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An integrated rough group multicriteria decision-making model for the ex-ante prioritization of infrastructure projects: The Serbian Railways case

Dragan Pamucar [a], Dragana Macura [b], Madjid Tavana [c,d,*], Darko Božanić [e], Nikola Knežević [b]

[a] Department of Logistics, University of Defense in Belgrade, 11000, Belgrade, Serbia
[b] Faculty of Transport and Traffic Engineering, University of Belgrade, 11000, Belgrade, Serbia
[c] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA, 19141, USA
[d] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, Paderborn, Germany
[e] University of Defense in Belgrade, 11000, Belgrade, Serbia

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ABSTRACT

Railway transportation is the backbone of the economy significantly influences mobility and life quality in many developed and developing countries. Railway infrastructure investment problems are inherently complex and involve multiple and often conflicting criteria in an uncertain socio-economic environment. This study presents an integrated rough group FUll COnsistency Method (FUCOM) and Multi-Atributive Ideal-Real Comparative Analysis (MAIRCA) method for railway infrastructure project evaluation and prioritization. The FUCOM method evaluates the selection criteria through a simple algorithm, and the MAIRCA method prioritizes alternative projects through structured and systematic mathematical computations. Sensitivity analysis measures the impact of the criteria weights on the final results. Spearman's rank correlation coefficient assesses the effect of criteria weight variations on alternative rankings' stability. This study's main contribution is developing and implementing a comprehensive and robust framework for ex-ante evaluation and prioritization of railway infrastructure projects. A case study in Serbian Railways demonstrates the proposed integrated framework's applicability and efficacy in evaluating the railway infrastructure projects for Serbian Railways.

1. Introduction

One of the significant challenges facing developed and developing countries is a sustainable investment in transportation infrastructure. Ex-ante evaluation is an initial assessment of infrastructure projects to identify alternative projects with the greatest economic benefits to society. Transportation infrastructure project prioritization requires evaluating, selecting, and ranking projects and formulating an economically viable investment plan that provides society with the maximum benefits. This study is designed to assess and select the most suitable railway infrastructure project for the Serbian Railways. Evaluating and selecting railway infrastructure projects is a complex task with several stakeholder groups from public to government agencies assessing multiple and often conflicting criteria in an uncertain economic environment. Other factors adding to this complexity are competing interests among various stakeholder groups, including government, transportation companies, policymakers, local and national authorities, suppliers, and public interest groups. The budgetary constraints, limited economic growth, and the worldwide pandemic have also contributed to the significance of this challenging task for the decision-makers, policymakers, and managers.

A wide range of Multicriteria Decision-Making (MCDM) methods has been proposed to prioritize infrastructure projects, including the Analytic Hierarchy Process (AHP) [1] and Analytic Network Process (ANP) [2]. ANP is a more general form of AHP developed to deal with interdependencies within MCDM problems. The conventional AHP and ANP require a large number of pairwise comparisons and often lead to weak consistency in large pairwise comparison matrices. The Step-wise Weight Assessment Ratio Analysis (SWARA) is another subjective method for determining the weight coefficients of criteria proposed by Ref. [3]. While SWARA is known for its simplicity and a small number of steps, unlike the AHP and ANP methods, it cannot determine the

* Corresponding author. Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA, 19141, United States.

E-mail addresses: dpamucar@gmail.com, dragan.pamucar@va.mod.gov.rs (D. Pamucar), d.macura@sf.bg.ac.rs (D. Macura), tavana@lasalle.edu (M. Tavana), dbozanic@yahoo.com (D. Božanić), n.knezevic@sf.bg.ac.rs (N. Knežević).

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consistency of the comparisons obtained.

For this reason, the SWARA method is used less frequently in the literature compared to AHP and ANP. The Best-Worst Method (BWM) method is a new MCDM method proposed by Ref. [4]. The BWM has been widely used because of its simplicity (few pairwise comparisons (2*n*-3)) and accuracy (high consistency) to solve many MCDM problems [5–10]. The most significant advantage of the BWM is a smaller number of comparisons in pairs (2*n*-3) compared to the AHP. However, the degree of consistency in this method could rise to one, which in some cases reflects a high degree of subjectivity. Razei (2015) proposed a solution to this problem by determining the interval values of weight coefficients, determining the interval mean value, and taking this value as the final value of a criterion's weight. However, there is no guarantee that the optimal weight values are within the defined intervals due to the inconsistent results [11]. made a significant contribution to the application of rough sets theory in MCDM by proposing the decision rule preference model. They showed their model is more general than the existing conjoint measurement models due to its capacity to handle inconsistent preferences in MCDM problems.

We use the FUll COnsistency Method (FUCOM) proposed by Ref. [12] to overcome the shortcomings in the existing methods. FUCOM has three unique features: (*i*) it requires a small number of pairwise comparisons, (*ii*) it defines a Deviation from Full Consistency (DFC) of the criteria comparison, and (*iii*) it follows transitivity when making pairwise comparisons. Decision-makers can use FUCOM to manage subjectivity in criteria prioritization by obtaining the optimal weight coefficients and validating them with the DFC results. A simple mathematical computation is used to obtain the optimum values of the weight coefficients and minimize the risks. We also use the Multi-Atributive Ideal-Real Comparative Analysis (MAIRCA) method proposed by Ref. [13] to rank-order alternative projects through stable and straightforward mathematical computation. A unique feature of the MAIRCA method is its simple mathematical computation and high solution stability [14].

We present a case study to demonstrate the applicability of the proposed framework in evaluating the railway infrastructure projects for the Serbian Railways (see Ref. [15]. Nine railway infrastructure projects are identified in the RMPS as projects of utmost importance to the railway network infrastructure in Serbia. We proposed a priority list according to six relevant criteria used in RMPS and developed an MCDM evaluation method in a group decision-making environment under uncertainty using rough sets. To overcome the single decision-maker and environmental certainty drawbacks of RMPS, we develop a group decision-making model under uncertainty. The simultaneous consideration of group decision-making and environmental uncertainties are the main contributions of the model proposed in this study.

The proposed method considers a wide range of measures, including investment management concerns in the transportation industry, with the ultimate goal of improving the quality and efficiency of railway services. Decision-makers often exclude uncertainty-consideration in real-life problem-solving and decision-making for the sake of simplicity. However, uncertainty does exist, and ignoring this critical aspect in problem-solving often results in poor decisions. Rough sets can help managers effectively capture and include uncertainty in their decision models. The decision support system proposed in this study can effectively handle many real-life group decision-making problems in private and public sectors, including the government investment decisions on complex, multi-faceted, and expensive railway infrastructure decisions involving environmental uncertainties. In summary, the comprehensive and robust framework for ex-ante evaluation and prioritization of railway infrastructure projects under uncertainty in a group decision-making environment is the unique feature of the method proposed in this study.

The remainder of the paper is organized as follows. In Section 2, we present a brief overview of the relevant literature. Section 3 is devoted to the problem description. In Section 4, we use the method proposed in this study to prioritize the railway infrastructure projects. The results and the discussion are given in Section 5. Finally, we conclude with our conclusions in Section 6.

2. Literature review

A wide range of MCDM methods has been proposed to evaluate and select transportation infrastructure projects [16]. provided an overview of the MCDM methods for the assessment of transportation projects. They analyzed 276 publications focusing on the applicability of the MCDM methods for evaluating transportation projects, paying special attention to the multi-actor approach in MCDM. The authors emphasized the increasing use of MCDM methods in the evaluation of transport projects and found the AHP as the most frequently applied MCDM method in the decision problems related to transportation projects appraisal.

The literature review suggests several applications of various MCDM methods in railway project evaluation. The following table summarizes these studies:

The most common applications of rough sets in the transportation industry have not focused on the railway sector and project evaluation problems [17–23]. To the best of our knowledge, the R-FUCOM and R-MAIRCA methods have not been used for the ex-ante evaluation of transportation or railway projects. The R-FUCOM-MAIRCA model proposed in this study is a novel, structured, and systematic framework used to fill this gap in the literature and practice. The FUCOM method prioritizes the selection criteria, and the MAIRCA method ranks the alternative projects within a seamless and integrated framework.

3. Proposed R-FUCOM-MAIRCA method

Several methods have been used to deal with the complexities and uncertainties inherent in real-world MCDM problems, including interval numbers [24], fuzzy sets [25–27], rough numbers (RNs) [8,28–30] [31, 32], and grey theory [33,34] among others. Interval numbers have been proposed to present the uncertainties in the value of the decision attributes. However, it is difficult to determine the interval limits in interval numbers according to the decision-makers' experience and intuition. Therefore, many studies use fuzzy sets or other types of fuzzy theory extensions to exploit uncertainty in MCDM [35]. Although fuzzy sets are a powerful tool for presenting imprecision, the membership function's selection in fuzzy sets is based on subjectivity and is grounded in experience and intuition [36]. Rough sets are a convenient tool for treating uncertainty without the influence of subjectivism [37]. Unlike the fuzzy sets theory, whose application requires the definition of a partial membership function without the clear limits of a set, rough sets use the limiting field of a set for the expression of ambiguity. In rough set theory, only internal knowledge and operational data are used. In other words, in the application of rough sets, only the given data structure is used instead of different additional/external parameters [38]. [38] believe that the rough sets theory's basic logic is that data should speak for themselves. In rough sets, uncertainty measurement is performed based on the imprecision already contained in the data [39]. Considering all of the mentioned advantages of rough theory, the authors propose using rough interval coefficients presented in Fig. 1 in this study.

3.1. Rough full consistency method

The rough full consistency method (R-FUCOM) reduces errors during comparison to the least possible level due to: (1) a small number of comparisons (*n-1*), and (2) the limits defined when calculating the optimal values of criteria [12]. FUCOM allows for validating the model by calculating the obtained weight vector's error size by determining a deviation from the comparison's maximum consistency. On the other hand, in other methods (such as the BWM, the AHP, etc.), pairwise comparisons are used to determine the criteria weights. The redundancy in pairwise comparisons makes them less sensitive to errors in judgment. The FUCOM methodological procedure eliminates this problem.

The following section presents the procedure for obtaining the weight coefficients of criteria by using R-FUCOM in a group decision-making environment.

Step 1 Under the assumption that there are m experts in the observed research and n criteria from the predefined set of the evaluation criteria $C = \{C_1, C_2, \dots, C_n\}$, every expert ranks the criteria by their significance. The experts present the ranks of the criteria in descending order in accordance with the expected values of the weight coefficients

$$C_{j(1)}^{(e)} > C_{j(2)}^{(e)} > \dots > C_{j(k)}^{(e)} \tag{1}$$

where k represents the rank of the observed criterion, whereas e represents the mark of the expert $1 \le e \le m$. If there is an assessment confirming that two or more criteria are of the same importance, the equality sign is placed between these criteria in Eq. (1) instead of">."

