Modeling environmental noise using Artificial Neural Networks

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***Abstract*—Since 1972, when the World Health Organization (WHO) classified noise as a pollutant, most industrialized countries have enacted laws or local regulations that regulate noise levels. Many scientists have tried to model urban noise, but the results have not been as good as expected because of the reduced number of variables. This paper describes artificial neural networks (ANN) to model urban noise. This model was applied to data collected at different street locations in Granada, Spain. The results were compared to those obtained with mathematical models. It was found that the ANN system was able to predict noise with greater accuracy, and therefore it was an improvement on these models. Furthermore, this paper reviews literature describing other research studies that also used soft computing techniques to model urban noise.**

***Index Terms*—urban noise; environmental noise; neural networks; noise prediction**

I. Introduction

Since 1972, when the World Health Organization (WHO) decided to catalogue noise generically as a kind of pollutant, authorities have begun to respond to this serious problem. In 1979, the Stockholm Conference also classified noise as a pollutant. Those first official resolutions were subsequently ratified by the European Union, who required member countries to make an effort to regulate environmental noise [20]. In Spain, the anti-noise law [28] was the first official measure to limit environmental noise since no national regulations had ever been enacted. Its goal was to prevent, monitor, and reduce acoustic pollution. Since February 2001 Granada has had a municipal ordinance that protects the acoustic environment [31]. Table I shows the noise levels permitted by this regulation. Since these regulations are of recent date, urban noise prediction and assessment systems are needed, such as those proposed in this paper.

Environmental noise is mostly produced by light vehicles, heavy vehicles or motorcycles. It is also caused by other noises such as those produced in commercial or leisure areas or those produced by events like the sirens of ambulances, fire trucks, etc. When analyzing noise problems, three aspects are generally considered: prediction of the noise level, prediction of noise annoyance, and classification of types of noise. In this paper, the focus is set on the prediction of noise level.

TABLE I
Maximum noise level permitted in Granada, Spain

City area	Daytime (7:00 - 23:00)	Night time (23:00 - 7:00)
Hospital zone	60 dbA	50 dbA
Residential area	65 dbA	55 dbA
Commercial zone	70 dbA	60 dbA
Industrial zone	75 dbA	70 dbA

Many countries use different models to measure and/or predict noise. These models consider urban vehicle traffic as the main noise source, and try to mathematically calculate the noise level, based on a given set of characteristics. Some of the best known models are: French [19], MOPU [30], Planverk'96 [32], RLS90 [33] and E.Gaja [24]. Also of relevance are two models specifically developed for the city of Granada [35].To measure noise the parameter L_{eq} is used, known universally as the average essential parameter for measuring noise, representing a noise level equivalent and measured in decibels. In practice, the modified version of L_{eq}, L_{Aeq}, was used. This parameter is better suited to what a human ear perceives.

The goal of this paper is to model the prediction of urban noise using Artificial Neural Networks (ANN), improving the classical mathematical methods used actually, each one using a little number of variables. The first idea is to consider all the variables that the different indicated methods use, and secondly, try to reduce the number of relevant variables, maintaining an enough accuracy, in two phases; using, in phase one, the Principal Component Analysis (PCA), and in a second phase, considering feature selection methods. In this paper, the results obtained with all the variables are showed and some results using PCA are also indicated. In future works, the study

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TABLE II
CLASSIFICATION OF PUBLICATIONS

Soft Computing Technique	Noise level prediction	Noise annoyance prediction	Noise classification	Traffic Flow Prediction
Artificial Neural Networks	[2] [15]	[37]	[3] [5] [18]	[21] [22] [27] [36]
Fuzzy Techniques	[1] [16]	[6] [7] [8] [9] [10] [11] [12] [13] [14] [37]	[4]	[22] [36]
Genetic Algorithms	[16]	[10] [11] [13]		
Hidden Markov Models			[5] [17] [18] [23] [29]	

will be completed.

The first part of this paper gives an overview of the literature on modeling urban noise with Soft Computing techniques. In the second part, the design and implementation of the ANN that was used to predict noise levels in the city of Granada is described. In the conclusions, the results of the study are summarized. Finally, the used references are included.

