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A Novel Integrated Fuzzy PIPRECIA–Interval Rough Saw Model: Green Supplier Selection

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Abstract: *A novel integrated fuzzy–rough Multi-Criteria Decision-Making (MCDM) model based on integration fuzzy and interval rough set theories is presented. The model integrates the Fuzzy PIvot Pairwise RElative Criteria Importance Assessment - fuzzy PIPRECIA and Interval Rough Simple Additive Weighting (SAW) methods. An illustrative example of the model demonstration is proposed, representing the evaluation and supplier selection based on nine environmental criteria. The fuzzy PIPRECIA method is used to determine the significance of the following seven criteria: C1 – the environmental image, C2 – recycling, C3 – pollution control, C4 – the environmental management system, C5 – environmentally friendly products, C6 – resource consumption, and C7 – green competencies. The interval rough SAW method is applied so as to evaluate four alternatives. The results show that the third criterion is most important, whereas the fourth alternative is the best solution.*

Key words: *Fuzzy PIPRECIA, Interval Rough SAW method, supplier selection, environment.*

1. Introduction

Green supplier selection is one of the most important tasks for the functioning of the whole supply chain, especially for production companies. In this paper, an innovative integrated fuzzy–rough MCDM model is proposed for the evaluation of suppliers, based on environmental criteria. MCDM is an important and powerful tool for solving such problems, as is confirmed by Stević et al. (2020): Multi-criteria decision-making is quite an applicable tool for analyzing complex real problems

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because of its ability to evaluate different alternatives by using certain criteria. There are a certain number of research studies of green supplier selection by using various MCDM methods. Büyüközkan & Çifçi (2012) used a combination of MCDM methods in order to evaluate green suppliers. Qin et al. (2017) solved the problem of making a decision on green supplier selection by using a combination of MCDM methods. Considering various environmental performance requirements and criteria, Yazdani et al. (2017) introduced a new model, i.e. an integrated approach to green supplier selection. Green supplier selection is carried out in various business areas. Zhao & Guo (2014) made the green supplier selection for a supplier of thermal power equipment by using MCDM methods. Banaeian et al. (2018) made green supplier selection in the agri-food industry, while Tsui & Tzeng used the MCDM approach to improve the performance of green suppliers in the TFT-LCD industry. Uppala et al. (2017) used the MCDM approach to green supplier selection in an electronics company, whereas Yu & Hou (2016) conducted green supplier selection in the automotive manufacturing industry. From the economic and environmental aspects, Chen et al. (2016) used the fuzzy MCDM approach to green supplier selection. The paper is aimed at taking the advantages of the implemented approaches and allowing for more accurate and balanced decision-making through their integration.

The rest of the paper is structured as follows: in the second section, the applied methods are presented, i.e. the fuzzy PIPRECIA and interval rough SAW methods, and some basic operations with interval rough numbers are also shown; in the third section, the results obtained are demonstrated in detail, and the section is divided into two subsections; in the fourth section, the conclusion of the paper is given, inclusive of an emphasis on the advantages offered by the proposed integrated model.

2. Methods

2.1. Fuzzy PIvot Pairwise RElative Criteria Importance Assessment – the Fuzzy PIPRECIA Method

The main advantage of the PIPRECIA (Stanujkić et al. 2017) method is that it allows the evaluation of criteria without sorting them first by significance, which is not the case with the SWARA method (Keršuliene et al. 2010; Vesković et al. 2018). Today, the largest number of multi-criteria decision-making problems are solved by applying group decision-making. In such cases, especially as the number of decision-makers involved in the fuzzy PIPRECIA model increases, achieves its benefits. The Fuzzy PIPRECIA method was developed by Stević et al. (2018). It consists of the 11 steps shown below.

Step 1. Forming the required benchmarking set of criteria and forming a team of decision-makers. Sorting the criteria according to the marks from the first to the last, which means they need to be sorted unclassified. Therefore, their significance is irrelevant in this step.

Step 2. In order to determine the relative importance of the criteria, each decision-maker individually evaluates the presorted criteria by starting from the second criterion, Equation (1).

$$\overline{s_j^r} = \begin{cases} >\bar{1} & if \quad C_j > C_{j-1} \\ =\bar{1} & if \quad C_j = C_{j-1} \\ <\bar{1} & if \quad C_j < C_{j-1} \end{cases} \tag{1}$$

where $\overline{s_j^r}$ denotes the evaluation of the criteria by the decision-maker r.

In order to obtain the matrix $\overline{s_j}$, it is necessary to perform the averaging of the matrix $\overline{s_j^r}$ by using the geometric mean. The decision-makers evaluate the criteria by applying the defined scales shown in Tables 1 and 2.

The second and third steps of the developed method are closely interdependence, and new fuzzy scales are defined so as to meet the second and third steps of the fuzzy PIPRECIA method. If the fact that the nature of fuzzy number operations and the fact that, in the third step, the values $\overline{s_j}$ are subtracted from two, it is then required that these scales should be define. It is important to note that, by defining these scales, the appearance of the number two is avoided, which might cause difficulties and wrong results when the calculation is concerned. Therefore, no other previously used fuzzy scales could be used. Only the scales defined in this paper are applicable.

Table 1. The 1-2 scale for the assessment of the criteria

			l	m	u	DFV
An almost equal value	**Scale 1-2**	1	1.000	1.000	1.050	1.008
Slightly more significant		2	1.100	1.150	1.200	1.150
Moderately more significant		3	1.200	1.300	1.350	1.292
More significant		4	1.300	1.450	1.500	1.433
Much more significant		5	1.400	1.600	1.650	1.575
Dominantly more significant		6	1.500	1.750	1.800	1.717
Absolutely more significant		7	1.600	1.900	1.950	1.858

When the criterion is of greater importance in relation to the previous one, an assessment is made by using the above-mentioned scale in Table 1. In order to make it easier for the decision-makers to evaluate the criteria, the table shows the defuzzified value (DFV) for each comparison.

Table 2. The 0-1 scale for the assessment of the criteria

	l	m	u	DFV	
Scale 0-1	0.667	1.000	1.000	0.944	Weakly less significant
	0.500	0.667	1.000	0.694	Moderately less significant
	0.400	0.500	0.667	0.511	Less significant
	0.333	0.400	0.500	0.406	Really less significant
	0.286	0.333	0.400	0.337	Much less significant
	0.250	0.286	0.333	0.288	Dominantly less significant
	0.222	0.250	0.286	0.251	Absolutely less significant

When the criterion is of lesser importance compared to the previous one, an assessment is made by using the above-mentioned scale in Table 2.