Step 2 In the second step, every expert performs a mutual comparison of the ranked criteria. Based on the predefined scale for criteria comparison, the experts compare the criteria according to Eq. (1). The comparison is performed about the first-ranked (the most important) criterion. In that manner, the importance of the criteria ($\varpi_{C_{j(k)}}$) is obtained for all the criteria ranked in Step 1. Based on the obtained importance of the criteria by applying Eq. (2), *comparative importance* ($\phi_{k/(k+1)}^{(e)}$, $k = 1, 2, \dots, n$, where k represents the rank of the criteria) of the evaluation criteria is determined:

$$\phi_{k/(k+1)}^{(e)} = \frac{\varpi_{C_{j(k)}}^{(e)}}{\varpi_{C_{j(k+1)}}^{(e)}} \tag{2}$$

The obtained vectors of the comparative importance of the evaluation criteria are calculated by using Eq. (3):

$$\Phi^{(e)} = \left(\phi_{1/2}^{(e)}, \phi_{2/3}^{(e)}, \dots, \phi_{k/(k+1)}^{(e)}\right) \tag{3}$$

where $\phi_{k/(k+1)}^{(e)}$ represents the importance (advantage) of the criterion ranked as $C_{j_{(k)}}$ compared to the criterion ranked as $C_{j_{(k+1)}}$. The vectors of the comparative importance of the evaluation criteria are defined for every expert separately.

Step 3 In the third step, the final values of the weight coefficients of every decision-maker's evaluation criteria $\left(w_1^{(e)}, w_2^{(e)}, \dots, w_n^{(e)}\right)^T$ are calculated. The final values of the weight coefficients should meet the following two conditions:

(1) The relation of the weight coefficients should be the same as the comparative importance between the observed criteria ($\phi_{k/(k+1)}^{(e)}$), which is defined in Step 2, meeting the condition:

$$\frac{w_k^{(e)}}{w_{k+1}^{(e)}} = \phi_{k/(k+1)}^{(e)} \tag{4}$$

(2) Apart from Condition (4), the weight coefficients' final values should meet the condition of mathematical transitivity, so that $\phi_{k/(k+1)}^{(e)} \otimes \phi_{(k+1)/(k+2)}^{(e)} = \phi_{k/(k+2)}^{(e)}$. Taking into consideration the fact that $\phi_{k/(k+1)}^{(e)} = \frac{w_k^{(e)}}{w_{k+1}^{(e)}}$ and $\phi_{(k+1)/(k+2)}^{(e)} = \frac{w_{k+1}^{(e)}}{w_{k+2}^{(e)}}$, $\frac{w_k^{(e)}}{w_{k+1}^{(e)}} \otimes \frac{w_{k+1}^{(e)}}{w_{k+2}^{(e)}} = \frac{w_k^{(e)}}{w_{k+2}^{(e)}}$ is obtained. In that manner, the second condition that the final values of the weight coefficients of the evaluation criteria should meet is:

$$\frac{w_k^{(e)}}{w_{k+2}^{(e)}} = \phi_{k/(k+1)}^{(e)} \otimes \phi_{(k+1)/(k+2)}^{(e)} \tag{5}$$

The DFC of the comparison (χ) is only met if transitivity is fully complied with, when the conditions are met, where $\frac{w_k^{(e)}}{w_{k+1}^{(e)}} - \phi_{k/(k+1)}^{(e)} = 0$ and $\frac{w_k^{(e)}}{w_{k+2}^{(e)}} - \phi_{k/(k+1)}^{(e)} \otimes \phi_{(k+1)/(k+2)}^{(e)} = 0$. Then, the maximum consistency condition is met, respectively, for the obtained values of the weight coefficients, the deviation from the maximum consistency being $\chi = 0$. To meet the abovementioned conditions, it is necessary to determine the values of the weight coefficients of the evaluation criteria $\left(w_1^{(e)}, w_2^{(e)}, \dots, w_n^{(e)}\right)^T$ meeting the condition, where $\left|\frac{w_k^{(e)}}{w_{k+1}^{(e)}} - \phi_{k/(k+1)}^{(e)}\right| \le \chi$ and $\left|\frac{w_k^{(e)}}{w_{k+2}^{(e)}} - \phi_{k/(k+1)}^{(e)} \otimes \phi_{(k+1)/(k+2)}^{(e)}\right| \le \chi$, while minimizing the values, thus meeting the condition of the maximum consistency.

Based on the mentioned assumptions, the final model for determining the values of the weight coefficients of the evaluation criteria can be defined as follows:

$$\begin{aligned}
&\min \chi \\
&s.t. \\
&\left|\frac{w_k^{(e)}}{w_{k+1}^{(e)}} - \phi_{k/(k+1)}^{(e)}\right| \le \chi, \quad \forall j \\
&\left|\frac{w_k^{(e)}}{w_{k+2}^{(e)}} - \phi_{k/(k+1)}^{(e)} \otimes \phi_{(k+1)/(k+2)}^{(e)}\right| \le \chi, \quad \forall j \\
&\sum_{j=1}^{n} w_j^{(e)} = 1, \quad \forall j \\
&w_j^{(e)} \ge 0, \quad \forall j
\end{aligned} \tag{6}$$

By solving Model (6), the final values of the evaluation criteria . and the DFC ($\chi^{(e)}$) for every expert are obtained.

In the case of full agreement between the experts, when all the experts assign the same values to all the criteria during comparison in pairs, then the same values of the experts' criteria are obtained $\left(w_1^{(e)}, w_2^{(e)}, \dots, w_n^{(e)}\right)^T = (w_1, w_2, \dots, w_n)^T$. As the full agreement case is very rare (especially when a larger number of criteria and experts are concerned), it is assumed that the experts will assign the different values of the criteria during individual comparisons. With the purpose of the following imprecision, the procedure of transferring weight coefficients carried out by the experts $\left(w_1^{(e)}, w_2^{(e)}, \dots, w_n^{(e)}\right)^T$ of the optimal values of the weight coefficients presented by interval RNs is described in the following step.

Step 4 Determining the rough optimal values of the weight coefficients. Let us assume W to be a set containing all the weight coefficients obtained during the expert's evaluations and w_x a random weight coefficient from the set W. A set of $\omega = (w_1, w_2, \dots, w_n)$ weight coefficients are obtained based on the experts' preferences (Steps 1 to 3) meeting the condition $w_1 < w_2 <, \dots, < w_n$. Then, $\forall\, w_x \in W$, $w_j^{(e)} \in \omega$, $1 \le e \le m$; $j = 1, 2, \dots, n$; the lower approximation $\underline{Apr}\left(w_j^{(e)}\right)$ and the upper approximation $\overline{Apr}\left(w_j^{(e)}\right)$ can be determined by applying the following expressions:

$$\underline{Apr}\left(w_j^{(e)}\right) = \bigcup_{1 \le e \le m} \left\{ w_x \in W \big/ \omega(w_x) \le w_j^{(e)} \right\} \tag{7}$$

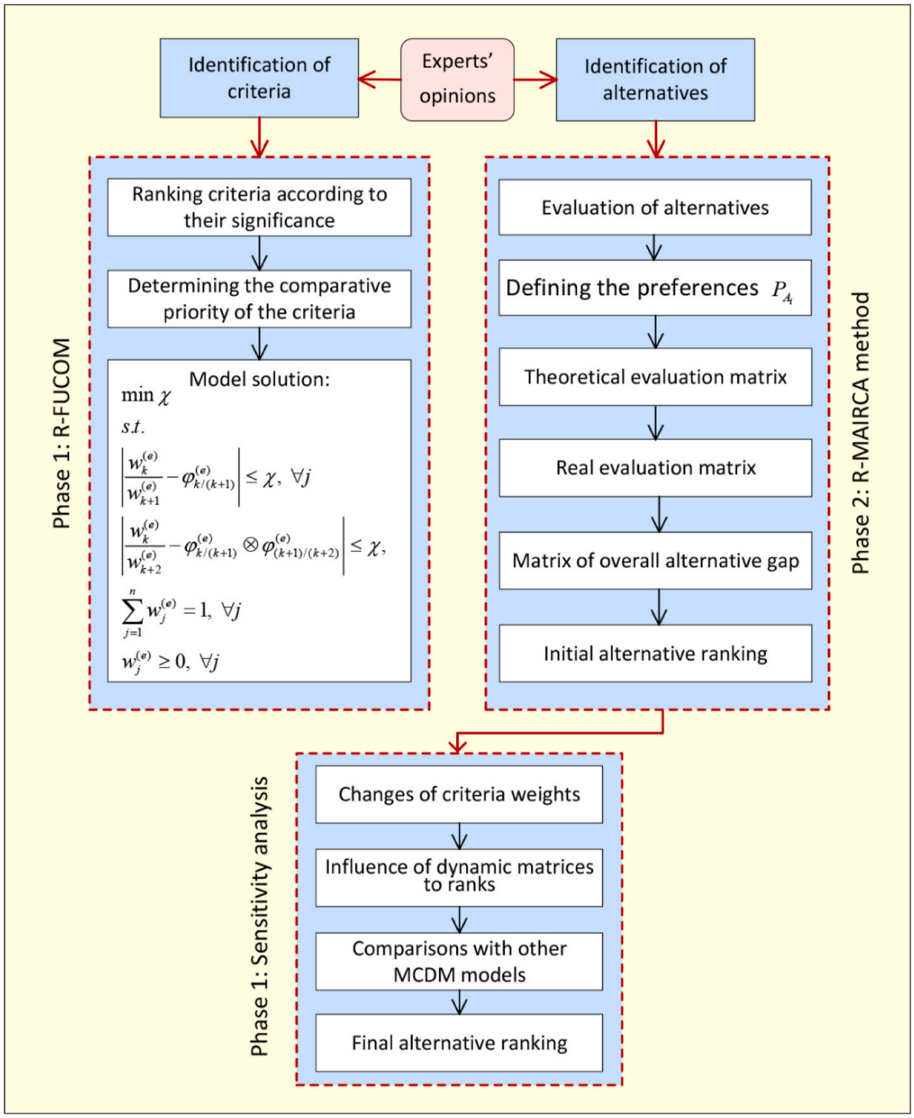

Fig. 1. The rough FUCOM-MAIRCA model.

$$\overline{Apr}\left(w_j^{(e)}\right) = \underset{1\le e\le m}{\cup}\left\{w_x \in W \middle/ \omega(w_x) \ge w_j^{(e)}\right\} \tag{8}$$

The boundary intervals $Bnd(w_j^{(e)})$ are determined as follows $Bnd(w_j^{(e)}) = \underset{1\le e\le m}{\cup}\{w_x \in W/\omega(w_x) \ne w_j^{(e)}\} = \{w_x \in W/\omega(w_x) > w_j^{(e)}\} \cup \{w_x \in W/\omega(w_x) < w_j^{(e)}\}$.

The weight coefficients of the criteria obtained by the experts as interval RNs with the defined lower limit $\underline{Lim}\left(w_j^{(e)}\right)$ and the upper limit $\overline{Lim}(w_j^{(e)})$, respectively, can be presented as follows:

$$\underline{Lim}\left(w_j^{(e)}\right) = \frac{1}{M_L}\sum_{l=1}^{m}\omega(w_x)|w_x \in \underline{Apr}\left(w_j^{(e)}\right) \tag{9}$$

$$\overline{Lim}\left(w_j^{(e)}\right) = \frac{1}{M_U}\sum_{l=1}^{m}\omega(w_x)|w_x \in \overline{Apr}\left(w_j^{(e)}\right) \tag{10}$$

where M_L and M_U represent the amount contained in the lower and the upper approximations of the object $w_j^{(e)}$.