II. REVIEW OF THE LITERATURE

As a background for this study, a classification of the literature on the modeling of urban noise with Soft Computing methods is made. According to the Soft Computing technique used and the type of environmental noise analysis, this overview includes 25 publications. Most of them describe studies using fuzzy techniques to predict noise annoyance. Hidden Markov Models were the most frequently used for noise classification, finding only a few references to genetic algorithms, whereas ANNs were used in various fields. Also included are five papers related to traffic flow prediction as vehicle traffic is the most important source of urban noise. A taxonomy of the found articles is shown in table II.

III. A NEURAL NETWORK FOR ENVIRONMENTAL NOISE PREDICTION

For the study of urban noise in the city of Granada, a neural network system that was capable of giving more accurate results than other systems was created. For this purpose, after a process of data collection in the city of Granada, which included a total of 12 streets with different characteristics, an artificial neural network structure to solve the problem was designed. The results obtained with this network were compared with data from other predictive models of urban noise, and this confirmed the goodness of the system.

A. Data collection

The sound measurements were taken with a sonometer integrator 2260 ObserverTM, equipped with the software BZ7219.

All the variables included in the previously mentioned mathematical models are considered, and certain others, regarded as influential by a group of experts. They are shown in table III). A set of 289 data records was obtained, each of which had 26 features. Twenty-five of these features (i.e. the variables in table III), constituted the input of the ANN. The equivalent noise level L_{Aeq} was the output. The 25 input variables underwent a process of normalization and it was also necessary to normalize the output between 20dB and 120dB since this is the range for normal hearing.

TABLE III
INPUT VARIABLES CONSIDERED BY THE ANN

1	Time of day
2	Commercial or leisure environment
3	Construction work in the area
4	Stabilization time
5	Traffic flow type
6	Ascendant light vehicle flow
7	Descendant light vehicle flow
8	Ascendant motorcycle flow
9	Descendant motorcycle flow
10	Ascendant heavy vehicle flow
11	Descendant heavy vehicle flow
12	Number of vehicles with siren
13	Abnormal events related to traffic
14	Abnormal events unrelated to traffic
15	Average vehicle speed
16	Road slope
17	Number of lanes upward
18	Number of lanes downward
19	Pavement Type
20	State of the pavement
21	Street Type
22	Street Width
23	Average building height
24	Road width
25	Distance from noise source

B. Artificial Neural Network for noise level prediction

In the study, a MLP-backpropagation neural network (variant Levenberg-Marquardt) is used, which was implemented with MATLAB 6.5. After considering several ANN topologies, the one with 9 hidden neurons was finally selected (the one with 7 hidden neurons obtained similar results). So the selected structure of the ANN included 25 inputs, 9 hidden neurons, and 1 output, as it is shown in figure 1. Five different data sets were randomly constructed from the 289 input records. These five data sets contained a training set with 200 records and a test set with 89 records, each of which was made up of different records. The ANN was run five times with different initial weights for each of the five sets of data. This provided 25 trials to evaluate for the prediction of the level of noise. A variable learning rate was considered, and the run ends when an error level below 0.00001 is reached.

The performance of the network was evaluated by taking into account the error regarding the expected outcome, as well as statistical measurements of the mean and the standard deviation of the error. Table IV shows the results obtained for the second of the five datasets. They correspond to the 5 runs of the network and the average output of these runs. This is of interest because it takes into account the error theory on the error of the measuring instruments.