Step 3. Determining the coefficient $\overline{k_j}$

$$\overline{k_j} = \begin{cases} =\bar{1} & if \quad j=1 \\ 2-\overline{s_j} & if \quad j>1 \end{cases}. \tag{2}$$

Step 4. Determining the fuzzy weight $\overline{q_j}$

$$\overline{q_j} = \begin{cases} =\bar{1} & if \quad j=1 \\ \dfrac{q_{j-1}}{\overline{k_j}} & if \quad j>1 \end{cases}. \tag{3}$$

Step 5. Determining the relative weight of the criterion $\overline{w_j}$

$$\overline{w_j} = \frac{\overline{q_j}}{\sum_{j=1}^{n} \overline{q_j}}. \tag{4}$$

In the following steps, it is necessary to apply the inverse methodology of the fuzzy PIPRECIA method.

Step 6. The evaluation of the applicable scale defined above, this time starting from the penultimate criterion.

$$\overline{s_j^r}' = \begin{cases} >\bar{1} & if \quad C_j > C_{j+1} \\ =\bar{1} & if \quad C_j = C_{j+1} \\ <\bar{1} & if \quad C_j < C_{j+1} \end{cases}. \tag{5}$$

$\overline{s_j^r}'$ denotes the evaluation of the criteria by the decision-maker *r.*

It is again necessary to average the matrix $\overline{s_j^r}$ by applying the geometric mean.

Step 7. Determining the coefficient $\overline{k_j}'$

$$\overline{k_j}' = \begin{cases} =\bar{1} & if \quad j=n \\ 2-\overline{s_j}' & if \quad j>n \end{cases}. \tag{6}$$

n denotes a total number of the criteria. Specifically, in this case, it means that the value of the last criterion is equal to the fuzzy number one.

Step 8. Determining the fuzzy weight $\overline{q_j}'$

$$\overline{q_j}' = \begin{cases} =\bar{1} & if \quad j=n \\ \dfrac{q_{j+1}'}{\overline{k_j}'} & if \quad j>n \end{cases}. \tag{7}$$

Step 9. Determining the relative weight of the criterion $\overline{w_j}'$

$$\overline{w_j}' = \frac{\overline{q_j}'}{\sum_{j=1}^{n} \overline{q_j}'} . \tag{8}$$

Step 10. In order to determine the final weights of the criteria, it is first necessary to perform the defuzzification of the fuzzy values $\overline{w_j}$ and $\overline{w_j}'$

$$\overline{w_j}'' = \frac{1}{2}(w_j + w_j') . \tag{9}$$

Step 11. Checking the results obtained by applying the Spearman and Pearson correlation coefficients.

2.2. Interval Rough Numbers

The process of group decision-making is accompanied by a large amount of uncertainty and subjectivity, so decision-makers often have dilemmas when assigning certain values to decision attributes. In this paper, a new approach in rough sets theory based on interval rough numbers (IRN) is applied so as to process uncertainty contained in data in group decision-making. Suppose that one decision attribute should be assigned a value represented by a qualitative scale, whose values range from 1 to 5. The first decision-maker (DM) may consider that the decision attribute should have a value ranging between 3 and 4, the second DM may consider that a value between 4 and 5 should be assigned, whereas the third DM has no dilemma about the value of the decision attribute and assigns it the value 4. The presented dilemmas are extremely common in the group decision-making process. In such situations, one of the solutions is to geometrically average two values, which individual decision-makers are in doubt which one to assign. In such situations, however, the uncertainty (ambiguity) that prevailed in the decision-making process would be lost, and a further calculation would be reduced to crisp values. On the other hand, the use of fuzzy or grey techniques would entail predicting the existence of uncertainty and subjectively defining the interval which such uncertainty is exploited by. Subjectively defined intervals in further data processing may significantly influence the final decision (Duntsch et al., 1997), which should definitely be avoided if impartial decision-making is aimed at.

On the contrary, the approach based on interval rough numbers includes the exploitation of the uncertainty contained in the obtained data. By applying the arithmetic operations explained in the following section, the values of the attributes that fully describe the specified uncertainties without subjectively affecting their values are obtained. Thus, the uncertainties of the first DM can be described by an interval rough number IRN = [(3,3.67), (4,4.33)], of the second DM by IRN = [(3.67,4), (4.33,5)], while those of the third DM can be described by IRN = [(3.67,4), (4,4.33)]. The detailed procedure for the determination of an IRN is explained in the following section.

Suppose that there is a set of k classes representing the DM's preferences, $R = (J_1, J_2, ..., J_k)$, provided that they belong to the sequence that satisfies the condition $J_1 < J_2 <, ..., < J_k$, and another set of m classes, which also represents the DM's preferences, $R^* = (I_1, I_2, ..., I_k)$. All objects are defined in the universe and related to the DM's preferences. In R^*, each class of objects is presented in an interval $I_i = \{I_{li}, I_{ui}\}$, where the conditions that $I_{li} \le I_{ui}$ ($1 \le i \le m$) $I_{li}, I_{ui} \in R$, too, are satisfied. Then, I_{li} is the lower limit of the interval, while I_{ui} is the upper limit of the interval of the i th class of the objects. If both limits of the object classes (the upper and the lower limits) are arranged in such a way that $I^*_{l1} < I^*_{l2} <, ..., < I^*_{lj}, I^*_{u1} < I^*_{u2} <, ..., < I^*_{uk}$ ($1 \le j, k \le m$), respectively, then the two new sets that contain the lower object class $R^*_l = (I^*_{l1}, I^*_{l2}, ..., I^*_{lj})$ and upper object class $R^*_u = (I^*_{u1}, I^*_{u2}, ..., I^*_{uk})$, respectively, can be defined. Then, for any class of objects $I^*_{li} \in R$ ($1 \le i \le j$) and $I^*_{ui} \in R$

($1 \le i \le k$), it is possible to define the lower approximation of I^*_{li} and I^*_{ui} as follows:

$$\underline{Apr}(I^*_{li}) = \bigcup \left\{ Y \in U / R^*_l(Y) \le I^*_{li} \right\} \tag{10}$$

$$\underline{Apr}(I^*_{ui}) = \bigcup \left\{ Y \in U / R^*_u(Y) \le I^*_{ui} \right\} \tag{11}$$

