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RESEARCH ARTICLE

Application of Fuzzy-Rough Approach in Tractor Selection

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Abstract: The process of selecting a tractor exemplifies decision-making in a multi-criteria context. With the integration of the fuzzy-rough concept, this paper employs a hybrid multi-criteria decision-making methodology. The fuzzy-rough approach is employed to facilitate decision-making with imprecise information, incorporating uncertainty while mitigating the subjectivity inherent in expert judgments. The Logarithm Methodology of Additive Weights method is utilized to evaluate the importance of criteria influencing the evaluation of selected tractors. Subsequently, the Simple Additive Weighting (SAW) method is employed to identify the optimal tractor aligning with the specified criteria. Among the five observed tractors, the Solis S 26 exhibited the most favorable results. Sensitivity analysis and result validation support the validity of the results obtained. Result validation involves a comparison of fuzzy-rough SAW outcomes with alternative methods utilizing the fuzzy-rough approach, while the influence of criteria importance on the decision's final outcome was examined through sensitivity analysis. This paper contributes to comprehending the fuzzy-rough concept's applicability in multi-criteria decision-making. Demonstrated flexibility of the fuzzy-rough methodology suggests its potential for future research reliant on imprecise data, uncertainty incorporation, and subjectivity reduction in decision-making processes.

Keywords: decision making, fuzzy-rough approach, LMAW, SAW, expert evaluation, tractors

1. Introduction

Agricultural activity is the lifeblood of rural communities, underpinning their subsistence and economic sustainability (Bisht, 2021). The prudent selection of agricultural machinery, particularly small tractors, has emerged as a pivotal concern for households engaged in farming. The importance of this choice cannot be overstated, as it encompasses profound financial implications and holds the key to the success or failure of agricultural production (Li et al., 2023). The multifaceted nature of this decision requires a systematic and sophisticated approach to ensure its efficacy. This paper delves into the intricacies of small tractor selection, exploring the application of advanced fuzzy-rough methods to address this challenge.

Rural communities heavily rely on agriculture for their sustenance and economic well-being (Kumar et al., 2023). As such, the performance and efficiency of agricultural activities are essential for the vitality of these communities. Central to these activities is the role of tractors, which have evolved from being mere instruments of labor to becoming indispensable assets for agricultural households (Przywara et al., 2022). Tractors are the most commonly used machinery in agriculture. With the ability to have various accessories installed, they serve nearly all agricultural purposes, underscoring their crucial role in farming. Small tractors, in particular, have garnered increased attention due to their suitability for the scale of operations in rural settings. They offer a means to enhance productivity, reduce labor-intensive efforts, and foster competitiveness within the agricultural landscape (Ahmed & Takeshima, 2020). However, the acquisition of a tractor entails substantial financial investments, making it a high-stakes decision for agricultural households (Sok & Hoestra, 2023). Consequently, selecting the most suitable tractor becomes imperative to meet the specific needs of these households.

The criticality of the decision-making procedure lies in the choice of the right tractor aligning with the specific needs, constraints, and objectives of the household. An ill-informed decision can result in a cascade of detrimental consequences, with profound ramifications for agricultural productivity and the broader economic well-being of the community (Durczak et al., 2020). Hence, it is clear that a systematic and informed approach to small tractor selection is imperative to mitigate these risks and optimize the benefits.

While the significance of tractor selection in rural agriculture is indisputable, the methods employed in guiding these decisions have not kept pace with the complexity of the task. Conventional decision-making processes often lack the rigor and precision required to evaluate the multitude of attributes and alternatives

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inherent to tractor selection (Karmarkar & Gilke, 2020). As a result, there is a pressing need for advanced methodologies that can navigate the intricate landscape of small tractor acquisition. This paper addresses this research gap by introducing the application of fuzzy-rough methods to enhance the decision-making process for small tractor selection.

This paper's main goal is to provide an academically rigorous and practically applicable methodology to assist agricultural households in making informed decisions regarding small tractor selection. To achieve this objective, we will explore the application of two distinct yet complementary fuzzy-rough methods: the Logarithm Methodology of Additive Weights (LMAW) method (Pamučar et al., 2021) for determining attribute weights and the Simple Additive Weighting (SAW) method (Churchman & Ackoff, 1954) for ranking alternatives. By integrating these methodologies, we aim to provide a structured framework that facilitates comprehensive evaluations of the diverse attributes and alternatives associated with small tractors. Through this approach, we aspire to enable agricultural households to make well-informed and strategically advantageous decisions.

The importance of this research stems from its potential to revolutionize decision-making for small tractor selection in agricultural households. By introducing and applying fuzzy-rough methods, we aim to provide a structured, scientific, and transparent approach that empowers households to make optimal decisions. This research also carries broader implications for the agricultural sector, as it underscores the importance of advanced decision-support techniques in enhancing agricultural productivity. Additionally, it contributes to the ongoing discourse on the role of technology and data-driven decision-making in rural development, which has been gaining traction in recent years.

This paper aims to address specific gaps prevalent in current practices. Firstly, it introduces a methodology designed not only for ranking small agricultural machinery but also for assessing all types of agricultural equipment. Secondly, it presents a hybrid methodology integrating LMAW and SAW methods. Thirdly, it lays the foundation for the fuzzy-rough approach in evaluating agricultural mechanization. Fourthly, the developed procedure leverages the advantages of both fuzzy and rough approaches in decision-making processes.

This paper follows a structured organization. The literature review provides a comprehensive overview of existing research on small tractor selection in agricultural households. The methodology section outlines the practical steps involved in using the LMAW method for attribute weighting and the SAW method for ranking alternatives. Empirical findings present the results of the research and highlight the application of fuzzy-rough methods in real-world scenarios, with the discussion section critically evaluating the research findings, highlighting both the strengths and limitations of the proposed approach. It also provides practical recommendations for agricultural households and policymakers, focusing on potential benefits and areas for improvement. The conclusion synthesizes the paper's findings and underscores the broader implications of the research. It emphasizes how the proposed approach can enhance decision-making processes not only in small tractor selection but also in other domains involving complex choices.

2. Literature Review

The rural reforms initiated in early 1980s China (Hossen, 2019), which provided land tenure to peasants and transformed collective farms into smaller household farms (Vorozhtsov et al., 2022), had profound implications for tillage technology (Chen & Lan, 2020). A comprehensive analysis of data from 1755 counties spanning the years 1976–1988 revealed that these reforms led to a decline in tractor use and a surge in draft animal utilization. Post-reform, tractor usage became more aligned with local resources and farm size, with smaller tractors gaining popularity while larger ones experienced a decline. Subsequently, tractors became increasingly prevalent, particularly in small agricultural households.

While these reforms brought about a technological shift in China, a similar discourse on farm mechanization is unfolding in Africa, focusing on pathways such as animal power, two- and four-wheel tractors that best suit the needs of smallholder farmers (Daum et al., 2023). Proponents and opponents offer contrasting views in this debate. To address these concerns, Daum et al. (2023) introduced a "best-fit" framework tailored to assess these mechanization pathways in various contexts. Their research underscores that the success of mechanization depends on a harmonious fit with specific conditions, highlighting the pivotal role of public policies and investments in fostering market-driven innovation. Africa is also witnessing a shift toward private-sector initiatives as a viable alternative to government-led efforts, exemplified by John Deere's initiative in Zambia, promoting smallholder mechanization through a contractor model (Adu-Baffour et al., 2019). Their study focuses on its impact on farmers employing propensity score matching and indicates that farmers could substantially increase their earnings by expanding their cultivated land, primarily directing it toward education and additional food. However, this expansion has raised questions about labor dependency and strategies to enhance tractor services and land productivity.

