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APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR PREDICTION OF TRAFFIC NOISE BASED ON THE TRAFFIC FLOW STRUCTURE

Abstract: *Techniques for noise prediction are mainly based on regression analysis, wich generally do not good enough describe the trends of noise. In this paper the application of artificial neural networks (ANN) for the prediction of traffic noise for periods of 1 hour and 15 minutes is presented. As input variables of the neural network, the proposed structure of the traffic flow and the average speed of the traffic flow are chosen. The output variable of the network is equivalent noise level in the given time period Leq. Based on these parameters, the network is modelled, trained and tested through a comparative analysis of the calculated values and measured levels of traffic noise. It is shown that the artificial neural networks can be a useful tool for the prediction of noise with sufficient accuracy in the observed time intervals.*
Keywords: *artificial neural network, structure of traffic flow, traffic flow*

1. INTRODUCTION

As observed in the literature, there are many methods and models for noise assessment and among them each country tends to use its own approach. A review of this matter is critically presented in [1-2] where the main characteristics of some methods like the approaches advocated by American FHWA, the English CoTRN, the German RLS 90, the French NMPB and other are shown. There is no overall pattern of these methodologies and those countries that do not use a national model, usually apply the French NMPB-method, which is a model also suggested by the EU Directive [3]. In all these methods, calculations needed to predict environment noise in large settlements are usually simplified algorithms, and with optimization over time, a reasonable precision in results can be achieved. Even when the same method is applied with different software packages, some discrepancies in results may occur.

Similar to the above mentioned methods, modeling with Artificial Neural Networks (ANN) is a simplified solution for the prediction of noise levels. An ANN is a system of linked equations used to model relationships between variables. ANN can be successfully used to model even the complex non-linear relationships between variables [4]. In addition, ANN models embed information about importance of independent variables. Several authors have used ANNs for noise-level prediction, noise-annoyance prediction, and noise classification [4-5]. All the mentioned papers indicate the high performance of using ANN for environmental noise prediction.

In this paper an application of artificial neural networks for the prediction of traffic noise for periods of 15 minutes and 1 h on the Serbian road is presented. Furthermore, a copmarision of predictive aptitudes of ANN model and classical models is given.

2. PROBLEM STATEMENT

The general objective of this paper is to analyze the noise levels of a certain area as a function of several features. To achieve this goal, this paper first presents the main concepts involved in an environment noise assessment. Most studies dealing with noise problems use the concept of equivalent sound level (L_{eq}), which is expressed in units of dBA. The L_{eq} is a sound descriptor defined as an equivalent steady noise level, which in a period of time would contain the same amount of energy of noise fluctuating over that period of time.

In order to reduce noise it is necessary to know the functional relationship between noise emission and measurable parameters. The physical parameters to which L_{eq} is correlated are, among others, traffic intensity, type of road surface, type of urban area, height of buildings, width of road, etc. Up to now, the functional relationships have been stated on the basis of data measured through semi-empirical models, typically regression analysis. Although these correlations are nonlinear, they do not provide very accurate approximations of the trend followed by sound pressure level according to a certain number of physical parameters.

ANN based on equivalent sound level in the given time period is built and trained using the set of training data. As input variables of the network the structure of the traffic flow and the average speed of the traffic flow are adopted. The output network variable is equivalent noise level in the given time period L_{eq} (t). The network is tested using the set of test data.

3. DATA SAMPLING

In an effort to include the great diversity of situations present in urban environments, a sample measurement of environmental noise was made on the road M5. A total of 130 measurements for 15 min, and 36 measurements for 1 h of eqvivalent noise level were selected to be as generally representative as possible for the wide range of urban scenarios. Simulaneously, variations in traffic flow, traffic speed and composition of traffic flow were measured. For that reasons the surveys at the same time also consist of the following parameters: the number of light motor vehicles, the number of medium trucks, the number of heavy trucks, the number of buses, and the average traffic speed in a given time period. To reflect the heterogeneity of acoustically relevant situations, the selection included locations where the main source of environmental noise at the time of measurement was road traffic. We selected settings without other sound sources, such as pedestrian areas, locations with commercial/leisure activities, and squares or urban parks where the sound scape would involve primarily social and natural sounds. Measurements were taken following international procedures of reference; microphone was mounted away from reflecting facades, at a height of 1.2 m above the ground level and 7.5 m away from central line of the roud. For traffic data measurement and for noise measurement, automatic traffic counters QLTC-10C and sound level meter Bruel&Kajer type 2230 class 1 were used.

4. NEURAL NETWORK MODEL

An ANN is a computational model based on biological neural networks.