To measure the results, the instances that exceed 5% of the

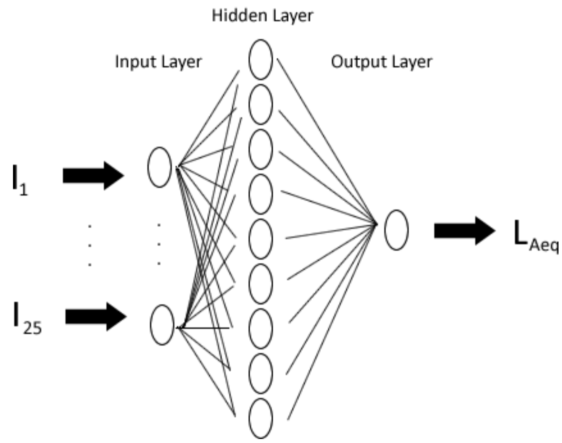

Fig. 1. Structure of the neural network

TABLE IV
RESULTS OF THE FIVE RUNS OF THE NETWORK, DATASET 2

Dataset 1	Run 1	Run 2	Run 3	Run 4	Run 5	Average
Epochs	14	14	12	12	10	
Instances that exceed 5% of error (Train/Test)	0/2	0/4	0/3	0/0	0/0	0/0
Error mean (dB) - Test	0.76	0.62	0.68	0.66	0.62	0.66
Standard Deviation - Test	0.78	1.05	0.87	0.76	0.67	0.83

error, which the experts consider a good approximation, were considered. The average and the standard deviation of the error on the test sets are also showed.

As can be observed in table IV, the number of epochs or iterations was very low for all runs, meaning that the training was very fast, and facilitated the use of the trained ANN. In all data sets, the majority of runs learned correctly, and in the test set, 4 is the maximum number of instances that exceeded 5% of the error, regarding the expected output. Except for datasets 1 and 5, there was always at least one run in which the whole test set was below 5% in the output error. Only dataset 2 is shown in table IV, as the results of all the datasets were very similar. The average for the total number of examples that exceeded 5% error did not reach 2 (e.g. the average of the 25 runs was 1.92). The average error was kept very low (less than 0.79 dB), which indicated a very good global learning. The standard deviation remained steady, i.e. between 0.5 and 0.8 in all instances, except in two cases, in datasets 2 and 4. This confirmed that the global learning obtained by the ANN was very good. Similar results were obtained with the other datasets.

Special consideration was given to the average of the five outputs (sixth column of table IV). In all data sets, the learning was correct, and in the test set, there was only one instance in data set 4 that had one error over 5%. The error mean was always less than 0.71dB, and the standard deviation did not exceed the value 0.83, which indicated an excellent global learning. The fact that the training of the ANN in the study was very fast, and the fact that this training took place simultaneously, was convincing evidence in favor of the use of values from the outputs of several ANNs, as an output computed by this system.

In view of these results, a very low error mean of 25 runs was obtained, 0.716 dB. Taking into account that experts consider 5% of error a good approximation, these are excellent results. The standard deviation of the 25 runs was 0.786, with a value also very good, given that the mean of error is low.

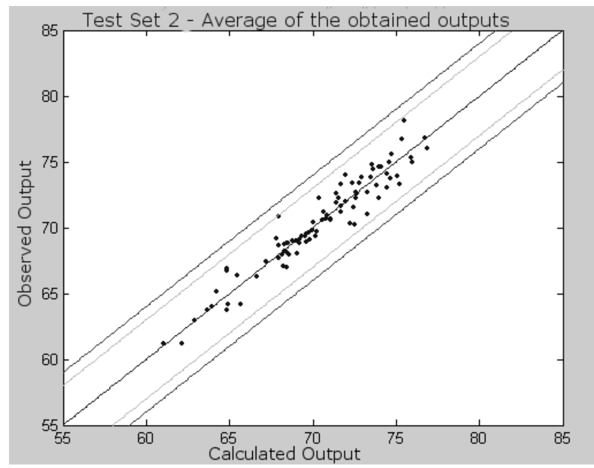

Fig. 2. Comparative graph of test set 2

Figure 2 is a graph comparing the noise level measured with the one obtained for the test set. These results are for data set 2. The dotted lines are 5% over 60dB (3dB) and the continuous lines are 5% over 80dB (4dB). No data goes beyond these limits.

