

Evaluation of Pedestrian Crossings Based on the Concept of Pedestrian Behavior Regarding Start-Up Time: Integrated Fuzzy MCDM Model

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Abstract: Planning, designing, defining relevant parameters, and managing traffic represent essential characteristics of its sustainability and safety. However, one of the key characteristics that traffic planners and managers cannot always influence are the characteristics of vehicle and pedestrian traffic flows. Namely, pedestrian behavior, as well as driver behavior, depend on numerous factors, which are influenced by the characteristics of the road, the environment, and socio-economic characteristics. Pedestrians are the most heterogeneous group of traffic participants for whom there are no specific restrictions or conditions, as is the case for drivers. In complex traffic conditions and high traffic loads, the behavior of pedestrians can affect traffic conditions, that is, the level of service. The most complex traffic conditions for pedestrians occur at surface intersections where a limited traffic area - pedestrian crossing, is used by both vehicles and pedestrians, in accordance with traffic regulation and general traffic rules. This paper defines the goal of determining the concept of pedestrian behavior at pedestrian crossings in different cities based on start-up time classified by gender and age groups. Intersections with counters showing pedestrian phase times and those without counters were specifically considered. A novel integrated fuzzy MCDM (Multi-criteria decision-making) model was created to evaluate and rank cities based on start-up time. Fuzzy FUCOM (Full Consistency Method) was used to determine the weights of criteria, while Fuzzy ROV (Range of Value) was used to evaluate and rank cities. Different models were created on a sample of ten thousand pedestrians, segmented by gender and age, for which different results were obtained through analysis. In order to verify the results, sensitivity analysis, comparative analysis, and calculated statistical correlation tests were presented. The results presented are reflected in the following. Female pedestrians in Novi Sad show a higher level of concentration and carefully observe the moment when the pedestrian signal turns green when there is no counter. Doboj represents the city with the best start-up time for pedestrian crossings with counters, while Sarajevo holds that position for crossings without counters. It is important to point out that the sample of female pedestrians shows exceptional results on the same type of pedestrian crossings, as the start-up time is around one second.

Keywords: Fuzzy FUCOM; Fuzzy ROV; start-up time of pedestrians; traffic safety

1 INTRODUCTION

Crossing the road represents the greatest risk for pedestrians given that there is a potential danger of conflict with vehicles in these situations, even in situations where a pedestrian crossing is marked on the road. Consequently, pedestrian signaling becomes imperative to assign the right of way for safe pedestrian crossing at intersections.

The time required for pedestrians to cross a pedestrian crossing depends on the length of the crossing and the speed of pedestrians. Individual crossing times, i.e., pedestrian speeds, can vary significantly due to the heterogeneity of traffic flows; however, for the purpose of analysis, it is important to determine the average total crossing time for pedestrians across the pedestrian crossing. According to the Manual of Uniform Traffic Control Devices for Streets and Highways [1], the total time required for pedestrians to cross the roadway is the summation of pedestrian start-up time and the time required to cross the pedestrian crossing. In scientific and professional literature, this time is also referred to as start-up time or pedestrian delay time. Pedestrian start-up time refers to the period from the time the pedestrian signal turns green (pedestrian phase) until the pedestrians step onto the road. Start-up time is divided into two categories as early start-up and delayed start-up time. If a pedestrian starts to move from the curb during the red light, it is termed as early start-up time whereas if the pedestrian starts moving from the curb after the green light, then it is termed as delayed start-up time [2].

Early start-up time exposes pedestrians to potential danger, as there is a possibility of conflicts between pedestrians and vehicles. Delayed start-up times affect the total pedestrian crossing time, i.e., a longer crossing time, and also affect other pedestrians waiting in line or in groups to cross the road. In this context, it is necessary to pay

attention to pedestrian start-up times when designing the pedestrian phase at signalized pedestrian crossings. In accordance with the aforementioned facts, the research in this paper was conducted with the aim of determining the pedestrian start-up times at signalized pedestrian crossings with a countdown pedestrian signal display (CPSD) as well as at conventional signalized pedestrian crossings, without displays, in order to determine variation depending on the age and gender of pedestrians. In particular, this study attempts to investigate whether the application of CPSD causes better utilization of the pedestrian green phase.

The research was carried out in a total of five cities, one of which is located in Serbia, and four in Bosnia and Herzegovina. The final sample, after discarding extreme values, consisted of approximately 10,000 pedestrians of different ages. The contribution of this paper can be viewed in two ways, from both the classical scientific and the professional engineering aspect. The scientific contribution is reflected in the integration of Fuzzy FUCOM and Fuzzy ROV methods into a single model, which is presented to the public for the first time in this study. This model enables precise decision-making in any segment of traffic management with multiple alternative solutions and at least several criteria. The professional engineering contribution lies in defining start-up times for pedestrians that apply to our current traffic functioning conditions.

The remainder of this study is structured through a literature review as Section 2, briefly outlining relevant studies in the field. Section 3 refers to the presentation of the fuzzy MCDM model algorithm, and Section 4 is the essential part of the research. This section defines the input elements of the model, describes the experimental sample, and presents the results. Section 5 consists of various verification tests, while Section 6 is the conclusion, with a reflection on some subsequent activities.