The upper approximations of I^*_{li} and I^*_{ui} are defined by applying the following equations:

$$\overline{Apr}(I^*_{li}) = \bigcup \left\{ Y \in U / R^*_l(Y) \ge I^*_{li} \right\} \tag{12}$$

$$\overline{Apr}(I^*_{ui}) = \bigcup \left\{ Y \in U / R^*_u(Y) \ge I^*_{ui} \right\} \tag{13}$$

Both classes of objects (the upper and the lower classes of the objects I^*_{li} and I^*_{ui}) are defined by their lower limits $\underline{Lim}(I^*_{li})$ and $\underline{Lim}(I^*_{ui})$, and their upper limits $\overline{Lim}(I^*_{li})$ and $\overline{Lim}(I^*_{ui})$, respectively,

$$\underline{Lim}(I^*_{li}) = \frac{1}{M_L} \sum R^*_l(Y) \middle| Y \in \underline{Apr}(I^*_{li}) \tag{14}$$

$$\underline{Lim}(I^*_{ui}) = \frac{1}{M^*_L} \sum R^*_u(Y) \middle| Y \in \underline{Apr}(I^*_{ui}) \tag{15}$$

where M_L and M^*_L represent the total number of the objects contained in the lower approximation of the classes of the objects I^*_{li} and I^*_{ui}, respectively. The upper limits $\overline{Lim}(I^*_{li})$ and $\overline{Lim}(I^*_{ui})$ are defined by applying the equations (16) and (17), as follows:

$$\overline{Lim}(I^*_{li}) = \frac{1}{M_U} \sum R^*_l(Y) \middle| Y \in \overline{Apr}(I^*_{li}) \tag{16}$$

$$\overline{Lim}(I_{ui}^{*}) = \frac{1}{M_{U}^{*}} \sum R_{u}^{*}(Y) \middle| Y \in \overline{Apr}(I_{ui}^{*}) \tag{17}$$

where M_U and M_U^* represent a total number of the objects contained in the upper approximation of the classes of the objects I_{li}^* and I_{ui}^*, respectively.

For the lower class of the objects, a rough boundary interval of I_{li}^* is presented as $RB(I_{li}^*)$, denoting the interval between the lower and the upper limits:

$$RB(I_{li}^{*}) = \overline{Lim}(I_{li}^{*}) - \underline{Lim}(I_{li}^{*}) \tag{18}$$

Whereas for the upper class of the objects the rough boundary interval of I_{ui}^* is obtained as

$$RB(I_{ui}^{*}) = \overline{Lim}(I_{ui}^{*}) - \underline{Lim}(I_{ui}^{*}) \tag{19}$$

the uncertain class of the objects I_{li}^* and I_{ui}^* can be presented by using their lower and upper limits

$$RN(I_{li}^{*}) = \left[\overline{Lim}(I_{li}^{*}), \underline{Lim}(I_{li}^{*}) \right] \tag{20}$$

$$RN(I_{ui}^{*}) = \left[\overline{Lim}(I_{ui}^{*}), \underline{Lim}(I_{ui}^{*}) \right] \tag{21}$$

As can be seen, each class of the objects is defined by its lower and upper limits, which represent the interval rough number defined as

$$IRN(I_{i}^{*}) = \left[RN(I_{li}^{*}), RN(I_{ui}^{*}) \right]. \tag{22}$$

The IRN determination procedure will be explained by the example of the determination of the weight coefficient of the criterion w_i, which is participated in by four experts. The experts evaluated the criteria by using the scale that includes integer values, ranging within the following 1-5 intervals: 1 – a very small impact, 2 – a small impact, 3 – a medium impact, 4 – a large impact, and 5 – a very large impact. The experts' evaluations are shown in Table 3.

Table 3. The experts' evaluation of the criterion w_i

Criterion	Experts			
	E1	E2	E3	E4
w_i	(2;3)	(3;4)	(4;5)	(5;5)

The experts' evaluations in Table 3 are presented in the form of ordered pairs (ai;bi), where ai and bi are the values assigned by the experts to the criteria from the 1-5 scale. The experts who cannot confidently opt for one of the values in the scale enter both values they have a dilemma of (E1, E2 and E3). In our example, only the expert E4 had no dilemma and chose a unique value from the scale.

These uncertainties can be represented by trapezoidal fuzzy numbers of the form A=(a1, a2, a3, a4), where a2 and a3 represent the values in which the membership function reaches its maximum value, whereas a1 and a4 represent the left and the right limits of a fuzzy set, respectively. In our example (Table 3), the four trapezoidal fuzzy numbers A (E1) = (1,2,3,4), A (E2) = (2,3,4,5), A (E3) = (3. 4,5,5) and A (E4) = (4,5,5,5) were obtained. The trapezoidal fuzzy numbers are graphically shown in

Figure 1, where the darker nuance indicates the values in which the membership function reaches its maximum value (a2 and a3), whereas the light nuance indicates the elements of the set more or less belonging to the fuzzy set (a1 and a4).

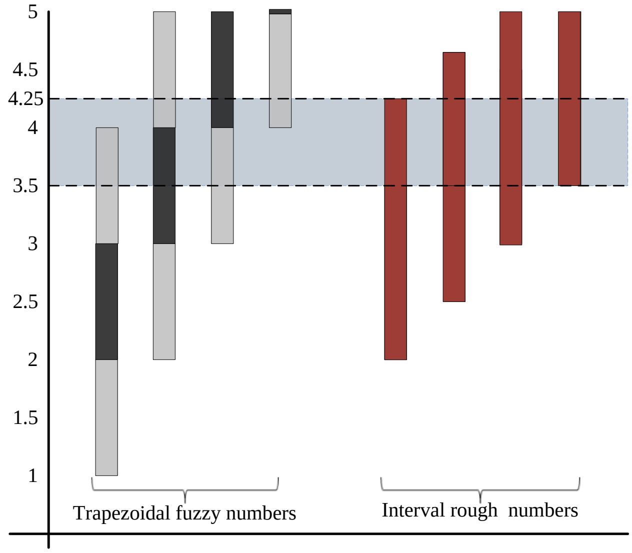

Figure 1. The criterion evaluation – the interval rough and fuzzy evaluations

In addition to the fuzzy approach, the uncertainties described can also be presented by interval rough numbers, since it was defined in the previous section (the equations (10)-(21)) that an IRN consists of two rough sequences and the two classes of the objects w_i and w'_i: $w_i = \{2;3;4;5\}$ and $w_i^{'} = \{3;4;5;5\}$ were defined. By applying the equations (10)-(17), the rough sequences (20) and (21) are formed for each class of the objects. For the first class of the objects, the following was obtained:

