Multiphase Interval Fuzzy-Rough MCDM Model for Intersections Evaluation Based on Pedestrian Behaviour

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Abstract: Traffic represents a complex field containing many challenges, especially for decision-makers responsible for traffic management. One of its most significant areas is the management of signalised intersections with regard to pedestrian behaviour. Measuring the start-up time of pedestrians and its influence on the rest of the traffic participants is necessary. This paper proposes a new interval fuzzy rough MCDM (Multi-Criteria Decision-Making) framework in order to conduct a complex analysis of different intersections in five selected cities in Bosnia and Herzegovina and Serbia with regard to pedestrian behaviour. The proposed model combines the IFRN SWARA (Interval Fuzzy Rough Number Stepwise Weight Assessment Ratio Analysis) and IFRN CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution) methods, representing novelty from a scientific perspective. The main methodological contribution of this research consists in developing an extension of the CRADIS method based on IFRNs. The IFRN SWARA method is applied for calculating the weights of the employed criteria, while the selected cities are ranked by using the IFRN CRADIS method. The research involved many intersections with and without countdown displays and a sample of over 10,000 pedestrians, which is enough to draw solid conclusions. The verification tests carried out confirm the obtained results, proving that the proposed model is stable.

Keywords: Pedestrian behaviour, IFRN CRADIS, Intersection, IFRN SWARA, Pedestrians, Traffic.

1. Introduction

Pedestrian behaviour when crossing a pedestrian crossing requires complex cognitive skills, including an increased attention, visual and auditory perception, information processing, and decision-making (Schwebel et al., 2012). The bad behaviour of pedestrians can reduce their mental skills; one example is using a mobile phone when crossing the street in a group (Gillette et al., 2016). The human factor represents the critical safety element for drivers and pedestrians (Gates et al., 2006). In that sense, safety is affected by various factors and aspects, such as the performance of pedestrians or the types of pedestrian behaviour, the performance of vehicles in conflict and the environment in which they are located (Ferenchak, 2016). According to Zegeer et al. (1993), pedestrian behaviour when crossing a pedestrian crossing is related to physical, psychological, and educational aspects. They found that, on average, older pedestrians wait longer to cross because they feel physically more tired. Li et al. (2013) found that pedestrian crossings are designed based on the behavioural characteristics of adult pedestrians, even in places where students go to elementary school, which exposes children to danger. Ferenchak (2016) found that the time it takes to cross a pedestrian crossing and the awareness of using marked pedestrian crossings increase with age. Therefore, the older the pedestrians, the fewer conflicts between pedestrians and vehicles. The results show that men show a more dangerous behaviour when crossing a pedestrian crossing than women by using the marked pedestrian crossings less, waiting for a shorter time, and causing more conflict situations with motor vehicles. The older the pedestrians are, the more they are associated with a reduced risk of perception, a better acceptance of the minimum time, and longer waiting times when crossing the street (Hamed, 2001; Kadali & Perumal, 2012). Diverse approaches can help model pedestrian behaviour, and according to Lim et al. (2015), fuzzy logic theory helps with human factors modelling. Fuzzy logic contains uncertainty and approximations suitable for representing multiple cooperation and even conflicts. Using

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fuzzy control in the assessment of the behaviour patterns of pedestrians reveals the causal connection between cognition and behaviour. Specific linguistic terms describe the environment and responses in fuzzy logic. Chai et al. (2015) described pedestrian cognition in linguistic terms, by referring to perception, intention, and attitude, which further indicates that the MCDM models' utilisation based on linguistic variables has a foothold. The authors directly and concisely analysed individual pedestrians' activities when making decisions. The basis of Chai et al.'s (2016) study is the application of fuzzy logic to examine the differences in perception based on age and gender characteristics at unsignalised and signalised pedestrian crossings. This study set forth a new approach based on fuzzy logic, which provides more information about how individuals think and make decisions than traditional behavioural approaches.

