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Comparison of classical statistical methods and artificial neural network in traffic noise prediction

Vladimir Nedic [a,1], Danijela Despotovic [b,2], Slobodan Cvetanovic [c,3], Milan Despotovic [d,*], Sasa Babic [e]

[a] Faculty of Philology and Arts, University of Kragujevac, Jovana Cvijića bb, 34000 Kragujevac, Serbia
[b] Faculty of Economics, University of Kragujevac, Djure Pucara Starog 3, 34000 Kragujevac, Serbia
[c] Faculty of Economics, University of Niš, Trg kralja Aleksandra Ujedinitelja, 18000 Niš, Serbia
[d] Faculty of Engineering, University of Kragujevac, Sestre Janjic 6, 34000 Kragujevac, Serbia
[e] College of Applied Mechanical Engineering, Trstenik, Serbia

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A B S T R A C T

Traffic is the main source of noise in urban environments and significantly affects human mental and physical health and labor productivity. Therefore it is very important to model the noise produced by various vehicles. Techniques for traffic noise prediction are mainly based on regression analysis, which generally is not good enough to describe the trends of noise. In this paper the application of artificial neural networks (ANNs) for the prediction of traffic noise 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 the equivalent noise level in the given time period L_{eq}. Based on these parameters, the network is modeled, trained and tested through a comparative analysis of the calculated values and measured levels of traffic noise using the originally developed user friendly software package. It is shown that the artificial neural networks can be a useful tool for the prediction of noise with sufficient accuracy. In addition, the measured values were also used to calculate equivalent noise level by means of classical methods, and comparative analysis is given. The results clearly show that ANN approach is superior in traffic noise level prediction to any other statistical method.

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Introduction

In recent years, due to the constant increase of population and the number of circulating vehicles in urban areas, pollution reached an alarming level. Apart from air pollution, a very important factor regarding environmental pollution in urban areas is noise. Among different sources of noise that are present in an urban area, traffic noise is by far the most annoying noise source (Calixto et al., 2003). The influence of traffic noise on human health has been studied numerously in recent years (Babisch et al., 2013; Brink, 2011; Caciari et al., 2013; Fyhri and Klboe, 2009; Pirrera et al., 2010), the results of which confirmed that this kind of annoyance significantly affects both mental and physical health. Therefore, traffic noise is to be considered not only as a cause of nuisance, but also as a concern for public health and environmental quality (Kassomenos et al., 2014). To successfully implement the most efficient noise action plans for preventing and reducing exposure to harmful levels of noise in a sustainable and resource efficient way, it is first necessary to obtain information about the noise levels to which people are exposed (Suarez and Barros, 2014; Kassomenos et al., 2014). Thus, in order to control noise sound level in urban areas, it is very important to develop methods for prediction of the traffic noise. The first traffic noise prediction (TNP) models date back to early 1950s. Since then a large number of methods and models for traffic noise prediction have been developed. The critical reviews of the most used ones are given in Steele (2001) and Quartieri et al. (2009) as well as in Garg and Maji (2014). Most of the TNP models that are presented in literature are based on linear regression analysis. The main limit of those models, as concluded in Quartieri et al. (2009) and Claudio Guarnaccia et al. (2011), is "that they don't take into account the intrinsic random nature of traffic flow, in the sense that they don't take care of how vehicles really run, considering only how many they are". More advanced models involve artificial neural networks (ANN) (Cammarata et al., 1995; Givargis and Karimi, 2010) and genetic algorithms (Güdogdu et al., 2005; Rahmani et al., 2011). ANN model that was used in Cammarata et al. (1995) has 3 inputs: equivalent number of vehicles, which was obtained by adding to the number of cars the number of motorcycles multiplied by 3 and the number of trucks multiplied by 6, the average height of the buildings on the sides of the road, and the width of the road. In order to increase the number of inputs the authors decomposed equivalent number of vehicles into the number of cars, the number of motorcycles, and the number of

* Corresponding author. Tel.: + 381 69 844 96 79.
E-mail addresses: vnedic@kg.ac.rs (V. Nedic), ddespotovic@kg.ac.rs (D. Despotovic), slobodan.cvetanovic@eknfak.ni.ac.rs (S. Cvetanovic), mdespotovic@kg.ac.rs (M. Despotovic), babicsf@yahoo.com (S. Babic).
[1] Tel.: +381 63 81 35 373; fax: +381 34 304 275.
[2] Tel.: +381 63 40 80 23; fax: +381 34 303 516.
[3] Tel.: +381 63 42 43 11; fax: +381 18 293 932.

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trucks, and got the ANN model with 5 inputs. The principle of neural architecture consists of two phases, first of which is the filtering of acoustic measurements affected by error by means of learning vector quantization (LVQ) network. The model is tested on measured data set, and also compared with three classical models (Burgess, Josse, and CSTB). It was found that agreement between predictions and measurements was much better for the neural network approach than for the classical ones. However, the main drawback of that approach using LVQ network is, as authors point out, its dependency on the data used in the training phase. That creates difficulties that network trained for one town layout (road width and building height), be applied for a town with a totally different layout. In terms of the parameters involved in the CoRTN (calculation of road traffic noise) model (Quartieri et al., 2009), which was initially developed in 1975 by the Transport and Road Research Laboratory and the Department of Transport of the United Kingdom, the ANN model that was used in Givargis and Karimi (2010) has 5 input variables: the total hourly traffic flow, the percentage of heavy vehicles, the hourly mean traffic speed, the gradient of the road, and the angle of view. The authors tested the developed model on the data collected on Tehran's roads, and found no significant differences between the outputs of the developed ANN and the calibrated CoRTN model.

