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SHORT TERM LOCAL ROAD TRAFFIC FORECAST USING FEED-FORWARD AND RECURRENT ANNS

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Jelena Milojković[1], Dragan Topisirović[2], Miljana Milić[3], Milorad Stanojević[4]

[1]Innovation Centre of Advanced Technologies, Serbia
[2]High School of Economics, Niš, Serbia
[3]University of Niš, Faculty of Electronic Engineering, Serbia
[4]University of Belgrade, Faculty of Transport and Traffic Engineering, Serbia

Abstract. *The subject of short term municipal traffic prediction has been considered. Artificial neural networks (ANNs) were implemented for prediction. Starting with the hypothesis that one needs two predictions supporting each other, in order to be confident in the obtained result we have implemented two different ANN structures. These structures were earlier developed for and successfully implemented to short term electricity load prediction at suburban area, a problem having inherent similarities with local municipal road traffic flow. The final prediction was obtained as an average of the two predictions. A new algorithm is proposed for estimation of the number of hidden neurons in each of the two ANN structures.*

Key words: *urban traffic, prediction, artificial neural networks*

1. INTRODUCTION

As stated in [1] the three key drivers for road traffic on the strategic road network are population, income and the fuel costs. As for the number of vehicles, being mostly driven by the income, in the OECD countries [2] there were more than 50 vehicles per 100 inhabitants in the year 2011. Despite increase in ownership and consequently in traffic, however, CO_2 emissions [3] are forecast to decline by around 15% from 2010 levels, reflecting fleet fuel efficiency improvements and use of bio-fuels. Having all that in mind, and with the intention to preserve sustainable future, the importance of prediction of local traffic in large cities comes in for many reasons such as: environmental and pollution monitoring; fuel usage reduction; journey planning; traffic control; urban

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Corresponding author: Miljana Lj. Milić
Faculty of Electronic Engineering, University of Niš, 14 Aleksandra Medvedeva, 18000 Niš, Serbia
E-mail: miljana.milic@elfak.ni.ac.rs

planning; real-time route guidance; and ITS (intelligent transport system). In that way models were developed for traffic prediction enabling predicting travel times, travel speeds, and traffic volumes on transportation networks using historic and real-time data.

The research in short-term traffic flow prediction we describe here is part of a larger project of traffic control in municipal areas. We represent the collaborative results of the Faculty of Transport and Traffic Engineering of the University of Belgrade, the Faculty of Electronic Engineering of the University of Niš, and the Innovation Centre of Advanced Technologies of Niš.

We are presenting here a new algorithm of short-term traffic prediction based on our previous results - applying artificial neural networks (ANN) - implemented for electricity load prediction at suburban level [4][5]. In addition to the change of the context we here propose additional algorithmic steps with the intention to allow for automatic reach of the complexity of the ANN while keeping it as small as possible.

Our work here may be categorized as off-line deterministic prediction [6] while if a proper infrastructure is implemented it may be used in a mixed mode: the training of the ANN to be performed off-line with historical data while their implementation may be in real-time with dynamic data collection.

Our method is based on traffic flow data only. The reason for that is the fact that, as we claim, in the case of short-term prediction all other influential factors have already been impregnated into the historical data we use.

The method is implemented on data given for one of the Belgrade's busiest round-about. The results obtained exhibit prediction error mostly within the margin of 10%, which we consider acceptable.

In the part to follow, after a short review of the related work, we will describe our approach of implementation of ANNs for prediction, which was already implemented to electricity load forecasting. Then, we will describe the new algorithm - the procedure - which will be consequently implemented on a case study.

2. Related Work

There are several surveys of the traffic forecasting methods such as [7], [8], and [9] where a general conclusion is offered saying that no method can be qualified as the "best". Similar claim may be found in [10]. Based on these we decided to implement our forecasting ideas to the subject of traffic.

In the near past, the researchers from all over the world have proposed a number of methods for short-term traffic flow prediction, including ones that are based on a graphical dynamic model [11], time series models [12], [13], [14], Kalman filter theory [15], Markov chain model [16] and absorbing Markov chain model [10], simulation models [17], local regression models [18], [19], [20], [21], sequential learning [22], semantic web technologies [23], spectral analysis [24], [25], Bayesian networks [26], [27], probabilistic transition matrix [28], partitioning cluster analysis [29], neural networks [6] [17], [30], [31], [32], fuzzy-neural approach [33], [34], neuro-genetic algorithm [35], machine learning [36], adaptive ramp metering algorithm [37], mutual information theory [31] and other. One may say that the ANNs were most frequently applied which was additional encouragement for us to implement our concepts.

