Traffic Noise Modeling Using Artificial Neural Network: A Case Study

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Abstract The heterogeneous features of traffic noise, together with the characteristics of environmental noise, with their great spatial, temporal, and spectral variability makes the matter of modeling and prediction a very complex problem. A need is being felt to develop a traffic noise prediction model suitable for the Indian condition. The present work represents a traffic noise prediction model taking Patiala–Sangrur highway as a representative/demonstrative site. All the measurements of noise levels were made at selected points around the highway at different time on number of days in a staggered manner in order to account for statistical and temporal variations in traffic flow conditions. The noise measurement parameters recorded were traffic volume, i.e., number of vehicles passing through in a particular time period, vehicle speed, and the noise descriptors recorded were the equivalent noise level (L_{eq}) and percentile noise level (L_{10}). Artificial neural network (ANN) approach has been applied for traffic noise modeling in the present study. After training and testing of the ANN, it was found that the values of correlation coefficient (R) were 0.9486, 0.9577, and 0.9255 for the training, validation, and testing samples, respectively, and the percentage error varied from −0.19 to 0.64 and 0.54 to 0.99 for L_{eq} and L_{10}. Therefore, a good correlation coefficient and less percentage error between experimental and predicted output obtained is an indication of prediction capability of neural network.

Keywords ANN · Traffic noise model

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1 Introduction

Highway traffic noise has been a federal, state, and local problem. Emanating from vehicle engines, exhaust systems, and tires interacting with pavement, traffic noise affects the quality of life for nearby residents and businesses by drowning out conversations, disrupting sleep, and discouraging outdoor activities. Over the years, community and motorist concerns have fueled the push to improve noise measurement and modeling tools that help transportation agencies address the highway traffic noise problem. Traffic noise prediction models are required means in designing new highways and other roads or redesigning traffic flow in existing roads to have comfortable traffic noise conditions. In the last few years, a number of prediction tools have been created to estimate noise levels in several countries. For instance, Steele (2001) has reviewed commonly used models such as CORTN, STAMINA, and FHWA. A GIS-based road traffic noise prediction model was developed for use in China by Lia et al. (2002). Pichai and Prakob (2002) formulated a model of highway traffic noise based on vehicle types in Thailand; Calixto et al. (2003) from Brazil developed a statistical model to estimate road traffic noise in an urban setting.

2 Methodology

This study is aimed to develop a more relevant and accurate free-flow traffic noise prediction model for a 2-lane highway in India, taking Patiala (Punjab) city as a representative city, based on L_{eq} and L_{10} as noise descriptors and traffic flow, percentage of heavy vehicle, and average speed as traffic noise parameters. Data were recorded for a total of 133 h duration on different dates and timings in a random or staggered manner in order to account for the statistical and temporal variations in traffic flow characteristics. To fulfill the above objective, artificial neural network (ANN) approach was applied in the present study. The measured parameters were divided into two classes, i.e., output parameters (L_{10}, L_{eq}) and input parameters (vehicle volume/h., percentage of heavy vehicles and average vehicle speed). The input parameters were randomly subdivided into three sets:

Training These are presented to the network during training, and the network is adjusted according to the error.

Validation These are used to measure network generalization and to halt training when generalization stops improving.

Testing These have no effect on training and so provide an independent measure of network performance during and after training.

A comparison was also made between experimental and the ANN output parameters.

Fig. 1 Sound level meter on a tripod with windscreen

2.1 Measurement Procedure

For traffic noise measurements at a suitable site, systematic noise monitoring was done during April–May 2012 using sound level meters (Cesva SC-310) (Fig. 1).

The sound level meter was suitably calibrated, and microphone mounted on a tripod was suitably leveled.

The SLM was mounted at a height of 1.2 m above the ground level and was located at a distance of 10 m from the center of the road lane. Continuous data were recorded with sound level meter during daytime from 9.00 a.m. to 5.00 p.m. at the selected site. The noise descriptors L_{eq} and L_{10} were measured for 15 min. duration in dB (A) weighting with slow response.

