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ORIGINAL PAPER

Optimized height of noise barrier for non-urban highway using artificial neural network

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Abstract This study applies artificial neural network (ANN) for the determination of optimized height of a highway noise barrier. Field measurements were carried out to collect traffic volume, vehicle speed, noise level, and site geometry data. Barrier height was varied from 2 to 5 m in increments of 0.1 m for each measured data set to generate theoretical data for network design. Barrier attenuation was calculated for each height increment using Federal Highway Administration model. For neural network design purpose, classified traffic volume, corresponding traffic speed, and barrier attenuation data have been taken as input parameters, while barrier height was considered as output. ANNs with different architectures were trained, cross validated, and tested using this theoretical data. Results indicate that ANN can be useful to determine the height of noise barrier accurately, which can effectively achieve the desired noise level reduction, for a given set of traffic volume, vehicular speed, highway geometry, and site conditions.

Keywords Attenuation · Central pollution control board · Federal highway administration · Traffic

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Introduction

Noise generated from vehicular traffic is a major source of environmental pollution. The WHO has recognized environmental noise to be a harmful environmental pollutant, which has been reported to have adverse psychosocial and physiological effects on human health (Kim et al. 2012; WHO 2011). In the modern world, transportation is the major source of environmental noise regardless of economic development status (Ko et al. 2011). Traffic-noise prediction models are required as aids in the planning and design of urban projects and roads, and also in the assessment of existing or envisaged changes in traffic-noise conditions. These models are commonly needed to predict sound pressure levels (SPLs), specified in terms of L_{eq}, L_{10}, L_{90} etc., at selected locations and in the analysis of mitigation measures during road construction and in identifying the variables with the highest noise incidence. Since traffic, environmental and geospatial characteristics, emission level of vehicles, noise surveying methods, and road traffic conditions differ from region to region and from one country to another. Different countries have developed noise prediction models according to their traffic, environmental and geospatial characteristics. The more popular ones include Federal Highway Administration (FHWA) model in United States, Calculation of Road Traffic Noise (CoRTN) model in United Kingdom, Acoustical Society of Japan (ASJ) model in Japan, Stop and Go model in Bangkok, Mithra in France, Geographic Information System (GIS) model in China and Richtlinien fur den Larmschutz an Straβen (Guidelines for Noise Protection on Streets), i.e., RLS-90 in Germany, etc. Steele (2001), Rajakumara and Mahalinge Gowda (2008) presented detailed review of various noise prediction models including above mentioned models. Several attempts have been made to predict and model road traffic noise statistically by different researchers (Calixto et al. 2003; Abo-Qudais and Alhiary 2007). These models are based on theoretical factors that are applicable based on statistical relationships and on macroscopic traffic variables such as traffic flow and average speed. Their results have been very good related to roads and highways where traffic prevails, and flow conditions are relatively homogeneous. Under heterogeneous traffic flow and speed conditions, these models gives poor performance. To overcome problems associated with heterogeneous traffic conditions, researchers applied stochastic models for traffic-noise prediction (Ramírez and Domínguez 2013). A novel traffic-noise prediction method for non-straight roads was presented (Zhao et al. 2012). Despite mathematical, statistical, and stochastic models, models based and soft computing techniques such as Artificial neural networks (ANN) (Cammarata et al. 1995), GA (Rahmani et al. 2011), and advanced engineering tool such as GIS were developed (Li et al. 2002; Tang and Wang 2007; Sheng and Tang 2011).

Noise level depends on many factors such as number of vehicles, speed of vehicles, background noise, meteorological, and geospatial conditions. These parameters together make noise modeling a complex task and highly nonlinear phenomena, which turns out conventional deterministic models inappropriate. ANN provides flexibility, massive parallelism, learning and generalization ability, accuracy, and some amount of fault tolerance in noisy and changing environments. ANN are appropriate soft computing tools for modeling multifunction, nonlinear, and complex data-related problems. Dougherty (1995) presented a review based on application of neural networks to transportation system. A review article on the use of ANN for traffic noise modeling was reported (Kumar et al. 2011). To create a noise-free environment, noise abatement techniques and equipments are required so that the noise level along a highway can be minimized up to an acceptable value. The installation of noise barriers between noise source and noise sensitive areas along major roads and freeways is another way to combat traffic noise.

During past four decades, extensive research has been carried out on different noise barrier shapes using analytical and physical modeling as well as full scale testing. There are many barrier profiles, which have designed to utilize various physical phenomena for achieving noise reduction. An interesting review related to environmental noise barrier was reported, which provides a catalog of noise barrier profiles, identifying the relative acoustic benefits of each and the physical principles on which they operate (Ekici and Bougdah 2003). A novel method to design a desired noise barrier using the global optimization of a simulated annealing (SA) algorithm was proposed (Mun and Cho 2009). This method focuses on minimizing the barrier dimensions, which were related to material and construction costs, as well as satisfying the target SPLs at receiver points on the condition of traffic noise. Various examples were presented to evaluate the optimized barrier dimensions according to given traffic noise sources, ground topography, surface conditions, and the influence of different receiver positions. An optimization method was used in order to find the best noise barrier profile considering several variable parameters with the aim to optimize the acoustical efficiency of T-shaped noise barriers whose top was covered with a series of wells (Baulac et al. 2008). The acoustic performance of pairs of diffusive roadside barriers was tested experimentally on a 1:10 scale model, and compared to that of more traditional secularly reflecting barriers (Cianfrini et al. 2007). Significant attenuation benefits were detected in the shadow zone behind the barriers and also in the unprotected zone immediately above the barriers. From the study, it was concluded that diffusive traffic faces of the barriers may effectively help in counteracting multiple reflection effects. In addition, a radiosity-based theoretical model developed for the evaluation of the sound field behind pairs of diffusive noise barriers was described, and its ability to predict the extra SPL attenuation deriving from the replacement of geometrically reflecting barriers with diffusely reflecting barriers was verified. Investigations were carried out to study the shadowing effect of barriers of infinite or finite length in the presence of directional noise sources (Menounou and Papaefthymiou 2010).

