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Comparison of ANN and analytical models in traffic noise modeling and predictions

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***Abstract* - The major environmental challenges encountered by metropolitan cities now-a-days is the traffic noise besides air pollution. During urban planning, one thus needs methods/tools which can assist the designer in designing, planning and adoption of suitable measures for traffic noise abatement and control. The objective of the present work is to model traffic noise in terms of single-noise metrics L_{Aeq}, *TNI* and *NPL*. ANN has a capability to model complicated multi-variable functions and thus can model a system with more variables than that can be included in any other conventional models. The problem of traffic noise is non-linear in nature, so, a model based on Artificial Neural Networks (ANN) is suggested and compared with the analytical models in this work.**

***Keywords* — Traffic noise, Artificial Neural Networks, Equivalent continuous sound pressure level, L_{Aeq}.**

I. Introduction

Technological development has led to the urbanization which has also given rise to the problem of increasing traffic noise. It has been scientifically proven that high noise levels seriously affects the health of the people exposed to it. Different studies have been conducted to generate a model which can predict the noise levels with a definite accuracy and precision. In Indian context, there have been many studies reported for various cities. Since Delhi has been severely facing traffic related problems, so a model based on Delhi's traffic noise would be sufficient to generalize this problem and can be used to predict the traffic noise in other parts of the country as well. The previous studies in Indian context are generally focused on regression based approach [1-6].Various models have been developed for different Indian cities in past few years. Rao *et al.* [1] developed a regression equation for modelling L_{A10} as a function of traffic density. In urban areas, most of the traffic flow is often interrupted by traffic signals and thus interrupted traffic flow conditions on urban roads create substantially different noise characteristics from the highways to expressways [2 & 3]. Rajakumara *et al*. [3] developed a regression noise prediction model for both acceleration and deceleration lanes. Agarwal [4] introduced equivalent number of light and heavy vehicles for the calculation of L_{eq} values. Light motor vehicles have found to be the major culprit in noise pollution. The recent investigations of Kalaiselvi [5] also accounted horn noise component in his work.

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It has been observed that horn noise occurs with frequency of 16 per minute and raises L_{eq} by 12 dB (A). The recent studies by Kumar *et al.* [6] and Sharma *et al.* [7] have also tried to model the traffic noise by using ANN and regression approach. In the developed nations, there has been an extensive research in this area and every nation has developed its own scientific tools/models and validated these models like CORTN for UK, RLS 90 for Germany and ASJ-RTN 2008 for Japan etc. [8].

As such, the dependence of noise levels with traffic density, average vehicular speed is non-linear in nature, so other approaches especially the soft computing algorithms should be also tried to ascertain their compatibility in comparison to regression based approach. The present study focuses the use of Artificial Neural Network (ANN) approach in modeling traffic noise levels. Several studies have used this technique to predict traffic noise. Givargis *et al.* [9] developed an ANN model to predict hourly A-weighted equivalent sound pressure levels for roads in Tehran at a distance less than 4 m from the nearside carriageway edge. It was highlighted that neural network models allow for significantly more variables than those often included in conventional models as ANN have capacity to model complicated, multi-variable functions. Parabat and Nagarnaik [10] developed an ANN model to predict the sound pressure level for continuous traffic flow conditions. Nucara *et al.* [11] investigations revealed that dynamic behavior of neural networks which allow complete and detailed description of the involved phenomena has found increasing applications in the research field. Based on study of 25 previously selected input variables, Genaro *et al.* [12] developed an ANN based model to predict urban environmental noise (L_{Aeq}). The recent studies, thus, have shown that ANN can be efficiently utilized for traffic noise predictions with definite accuracy and precision. Toriza [13] demonstrated a STACO model intended to predict the short-term (5 min integration period) level and temporal-spectral composition of the sound pressure of urban sonic environments. The ANN advantages are fast, precise and reliable computation of multi-variable, non-linear and complex computations compared to the mathematical conventional and numerical methods [14]. The ANNs has shown superiority as a modeling technique for data sets showing non-linear relationships, and thus can be efficiently utilized for both data fitting and prediction abilities. In present study, noise measurements are carried out at different locations in Delhi and these are utilized to ascertain the applicability of ANN in the traffic noise predictions and forecasting. Based on this, a model based on Artificial Neural Networks (ANN) is suggested and is compared with the analytical models.

II. Experimental Data Acquisition & Analysis

During the experimentation, precision integrating digital sound level meter used was kept at a distance of 0.4 m from the body and at a height of 1.2 m from the ground level and 3-4 m from the road for avoiding any reflections from road side barriers. The measurement of sound pressure in dB(A) was done along with the monitoring of the average speed of vehicles with the speed gun (Make: Bushnell) and numbers of vehicles were counted manually. Precision digital sound level meter helped in measuring L_{eq} and statistical parameters *e.g.* L_{10}, L_{50}, L_{90} *etc.* Short term, L_{AeqT} measurements (B & K 2250 and Norsonic, Nor 118) ranging from 15 minutes to 60 minutes were undertaken at different busy road locations of Delhi. While measurements, it was ensured that there is no reflections from the adjoining building facades or wall. The output variables L_{eq}, L_{10}, L_{50} and L_{90} are also measured with the help of sound level meter in A-weighing mode. The other parameters like Traffic Noise Index (*TNI*), Noise Pollution Level (*NPL*) were calculated using the statistical parameters [15 & 16]. These parameters are calculated in terms of (L_{10}-L_{90}), which is a quantitative measure of spread of sound. Traffic noise index (*TNI*) indicates the degree of variation in a traffic flow and is expressed as:

