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A Fuzzy–Rough MCDM Approach for Selecting Green Suppliers in the Furniture Manufacturing Industry: A Case Study of Eco-Friendly Material Production

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Abstract: Green supplier selection is always one of the most important challenges in all of supply chain management, especially for production companies. The purpose is to have reliable suppliers which can fulfill all requests and be flexible in any supply chain stage. The aim of this paper is to create an adequate and strong MCDM (multicriteria decision making) model for the evaluation and selection of suppliers in a real environment. The main contribution of this study is proposing a novel fuzzy–rough MCDM model containing extension stepwise weight assessment ratio analysis (SWARA) and additive ratio assessment (ARAS) methods with fuzzy–rough numbers (FRN). The integrated FRN SWARA–FRN ARAS model was implemented in a case study of eco-friendly material production. The FRN SWARA method was used to calculate the weights of 10 green criteria, while using FRN ARAS, 6 suppliers were evaluated. The results of the applied model show that supplier S3 received the highest ranking, followed by supplier S2, while supplier S5 performed the poorest. In order to verify the strengths of the developed fuzzy–rough approach, we created a comparative analysis, sensitivity analysis, and dynamic matrix, which confirm the robustness of our model.

Keywords: fuzzy–rough approach; FRN SWARA; FRN ARAS; green supplier; furniture manufacturing

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1. Introduction

1.1. Motivation of the Research

In recent years, sustainability and eco-friendliness have gained increasing importance across various industries, including the furniture manufacturing industry [1–3]. As a result, furniture manufacturers are facing mounting pressure to use eco-friendly materials and adopt environmentally conscious production methods [4]. To meet this challenge, selecting green suppliers has become crucial, and it involves evaluating potential suppliers based on their environmental and social performance, as well as their economic viability [5].

The furniture manufacturing industry is uniquely characterized by its specific requirements and considerations [6,7]. The selection of suppliers in this industry involves a comprehensive evaluation process that encompasses ecological, social, and economic criteria, including environmental performance, product quality, reliability, and cost [8,9]. Given the distinctive nature of this industry, it serves as an excellent example for demon-starting the importance of a systematic and objective approach in selecting green suppliers. With multiple potential suppliers to choose from, each with their own strengths and weaknesses, it becomes crucial to adopt a systematic and objective approach that considers all relevant criteria for selecting green suppliers in the furniture manufacturing industry [10].

1.2. Aims and Contributions of the Research

To address the mentioned challenges, this paper presents a novel method for selecting green suppliers using the fuzzy–rough MCDM approach. This approach is gaining popularity due to its ability to handle uncertain and imprecise data. It involves converting linguistic values to fuzzy numbers and then applying rough sets to these numbers, resulting in the same outcomes as traditional methods but with the added benefit of being able to handle more complex and uncertain data [11,12].

This paper focuses on the selection of green suppliers for furniture production using eco-friendly materials, such as vegan leather. The selection process is based on both ecological and economic criteria, with six potential suppliers to choose from. Two methods are utilized to select the green suppliers: the FRN SWARA method and FRN ARAS method. The FRN SWARA method determines the weights of the criteria, while the FRN ARAS method ranks the alternatives. These methods enable a systematic and objective selection process that considers the preferences of the decision makers, which represents the advantage of the proposed approach. The fuzzy–rough approach provides decision makers in this industry with a useful tool for selecting green suppliers in a systematic and objective manner.

1.3. Structure of the Paper

The rest of the paper is structured as follows. Section 2 provides a detailed literature review of green supplier selection and the fuzzy–rough MCDM approach. Section 3 outlines the methodology used to select green suppliers for furniture production. In this section, we show preliminaries and developed the fuzzy–rough approach with clear explanations of both extended methods. Section 5 presents the results of the selection process with comparative, sensitivity, and dynamic fuzzy–rough matrix analyses performed. In Section 6, we analyze and interpret the results, discuss their implications, compare them with previous research, and address any limitations. Finally, Section 7 concludes the paper with a summary of the findings and their implications for future research.

2. Literature Review

Green supply chain management (GSCM) has gained significant attention in recent years as a way to mitigate the environmental impact of supply chains [13–15]. GSCM involves integrating environmental considerations into the entire supply chain, from the selection of suppliers to the disposal of products at the end of their lifecycle. The selection of green suppliers, one of the critical components of GSCM, involves evaluating suppliers based on their environmental and social performance, as well as their economic viability [16]. Selecting green suppliers is a vital step in achieving a sustainable supply chain and reducing the environmental impact of production processes [17].

Several methods have been proposed for selecting green suppliers, including the use of multiple-criteria decision making (MCDM) techniques like analytical hierarchy process (AHP), technique for order of preference by similarity to ideal solution (TOPSIS), and the simple additive weighting (SAW) method. These methods have been widely used in the literature [18–24] and shown to be effective in selecting green suppliers based on various criteria. The drawback of classical methods is that they can only work with quantitative ratings and not qualitative ratings. Therefore, a fuzzy approach has been introduced which enables the use of both qualitative and quantitative ratings in supplier selection.

However, traditional MCDM methods may not be suitable for handling uncertain and imprecise data [25], which is a challenge in the selection of green suppliers. Fuzzy set theory has been proposed as a way to handle uncertain and imprecise data in MCDM problems. Fuzzy sets enable the representation of uncertain and imprecise data as linguistic variables that can be transformed into numerical values using fuzzy membership functions [26]. This allows for the integration of qualitative and quantitative criteria in the selection process.

Fuzzy set theory has been utilized in various applications in operations [27] and supply chain management, including supplier selection [28], inventory control [29], and logistics management [30]. Fuzzy set theory has been combined with other methods, such as AHP and TOPSIS, to handle uncertainty and imprecision in the decision-making process. However, fuzzy set theory has limitations in handling complex and uncertain data, particularly in cases where there are a large number of criteria or alternatives [31].

Fuzzy–rough set theory has gained attention as a solution to the limitations of traditional MCDM methods in handling uncertain and complex data in decision-making problems. Fuzzy–rough set theory is a hybrid of fuzzy set theory and rough set theory that allows for the handling of complex and uncertain data in decision-making problems [32,33]. It involves converting linguistic values to fuzzy numbers and then applying rough sets to these numbers, resulting in the same outcomes as traditional methods but with the added benefit of being able to handle more complex and uncertain data.

Fuzzy–rough set theory has been applied in various applications in supply chain management [34], including supplier selection [35], quality control [36], and inventory management [37]. The use of fuzzy–rough set theory has been shown to be effective in handling uncertainty and imprecision in decision-making problems, particularly in cases where there is a large number of criteria or alternatives.

The application of fuzzy–rough set theory in green supplier selection has been limited in the literature, particularly in the furniture manufacturing industry. However, this industry has been under pressure to adopt sustainable production practices, including the use of eco-friendly materials and the selection of green suppliers [38,39]. Selecting green suppliers in the furniture manufacturing industry requires assessing potential suppliers based on their environmental and social performance, as well as their economic viability. The selection of green suppliers can be a challenging task due to the complexity of the criteria involved.

In recent years, there has been a growing interest in utilizing fuzzy–rough set theory for green supplier selection. Several studies have implemented fuzzy–rough set theory in the selection of green suppliers, based on diverse criteria, including environmental performance, product quality, reliability, and cost. These studies have demonstrated that fuzzy–rough set theory can be an effective approach for handling uncertainty and imprecision in decision-making problems, leading to more precise and dependable outcomes.

One example of the application of fuzzy–rough set theory in green supplier selection is the study conducted by [40]. This study proposes a technique based on the Fermatean hesitant fuzzy–rough set (FHFRS) for green supplier selection (GSS) in the process industry. The proposed model addresses the ambiguity and incompleteness of real-world decision-making challenges by developing a DM algorithm. The technique was applied to a numerical example in the chemical processing industry, demonstrating its scalability for GSS. Improved FHFR-VIKOR and TOPSIS approaches were used to validate the proposed technique, showing its practicality and effectiveness in addressing uncertainty in DM problems.

Another study by P. Liu et al. [41] presented a multiobjective linear programming model that prioritized and weighed suppliers for effective supply chain management (SCM). The model used fuzzy variables to determine the number of suppliers and order quantities of raw materials and solved constraints using the goal programming method. Four objective functions were used to take opposing goals into account and prioritize them to maximize access. The model incorporated fuzzy and rough theories to handle imprecise information. An example was presented and solved using the analytic network process and modified best–worst method (BWM). The results were compared with the interval-valued fuzzy–rough numbers BWM (IVFRN-BWM), which showed that the modified BWM approach produced lower costs and better criteria.

Similarly, in a study by [42], a decision-making method for supplier selection in industrial manufacturing is proposed by integrating rough approximations with fuzzy numbers and PROMETHEE. The proposed method aims to address subjective and objective vagueness in the assessment of decision makers by computing entropy weights from the original dataset and ranking alternatives using the intersection of both positive and negative flow. A case study was conducted to demonstrate the effectiveness of the proposed method in ranking supplier alternatives under given criteria, and its results were compared with different rough numbers and fuzzy numbers based on MCDM methods. The study found that the fuzzy–rough PROMETHEE method was efficient in selecting the best suppliers to reduce losses and maximize the production process.