The relative acoustical performances established by scale model testing of a number of relatively novel noise barriers in typical highway situations was described (May and Osman 1980). Considered barriers include thin, wide, T-profiled, cylindrically topped, corrugated, inclined, Y-profiled, arrow-profiled, etc. Aspects of diffraction theory relevant to design and performance of noise barriers were described and suggestions for improving attenuation provided by an acoustic screen were put forward (Butler 1974). Atmospheric turbulence is an important factor that limits the amount of attenuation a barrier can provide in the outdoor environment. The boundary element method (BEM) is a very effective technique for predicting barrier insertion loss in the absence of turbulence. A simple and efficient modification of the BEM formulation to predict the insertion loss of a barrier in the presence of atmospheric turbulence was reported (Lam 2004). A new formula that incorporates the effects of diffraction theory and the reflection of sound between room surfaces was proposed (Lau and Tang 2009). Study involves experimental, theoretical, and numerical analyses of the insertion loss provided by rigid noise barriers in an enclosed space. Results indicate that the present formula provides more realistic and practical predictions of the barrier insertion loss than existing approaches. Analytical modeling methods of complex noise barriers were reported (Hayek 1990). The models were developed by use of the geometrical theory of diffraction, which allows for modeling of simple- and complex-shaped noise barriers. These models involve diffraction coefficients that include the influence of frequency, grazing angle, surface impedance, and the source and receiver positions.

Based on the investigation of characteristics of current barrier design methods and the road noise prediction model, an optimal design method of noise barrier used in reducing noise emission from traffic flow was presented (Xintan et al. 2005; Xintan and Shuiliang 2009). In the designs of road noise barrier and elevated urban expressway noise barrier, the availability of the new method in reducing the noise and improving the economic solution was proved through the comparison between the current methods and the optimal design method. Results of study shows that the distance to a great extent determines cost for noise barrier. Cost of the erection-shaped noise barrier was found lower as compared with L-shaped noise barrier, which means increase in height is more effective than reducing the distance between noise source and receiver to attain required noise reduction and lower construction cost of barrier. A systematic approach to determine reasonable heights and locations for noise barriers adjacent to railway lines was presented (Weber and Atkinson 2008). Considering finite length of traffic flow, an optimized design method of noise barrier used in reducing noise emission from traffic vehicles was presented (Xintan and Shuiliang 2011). Cost of noise barrier was chosen as objective function. Results of study shows that the finite length of sound source is notable to shortening the length of noise barrier, which is important to noise reduction and cost of noise barrier. Based on noise prediction model and all parameters considered comprehensively, the optimal design parameters and lowest cost were achieved by the new method.

Due to rapid urbanization and corresponding increase in vehicular population, the noise level in most of the metropolitan cities as well as near major highways in India is above the acceptable limits (CPCB 2000). Noise pollution has become a major concern of communities living in the vicinity of highways, road corridors and intersections. Most of the studies related to noise pollution and barrier design were carried out in metropolitan cities in India and abroad (Parabat and Nagarnaik 2007). It is observed that less attention has been given by the researchers to assess the noise status for the people living near-by non-urban highways of developing nations like India. Few attempts have been made for the design of noise barrier using different approaches in India. Mohan et al. (2002) investigated about the need for construction of noise barriers in India. Types of noise barriers including their characteristics and design factors were described pertaining to suitability of noise barriers for Indian conditions. In a report submitted to All India Council for Technical Education (AICTE), New Delhi, Jain and Parida (2004) collected and statistically analyzed traffic volume, speed and noise level data for road traffic noise prediction for five Indian cities at various locations of Delhi, Jaipur, Chandigarh, Allahabad, and Lucknow and designed noise barriers at sensitive zones. FHWA and CoRTN models (Steele 2001) were calibrated according to Indian road conditions for the study and model development. Investigations were carried out to describe the use of ANN in the transport related pollution modeling (Sharma 2007). An attempt was made to determine the height of noise barrier using ANN. Research was carried out to quantify and analyze the traffic noise emissions along bus rapid transit corridor in Delhi, India (Mishra et al. 2010). Field measurements were carried out to understand and assess various aspects of the impact of bus rapid transit system corridor on land use and social lives of residents and road users. Results were compared between observed and predicted noise level at selected corridors and mitigation measures were described to overcome such type of traffic noise pollution through design of noise barrier along the road. Shukla (2011) measured noise levels on the flyover in front of Institute of Engineering and Technology (IET Lucknow, Uttar Pradesh, India) and designed a noise barrier for this location for predicted noise levels using modified FHWA model. In the present study, an attempt has been made to determine optimized height of noise barrier for non urban highway NH-58, near Muzaffarnagar by-pass, India, which can provide desired level of attenuation with the help of ANN due to its capability to provide flexibility, accuracy, and fault tolerance in noisy and changing environment. This situation offers a substantial scope for future studies, which would be relevant for intermediate cities and areas nearby non-urban major highways, hence, would have wider scope of application. Data collection was carried out at Km 115, NH-58 (i.e., National Highway-58, direction from Roorkee to Delhi) near Muzaffarnagar bye pass, Uttar Pradesh, India, on 18/11/2011.

