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Calibration of microsimulation traffic model using neural network approach

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ABSTRACT

This paper presents the results of research on the applicability of neural networks in the process of computer calibration of a microsimulation traffic model. VISSIM microsimulation model is used for calibration done at the example of roundabouts in an urban area. The calibration method is based on the prediction of a neural network for one traffic indicator, i.e. for the traveling time between measuring points. Besides the traveling time, the calibration process further/also involves a comparison between the modeled and measured queue parameters at the entrance to the intersection. The process of validation includes an analysis of traveling time and queue parameters on new sets of data gathered both at the modeled and at a new roundabout. A comparison of the traffic indicators measured in the field and those simulated with the calibrated and uncalibrated microsimulation traffic model provides an insight into the performance of the calibration procedure.

1. Introduction

The functioning of a traffic system is under the influence of various aspects of human behavior (Onieva, Milanés, Villagrá, Pérez, & Godoy, 2012). Studies show that the behavior of traffic participants is, among other things, territorially and culturally conditioned (Olstam & Tapani, 2004). Microsimulation models include variable behavior of drivers at a level of each particular entity, and the reality of modeling results depends on the initial choice of the model (Fang & Elefteriadou, 2005) and success of the calibration process (Transportation Research Bord, 2000).

Calibration of a traffic model is actually an adjustment of a model to a specific local traffic network and its users. Calibration is defined as the process of comparing and minimizing the differences between the modeling results and the real data obtained by counting and measuring in the local network (Transportation Research Bord, 2000). Validation of the model is an estimate of the success of the model calibration made through a comparison of indicators obtained from the calibrated model and the ones measured in traffic.

Analysis of bigger spacial and time scopes of a traffic network and prediction of a future state both need a larger number of models, including traffic demand models (Ettema, Arentze, & Timmermans, 2011), dynamic traffic distribution (Flötteröd, Chen & Nagel, 2012), daily mobility (Flötteröd, Bierlaire, & Nagel, 2011), flow prediction under typical and atypical traffic conditions (Castro-Neto, Jeong, Jeong, & Han, 2009) etc. It is realistic to expect that modeling of the selection of a travel mode and users' routes is connected with the modeling of traffic (Park & Kim, 2001; Rickert & Nagel, 2001), economic and environmental indicators, both for real time modeling and for the prediction of the future traffic demand and its consequences. The degree of reliability of results of modeling a future state of the system is a subject to a debate (Dorothy, Ambadipudi, & Kill, 2006; Stevanović & Martin, 2008), but scientific efforts are directed towards an adoption of reliability criteria in selecting tools in planning and optimization processes.

Prediction of selection of users' routs on the microsimulation level (Flötteröd et al., 2011) and calibrations of traffic distribution model are not included. In this paper, the selection of users' routs, which is the traffic distribution in an examined segment of the traffic network, is a user defined input parameter of the microsimulation model. The aim of this paper is to obtain a calibrated microsimulation model which is able to give good correlation with measured functional characteristics of a particular segment of the network in real traffic conditions.

Genetic algorithm (GA) is the most commonly used calibration algorithm for input parameters of the simulation model. Positive utilization experiences of GA are reported in the following examples: in the calibration of FRESIM model (Cheu, Jin, Ng, Ng, & Srinivasan, 1998), PARAMICS model, VISSIM and CORSIM model (Park, Won, & Yun, 2006) and in the calibration of a VISSIM model (Kim, 2006). Analysis of acceptable time gaps and determination of

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(a) (b)

Fig. 1. The first (a) and the second (b) examined roundabout.

a critical time interval by means of Greenshields' model (Cicu, Illotta, Bared, & Isebrands, 2011) represent a description of the calibration method of the VISSIM microsimulation model at roundabouts in New York.

For the purpose of calibrating a microsimulation traffic model, a new calibration method is analyzed. This paper shows results obtained by applying neural networks in the microsimulation traffic model calibration process.

The first traffic indicator, chosen in the calibration process, is the traveling time between measuring points. Measuring points were chosen in the real environment and connected to existing objects – a light pole at the beginning of the section and an electric supply pole at the end, because it was easier to enter them into the model layout that way. The traveling time is easily measurable in the field, and it is under the influence of the variable driver's reaction time. In this paper, the mean traveling time is used in order to test the response of neural networks for the given indicator. Furthermore, another easily measurable traffic indicator – queue parameters – is introduced in the calibration process. Validation is done for the traveling time and queue parameters for new sets of measured data. The findings of the comparison of modeled and measured data of the microsimulation traffic model, calibrated to one roundabout, are also shown, and the validation is done on another roundabout.

Prediction of traveling time, obtained by application of neural network (Park et al., 1999; Dia, 2001) can be analyzed in a broader context of traffic modeling, but a special emphasis is, in this case, used in microsimulation modeling.

The microsimulation model, selected to investigate the applicability of neural networks in the calibration process, is the VISSIM.[1] Analyses are performed on the basis of results obtained by one-hour traffic simulations, corresponding to the duration of the data gathering in the field for every set of data measured in real traffic conditions.

2. Data gathering

As the basis for testing the neural network applicability in the process of calibration, the one-lane urban roundabout Vinkovačka–Drinska in Osijek (Croatia) – roundabout I (Fig. 1a) – was used. The calibration process was done in two steps. The first step is based on the traveling time prediction obtained from the neural network, and the other step introduces queue parameters into the analysis. Maximum queue length and the number of vehicle stopping at the entrance into the roundabout, both easily collected under real traffic conditions, are selected. An estimate of the success of the calibration process is made iteratively also in two steps. The first validation is done at the same roundabout, but for new sets of data, and the second validation is done at a new one-lane roundabout Kirova–Opatijska in Osijek – roundabout II (Fig. 1b).

Data was gathered, during 2010, at both roundabouts by means of one-hour video camera recordings (Table 1). Both points for measuring the traveling time at both roundabouts are included in the video.

