Modeling of Construction Noise for Environmental Impact Assessment

Mohamed F. Hamoda

Abstract: This study measured the noise levels generated at different construction sites in reference to the stage of construction and the equipment used, and examined the methods to predict such noise in order to assess the environmental impact of noise. It included 33 construction sites in Kuwait and used artificial neural networks (ANNs) for the prediction of noise. A back-propagation neural network (BPNN) model was compared with a general regression neural network (GRNN) model. The results obtained indicated that the mean equivalent noise level was 78.7 dBA which exceeds the threshold limit. The GRNN model was superior to the BPNN model in its accuracy of predicting construction noise due to its ability to train quickly on sparse data sets. Over 93% of the predictions were within 5% of the observed values. The mean absolute error between the predicted and observed data was only 2 dBA. The ANN modeling proved to be a useful technique for noise predictions required in the assessment of environmental impact of construction activities.

Keywords: Construction noise, Environmental health, Neural networks, Prediction models

INTRODUCTION

Noise is defined as unwanted sound. The main sources of environmental (community) noise include traffic noise (e.g., road, rail and air traffic), industries, construction and public works, and the neighbours. Most environmental noise can be described by several simple measures which consider the frequency of the sound, the overall sound pressure level, and the variations of these levels with time. Sound pressure is a basic measure of the vibrations of air that make up sound. Since the range of sound pressures that human can detect is very wide, these levels are measured on a logarithmic scale with units of decibels (dB). Consequently sound pressure levels cannot be added or averaged arithmetically.

Recent interest in environmental health worldwide has called for the assessment of environmental impact of construction noise since the construction industry is considered the backbone of development. In the construction industry, noise-induced hearing impairment is the most prevalent irreversible occupational hazard and it is estimated that 120 million people worldwide have developed hearing difficulties due to noise. In developing

Department of Environmental Technology Management, College for Women, Kuwait University, P.O. Box 5969, Safat 13060, KUWAIT. Corresponding author: mfhamoda@yahoo.com

countries, not only occupational noise but also environmental noise is increasing risk factor for hearing impairment (WHO, 1990). Workers in the construction industry are at a particular risk (Ringen and Seegal, 1995). Therefore, assessment of the construction noise has become a major concern to environmental and occupational health authorities. Future scenarios consider appropriate techniques for prediction of construction noise in order to assess the environmental impact of noise and formulate control strategies for occupational health at the construction sites.

There are different sources of noise pollution at construction sites. The use of heavy vehicles as well as noisy tools and equipment is common in many construction sites. Occupational exposure to high noise levels from such vehicles, tools and equipment places hundreds of thousands of construction workers at risk of developing hearing impairment and hypertension (NIOSH, 1990). In Singapore, nearly 18% of all noise complaints were directly related to noise from construction sites (Raymond et al., 1985). A study of construction noise in Ontario, Canada has reported average noise levels ranging from 93.1 dBA to 107.7 dBA. Tools and equipment were found to be the major source of noise at construction sites (Sinclaire and Haflidson, 1995).

Modeling is considered a powerful tool for assessing the environmental impact of noise but the prediction models currently available are limited in their suitability to construction noise patterns (Boussabine, 1997). It is imperative, yet difficult, because of the complex interaction between noise levels, distance from the noise source, project size, type of construction equipment used, and construction stage. Moreover, it has been recognised that noise modeling is also a complex task as noise propagation is non-linear. It cannot be simply modeled using traditional mathematical and statistical models. Although a number of studies have been conducted to measure noise at construction sites and determine the exposure of workers and health effects, very limited work has been reported on the modeling and prediction of noise levels at construction sites.

Expert systems technology such as artificial neural networks (ANNs) has been thought of as a viable alternative method to model noise levels at construction sites. In fact, ANNs have been applied for modeling and prediction in various fields (Perdicoulis and Glassan, 2006; Hamoda et al., 1999) but their application in modeling the construction noise was tested only recently (Gardner, 1998). This paper examined the application of ANNs as sophisticated techniques having elastic and independent structure to model the variation of noise levels on construction sites. The main objective was to measure noise at construction sites and use the noise measurements to test the ability of a structured network to predict the construction noise. Such predictions are required for the environmental impact assessment and formulation of strategies for occupational health protection at construction sites.