At the same time, no time is wasted on surveying using a questionnaire, whereby decision-makers can determine pedestrians' perception and movement. If pedestrians are distracted while crossing a street this can also affect their behaviour and the safety of some pedestrian crossings. The use of mobile phones when crossing a pedestrian crossing affects the behaviour of pedestrians in terms of reaction time (start-up time) and walking speed (primarily at signalised intersections), which represents an unsafe behaviour. Further, Gillette et al. (2016) determined pedestrians' starting time and behaviour when crossing a pedestrian crossing, depending on distractions, waiting time, and the types of groups crossing. The study considered differences between genders, age categories, and location characteristics to account for variability in results. With an increased distraction in today's society, the presence of distracted pedestrians could be another factor affecting the pedestrian start times. In one of their earlier studies, Knoblauch et al. (1996) examined the starting times and walking speeds of different populations. The average starting time for younger and older adult pedestrians was 1.93 seconds and approximately 2.5 seconds, respectively. Fugger et al. (2000) examined the starting times of individuals at intersections with three different types of signals and found the mean times to be 1.87 s, 0.84 s, and 0.77 s, respectively. They found that gender and age are important factors when pedestrians decide to cross a street. Male pedestrians expose themselves to a greater risk when crossing than female pedestrians, while younger pedestrians are more willing to commit violations, errors, and omissions than older pedestrians (Diaz, 2002). Having noted gender differences, they also examined traffic accident records, which showed that 60% and 64% of accidents involving pedestrians crossing the street without regard to traffic and running a red light involved male pedestrians, in comparison with 40% and 36% of accidents involving female pedestrians (Rosenbloom et al., 2004). Also, the characteristics of an intersection will influence a pedestrian's decision to violate traffic signals. Undeniably, the presence of pedestrian signals (Cambon de Lavalette et al., 2009) and countdown displays (Lipovac et al., 2013) directly contribute to reducing the percentage of violations. Based on the previously reviewed studies, policymakers can conclude that pedestrian age and gender play the most dominant role in assessing pedestrian behaviour and signalised intersection start-up times. This research aims to determine the differences in the behaviour patterns of pedestrians in different cities at intersections with and without countdown displays. For a comparative analysis of the selected group of towns, an integrated IFRN SWARA-IFRN CRADIS model was created, which implies group decision-making based on linguistic variables that convert it into interval fuzzy rough numbers. The proposed multiphase interval fuzzy-rough MCDM model for intersection evaluation, based on pedestrian behaviour, aligns with the recent advances in MCDM research. For instance, Popa (2023) developed a novel ranking function for intuitionistic fuzzy numbers, highlighting the importance of subjective attitudes in decision-making processes. Filip (2022) and Radulescu et al. (2021) addressed complex multi-criteria problems by using MADM/MCDM methods in collaborative decision-making, and cloud service provider selection, respectively. In (Radulescu et al., 2023), a Multi-Criteria Weighting Approach (MCWA) is proposed for IoT evaluation. These studies underscore the critical role of MCDM tools in managing complexity and uncertainty in modern decision-making contexts.

The most significant methodological contribution of this paper consists in developing an extension of the CRADIS method with IFRNs and verifying the developed model by using multiphase methods. The professional contribution is evident in identifying a city benchmark analysis process that shows the best results according to the observed parameters.

The remainder of this paper is structured as follows. Section 2 presents the preliminaries of the IFRN. Section 3 presents the research flow and describes the employed methods. Section 4 presents the results through which the calculation defined by the proposed model is shown in detail. Section 5 focuses on determining the stability of the proposed model through several analyses. Finally, Section 6 concludes this paper and outlines possible future research directions.

2. Preliminaries

An interval fuzzy rough number (IFRN) has been represented by "A" (Liu & Weng, 2024) as follows:

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

where a_{jq}^{L} is the lower limit, and a_{jq}^{U} the upper limit of IFRN ($j = 1,2,3;\ 1 \le q \le k$).

Addition of two (IFRNs):

$$A+B=\begin{bmatrix}\left(a_1^L+b_1^L, a_1^U+b_1^U\right),\left(a_2^L+b_2^L, a_2^U+b_2^U\right), \\ \left(a_3^L+b_3^L, a_3^U+b_3^U\right)\end{bmatrix} \quad (2)$$

Subtraction of two (IFRNs):

$$A-B=\begin{bmatrix}\left(a_1^L-b_3^U, a_1^U-b_3^L\right),\left(a_2^L-b_2^U, a_2^U-b_2^L\right), \\ \left(a_3^L-b_1^U, a_3^U-b_1^L\right)\end{bmatrix} \quad (3)$$

Multiplication of two (IFRNs):

$$A\times B=\begin{bmatrix}\left(a_1^L\times b_1^L, a_1^U\times b_1^U\right),\left(a_2^L\times b_2^L, a_2^U\times b_2^U\right), \\ \left(a_3^L\times b_3^L, a_3^U\times b_3^U\right)\end{bmatrix} \quad (4)$$

Division of two (IFRNs):

$$A\div B=\begin{bmatrix}\left(a_1^L\div b_3^U, a_1^U\div b_3^L\right),\left(a_2^L\div b_2^U, a_2^U\div b_2^L\right), \\ \left(a_3^L\div b_1^U, a_3^U\div b_1^L\right)\end{bmatrix} \quad (5)$$

3. Materials and Methods

3.1 Research Description

Figure 1 shows an outline of the research flow, which involves activities carried out during nine main stages, each of them including many processes. Each activity indicates a critical aspect of the complete research to determine its goal as precisely as possible. It involves a comparative analysis for different cities regarding pedestrian behaviour at signalised intersections with a countdown display and without intersections. The first phase represents the need for research, which primarily refers to the possibility of benchmarking the process of managing traffic flows related to pedestrians based on objective indicators.

