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Developing an Artificial Neural Network for Modeling and Prediction of Temporal Structure and Spectral Composition of Environmental Noise in Cities

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1. Introduction

Noise pollution in large cities is an ever-growing problem, due to several factors: the increase in demographic density, the increase in the number of per capita devices, appliances and vehicles capable of generating loud noise, and the fact that society is getting used to higher noise levels.

One of the most important factors that help us to explain this fact is the road traffic, since as is generally established, road traffic is the most important and generalized sound source in the urban zones of the developed countries. Generally speaking, this one is also, with difference, the sound source that produces more disturbances and nuisances on the urban residents. However, road traffic is not the only noisy source in urban environments: other noisy sources relating to construction work, commercial activity, recreation, etc. have been found. At the same time, sound spaces where road traffic does not have a direct incidence and in which natural and social sounds predominate, e.g. green areas, can be observed (Torija et al., 2010a).

The European Directive 2002/49/EC on the Assessment and Management of Environmental Noise aims to create a common framework for assessing exposure to environmental noise in all Member States. With the use of indicators and evaluation methods harmonized the results will be grouped into strategic maps. These maps are designed to comprehensively assess noise exposure in a given area, or for overall predictions in that area. In addition, they will be the basis for developing both action plans and strategies in the fight against noise (Directive 2002/49/EC).

For the development of assessment and achievement of the objectives stated in the above mentioned directive, from the European Commission the methods used to predict different emission sources present in urban environments (industrial noise, road traffic, railway traffic and aircraft traffic) are recommended (Commission Recommendation 2003/613/EC). All these methods are based only on the obtaining of the A-weighted energy-equivalent sound pressure level (L_{Aeq}). Nevertheless, any physical characterization of a sound environment calls not only for consideration of the A-weighted sound pressure level (L_{Aeq}), but also requires description of the temporal structure and spectral composition of the sound (Berglund & Nilsson, 2001; Botteldooren et al., 2006). These factors bear great weight in the perception of noise (Viollon & Lavandier, 2000; Berglund & Nilsson, 2001;

Botteldooren et al., 2006) and in its negative impact (specific annoyance) on the population (Berglund et al., 2002; Björk, 2002; Lercher & Schulte-Fortkam, 2003).

The heterogeneous physiognomy of urban environments, together with the characteristics of environmental noise, with their great spatial, temporal and spectral variability, makes the matter of modeling and prediction a very complex and non-linear problem, to which we may apply a powerful tool of data mining —artificial neural networks. These constitute a paradigm of automatic processing that ultimately seek to emulate the biological brain, or at least some of its functions, such as learning (Patra & Panda, 1998). Artificial neural networks (ANNs) are widely used in environmental modeling and prediction (Chelani et al., 2002; Hamed et al., 2004; Maier et al., 2004; Almasri & Kaluarachchi, 2005; Ordieres et al., 2005) as a preference to more conventional statistical techniques (Maier & Dandy, 1998). The reason is that ANNs are non-linear (Chakraborty et al., 1992), relatively insensitive to data noise (Tang et al., 1991; Burke & Ignizio, 1992), they perform reasonably well when limited data are available (Tang et al., 1991; Schizas et al., 1994), and they provide flexibility, accuracy and some amount of fault tolerance in changing environments (Patra & Panda, 1998).

2. Literature review of the application of soft-computing techniques in urban noise field

	Artificial Neural Networks	Fuzzy Techniques	Genetic Algorithms	Hidden Markov Models
Sound Pressure Level Prediction	(Cammarata et al., 1995; Avsar et al., 2004; Genaro et al., 2010)	(Aguilera de Maya, 1997; Caponetto et al., 1997)	(Caponetto et al., 1997)	
Noise Annoyance Prediction	(Zaheeruddin & Garima, 2006)	(Botteldooren & Verkeyn, 2001; Botteldooren & Verkeyn, 2002a,b,c,d,e; Botteldooren et al., 2002a,b; Botteldooren et al., 2003a,b; Botteldooren & Lercher, 2004; Zaheeruddin & Garima, 2006)	(Botteldooren & Verkeyn, 2001; Botteldooren et al., 2002b; Botteldooren et al., 2003b)	
Noise Classification	(Berg, 2002; Couvreur & Laniray, 2004; Betkowsa et al., 2005) (Caponetto et al., 1997)	(Beritelli et al., 2000)		(Couvreur et al., 1998; Gaunard et al., 1998; Ma et a., 2003a,b; Couvreur & Laniray, 2004; Betkowsa et al., 2005;
Urban Traffic Flow Prediction	(Fortuna et al., 2004; Dougherty & Cobbett, 1997; Ledoux, 1997; Dia, 2001; Yin et al., 2002)	(Fortuna et al., 1994; Yin et al., 2002)		

Table 1. Taxonomy of the urban noise vs. soft-computing methods publications (Genaro et al., 2010)

This section deals with a detailed review of publications at the international level that link urban noise with soft-computing techniques. To carry out this review, four soft-computing techniques are considered: Artificial Neural Networks, Fuzzy Techniques, Genetic Algorithms and Hidden Markov Models. In turn, we explore its use in the treatment of the following aspects of environmental noise: Sound Pressure Level Prediction, Noise Annoyance Prediction, Noise Classification and Urban Traffic Flow Prediction. A taxonomy of the found articles is shown in table 1.

