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MODELING OF FUZZY LOGIC SYSTEM FOR INVESTMENT MANAGEMENT IN THE RAILWAY INFRASTRUCTURE

Dragan Pamučar, Predrag Atanasković, Milica Miličić

Original scientific paper
The railway level crossings (RLCs), places where a railway line and road cross each other at the same level, are considered to be potentially dangerous points for all traffic participants. In general, level crossings may be fitted with automatic and/or mechanically-operated signaling/interlocking systems (RLCsAO) that allow passing of trains by lowering the barrier for the road users. In addition, there are also RLCs provided only with traffic signs and related inventory that have no barriers at all (RLCsNO). Protection of these level crossings by introducing the automatic signaling/interlocking system (AO) calls for significant investments considering the fact that equipment required for RLC modernization is very expensive, not to mention the great number of RLCsNO planned for improvement. Therefore it cannot be expected all level crossings without barriers (RLCsNO) to be upgraded at the same time so as traffic safety level can be properly increased. The method to be followed when choosing which RLC is to be provided with the adequate safety equipment depends on certain criteria relevant for making the proper investment decision. The paper herein deals with modeling of fuzzy logic-based approach that will offer adequate support to management when prioritizing RLCsNO to be provided with automatic signaling/interlocking system (AO). Seven (7) criteria that may affect the investment decision have been identified. The experience-based knowledge of managers (experts) was transferred into the fuzzy logic rule-based system to create the unique knowledge base to be used for making decision on investment priorities (list of RLC according to priorities). The output is a criterion function value that may be applied to any RLC analyzed. Based on the obtained value of the criterion function, RLCsNO are classified in line with investment priorities. The paper also shows a research that covered 88 RLCsNO planned for upgrading on the territory of the City of Belgrade out of which only 25 were nominated for investment due to limited financial resources.

Keywords: *decision making; fuzzy logic system; investment decision; multiciriteria decision making*

Modeliranje neizrazitog (fuzzy) logičkog sustava za upravljanje investicijama na željezničkoj infrastrukturi

Izvorni znanstveni članak
Željeznički putni prijelazi (RLC) su mjesta križanja dviju vrsta prometovanja: cestovnog i željezničkog i potencijalno predstavljaju opasne točke za sudionike u prometu. U općem smislu putni prijelazi mogu biti osigurani nekim od tipova automatskog ili mehaničkog osiguranja (RLC AO) gdje pri prolazu vlaka dolazi do spuštanja rampe za cestovna vozila. Pored toga RLC mogu biti i neosigurani (RLC NO) gdje rampe za vozače ne postoje i gdje su postavljeni samo prometni znakovi i druga oprema. Osiguranje putnog prijelaza s automatskim osiguranjem (AO) zahtijeva veliku investiciju jer su uređaji za osiguranje RLC vrlo skupi i zato što postoji velik broj RLC koji su osigurani prometnim znakovima (RLC NO). Iz tog razloga ne može se očekivati da svi RLC NO budu u programu osiguranja u istom trenutku kako bi se povećala sigurnost prometa na RLC. Proces izbora same lokacije pružnog prijelaza za ugradnju sigurnosne opreme praćen je većim ili manjim stupnjem neodređenosti kriterija koji su neophodni za donošenje relevantne investicijske odluke. U radu je prikazano modeliranje neizrazitog (fuzzy) logičkog sustava koji predstavlja podršku procesu izbora i rangiranja RLC NO koje je potrebno osigurati AO u cilju donošenja pravilne investicijske odluke. Prihvaćeno je sedam kriterija koji imaju utjecaj na donošenje investicijske odluke. Iskustvena znanja eksperata vezano za izbor kriterija i njihove relativne težine, preslikana su u bazu pravila neizrazitog logičkog sustava i formirana je jedinstvena baza znanja pomoću koje se donosi odluka o prioritetima investicije (lista RLC prema prioritetima). Kao izlaz iz sustava dobiva se vrijednost kriterijske funkcije za svaki promatrani RLC. Na osnovu dobivene vrijednosti kriterijske funkcije vrši se rangiranje RLC NO što prikazuje u praksi redoslijed investicijskih ulaganja u AO. U radu je prikazano istraživanje u kojem je izvršeno rangiranje i izbor za investiranje RLC NO na teritoriju Beograda.

Ključne riječi: *donošenje odluke; fuzzy logički sustav; investicijska odluka; višekriterijsko odlučivanje*

1 Introduction

Level crossings are recognized to be places where traffic accidents usually occur resulting in extensive material damage and loss of human lives. Increment of safety level at RLCs and making of relevant investment decisions referring to selection of top-priority RLCs to be upgraded by installing automatic signaling/interlocking system is subject matter of numerous traffic experts worldwide.

According to the Report of the European Railway Agency [1], level crossing accidents constitute 27 % of all fatalities reported in railway accidents. The majority of traffic accidents at level crossings are caused by improper and neglectful behavior of road users. In Serbia, 77 % of level crossings are not adequately secured according to the Traffic Safety Act and available instructions issued by the Serbian Railways [2, 3]. The Serbian Railway Network, 6974 km long, is provided with 2354 level crossings, out of which 588 are fitted with automatic and/or mechanically-operated devices with barriers while the remaining level crossings are provided only with traffic signs/signals and related inventory [2]. Tab. 1 shows total number of level crossings within the Serbian Railway Network according to the type of protection applied (STSA, 2011).

