FUZZY LOGIC APPLICATION IN GREEN TRANSPORT - PREDICTION OF FREIGHT TRAIN ENERGY CONSUMPTION

Jovana Ćalić [a], Milica Šelmić [a,*], Dragana Macura [a], Miloš Nikolić [a]

[a] University of Belgrade, Faculty of Transport and Traffic Engineering, Serbia

Abstract: *Rail freight transport is one of the most preferred modes of green transport since it emits three times less CO_2 and particulates per ton-mile than road transport. Train energy consumption is the biggest issue related to rail traction costs. Data about freight trains energy consumption per year are not possible to define precisely, so it is convenient to use fuzzy logic as a tool for data prediction. In order to predict it, we provide Wang - Mendel method for combining both numerical and linguistic information into a common framework – a fuzzy rule base. Relevant input variables are: freight train kilometers, average freight trains weight and non-productive kilometers. The output variable from the defined fuzzy logic system is average energy consumption per year for rail freight transport. The proposed model is applied and tested on real data collected in the Republic of Serbia.*

Keywords: *Train energy consumption; Rail freight transport; Prediction model; Wang-Mendel method; Fuzzy rules.*

1. INTRODUCTION

The term green logistics represents all efforts to manage and minimize the ecological impact of logistics activities. The main aim of this concept is moving and delivering goods with the lowest cost, but with the highest standards and minimal environmental impact.

In that sense, rail freight transport is one of the most preferred modes of transport since it emits three times less CO_2 and particulates per ton-mile than road transport. Besides these ecological benefits, rail transport is the most cost-effective mode of transport.

Rail transport gives the most important contribution to the green logistic concept, compared to all transport modes, because it is the least harmful to the environment. Table 1 shows date given in the studies for the years 2000 and 2008. In both studies, rail freight transport has the lowest external costs. One can notice that all modes of transport significantly decreased external cost in 2008 compared with the cost in 2000.

* m.selmic@sf.bg.ac.rs

Table 1. Average external costs - EU-27 Member States (Periods: 2000 and 2008) [€/tonne km]

	INFRAS/IWW, 2004	CE/INFRAS/ISI, 2011
	for 2000	for 2008
HDV	71.2	34
Road freight total	87.8	50.5
Rail freight	17.9	7.9
Inland waterways	22.5	11.2

Data source: CE Delft, Infras, Fraunhofer ISI, 2011

Figure 1 shows a comparison of the external cost road and inland waterway modes of transport with the external cost of rail transport. Figure 1 gives a ration of these costs. One can notice that ration for HDV (heavy duties vehicles) is increased from 3.98 in 2000 to 4.3 in 2008. The biggest difference in the rations is for road freight total (from 4.91 in 2000 to 6.39 in 2008). Rations for inland waterways are the smallest in the both years (1.26 in 2000 and 1.42 in 2008). Figure 2 gives a structure of external costs in 2008.

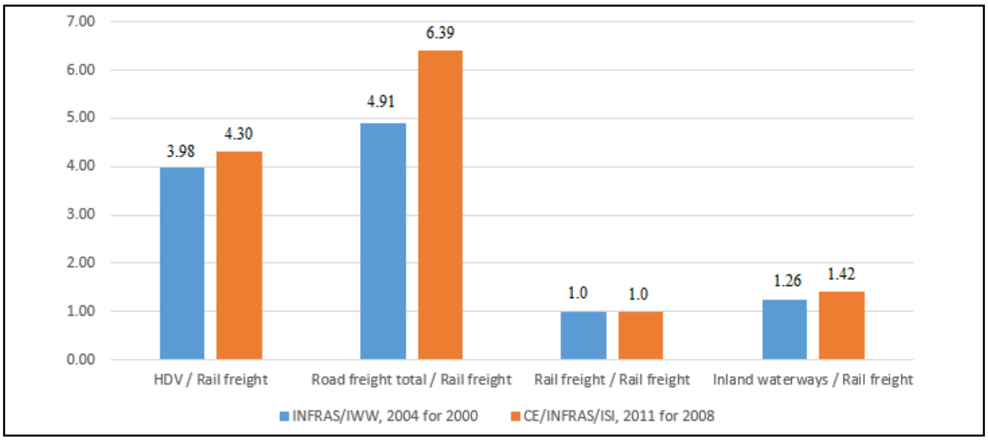

Figure 1. Average cost ration compared to rail (freight transport)
Data source: CE Delft, Infras, Fraunhofer ISI, 2011

Table 1 and Figures 1 and 2 show the advantages of the railway transport mode, which lead to an evident growth in rail freight logistics such as: cheap transport when compared to other modes of transport; more efficient as it allows larger volume of cargo transport to long distances; the transport of goods by train reduces the amount of fuel and emissions; the rail transport is considered to be six to seven times more efficient than road transport and reduces emissions by ~30-70%. The road transport is still dominant mode of transport in most of the countries around the world. However, some facts (increasing road congestion, costs, and emissions of CO_2) change the focus toward the railway transport.