3. ANN AND IMPLEMENTATION FOR ONE-STEP-AHEAD PREDICTION

A time series is a number of observations that are taken consecutively in time. A time series that can be predicted precisely is called deterministic, while a time series that has future elements which can be partly determined using previous values, while the exact values cannot be predicted, is said to be stochastic. We are here addressing only deterministic type of time series.

Consider a scalar time series denoted by y_i, i=1,2, … m. It represents a set of observables of an unknown function $\hat{y} = \hat{f}(t)$, taken at equidistant time instants separated by the interval Δt i.e. $t_{i+1} = t_i + \Delta t$. One step ahead forecasting means to find such a function f that will perform the mapping

$$y_{m+1} = f(t_{m+1}) = \hat{y}_{m+1} + \varepsilon \tag{1}$$

where $\hat{y}_{m+1}$ is the desired response, with an acceptable error ε.

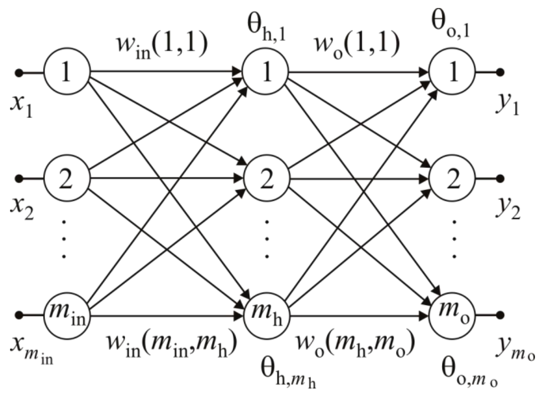


Fig. 1 Fully connected feed-forward neural network with one hidden layer and multiple outputs

The prediction of a time series is synonymous with modeling of the underlying physical or social process responsible for its generation. This is the reason of the difficulty of the task.

In the past decades ANNs have emerged as a technology with a great promise for identifying and modeling data patterns that are not easily discernible by traditional methods. A comprehensive review of ANN use in forecasting may be found in [38]. Among the many successful implementations we may mention [39]. A common feature, however, of the existing application is that they ask for a relatively long time series to become effective. Typically, it should be not shorter than 50 data points [38]. This is due to the fact that they all look for periodicity within the data. Very short time series were treated in [39]. Here additional “non-sample information” was added to the time series in order to get statistical estimation from deterministic data.

In our view of the prediction one is to give much attention to the most recent data while keeping track of the long-term properties of the phenomenon under consideration. That is why we went for a search for topological structures of ANN that promise prediction based on short time series. In the next, we will first briefly introduce the feed-forward neural networks that will be used as a basic structure for prediction throughout this paper and then we will represent its evolution for proper implementation.

The network is depicted in Fig. 1. It is a "multi-layer perceptron" or "feed-forward ANN" with three layers. It has only one hidden layer, which has been proven sufficient for this kind of problem [40]. Indices: “in”, “h”, and “o”, in this figure, stand for input, hidden, and output, respectively. For the set of weights, w (k, l), connecting the input and the hidden layer we have: k = 1, 2, ..., m_{in}, l=1, 2, ..., m_{h}, while for the set connecting the hidden and output layer we have: k = 1,2, ...mh, l=1,2,..., mo. The thresholds are here denoted as $\theta x,r$, r = 1,2, …, m_{h} or m_{o}, with x standing for “h” or “o”, depending on the layer. The neurons in the input layer are simply distributing the signals, while those in the hidden layer are activated by a sigmoidal (logistic) function. Finally, the neurons in the output layer are activated by a linear function. The learning algorithm used for training is a version of the ste-epest-descent minimization algorithm [41]. The number of hidden neurons, mh, is of main concern. To get it we applied a procedure that is based on proceedings given in [42].