Unusually, high values of L_{eq} represent the cases of vehicles honking continuously or the vehicles are without proper silencers, etc.

2.2 Measurements

The data were measured at the selected site as per the described procedure (Fig. 2).

The measured parameters were traffic volume, average speed of vehicles, and noise descriptors (L_{eq} and L_{10}). Traffic volume was measured during the measurement period, and it was varied from 1,155 to 1,380 Veh/h out of which range

Fig. 2 Measurement site

Table 1 Measured data

Time	Traffic vol. Q (Veh/h)	Heavy vehicles P (%)	Avg. vehicle speed V (km/h)	Sound pressure level dB (A)			
				L_{eq}	L_{10}	L_{max}	L_{min}
Date: 31/03/12 (Wednesday)							
09:00–10:00 a.m.	1,218	32.67	48.6	76.7	79.9	92.5	52.8
10:00–11:00 a.m.	1,221	34.31	49.2	75.6	80.4	91.8	56.3
11:00–12:00 a.m.	1,270	32.12	48.6	75.2	80.5	92.6	55.1
12:00–01:00 p.m.	1,227	33.82	47.1	75.8	80.4	88.9	54.6
02:00–03:00 p.m.	1,261	32.51	49.3	74.9	79.6	89.6	57.5
03:00–04:00 p.m.	1,205	31.12	46.1	76.3	80.8	96.3	54.6
Date: 01/04/12 (Thursday)							
09:00–10:00 a.m.	1,285	37.19	50.3	75.8	78.9	98.0	56.3
10:00–11:00 a.m.	1,255	33.69	51.9	76.3	79.2	96.7	54.4
11:00–12:00 a.m.	1,320	34.57	47.1	75.6	79.6	98.8	55.8
12:00–01:00 p.m.	1,278	31.84	48.0	74.8	79.4	96.3	56.6
02:00–03:00 p.m.	1,246	35.79	50.6	75.4	79.2	98.5	54.8
03:00–04:00 p.m.	1,265	36.04	52.4	75.5	78.8	96.4	53.3

of percentage of heavy vehicle is 27.45–39.73 %, and average vehicle speed varied from 45.0 to 55.0 km/h. Vehicles are categorized into seven different types as heavy trucks, medium trucks, buses, cars, tractors, three wheelers, and two wheelers considering the Indian conditions. The noise descriptors L_{eq} and L_{10} were displayed on the SLM screen and were recorded in its memory. Representative data for 2 days, and similar data were recorded for 24 days spread over 133 h of measurement time (Table 1).

3 Modeling

In the present study, the multilayer feedforward neural network was trained by the backpropagation learning algorithm which is based on gradient descent with momentum weight and bias learning function. The Levenberg–Marquardt optimization technique was used in backpropagation algorithm. The training of a network by backpropagation involves the feedforward of the input training pattern, calculation of backpropagation of the associated error and adjustment of weights to minimize the error. The hyperbolic tangent sigmoid transfer function $F(x) = [(ex - e\text{-}x)/(ex + e\text{-}x)]$ was chosen for hidden layer and linear transfers function $[f(x) = x]$ for output layer. The performance of the neural network was evaluated in terms of mean square error (MSE) between the targeted output and predicted output for given samples size.

In order to develop a traffic noise prediction model, steps given below are followed:

Step 1 The MATLAB neural network tool box was used for ANN analysis which includes neural network training, testing, performance evaluation, and comparison.

Step 2 Total of 133 hours data was randomly divided into training, validation, and testing data. Data Distribution:

Training = 60 %

Validation = 15 %
Testing = 25 %

Step 3 ANN Architecture

The prediction accuracy of any neural network is dependent on the number of hidden layer and the numbers of neurons in each layer. So to find out the optimal neural network architecture, in the present case, a number of neural networks architecture have been trained and tested by varying number of neurons in hidden layer as shown in Table 2. One-layered neural network architecture 3–12–2 (3—input neurons, 12—neurons in hidden layer, and 2—output neurons) was found to be optimum because of better performance in terms of MSE during training, validation, and testing in both the highway noise descriptors.