The fuzzy–rough set theory has also been combined with other decision-making methods, such as decision-making trial and evaluation laboratory (DEMATEL) and TOPSIS, to select sustainable suppliers. For instance, a study by Chen et al. [43] proposed a novel framework for smart–sustainable supplier selection in supply chain management. The proposed hybrid rough–fuzzy DEMATEL–TOPSIS approach combines the strengths of fuzzy sets and rough sets to handle both internal and external uncertainties. The effectiveness of the proposed methodology was illustrated through its application in sustainable vehicle transmission supplier selection and comparisons with other methods.

The literature suggests that fuzzy–rough set theory can be an effective method for handling uncertainty and imprecision in green supplier selection. By combining fuzzy–rough set theory with other multicriteria decision-making methods, decision makers can obtain more accurate and reliable results and make informed decisions. The following section presents the methodology adopted in this study, which integrates fuzzy–rough set theory with SWARA and ARAS methods to select green suppliers in the furniture industry.

3. Methods

3.1. Preliminaries

When using interval fuzzy–rough sets, the first step is to transform the linguistic values into numerical values using fuzzy logic. These numerical values are then utilized in the rough set. This approach yields three rough sets, which are represented as an interval. The resulting representation is called an interval fuzzy–rough number "A".

$$A = \left[A_q^L, A_q^u\right] = \left[\left(a_{1q}^L, a_{1q}^U\right), \left(a_{2q}^L, a_{2q}^U\right), \left(a_{3q}^L, a_{3q}^U\right)\right] \tag{1}$$

where $a_{jq}^L = \underline{Lim}\left(I * (a_j)_{lq}\right) and\ a_{jq}^U = \overline{Lim}\left(I * (a_j)_{uq}\right); (j = 1,2,3; 1 \le q \le k)$.

The interval fuzzy–rough number A defined in the interval $(-\infty, +\infty)$ can be represented using Equations (2) and (3) [44].

$$A = \left\{x, \left[\mu_{A_q^L}(x), \mu_{A_q^U}(x)\right]\right\},\ x \in (-\infty, +\infty), \mu_{A_q^L}(x), \mu_{A_q^U}(x) : (-\infty, +\infty) \to [0,1] \tag{2}$$

$$\mu_A(x) = \left[\mu_{A_q^L}(x), \mu_{A_q^U}(x)\right], \mu_{A_q^L}(x) \le \mu_{A_q^U}(x), \forall\ x \in (-\infty, +\infty) \tag{3}$$

The values $\mu_{A_q^L}(x)$ and $\mu_{A_q^U}(x)$ represent the degree of membership to the lower and upper functions, respectively, of the interval fuzzy–rough number A.

When dealing with two interval fuzzy numbers A and B, it is possible to perform various mathematical operations between them, including the following:

Addition of two interval fuzzy numbers:

$$\begin{aligned} A + B = &\left[\left(a_1^L, a_1^U\right), \left(a_2^L, a_2^U\right), \left(a_3^L, a_3^U\right)\right] + \left[\left(b_1^L, b_1^U\right), \left(b_2^L, b_2^U\right), \left(b_3^L, b_3^U\right)\right] \\ &= \left[\left(a_1^L + b_1^L, a_1^U + b_1^U\right), \left(a_2^L + b_2^L, a_2^U + b_2^U\right), \left(a_3^L + b_3^L, a_3^U + b_3^U\right)\right] \end{aligned} \tag{4}$$

Subtraction of two interval fuzzy numbers:

$$\begin{aligned} A - B = &\left[\left(a_1^L, a_1^U\right), \left(a_2^L, a_2^U\right), \left(a_3^L, a_3^U\right)\right] - \left[\left(b_1^L, b_1^U\right), \left(b_2^L, b_2^U\right), \left(b_3^L, b_3^U\right)\right] \\ &= \left[\left(a_1^L - b_3^U, a_1^U - b_1^L\right), \left(a_2^L - b_2^U, a_2^U - b_2^L\right), \left(a_3^L - b_1^U, a_3^U - b_1^L\right)\right] \end{aligned} \tag{5}$$

Multiplication of two interval fuzzy numbers:

$$\begin{aligned} A \times B &= \left[\left(a_1^L, a_1^U\right), \left(a_2^L, a_2^U\right), \left(a_3^L, a_3^U\right)\right] \times \left[\left(b_1^L, b_1^U\right), \left(b_2^L, b_2^U\right), \left(b_3^L, b_3^U\right)\right] \\ &= \left[\left(a_1^L \times b_1^L, a_1^U \times b_1^U\right), \left(a_2^L \times b_2^L, a_2^U \times b_2^U\right), \left(a_3^L \times b_3^L, a_3^U \times b_3^U\right)\right] \end{aligned} \tag{6}$$

Division of two interval fuzzy numbers:

$$\begin{aligned} A \div B &= \left[\left(a_1^L, a_1^U\right), \left(a_2^L, a_2^U\right), \left(a_3^L, a_3^U\right)\right] \div \left[\left(b_1^L, b_1^U\right), \left(b_2^L, b_2^U\right), \left(b_3^L, b_3^U\right)\right] \\ &= \left[\left(a_1^L \div b_3^U, a_1^U \div b_1^L\right), \left(a_2^L \div b_2^U, a_2^U \div b_2^L\right), \left(a_3^L \div b_1^U, a_3^U \div b_1^L\right)\right] \end{aligned} \tag{7}$$

By applying these operations, the initial methods of multicriteria analysis can be refined, including the modified interval fuzzy–rough SWARA and ARAS methods. The modified interval fuzzy–rough SWARA method is used to determine the weight of the criteria, while the modified interval fuzzy–rough ARAS method is used to rank the suppliers.

3.2. A Novel Fuzzy–Rough SWARA Method

In this section of the study, we perform an extension of the SWARA [45] method with fuzzy–rough numbers, which has large applications in decision-making processes. This method, through more than a decade of use, is extended with various theories, such as rough [46], interval rough [47], fuzzy [48,49], and neutrosophic [50]. However, in the literature, we did not find the fuzzy–rough SWARA method, so we decided to develop it. In what follows, we show the steps of the novel developed FRN SWARA method:

Step 1: Form a group of m criteria.

Step 2: Define a team of e experts for evaluation criteria. Experts can use any of the defined scales for determining the criteria's importance.

Step 3: Transformation of separate evaluation of experts into a group fuzzy–rough matrix x_j.

$$FRN(X_j) = \left[\left(x_j^{L1}, x_j^{U1}\right), \left(x_j^{L2}, x_j^{U2}\right), \left(x_j^{L3}, x_j^{U3}\right)\right]_{1\times m} \tag{8}$$

Step 4. Ranking of criteria according to significance obtained using fuzzy–rough matrix from the previous step.

Step 5: Normalization of the matrix $FRN(X_j)$ in order to obtain the matrix $FRN(N_j)$:

$$FRN(N_j) = \left[\left(n_j^{L1}, n_j^{U1}\right), \left(n_j^{L2}, n_j^{U2}\right), \left(n_j^{L3}, n_j^{U3}\right)\right]_{1\times m} \tag{9}$$

The elements of the matrix $FRN(N_j)$ are computed as follows:

$$FRN(N_j) = \frac{FRN(X_j)}{FRN(Z_j)} \tag{10}$$

where $FRN(Z_j) = \left[\left(z_j^{L1}, z_j^{U1}\right), \left(z_j^{L2}, z_j^{U2}\right), \left(z_j^{L3}, z_j^{U3}\right)\right] = \max FRN(X_j)$.

The first element of $FRN(N_j)$, i.e., $\left[\left(n_j^{L1}, n_j^{U1}\right), \left(n_j^{L2}, n_j^{U2}\right), \left(n_j^{L3}, n_j^{U3}\right)\right] = [(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$, because $j = 1$. For other elements, $j > 1$ should be used the Equation (11):

$$FRN(N_j) = \left[\left(\frac{n_j^{L1}}{z_j^{U3}}, \frac{n_j^{U1}}{z_j^{L3}}\right), \left(\frac{n_j^{L2}}{z_j^{U2}}, \frac{n_j^{U2}}{z_j^{L2}}\right), \left(\frac{n_j^{L3}}{z_j^{U1}}, \frac{n_j^{U3}}{z_j^{L1}}\right)\right]_{1\times m} \quad j = 2, 3, \ldots, m \tag{11}$$

In case we have two most important criteria, the second element will be a fuzzy–rough number $[(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$.