Liao et al. (2022) have examined China's agricultural mechanization and offer key insights for enabling smallholders' access to machinery. Their findings emphasize the importance of gradual, self-reliant development, suitable mechanization theories, and effective, farmer-focused policies. This research offers valuable lessons for nations at the beginning of the process of agricultural mechanization in small-scale farming. In South Asia, labor shortages because of out-migration and the requirement for environmentally friendly farming methods have prompted a call for mechanizing small-scale agriculture (Aryal et al., 2021). This study focuses on India, Nepal, and Bangladesh, where tractors, pumps, threshers, harvesting machines, and power tillers are commonly utilized. The authors emphasize that policymakers should target marginalized and struggling farmers for ensuring sustainable agriculture as well as secure food supplies. Dzuganov et al. (2020) address crop production and technical challenges faced by peasant households and individual entrepreneurs in the Kabardino-Balkarian Republic. Their comparative research method examines factors like cultivated area dynamics, production volumes, crop yields, and the state of technical equipment, underscoring the vital role of technical equipment in enhancing efficiency and providing insights for creating effective mechanized structures with the necessary parameters. Phakdee and Suvanjumrat (2023) investigate the impact of soil compaction on sugarcane cultivation due to tractor tires' weight, introducing a tire-testing machine to assess tire-soil consolidation in crop fields, aiding farmers in tire selection. This research highlights the vital role that technology plays in optimizing farming practices. In a similar vein, Huo et al. (2020) assess the impact of small rice harvesters on soil disturbance, identifying methods to mitigate soil damage, including pre-harvesting drainage and equipment modifications like floating chassis and ultra-narrow wheels. These findings emphasize the importance of innovative solutions for sustainable agriculture.

Continuing the exploration of innovative solutions, Matache et al. (2020) delve into the use of electric tractors as an environmentally friendly alternative to conventional heat engine tractors. Their research underscores the potential for eco-friendly technology to transform the agricultural landscape. Vogt et al. (2021) highlight the potential of digital agriculture to revolutionize the agricultural sector, emphasizing the private business's role, that includes input companies and emerging software launches. Their study further underscores the ever-evolving landscape of agricultural technology. Concluding the narrative, Birner et al. (2021) investigate the potential of "Uber for tractors" in digital agriculture, focusing on smallholder farmers in developing regions and emphasizing the need for further investment in enabling conditions. This study highlights the evolving digital landscape in agriculture and the ongoing quest for inclusive technological solutions. Consequently, tractor manufacturers are increasingly pivoting toward the production of electric tractors, a technology yet to gain widespread practical usage. The primary limitation lies in their operational time being restricted by battery life, followed by lengthy recharging periods, inhibiting seamless and continuous use.

In the multifaceted landscape of agricultural machinery selection, several critical aspects come to the forefront. With technological advancements, the market offers a plethora of small tractor models, each designed with distinct features and capabilities, creating a complex decision-making environment. To complicate matters further, the economic dimension of these choices cannot be understated. For rural households, the selection of a small tractor is not merely a matter of convenience; it represents a substantial financial investment. These choices can significantly influence the economic stability and sustainability of families and their broader communities. Erroneous selections may lead to financial burdens, reduced productivity, and cascading adverse effects on the community.

Lu et al. (2022) recognized the challenges in agricultural machinery selection and introduced a model that integrated the improved CRiteria Importance Through Intercriteria Correlation (CRITIC)-entropy weight method and Grey Relational Analysis – Technique for Order Preference by Similarity to an Ideal Solution (GRA-TOPSIS). Their approach aimed to offer a comprehensive evaluation system that could be applied to diverse machinery choices. By validating their model using power machinery from Xinjiang Production and Construction Corps, they laid the groundwork for consistent and discriminating results, which would aid the selection and evaluation of agricultural machinery. In a similar vein, Banaeian and Pourhejazy (2020) understood the need for a well-informed decision-making framework, especially in the context of rice harvest machinery. Their framework combined sustainability and technical considerations, acknowledging the shift toward sustainability criteria in a highly competitive market. The Delphi method identified relevant criteria, the analytic hierarchy process (AHP) determined their importance, and the fuzzy TOPSIS ranked alternatives. Their research not only demonstrated the importance of considering sustainability but also offered insights for the local brand production to meet the demands of international markets. Puška et al. (2022) directed their attention to heavy tractors in Bosnia and Herzegovina (BiH), recognizing the need for efficient agricultural production. They utilized five methods to determine the criteria weights, introducing a novel one named the modified standard deviation. The CRADIS method (Compromise Ranking of Alternatives from Distance to Ideal Solution) was employed to attain tractor rank. The significance of their research lies in the introduction of new decision-making tools and the potential for guiding better choices in the agriculture sector. Özdağoğlu et al. (2021) tackled the complexities of selecting truck tractors for road freight logistics companies. The decision's intricacy arises from the conflicting criteria and abundant alternatives. Their innovative approach, which combined Fuzzy PIvot Pairwise RElative Criteria Importance Assessment (F-PIPRECIA) and Fuzzy COmplex PRoportional Assessment (F-COPRAS) methods, marks a significant contribution to the field. Notably, it addresses a unique and practical application for the logistics sector, offering benefits for both academic researchers and industry professionals. Lalghorbani and Jahan (2022) delved into the nuanced task of selecting wheat combines, a challenge due to the array of criteria and alternatives. Their application of the Multi-Objective Optimization on the basis of Ratio Analysis plus full multiplicative form (MULTIMOORA) method for evaluating alternatives, coupled with a model of group decision-making using qualitative criteria, demonstrates how to mitigate conflicts among decision-makers. Their consensus model represents a practical approach for various decision-making scenarios, fostering efficiency in industrial agriculture and aiding wheat combine purchasers.

In an era marked by technological advancements and complex decision landscapes, studies presented in this literature review collectively underscore the pressing need for sophisticated methodologies to navigate the intricate process of small agricultural machinery selection, particularly given the far-reaching implications for rural economies and sustainability.

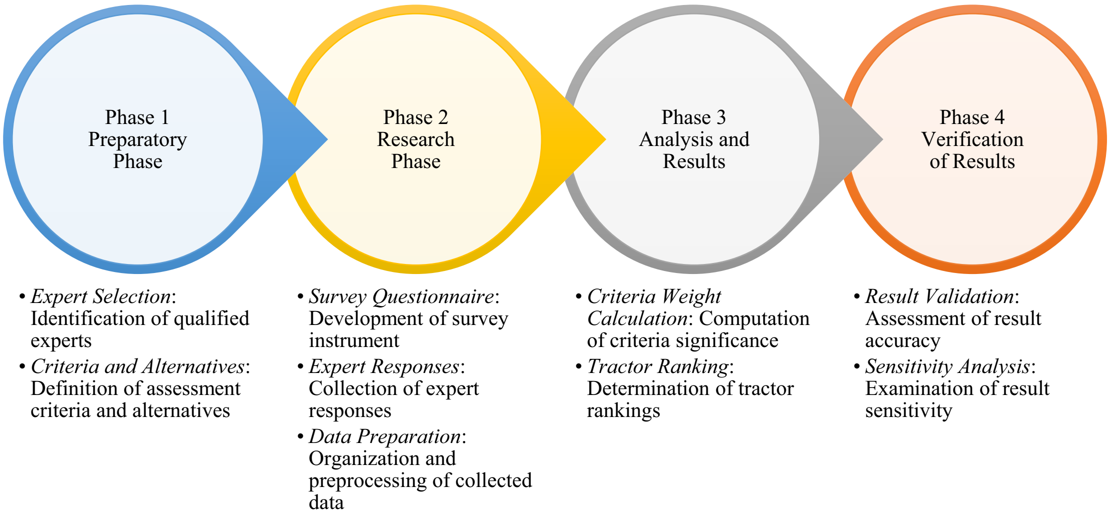
3. Methodology

In order to facilitate agricultural activities, the utilization of specific agricultural machinery is imperative. Households engaged in small-scale agricultural endeavors often face financial constraints that hinder their ability to acquire the full complement of required machinery. Given the limited scale of their agricultural operations, these households frequently opt to invest in a compact tractor to augment their capabilities. A tractor, as established by Puška et al. (2022), stands as the cornerstone of agricultural machinery. Consequently, it is unsurprising that the predominant choice in machinery procurement is the acquisition of a tractor. The versatility of a tractor is notable, as it can be upgraded and employed across a spectrum of agricultural tasks, ranging from plowing and land preparation for sowing to the harvesting process. This research introduces an innovative methodological framework designed for the assessment of small-scale agricultural strategies, illustrated in Figure 1.