For the object $w_j^{(e)}$, the rough boundary interval $(IRBnd(w_j^{(e)}))$ is the interval between the lower and upper limits $IRBnd\left(w_j^{(e)}\right) = \overline{Lim}\left(w_j^{(e)}\right) - \underline{Lim}\left(w_j^{(e)}\right)$. The rough boundary interval represents a measure of uncertainty. The greater $IRBnd(w_j^{(e)})$ value shows variations in the experts' preferences, whereas smaller values show that the experts' opinions do not considerably differ. All the objects between the lower limit $\underline{Lim}\left(w_j^{(e)}\right)$ and the upper limit $\overline{Lim}(w_j^{(e)})$ of the interval rough number $RN(w_j^{(e)})$ are included in $IRBnd(w_j^{(e)})$. This means that $RN(w_j^{(e)})$ can be presented using $\underline{Lim}\left(w_j^{(e)}\right)$ and $\overline{Lim}(w_j^{(e)})$ as. $RN\left(w_j^{(e)}\right) = \left[\underline{Lim}\left(w_j^{(e)}\right), \overline{Lim}\left(w_j^{(e)}\right)\right]$

Therefore, the interval rough weight coefficients are obtained for every expert:

$$RN\left(w_j^{(l)}\right) = \left(RN\left(w_1^{(l)}\right), RN\left(w_2^{(l)}\right), \ldots, RN\left(w_n^{(l)}\right)\right)^T, l = 1, 2, \ldots, m \tag{11}$$

The optimal values of the interval rough weight coefficients of the criteria are obtained by averaging the individual groups of the weight coefficients by the experts, according to Eq. (12):

$$RN\left(w_j\right) = \begin{cases} \underline{Lim}\left(w_j\right) = \frac{1}{m}\sum_{l=1}^{m}\underline{Lim}\left(w_j^{(l)}\right) \\ \overline{Lim}\left(w_j\right) = \frac{1}{m}\sum_{l=1}^{m}\overline{Lim}\left(w_j^{(l)}\right) \end{cases} \quad (12)$$

By applying Eq. (12), the optimal values of the weight coefficients of the criteria $RN(w_j) = (RN(w_1), RN(w_2), \ldots, RN(w_n))^T$can be obtained.

3.2. Interval rough MAIRCA method

The basic setting of the MAIRCA method is reflected in determining the gap between the ideal and the empirical assessments. By summing up the gap according to every single criterion, every observed alternative's total gap is obtained. Finally, the alternatives' ranking is performed, where the best-ranked alternative is that with the lowest value of the total gap. The alternative with the lowest total gap was the values that were closest to the ideal assessments (the ideal criteria values) according to the largest number of the criteria. The MAIRCA method is implemented through 6 steps [40]:

Step 1 Forming the initial decision-making matrix $X = [x_{ij}]_{m\times n}$, ().
Step 2 Determining the preferences of the alternatives, P_{A_i}. During the selection of the alternatives, the experts do not have preferences towards any of the offered alternatives. That the probability of the selection of any alternative from the set is the same can further be considered, as well as the preference towards the selection of one of the m possible alternatives, namely:

$$P_{A_i} = \frac{1}{m}; \quad \sum_{i=1}^{m} P_{A_i} = 1, \quad i = 1, 2, \ldots, m \quad (13)$$

where m stands for the total number of the alternatives being selected.

Step 3 Calculating the x_{ij}, $i = 1, 2, \ldots m$; $j = 1, 2, \ldots n$ elements of the matrix of the theoretical assessments (T_p). The matrix of theoretical assessments $T = [t_{ij}]_{m\times n}$is formed. The elements of the matrix of theoretical assessments (t_{ij}) are interval RNs and are calculated by multiplying the preferences towards the selection of the alternatives P_{A_i} and the weight coefficients of the criteria ($RN(w_j)$, $j = 1, 2, \ldots, n$) obtained by applying R-FUCOM.

$$T = \begin{array}{c} \\ P_{A_1} \\ P_{A_2} \\ \ldots \\ P_{A_m} \end{array} \begin{array}{c} \begin{array}{cccc} RN(w_1) & RN(w_2) & \cdots & RN(w_n) \end{array} \\ \begin{bmatrix} RN(t_{11}) & RN(t_{12}) & \cdots & RN(t_{1n}) \\ RN(t_{21}) & RN(t_{22}) & \cdots & RN(t_{2n}) \\ \ldots & \ldots & \ldots & \ldots \\ RN(t_{m1}) & RN(t_{m2}) & \cdots & RN(t_{mn}) \end{bmatrix} \end{array} \quad (14)$$

where P_{A_i} are the preferences towards the selection of the alternatives, $RN(w_j)$ is the weight coefficients of the evaluation criteria, and $RN(t_{ij})$ the theoretical assessment of the alternative for the observed evaluation criterion. The elements of the matrix T are determined by applying Eq. (15):

$$t_{ij} = P_{Ai}\cdot RN\left(w_j\right) = P_{Ai}\cdot\left[w_j^L, w_j^U\right] \quad (15)$$

where w_j^L and w_j^U, respectively, represent the lower and the upper limits of the interval rough number interval $RN(w_j)$.

Step 4 Determining the elements of the real assessment matrix $Y = [RN(y_{ij})]_{m\times n}$. The calculation of the elements of the real assessment matrix (Y) is performed by multiplying the elements of the matrix of theoretical assessments (T) and the elements of the initial decision-making matrix (X) according to the expression:

$$RN\left(y_{ij}\right) = RN\left(t_{ij}\right)\cdot\widehat{x}_{ij} = \left[t_{ij}^L, t_{ij}^U\right]\cdot\widehat{x}_{ij} \quad (16)$$

where t_{ij}^L and t_{ij}^U, respectively, represent the lower and the upper limit of the interval rough number interval $RN(t_{ij})$, and $\widehat{x}_{ij}$ represents the normalized elements of the initial decision-making matrix X . The normalization of the elements of the initial decision-making matrix is performed by applying Expression (18):

$$\widehat{x}_{ij} = \begin{cases} \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} & if \quad x_{ij} \in \text{Benefit} \\ \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} & if \quad x_{ij} \in \text{Cost} \end{cases} \quad (17)$$

where x_{ij}^- and x_{ij}^+ , respectively, represent the minimum and the maximum values of the observed criterion, $x_i^- = \min_i\{x_{ij}\}$ and $x_i^+ = \max_i\{x_{ij}\}$.

Step 5 Calculating the total gap matrix (G). The elements of the matrix G are obtained as the difference (gap) between the theoretical $RN(t_{ij})$ and the real assessments $RN(y_{ij})$:

$$G = T - Y = \begin{bmatrix} RN(g_{11}) & RN(g_{12}) & \ldots & RN(g_{1n}) \\ RN(g_{21}) & RN(g_{22}) & \ldots & RN(g_{2n}) \\ \ldots & \ldots & \ldots & \ldots \\ RN(g_{m1}) & RN(g_{m2}) & \ldots & RN(g_{mn}) \end{bmatrix} \quad (18)$$

where $RN(g_{ij})$ represents the obtained gap of the alternative i by the criterion j. The gap $RN(g_{ij})$ represents a interval rough number and is obtained by applying Eq. (19):

$$RN\left(g_{ij}\right) = RN\left(t_{ij}\right) - RN\left(y_{ij}\right) = \left[t_{ij}^L, t_{ij}^U\right] - \left[y_{ij}^L, y_{ij}^U\right] \quad (19)$$

It is desirable that the value g_{ij} should be striving to zero, as the alternative with the smallest difference between the theoretical and the real assessments is chosen.

Step 6 Calculating the final values of the criteria function (Q_i) by the alternatives. The values of the criteria functions are obtained by summing up the gap from the matrix (19) for every single alternative.

$$RN(Q_i) = \sum_{j=1}^{n} RN\left(g_{ij}\right) \quad (20)$$

4. Case study

Railway transport is crucial for sustainable mobility and the economic development of a country. The railway transport system should achieve a certain level of development to impact economic progress positively. However, the railway network in the Republic of Serbia (3809 km) is very old (more than 55% of all the railway lines were built as early as in the 19th century) and are in bad condition (National Program for Public Railway Infrastructure for the period 2017–2021, 2017). Serbia's main national railway corridor is the Rail Corridor 10, which connects Serbia with Croatia, Hungary, Bulgaria, and Macedonia. The railway infrastructure improvements in Serbia will make better the connections inside the Balkans and throughout the Central European region.

Bearing in mind the fact that the General Master Plan for Transport (GMPTS) project in Serbia[1] is concerned with the period until 2027 and that many transport projects and activities related to it have not been finished or have not even been started yet, the need to revise the strategy related to the railway sector emerged. This is done through the RMPS

[1] http://www.seetoint.org/wp-content/uploads/downloads/2014/01/Serbia_General-Master-Plan-for-Transport-2009.pdf).

project, which was finished at the end of 2014.

The main railway goals defined in the RMPS project are as follows: the modernization of the Rail Corridor 10 and the Belgrade-Vrbnica (Montenegro Border) and Belgrade-Vršac (Romanian Border) railway lines; the improvement of the efficiency of the main railway nodes (Belgrade, Niš, Novi Sad); the strengthening of intermodal transport through the development of the railway terminals with certain intermodal terminals; and the improvement of the safety, security, and reliability of the whole railway system (RMPS) (see Table 1).

4.1. Alternatives

In the stated projects, the GMPTS and the RMPS, the nine railway infrastructure projects are defined as those being of the utmost importance (Table 2 and Fig. 2). The projects are the alternatives to the model presented in this paper (see Table 3).

Each railway infrastructure project implies a certain type of improvement of the infrastructure (the last column of Table 2). The National Program for Public Railway Infrastructure for the period 2017–2021, (2017) published in 2017, defined the types of improvement of the railway infrastructure in the following way:

1) New construction (the construction of new railway lines);
2) Modernization (significant modifications of the existing railway lines, harmonization with international standards, increasing the speed up to 160 km/h);
3) Reconstruction (without significant changes in the railway infrastructure, only the improvement of the capacity and travel time);
4) Rehabilitation (the reconstruction of the initial conditions of the railway track, to the design speed, without significant changes in the existing railway line).

4.2. Cost-benefit analysis

CBA has a major responsibility in the ex-ante evaluation of railway projects in many western countries [41]. Due to this fact, the financial and economic CBAs are made for all the projects considered in this research study (RMPS). These two approaches differ from each other in the adopted points of view. Financial CBA considers costs and benefits from a financial point of view; here, the goal is to evaluate the project's

Table 2
The railway projects.

Alternative	Project	km	Type of improvements
A1	Beli Potok – Pancevo	28.3	Reconstruction
A2	Stara Pazova – HU Border	131	Upgrading 160 km/h + ERTMS
A3	Stara Pazova – CRO Border	84.4	Upgrading 160 km/h + ERTMS
A4	Rakovica – Velika Plana	69	Upgrading 160 km/h + ERTMS
A5	Resnik – Trupale	188	Upgrading 160 km/h + ERTMS
A6	Sicevo – BUG Border	81	Rehabilitation + ERTMS
A7	Doljevac – MK Border	131	Rehabilitation + ERTMS
A8	Resnik – ME Border	285	Upgrading single track + ERTMS
A9	Pancevo – RO Border	84	Upgrading single track + ERTMS

Table 3
The financial and economic CBAs (RMPS).

CBA	Benefits	Costs
Economic	• The residual value of the infrastructure; • Savings due to the reduction of maintenance for the "with project" scenario; • Savings due to the reduction of train running costs; • Savings for the users, mainly due to the lower cost of the rail mode compared to the road.	• Investment costs; • Infrastructure maintenance costs.
Financial	• Savings on yearly maintenance respect the "without project" situation; • Earnings on TAC (Track Access Charges) due to an increase in rail traffic; • The residual value of the investment.	• The value of the investment; • Yearly maintenance costs for the "with project" scenario.

