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Assessment of traffic noise levels in urban areas using different soft computing techniques

J. Tomić,[1,a)] N. Bogojević,[2] M. Pljakić,[2] and D. Šumarac-Pavlović[1]
[1]*School of Electrical Engineering, University of Belgrade, Bulevar kralja Aleksandra 73, Belgrade, Serbia*
[2]*Faculty of Mechanical and Civil Engineering, University of Kragujevac, Dositejeva 19, Kraljevo, Serbia*
tomic.j@mfkv.kg.ac.rs, bogojevic.n@mfkv.kg.ac.rs, pljakic.m@mfkv.kg.ac.rs, dsumarac@etf.bg.ac.rs

Abstract: Available traffic noise prediction models are usually based on regression analysis of experimental data, and this paper presents the application of soft computing techniques in traffic noise prediction. Two mathematical models are proposed and their predictions are compared to data collected by traffic noise monitoring in urban areas, as well as to predictions of commonly used traffic noise models. The results show that application of evolutionary algorithms and neural networks may improve process of development, as well as accuracy of traffic noise prediction.

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1. Introduction

In order to control road traffic noise, it is necessary to have a suitable method for prediction of noise levels. The prediction method can be of fundamental importance in the process of urban planning and designing, as well as for the traffic noise reduction through traffic management. As almost all mathematical models have been developed by statistical analysis of experimental data, each of the models is strongly influenced by the composition and peculiarities of the traffic flow and characteristics of the measurement locations. This is the reason why the existing models are not universally applicable and often are limited to the urban area where measurements were conducted.

Since the early 1950s many mathematical models for traffic noise prediction have been developed and most of the available models found in literature are based on linear regression analysis. Recently, several prediction models were developed using artificial neural networks (ANNs) (Genaro *et al.*, 2010; Givargis and Karimi, 2010) and genetic algorithms (Gundogdu *et al.*, 2005; Rahmani *et al.*, 2011).

This paper presents a research of application of soft computing techniques for improvement of conventional methodologies for traffic noise prediction. Soft computing techniques are a family of methodologies designed to find approximate solutions to problems that require huge computing resources, for which there is no known algorithm that can compute an exact solution in a reasonable time. While inexact, the soft computing techniques are tolerant of imprecision and uncertainty of input parameters, and seem to be a suitable tool for approaching the problem of traffic noise prediction. Basic soft computing techniques include methodologies such as machine learning (neural networks, etc.) fuzzy logic, evolutionary computation, and chaos theory.

2. Measurements

In order to develop traffic noise prediction models for the territory of the city of Niš (Serbia), measurements of the equivalent A-weighted noise levels were performed at 18 locations at the city. The selection of measurement locations was performed to represent the whole territory (Prascevic *et al.*, 2014). The methodology of measurements is described in detail in Mihajlov *et al.* (2012). The measurements were performed at points 1.5 m above ground, at distances 7–15 m from the axis of the road, in dry weather conditions, without snow coverage, and with wind speeds lower than 5 m/s. A total of 270 measurements during the 15-min periods were carried out.

[a)]Author to whom correspondence should be addressed. Also at: Faculty of Mechanical and Civil Engineering, University of Kragujevac, Dositejeva 19, Kraljevo, Serbia.

In addition, during each of the measurements data were collected about traffic flow composition, which was described by the number of light motor vehicles N_c, medium trucks N_{mt}, heavy trucks N_{ht}, buses N_b, and motorcycles N_m.

3. Models

Two models for traffic noise prediction were developed using soft computing techniques. The first model is based on a simple functional dependence between input and output quantities. The simple functional dependence was optimized using a modern evolutionary algorithm. The second model uses a neural network to establish complex functional dependencies between input and output quantities. The two models are selected as extreme solutions to the two opposite requirements of traffic noise modeling: accuracy and the ability to be used for traffic management. On one hand, simple functional models enable easy prediction of effects of traffic management measures, while on the other hand, neural networks have superior accuracy.