In order to improve traffic safety level on the Serbian railway lines and reduce number of traffic accidents at RLCs, significant financial resources are required for upgrading the interlocking system on RLCsNO. However, since the Serbian Railways are public enterprise funded from the budget of the Republic of Serbia, it cannot be expected all RLCsNO to be upgraded at the same time. Therefore both, the Serbian Railways and competent government authorities shall define the reliable strategy for top-priority RLCs which shall be included into the modernization program. This further means that adequate strategy plan needs to be developed and sequence of investments for RLCsNO upgrading defined. In past, the management staff of the Serbian Railways invested into modernization of RLCs under the immense public pressure which was the result of accidents reported on these RLCs. In such situation, the basic criterion considered was the emergency criterion that belongs to the group of criteria typical for non-strategic systems.

Pursuant to statistical data and forecasts issued by EU [1], the railway traffic is expected to double in volume during the next 30 years which is in direct relation with increased number of accidents at level crossings that should be expected not only on Serbian railway lines but in railway line networks all over Europe. Since railway traffic is expected to be increased in volume, it may be concluded with certainty that number of accidents on RLCs will be increased accordingly. Therefore, it will be necessary to prepare a relevant investment plan for protection of level crossings to increase traffic safety and reduce number of traffic accidents. Having in mind that interlocking of RLCsAO (with barriers) is an expensive investment, during the decision making process the management will bear high responsibility since the approved resources must be in line with the expected results. Therefore it is highly important for management to deal with adequate tools that will facilitate procedure for selecting the adequate RLC and making the proper investment decision.

Table 1 Type of interlocking systems employed on level crossings within the Serbian Railway Network

Railway line class	Level crossings (STP*)	Pedestrian crossings (MOTP*)	Interlocked with automatic or mechanically-operated devices					Total
			MB*	SZS*	SZSP*	Pedestrian crossings (SZSMO*)	Total	
International	382	35	87	116	176	8	387	804
Regional	456	42	34	13	86	0	133	631
Local	820	31	11	12	45	0	68	919
Total	**1658**	**108**	**132**	**141**	**307**	**8**	**588**	**2354**

* Traffic signs and visibility triangle (STP), Pedestrian barriers and visibility triangle (MOTP), Mechanically-operated barriers (MB), Light and sound signals (SZS), Light-sound signals and semi-barriers (SZSP), Light-sound signals and pedestrian barriers (SZSMO).

The paper herein deals with modeling of fuzzy logic system (FLS) which shall be used in the course of making the most optimal decision for investment into the RLCs upgrading. One shall start with an assumption that the financial resources are available only for limited number of RLCsNO planned to be fitted with new equipment for automatic interlocking.

When choosing which of RLCsNO shall be considered for investment, the management shall analyze the criteria of FLS input parameters. Indicators that describe the given criteria are expressed by linguistic variables in a form of membership functions. The experience-based knowledge of experts was transferred into the fuzzy logic rule base to create the unique knowledge base which will help in deciding which of level crossings shall be prioritized for upgrading by installing the automatic interlocking devices. The output is a value of criterion function that may be applied to any RLC analyzed. Based on the obtained value of the criterion function, RLCsNO will be ranked for investment according to their priority. FLS was tested on the chosen RLCsNO on the territory of the City of Belgrade at the moment when Serbian Railways management has limited financial resources that may cover installation of automatic interlocking system on only 25 RLCs out of total 88 RLCs.

2 Designing FLS for Investment Management in the Railway Infrastructure (FLS-IMRI)

The first mathematical models developed in the middle of the 20 century were used for evaluation and ranking of RLCs based on forecasted number of associated traffic accidents [4, 5]. In addition to the stated models in many countries worldwide, evaluation of RLC is performed by applying the Quantified Risk Analysis. Quantified Risk Analysis (QRA) provides a suitable basis for establishing level crossing improvement priorities. This it does by allowing a ranking of level crossings in terms of their accident risk probability. Those crossings with high accident probabilities would normally qualify for funding allocations (subject to satisfactory cost/benefit results), while those with low accident probabilities would be assigned a low priority for improvement funding. QRA results were linked to the Level Crossing Inventory Recording System which provides for the reporting of hazard probabilities against each level crossing. Application of the said technique can be found in works of numerous authors [6, 7, 8, 9, 10, Roop [11] and Mendoza [12] adopted multi-criteria analysis technique to assess the relative merits of the candidate protection systems and evaluation of RLCs. As compared to conventional cost-benefit approach, multi-criteria analysis allows effective comparative evaluation among options and stakeholders over a common set of evaluation objectives. Furthermore, multi-criteria analysis could overcome the limitation of cost-benefit analysis whereby all the costs and benefits have to be expressed in monetary terms.

The majority of the obtained data for making the investment decision for AO RLCs upgrading is accompanied by high degree of uncertainty, subjectivity and indeterminacy. The paper herein applies fuzzy logic to show the described uncertainties and indeterminacies. Criteria used for selection of RLCs are presented by introducing the linguistic descriptors. In such a way, fuzzy logic offered exploitation of tolerance that may be identified in the results characterized with uncertainty, obscurity and partial verity.