2 LITERATURE REVIEW

Most previous studies have shown that pedestrian crossings with traffic lights can reduce the number of jaywalking incidents and increase the level of service for pedestrians and vehicles. Previous research, as well as the results of the research conducted for the purposes of this paper, indicate that pedestrians behave differently depending on the presence of pedestrian signals with CPSD. Differences in pedestrian behavior are manifested as early or delayed start-up. Additionally, the start-up time of pedestrians is influenced by pedestrian characteristics (age, gender, group size, etc.), socio-economic characteristics, micro-location of the pedestrian crossing, environmental characteristics, local weather conditions, etc.

Among the initial studies focusing on pedestrian start-up times, Knoblauch et al. [3] conducted a series of field studies collecting data to assess pedestrian walking speeds and pedestrian start-up times relative to location and environmental factors. They considered the influence of certain elements such as: age, gender, pedestrian speed, cycle length, street width, type of pedestrian crossing, curb height, etc. In their paper, Easa and Cheng [4] established a correlation coefficient between start-up time and pedestrian speed and presented a probability method for calculating the minimum green time. Golani and Damti [5] focused on the behavior of a group of pedestrians, considering gender, age, group size, and pedestrian familiarity with signal phases, all with the aim of forming a model for estimating the delayed start-up time of pedestrians at signalized pedestrian crossings. Jaiatilake et al. [6] conducted a series of field studies to estimate pedestrian start-up times considering the following factors: gender, age, group size, and pedestrians' awareness of signal phases. Results showed a significant difference in pedestrian start-up time when pedestrians were familiar with the signal phase compared to when they were not. Kong and Chua [7] conducted a study to determine the start-up time of pedestrians under controlled laboratory conditions, classifying the respondents into four groups of pedestrians: unloaded pedestrians, pedestrians carrying two bags, pedestrians with strollers, and pedestrians with shopping carts. The study by Gillette et al. [8] provided insights into pedestrians waiting to cross the roadway and investigated how distraction and other factors could affect pedestrian start-up time and crossing behavior. The effects of age, gender, types of distraction and group complexities were investigated.

In many other studies, the behavior of pedestrians and the influence on the start-up time and the crossing time on pedestrian crossings were also investigated. However, few studies have focused on the configuration and equipment of pedestrian crossings regarding start-up time. Ma et al. [9] conducted an empirical analysis to examine the impact of countdown displays on pedestrian behavior. In the research, pedestrians were classified into two age groups, and their behavior was observed during peak hours on three weekdays. Video recording systems were installed at three intersections with countdown displays and two intersections without countdown displays. Lipovac et al. [10], during video recording of intersections before and after the installation of countdown displays, collected data

to assess the behavior of pedestrians when crossing signalized pedestrian crossings. The analysis provided an insight into the number of illegal crossings (when pedestrians faced a red signal) of different categories of pedestrians by gender and age group, concluding that countdown displays significantly reduce the total number of violators regardless of their location and the demand volume of the flow. Prasanthika et al. [11] conducted a study to examine pedestrian crossing speeds at crosswalks with and without countdown displays. They found a significant difference between the two types of pedestrian crossings, and that the average speed of pedestrians was higher at pedestrian crossings with countdown displays. Kim et al [12] conducted a study to evaluate the effects of countdown displays on pedestrians in Korea with the aim of comparing numerical and graphical countdown signals. When comparing these two types of countdown signals, numerical countdowns proved to be more efficient than graphical countdowns. Vujanić et al. [13] proposed a method to assess the risk of pedestrians at signalized pedestrian crossings equipped with countdown displays. They determined the percentages of men and women at risk while crossing the road at a signalized pedestrian crossing with a countdown. The conclusion of their study is that the application of countdown displays is unfavorable due to the large number of pedestrians who crossed the road during the red signal. Paschalidis et al. [14] consider that when signalized pedestrian crossings lack countdown displays, a large number of pedestrians violate the red signal and cross the street illegally. Their study aimed to investigate the impact of countdown displays on pedestrian compliance in terms of their behavior when crossing intersections, as well as to examine parameters affecting the adjustment of walking speed. The results showed that gender, age, perceived comfort and time remaining until the start of the red light were the main parameters that influence pedestrian compliance. Several studies have shown that pedestrian signals with countdown displays are effective in increasing pedestrian safety [15, 16], while Richmond et al. [17], through a ten-year analysis of collision data in Toronto, concluded that countdown displays for pedestrians increase the number of conflicts between pedestrians and motor vehicles.

Therefore, the results of previous studies have shown that the implementation of countdown displays can have different effects on pedestrian behavior, that is, that studies in different locations yield different results. Accordingly, it can be concluded that the behavior of pedestrians at pedestrian crossings depends not only on the presence of countdown displays but also on other factors, primarily local conditions. Due to differences in signal display types, pedestrian composition, crossing behavior, and overall traffic conditions, literature results are informative but insufficient to assess the effectiveness of countdown displays in our region. In addition, few studies investigate the impact of countdown displays on pedestrians of different age groups.

3 METHODS

3.1 Fuzzy FUCOM Method

The Fuzzy FUCOM has been created in study [18].

Step 1. Forming a set of criteria.