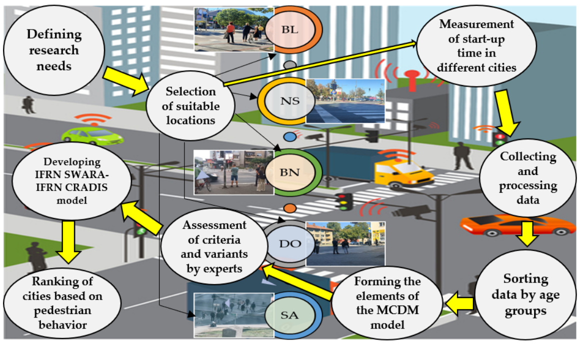

Figure 1. Research flow through nine stages

Afterwards, acceptable locations were selected for observing the pedestrian behaviour and measuring the start-up time. Five cities were considered, namely Banja Luka (BL), Novi Sad (NS), Bijeljina (BN), Doboj (DO), and Sarajevo (SA) with a more significant number of intersections and a total sample of pedestrian traffic flow of over ten thousand participants, which can be a relevant indicator of the mutual comparison of cities. All measurements and observations of pedestrian behaviour regarding the start-up time need to be processed, first in relation to each city where the research was carried out and then according to the pedestrians' age groups and genders. It is essential to state that the start-up time values are given in the 85th percentile and that 9.21% of the total sample was rejected, representing extreme start-up time values caused by certain disturbances, i.e. where normal pedestrian traffic conditions did not prevail. The next phase involves forming the elements of the MCDM model by creating the criteria based on which the cities will be evaluated, namely four criteria representing the age groups of pedestrians: C1(<18), C2(19-40), C3(41-65) and C4(>65). Of course, to apply the uncertainty theory, it is necessary to form a team of domain experts who will assess the criteria and alternatives through linguistic variables, which is the seventh phase of the research. The eighth phase represents the development of the IFRN MCDM model, which consists of the IFRN SWARA method for determining the importance of the employed criteria and the IFRN CRADIS method for evaluating cities based on the quantification of pedestrian behaviour reflected in the start-up time.

3.2 The IFRN SWARA Method

Since its development (Keršulienė et al., 2010), the SWARA method has been integrated with various uncertainty theories and applied in multiple areas to determine weighting coefficients (Zavadskas et al., 2018; Damjanović et al., 2022; Stević et al., 2022a). The IFRN SWARA method consists of the following steps (Chen et al., 2023):

Step 1: Create a list of *m* criteria.

Step 2: Create a team of experts to make a group decision using any of the linguistic scales for criteria assessment.

Step 3: Convert a separate assessment by experts into a group fuzzy-rough initial decision-making matrix X_j:

$$FRN(X_j) = \left[\left(x_j^{L1}, x_j^{U1}\right), \left(x_j^{L2}, x_j^{U2}\right), \left(x_j^{L3}, x_j^{U3}\right)\right]_{1\times m} \tag{6}$$

Step 4: Process of sorting criteria by significance.

Step 5: Normalisation of the matrix $FRN(X_j)$ to calculate the matrix $FRN(N_j)$:

$$FRN(N_j) = \left[\left(n_j^{L1}, n_j^{U1}\right), \left(n_j^{L2}, n_j^{U2}\right), \left(n_j^{L3}, n_j^{U3}\right)\right]_{1\times m} \tag{7}$$

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

$$FRN\left(N_j\right) = \frac{FRN\left(X_j\right)}{FRN\left(Z_j\right)} \tag{8}$$

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

The first part of matrix $FRN(N_j)$, can be expressed as [(1.00,1.00),(1.00,1.00),(1.00,1.00)], because $j=1$. For other parts $j>1$, equation 9 should be used:

$$FRN(N_j) = \begin{bmatrix} \left(\dfrac{n_j^{L1}}{z_j^{U3}}, \dfrac{n_j^{U1}}{z_j^{L3}}\right), \left(\dfrac{n_j^{L2}}{z_j^{U2}}, \dfrac{n_j^{U2}}{z_j^{L2}}\right), \\ \left(\dfrac{n_j^{L3}}{z_j^{U1}}, \dfrac{n_j^{U3}}{z_j^{L1}}\right) \end{bmatrix}_{1\times m} \quad j = 2,3,\ldots,m \tag{9}$$

If two of the most significant criteria are considered, the second will be a rough fuzzy number [(1.00,1.00),(1.00,1.00),(1.00,1.00)].

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

$$FRN(\Im_j) = \left[\left(\Im_j^{L1}, \Im_j^{U1}\right), \left(\Im_j^{L2}, \Im_j^{U2}\right), \left(\Im_j^{L3}, \Im_j^{U3}\right)\right]_{1\times m} \tag{10}$$

by applying the equation:

$$FRN\left(\Im_j\right) = \begin{bmatrix} \left(n_j^{L1}+1, n_j^{U1}+1\right), \\ \left(n_j^{L2}+1, n_j^{U2}+1\right), \\ \left(n_j^{L3}+1, n_j^{U3}+1\right) \end{bmatrix}_{1\times m} \quad j = 2,3,\ldots,m \tag{11}$$

If two of the most significant criteria are considered, the second will be a rough fuzzy number [(1.00,1.00),(1.00,1.00),(1.00,1.00)].

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

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

The parts of the matrix $FRN(\Re_j)$ are obtained as:

$$FRN(\Re_j) \begin{bmatrix} \Re_j^{L1} = \begin{pmatrix} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{L1}}{\Im_j^{U3}} & j>1 \end{pmatrix}, & \Re_j^{U1} = \begin{pmatrix} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{U1}}{\Im_j^{L3}} & j>1 \end{pmatrix}, \\ \Re_j^{L2} = \begin{pmatrix} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{L2}}{\Im_j^{U2}} & j>1 \end{pmatrix}, & \Re_j^{U2} = \begin{pmatrix} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{U2}}{\Im_j^{L2}} & j>1 \end{pmatrix}, \\ \Re_j^{L3} = \begin{pmatrix} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{L3}}{\Im_j^{U1}} & j>1 \end{pmatrix}, & \Re_j^{U3} = \begin{pmatrix} 1.00 & j=1 \\ \dfrac{\Re_{j-1}^{U3}}{\Im_j^{L1}} & j>1 \end{pmatrix}, \end{bmatrix} \tag{13}$$