ENVIRONMENTAL HEALTH IMPACT OF NOISE

The health significance of noise pollution has been classified by WHO (WHO, 1990) according to the specific effects: noise-induced hearing impairment, interference with speech communication, disturbance of rest and sleep, psycho-physiological, mental health and performance effects, interference with intended activities, annoyance and effects on residential behaviour.

Hearing impairment is typically defined as an increase in the threshold of hearing (WHO, 1990). Hearing deficits may be accompanied by tinnitus (ringing in the ears). Hearing damage (Kryter, 1985) may occur when associated with certain diseases, some industrial chemicals, toxic drugs, blows to the head, accidents and heredity origins. Hearing deterioration is also associated with the aging process itself (presbyacusis). The extent of hearing impairment in populations exposed to occupational noise depend on the value of the mean equivalent sound level "LA_{eq}", 8h, the number of noise-exposed years, and on individual susceptibility. Men and women are equally at risk for noise-induced hearing impairment. It is expected that environmental and leisure-time noise with a LA_{eq}, 24h of 70 dBA or below will not cause hearing impairment in the large majority of people, even after a lifetime exposure.

The main social consequence of hearing impairment is the inability to understand speech in daily living conditions, and this is considered to be a severe social handicap. Even small values of hearing impairment (10 dB averaged over 2000 and 4000 Hz and over both ears) may adversely affect speech comprehension.

Noise contours at construction sites indicate that large portions of construction sites may have sound levels over 85–90 dBA. Existing noise dosimetry data indicate that time-weighed average (TWA) levels on construction sites can range from 74–105 dBA (Sinclaire and Haflidson, 1995). Construction workers working on or around heavy equipment have particularly high noise exposures (Utley and Miller, 1985).

MATERIALS AND METHOD

Model Development

A neural network is a special structure consisting of basic blocs, organised and interconnected in one or more layers (Gardner, 1998). It initiates the functioning of human brain. The ANN modeling consists of several steps as shown in Figure 1. The steps include collecting training data, pre-processing the collected data, choosing a learning paradigm, selecting an ANN structure, determining the ANN parameters, training the ANN, and analysing the training errors. The design steps are iterated until the user is satisfied. In order to examine the relationships among the input variables of the construction site and the dependent output variable of noise, a model with back-propagation neural network (BPNN) as shown in Figure 2 could be used. It consists of a layered architecture. The layers are: an input layer, one or more hidden layer(s), and an output layer in all of which neurons are connected with weighted connections. Each neuron has a specific mathematical function called activation (or transfer) function which is used for the training procedure. In this study, two algorithms, namely the back-propagation (BP) and the general regression (GR) structure with genetically modification were used. Second, the model is tested with a data set (called test data set) in which the output parameter does not exist. The model takes the input parameters and produces the output. The error function is calculated between the model output and measured values. This indicates the capability of the network model. The lower the error, the more capable is the model. Details of ANN models can be found in related literature (Gardner, 1998). The following is a brief description of each neural network used in this study.

Back-Propagation Neural Network (BPNN)

The BPNN is a type of supervised, feed-forward, neural netwok (Figure 2). In BPNN architecture, information is processed in a forward manner through the network while the prediction error is propagated backwards through the network. It is an iterative method of learning, which passes several times through the entire set of patterns to understand the relation between input x and output y variables and hence improving its capability in predicting outputs for any new pattern. The prediction process of BPNN consists of the following steps. All weights are assigned initial small random values within a range previously specified. Input data are propagated in a feed-forward manner through the network to produce output data according to the connection weights and the activation function. The outputs produced are compared with the target outputs which are known in advance. The errors generated are then propagated backwards in a certain manner through the network for adjustments of the present weights, by raising or lowering them, using two factors, namely, a learning rate factor and a momentum factor. This procedure is repeated for each training example in the training set; multiple cycles (epochs) are required until a satisfactory data mapping is achieved.