In the initial phase of this research, denoted as the preparatory phase, the first step involves the selection of seven experts specializing in agricultural mechanization, holding the academic title of Doctor of Agricultural Sciences. These experts, comprising university professors and institute researchers, play a pivotal role in this study. In collaboration with these experts, the research then proceeds to determine the essential criteria and suitable alternatives for evaluation (Amiri et al., 2023). Ten criteria were considered for this study.

- Average Reference Price ($C1$): Signifying its significance in farmers' financial decisions, this criterion determines the affordability of a tractor for the agricultural community.
- Average Fuel Consumption ($C2$): This criterion holds paramount importance as tractor fuel consumption directly influences operational expenses and the long-term sustainability of farming endeavors. Lower fuel consumption is a key economic factor for farmers.
- Average Maintenance Costs ($C3$): A critical parameter, this criterion directly affects the financial burden on farmers. Lower maintenance costs translate to reduced economic strain.

Figure 1
Methodological framework



- Maximum Service Life (*C*4): This criterion evaluates the durability of a tractor, as a longer service life with infrequent replacements proves to be financially advantageous for farmers.
- Technological Upgradeability (*C*5): Tractors with this attribute can adapt to evolving technological needs, enhancing overall farmer productivity.
- Convenience of Operation (*C*6): This criterion simplifies farm operations, reduces driver fatigue, and increases overall farmer efficiency.
- Safety and Comfort (*C*7): Ensuring the protection of the driver and creating a conducive working environment are primary considerations in this criterion.
- Interchangeability of Parts (*C*8): A measure of a tractor's ease of maintenance and repair, this criterion reduces downtime and operational interruptions.
- Availability of Repair Points (*C*9): Efficient repair options ensure quick resolutions to issues, minimizing tractor downtime and associated disruptions.
- Farmers' Response to Purchase (*C*10): This criterion reflects farmer confidence in a tractor's brand or model and its alignment with their specific needs in the market.

These criteria have been established to provide comprehensive insights into tractors from the perspective of small-scale producers. Primarily, they focus on the technical and economic characteristics crucial for agricultural producers (Puška et al., 2022).

Utilizing these ten criteria, we evaluate the performance of the following five prominent tractors available in the markets of Serbia and BiH: Fort Diablo F 140D (*T*1), Same Frutteto Classic (*T*2), Tractor M5002 Narrow (*T*3), Tractor Solis S 26 (*T*4), and Tractor John Deere 5G (*T*5). These specific models were selected as they are among the most frequently purchased in these countries and are readily accessible through major tractor dealerships. Additionally, these tractors have readily available servicing options, simplifying their maintenance process.

After the experts, criteria, and alternatives in the form of small tractors have been selected, the subsequent phase is the research phase. Within this phase, the first step involves the creation of a survey questionnaire, which is divided into 2 parts: the first part, expert evaluation of the selected tractor selection criteria's significance, and the second part, experts evaluate the extent to which the selected tractors with these criteria. The completion of the surveys follows a structured process, with experts selecting from a range of appropriate linguistic values spanning from "Absolutely Low" (AL) to "Absolutely High" (AH), each represented by nine distinct levels. In rating the tractors, linguistic values are employed, covering the spectrum from "Very Bad" (VB) to "Very Good" (VG), comprising seven different levels (Table 1). The reason for employing different value scales for criteria and alternatives lies in the nature of evaluation, while experts assess ten criteria requiring ten ratings, evaluating alternatives entails assessing five options against ten criteria, thus resulting in 50 ratings. Hence, a value scale comprising seven levels was adopted for the alternatives.

Table 1
Linguistic values and associated fuzzy number membership functions

Linguistic values	Fuzzy numbers	Linguistic values	Fuzzy numbers
Absolutely low (AL)	(1, 1, 1)	Very bad (VB)	(1, 1, 2)
Very low (VL)	(1, 1.5, 2)	Bad (B)	(1, 2, 4)
Low (L)	(1.5, 2, 2.5)	Medium bad (MB)	(2, 4, 6)
Medium low (ML)	(2, 2.5, 3)	Medium (M)	(3, 5, 7)
Equal (E)	(2.5, 3, 3.5)	Medium good (MG)	(5, 7, 9)
Medium high (MH)	(3, 3.5, 4)	Good (G)	(7, 9, 10)
High (H)	(3.5, 4, 4.5)	Very good (VG)	(9, 10, 10)

After the survey questionnaires are created, they are distributed to the experts, and the completed questionnaires are subsequently collected from them (Bošković et al., 2023). Following this, the acquired data are organized for analysis (Vahidinia & Hasani, 2023).

The results are analyzed and presented in the third phase of this research. Since the data were initially gathered in a format consisting of linguistic values (Nezhad et al., 2023), it is essential to convert these data into numerical values to facilitate analysis and derive research outcomes. A fuzzy-rough methodology is employed here. Initially, linguistic values undergo transformation to fuzzy values using a membership function. For instance, the linguistic value “Absolutely low” converts to a fuzzy value (1, 1, 1), “Very low” into a fuzzy value (1, 1.5, 2), and so on, until all linguistic statements have been transformed to their equivalent fuzzy values (Table 1). The lower and upper limits are subsequently determined using the rough approach. Assuming a set $\theta^e = \{x_1^e, x_2^e, \ldots, x_n^e\}$ $(e = l, m, n)$, the lower and upper limits of $\widetilde{X}_i$ may be expressed in the following manner (Zhu et al., 2022):

$$\underline{Lim}(c_i^e) = \frac{1}{\underline{N}^e}\sum_{i=1}^{\underline{N}^e} \varphi \in \underline{Apr}(c_i^e), \tag{1}$$

$$\overline{Lim}(c_i^e) = \frac{1}{\overline{N}^e}\sum_{i=1}^{\overline{N}^e} \varphi \in \overline{Apr}(c_i^e) \tag{2}$$

It is important to note that the set θ^e represents the transformed values of experts’ linguistic responses, while the values “l”, “m”, “i”, “n” correspond to the first, second, and third representation of the fuzzy values. Lower and upper limits for a specific expert are determined by taking the same or lower values for that criterion or alternatives from all experts, and the upper limit is established by considering the same or higher values for that criterion or alternatives from all experts. The practical calculation of criterion weights will elucidate the exact procedure for setting these limits. Once the limits are determined in this manner, the fuzzy-rough value $\widetilde{X}_i$ could be expressed as follows (Pamučar et al., 2018):

$$FR(\widetilde{X}_i) = \left([x_i^{lL}, x_i^{lU}], [x_i^{mL}, x_i^{mU}], [x_i^{uL}, x_i^{uU}]\right) = \\ = \begin{pmatrix} [\underline{Lim}(x_i^l), \overline{Lim}(x_i^l)], [\underline{Lim}(x_i^m), \overline{Lim}(x_i^m)], \\ [\underline{Lim}(x_i^u), \overline{Lim}(x_i^u)] \end{pmatrix} \tag{3}$$

By employing the fuzzy-rough approach, the research aims to ascertain the importance of individual criteria and establish the ranking of tractors. To achieve this, the fuzzy-rough LMAW methodology will be utilized to establish criterion importance, as well as the fuzzy-rough SAW method for further analysis. Unlike certain other methods in practice, the LMAW method does not necessitate ranking or direct comparison among criteria: evaluation suffices. On the other hand, the SAW method represents one of the simplest MCDM approaches in practice. However, its outcomes align closely with those of more complex methods, justifying its selection in this study.

