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Road Traffic Noise Prediction with Neural Networks-A Review

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Abstract. This paper aims to summarize the findings of research concerning the application of neural networks in traffic noise prediction. Modeling and prediction of traffic noise by means of classical approaches is a very complex and nonlinear process, due to involvement of several factors on which noise level depends. To overcome these problems, researchers and acoustical engineers have applied the artificial neural network in the field of traffic noise prediction. After a critical review of various neural network based models developed for road traffic noise prediction cited in the literature it was concluded that ANN based models were capable of predicting traffic noise more accurately and effectively as compared to deterministic and statistical models.

Keywords: Artificial neural networks, Traffic noise, Deterministic and statistical models.
AMS Classification: 92B20, 90C99

1. Introduction

Noise is one of the environmental pollutants encountered in daily life. Noise pollution has become a major concern of communities living in the vicinity of major highway corridors. In the view of rapid development, it is essential to study highway noise with respect to various causative factors.

With urbanization and the corresponding increase in the number of vehicles in metropolitan cities, pollution is increasing at an alarming rate. Main areas of concern are related to air and noise pollution. More than 70% of total noise in our environment is due to vehicular noise [1]. Noise levels are showing an alarming rise and in fact the level exceeds the prescribed levels in most areas. Investigations in several countries in the past few decades have shown that exposure to noise, such as occurs when living in close proximity to busy roads or highways, has adverse effect on human health [2-7].

The level of highway traffic noise depends mainly on the following factors:

i. Volume of the traffic
ii. Speed of the traffic
iii. Number of the heavy vehicles in the flow of traffic
iv. Type of location
v. Number of lanes present on highway
vi. Road surface
vii. Background noise etc.

To create a healthy and noise pollution free environment, a noise prediction model is needed so that the noise level along a busy highway can be predicted and investigated in advance during planning and design process [8].Traffic noise prediction models are required as aids in the design of highways and other roads and sometimes in the assessment of existing or envisaged changes in traffic noise conditions [9-14]. These models are commonly needed to predict sound pressure levels, specified in terms of $L_{eq.}$, L_{10} etc., set by the

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government authorities. Neural networks offer a new strategy with enormous potential for many tasks in the planning, geographical and spatial. It is an area of interest how neural network addresses the shortcomings of conventional deterministic models. In the present manuscript an attempt has been made to explore the application of neural networks to road traffic noise prediction.

2. 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:

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

An artificial neuron is characterized by:

i. Architecture (connection between neurons)
ii. Training or learning (determining weights on the connections)
iii. 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 as shown in Figure 1. The relationship between the input signals $X_{0,}$ $X_{1\ldots}$ X_n of neuron j and its output Y_j is given by

$$I_j = \sum_{i=0}^{n} W_{ji} X_i \qquad (1)$$

$$Y_j = f(I_j) \qquad (2)$$

where W_{jo}, W_{j1},…, W_{jn} are the respective synaptic weights of neuron j, I_j is the linear combiner output due to input signals and f is the activation function. 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 learning. Generally the three types of training are as follows:

Supervised training: In a neural network, if for the training input vectors, the corresponding target output is known, the training method adopted is called supervised training. It is a process of providing the network with a series of sample inputs and comparing the output with the expected response. The training continues until the network is able to provide the expected response.

Unsupervised training: If for the input vectors, the corresponding target output is not known in a neural network, the training method adopted is called unsupervised training. A network can modify weights so that the most similar input vector is assigned to the output unit. The training process extracts the statistical properties of the training set and groups similar vectors into classes.

Reinforcement Learning: In this method, a teacher is also assumed to be present, but the right answer is not presented to the network. Instead, the network is only given an indication of whether the output answer is right or wrong. In this learning process, network attempts to learn the input-output mapping through trial and error with the view to maximize the performance index called the reinforcement learning signal. Reinforcement learning lies between supervised and unsupervised learning. It operates through continuing interactions between a learning system and the environment.

Weights: Weight is information used by the neural network to solve a problem. Neural networks consist of a large number of simple processing elements called neurons. These neurons are connected to each other by directed communication links, which are associated with weights. A bias acts exactly as a weight on a connection from a unit whose activation is always 1.