Step 6: Calculate the matrix $FRN(\Im_j)$:

$$FRN(\Im_j) = \left[\left(\Im_j^{L1}, \Im_j^{U1}\right), \left(\Im_j^{L2}, \Im_j^{U2}\right), \left(\Im_j^{L3}, \Im_j^{U3}\right)\right]_{1\times m} \tag{12}$$

using the Equation (13):

$$FRN(\Im_j) = \left[\left(n_j^{L1}+1, n_j^{U1}+1\right), \left(n_j^{L2}+1, n_j^{U2}+1\right), \left(n_j^{L3}+1, n_j^{U3}+1\right)\right]_{1\times m} j = 2,3,\ldots,m \tag{13}$$

In case we have two most important criteria, the second element will be a fuzzy–rough number $[(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$.

Step 7: Computation the matrix of recalculated weights $FRN(\Re_j)$:

$$FRN(\Re_j) = \left[\left(\Re_j^{L1}, \Re_j^{U1}\right), \left(\Re_j^{L2}, \Re_j^{U2}\right), \left(\Re_j^{L3}, \Re_j^{U3}\right)\right]_{1\times m} \tag{14}$$

The elements of matrix $FRN(\Re_j)$ are obtained as

$$FRN(\Re_j)\left[\begin{array}{l} \Re_j^{L1} = \left(\begin{array}{ll} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{L1}}{\Im_j^{U3}} & j>1 \end{array}\right), \; \Re_j^{U1} = \left(\begin{array}{ll} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{U1}}{\Im_j^{L3}} & j>1 \end{array}\right), \\ \Re_j^{L2} = \left(\begin{array}{ll} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{L2}}{\Im_j^{U2}} & j>1 \end{array}\right), \; \Re_j^{U2} = \left(\begin{array}{ll} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{U2}}{\Im_j^{L2}} & j>1 \end{array}\right), \\ \Re_j^{L3} = \left(\begin{array}{ll} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{L3}}{\Im_j^{U1}} & j>1 \end{array}\right), \; \Re_j^{U3} = \left(\begin{array}{ll} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{U3}}{\Im_j^{L1}} & j>1 \end{array}\right), \end{array}\right] \tag{15}$$

In case any two m criteria have equal significance, then the following equation should be applied:

$$FRN(\Re_j) = FRN(\Re_{j-1}) \tag{16}$$

Step 8: Computation of final weight values $FRN(W_j)$:

$$FRN(W_j) = \left[\left(w_j^{L1}, w_j^{U1}\right), \left(w_j^{L2}, w_j^{U2}\right), \left(w_j^{L3}, w_j^{U3}\right)\right]_{1\times m} \tag{17}$$

Individual weight values of criteria are obtained:

$$FRN(W_j) = \left[\frac{FRN(\Re_j)}{FRN(\aleph_j)}\right] \tag{18}$$

where $FRN(\aleph_j) = \sum_{j=1}^{m} FRN(\Re_j)$. Finally,

$$FRN(W_j) = \left[\left(\frac{\Re_j^{L1}}{\aleph_j^{U3}}, \frac{\Re_j^{U1}}{\aleph_j^{L3}}\right), \left(\frac{\Re_j^{L2}}{\aleph_j^{U2}}, \frac{\Re_j^{U2}}{\aleph_j^{L2}}\right), \left(\frac{\Re_j^{L3}}{\aleph_j^{U1}}, \frac{\Re_j^{U3}}{\aleph_j^{L1}}\right)\right]_{1\times m} j = 2,3,\ldots,m \tag{19}$$

3.3. A Novel Fuzzy–Rough ARAS Method

The steps involved in conducting the fuzzy–rough ARAS method are as follows:

Step 1. Forming the initial decision matrix, where experts evaluate suppliers based on observed criteria using linguistic values.

Step 2. Transforming the linguistic values into fuzzy numbers using the membership function of fuzzy numbers. Each linguistic value is assigned a corresponding fuzzy number based on the membership function.

Step 3. Transforming the fuzzy numbers into a rough set by determining the lower and upper limits of the interval for each expert. The final value is obtained by taking the rough set for all experts and finding the average value of this set. It is important to ensure that the upper limit of the first interval is not greater than the first limit of the second interval, as well as that the upper limit of the second interval is not greater than the lower limit of the third interval during this formation. The decision matrix formed in this way represents the initial decision matrix on which the steps of the modified fuzzy–rough ARAS method are implemented.

$$A = \begin{bmatrix} \left(a^L_{1,11}, a^U_{1,11}\right), \left(a^L_{2,11}, a^U_{21}\right), \left(a^L_{3,11}, a^U_{3,11}\right) & \cdots & \left(a^L_{1,1n}, a^U_{1,1n}\right), \left(a^L_{2,1n}, a^U_{2,1n}\right), \left(a^L_{3,1n}, a^U_{3,1n}\right) \\ \vdots & \ddots & \vdots \\ \left(a^L_{1,m1}, a^U_{1,m1}\right), \left(a^L_{2,m1}, a^U_{2,m1}\right), \left(a^L_{3,m1}, a^U_{3,m1}\right) & \cdots & \left(a^L_{1,nm}, a^U_{1,nm}\right), \left(a^L_{2,nm}, a^U_{2,nm}\right), \left(a^L_{3,nm}, a^U_{3,nm}\right) \end{bmatrix} \tag{20}$$

Step 4. Finding the optimal alternative. If the observed criterion is a benefit-type criterion, the optimal alternative is the maximum value of the alternative for that criterion. If the criterion is a cost criterion, the optimal alternative is the minimum value of the alternative for that criterion.

$$S_{0j} = \begin{cases} max_i\left[a^L_{ij}, a^U_{ij}\right];\ j \in \Omega_{max} \\ min_i\left[a^L_{ij}, a^U_{ij}\right];\ j \in \Omega_{min} \end{cases} \tag{21}$$

Step 5. Normalizing the initial decision matrix. In this step, the values of the initial decision matrix are divided by the sum of the values for each criterion.

$$n_{ij} = \left(\frac{a^L_1}{\sum_{i=1}^m a^U_3}, \frac{a^U_1}{\sum_{i=1}^m a^L_3}\right), \left(\frac{a^L_2}{\sum_{i=1}^m a^U_2}, \frac{a^U_2}{\sum_{i=1}^m a^L_2}\right), \left(\frac{a^L_3}{\sum_{i=1}^m a^U_1}, \frac{a^U_3}{\sum_{i=1}^m a^L_1}\right) \text{ for benefit} \tag{22}$$

$$n_{ij} = \left(\frac{1/a^L_1}{\sum_{i=1}^m 1/a^U_3}, \frac{1/a^U_1}{\sum_{i=1}^m 1/a^L_3}\right), \left(\frac{1/a^L_2}{\sum_{i=1}^m 1/a^U_2}, \frac{1/a^U_2}{\sum_{i=1}^m 1/a^L_2}\right), \left(\frac{1/a^L_3}{\sum_{i=1}^m 1/a^U_1}, \frac{1/a^U_3}{\sum_{i=1}^m 1/a^L_1}\right) \text{ for cost} \tag{23}$$

Step 6. Calculating the weighted decision matrix. In this step, the normalized decision matrix is multiplied by the corresponding weights, which are obtained using the fuzzy–rough SWARA method.

$$v_{ij} = n_{ij} \times w_{ij} = \left[\left(n^L_1 \times w^L_1, n^U_1 \times w^U_1\right), \left(n^L_2 \times w^L_2, n^U_2 \times w^U_2\right), \left(n^L_3 \times w^L_3, n^U_3 \times w^U_3\right)\right] \tag{24}$$

Step 7. Calculating the overall performance for each alternative. This is performed by adding the values of the corresponding fuzzy–rough numbers.

$$S_{ij} = \sum_{j=1}^n v_{ij} = \sum_{j=1}^n \left[\left(v^L_1, v^U_1\right), \left(v^L_2, v^U_2\right), \left(v^L_3, v^U_3\right)\right] \tag{25}$$

Step 8. Calculating the degree of utility for each alternative. In this step, each individual performance value is divided by the performance value of the optimal alternative.

$$Q_i = \frac{S_i}{S_0} = \left(\frac{S^L_{i1}}{S^U_{03}}, \frac{S^U_{i1}}{S^L_{03}}\right), \left(\frac{S^L_{i2}}{S^U_{02}}, \frac{S^U_{i2}}{S^L_{02}}\right), \left(\frac{S^L_{i3}}{S^U_{01}}, \frac{S^U_{i3}}{S^L_{03}}\right) \tag{26}$$

Step 9. Calculating the final values. This step is performed by finding the average value of the degree of utility.

$$R_i = \frac{Q^L_1 + Q^U_1 + Q^L_2 + Q^U_2 + Q^L_3 + Q^U_3}{6} \tag{27}$$

The best alternative is the one with the highest value of the modified interval fuzzy–rough ARAS method, and vice versa.