3.1. The fuzzy-rough LMAW methodology

The application of fuzzy-rough LMAW is distinctive in that it does not require the decision-maker to rank criteria, as is the case with the Full Consistency Method (FUCOM) method (Jusufbašić & Stević, 2023) or Stepwise Weight Assessment Ratio Analysis (SWARA) (Sivageerthi et al., 2022). Moreover, it avoids the need to compare individual criteria, as is typically done in the AHP method (Saqlain, 2023). Instead, this approach allows assessing all of the criteria through linguistic values. This simplifies the decision-making process and reduces the time required for decision-making.

The following is a summary of the steps in the fuzzy-rough LMAW method (Puška et al., 2023):

Step 1. The initial decision-making matrix creation: Comprising the linguistic values provided by experts for the identified criteria.

Step 2. Linguistic values’ transformation: Linguistic values are transformed into fuzzy numbers by applying a membership function.

Step 3. Lower and upper limits definition: Assigning upper as well as lower limits to each of the fuzzy numbers as follows:

$$\widetilde{\gamma}_{Cn}^e = \left([\alpha^{lL}, \alpha^{lU}], [\alpha^{mL}, \alpha^{mU}], [\alpha^{uL}, \alpha^{uU}]\right) \tag{4}$$

Step 4. The absolute anti-ideal point definition: Determining the value smaller than the smallest value in the fuzzy-rough decision matrix.

Step 5. Definition of the ratio vector: Dividing the initial fuzzy-rough decision matrix by the anti-ideal point value as follows.

$$\widetilde{\mu}_{Cn}^e = \left(\frac{\widetilde{\gamma}_{Cn}^e}{\widetilde{\gamma}_{AIP}}\right) = \\ = \left(\left[\frac{\alpha^{lL}}{\widetilde{\gamma}_{AIP}}; \frac{\alpha^{lU}}{\widetilde{\gamma}_{AIP}}\right]; \left[\frac{\alpha^{mL}}{\widetilde{\gamma}_{AIP}}; \frac{\alpha^{mU}}{\widetilde{\gamma}_{AIP}}\right]; \left[\frac{\alpha^{uL}}{\widetilde{\gamma}_{AIP}}; \frac{\alpha^{uU}}{\widetilde{\gamma}_{AIP}}\right]\right) \tag{5}$$

Step 6. Weight coefficients‘ vector determination: Finding the natural logarithm for ratio vector matrix‘s values and dividing the obtained value by the natural logarithm derived from the product of corresponding elements of the fuzzy-rough number:

$$\widetilde{\omega}_j^e = \left(\frac{\ln(\widetilde{\mu}_{Cn}^{LU})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{LU}\right)}\right) \\ = \begin{pmatrix} \left[\frac{\ln(\widetilde{\mu}_{Cn}^{lL})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{uU}\right)}; \frac{\ln(\widetilde{\mu}_{Cn}^{lU})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{uL}\right)}\right] \\ \left[\frac{\ln(\widetilde{\mu}_{Cn}^{mL})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{mU}\right)}; \frac{\ln(\widetilde{\mu}_{Cn}^{mU})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{mL}\right)}\right] \\ \left[\frac{\ln(\widetilde{\mu}_{Cn}^{uL})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{lU}\right)}; \frac{\ln(\widetilde{\mu}_{Cn}^{uU})}{\ln\left(\prod_{j=1}^n \widetilde{\mu}_{Cn}^{lL}\right)}\right] \end{pmatrix} \tag{6}$$

Step 7. Criteria weights definition: Determining the weight of criteria, typically achieved by calculating the average value of individual criterion weights per expert. The Bonferroni aggregator can be applied in this case.

3.2. The fuzzy-rough SAW methodology

Utilization of the fuzzy-rough SAW methodology simplifies the process of ranking alternatives in the case of tractors. This method is particularly advantageous because it presents fewer challenges compared to some other methods and yields results that align closely with more intricate methodologies (Chen, 2012). The following steps outline the fuzzy-rough SAW method.

Step 1. Fuzzy-rough decision matrix establishment. This step involves creating a decision matrix using the initially generated linguistic decision matrix as a basis. The linguistic values are initially converted into fuzzy numbers, and for every fuzzy number, the lower and upper limits are obtained.

$$A = \begin{bmatrix} \left(a^L_{1,11}, a^U_{1,11}\right), \left(a^L_{2,11}, a^U_{21}\right), \left(a^L_{3,11}, a^U_{3,11}\right) & \cdots & \left(a^L_{1,1n}, a^U_{1,1n}\right), \left(a^L_{2,1n}, a^U_{2,1n}\right), \left(a^L_{3,1n}, a^U_{3,1n}\right) \\ \vdots & \ddots & \vdots \\ \left(a^L_{1,m1}, a^U_{1,m1}\right), \left(a^L_{2,m1}, a^U_{2,m1}\right), \left(a^L_{3,m1}, a^U_{3,m1}\right) & \cdots & \left(a^L_{1,nm}, a^U_{1,nm}\right), \left(a^L_{2,nm}, a^U_{2,nm}\right), \left(a^L_{3,nm}, a^U_{3,nm}\right) \end{bmatrix} \quad (7)$$

Step 2. Initial fuzzy-rough decision matrix normalization. Normalization is carried out for both cost and benefit criteria.

$$n_{ij} = \left(\frac{a_1^L}{\sum_{i=1}^m a_3^U}, \frac{a_1^U}{\sum_{i=1}^m a_3^L}\right), \left(\frac{a_2^L}{\sum_{i=1}^m a_2^U}, \frac{a_2^U}{\sum_{i=1}^m a_2^L}\right), \quad (8)$$
$$\left(\frac{a_3^L}{\sum_{i=1}^m a_1^U}, \frac{a_3^U}{\sum_{i=1}^m a_1^L}\right), \text{ for benefit criteria;}$$

$$n_{ij} = \left(\frac{\frac{1^L}{a_1}}{\sum_{i=1}^m \frac{1^U}{a_3}}, \frac{\frac{1}{a_1^U}}{\sum_{i=1}^m \frac{1^L}{a_3}}\right), \left(\frac{\frac{1}{a_2^L}}{\sum_{i=1}^m \frac{1^U}{a_2}}, \frac{\frac{1}{a_2^U}}{\sum_{i=1}^m \frac{1^L}{a_2}}\right), \quad (9)$$
$$\left(\frac{1/a_3^L}{\sum_{i=1}^m 1/a_1^U}, \frac{1/a_3^U}{\sum_{i=1}^m 1/a_1^L}\right), \text{ for cost criteria.}$$

Step 3. Initial fuzzy-rough decision matrix weighting. Here, the weights assigned to the criteria are multiplied by the values in the initial fuzzy-rough decision matrix.

$$\overline{\overline{v}}_{ij} = \overline{\overline{n}}_{ij} \cdot \overline{\overline{w}}_j \quad (10)$$

Step 4. Fuzzy-rough SAW value calculation. The fuzzy-rough SAW method's value is calculated by adding all of the values of individual fuzzy-rough elements for each alternative.

$$\overline{\overline{S}}_i = \sum_{i=1}^m \overline{\overline{v}}_{ij} \quad (11)$$

Step 5. Determine the average SAW value. This step generates a single value to represent the order of the alternatives.

$$R_i = \frac{S_1^L + S_1^U + S_2^L + S_2^U + S_3^L + S_3^U}{6} \quad (12)$$

4. Results

Prior to selecting the most suitable tractor in accordance with established objectives and criteria, it is essential to initially evaluate the importance of these criteria. This assessment is conducted by chosen experts, who evaluate the importance of these criteria using linguistic values (Table 2). Based on these assessments, an initial linguistic decision matrix is formulated, marking the first step in the calculation of criterion importance through the application of weights in the fuzzy-rough LMAW methodology.

