VOL. 10, NO 22, DECEMBER, 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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ARTIFICIAL NEURAL NETWORK FOR TRAFFIC NOISE MODELLING

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ABSTRACT

Noise is one of the most prevalent sources of environmental pollution, and vehicular traffic noise is considered one of the most invasive type of pollution and often the most intrusive of all. The trend of noise pollution modelling varies from the smart result of classic regressive models to the performance of many assessment models based on mathematical expression, genetic algorithms and neural networks. In this study, multilayer feed forward back propagation neural network has been developed to predict vehicular traffic noise in urban area. The proposed ANN model has been used to predict the equivalent continuous sound level (Led) in dB (A). The model input parameters are the characteristics of the vehicular traffic flows (total vehicle, percentage of heavy vehicles and average vehicle speed) and the typology of the roads (width of the roadway). The predicted Led from neural network approach and the regression analysis have also compared with the filed measurement. The results show how the neural network approach provides better performance than the classical solution based on statistical analysis.

Keywords: noise, traffic, neural networks, model.

INTRODUCTION

Traffic noise and vibration is a source of pollution that can cause severe damage to communities in terms of health and social welfare [1-4].

Different traffic noise models for the analysis and the prediction of the noise levels in different urban areas have been developed by many researches based on the field measurement of different road noise descriptor and traffic noise parameters.

Suksaard, *et al* [5] studied a model to predict the environmental impact of traffic noise based on two vehicle classes. A road traffic noise prediction method for northern European countries was discussed by Bendtsen [6]. A noise prediction model based on Monte-Carlo approach was proposed by Lam, *et al* [7]. Li, *et al* [8] developed a GIS based road traffic noise prediction model. Pamanikabud, *et al* [9] have also used GIS for analyzing highway traffic noise. A statistical model to estimate road traffic noise in an urban setting was applied by Calixto, *et al* [10]. Cirianni, *et al* [11, 12] proposed ANFIS and neural models to estimate traffic noise in urban condition in an Italian context. A exhaustive discussion on early and recent traffic noise prediction models can be found in the review by Steele [13]. Cammarata, *et al* [14] used a neural network scheme as a substitute for the linear regression of earlier models, and comparing the results with some classical regressive models found significant improvements with the use of the neural network. This approach has shown to be particularly interesting and was followed by other authors [15-17] Gundogdu, *et al* [18] and Rahmani, et al [19] have developed a model by using a genetic algorithm as optimization method. The main objective of this study is the development of an Artificial Neural Networks (ANN) approach to assess traffic noise. The paper concludes with a benchmarking of the proposed neural technique with data from the measured noise levels in the urban area of Villa S. Giovanni (Italy) and the results of traditional regressive models.

MATERIALS AND METHODS

Noise data was recorded in 14 survey sites of Villa S. Giovanni. The city was chosen for its territorial characteristics and its geographic location, being the gateway from Italy to Sicily.

The survey sites were chosen on the base of the traffic flow patterns of the cities, setting the sites along the route with the highest crossing flows, on urban roads, with medium to high traffic, and therefore with medium speeds. These 14 survey sites (Figure-1) are at a reasonable distance from stop signs and intersections so that the effects of acceleration and deceleration of vehicles can be considered not relevant on the recordings. The noise data recording campaign was led using a Larson Davis SoundTrack LXT-1 Real Time Sound Level Meter Analyser. It was located at a point with a distance of 15 m from the closest traffic flow direction, and at a height of 1.5 m above ground level.

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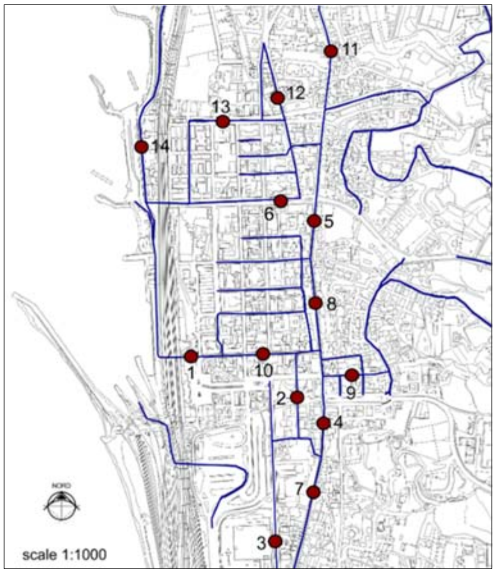

Figure-1. Location of the survey sites on the urban grid of Villa S. Giovanni.