4. Case Study—Description of Forming the MCDM Model

Changes in business practices have a widespread impact on all companies, compelling them to adapt and integrate ecological considerations in their strategies. The trend towards sustainable materials and eco-friendly products is gaining momentum across various industries, and furniture manufacturing is no exception. Oglavina Brčko, a furniture production company, is planning to launch a new line of furniture emphasizing ecological materials, particularly in the case of textiles and leather. Given the negative environmental impact of traditional leather, the company is seeking alternative materials that are more sustainable. Therefore, the company has adopted a supplier selection process that takes both economic and ecological criteria into account.

To identify the most suitable suppliers for the eco-materials, the company first recruited a team of experts comprising marketing, procurement, and production directors. This team then identified six potential suppliers who offered the required materials and determined the criteria to be used in the evaluation process. The selection process employed a GSS-based approach, which considers both economic and environmental criteria [51]. This approach expands the conventional supplier selection process, which traditionally relied solely on economic criteria. The incorporation of ecological criteria reflects the need for materials that meet the rigorous environmental standards expected by customers. As customers become increasingly environmentally conscious and demanding, companies must adapt and respond by offering eco-friendly products that increase customer satisfaction. Thus, Oglavina Brčko's decision to incorporate environmentally friendly materials into its production line is a strategic move to meet customer demands and increase customer satisfaction.

The criteria for GSS comprise a mixture of economic and environmental factors. A total of ten criteria were used (Table 1), each assigned equal importance in supplier selection. These criteria were not grouped into two categories but were considered together. This approach eliminated the need to determine importance for individual groups but rather for specific criteria. A unique aspect of this research is that all criteria were considered as benefit criteria and evaluated using linguistic evaluations (Table 2). This was achieved by having experts provide linguistic evaluations of suppliers based on the observed criteria, ranging from very bad to very good. This simplifies the evaluation process for experts, as they need not distinguish between benefit and cost criteria. Very bad costs represent large costs, while very good costs represent small costs. The same principle applies to other criteria.

Table 1. GSS criteria.

ID	Criteria	Description	References
C1	Expenses	All expenses associated with procurement	[25,28,52]
C2	Quality	Material quality and excellence application	[7,8,10,18,21]
C3	Services	All services related before and after purchase	[20,43,53]
C4	Deliveries	Delivery on time	[7,10,18,20,52]
C5	Technical capacities	Possibility of delivery of desired materials	[28,53]
C6	EMS	Environmental management systems	[7,10,19]
C7	Pollution control	Implementation of environmental management systems	[7,18–20]
C8	Eco-design	Ecological design of materials	[8,52,53]
C9	Using environmentally friendly technologies	Using materials that do not harm the environment	[24,52,53]
C10	Consumption of resources	Consumption of materials, energy, and water	[19,52,53]

Table 2. Linguistic values in supplier evaluation.

Linguistic Variable	Triangular Fuzzy Number
Very bad (VB)	0, 0, 1
Bad (B)	0, 1, 3
Medium bad (MB)	1, 3, 5
Medium (M)	3, 5, 7
Medium good (MG)	5, 7, 9
Good (G)	7, 9, 10
Very good (VG)	9, 10, 10

Based on these evaluations, it is evident that experts will evaluate the observed suppliers according to linguistic values. This is because it is more challenging to determine the accurate numerical rating of a particular supplier than to provide a linguistic rating. To give a numerical rating, it is essential to establish the conditions that certain suppliers must meet to obtain a specific rating. For instance, what are the costs that receive a rating of two and not one or three, or what are the costs that receive a rating of four and not three or five. Thus, linguistic evaluations are used, which do not require meeting precise conditions to give certain evaluations. However, this introduces imprecision into the evaluation or decision making. Fuzzy logic is used to resolve this imprecision.

The linguistic evaluations used consist of seven levels ranging from very bad to very good (Table 2). To use these linguistic evaluations, it is necessary to transform them into corresponding fuzzy numbers using the membership function.

The limitation of using fuzzy logic is the subjectivity when setting the limits of fuzzy numbers [54,55]. These limits can affect the final solution, so it is desirable to eliminate this limitation. In order to do this, it is possible to use the rough set, which is a good tool for processing imprecise evaluations without subjectivity. However, by using a rough set, it is not possible to define the degree of membership of certain claims, so this paper uses the fuzzy–rough approach to process these evaluations and select suppliers. By applying this approach, the final value of the observed suppliers will be obtained, and the supplier that best meets the set goals of the Oglavina Brčko company will be selected.

5. Results

5.1. Calculation of Criteria Weights Using Fuzzy–Rough SWARA Method

In order to apply the novel developed FRN SWARA method, the transformation of the separate expert's assessments shown in Table 3 to fuzzy–rough numbers should be performed first.

Table 3. Expert's assessment of criteria importance.

	Criterion	DM1	DM2	DM3
C1	Expenses	(1, 2, 3)	(2, 3, 4)	(1, 2, 3)
C2	Quality	(1, 1, 2)	(1, 1, 2)	(1, 2, 3)
C3	Services	(5, 6, 7)	(5, 6, 7)	(6, 7, 8)
C4	Deliveries	(4, 5, 6)	(3, 4, 5)	(2, 3, 4)
C5	Technical capacities	(3, 4, 5)	(2, 3, 4)	(4, 5, 6)
C6	EMS	(5, 6, 7)	(5, 6, 7)	(6, 7, 8)
C7	Pollution control	(3, 4, 5)	(3, 4, 5)	(3, 4, 5)
C8	Eco-design	(6, 7, 8)	(4, 5, 6)	(4, 5, 6)
C9	Using environmentally friendly technologies	(1, 2, 3)	(1, 1, 2)	(1, 1, 2)
C10	Consumption of resources	(7, 8, 9)	(4, 5, 6)	(5, 6, 7)

A rough matrix for C1 is obtained as follows.

According to expert's evaluation shown in Table 3, we select three classes of objects *l*, *m* and *u*: *l* = (1; 2; 1), *m* = (2; 3; 2), and *u* = (3; 4; 3).

For *l:*

$$\underline{Lim}(1) = 1, \overline{Lim}(1) = \frac{1}{3}(1+2+1) = 1.333;$$

$$\underline{Lim}(2) = \frac{1}{3}(1+2+1) = 1.333, \overline{Lim}(2) = 2$$

For *m:*

$$\underline{Lim}(2) = 2, \overline{Lim}(2) = \frac{1}{3}(2+3+2) = 2.333;$$

$$\underline{Lim}(3) = \frac{1}{3}(2+3+2) = 2.333, \overline{Lim}(3) = 3$$

For *u:*

$$\underline{Lim}(3) = 3, \overline{Lim}(3) = \frac{1}{3}(3+4+3) = 3.333;$$

$$\underline{Lim}(4) = \frac{1}{3}(3+4+3) = 3.333, \overline{Lim}(4) = 4$$

In this way, we obtained fuzzy–rough numbers:

$$FRN(E_1) = [(1.00, 1.33), (2.00, 3.00), (3.00, 3.33)]$$

$$FRN(E_2) = [(1.33, 2.00), (2.33, 3.00), (3.33, 4.00)]$$

$$FRN(E_3) = [(1.00, 1.33), (2.00, 2.33), (3.00, 3.33)]$$

By applying the aggregation equation, the final fuzzy–rough number for C1 is obtained:

$$FRN(C_1) = [(1.11, 1.55), (2.11, 2.55), (3.11, 3.55)]$$

and the final fuzzy–rough matrix $FRN(X_j)$ is obtained and shown in Table 4.

Table 4. Initial fuzzy–rough matrix in the FRN SWARA method.

	X_j
C2	[(1.000, 1.000), (1.110, 1.553), (2.110, 2.553)]
C9	[(1.000, 1.000), (1.110, 1.553), (2.110, 2.553)]
C1	[(1.110, 1.553), (2.110, 2.553), (3.110, 3.553)]
C4	[(2.500, 3.500), (3.500, 4.500), (4.500, 5.500)]
C5	[(2.500, 3.500), (3.500, 4.500), (4.500, 5.500)]
C7	[(3.000, 3.000), (4.000, 4.000), (5.000, 5.000)]
C8	[(4.223, 5.003), (5.223, 6.003), (6.223, 7.113)]
C10	[(4.610, 5.610), (5.610, 6.610), (6.610, 8.110)]
C6	[(5.110, 5.553), (6.110, 6.553), (7.110, 7.553)]
C3	[(5.110, 5.553), (6.110, 6.553), (7.110, 7.553)]

The normalized matrix $FRN(X_j)$ is shown below and obtained in the following way. The first element of the matrix $FRN(N_j)$, i.e., $\left[\left(n_2^{L1}, n_2^{U1}\right), \left(n_2^{L2}, n_2^{U2}\right), \left(n_2^{L3}, n_2^{U3}\right)\right] = [(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$. This is a rule and must be applied in each decision-making process. If two criteria are the most important, then the second element is also equal to the first, i.e.,: $\left[\left(n_9^{L1}, n_9^{U1}\right), \left(n_9^{L2}, n_9^{U2}\right), \left(n_9^{L3}, n_9^{U3}\right)\right] = [(1.00, 1.00), (1.00, 1.00), (1.00, 1.00)]$. In this case, the first and second elements of matrix $FRN(N_j)$ represent the C2 and C9 criteria, respectively.