3.1 Optimization of noise traffic models using evolutionary algorithms

Simple models for prediction of traffic noise, which are frequently used, are based on the assumption that the traffic noise level in a certain point or territory predominantly depends on traffic flow composition and vehicle speed. Some of the most used mathematical models for traffic noise prediction are those proposed by Griffiths and Langdon (1968), Burgess (1977), and Fagotti and Poggi (1995).

This paper proposes a simple mathematical model for prediction of traffic noise level L_{eq} in the city of Niš, given by the following equation:

$$Leq = Leq_0 + \mathrm{C}_R + C_\alpha, \tag{1}$$

where Leq_0 represents the prediction of traffic noise level of an infinite road in an open field, C_R represents correction due to the reflection of sound from buildings, while C_α is correction due to the finite length of the road.

All the measurement sites are at flat ground and above asphalt or concrete surface, so that corrections due to slope of the terrain and ground type were not included in the model. Since all measurement positions were distant from the intersections and traffic-control lights, it was assumed that all vehicles moved at a steady speed of 50 km/h, which is the speed limit for the territory of Niš. Therefore, the influence of vehicle speed was not considered. Since all measurement positions were close to the roads, the distances between the noise source and receivers were small. Therefore, the corrections due to atmospheric absorption were not included in the model, and the influence of meteorological conditions was considered negligible.

The dependence of the equivalent noise level Leq_0 on traffic flow composition and distance of a measurement point from the road was modeled by the equation

$$Leq_0 = L_0 + 10 \cdot \log(N_c + a_{mt} \cdot N_{mt} + a_{ht} \cdot N_{ht} + a_b \cdot N_b + a_m \cdot N_m) - 10 \log(d/d_0). \tag{2}$$

In Eq. (2) d represents distance of the measurement point from the axis of the road, while d_0 is referent distance, which was adopted to be 7.5 m. L_0 represents average noise level of a light motor vehicle at distance d_0, and the third member in the sum in Eq. (2) accounts for spreading of the sound, which is assumed to be generated by a line source at height of 0.5 m above the axis of the road. The second member in the sum in Eq. (2) accounts for the traffic flow composition. The influence of variability of the traffic flow composition is included in the model by weighting the contributions of different types of vehicles in comparison with light motor vehicles. The weighting is done by introducing the coefficients a_{mt}, a_{ht}, a_b, and a_m, which represent the number of light motor vehicles that generate the same noise level as one vehicle of the respective category (a_{mt} for medium trucks, a_{ht} for heavy trucks, a_b for buses, and a_m for motorcycles).

The influence of reflection of the sound from buildings around a measurement site may be modeled by adding an image source of the road for each of the reflecting surfaces. If n is the total number of the reflecting surfaces and ρ_i stands for the reflection coefficient of the ith reflection surface, then the correction for the reflection may be calculated using the term

$$C_\mathrm{R} = 10 \cdot \log\left(1 + \sum_{i=1}^{n} \rho_i \frac{\beta_i}{\alpha} \frac{d}{d_i}\right), \tag{3}$$

where d_i is the normal distance from the ith image source to the receiver, while α and β_i represent the angles of view of the road segment and reflective surface, respectively, as seen from the receiver position. If a road cannot be considered as an infinitely long line source, the correction for angle of view of the road segment, as seen from the receiver position, should be calculated according to the following equation:

$$C_\alpha = 10\log\left(\frac{\alpha}{180}\right). \tag{4}$$

The proposed model should, in a simple and sufficiently accurate manner, predict traffic noise levels not only in Niš, but also in other Serbian cities that are located in flat plains, since composition of traffic fleet and speed limits are the same. The advantages of the proposed model is that it keeps the simple analytic form of the models proposed by Griffiths and Langdon, Burgess, and Fagotti and Poggi, but has a refined description of traffic flow composition and includes effects of reflection and finite road length, which are peculiar to the measurement site.

