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Modeling and Simulation of Road Traffic Noise Using Artificial Neural Network and Regression

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Modeling and simulation of noise pollution has been done in a large city, where the population is over 2 millions. Two models of artificial neural network and regression were developed to predict in-city road traffic noise pollution with using the data of noise measurements and vehicle counts at three points of the city for a period of 12 hours. The MATLAB and DATAFIT softwares were used for simulation. The predicted results of noise level were compared with the measured noise levels in three stations. The values of normalized bias, sum of squared errors, mean of squared errors, root mean of squared errors, and squared correlation coefficient calculated for each model show the results of two models are suitable, and the predictions of artificial neural network are closer to the experimental data.

Key words: *Artificial neural network, road traffic noise, regression, modeling, simulation*

1. Introduction

The disturbance produced in our environment by various kinds of undesirable loud sounds is called noise pollution. Noise is one of the most pervasive pollutants. Like other pollutants, noise is a product of industrialization and modern civilization. It is an inescapable part of everyday life. It has become a growing concern throughout the world as it affects not only daily activities of people but also their productivity, health, and emotion.

Noise pollution is an increasing problem throughout the world. Traffic noise is considered as one of the major contributors to noise pollution. Particularly, road traffic noise is considered to be one of the most widespread and growing environmental problems in urban areas. People consider noise pollution to be the main local environmental problem, sometimes even more than air pollution or quality of drinking water.

Airport, railway, seaport and vehicular noises are major groups of traffic noise. Vehicular traffic noise sources include any cars, vans, trucks, motorcycles and buses that exist in roads and streets of a city. Vehicular traffic noise is one of the most invasive types of noise pollution, so it has become an issue of immediate concern for authorities in cities. The main sources of vehicular noise are: vehicle engine, exhaust systems and aerodynamic friction. The other factors affecting moving vehicle noise propagation level are stop signs, acceleration and deceleration, road surface gradient, tire–pavement interaction[1], speed bumps[2] and traffic lights[3]. Thus, traffic noise is affected by traffic volume, composition, location, speed, road surface and its gradient. As a result, road traffic noise is among the extensively most studied fields of noise pollution and therefore, several studies have been made on different aspects of traffic noise[4-10].

Some researchers have investigated noise pollution and its propagation levels in different countries. Sheadel classified noise models into four categories, i.e. regulatory, commercial, trade, and design[11]. Steele reviewed some of the most popular developed models, such as Federal Highway Administration Traffic Noise Model (FHWA TNM) with STAMINA 2.0/ OPTIMA for United States, Calculation of Road Traffic Noise (CoRTN) for United Kingdom, Richtlinien zum Lärmschutz an Straßen (RLS) 90 Standard for Germany, etc[12].

Some models assume point source[13]. While this assumption is a simple assumption, noise sources, with good approximation, behave as area sources[14]. For closely spaced sources, i.e. major roadways, they have a linear behavior [15]. A dynamic optimization was suggested for the prediction of periodic non-stationary road traffic noise[16]. The researchers developed the methods for the determination of road traffic noise downstream of a traffic signal[3, 17]. Lam and Tam proposed a noise prediction tool based on the Monte-Carlo technique[18]. Calixto et al. presented a statistical model to predict road traffic noise[19].

Large cities suffer a great deal of noise pollution due to vehicular traffic. The main objective of the present paper is to develop two models of regression and artificial neural

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network for estimation of road traffic noise level in a large city and check their performance.