$$FRN(N_j) = \begin{matrix} [(1.000, 1.000), (1.000, 1.000), (1.000, 1.000)] \\ [(1.000, 1.000), (1.000, 1.000), (1.000, 1.000)] \\ [(0.137, 0.218), (0.319, 0.418), (0.554, 0.695)] \\ [(0.308, 0.492), (0.530, 0.736), (0.802, 1.076)] \\ [(0.308, 0.492), (0.530, 0.736), (0.802, 1.076)] \\ [(0.370, 0.422), (0.605, 0.655), (0.891, 0.978)] \\ [(0.521, 0.704), (0.790, 0.983), (1.109, 1.392)] \\ [(0.568, 0.789), (0.849, 1.082), (1.178, 1.587)] \\ [(0.630, 0.781), (0.924, 1.073), (1.267, 1.478)] \\ [(0.630, 0.781), (0.924, 1.073), (1.267, 1.478)] \end{matrix}$$

$$FRN(Z_j) = [(5.11, 5.61), (6.11, 6.61), (7.11, 8.11)]$$

$$\left[\left(n_1^{L1}, n_1^{U1}\right), \left(n_1^{L2}, n_1^{U2}\right), \left(n_1^{L3}, n_1^{U3}\right)\right] = \left[\left(\frac{1.11}{8.11}, \frac{1.55}{7.11}\right), \left(\frac{2.11}{6.61}, \frac{2.55}{6.11}\right), \left(\frac{3.11}{6.61}, \frac{3.55}{5.11}\right)\right] = [(0.137, 0.218), (0.319, 0.418), (0.554, 0.695)]$$

The next steps are the calculation of the following fuzzy–rough matrix:

$$FRN(\Im_1) = [(0.137 + 1.00, 0.218 + 1), (0.319 + 1.00, 0.418 + 1.00), (0.554 + 1.00, 0.695 + 1.00)] = [(1.137, 1.218), (1.319, 1.418), (1.554, 1.695)]$$

$$FRN(\Im_j) = \begin{array}{l} [(1.000, 1.000), (1.000, 1.000), (1.000, 1.000)] \\ [(1.000, 1.000), (1.000, 1.000), (1.000, 1.000)] \\ [(1.137, 1.218), (1.319, 1.418), (1.554, 1.695)] \\ [(1.308, 1.492), (1.530, 1.736), (1.802, 2.076)] \\ [(1.308, 1.492), (1.530, 1.736), (1.802, 2.076)] \\ [(1.370, 1.422), (1.605, 1.655), (1.891, 1.978)] \\ [(1.521, 1.704), (1.790, 1.983), (2.109, 2.392)] \\ [(1.568, 1.789), (1.849, 2.082), (2.178, 2.587)] \\ [(1.630, 1.781), (1.924, 2.073), (2.267, 2.478)] \\ [(1.63, 1.781), (1.924, 2.073), (2.267, 2.478)] \end{array}$$

Next, the matrix $FRN(\Re_j)$ is computed as follows:

$$FRN(\Re_1)\begin{bmatrix} \Re_1^{L1} = \left(\dfrac{\Re_9^{L1}}{\Im_1^{U3}}\right) = \left(\dfrac{1}{1.695}\right), \ \Re_1^{U1} = \left(\dfrac{1}{1.554}\right) = (0.590, 0.643) \\ \Re_1^{L2} = \left(\dfrac{\Re_9^{L2}}{\Im_1^{U2}}\right) = \left(\dfrac{1}{1.418}\right), \ \Re_1^{U2} = \left(\dfrac{1}{1.319}\right) = (0.705, 0.758) \\ \Re_1^{L3} = \left(\dfrac{\Re_9^{L3}}{\Im_1^{U1}}\right) = \left(\dfrac{1}{1.219}\right), \ \Re_1^{U3} = \left(\dfrac{1}{1.137}\right) = (0.821, 0.880) \end{bmatrix}$$

In case any two m criteria have equal significance, the following equation should be applied:

$FRN(\Re_j) = FRN(\Re_{j-1})$. Then, $FRN(\Re_5) = FRN(\Re_4) = [(0.284, 0.357), (0.406, 0.496), (0.55, 0.672)]$ and $FRN(\Re_3) = FRN(\Re_6) = [(0.009, 0.018), (0.029, 0.048), (0.071, 0.126)]$.

The total matrix is

$$FRN(\Re_1) = \begin{array}{l} [(1.000, 1.000), (1.000, 1.000), (1.000, 1.000)] \\ [(1.000, 1.000), (1.000, 1.000), (1.000, 1.000)] \\ [(0.590, 0.643), (0.705, 0.758), (0.821, 0.880)] \\ [(0.284, 0.357), (0.406, 0.496), (0.550, 0.672)] \\ [(0.284, 0.357), (0.406, 0.496), (0.550, 0.672)] \\ [(0.144, 0.189), (0.245, 0.309), (0.387, 0.491)] \\ [(0.060, 0.089), (0.124, 0.172), (0.227, 0.323)] \\ [(0.023, 0.041), (0.059, 0.093), (0.127, 0.206)] \\ [(0.009, 0.018), (0.029, 0.048), (0.071, 0.126)] \\ [(0.009, 0.018), (0.029, 0.048), (0.071, 0.126)] \end{array}$$

The sum of this matrix is calculated and $FRN(\aleph_j) = [(3.404, 3.713), (4.004, 4.421), (4.804, 5.496)]$ is obtained.

Finally, $FRN(W_2) = \left[\left(\frac{1}{5.496}, \frac{1}{4.804}\right), \left(\frac{1}{4.421}, \frac{1}{4.004}\right), \left(\frac{1}{3.713}, \frac{1}{3.404}\right)\right] = [(0.182, 0.208), (0.226, 0.25), (0.269, 0.294)]$, and the final criteria values are represented in Table 5.

Table 5. Results of the applied FRN SWARA method.

	wj		*wj*
C2	[(0.182,0.208), (0.226,0.250), (0.269,0.294)]	C1	[(0.107,0.134), (0.160,0.189), (0.221,0.258)]
C9	[(0.182,0.208), (0.226,0.250), (0.269,0.294)]	C2	[(0.182,0.208), (0.226,0.250), (0.269,0.294)]
C1	[(0.107,0.134), (0.160,0.189), (0.221,0.258)]	C3	[(0.002,0.004), (0.006,0.012), (0.019,0.037)]
C4	[(0.052,0.074), (0.092,0.124), (0.148,0.198)]	C4	[(0.052,0.074), (0.092,0.124), (0.148,0.198)]
C5	[(0.052,0.074), (0.092,0.124), (0.148,0.198)]	C5	[(0.052,0.074), (0.092,0.124), (0.148,0.198)]
C7	[(0.026,0.039), (0.056,0.077), (0.104,0.144)]	C6	[(0.002,0.004), (0.006,0.012), (0.019,0.037)]
C8	[(0.011,0.019), (0.028,0.043), (0.061,0.095)]	C7	[(0.026,0.039), (0.056,0.077), (0.104,0.144)]
C10	[(0.004,0.009), (0.013,0.023), (0.034,0.060)]	C8	[(0.011,0.019), (0.028,0.043), (0.061,0.095)]
C6	[(0.002,0.004), (0.006,0.012), (0.019,0.037)]	C9	[(0.182,0.208), (0.226,0.250), (0.269,0.294)]
C3	[(0.002,0.004), (0.006,0.012), (0.019,0.037)]	C10	[(0.004,0.009), (0.013,0.023), (0.034,0.060)]

5.2. Calculation of Supplier Ranking Using the Fuzzy–Rough ARAS Method

After obtaining the criteria weights, the ranking of the observed suppliers is performed. Using linguistic values, the experts assessed the observed suppliers (Table 6).

Table 6. Linguistic evaluations of observed suppliers.