2.1 Defining input parameters of FLS- IMRI model

Based on analysis of works of different authors who were interested in AO RLCs investment issues [4, 6, 5, 12, 13, 14] and by interviewing the railway engineering experts, 7 criteria that may have influence on selection of RLCsNO in the course of investment decision making process have been identified. Relative criteria weights were defined. These relative weights were later used for developing of FLS-IMRI rule bases.

Frequency of railway traffic at RLC (K_1) is a criterion that affects the railway traffic safety, i.e. probability that accident may occur on the analyzed RLC. In FLS-IMRI model, this criterion is presented as beneficial criterion characterized with relative weight of ω_1 = 0,12. The criterion is described by the following three domains: [0; 49] trains/day, [50; 100] trains/day and >100 trains/day. These domains were later used for defining the intervals of fuzzy sets membership functions.

Frequency of road traffic at RLC (K_2) is in correlation with number of trains reported at the analyzed RLC. In addition, criterion K_2 is also in correlation with number of accidents at RLC. Increment of road traffic frequency at RLC is in correlation with the increased probability of accidents that may be expected. This criterion falls into the group of beneficial criteria and has the relative weight of ω_2 = 0,20. The criterion is described by the following four domains: [1; 40] vehicles/hour, [40; 130] vehicles/hour, [130; 200] vehicles/hour and >200 vehicles/hour.

Number of tracks at RLC (K_3). The criterion herein is in direct correlation with the time road users need to pass over the RLC and leave the dangerous area. The increased time for passing over increases probability of accident occurrence on the analyzed RLC in a case of train approaching. This criterion that belongs to the group of beneficial criteria is provided with relative weight of ω_3 = 0,11 and described by the following three domains: [0; 1] track, [1; 3] tracks and >3 tracks.

Maximum allowable speed of trains on the line sections with RLC (K_4). Higher speeds of trains on the line section with level crossing reduce time required for vehicle to pass over the level crossing in the case of train approaching. This criterion that falls into the group of beneficial criteria and has the relative weight of ω_4 = 0,15 is described by the following three domains: [20; 59] km/h, [60; 100] km/h and >100 km/h.

Angle of intersection between the tracks and the road (K_5). The optimum angle at which the road crosses the track at the level crossing is considered to be 90 degrees. In practice, however, due to construction restrictions, ground configuration, position of the present arterials and similar circumstances the angle of intersection between the line and the road may vary from 30 degrees to 175 degrees. The criterion K_5 at the same time falls into the group of beneficial and cost criteria. Criteria values found in the interval $30 \le x_1 \le 90$ are in the group of beneficial criteria, while criteria values found in the interval $90 \le x_1 \le 175$ belong to the group of cost criteria. This criterion characterized with relative weight of ω_4 = 0,17 is described by three domains: [30; 80] degrees, [80; 120] degrees and [120; 175] degrees.

Number of accidents reported on RLC (K_6). This criterion shows number of accidents reported at every and each level crossing during the one-year period. A RLC at which accidents were reported have priority as compared to RLC with no accidents reported. This beneficial criterion is characterized with relative weight of ω_4 = 0,11 and described by using the following three domains: [0; 2] accidents, [2; 4] accidents and >4 accidents.

Visibility at RLC from the aspect of road users (K_7). Visibility at RLC is a criterion that affects the driver's decision to pass over the RLC in cases when the level crossing is not secured with active protection (semi-barriers or barriers). This criterion that belongs to the group of cost criteria has the relative weight of ω_4 = 0,14 and is described by two domains: poor visibility in domain [0; 0,5] and good visibility in domain [0,5; 1].

The criteria described above are at the same time input variables for FLS-IMRI model. The input criteria may be described by numerical values (criteria $K_1 \div K_6$) and linguistic descriptors (criterion K_7). For the purpose of quantification of linguistic values of input criterion K_7 a scale composed of 7 triangular fuzzy numbers (Tab. 2) shall be used:very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H) and very high (VH).

Table 2 Linguistic variables (criteria K_7)

Linguistic variables	Triangular fuzzy number (TFN)
Very Low	(0;0;0,1)
Low	(0;0,1;0,3)
Medium Low	(0,1;0,3;0,5)
Medium	(0,3;0,5;0,7)
Medium High	(0,5;0,7;0,9)
High	(0,7;0,9;1)
Very High	(0,9;1;1)

Set of criteria $K_i(i$ = 1,..., 7) is composed of two subsets:

K^+ − subset of benefit-type criteria, higher values desirable and

K^- − subset of cost-type criteria, lower values desirable.

Linguistic variables of criterion K_7 should be normalized to enable their filtering through the FLS-IMRI model. Since the criterion K_7 belongs to the group of beneficial criteria (higher values desirable) the normalization procedure shall be performed according to the following Eq. (1).

$$(l_{ki})_n = \frac{l_{ki}}{l_{k\,\max}}, \tag{1}$$

where $l_{k\,\max}$ is maximum value of fuzzy number $\widetilde{l}_{ki}$ (k = 1, 2,..., K), for $\mu_{\widetilde{l}_{ki}}(l_{ki}) \neq 0$.

