A NEURAL NETWORK NOISE PREDICTION MODEL
FOR TEHRAN URBAN ROADS

Ali MANSOURKHAKI, Mohammadjavad BERANGI[*], Majid HAGHIRI,
Mohammadreza HAGHANI

*Iran University of Science and Technology, Civil engineering, Narmak,
Tehran, 16844 Iran (the Islamic Republic of)*

Abstract. Over the last decades, the number of motor vehicles has increased dramatically in Iran, where different traffic characteristics and urban structures are notable. In the present study, a multilayer perceptron neural network model trained with the Levenberg-Marquardt algorithm was used for predicting the equivalent sound level (L_{Aeq}) originating from traffic. Fifty-one samples were collected from different areas of Tehran. Input parameters consisted of total traffic volume per hour, average speed of vehicles, percentage of each category of vehicles, road gradient, density of buildings around the road section and a new parameter named "Building Reflection Factor". These data were randomly used with 80, 10 and 10 percentiles respectively for training, validation and testing of the Artificial Neural Network (ANN). Results yielded by the ANN model were compared with field measurement data, a proposed regression model and some classical well-known models. Our study indicated that the prediction error of the neural network model was much less than that of the regression model and other classical models. Moreover, a statistical t-test was applied for evaluating the goodness-of-fit of the proposed model and proved that the neural network model is highly efficient in estimating road traffic noise levels.

Keywords: artificial neural network, ANN, traffic noise prediction, modeling, building reflection, building density.

Introduction

In the last decades, the growth in population and vehicles per capita that has led to an increase in urban trips has made our world noisier than ever before. According to WHO reports, traffic noise alone is harmful to the health of almost every third person in the WHO European Region (Euro WHO 2015). Living in a noise-polluted area can cause many short and long-term health problems such as sleep disturbance, as reported by the WHO. Cardiovascular diseases like hypertension and other mental and physical problems are the outcomes of being exposed to excessive noise levels (Euro WHO 2015) so that a vast number of research papers are directed to delineate this issue (Babisch *et al.* 2013; Brink 2011; Caciari *et al.* 2013; Fyhri, Klboe 2009; Pirrera *et al.* 2010). Therefore, a lot of research was conducted to investigate the impact of traffic noise pollution on the environment and the methods of predicting, reducing or controlling this phenomenon (Johnson, Saunders 1968; Delany *et al.* 1976; Pamanikabud, Vivitjinda 2002; Paulauskas, Klimas 2011; Dintrans, Prendez 2013; Bastián-Monarca *et al.* 2016) and in many countries, some

regulations and guidelines are being applied for maximum allowed noise levels in different land uses. Most of the well-known models such as CoRTN, RLS90 and FHWA TNM which were reviewed critically in Steele (2001), Quartieri *et al.* (2009) and Garg and Maji (2014) are based on linear regression analysis (Nedic *et al.* 2014). The major limit of these models, as mentioned in Quartieri *et al.* (2009) and Claudio Guarnaccia *et al.* (2011), is "that they don't take into account the intrinsic random nature of traffic flow, in the sense that they don't take care of how vehicles really run, considering only how many they are."

On the other hand, the power and usefulness of the artificial neural network and variety of its application in various branches of science, especially when accurate prediction and classification is needed, have been proven. Generally, the ANN method is appropriate for procedures that show a certain connection between dependent and independent variables but we don't know the exact nature of the relationship between them and it is hard to articulate using common techniques of correlation and group difference (StatSoft, Inc. 2013).

*Corresponding author. E-mail: mj.berangi@gmail.com

The ability of neural networks in solving nonlinear and complex problems has been proven and has made it a suitable substitute for linear regression analysis for traffic noise modeling in recent research (Cammarata *et al.* 1995; Parabat, Nagarnaik 2008; Genaro *et al.* 2009; Kumar *et al.* 2014).

Despite tremendous efforts by numerous experts worldwide to develop various prediction models, these models are not reliable for Iran with different traffic characteristics and contribution of older and noisier vehicles. In many areas of Tehran, the capital city of Iran, highways are passing through the residential regions adjacent to the buildings which are considered as a health threat for residents. Also, the proximity of buildings to the highways causes traffic noise to be reflected by the buildings' facades and, as a consequence, noise levels increase. This key point should be considered in developing noise prediction models for this city.