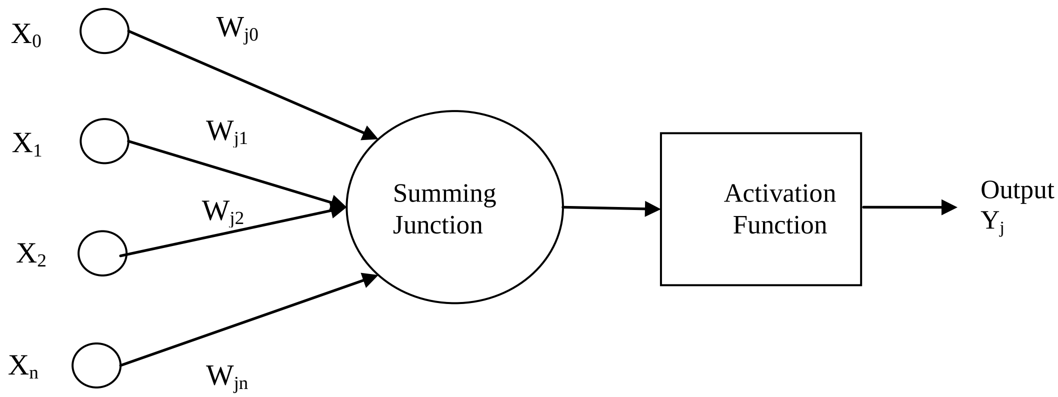

Figure 1. Nonlinear model of a neuron

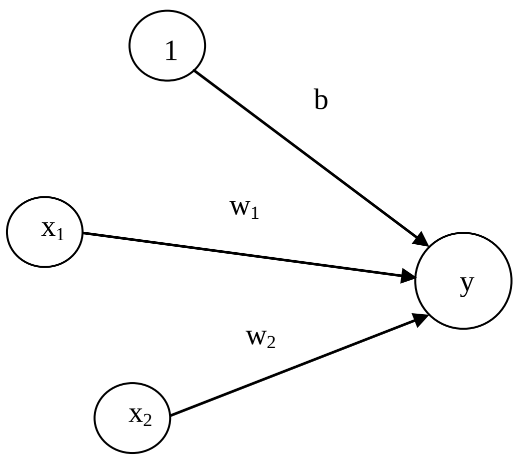

Figure 2. A simple net with bias

Bias improves the performance of a neural network. If bias is present, then the net input is calculated as (Figure 2),

$$Net = b + \sum X_i \; W_i$$

where, Net = net input
b = bias
X_i = input from neuron i
W_i = weight connecting neuron i to output.

An activation function is used to calculate the output response of a neuron. The sum of a weighted input signal is applied to an activation function to obtain a response. Basically activation functions can be categorized in two types:- threshold and sigmoid functions.

Many types of ANN [15,16] have been developed such as the Kohonen network, the Learning vector quantization network, Grossberg's ART network, the Hopifield feedback network, the Competitive network and the Multi-layered feed-forward network. Among these networks, the Multi-layered feed-forward network has been used extensively [17]. A Multi-layered feed-forward network (MFFN) includes an input layer, a hidden layer and an output layer as presented in Figure 3.

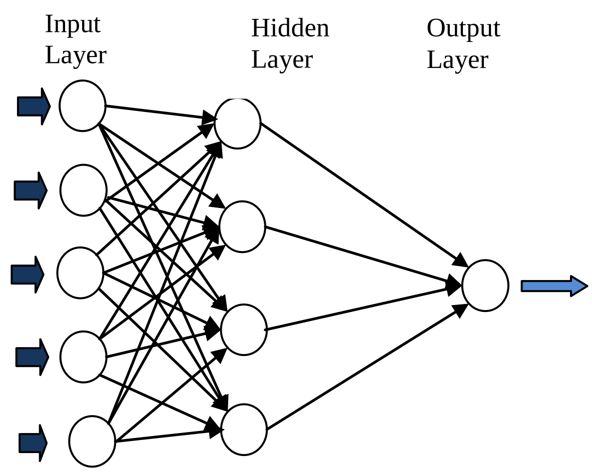

Figure 3. Structure of feed-forward neural network

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.

3. Review

Several attempts have been made to predict and model road traffic noise mathematically and statistically by different researchers. Due to the capability of neural networks to model nonlinear systems, Cammarata [18] studied the functional relationship between road traffic noise and related physical parameters. A back propagation network was applied to extract the functional relationship between particular road parameters (number of vehicles, average height of buildings, road width) and the level of sound pressure. The neural network approach was compared with those provided by a selected relationship found in the literature and showed that agreement between predictions and measurements are much more favorable to a neural network than to linear regression approach [19].