Defuzzification of linguistic descriptors is done through application of the Centre of Gravity method as per expression:

$$l_{ki} = \frac{\int_{x_1}^{x_2} \mu_{l_{ki}}(x) x \mathrm{d}x}{\int_{x_1}^{x_2} \mu_{l_{ki}}(x) \mathrm{d}x} \rightarrow l_H$$

$$l_H = \frac{\int_{0,5}^{0,62} \frac{x-0,5}{0,12} x\mathrm{d}x + \int_{0,62}^{0,77} \frac{0,77-x}{0,15} x\mathrm{d}x}{\int_{0,5}^{0,62} \frac{x-0,5}{0,12} \mathrm{d}x + \int_{0,62}^{0,77} \frac{0,77-x}{0,15} \mathrm{d}x} = 0,6382 \approx 0,64.$$

Once the FLS-IMRI model criterion has been defined, parameters that describe the criteria are identified (Tab. 3). In the process of FLS-IMRI modeling, these parameters were further used for defining the membership function intervals of input criteria.

Table 3 Criterion indicators and output preferences

Variable	Domain
K_1	[0; 100]
K_2	[0; 200]
K_3	[1; 3]
K_4	[20; 120]
K_5	[30; 175]
K_6	[0; 5]
K_7	[0; 1]
Y	[0; 1]

By defining criteria for selection and evaluation of RLCs it is possible to create a data base that contains all level crossings in Serbia in which every RLC may be analyzed by using the unique criteria.

2.2 Creation of FLS-IMRI model

Fuzzy logic systems are one of the main developments and successes of fuzzy sets and fuzzy logic. A FLS-IMRI model is a rule-base system that implements a nonlinear mapping between its inputs and outputs. A FLS-IMRI model is characterized by four modules:

- fuzzifier,
- defuzzifier,
- inference engine,
- rule base.

A schematic representation of a FLS-IMRI model is presented in Fig. 1. The operation of a FLS-IMRI is based on the rules contained in the rule base. The l^{th} rule in the rule-base has the following form:

$R^{(l)}$: IF u_1 is A_{1l} and u_2 A_{2l} and ... u_n is A_{nl}, THEN v is B^l

The first n terms are called the *antecedents* of the rule while the last term (the one after the THEN) is the *consequent* of the rule. The terms u are fuzzy variables and the terms A are linguistic variables.

The inputs to the FLS-IMRI, as can be seen in Fig. 1, come from the outside world (e.g., controlled process) and are *crisp* variables in general (except criteria K_7). On the contrary, the antecedents of the fuzzy rules are always fuzzy sets. The role of the fuzzifier in a FLS-IMRI is to convert a *crisp* input variable into a fuzzy set that is ready to be processed by the inference engine. The inference engine using the fuzzified inputs and the rules stored in the rule base processes the incoming data and produces an (fuzzy) output. This output needs to be used in the outside world and thus needs to be converted from fuzzy to crisp. The defuzzifier performs this operation.

The basic problem for an analyst who works on the fuzzy system development is to define the fuzzy rule base and parameters of membership functions of fuzzy sets that describe both input and output parameters. In FLS-IMRI model, Gaussian curves (gmf), S-shaped membership functions (smf) and Z-shaped membership functions (zmf) are used as membership functions. These functions are chosen because they are easy for handling in the course of FLS adjustment. Parameters of membership functions and their properties are described in the text below. In addition, by applying these functions, FLS-IMRI has showed acceptable sensitivity and minimum error at the output.

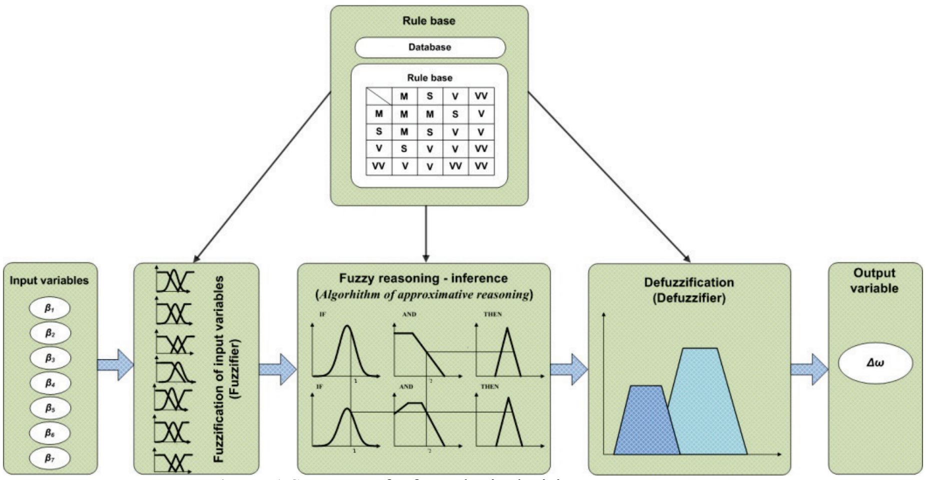

Figure 1 Structure of a fuzzy logic decision support system

In addition to type of membership functions, for any input variable it will be also necessary to define number of membership functions. Increased number of functions will call for increased number of in-base rules. However, increased number of rules obstructs the system adjustment. Therefore, it is recommended to start with the smallest number of membership functions taking care of variable properties. However, decreased number of membership functions will not affect the description of the input variable. Taking into account everything mentioned above it is defined that in FLS-IMRI model, input variable K_7 has two membership functions ($K_{7\mathrm{MF1}}$zmf(0,166; 0,784), $K_{7\mathrm{MF2}}$ smf(0,14; 0,79)), input variables K_1, K_3, K_4, K_5 and K_6 have three membership functions each ($K_{1\mathrm{MF1}}$ zmf(40,7; 154,5), $K_{1\mathrm{MF2}}$ gmf(33,6; 53; 4,3; 87,5), $K_{1\mathrm{MF3}}$ smf(7,6; 109), $K_{3\mathrm{MF1}}$ zmf(1,3.62), $K_{3\mathrm{MF2}}$ gmf(0,94; 2), $K_{3\mathrm{MF3}}$ smf(0,38; 2,7), $K_{4\mathrm{MF1}}$ gmf(34,3; 18,6; 31,5; 49,8), $K_{4\mathrm{MF2}}$ gmf(35,4; 64,2; 38,2; 93,4), $K_{4\mathrm{MF3}}$