2.1 Sound pressure level prediction

Cammaratta et al. (1995) develop a model for predicting noise based on a back-propagation neural network. In this work it was proposed an architecture based on two levels. In the first level, a network LVQ (Learning Vector Quantization) filtered the data, eliminating the data considered erroneous, while in the second tier, the back-propagation neural network predicts the sound pressure level.

Turkish standards allow up to 45 dB in places of study environment. In (Avsar et al., 2004) it is studied whether these standards are met using a multilayer perceptron neural network with noise data of 16 points in a Turkish campus. The neural network is built with seven inputs: position of the measuring point, distance from the source to the point of action, wind speed and direction, air temperature, relative humidity and time of day. The output is the descriptor A-weighted energy-equivalent sound pressure level (L_{Aeq}).

A method based on fuzzy logic for urban noise prediction is briefly described in (Aguilera de Maya, 1997). The results obtained are not accurate enough, however in the section of conclusions it is indicated that the results of the fuzzy model have been contrasted with actual data from measurements made in the prediction scenarios and it has been proved to be highly successful.

Caponetto et al. (1997) put forth a method based on genetic algorithms, which seeks the optimization of fuzzy rules based system for environmental noise prediction. The obtained results demonstrate the success of their method.

In (Genaro et al., 2010) a neural network based model for urban noise prediction is developed. In this paper a selection of 12 street locations with different characteristics of the city of Granada (Spain) is carried out to obtain a representative sample of the complexity of urban streets with presence of road traffic. A set of 289 data vectors, each one with 26 components, was obtained. A total of 25 input variables were used (Torija et al., 2010a), being the only output variable the A-weighted energy-equivalent sound pressure level (L_{Aeq}). The results were compared to those obtained with mathematical models. It was found that the proposed ANN system was able to predict noise with greater accuracy, and thus was an improvement on these models.

2.2 Noise annoyance prediction

With regard to noise annoyance prediction, Zaheeruddin & Garima (2006) propose a neurofuzzy model to predict the annoyance suffered by workers exposed to high noise levels. Once demonstrated that the parameters that most affect workers are noise pollution, type of task and the exposure time to it, a neurofuzzy system is developed.

The most prolific authors who have dealt with techniques based on fuzzy logic modeling of environmental noise are Botteldooren and Verkeyn (Botteldooren & Verkeyn, 2001; Botteldooren & Verkeyn, 2002a,b,c,d,e; Botteldooren et al., 2002a,b; Botteldooren et al., 2003a,b; Botteldooren & Lercher, 2004). Their main field of study is the prediction of the noise annoyance level on people. For this reason, a fuzzy model is used in the majority of its

proposals, looking for a set of rules that describe the fuzzy system. It deals with the study creating a fuzzy rules based system that predicts responses from the public about the noise annoyance caused by road and railway traffic noise.

2.3 Noise classification

Couvreur & Laniray (2004) describes an Automatic Noise Recognition System. The system is based on neural networks and Hidden Markov Models and is able to distinguish, from 1000 sound recordings, between two sounds: horn or motorcycle engine. The neural network phase includes a multilayer perceptron ANN, where the coefficients were obtained by supervised training.

Another noise classifier is developed in (Berg, 2002), which recognizes sounds of planes, with the use of neural networks. The neural network is built with a backpropagation architecture with three neurons in the hidden layer.

In (Beritelli et al., 2000) an urban noise classifier based on fuzzy techniques is presented. Considering a set of acoustic characteristics it tries to distinguish among seven categories: bus, car, rail, construction works, people talking, street and factory.

Several works (Gaunard et al., 1998; Couvreur et al., 1998; Ma et a., 2003a,b) develop a Hidden Markov Model based noise classifier system. These publications describe how a Hidden Markov Model can be used to develop a recognition system based on the ambient noise frequency analysis. A preprocessor provides frequency representation in time of the audio signal, which is then used by a classifier. The classifier makes a decision depending on the nature of the noise source, according to the characteristics given by the preprocessor.

Two ways of improving the performance of automatic noise recognition are presented in (Betkowsa et al., 2005). Firstly, it is proposed the minimization of the number of parameters of a Hidden Markov Model based noise classifier, in order to reduce its complexity. Secondly, it seeks to combine the results of different recognition systems, applying the method of combining expert (MoE, Mixture of Experts). It uses neural networks, which are applied to combine the results and make a final decision on the status of the signal.