Step 4 Training and Testing ANN Architecture

A total of 24 days experimental data sets (samples), including vehicle volume/ h. (Log Q), percentage of heavy vehicles (P), average vehicle speed (Log V), L_{10}, and L_{eq}, are randomly distributed for training and testing the ANN model. Initial weights and biases were generated and updated depending upon the error between

Table 2 Comparison of training, validation, and testing data for ANN architecture (3–N–2)

No. of hidden layer neurons (N)	Correlation coefficient (R)			Mean square error (MSE)		
	Training	Validation	Testing	Training	Validation	Testing
5	0.9342	0.9220	0.9343	0.7081	0.9888	0.6937
6	0.9454	0.9482	0.9202	0.5411	0.5333	0.8232
7	0.9580	0.9653	0.8985	0.4246	0.3325	1.1219
8	0.9560	0.9055	0.9189	0.4316	0.9453	0.7756
9	0.9635	0.8868	0.8903	0.3818	1.0612	1.0562
10	0.9586	0.9427	0.8970	0.4454	0.5580	1.0417
11	0.9377	0.8985	0.9229	0.9473	0.9654	0.9285
12	0.9486	0.9577	0.9255	0.5641	0.4058	0.6638
13	0.9579	0.8777	0.9064	0.4220	1.2652	0.9572
14	0.9402	0.9093	0.9439	0.5725	0.9093	0.5917
15	0.9723	0.9301	0.8826	0.2805	0.7242	1.1575
16	0.9611	0.9179	0.8746	0.3806	0.8303	1.2017
17	0.9519	0.9326	0.8845	0.4978	0.6580	1.2343
18	0.9697	0.9050	0.8669	0.3105	1.0356	1.3347
19	0.9719	0.9151	0.8855	0.2750	1.0117	1.1885
20	0.9711	0.9164	0.8475	0.2964	0.7862	1.5105
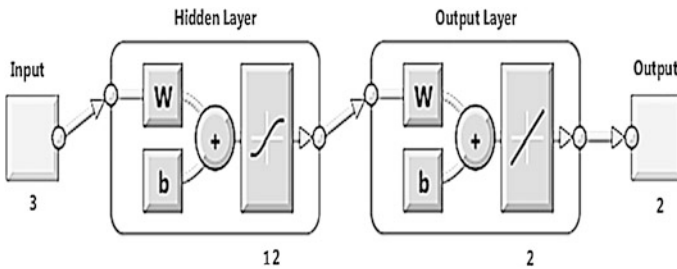
Fig. 3 ANN architecture (3–12–2). *W* weights of connections, *b* bias

predicted and targeted output. The program was terminating the training process if any one of the following condition was achieved:

Maximum number of epochs
Error goal achieved
Minimum gradient reached.

The output equation from the ANN was obtained as: Output $= 0.89 \times$ Target $+ 8.4$. (Fig. 3).

4 Results and Discussion

Since the values of correlation coefficient (R) were 0.9486, 0.9577, and 0.9255 for the training, validation, and testing samples, respectively, and the percentage error varied from -0.19 to 0.64 and 0.54 to 0.99 for L_{eq} and L_{10}; therefore, a good correlation coefficient and less percentage error between experimental and predicted output is an indication of better prediction capability of neural network.

5 Conclusions

Multilayer feedforward backpropagation (BP) neural networks were trained and tested by Levenberg–Marquardt (LM) optimization algorithm to predict L_{10} and L_{eq}, highway noise descriptors with different number of neurons in the hidden layer of the neural network, and among all the neural networks tested, one-layered neural network architecture 3–12–2 (3—input neurons, 12—neurons in hidden layer, and 2—output neurons) was found to be optimum because of better performance in terms of MSE during training, validation, and testing in both highway noise descriptors. The values of L_{eq}, L_{10}, and L_{max} from the highway were observed to be high as per Indian standards; therefore, remedial measures are essential to reduce its harmful effect.

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