Turkish J. Eng. Env. Sci.
28 (2004) , 149 – 155.

Neural Network Modelling of Outdoor Noise Levels in a Pilot Area

Yaşar AVŞAR, Arslan SARAL, M. Talha GÖNÜLLÜ,
Ertan ARSLANKAYA, Uğur KURT
Yıldız Technical University, Environmental Engineering Department,
34349 Beşiktaş, İstanbul-TURKEY
e-mail: avsar@yildiz.edu.tr

Received 27.01.2003

Abstract

Noise measurements were made for 16 relevant outdoor points in the central campus area of Yıldız Technical University. All measurements were performed in accordance with Turkish Standards using an HD 9019 sound level meter. A new and sophisticated modelling technique called artificial neural networks was used to model the variation of noise levels from traffic around the campus area. The model inputs were 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. All parameters were measured throughout the study for 5 months.

Key words: Noise, Outdoor noise, Noise modelling, Artificial neural networks.

Introduction

Background noise levels in an educational area should be within the range of an acoustical standard in terms of noise criteria values. (Sargent *et al.*, 1980). The acoustical quality requirements of such places as classrooms in various European countries vary between 30 and 45 dBA Leq (Belgium: 30-45, France: 38, Germany: 30, Italy: 36, Portugal: 35, UK: 40, Sweden: 30 and Turkey: 45 dBA) (Noise Control Regulation of Turkish Republic, 1986). For these countries, acoustical quality requirements in other educational places like libraries, offices and dining rooms are similar (Vallet, 2000).

Noise from outdoor sources penetrates through windows and other weak parts of buildings. Adequate isolation precautions should be considered during the planning and construction of educational buildings to be built in areas with high outdoor noise levels.

There are many methods for the determination of noise propagation in environmental studies. Noise propagation depends on various environmental parameters such as climate, geographical conditions and structure, natural and artificial noise barriers, and time. All these parameters make noise modelling a very complex and non-linear problem. A new and sophisticated method, called artificial neural networks, was used for modelling and predicting noise levels. This metnod provides flexibility, accuracy and some amount of fault tolerance in noisy and changing environments. It has a potential future in other fields of instrumentation and measurement science, and has an independent modelling structure (Patra *et al.*, 1998). Artificial neural networks have been used as predictors for many regression problems. Knowing how well predictions match the real world is crucial to some of them, and so many research groups have developed strategies to tackle this problem (Webera *et al.*, 2003).

The study area and database

The central campus of Yıldız Technical University, which is located on Barbaros Boulevard in the Beşiktaş district of İstanbul, has a capacity of 15,000 students. There are 2 education periods, daytime and evening, in the university. The total area of the central campus is 113,400 m^2. It is located on Barbaros Boulevard, one of the busiest main roads in İstanbul. Sixteen noise measurement points representing the influence of mainly traffic noise emitting from Barbaros Boulevard are shown on the map in Figure 1. This noise source is considered to be a linear noise source separate from 2 other noise sources, point and layer noise sources. The measurement points were both inside and near the campus.

Measurements were obtained 2 days a month over 5 months from August to December 1997. At all points, measuring was performed at 5 time intervals: 06.00-08.00, 10.00-12.00, 14.00-16.00, 18.00-20.00 and 24.00-02.00. Thus, noise level fluctuations during the whole day were obtained. Acoustical measurements were obtained according to Turkish Standards Institute method no. TS9315 (Turkish Standards Institute, 1991) throughout the study.

Since meteorological conditions such as wind speed and direction, air temperature and relative humidity have considerable effects on noise levels, these parameters were measured at the same time. There was no precipitation during the survey.The minimum measuring time at each measurement point was 5 min. Noise level measurements were obtained with a HD 9019 sound level meter class 1 according to IEC 651 and HD 9102 calibrator for sound level meters type 2 - IEC 942–1988, BS 7189, ANSI S1, 40-1984, a half inch condenser microphone and a tripod.