Detailed data on the traffic load of the roundabouts for all sets of measured data are available in the dissertation (Ištoka Otković, 2011).[2] The results of measured traffic indicators for all sets of measured data are shown in the Table 1 with the calibration data set shaded. The other sets of measured data were used for validation of the calibrated model. The traffic load counted on March 3rd 2010, between 3 and 4 p.m., shows that nearly 1600 vehicles, overall, entered the roundabout. An hour later, one hundred vehicles less entered the roundabout. Measuring, done on July 14th 2010, shows that 250 less vehicles entered the roundabout, which reflected on the traffic indicators of the roundabout. Traffic loads of pedestrian flows are not large and this should be taken into account when the results of modeling are interpreted.

3. Calibration of microsimulation model using neural network approach

Microsimulation models have a considerable number of model input parameters. Examination of all combinations of input parameters of the model in their range by means of application of microsimulation model, in order to find a combination of input parameters that approximates the real traffic situation the best, would be an extremely time-consuming task.

A computer can examine a large number of combinations of values of model input parameters in real time, in case that it can obtain software simulation output values (e.g. traveling time) of the examined microsimulation traffic model (in this case the VISSIM). The role of a neural network is to predict values of the VISSIM simulations in the process of software examination of combinations of input parameters.

In Fig. 2 a simplified scheme of program calibration is shown.

The program calibration begins with the creation of a VISSIM simulation database for neural network training (Fig. 2). The task of the neural network is to predict the time of travel between measuring points for particular values of input parameters, which would be obtained by the microsimulation model. The program calibration (MATLAB) calls the prediction function, provided by

[1] VISSIM is a stochastic, discrete, micro-simulated (models each entity separately) model designed for traffic analyses. It started to develop in Germany at the University of Karlshruhe in the early 70-ies of the last century.

[2] Dissertation is available on-line, in Digital library of the University of Maribor (DKUM).

Table 1
Values of measured traffic indicators at examined roundabouts.

	Roundabout I			Roundabout II
	March 3rd 3–4 p.m.	March 3rd 4–5 p.m.	July 14th 2–3 p.m.	July 14th 8–9 a.m.
Mean value of traveling time (s)	21.8	19.9	18.1	13.3
Maximum queue (m)	26	21	15.5	23
Number of stopping at the entrance	89	61	54	56

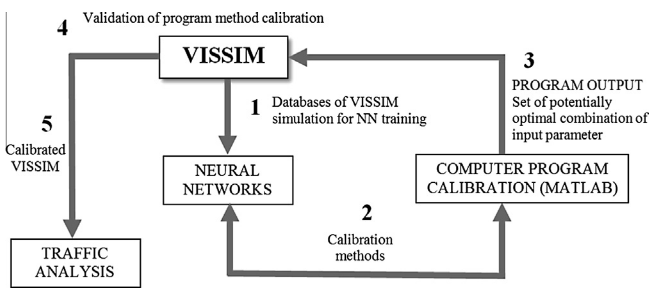

Fig. 2. Scheme of computer program calibration.

the neural network within the calibration program (subroutine), for each combination of values of input parameters within the given ranges of values and by a chosen/defined step (Table 2). The preset criterion of comparison of modeled (by neural network prediction) and measured values of traveling time according to expression (1) generates a set of potentially optimal combinations of input parameters values into an output file.

$$\left|\frac{T_{\mathrm{MOD}} - T_{\mathrm{MEAS}}}{T_{\mathrm{MEAS}}}\right| \leqslant 5\% \qquad (1)$$

where: T_{MOD} is the mean value of modeled traveling time between measurement points, and T_{MEAS} is the mean value of measured traveling time between measurement points.

The final selection of optimal input parameters from a set of potentially optimal solutions, generated by the calibration program, is performed based on the simulation results of the original microsimulation traffic model (VISSIM). Validation process of the calibration method is also done (Fig. 2) by application of the real microsimulation model (VISSIM).

3.1. Input parameters of the model

The number and the extent of input parameters used in the analysis are directly correlated to the number of possible combinations of input parameters necessary to be analyzed in the calibration process. In the process of optimizing the number of model input parameters and their ranges, various statistical methods, described in detail in literature (Kim, 2006; Park & Qi, 2005), are used. In this paper, neural networks were used for optimisation of input parameters and ranges. Backpropagation type of neural networks can provide a coefficient of influence of every input parameter on the output result, which gives a possibility to select only input parameters influential on the modeled traveling time. Neural networks have the ability of extrapolation of results, which makes the question of selection of initial ranges of input parameters a less sensitive issue in the process of calibration. The selection of input parameters of the model and their ranges in two steps is described in detail in the dissertation (Ištoka Otković, 2011), and the final result is shown in Table 2.

3.2. Application of neural networks to traveling time prediction

The NeuroShell2 software package is used for neural network learning as well as prediction results analysis. The following basic neural networks were tested: Ward Nets, Standard Nets, Jump Connection Nets, Jordan–Elman Nets and General Regression Net (Fig. 3).

In total, 70 neural networks, which differed in basic architecture, number of hidden layers, number of neurons in hidden layers and activation functions, are analyzed.

Neural networks are compared by two basic criteria – training and the ability to generalize. Training is a success of prediction on a training set of data (the set network has learned on), and generalization is the success of prediction on an unknown set of data. A sufficiently large training database partially prevents the network overtraining[3] effect and creates a precondition for achieving better generalization (Lawrence, Giles, & Tsoi, 1997). For the specific problem, it is possible to create a database for neural network learning of desired size and, therefore, a database of 1379 examples of variations of input parameters and output results of VISSIM simulations is generated. From the database, within the NeuroShell2 program, 20% of data (276 data) is separated in order to be used as a network validation test set. The program offers a possibility of memorizing the best result (the best prediction) on a test set of data, as well as memorizing the best result on set of data used for the network to learn (training data set).