In this paper an application of artificial neural networks for the prediction of traffic noise is presented. The developed ANN model has 5 input variables: the number of light motor vehicles, the number of medium trucks, the number of heavy trucks, the number of buses and the average traffic flow speed. The network is modeled, trained and tested on data measured on Serbian road using the originally developed user friendly software package. Furthermore, the comparison between the outputs of the developed network and the outputs of some classical methods is given. As it will be shown, the developed ANN model has much better capabilities to predict traffic noise level than any other classical method.

Problem formulation

The most suitable parameter for depicting traffic noise emission is equivalent sound pressure level (L_{eq}), which is expressed in units of dBA and corresponds to fictitious noise source emitting steady noise, which in a specific period of time contains the same acoustic energy as the observed source with fluctuating noise. The L_{eq} for time interval between times t_1 and t_2 in seconds is expressed by the following equation:

$$L_{eq} = 10\log\left[\frac{1}{t_2 - t_1}\int_{t_1}^{t_2}\frac{p_A^2}{p_0^2}dt\right] \quad (1)$$

where $p_A(Pa)$ is the time varying sound pressure and p_0 is a reference sound pressure taken as 20 μPa.

In order to predict the noise it is necessary to know the functional relationship between the equivalent sound pressure level and the influential parameters. L_{eq} is correlated to numerous parameters, such as numbers and types of vehicles, their velocities, type of road surface, width and slope of the road, and height of buildings facing the road.

Table 1
Definition of acoustic classes of vehicles.

Acoustic class	QLTC-10C classification
LMV	A1, A2, B1
STV	B2, B3
TTV	B4, B5
BUS	C1, C2
	A0, XX

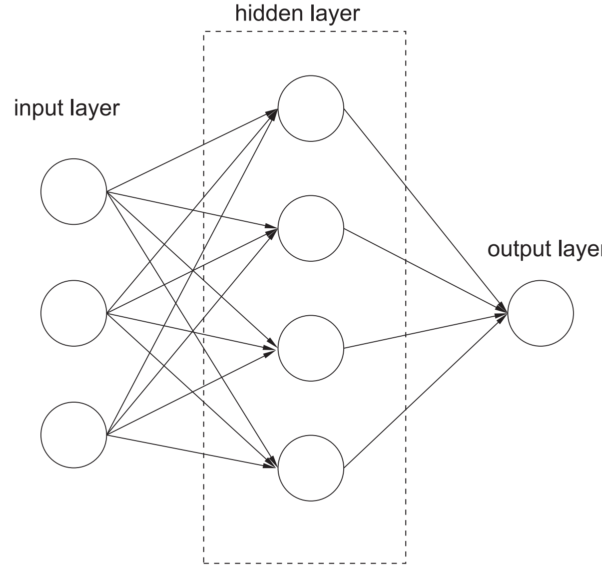

Fig. 1. Schematic representation of neural network.

As mentioned in the Introduction section, in this paper the following variables were considered: the number of light motor vehicles (LMV), the number of medium trucks (STV), the number of heavy trucks (TTV), the number of buses (BUS) and the average traffic flow speed (Vavg). A brief description of how these variables were measured is given in the following section.

Data measurement procedure

The research was carried out on a two-lane motorway road with a two-way traffic. The number of vehicles per particular acoustic class and the average traffic flow speed were determined by means of automatic vehicle counter QLTC-10C. This appliance operates with two inductive loops mounted onto the road surface, which makes it possible to classify vehicles and calculate the average traffic flow speed. It recognizes 11 subclasses of vehicles in compliance with the EEC 1108/70 EU Directive (http://www.mikrobit.si/pages/eng/hardware/QLTC-10.htm). On the basis of that classification we defined four acoustic classes: light motor vehicles (LMV), medium trucks (STV), heavy trucks (TTV), and buses (BUS), by uniting some subclasses as presented in Table 1.

Subclasses A0 and XX were not taken in consideration because of a very small number of vehicles of this type in the analyzed traffic flow.

For measuring the traffic noise the noise level meter Bruel & Kajer type 2230 whose measurement error is 0.1 dB was used. The noise detection was carried out in the Fast regime. The noise level is measured

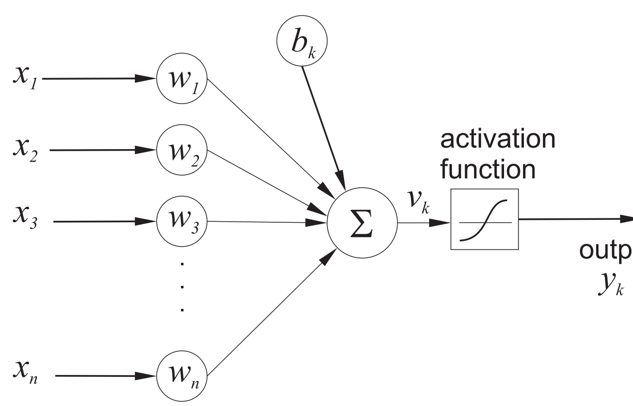

Fig. 2. Information processing in ANN.

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