In prediction of time series, in our case, a set of observables (samples) is given (approximately every fifteen minutes) meaning that only one input signal is available being the discretized time. According to (1) we are predicting one quantity at a time meaning one output is needed, too. The values of the output are numbers (traffic flow). To make the forecasting problem numerically feasible we performed transformation in both the time variable and the response. The time was reduced by t_0 so:

$$t = t^* - t_0 \tag{2}$$

Having in mind that t^* stands for the time (in minutes) during one day, this reduction gives the value of 0 to the time (t_0) related to the first sample. In addition, the time was represented as integer numbers by incrementing the number value by one at every 15 minutes. So, in the rest we will use "Sample No." instead of time. The sample values were transformed in the following way:

$$y_i^* = (y_i + y_{i-1} + y_{i-2})/3 - M \tag{3}$$

where y_i^* stands for the current value of the target function, M is a constant (for example M=140). By (3) smoothing (filtering of high frequency components) of input data is performed as well as translation downwards by the amount of the expected average traffic flow.

If the architecture depicted in Fig. 1 was to be implemented (with one input and one output terminal) the following series would be learned: (t_i, $f(t_i)$), i=1,..., m.

We may express the functionality of the new structure, FFAP - Feed Forward Accommodated for Prediction, network as:

$$\{y_{i+k}, y_i, y_{i-1}, ..., y_{i-q}\} = \mathbf{f}(t_i), \ i=q+1,..,m, \tag{4}$$

where $Output_1=\{y_{i-1},...,y_{i-q}\}$, meaning: one future, one present, and q previous responses are to be learned.

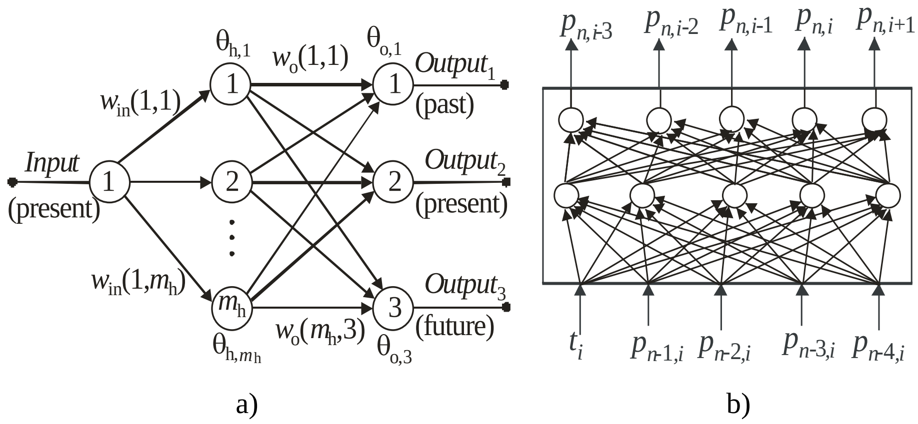


Fig. 2 FFAP - Feed Forward Accommodated for Prediction (a) and EFFAP / Extended Feed Forward Accommodated for Prediction (b)

In the case of prediction of power consumption, we extended the FFAP to introduce the influence of the response values from the previous days at the given time of the day. In that way for the extrapolation function we may write the following

$$\begin{aligned}&\{p_{n,i+1}, p_{n,i}, p_{n,i-1}, p_{n,i-2}, ..., p_{n,i-q}\} = \\ &= \mathbf{f}(t_i, p_{n-1,i+k}, p_{n-2,i+k}, p_{n-3,i+k}, p_{n-4,i+k})\end{aligned}, \quad i=q, ...,m. \tag{5}$$

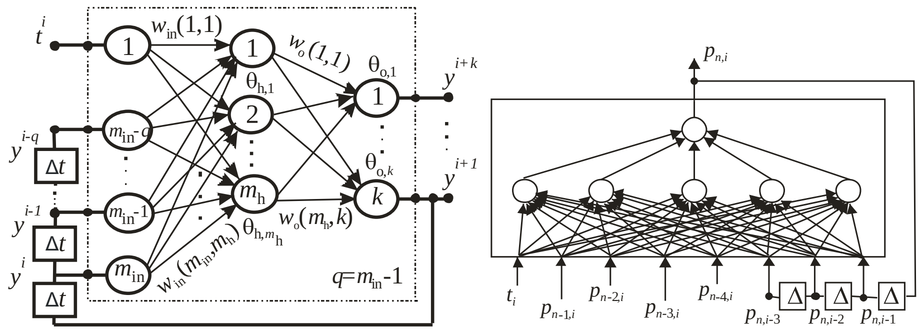
The new network is learning the future (unknown) value pn,i, based on the actual time t_i, the actual traffic flow $p_{n,i}$, the past traffic flow values for the given day in n–th (actual) day ($p_{n,i-j}$, j=1,2,…,q), and the past traffic flow values for the same time of the previous days ($p_{n-j,i+k}$, j= 1,2,3,4). Namely, only four past days are observed what was considered sufficient. The new structure is referred to as Extended Feed Forward Accommodated for Prediction (EFFAP). It is depicted in Fig. 2b.