The ANN received records consisting of 25 variables as input, while mathematical models only used a lower number of inputs. Since this seemed to indicate that some of the variables might not be relevant to noise level prediction, a process of data reduction and/or feature selection would be necessary. By using the principal component analysis, it was achieved to reduce the high number of inputs the network received. Inputs were thus reduced from 25 to 11 (these inputs did not correspond to any of the primitives, but were linear combinations of them), and although goodness declined slightly, the results were acceptable, and yet better than those given by the mathematical models. This was a very satisfying solution, as it is preferable to have a reduced data set.

With this input reduction, the average of the total number of instances exceeding 5% error was higher, with an average of 6 per set. The average error for all data was 0.92 dB, which was quite acceptable, and the standard deviation was kept around 1. The average standard deviation of the 25 executions was 1.03, which was a satisfactory value, given the fact that the average error was low. The analysis of the average output of the five runs improved the outcomes of each individual ANN,

TABLE V
COMPARISON OF CLASSIC MODELS AND NEURAL NETWORK

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

which justifies its use.

Despite the fact that the results obtained were not as good as the ones in which the inputs were no preprocessed and considering that they are also better than the classic mathematical models, the significant reduction in the input set was considered positive.

C. Comparison between the neural network proposal and the known predictive models

One of the main goals of this ANN was to improve the performance of existing predictive models. Such models calculate the noise level, based on a set of environmental characteristics with the help of mathematical calculations. To verify that the approach obtained a noise level close to the real one, in the graph in figure 3 each of the models is compared with the results obtained by the network. The comparison is established with the performance of the network without inputs preprocessing. Furthermore, table V shows some numerical results of this comparison: the average of the errors and the number of instances where the output error is greater than 3 dB, for each model including the artificial neural network presented in this paper, in the test set.

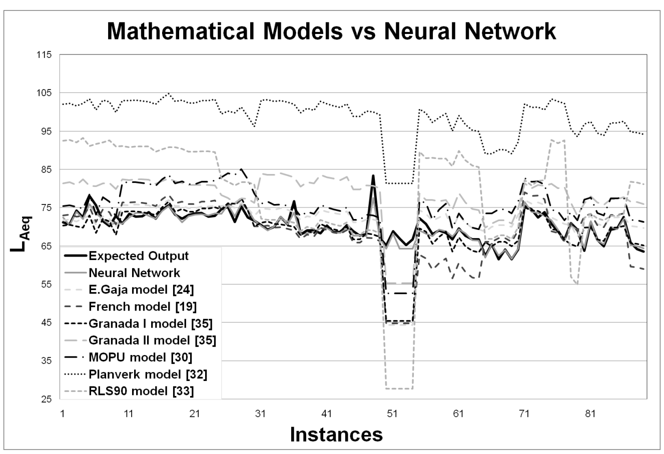

Fig. 3. Graph comparing the results of classic models with those of the neural network model

Although the neural network always obtained the best performance as can be observed in figure 3 and table V, the models closest to actual noise levels were Granada I [35] and E. Gaja [24]. One of the strengths of the network lies in the fact that, when in the given instance the flow of vehicles is zero, the network provides a very good approximation. Since predictive models base their calculation primarily on the flow of vehicles, when the flow is zero, the noise level of the output is valued only by the corrections and thus a very low value is given.

IV. Conclusions

This paper first offered an overview of current literature on urban noise and Soft Computing techniques. According to the Soft Computing technique used and according to the treatment of noise adopted, a total of 25 papers were classified.

Against this background, the performance of a neural network based system for the prediction of urban noise was described. For the study, it was designed and implemented an artificial neural network capable of predicting the level of urban noise, based on a set of 25 environmental characteristics. The proposal backpropagation network has 9 neurons in the hidden layer and uses a Levenberg-Marquardt training algorithm. From this structure, 5 data sets were created and 5 runs for each of them were made. Excellent results were obtained from these 25 tests, earning an average error below 1 dB. The principal component analysis (PCA) was also used to simplify the model and the values obtained were also quite acceptable. This suggested that the reduction of inputs through feature selection was not immediate and required further study. The ANN will be also tested with new instances.

The results given by the network were compared with those of existing predictive models of urban noise, which were based on classical models. The tests confirmed that the results produced by the network were better for all data records.

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