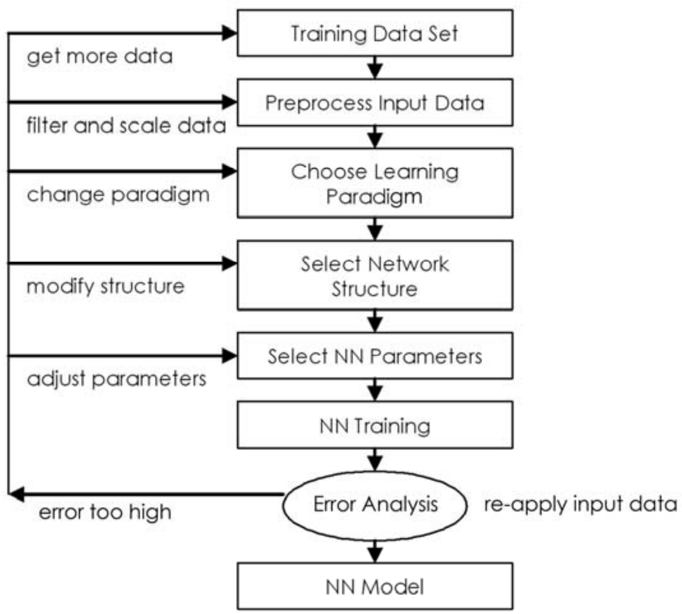

Figure 1. Design Flow Chart of the Artificial Neural Network (ANN)

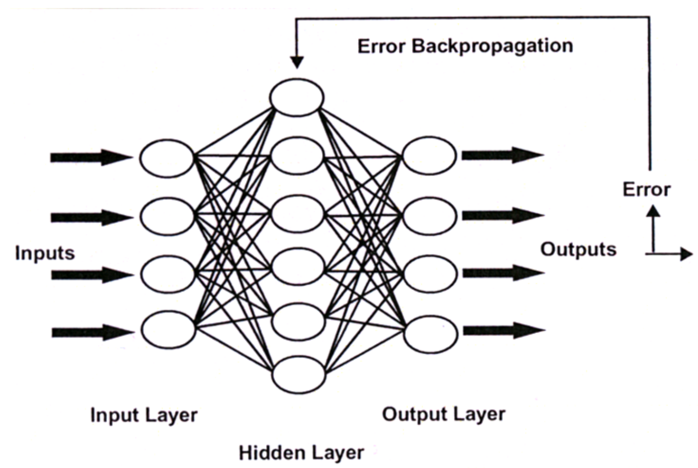

Figure 2. Simplified Schematic Architecture of a Multi Layer Neural Network

General Regression Neural Network (GRNN)

The GRNN is a type of supervised, feed-forward, neural network known for the ability to train quickly on sparse data sets. It is a one-pass learning algorithm (not iterative) with a highly parallel structure. The regression of a dependent variable, y (which is the system output), on an independent variable, x (which is the system input), is the computation of the most probable value of y for each value of x based on a finite number (n) of possible noise measurements of *xi* and the associated values of *yi*. For linear regression, the relation between x and *y* would be expressed as a probability density function (pdf), *F*(x, *y*). The joint pdf of a vector random variable x and a scalar random variable *y* will be estimated from examples using nonparametric estimators. The resulting regression equation can be implemented in a parallel, neural-network-like structure. Since the parameters of the structure are determined directly from examples rather than iteratively, the structure learns and can begin to generalise immediately. The GRNN uses only one parameter which is the smoothing parameter (σ). It is automatically determined and modified when the network is conducted to new data. The smoothing factor determines how tightly the network matches its predictions to the data in the training patterns. If there are multiple outputs, a proposed smoothing factor may be adequate for some outputs, while others need a modified one to produce better results.

Noise Measurements

Noise measurements were conducted in construction sites using 'Mediator 2238', which is an integrating sound level meter (SLM) from Brule & Jeer, Denmark. This SLM conforms to IEC 651 and IEC 804 type I standards (Murphy and Franks, 2002). A polarised ½" condenser microphone type 4188 was used with the SLM. Sound level calibrator type 4231 was used to calibrate the SLM at 94 and 114 dBA. Noise was measured using Fast (F) time weighing and A-frequency weighing.

A total of 33 construction sites throughout the city of Kuwait were selected for monitoring noise. Noise measurements were carried out three times at each site, and at a distance of 5, 10, and 15 m from the construction equipment. The construction sites were selected based on project type, project size and construction stage. Their areas ranged from about 500 to 60,000 m^2. The construction projects included residential complexes, schools, private villas, commercial complexes, sport clubs, office buildings and mosques. Projects were divided according to size into small, medium and large projects. Different construction stages include excavation and foundation, construction activity at different floors, and finishing works. Different types of equipment include excavators, bulldozers, concrete pumps, dewatering pumps, generators, tower cranes, concrete mixers, saws, drills and hammers.