Materials and methods

Basic background

Noise barriers reduces the sound, which enters a community from a busy highway by absorbing the sound, transmitting it, or reflecting it back across the highway and forcing it to take longer path over and around the barrier. A noise barrier must be tall enough to block the view of a highway from the area that is to be protected (the receiver).

A noise barrier can achieve a 5 dB noise level reduction, when it is tall enough to break the line of sight from the highway to the receiver. After it breaks the line-of sight, it can achieve approximately 1.5 dB of additional noise level reduction for each meter of barrier height (FHWA 2011).

Mathematical background

The acoustical performance of a vertical thin barrier is generally determined by the ratio of the path length difference (δ) to the acoustic wavelength (λ). Path difference can be defined as the difference between the diffracted path from source over the top of the barrier to the receiver, and the direct path from source to the receiver as if barrier were not present.

Performing some trigonometric calculations one can get from Fig. 1.

$$A = \sqrt{C_1^2 + (h - S)^2} \quad (1)$$

$$B = \sqrt{C_2^2 + (h - R)^2} \quad (2)$$

$$C = \sqrt{(C_1 + C_2)^2 + (R - S)^2} \quad (3)$$

Path length difference is given by,

$$\delta = A + B - C \quad (4)$$

Fresnel Number (N) is a dimensionless value used in predicting the attenuation provided by a noise barrier positioned between a source and the receiver. Fresnel number is defined as

$$N = \frac{2\delta}{\lambda} \quad (5)$$

where A is the distance of source from barrier top, B is the distance of receptor from barrier top, C is the distance of source from receptor, C_1 is the distance of source from barrier, C_2 is the distance of receiver from barrier, h is the height of barrier above the roadway, R is the height of the receiver above the roadway, and S is the source height of vehicle above the roadway.Wavelength of sound $\lambda = c/f$. Therefore, $N = 2\delta f/c$ where f is the frequency of the sound radiated by the source and c is the speed of sound.

For freestanding barriers, where the Fresnel number is positive, the barrier attenuation (Wilson 1989) is given by,

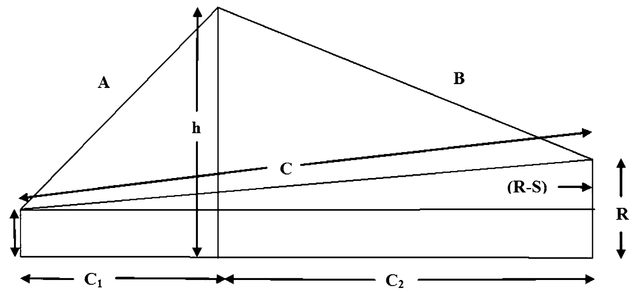


Fig. 1 Path length difference (δ)

Artificial neural network

An ANN is an information processing paradigm that is inspired by the way a biological nervous system, such as the brain processes information. In this information processing system, the elements called neurons, process the information. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.
2. Inter-neuron connection strengths known as synaptic weights are used to store the knowledge.

An artificial neuron is characterized by:

1. Architecture (connection between neurons).
2. Training or learning (determining weights on the connections).
3. Activation function.

All neural networks share some basic features. They are composed of simple processing elements known as neurons. These elements take data from source as input and compute an output dependent in some well-defined way on the values of inputs, using an internal transfer (i.e., activation) function. These neurons are joined together by some weights. Data flows along these connections and is scaled during transmission according to the values of weights. The arrangement of neurons into layers and the pattern of connection within and in-between layers are generally called the architecture of the net. The process of modifying weights according to the connections between the network layers, with the objective of achieving the expected output is called training a network. The internal process that takes place when a network is trained is called

$$\begin{aligned} \Delta B &= 10\log\left[\left(\frac{1}{\varphi_R - \varphi_L}\right)\left(\frac{1}{\sqrt{10}}\right)\left(\int_{\varphi_L}^{\varphi_R} \frac{\tanh^2\sqrt{2\pi N\cos\varphi}}{2\pi N\cos\varphi}\,d\varphi\right)\right] && \text{for} \quad 0 \le N < 5.03 \\ \Delta B &= 20 && \text{for} \quad N > 5.03 \end{aligned} \quad (6)$$

learning. Neural networks consist of a large number of processing elements called neurons. These neurons are connected to each other by directed communication links, which are associated with weights. An activation function is used to calculate the output response of a neuron. The sum of a weighted input signal is applied to activation function to obtain a response. Multi-layered feed-forward (MFFN) network is one of the extensively used network (Wu 1994). MFFN are layered feed-forward networks typically trained with static back propagation. Their main advantages are that they are easy to use and that they can approximate any input/output map. Back-propagation is a supervised learning method, which requires that for the training input vectors, the corresponding target output is known. Back-propagation network's learning process consists of four stages (Sivanandam et al. 2010; Haykin 2010)

1. Initialization of weights.
2. Forward computing of data sets stream.
3. Back-propagation of error signals.
4. Updation of the weights and biases.