2. Modeling

2.1 *Artificial neural networks*

Algorithms for analytic computer codes in engineering systems are usually complicated, involving the solution of complex differential equations. These programs usually require large computer power and need considerable amount of time to give accurate predictions. Instead of complex rules and mathematical routines, artificial neural networks (ANNs) are able to learn the key information patterns within a multi-dimensional information domain. In addition, they are fault tolerant in the sense that they are able to handle noisy and incomplete data, deal with nonlinear problems, and once trained can perform predictions and generalizations at high speed. An artificial neural network is a computational structure, consisting of a number of highly interconnected processing elements (or nodes) that produce a dynamic response to external input or stimuli. Neural networks were originally developed as approximations of the capabilities exhibited by biological neural systems, and they are based on a connectionist structure and mathematical functions that imitate the architecture and functions of the human brain. An artificial neural network consists of interconnected artificial neurons, interacting with one another in a concerted manner. Much of the interest in neural networks arises from their ability to learn to recognize patterns in large data sets. This is accomplished by presenting the neural network with a series of examples of the conditions that the network is being trained to represent. The neural network then learns the governing relationships in the data set by adjusting the weights between its nodes. In essence, a neural network can be viewed as a function that maps input vectors to output vectors. A multi-layered feed-forward back-propagation algorithm is used as current case. Input–output pairs are presented to the network, and weights are adjusted to minimize the error between the network output and the actual value. The back-propagation training algorithm is an iterative gradient algorithm, designed to minimize the mean square error between the predicted output and the desired output. The flow chart of the back-propagation learning algorithm is illustrated in **Fig. 1**[20, 21].

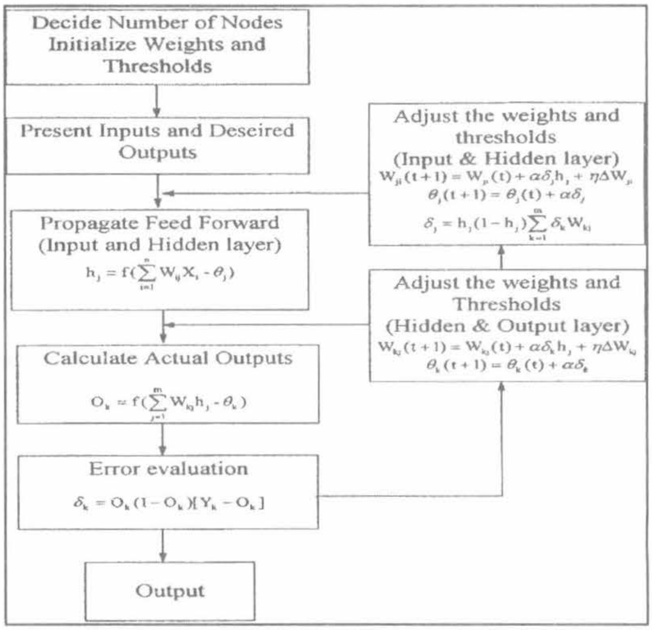

Fig. 1 : The algorithm of training a back propagation network

2.2 *Regression*

Regression is the statistical technique that identifies the relationship between two or more quantitative variables: a dependent variable, whose value must be predicted, and an independent variable (or variables), about which knowledge is available. The technique is used to find the equation that represents the relationship between the variables. Regression is used to understand the statistical dependence of one variable on other variables. The technique can show what variance proportions between the variables are due to the dependent and independent variables. The relation between the variables can be illustrated graphically, or more usually using an equation[22].

3. Experimental

For measuring the noise, three different points of Mashhad (second large city of Iran) were selected. These stations are: Station 1: A point along a street with light to medium traffic flow in downtown; Station 2: A point near one of the most crowded intersections in the city center; and Station 3: A point along a semi-highway road consists of two separate bands; each consists of four traffic lanes.

These stations located far from stop signs and intersections, so that accelerations and decelerations can be ignored. Noise empirical data were obtained by using Brüel and Kjær microphones as receiving points, at 3 m height above the ground level, Brüel and Kjær 4435 analyzers, NMSWin 7802 software for analyzing the recorded data and calculation of hourly equivalent noise level, L_{eq}. The measurements were done from Saturday to Wednesday, between 7:00 am to 7:00 pm. Simultaneous vehicle counts were performed for 1 hour intervals. Measured hourly equivalent noise levels are shown in **Table 1** for each station.

Vehicles were classified in three groups: 1. Light cars (LC): this group include private cars, taxis, motorcycles, and vans; 2. Medium trucks (MT): minibuses, buses carrying small

Table 1. Hourly measurements of equivalent noise level (dBA) [23]

Time(h)	7	8	9	10	11	12	13	14	15	16	17	18	19
Station 1	67.8	67.7	67.3	67.6	67.9	68.2	68	67.4	66.4	67.5	68	68	68
Station 2	70	68.9	68.9	68.9	69.3	69.5	68.9	67.8	67.8	68.6	69.2	68.8	68.7
Station 3	70.4	70.3	70.3	70.2	70.5	70.3	70.2	70	69.8	70.3	70.6	70.6	70.4

number of passengers, and vans carrying heavy cargos were put under this classification; and 3. Heavy trucks (HT): Buses nearly full of passengers, trucks, and trailers were included in this group. The more details have been introduced in the previous paper[23].