A time-varying noise, measured in dab can be described in terms of its cumulative distribution. Different sound level values were determined in this study. Commonly used values are L10, L30, L50 and L90, denoting the levels exceeded for 10%, 30%, 50% and 90% of the time, respectively. The L10 gives an indication of the top end of the level whereas L90 corresponds to the background noise level in the absence of nearby noise source. Meanwhile, the equivalent continuous sound level, called Lea, contains the same quantity of sound energy over a defined time period as the actual time varying sound level. It is obtained by averaging the mean energy of noise levels over the measurement period.

RESULTS AND DISCUSSION

A total of 257 noise measurements were made and data obtained were analysed. Table 1 presents a summary of statistical analysis of noise data. The overall mean equivalent noise level observed was 78.7 dBA which exceeds the threshold of 70 dBA. The mean measured noise levels increased with project size. Mean L_{eq} observed were 74.3 dBA, 76.8 dBA and 79.3 dBA for small, medium, and large projects, respectively. The maximum L_{eq} noted was 98.2 dBA. The noise level was also dependent upon the type of equipment. An electric generator produced a mean L_{eq} of 80.6 dBA whereas an electric drill produced a mean L_{eq} of 73.7 dBA. The noise levels were related to distance of measurement from the edge of the equipment. Table 2 presents the summary of noise levels measured at distances of 5, 10, and 15 m from the source of noise.

Noise data measured throughout this study were modeled using some independent parameters which are thought to affect the noise levels. ANN of BPNN architecture, of the type recurrent networks, and the genetically modification of GRNN were applied to the data for various input variable combinations to predict L_{eq}, using the software Neuroshell 2®. The parameters considered are: the type of equipment used in construction, the type of the project, the size of the project, the construction stage, and the distance. These were used as input variables for the ANN models. The output is the noise level L_{eq} measured in dBA. The whole database was randomly divided into two equal subsets as training and testing sets. The training set was used in training the networks for the best model performance. After this stage, the model was tested using the test data set to see what

Table 1. Overall Noise Levels at Construction Sites Surveyed

Indicator	Noise Levels (dBA)			
	Mean	**Minimum**	**Maximum**	**SD (1)**
L_{eq} (2)	78.7	58.0	98.2	6.705
$L_{min.}$ (3)	68.8	53.6	100.7	9.338
$L_{max.}$ (4)	88.5	70.3	112.4	8.165

(1) SD = Standard deviation (±)
(2) Equivalent sound level
(3) Minimum sound level
(4) Maximum sound level

performance it provides when unseen data is introduced. Results of the training stage were stopped at the best model point. A standard three-layer, feed-forward, BPNN architecture with 1 to 5 hidden layers was used in parallel with a general regression neural network with a GRNN with genetical modification model with a three-layer network that contains one hidden neuron for each training pattern.

The input variables such as the construction stage, the type of equipment and the distance of measurement from source produced best predictability using GRNN model, as presented in Table 3. Over 93% of the predictions were within 5% of the observed values, hence the application of ANN model is assumed to be satisfactory for the prediction.

Table 2. Measurement of Noise Levels as a Function of Distance at Construction Sites Surveyed

Distance(1) (m)	L_{eq} (2) (dBA)				L_{min} (3) (dBA)			L_{max} (4) (dBA)		
	Mean	Min.	Max.	SD(5)	Mean	Min.	Max.	Mean	Min.	Max.
5	79.8	58.0	101.5	7.2	70.9	53.6	100.7	90.6	70.9	112.4
10	76.8	63.2	97.1	6.8	69.5	57.0	96.2	88.1	70.9	112.4
15	74.6	61.5	97.1	6.9	65.8	55.3	95.7	86.5	70.3	112.4

(1) Distance from source of noise
(2) Equivalent sound level
(3) Minimum sound level
(4) Maximum sound level
(5) SD = Standard deviation (±)

Table 3. Statistical Results of the GRNN Predicted Model

R^2	=	0.6572	
Mean squared error	=	17.7	dBA
Mean absolute error	=	3.157	dBA
Min. absolute error	=	0.004	dBA
Max. absolute error	=	17.573	dBA
Correlation coefficient	=	0.8107	
Percent with 5%	=	70.652	
Percent with 5%-10%	=	22.826	
No. of patterns	=	184	

In order to compare the applicability of the ANN models tested in this study, the performance of each model was evaluated by its accuracy and efficiency. Four statistical measures, namely the correlation coefficient, the mean squared error, the mean absolute error, and the maximum absolute error were used to determine the accuracy of each network model. The comparison included three BPNN models with 1, 2 and 3 hidden layers and one GRNN model with 1 hidden layer in the training and testing or production pattern, as shown in Table 4. Based on the comparison between the actual, test set data and the predicted model results, there was a general agreement between the actual and observed values for all the models tested but the GRNN model showed the best agreement with a correlation coefficient of 0.84. The models proved to be suitable for the prediction of noise from construction sites. The mean absolute error (MAE) of the noise prediction for the training series did not exceed 2 dBA.