Artificial neural network models

A neural network is a special structure consisting of basic blocks, organized and interconnected in one or more layers (Rumelhart *et al.*, 1986). It imitates the functioning of the human brain. The neural network-based prediction model works in the same way. As input to the model, a historical set of significant independent data is used, and the outputs are the desired parameters, which are supposed to be dependent upon the input parameters predicted by the model. Of the many types of artificial neural network models, multi-layer perceptron (MLP) neural networks were used in this study. Figure 2 shows the main parts of the network model. 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 these neurons are connected with weighted connections.

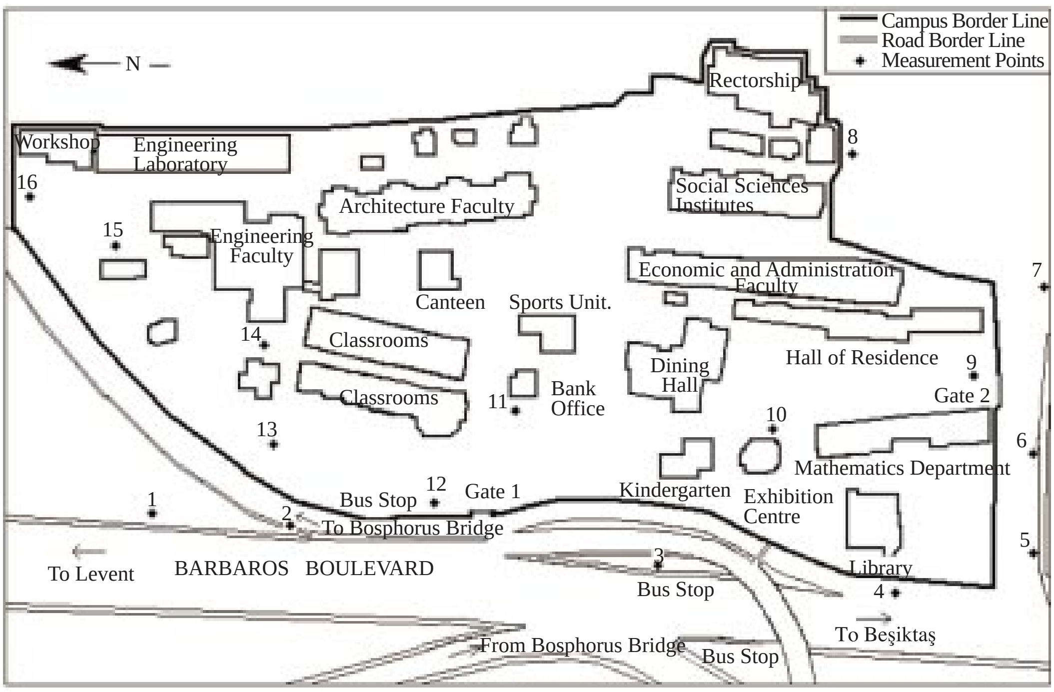

Figure 1. Map of Yıldız Technical University campus and noise measurement points.

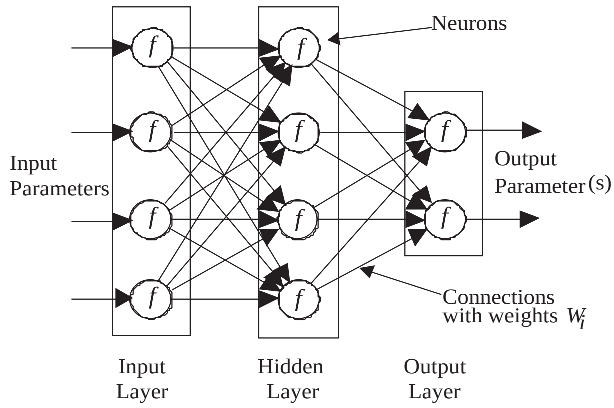

Figure 2. Simplified schematic architecture of multi-layer perceptron networks.