4. Simulation

4.1 Artificial neural network

Software of MATLAB (Math-Works Inc.) has been used for simulation by ANN. The input variables of ANN are the time, station of measured noise, and traffic flow that is separated into light cars and medium and heavy trucks and output variable is the equivalent noise level. The data series is separated in three sets, a training set, a testing set and a validating set. Three fifths (60%) of data are assigned to training set. The remaining data (40%) are assigned equally to testing and validating sets. Prediction errors are calculated from the difference between actual outputs and the outputs generated using the different methods on the test cases. The least errors are produced with the four-layer (two hidden layers) neural network. The first layer is "linear" that contains 5 neurons, second layer is "tangent" which includes 7 neurons, third layer is "saturating linear" that has 10 neurons, and the last layer which contains 1 neuron is "linear". The used training algorithm is "Levenberg-Marquardt back propagation".

4.2 Regression

Regression analysis can be used for present data set. Considering the traffic flow be classified into light cars and medium and heavy trucks, station of measured noise, and time as input variables and the equivalent noise level as the output variable, several models were tested. Using try and error method, the best model with the least error was selected. Experimental data series were simulated by using DATAFIT software (Oakdale Engineering) and choosing regression model from its option menu. The equation that has the best results is as follows:

$$L_{eq} = 4.17E\text{-}7 * t + 6.09E\text{-}7 * x_1 - 3.29E\text{-}5 * x_2 + 3.25E\text{-}5 * x_3 + 2.16E\text{-}2 * x_4 + 4.18 \quad (1)$$

5. Results and discussion

In **Figs. 2, 3 and 4,** the observed data are compared with both model's results. By comparing these figures, it is obviously recognized that in the third station both models have better results. For analyzing all stations results a scatter plot is generated (**Fig. 5**). As it shows, the computed data by regression and artificial neural network models fit very well. This is mostly because of the optimization of squared error between observed and both computed data. With respect to **Fig. 5**, the artificial neural network model has better results than the regression model.

Besides, some statistical parameters i.e. normalized bias (NB), sum of squared errors (SSE), mean of squared errors (MSE), root mean of squared errors (RMSE), and squared