During first stage, i.e., initialization of weights, some small random values are assigned. For forward computing, original data are transmitted from input layer to output layer through hidden processing layer. If the desired output cannot be obtained by from the output layer, it turns to the process of backward propagation in which error is propagated backward through the network against the direction of forward computing. During this process, synaptic weights are adjusted in accordance with error signal. Performing these steps iteratively, the error between network output and desired output is minimized using the delta rule.

Hidden layer neuron activation (H_j) can be computed as

$$H_j = f(I_j),\ I_j = \sum_i W_{ji} X_i \tag{7}$$

where W_{ji} is the weights from input node i to hidden node j, X_i is the value of input node i and $f(.)$ denotes the sigmoid transfer function

$$f(x) = \frac{1}{1 + \exp(-\sigma x)}$$

where σ is the steepness parameter.

Output layer neuron activation (O_k) is given by

$$O_k = f(I_k),\ I_k = \sum_j W_{kj} H_j \tag{8}$$

W_{kj} is weights from hidden j node to output node k.

Total error of the neural network is given by,

$$E_k = \frac{1}{2} \sum_k (T_k - O_k)^2 \tag{9}$$

where T_k is the target value of output node k for input pattern, O_k is the actual value output of node k for input pattern.

Error signal (δ_k) at output layer and weight adjustment between output to hidden node is computed as

$$\delta_k = (T_k - O_k) O_k (1 - O_k)$$

$$W_{kj}(\text{New}) = W_{kj}(\text{old}) + \alpha \delta_k H_k + \mu\left[W_{kj}(\text{old}) - W_{kj}(\text{old} - 1)\right] \tag{10}$$

Computation of error signal (δ_j) at hidden layer and adjustment of weights between hidden and input nodes is given by

$$\delta_j = H_j (1 - H_j) \sum \delta_k W_{kj}$$

$$W_{ji}(\text{New}) = W_{ji}(\text{old}) + \alpha \delta_j X_i + \mu\left[W_{ji}(\text{old}) - W_{ji}(\text{old} - 1)\right] \tag{11}$$

where α is known as the learning rate, which controls the speed of convergence to the minimum of errors and μ is the momentum rate.

Data collection

Km 115, NH-58 (i.e., National Highway-58, direction from Roorkee to Delhi) near Muzaffarnagar bye pass, Uttar Pradesh, India, was selected for the study. NH-58 is one of the important national highway in India, connecting Delhi to northern hill areas cities like Roorkee, Haridwar, Rishikesh, Joshimath, Badrinath, etc. It is a four-lane highway from Delhi to Muzaffarnagar and rest part is two lane. The site represents predominantly residential land use pattern. During field study, data like traffic volume, noise levels, spot speed, and geometrical parameters were collected. Vehicle count and vehicle classification were carried out manually at the site for a period of 8 h from 9:00 a.m. to 5:00 p.m. Noise levels were recorded in dB (A) using noise level meters at the distance of 17.1 m from median of road. Measurements were recorded every 15 s for a period of 15 min/h. This was considered to represent the variations in noise levels of the entire hour. The spot speeds were recorded for all categories of vehicles by using radar gun. A large number of speeds were recorded per vehicle during the entire span of the day to accurately estimate the average speeds of each vehicle category. Thus, eight data sets were obtained consisting traffic volume, average speed of vehicles, noise level, and surface geometry parameters. Site location of the study area with the proposed noise barrier is presented in Fig. 2.

The following points were taken into consideration during data collection:

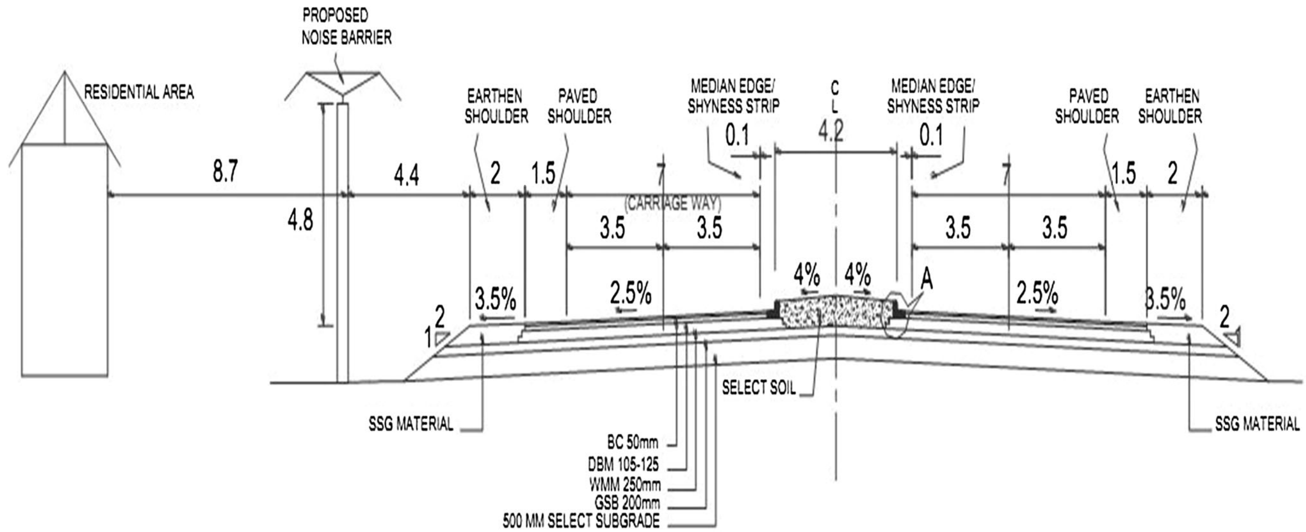


Fig. 2 Site location of study area (all distances in meter)