Developing road traffic noise prediction models has attracted several investigators in Iran as well. In a study conducted by Givargis and Karimi (2010), application of neural networks for prediction of traffic noise led to satisfactory results for the city of Tehran. A preliminary neural network using the parameters of UK Calculation of Road Traffic Noise (CoRTN) was utilized in their model without considering the reflection effect of buildings adjacent to the roads. Ignoring the reflection effect of facades on the noise levels in the previously proposed models for Iran was the justification of the present study to develop a more comprehensive model which takes into account this phenomenon.

In this paper, an artificial neural network consisting of 9 input variables, including total traffic volume per hour, the average speed of vehicles, the percentage of each category of vehicles, road gradient, the density of buildings adjacent to the roads and the Building Reflection Factor, is presented. The learning process of the network is based on the random division of gathered data for training, validation and testing. At last, the results of the proposed model were compared with those of a regression model and some well-known classical models. It was found that the results of the ANN model were satisfactory.

1. Methodology

Tehran, having the largest number of streets and highways and the heaviest traffic in Iran, is one of the most appropriate places for collecting data associated with traffic noise pollution in the country. In this study, after assessing several sites in the city regarding continuous traffic, the existence of buildings adjacent to the roads and absence of disturbing factors such as intersections and traffic lights, 51 samples from 34 points were obtained (Figure 1).

The data were collected from 7 a.m. till 8 p.m. for a one-month period in early summer. The instrument used in this study was (Lutron SL-4023SD) capable of recording the noise level in one-second intervals located at the height of 1.2 meters above the road surface (According to the ISO 362:1998) (Figures 2, 3).

Figure 1. Location of selected measurement points on map

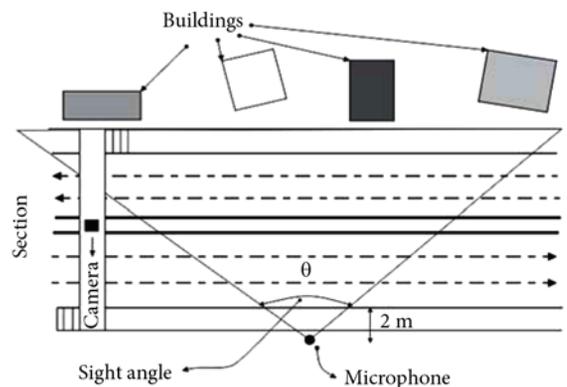Figure 2. Placement of sound level meter on sidewalk to measure traffic noise

Figure 3. Distance of instruments to carriageway and angle of view from observer point

The noise measurements were conducted in dB(A) for 15 minutes in the pilot stage and, by observing a very slight difference between the results of 15 and 5 minutes in the first samples, the measurement duration of 5 minutes was chosen for the remaining points. Results of Pearson correlation between L_{Aeq} in 15 and 5-minute intervals are shown in Table 1 which indicates a high correlation between them ($P = 0.98$). All the experimental data have been collected in absence of rain, with a wind speed below 5 m/s and relative humidity below 80%. Also, in all measurement sites, the ground type was hard and the sight angle was between 150–180 degrees.

Simultaneously, noise recording was accompanied by video recording of traffic flow for 5 minutes using a camera placed on a nearby pedestrian bridge at each point (Figure 4).

Table 1. Results of Pearson Correlation between L_{Aeq} in 15 and 5-minute intervals

		$L_{Aeq,5min}$	$L_{Aeq,15min}$
$L_{Aeq,\ 5min}$	Pearson Correlation	1	.980[*]
	Sig. (2-tailed)		.000
$L_{Aeq,15min}$	Pearson Correlation	.980[**]	1
	Sig. (2-tailed)	.000	

Correlation is significant at the 0.01 level (2-tailed).

1.1. Equivalent continuous (A-weighted) sound level, L_{Aeq}

Equivalent continuous (*A*-weighted) sound level is defined as the steady level of sound which, in a specific period of time contains the same acoustic energy as the actual time-varying sound level. The equivalent continuous sound level (L_{Aeq}) in the time period t_1 to t_2 is expressed as Eq. (1):

$$L_{Aeq} = 10 Log \left(\frac{1}{(t_2 - t_1)} \int_{t_1}^{t_2} \frac{p^2(t)}{p_0^2} \right) dt \ , \qquad (1)$$

where $p(t)$ is the *A*-weighted instantaneous acoustic pressure and p_0 is the reference acoustic pressure equal to 20×10^{-5} N/m^2 (Management and Planning Organization… 2006).