Table 1
The literature review on railway projects evaluation with MCDM methods.

Author(s)	Year	Country	Method(s)	Research topic
Ahern and Anandarajah [53]	2007	Ireland	Weighted Integer Goal-Programming	Rail projects prioritization
Mateus et al. [63]	2008	Portugal	MACBETH	Evaluation of the strategies for a high-speed railway station
Longo et al. [59]	2009	Italy	AHP and ANP	The strategic decision in Italy's railway transportation
Chang et al. [56]	2009	Taiwan	ANP approach	Selection of the most suitable alternative for the revitalization of the historical railway line
Mohajeri and Amin [64]	2010	Iran	AHP and Data Envelopment Analysis	Finding the best location for the railway station
Ambrasaite et al. [54]	2011	Baltic countries and Poland	Monte Carlo simulation, MCDM, and Cost-Benefit Analysis	Rail projects evaluation
Macura et al. [60]	2011	Serbia	ANP	Rail projects ranking
Poorzahedy and Rezaei [67]	2013		ELimination Et Choice Translating REality, Technique for Order of Preference by Similarity to Ideal Solution, linear assignment, simple additive weighting, and the Minkowski distance	Evaluation and selection of the light rail transit network
Ferretti and Degioanni [57]	2017	Italy	Multi-attribute value theory approach	Planning and decision-making processes related to the requalification of disused railways
Pedroso et al. [66]	2018	Brazil	The functional unit with the AHP approach	Assessment of the transport alternative options of the rapid bus transit, light rail transit, and monorail modes
Boveldt et al. [55]	2018	Belgium	Competence-based multicriteria analysis	Estimation of the solutions to the main bottleneck of the railway network
Macura et al. [61]	2020a	Serbia	Interval-valued Fuzzy Sets, AHP, and TOPSIS	Rail projects ranking
Macura et al. [62]	2020b	Serbia	AHP	Multiyear railway investment plan

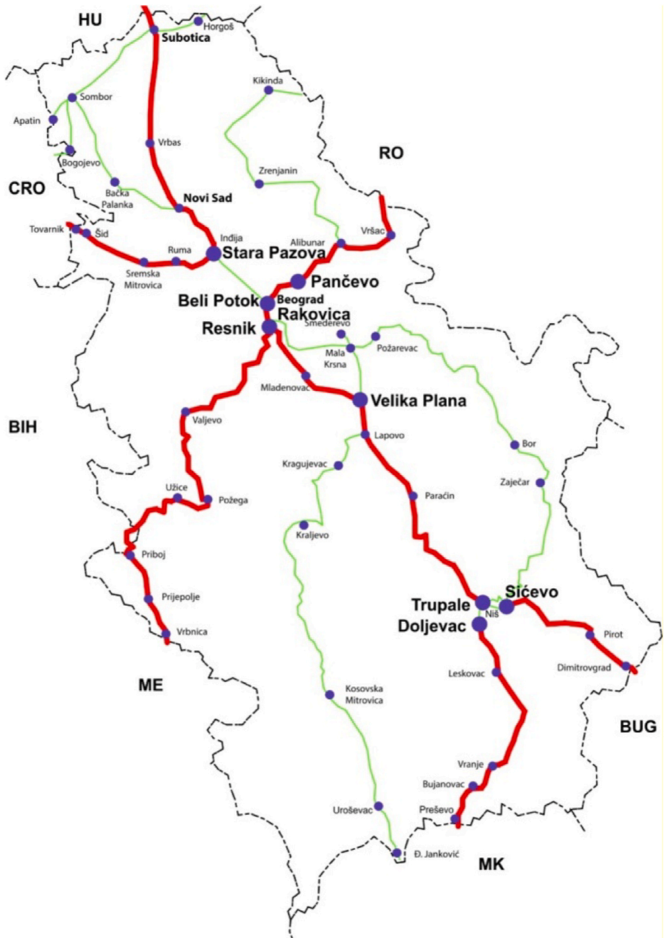

Fig. 2. The GMPTS and RMPS railway infrastructure projects (the red lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

financial feasibility. However, economic CBA assesses costs and benefits from the socio-economic point of view; now, the goal is to evaluate the projects' economic feasibility.

For the considered railway projects, the financial and economic CBAs are calculated in RMPS (Table 4) (see Table 5).

After the financial and economic CBAs are done, there is the same conclusion for all of these projects. The projects are not feasible from the financial point of view (the financial CBA being less than 1). Still, their benefits from the socio-economic perspective are pretty high, surely higher than their costs, so these projects are acceptable as social investments (Table 4).

Table 4
The benefits/costs ratio of the railway projects.

Alternative	Project	Financial CBA benefits/costs ratio	Economic CBA benefits/costs ratio
A1	Beli Potok – Pancevo	0.10	2.41
A2	Stara Pazova – HU Border	0.16	2.89
A3	Stara Pazova – CRO Border	0.26	1.94
A4	Rakovica – Velika Plana	0.04	2.58
A5	Resnik – Trupale	0.28	2.74
A6	Sićevo – BUG Border	0.18	1.14
A7	Doljevac – MK Border	0.22	1.41
A8	Resnik – ME Border	0.42	2.86
A9	Pancevo – RO Border	0.23	1.22

Table 5
The considered criteria. 8.

Criterion		Description	Value	Type
C1	Remove the bottlenecks or other specific critical issues	The question is: will the project remove the bottlenecks or other specific critical issues?	[0] no [1] yes	Max
C2	Improve functionality and make connectivity better	The question is: will the project improve the functionality (the speed, reliability, the time of the journey, etc.) and make connectivity better?	[1] between the sections of the TEN-T network in Serbia and the EU TEN-T network [2] between the sections of the TEN-T network in Serbia [3] between the sections of the other international corridors in Serbia [4] between local routes in Serbia	Min
C3	The number of the inhabitants affected by the project	The question is: what is the number of the inhabitants affected by the project?	[1] up to 300,000 inhabitants [2] between 300,000 and 800,000 inhabitants [3] more than 800,000 inhabitants	Max
C4	Cost-effectiveness	The value of the investment/overall daily traffic in the year 2027	Amount […]	Min
C5	Market development	The question is: will the project improve market development?	[1] in developed regions [2] in less developed regions (higher unemployment)	Max
C6	Economic feasibility	The economic internal rate of return	[%]	Max

There are also the other effects of these projects – not only are they of national significance, but also of international significance, because these investments are a factor relevant for connecting Serbia with other European countries, and making the railway network in Serbia better is also significant for the whole of the Balkan region, even beyond the borders of that region. Taking this fact into account, certain international assistance from the EU countries is both expected and justified.

4.3. MCDM approach

All of the considered strategic and functional indicators (C_1 and C_2), as well as the social and economic indicators (C_3, C_4, C_5, and C_6), are presented in Table 4 (RMPS). As the criteria of the model, these indicators are either the "benefit" (a higher value is favored) or the "cost" (a lower value is favored) type.

4. All the alternatives' values based on the considered criteria are accounted for in the following table (RMPS).
5. Group decision-making (stakeholders)
6. In the RMPS the weights of the criteria are quite simplified. The strategic and functional indicators were with a weight of 0.5, whereas the social and economic indicators were also at 0.5.
7. In order to make a more realistic model, group decision-making was included in the model presented in this paper. The railway experts were asked to define the weights for all of the considered criteria. The two of them were from the Serbian Railways Infrastructure JSC, and the other two experts were from the Ministry of Construction, Transport, and Infrastructure of the Republic of Serbia. Their

Table 6
The criteria values for the alternatives.

Alternative	Project	C1	C2	C3	C4	C5	C6
A1	Beli Potok – Pancevo	1	2	2	4.28	1	12.56
A2	Stara Pazova – HU Border	1	1	2	7.53	2	17.01
A3	Stara Pazova – CRO Border	1	1	2	3.08	1	13.15
A4	Rakovica – Velika Plana	1	2	3	8.88	2	14.83
A5	Resnik – Trupale	1	2	3	6.59	2	17.35
A6	Sićevo – BUG Border	1	1	2	4.99	2	6.68
A7	Doljevac – MK Border	1	1	2	8.07	2	8.60
A8	Resnik – ME Border	1	3	2	19.00	1	19.56
A9	Pancevo – RO Border	0	3	1	3.15	1	7.37

answers have different weights according to their work experience, i.e., their years of service.

4.4. Calculation of weight coefficients

The research involved the four experts who evaluated the criteria according to the previous section's R-FUCOM algorithm. The procedure for determining the interval rough weight coefficients of the criteria is demonstrated here.

Step 1 Ranking the criteria. In the first step, the experts ranked the criteria as follows:

E1: C4>C6>C2>C5>C3>C1, E2: C4>C6>C1>C2>C3>C5, E3: C4>C6>C5>C1>C2>C3, and E4: C4>C5=C2>C3=C6>C1.

Step 2 Determining the importance of the criteria. In the second step, the experts performed a comparison in pairs of the previously ranked criteria from Step 1. The comparisons were made in relation to the first-ranked criterion and based on the scale $[1,9]$. The importance of the criteria ($\varpi_{C_{j(k)}}$) was determined for every expert individually and presented in Table 7.

Based on the obtained importance of the criteria, the comparative importance values of the criteria for every single expert were calculated in the following manner:

E1: $\phi^{(1)}_{C_4/C6} = 1.63/1 = 1.63$, $\phi^{(1)}_{C_6/C_5} = 2.58/1.63 = 1.58$; $\phi^{(1)}_{C_5/C_2} = 2.58/2.58 = 1.00$; $\phi^{(1)}_{C_2/C_3} = 2.82/2.58 = 1.09$; $\phi^{(1)}_{C_3/C_1} = 3.87/\ 2.82 = 1.37$.

E2: $\phi^{(2)}_{C_4/C6} = 2/1 = 2.00$, $\phi^{(2)}_{C_6/C_1} = 3/2 = 1.50$; $\phi^{(2)}_{C_1/C_2} = 3.75/3 = 1.25$; $\phi^{(2)}_{C_2/C_3} = 5/3.75 = 1.33$; $\phi^{(2)}_{C_3/C_5} = 7.5/5 = 1.50$.

E3: $\phi^{(3)}_{C_4/C6} = 1.4/1 = 1.4$, $\phi^{(3)}_{C_6/C_5} = 2/1.4 = 1.43$; $\phi^{(3)}_{C_5/C_1} = 2.33/2 = 1.17$; $\phi^{(3)}_{C_1/C_2} = 3.11/2.33 = 1.33$; $\phi^{(3)}_{C_2/C_3} = 5.6/3.11 = 1.80$.

E4: $\phi^{(4)}_{C_4/C_5} = 1.5/1 = 1.50$, $\phi^{(4)}_{C_5/C_2} = 1.5/1.5 = 1.00$; $\phi^{(4)}_{C_2/C_3} = 3/1.5 = 2.00$; $\phi^{(4)}_{C_3/C_6} = 3/3 = 1.00$; $\phi^{(4)}_{C_6/C_1} = 6/3 = 2.00$.

Step 3 Determining the final values of the weight coefficients for every expert. The final values of the weight coefficients should meet the following two conditions:

1) The condition where $\phi^{(e)}_{k/(k+1)} = \frac{w^{(e)}_k}{w^{(e)}_{k+1}}$, the values of the comparative importance of the criteria obtained in the previous step are the same as the relation between the weight coefficients of the criteria:

E1: $w_4^{(1)}/w_6^{(1)} = 1.63$, $w_6^{(1)}/w_5^{(1)} = 1.58$; $w_5^{(1)}/w_2^{(1)} = 1.00$; $w_2^{(1)}/w_3^{(1)} = 1.09$; $w_3^{(1)}/w_1^{(1)} = 1.37$.