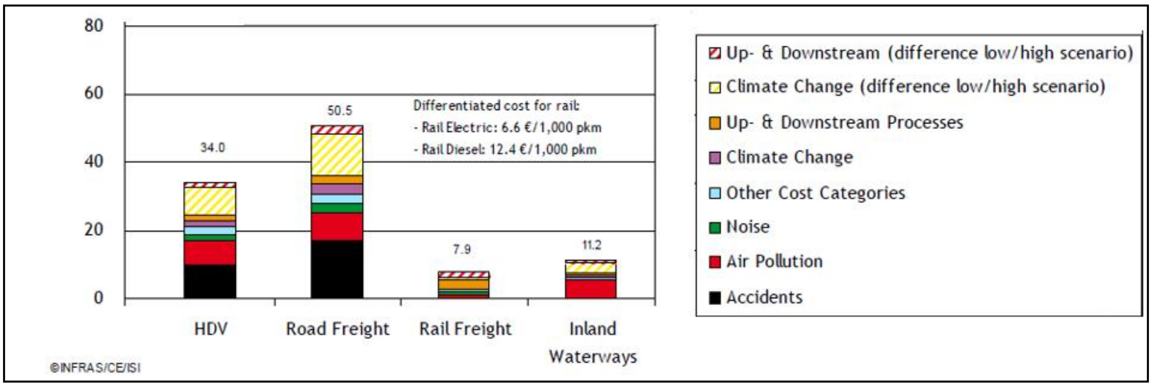

Figure 2. Structure of external costs (freight transport for 2008)
Data source: CE Delft, Infras, Fraunhofer ISI, 2011

The objectives of UIC (The International Union of Railways) are the rail share of freight land transport to be equal with the road and reducing specific average CO_2 emissions from train operations by 50% reduction by 2030. A consequence of these objectives is the energy consumption increasing. Train energy consumption is a basic and the biggest issue related to the rail traction costs. Data about freight trains energy consumption per year are not possible to define precisely, so it is convenient to use fuzzy logic as a tool for data prediction. In a defined problem, fuzziness appears due to the lack of ability of exactly predicting certain values.

In this paper, the model for train energy consumption prediction is developed. In order to forecast freight train energy consumption per year, we provide Wang-Mendel method for combining both numerical and linguistic information into a common framework – a fuzzy rule base. Relevant input values are: *freight trains kilometres*, *average freight trains weight*, *non-productive kilometres*. The output value from a defined fuzzy logic system is *average energy consumption* per year for rail freight transport. The proposed model is applied and tested on real data collected in the Republic of Serbia.

The paper is organized as follows. After Introduction, in Section 2, brief literature review is given. The developed model for determination of electric energy consumption for freight trains traction is presented in Section 3. Section 4 is dedicated to the case study, i.e. to the application of presented model on Serbian railway network. Last Section presents conclusions and future research directions.

2. BRIEF LITERATURE REVIEW

Wang Mendel method generates fuzzy rules from examples. Giving the literature review of the fuzzy systems in the transportation fields, Teodorović (1999) referred several papers with Wang Mendel method applications. Teodorović (1999) emphasized that Wang Mendel method represents a nonlinear mapping, with the possibility to approximate any real continuous function to arbitrary accuracy. Wang (2003) extended this method to enhance the practicality. The author presented the approach for ranking the importance of input variables and proposed an algorithm for solving pattern recognition problems. Chen et al. (2007) emphasized that Wang Mendel rule generation method is the one of the earliest algorithms, but with one disadvantage. This method selects the rules with the maximum degree, without taking into consideration other conflicting rules. The authors compared three methods, and the main conclusion of the paper is that the weighted mean method has the best robustness and error-tolerance, consequently this approach is suitable for extracting rules from the real data with noise. The results obtained by Yanar and Akyurek (2011) indicated that Wang Mendel method provides better starting configuration for simulated annealing compared to fuzzy C-means clustering method.