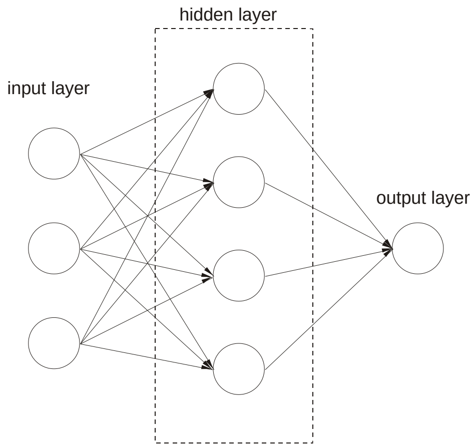

Figure 1. Schematic representation of neural network

It consists of interconnected artificial neurons that are grouped in input, hidden and output layers (Figure 1). The way in which ANN processes information from one layer to other is presented in Figure 2 and could be mathematically depicted by the following two equations:

$$v_k = \sum_{i=1}^{n} x_i w_i + b_k$$

$$y_k = \varphi(v_k)$$

where b is bias, and φ is activation function.

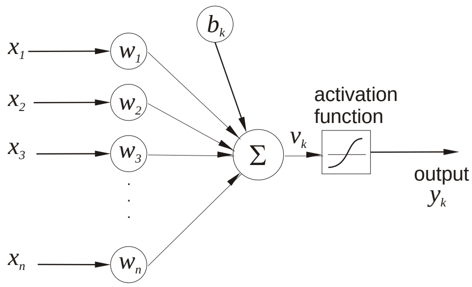

Figure 2. Information processing in ANN

The numbers of input and output neurons in neural network are determined by the nature of the problem. The number of hidden neurons, as well as the number of hidden layers, has in general significant influence on the final output. Neural networks with more hidden layers can model complex relationships between independent and dependent variables with any kind of shape. Apart from some rules of thumb there is no general algorithm for determining the optimal number of neurons in hidden layers. This number is determined empirically for particular instance. If there are too few neurons in hidden layers, the network could not properly catch the signals form the input neurons. On the other hand, too many neurons in the hidden layers can result in overfitting.

5. SIMULATION ARRANGEMENT

In this work, eight ANN models based on L_{eq} with different numbers of hidden neurons were created and trained using the same set of training data, and their performances were then compared using the validation set of data. The neural architecture that is used in this work is made up of one output neuron, i.e. the L_{eq}, different number of neurons in the hidden layer, and five inputs referring respectively to: the number of light motor vehicles, the number of medium trucks, the number of heavy trucks, the number of buses and the average trafic flow speed (Figure 3).

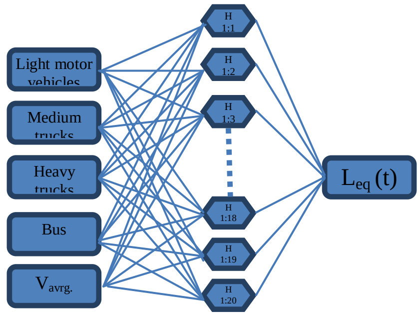

Figure 3. ***Structure of proposed ANN for $L_{eq}(t)$ prediction***

The simulation was done using the home made software (Figure 4).

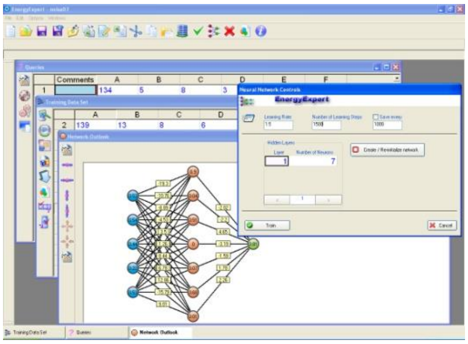

Figure 4. ***ANN software***

Like any other analysis technique, ANNs are sensitive to measurement data set. In order to discard concentration of possible errors and to obtain tne most representative set of training data, the training process was preceded by random selection of measurements.

For predicting L_{eq} (15 min) the number of learning examples was 110. The residual sum of squares (Serr) and coefficient of determination (R^2), which are shown in Table 1 are used to evaluate the prediction results. It is found that increasing the number of hidden neurons yields to more accurate prediction of dependent variable.

For predicting L_{eq}(1h) the number of learning examples was 30. The prediction results are shown in Table 2.