The following indicators were chosen to compare our particular trained networks: correlation coefficient between results of neural network prediction and results of VISSIM simulations, mean absolute error and maximum absolute error.

The names of all researched networks were coded in order to make them easy-to-survey. The numbers indicate the number of neurons in hidden layers as well as the number of hidden layers (e.g. 13-24-13 is a neural network with three hidden layers having 13 neurons in the first and the third hidden layer and 24 neurons in the second hidden layer). The names of the neural network models included the activation functions of the hidden layers in situations where they differ from the (proposed) default activation functions. The best prediction on the validation (test) data set is the one that is the most often memorized, but there is also the possibility to memorize the best prediction on the training data set which is in this case marked with the "TR" mark. For the General Regression Network, adaptive (AD) and iterative (IT) types of network were analyzed.

The comparison of those neural networks that achieved the best prediction results, according to the three chosen criteria, is shown in Table 3.

According to the obtained neural network learning results, the best correlation was obtained for the iterative type of regression neural network, as evident from Table 3. Considering the fact that traffic flow modeling is a stochastic problem and that a basic VISSIM model uses a random number generator, the achieved correlation of 88.3% is satisfactory.

In graphs, one set of input data on the abscissa represents one combination of input parameter values (Table 2). One set of values of model input parameters gives one modeled mean traveling time

[3] The ratio between the number of input parameters and size of the network training set can be one of the causes of the overtraining. If the number of input parameters is large, and the number of examples in the learning set is small, the network will rather remember, than learn and generalize on the training data set. It should be noted that the ratio between the number of input parameters and the size of network learning set is not the only cause of bad network generalization effect.

Table 2
Selection of input parameters of the VISSIM calibration model.

P	Input parameters	Value range	Step	Default value
P1	Simulation resolution	1–10	1	5
P2	Number of observed proceeding vehicles	1–4	1	2
P3	Max look ahead distance (m)	100–300	1	250
P4	Min look ahead distance (m)	0–20	1	0
P5	Average standstill distance (m)	1–3	0,1	2
P6	Additive part of desired safety distance (m)	1–5	0,1	2
P7	Multiplicative part of desired safety distance (m)	1–6	0,1	3
P8	Desired speed (km/h)	25–50	10	40*

* Expected (desired) travel speed at access lanes of the observed urban intersection. The selected range is designed based on measured velocity on access roads of the observed intersection.

Table 3
Performance indicators of trained neural networks – networks with a good response.

Type of neural network	Correlation coefficient	Mean absolute error	Maximum absolute error
Ward Nets-3 hidden layers 13-18-13	0.8270	0.332	3.000
Ward Nets-3 hidden layers 13-18-20	0.8286	0.331	3.132
Ward Nets-3 hidden layers 13-24-13	0.8309	0.330	3.201
Standard Nets-3 hidden layers13-13-13	0.8355	0.333	3.000
Standard Nets-2 hidden layers 19-19-tanh-logist	0.8208	0.292	3.200
Standard Net-3 hidden layers 26-18-15-tanh-logist	0.7955	0.262	4.421
Standard Nets-3 hidden layers 30-20-18-tanh-logist	0.8199	0.280	3.000
Standard Nets-3 hidden layers 18-15-15-TR	0.8480	0.306	3.000
Standard Nets-3 hidden layers 20-15-13-tanh-logist-TR	0.7881	0.288	4.100
Standard Nets-2 hidden layers 19-24-tanh	0.8402	0.334	3.027
Standard Nets-1 hidden layer 38	0.8378	0.328	3.000
General Regression Net-1 hidden layer 2200tanh-AD	0.8554	0.311	3.000
General Regression Net-1 hidden layer 2380logist-AD	0.8491	0.322	3.000
General Regression Net-1hidden layer 2480tanh-AD	0.8554	0.311	3.000
General Regression Net-1hidden layer 2550-AD	0.8501	0.317	3.000
General Regression Net-1hidden layer 3500tanh-AD	0.8581	0.308	3.000
General Regression Net-1hidden layer 3500tanh-IT	0.8811	0.285	3.328
General Regression Net-1hidden layer 5500logist-AD	0.8469	0.323	3.001
General Regression Net-1hidden layer 5500logist-IT	0.8830	0.278	3.432
Jump Connection Nets-2 hidden layers 19-19	0.8374	0.326	3.000
Jordan–Elman Nets-2 hidden layers 38-38-tanh-logist	0.8293	0.334	3.000

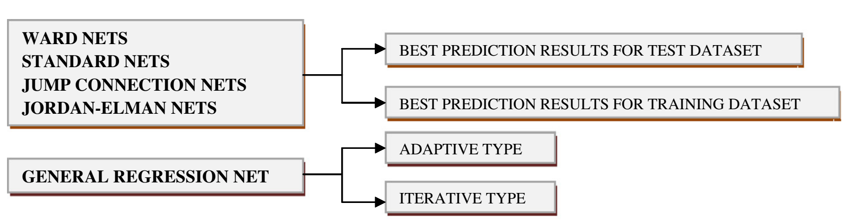

Fig. 3. Examined types of neural networks.

between measuring points depicted on the ordinate (Figs. 4–7). In Fig. 4, different combinations of input parameter values (1379 combinations) is depicted on the abscissa, and the ordinate shows the corresponding modeled mean traveling time for every set of input data. Traveling time obtained from the General Regression Network (Table 3) is compared to results of the VISSIM simulations for 1379 different combinations of values of input data used for neural network learning – training data set (Fig. 4).

Besides the software testing of the generalization ability, a two step independent estimate of neural networks is also designed. A set of 25 combinations of new input parameters was used for a comparison of results of generalization of all trained networks. Traveling time prediction provided by the neural network was compared with the traveling time obtained from the VISSIM model. A part of results obtained from Ward Net and Standard Net neural network in the first step of an independent validation is shown in the Fig. 5 and those from the General Regression Network is presented in the Fig. 6.