Wang Mendel method was used for energy consumption forecasting in Jozi et al. (2017). Results showed that the proposed method using the combination of energy consumption data and environmental temperature is able to provide more reliable forecasts for the energy consumption than several other methods experimented before, namely based on artificial neural networks and support vector machines. Authors Yang et al. (2010) presented an improved Wang Mendel method for electric load forecasting. They combined this approach with particle swarm optimization.

3. MODEL FOR PREDICTION OF ELECTRIC ENERGY CONSUMPTION FOR FREIGHT TRAINS TRACTION

Electric energy consumption for freight trains traction depends on various parameters such as: the utilization factor of the overhead line and the electrical substations, the power of the locomotive, the corrected virtual coefficient, train speed, the length of the section and the specific electric energy consumption per power. Since we do not have access to all these data, we apply Wang-Mendel method (Wang and Mendel, 1992) on the data which are available.

In order to predict the consumption of electric energy for the traction of freight trains on an annual basis, we take into account the following:

- Input variables:

1. *Trains kilometres -TK [km]* - It represents the number of kilometres that all electric locomotives passed by hauling freight trains, during one year. The greater the number of kilometres travelled, the greater the consumption of electric energy. Data are given annually.
2. *Average weight of trains - AWT [tonne]* - It provides information on how much a freight train is loaded on average. Electric locomotive hauling heavy freight trains consumes more electric energy. Data are given annually.
3. *Non-productive kilometres - NPK [km]* - The number of kilometres travelled by electric locomotives when they are out of the traction, or when they are not at the front of a train. Data are given annually.

- Output variable:

1. *Average energy consumption - AEC [kWh]* - It represents the amount of electric energy consumed by all the locomotives while they performed freight trains traction. Data are given annually.

For the implementation of Wang-Mendel model, it is necessary to have appropriate numerical data about the input and output variable (Table 2). As it can be noticed each set of desired input-output data is given in the form of: $\{(x_1^{(1)}, x_2^{(1)}, x_3^{(1)}; y^{(1)}), (x_1^{(2)}, x_2^{(2)}, x_3^{(2)}; y^{(2)}), \ldots, (x_1^{(8)}, x_2^{(8)}, x_3^{(8)}; y^{(8)})\}$.

Table 2. Values of input and output variables, in the 2007-2014 period†

Year	*TK*	*AWT*	*NPK*	*AEC*
2007	4 909 390	943	957 821	132 722 827
2008	6 890 035	1018	973 953	172 117 737
2009	6 547 541	1150	1 044 119	153 103 010
2010	5 091 884	998	841 230	114 569 156
2011	5 152 954	1100	690 245	118 585 848
2012	4 057 087	971	761 418	92 500 913
2013	4 628 479	912	693 911	110 200 700
2014	5 851 905	840	995 357	112 093 124

In the first step of Wang Mendel method, input and output spaces are divided into fuzzy regions. Assume that the domain intervals of x_1, x_2, x_3 and y are [x_1^-, x_1^+], [x_2^-, x_2^+], [x_3^-, x_3^+] and [y^-, y^+], respectively. We divide each domain interval into *2N+1* regions (*N* may vary from variable to variable) and assign each region a fuzzy membership (Table 3).

Table 3. Variable domains

Variable	Domain
Trains kilometres	[3.5, 7]‡
Average weight of trains	[700, 1300]§
Non-productive kilometres	[500, 1200]**
Average energy consumption	[80, 180]††

The domain division for the variable "*Trains kilometres*" has been done into 3 fuzzy sets (Figure 3):

- Small [3.5, 3.5, 4, 5] - represents a small volume of the freight train kilometres.
- Medium [4, 5, 6] - represents a medium volume of the freight train kilometres.
- Large [5, 6, 7, 7] - represents a large volume of the freight train kilometres.

† data collected in the Republic of Serbia.
‡ domain is expressed in million km.
§ domain is expressed in tonnes.
** domain is expressed in thousand km.
†† domain is expressed in million kWh.