Step 2. Performing the rank of criteria based on experts' assessment, the most important criterion is the first ranked.

$$\bar{C}_{j(1)} > \bar{C}_{j(2)} > \dots > \bar{C}_{j(k)} \tag{1}$$

Step 3. Fuzzy comparative significance $\bar{\varphi}_{k/(k+1)}$ is calculated by applying Eq. (2):

$$\bar{\varphi}_{k/(k+1)} = \frac{\bar{\varpi}_{C_{j(k)}}}{\bar{\varpi}_{C_{j(k+1)}}} = \frac{(\varpi_{C_{j(k)}}^l, \varpi_{C_{j(k)}}^m, \varpi_{C_{j(k)}}^u)}{(\varpi_{C_{j(k+1)}}^l, \varpi_{C_{j(k+1)}}^m, \varpi_{C_{j(k+1)}}^u)} \tag{2}$$

Thus, a fuzzy vector of comparative significance of evaluation criteria is obtained, Eq. (3):

$$\bar{\Phi} = (\bar{\varphi}_{1/2}, \bar{\varphi}_{2/3}, \dots, \bar{\varphi}_{k/(k+1)}) \tag{3}$$

where $\bar{\varphi}_{k/(k+1)}$ represents the significance of the criterion of $\bar{C}_{j(k)}$ rank compared to the criterion of $\bar{C}_{j(k+1)}$ rank.

Step 4. Calculation of the optimal fuzzy weights by Eqs. (4) and (5):

$$\frac{\bar{w}_k}{\bar{w}_{k+1}} = \bar{\varphi}_{k/(k+1)} \tag{4}$$

$$\frac{\bar{w}_k}{\bar{w}_{k+2}} = \bar{\varphi}_{k/(k+1)} \otimes \bar{\varphi}_{(k+1)/(k+2)} \tag{5}$$

where $\bar{\varphi}_{k/(k+1)}$ is the comparative significance of the criteria $\bar{C}_{j(k)}$ and $\bar{C}_{j(k+1)}$. Finally, a nonlinear model for determining the optimal fuzzy criteria weights is obtained using Eq. (6) $(\bar{w}_1, \bar{w}_2, \dots, \bar{w}_n)^T$:

$$\begin{cases} \min \chi \\ \left| \frac{\bar{w}_k}{\bar{w}_{k+1}} - \bar{\varphi}_{k/(k+1)} \right| \leq \chi, \forall j, \quad \left| \frac{\bar{w}_k}{\bar{w}_{k+2}} - \bar{\varphi}_{k/(k+1)} \otimes \bar{\varphi}_{(k+1)/(k+2)} \right| \leq \chi, \forall j \tag{6} \\ \sum_{j=1}^n \bar{w}_j = 1, \quad \bar{w}_j^l \leq \bar{w}_j^m \leq \bar{w}_j^u, \quad \bar{w}_j \geq 0, \forall j, \quad j = 1, 2, \dots, n \end{cases}$$

where $\bar{w}_j = (w_j^l, w_j^m, w_j^u)$ and $\bar{\varphi}_{k/(k+1)} = (\varphi_{k/(k+1)}^l, \varphi_{k/(k+1)}^m, \varphi_{k/(k+1)}^u)$.

3.2 Fuzzy ROV Method

The Fuzzy ROV method has been created by Ju et al. [19] and has been presented through the following algorithm:

Forming a MCDM model.

Computation of a fuzzy decision matrix

$$\mathfrak{N}_{ij} = (\mathfrak{N}_{ij}^l, \mathfrak{N}_{ij}^m, \mathfrak{N}_{ij}^u)_{n \times m}$$

Normalization process, which is as follows. First, it should be defined the elements \mathfrak{R}_j and \mathfrak{R}_j :

$$\mathfrak{R}_j = (\mathfrak{R}_j^l, \mathfrak{R}_j^m, \mathfrak{R}_j^u) = \max(\mathfrak{N}_{ij}) \tag{7}$$

$$\mathbb{R}_j = (\mathbb{R}_j^l, \mathbb{R}_j^m, \mathbb{R}_j^u) = \min(\mathfrak{N}_{ij}) \tag{8}$$

Next, it is needed to calculate the difference between the values in the initial matrix and the min value κ_{ij} , and the difference between the max and min values of TFN, (ς_j) :

$$\begin{aligned} \kappa_{ij} &= (\kappa_{ij}^l, \kappa_{ij}^m, \kappa_{ij}^u) = \mathfrak{N}_{ij} - \mathbb{R}_j = \\ &= (\mathfrak{N}_{ij}^l - \mathbb{R}_j^u, \mathfrak{N}_{ij}^m - \mathbb{R}_j^m, \mathfrak{N}_{ij}^u - \mathbb{R}_j^l) \end{aligned} \tag{9}$$

$$\begin{aligned} \varsigma_j &= (\varsigma_j^l, \varsigma_j^m, \varsigma_j^u) = \mathfrak{R}_j - \mathbb{R}_j = \\ &= (\mathfrak{R}_j^l - \mathbb{R}_j^u, \mathfrak{R}_j^m - \mathbb{R}_j^m, \mathfrak{R}_j^u - \mathbb{R}_j^l) \end{aligned} \tag{10}$$

The final normalized fuzzy values are as follows:

$$\begin{aligned} \mathfrak{g}_{ij} &= (\mathfrak{g}_{ij}^l, \mathfrak{g}_{ij}^m, \mathfrak{g}_{ij}^u) = 1 + \left(\frac{\kappa_{ij}}{\varsigma_j} \right) = \\ &= \left(\left(1 + \frac{\kappa_{ij}^l}{\varsigma_j^u} \right), \left(1 + \frac{\kappa_{ij}^m}{\varsigma_j^m} \right), \left(1 + \frac{\kappa_{ij}^u}{\varsigma_j^l} \right) \right) \end{aligned} \tag{11}$$