1.2. Traffic volume per hour, Q

Traffic volume is defined as the total number of passing vehicles through a section. The number of each category of vehicles passing through a defined section was counted for one hour at each station.

1.3. Average speed, V

Measuring the speed of vehicles in both directions was done using video analysis by considering a specific distance on the videos and dividing the travel distance by the travel time.

Afterward, the average speed of vehicles was determined for each point and employed in the model (Figure 5).

1.4. Vehicle classification

Each type of vehicle, based on its weight and emitted noise, contributes to the increase of the traffic noise level. Therefore, in this research, the vehicles are divided into four categories which consist of cars, vans and pickups, heavy vehicles and motorcycles. The percentage of each category in the total volume is calculated as well. Categories of vehicles and their descriptions are presented in Table 2. Types of heavy vehicles involved in the model2.

Figure 4. Placement of video recording camera on a pedestrian bridge

Figure 5. Measuring the average speed from videos

Table 2. Types of heavy vehicles involved in the model

Category No	Vehicle type	Description	Assigned parameter for percentage of each category
1	Cars	All types of passenger cars	PC
2	Vans & Pickups	All types of passenger vans and pickups	PV
3	Heavy vehicles	Minibuses, buses, medium trucks, heavy trucks	PH
4	Motorcycles	All powered two-wheelers	PM

1.5. Gradient, *G*

By using an automatic level (NIVO NAK2), the road gradient in each point was measured. The procedure for measuring the road gradient and the corresponding formula is depicted in Figure 6 and Eq. (2) respectively.

$$Gradient = \frac{a-b}{L}, \tag{2}$$

where the values for the parameters *a*, *b* and *L* are obtained as demonstrated in the Figure 6.

1.6. Density of buildings facing the observer (*D*) and Building Reflection Factor (BRF)

The density of buildings (*D*) at reception point was calculated using Eq. (3):

$$Density = \frac{\sum_{i=1}^{n} \theta_i}{\theta_t}, \tag{3}$$

where θ_i are the angles subtended by each facade on the opposite side of the road and θ_t is the total sight angle. These parameters are shown graphically in Figure 7 and the required data were obtained from Google satellite images.
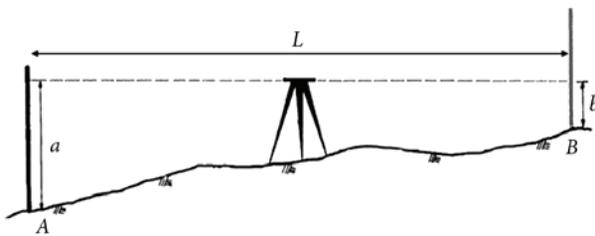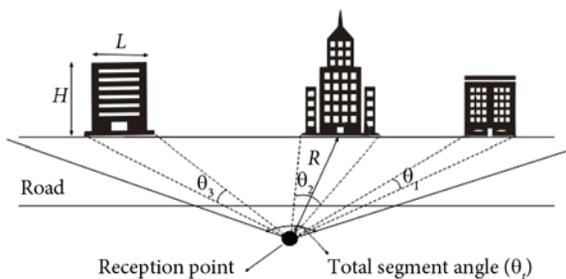

Figure 6. Measuring road gradient using level

Figure 7. Calculating density and average height of buildings

Figure 8. Panoramic photography of a sample location

In this study, the level of contribution of buildings in reflecting traffic noise was calculated by means of a novel method named Building Reflection Factor (BRF). For this purpose, to measure the height of the buildings in specified points, panoramic photography at each station was performed (Figure 8) and the height of all buildings in front of the sound level meter and limited to the angle of view were obtained. Furthermore, distance from each building to the receiver was measured using Google satellite images and finally, the building reflection factor was calculated using Eq. (4).

$$BRF = \sum_{i=1}^{n} \frac{L_i H_i}{n R_i}, \tag{4}$$

where R_i are the distances from each façade on the opposite side of the road to the reception point as depicted in Figure 7. L_i and H_i are the roadside width and height of those facades, respectively. θ_i and θ_t are the same as Eq. (3).

Finally, the collected data were imported into the ANN code for training and testing the network. Statistical descriptions of the data are given in Table 3.