1. Vehicles were categorized into seven categories based on their weights, noise emission levels and homogeneity.
2. Traffic noise was quantified by the equivalent noise level L_{eq}.
3. All measurements were carried out under normal weather conditions and the effects of wind speed direction and temperature variation were neglected.
4. The background noise in the study locations was limited to 10 dB(A).

Data analysis

Data analysis is an important part of designing of noise barriers. First, the noise generated due to the vehicles was analyzed. L_{eq} was calculated using FHWA model for the measured noise level. The value L_{Aeq} was determined from the following equation

$$L_{Aeq} = L_0 + \sum L_i \tag{12}$$

where L_{Aeq} is continuous steady noise level on A-weighted scale, L_0 is basic noise level for a stream of vehicles, and L_i is adjustments for each vehicle category, i.e., the number of vehicles, type of vehicles, reflections, road surface type, road gradient, speed, angle of view of the road, barriers, vegetation.

The hourly equivalent noise level from a given class of vehicle was computed by summing up the various adjustments to the mean energy emission level:

$$L_{eq(ij)} = L_0 + \Delta T + \Delta D + \Delta S + \Delta G + \Delta F + \Delta B \tag{13}$$

where L_0 is basic noise level for a stream of vehicles, ΔT is traffic flow adjustment for a given class of vehicles, ΔD is distance adjustment for a given class of vehicles, ΔG is grade adjustment for a given class of vehicles, ΔF is finite segment adjustment for a given class of vehicles, and ΔB is barrier adjustment for a given class of vehicles.

Equivalent noise level due to traffic at the receiver point is given by:

$$L_{eq} = 10 \log \left(\sum_{i}^{n} 10^{L_{eqij/10}} \right) \tag{14}$$

where n is the number of roadways.

Noise barrier height prediction using ANN

The basic objective behind the development of ANN model was to calculate the required barrier height at noise sensitive locations. The whole process was completed in two phases. First, theoretical data were generated by increasing barrier height from 2 to 5 m in steps of 0.1 m for each measured data (i.e., traffic volume, corresponding average speed of vehicles and site geometry data) set. Thus, we get 240 theoretical data sets corresponding to 8 measured data records. In this way, separate data sets were generated for each barrier height. Barrier attenuation for different height of barrier was calculated using the equation by FHWA model (Barry and Regan 1978). All measurements for attenuation calculation were carried out from middle point of carriageway, i.e., source was supposed to be situated in the middle of carriageway of four-lane highway. The length of barrier was considered as infinite. Detail of parameters for barrier attenuation calculation is given in Table 1. The code for barrier attenuation calculation was

Table 1 Parameters details for barrier attenuation calculation

Site identification	Near Muzaffarnagar by-pass, on NH-58, towards Delhi						
Vehicle category	Car/Jeep/Van	Mini bus	Bus	Truck	Motorcycle	Auto/three wheeler	Tractor/ trailor
Source height (m)	0.279	0.54	0.86	0.7	0.34	0.203	0.584
Distance from source to Barrier (m)	11.4	11.4	11.4	11.4	11.4	11.4	11.4
Barrier height (m)	Increased from 2 to 5 m in steps of 0.1 m						
Distance from Barrier to receiver (m)	8.4	8.4	8.4	8.4	8.4	8.4	8.4
Receptor height with respect to road (m)	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Left angle subtended by barrier (φ_L) (°)	−90	−90	−90	−90	−90	−90	−90
Right angle subtended by barrier(φ_R) (°)	90	90	90	90	90	90	90

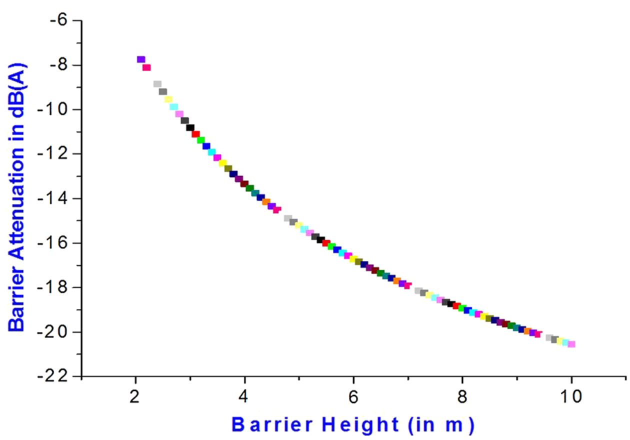


Fig. 3 Variation of attenuation provided by barrier with height

developed in Matlab 7.6. Variation of attenuation with barrier height provided by barrier is shown in Fig. 3. For construction of network classified traffic volume, corresponding average speed of vehicles and barrier attenuation was considered as input variables whereas barrier height was taken as output. During second phase ANN was trained, validated, and tested to determine the required barrier height.