In the final fuzzy normalized matrix, it may arise that the core concept of TFN is not satisfied, and it is needed to use Eq. (9).

$$\text{if } \mathfrak{g}_{ij}^m \leq \mathfrak{g}_{ij}^l \text{ then } \mathfrak{g}_{ij}^m = \mathfrak{g}_{ij}^l, \text{ if } \mathfrak{g}_{ij}^u \leq \mathfrak{g}_{ij}^m \text{ then } \mathfrak{g}_{ij}^u = \mathfrak{g}_{ij}^m \tag{12}$$

Eqs. (9) to (11) are applied for benefit criteria, while for the cost criteria, the Eq. (13) should be used:

$$\begin{aligned} \mathfrak{g}_{ij} &= (\mathfrak{g}_{ij}^l, \mathfrak{g}_{ij}^m, \mathfrak{g}_{ij}^u) = 1 + \left(\frac{\mathbb{R}_j}{\mathfrak{N}_{ij}} \right) = \\ &= \left(\left(1 + \frac{\mathbb{R}_j^l}{\mathfrak{N}_{ij}^u} \right), \left(1 + \frac{\mathbb{R}_j^m}{\mathfrak{N}_{ij}^m} \right), \left(1 + \frac{\mathbb{R}_j^u}{\mathfrak{N}_{ij}^l} \right) \right) \end{aligned} \tag{13}$$

Multiplication of the matrix \mathfrak{g}_{ij} with the values of the factor w_j .

$$\begin{aligned} \nu_{ij} &= (\nu_{ij}^l, \nu_{ij}^m, \nu_{ij}^u) = \mathfrak{g}_{ij} \otimes w_j = \\ &= (\mathfrak{g}_{ij}^l \otimes w_j^l, \mathfrak{g}_{ij}^m \otimes w_j^m, \mathfrak{g}_{ij}^u \otimes w_j^u) \end{aligned} \tag{14}$$

Computation of sum of the previous values depending on criteria types T_i^+ (B) and T_i^- (C).

$$T_i^+ = \sum_{j=1}^m (v_{ij}^+) \tag{15}$$

$$T_i^- = \sum_{j=1}^m (v_{ij}^-) \tag{16}$$

Ranking alternatives according to the results obtained using Eq. (17):

$$\Lambda_i = \left(\frac{T_i^+ + T_i^-}{2} \right) \tag{17}$$

3.3 Fuzzy Bonferroni Operator

Fuzzy Bonferroni aggregator [20, 21] Eq. (18) is applied in order to average the weights of criteria. e is the number of experts, while $p, q \geq 0$ are a set of non-negative numbers.

$$\tilde{a}_{ij} = (a_{ij}^l, a_{ij}^m, a_{ij}^u) = \left\{ \begin{array}{l} a_{ij}^l = \left(\frac{1}{e(e-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^e a_i^l{}^p \otimes a_j^l{}^q \right)^{\frac{1}{p+q}} \\ a_{ij}^m = \left(\frac{1}{e(e-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^e a_i^m{}^p \otimes a_j^m{}^q \right)^{\frac{1}{p+q}} \\ a_{ij}^u = \left(\frac{1}{e(e-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^e a_i^u{}^p \otimes a_j^u{}^q \right)^{\frac{1}{p+q}} \end{array} \right. \tag{18}$$

4 ANALYSIS AND RESULTS

In this section of the paper, the results of the defined Fuzzy FUCOM - Fuzzy ROV model are presented. As previously mentioned, the sample in five different cities consisted of approximately ten thousand pedestrians. The samples were processed according to gender and age groups in order to more precisely determine the concept of pedestrian behavior regarding start-up time for pedestrian crossings with and without counters. Four age groups were segmented from the total sample, representing criteria based on which the cities where the research was conducted were evaluated. The first criterion refers to the age group up to 18 years (C1), the second to the group 19-40 (C2), the third to 41-65 (C3) and the fourth to the age group > 65 years. The cities where field research was conducted are Banja Luka (BL), Novi Sad (NS), Bijeljina (BN), Dobož (DO) and Sarajevo (SA). It is important to note that in the first four cities there are signalized intersections with counters at pedestrian crossings, as well as those without counters, while in Sarajevo, the research only focuses on pedestrian crossings without counters, as they exist as such in that city. The sample is divided, as established, into age groups and by male and female gender, resulting in six different Fuzzy FUCOM - Fuzzy ROV models. Firstly, it is necessary to determine the weights of the defined criteria using the Fuzzy FUCOM

algorithm, taking into account the preferences of three experts. Their assessment is shown in Tab. 1.