Each neuron has a specific mathematical function called activation (or transfer), which accepts input from the previous layer and produces output for the next layer. The sigmoid function is the most widely used activation function capable of simulating the non-linear behaviour of the atmosphere in which sound waves propagate. Each of the input layer neurons accepts one of the input parameters and produces an output for the next layer (hidden layer). Then each of the hidden layer neurons takes the weighted sum of all outputs of input layer neurons and produces an output for the output layer (if there is only one hidden layer). Finally the output layer takes the weighted sum of the outputs of all hidden layer neurons and produces the output of the model. Details of MLP models can be found in Gardner and Dorling (1998).

MLP neural network models are capable of modelling highly non-linear relationships and can be trained, in the presence of a sufficient and unbiased training data set, to accurately generalise the new unseen data. MLP neural networks learn to model a relationship during a supervised training procedure, when they are repeatedly presented with series of input and corresponding output data. In the case of modelling noise levels, as in this study, the input data would consist of measurements of meteorological and geographical conditions, and the output would be noise level measurements.

Using supervised neural networks involves 2 operational steps. First, the network is trained with the training data set consisting of input parameters with corresponding known values of output parameter(s). Training is simply the adjustment of the interconnection weights between the neurons as shown in Figure 2. There are many algorithms for training. An error back propagation algorithm was used in this study. Detailed explanations of the algorithm may be found in the related references. An error (root mean square (RMS) error) function based on the difference between calculated and measured values of the output parameter shows the performance of the network model. Training is stopped at the desired value of RMS error. However when training neural networks, it is important to avoid overtraining. Overtraining occurs when the model learns the noises in the training set, resulting in poor generalising capability of the model when presented with new unseen data. What is aimed from training a neural network is to extract the generalising features of the data. This is achieved with a training data set containing sufficiently extensive and representative patterns of all parameters. In order to avoid overtraining, a validation data set, being a third group of data, is used during training in order to check the generalisation performance. Training is stopped when the RMS error on the validation data reaches its minimum. This point is called the best model point.

Second, the model is tested with a data set in which the output parameter does not exist. The model takes the input parameters and produces the output. Again the error function is calculated between the model output and measured values. This indicates the generalising capability of the network model. The lower the error, the more capable the model is of generalising. All network models tried in this study were trained up to the best model points in order to get the best performance on the testing data sets.To generalise the knowledge implicit in the data or training set and provide solutions to new neural network modelling situations, neural network analysis, using a combination of geometric, constructional and acoustical data, was used in this study to develop an alternative method of comprehending and predicting the relationships between sound propagation and environmental conditions (Hodgson *et al.*, 2001).

Results of neural network predictions

The magnitude levels of noise measurements throughout this study are shown in Figure 3a. The levels indicate that there are no monotonically increasing or decreasing trends in the data but rather randomised sharp scatterings throughout the measurement period. The time scale fluctuations of the input parameters show the same randomised behaviour as the output parameters shown in Figures 3b, 3c, 3d and 3e. This behaviour of the data causes difficulties in modelling studies when some traditional deterministic approaches are considered. Neural networks, when their non-linear and highly independent data handling capacity is considered, can provide reasonable and reliable results.

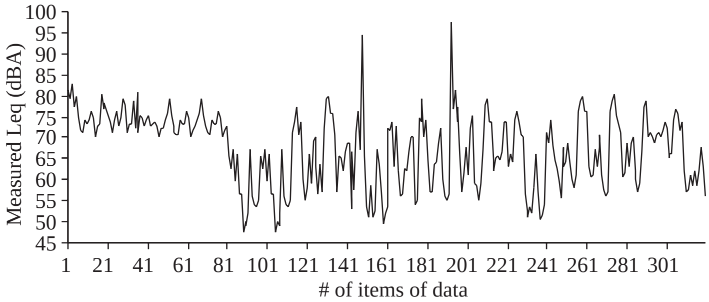

Figure 3a. Behaviour of the noise data measured throughout the study.