E2: $w_4^{(2)}/w_6^{(2)} = 2.00$, $w_6^{(2)}/w_1^{(2)} = 1.50$; $w_1^{(2)}/w_2^{(2)} = 1.25$; $w_2^{(2)}/w_3^{(2)} = 1.33$; $w_3^{(2)}/w_5^{(2)} = 1.50$.

E3: $w_4^{(3)}/w_6^{(3)} = 1.4$, $w_6^{(3)}/w_5^{(3)} = 1.43$; $w_5^{(3)}/w_1^{(3)} = 1.17$; $w_1^{(3)}/w_2^{(3)} = 1.33$; $w_2^{(3)}/w_3^{(3)} = 1.80$.

E4: $w_4^{(4)}/w_5^{(4)} = 1.50$, $w_5^{(4)}/w_2^{(4)} = 1.00$; $w_2^{(4)}/w_3^{(4)} = 2.00$; $w_3^{(4)}/w_6^{(4)} = 1.00$; $w_6^{(4)}/w_1^{(4)} = 2.00$.

2) In addition to the defined relations, the final values of the weight coefficients should also meet the condition (5):

E1: $w_4^{(1)}/w_5^{(1)} = 2.58$, $w_6^{(1)}/w_2^{(1)} = 1.58$; $w_5^{(1)}/w_3^{(1)} = 1.09$; $w_2^{(1)}/w_1^{(1)} = 1.50$.

E2: $w_4^{(2)}/w_1^{(2)} = 3.00$, $w_6^{(2)}/w_2^{(2)} = 1.88$; $w_5^{(2)}/w_2^{(2)} = 1.68$; $w_1^{(2)}/w_3^{(2)} = 2.00$.

E3: $w_4^{(3)}/w_5^{(3)} = 2.00$, $w_6^{(3)}/w_1^{(3)} = 1.67$; $w_5^{(3)}/w_2^{(3)} = 1.56$; $w_1^{(3)}/w_3^{(3)} = 2.40$.

E4: $w_4^{(4)}/w_2^{(4)} = 1.50$, $w_5^{(4)}/w_3^{(4)} = 2.00$; $w_2^{(4)}/w_6^{(4)} = 2.00$; $w_3^{(4)}/w_1^{(4)} = 2.00$.

By applying Eq. (6), the weight coefficients of the first-level criteria for each decision-maker can be defined.

$$
\begin{array}{lcl}
\min \chi^{(1)} & & \min \chi^{(4)} \\
s.t. & & s.t. \\
\left|w_4^{(1)}/w_6^{(1)} - 1.63\right| \le \chi^{(1)};\ \left|w_6^{(1)}/w_5^{(1)} - 1.58\right| \le \chi^{(1)}; & & \left|w_4^{(4)}/w_5^{(4)} - 1.50\right| \le \chi^{(4)};\ \left|w_5^{(4)}/w_2^{(4)} - 1.00\right| \le \chi^{(4)}; \\
\left|w_5^{(1)}/w_2^{(1)} - 1.00\right| \le \chi^{(1)};\ \left|w_2^{(1)}/w_3^{(1)} - 1.09\right| \le \chi^{(1)}; & & \left|w_2^{(4)}/w_3^{(4)} - 2.00\right| \le \chi^{(4)};\ \left|w_3^{(4)}/w_6^{(4)} - 1.00\right| \le \chi^{(4)}; \\
\left|w_3^{(1)}/w_1^{(1)} - 1.37\right| \le \chi^{(1)};\ \left|w_4^{(1)}/w_5^{(1)} - 2.58\right| \le \chi^{(1)}; & \cdots & \left|w_6^{(4)}/w_1^{(4)} - 2.00\right| \le \chi^{(4)};\ \left|w_4^{(4)}/w_2^{(4)} - 1.50\right| \le \chi^{(4)}; \\
\left|w_6^{(1)}/w_2^{(1)} - 1.58\right| \le \chi^{(1)};\ \left|w_5^{(1)}/w_3^{(1)} - 1.09\right| \le \chi^{(1)}; & & \left|w_5^{(4)}/w_3^{(4)} - 2.00\right| \le \chi^{(4)};\ \left|w_2^{(4)}/w_6^{(4)} - 2.00\right| \le \chi^{(4)}; \\
\left|w_2^{(1)}/w_1^{(1)} - 1.50\right| \le \chi^{(1)}; & & \left|w_3^{(4)}/w_1^{(4)} - 2.00\right| \le \chi^{(4)}; \\
\sum_{j=1}^{7} w_j^{(1)} = 1,\ \ \forall j & & \sum_{j=1}^{7} w_j^{(4)} = 1,\ \ \forall j \\
w_j^{(1)} \ge 0,\ \ \forall j & & w_j^{(4)} \ge 0,\ \ \forall j
\end{array}
$$

Table 7
The importance of criteria.

Expert 1						
Criteria	C4	C6	C5	C2	C3	C1
Importance ($\varpi_{C_{j(k)}}$)	1.00	1.63	2.58	2.58	2.82	3.87
Expert 2						
Criteria	C4	C6	C1	C2	C3	C5
Importance ($\varpi_{C_{j(k)}}$)	1	2	3	3.75	5	7.5
Expert 3						
Criteria	C4	C6	C5	C1	C2	C3
Importance ($\varpi_{C_{j(k)}}$)	1	1.4	2	2.333	3.111	5.6
Expert 4						
Criteria	C4	C5	C2	C3	C6	C1
Importance ($\varpi_{C_{j(k)}}$)	1	1.5	1.5	3	3	6

The obtained values of the weight coefficients by the decision-makers are shown in Table 8.

Step 4 Determining the interval rough optimal values of the weight coefficients. By applying Eqs. 7–10, the weight coefficients' crisp values are transferred to the interval rough weight coefficients, as shown in Table 9.

By applying Eqs. 7–10, every sequence (the weight coefficients) from Table 7 is transformed into a rough sequence, the rough weight coefficients. Therefore, for the weight coefficient w_1, there is a set of elements $w_1 = \{0.3328; 0.4109; 0.3183; 0.3158\}$, representing the weight coefficients obtained through experts' evaluations. By applying Eqs. 7–10, the upper and the lower approximations are calculated as follows:

Similarly, the rough sequences of the remaining weight coefficients are obtained. The rough sequences of the remaining weight coefficients are shown in Table 9.

The optimal values of the interval rough weight coefficients of the criteria are obtained by averaging the rough sequences from Table 9, in accordance with Eq. (12). The optimal value of the interval rough weight coefficient $RN(w_1)$ is obtained in the following manner:

$$RN(w_1)=[0.324,0.368]=\begin{cases}\underline{Lim}(w_1)=\frac{1}{4}(0.320+0.340+0.320+0.316)=0.324\\ \overline{Lim}(w_1)=\frac{1}{4}(0.370+0.411+0.350+0.340)=0.368\end{cases}$$

$$RN(w_2) = [0.206,\ 0.217];$$
$$RN(w_3) = [0.140,\ 0.180];$$
$$RN(w_4) = [0.111,\ 0.127];$$
$$RN(w_5) = [0.093,\ 0.110];$$
$$RN(w_6) = [0.053,\ 0.072];$$

4.5. Alternative evaluation

After the calculation of the weight coefficients of the criteria, the evaluation and selection of the optimal alternative by applying the MAIRCA method are performed. In Table 6, the characteristics of the nine alternatives representing the initial decision-making matrix are shown. After that, the preferences towards the selection of the alternatives $P_{A_i} = 1/m = 1/9 = 0.111$ are determined in Table 6. In the following step, the elements of the matrix of theoretical assessments (T) are calculated by applying Eq. (14) (Table 10).

$$\underline{Lim}(0.3328)=\frac{1}{3}(0.3328+0.3183+0.3158)=0.320, \overline{Lim}(0.3328)=\frac{1}{2}(0.3328+0.4109)=0.370;$$

$$\underline{Lim}(0.4109)=\frac{1}{4}(0.3328+0.3183+0.3158+0.4109)=0.340, \overline{Lim}(0.4109)=0.411;$$

$$\underline{Lim}(0.3183)=\frac{1}{2}(0.3183+0.3158)=0.320,\ \overline{Lim}(0.3183)=\frac{1}{3}(0.3183+0.4109+3328)=0.350;$$

$$\underline{Lim}(0.3158)=0.316, \overline{Lim}(0.3158)=\frac{1}{4}(0.3328+0.3183+0.3158+0.4109)=0.340.$$

Table 8
The weight coefficients of the decision-makers.

DFC/weights	E1	E2	E3	E4
DFC	0.0019	0.0021	0.0016	0.0000
w_1	0.3328	0.4109	0.3183	0.3158
w_2	0.2041	0.2056	0.2275	0.2105
w_3	0.1291	0.1371	0.1593	0.2105
w_4	0.1293	0.1095	0.1361	0.1053
w_5	0.1184	0.0822	0.1022	0.1053
w_6	0.0863	0.0548	0.0567	0.0526

Table 9
The rough weight coefficients.

Weights	E1	E2	E3	E4
w_1	[0.320, 0.370]	[0.340, 0.411]	[0.320, 0.350]	[0.316, 0.340]
w_2	[0.204, 0.210]	[0.200, 0.210]	[0.210, 0.227]	[0.210, 0.220]
w_3	[0.129, 0.160]	[0.130, 0.170]	[0.140, 0.180]	[0.160, 0.211]
w_4	[0.110, 0.130]	[0.110, 0.120]	[0.120, 0.136]	[0.105, 0.120]
w_5	[0.100, 0.118]	[0.082, 0.100]	[0.090, 0.110]	[0.100, 0.110]
w_6	[0.060, 0.086]	[0.050, 0.070]	[0.050, 0.070]	[0.053, 0.060]

Table 10
The matrix of the theoretical weights (T).

Alt.	C1	C2	C3	C4	C5	C6
A1	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A2	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A3	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A4	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A5	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A6	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A7	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A8	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]
A9	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[0.012, 0.014]	[0.01, 0.012]	[0.006, 0.008]

Table 11
The matrix of the real weights (Y).

Alt.	C1	C2	C3	C4	C5	C6
A1	[0.036, 0.041]	[0.011, 0.012]	[0.008, 0.01]	[0.011, 0.013]	[0.00, 0.000]	[0.003, 0.004]
A2	[0.036, 0.041]	[0.023, 0.024]	[0.008, 0.01]	[0.009, 0.010]	[0.01, 0.012]	[0.005, 0.006]
A3	[0.036, 0.041]	[0.023, 0.024]	[0.008, 0.01]	[0.012, 0.014]	[0.00, 0.000]	[0.003, 0.004]
A4	[0.036, 0.041]	[0.011, 0.012]	[0.016, 0.02]	[0.008, 0.009]	[0.01, 0.012]	[0.004, 0.005]
A5	[0.036, 0.041]	[0.011, 0.012]	[0.016, 0.02]	[0.010, 0.011]	[0.01, 0.012]	[0.005, 0.007]
A6	[0.036, 0.041]	[0.023, 0.024]	[0.008, 0.01]	[0.011, 0.012]	[0.01, 0.012]	[0.000, 0.000]
A7	[0.036, 0.041]	[0.023, 0.024]	[0.008, 0.01]	[0.008, 0.010]	[0.01, 0.012]	[0.001, 0.001]
A8	[0.036, 0.041]	[0.000, 0.000]	[0.008, 0.01]	[0.000, 0.000]	[0.00, 0.000]	[0.006, 0.008]
A9	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.00]	[0.012, 0.014]	[0.00, 0.000]	[0.000, 0.000]

Table 12
The total gap matrix.