Table 1 Fuzzy evaluation of the criteria

	Expert 1	Expert 2	Expert 3
C2	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
C1	(1.05, 1.10, 1.15)	(1.00, 1.10, 1.20)	(1.10, 1.20, 1.30)
C3	(1.20, 1.30, 1.40)	(1.25, 1.35, 1.45)	(1.10, 1.20, 1.30)
C4	(1.40, 1.50, 1.60)	(1.45, 1.55, 1.65)	(1.40, 1.50, 1.60)

Applying the steps of the Fuzzy FUCOM method to E1, we obtain the following equation:

$$\begin{aligned} & \min \chi \\ & \left(\frac{w_2^l}{w_1^m} - 1.05 \right) \leq \chi; \left(\frac{w_2^m}{w_1^m} - 1.10 \right) \leq \chi; \left(\frac{w_2^u}{w_1^l} - 1.15 \right) \leq \chi; \\ & \left(\frac{w_1^l}{w_3^u} - 1.04 \right) \leq \chi; \left(\frac{w_1^m}{w_3^m} - 1.18 \right) \leq \chi; \left(\frac{w_1^u}{w_3^l} - 1.33 \right) \leq \chi; \\ & \left(\frac{w_3^l}{w_4^u} - 1.00 \right) \leq \chi; \left(\frac{w_3^m}{w_4^m} - 1.15 \right) \leq \chi; \left(\frac{w_3^u}{w_4^l} - 1.33 \right) \leq \chi; \\ & \left(\frac{w_2^l}{w_3^u} - 1.10 \right) \leq \chi; \left(\frac{w_2^m}{w_3^m} - 1.30 \right) \leq \chi; \left(\frac{w_2^u}{w_3^l} - 1.53 \right) \leq \chi; \\ & \left(\frac{w_1^l}{w_4^u} - 1.04 \right) \leq \chi; \left(\frac{w_1^m}{w_4^m} - 1.36 \right) \leq \chi; \left(\frac{w_1^u}{w_4^l} - 1.78 \right) \leq \chi; \\ & (w_1^l + 4 \cdot w_1^m + w_1^u) / 6 + (w_2^l + 4 \cdot w_2^m + w_2^u) / 6 + \\ & (w_3^l + 4 \cdot w_3^m + w_3^u) / 6 + (w_4^l + 4 \cdot w_4^m + w_4^u) / 6 = 1; \\ & w_1^l \leq w_1^m \leq w_1^u; w_2^l \leq w_2^m \leq w_2^u; w_3^l \leq w_3^m \leq w_3^u; \\ & w_4^l \leq w_4^m \leq w_4^u; w_1^l, w_2^l, w_3^l, w_4^l \geq 0. \end{aligned}$$

By solving these models for all three experts, the values of the fuzzy weighting coefficients are obtained as follows:

$$\begin{aligned} \tilde{w}_1(E_1) &= (0.266, 0.266, 0.309), \\ \tilde{w}_2(E_1) &= (0.300, 0.300, 0.319) \\ \tilde{w}_1(E_2) &= (0.264, 0.264, 0.326), \\ \tilde{w}_2(E_2) &= (0.293, 0.297, 0.344) \\ \tilde{w}_1(E_3) &= (0.238, 0.238, 0.295), \\ \tilde{w}_2(E_3) &= (0.294, 0.310, 0.331) \\ \tilde{w}_3(E_1) &= (0.219, 0.227, 0.255), \\ \tilde{w}_4(E_1) &= (0.181, 0.185, 0.238) \\ \tilde{w}_3(E_2) &= (0.210, 0.212, 0.256), \\ \tilde{w}_4(E_2) &= (0.180, 0.199, 0.234) \\ \tilde{w}_3(E_3) &= (0.231, 0.247, 0.284), \\ \tilde{w}_4(E_3) &= (0.183, 0.183, 0.235) \end{aligned}$$

By applying the fuzzy Bonferroni operator, the averaged significance of the criteria was obtained. Thus, for criterion C1, we obtain aggregated significance, as follows:

$$BM^{p=1,q=1} \{ (0.266, 0.266, 0.309), (0.264, 0.264, 0.326), (0.238, 0.238, 0.295) \} =$$

$$\left\{ \begin{aligned} \omega_{C1}^l &= \left(\frac{1}{3(3-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^3 \omega_{C1i}^{lp} \otimes \omega_{C1j}^{lq} \right)^{\frac{1}{1+1}} = \left(0.167 (0.266^1 \cdot 0.264^1 + 0.266^1 \cdot 0.238^1 + \dots + 0.238^1 \cdot 0.264^1) \right)^{\frac{1}{1+1}} = 0.256 \\ \omega_{C1}^m &= \left(\frac{1}{3(3-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^3 \omega_{C1i}^{mp} \otimes \omega_{C1j}^{mq} \right)^{\frac{1}{1+1}} = \left(0.167 (0.266^1 \cdot 0.264^1 + 0.266^1 \cdot 0.238^1 + \dots + 0.238^1 \cdot 0.264^1) \right)^{\frac{1}{1+1}} = 0.256 \\ \omega_{C1}^u &= \left(\frac{1}{3(3-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^3 \omega_{C1i}^{up} \otimes \omega_{C1j}^{uq} \right)^{\frac{1}{1+1}} = \left(0.167 (0.309^1 \cdot 0.326^1 + 0.309^1 \cdot 0.295^1 + \dots + 0.295^1 \cdot 0.326^1) \right)^{\frac{1}{1+1}} = 0.310 \end{aligned} \right.$$

In this way, the final criterion values were obtained, indicating that the age group 19-40 is the most significant, that is, it contributes the most to the start-up time being as small as possible, which is a desirable value. The final values are as follows: $w_1 = (0.256, 0.256, 0.310)$, $w_2 = (0.296, 0.302, 0.331)$, $w_3 = (0.220, 0.228, 0.265)$, $w_4 = (0.181, 0.189, 0.236)$. The next step involves the evaluation of cities based on previously established parameters related to pedestrian age groups. The evaluation was carried out on the basis of the following scale: [22] Extremely poor (EP)

(- (1, 1, 1); Very poor (VP) - (1, 1, 3); Poor (P) - (1, 3, 3); Medium poor (MP) - (3, 3, 5); Medium (M) - (3, 5, 5); Medium good (MG) - (5, 5, 7), Good (G) - (5, 7, 7), Very good (VG) - (7, 7, 9); Extremely good (EG) - (7, 9, 9). Tab. 2 shows the initial linguistic matrix for all models, including models specifically for male gender participants, female gender participants, and the total sample, as well as pedestrian crossing intersections with and without counters.