Network details

For network generation classified traffic volume (Car/Jeep/Van, LCV/Minibus, Bus, Truck, Scooter/Motorcycle, 3-Wheeler and Tractor/Trailer), corresponding average speed of vehicles, barrier attenuation, and barrier height were entered in the required format. A set of 240 data records has been taken for analysis, each of which contains 15 features. Category of vehicles divided in seven parts, corresponding average speed of vehicles divided in seven parts and barrier attenuation were among these features. Whole database has been divided into three parts for training, cross validation, and testing in the ratio 60, 15, 25 %, respectively. After training and cross validating the neural network, 60 data records were considered for testing the constructed model.

Eight ANN models with different number of hidden neurons were constructed and trained using same set of training data. Performances of these ANN models were compared using cross validation and testing data sets. The mean square error (MSE), mean absolute error (MAE), normalized mean square error (NMSE), and coefficient of correlation (r) were used to evaluate the prediction results. Details of networks with different architectures used to determine the desired network has been illustrated in Table 2. It can be found that neural network with six hidden neurons produces the best prediction. Thus, used ANN structure in the present work has 15 inputs, 6 neurons in hidden layer and single output, which is shown in Fig. 4. In the present study, a multilayer perceptron network is used. Network was trained; cross validated and tested using the Neuro Solution software version 5.0. Minimum MSE was taken as the stopping criterion during training the network.

Results and discussion

Barrier height considered for variation was taken into on accounts of practical limitations to install a noise barrier nearby a residential area such as view blocking, air passage, and cost consideration. Graph between actual and predicted barrier heights (as calculated by ANN Model) for

Table 2 Details of networks with different architecture

Trial No	Train 1	Train 2	Train 3	Train 4	Train 5	Train 6	Train 7	Train 8
Number of hidden layers	1	1	1	1	1	1	1	1
Number of hidden neurons	3	3	3	4	3	3	4	6
Transfer Function	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Sigmoid
Number of epochs	300	300	400	500	200	300	500	1,000
Learning	Momentum	Momentum	Momentum	Momentum	Levenberg	Levenberg	Levenberg	Levenberg
Step Size/momentum	1/0.5	1/0.6	1/0.7	1/0.7	–	–	–	–
Minimum MSE (T)	0.0347	0.0302	0.0315	0.0134	7.62E–06	5.75E–07	4.55E–07	6.31E–08
Final MSE (T)	0.0347	0.0302	0.0315	0.0134	4.96E–05	5.75E–07	4.55E–07	6.31E–08
Minimum MSE(X)	0.0368	0.0257	0.03178	0.0146	9.69E–06	1.08E–06	2.07E–06	1.31E–07
Final MSE (X)	0.0368	0.0257	0.03178	0.0146	9.69E–06	1.08E–06	3.30E–06	1.36E–07
MSE (Y)	0.7532	0.7069	0.612	0.2029	3.77E–05	2.31E–05	2.87E–05	4.61E–06
NMSE (Y)	0.9788	0.8544	0.8886	0.3384	6.78E–05	3.22E–05	3.86E–05	6.88E–06
MAE (Y)	0.7356	0.7329	0.6967	0.3916	0.0047	0.0036	0.0038	0.0017
r (Y)	0.4851	0.8846	0.9168	0.9867	0.9999	0.9999	0.9999	0.9999

T During training stage, *X* During cross validation, *Y* During testing stage, *MSE* Mean square error, *NMSE* Normalized mean square error, *MAE* Mean absolute error, *r* Coefficient of correlation

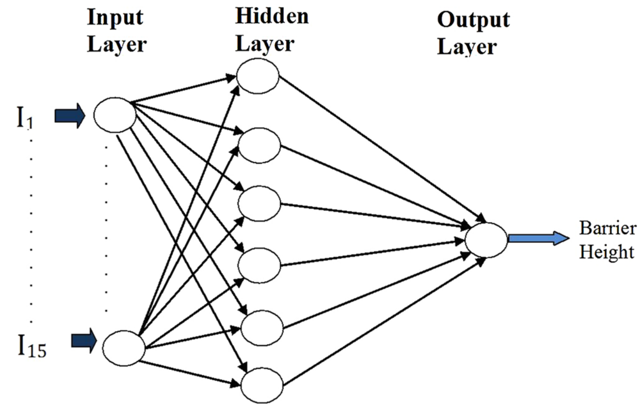


Fig. 4 Structure of neural network

testing stage is shown in Fig. 5. Scatter plot for model validation is shown in Fig. 6.