Unlike the usual approach to estimation of traffic noise model parameters (in this case the average noise level of a light motor vehicle L_0 and the weighing coefficients a_{mt}, a_{ht}, a_b, and a_m), where parameters are estimated by linear regression, this paper presents an estimation of the parameters using a soft computing technique, the evolutionary algorithm called Differential Search Algorithm (DSA) (Civicioglu, 2012). The algorithm is used for solving numerical optimization problems, and is inspired by migration behavior of living beings which constitute a super-organism whose movement can be described by the Brownian-like random-walk model. In DSA, the population made up of potential solutions of the optimization problem corresponds to an artificial super-organism whose migration goal is to find a global optimal solution. In this case, the result of the algorithm is the set of traffic noise model parameters that minimize the mean square difference between the measured and calculated noise levels. The advantage of the evolutionary algorithms is that they are faster and more reliable in finding the global minimum than linear regression methods.

Traffic noise model parameters L_0, a_{mt}, a_{ht}, a_b, and a_m were estimated using only 50 (out of the 270) experimental data sets that had been gathered on 3 measurement locations with negligible influence of reflections. The results of the optimization are given in Table 1.

The proposed model is compared to the models of Griffiths and Langdon, Burgess, and Fagotti and Poggi, by calculating the average values of absolute differences between measured and predicted noise levels ($\overline{\Delta L}$) and standard deviations of the differences (σ). The results of comparative analysis, given in Table 2, clearly show that the proposed model provided significantly better estimations of traffic noise levels in the environment with negligible influence of reflections.

In further research a model was used that adopted the reflection coefficient of the building facades to be 0.8, according to the recommendations of the ISO 9613 standard (ISO, 1996).

3.2 Neural networks

An ANN is a computational tool inspired by biological neural systems, with the ability to model complex relationships between inputs and outputs or find patterns in data. The relationships between the input and the output parameters are established in a network training process which involves tuning the values of the connection weights between the network elements. Once the neural network is "trained," it is capable of calculating outputs for a given sets of inputs, but the relationships between its inputs and outputs cannot be expressed in a simple analytic form.

A neural network which predicts equivalent A-weighted sound level as its only output was developed using the MATLAB software package. The input data set consists of measurement variables with the largest influence to the traffic noise level: the road width, the perpendicular distance from the road central line to the receiver, the perpendicular distance from the nearest building to the receiver, the number of light motor vehicles, medium trucks, heavy trucks, buses, and motorcycles during the 15-min period. The quantities that did not vary during the measurements (such as average vehicle speed, height of the source, and receiver, etc.) were not considered.

The structure of the developed neural network has one hidden layer, which includes 20 nodes. Bipolar sigmoid function and linear function are used as transfer

Table 1. Optimized parameters.

L_0	a_{mt}	a_{ht}	a_b	a_m
44.15	3.36	6.36	3.26	1

Table 2. Parameters of comparative analysis of different prediction models.

	Griffiths and Langdon	Fagotti and Poggi	Burgess	Model - DSA
$\overline{\Delta L}$	4.49	2.19	2.05	1.21
σ	1.44	1.55	1.24	0.72

functions of the hidden layer and the output layer, respectively. During the neural network training process, backpropagation algorithm updates weight and bias values according to Levenberg-Marquardt optimization.

Network weights and biases were determined by performing 20 training sessions of the neural network with the developed structure. The training sessions were performed using 4 different input data sets, which consisted of the randomly selected 210 (out of the 270) measurement data sets. The remaining 60 measurement data sets were used for validation of the prediction of the neural networks. For each of the input data sets, five training sessions were performed, starting each time from the un-trained network.

The average number of network training epochs was 20, which may be considered as a quite fast training. The mean value of the absolute difference between the experimental data and the predictions of the 20 neural networks was in the range 0.66–0.95 dB, and the standard deviation of the difference was in the range 0.63–0.88 dB. The neural network that had the lowest average absolute difference between the predicted and measured data is adopted for further use.

4. Results and discussion

The results of the described noise prediction models are compared with experimental results of noise level monitoring and the results obtained by some most commonly used traffic noise prediction models. The validity of the models was performed by statistical analysis of differences between measured and calculated noise levels for all 270 measurement data sets. The mean values of the absolute differences between noise levels ($\overline{\Delta L}$) and standard deviations of the differences (σ) were calculated. Furthermore, the total number m of predictions with an error larger than 3 dB was also determined for each of the applied models. Since the neural network model was developed using 210 measurement data sets for the network training, the results of predictions for the data sets used for training (index "train") and testing ("test") are also separately presented.