smf(17,31; 113), K_{5MF1} gmf(24,06; 40), K_{5MF2} gmf(21,2; 80; 21,9; 100), K_{5MF3} gmf(24,79; 142), K_{6MF1} zmf(1; 1,67), K_{6MF2} gmf(0,44; 1,31), K_{6MF3} smf(0,87; 1,67)), while the input variable K_2 has four membership functions (K_{2MF1} zmf(36,9; 183,3), K_{2MF2} gmf(44,2; 64; 48,2; 130,4), K_{2MF3} gmf(41,2; 151; 36,9; 184,5), K_{2MF4} smf(65,8; 207)). In such a way, acceptable sensitivity and complete description of input parameters is obtained.Since we are talking about *Mamdani* FLS, the membership functions of the output variable *Decision preference* shall be defined as well. The possible decision preference in the FLS-IMRI model is described by four membership functions: low, medium, high and very high decision preference.

After comparison of the FLS-IMRI model output data and desired set of solutions, the system did not provide satisfactory results. A difference between the expected result and value of output criteria function (Y) was out of tolerance limits. The analysis of obtained data at the FLS-IMRI model output has shown that an average error was 1,371. An attempt to change the type and parameters of membership functions at the output in order to obtain satisfactory values did not gave the expected results.

In addition to error which was high, the FLS-IMRI was too sensitive for some input parameters and insufficiently sensitive for the other ones. Due to the above-mentioned facts, the FLS-IMRI was transferred into an adaptive neural network. A neural network was used for additional adjustment of membership functions of the FLS-IMRI model. Adjustment and/or change of membership function parameters was made in the process of neural network training. The backpropagation algorithm was used for training the FLS-IMRI model.

FLS-IMRI model was trained with 150 expert decisions (set of 150 RLCs). In the course of training, data from the training set x_k, k = 1, 2, ..., n, where n is total number of input values, were periodically passed through the FLS-IMRI model. Comparative review of criteria function values of the FLS-IMRI model ($f_{\text{FLS-IMRI}}$) and criteria functions of the training set (f_{training}) are shown in Tab. 4.

Table 4 Test results for the fitting capability of the FLS-IMRI

No.	Relative error (0,250)		Relative error (0,1547)		Relative error (0,089)		Relative error (0,0353)	
	Measured value	Predicted value	Measured value	Predicted value	Measured value	Predicted value	Measured value	Predicted value
1.	0,613	0,363	0,613	0,467	0,613	0,524	0,613	0,577
2.	0,334	0,084	0,334	0,188	0,334	0,245	0,334	0,298
3.	0,705	0,455	0,705	0,559	0,705	0,616	0,705	0,669
4.	0,332	0,082	0,332	0,186	0,332	0,243	0,332	0,296
5.	0,569	0,319	0,569	0,423	0,569	0,480	0,569	0,533
6.	0,458	0,208	0,458	0,312	0,458	0,369	0,458	0,422
7.	0,637	0,387	0,637	0,491	0,637	0,548	0,637	0,601
8.	0,395	0,145	0,395	0,249	0,395	0,306	0,395	0,359
9.	0,732	0,482	0,732	0,586	0,732	0,643	0,732	0,696
10.	0,528	0,278	0,528	0,382	0,528	0,439	0,528	0,492
11.	0,532	0,282	0,532	0,386	0,532	0,443	0,532	0,496
12.	0,588	0,338	0,588	0,442	0,588	0,499	0,588	0,552
13.	0,590	0,340	0,590	0,444	0,590	0,501	0,590	0,554
14.	0,387	0,137	0,387	0,241	0,387	0,298	0,387	0,351
15.	0,574	0,324	0,574	0,428	0,574	0,485	0,574	0,538
16.	0,493	0,243	0,493	0,347	0,493	0,404	0,493	0,457
17.	0,250	0,000	0,250	0,104	0,250	0,161	0,250	0,214
18.	0,463	0,213	0,463	0,317	0,463	0,374	0,463	0,427
19.	0,549	0,299	0,549	0,403	0,549	0,460	0,549	0,513
20.	0,670	0,420	0,670	0,524	0,670	0,581	0,670	0,634
21.	0,710	0,460	0,710	0,564	0,710	0,621	0,710	0,674
22.	0,622	0,372	0,622	0,476	0,622	0,533	0,622	0,586
23.	0,418	0,168	0,418	0,272	0,418	0,329	0,418	0,382
24.	0,643	0,393	0,643	0,497	0,643	0,554	0,643	0,607
25.	0,311	0,061	0,311	0,165	0,311	0,222	0,311	0,275
26.	0,192	-0,058	0,192	0,046	0,192	0,103	0,192	0,156
27.	0,580	0,330	0,580	0,434	0,580	0,491	0,580	0,544
28.	0,629	0,379	0,629	0,483	0,629	0,540	0,629	0,593
29.	0,695	0,445	0,695	0,549	0,695	0,606	0,695	0,659
30.	0,693	0,443	0,693	0,547	0,693	0,604	0,693	0,657
31.	0,884	0,634	0,884	0,738	0,884	0,795	0,884	0,848