If any two of the *m* criteria have equal significance, then equation (14) should be applied:

$$FRN(\Re_j) = FRN(\Re_{j-1}) \tag{14}$$

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

$$FRN(W_j) = \left[\left(w_j^{L1}, w_j^{U1}\right), \left(w_j^{L2}, w_j^{U2}\right), \left(w_j^{L3}, w_j^{U3}\right)\right]_{1\times m} \tag{15}$$

The individual weight values of the employed criteria are obtained:

$$FRN\left(W_j\right) = \left[\frac{FRN\left(\Re_j\right)}{FRN\left(\aleph_j\right)}\right] \tag{16}$$

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

$$FRN(W_j) = \begin{bmatrix} \left(\dfrac{\Re_j^{L1}}{\aleph_j^{U3}}, \dfrac{\Re_j^{U1}}{\aleph_j^{L3}}\right), \\ \left(\dfrac{\Re_j^{L2}}{\aleph_j^{U2}}, \dfrac{\Re_j^{U2}}{\aleph_j^{L2}}\right), \\ \left(\dfrac{\Re_j^{L3}}{\aleph_j^{U1}}, \dfrac{\Re_j^{U3}}{\aleph_j^{L1}}\right) \end{bmatrix}_{1\times m} \quad j = 2,3,\ldots,m \tag{17}$$

3.3 The IFRN CRADIS Method

The methodology of the IFRN CRADIS method involves the procedure described as follows.

Step 1: Forming the initial decision matrix *Xij*.

Step 2: Converting the fuzzy numbers into IFRNs.

Step 3: Normalisation of the decision matrix:

$$\overline{n_{ij}} = \frac{\overline{x_{ij}}}{\overline{x_{j\max}}} \tag{18}$$

and

$$\overline{n_{ij}} = \frac{\overline{x_{j\min}}}{\overline{x_{ij}}} \tag{19}$$

where $\overline{x_{ij}}$ represents the values of the initial IFRN matrix, and $\overline{n_{ij}}$ represents the nomalised values of the IFRN matrix. The elements $\overline{x_{j\max}}$ and $\overline{x_{j\min}}$ represent the maximum and minimum values of the initial matrix *Xij*. Equation (18) should be used if a certain criterion represents a benefit and equation (19) if it represents a cost.

Step 4: Weighting the decision matrix:

$$\overline{v_{ij}} = \overline{n_{ij}} \otimes \overline{w_j} \tag{20}$$

where $\overline{v_{ij}}$ is the weighted normalised IFRN matrix, and $\overline{w_j}$ denotes the criteria weights.

Step 5: Determination of the ideal solution $\overline{t_{ij}}$ and of the anti-ideal solution $\overline{t_{aij}}$:

$$\overline{t_{ij}} = \max\left(\overline{v_{ij}}\right) \tag{21}$$

$$\overline{t_{aij}} = \min\left(\overline{v_{ij}}\right) \tag{22}$$

Equations (21) and (22) denote the maximum and minimum values of the weighted IFRN matrix.

Step 6: Calculate the deviations from the ideal and anti-ideal solutions:

$$\overline{d_{ij}^{+}} = \max\left(\overline{t_{ij}}\right) - \overline{v_{ij}} \tag{23}$$

$$\overline{d_{ij}^{-}} = \overline{v_{ij}} - \min\left(\overline{t_{aij}}\right) \tag{24}$$

where $\max\left(\overline{t_{ij}}\right)$ is the maximum value of the ideal solution $\overline{t_{ij}}$ and $\min\left(\overline{t_{ij}}\right)$ is the minimum value of the anti-ideal solution $\overline{t_{aij}}$.

Step 7: Calculate the deviation grades of individual alternatives from both solutions:

$$\overline{s_i^{+}} = \sum_{j=1}^{n} \overline{d_{ij}^{+}} \tag{25}$$

$$\overline{s_i^{-}} = \sum_{j=1}^{n} \overline{d_{ij}^{-}} \tag{26}$$

Step 8: Calculate the utility function for each alternative related to the deviations from the optimal options:

$$\overline{K_i^{+}} = \frac{\overline{s_o^{+}}}{\overline{s_i^{+}}} \tag{27}$$

$$\overline{K_i^{-}} = \frac{\overline{s_i^{-}}}{\overline{s_o^{-}}} \tag{28}$$

S_o^{+} and S_o^{-} are the optimal alternative solutions regarding to ideal and anti-ideal solutions.

Step 9: Ranking the alternatives:

$$\overline{Q_i} = \frac{\overline{k_i^{-}} + \overline{k_i^{+}}}{2} \tag{29}$$

The alternative with the highest value of Q_i is the best one.

4. Results

This section gives the results obtained by the proposed IFRN SWARA-IFRN CRADIS model. The data, that is, the behaviour of pedestrians, was processed from the perspective of several parameters, including the gender of pedestrians, age groups, and both types of signalised intersections – signalised and unsignalised. When observing the behaviour of pedestrians and measuring the start-up time, the aim was to balance the samples in relation to the cities where the measurements were made.

4.1 Calculation of the Criteria Weights

To perform a comparative evaluation in relation of the cities involved, it is primarily necessary to calculate the weights of the influential indicators, which was performed using the IFRN SWARA method. Based on the three experts' experience, knowledge and expertise, their assessment was carried out, as shown in Table 1.