Alt.	C1	C2	C3	C4	C5	C6
A1	[-0.005, 0.005]	[0.011, 0.013]	[0.006, 0.012]	[-0.001, 0.003]	[0.01, 0.012]	[0.002, 0.005]
A2	[-0.005, 0.005]	[-0.001, 0.001]	[0.006, 0.012]	[0.002, 0.005]	[-0.002, 0.002]	[0.000, 0.003]
A3	[-0.005, 0.005]	[-0.001, 0.001]	[0.006, 0.012]	[-0.002, 0.002]	[0.01, 0.012]	[0.002, 0.005]
A4	[-0.005, 0.005]	[0.011, 0.013]	[-0.004, 0.004]	[0.003, 0.006]	[-0.002, 0.002]	[0.001, 0.004]
A5	[-0.005, 0.005]	[0.011, 0.013]	[-0.004, 0.004]	[0.001, 0.004]	[-0.002, 0.002]	[-0.001, 0.003]
A6	[-0.005, 0.005]	[-0.001, 0.001]	[0.006, 0.012]	[0.000, 0.003]	[-0.002, 0.002]	[0.006, 0.008]
A7	[-0.005, 0.005]	[-0.001, 0.001]	[0.006, 0.012]	[0.003, 0.006]	[-0.002, 0.002]	[0.005, 0.007]
A8	[-0.005, 0.005]	[0.023, 0.024]	[0.006, 0.012]	[0.012, 0.014]	[0.01, 0.012]	[-0.002, 0.002]
A9	[0.036, 0.041]	[0.023, 0.024]	[0.016, 0.02]	[-0.002, 0.002]	[0.01, 0.012]	[0.005, 0.008]

Table 13
The alternative rankings of the MAIRCA method.

Alternative	Q_i	Rank
A1	[0.023, 0.050]	7
A2	[-0.001, 0.029]	1
A3	[0.010, 0.037]	6
A4	[0.004, 0.034]	5
A5	[0.000, 0.031]	2
A6	[0.004, 0.031]	3
A7	[0.005, 0.033]	4
A8	[0.044, 0.069]	8
A9	[0.089, 0.107]	9

After forming the matrix of the theoretical weights (T), the matrix of the real weights (Y) is obtained. The calculation of the elements of the matrix of the real weights (Table 11) is done by multiplying the elements of the matrix of the theoretical weights (T) and by normalizing the elements of the initial decision-making matrix.

The total gap matrix (G) is obtained as the difference (gap) between the theoretical and the real assessments. By applying Eq. (18), the final total gap matrix is made (Table 12).

The values of the criteria functions (Q_i) by the alternatives (Table 13) are obtained by summing up the gap (g_{ij}) by the alternatives, in accordance with Eq. (20).

It is desirable that the alternative should not have the lowest possible value of the total gap; so, according to the MAIRCA method, A2 is the highest-ranked alternative.

5. Results and discussion

The discussion of the results is conducted in the three sub-sections. In the first part of the discussion, a sensitivity analysis of the rough FUCOM-MAIRCA model is performed by changing the criteria's weight coefficients. The sensitivity analysis is carried out through11 scenarios. In the second part, an analysis of the influence of the decision-making dynamic matrices on the change in the alternatives' ranking is performed. In the third part, the results obtained with the rough extensions of the other MCDM models: Rough MABAC, Rough COPRAS, Rough VIKOR, Rough CODAS, and Rough WASPS, are compared. A more detailed analysis of the first, second, and third parts of the results' discussion is presented in the following section.

5.1. Sensitivity analysis

After determining the weight coefficients of the criteria, the most important criterion is identified by applying the R-FUCOM for the purposes of conducting a sensitivity analysis. The sensitivity analysis objective is the assessment of the influence of the most influential criterion on the performances of the ranking of the suggested model. Based on the recommendations by Refs. [42,43]; Eq. (21), expressing the proportionality of the weights during the sensitivity analysis, is defined as follows:

$$w_c = (1 - w_s) \times \left(w_c^o \big/ W_c^o\right) = w_c^o - \Delta x \alpha_c \tag{21}$$

where w_c represents the change in the weights of the criteria in the sensitivity analysis, w_s represents the weight of the sensitive criterion (the most important criterion), w_c^o represents the original values of the weights of the criteria (obtained by applying R-FUCOM), and W_c^o represents the sum of the original values of the weights of the criteria which are to be changed. The parameter α_c is defined as the weight coefficient of elasticity, expressing the relative compensation of the other values of the weight coefficients concerning the given changes in the most important criterion's weight. The value α_c is calculated by using Eq. (22):

$$\alpha_c = w_c^o \big/ W_c^o \tag{22}$$

Table 14
The weight coefficient of elasticity for changing weights.

Criteria	α_c^{G1}	α_c^{G2}	α_c^{G3}	α_c^{G4}
C1	1.000	1.000	1.000	1.000
C2	0.306	0.349	0.334	0.308
C3	0.499	0.698	0.467	0.462
C4	0.194	0.186	0.200	0.154
C5	0.177	0.140	0.150	0.154
C6	0.129	0.093	0.083	0.077

Table 15
The limits of the change in the weight coefficients for the most important criterion.

Scenario	Δx_{G1}	Δx_{G2}	Δx_{G3}	Δx_{G4}
S1	−0.33281	−0.41092	−0.31579	−0.31579
S2	−0.223	−0.223	−0.223	−0.223
S3	−0.123	−0.123	−0.123	−0.123
S4	−0.023	−0.023	−0.023	−0.023
S5	0.0	0.0	0.0	0.0
S6	0.1	0.1	0.1	0.1
S7	0.2	0.2	0.2	0.2
S8	0.3	0.3	0.3	0.3
S9	0.4	0.4	0.4	0.4
S10	0.5	0.5	0.5	0.5
S11	0.66	0.589	0.68	0.68

Table 16
The new criteria weights.

Scenario	RN(w1)	RN(w2)	RN(w3)	RN(w4)	RN(w5)	RN(w6)
S1	[0.000, 0.000]	[0.314, 0.335]	[0.216, 0.269]	[0.171, 0.192]	[0.147, 0.167]	[0.084, 0.110]
S2	[0.101, 0.147]	[0.278, 0.290]	[0.188, 0.242]	[0.150, 0.173]	[0.126, 0.147]	[0.072, 0.096]
S3	[0.201, 0.247]	[0.248, 0.260]	[0.168, 0.215]	[0.134, 0.153]	[0.110, 0.130]	[0.066, 0.083]
S4	[0.301, 0.347]	[0.213, 0.226]	[0.146, 0.184]	[0.115, 0.133]	[0.099, 0.116]	[0.059, 0.072]
S5	[0.324, 0.368]	[0.206, 0.217]	[0.140, 0.180]	[0.111, 0.127]	[0.093, 0.110]	[0.053, 0.072]
S6	[0.424, 0.468]	[0.173, 0.186]	[0.117, 0.152]	[0.095, 0.109]	[0.080, 0.095]	[0.049, 0.061]
S7	[0.524, 0.568]	[0.141, 0.153]	[0.098, 0.127]	[0.076, 0.089]	[0.064, 0.078]	[0.039, 0.050]
S8	[0.624, 0.668]	[0.108, 0.119]	[0.077, 0.100]	[0.061, 0.072]	[0.050, 0.061]	[0.029, 0.039]
S9	[0.724, 0.768]	[0.074, 0.089]	[0.051, 0.074]	[0.041, 0.052]	[0.034, 0.044]	[0.019, 0.029]
S10	[0.824, 0.868]	[0.043, 0.058]	[0.030, 0.047]	[0.024, 0.032]	[0.018, 0.027]	[0.010, 0.018]
S11	[0.996, 1.000]	[0.000, 0.001]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]

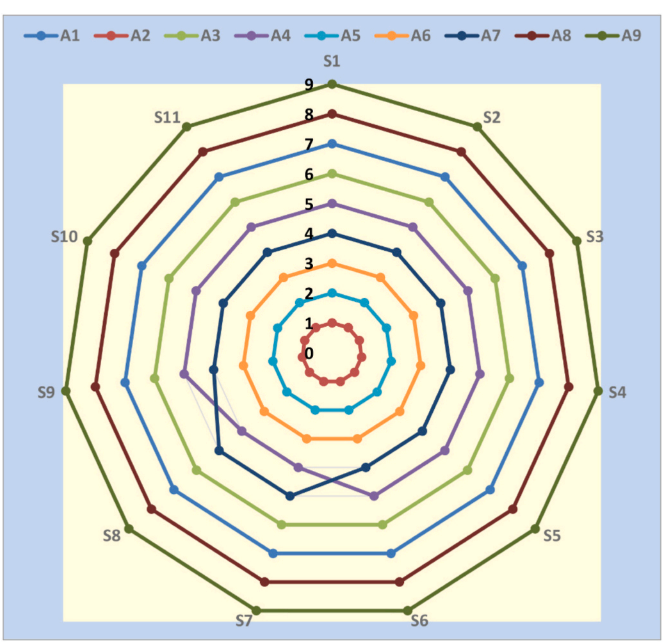

Fig. 3. The sensitivity analysis results for 11 scenarios.

The value of the weight coefficient of elasticity for the most important criterion is always defined as one. The ratio of the variable weights remains constant throughout the analysis. The parameter Δx represents the amount of the change applied to a set of the weight coefficients, depending on their respective weight-elasticity coefficients. Changing the weights of the most important criterion should be limited; otherwise, the weights may have negative values. This would lead to a violation of the proportionality limits of the weights. The parameter Δx can be (1) positive, indicating an increase in relative significance, or (2) negative, indicating a decrease in relative significance. The limits of Δx are defined as the largest weight change in the most important criterion in the negative and positive directions. The limit values of Δx are defined by applying Eq. (23):

$$-w_s^o \le \Delta x \le \min\{w_c^o / \alpha_c\} \tag{23}$$

After defining the limits of Δx the new weights of the criteria are calculated according to the predefined parameters for the sensitivity analysis. A set of the new values of the weight coefficients is calculated by applying Eqs. (24) and (25):

$$w_s = w_s^o + \alpha_s \Delta x \tag{24}$$

$$w_c = w_c^o - \alpha_c \Delta x \tag{25}$$

where w_s^o is the source weight of the criteria subjected to the sensitivity analysis, w_c^o represents the original values of the variable weights. This new set of criteria always meets the universal proportionality of the weight coefficients, where $\sum w_s + \sum w_c = 1$. Based on the obtained new values, the ranks of the alternatives for the considered scenario are calculated.

Given that four experts participated in this research, the weight coefficients' values are obtained for each expert. Therefore, the assessment of the coefficient of the weight elasticity (α_s) of the most significant criterion is made for every group of the weight coefficients (the weights obtained for every expert). For all the groups of the weight coefficients, the criterion C1 is the most influential. The same coefficient is determined for the remaining criteria (α_c) within the groups of the weight coefficients as shown in Table 14.