From graphs in Figs. 5 and 6, it is noticeable that the General Regression Networks usually give better generalization results (Fig. 6), than Ward and Standard Net neural network types (Fig. 5).

The final validation is done on the basis of data received from 64 new combinations of input parameters, for networks which have shown the best results in the trial validation (Fig. 7). Comparison and assessment are made according to the criterion of minimal mean absolute error. Prediction error is an absolute value of

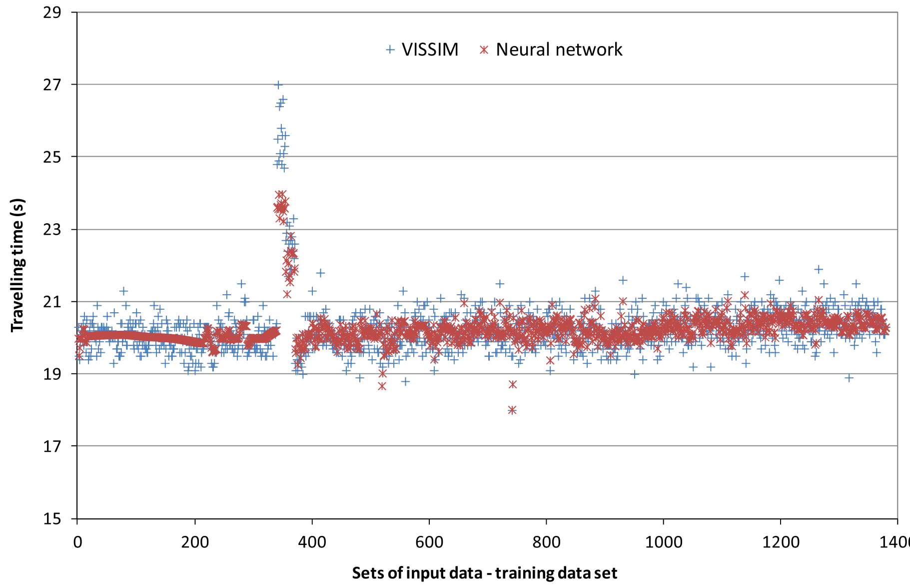

Fig. 4. VISSIM simulations vs. neural network GR 5500logist IT – training data set.

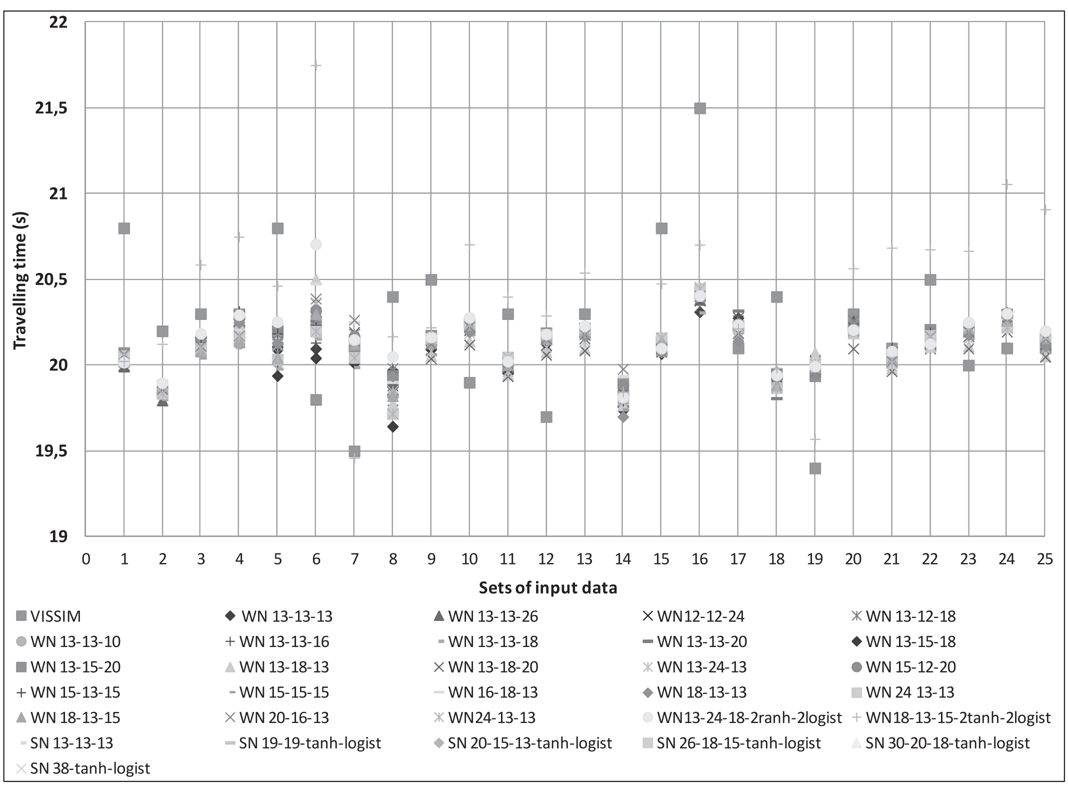

Fig. 5. Traveling time prediction for a part of examined neural network.

difference between neural network prediction results and the expected value obtained by VISSIM simulation.

The General Regression Network of the iterative type with a one hidden layer, 5500 neurons in that layer and logistic function of activation, with the approximate configuration depicted in the Fig. 8, had the best correlation with the mean traveling time obtained by the VISSIM simulation model. The same network has achieved the best generalization result in both steps of the independent estimate of neural networks, as it is described in detail and presented in the dissertation (Ištoka Otković, 2011), and therefore it was chosen for traveling time predictions (replacement for the VISSIM) in the program calibration process (Fig. 2).