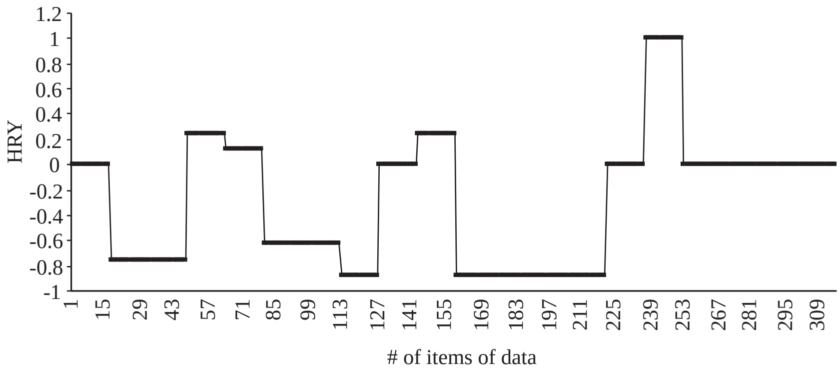

Figure 3b. Behaviour of the wind direction data measured throughout the study.

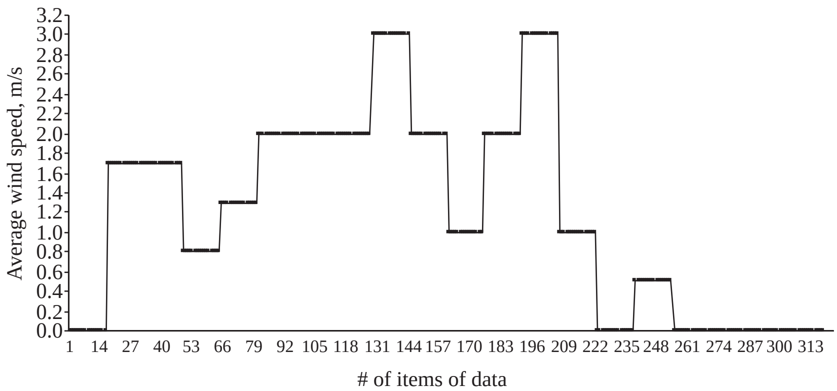

Figure 3c. Behaviour of the average wind speed data measured throughout the study.

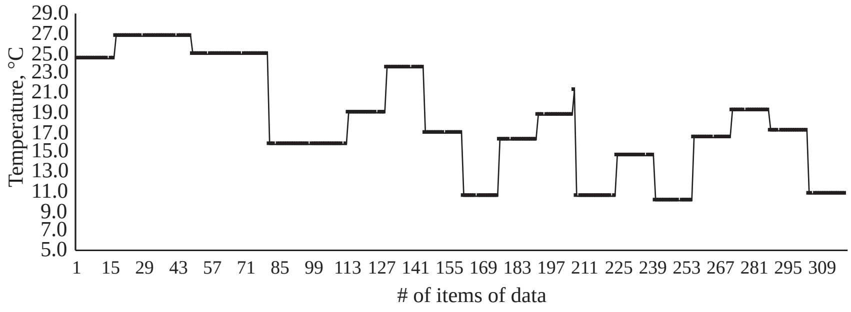

Figure 3d. Behaviour of the temperature data measured throughout the study.

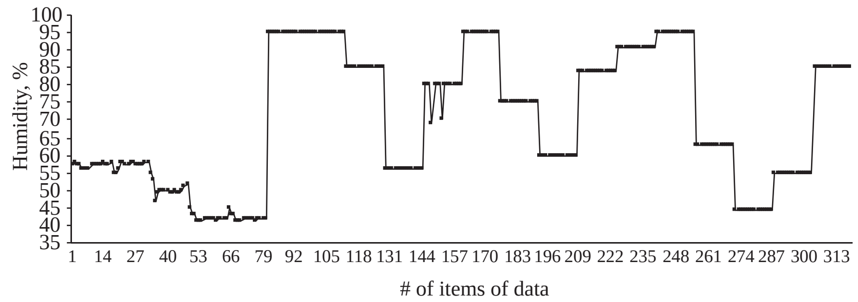

Figure 3e. Behaviour of the humidity data measured throughout the study.