Table 2
Initial linguistic decision matrix for criteria evaluation

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
Expert 1 (E1)	EH	H	H	H	E	MH	EH	H	MH	MH
Expert 2 (E2)	EH	EH	H	EH	E	E	EH	H	H	MH
Expert 3 (E3)	AH	EH	H	H	MH	E	EH	EH	H	MH
Expert 4 (E4)	AH	EH	H	EH	MH	H	EH	H	H	H
Expert 5 (E5)	AH	AH	EH	MH	MH	MH	EH	H	AH	H
Expert 6 (E6)	EH	AH	EH	H	H	MH	EH	H	AH	H
Expert 7 (E7)	AH	AH	EH	EH	H	MH	EH	H	EH	EH

Once the linguistic initial decision matrix has been established, it becomes imperative to convert these linguistic values into fuzzy numbers, employing a membership function (Table 1). For example, the linguistic value "H" is translated into a fuzzy number (3.5, 4, 4.5). Utilizing the membership function (Table 1), all linguistic values undergo this transformation, establishing the initial fuzzy decision matrix (Table 3). This decision matrix provides the foundational matrix upon which operations are executed within the fuzzy-rough approach.

Following the creation of the initial fuzzy-rough decision matrix, the subsequent step involves the determination of lower and upper limits through the rough approach. Taking Expert 1 to be an illustration, the lower and upper limits for criterion $C1$ are calculated as follows:For the first fuzzy number "l":

$$\underline{Lim}(1) = \frac{4+4+4}{3} = 4.00,$$
$$\overline{Lim}(1) = \frac{4+4+4.5+4.5+4.5+4+4.5}{7} = 4.29; \quad (13)$$

Table 3
Initial fuzzy decision matrix for criteria evaluation

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	...	$C10$
$E1$	(4, 4.5, 5)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(2.5, 3, 3.5)	(3, 3.5, 4)	...	(3, 3.5, 4)
$E2$	(4, 4.5, 5)	(4, 4.5, 5)	(3.5, 4, 4.5)	(4, 4.5, 5)	(2.5, 3, 3.5)	(2.5, 3, 3.5)	...	(3, 3.5, 4)
$E3$	(4.5, 5, 5)	(4, 4.5, 5)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(3, 3.5, 4)	(2.5, 3, 3.5)	...	(3, 3.5, 4)
$E4$	(4.5, 5, 5)	(4, 4.5, 5)	(3.5, 4, 4.5)	(4, 4.5, 5)	(3, 3.5, 4)	(3.5, 4, 4.5)	...	(3.5, 4, 4.5)
$E5$	(4.5, 5, 5)	(4.5, 5, 5)	(4, 4.5, 5)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(3, 3.5, 4)	...	(3.5, 4, 4.5)
$E6$	(4, 4.5, 5)	(4.5, 5, 5)	(4, 4.5, 5)	(3.5, 4, 4.5)	(3.5, 4, 4.5)	(3, 3.5, 4)	...	(3.5, 4, 4.5)
$E7$	(4.5, 5, 5)	(4.5, 5, 5)	(4, 4.5, 5)	(4, 4.5, 5)	(3.5, 4, 4.5)	(3, 3.5, 4)	...	(4, 4.5, 5)

For the second fuzzy number "m":

$$\underline{Lim}(2) = \frac{4.5 + 4.5 + 4.5}{3} = 4.50,$$
$$\overline{Lim}(2) = \frac{4.5 + 4.5 + 5 + 5 + 5 + 4.5 + 5}{7} = 4.79; \tag{14}$$

For the third fuzzy number "n":

$$\underline{Lim}(3) = \frac{5 + 5 + 5 + 5 + 5 + 5 + 5}{7} = 5.00,$$
$$\overline{Lim}(3) = \frac{5 + 5 + 5 + 5 + 5 + 5 + 5}{7} = 5.00; \tag{15}$$

The calculation of lower and upper limit values for all criteria and all experts follows a similar approach. When determining the lower limit, the assessment of the expert for whom the lower limit is being calculated is taken into account, along with the assessments of all other experts that are either the same or lower (Dragan et al., 2019). The average of these values is then computed. In the case of determining the upper limit, the expert's ratings are observed, along with the ratings of other experts that are equal to or greater than the expert's ratings. Again, the average of these values is calculated. This approach is applied consistently to form a fuzzy-rough decision matrix (Table 4).

by the product of the corresponding elements for all experts and criteria. Taking Expert 1 and Criterion $C1$ as an example:

$$\widetilde{\omega}_1^{ll} = \frac{\ln(1.67)}{\ln(23923)} = 0.05,\ \widetilde{\omega}_1^{lu} = \frac{\ln(1.79)}{\ln(4716)} = 0.07, \widetilde{\omega}_1^{ml} = \frac{\ln(1.88)}{\ln(240)} = 0.11,\ \widetilde{\omega}_1^{mu} = \frac{\ln(2.00)}{\ln(97)} = 0.15,\ \widetilde{\omega}_1^{nl} = \frac{\ln(2.08)}{\ln(66)} = 0.18,\ \widetilde{\omega}_1^{nu} = \frac{\ln(2.08)}{\ln(23)} = 0.23 \tag{16}$$

Using this procedure, the weight values for each expert are individually calculated, and, ultimately, the combined weight for all experts is determined (Table 5). The final results indicate that, according to expert opinions, Criterion $C1$ holds the most significance. However, there is only a slight variation between this criterion and Criteria $C2$ and $C7$. This suggests that these three criteria are the most crucial in the eyes of the experts when selecting a tractor. Conversely, Criteria $C6$ and $C5$ are considered to be of lesser importance in the experts' decision-making process. Notably, there is minimal disparity in the weights assigned to the criteria, with each criterion exerting its unique impact on the decision. Thus, the choice that will prevail is shaped by a comprehensive consideration of all criteria. The lack of substantial variance in the weights of these criteria stems from their uniformly high ratings. Consequently, their weights do not significantly differ due to the consistently high ratings across all criteria.