Table 1. Experts' assessment of criteria importance

	Criterion	DM1	DM2	DM3
C1	<18	(1,2,3)	(2,3,4)	(1,2,3)
C2	19-40	(0,1,3)	(1,2,3)	(1,2,3)
C3	41-65	(2,3,4)	(1,2,3)	(2,3,4)
C4	>65	(1,2,3)	(3,4,5)	(2,3,4)

The rough matrix is first calculated and fuzzy rough numbers are obtained:

$$FRN(E_1)=\left[(1.00,2.00),(2.00,3.00),(3.00,4.00)\right]$$

$$FRN(E_2)=\left[(2.00,3.00),(3.00,4.00),(4.00,5.00)\right]$$

$$FRN(E_3)=\left[(1.50,2.50),(2.50,3.50),(3.50,4.50)\right]$$

The final fuzzy rough matrix $FRN(X_j)$ is obtained, as shown in Table 2.

Table 2. The initial fuzzy rough matrix in IFRN SWARA

	Xj
C2	[(0.447,0.890),(1.447,1.890),(3.000,3.000)]
C1	[(1.110,1.553),(2.110,2.553),(3.110,3.553)]
C3	[(1.447,1.890),(2.447,2.890),(3.447,3.890)]
C4	[(1.500,2.500),(2.500,3.500),(3.500,4.500)]

The normalised matrix $FRN(X_j)$ is shown below. The first element of the matrix $FRN(N_j)$, was obtained as:

$$\left[(n_2^{L1},n_2^{U1}),(n_2^{L2},n_2^{U2}),(n_2^{L3},n_2^{U3})\right]=$$
$$\left[(1.00,1.00),(1.00,1.00),(1.00,1.00)\right].$$

$$FRN(N_j)=\begin{bmatrix}(1.000,1.000),(1.000,1.000),(1.000,1.000)\\(0.247,0.444),(0.603,1.021),(1.244,2.369)\\(0.321,0.540),(0.669,1.156),(1.379,2.593)\\(0.333,0.714),(0.714,1.400),(1.400,3.000)\end{bmatrix}$$

$$FRN(Z_j)=\left[(1.50,2.50),(2.50,3.50),(3.50,4.50)\right]$$

$$\left[(n_1^{L1},n_1^{U1}),(n_1^{L2},n_1^{U2}),(n_1^{L3},n_1^{U3})\right]=$$
$$\left[\left(\frac{1.11}{4.50},\frac{1.55}{3.50}\right),\left(\frac{2.11}{3.50},\frac{2.55}{2.50}\right),\left(\frac{3.11}{2.50},\frac{3.55}{1.50}\right)\right]=$$
$$\left[(0.247,0.444),(0.603,1.021),(1.244,2.369)\right]$$

The next step is the calculation of the following fuzzy rough matrix:

$$FRN(\Im_1)=\begin{bmatrix}(0.247+1.00,0.444+1),\\(0.603+1.00,1.021+1.00),\\(1.244+1.00,2.369+1.00)\end{bmatrix}=$$
$$\left[(1.247,1.444),(1.603,2.021),(2.244,3.369)\right]$$

$$FRN(\Im_j)=\begin{bmatrix}(1.000,1.000),(1.000,1.000),(1.000,1.000)\\(1.247,1.444),(1.603,2.021),(2.244,3.369)\\(1.321,1.540),(1.669,2.156),(2.379,3.593)\\(1.333,1.714),(1.714,2.400),(2.400,4.000)\end{bmatrix}$$

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

$$FRN(\Re_1)\begin{bmatrix}\Re_1^{L1}=\left(\frac{\Re_2^{L1}}{\Im_1^{U3}}\right)=\left(\frac{1}{3.369}\right),\ \Re_1^{U1}=\left(\frac{1}{2.244}\right)=(0.297,0.446)\\\Re_1^{L2}=\left(\frac{\Re_2^{L2}}{\Im_1^{U2}}\right)=\left(\frac{1}{2.021}\right),\ \Re_1^{U2}=\left(\frac{1}{1.603}\right)=(0.495,0.624)\\\Re_1^{L3}=\left(\frac{\Re_2^{L3}}{\Im_1^{U1}}\right)=\left(\frac{1}{1.444}\right),\ \Re_1^{U3}=\left(\frac{1}{1.247}\right)=(0.693,0.802)\end{bmatrix}$$

The total matrix is:

$$FRN(\Re_j)=\begin{matrix}\left[(1.000,1.000),(1.000,1.000),(1.000,1.000)\right]\\\left[(0.297,0.446),(0.495,0.624),(0.693,0.802)\right]\\\left[(0.083,0.187),(0.229,0.367),(0.450,0.607)\right]\\\left[(0.021,0.078),(0.096,0.214),(0.262,0.455)\right]\end{matrix}$$

The sum for this matrix is calculated and $FRN(\aleph_j)=\left[(1.400,1.711),(1.820,2.205),(2.405,2.864)\right]$ is obtained. Finally,

$$FRN(W_2)=\left[\left(\frac{1}{2.864},\frac{1}{2.405}\right),\left(\frac{1}{2.205},\frac{1}{1.820}\right),\left(\frac{1}{1.711},\frac{1}{1.400}\right)\right]=$$
$$\left[(0.349,0.416),(0.453,0.550),(0.584,0.714)\right]$$

The final criteria values are shown in Table 3.