$$\underline{Lim}(2) = 2,\ \overline{Lim}(2) = \frac{1}{4}(2+3+4+5) = 3.5;\ RN(2) = [2, 3.5]$$

$$\underline{Lim}(3) = \frac{1}{2}(2+3) = 2.5,\ \overline{Lim}(3) = \frac{1}{3}(3+4+5) = 4;\ RN(3) = [2.5, 4]$$

$$\underline{Lim}(4) = \frac{1}{3}(2+3+4) = 3,\ \overline{Lim}(4) = \frac{1}{2}(4+5) = 4.5;\ RN(4) = [3, 4.5]$$

$$\underline{Lim}(5) = \frac{1}{4}(2+3+4+5) = 3.5,\ \overline{Lim}(5) = 5;\ RN(4) = [3.5, 5]$$

For the second class of the objects, the following was obtained:

$$\underline{Lim}(3) = 3,\ \overline{Lim}(3) = \frac{1}{4}(3+4+5+5) = 4.25;\ RN(2) = [3, 4.5]$$

$$\underline{Lim}(4) = \frac{1}{2}(3+4) = 3.5,\ \overline{Lim}(4) = \frac{1}{3}(4+5+5) = 4.67;\ RN(3) = [2.5, 4]$$

$$\underline{Lim}(5) = \frac{1}{4}(3+4+5+5) = 4.25,\ \overline{Lim}(5) = 5;\ RN(5) = [4.25, 5]$$

Based on the rough sequences, the following interval rough numbers: $IRN(E1)=([2,3.5],[3,4.25])$, $IRN(E2)=([2.5,4],[3.5,4.67])$, $IRN(E3)=([3,4.5],[4.25,5])$ and $IRN(E4)=([3.5,5],[4.25,5])$ were obtained.

Rationally reasoning, without applying the rough and fuzzy sets, it can be concluded that the values of the criterion w_i should range between the values 3.5 and 4.25. These values are obtained by the geometrical averaging of the classes of the objects $w_i=\{2;3;4;5\}$ and $w_i^{'}=\{3;4;5;5\}$. In Figure 3, the rational (expected) values 3.5 and 4.25 are shown by the dashed line. Figure 3 allows us to notice that the expected values (3.5 and 4.25) are completely within the range of all the IRNs. On the other hand, the fuzzy numbers only partially cover the expected values. The affiliation function of the fuzzy numbers A(E2) and A(E3) with the maximum affiliation only partially covers the expected values, whereas the fuzzy numbers A(E1) and A(E4) cover the expected values, with an affiliation degree of 0.5. On the other hand, all the IRNs fully cover the expected values (3.5 and 4.25) by their intervals.

Interval rough numbers are characterized by specific arithmetic operations, which are different from the arithmetic operations with classical rough numbers. Arithmetic operations between two interval rough numbers $IRN(A)=([a_1,a_2],[a_3,a_4])$ and $IRN(B)=([b_1,b_2],[b_3,b_4])$ are performed by using the following equations (23), (24), (25), (26) and (27):

(1) The addition of interval rough numbers, "+",

$$IRN(A)+IRN(B)=([a_1,a_2],[a_3,a_4])+([b_1,b_2],[b_3,b_4])=([a_1+b_1,a_2+b_2],[a_3+b_3,a_4+b_4]) \quad (23)$$

(2) the subtraction of interval rough numbers, "-",

$$IRN(A)-IRN(B)=([a_1,a_2],[a_3,a_4])-([b_1,b_2],[b_3,b_4])=([a_1-b_4,a_2-b_3],[a_3-b_2,a_4-b_1]) \quad (24)$$

(3) the multiplication of interval rough numbers, "×",

$$IRN(A)\times IRN(B)=([a_1,a_2],[a_3,a_4])\times([b_1,b_2],[b_3,b_4])=([a_1\times b_1,a_2\times b_2],[a_3\times b_3,a_4\times b_4]) \quad (25)$$

(4) the division of interval rough numbers, "/",

$$IRN(A)/IRN(B)=([a_1,a_2],[a_3,a_4])/([b_1,b_2],[b_3,b_4])=([a_1/b_4,a_2/b_3],[a_3/b_2,a_4/b_1]) \quad (26),$$

and

(5) the scalar multiplication of interval rough numbers where $k>0$

$$k\times IRN(A)=k\times([a_1,a_2],[a_3,a_4])=([k\times a_1,k\times a_2],[k\times a_3,k\times a_4]) \quad (27)$$

Any two interval rough numbers $IRN(\alpha)=\left(\left[\alpha^L,\alpha^U\right],\left[\alpha^{'L},\alpha^{'U}\right]\right)$ and $IRN(\beta)=\left(\left[\beta^L,\beta^U\right],\left[\beta^{'L},\beta^{'U}\right]\right)$ are ranked according to the following rules:

(1) If the interval of the interval rough number is not strictly bounded by another interval, then:

(a) ff the condition that $\{\alpha^{'U}>\beta^{'U}$ and $\alpha^L\geq\beta^L\}$ or $\{\alpha^{'U}\geq\beta^{'U}$ i $\alpha^L<\beta^L\}$ is met, then $IRN(\alpha)>IRN(\beta)$, Figure 2a;

(b) if the condition that $\{\alpha^{'U}=\beta^{'U}$ and $\alpha^L=\beta^L\}$ is met, then $IRN(\alpha)=IRN(\beta)$, Figure 2b.

(2) If the intervals of the interval rough numbers $IRN(\alpha)$ and $IRN(\beta)$ are strictly bounded, then it is necessary to determine the intersection points $I(\alpha)$ and $I(\beta)$ of the interval rough numbers $IRN(\alpha)$ and $IRN(\beta)$. If the condition that $\beta'^{U} < \alpha'^{U}$ and $\beta^{L} > \alpha^{L}$ is met, then

(a) ff the condition that $I(\alpha) \le I(\beta)$ is met, then $IRN(\alpha) < IRN(\beta)$, Figures 2c and 2d;

(c) if the condition that $I(\alpha) > I(\beta)$ is met, then $IRN(\alpha) > IRN(\beta)$, Figure 2e.