Table 4
Ratio vector decision matrix

	$C1$	$C2$	...	$C10$
$E1$	[1.67, 1.79][1.88, 2.00][2.08, 2.08]	[1.46, 1.73][1.67, 1.93][1.88, 2.05]	...	[1.25, 1.40][1.46, 1.61][1.67, 1.82]
$E2$	[1.67, 1.79][1.88, 2.00][2.08, 2.08]	[1.62, 1.77][1.83, 1.98][2.05, 2.08]	...	[1.25, 1.40][1.46, 1.61][1.67, 1.82]
$E3$	[1.79, 1.88][2.00, 2.08][2.08, 2.08]	[1.62, 1.77][1.83, 1.98][2.05, 2.08]	...	[1.25, 1.40][1.46, 1.61][1.67, 1.82]
$E4$	[1.79, 1.88][2.00, 2.08][2.08, 2.08]	[1.62, 1.77][1.83, 1.98][2.05, 2.08]	...	[1.35, 1.51][1.56, 1.72][1.77, 1.93]
$E5$	[1.79, 1.88][2.00, 2.08][2.08, 2.08]	[1.73, 1.88][1.93, 2.08][2.05, 2.08]	...	[1.35, 1.51][1.56, 1.72][1.77, 1.93]
$E6$	[1.67, 1.79][1.88, 2.00][2.08, 2.08]	[1.73, 1.88][1.93, 2.08][2.05, 2.08]	...	[1.35, 1.51][1.56, 1.72][1.77, 1.93]
$E7$	[1.79, 1.88][2.00, 2.08][2.08, 2.08]	[1.73, 1.88][1.93, 2.08][2.05, 2.08]	...	[1.40, 1.67][1.61, 1.88][1.82, 2.08]

Table 5
Final weight of criteria

Criteria	Weights
$C1$	([0.05, 0.07] [0.11, 0.14] [0.16, 0.20])
$C2$	([0.05, 0.06] [0.11, 0.14] [0.16, 0.20])
$C3$	([0.04, 0.05] [0.09, 0.12] [0.14, 0.19])
$C4$	([0.03, 0.05] [0.08, 0.12] [0.13, 0.19])
$C5$	([0.01, 0.03] [0.05, 0.09] [0.10, 0.16])
$C6$	([0.01, 0.03] [0.05, 0.08] [0.10, 0.15])
$C7$	([0.05, 0.06] [0.11, 0.13] [0.16, 0.20])
$C8$	([0.04, 0.04] [0.09, 0.11] [0.14, 0.18])
$C9$	([0.03, 0.06] [0.09, 0.13] [0.13, 0.19])
$C10$	([0.03, 0.04] [0.07, 0.11] [0.12, 0.18])

Upon establishment of this decision matrix, the absolute anti-ideal point is established, which is set to be less than the smallest value among the lower limits for all experts and criteria. Given that the smallest value is 2.5, the absolute anti-ideal point is calculated to be 2.4 in this particular instance. All elements within the fuzzy-rough decision matrix are then divided by this value, resulting in the computation of the ratio vector.

Following this, step 6 is executed, where the natural logarithm of the ratio vector matrix is calculated, and this value is then divided

Following the determination of criterion weights, the tractors featured in this study are ranked. The initial step in this ranking process involves the creation of an initial fuzzy-rough decision matrix. To form this matrix, the steps mirror those employed in the fuzzy-rough LMAW method. Initially, experts evaluate the selected tractors based on the criteria. Each expert assigns a specific evaluation to each tractor in a manner of linguistic values (Table 6). Subsequently, such linguistic values are transformed into fuzzy numbers (Table 1) through the use of a membership function. Finally, the lower and upper limits for the rough values are established in a manner similar to that employed in the fuzzy-rough LMAW methodology. This decision matrix serves as the foundation for computing the ranking of tractors utilizing the fuzzy-rough SAW methodology.

The subsequent procedure in the fuzzy-rough SAW method entails normalizing the initial fuzzy-rough decision matrix for alternatives. Given that this research employs a rating scale ranging from "Very Bad" to "Very Good" for each criterion, each criterion is considered a benefit criterion. Thus, Equation (8) is applied for data normalization. For instance, considering the first alternative and the first criterion, the calculation is as follows:

$$n_{11} = \left(\left[\frac{6.6}{10.0} = 0.66,\ \frac{8.0}{9.7} = 0.82 \right], \left[\frac{8.5}{9.5} = 0.90, \frac{9.5}{8.5} = 1.12 \right], \left[\frac{9.7}{8.0} = 1.22, \frac{10.0}{6.6} = 1.52 \right] \right) \tag{17}$$

In the same manner, normalized values for all elements in the fuzzy-rough decision matrix are computed, resulting in the creation of the fuzzy-rough normalized decision matrix (Table 7).

Subsequently, decision matrix weighting (Table 7) is carried out by multiplying each element with the corresponding criterion weights. For instance, for tractor 1 and criterion 1, it can be illustrated as follows:

$$\begin{aligned} v_{11} &= ([0.66,\ 0.82][0.90,\ 1.12][1.22,\ 1.52]) \\ &\quad \cdot ([0.05,\ 0.07][0.11,\ 0.14][0.16,\ 0.20]) \\ &= ([0.03,\ 0.05]\ [0.10,\ 0.16]\ [0.20,\ 0.31]) \end{aligned} \tag{18}$$

In this example, the element representing tractor 1 and criterion 1 is multiplied by the weights for criterion $C1$. The other elements in the decision matrix are computed in the same manner. At the conclusion of the fuzzy-rough SAW decision matrix, the corresponding elements of the fuzzy-rough numbers for all alternatives are summed, ultimately resulting in the establishment of a final ranking order (Table 8). Based on these results, it is evident that the highest-ranked tractor is $T4$ (Tractor Solis S), followed by tractor $T3$ (Tractor M5002 Narrow). Conversely, the experts' evaluations indicate that the lowest-ranked tractor is $T5$ (Tractor John Deere 5G).

To validate these results, a verification process will be applied, employing identical initial fuzzy decision matrix for alternatives and the identical criteria weights (Ali et al., 2023; Naseem et al., 2023; Więckowski et al., 2023). This approach aims to assess how specific steps in alternative methods impact the final ranking of tractors. In this research, four fuzzy-rough methods have been selected for comparison with the rankings obtained through the fuzzy-rough SAW method. The chosen methods are fuzzy-rough Additive Ratio Assessment (ARAS), fuzzy-rough CRADIS, fuzzy-rough Multi-Attributive Border Approximation Area Comparison (MABAC), and fuzzy-rough Weighted Product Model (WPM). The rationale for selecting these methods is as follows: the ARAS and MABAC methods utilize distinct normalization formulas, allowing for examination of the impact of normalization on alternative rankings. On the other hand, the CRADIS and WPM methods employ the same normalization as the SAW method, enabling assessment of whether specific methodological steps influence the final ranking when the same initial decision matrix, identical normalization, and criteria weights are applied. Upon the implementation of these methodologies, the following results were obtained (Figure 2): Tractors $T4$ and $T5$ received consistent rankings across all methods, while the fuzzy-rough ARAS method delivered results that differed mostly from the others. SAW and WPM shared the same ranking order as CRADIS and MABAC. The reason for SAW and WPM yielding the same ranking order lies in several factors. Firstly, both methods employ identical normalization techniques. Secondly, they utilize a similar approach of multiplying or scaling the normalized decision matrix with corresponding weights. Thirdly, these methods operate through fundamental rather than intricate steps. In contrast,