Schematic overview of the configuration of the chosen neural network is shown in the Fig. 8.

3.3. Traffic microsimulation model calibration program

The mean traveling time measured in the field, for the calibration data set, is 21.8 s (Table 1). The mean traveling time obtained by VISSIM simulation, with default values of input parameters, is

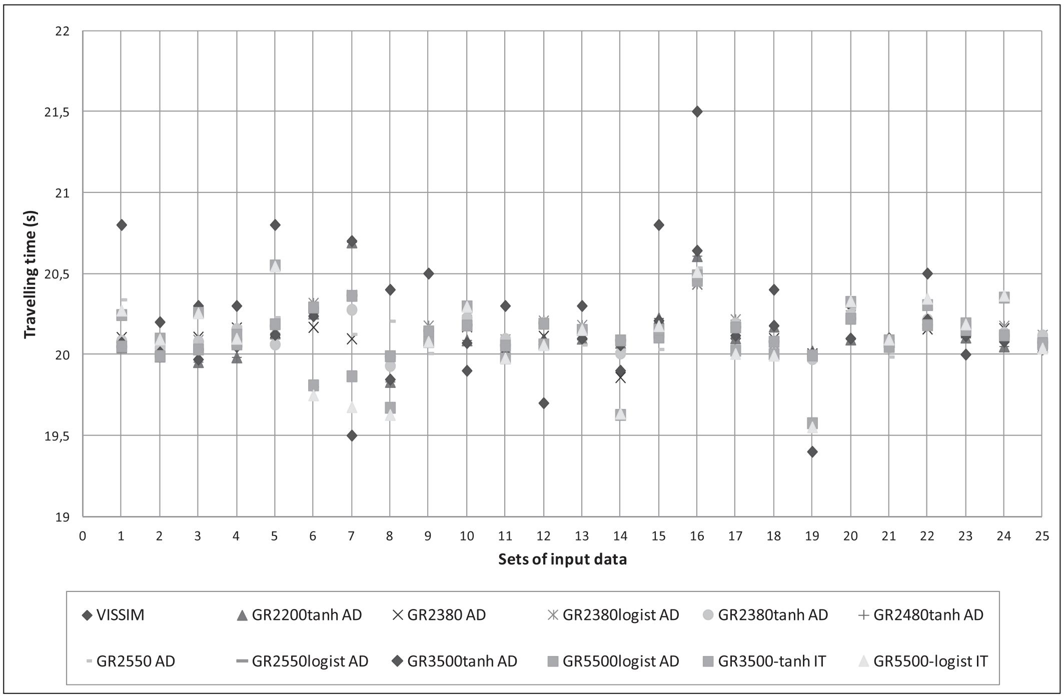

Fig. 6. Test prediction for adaptive and iterative type of General Regression Networks.

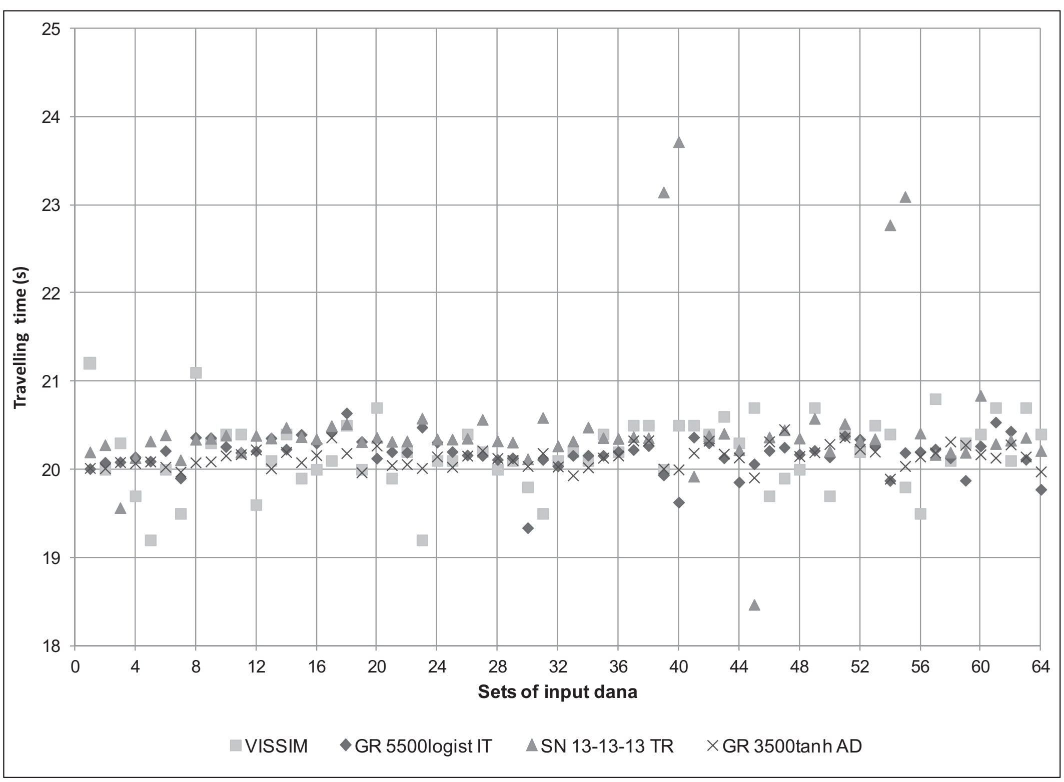

Fig. 7. Prediction results of the best neural networks on the validation set of data.

20.3 s. The aim of the calibration procedure is to find such combination of values of input parameters, which will approximate the mean measured traveling time.