Traffic noise descriptor and traffic parameters

In order to assess the environmental noise, the parameters chosen were: equivalent noise level L_{eq}, percentile levels: L_{10}, L_{50} and L_{90}, which are the parameters adopted by the main Italian Legislation [20] for noise pollution.

The measures were carried out during day hours, in an interval of time between 8:00 a.m. and 7:00 p.m. for all the 14 sites (a daily record is listed in Table-1), obtaining a set consisting of 154 records. L_{10}, L_{50} and L_{90} are defined as the levels, which are exceeded for 10%, 50% and 90% measurement period.

The equivalent sound level (A-weighted) is defined as the steady sound level that transmits to the receiver the same amount of acoustic energy as the actual time varying sound over the prescribed period. The equivalent sound level in the period from t_1 to t_2 is:

$$L_{eq} = 10\log\left[\frac{1}{(t_2 - t_1)}\int_{t_1}^{t_2}\frac{p^2(t)}{p_0^2}dt\right],$$

where $p(t)$ is the A-weighted instantaneous acoustic pressure and p_0 is the reference acoustic pressure (20×10-5 N/m^2).

For the 16 monitoring sites, the following characteristics were recorded: geometry (width of the road, width of the footway on the monitoring side and the opposite side, number of available lanes for the vehicular traffic); composition of the traffic flow; average running speed; levels of noise; direction of movement; parking; characteristics of street paving; and longitudinal slope.

Vehicles were classified in the following five categories according to Italian legislation: Motorcycles (M), Cars (C), Light Goods Vehicles (LGV), Heavy Goods Vehicles (HGV) and Buses (B).

Table-2 presents the principal traffic parameters and their ranges.

Table-1. Traffic record on a survey site.

Time	Moto-cycles	Cars	Light goods vehicles	Heavy goods vehicles	Buses	Average speed (km/h)	Leq (dBA)
8:00-9:00	32	548	36	32	20	15	72,20
9:00-10:00	20	560	24	36	16	15	71,60
10:00-11:00	24	476	28	52	12	20	72,00
11:00-12:00	16	596	40	40	12	15	72,50
12:00-13:00	28	404	16	28	8	25	71,00
13:00-14:00	12	388	28	56	8	25	73,00
14:00-15:00	8	416	16	36	12	25	68,00
15:00-16:00	12	392	12	44	16	25	72,90
16:00-17:00	8	440	24	36	20	20	72,20
17:00-18:00	8	360	28	28	16	25	70,90
18:00-19:00	20	512	12	44	16	20	72,70

Table-2. Principal traffic parameters and their related ranges.

Hourly traffic flow (vehic/h)	**Motocycles** (%)	**Cars** (%)	**Light vehicles** (%)	**Heavy vehicles** (%)	**Buses** (%)	**Average traffic speed** (km/h)	**Half road width *d*** (m)
124 - 968	0.0- 8.4	18.6-121.6	0.0 - 7.8	0.0 - 14.00	0.0 - 4.2	15.0 - 40.0	6.00 - 16.00

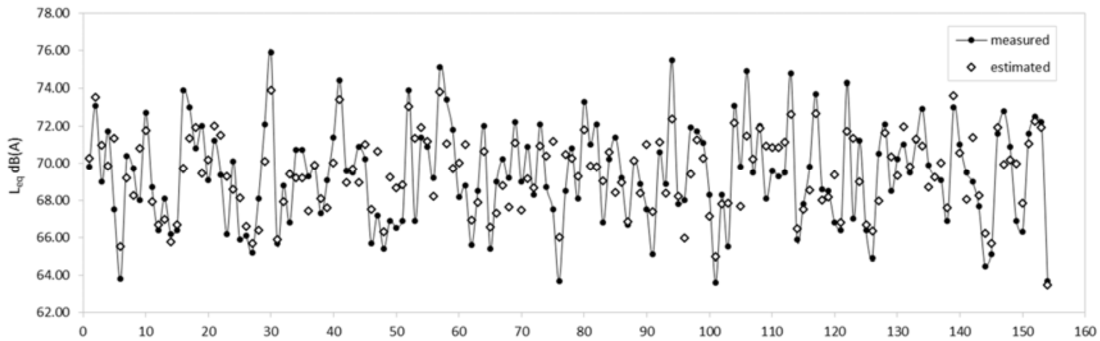

Figure-2. Graphic comparison L_{eq} measured-estimated.