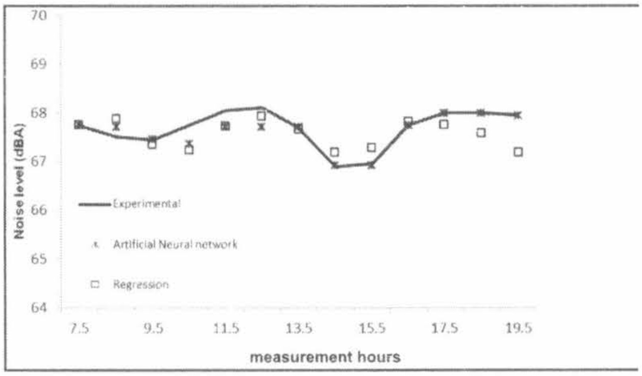

Fig. 2 : Comparison of results for station 1

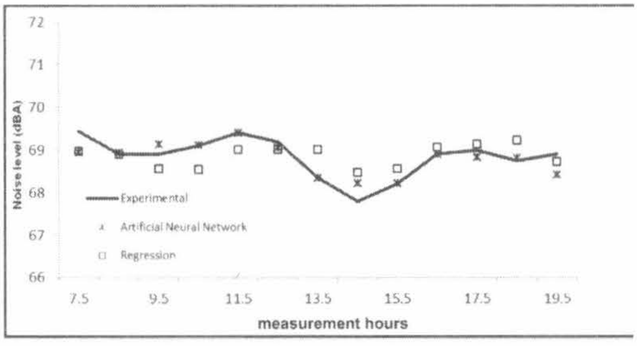

Fig. 3 : Comparison of results for station 2

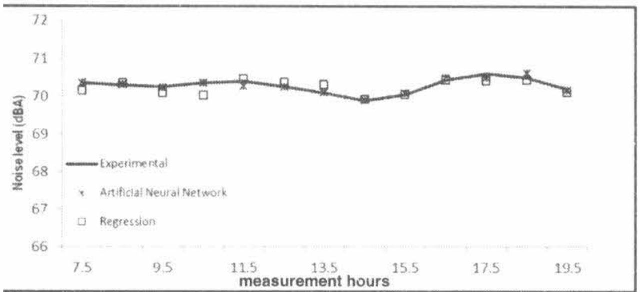

Fig. 4 : Comparison of results for station 3

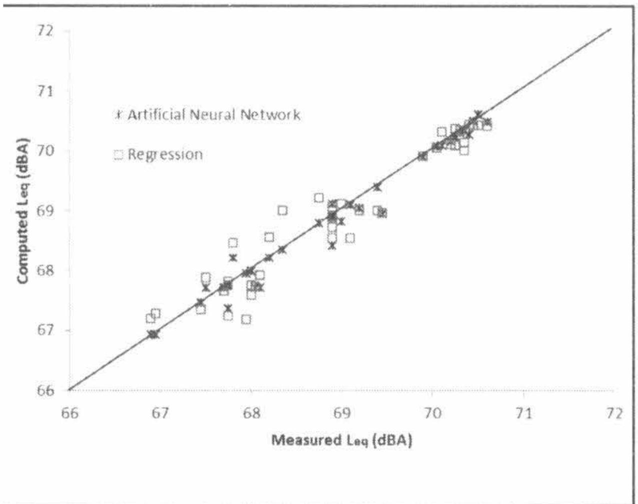

Fig. 5 : Scatter plot for data of two models

correlation coefficient (R^2), which are described by Eqs. (2-6), are used for the fitness investigation and error determination of the models:

$$NB = \sum_i^n \frac{(L_{model,i} - L_{exp.,i})/L_{exp.,i}}{n} * 100 \qquad (2)$$

$$SSE = \sum_i^n (L_{model,i} - L_{exp.,i})^2 \qquad (3)$$

$$MSE = \frac{\sum_i^n (L_{model,i} - L_{exp.,i})^2}{n} \qquad (4)$$

$$RMSE = \sqrt{\frac{\sum_i^n (L_{model,i} - L_{exp.,i})^2}{n}} \qquad (5)$$

$$R^2 = \frac{\sum_i^n (L_{exp.,i} - L_{model,mean})^2 - \sum_i^n (L_{model,i} - L_{exp.,i})^2}{\sum_i^n (L_{exp.,i} - L_{model,mean})^2} \qquad (6)$$

The results for both models are presented in **Table 2**. With regard to NB values, both the models under predict the noise, but the under predictions are very little. The values of SSE, MSE and RMSE show the results of models have some insignificant errors. The values of R-square, coefficient of fitness, show the models results are fitted to the experimental data very well. Totally, the results of artificial neural network model are better than the results of regression model.

6. Conclusion

According to the Environmental Protection Agency of Iran policies, there is a serious noise pollution due to traffic in Mashhad city, so it is in an improper range. Two artificial neural network and regression models were developed to predict road traffic noise level in the city. Both models are based on three variables, namely, the traffic flow, station of measured noise and time. These models predict the measured data very well, and the artificial neural network model presents better results.

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Nomenclature

f, logistic sigmoid activation function

h, vector of hidden layer neurons

L_{exp}, experimental equivalent noise level (dBA)

$L_{model,}$ equivalent noise level predicted by model (dBA)

$L_{model,\ mean}$, mean equivalent noise level predicted by model (dBA)

MSE, mean of squared errors

n, number of experimental points

NB, normalized bias

O, output

Table 2. Statistical data for each model

Model	NB	SSE	MSE	RMSE	R-square
Artificial Neural Network	-0.18844	1.1523	0.08863	0.29772	0.9844
Regression	-0.21446	4.041	0.31084	0.55753	0.9412

R^2, squared correlation coefficient

RMSE, root mean of squared errors

SSE, sum of squared errors

t, time (s)

W, weights

X, input

x_1, hourly number of light cars

x_2, hourly number of medium trucks

x_3, hourly number of heavy trucks

x_4, station of measured noise

Y, target activation of the output layer

Greek symbols

α, learning rate

δ, error for output neuron

ν, threshold between the input and hidden layers

η, momentum factor

References

1. Koizum T, Tsujiuch N, Tamaki R and Iwagase I, An analysis of radiated noise from rolling tire vibration, *JSAE Review*, **24(4)**, 465–469 (2003).