The calibration computer program for the analyzed problem is written in MATLAB programming language. The algorithm, a detailed description of the program and the calibration program itself are available in Dissertation (Ištoka Otković, 2011). The basic steps of the program are shown in Fig. 2. For every combination of values of input parameters (Table 2) the program calls the prediction function given by the neural network as a subroutine. A practical problem, which occurred at this research stage, was the connection of neural network prediction function and the MATLAB program.

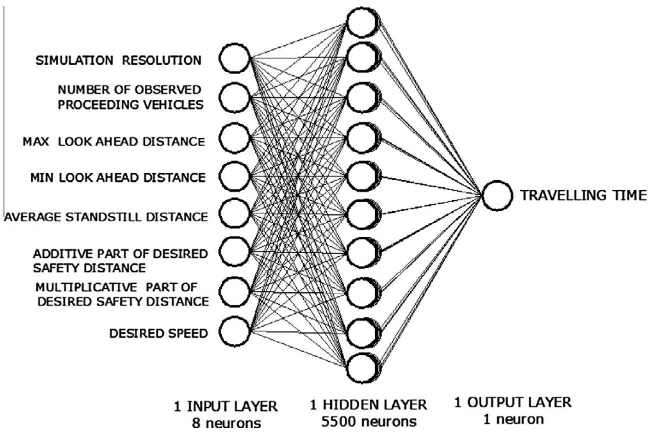

Fig. 8. Scheme of artificial neural network for traveling time prediction.

Since this was a large output file, manual programming of the prediction function in MATLAB format was a time-consuming job. Therefore a special MATLB program, which used the output prediction function of the trained neural network in MATLAB format (Ištoka Otković, 2011), had been designed.

According to the criterion set in the expression (1), the program generated a set of potentially optimal combinations of input parameter values, and the final selection of the optimal combination was done by application of the original microsimulation traffic model (VISSIM), analysis of traveling time and queue parameters for the existing and new sets of measured data.

3.4. Analysis of program calibration results

Analysis of the output file of the calibration program of potentially optimal input parameters combinations makes it obvious that there is a certain number of combinations with the maximum values of input parameters P5, P6 and P7 (Table 2). Maximum values of those input parameters influence the modeled capacity of the intersection. Results of the simulation in the VISSIM show that the VISSIM does not manage to generate the overall traffic load in the designated time, which indicates that the capacity of the modeled section is smaller than the real one. Generally, the neural networks gave the correct setting, but realistically, combinations of input parameters P5, P6 and P7 with a maximum value or a value close to the maximum, in the combination, significantly reduce the capacity in comparison to the real one and in this case they are not applicable.

The output file analysis procedure is described in detail in the dissertation, but when the combination of input parameter with maximum values (P5, P6, P7) is left out, matching of the results of the output file and VISSIM simulations (80% of the results has less than 5% difference), is seen in Fig. 9.

The final selection of values of model input parameters, which will make the best approximation of local traffic conditions (calibrated model), was made through the second step of calibration, by the comparison of modeling results to measured values of traveling time and queue parameters at the examined roundabout.

3.5. Queue parameters

During the second step of calibration a set of potentially optimal combinations of input parameters is analyzed in the context of VISSIM simulation values obtained for queue parameters – maximum queue length and number of stopping at the entrance into the roundabout. When the results of the modeling in the VISSIM for 80 combinations of values of input parameters are compared with results of traffic indicators measured in the field according to expression (2), 13 combinations of input parameters, which satisfy the criterion set for three examined traffic indicators, are obtained. In the real traffic conditions, 21.8 s mean traveling time, maximum queue length of 26 m and the number of stopping at the entrance of 89 are measured (Table 1).

$$\left|\frac{T_{\mathrm{MOD}} - T_{\mathrm{MEAS}}}{T_{MEAS}}\right| \text{and} \left|\frac{\mathrm{Qmax_{MOD}} - \mathrm{Qmax_{MEAS}}}{\mathrm{Qmax_{MEAS}}}\right| \text{and} \left|\frac{STOP_{\mathrm{MOD}} - STOP_{\mathrm{MEAS}}}{STOP_{\mathrm{MEAS}}}\right| \leqslant 5\% \tag{2}$$

where: T_{MOD} is the mean value of modeled traveling time between measurement points, and T_{MEAS} is the mean value of measured traveling time between measurement points, and $Q\max_{\mathrm{MOD}}$ mean value of modeled maximum queue at the entrance, and $Q\max_{\mathrm{MEAS}}$ is the mean value of measured maximum queue at the entrance, and $STOP_{\mathrm{MOD}}$ is the mean value of the modeled number of stopping at the entrance, and $STOP_{\mathrm{MEAS}}$ is the mean value of the measured number of stopping at the entrance.

In Table 4 those combination values of input parameters that were the closest to the measured values in the field are shaded.

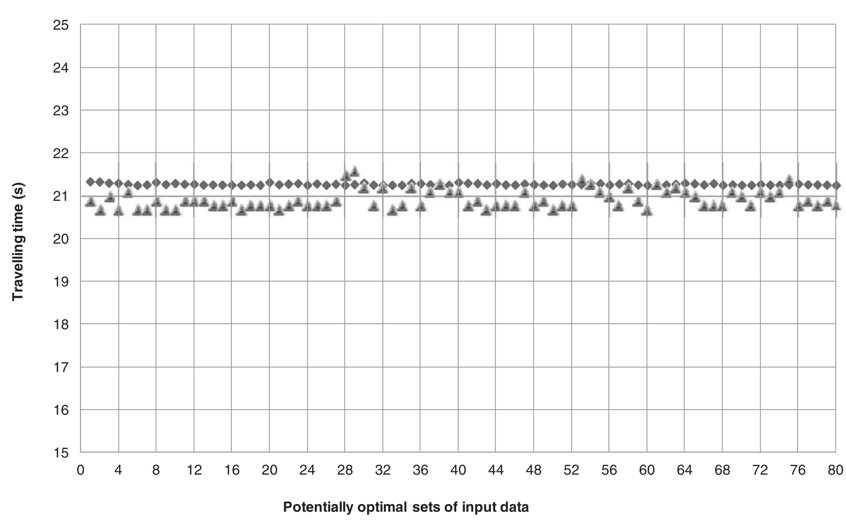

Fig. 9. Output data-file of calibration program compared with the VISSIM simulation results.