Table 2 Initial decision matrix in linguistic form

M	C1	C2	C3	C4	W	C1	C2	C3	C4	M+W	C1	C2	C3	C4
BL	G	G	G	MG	BL	MP	MG	MG	M	BL	M	MG	MG	MG
NS	P	MG	P	MG	NS	M	MG	MP	M	NS	MP	MG	MP	M
BN	MP	P	M	MP	BN	MG	M	P	P	BN	MP	MP	MP	MP
DO	EG	VG	M	MG	DO	MG	EG	VG	VP	DO	VG	EG	M	MP
M	C1	C2	C3	C4	W	C1	C2	C3	C4	M+W	C1	C2	C3	C4
BL	P	P	MP	VP	BL	EP	MP	P	EP	BL	VP	VP	P	EP
NS	M	MP	MP	M	NS	MP	M	M	M	NS	MP	MP	MP	M
BN	P	M	M	MP	BN	MG	MP	MP	M	BN	VP	MP	MP	MP
DO	M	MG	MP	M	DO	M	MP	MP	MP	DO	M	M	MP	MP
SA	M	M	MG	MG	SA	MP	M	M	P	SA	M	M	M	P

Since the formation involves six individual models incorporating the previously described parameters, only

the final results are shown in Tab. 3, obtained by applying the integrated Fuzzy FUCOM - Fuzzy ROV model.

Table 3 Results obtained by the F-ROV method

	T_i^+	Rank	T_i^+	Rank	T_i^+	Rank
	M		W		M+W	
BL (D)	(1.164, 1.866, 3.133)	2	(0.88, 1.279, 2.437)	3	(0.867, 1.622, 2.614)	2
NS (D)	(0.889, 1.316, 2.294)	3	(0.825, 1.42, 2.614)	2	(0.667, 1.265, 2.35)	3
BN (D)	(0.788, 1.09, 2.382)	4	(0.709, 1.326, 2.033)	4	(0.568, 0.976, 1.783)	4
DO (D)	(1.228, 1.837, 3.189)	1	(1.071, 1.762, 2.975)	1	(0.936, 1.762, 3.33)	1
BL (ND)	(0.556, 0.976, 1.709)	5	(0.547, 0.976, 1.142)	5	(0.567, 0.976, 1.142)	5
NS (ND)	(0.843, 1.42, 2.585)	4	(0.833, 1.823, 2.519)	1	(1.043, 1.444, 1.934)	3
BN (ND)	(0.715, 1.601, 2.54)	3	(0.918, 1.42, 2.078)	3	(0.915, 1.221, 1.779)	4
DO (ND)	(0.941, 1.723, 2.917)	2	(0.833, 1.326, 1.923)	4	(1.043, 1.628, 2.254)	2
SA (ND)	(1.013, 1.951, 3.086)	1	(0.742, 1.729, 2.283)	2	(0.953, 1.857, 2.283)	1

Tab. 3 shows the results for all conducted sample segmentations and for the total sample for pedestrian crossings with and without counters. When considering the sample related to the male gender at intersections with counters, the results are DO (D) > BL (D) > NS (D) > BN (D). The identical ranking of the observed set of cities is also for the total sample, while for the sample related to the female gender, BL (D) and NS (D) differs, and they switch

their positions. When it comes to intersections with pedestrian crossings where there are no counters, the results differ, thus for the total sample, the ranking is as follows: SA (ND) > DO (ND) > NS (ND) > BN (ND) > BL (ND). Here, it is noticeable that there are much greater distractions compared to crossings with counters because the sample related to the female gender is visibly different compared to the total sample or the male gender. Also, it

can be concluded that female pedestrians in Novi Sad show a higher level of concentration and carefully observe the moment when the pedestrian signal turns green when there is no counter. The ranking here is as follows: NS (ND) > SA (ND) > BN (ND) > DO (ND) > BL (ND). For the total sample, the results represent a mix of both genders' results, so the ranking is: SA (ND) > DO (ND) > NS (ND) > BN (ND) > BL (ND).

5 SENSITIVITY ANALYSIS AND COMPARATIVE ANALYSIS

In contemporary conditions of decision-making, it has practically become unthinkable to avoid examining the influence of the importance of input parameters on result changes, as evidenced by studies [23-26]. Considering a significant aspect of potential changes in initial results, a simulation of criterion weights was carried out across 40 scenarios. In these scenarios, criterion weights were reduced from 5% to 95%, with specific values shown in Fig. 1.