2. Evaluation of noise pollution in the study area

Evaluation of noise levels at the measurement points indicated the violation of the maximum permissible noise level for commercial-residential areas legislated by the Department of Environment of Iran (60 dBA) in all 51 samples and decibel levels exceeding 75 dB(A) in 14 samples as presented in Figure 9 which could be harmful to human health. Therefore, Tehran's Municipality should consider the noise abatement programs seriously to mitigate the negative impacts of traffic noise pollution in the city. Noise mitigation measures such as the implementation of noise barriers and the insulation of buildings against noise should be considered as well as the scientific arrangement of roads and traffic flow (İlgürel *et al.* 2016).

Fortunately, the Municipality of Tehran has begun to install noise barriers in these areas in order to reduce the harmful effect of noise pollution on the public health of citizens. In some points which were measured in our study, such barriers were installed after a few months (Figure 10).

3. Developing an artificial neural network with collected data

An artificial neural network is a machine learning method inspired by the biological neural networks. It consists of interconnected neurons. The numeric weight corresponding to each connection can be tuned by information in data which makes the network adaptive to inputs and capable of learning. This network is comprised of three layers of neurons; input layer, hidden layer and output layer, all of them having interactions with each other. Data

Table 3. Descriptive statistics of variables

|	Q	V	PM	PH	PV	G	D	BRF	L_{Aeq}
Mean	3285.99	59.19455	4.141423	1.886133	4.151308	2.922745	0.620486	5.418242	71.56608
Standard Error	295.3797	2.43587	0.270672	0.141659	0.238353	0.284049	0.037785	0.586343	0.52578
Standard Deviation	2109.433	17.39559	1.932986	1.01165	1.702178	2.028515	0.269838	4.187324	3.754818
Minimum	1205	24.435	0.387597	0.313637	1.227106	0.06	0	0	64.59
Maximum	9548.5	94.887	8.382156	4.285236	9.548565	9	0.97	22.89	78.52
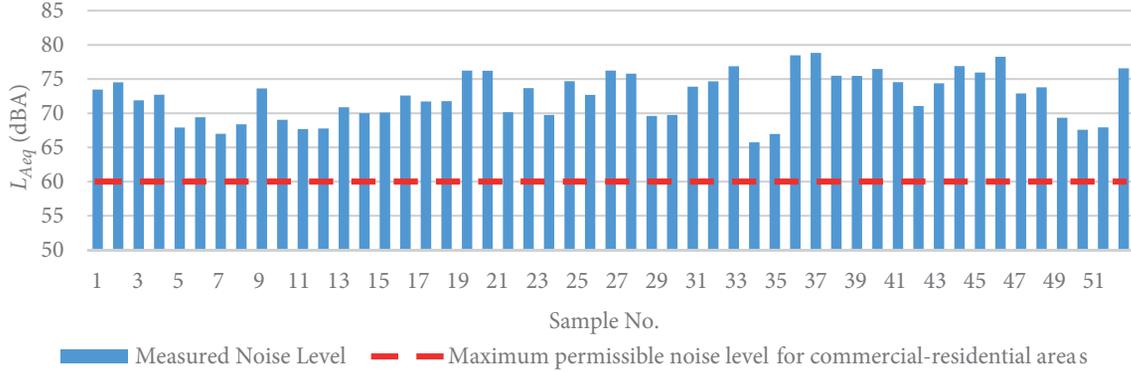
Figure 9. Comparison of measured noise level with maximum permissible noise level in commercial-residential areas

processing is carried out in this network according to Figure 11 and Eqs (5) and (6):

$$V_K = \sum_{i=1}^{n} x_i w_i + b_k; \qquad (5)$$

$$y_k = \varphi(V_K), \qquad (6)$$

where x_i are the inputs, w_i are weights, b_k is the bias, φ is the activation function and y_k is the output of the network. Selecting the type of activator function depends on the application of the network. In this study, the sigmoid function was utilized, which is defined as Eq. (7) (Haykin 1999; Demuth, Beale 1998):

$$\varphi(x) = \frac{1}{1 + e^{-x}}. \qquad (7)$$

In this research, a multilayer feed forward neural network (Fausett 1994) was developed using MATLAB (R2014b). The dataset was split into 3 subsets of 80%, 10% and 10% for training, validation and testing, respectively. To train the network, the Levenberg-Marquardt optimization technique was used. This technique is a combination of the Gradient Descent Method (GDM) and Gauss–Newton's Method (GNM) with a blending factor, which makes the convergence of weights to the optimal values faster and is defined by the Eq. (8):

$$W^{p+1} = W^p - (H + \tau \, diag[H])^{-1} \nabla E, \qquad (8)$$

where W^{p+1} is the weight in the $(p+1)$th iteration, W^p the weight in the pth iteration, H is the Hessian matrix, τ is a blending factor, diag[H] is the diagonal of the Hessian matrix and ∇E is the gradient of error (Levenberg 1944; Marquardt 1963).