Table 4
Calibration by the other traffic indicator (1st set of measured data).

Input parameters								Neural network	VISSIM		
P1	P2	P3	P4	P5	P6	P7	P8	*T*	*T*	Q_{max}	*STOP*
6	4	164	8	2.4	2	3.3	40	21.267	20.8	25	86
6	4	172	8	2.4	1.9	3.4	40	21.303	20.8	25	90
6	4	172	8	2.4	1.9	3.5	40	21.295	20.9	25	89
6	4	172	8	2.5	1.9	3.3	40	21.295	20.8	25	86
6	4	172	12	2.4	1.9	3.4	40	21.271	20.8	25	90
6	4	172	12	2.4	1.9	3.5	40	21.264	20.9	25	89
6	4	172	12	2.5	1.9	3.3	40	21.283	20.8	25	86
6	**4**	**173**	**8**	**2.4**	**1.9**	**3.4**	**40**	**21.298**	**21.1**	**25**	**85**
6	4	173	12	2.4	1.9	3.4	40	21.298	21.1	25	85
6	4	175	8	2.5	1.9	3.5	40	21.262	21.0	25	85
6	**4**	**176**	**8**	**2.4**	**1.8**	**3.5**	**40**	**21.275**	**21.4**	**27**	**88**
6	4	176	8	2.5	1.8	3.4	40	21.273	20.9	27	90
6	4	176	12	2.5	1.8	3.4	40	21.273	20.9	27	90

Two bolded combinations of input parameters, which present the best result, entered the validation procedure. The value of simulated time of 21.4 s was the best result, and, for the second combination, one out of two practically the same combinations was selected. VISSIM, unlike neural networks, provides the same values of traffic indicators (P4 = 8 and P4 = 12), thus one of two combinations that differ only by the fourth input parameter P4, was selected.

4. Validation of the calibrated model

The validation procedure is comprised of two steps and it involves a comparison of simulation results obtained by an uncalibrated and a calibrated VISSIM microsimulation model with traffic indicators measured in the field. The first validation was done for two new sets of data measured at the same roundabout where the calibration is done (roundabout I). The second validation, done on the set of data measured at the second roundabout (roundabout II), gives an insight into the dilemma whether the calibration process is tied to the one particular roundabout or it may be considered in a broader context.

4.1. First validation

The first validation was performed at the same roundabout at which calibration procedure was carried out. The first validation data set of traffic parameters was measured on Wednesday, March 3rd 2010, between 4 and 5 p.m., and the second one was gathered on Wednesday, July 14th 2010, between 2 and 3 p.m.

In Dissertation (Ištoka Otković, 2011), data on traffic volume and traffic distribution in the roundabout for all performed counting and the measured traffic parameters are presented and a single measured passing time between the measurement points for each vehicle in the reference period for all counting was given.

It is evident from the Table 5 that default values of input parameters have provided traffic parameters which did not meet one of the three indicators, i.e. maximum queue differs for 28% from the measured values. The first combination of calibrated model input parameters satisfied all three criteria with an error smaller than 5% for the first measured data set. Both parameter combinations, obtained by calibration procedure (shaded), satisfied the limit set by expression (2) approaching the values measured in the field for the second data set.

4.2. Second validation

The second validation was performed at the new location, at the second observed roundabout (roundabout II). Data were collected and traffic parameters measured, on Wednesday morning, July 14th 2010, between 8 and 9 a.m. A graphic presentation of the main roundabout project and measured data of traffic volume and traffic distribution, given in Dissertation (Ištoka Otković, 2011), served as the background for the second validation.

VISSIM simulation values for input parameters default values and the two best parameter combinations were compared with measured values of traffic parameters and presented in the Table 6. Default values of input parameters provided simulation values of traveling time within specified limits, but the queue parameter

Table 5
Comparison of traffic indicators – first validation.

Input parameters of VISSIM model								Traffic indicators		
P1	P2	P3	P4	P5	P6	P7	P8	*T*	Q_{max}	*STOP*
Measured values										
First validation data set								19.9	21	61
Second validation data set								18.1	15.5	54
Values obtained by VISSIM model simulations										
Default values of input parameters – first validation measured data set										
5	2	250	0	2	2	3	40	20.3	15	60
Default values of input parameters – second validation measured data set										
5	2	250	0	2	2	3	40	17.6	23	50
Calibrated model – first validation measured data set										
6	4	176	8	2.4	1.8	3.5	40	19.8	22	58
6	4	173	8	2.4	1.9	3.4	40	20.2	15	63
Calibrated model – second validation measured data set										
6	4	176	8	2.4	1.8	3.5	40	17.6	15	52
6	4	173	8	2.4	1.9	3.4	40	17.8	15	53

Table 6
Comparison of traffic indicators – second validation, second roundabout.

Input parameters of VISSIM model								Traffic indicators		
P1	P2	P3	P4	P5	P6	P7	P8	*T*	Q_{max}	*STOP*
Measured values										
								13.3	**23**	**56**
Values obtained by VISSIM model simulations										
Default values of input parameters										
5	2	250	0	2	2	3	40	13.1	27	50
Calibrated model – third validation measured data set										
6	4	176	8	2.4	1.8	3.5	40	13.1	22	58
6	4	173	8	2.4	1.9	3.4	40	13.1	22	54

results were not within the expected range. The simulation results showed 26% greater maximum queue value and 10.7% lower value for the number of stopping at the roundabout entrance. Combinations of input parameters, obtained by calibration procedure, were within limits set by expression (2) and are shaded in the table.