Table 6
Initial linguistic decision matrix for evaluation of alternatives

*E*1	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	G	M	M	G	M	MG	MG	MB	M	MG
*T*2	MG	MG	MG	G	M	G	MB	B	MG	M
*T*3	M	MG	MB	MG	M	G	MG	MB	G	MB
*T*4	MG	M	MG	G	MG	VG	MG	M	G	MG
*T*5	G	MB	M	G	M	MG	MG	MB	MG	MG
*E*2	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	G	MG	M	VG	MG	MG	MG	MB	MB	M
*T*2	G	MG	M	MG	M	VG	G	M	MG	M
*T*3	G	M	MG	M	MG	MG	MG	MG	MG	MG
*T*4	MG	MG	G	MG	MG	G	M	M	MB	M
*T*5	MG	MG	MG	M	MG	MG	MG	MB	MG	G
*E*3	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	VG	MG	MG	VG	MG	MG	MG	MB	MB	M
*T*2	MG	M	MG	MG	M	VG	M	B	MG	M
*T*3	G	MG	MG	MG	M	G	MG	M	MG	MB
*T*4	MG	MG	G	MG	MG	G	M	MG	G	M
*T*5	MG	MB	M	MG	MG	MG	MG	MB	MG	M
*E*4	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	G	MG	MG	VG	VG	MG	MG	MB	M	MG
*T*2	MG	G	VG	MG	M	VG	M	MG	MG	M
*T*3	G	MG	MG	MG	G	VG	MG	M	MB	MB
*T*4	MG	MG	G	MG	MG	G	MG	MG	G	MG
*T*5	MG	MB	M	MG	MG	MG	MG	MG	MG	M
*E*5	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	VG	MG	MG	VG	VG	MG	MG	MB	MG	MG
*T*2	MG	VG	VG	MG	M	VG	M	G	MG	M
*T*3	G	MG	G	MG	G	VG	G	M	MG	M
*T*4	MG	MG	G	M	MG	MG	MG	MG	G	MG
*T*5	MG	MB	M	MG	MB	MG	MG	MG	MG	M
*E*6	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	MG	MG	MG	VG	G	MG	M	MB	MG	G
*T*2	MG	G	VG	G	M	VG	G	G	G	M
*T*3	MG	MG	MG	MG	G	VG	G	M	MG	G
*T*4	MG	MG	G	M	MG	G	MG	G	G	MG
*T*5	MG	MB	M	MG	MB	MG	MG	MG	G	M
*E*7	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10
*T*1	G	MG	MG	VG	G	G	M	MB	M	G
*T*2	MG	G	VG	MG	M	VG	G	G	G	M
*T*3	G	MG	MG	MG	MG	VG	VG	M	VG	G
*T*4	MG	MG	MG	MB	MG	G	MG	VG	G	VG
*T*5	MG	MG	M	MG	MB	MG	MG	MG	G	M

Table 7
Normalized fuzzy-rough decision matrix for evaluation of alternatives

	*C*1	*C*2	…	*C*10
*T*1	[0.66, 0.82][0.90, 1.12][1.22, 1.52]	[0.46, 0.57][0.72, 1.00][1.16, 1.80]	…	[0.40, 0.72][0.77, 1.30][1.36, 2.52]
*T*2	[0.51, 0.57][0.74, 0.89][1.13, 1.41]	[0.51, 0.84][0.78, 1.29][1.19, 1.97]	…	[0.32, 0.37][0.63, 0.82][1.19, 1.88]
*T*3	[0.54, 0.70][0.78, 1.04][1.11, 1.51]	[0.46, 0.57][0.72, 1.00][1.16, 1.80]	…	[0.29, 0.68][0.60, 1.22][1.13, 2.38]
*T*4	[0.50, 0.51][0.74, 0.82][1.13, 1.37]	[0.46, 0.57][0.72, 1.00][1.16, 1.80]	…	[0.39, 0.73][0.76, 1.27][1.36, 2.46]
*T*5	[0.51, 0.57][0.74, 0.89][1.13, 1.41]	[0.23, 0.40][0.47, 0.79][0.86, 1.50]	…	[0.34, 0.58][0.65, 1.09][1.22, 2.23]

Table 8
Final ranking of tractors

	$\bar{\bar{S}}_i$	R_i	Rank
*T*1	[0.22, 0.41][0.71, 1.21][1.58, 3.03]	1.194	3
*T*2	[0.21, 0.38][0.68, 1.24][1.55, 3.07]	1.189	4
*T*3	[0.20, 0.42][0.68, 1.28][1.57, 3.14]	1.215	2
*T*4	[0.22, 0.43][0.73, 1.28][1.65, 3.20]	1.253	1
*T*5	[0.19, 0.35][0.64, 1.11][1.52, 2.95]	1.124	5

other methods employed various types of normalization and distinct weighting, with the MABAC method as the primary example. This demonstrates that the normalization applied by other methods has the greatest influence on the deviation in results from the SAW method. All these methods confirmed that Tractor *T*4 is the top-rated choice among the observed tractors, as per expert assessments. Since the results are consistent between pairs of methods, a sensitivity analysis will also be carried out to assess the extent to which criteria weights impact alternative rankings (Ihsan et al., 2023).

In the course of the sensitivity analysis, criteria weights are adjusted by gradually reducing them, decrementing each criterion's weight by 15% until it reaches 10% of its initial weight. As there are 10 criteria, each criterion undergoes six reductions, resulting in a total of 60 sensitivity analysis scenarios. It is important to note that only the weights of one criterion are altered individually (Damjanović et al., 2022), while the weights of the remaining criteria remain unaltered (Zhou et al., 2022). This approach allows for the determination of the impact of each criterion on alternatives' ranking (Gergin et al., 2022; Tešić et al., 2022). According to the sensitivity analysis results (Figure 3), the rankings of tractors *T*2 and *T*1 experienced the most significant changes. When the rankings of these tractors were modified, the outcomes mirrored those obtained when employing the CRADIS and MABAC methods. These findings corroborate that the rankings of tractors *T*1 and *T*2 are closely aligned and underscore how even slight adjustments in criteria weights can influence the ranking of these tractors. Notably, the fuzzy-rough SAW method provided the most proximate values, revealing that changes in criteria weights affected the ranking of tractors. This explains why the order of alternatives *T*4 and *T*5 remained unchanged, as their evaluations were the best for *T*4 and the worst for *T*5, thereby remaining unaffected by alterations in criteria weights. Conversely, because the ratings of tractor *T*2 closely resembled those of tractors *T*1 and *T*3, its placement as second, third, or fourth varied across different methods due to normalization. Furthermore, these results highlight that Tractors *T*4 and *T*3 are the preferred choices for purchase, according to expert assessments, particularly for small agricultural households.

Figure 2
Validation results using different methods

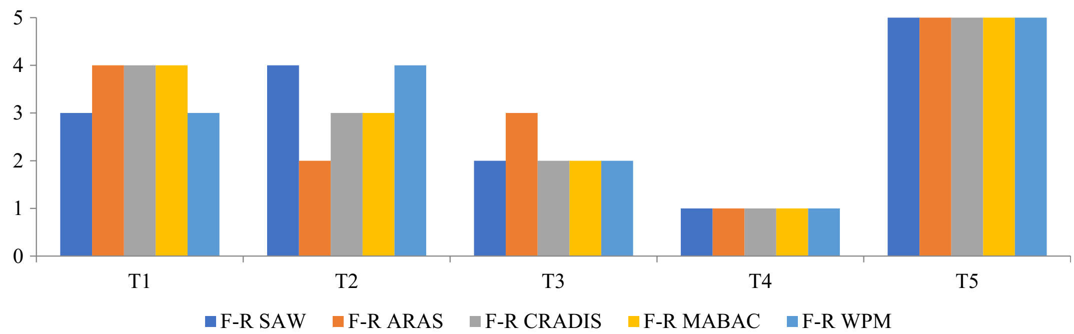
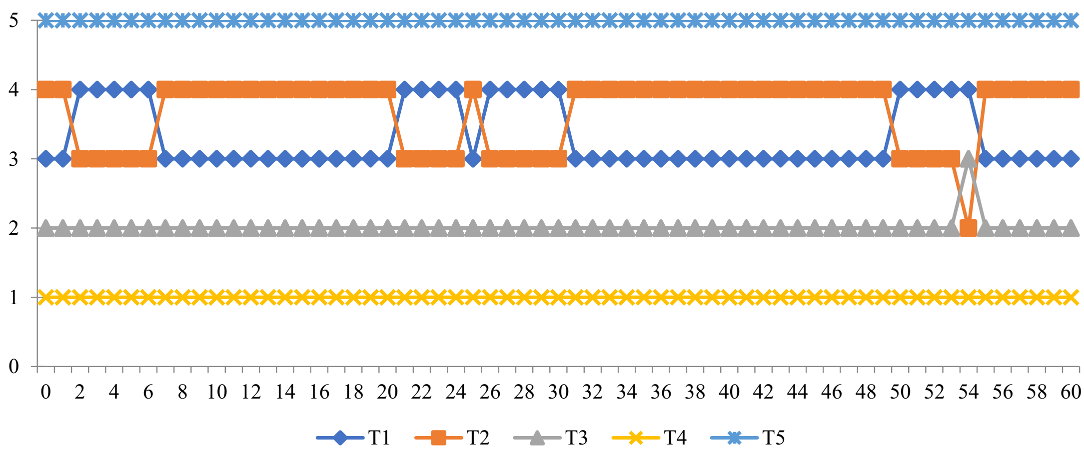