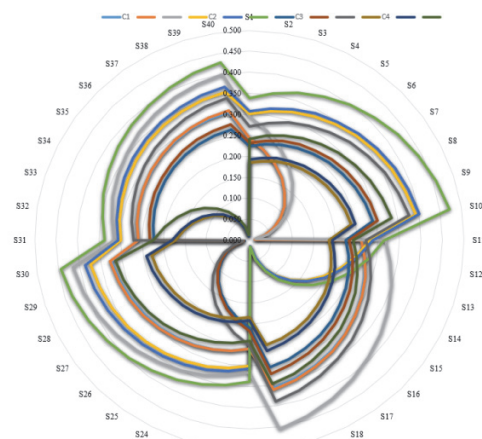


Figure 1 Criterion simulation values

In order to gain a clear understanding of the impact of changing criterion weights on final results, it is necessary to apply the Fuzzy FUCOM - Fuzzy ROV model across all 40 scenarios, including simulated criterion values for each scenario individually. The results are presented in Fig. 2.

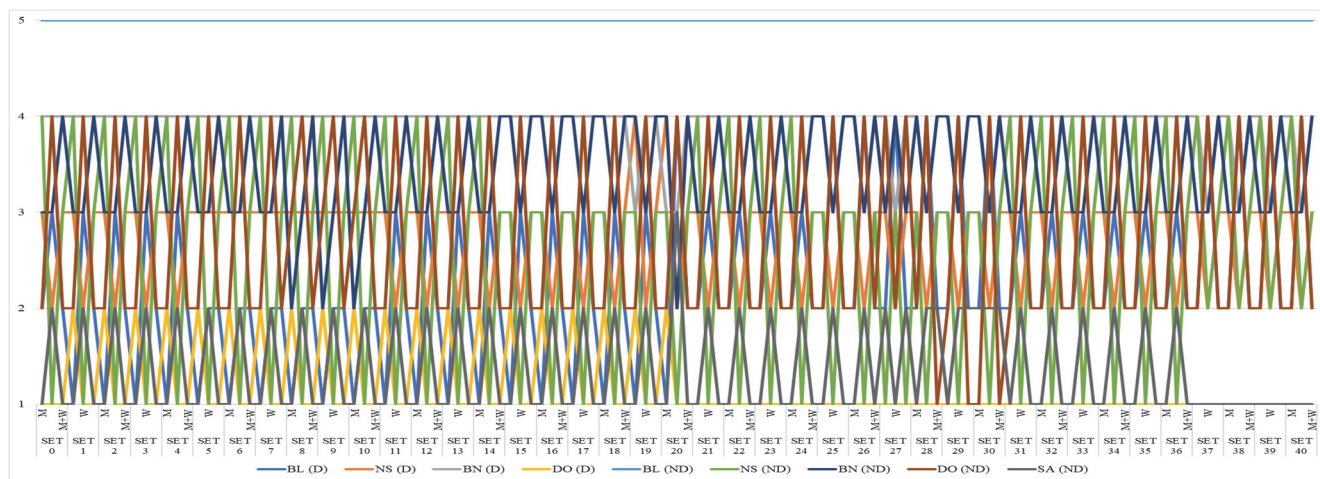


Figure 2 Results of the sensitivity analysis

Fig. 2 shows the SA results for all models, but their discussion needs to be specifically based on models applicable to intersections with pedestrian crossings with and without counters.

Regarding pedestrian crossings with counters (male gender), in 50% of cases, i.e., 20 scenarios, there is no change in the rankings of any city, while in the remaining 20 scenarios, there are certain changes. This leads to the conclusion that the third and fourth criterion have no impact on result changes, while the first and second certainly do. Therefore, the age groups < 18 and 19-40 years have an influence on the change in a city's position regarding pedestrian behavior, because by reducing their weights, cities rotate their positions. Specifically, with a reduction in weight of the first two criteria, BL and DO switch places, making BL the best-naked city compared to the initial results when it was DO. Such a change is not surprising considering that in the initial results, these two cities are almost equal in terms of final values. It has already been noted that DO has only a slight advantage over BL. It is also important to emphasize that in scenarios S19 and S20, NS and BN change their positions, as the significance of the 19-40 age group tends toward zero,

causing the better characteristic of the start-up time of the city of NS to lose its value.

When it comes to pedestrian crossings with counters (female gender), in 57.5% of cases, i.e., 23 scenarios, there is a change in the rankings of three out of four cities, while in the remaining 17 scenarios, there are no changes. It is important to emphasize here that regardless of the criterion value, the city of DO always maintains the first position, meaning that the criterion value plays no role for this city. In professional terms, the sample based on the same gender in Dobož has the shortest start-up time (around 1 s for ages 19-40 and 41-65, and 2.34 s for < 18) compared to the rivalry in three out of four age groups. In scenarios S5-S10, BL (3) and NS (2) switch positions because the first criterion, by which NS is slightly better, loses its value. In scenario S20, when the lowest value of the 19-40 age group is reached, BL falls from fourth to third position, that is, it exchanges its place with BN. The same situation occurs in scenarios S25-S30 when the importance of the 41-65 age group decreases, and in scenarios S37-S40 when the importance of the > 65 age group tends toward zero.

When it comes to pedestrian crossings with counters (total sample with both genders), it is interesting to note

that there is no change in any scenario, meaning the results are not sensitive to changes in the importance of age groups, thus retaining the initial ranking of DO (D) > BL (D) > NS (D) > BN (D). Additionally, it is important to note that the results are identical to the sample consisting only of the male gender, even though their number in the total sample is smaller compared to females. It is also important to emphasize that the female gender in Doboj achieves exceptional start-up times in the two age groups, 19-40 and 41-65, reflected in -0.07 and 1.03 seconds.