Tab. 4 shows the deviation values of the function f_{training} (Measured value) and f_{FLSUI} (Predicted value) which are presented above. Training the FLS-IMRI model was carried out in four phases, which lasted a total of 250 epochs. The first training phase of the FLS-IMRI model was completed after 70 epochs. After completion of the first phase, an error of 0,250 was obtained at the output (Fig. 4a). In the following phase, after 120 epochs, an error of 0,1547 was obtained at the output (Fig. 4b), which compared to the previous phase is a 38,12 % reduction in error. The third phase of training the FLS-IMRI model was completed after 200 epochs and an error of 0,089 was obtained (Fig. 4c), which in relation to the second phase is a reduction in error of 42,46 %. In the fourth and final phase, which was completed after 250 epochs, at the output from the model the error was 0,0353 (Fig. 4d), which compared to the third phase is a reduction in error of 60,33 %. Upon completion of the fourth phase, it was concluded that the error obtained at the output of the FLS-IMRI model was negligible. In addition, the conclusion is that the FLS-IMRI model is trained and capable of generalizing to new entry data for which it is not trained.

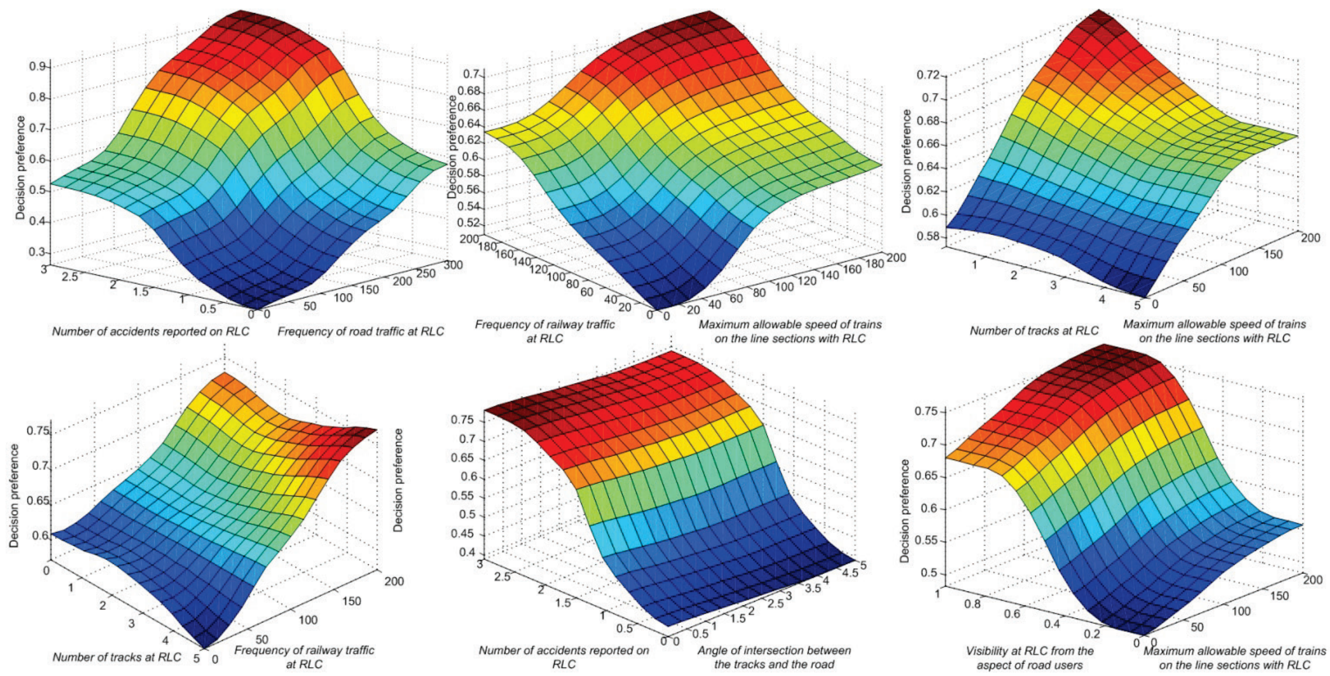

Figure 2 Graphic presentation of the set of possible solutions for the FLS-IMRI model