Expert 1 (E1)	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
Supplier 1 (S1)	M	MB	M	MG	M	MG	M	MB	MB	M
Supplier 2 (S2)	MG	M	M	M	MG	MB	M	MG	MB	M
Supplier 3 (S3)	G	MG	G	MG	MG	M	M	MG	M	MG
Supplier 4 (S4)	MG	MB	M	M	MB	M	MG	M	MG	M
Supplier 5 (S5)	MB	M	MB	MB	MB	M	MB	MB	M	MB
Supplier 1 (S6)	MB	MB	M	MB	MB	M	M	M	MB	MB
Expert 2	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
Supplier 1 (S1)	MG	MG	M	M	MG	M	M	G	M	M
Supplier 2 (S2)	G	MG	MG	MG	G	MG	MG	MG	G	MG
Supplier 3 (S3)	G	G	MG	G	MG	MG	G	MG	MG	G
Supplier 4 (S4)	MG	MG	M	MG	MG	M	MG	G	M	M
Supplier 5 (S5)	M	M	MG	MB	MB	M	MG	M	MB	MB
Supplier 1 (S6)	MG	M	MG	M	M	M	MG	M	MB	M
Expert 3	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
Supplier 1 (S1)	M	MB	M	MG	M	M	MB	MB	M	M
Supplier 2 (S2)	M	MG	M	MG	M	MG	MG	M	M	MG
Supplier 3 (S3)	MG	MG	M	MG	MG	M	G	M	MG	MG
Supplier 4 (S4)	M	M	MG	M	MB	M	M	MG	M	M
Supplier 5 (S5)	MB	B	MB	MB	MB	M	MB	B	MB	MB
Supplier 1 (S6)	M	MB	MB	MB	M	M	MB	MB	B	MB

The next step is to transform these linguistic values into fuzzy numbers. This is carried out using a fuzzy number membership function (Table 2), with each linguistic value being transformed into a corresponding fuzzy number. Subsequently, the grouping of fuzzy numbers for the individual suppliers is carried out, as shown in Table 7. To illustrate the procedure for forming the interval fuzzy–rough decision matrix, the example of Supplier 1 is used.

Table 7. The values of the fuzzy numbers for Supplier 1.

S1	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**	**E1**	**E2**	**E3**
		l			***m***			***u***	
C1	3	5	3	5	7	5	7	9	7
C2	1	5	1	3	7	3	5	9	5
C3	3	3	3	5	5	5	7	7	7
C4	5	3	5	7	5	7	9	7	9
C5	3	5	3	5	7	5	7	9	7
C6	5	3	3	7	5	5	9	7	7
C7	3	3	1	5	5	3	7	7	5
C8	1	7	1	3	9	3	5	10	5
C9	1	3	3	3	5	5	5	7	7
C10	3	3	3	5	5	5	7	7	7

The rough set's values are then computed. The following calculation is based on the criterion C1 example:

For *l:*

$$\underline{Lim}(1) = 3,\ \overline{Lim}(1) = \frac{1}{3}(3+5+3) = 3.67;\ \underline{Lim}(2) = \frac{1}{3}(3+5+3) = 3.67,\ \overline{Lim}(2) = 5$$

For *m:*

$$\underline{Lim}(2) = 5,\ \overline{Lim}(2) = \frac{1}{3}(5+7+5) = 5.67;\ \underline{Lim}(3) = \frac{1}{3}(5+7+5) = 5.67,\ \overline{Lim}(3) = 7$$

For *u:*

$$\underline{Lim}(3) = 7,\ \overline{Lim}(3) = \frac{1}{3}(7+9+7) = 7.67;\ \underline{Lim}(4) = \frac{1}{3}(7+9+7) = 7.67,\ \overline{Lim}(4) = 9$$

By applying this approach, Supplier 1 was assigned the following fuzzy–rough numbers for criterion C1:

FRN (E_1) = [(3.00, 3.67), (5.00, 5.67), (7.00, 7.67)]
FRN (E_2) = [(3.67, 5.00), (5.67, 7.00), (7.67, 9.00)]
FRN (E_3) = [(3.00, 3,67), (5.00, 5,67), (7,00, 7,67)]

In this way, all values for all criteria and alternatives are calculated. The final value of the fuzzy–rough numbers is formed by calculating the average values for all experts. By applying this approach, an interval fuzzy–rough decision matrix is formed (Table 8). Care should be taken to ensure that the upper limits of the "*l*" fuzzy–rough number are not greater than the lower limits of the "*m*" fuzzy–rough number and that the upper limits of the "*m*" fuzzy–rough number cannot be greater than the lower limits of the "*u*" fuzzy–rough number. Any numbers that do not meet these conditions should be corrected. In this case, corrections were necessary for 25 cases.

Table 8. Interval fuzzy–rough decision matrix.

	C1	**C2**	...	**C10**
S1	[(3.2, 4.1) (5.2, 6.1) (7.2, 8.1)]	[(1.4, 3.0) (3.4, 5.0) (5.4, 7.2)]	...	[(3.0, 3.0) (5.0, 5.0) (7.0, 7.0)]
S2	[(4.0, 6.0) (6.0, 7.9) (7.9, 9.4)]	[(3.9, 4.8) (5.9, 6.8) (7.9, 8.8)]	...	[(3.9, 4.8) (5.9, 6.8) (7.9, 8.8)]
S3	[(5.9, 6.8) (7.9, 8.8) (9.4, 9.9)]	[(5.2, 6.1) (7.2, 8.1) (9.1, 9.6)]	...	[(5.4, 6.6) (7.0, 7.0) (9.0, 9.0)]
S4	[(3.9, 4.8) (5.9, 6.8) (7.9, 8.8)]	[(2.0, 4.0) (4.0, 6.0) (6.0, 8.0)]	...	[(3.0, 3.0) (5.0, 5.0) (7.0, 7.0)]
S5	[(1.2, 2.1) (3.2, 4.1) (5.2, 6.1)]	[(1.3, 2.3) (2.8, 4.3) (4.8, 6.6)]	...	[(1.0, 1.0) (3.0, 3.0) (5.0, 5.0)]
S6	[(2.0, 4.0) (4.0, 6.0) (6.0, 8.0)]	[(1.2, 2.1) (3.2, 4.1) (5.2, 6.1)]	...	[(1.2, 2.1) (3.2, 4.1) (5.2, 6.1)]
S0	[(5.9, 6.8) (7.9, 8.8) (9.4, 9.9)]	[(5.2, 6.1) (7.2, 8.1) (9.1, 9.6)]	...	[(5.4, 6.6) (7.0, 7.0) (9.0, 9.0)]
sum	[(26.1, 27.8) (32.2, 39.7) (43.7, 50.3)]	[(15.1, 22.3) (26.6, 34.3) (38.4, 46.2)]	...	[(17.6, 20.4) (29.1, 30.9) (41.1, 42.9)]

After forming the interval fuzzy–rough matrix, the steps of the ARAS method are applied. The first step is to determine the optimal alternative (S0) for all criteria and all fuzzy–rough numbers. Then, the normalization of this decision matrix is performed. Due to the specificity of linguistic values, all criteria are of the benefit type. Before normalization is carried out, the sum of values for each criterion needs to be calculated. Normalization is carried out by dividing individual values of fuzzy–rough numbers by the sum of these values according to Equation (22). The lower limit of the fuzzy–rough number "*l*" is divided by the upper limit of the fuzzy–rough number "*u*", then the upper limit of the fuzzy–rough number "*l*" is divided by the lower limit of the fuzzy–rough number "*u*". Similarly, other elements of the fuzzy–rough number are normalized. An example of normalization for two fuzzy–rough numbers is presented through the following:

$$n_{11} = \left(\frac{3.2}{50.3}, \frac{4.1}{43.7}\right), \left(\frac{5.2}{39.7}, \frac{6.1}{32.2}\right), \left(\frac{7.2}{27.8}, \frac{8.1}{26.1}\right) = [(0.06,\ 0.09),\ (0.13,\ 0,19),\ (0.26, 0.31)]$$

$$n_{24} = \left(\frac{2.0}{46.2}, \frac{4.0}{38.4}\right), \left(\frac{4.0}{34.3}, \frac{6.0}{26.6}\right), \left(\frac{6.0}{22.3}, \frac{8.0}{15.1}\right) = [(0.04,\ 0.10),\ (0.12,\ 0.23),\ (0.27,\ 0.53)]$$

Following that, the weighting of the normalized decision matrix is performed, in which the normalized data are multiplied by corresponding weights. For the previous examples, the calculation is as follows:

$$\begin{aligned} n_{11} &= (0.06 \times 0.11,\ 0.09 \times 0.13),\ (0.13 \times 0, 16,\ 0, 19 \times 0.19),\ (0.26 \times 0.22, \&0.31 \times 0.26) \\ &= (0.01,\ 0.01),\ (0.02,\ 0.04), (0.06,\ 0.08) \end{aligned}$$

$$\begin{aligned} n_{24} &= (0.04 \times 0.18,\ 0.10 \times 0.21),\ (0.12 \times 0.23,\ 0.23 \times 0.25),\ (0.27 \times 0.27,\ 0.53 \times 0.29) \\ &= (0.01,\ 0.02),\ (0.03,\ 0, 06),\ (0, 07,\ 0.16) \end{aligned}$$

Following that, the values of suppliers for individual fuzzy–rough numbers are added using Equation (25). This value summation is also carried out for the most optimal alternative. Next, the degree of utility for each supplier is determined. The same process as normalization is used here; however, the sum is replaced with the optimal alternative.

$$S_1 = \left(\frac{0.05}{1.02}, \frac{0.09}{0.61}\right), \left(\frac{0.16}{0.37}, \frac{0.26}{0.24}\right), \left(\frac{0.46}{0.16}, \frac{0.82}{0.10}\right) = [(0.05,\ 0.14),\ (0.44,\ 1.05),\ (2.86,\ 8.00)]$$

$$S_4 = \left(\frac{0.06}{1.02}, \frac{0.10}{0.61}\right), \left(\frac{0.17}{0.37}, \frac{0.28}{0.24}\right), \left(\frac{0.49}{0.16}, \frac{0.88}{0.10}\right) = [(0.06,\ 0.17),\ (0.47,\ 1.17),\ (3.04,\ 8.59)]$$

Finally, the ARAS method's final value is calculated using Equation (27). Here, the average of these fuzzy–rough numbers is calculated (Table 9).