In the following step, the limits of the change in the weight coefficient of the most important criterion (Δx) for the criterion C1 by the expert groups (G1, G2, G3, and G4) are determined. Thus, the limit values of the criterion C1 for the first group of the criteria (the first expert's group of the criteria – G1) amounting to −0.33281 and 0.66 are obtained, which is indicative of the fact that the weight coefficient of the criterion C1 can be increased by maximum 0.66, respectively, it can be reduced by maximum 0.33281. Beyond these limits, the weights of the criterion C1 will have negative values. Similarly, the limits of the change in the weight coefficient of the criterion C1 for the remaining three sets of the criteria G2, G3, and G4 are determined (Table 15).

When $\Delta x = 0$ (Scenario 5), the weights of the criteria become equal to the original set of the weights. After defining the limit values of the most influential criterion by applying Eqs. (24) and (25), the new values

Table 17
The rank correlation of the 11 scenarios.

Scenario	SCC
S1	1.00
S2	1.00
S3	1.00
S4	1.00
S5	1.00
S6	1.00
S7	0.98
S8	0.98
S9	1.00
S10	1.00
S11	1.00

Table 18
The ranges of the alternatives within the dynamic decision matrices.

Scenario	Rank
S1	A2>A5>A6>A7>A4>A3>A1>A8>A9
S2	A2>A5>A6>A7>A4>A3>A1>A8
S3	A2>A5>A6>A7>A4>A3>A1
S4	A2>A5>A6>A7>A4>A3
S5	A2>A5>A6>A7>A4
S6	A2>A5>A6>A7
S7	A2>A5>A6
S8	A2>A5

of the weight coefficients presented in Table 16 are calculated for 11 scenarios within every group of the criteria. By converting the new values of the groups' weight coefficients, the interval rough weight coefficients by the scenarios are obtained. The changes in the ranks of the alternatives during 11 scenarios are presented in Fig. 3.

Fig. 3 shows that assigning different weights to the criteria through the scenarios causes changes in the rankings of certain alternatives, which confirms that the model is sensitive to changes in weight coefficients. By comparing the first-ranked alternatives (A2 and A5) in scenarios 1–11 with the results shown in Table 13, their initial rank is confirmed. Analyzing the rankings in the 11 scenarios shows alternatives A2 and A5 have maintained their ranking through all scenarios. Varying the criteria weights in each scenario results in a change in the alternative rankings for alternatives A4 and A7. However, these changes were not extreme, as confirmed by the ranks' correlation through the scenarios presented in Table 17.

Spearman's correlation coefficient (*SCC*) is used to determine the correlation of the ranks. Spearman's ranking correlation coefficient is one of the most useful and important criteria for determining the relationship between the results obtained from different approaches [44]. In this paper, Spearman's coefficient is used to determine the ranks' statistical importance through the scenarios. The values of Spearman's correlation coefficient are obtained by comparing the initial rankings of the rough FUCOM-MAIRCA model presented in Table 13, with the ranks obtained through the scenarios. Table 17 shows a very high correlation of the ranks since, in nine out of 11 scenarios, the *SCC* is 1.00, whereas, in the remaining scenarios, it is 0.98. The mean value of *SCC* is 0.997 in all the scenarios, which demonstrates a very high correlation. Since all the *SCC* values are significantly higher than 0.90, it can be concluded that there is a very high correlation (closeness) of the ranks and that the proposed ranking is confirmed and credible.

5.2. Dynamic matrices' impact on alternative rankings

In many real-life problems, the conditions or limits of a problem may change from time to time under the influence of internal or external factors. Internal changes in the decision-making matrix, such as introducing or removing a new alternative in the existing list of alternatives, may lead to change in the final preferences [45]. Accordingly, we analyze the performance of the proposed model for varying conditions in the dynamic initial decision matrix. The rankings were analyzed for the changes to the dynamic initial matrix for different scenarios. The scenarios are formed for situations where one inferior alternative is removed from the subsequent considerations. The remaining dominant alternatives are ranked according to the newly-established initial decision matrix.

The initial solution is generated in Table 11 as A2> A5> A6> A7> A4> A3> A1> A8> A9 by applying the rough FUCOM-MAIRCA model. Clearly, alternative A9 is the worst option. In the first scenario, the alternative A9 is eliminated from the list of the alternatives, and a new decision matrix is obtained with eight alternatives. The new decision matrix is solved again by using the MAIRCA method. Thus, the new ranks of the alternatives A2> A5> A6> A7> A4> A3> A1> A8 are obtained. As shown in Table 18, A2 is still the best alternative, and A8 is the worst alternative. In the following scenario, the following worst alternative is eliminated, and the remaining alternatives are ranked. Thus, a total of eight scenarios are presented.

It is clear from Table 18 that when the worst alternative is eliminated, there is no change in the reorganized matrix's best-ranked alternative. It is possible to notice that the MAIRCA model does not cause a rank reversal amongst the alternatives when additional modifications of the initial matrix are performed through the elimination of the worst alternative. The alternative A2 remains the highest-ranked alternative in all the scenarios. This confirms the robustness and accuracy of the alternative rankings in a dynamic environment.

5.3. Comparative comparison

In this section, we compare our results with the results of other multicriteria techniques from the literature. A compromise solution to a problem with conflicting criteria can help decision-makers arrive at a final decision in complex and multi-faceted problems [46]. The foundation for a compromise solution was established by Ref. [47]. Compromise means an agreement established by mutual concessions, and a compromise solution is a feasible solution that is the closest to the ideal.

The MAIRCA solution is a compromise solution based on the aggregating function representing closeness to the ideal solution, similar to MABAC, COPRAS, CODAS, WASPAS, and VIKOR. Therefore, we compare our results with the results obtained from the competing rough MABAC, COPRAS, CODAS, WASPAS, and VIKOR methods.

The rough VIKOR (R-VIKOR) method introduces an aggregating function representing the distance from the ideal solution. This ranking index represents an aggregation of all criteria, their relative importance, and the balance between total and individual satisfaction [48]. The R-VIKOR method emphasizes the ranking and selection from a set of alternatives in the presence of conflicting criteria. This method produces a multicriteria ranking index based on a particular measure of closeness to the ideal solution [49]. The rough MABAC (R-MABAC) defines a border approximation area and measures the observed alternative and the approximation gap. This method focuses on the ranking and selection from a set of alternatives in the presence of conflicting criteria. The

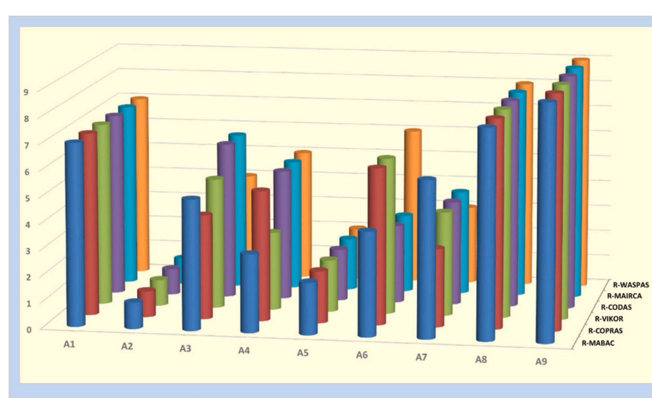

Fig. 4. The ranking comparison between R-MAIRCA and five competing methods.

Table 19
The rank correlation of the tested models.

MCDM technique	R-CODAS	R-COPRAS	R-VIKOR	R-MABAC	R-WASPAS
SCC	0.917	0.883	0.883	1.000	0.883

rough CODAS (R-CODAS) method introduces a ranking index, which includes distances from the ideal and negative-ideal points [50]. These distances in R-CODAS are used to define the relative importance of alternatives. However, establishing a reference point as close as possible to the ideal point is often difficult and impractical. Being far away from the nadir point could only be a goal in a particular situation, and relative importance remains an open question. The R-CODAS method uses *n*-dimensional Euclidean and Hamming distances to represent some balance between the total and individual satisfactions, different from WASPAS, VIKOR, COPRAS MABAC methods. In contrast to these methods, the rough COPRAS (R-COPRAS) method has a slightly more complex aggregation procedure but requires no transformation of cost-type criteria to benefit-type criteria. The overall ranking index of each alternative is calculated by using the proportional assessment procedure. The R-COPRAS method can show inherent inconsistency. For example, suppose the value of the most important alternative of a minimizing criterion is the smallest and matches the largest criterion weight. In that case, the sum of these weighted values is in the denominator of the aggregation function. This may lead to an inaccurate evaluation of the alternatives.

In addition, these five MCDM methods use different normalization procedures to eliminate the units of criterion functions: the R-VIKOR, R-CODAS, and R-MABAC methods use linear normalization, whereas the R-COPRAS and R-WASPAS methods use linear transformation – the sum method. In the MCDM models with linear normalization, the normalized value does not depend on the evaluation unit of a criterion [51]. [52] showed that the normalized value could be different for the different evaluation units of a particular criterion in the models with vector normalization. The main difference between these five methods appears to be in their aggregation procedures. The results from these comparative comparisons between R-MAIRCA and R-MABAC, R-COPRAS, R-CODAS, R-WASPAS, and R-VIKOR are presented in Fig. 4.

As shown in this figure, the alternative ranking results obtained from the six competing methods are similar. R-MAIRCA and R-MABAC have identical rankings. The ranking obtained by the R-CODAS, R-COPRAS, R-VIKOR, and R-WASPAS methods are slightly different, but all methods gave preference to Alternatives A2 and A5. The results identify the set {A2,A5} as the preferred alternatives. In addition, the rankings for the second-ranked alternative (A5), the seventh-ranked alternative (A1), the eighth-ranked alternative (A8), and the ninth-ranked alternative (A9) are identical in all methods. The rankings of the remaining alternatives (A3, A4, A6, and A7) are not consistent in the six methods.

Spearman's coefficient correlation (SCC) results presented in Table 19 are used to test the statistical significance of the rankings obtained by the FUCOM-MAIRCA and the other competing approaches: R-MABAC, R-COPRAS, R-VIKOR, R-CODAS, and R-WASPAS. As shown in this table, the SCCs take values from the interval [-1,1]. The SCC values between 0 and 1 represent a positive statistical correlation, and values between −1 and 0 illustrate a negative statistical correlation between the compared results. The SCC values from Table 19 show that there is a complete correlation between the results of the R-CODAS and R-MAIRCA methods ($SCC = 1.00$). There is also a high correlation with the results from the R-MABAC method ($SCC = 0.917$). A slightly lower correlation value was observed with the results of the R-COPRAS, R-VIKOR, and R-WASPAS methods ($SCC = 0.883$).

The highest-ranked alternative obtained from the R-VIKOR, R-COPRAS, R-MABAC, R-WASPAS, and R-MAIRCA methods is the closest to the ideal solution. However, the highest-ranked alternative for R-CODAS is the best in terms of the ranking index, even though it may not be the closest alternative to the ideal solution. Alternatives A2 and A5 are very close to each other and are top-ranked in the R-CODAS method. Some of the results obtained from the R-CODAS method are different from the other methods, and the solution obtained by the R-CODAS method is not always the closest alternative to the ideal solution. The best solution for the R-CODAS method is A2 ($H_2=4.368$) since $E_2=1.1135$, representing the separation of each alternative from the ideal solution according to the Euclidean distance. However, A2 is not the closest alternative to the ideal solution according to the Hamming distance ($T_2=1.7144$ and $T_5=1.7486$) (the separation of each alternative from the ideal solution). According to the R-CODAS method, these values allow us to conclude that A2 is the best alternative, even though it is not the closest alternative to the ideal solution by all criteria.