$$TNI = 4(L_{10}-L_{90})+L_{90} - 30 \text{ dB(A)} \quad (1)$$

Noise Pollution Level (*NPL*) takes into account the variations in sound signal and is calculated as:

$$NPL = L_{eq} + (L_{10}-L_{90}) \quad (2)$$

It may be noted that neither of these indices viz., *NPL*, *TNI* have proved to better correlated with annoyance than simpler indices like L_{eq} [17].

III. Analytical Models

There are numerous analytical models available in literature for prediction of traffic noise. Some of these are as follows [18,19]:

- Burgess model: $L_{eq} = 55.5 + 10.2 \log Q + 0.3p - 19.3 \log (L/2)$ (3)
- Josse model: $L_{eq} = 38.8 + 15\log Q - 10 \log (L)$ (4)
- Fagoti model: $L_{eq} = 10 \log (N_c+N_m+8N_{hv}+88N_b) + 33.5$ dB(A) (5)
- NAISS model: $L_{eq} = 10 \log (N_c+11.7 N_{hv}+3.1N_b) + 44.3$ dB(A) for $65 < L_{eq} < 75$ dB(A) (6)
- Griffith and Langdon model: $L_{eq} = L_{50}+0.018(L_{10}-L_{90})^2$ dB(A) (7)
- CSTB model: $L_{eq} = 0.65 L_{50} + 28.8$ dB(A) (8)

where L is the road width, p is the percentage of heavy vehicles, Q is the total number of vehicles per hour, N_c is number of light vehicles per hour, N_m is the number of motorcycles per hour, N_{hv} is the number of heavy vehicles per hour and N_b is the number of buses per hour. Based on multiple-regression analysis of the experimental data, an empirical formulation was developed as:

$$L_{Aeq} = 67.277 + 4.751\log Q - 4.90\log V + 0.058p \quad (9)$$

where V is average speed of vehicles, Q is total number of vehicles per hour and p is percentage heavies.

IV. Artificial Neural Network (ANN) Model

Neural networks are similar to linear and non-linear least squares regression and can be viewed as alternative statistical approach in solving the least squares problem or multiple regression analysis. Since the ANN architecture is based on biological neural network and it consists of interconnected artificial neurons which are grouped under the input, hidden and output layers, where the number of input and output decides the number of neuron in the respective layer. The most significant part is the hidden layer influences the final output. There is no thumb rule for determining the optimum number of neurons as revealed in the previous studies. Some studies [20] recommended that all neural networks should start with preferably one or atmost two hidden layers. The hidden layers provide the network with its ability to generalize. In practice, neural networks with one and occasionally two hidden layers are used widely and have performed well in many studies. For back propagation ANN architecture, the network topology *i.e.* number of neurons, hidden layers, output neurons, error function to be designed following steps should be considered. The selection of training parameters *i.e.* learning rate, epoch size, momentum constant, size of training, testing and validation data set is an important trivial task in developing an efficient validated model. The data set is divided randomly for training, testing and validation. The validation is accomplished by performance criteria *i.e.* MSE, MAPE (Mean Absolute Percentage Error) *etc*. The sigmoidal function is used as activation function for the network so developed. With faster learning rate, the model will learn faster; while if the learning rate is too high, the oscillations of weight changes can impede the convergence of error surface that may lead to overshooting an optimal weight factor [20]. The momentum coefficient determines the proportion of the last weight change that is added into the new weight change. The back-propagation algorithm utilized in present study updates the weights and bias values according to the Levenberg-Marquardt optimization. Back-propagation networks are a class of feed-forward neural networks with supervised learning rules. Supervised learning is a process of comparing each of the network's forecasts with the known correct answer and adjusting the weights based on the resulting forecast error to minimize the error function [20]. Optimization of weights is made by backward propagation of error during learning phase. The algorithm is based on minimization of error function on each pattern by use of steepest descent method. Back-propagation (or its variants) is habitually used for non-linear mathematical optimization [21 & 22].

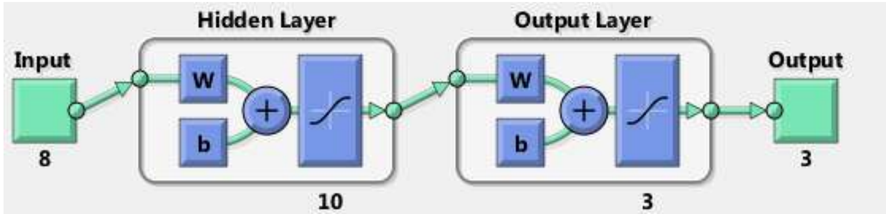

Fig. 1. Architecture of ANN model developed with 8 inputs and 3 outputs.