Noise data measured throughout this study were modelled using some independent parameters, which we think affect noise levels. These parameters are the position of the measurement station, the geographical situation between the noise source and measurement station, wind speed and direction, air temperature and relative humidity, and time of day. These 7 parameters were used as the input parameters for the neural network models. The output is the noise level measured in dBA as Leq at the point of measurement. The data collected throughout the study consist of a total of 319 measurement patterns. The whole database was randomly divided into 2 equal subsets; 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 performance it provides when unseen data are introduced. Results of the training stage stopped at the best model point and the results of model predictions on unseen test data are shown in Figures 4 and 5, respectively. The time scale characteristics of both the training and testing sets (Figures 4 and 5, respectively) are similar to those of the whole database (Figure 3a). Therefore, results of training and testing stages are also similar.

The neural network models predicted the unseen testing data set well enough when the randomised trends in the test data set are considered. The first 80 data patterns fluctuate in a relatively narrower domain (70-80 dBA as Leq) when compared to the whole database (Figure 3a). Therefore, the neural models predicted this range of data better than the rest. This is clearly shown in the x-y scatter plot representation of the same data in the both training and testing sets in Figure 6.

The correlation coefficients (R) of both training and testing results are 0.7277 and 0.6899, respectively. The R of the training set is slightly greater than that of the testing set since the neural models, during training, may concentrate on the training data set and calibrate the inner connection weights according to the individual characteristics of the training set. However, this difference is not considerable since, as stated above, the general behaviour of both data sets is very similar. If the all data were divided in another randomised form some other R values would be obtained. What is important here is to obtain as much generalised training data as possible in order for the neural models to learn all possible data patterns. Another important point is to train the model not up to the global minimum error point but just up to the best model point, i.e. the point at which the model has the highest generalising ability although the training error is not at its minimum.

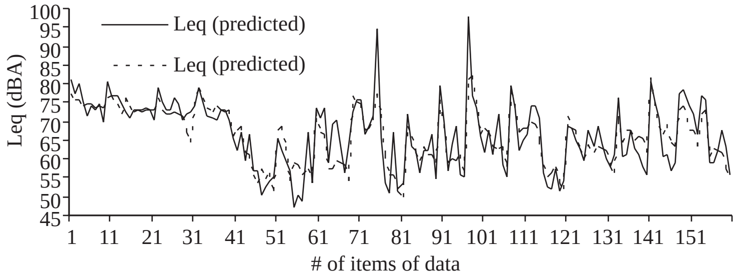

Figure 4. Training results at the best network point.

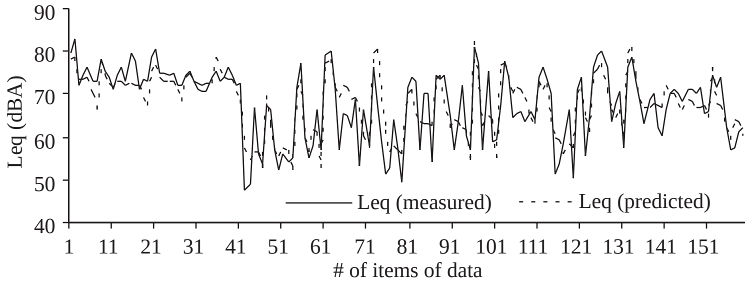

Figure 5. Model predictions at the best network point.

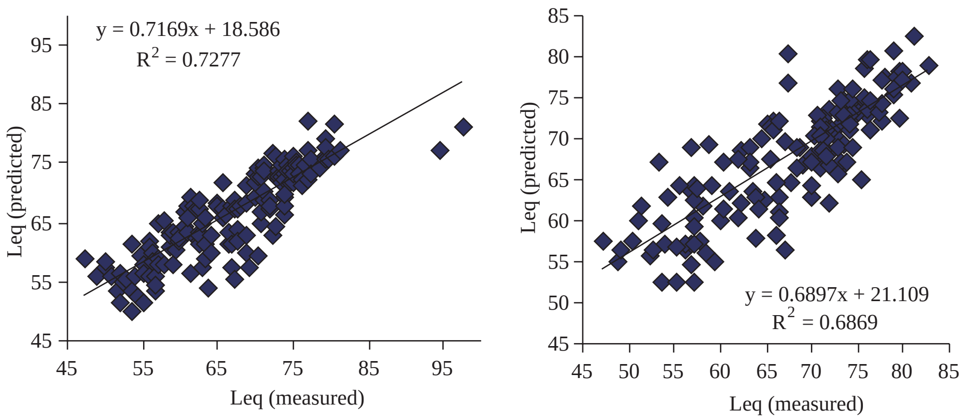

Figure 6. Linear correlation between actual and predicted Leq data in training (left) and testing (right) sets.