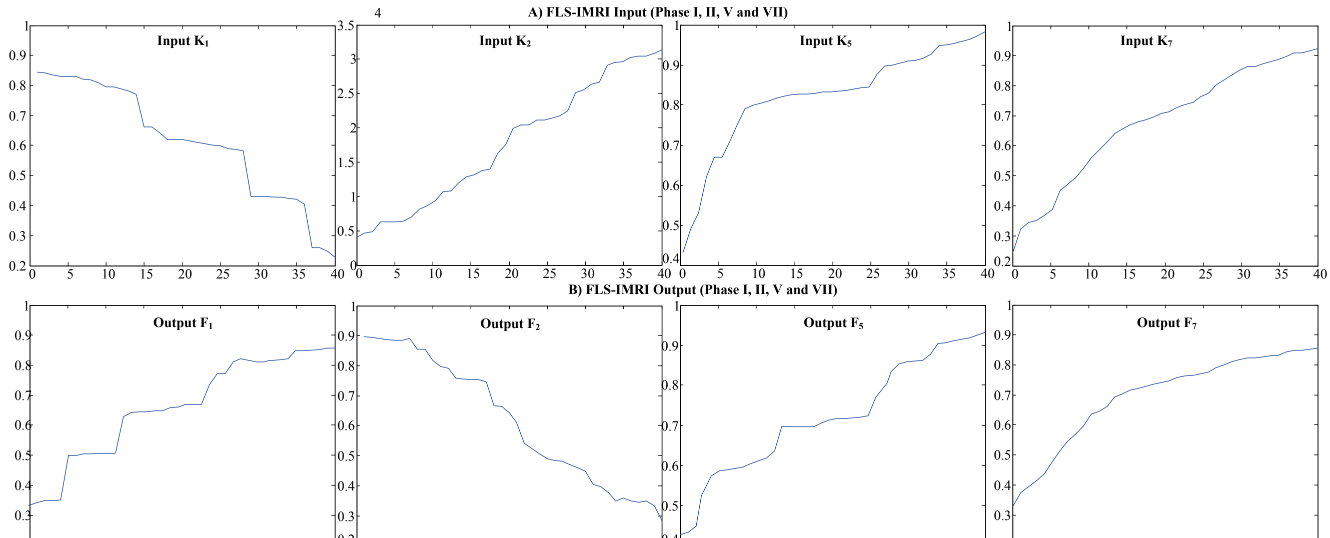

Figure 3 Sensitivity analysis of the FLS-IMRI model (Phase I, II, V and VII)

System sensitivity and output gradation were noticed after training. Inert and too sensitive system segments were eliminated, as it was the case prior to training the FLS-IMRI model. Fig. 2 shows the set of possible solutions for the FLS-IMRI model after training and scenario that describes system reactions for specific input values.

After design of FLS-IMRI, a sensitivity analysis of the FLS-IMRI model was performed. The sensitivity analysis was conducted in seven phases. In each phase, the sensitivity of the system was analyzed on one input criterion. At the same time, in each phase of the sensitivity analysis each of the observed criteria were given values in the interval $[K_{i\ \min}, K_{i\ \max}]$, where $K_{i\ \min}$ is the minimum value, and $K_{i\ \max}$ is the maximum value of the input criterion. When changing the input parameters of the observed criterion the parameters of the remaining input criteria did not change. Thus, different values of the output criteria functions of the FLS-IMRI model were obtained.

In each phase, a set of 40 input values of the criteria K_i were passed through the FLS-IMRI model. In this way, criteria function values were obtained which show response and sensitivity of the system to changing only one of the observed criteria. Fig. 3 shows the sensitivity of the FLS-IMRI model and the values of the criteria functions obtained in phases I, II, V and VII.

By looking at the graph of the sensitivity analysis (Fig. 6) we can conclude that the output values of the criteria functions of the FLS-IMRI model depend on the weight values of the criteria K_i and on the nature of the criteria themselves (benefit or cost criteria). Fig. 6 shows the four criteria which have the greatest weight as defined in the database of rules. Sensitivity analysis showed that benefit-type criteria with higher input values correspond with higher values of the output functions. In addition, it was found that small changes in the values of input criteria with greater weight lead to proportional increase in the value of output functions. However, with cost-type criteria the value of the output functions is inversely proportional to the values of the input criteria.

5 Results and discussion

Testing the FLS-IMRI model was carried out on the example of prioritization of level crossings in Belgrade territory. The level crossings in Belgrade territory were chosen on grounds of high frequency of road and railway traffic and disturbing statistics referring to accidents at level crossings in Belgrade. Total number of railway accidents in Belgrade territory for the period 2001 ÷ 2011 did not have increasing trend. However, share of traffic accidents at RLCs in the total number of accidents has an increasing trend from 2002. The analyzed period 2001-2011 includes 767 accidents in total, out of which 214 accidents occurred at level crossings (SBT, 2012). Such data points to fact that safety of road users shall be improved at level crossings.

In 2013 the Government of the Republic of Serbia donated 3,1 million euros to Serbian Railways for improvement of safety equipment at level crossings. Serbian Railways decided to invest 85 % (2,63 million euros) of donated funds for safety improvement at 88 level crossings in Belgrade. The FLS-IMRI model was used in the process of selecting the level crossings for installation and improvement of safety equipment. Prioritization at all 88 level crossings was made by application of FLS-IMRI model and expert opinions. Comparative review of results of expert prioritization and prioritization based on the FLS-IMRI model for 25 RLCs is shown in Tab. 5. Parameters shown in Tab. 5 were obtained by surveying the traffic parameters at level crossings in the period 2009 ÷ 2011.

For each level crossing the characteristics of input parameters were passed through the FLS-IMRI model and specific values of output criteria functions were obtained. Level crossings shall be selected according to expression (2).

$$f_{V_i} = \max\,(f_{V_i}),\, i = 1,\ldots,n, \tag{2}$$

where n is total number of level crossings. When values of criteria functions f_{V_i} for each analyzed level crossing V_i are obtained, they shall be ranked according to obtained preferences from the set of alternatives $A = \{V_1, V_2,\ldots,V_n\}$.