The intersection points of the interval rough numbers are obtained in the following manner:

$$\mu_{\alpha} = \frac{RB(\alpha_{ui})}{RB(\alpha_{ui}) + RB(\alpha_{li})}; \quad RB(\alpha_{ui}) = \alpha'^{U} - \alpha'^{L}; \quad RB(\alpha_{li}) = \alpha^{U} - \alpha^{L} \tag{28}$$

$$\mu_{\beta} = \frac{RB(\beta_{ui})}{RB(\beta_{ui}) + RB(\beta_{li})}; \quad RB(\beta_{ui}) = \beta'^{U} - \beta'^{L}; \quad RB(\beta_{li}) = \beta^{U} - \beta^{L} \tag{29}$$

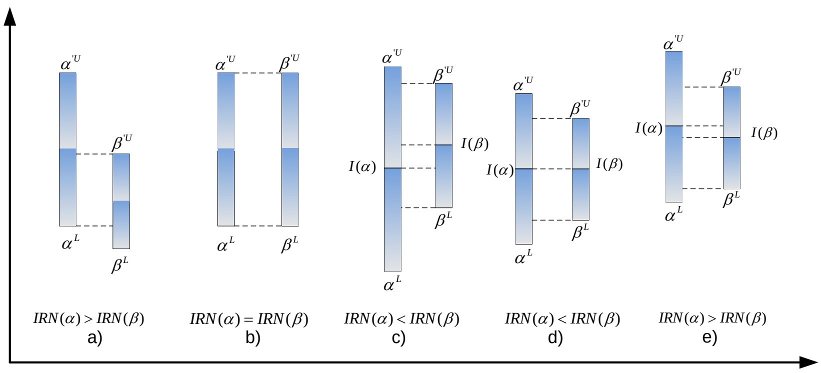

Figure 2. Ranking interval rough numbers

$$I(\alpha) = \mu_{\alpha} \cdot \alpha^{L} + (1 - \mu_{\alpha}) \cdot \alpha'^{U} \tag{30}$$

$$I(\beta) = \mu_{\beta} \cdot \beta^{L} + (1 - \mu_{\beta}) \cdot \beta'^{U} \tag{31}$$

2.3. Interval Rough SAW Method

The SAW method is a simple and easily applicable multi-criteria decision-making method. Using only crisp numbers, however, it is impossible to obtain the results that treat uncertainty and objectivity in an adequate way (Stević et al. 2017). The Rough SAW method was developed two years ago and presented in the study (Stević et al., 2017). The Interval Rough SAW method consists of the following steps (Stević et al., 2019):

Step 1: Forming a multi-criteria decision-making model which consists of *m* alternatives and *n* criteria.

Step 2: Forming a team of *r* experts, who will make an assessment of alternatives according to all the criteria and sub-criteria.

Step 3: The transformation of individual matrices into a group interval rough matrix. In this step, it is necessary to transform each individual matrix of the experts $r_1,r_2,...,r_n$ into an interval rough group matrix by using the equations (10)-(21):

$$Y=\begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 \\ A_2 \\ \dots \\ A_m \end{matrix}\begin{bmatrix} IRN(x_{11}) & IRN(x_{12}) & \dots & IRN(x_{1n}) \\ IRN(x_{21}) & IRN(x_{22}) & & IRN(x_{2n}) \\ \dots & \dots & \dots & \dots \\ IRN(x_{l1}) & IRN(x_{l2}) & \dots & IRN(x_{ln}) \end{bmatrix}_{m\times n} \tag{32}$$

where m denotes the number of alternatives and n denotes the number of criteria.

Step 4: The normalization of the initial interval rough group matrix (33) by using the equations (34) and (35):

$$Y=\begin{matrix} & C_1 & C_2 & \dots & C_n \\ A_1 \\ A_2 \\ \dots \\ A_m \end{matrix}\begin{bmatrix} IRN(n_{11}) & IRN(n_{12}) & \dots & IRN(n_{1n}) \\ IRN(n_{21}) & IRN(n_{22}) & & IRN(n_{2n}) \\ \dots & \dots & \dots & \dots \\ IRN(n_{l1}) & IRN(n_{l2}) & \dots & IRN(n_{ln}) \end{bmatrix}_{m\times n} \tag{33}$$

If the criterion belongs to the benefit group, then Equation (34) is used for the normalization process:

$$IRN(n_{ij})=\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)=\frac{\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)}{\max\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)}\quad , \tag{34}$$

whereas for the criteria belonging to the cost group, Equation (35) is applied:

$$IRN(n_{ij})=\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)=\frac{\min\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)}{\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)} \tag{35}$$

Equations (25) and (26) are further broken down into Equations (36) and (37):

$$\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)=\left(\left[\frac{n_{ij}^{L}}{\max n_{ij}^{'U}},\frac{n_{ij}^{U}}{\max n_{ij}^{'L}},\frac{n_{ij}^{'L}}{\max n_{ij}^{U}},\frac{n_{ij}^{'U}}{\max n_{ij}^{L}}\right]\right)\quad if\quad C_n\in B \tag{36}$$

$$\left(\left[n_{ij}^{L},n_{ij}^{U},n_{ij}^{'L},n_{ij}^{'U}\right]\right)=\left(\left[\frac{\min n_{ij}^{L}}{n_{ij}^{'U}},\frac{\min n_{ij}^{U}}{n_{ij}^{'L}},\frac{\min n_{ij}^{'L}}{n_{ij}^{U}},\frac{\min n_{ij}^{'u}}{n_{ij}^{L}}\right]\right)\quad if\quad C_n\in C \tag{37}$$

Step 5: Weighting the previously normalized matrix:

$$IRN(V_{ij})=\left(\left[v_{ij}^{L},v_{ij}^{U},v_{ij}^{'L},v_{ij}^{'U}\right]\right)_{m\times n}=\left(\left[n_{ij}^{L}\times \mathrm{w}_{ij}^{L},n_{ij}^{U}\times \mathrm{w}_{ij}^{U},n_{ij}^{'L}\times \mathrm{w}_{ij}^{'L},n_{ij}^{'U}\times \mathrm{w}_{ij}^{'U}\right]\right) \tag{38}$$

Step 6: Summing up all of the values of the obtained alternatives (summing up by rows):

$$IRN(S_i)=\left(\left[s_i^{L},s_i^{U},s_i^{'L},s_i^{'U}\right]\right)_{1\times m} \tag{39}$$

Step 7: Ranking the alternatives in descending order, i.e. the highest value is the best alternative. In order to rank the potential solutions more easily, a rough number can be converted into a crisp number by using the average value.