Developed noise level prediction models were compared to several prediction models that account for the influence of reflections and ground, German RLS 90 (Richtlinien für den Lärmschutz an Straßen, 1990), Nordic Prediction Method (Nielsen, 1996), and Italian model (denoted with CNR in the following text) (Canelli *et al.*, 1983). The results of statistical analysis are given in Table 3, while the comparative chart of the measured and calculated noise levels for the randomly selected 30 of 60 measurements used for the neural network testing is shown in Fig. 1.

The statistical analysis shows that the application of the models proposed in the paper leads to more accurate predictions of noise levels in the city of Niš. It is important to notice that the number of predictions with an error larger than 3 dB is

Table 3. Comparison of different models for noise prediction. Results denoted with the index *train* are obtained from data sets used for the neural network training, while the index *test* denotes results obtained from the neural network test set.

	CNR	RLS 90	Nordic	Model - DSA	ANN
$\overline{\Delta L}$	4.45	2.91	2.33	1.44	0.66
$\overline{\Delta L}_{\text{train}}$	4.33	2.82	2.25	1.38	0.53
$\overline{\Delta L}_{\text{test}}$	4.87	3.20	2.60	1.62	1.08
σ	1.96	1.69	1.34	1.00	0.63
σ_{train}	2.00	1.70	1.31	0.98	0.51
σ_{test}	1.78	1.65	1.42	1.05	0.79
m	210	128	91	25	2
m_{train}	159	95	63	19	1
m_{test}	51	33	28	6	1

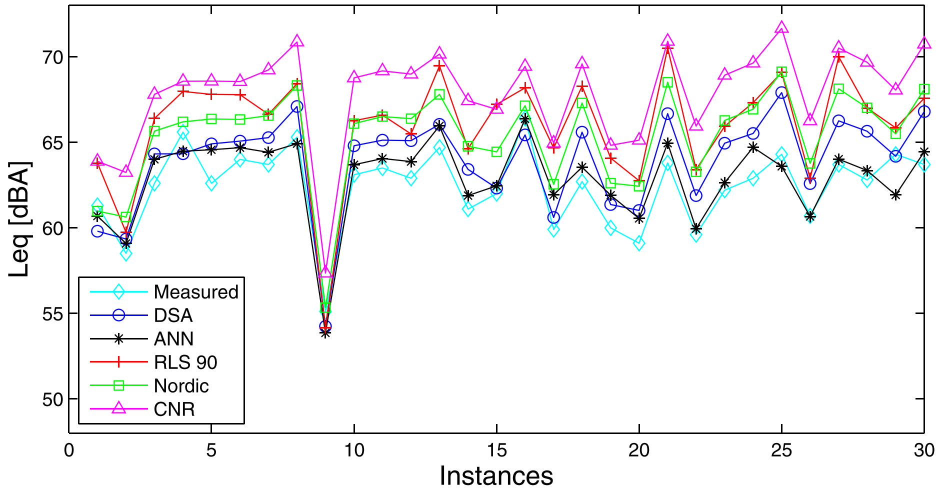

Fig. 1. (Color online) Comparative chart of noise levels.

significantly reduced. The smallest differences between measured and estimated noise levels are obtained using the neural network based model, whose application resulted with only two predictions with an error larger than 3 dB.

The reason for the superior performance of the models presented in this paper is that they are tuned to the conditions in the city of Niš. The Nordic Prediction Model considers only two types of vehicles, and therefore, this model describes the traffic flow composition simpler than the models proposed in this paper. The analysis of results of RLS 90 performance shows that this mathematical model overestimates the contribution of heavy vehicles to traffic noise. The differences are therefore not unexpected, as those models are specific for the respective conditions of these countries, and that they should be adjusted for application in other countries.