One limit of the neural method proposed, is its dependence on the acoustic measurements made. Errors in the measurement or incorrect interpretation make it impossible to supply (in the learning phase) the network with a set of data which can significantly represent the correlation between the parameters taken into consideration and the sound pressure level.

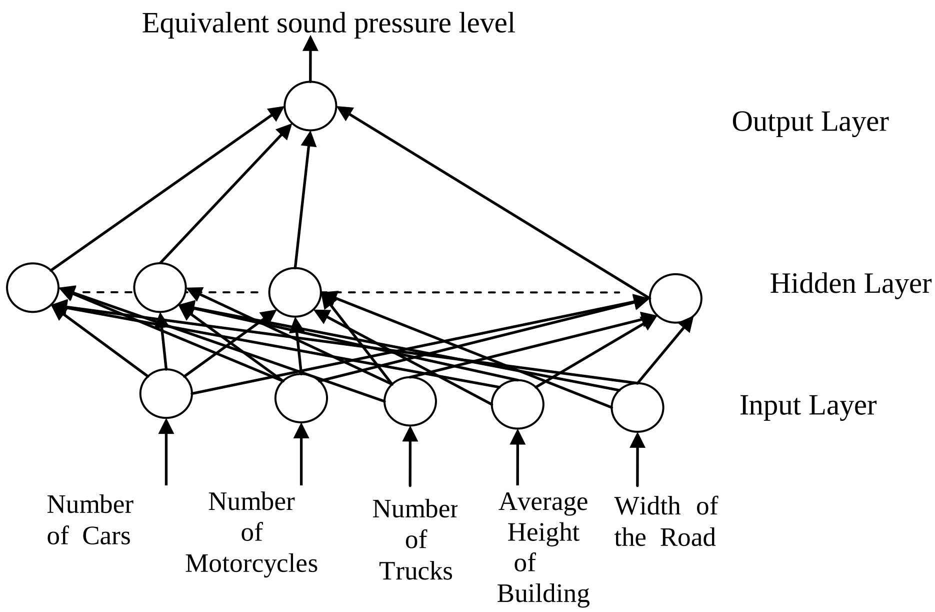

Figure 4. The BPN Model given by Cammarata et al. [21]

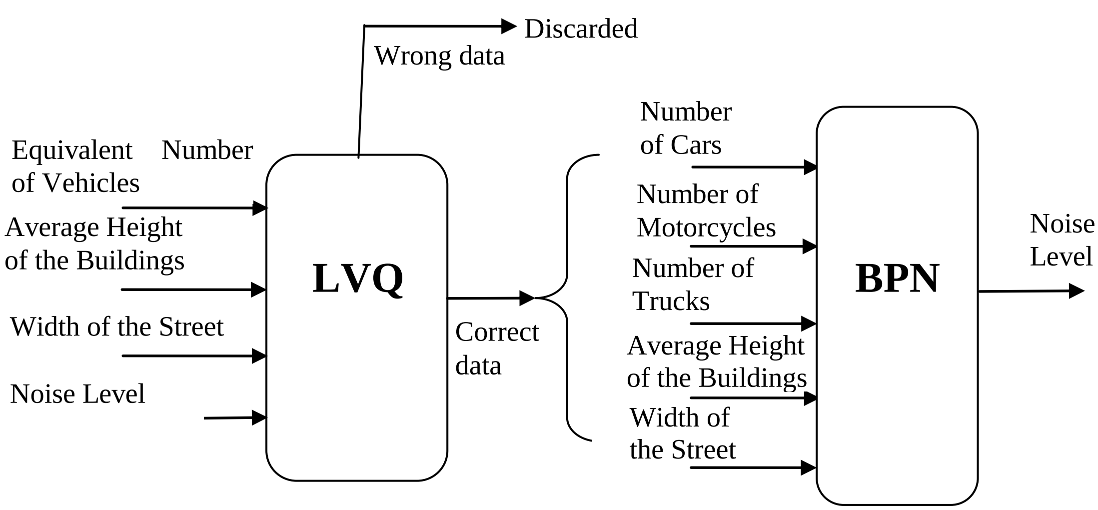

Figure 5. The Neural architecture proposed by Cammarata et al. [21]

In addition, during the production phase it is difficult to check whether a neural network output value (which is rather different from the value measured) is to be attributed to a defect in the learning phase or to an error in measurement. To present a strategy based on neural networks for the automatic recognition of acoustic measurements affected by errors they proposed [20] a neural approach to filter data provided by acoustic measurements. It was based on the use of a Kohonen Self-organizing Map network which receives correct acoustic measurements in the learning phase. The Kohonen neural network learning on the basis of this set of measurements would allow the network to be used as a filter. Having received a set of acoustic measurements in input, it would be able, in production phase, to discard any acoustic measurements which were insignificant or affected by errors.