Table 1. Prediction results of different number of hidden neurons in ANN for L_{eq} (15 min) in learning process

Number of hidden neurons	Learning rate	Number of learning steps	Structure of ANN	R^2	S_{err}
5	1,5	5500	5-51	0,943	9,92
6	1,5	5500	5-6-1	0,955	7,88
7	1,5	5500	5-7-1	0,943	10,00
8	1,5	5500	5-8-1	0,945	9,78
11	1,5	5500	5-11-1	0,973	4,59
20	1,5	5500	5-20-1	0,980	3,48
25	1,5	5500	5-25-1	0,945	9,70
30	1,5	5500	5-30-1	0,940	10,52

Table 2. Prediction results of different number of hidden neurons in ANN for L_{eq} (1h) in learning process

Number of hidden neurons	Learning rate	Number of learning steps	Structure of ANN	R^2	S_{err}
5	1,5	5500	5-5-1	0,980	0,33
6	1,5	5500	5-6-1	0,979	0,35
7	1,5	5500	5-7-1	0,987	0,22
8	1,5	5500	5-8-1	0,984	0,26
11	1,5	5500	5-11-1	0,990	0,15
20	1,5	5500	5-20-1	0,996	0,06
25	1,5	5500	5-25-1	0,989	0,18
30	1,5	5500	5-301	0,987	0,21

The computational results for L_{eq} (15 min), and L_{eq} (1 h) obtained for 20 neurons in hidden layer are presented in the next section.

6. RESULTS

Comparisions between measured values and computational results for learning data sets for intervals of 15 min and 1h are shown in Figure 5 and Figure 9 respectively. To validate and test the models whole measurement data sets were used. Comparisions between measured values and computational results for whole data sets for intervals of 15 min and 1h are shown in Figure 7 and Figure 11 respectively. The correlation analysis between predicted and measured values is conducted and all the coefficients of determination shown in Figure 6, Figure 8, Figure 10 and Figure 12 suggest a good correlation.

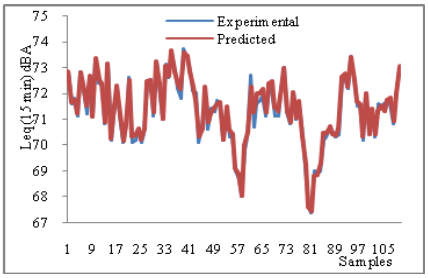

Figure 5. The difference between predicted and measured values in learning process for L_{eq} (15 min)

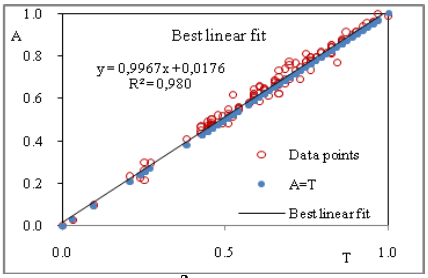

Figure 6. R^2 value between estimated and measured data in learning proces for L_{eq} (15 min)

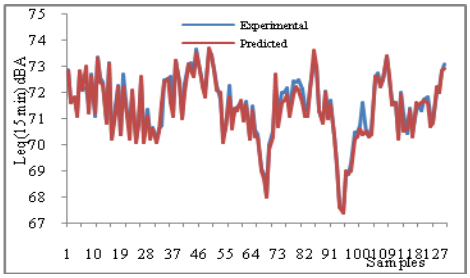

Figure 7. The difference between predictet and measured values for whole data set for L_{eq} (15 min)

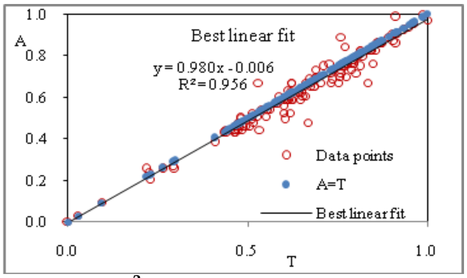

Figure 8. R^2 value between estimated and measured data for whole data set for Leq (15 min)

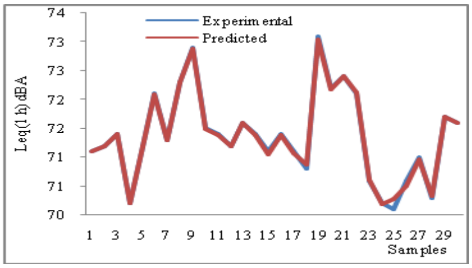

Figure 9. The difference between predicted and measured values in learning process for L_{eq} (1h)

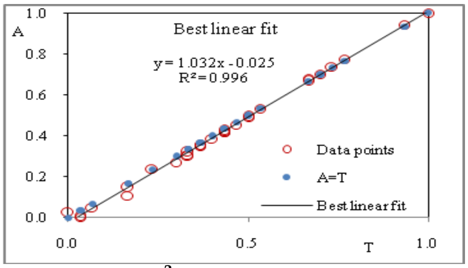

Figure 10. R^2 value between estimated and measured data in learning proces for

Leq (1 h)