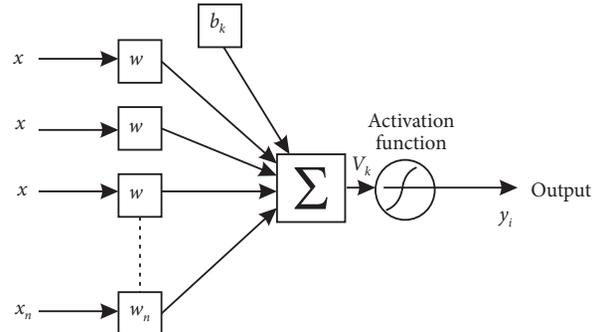Figure 10. Before & after installation of noise barriers in some measurement points

Figure 11. Architecture of an artificial neuron

To develop a model with minimum error, six different scenarios were defined. In each scenario, a number of parameters were included. Prediction accuracy in a neural network relies on its architecture, which consists of the number of hidden layers and the number of neurons in each layer.

In order to find the optimal number of neurons, the network is trained for each scenario with a different number of neurons (from the number of input parameters in that scenario to 25). To achieve the best architecture for the neural network, out of 100 iterations of the training process for each number of neurons, the best performance – based on the least Mean Square Error (MSE) and the best correlation coefficient – is selected and compared with the results of different number of neurons (the procedure is shown in Table 4. Comparison of different ANN architecture results in 100 iterations for (LAeq) in the 4th scenario4 for the 4th scenario). The Mean Square Error (MSE) is calculated using Eq. (9):

$$MSE = \frac{1}{N}\sum_{i=1}^{N} e_i^2 ,\qquad (9)$$

where N is the number of samples and e_i is the difference between predicted and measured values for each sample.

Comparing the results of different scenarios in Table 4 indicates that among all investigated neural networks, the 4th scenario yielded the highest correlation coefficient with measured data and the 6th offered the least average of MSE in 100 iterations. Regarding the number of inputs in these two scenarios, the 4th scenario was selected due to a lower number of input parameters which needs less data collection. As shown in Table 5, incorporation of the BRF parameter in the model lowered the average of MSE and increased the correlation coefficient to the measured values in comparison with the scenarios not containing this parameter.

Therefore, the optimal neural network structure is 6-10-1 and its characteristics are presented in Table 6. Optimal Architecture of Neural Network6 and Figure 12.

Table 5. Summary of defined scenarios and their best performance

Scenario No.	No. of inputs	Input variables	No. of neurons in hidden layer	Average MSE	R
1	3	Q, V, PH	21	7.8826	0.9814
2	4	Q, V, PH, G	14	7.7554	0.9873
3	5	Q, V, PH, G, D	21	7.5946	0.9868
4	*6*	*Q, V, PH, G, D, BRF*	*10*	*6.5401*	*0.9915*
5	7	Q, V, PH, G, D, BRF, PM	13	7.1968	0.9852
6	8	Q, V, PH, G, D, BRF, PM, PV	19	6.0411	0.9900

Table 4. Comparison of different ANN architecture results in 100 iterations for (L_{Aeq}) in the 4th scenario

Number of neurons	Best minimum mean square error	Mean of minimum mean square error	Mean correlation coefficient	Best correlation coefficient
6	0.9825	4.3553	0.9693	0.8536
7	0.6388	5.473	0.9769	0.8304
8	0.7135	4.9954	0.9777	0.8424
9	0.5911	5.46	0.9787	0.8442
10	0.2359	6.5401	0.9915	0.8341
11	0.4613	5.8883	0.9835	0.8342
12	0.6606	6.6728	0.9777	0.8213
13	0.5214	5.6239	0.9819	0.8326
14	0.7441	5.583	0.9749	0.8578
15	0.7047	9.4333	0.9744	0.7911
16	0.4777	7.4592	0.9831	0.8161
17	0.7205	9.3704	0.9771	0.7712
18	0.3748	9.0609	0.9874	0.7935
19	0.5137	9.0916	0.9871	0.7976
20	0.7108	7.3885	0.9742	0.8094
21	0.8313	10.0549	0.9699	0.7749
22	0.8884	9.1914	0.9691	0.7721
23	0.7978	12.2039	0.9708	0.7561
24	1.1058	10.681	0.9651	0.7617
25	0.6218	8.3606	0.9818	0.8052