Cammarata et al. [21] proposed use of a neural architecture made up of two cascading levels. At the first level a supervised classifying network, learning vector quantization (LVQ) network, filters data discarding all the wrong measurements, while at second level the BPN predicts the sound pressure level, which has been shown in Figure 4 and 5 respectively. Mark Dougherty [22] presented an interesting review based on application of neural networks to transport. Noise prediction models having acoustic energy descriptors, usually explicit as L_{eq} or in two cases as a pseudo - L_{10}, were critically reviewed [23]. Based on the traffic noise data measured near a highway in China, an artificial neural network was formed to predict further traffic noise levels. It was found that the predicted data by the ANN model were in good agreement with measured data and it was concluded that an artificial neural network provides a new method for traffic noise prediction [24]. The position of the measurement station, the geographical situation between the noise source and the measurement station, wind speed and direction, air temperature and relative humidity, and time of day, [25] were considered in artificial neural networks to model the variation of noise levels from traffic around campus area. To have both the capabilities of learning and interpretability in networks and fuzzy logic are used for predicting the effects of noise pollution on human work efficiency [26, 27]. A neuro fuzzy computing system provides system identification and interpretability of fuzzy models and learning capability of neural networks in a single system. The neuro-fuzzy model was developed for predicting the effects of noise pollution on human work efficiency as a function of noise level, type of task, and exposure time. Noise generated from vehicular traffic is a major source of environmental pollution. A comprehensive study [28, 29] on the assessment and ANN modeling of noise levels due to vehicular traffic flow at interrupted traffic flow conditions was reported in Yavatmal city, in the Vidarbha Region of the state of Maharashtra (India). The ANN technique for modeling provides lower interpolation errors as compared to other classical methods. ANN can generalize results obtained from known solutions to unforeseen situations. ANN modeling was performed with input parameters including traffic composition (Bus/Truck, LCV, TW, Bicycle and Others), carriageway width, and distance of receiver from pavement. ANN software (Elite ANN) was used for the development of Multi Layer Perceptron (MLP). Table 1 shows various statistical results of their model for interrupted flow condition.

Table 1. Summary of output from ANN Modeling for Interrupted traffic flow [28]

Statistical parameters	L_{10}	L_{eq}	LNP	TNI	NC
Correlation Coefficient	0.89	0.94	0.96	0.95	0.94
Root mean square error	1.01	0.74	1.09	2.46	0.74
Average Percentage error	0.93	0.81	0.91	2.15	4.47
Standard deviation	1.02	0.55	1.20	6.11	0.56
T-test	2.23	5.35	1.82	0.37	0.19

Givargis et al. [30] presented a comparative study of mathematical logarithmic, statistical linear regression, and neural models capable of predicting maximum A-weighed noise level ($L_{A\max}$) for the Tehran–Karaj express train. The model is developed upon the basis of the measurements from sampling locations at distances of 25 m, 45 m, and 65 m from the centreline of the track and at a height of 1.5 m. In the next step, the predictive capability of the model has been tested on the data associated with sampling locations, situated, respectively at distances of 35 m and 55 m from the centreline of track at a height of 1.5 m. It was observed that none of the models outweighs others as the best fit in a significant mode. After review of current literature on urban noise and Soft Computing techniques, performance of a neural network based system for the prediction of urban noise was described [31, 32]. An artificial neural network capable of predicting the level of urban noise, based on a set of 25 environmental characteristics was designed and implemented.