Table 3. Results obtained after using the IFRN SWARA method

	w_j
C1	[(0.104,0.185),(0.224,0.343),(0.405,0.573)]
C2	[(0.349,0.416),(0.453,0.55),(0.584,0.714)]
C3	[(0.029,0.078),(0.104,0.202),(0.263,0.434)]
C4	[(0.007,0.032),(0.043,0.118),(0.153,0.325)]

The results show that the second factor related to the age group of 19-40 years highlights it as the most dominant group in the pattern of pedestrian behaviour at signalised intersections regarding the start-up time.

4.2 Ranking of Alternatives

This subsection presents an example of a calculation based on the new extension of the CRADIS approach, that is, the IFRN CRADIS method. First, the evaluation of the chosen cities by the three DMs (decision-makers) based on a linguistic scale for criteria assessment is performed. After that, the linguistic values are transformed into TFNs (Triangular Fuzzy Numbers), as shown in Table 4. The initial TFN decision matrix in the IFRN CRADIS method is as follows.

The DMs calculating the initial IFRN MCDM matrix must convert it into interval rough numbers. After applying the same conversion method, the initial matrix is obtained using the IFRN CRADIS method, as shown in Table 5, while the final results are included in Table 6.

The C1 and the A1 are given examples of normalisation.

$$\overline{n_{11}} = \frac{\overline{x_{11}}}{x_{j\max}} = \left[\left(\frac{3}{9},\frac{3}{9}\right),\left(\frac{5}{8.78},\frac{5}{7.89}\right),\left(\frac{5}{7},\frac{5}{7}\right)\right] = \left[(0.33,0,33),(0.57,0,63),(0.71,0.71)\right]$$

First, the DMs weighted the normalised IFRN matrix with the values of the factors obtained with the calculation of the IFRN SWARA method. The next step involved determining $\overline{t_{ij}}$ and $\overline{t_{aij}}$ calculating the deviations from the ideal and anti-ideal solutions $\overline{d_{ij}^{+}}$ and $\overline{d_{ij}^{-}}$, respectively, after which the DMs calculated $\overline{s_i^{+}}$ $\overline{s_i^{-}}$ sums. The results, which are obtained by applying the IFRN SWARA-IFRN CRADIS model, indicate that pedestrians have the best behavioural performance at intersections with a countdown display in Doboj. The second place in the comparative analysis of cities is related to the behaviour of pedestrians with regard to the start-up time in Banja Luka at intersections with countdown displays. In contrast, the third place went to the same type of intersections in Novi Sad. In general, the conclusion that can be drawn based on the comparative analysis of cities with regard to pedestrian behaviour

Table 4. TFN values for the IFRN CRADIS matrix

	DM1				DM2				DM3			
	C1	**C2**	**C3**	**C4**	**C1**	**C2**	**C3**	**C4**	**C1**	**C2**	**C3**	**C4**
A1	(3,5,5)	(5,5,7)	(5,7,7)	(5,5,7)	(3,5,5)	(5,5,7)	(5,5,7)	(5,5,7)	(3,5,5)	(5,5,7)	(5,7,7)	(5,5,7)
A2	(3,3,5)	(5,5,7)	(3,3,5)	(3,5,5)	(3,3,5)	(5,5,7)	(3,3,5)	(3,5,5)	(3,3,5)	(5,5,7)	(3,3,5)	(3,5,5)
A3	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)	(3,3,5)
A4	(7,7,9)	(7,9,9)	(3,5,5)	(3,3,5)	(7,9,9)	(7,9,9)	(3,5,5)	(3,3,5)	(7,9,9)	(7,9,9)	(3,5,5)	(3,3,5)
A5	(1,1,1)	(1,1,3)	(1,3,3)	(1,1,1)	(1,1,3)	(1,1,3)	(3,3,5)	(1,3,3)	(1,1,1)	(1,1,3)	(1,3,3)	(1,1,1)
A6	(3,3,5)	(3,3,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,3,5)	(3,3,5)	(3,5,5)	(3,5,5)
A7	(1,1,3)	(3,3,5)	(3,3,5)	(3,3,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,3,5)	(1,1,3)	(3,3,5)	(3,3,5)	(3,3,5)
A8	(3,5,5)	(3,5,5)	(3,3,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,5,5)	(3,3,5)	(3,5,5)
A9	(3,5,5)	(3,5,5)	(3,5,5)	(1,3,3)	(3,5,5)	(3,5,5)	(5,5,7)	(3,3,5)	(3,5,5)	(3,5,5)	(3,5,5)	(1,1,3)