Table 5 Comparative review of expert decisions and FLS-IMRImodel

RLC	K_1^*	K_2^*	K_3	K_4	K_5	K_6^*	K_7	FLS-IMRI out		Expert decision		Final rank
								$f_{\text{FLS-IMRI}}$	Rank	f_{Expert}	Rank	
1.	62	56	1	60	70°	2	L	0,50	17	0,45	20	19
2.	51	80	1	55	60°	1	VL	0,54	7	0,50	5	7
3.	64	61	2	60	90°	1	M	0,52	12	0,58	11	12
4.	24	79	2	60	80°	1	M	0,51	13	0,53	13*	13*
5.	35	67	4	60	100°	2	M	0,56	5	0,55	5*	5*
6.	39	53	1	60	95°	2	M	0,49	18	0,51	17*	17*
7.	48	86	4	70	110°	2	VH	0,60	3	0,62	3*	3*
8.	35	41	1	65	130°	4	VH	0,49	18	0,52	17*	17*
9.	72	93	2	65	60°	3	L	0,62	2	0,60	2*	2*
10.	54	77	2	55	60°	1	VL	0,54	7	0,55	5	8
11.	49	69	2	70	150°	4	L	0,69	1	0,66	1*	1*
12.	47	62	2	70	95°	0	M	0,51	13	0,52	14*	14*
13.	56	31	1	70	90°	1	L	0,45	22	0,45	20	22
14.	37	55	1	70	40°	3	H	0,40	24	0,40	24*	24*
15.	41	23	1	65	45°	1	H	0,30	25	0,33	25*	25*
16.	35	49	1	50	130°	3	H	0,51	13	0,50	15*	15*
17.	58	56	1	50	115°	0	M	0,51	13	0,51	15*	15*
18.	46	53	4	50	75°	1	M	0,47	20	0,45	20	21
19.	53	72	4	65	80°	2	H	0,54	7	0,55	5	9
20.	31	57	1	70	65°	2	L	0,47	20	0,46	19	20
21.	49	82	2	50	70°	1	L	0,54	7	0,55	5	10
22.	47	75	2	45	85°	1	VL	0,56	5	0,55	5*	5*
23.	53	98	2	45	100°	0	H	0,57	4	0,56	4*	4*
24.	34	58	2	50	55°	2	L	0,45	22	0,45	20	23
25.	42	75	2	70	90°	0	M	0,53	11	0,54	11*	11*

Values of input parameters for the FLS-IMRI model (Tab. 5) are average indicators at annual level. The RLCs marked as * are RLCs for which prioritization based on the FLS-IMRI model and expert prioritization were identical. Rank of preferences for theFLS-IMRI model and of expert preferences is identical for level crossings under Nos. 4, 5, 6, 7, 8, 9, 11, 12, 14, 15, 16, 17, 22, 23 and 25. Among 25 RLCs, the preferences based on the FLS-IMRI model and expert preferences were identical for 15 RLCs. Deviations of remaining level crossings are minimal, that is ±1,5 ranking position in average. After comparison of output FLS-IMRI model preferences and expert preferences the mean error of 0,058 was obtained. The data in Tabs. 4 and 5 show that FLS-IMRI model successfully simulate preferences of experts in the area of road and railway traffic safety at RLCs. The experience-based knowledge of experts was successfully transferred into FLS model rule base so that a single knowledge base was created to select RLCs for safety improvement.

6 Conclusion

One of the main criteria for evaluation of quality of new methodologies in the soft computing is their usability in the analysis of real data. A development of FLS-IMRI model has enabled transformation of strategy for selection of level crossings needed investment in safety equipment into automatic control strategy. The research results have shown that developed fuzzy logic system is capable to learn and imitate expert evaluations as well as to demonstrate a competence level comparable with a competence level of experts.

Fuzzy multicriteria approach developed in this paper enables quantification of criteria and selection of the best alternative from the set of offered alternatives. The presented FLS-IMRImodel enables selection of RLCs and the best alternative from the set of offered alternatives described by benefit or cost criteria. The criteria relevant to selection of the RLCs and their effect on selection of the RLCs have values expressed in numerical values and fuzzy linguistic descriptors.

After analysis of the FLS-IMRI model preferences and obtained results, we may conclude that FLS-IMRI model can reproduce expert decisions with a high degree of accuracy. In that way, the RLCs requiring investment in safety equipment may be selected easily without applying complicated statistic and mathematic transformations used so far [4, 5]. In addition, the FLS-IMRI model saves time needed for decision making.

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Authors' addresses

Dragan Pamučar, Ph.D. Assistant professor
University of Defence, Department of Logistic,
Pavla Jurisica Sturma 33, 11000 Beograd, Serbia
E-mail: draganpamucar@gmail.com

Predrag Atanasković, Ph.D. Full time professor
University of Novi Sad, Faculty of Technical Science,
Dositeja Obradovica 6, 21000 Novi Sad, Serbia
E-mail: pedja.atanaskovic@yahoo.com

Milica Miličić, Ph.D. Associate professor
University of Novi Sad, Faculty of Technical Science,
Dositeja Obradovica 6, 21000 Novi Sad, Serbia
E-mail: milica.milicic@gmail.com