Table 9. Results of application of the modified interval fuzzy–rough method.

	S_{ij}	Q_i	R_i	Rank
S1	[(0.05, 0.09), (0.16, 0.26), (0.46, 0.82)]	[(0.05, 0.14), (0.44, 1.05), (2.86, 8.00)]	2.09	4
S2	[(0.07, 0.13), (0.20, 0.33), (0.53, 0.97)]	[(0.07, 0.21), (0.54, 1.38), (3.29, 9.52)]	2.50	2
S3	[(0.10, 0.16), (0.24, 0.36), (0.61, 1.01)]	[(0.10, 0.26), (0.66, 1.48), (3.83, 9.91)]	2.71	1
S4	[(0.06, 0.10), (0.17, 0.28), (0.49, 0.88)]	[(0.06, 0.17), (0.47, 1.17), (3.04, 8.59)]	2.25	3
S5	[(0.02, 0.05), (0.11, 0.18), (0.35, 0.65)]	[(0.02, 0.08), (0.29, 0.75), (2.22, 6.35)]	1.62	6
S6	[(0.02, 0.06), (0.11, 0.20), (0.36, 0.69)]	[(0.02, 0.10), (0.30, 0.84), (2.28, 6.79)]	1.72	5
S0	[(0.10, 0.16), (0.24, 0.37), (0.61, 1.02)]			

The results obtained from applying the proposed approach indicate that supplier S3 exhibits the best characteristics, followed by supplier S2, whereas supplier S5 shows the worst indicators. To further validate these results, they are compared with those obtained from other MCDM methods. In addition to the ARAS method, which was used in the proposed approach, five other methods are employed: simple additive weighting (SAW), compromise ranking of alternatives from distance to ideal solution (CRADIS), multiattributive border approximation area comparison (MABAC), weighted product model (WPM), and measurement of alternatives and ranking according to compromise solution (MARCOS). Each of these methods has its own specifics and employs different steps, but they all use the interval fuzzy–rough decision matrix and the same criteria weights. The results demonstrate that there are no differences in the rankings when using different methods (Figure 1). This confirms the advantage of the proposed approach, which remains stable regardless of the normalization used in certain methods. It should be noted that all other MCDM methods use a different normalization than the ARAS method.

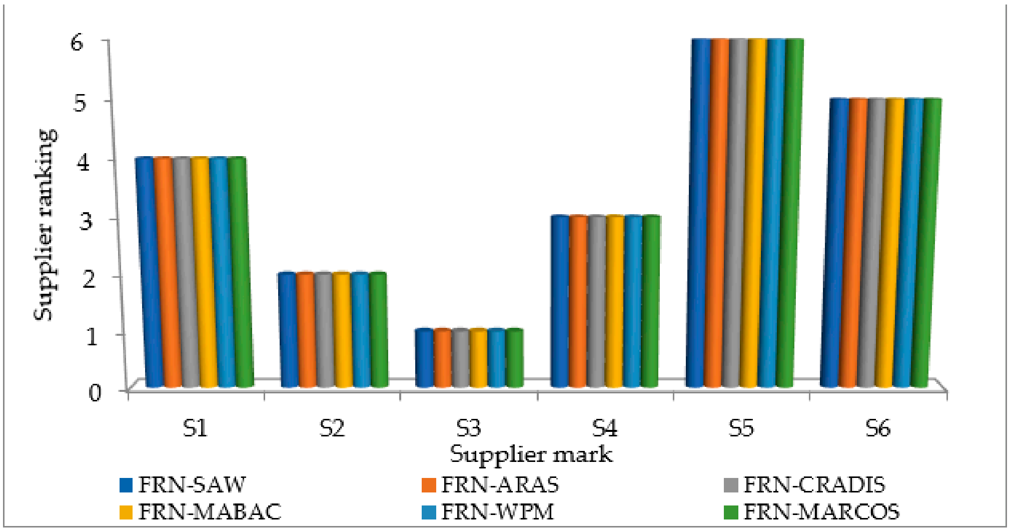

Figure 1. The results of supplier ranking using different methods.

5.3. Sensitivity and Dynamic Fuzzy–Rough Matrix Analysis

Criteria weights often play a crucial role in the decision-making process, so it is very important to simulate their influence on final decisions with various values. This part of the paper performs a simulation that contains 100 scenarios. Each represents changing criteria values in an interval of 5–95%. For example, the first scenario means decreasing the value of the first criterion by 5% of own original values, the second by 15%, the third by 25%, and finally, the S10 by 95%. Scenarios S20–S100 represent the changing criteria weights of the C2–C10 criterion, respectively. The values of the criteria in the simulation process are shown in Figure 2.

After performing the simulation process, the obtained results completely support the initial ranking of suppliers: S3 > S2 > S4 > S1 > S6 > S5. This is a consequence of the larger number of criteria (10) and the small number of alternatives.

Besides performing the analysis above, we checked the influence of the initial fuzzy–rough matrix on ranking suppliers. Five sets are formed, with the elimination of the worst alternatives in each of them. In the first set, alternative A5 is eliminated, in the second, A6, etc. The results of changing the size of the initial fuzzy–rough matrix are represented in Figure 3.

As can be seen, there are no changes in the ranking of suppliers. Each of them keeps the rank from the original results and the developed fuzzy–rough SWARA–fuzzy–rough ARAS method.

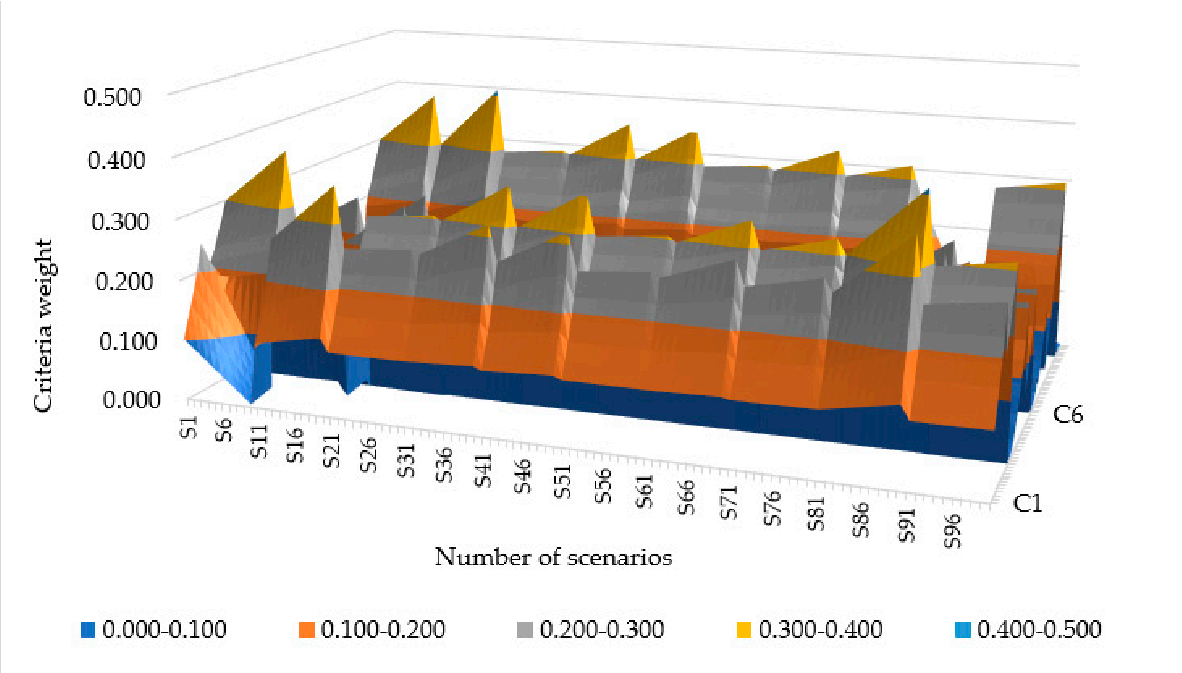

Figure 2. Criteria weights in simulation process.