The error function that was minimized during the training process, for the network structure depicted in Fig. 2b, was as follows:

$$\delta = \frac{1}{2}\left\{\sum_{r=-q}^{0}\left[\sum_{i=q+1}^{m}(p_{n,i+r}(t_i,\mathbf{w},\boldsymbol{\theta}) - \hat{p}_{n,i+r}(t_i))^2\right] + \left[\sum_{i=4}^{m}(p_{n,i+1}(t_i,\mathbf{w},\boldsymbol{\theta}) - \hat{p}_{n,i+1}(t_i))^2\right]\right\}. \tag{6}$$

where $\hat{p}_{n,i+1}(t_i)$ stands for the known values, $p_{n,i+1}(t_i,\mathbf{w},\boldsymbol{\theta})$ is the actual response at the ANNs output, and **w** and **θ** are vectors of unknown weights and threshold, respectively.

Prediction may be seen as a walk into darkness. To appreciate the step done one needs some kind of reference. That is why we are implementing two predictions, supporting each other, in order to have the right to claim that there is a proper probability for our prediction to be acceptable. To that end we use the so called TCR (Time Controlled Recurrent) ANN as depicted in Fig. 3a. In this case the recent sample values are fed-back so a recurrent ANN arises. If previous days were to be introduced as in the case of the EFFAP structure, new architecture was proposed as depicted in Fig. 3b. It was referred to as ETCR (Extended Time Controlled Recurrent). For training of that network a function similar to (6) is applied.



a) b)

Fig. 3 TCR - Time Controlled Recurrent (a) and ETCR - Extended Time Controlled Recurrent (b). q=3.

Both ETCR and EFFAP were trained on the same training data. The number of neurons was estimated according to [45] for each network separately.

4. The Procedure

We define the traffic flow, or traffic volume, as the number of vehicles passing an observation point per unit of time (usually 15 minutes). There are various ways of "measuring" the traffic flow and consequently various sources of data such as: simulation [46], sensors [19], taxi GPS [28], floating car [47] and similar. According to the type of data a prediction model is based on, we can classify existing models into two categories: models based on historical traffic data and models based on real-time traffic data [48]. In our case we are doing with historical data. Traffic flow forecasting is mainly specified in two categories: long-term and short term prediction. In short term prediction, which is our goal, the traffic is predicted in the next moments (typically 15 or 30 minutes) on the basis of real-time historical data. Of course for short term prediction online data may be used, too.

The new procedure we are promoting within these proceedings is depicted in Fig. 4. We start with a time series obtained from [46]. These are expressing the traffic at one of the busiest round-about in Belgrade. Then we arrange the training sets in two ways appropriate to the two ANN structures we use. Table 1. represents one training vector for the EFFAP ANN. To get a prediction for ti=502, we add nine additional rows to Table 1. with every one shifted by one backwards in time.

Note, what is new, for both EFFAP and ETCR we make eight predictions with eight networks with rising number of hidden neurons starting with 3 and ending with 10. In that way we obtain two vectors of predictions; one for the EFFAP and the other for the ETCR ANN.