Analysis of the data with the regressive models

A correlation analysis was led in order to determine the variables, which mainly condition the measured noise levels, and to find the most suitable prediction model. To obtain a mathematical relation that is able to predict the L_{eq}, it is necessary for the model to:

- be simple enough so it can be used by all professionals involved in urban planning and traffic management;
- require only data which can be easily obtained for the noise level forecast;
- adapt to the conformation of the urban environment and planning of the city of Villa S. Giovanni
- incorporate accurate results according to the subjective perception of the noise.

Among the classical regressive models [13, 21, 22] the following relations best fit these characteristics

$$L_{eq} = a_1 \cdot \log(Q) + a_2 \cdot p - a_3 \cdot \log(d) - a_4 \cdot V + a_5 \quad (1)$$

where the equivalent continuous level Leq (dB(A)) can be predicted as function of traffic volume (Q), heavy vehicle percentage (p%), width of the roadway d and average flow speed V.

The following relation was found from regression analysis. Where the coefficient relative to the distance d and the speed V is negligible in regards to the others.

$$L_{eq} = 10.69 \cdot \log(Q) + 0.128 \cdot p + 41.09 \quad (2)$$

Figure-2 shows comparisons between the measured L_{eq} values and the calculated ones according to the mathematical model.

Observing Figure-2, we can see how, even if the correlation coefficient is close to 0.754, therefore giving overall a good approximation value, the evaluation quality is still insufficient, as seen in a point to point detail, especially for those values of L_{eq} which greatly differ from the average trend.

To overcome the limits of traditional forecasting approaches, we examined the applicability of a neural approach for traffic noise forecasting and compared the results obtained with the classical regressive models previously proposed.

ANALYSIS OF THE DATA WITH NEURAL NETWORKS

A neural network (ANN) can be seen as a system which can answer a question or supply an output in reply to an input and is defined from a certain number of interconnected units of calculation, which operate as a parallel calculation structure and that acquire their knowledge from the experience supplied, that is, the transfer function of the network is not programmed, but is obtained through a process of training with empirical data. In other terms the network learns the function that ties the output with the input by means of the presentation of correct examples of input/output pairs [23].

Effectively, for every input introduced to the network, in the learning process, the network supplies an output that differs of a given δ amount from the desired output: the training algorithm modifies some parameters of the network in the desired direction. Every time that an

VOL. 10, NO 22, DECEMBER, 2015 ISSN 1819-6608
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example is introduced, therefore, the algorithm fits slightly the parameters of the network to the values optimal for the solution of the example: in this way the algorithm tries to please all the examples a little at a time [24].

Construction of the neural network

As illustrated, the independent variables assumed in the regression formulas are generally the vehicular flow, the average speed of the flow, the composition of the flow and in particular the percentage of the heavy vehicles and the width of the roadway, these same indicators are, therefore, been used as input data for the achievement of the network [25].

Different neural network architectures exist, but the most popular is the multilayer feed-forward network (MLF). The architecture of the multilayer feed forward network consists of the interconnection of several layers, i.e. input layer, hidden layer and output layer, and has at least one intermediate hidden layer between input and output layer (Figure-3). The basic processing elements of neural networks are the neurons (nodes). Each neuron of a layer is connected with all the neurons in the next layer in order to transmit the information or signal from input layer to output layer through hidden layer [23].

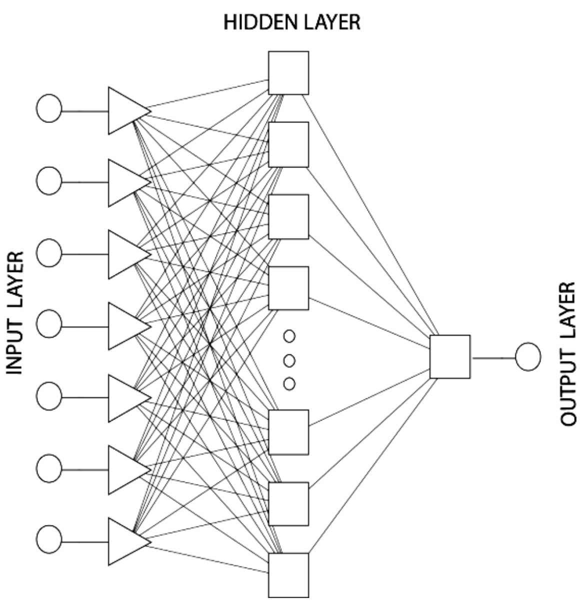


Figure-3. Typical feed-forward neural network composed of three layers.