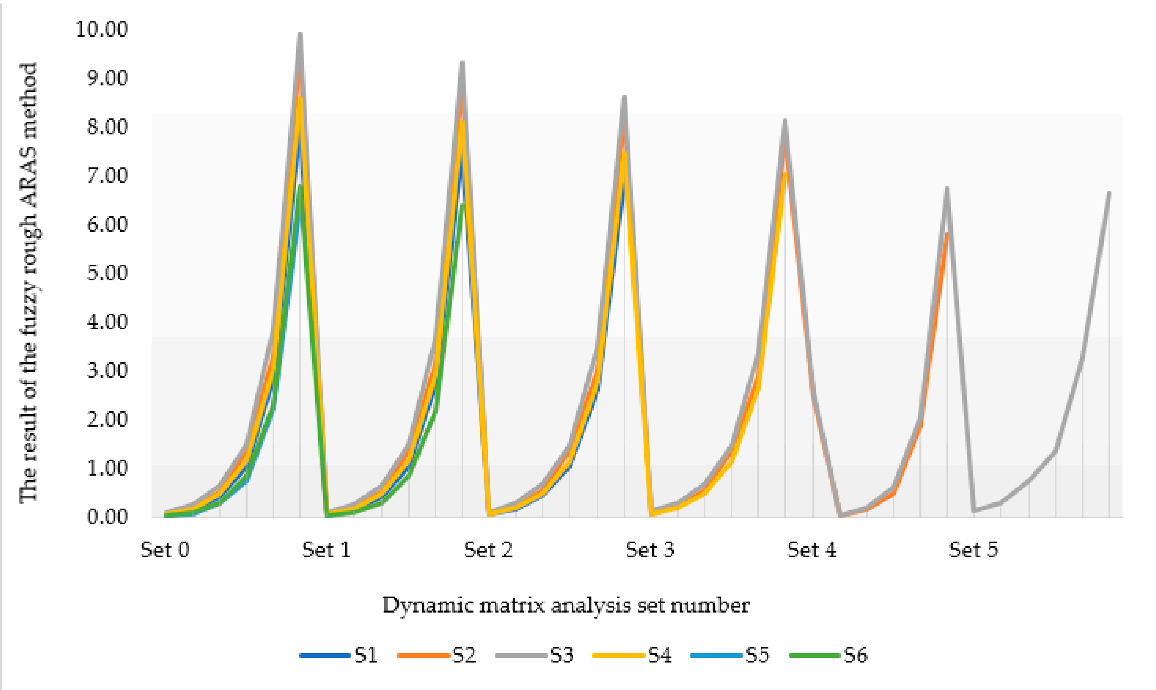

Figure 3. Results of dynamic matrix analysis.

6. Discussion

The selection of suppliers is a fundamental problem in business decision making, as it forms the basis of every business operation. With the growing pressures of market and consumer demands, companies are increasingly turning to environmentally sustainable products. In order to manufacture such products, it is imperative to source raw materials and materials that meet environmentally acceptable standards. Consequently, the selection of suppliers has been adapted and altered to accommodate these requirements. Besides economic considerations, ecological criteria now play a significant role in the supplier selection process, particularly in the production of ecologically acceptable products. The integration of economic and environmental criteria is referred to as the GSS approach [39]. In this study, the GSS approach is employed to assist the Oglavina Brčko company in adapting to market demands. The company strives to source environmentally friendly materials and raw materials during the selection process to enhance the attractiveness of its products in the market.

During the GSS process, the selection of suppliers involves the consideration of several criteria. This paper presents an innovative approach to addressing the GSS problem at Oglavina Brčko through the application of interval fuzzy–rough numbers. The use of this approach stems from the fact that expert decision making is based on the evaluation of suppliers using linguistic values. The transformation of these values into appropriate numerical values is necessary for their use during selection, which is achieved through the application of fuzzy logic. However, this logic has certain advantages and disadvantages. To mitigate the issue of subjectivity when determining the value scale, rough numbers are utilized. The combination of these two fuzzy–rough approaches enables the use of incomplete and unspecified information in decision making [54,56]. Incomplete information exists when deciding, as it is often impossible to obtain all the necessary information [57]. Consequently, decisions are typically made based on incomplete information. Furthermore, the application of linguistic values introduces unspecified information, as it is often challenging to fully determine the value of "medium" or "good". In this context, value scales are established to define the interval of these values, which is the task of fuzzy logic [58].

Fuzzy–rough set theory is considered to be an effective tool for solving decision-making problems in situations where information is imprecise and incomplete and where a rational decision needs to be made [59,60]. In this paper, expert decision making is employed to address the problem of the factual situation regarding the observed suppliers. These suppliers can have a better or worse performance than the experts' estimate, but this uncertainty stems from the lack of complete information that would facilitate a more informed decision [61]. Therefore, in practice, the approach of applying linguistic evaluations is often used for assessing the importance of criteria or evaluating suppliers, as this approach is more aligned with human thinking than numerical ratings [62–64]. To determine which suppliers can best assist Oglavina in adapting to market requirements, the fuzzy–rough SWARA and ARAS methods were utilized in this research. These methods were adapted to this study, and new approaches were devised for their implementation. Specifically, the classic SWARA method was adapted to interval fuzzy–rough numbers, and its steps were adjusted accordingly. The experts were asked to evaluate specific criteria without being required to compare them with each other. This allowed the method to be utilized for determining the weights of the criteria. Because determining the weights of the criteria is crucial for ranking the alternatives [65,66], the weight of each criterion was determined based on expert evaluations, which were obtained for ten different criteria, including economic and ecological factors, in the context of GSS selection.

The present study employed the fuzzy–rough SWARA and fuzzy–rough ARAS methods to determine the most suitable suppliers for Oglavina's GSS. The use of these methods was adapted to interval fuzzy–rough numbers, and the criteria were evaluated based on expert decision making. Ten different criteria, including economic and ecological criteria, were evaluated by experts to determine their relative importance in the selection of GSS. The results of the analysis showed that two criteria were given the highest weight, as they were deemed to be the most important by the experts. This was because the decision-making problem was based on the need to procure quality and environmentally friendly materials from suppliers. Besides the two dominant criteria, two criteria also demonstrated the worst weights. It is worth noting that all observed suppliers possessed the ISO 14001 standard, which is essentially EMS, and therefore, this criterion was deemed to be less important in the decision-making process. Similarly, the suppliers essentially all offered individual services [67], and hence, the services criteria were not deemed to be crucial in the decision-making process.

After determining the criteria weights, the suppliers were evaluated based on the ratings provided by the experts. A modified interval fuzzy–rough ARAS method was used to determine the suppliers' ranking. The method was adapted to this research, and its steps were altered compared with the classic ARAS method. The comparative analysis showed that the suppliers' rankings did not differ, regardless of which MCDM method was used. This confirmed that this approach enhances decision-making stability, and regardless of the MCDM method applied, the same outcome will be obtained. Additionally, the sensitivity analysis and dynamic matrix analysis confirmed the results. The proposed approach demonstrated considerable flexibility and enabled decision making based on incomplete and imprecise information, and thus, it was more user-friendly, since it relied on linguistic values only.

7. Conclusions

In this paper, a novel approach utilizing fuzzy–rough numbers is proposed. The approach is designed to handle incomplete and unreliable information, utilizing linguistic values provided by experts. As experts do not possess complete information and often assume the characteristics of suppliers, this approach overcomes the limitations of fuzzy logic and rough sets. To implement this approach, the SWARA and ARAS methods were modified and adapted. The case study conducted for GSS, with the example of the Oglavina Brčko company, aimed to adapt the furniture product line to meet market demands for environmentally acceptable products. The economic and ecological dimensions of GSS were used as criteria, and the SWARA method was employed to determine their weights. The results of this method indicate quality and environmentally friendly technologies as the most important criteria, while EMS and services are found to be the least important. The ARAS method was utilized to rank and evaluate suppliers, where S3 demonstrated the best characteristics and S5 the worst. These results were confirmed through comparative analysis using other MCDM methods. Moreover, the sensitivity analysis showed that the ranking of suppliers remained the same regardless of any changes in the criteria's weight. The dynamic analysis results provide similar findings, highlighting the stability of the decision making afforded by this new approach.

The proposed approach has demonstrated stability and flexibility in its application, indicating its potential usefulness in other practical scenarios where decisions are based on the evaluation of linguistic values. Linguistic values are used due to their ease of application, as they are more intuitive and closer to human thinking than numerical ratings. This is due to the fact that it is often challenging to provide an assessment that accurately represents a given criterion or alternative. Fuzzy logic is used to represent these values in the form of intervals, making them more accessible for decision making. The approach used in this paper leverages these interval ratings as indicative ratings for rough set application, leading to a methodological merging of these approaches. As a result, the key advantages of this approach are as follows:

- The integration of two different approaches into one enables the use of imprecise data.
- The approach can also be applied to other MCDM methods by adapting the necessary steps to align with this approach.
- The results obtained using this approach demonstrate stability in decision making, which is confirmed by comparative analysis, sensitivity analysis, and dynamic analysis.
- The proposed approach enables problem solving based on multicriteria decision making.

While this novel approach presents potential for future development and use, this paper also has some limitations, mainly related to the selection of experts and criteria. Since Oglavina Brčko is a relatively small company, only three experts were selected, and these experts assessed the criteria's relative importance. Future research should expand upon this approach and consider other methods such as z-numbers and d-numbers.

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