3. Results

The selection of a green supplier depends on the precise determination and selection of adequate criteria and their evaluation. A novel integrated MCDM model is modified from (Stević et al 2019) where supplier selection carried out 21 sustainable criteria. In this example we left only environmental criteria and made decision. The criteria for selecting a sustainable supplier are as follows: C1 – environmental image, C2 – recycling, C3 – pollution control, C4 – environmental management system, C5 – environmentally friendly products, C6 – resource consumption and C7 – green competencies.

3.1. Determining Criteria Weights by Using the Fuzzy PIPRECIA Method

The evaluation of the criteria was performed by using the linguistic scale that involves quantification into fuzzy triangle numbers. Table 4 shows the evaluation of the criteria for fuzzy PIPRECIA and Inverse fuzzy PIPRECIA carried out by the decision-makers.

Based on the evaluation of the criteria and Equation (1), the matrix *sj* was formed.

$$s_j = \begin{bmatrix} & \cdots & \\ 1.100 & 1.150 & 1.200 \\ 1.050 & 1.075 & 1.125 \\ 0.310 & 0.367 & 0.450 \\ 1.150 & 1.225 & 1.275 \\ 0.310 & 0.367 & 0.450 \\ 1.050 & 1.075 & 1.125 \end{bmatrix}$$

Applying Equation (2), these values were subtracted from two. Following the rules of operations with the fuzzy numbers of the matrix *kj*

$$k_j = \begin{bmatrix} 1.000 & 1.000 & 1.000 \\ 0.800 & 0.850 & 0.900 \\ 0.875 & 0.925 & 0.950 \\ 1.550 & 1.633 & 1.690 \\ 0.725 & 0.775 & 0.850 \\ 1.550 & 1.633 & 1.690 \\ 0.875 & 0.925 & 0.950 \end{bmatrix}$$

the following was obtained:

According to Equation (2), the value $\overline{k_1} = (1.000, 1.000, 1.000)$

$$\overline{k_2} = (2 - 1.200, 2 - 1.150, 2 - 1.100) = (0.800, 0.850, 0.900)$$

Applying Equation (3), the values *qj*

$$q_j = \begin{bmatrix} 1.000 & 1.000 & 1.000 \\ 1.111 & 1.176 & 1.250 \\ 1.170 & 1.272 & 1.429 \\ 0.692 & 0.779 & 0.922 \\ 0.814 & 1.005 & 1.271 \\ 0.482 & 0.615 & 0.820 \\ 0.507 & 0.665 & 0.937 \end{bmatrix}$$

were obtained as follows:

$$\overline{q_1} = (1.000, 1.000, 1.000)$$

$$\overline{q_2} = \left(\frac{1.000}{0.900}, \frac{1.000}{0.850}, \frac{1.000}{0.800}\right) = (1.111, 1.176, 1.250)$$

Applying Equation (4), relative weights were calculated:

$$\overline{w_1} = \left(\frac{1.000}{7.629}, \frac{1.000}{6.512}, \frac{1.000}{5.775}\right) = (0.131, 0.154, 0.173)$$

In order to determine the final weights of the criteria, it was necessary to apply Equations (5)-(9), or the methodology of the inverse fuzzy PIPRECIA method. Based on the evaluation performed by the decision-makers, the matrix *sj'* was obtained as follows:

$$s_j' = \begin{bmatrix} & \cdots & \\ 0.517 & 0.708 & 0.917 \\ 0.583 & 0.833 & 1.000 \\ 1.350 & 1.525 & 1.575 \\ 0.450 & 0.583 & 0.833 \\ 1.350 & 1.525 & 1.575 \\ 0.583 & 0.833 & 1.000 \end{bmatrix}$$

Applying equation (6), the values of the matrix *kj'* were obtained as follows:

$$k_j' = \begin{bmatrix} 1.083 & 1.292 & 1.483 \\ 1.000 & 1.167 & 1.417 \\ 0.425 & 0.475 & 0.650 \\ 1.167 & 1.417 & 1.550 \\ 0.425 & 0.475 & 0.650 \\ 1.000 & 1.167 & 1.417 \\ 1.000 & 1.000 & 1.000 \end{bmatrix}$$

$$\overline{k_7}' = (1.000, 1.000, 1.000)$$

$$\overline{k_3}' = (2 - 1.575, 2 - 1.525, 2 - 1.350) = (0.425, 0.475, 0.650)$$

Table 4. Evaluation of the criteria for fuzzy PIPRECIA and Inverse fuzzy PIPRECIA

PIPR.	C1	C2			C3			C4			C5			C6			C7		
DM1		1.100	1.150	1.200	1.000	1.000	1.050	0.333	0.400	0.500	1.100	1.150	1.200	0.333	0.400	0.500	1.000	1.000	1.050
DM2		1.200	1.300	1.350	1.100	1.150	1.200	0.286	0.333	0.400	1.200	1.300	1.350	0.286	0.333	0.400	1.100	1.150	1.200
DM3		1.100	1.150	1.200	1.000	1.000	1.050	0.333	0.400	0.500	1.100	1.150	1.200	0.333	0.400	0.500	1.000	1.000	1.050
DM4		1.000	1.000	1.050	1.100	1.150	1.200	0.286	0.333	0.400	1.200	1.300	1.350	0.286	0.333	0.400	1.100	1.150	1.200
AV		1.100	1.150	1.200	1.050	1.075	1.125	0.310	0.367	0.450	1.150	1.225	1.275	0.310	0.367	0.450	1.050	1.075	1.125
PIPR-I	**C7**	**C6**			**C5**			**C4**			**C3**			**C2**			**C1**		
DM1		0.667	1.000	1.000	1.300	1.450	1.500	0.500	0.667	1.000	1.300	1.450	1.500	0.667	1.000	1.000	0.500	0.667	1.000
DM2		0.500	0.667	1.000	1.400	1.600	1.650	0.400	0.500	0.667	1.400	1.600	1.650	0.500	0.667	1.000	0.400	0.500	0.667
DM3		0.667	1.000	1.000	1.300	1.450	1.500	0.500	0.667	1.000	1.300	1.450	1.500	0.667	1.000	1.000	0.500	0.667	1.000
DM4		0.500	0.667	1.000	1.400	1.600	1.650	0.400	0.500	0.667	1.400	1.600	1.650	0.500	0.667	1.000	0.667	1.000	1.000
AV		0.583	0.833	1.000	1.350	1.525	1.575	0.450	0.583	0.833	1.350	1.525	1.575	0.583	0.833	1.000	0.517	0.708	0.917