2. Behzad M, Hodaei M and Alimohammadi I, Experimental and numerical investigation of the effect of a speed bump on car noise emission level, *Applied Acoustics*, **68(11-12)**, 1346-1356 (2006).

3. Stoilova K and Stoilov T, Traffic noise and traffic light control, *Transportation Research Part D*, **3(6)**, 399–417 (1998).

4. Björkman M, Maximum noise levels in road traffic noise, *Journal of Sound and Vibration*, **127(3)**, 583-587 (1988).

5. Brown A L, Exposure of Australian population to road traffic noise, *Applied Acoustics*, **43(2)**, 169–176 (1994).

6. Cannelli G B, Traffic noise pollution in Rome, *Applied Acoustics*, **7(2)**, 103-115 (1974).

7. Carter N L, Ingham P and Tran K, Overnight traffic noise measurements in bedrooms and outdoors, Pennant Hills Road, Sydney–comparisons with criteria for sleep, *Acoustics Australia,* **20**, 49-55 (1991).

8. Ko N, W M, Traffic noise in a high rise city, *Appl Acoustics*, **11(3)**, 225–239 (1978).

9. Öhrström E, Effects of low levels of road traffic no during the night: a laboratory study on number of ever maximum noise levels and noise sensitivity, *Journal Sound and Vibration*, **179(4)**, 603–615 (1995).

10. Rylander R, Sörensen S and Kajland A, Traffic no exposure and annoyance reactions, *Journal of Sou and Vibration*, **47(2)**, 237–242 (1976).

11. Sheadel D L, *Considerations for selecting an appropri computer model for noise impact assessment*, Proceedi of the 90th Air and Waste Management Association, d TA29.04, Toronto, Ontario, Canada, 1997.

12. Steele C, A critical review of some traffic noise predicti model, *Applied Acoustics*, **62(3)**, 271–287 (2001).

13. Barry T M, Reagan J A, *FHWA Highway Traffic No Prediction Model*, Report No FHWA-RD-77-108, Fede Highway Administration, Washington DC, 1978.

14. Baverstock S J, Pocock R L and Attenborough Development of area-based methods for predicti ambient noise, *Applied Acoustics*, **33(4)**, 303-312 (199

15. El-Fadel M, Shazbak S, Baaj M H and Saliby E, Paramet sensitivity analysis of noise impact of multi highways urban areas, *Environmental Impact Assessment Revie* **22(2)**, 145-162 (2002).

16. Yamaguchi S, Ishihara S and Kato Y, A practical meth of predicting periodic non stationary road traffic no based on the time rate of average number of flowi vehicles, *Acoustics Letters*, **16(6)**, 123–128 (1992).

17. Kato Y, Yamaguchi S and Takagi K, A practical predicti method of road traffic noise around traffic signals and experimental studies in actual roads prediction at the side of the road downstream from the traffic sign *Journal of the Acoustical Society of Japan*, **50(2)**, 91-1 (1994).

18. Lam W H K and Tam M L, Reliability analysis of traf noise estimates in Hong Kong, *Transportation Resea Part D*, **3(4)**, 239–248 (1998).

19. Calixto A, Diniz FB and Zanin P H T, The statisti modeling of road traffic noise in an urban setting, *Citi* **20(1),** 23-29 (2003).

20. Chun M S, Biglou J, Lenard J G and Kim J G, Using neu networks to predict parameters in the hot working aluminum alloys, *Journal of Materials Processi Technology*, **86(1)**, 245–251 (1999).

21. Taymaz I and Islamoglu Y, Prediction of convection heat transfer in converging–diverging tube for laminar air flowing using back-propagation neural network, *International Communications in Heat and Mass Transfer*, **36(6)**, 614–617 (2009).

22. Wonnacott T, Wonnacott R, *Introductory Statistics 5th edition* (John Wiley and Sons) 1990, 50-68.

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

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