Table 6. Optimal Architecture of Neural Network

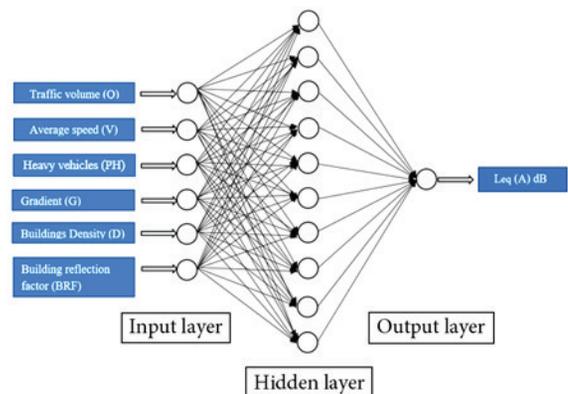| No. of Input Parameters	No. of Hidden Layers	No. of Hidden Neurons	Transfer Function	Number of Epochs	Training / Learning Algorithm
6	1	10	Sigmoid	1000	Levenberg-Marquardt

Figure 12. Proposed ANN architecture for traffic noise modeling (6-10-1)

Table 7. Summary of regression model properties [a]

Mode	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	Df1	Df2	Sig. F Change
1	0.837[a]	0.701	0.660	2.18934507	0.701	17.178	6	44	0.000

[a] Predictors: (constant), BRF, PH, Q, D, G, V; [b] Dependent Variable: L_{Aeq}

As depicted in Figure 12, parameters which are involved in the model are traffic volume, average speed, heavy vehicles gradient, building density and building reflection factor.

4. Results and discussion

4.1. Regression model

After developing the neural network, a multiple linear regression analysis was carried out to predict L_{Aeq} using the same parameters. A summary of the regression model properties is given in Table 7. Summary of regression model properties a7.

Eq. (10) resulted from the regression analysis:

$$L_{Aeq} = 59.826 + (0.001Q) + (0.113V) + (-0.298PH) + (0.057G) + (2.115D) + (0.170BRF), \qquad (10)$$

where: Q = Total one-hour vehicle count in both directions; V = Average speed of traffic; PH = Percentage of heavy vehicles; G = Gradient of road; D = Density of buildings facing the observer; BRF = building reflection factor.

Comparing the results of the regression model and the measurement data showed a prediction error between −4.63 to +3.61 dB(A) (Figure 13).

4.2. Neural network model results

The proposed model in the 4th scenario resulted in a correlation coefficient of R = 0.9914 as shown in Figure 14. The prediction error for L_{Aeq} using the ANN model in comparison with field measurement data was between −1.41 to 1.34 dB(A) (Figure 15).

4.3. Goodness of fit

In order to evaluate the performance of the developed model, a statistical paired t-test was applied at 5% significance level and 51 degrees of freedom. If the value of the t-statistic for output data is smaller than the critical t value, then, by accepting the null hypothesis (H0), it can be concluded that the averages of measured and predicted values do not differ significantly (Montgomery, Runger 2004).

The results of the regression and neural network models were compared with field measurements, shown in Table 8. Statistical paired t-test results for neural network and regression models8. The t-value for the neural network model was −0.130 which is much less than the critical t-value ±2.009 indicating a proper fit of predicted results to the measured values.
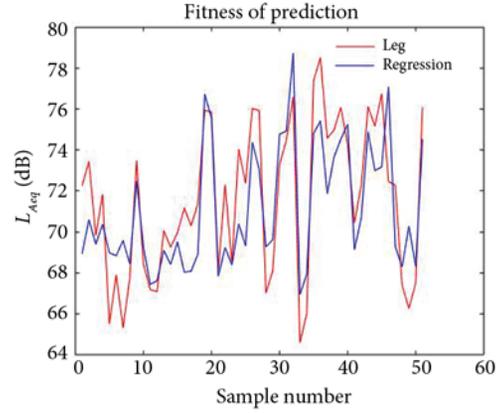