Table 5. Initial matrix for the IFRN CRADIS method

	C1	C2	C3	C4
A1	[(3,3),(5,5),(5,5)]	[(5,5),(5,5),(7,7)]	[(5,5),(5.887,6.777),(7,7)]	[(5,5),(5,5),(7,7)]
A2	[(3,3),(3,3),(5,5)]	[(5,5),(5,5),(7,7)]	[(3,3),(3,3),(5,5)]	[(3,3),(5,5),(5,5)]
A3	[(3,3),(3,3),(5,5)]	[(3,3),(3,3),(5,5)]	[(3,3),(3,3),(5,5)]	[(3,3),(3,3),(5,5)]
A4	[(7,7),(7.887,8.777),(9,9)]	[(7,7),(9,9),(9,9)]	[(3,3),(5,5),(5,5)]	[(3,3),(3,3),(5,5)]
A5	[(1,1),(1,1),(1.22,2.11)]	[(1,1),(1,1),(3,3)]	[(1.22,2.11),(3,3),(3.22,4.11)]	[(1,1),(1.22,1.45),(1.223,2.11)]
A6	[(3,3),(3.22,4.11),(5,5)]	[(3,3),(3.223,4.113),(5,5)]	[(3,3),(5,5),(5,5)]	[(3,3),(5,5),(5,5)]
A7	[(1.22,2.11),(1.43,3.22),(3.22,4.11)]	[(3,3),(3.223,4.113),(5,5)]	[(3,3),(3.22,4.11),(5,5)]	[(3,3),(3,3),(5,5)]
A8	[(3,3),(5,5),(5,5)]	[(3,3),(5,5),(5,5)]	[(3,3),(3.22,4.11),(5,5)]	[(3,3),(5,5),(5,5)]
A9	[(3,3),(5,5),(5,5)]	[(3,3),(5,5),(5,5)]	[(3.22,4.11),(5,5),(5.22,6.11)]	[(1.22,1.89),(1.89,2.78),(3.22,4.11)]

Table 6. Results of the application of the IFRN CRADIS method

	$\overline{K_i^{+}}$	$\overline{K_i^{-}}$	$\overline{Q_i}$	Crisp value	Rank
A1	[(0.91,1),(0.78,1),(0.43,1.22)]	[(0.25,0.97),(0.34,1.01),(0.51,1.19)]	[(0.58,0.99),(0.56,1.01),(0.47,1.21)]	0.803	2
A2	[(0.91,0.99),(0.76,0.93),(0.4,1.02)]	[(0.23,0.83),(0.25,0.67),(0.44,1.02)]	[(0.57,0.91),(0.5,0.8),(0.42,1.02)]	0.704	3
A3	[(0.89,0.96),(0.73,0.89),(0.37,0.91)]	[(0.03,0.42),(0.14,0.45),(0.38,0.9)]	[(0.46,0.69),(0.43,0.67),(0.38,0.9)]	0.589	7
A4	[(0.95,1.04),(0.85,1.13),(0.48,1.44)]	[(0.54,1.62),(0.57,1.54),(0.6,1.33)]	[(0.74,1.33),(0.71,1.33),(0.54,1.39)]	1.007	1
A5	[(0.86,0.92),(0.7,0.84),(0.3,0.67)]	[(-0.27,-0.25),(-0.02,0.1),(0.15,0.48)]	[(0.31,0.33),(0.34,0.47),(0.22,0.58)]	0.373	9
A6	[(0.89,0.96),(0.75,0.95),(0.37,0.91)]	[(0.03,0.42),(0.2,0.77),(0.38,0.9)]	[(0.46,0.69),(0.47,0.86),(0.38,0.9)]	0.627	6
A7	[(0.89,0.96),(0.73,0.93),(0.36,0.88)]	[(-0.02,0.33),(0.11,0.64),(0.34,0.85)]	[(0.43,0.65),(0.42,0.78),(0.35,0.87)]	0.582	8
A8	[(0.89,0.96),(0.77,0.97),(0.37,0.91)]	[(0.03,0.42),(0.3,0.87),(0.38,0.9)]	[(0.46,0.69),(0.54,0.92),(0.38,0.9)]	0.648	5
A9	[(0.89,0.96),(0.77,0.98),(0.37,0.93)]	[(0.03,0.45),(0.3,0.89),(0.36,0.92)]	[(0.46,0.71),(0.54,0.93),(0.36,0.92)]	0.654	4

is that intersections with a countdown display are characterised by a shorter start-up time and a better concentration and focus of pedestrians when starting to go over the pedestrian crossing. The results were obtained for the total sample. At the same time, the segmented analysis related to the gender of pedestrians was performed (Ristić et al., 2024), according to which interesting results were obtained.

5. Verification Tests and Discussion

This section presents the verification procedure for the solutions that were initially obtained. It includes simulating new criteria weights, conducting a comparative MCDM analysis, and carrying out statistical correlation tests.

5.1 Sensitivity Analysis

In models that feature a few criteria and variants, the weights of criteria can have a dominant influence on the final ranking and making decisions (Radovanović et al., 2023; Tešić et al., 2023; Damjanović et al., 2024). Therefore, it is necessary to determine whether there is a change in the order of the ranks or if there is a disturbance with regard to the criteria preferences and their weights. In this case, an analysis was performed which included 40 scenarios - since four factors were considered relevant with regard to the total sample in this research, 4x10=40 scenarios were formed. In the scenarios S1-S10, a decrease of the weight of the first criterion is simulated from 5% in S1 to as much as 95% in S10, so it has values in the mentioned scenarios [(0.098,0.176), (0.213,0.326), (0.385,0.544)] and [(0.005,0.009), (0.011,0.017), (0.020,0.029)] respectively. In the scenarios S11-S20, a decrease of the weight of the second criterion was simulated for the same interval, in the scenarios S21-S30 the same was applied for the third criterion and in scenarios S31-S40 for the fourth criterion. After setting the input indicators in the simulation scenarios, the model was repeated 40 times to establish potential differences in the cities' ranks in their comparative analysis. Figure 2 shows the trend of ranking changes.