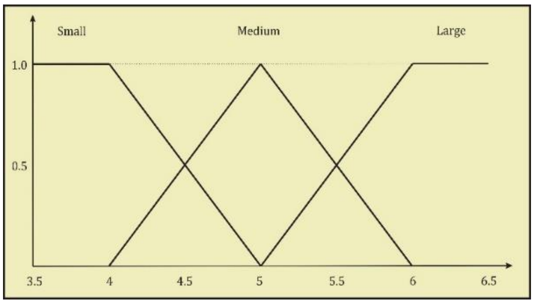

Figure 3. Membership functions of “*Trains kilometres*” fuzzy variable

The domain division for the variable “*Average weight of trains*” has been done in same way. Domain division is shown in Figure 4:

- Light [700, 700, 800, 900] - represents a light weight of freight trains.
- Medium [800, 100, 1200] - represents a medium weight of freight trains.
- Heavy [1100, 1200, 1300, 1300] - represents a heavy weight of freight trains.

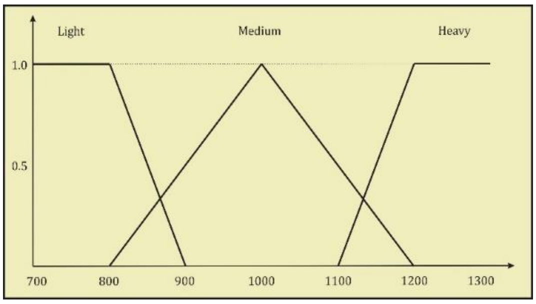

Figure 4. Membership functions of “*Average weight of trains*” fuzzy

For the variable “*Non-productive kilometres*” domain has been divided in three fuzzy sets (Figure 5):

- Small [500, 500, 600, 800] - represents a small amount of non-productive locomotive kilometres.
- Medium [600, 800, 1000] - represents a medium amount of non-productive locomotive kilometres.
- Large [800, 1000, 1200, 1200] - represents a large amount of performed non-productive locomotive kilometres.

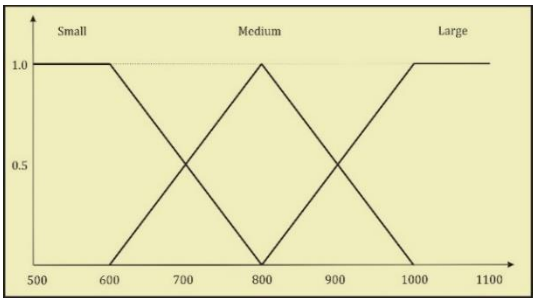

Figure 5. Membership functions of “*Non-productive kilometres*” fuzzy variable

Finally, it is necessary to cover a domain for "*Average energy consumption*" fuzzy variable (Figure 6) with the membership functions. The division has been carried out on 5 intervals.

- Very low [80, 80, 100] - represents a very low energy consumption.
- Low [90, 100, 120] - represents a low energy consumption.
- Medium [100, 120, 140] - represents a medium energy consumption.
- High [120, 140, 160] - represents a high energy consumption.
- Very High [140, 160, 180, 180] - represents a very high energy consumption.

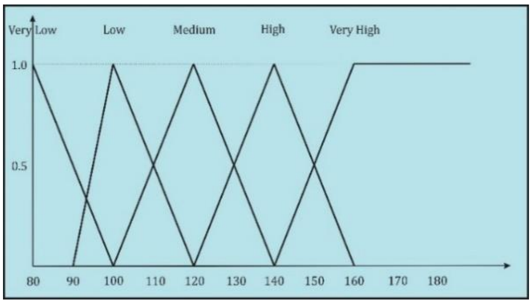

Figure 6. Membership functions of the output variable "*Average energy consumption*"

In the next step of Wang-Mendel method, the generation of the fuzzy rules should be done, based on numerical data. For each of the input-output pair, it is necessary to determine the membership degree to fuzzy sets that cover some of the intervals. After the membership degree determination, the considered values join that fuzzy set to which they belong with the highest membership degree (Teodorović and Šelmić, 2012).

Finally, we obtain one rule from one pair of desired input-output data, e.g.:

($x_1^{(1)}, x_2^{(1)}, x_3^{(1)}; y^{(1)}$) =›[$x_1^{(1)}$(4.9 in **Medium**, max), $x_2^{(1)}$ (943 in **Medium**, max), $x_3^{(1)}$ (957.821 in **Large**, max); $y^{(1)}$ (132.7 in **High**, max)] =› **Rule 1**.

Rule 1: IF x_1 is **Medium** and x_2 is **Medium** and x_3 is **Large**, THEN y is **High**

After this procedure we made 8 fuzzy rules, the one for each input-output pair of data.