A network is said feed forward if no neurons in the output layer take part as a feedback element to any of the neuron. Each neuron produces the output signal as it receives the input signal according to the chosen activation function.

In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights w_{ij} and by the threshold coefficient θ_i that modulate the effect of the associated input signals x_k, and the nonlinear characteristic exhibited by neurons is represented by a transfer function $f(\xi_i)$. The neuron impulse is then computed as:

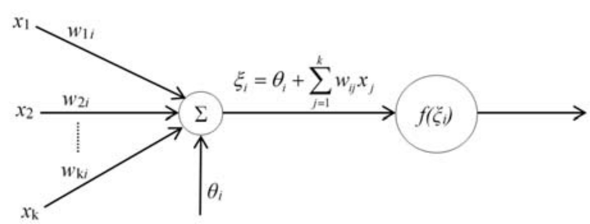
$$\xi_i = \theta_i + \sum_{j=1}^{k} w_{ij} x_j \tag{3}$$

The resulting ξ_i is the input to the transfer function f. The transfer-function was originally chosen to be a relay function, but for mathematical convenience a hyberbolic tangent or a sigmoid function are most commonly used:

$$f(\xi) = \frac{1}{1+\exp(-\xi)} \tag{4}$$

The output value (activity) of the node i-th neuron is determined by equations (3) and (4):

$$y_i = f\left(\theta_i + \sum_{j=1}^{k} w_{ij} x_j\right)$$



The supervised adaptation process varies the threshold coefficients θ_i and weight coefficients w_{ij} to minimise the sum of the squared differences between the computed and required output values. This is accomplished by minimisation of the objective function evaluated in terms of mean square error (MSE).

If the MSE is less than the desired error the neural network training is complete and the network is ready for prediction. Otherwise the weights are updated until the desired error goal is achieved.

The Levenberg–Marquardt (L–M) algorithm is used to update weights in the proposed ANN model. Once the training is completed, the prediction capability of the network is checked for unknown input data to verify whether it is correctly predicting or not [25].

The MATLAB neural network toolbox is used for ANN analysis, which includes neural network training, testing, performance evaluation and comparison.

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Proposed artificial neural network for traffic noise modelling

The proposed neural network architecture for traffic noise prediction is shown in Figure-4.

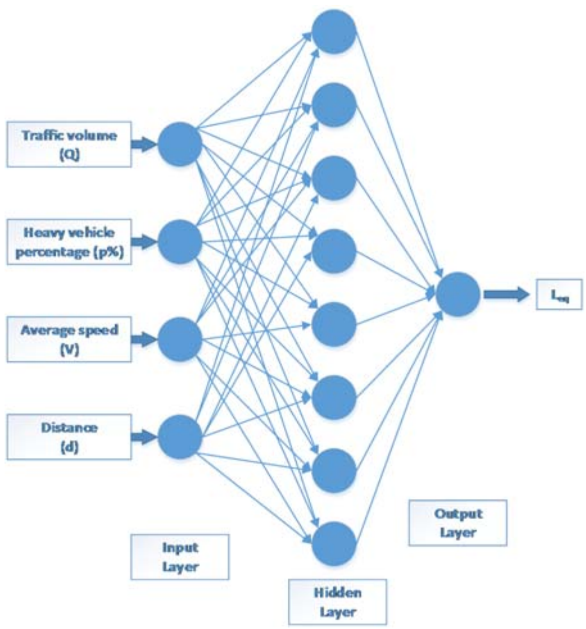

Figure-4. Proposed ANN architecture for traffic noise prediction.

The input parameters to the ANN are the same of the regression model (*Q*, *p*, *d* and *V*) and the output parameter is the equivalent sound level (L_{eq}) in dB (A).

The creation of example patterns is the most delicate step on the way to obtaining reliable results from the neural elaboration. The available data was grouped by mostly random criteria in three sets: training-set, verification-set and test set.

The first set, preponderant on the other two, trains the network on the specific problem and for the determination of the weights, the second (verification) estimates the performance and efficiency of the network and definition of the best architecture, lastly, the test data is for the validation of the network once the construction procedure is completed.

A comparative analysis for single hidden layer by varying the number of neurons has been conducted in order to find the best network structure.

It has been observed that among the entire neural network tested, the single hidden layer neural network structure with 8-number of neurons gave minimum mean square error and good correlation coefficient between the target and predicted output for training and verification data sets. Therefore, the optimal structure is 4-8-1, as shown in Figure-4, which connected 4-input parameters and 1-output results through 8-number of neurons in the hidden layer.