Figure 3
Results of the sensitivity analysis



5. Discussion

In order to enhance agricultural productivity, agricultural mechanization plays a pivotal role (Popović et al., 2020), with the tractor serving as the cornerstone of this mechanization process. Agricultural households commonly possess tractors to facilitate their daily agricultural activities. Tractors come in various sizes and serve diverse purposes (Puška et al., 2022). The choice of which tractor to procure is contingent upon the scale of the agricultural enterprise and the magnitude of agricultural production (Huo et al., 2020). Tractors constitute a versatile category of agricultural machinery, with their specific functions dictated by the attachments that can be affixed to them. These attachments expand the range of tasks tractors can perform, from soil preparation for sowing to harvesting. Moreover, tractor attachments are subject to continual innovation, enabling new applications and reinforcing the tractor's indispensable role in agriculture (Durczak et al., 2020).

Acquiring a tractor represents a substantial investment, necessitating the allocation of financial resources (Yakymchuk et al., 2023). Consequently, the selection of the most fitting tractor that aligns with the user's requirements within the budget becomes a paramount consideration. This study, therefore, endeavors to ascertain which among the chosen small tractors best caters to the needs of small agricultural sub-contractors. By doing so, this research aims to assist farmers in making informed decisions regarding tractor acquisitions. Individual farmers often exhibit preferences for particular tractor brands (Andrew Rohanaraj, 2023), even when alternative tractors may offer superior features. To select the most suitable tractor for the objectives of small agricultural sub-contractors, this study employs expert group decision-making. Seven experts with extensive experience in the realm of agricultural mechanization, all holding doctoral degrees in agricultural sciences, were selected. Collaboratively with these experts, a set of ten criteria was established to evaluate small tractors in the form of alternatives. Five tractors, which are most prevalent in the Serbian and Bosnian-Herzegovinian markets, were included in this assessment.

To select a tractor that aligns most closely with the established criteria, experts initially conducted evaluations of both the criteria and the tractors based on these criteria. These assessments were provided in manner of linguistic values. Given the quantitative nature of obtained ratings, it became essential to translate them into numerical values for further computational operations (Khan et al., 2023; Radovanović et al., 2023). To achieve this, fuzzy numbers were employed, whereby linguistic values were transformed as corresponding fuzzy numbers through the application of membership functions (Salim & Hamid, 2023). To introduce an element of uncertainty into this decision-making process, the determination of lower and upper limits for rough numbers was subsequently integrated. This approach allowed for decisions to be made under conditions of ambiguity and incomplete information (Ayub et al., 2022). Evaluations presented in linguistic form using fuzzy numbers were thus subjected to the inclusion of uncertainty in the decision-making process, courtesy of the rough approach (Pamučar et al., 2018). This nuanced approach ensures a more cautious decision-making process, enhancing its certainty for the decision-maker (Zheng & Yu, 2023).

To obtain a definitive result and ascertain which tractor best serves the requirements of small agricultural households, the fuzzy-rough LMAW and fuzzy-rough SAW methodologies were employed. The fuzzy-rough LMAW method was instrumental in determining the significance of criterion weighting. Unlike several other methodologies such as FUCOM, SWARA, PIPRECIA, and AHP, the need for prior criterion ranking based on importance or direct expert comparisons is obviated. Instead, this method allows the direct assessment of specific criteria without necessitating comparisons, thereby streamlining the decision-making process and expert evaluations. Experts provided ratings ranging from "Absolutely Low" (AL) to "Absolutely High" (AH). The application of the fuzzy-rough LMAW method yielded results demonstrating that the most critical criterion is $C1$ (Average Reference Price). Notably, criteria $C2$ (Average Fuel Consumption) and $C7$ (Safety and Comfort) exhibit closely aligned importance levels. Consequently, the selection of a tractor that is cost-effective, fuel-efficient, and offers a secure and comfortable working environment is warranted based on these findings. On the other hand, criteria $C5$ (Technological Upgradeability) and $C6$ (Convenience of Operation) are considered of lower importance. This is attributed to the universal support for accessory upgrades among all tractors, enhancing their multifunctionality. Moreover, all the selected tractors are equipped with a comparable control system, ensuring ease of operation.

Following the determination of criteria importance, the selected tractors underwent a ranking process. Similar to the fuzzy-rough LMAW method, the assessment was based on the chosen criteria. Tractor ranking was carried out using the fuzzy-rough SAW method, which is distinctive in its capacity to provide straightforward, yet reliable results, aligning closely with outcomes from more intricate methodologies. The analysis of the results identified the $T4$ tractor (Tractor Solis S 26) as the top-performing option. To validate these findings, a comparative evaluation with other methodologies was executed. The validation results underscore a strong alignment between the SAW method and the WPM method, mainly because of their streamlined procedures and similar data normalization techniques. Notably, the results of the SAW method deviate from those produced by the CRADIS and MABAC methods in the ranking of tractors $T1$ and $T2$, while the rankings of other tractors remain consistent. The most substantial divergence from the various methods was observed in the ARAS method, particularly concerning tractors $T2$ and $T3$, where the rank order differed. Furthermore, a sensitivity analysis was carried out to assess the stability of rankings. This analysis revealed that the rankings of the aforementioned three tractors changed under certain sensitivity scenarios. In light of these additional analyses, it is evident that the $T4$ tractor stands as the preferred choice for small-scale agricultural producers.

6. Conclusion

This study focuses on the selection of tractors suited for small-scale agricultural activities. The research employed group expert opinion and employed the fuzzy-rough approach for the assessment. A total of five tractors, widely popular in the markets of Serbia and BiH, were scrutinized using ten pre-defined criteria. The research findings underscore that the Solis S 26 tractor delivers optimal results and stands as the preferred choice for individuals seeking to procure a smaller tractor.

The study does present certain limitations, primarily stemming from the specific tractors considered and the sample size of five. The rationale for selecting these particular tractors was their widespread availability in the observed countries' markets. Future research should incorporate newer types of tractors that are emerging in the field, especially focusing on comparing these classic tractors with electric counterparts. Furthermore, the research's choice of criteria introduces a constraint. Nevertheless, these criteria align with expert consensus on their significance for prospective tractor buyers. Future research in this domain should consider the inclusion of additional criteria and tractors for comparative analysis against the ones studied here. Moreover, future research should further develop this approach, which demonstrated significant flexibility and offered greater certainty to decision-makers. This approach combines two distinct methodologies, encompassing more advantages than separate approaches alone. The research methodology presented exhibits a degree of adaptability, making it suitable for application in analogous scenarios where linguistic values play a role in criteria and alternative evaluation.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

Darko Božanić is an editorial board member for *Journal of Computational and Cognitive Engineering* and was not involved in the editorial review or the decision to publish this paper. The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this paper as no new data were created or analyzed in this study.

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