Figure 13. Comparing results of regression model and field measurement data
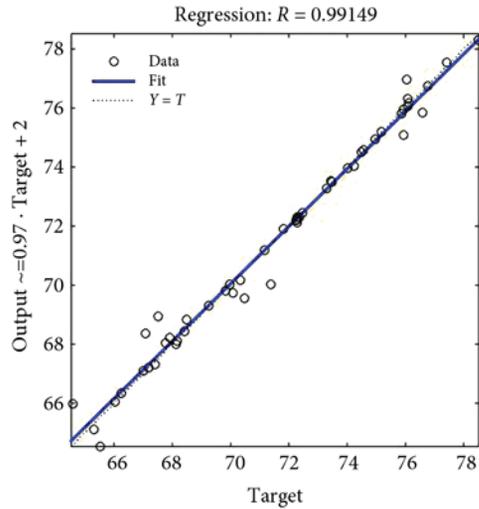

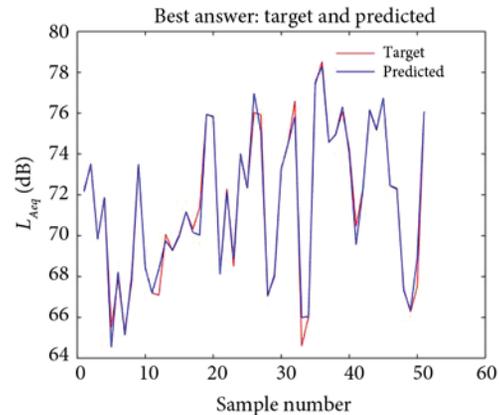Figure 14. Correlation coefficient of neural network model

Figure 15. Comparing results of neural network model and field measurement data

Table 8. Statistical paired t-test results for neural network and regression models

	L_{Aeq}	Regression	Ann
Mean	71.57	71.08	71.57
Variance	14.10	11.41	13.43
Observations	51.00	51.00	51.00
Pearson Correlation		0.82	0.99
Hypothesized Mean Difference		0	0
Level of significance (α)		0.05	0.05
Degree of freedom		50	50
t-Statistic		1.598	−0.130
Probability two-tail		0.12	0.90
t Critical two-tail		2.009	2.009

4.4. Comparison of proposed neural network with classical statistical models

To have a better understanding of the advantages of the neural network in prediction of road traffic noise, the prediction results were compared with the proposed regression model, the model presented in Iran Issue No. 342 (Management and Planning Organization… 2006) and some other well-known models being used in western countries reviewed by Quartieri *et al.* (2009), as are reported below:

$$IRAN\ model = 38.3 + 10logQ + 33Log\left(V + 40 + \left(\frac{500}{V}\right)\right) +$$

$$10\log\left(1 + \left(5 \star \frac{P}{V}\right)\right) - 68.8 + (0.3G); \quad (11)$$

$$RLS\,90 = L_{m.E(25)} = 37.5 + 10\log\left[Q(1 + 0.082P)\right]; \quad (12)$$

$$C.N.R = 35.1 + 10\log\left(Q_L + 6Q_P\right) - 10\log\left(\frac{d}{25}\right) + 1.5; \quad (13)$$

$$CORTN = 42.2 + 10logQ + 33Log\left(V + 40 + \left(\frac{500}{V}\right)\right) +$$

$$10\log\left(1 + \left(5\frac{P}{V}\right)\right) - 68.8 + (0.3G), \quad (14)$$

where Q is the traffic volume per hour, V is the average speed of traffic, P is the percentage of heavy vehicles, G is the gradient of road, Q_L is the number of light vehicles per hour, Q_P is the number of heavy vehicles per hour and d is the distance from observation point to the center of the traffic lane. The $L_{m.E(25)}$ is the average sound level at a distance of 25 meters from the center of the road lane. The results which consisted of standard deviation, correlation coefficient, MSE and R-Squared are summarized in Table 9. Comparison of proposed neural network with other well-known models 9. Better prediction of the neural network model is concluded based on lowest MSE (0.23463) and highest coefficient of determination ($R^2 = 0.983$). The comparison of these models to the measurement data is also shown in Figure 16. The better performance of the neural network is due to its greater capability in estimating non-linear relationships between the sound level and the factors affecting it.