The fuzzy rules obtain from numerical data are given below:

- If "*TK*" is **Medium** and "*AWT*" is **Medium** and "*NPK*" is **Large** then "*AEC*" is **High**;
- If "*TK*" is **Large** and "*AWT*" is **Medium** and "*NPK*" is **Large** then "*AEC*" is **Very High**;
- If "*TK*" is **Large** and "*AWT*" is **Heavy** and "*NPK*" is **Large** then "*AEC*" is **Very High**;
- If "*TK*" is **Medium** and "*AWT*" is **Medium** and "*NPK*" is **Medium** then "*AEC*" is **Medium**;
- If "*TK*" is **Medium** and "*AWT*" is **Heavy** and "*NPK*" is **Small** then "*AEC*" is **Medium**;
- If "*TK*" is **Small** and "*AWT*" is **Medium** and "*NPK*" is **Medium** then "*AEC*" is **Low**;
- If "*TK*" is **Medium** and "*AWT*" is **Medium** and "*NPK*" is **Small** then "*AEC*" is **Medium**;
- If "*TK*" is **Large** and "*AWT*" is **Light** and "*NPK*" is **Large** then "*AEC*" is **Medium**;

Next step is to check all obtained rules and to eliminate same or conflict rules, i.e. rules that have same IF part but a different THEN part. In this example all defined rules are correct, there are no conflict or same rules.

Most often, available pairs of input-output data are not sufficient to “cover” all the different situations that can happen in a particular system. Fuzzy rule base is more complete if the number of different input-output data pairs is bigger. In order to obtain better results fuzzy rule base may be amended with additional fuzzy rules generated by an expert. The final fuzzy rule base in the case of prediction of freight train average energy consumption in Serbia is shown in Table 4. Fuzzy rules generated by the experts are underlined.

Table 4. Final fuzzy rule base

	***TK*-Small**			***TK*-Medium**			***TK*-Large**		
	***AWT* small**	***AWT* medium**	***AWT* heavy**	***AWT* small**	***AWT* medium**	***AWT* heavy**	***AWT* small**	***AWT* medium**	***AWT* heavy**
***NPK* small**	<u>Very low</u>	<u>Very low</u>	<u>Low</u>	<u>Low</u>	Medium	Medium	<u>Medium</u>	<u>High</u>	<u>Very high</u>
***NPK* medium**	<u>Very low</u>	Low	<u>Low</u>	<u>Low</u>	Medium	<u>High</u>	<u>Medium</u>	<u>High</u>	<u>Very high</u>
***NPK* large**	<u>Very low</u>	<u>Low</u>	<u>Low</u>	<u>Medium</u>	High	<u>Very high</u>	Medium	Very high	Very high

4. CASE STUDY – RESULTS AND DISCUSSION

Considering the Serbian railway network, there is only 1278.7 km electrified railway lines that are one-third of the total network length (3735.8 km). The forecast of freight traffic on Serbian railway network (Figure 7) for period 2018-2022 shows an increase in freight traffic (Ćalić, 2018), and it is considered that most of the forecasted transport of goods will be carried out on electrified lines, as they are main lines.

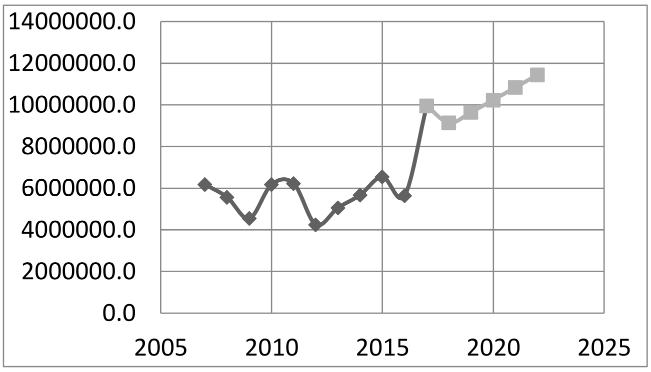

Figure 7. Forecast freight train transport for period 2018-2022, on Serbian railway networks

In order to test our model we apply the following input data (for year 2013):

- TK = 4.628 million kilometres,
- AWT = 912 tonnes,
- NPK = 693.911 thousand kilometres.

After defuzzification process, for which the centre of gravity is used, the output value is obtained: *AEC* is 109 million kWh.

Table 5 shows comparison of the results between real data and the one obtained from Wang - Mendel method.