The model implements training function "trainlm", the learning function "learngdm" to establish a relationship between the input and output variables. The input variables are classified as distance from road way, number of cars, two-wheelers, three-wheelers, medium commercial vehicles, trucks and buses and average weighted speed of vehicles calculated using acoustic equivalence approach [23]. The output variables are L_{Aeq}, Traffic noise index (*TNI*) and Noise Pollution Level (*NPL*). In the current study, the back propagation neural networks were trained utilizing data set with 75 % of the data for training, 10 % for validation and rest 15 % for testing the developed model.

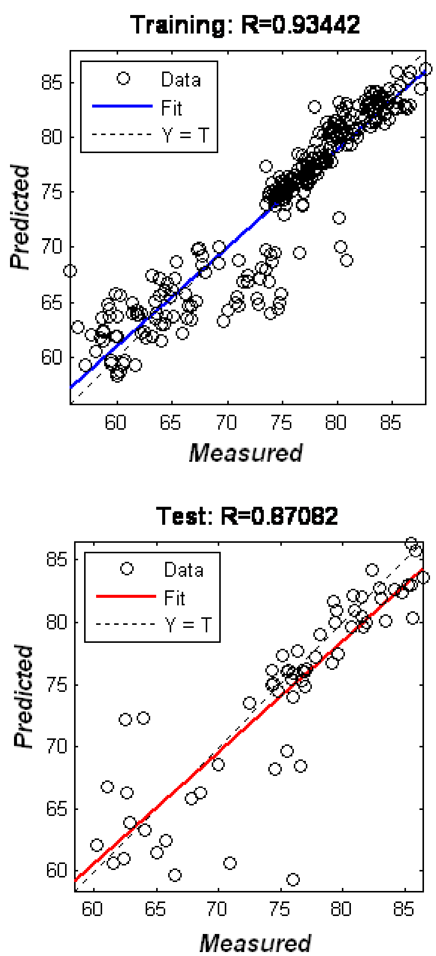

Fig 2. Measured versus predicted sound pressure levels in dB(A) for training and test data

The network was trained by varying the number of neurons from 4 to 20 in a single hidden layer. It is observed that single hidden layer neural network structure with 10 neurons gives minimum mean squared error and good correlation coefficient between the targeted and predicted output for training as well as testing data set. So, the optimal neural network structure is *8-10-3* as shown in fig 1. The mean squared error for L_{Aeq} is observed to be 1.83 dB. Fig 2 shows the comparison of measured values versus the predicted values for ten neurons in the hidden layer. The model goodness of fit with experimental data is tested using paired *t* test as shwn in table 1

Paired *t*-test yield a *t*-statistic value of -1.44 indicating statistically significance at the 5 % level. The correlation coefficient between the measured and predicted data in case of ANN model is observed to be 0.78, while that for the regression model, it is observed to be 0.53.

Conclusions

The paper presents a soft computing approach of modeling traffic noise. As the traffic noise problem is non-linear in nature and dependent upon many variables, the conventional regression methodologies sometimes over-predicts the results. The value of correlation coefficient is 0.87 for the test data set in ANN model so developed. The training function used is "trainlm' and the learning function is "learngdm". From these results, we can deduce that the model aids in predicting the noise levels accurately and thus can aid in traffic planning and can be instrumental in planning for traffic patterns and road layouts for new projects for abatement of road traffic noise. The accuracy of the model so developed can be further improved with more number of readings at greater number of sites and considering more number of variables including road characteristics, vehicle characteristics, weather, environmental conditions, vegetation, type of locality, presence of industries nearby etc. The study reveals that back propagation algorithm has good capability in data modeling. However, despite many advantages, there are some disadvantages too. Construction of ANN model is time consuming and depends on the size of training data and network structure. Also it is sometimes like a black box wherein one can't adjudge the weights and biases developed while training the network. However, inspite of these shortcomings, ANN can serve as vital substitute for analytical models in traffic noise predictions and forecasting.

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Table 1. Paired *t*-test for predicted L_{Aeq} by various analytical models.

Parameters	Measured Value	Burgess Model	Fagoti Model	NIASS Model	Josse Model	ANN Model	Regression Model
Mean Value	76.5	74.1	75.2	81.6	82.4	76.3	77.7
Variance	3.23	3.40	2.92	6.90	8.89	2.42	0.92
Pearson Correlation		0.55	0.57	0.40	0.58	0.78	0.54
Hypothesized Mean Difference		0	0	0	0	0	0
df		131	131	131	131	131	131
t Stat		17.8	11.4	-21.0	-26.6	-1.44	-1.048
P(T<=*t*) one-tail		9.15E-39	3.16E-22	2.17E-46	2.17E -58	0.008	9.32E-16
t Critical one-tail		1.66	1.66	1.66	1.66	1.66	1.66
P(T<=*t*) two-tail		1.83E-38	6.32E-22	4.35E-46	4.35 E-58	0.016	1.86E-15
t Critical two-tail		1.98	1.98	1.98	1.98	1.98	1.98

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