By analyzing and comparing the results of values of traffic parameters shown in Tables 4–6, the combination of input parameters, that satisfied all the observed indicators within the pre-set statistical limits, according to expression (2), can be observed. The first combination, obtained by calibration procedure, achieved the optimal combination of values of input parameters for single-line roundabouts in local traffic conditions shown in Table 7.

5. Discussion

In the dissertation (Ištoka Otković, 2011) several calibration methods were analyzed using computer software calibrations based on the following:

- Prediction of a neural network for a traffic indicator – traveling time between measuring points;
- Prediction of a neural network for three traffic indicators – time of travel between measuring points, maximum length of a queue and number of stopping at the entrance into a roundabout;
- Three independent neural networks which give three independent predictions for the examined traffic indicators.

This paper describes in details the method, which provided the best result. This method is based on the prediction of one neural network for the traveling time between measuring points.

Results presented in this paper clearly show that a neural network is not an alternative to a microsimulation model. The neural network achieved accurate results of traveling time prediction, but in this research no neural network gave good results for queue parameter prediction. This paper does not implement neural networks in the prediction of other traffic indicators obtained by means of microsimulation model.

A database of 1379 combinations of values of the model input parameters and the simulation traveling time results made in the VISSIM is used for neural network learning. Such a large database is used in order to investigate the real neural networks response and in order to prevent the network overtraining or lack of variability in the network database to be the causes of possible bad results. It is presumed that such a large database is not necessary for achieving optimal results of neural network learning.

Table 7
Optimal values of VISSIM model input parameters.

Optimal values of VISSIM model input parameters							
P1	P2	P3	P4	P5	P6	P7	P8
6	4	176	8	2.4	1.8	3.5	40

The calibration computer program calls the neural network prediction as a subroutine and each combination of values of input parameters that meet the set statistical criteria – expression (1), is entered in the output file.

Upon the analysis of the calibration program output file in VISSIM, 80 potentially optimal combinations of input parameters, which satisfy the criterion (1) set for the traveling time, are obtained. In the second step, 80 combinations were analyzed by applying the VISSIM, and in the context of the second traffic indicator, in order to choose combinations of values of input parameters which provide good simulation results for both traveling time and queue parameters. 13 combinations, which satisfy the condition set in accordance with expression (2), were obtained. Two combinations, which were the best in approximating values measured in the field on the calibration data set, were selected out of those thirteen combinations.

The validation procedure was done in two steps, and traveling time and queue parameters, obtained by calibrated and uncalibrated traffic model, were compared to values measured in the field. In the first validation, a new data set, measured at the same roundabout for which the model calibration was done, was compared (Table 5). From Table 5 it is obvious that the calibrated model gives simulation results for traveling time between measuring points and queue parameters closer to values measured in the field, than the uncalibrated model with default values of input parameters of the model.

The second validation is done at the other roundabout (Table 6). Results, obtained by the comparison of modeling results and traffic indicators measured in the field, show that better results are reached with the model calibrated on the second roundabout of the same type in the local traffic network than with the uncalibrated model. The results in Table 6 show that the calibrated microsimulation model is applicable to the one-lane roundabouts in a local condition and that it is not necessarily related to the location of the intersection where the calibration is made. Such a conclusion should not be taken too seriously, given that the research was based on two one-lane roundabouts. Possibility of generalized application of the obtained values of input parameters to other types of roundabouts or intersections in a local traffic network in general should be additionally explored. However, such an opinion is not unfounded, because most of calibrated input parameters are related to the behavior (psychology) of driver, which is to some extent territorially and culturally conditioned.

The combination of model input parameters, which approximates local traffic conditions the best, is selected by the analysis of achieved results, presented in Tables 4–6. Optimal combination of values of model input parameters (Table 7) represents the calibrated microsimulation traffic model for one-lane roundabouts in the examined local network.

6. Conclusion

Within this paper, a new calibration method encompassing the application of a neural network for the prediction of the results of simulations of microsimulation traffic model within the computer calibration program is analyzed.

Traveling time and queue parameters are the traffic indicators which are analyzed in the process of calibration and validation of the model, because they are easily measurable in real traffic conditions. The microsimulation model selected for the study of the applicability of neural networks in the calibration procedure is the VISSIM, and two urban roundabouts were used as the basis of the experiment.

Results have shown that a neural network is applicable in the process of calibration of the examined microsimulation model.

Basic steps of the calibration method by means of neural network application include:

- A minimum of two sets of measured data (the first for the model calibration and the second for the validation), which are: vehicle and pedestrian traffic load, traffic distribution, mean traveling time between two chosen measuring points easy to enter into the model layout, queue parameters at one of the entrances into the roundabout;
- Creating the VISSIM simulation database (variations of values of input parameters) for neural network learning;
- Selection of neural network (General Regression Net, Iterative type, with a logistic activation function gave the best response in this study) and obtaining the function of prediction for the program calibration;
- Program calibration (program designed in MATLAB);
- Checking the results of the program calibration output file in the VISSIM model for the mean traveling time and queue parameters as well as checking the best result in the validation procedure;
- Validation procedure involves comparison of simulated and measured data for the second set of data measured in the field;
- Combination of input parameters, that gives the simulation results which best approximate the measured data, is optimal = calibrated VISSIM.
- The described basic steps of calibration are applicable, not only in the VISSIM, but in other microsimulation models.

The question about the optimal size of database for microsimulation modeling of neural network learning and the question about a possibility of finding a configuration of neural network which would provide a better response than the chosen General Regression Network both remain unanswered, since these answers require further research.

Regarding the optimisation issues, the question is whether the obtained optimum is local or absolute minimum and how good should possible local minimum approximate the absolute one. In practical terms, the comparison of the measured field results with simulation results obtained with calibrated and default values of input parameters, gives a basic insight into the performance of the calibration procedure.

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