The ANN enables the best predictions since it is able to find the complex functional relationship between the input and the output data, unlike the application of the model expressed by the analytic expression obtained by DSA, which requires *a priori* assumption about the functional relationship. On the other hand, the described procedure for developing the mathematical prediction model by using DSA requires less measurement results and a much faster procedure than the neural network training process. Furthermore, the analytic expression obtained using the optimization algorithm clearly shows the influence of each traffic flow parameter to the predicted equivalent noise levels.

5. Conclusion

As the application of the available models for traffic noise prediction does not provide satisfying results for the territory of the city of Niš, a total of 270 noise level measurements were performed in 18 streets of this city, with the aim to develop more precise models. The development of two new traffic noise models was made using modern soft computing techniques. The first model calculates equivalent traffic noise levels using an analytic formula, with model parameters determined using an evolutionary algorithm. The second model calculates equivalent traffic noise levels using a neural network.

The noise levels calculated by the developed models were compared with experimental results, as well as with results of extensively used mathematical models. The results of the comparative analysis show that the application of the models proposed in this paper improves noise level prediction at the territory of the city of Niš.

A comparison of the models proposed in the paper shows that the neural networks provide the best agreement with the experimental data. However, the process of development of neural networks is complex and resource consuming, and the neural networks do not provide insight into physical meaning of their parameters. Since the proposed models are used for urban planning and traffic management purposes that do not require high accuracy, the customized analytic formulas, which include an increased number of input quantities, deserve attention. This paper showed that evolutionary algorithms provide the possibility for fast calculation of model parameters using limited input data sets, thus representing a reasonable alternative to application of neural networks.

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References and links

Burgess, M. A. (**1977**). "Noise prediction for urban traffic conditions—Related to measurement in Sydney metropolitan area," Appl. Acoust. **10**, 1–7.

Canelli, G. B., Gluck, K., and Santoboni, S. (**1983**). "A mathematical model for evaluation and prediction of the mean energy level of traffic noise in Italian towns," Acustica **53**, 31–36.

Civicioglu, P. (**2012**). "Transforming geocentric Cartesian coordinates to geodetic coordinates by using differential search algorithm," Comput. Geosci. **46**, 229–247.

Fagotti, C., and Poggi, A. (**1995**). "Traffic noise abatement strategies. The analysis of real case not really effective," in *Proceedings of the 18th International Congress for Noise Abatement*, Bologna, Italy, pp. 223–233.

Genaro, N., Torija, A., Ramos-Ridao, A., Requena, I., Ruiz, D. P., and Zamorano, M. (**2010**). "A neural network based model for urban noise prediction," J. Acoust. Soc. Am. **128**, 1738–1746.

Givargis, S., and Karimi, H. (**2010**). "A basic neural traffic noise prediction model for Tehran's roads," J. Environ. Manage. **91**, 2529–2534.

Griffiths, I. D., and Langdon, F. J. (**1968**). "Subjective response to road traffic noise," J. Sound Vib. **8**, 16–32.

Gundogdu, O., Gokdag, M., and Yuksel, F. (**2005**). "A traffic noise prediction method based on vehicle composition using genetic algorithms," Appl. Acoust. **66**(7), 799–809.

ISO. (**1996**). ISO 9613-2:1996{E}, *Acoustics—Attenuation of Sound During Propagation Outdoors, Part 2: General Method of Calculation* (International Standards Organization).

Mihajlov, D., Prascevic, M., and Cvetkovic, D. (**2012**). "An analysis of the environmental noise levels on the territory of the city of Nis," in *Proceedings of the 23rd National and 4th International Conference "Noise and Vibration*," Niš, Serbia, pp. 49–58.

Nielsen, H. L. (**1996**). "Road traffic noise: Nordic prediction method," Nordic Council of Ministers.

Prascevic, M. R., Mihajlov, D. I., and Cvetkovic, D. S. (**2014**). "Measurement and evaluation of the environmental noise levels in the urban areas of the city of Nis," Environ. Monitor. Assess. **186**(2), 1157–1165.

Rahmani, S., Mousavi, S. M., and Kamali, M. J. (**2011**). "Modeling of road-traffic noise with the use of genetic algorithm," Appl. Soft Comput. **11**(1), 1008–1013.

Richtlinien für den Lärmschutz an Straßen (RLS), Germany, 1990.