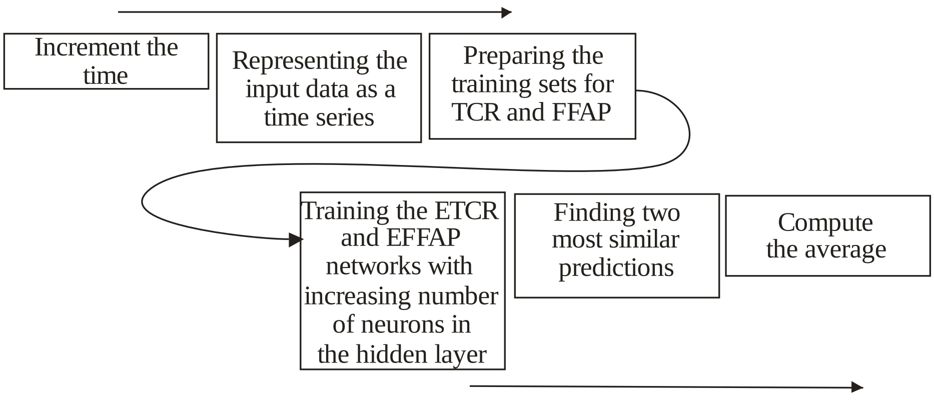


Fig. 4 Steps in obtaining a prediction

In the next step we search the two vectors for the most similar prediction that is for predictions which support each other. These are picked from their vectors as final ETCR and final EFFAP prediction. The process ends by adopting the final prediction obtained as an average of the above two. Namely, if the two predictions are supporting each other they are of equal importance while none may be qualified as the better one. So, the average is the best representative.

Table 1 A training vector for the EFFAP ANN (according to (Fig.2b))

No.	t_i	$p_{n,i+1}$	$p_{n,i}$	$p_{n,i-1}$	$p_{n,i-2}$	$p_{n,i-3}$	$p_{n-1,i}$	$p_{n-2,i}$	$p_{n-3,i}$	$p_{n-4,i}$
i	500	44	40	35.5	31	-1	142	131.5	147.5	148.5

Before proceed with the case study we want to stress that an ANN with 5 hidden neurons as the one depicted in Fig. 2b, has 60 free parameters for optimization which is not even a moderate number as it is known from approximation theory. That should one have in mind when judging why we use ANN with number of hidden neurons no larger than 10.

4. A Case Study

Fig. 5 represents part of the input data that were used for prediction. The time is here discretized at 15 minutes and reduced to 390 (as given by (2)) while the value of the traffic flow is as given in the original data. The same data, after transformation by use of (3) are depicted in Fig. 6. As can be seen the curve is smoothed and shifted downwards which, in our experience, makes the training process numerically better conditioned.

Table 2 contains the prediction results obtained for ten different time instants (in fact, ten predictions). Note for every row in Table 2. 8 ETCR and 8 EFFAP ANNs were to be trained with rising number of hidden neurons. As can be seen most similar prediction are obtained for ANNs with different number of neurons. For example, look at row 4, the ETCR network with 7 hidden neurons gives similar prediction to the EFFAP network with 5 hidden neurons.

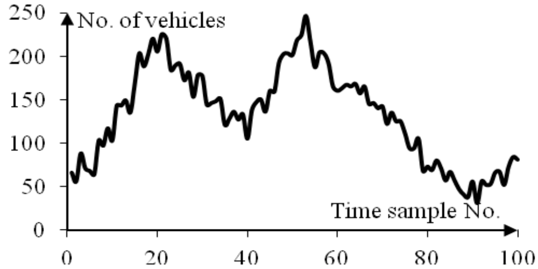


Fig. 5 Input data for 25 hours

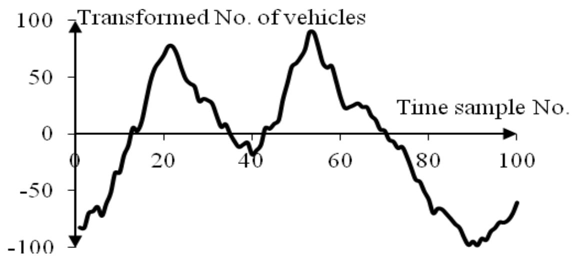


Fig. 6 Transformed input data for 25 hours

Table 2 Explanation of the implemented procedure

Sample No.	Expected Value (1)	ANN1 (ETCR) No. of neurons	ANN1 (ETCR) Predicted (2)	ANN2 (EFFAP) No. of neurons	ANN2 (EFFAP) Predicted (3)	Avg. (4)=[(2)+(3)]/2	Diff. (1)-(4) [%]
1	-82,6667	8	-82,3093	3	-82,3518	-82,3306	-0,59
2	-83,0000	7	-80,8973	10	-80,9685	-80,9329	-3,63
3	-70,0000	3	-65,2589	3	-65,0118	-65,1354	-6,95
4	-68,3333	7	-61,7355	5	-62,6274	-62,1815	-8,58
5	-64,3333	8	-71,5277	4	-72,1641	-71,8459	9,93
6	-72,3333	5	-61,1501	5	-61,7579	-61,454	-16,08
7	-61,6667	3	-70,0822	4	-70,0571	-70,0697	10,73
8	-52,0000	7	-33,939	6	-39,3113	-36,6252	-17,47
9	-34,3333	6	-41,872	8	-41,3462	-41,6091	6,89
10	-34,3333	9	-30,8622	4	-31,1223	-30,9923	-3,16

Fig. 7 visualizes the traffic flow values of Table 2. while Fig. 8. illustrates the prediction error. As can be seen almost equi-ripple error function is obtained with extreme at about 10%.