At intersections of pedestrian crossings without counters (male sample), changes occur in 37.5% of cases, caused by the reduction in the values of the first three age groups. SA is the best-ranked city in terms of pedestrian behavior in 39 out of 40 scenarios. SA only loses the first position in S30 when the value of the 41-65 age group drops to (0.011, 0.011, 0.013), as SA has the best performance, i.e., the shortest start-up time in that age group. It is noteworthy that the reduction in the importance of the influence of this age group leads to the most significant disturbances in ranks. This is reflected in the fact that only BL remains in its position, while the other cities change positions by one place. In other scenarios where rank changes occur, they are within one position.

With the sample of the female gender, changes in the influence of age groups occur in less than 10%, that is, in five scenarios (S20, S37-S40). The cause of these changes is the insignificant influence of the second and fourth age group. In S20, SA and BN switch positions, so SA is in the third instead of the second position, and BN vice versa. Regarding S37-S40, SA takes the first place, while NS is in the second position because it has the best start-up time in the > 65 age group, and this parameter has a negligible value in these scenarios.

For the total sample of pedestrian crossings without counters, rankings remain the same in 92.5%, with only SA and DO changing their positions.

After the sensitivity analysis, a comparative analysis was conducted with three other fuzzy MCDM methods: Fuzzy MARCOS [22, 27], Fuzzy SAW [28] and Fuzzy WASPAS [29]. The comparative analysis that includes all six models previously explained with different samples, both with and without counters, is given in Fig. 3.

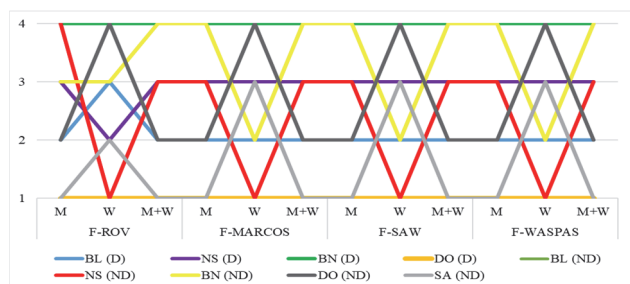


Figure 3 Results of comparative analysis

Observing the results of pedestrian crossings with counters, it can be concluded that the results are consistent and that there are no significant deviations. The only difference lies in the positions of BL and NS, which exchange positions when it comes to the female sample. According to all applied methods, DO is in the first position, with verified best start-up time performance. When it comes to crossings without counters, the situation

is similar and the changes are within one position, especially when talking about segmental samples and the total sample.

In addition to previous analyses where deviations in city rankings were determined, a calculation test of statistical correlation tests of SCC [30] and WS [31] was formed, as shown in Fig. 4.

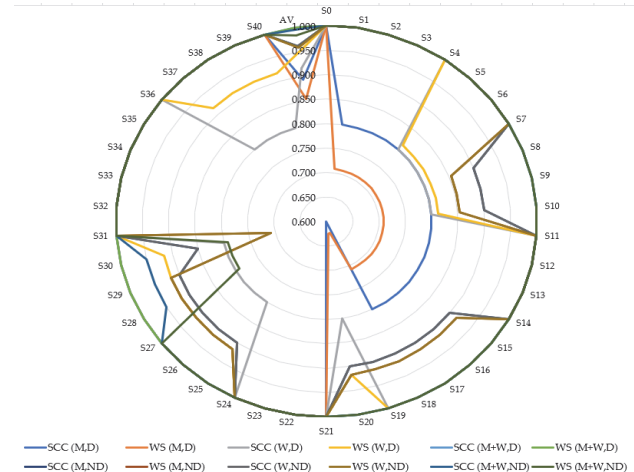


Figure 4 SCC and WS for sensitivity analysis

The SCC and WS coefficients, with their average values ranging from 0.854 to 1.000, indicate high, very high and total correlation of ranks in comprehensive analyses related to changes in criterion weights. The lowest value of the statistical correlation test is 0.600, which refers to SCC and is related to the sensitivity analysis of crossings with counters with a male sample.

6 CONCLUSION

Through research conducted in different cities, start-up times have been defined at signalized intersections with and without counters. The evaluation of cities based on the concept of pedestrian behavior depending on the start-up time was performed using a novel integrated fuzzy MCDM model. The development of integrating Fuzzy FUCOM and Fuzzy ROV models represents an important scientific contribution of the paper. The sample upon which representative start-up times were defined consists of ten thousand pedestrians. Cities were evaluated separately for pedestrian crossings with counters and without counters. Separate models were also created for both genders, and the results presented are reflected in the following. Female pedestrians in Novi Sad show a higher level of concentration and carefully observe the moment when the pedestrian signal turns green when there is no counter. Doboj represents the city with the best start-up time for pedestrian crossings with counters, while Sarajevo holds that position for crossings without counters. In this group, Doboj ranks second. Regarding pedestrian crossings with counters with a sample of male pedestrians, age groups < 18 and 19-40 years have an influence on the change in a city's position regarding pedestrian behavior. It is important to point out that the sample of female pedestrians shows exceptional results on the same type of pedestrian crossings, as the start-up time is around one second.

Subsequent activities related to this research should be carried out based on determining the interdependence of

age groups across cities, creating regression models, and expanding the sample to a larger number of cities. Finally, it is necessary to determine the exact required start-up time applicable to the testing conditions.

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