These results were used to verify the rankings obtained in this study. The obtained SCC values confirm that the rough FUCOM-MAIRCA method's results are credible and valid, confirming the robustness of the method employed in this study. The R-MABAC, R-COPRAS, R-VIKOR, R-CODAS, and R-WASPAS results only work for certain alternatives. The inclusion (or exclusion) of an alternative could affect the R-MABAC, R-COPRAS, R-VIKOR, R-CODAS, and R-WASPAS rankings, whereas R-MAIRCA demonstrated stability in the experiment. By fixing the best and the worst values, this effect could be avoided. In other words, the decision-maker could define the fixed ideal solution. We do not consider the normalization trade-offs for obtaining the aggregating function in the MAIRCA method. This topic remains for further research.

6. Management implications

The utility of the proposed decision-making tool is evident, but its acceptance by management might be a concern. The largest number of managers and decision-makers will accept the tools models that are easy to understand. The rough FUCOM-MAIRCA model used in this paper may not readily fall into the "easily understood" category. This situation is true for the biggest number of mathematically complex approaches. The utilization of this tool as a part of the toolset of a decision support system will make it more acceptable to management. This tool will be more acceptable to the managers who have to deal with the greater magnitudes of uncertainties and imprecision in infrastructure project ranking, as well as those who have prior knowledge in project management.

The objective of this case study is to select the best rail infrastructure project. By examining the main six criteria, this study helps managers understand the infrastructure project evaluation and selection process and offers different benefits. The first benefit of this study reflects in the development of criteria selection using a rational algorithm with the implementation of RNs and the R-FUCOM model based on a comprehensive literature review. The second benefit is not only in the selection of the best rail infrastructure project, but they are also used to analyze the project that did not satisfy the requirements. The considered problem of the ranking of rail infrastructure projects is a multicriteria decision-making problem relevant for a broader audience, such as the government, the competent Ministry of Transport, the Ministry of Finance, the Ministry of Economy, an infrastructure manager, railways operators, and other interested groups on the railway market. The developed model would facilitate the development of a long-term sustainable investment plan. The flexibility of the methodology in the selection and weighting of the performance measures to be used is also valuable. This flexibility will allow management to perform sensitivity analyses at many levels, thus obtaining more robust and relevant solutions. This technique can also provide strategic guidance for the railway organization. For example, suppose the railway organization and its management feel that stockholders, consumers or government partners are putting more pressure on various sustainability practices (a greater emphasis on, for example, the financial aspect or environmental protection). In that case, the technique can be used to select a rail infrastructure project to develop more effective partnership opportunities. The methodology helps managers to select the most appropriate set of rail infrastructure projects by choosing suitable sets of measures for their current operating environment.

7. Conclusions

In this study, we presented an integrated rough FUCOM-MAIRCA group decision-making method for railway infrastructure project prioritization. The rough FUCOM method was used to prioritize the selection criteria through a simple algorithm, and the rough MAIRCA method was used to rank-order alternative projects through stable and straightforward mathematical computation. Sensitivity analysis determined the impact of the criteria weights and decision-makers preferences on the final results.

The strategic directions of the infrastructure development in Serbia are documented in four sources: (1) General Master Plan for Transport in Serbia; (2) Rail Master Plan in Serbia; (3) National Program of Public Railway Infrastructure for the Period 2017–2021 (Official Gazette of the Republic of Serbia: No. 53/17); and (4) Regulation (EU) No. 1315/2013 of the European Parliament and the Council on the Union guidelines for the development of the Trans-European Transport Network (Western Balkans 6 member, the Republic of Serbia signed a high-level agreement[2] on the extension of the Trans-European Transport Networks in the Western Balkans Region, where the Core TEN-T network is to be in place by the end of 2030). The obtained results are consistent with the fundamental principles (i.e., the modernization of the Rail Corridor 10, the railway lines Resnik (Belgrade)-Vrbnica (ME), and Pančevo (Belgrade)-Vršac (RO)) outlined in these documents. In addition, all considered rail lines belong to the Core TEN-T network and have to be developed consistent with the EU recommendations by the end of 2030. This is the main goal of the national rail strategy. The results from the model proposed in this study are consistent with the overall strategic directions of the rail infrastructure development in Serbia.

The model is tested on the real data obtained from the Rail Master Plan in the Serbia project. The new results converge to those obtained in the RMPS project, but the proposed methodology differs from those developed in the RMPS due to the inclusion of the group decision-making process and the consideration of uncertainty and imprecision. The final rankings of the projects are obtained by using the integrated R-FUCOM and MAIRCA models. We further rank the railway infrastructure projects with the R-MABAC, R-CORPAS, R-VIKOR, R-CODAC, R-MAIRCA, and R-WASPAS methods. The results show that there is a high correlation between the ranks obtained from these different MCDM methods.

The theoretical contributions and novelties of this study are fivefold: (1) This study introduces a novel integrated rough FUCOM and MIARCA method for solving MCDM problems under uncertainty; (2) This is the first MCDM model in the literature to integrate RNs, FUCOM, and MAIRCA techniques effectively. The integration of RNs in the FUCOM methodology increases objectivity in the decision-making process since interval values for criteria weights reflect environmental uncertainties. The rough MCDM framework uses exclusively internal knowledge, i.e., operative data, and there is no need to rely on assumptions in the model. In other words, only the given data structure is used in the application of rough numbers with no need for additional/external parameters. This uncovers the objective indicators hidden in the data. The basic logic of RNs is that the data should speak for itself [30]. RN eliminates the shortcomings of the traditional fuzzy approaches relating to the interval borders since a unique interval border is formed for every expert rating. This means interval borders do not depend on subjective assessment but rather are defined based on uncertainty and imprecision in the data; (3) Integrating RNs into traditional MCDM models (like FUCOM and MAIRCA) exploits the subjectivity and unclear judgments provided by the experts. It avoids assumptions, which is not the case when applying fuzzy theory [39]. [28] state that rough MCDM models, like AHP, enable adequate manipulation of inconsistency in judgments. Saaty and Tran (2007) showed that fuzzification of the AHP method does not produce reliable results and recommends eliminating uncertainty using intermediate values. Therefore, the application of rough numbers and development of the rough-based MCDM models has a significant foundation and contribution; (4) This study, for the first time, extends the MAIRCA and FUCOM methods in an interval rough environment; and (5) This study develops an original methodology for the verification of results, which includes: (*i*) an analysis of the impact of changes in the values of the weighting factors of the best criterion on the ranking results, (*ii*) the introduction of an algorithm for correcting the values of the weighting coefficients; (*iii*) an analysis of the impact of the rank reversal on the ranking results, and (*iv*) the comparison with the competing approaches in the literature, and (*v*) using the SCCs for statistical comparison of the results.

The practical implications of this study are threefold. This study (1) develops an integrated group decision-making method considering environmental uncertainties, (2) implements a sustainable method for the Serbian national rail project called "Rehabilitation in Serbia: Technical Assistance for Railway Infrastructure," and (3) create suitable investment management measures for the Serbian railway, with the ultimate goal of improving the quality and efficiency of the national rail transportation and infrastructure system. Future research should be dedicated to the development of the dynamic model for considering financial constraints. In addition, whether the projects are clustered in groups or not, and if yes, which projects should be considered in a single group, i.e., which of the projects contributes to another project's more positive effect, should be analyzed. Some rail infrastructure projects seem to have greater effects if they are implemented in correlation with other projects, i.e., they produce better effects when implemented concurrently.

CRediT authorship contribution statement

Dragan Pamucar: Conceptualization, Formal analysis, Methodology, Writing. **Dragana Macura:** Conceptualization, Formal analysis, Project administration, Writing. **Madjid Tavana:** Methodology, Formal analysis, Project administration, Visualization, Writing. **Darko Božanić:** Investigation, Formal analysis, Validation, and. **Nikola Knežević:** Investigation, Formal analysis, Supervision, Visualization.

Declaration of competing interest

The above authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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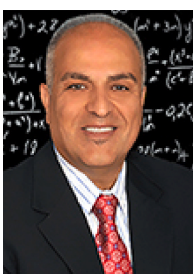
Dr. Dragan Pamucar is an Associate Professor at the University of Defence in Belgrade, the Department of Logistics, Serbia. Dr. Pamucar obtained his MSc at the Faculty of Transport and Traffic Engineering in Belgrade, and his PhD degree in Applied Mathematics with specialization in Multi-Criteria Modelling and Soft Computing Techniques at the University of Defence in Belgrade, Serbia. His research interest includes the fields of computational intelligence, multi-criteria decision-making problems, neuro-fuzzy systems, fuzzy, rough, and intuitionistic fuzzy set theory, neutrosophic theory, with applications in a wide range of logistics problems. He has published five books and over 150 research papers in international scholarly academic journals.

Dr. Dragana Macura is an Associate Professor at the University of Belgrade, Faculty of Transport and Traffic Engineering, Department for Railway Engineering. Her main fields of interest are railway transport, transport project management, transport economics, railway marketing, and operations research methods in the transport industry. Dr. Macura is an author and co-author of two monographs and over 50 scientific papers.



Dr. Madjid Tavana is Professor and Distinguished Chair of Business Analytics at La Salle University, where he serves as Chairman of the Business Systems and Analytics Department. He also holds an Honorary Professorship in Business Information Systems at the University of Paderborn in Germany. Dr. Tavana is Distinguished Research Fellow at the Kennedy Space Center, the Johnson Space Center, the Naval Research Laboratory at Stennis Space Center, and the Air Force Research Laboratory. He was recently honored with the prestigious Space Act Award by NASA. He holds an MBA, PMIS, and PhD in Management Information Systems and received his Post-Doctoral Diploma in Strategic Information Systems from the Wharton School at the University of Pennsylvania. He has published 21 books and over 300 research papers in international scholarly academic journals. He is the Editor-in-Chief of *Decision Analytics, Healthcare Analytics, International Journal of Applied Decision Sciences, International Journal of Management and Decision Making, International Journal of Communication Networks and Distributed Systems, International Journal of Knowledge Engineering and Data Mining, International Journal of Strategic Decision Sciences, and International Journal of Enterprise Information Systems*.

Dr. Darko Božanić is an Assistant Professor of Decision Sciences at the Military Academy, the University of Defence in Belgrade. He received his BS degree from the Military Academy in Belgrade and MS degree from the Faculty of Political Science in Belgrade. He earned his PhD degree from the University of Defence in Belgrade. He has published over 60 research papers in scholarly academic journals and research conferences. His main research interests include Multi-Criteria Decision Making, Decision science, Risk analysis, Fuzzy Logic, Rough sets, etc.

Dr. Nikola Knežević is an Assistant Professor at the Faculty of Transport and Traffic Engineering, University of Belgrade, Serbia. His areas of academic interest include project management, organization design, performance management, and the application of quantitative methods in management. He is the author and co-author of one book and over 50 papers published in scientific journals and conferences. He is an author of one book (monograph). In his previous career, he was engaged by the Government of the Republic of Serbia in the Development Strategy of postal services and by the Government of Montenegro in the Development Strategy of postal traffic. He has been involved by the European Union in PLAC II and PLAC III projects as an expert for the provision of consultant services in the area of EU Negotiating Right of Establishment and Freedom to Provide Services; Postal Services.