Noise prediction is an integral part of environmental impact assessment of highway projects. From measured values of traffic noise, it has been concluded that noise level exceeds at all the identified locations and is significantly higher than prescribed standards set by Central Pollution Control Board (CPCB 2000) India as presented in Fig. 7. The value of required L_{eq} was taken in accordance with the laid down standards as 55 dB(A) for day time and 45 dB(A) for night time as the sight is adjacent to major highway (residential area). The analysis of data by ANN architecture, for residential area near Muzaffarnagar bypass on NH-58, India, shows that there is a requirement of 4.8 m height of the barrier to reduce noise level up to 15 dB(A). It is obvious that designed noise barrier is not able to reduce noise level up to the CPCB standard of 55 dB(A) as shown in Fig. 8. NH-58 is the four lane divided non-urban highway having heavy traffic flow, which produces high level of noise not only in peak hours, but also in off peak hours. The average noise level recorded is approximately 77 dB, which is 22 dB above the CPCB standard whereas for the peak hour noise level is about 80 dB(A). Theoretically, a noise barrier can provide attenuation of about 20 dB(A) but in practice this limit is about 15 dB(A) (Kotzen and English 2009). Barrier designed in the present study theoretically provides attenuation of about 15 dB(A). Although 10 dB(A) noise level difference between CPCB standard and for 9–10 h period (with designed barrier) is more than enough in terms of noise reduction but the average difference between these two is about 7 dB(A) for the whole measurement period. There are many reasons why designed barrier does not perform well. The first reason is that height of the proposed barrier at the study location cannot be increased beyond the 5 m since the dwellings are of first storied having average height of about 5 m. If the height of the barrier is increased beyond 5 m then it will create other problem like blocking view and passage of air and sunlight. A transparent barrier can avoid the issue of view blocking but it is relatively expensive solution to implement. Taking cost considerations into account it is not easily possible to increase the height of the barrier. Performance of any barrier depends heavily on the influence of the ground, the atmosphere, and reflective surfaces in built-up areas (Ekici and Bougdah 2003). Other factors include thickness, shape, mounting angle, and material used for the construction of the barrier.

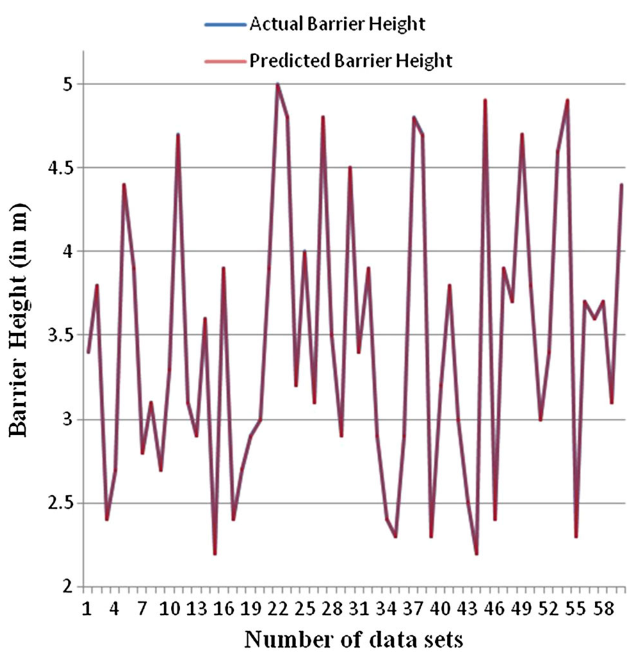


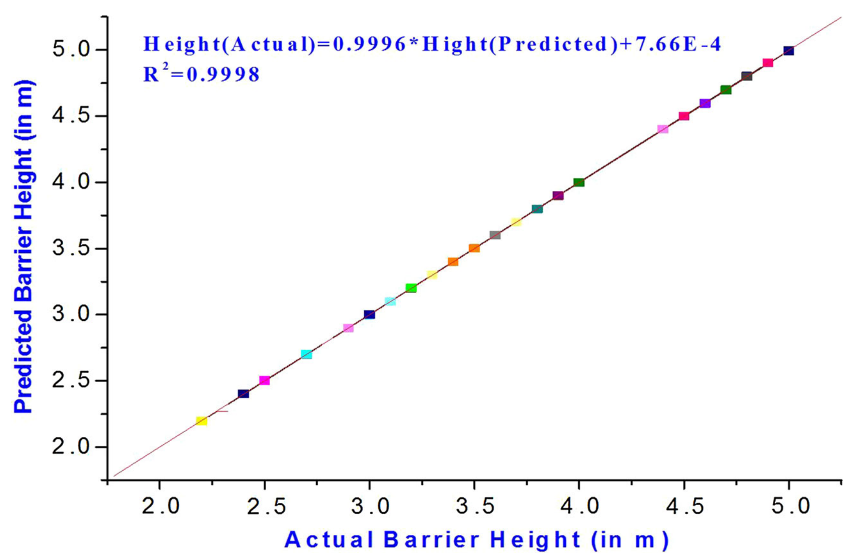
Fig. 5 Actual and predicted barrier height (by ANN)

In the present study, simple free standing barrier has been designed. By considering other barrier shapes such as multiple diffracting edges T, Y shape with reactive surface and tubular capping (i.e., use of absorbing obstacles on top of the barrier), efficiency of the proposed barrier can be further increased (Watson 2006). The difference in the noise level can be reduced up to CPCB standards by considering other steps such as imposing speed limit on vehicles, tree plantation, ban on pressure horns, strict measures not to allow inhabitants to construct homes before the prescribed distance limit.

To test the significance of discrepancy between actual and predicted barrier heights χ^2 test was applied. It enables us whether deviation of actual from predicted is not by chance but due to inadequacy of the theory to fit measured data. It therefore, provides a test of goodness of fit. Since calculated χ^2 value (7.43651E–05) is too small to tabulated χ^2 value (77.93), therefore, actual and predicted barrier height values are in good agreement at 59 *df* and 5 % significance level.