Conclusions

The noise pollution produced by road vehicles is really a matter of huge concern in big cities, including Tehran. By selecting 51 stations for noise measurement in different areas of the city, it was shown that the noise levels were higher than the Iran environmental noise guidelines for residential-commercial areas and therefore, special attention from the municipality is required for mitigation or

Table 9. Comparison of proposed neural network with other well-known models

|	Average	Median	Standard Deviation	Sample Variance	Minimum	Maximum	R	R^2	MSE
L_{Aeq}	71.566	72.260	3.755	14.099	64.590	78.520			
Regression	71.090	69.589	3.053	9.321	66.949	78.738	0.816	0.666	4.847
Regression error	0.476	0.839	2.171	4.712	−4.640	3.617			
ANN	71.575	72.110	3.665	13.432	64.530	78.290	0.992	0.983	<u>0.235</u>
ANN error	−0.009	0.000	0.489	0.239	−1.410	<u>1.340</u>			
IRAN	72.559	71.152	3.191	10.184	67.768	80.367	0.829	0.687	5.315
IRAN error	−0.993	−0.508	2.101	4.415	−6.505	2.385			
RLS90	73.502	73.433	1.949	3.798	69.989	77.386	0.597	0.356	15.477
RLS90 error	−1.936	−1.660	2.996	8.976	−6.750	4.580			
CORTN	76.459	75.052	3.191	10.184	71.668	84.267	0.829	0.687	10.060
CORTN error	−1.117	−0.892	2.998	8.988	−5.961	5.450			
C.N.R	72.683	72.636	1.934	3.740	69.330	76.550	0.609	0.371	10.060
C.N.R error	−1.117	−0.892	2.998	8.988	−5.961	5.450			
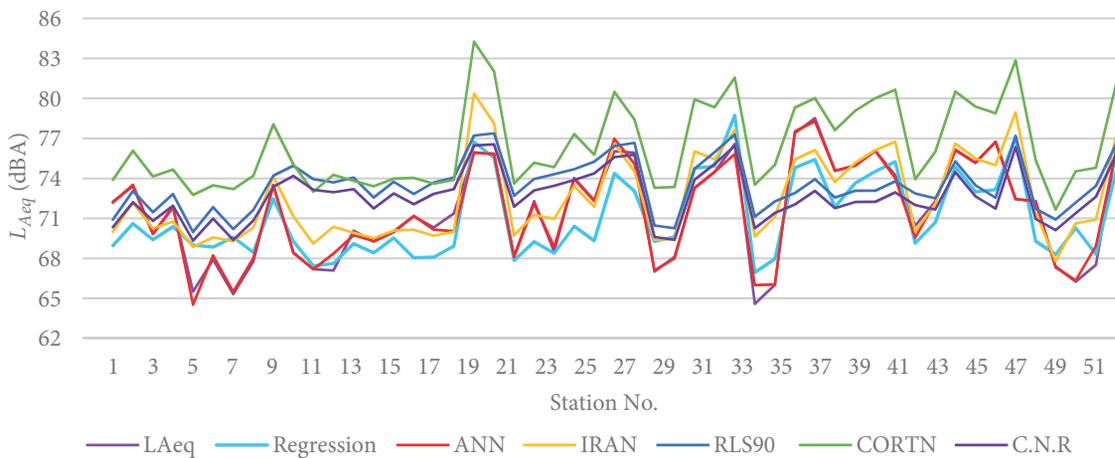
Figure 16. Comparison of neural network with other statistical models in prediction of L_{Aeq}

abatement of noise pollution in the city. As an intelligent noise prediction model, our proposed model can serve to assess the impact of the government's noise mitigation strategies or development plans before the implementation stage, such as examination of the environmental impact of highway design alternatives or the prediction of future noise levels.

By considering traffic parameters such as hourly traffic volume, average speed, the percentage of each category of vehicles and environmental factors including gradient, building density and Building Reflection Factor (BRF), six scenarios with different architectures of the multilayer neural network were investigated to estimate the equivalent continuous (A-weighted) sound level (L_{Aeq}). Among them, a multilayer neural network with a 6-10-1 structure with six input parameters including the BRF novel parameter was selected as the best model. It's high coefficient of determination ($R^2 = 0.983$) and low amount of prediction error in comparison with regression analysis and other classical models are in favor of the superiority of this model which was confirmed by a statistical paired *t*-test at 5% significance level.

Since the neural networks are capable of resolving complex problems with a great number of variables, researchers have the opportunity to include more related parameters in the process of noise prediction modeling compared to conventional models. Therefore, developing more precise and comprehensive models by incorporation of more valid and operational variables such as road surface, building facade material, the effect of green areas, etc. would be attainable. It is noteworthy to mention that the different characteristics of vehicles in terms of the modernity and level of noise production makes the results of this study more applicable in Asia region.

Disclosure Statement

There are not any competing financial, professional or personal interests from other parties.

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