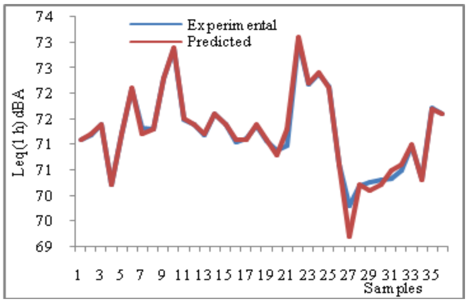

Figure 11. The difference between predicted and measured values for whole data set for L_{eq} (1 h)

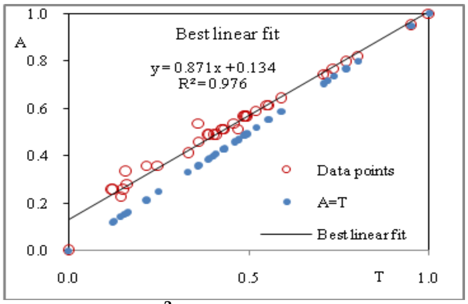

Figure 12. R^2 value between estimated and measured data for whole data set for Leq (1 h)

7. THE NEURAL NETWORK BASED APPROACH VERSUS THE CLASSICAL APPROACH

In order to assess advantages of ANN model, the simulation results are compared with the results obtained using classical methods. The results of the comparison are given in Fig. 13 and Table 3. All the graphs shown in Fig. 3 clearly show that the neural network approach allows better predictions of noise pollution levels than any other empirical relationship.

In Table 3 the mean noise level, standard deviation, standard error and coefficient of determination obtained using different methods on the measurement data set are given. According to Table 3 results can without doubt be attributed to the greater capacity offered by neural networks in approximating non-linear relationship between the traffic flow structure and the equivalent noise level.

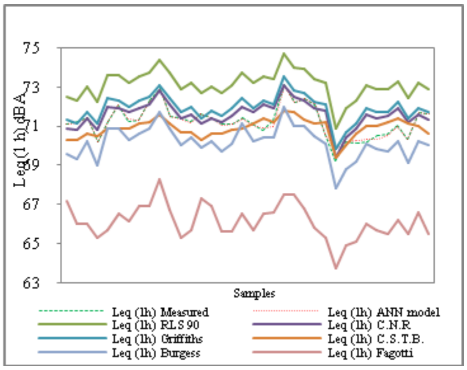

Figure 13. ANN approach versus classical models for L_{eq} (1h)

Table 3. Descriptive statistic of the analyzed models

Model	Mean noise level	Standard deviatin	Standard error	R^2
Measured value	71,24	0,8110		
ANN model	71,22	0,7753	0,2226	0.9231
Burgess model	70,17	0,8157	1,1479	0.7398
Fagotti et al. model	66,14	0,8877	5,1319	0.6254
Griffiths and Langdon model	71,91	0,6828	0,8154	0.6562
C.S.T.B. model	70,89	0,4789	0,7324	0.3499
RLS 90 model	73,11	0,7087	1,9281	0.6864
C.N.R mode	71,59	0,6749	0,6057	0.6169

8. CONCLUSION

Noise pollution near urban arterials has a complex relationship with many factors. These relationships are highly non-linear [6]. In this paper factors that affect the noise level are divided into five groups and all have been used as inputs in neural networks to predict hourly equivalent noise level L_{eq}(1h) and equivalent noise level at 15 minutes L_{eq}(15 min). In comparision with classical models, artificial neural networks show much better capabilities to predict equivalent noise level based on the traffic flow structure.

REFERENCES:

[1] Quartieri, J., Mastorakis, N. E., Iannone, G., Guarnaccia, C., D'Ambrosio, S., Troisi, A., & Lenza, T. L. L. A review of traffic noise predictive models. Recent advances in applied and theoretical mechanics, ISBN: 978-960-474-140-3.

[2] Claudio, G. New perspectives in road traffic noise prediction. Latest advances in acoustics and music, ISBN: 978-1-61804-096-1.

[3] King, E. A., Murphy, E., & Rice, H. J. (2011). Implementation of the EU environmental noise directive: Lessons from the first phase of strategic noise mapping and action planning in Ireland. *Journal of Environmental Management, 92*(3), 756-764.

[4] Cammarata, G., Cavalieri, S., & Fichera1, A. (1995). A neural network architecture for noise prediction. *Neural Networks, 8*(6), 963-973.

[5] Cammarata, G., Cavalieri, S., Fichera, A., & Marletta, L. (1993). *Neural networks versus regression techniques for noise prediction in urban areas.* World Congress on Neural Networks, Portland, Oregon, USA.

[6] Givargis, S., & Karimi, H. (2010). A basic neural traffic noise prediction model for Tehran's roads. *Journal of Environmental Management*, *91*, 2529-2534.