Major advantage of ANN is that its applicability to a wide variety of problems and relatively easy to use. In a neural network, relationships between variables are discovered automatically and fitting takes place naturally. Overall network structure is the only place where our intuition comes into play. In the ANN modeling there is no restriction on the number of variables, i.e., one can choose desired number of variables based on the problem. There is no general method or theory for the design of neural networks. Generally a trial and error approach is used. The complexity of neural network design arises from high dimension, heterogeneity and high order nonlinearity of the problems to be modeled. The basic features which are of concern in the design of neural network are the

Fig. 6 Linear correlation between actual and predicted barrier height



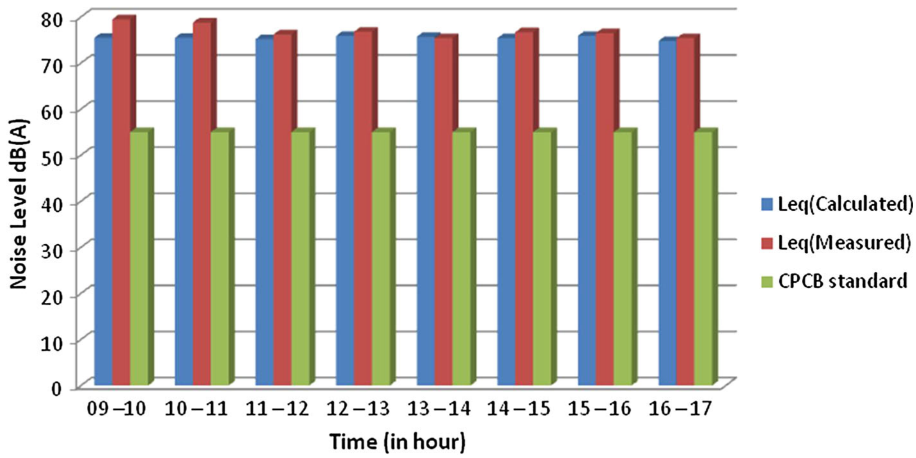


Fig. 7 Calculated (using FHWA model), measured and CPCB standard noise levels near Muzaffarnagar by-pass on NH-58, India

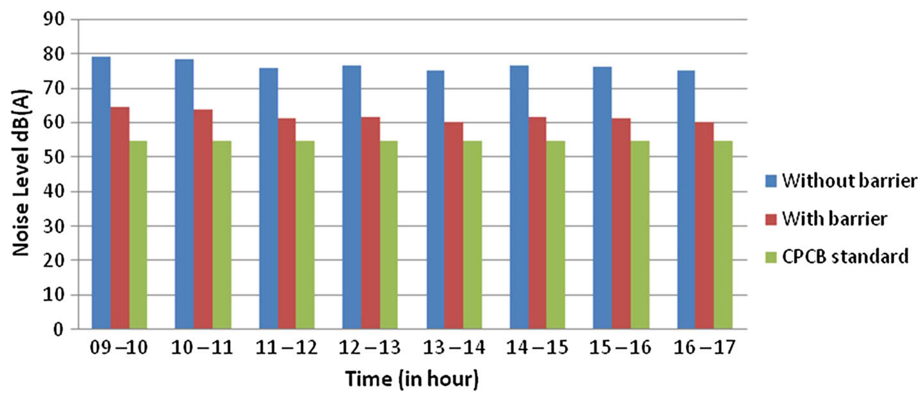


Fig. 8 Noise levels before and after the installation of suggested noise barrier near Muzaffarnagar by-pass on NH-58, India

structure of the network, number of input variables to be considered, activation function and selection of learning or training algorithm. All these quantities are problem dependent.

Despite these advantages, the ANN model has its own drawbacks. Development of an ANN model is very time-consuming. The time required to develop an ANN model depends on the size of training data and network structure. Once a network is specified, it usually takes hours to complete an experiment especially when the size of training data is large because a training algorithm usually needs to go through several hundred of iterations to obtain an "optimal" weighting for the network. In statistical modeling, one can find cause and effect of each of independent variable but in ANN framework same is not possible. In ANN modeling, it is not possible to determine the effect of all the individual variables independently. Like disaggregate models, neural networks also suffer from explanatory problems as there is a difficulty in interpreting the weights.

Conclusion

Based on the present study, it is concluded that traffic noise caused by heavy traffic flow condition near Muzaffarnagar by-pass on NH-58, India, is significant and exceeding the national CPCB standards. This is alarming situation by considering the fact that the traffic volume is going to increase further in coming years. Due to heavy traffic volume, traffic noise will also increase nearby this particular highway. Results of present study reveal that ANN has produced good results with classified volume, speed, barrier attenuation, and site geometry parameters. To evaluate model performance coefficient of correlation, MSE, MAE were used. Other design factors for noise barriers include aesthetics, traffic safety, maintenance, structural performance, and cost. Performance of a noise barrier depends upon many other factors such as barrier shape, barrier material, thickness of barrier, and weather conditions. In the present study, ANN has been able to determine the height of noise barrier required to achieve the desired noise level (L_{eq}), for a given set of traffic volume and speed conditions. Results reveal that present model is applicable in the designing of barrier height needed for satisfying target noise levels.

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