The observed and predicted values of construction site noise obtained for all models were compared for each of the training-testing set of data and the production set of data. The GRNN model was superior to the BPNN model. The results shown in Figure 3 indicated that the GRNN model was capable of predicting construction noise based on what it learned from the training sets. The average absolute errors and squared errors for this model were 1.8 dBA and 7.6 dBA, respectively for the training and testing set, and were 2.8 dBA and 14.3 dBA, respectively for the production set. The GRNN model responded much better than the other BPNN models to noise data from construction sites due to its ability to train quickly on sparse data sets.

Table 4. Comparison of Statistical Results from Combined Processed Patterns using the Tested Models

Model	**Correlation Coefficient (r^2)**	**Mean Squared Error (MSE) (dBA)**	**Mean Absolute Error (MAE) (dBA)**	**Maximum Absolute Error (dBA)**
2 hidden layer in Parallel BPNN	0.27	39.4	4.8	26
3 hidden layer in Parallel BPNN	0.27	38.6	4.8	25.5
1 hidden layer in Series BPNN	0.3	38.0	4.8	24.8
1 hidden layer with GRNN (Training and Testing)	0.84	17.6	1.8	14.0
1 hidden layer with GRNN (Production)	0.70	14.3	2.8	9.8

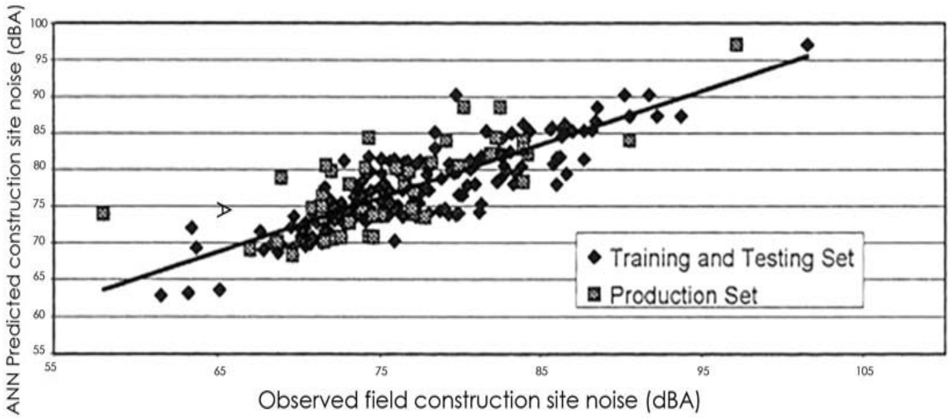

Figure 3. Field (observed) versus ANN (predicted) Construction Noise using the GRNN Model

CONCLUSIONS

An overall mean equivalent noise level of 77.2 dBA was observed for all the measurements at 33 construction sites, which exceeds the threshold of 70 dBA that represents a cautionary risk of hearing damage of construction workers. The L_{eq} ranged from a minimum of 58 dBA to a maximum of 101.5 dBA. Construction stage, type of equipment and distance of measurement were modeled as input variables to predict the equivalent noise level, L_{eq} using ANN back-propagation model. Over 93% of the predicted values of the noise levels using this model were close to the observed values within a range of 5% error. Only 184 data points were analysed for the development of the model. More data can be used to improve the predictability of the model.

Noise was measured at 5, 10 and 15 m from the construction equipment. The mean measured noise levels increased with project size. Mean L_{eq} observed were 74.6 dBA, 77.7 dBA and 78.4 dBA for small, medium, and large projects, respectively. The noise level was also dependent upon the type of equipment. Electric generators produced a mean noise level of 86.3 dBA, whereas an electric drill produced a mean L_{eq} of 71.6 dBA. The ANNs proved to be a useful tool to model and predict the construction noise with good accuracy. For the GRNN model, over 93% of the predicted values of the noise levels were close to the observed values within a range of 5% error. It proved to be superior to the BPNN model due to its ability to train quickly on sparse data sets such as those of noise collected from construction sites.

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