Applying Equation (7), the following values were obtained:

$$q_j' = \begin{bmatrix} 0.513 & 1.780 & 4.380 \\ 0.761 & 2.299 & 4.745 \\ 1.078 & 2.682 & 4.745 \\ 0.701 & 1.274 & 2.017 \\ 1.086 & 1.805 & 2.353 \\ 0.706 & 0.857 & 1.000 \\ 1.000 & 1.000 & 1.000 \end{bmatrix}$$

$$\overline{q_7}' = (1.000, 1.000, 1.000)$$

$$\overline{q_3}' = \left(\frac{0.701}{0.650}, \frac{1.274}{0.475}, \frac{2.017}{0.425}\right) = (1.078, 2.682, 4.745)$$

After that, it was necessary to apply equation (8) in order to obtain the relative weights for the fuzzy Inverse PIPRECIA method.

$$\overline{w_4}' = \left(\frac{0.701}{20.241}, \frac{1.274}{11.695}, \frac{2.017}{5.844}\right) = (0.035, 0.109, 0.345)$$

The results of the applied methodology are presented in Table 5. Using Equation (9), the final weights of the criteria were obtained. Before applying this equation, it was necessary to defuzzify the values of the criteria obtained by applying the equations (1)-(9). Table 5 shows the complete previous calculation, and the last column shows the defuzzified values of the relative weights of the criteria.

The Spearman (Erceg et al., 2019) correlation coefficient for the obtained ranks is 0.964, which means that there is a minimum difference in these ranks. The first and the fifth criteria are replaced in the third and the fourth place, respectively. The Pearson (Stevic et al., 2018) correlation coefficient for the criterion weights (0.977) was also calculated.

Table 6 presents the final weight results obtained by using the fuzzy PIPRECIA method. In Table 6, the criteria are ranked by significance. The most significant criterion is C3 – pollution control. The function value of this criterion is 0.247. The least significant criterion is C6 – resource consumption. The function value of this criterion is 0.090.

Table 6. The final weight results obtained by applying the fuzzy PIPRECIA method

	I	II	wj	
C1	0.153	0.231	0.192	**3**
C2	0.181	0.273	0.227	**2**
C3	0.197	0.297	0.247	**1**
C4	0.121	0.136	0.129	**5**
C5	0.157	0.179	0.168	**4**
C6	0.097	0.083	0.090	**7**
C7	0.106	0.094	0.100	**6**

Table 5. Criteria weights obtained using fuzzy PIPRECIA method

P		**sj**			**kj**			**qj**			**wj**		**Defazi**	**wj**	**Rang**
C1				1,000	1,000	1,000	1,000	1,000	1,000	0.131	0.154	0.173	0.153	0.192	3
C2	1.100	1.150	1.200	0.800	0.850	0.900	1.111	1.176	1.250	0.146	0.181	0.216	0.181	0.227	2
C3	1.050	1.075	1.125	0.875	0.925	0.950	1.170	1.272	1.429	0.153	0.195	0.247	0.197	0.247	1
C4	0.310	0.367	0.450	1.550	1.633	1.690	0.692	0.779	0.922	0.091	0.120	0.160	0.121	0.129	5
C5	1.150	1.225	1.275	0.725	0.775	0.850	0.814	1.005	1.271	0.107	0.154	0.220	0.157	0.168	4
C6	0.310	0.367	0.450	1.550	1.633	1.690	0.482	0.615	0.820	0.063	0.094	0.142	0.097	0.090	7
C7	1.050	1.075	1.125	0.875	0.925	0.950	0.507	0.665	0.937	0.066	0.102	0.162	0.106	0.100	6
P-I		sj			kj			qj			wj				
C1	0.517	0.708	0.917	1.083	1.292	1.483	0.513	1.780	4.380	0.025	0.152	0.750	0.231		
C2	0.583	0.833	1.000	1.000	1.167	1.417	0.761	2.299	4.745	0.038	0.197	0.812	0.273		
C3	1.350	1.525	1.575	0.425	0.475	0.650	1.078	2.682	4.745	0.053	0.229	0.812	0.297		
C4	0.450	0.583	0.833	1.167	1.417	1.550	0.701	1.274	2.017	0.035	0.109	0.345	0.136		
C5	1.350	1.525	1.575	0.425	0.475	0.650	1.086	1.805	2.353	0.054	0.154	0.403	0.179		
C6	0.583	0.833	1.000	1.000	1.167	1.417	0.706	0.857	1.000	0.035	0.073	0.171	0.083		
C7				1.000	1.000	1.000	1.000	1.000	1.000	0.049	0.086	0.171	0.094		

3.2. The evaluation of the Alternatives by Applying the Interval Rough SAW Method

Table 7. The initial interval rough matrix

	A1	A2	A3	A4
C_1	[4.11, 4.55]; [4.5, 5.5]	[4.11, 4.55]; [4.45, 4.89]	[4.45, 4.89]; [5.45, 5.89]	[5.45, 5.89]; [6, 6]
C_2	[5.45, 5.89]; [6, 6]	[5, 5]; [5.45, 5.89]	[5.45, 5.89]; [6.45, 6.89]	[4.89, 5.78]; [5.45, 5.89]
C_3	[4.22, 5.11]; [4.22, 5.11]	[5, 5]; [5.45, 5.89]	[4.5, 5.5]; [4.5, 5.5]	[4.5, 5.5]; [5.45, 5.89]
C_4	[3.11, 3.55]; [3.45, 3.89]	[4, 4]; [4.11, 4.55]	[3.28, 5.28]; [3.89, 5.39]	[3.89, 5.39]; [4.5, 5.5]
C_5	[4.11, 4.55]; [5.11, 5.55]	[3.45, 3.89]; [4, 4]	[3.89, 5.39]; [4.5, 5.5]	[4.45, 4.89]; [5, 5]
C_6	[4.45, 4.89]; [4.45, 4.89]	[4.45, 4.89]; [5, 5]	[4.5, 5.5]; [5.11, 5.55]	[3.11, 3.55]; [4, 4]
C_7	[3.11, 3.55]; [4, 4]	[3.45, 3.89]; [4.11, 4.55]	[3.5, 4.5]; [4.45, 4.89]	[4.45, 4.89]; [4.5, 5.5]

Then, Equations (33)-(37) need to be applied in order to normalize the initial interval rough matrix. Criterion C_6 belongs to the cost group, while the other criteria need to be maximized, i.e. they belong to the beneficial criteria group. Table 8 shows the normalized interval rough matrix.