The results, highlighting the changes in the values of the employed criteria prove that these criteria play a significant role in decision-making and the evaluation of alternatives. In the specific cases, when the values of the employed criteria change, the ranks change in 22 out of 40 scenarios, that is in 55% of all scenarios. It should be emphasised that A4 and A1, the two best-placed variants, do not change their position in any scenario, which means that they are not sensitive to changes in the weight of the criteria involved. The same is true for the A5 variant, the last ranked alternative. The other alternatives change their positions, primarily by one position, while A2 does so by as many as three positions. These changes occur in the scenarios S15-S20 when the value of the second criterion for the respective age group, that is 19-40 years, which is the most dominant one with regard to pedestrian behavior, decreases.

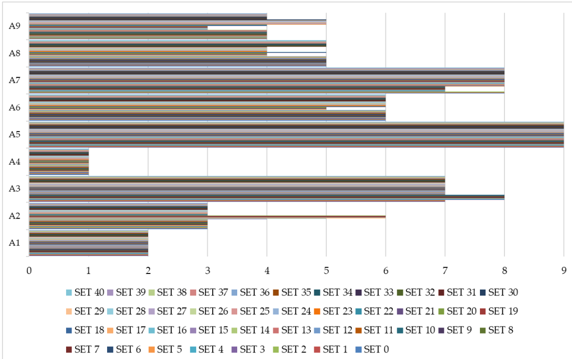

Figure 2. Rank changes in the context of the Sensitivity Analysis (SA)

5.2 Comparative Analysis

This subsection presents a comparative MCDM analysis that refers to the rank checking with five other IFRN MCDM methods under the same conditions as the IFRN SWARA-IFRN CRADIS model. It presents the analysis results of the methods IFRN MABAC (Puška et al., 2024), IFRN WPM (Kizielewicz & Bączkiewicz, 2021), IFRN MARCOS (Abualkishik et al., 2022), IFRN SAW (Chen et al., 2023), and IFRN ARAS (Chen et al., 2023). The ranking results obtained through the comparative MCDM analysis show that the proposed IFRN SWARA-IFRN CRADIS model is stable, which is confirmed in almost all cases.

5.3 Rank Reversal Analysis

To verify the proposed IFRN MCDM model, a rank reversal analysis was performed involving 10 sets. The first seven sets (SET1-SET7) involve the elimination of the alternative that is the worst according to the ranking. Therefore, in each set, the size of the initial matrix is reduced in such a way as to eliminate A5 first, which is the worst variant in the initial set (SET0). In the eighth set (SET8), the size of the initial matrix was expanded by adding the worst variant to the initial model, while in the ninth set (SET9), the worst alternative was replaced with the second worst one (A5 with A7). In the last set, the tenth one (SET10), the most significant criterion (C2) was deleted, so the matrix size was 9x3. The rank reversal analysis shows that alternatives do not suffer significant changes with regard to their value. It is only important to emphasise that their values decrease with the reduction of the matrix size, which is a logical process. The ranks obtained in this analysis show that the different sizes of the initial decision matrix change. As with the sensitivity analysis, the best-placed and worst-placed variants do not change their positions. However, this is a different type of analysis, so the obtained results are different. With the elimination of the worst variant already in the first set (SET1), there is a change because the rank of A2 falls from the third to the fifth place.

5.4 Calculation of Correlation for the Newly Obtained Ranks in Verification Tests

This part of the analysis focuses on the degree of correlation between the ranks obtained in all previous verification tests. The calculated correlation ratio refers to the WS (Sałabun & Urbaniak, 2020; Więckowski et al., 2023) and SSC (Tešić & Božanić, 2023; Stević et al., 2022b) coefficients. Sets 0 to 40 represent the correlation of ranks in the sensitivity analysis when changing the value of the criteria involved and the degrees of correlation in the comparative analyis. The research further presents the IFRN MCDM analysis and SET1-SET10 represent the correlation ratio in the rank reversal analysis. By observing the rank correlation ratio for all the three analyses which were carried out, it can be concluded that the smallest correlation coefficient is SCC=0.858 in set 9. In the rank reversal analysis, the worst alternative is replaced with the second worst one, and the rank of the latter decreases by two positions. In general, observing all the correlation coefficients reveals that the ranks obtained in the verification tests are highly correlated.

6. Conclusion

The concept of sustainable traffic management implies the sustainability of several factors, one of which is the behaviour of pedestrians as the most vulnerable group of traffic participants. Through direct patterns of behaviour, pedestrians can create conflict situations, and one of those is certainly the measurement of the start-up time for pedestrians. In this research, a comparative analysis of five selected cities in Bosnia and Herzegovina and Serbia was carried out using the IFRN SWARA-IFRN CRADIS model based on the pattern of pedestrian behaviour at signalised intersections and the start-up time measurement.

In this paper, an extension of the CRADIS method with IFRN was created, which represents a methodological contribution since, according to the authors` knowledge, this model was developed for the first time in the literature. Based on a sample of over ten thousand pedestrians, the data for signalised intersections with and without a countdown display was processed, and a comparative analysis was performed according to the chosen cities. The obtained results show that the pedestrians have the best behaviour when they are in intersections with countdown displays, based on the integrated measurements made for both types of intersections – with and without countdown displays. The verification of the results is carried out through a multiphase analysis, and future research could focus on an in-depth analysis of the causes related to the negative behaviour of pedestrians in cities that have a low ranking and on the possibility of benchmarking the process leading to the best behaviour of pedestrians. Also, further research should be based on unsignalised intersections to obtain a complete picture of the pedestrian traffic flow for the observed cities and of the concept of pedestrian behaviour.

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