RESULTS AND DISCUSSIONS

Completed the phase of training the results were analysed, in particular regressive model and ANN model were compared in function of the parameters: absolute mean error, standard deviation of error, standard Pearson-R correlation coefficient and root mean square error (RMS).

It can be observed that the considered neutral network succeeds to describe the problem in adequate way, as the error of estimate of the results is contained within acceptable values.

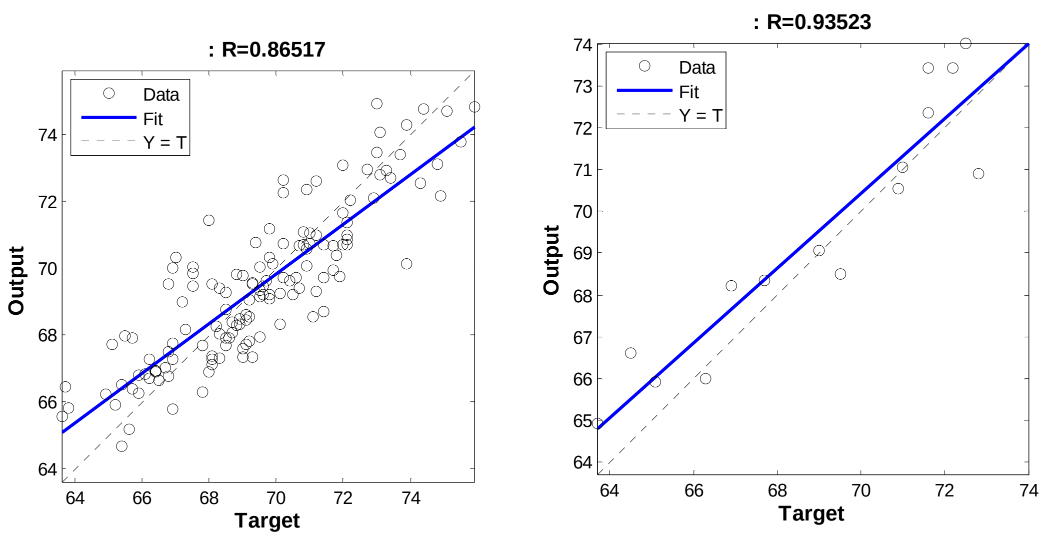

Figure-5. Graphic comparison between measured (target) and estimated (output) L_{eq} for training and testing data.

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The ANN and regressive result (Table-3) are compared on the following statistic parameters: absolute mean error, standard deviation of error, correlation coefficient e root mean square error (RMSE).

Table-3. Statistic parameters of regression and ANN result.

Comparison between models and neural network		**RMSE**	**Mean error**	**Correlation**	**Standard Deviation**
Neural network	training set	1.324	1.048	0.865	1.333
	test set	1.192	1.008	0.935	1.142
Recalibrated regressive model	training set	1.734	1.434	0.754	1.747
	test set	1.480	1.134	0.874	1.566

Figure-5 shows a comparison between the measured values and forecast values according to the neural models. It can be observed that the considered ANN succeeds in describing the problem adequately, and the estimation error on the output is contained within acceptable values, and it always guarantees a greater precision than the considered regressive model (Table-4).

This fact allows us to affirm that the ANN is able to predict satisfactorily the equivalent noise level generated by vehicle flow in roads.

CONCLUSIONS

The first aim of the study presented was to define an analysis of different methodologies for the assessment of noise pollution related to road traffic.

The second aim was the development of a traffic noise prediction model that can be used in traffic planning, thus researching traffic noise reduction by redesigning traffic patterns and road layout.

An application with the use of classical regressive model was led, opportunely recalibrating the parameters of the model and the results obtained compared with those obtained from a multilayer feed forward back propagation neural network.

The ANN model was trained and tested by Levenberg-Marquardt (L-M) optimization algorithm to predict Leq noise level. Among all the networks tested, one layered neural network architecture 4-8-1 (4-input neurons, 8-neurons in hidden layer and 1-output neuron) is found to be optimum because of the best performance during the training and testing phase.

The correlation coefficients are 0.865 during training and 0.935 during testing.

The results illustrated in the paper show how the ANN approach is best suited to the simulation of the phenomenon and for the application in more complex areas, with greater variability in the traffic patterns, such as the case considered.

Undoubtedly, taking into account factors such as ground type, classification of vehicles, road surface, reflective surface, would give a more comprehensive model, at the price of more extensive data recording campaigns. However, the results of this study indicate that the neural model can be applied with satisfying results even using restricted database.

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