Table 8. The normalized interval rough matrix

	A1	A2	A3	A4
C_1	[0.69, 0.76], [0.76, 1.01]	[0.69, 0.76], [0.76, 0.9]	[0.74, 0.82], [0.93, 1.08]	[0.91, 0.98], [1.02, 1.1]
C_2	[0.79, 0.91], [1.02, 1.1]	[0.73, 0.78], [0.93, 1.08]	[0.79, 0.91], [1.1, 1.26]	[0.71, 0.9], [0.93, 1.08]
C_3	[0.72, 0.94], [0.77, 1.02]	[0.85, 0.92], [0.99, 1.18]	[0.76, 1.01], [0.82, 1.1]	[0.76, 1.01], [0.99, 1.18]
C_4	[0.57, 0.79], [0.64, 0.97]	[0.73, 0.89], [0.76, 1.14]	[0.6, 1.17], [0.72, 1.35]	[0.71, 1.2], [0.83, 1.38]
C_5	[0.74, 0.89], [0.95, 1.25]	[0.62, 0.76], [0.74, 0.9]	[0.7, 1.05], [0.83, 1.24]	[0.8, 0.96], [0.93, 1.12]
C_6	[0.64, 0.8], [0.82, 0.9]	[0.62, 0.71], [0.82, 0.9]	[0.56, 0.69], [0.73, 0.89]	[0.78, 0.89], [1.13, 1.29]
C_7	[0.57, 0.79], [0.82, 0.9]	[0.63, 0.86], [0.84, 1.02]	[0.64, 1], [0.91, 1.1]	[0.81, 1.09], [0.92, 1.24]

An example of the calculation of the normalized matrix for the criteria belonging to the cost group is:

$$IRN\ (n_{16}) = ([0.636, 0.798, 0.818, 0.899]) = \left(\left[\frac{3.110}{4.890}, \frac{3.550}{4.450}, \frac{4.000}{4.890}, \frac{4.000}{4.450}\right]\right)$$

for the alternative A_1.

An example of the calculation of the normalized matrix for the criteria belonging to the benefit group is:

$$IRN\ (n_{27}) = ([0.527, 0.864, 0.840, 1.022]) = \left(\left[\frac{3.450}{5.500}, \frac{3.890}{4.500}, \frac{4.110}{4.890}, \frac{4.550}{4.450}\right]\right)$$

for the alternative A_2.

Subsequently, the normalized interval rough matrix was weighted by the criterion values obtained by applying the fuzzy PIPRECIA method. The weighting was performed by applying Equation (38), while the summing up of the values for the alternatives by rows was performed by applying Equation (39). Table 9 shows the weighted normalized interval rough matrix.

Table 9. The weighted normalized interval rough matrix

	A1	A2	A3	A4
C_1	[0.13, 0.14], [0.16, 0.19]	[0.13, 0.14], [0.14, 0.17]	[0.14, 0.16], [0.18, 0.21]	[0.17, 0.19], [0.19, 0.21]
C_2	[0.18, 0.21], [0.23, 0.25]	[0.16, 0.18], [0.21, 0.24]	[0.18, 0.21], [0.25, 0.29]	[0.16, 0.2], [0.21, 0.24]
C_3	[0.18, 0.23], [0.19, 0.25]	[0.21, 0.23], [0.24, 0.29]	[0.19, 0.25], [0.2, 0.27]	[0.19, 0.25], [0.24, 0.29]
C_4	[0.07, 0.1], [0.08, 0.12]	[0.09, 0.11], [0.1, 0.15]	[0.08, 0.15], [0.09, 0.17]	[0.09, 0.15], [0.11, 0.18]
C_5	[0.12, 0.15], [0.16, 0.21]	[0.1, 0.13], [0.12, 0.15]	[0.12, 0.18], [0.14, 0.21]	[0.13, 0.16], [0.16, 0.19]
C_6	[0.06, 0.07], [0.07, 0.08]	[0.06, 0.06], [0.07, 0.08]	[0.05, 0.06], [0.07, 0.08]	[0.07, 0.08], [0.1, 0.12]
C_7	[0.06, 0.08], [0.08, 0.09]	[0.06, 0.09], [0.08, 0.1]	[0.06, 0.1], [0.09, 0.11]	[0.08, 0.11], [0.09, 0.12]

Table 10 shows the final results of the integrated fuzzy PIPRECIA-Interval Rough SAW approach.

Table 10. The results of supplier selection by applying the integrated fuzzy PIPRECIA-Interval Rough SAW approach

Si				AV	Rank
0.799	0.986	0.964	1.201	0.988	**3**
0.823	0.941	0.980	1.189	0.983	**4**
0.819	1.104	1.018	1.337	1.069	**2**
0.901	1.144	1.107	1.353	1.126	**1**

The ranking was performed in descending order, which means that the highest value was the best and the lowest value was the worst solution. The alternative 4 is the most acceptable solution according to the results obtained.

4. Conclusion

In this paper, the evaluation of green suppliers was carried out by applying an innovative fuzzy-rough MCDM model. The advantages of fuzzy PIPRECIA, which was used to determine the criteria weights, and the interval rough SAW method, applied for supplier evaluation, are demonstrated throughout the paper. The fuzzy PIPRECIA method allows for the evaluation of criteria without first sorting them by significance. Group decision-making is also an advantage of this method. Today, the largest number of multi-criteria decision-making problems are solved by applying group decision-making. In such cases, especially given the fact that the number of decision-makers involved in the fuzzy PIPRECIA model increases, benefits are achieved from it. The SAW method is a simple and easily applicable multi-criteria decision-making method. Using only crisp numbers, however, it is impossible to obtain the results that treat uncertainty and objectivity in an adequate manner. For that reason, the interval rough SAW method was implemented for supplier selection based on the environmental criteria. The obtained results show that the fourth supplier is the best solution.

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