Table 2. Comparison of classic models and neural network by Genaro et al. [32]

Model	Error average in dB Test Set	Error over 3 dB (# of instances) Test Set
ANN	0.76	2
Gaja	4.47	47
French model	4.65	45
Granada I	3.03	21
Granada II	9.08	85
Linear model	6.32	38
Multivariant linear model	6.08	61
MOPU model	6.99	79
Planverk model	28.37	89
RLS90 model	12.86	70

Results reported by the network were compared with those of existing predictive models of urban noise, which were based on classical models. Tests confirmed that results produced by the network were better for all data records. Table 2 shows a comparison of classical models and the result obtained by neural network. Assuming bituminous road surfaces with mean traffic speeds of less than 75km/h, Givargis et al. [33] presented a basic and preliminary neural network model using a restricted database to predict $L_{A\,eq,1h}$ for Tehran's roads at distances less than 4 m from the nearside carriageway edge and at a height of 1.4 m above the ground. They used the UK Calculation of Road Traffic Noise (CoRTN) approach. Overall model efficiency was examined using non-parametric tests, such as the Wilcoxon matched-pairs signed-rank test for the training step and the Kolmogorove Smirnov test for two independent samples for the validation step.

Results indicate that a neural network approach can be applied for traffic noise prediction in Tehran in a statistically sound manner. The Wilcoxon matched-pairs signed-ranks test detects no significant difference between the absolute testing set errors of the developed neural network and a calibrated version of the CoRTN model. Table 3 shows absolute prediction errors given by their model.

4. Discussion

Two major advantages of ANN are that they are applicable 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. Individual level data are necessary while using neural networks. The network operates on the data directly without the medium of an additional model. Like disaggregate models, neural networks also suffer from explanatory problems as there is a difficulty in interpreting the weights at this time.

Table 3. Descriptive data related to absolute prediction error by Givargis et al. [33]

Subsets	$L_{Aeq,1hr}$ ranges dB(A)		Absolute prediction error dB (A)			
	Model predictions	Field measurements	M*	SD*	Min*	Max*
Training	73.9-81.1	82.6-81.2	0.9	0.6	0.0	2.5
Testing	74.4-81.1	73-82.4	0.6	0.6	0.0	1.4
Holdout	74.1-80.3	72.1-79.1	0.9	0.8	0.0	2.4

M*: Mean
SD*: Standard Deviation
Min*: Minimum
Max*: Maximum

On the other hand, the fitting of parameters in a neural network is mathematically well founded. Neural networks provide a data tool through which we can model our intuition, without complications of having to formalize all complex causal variables and relationships with other models.

The level of highway traffic noise depends on many factors, such as the volume and speed of traffic, the number of heavy vehicles in the flow of traffic, condition of the vehicles and the road surface. All these parameters make noise modeling a complex process and nonlinear problem. ANN provides flexibility, massive parallelism, a learning and generalization ability, accuracy and some amount of fault tolerance in noisy and changing environments.

In the present review, it is concluded that Multi-layered feed-forward network, which has been used extensively for noise reduction in ANN models, is the most mature one. It can also be concluded that back propagation is one of the most widely used paradigms surpassing (even) learning vector quantization and adoptive resonance theory in frequency of use.

We believe that detailed research and documentation of how neural based models in noise modeling and prediction are built will attract and encourage other persons working in this area. We also hope that this review will inspire a more methodological approach to emerge for modeling and prediction of traffic noise.

5. Conclusion

Problems related to noise prediction are highly complex and nonlinear in nature. Data sources are often numerous and complex. Neural networks are highly relevant to problems requiring large scale, highly dimensional, data analysis, such as noise prediction problems. Based on critical reviews (cited here), it was concluded that ANN has advantages over deterministic and statistical models, as it is well suited for implementation using very large scale integrated (VLSI) technology. But there still exist some problems, with ANN modeling such as its black box nature, convergence inaccuracy and highly data oriented nature. In order to overcome these problems, it is our thought that ANN should be implemented with other soft computing techniques such as fuzzy logic, particle swarm optimization and genetic algorithm.

List of Abbreviations

ANN= Artificial neural network
RLS-90= Richtlinien fur den Larmschutz an Straβen (Guidelines for Noise Protection on Streets)
FHWA= Federal Highway Administration
CoRTN= Calculation of Road Traffic Noise
ASJ= Acoustical Society of Japan
LNP= Noise Pollution Level
TNI= Traffic Noise Index
NC= Noise Climate
LCV= Light Commercial Vehicle
TW= Two Wheeler
RMSE= Root Mean Square Error
BPN= Back Propagation Network
LVQ= Learning Vector Quantization
Leq= Equivalent Noise level
L_{10} = Sound level exceeded in 10% of the measurement period
L_{90}= Sound level exceeded in 90% of the measurement period
dB= decibel
Anon.= Anonymous
ART= Adaptive resonance theory

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