The data distribution in the range 70-80 dBA (Leq) is in a relatively smaller area compared to the whole distribution in both training and testing sets. This is related to the learning logic of the neural models. Neural models learn and characterise the data better when introduced in higher quantities and in combinations of input parameters. This fact is shown in the frequency distributions of both training and testing sets in Figure 7. The number of items of data in the range 70-80 dBA (Leq) is greater than for all other ranges in both data sets.Another point is that the database has sharp (almost one-point) up and down fluctuations in the rest of the measurement period. These sharp fluctuations are not well predicted, compared to the first part of the 80 data patterns, since the data behind those points are not sufficient in quantity or quality for the neural models to recognise them.

Conclusions

All studies with artificial neural network models for modelling and predicting the noise levels in the presence of related input parameters have encouraged us to perform further work with a larger database and to investigate the effects of input parameters on noise levels. The number of parameters we used in this study can be increased if available, or can be optimised for the most influential ones. In other words, some of those input parameters may need to be eliminated if they have negligible effects on output. On the other hand, some new parameters may be introduced into the models, which may have significant effects on the parameter that is modelled. The study of modelling noise levels may be extended in these directions if and only if a sufficiently large and error-free database is available. The data must be measured and collected regularly and periodically and be as error-free as possible. Our goal will be to investigate this extension of the study.

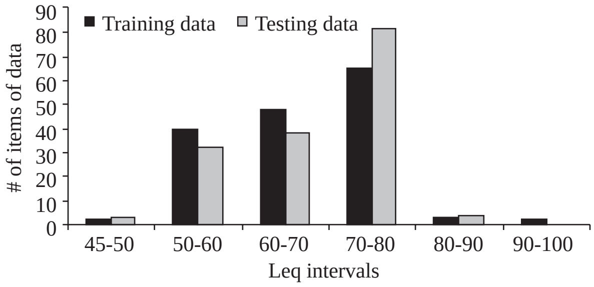

Figure 7. Frequency distributions of training and testing data sets.

References

Gardner M.W. and Dorling S.R., “Artificial Neural Networks (The Multi Layer Perceptron), “A Review of Applications in the Atmospheric Sciences”, Atmospheric Environment, 32(14/15), 2627-2636, 1998.

Hodgson M., Nannariello J. and Fricke F.R. “Neural Network Predictions of Speech Levels in University Classrooms”, Applied Acoustics, 62, 749-767, 2001.

Noise Control Regulation of Turkish Republic, 29, numbered 19308 and dated 11.12.1986.

Patra J.C. and Panda G., “ANN-based Intelligent Pressure Sensor in Noisy Environment”, Measurement, 23, 229–238, 1998.

Rumelhart D.E. and McClelland J.L., “Parallel Distributed Processing 1,2”, MIT Press, Cambridge, MA, 1986.

Sargent, J.W., Gidman, M.I., Humphreys, M.A. and Utley, W.A., “The Disturbance Caused to School Teachers by Noise”, Journal of Sound and Vibration 70, 557-572, 1980.

Turkish Standards Institute, “Acoustics-Description and Measurement of Environmental Noise Part 1-Basic Quantities and Procedures”, TS 9315, 1991.

Turkish Standards Institute, “Traffic Noise and the Measures for Its Prevention”, TS 10713, 1993.

Vallet, M., “Some European Standards on Noise in Educational Buildings”, International Symposium on Noise Control & Acoustics for Educational Buildings, 13-20 İstanbul, Turkey, 2000 may 24-25.

Webera K.E., Schlagnerb W. and Schweierc K., “Estimating Regional Noise on Neural Network Predictions”, The Journal of the Pattern Recognition Society. 2003.