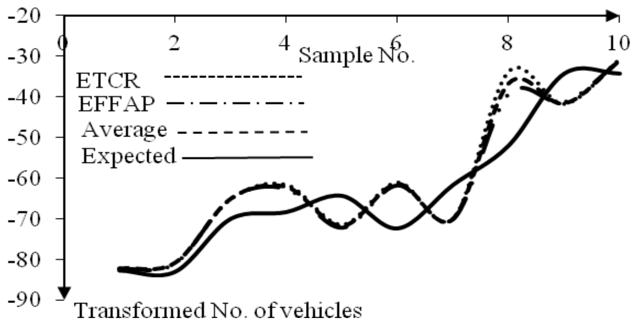


Fig. 7 Selected ten transformed samples and corresponding responses (Depiction of Table 1)

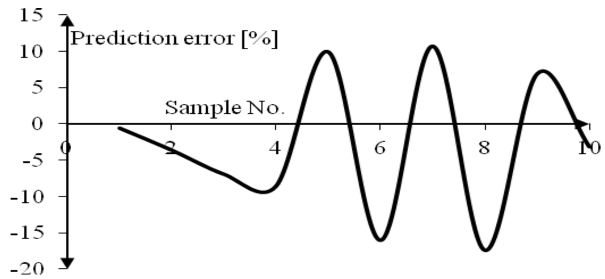


Fig. 8 Selected ten transformed samples: the prediction error (Depiction of Table 2)

5. Conclusion

The subject of municipal local traffic flow is of prime interest for predicting congestions in large cities, as well as for journey planning and avoiding traffic jams. From that reason short term prediction is essential. Thanks to modern technology, historical data are nowadays available to the traffic control institutions and prediction is enabled.

Practically every existing forecasting concept was implemented to the subject of short term traffic flow prediction. Having available concepts implemented to electricity load forecasting at suburban level, we implemented part of the underlying concepts with some improvements leading to fully automated algorithm for predicting. In summary, the main contributions of this paper may be stated as follows: 1. A method used for short term electricity load prediction at suburban level was successfully implemented for local traffic flow prediction, 2. A new algorithm was created for finding the number of hidden neurons in the ANNs used, and 3. Complete new procedure for automatic traffic flow prediction was successfully implemented to a given set of data.

The obtained forecasting error values are within 10% which is encouraging and qualifies the method to be of equal value or even better of some other existing solutions such as some reported in [18] [28].

At the moment the work of the forecasting system is conceived as off-line while the data is permanently collected. Improvement of the system i.e. retraining of the ANNs according to the latest traffic information may be performed off-line at every our and the prediction run with new ANNs that is with new values of the weights and thresholds.

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KRATKOROČNO PREDVIĐANJE SAOBRAĆAJA NA LOKALNIM PUTEVIMA KORIŠĆENJEM NEREKURENTNIH I REKURENTNIH VEŠTAČKIH NEURONSKIH MREŽA

U radu je razmatran problem kratkoročnog predviđanja gradskog saobraćaja. Za implementaciju metoda, korišćene su veštačke neuronske mreže (ANN). Polazi se od pretpostavke da dva predviđanja dobijena različitim metodama, koja su međusobno saglasna, daju pouzdanije rezultate predviđanja, pa je metod implementiran sa dva različita tipa neuronskih mreža. Ovakve strukture su ranije bile razvijene i uspešno primenjene za kratkoročno predviđanje potrošnje električne energije u prigradskim naseljima, što predstavlja problem koji je po svojim svojstvima sličan problemu predviđanja drumskog saobraćaja na lokalnim putevima. Konačna predviđanja se dobijaju kao srednja vrednost predviđanja dobijenih korišćenjem dve različite topologije neuronskih mreža. U radu se takođe predlaže i novi aligoritam za procenu broja neurona u skrivenom sloju kod obe ANN strukture.

Ključne reči: *gradski saobraćaj, predviđanje, veštačke neuronske mreže*