Table 5. Comparison of the results

Year	*TK* [mil km]	*AWT* [tonne]	*NPK* [thousands of km]	*AEC* [mil kwh]	*AEC using Wang Mendel* [mil kwh]	Deviation [%]
2007	4.909	943	957.821	132.723	133	0.21%
2008	6.890	1018	973.953	172.118	164	-4.95%
2009	6.547	1150	1 044.119	153.103	163	6.07%
2010	5.092	998	841.230	114.569	128	10.49%
2011	5.153	1100	690.245	118.586	125	5.13%
2012	4.057	971	761.418	92.501	103	10.19%
2013	4.628	912	693.911	110.201	109	-1.10%
2014	5.852	840	995.357	112.093	133	15.72%

From Table 5 and Figure 8 it can be seen that developed Wang - Mendel method is able to predict energy consumption within 10% deviation in 5 cases, in 2 cases deviations are near 10%, and in just one case deviation is close to 16%. These results are very encouraging for the further implementation of this model.

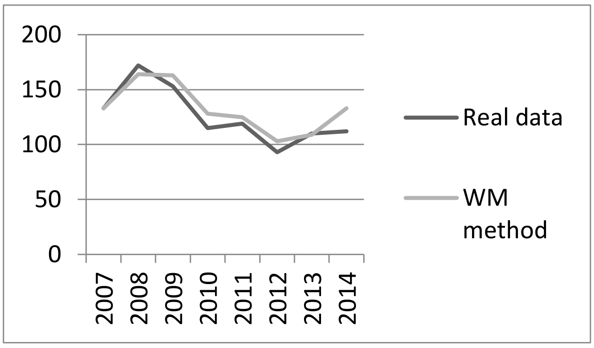

Figure 8. Comparison of the results

5. CONCLUSION

Electric energy consumption for rail freight transport is uncertain and hard to be predicted. When the data on energy consumption from previous period are available, Wang-Mendel method could be used to obtain fuzzy rules. However, fuzzy rules that could be defined according to data from the past most often do not reproduce all possible situations, which could emerge as a result of input variables membership functions combinations. This often leads to imprecision and inaccuracy.

This paper presents the model for prediction of freight train energy consumption. Relevant considered input are: *freight train kilometers, average freight train weight* and *non-productive kilometers*. The developed model is verified through the real data collected in the Republic of Serbia.

ACKNOWLEDGMENT

This work has been supported by Serbian Ministry of Education, Science and Technological Development through grants No. TR36002 and TR36022.

REFERENCES

[1] Ćalić J. (2018). Prognoza veličine i strukture teretnog kolskog parka za Srbija Kargo a.d. (Volume and structure forecast of freight wagon fleet for Serbia Cargo a. d.), BSc. thesis, University in Belgrade, Faculty of transport and traffic engineering, Belgrade.
[2] CE Delft, Infras, Fraunhofer ISI, 2011. External Costs of Transport in Europe: Update Study for 2008. Report commissioned by International Union of Railways UIC, CE Delft, Delft.
[3] Chen, D., Zhang, J., & Jia, Sh. (2007). WM method and its application in traffic flow modeling. In: International Conference on Transportation Engineering, 339-345.
[4] Jozi, A., Pinto, T., Praça, I., Ramos, S., Vale, Z., Goujon, B., Petrisor, T., "Energy consumption forecasting using neuro-fuzzy inference systems: Thales TRT building case study", Computational Intelligence (SSCI) 2017 IEEE Symposium Series on, pp. 1-5, 2017.
[5] Teodorović D. (1999). Fuzzy logic systems for transportation engineering: the state of the art. Transportation Research Part A, 33, 337-364.
[6] Teodorović D., Šelmić M. (2012). Računarska inteligencija u saobraćaju (Computer intelligence in traffic), University in Belgrade, Faculty of transport and traffic engineering, Belgrade.
[7] Wang, L. & Mendel, J. (1992). Generating fuzzy rules by learning from examples. IEEE Transactions on systems, man and cybernetics, 22 (6), 1414-1427.
[8] Wang, L.X. (2003). The WM method completed: A flexible fuzzy system approach to data mining. IEEE Transactions on Fuzzy Systems, 11 (6), 768–782.
[9] Yanar, T. A. & Akyurek, Z. (2011). Fuzzy model tuning using simulated annealing. Expert Systems with Applications, 38, 8159-8169.
[10] Yang, X., Yuan, J., Yuan, J. & Mao, H. (2010). An improved WM method based on PSO for electric load forecasting, Expert Systems with Applications, 37, 8036-8041.