295 in scenario S0, while in scenarios S7 to S9, it falls below 0.1. A similar pattern appears when criterion C6 is reduced (Fig. 13).

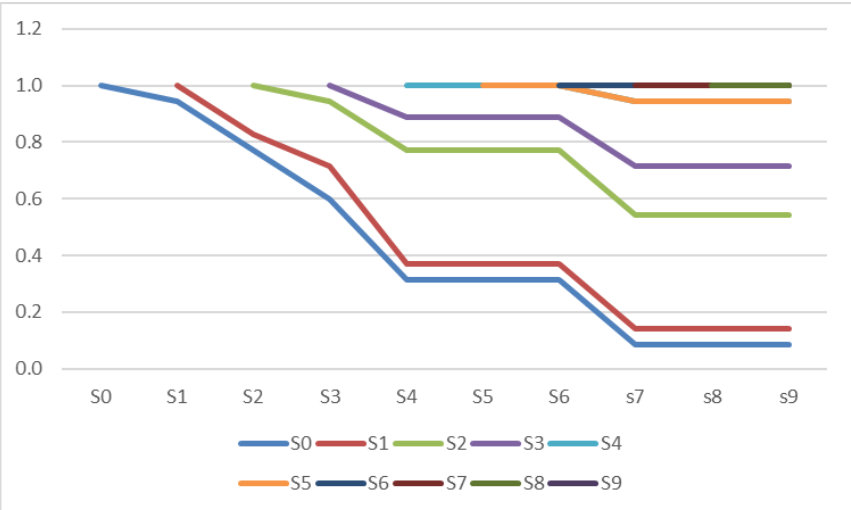

Fig. 12 Values of S_{rcc} when reducing the weight coefficient of criterion C1

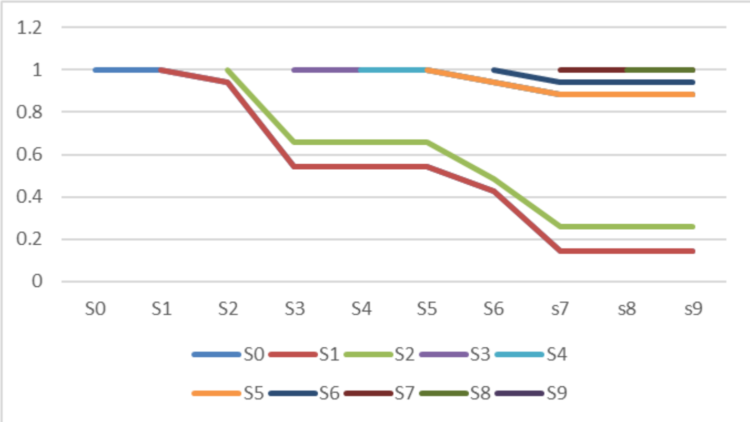

Fig. 13 Values of S_{rcc} when reducing the weight coefficient of criterion C6

The sensitivity analysis performed on the two most important criteria showed that the results are stable and fall within expected variations. The analysis also indicated that small errors in defining the weight coefficients do not influence the final alternatives ranking.

4.2 Comparative Analysis

Comparative analysis has become an essential part of validating results in the development of MCDM models [71, 72]. In this paper, the results obtained are compared with those from fuzzy TOPSIS [73] and fuzzy MAIRCA [74] methods. Figure 14 displays the ranking of alternatives using the mentioned methods. It is evident that alternative A1 ranks first in all cases. It is also apparent that alternatives A2 and A3 are always last or second to last. Alternatives A4, A5, and A6 experience rank fluctuations. These changes are due to differences in the mathematical methods used and the close results among these three alternatives. Specifically, even with the FMABAC method, these three alternatives have very similar values for the criterion functions. Overall, it can be stated that the results obtained using the FMABAC method are consistent, while the outcomes of other methods are more likely to vary. Additionally, S_{rcc} supports this conclusion, ranging from 0.77 to 0.94.

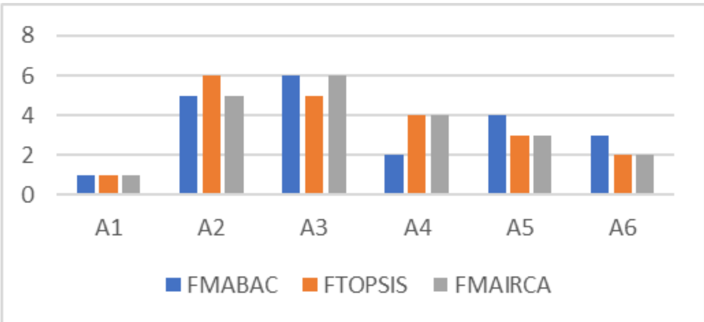

Fig. 14 Ranking of alternatives using different MCDM methods

5. CONCLUSION

The hybrid model F2AHP-FMABAC has been successfully used to determine the criteria weight coefficients for selecting backhoe loaders and for choosing the best option among the alternatives.

By applying the F2AHP method, several levels of uncertainty have been effectively addressed, and potential dilemmas faced by decision-makers have been quantified. The common dilemma of decision-makers when comparing alternatives in pairs using Saaty's scale is not overlooked; instead, during weight coefficients calculation, it is quantified by the degree of certainty they have in their comparisons. Additionally, the potential knowledge and experience of decision-makers are quantified via their competence coefficient. Notably, pairwise comparison remains a key element in defining the weight coefficients of criteria. The degrees of certainty and competence lead to smaller variations in the criteria's weight coefficients, which can become quite significant under greater uncertainty or lower competence levels. When decision-makers are fully confident in their knowledge ($\gamma = 1$) and entirely competent ($k = 1$), the standard AHP method is used without fuzzification, emphasizing the importance of improving the AHP method itself.

The FMABAC method has been successfully used to select the best alternative, considering the uncertainties involved in this type of decision-making. This is especially true when there are linguistic criteria, which is also the case in this study. The defined criteria clearly indicate that the structural features of backhoe loaders are key to the selection process. This is demonstrated by the weight coefficients of the first four criteria related to structural solutions, which together have a total weight of 0.63. Additionally, the last criterion is related to structural characteristics in some segments, although it mainly addresses economic costs. Criterion C6, which pertains to the purchase price of backhoe loaders, has a weight coefficient of 0.104. This suggests that price is not the most important factor when buying this type of construction equipment.

Model validation demonstrated that the results are consistent. This was first shown through sensitivity analysis, which involved reducing the weight coefficients of the two most significant criteria. The results stayed within expected variations. Additionally, the stability of the results was confirmed by the comparative analysis. Results from the comparative analysis using other methods closely match those obtained with the FMABAC method.

The developed model F2AHP-FMABAC can also be used to solve other problems with higher levels of uncertainty. For each application, it is important to analyze the sensitivity of the output results to assess the model's stability.

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