2.4 Urban traffic flow prediction

There are some works that develop urban traffic flow prediction models. It is necessary annotate here as most mathematical noise prediction models consider traffic flow the most influential variable. Urban traffic flow is predicted in (Fortuna et al., 2004; Dougherty & Cobbett, 1997; Ledoux, 1997; Dia, 2001; Yin et al., 2002).

3. Pursued goal

After review the use of ANN for modeling and prediction of sound levels, we will introduce a new model to predict both temporal structure and spectral composition of the sound pressure level by using artificial neural networks. The process of model developing is made in an inductive way, first selecting the input and output variables and then building an ANN based on an error minimization criterion. The net is then validated using real noise data. An extensive measurement campaign, conducted in the city of Granada (Spain), gives a wide database, which includes the spatial and temporal heterogeneity characteristic of urban agglomerations. With this measurement campaign the short-term information (integration period of 5 minutes) necessary for the input and output variables involved in model development is obtained.

The constructed ANN model allows not only the equivalent sound level to be predicted but also the average temporal and spectral structure of sound. In view of the large impact of temporal and spectral structure on sound perception, the model could achieve both a precise modeling and evaluation of the studied soundscape. The accompanying results given in this chapter show that this prediction model based on ANN along with a perceptual and psychosocial assessment of sound ambient can be a very useful tool for urban soundscapes management becoming an interesting application of Neural Networks for environmental sound modeling.

4. Selection of input and output variables for the development of the model

This section focuses on the selection of input and output variables for the construction of temporal structure and spectral composition of the sound pressure level prediction model.

To accurately describe and assess urban noise, a critical issue is the selection of input variables, conducive to the implementation of a model, which is representative of urban complexity (Torija et al., 2010a). In our opinion, prior to the model construction stage, it is necessary to study the acoustic variables for the characterization of the sound environment, as well as their range of possible values. This is a necessary condition for the development of an urban noise prediction model. For this purpose, as we see in Table 2, a series of 24 input variables was selected.

The input variables for the built of the artificial neural network based model are chosen from a previous existing knowledge in the field, both obtained from our own experience in our experimental work and the used and studied bibliography about environmental acoustics (see references at Torija et al., 2010a).

On the other hand, 30 output variables, the A-weighted equivalent sound pressure level (L_{Aeq}) and no weighted equivalent sound pressure level (L_{eq}), the temporal sound level variance (TSLV) and the crest factor (temporal composition) (Torija et al., 2010b), as well as the sound level for each of the 1/3-octave bands between 31.5-10000 Hz (spectral composition) have been selected.

The energy equivalent sound pressure level (L_{eq}) is a parameter that corresponds to the value of sound pressure level in dB, of a hypothetical steady sound that in a time interval T has the same mean squared sound pressure that the measured sound and whose level varies with time. Its mathematical expression is:

$$L_{eq} = 10 \cdot Log\left(\frac{1}{t_2 - t_1} \cdot \int_{t1}^{t2} \frac{P_i(t)}{P_0^2} dt \right) \tag{1}$$

where:

L_{eq} is the continuous sound level in dB (dB(A) for the descriptor L_{Aeq}), determined in the time interval T, between instants t_1 and t_2.

P_0 is the reference sound pressure (20 µPa).

$P_i(t)$ is the instantaneous sound pressure.

With respect to the descriptor TSLV, let $L_p(t)$ with t in [0 s, 300 s] be the one second measured sound pressure. The standard deviation of the instantaneous sound pressure is noted as σ_L. Furthermore, let us define the energy-equivalent sound pressure level $L_{eq}(T)$ of the sound measured up to time T, as

$$L_{eq}(T) = 10 \cdot \log_{10}\left[\frac{1}{T}\int_0^T 10^{L_{p(t_i)}/10} dT\right] \tag{2}$$

and let us further note the standard deviation of $L_{eq}(T)$ as σ_{eq}. We then define the Temporal Sound Level Variance (TSLV) as

$$TSLV = \sigma_L * \sigma_{eq} \tag{3}$$

With this indicator, the more commonly used standard deviation of the instantaneous (1 s) sound level, σ_L is multiplied or 'weighted' by σ_{eq} (Torija et a., 2010b).
Finally, the Crest Factor (CF) is defined as the ratio between the maximum sound pressure and the RMS value of the sound pressure:

$$CF = \frac{\max_T 10^{L_{p(t_i)/10}}}{10^{L_{eq,T/10}}} \tag{4}$$

We have $L_p(t_i)$ as the instantaneous sound pressure level (one second SPL) and $L_{eq,T}$ as the energy-equivalent sound pressure level in 5-min period. The CF gives the value of sound-pressure impulsiveness within 5-min of measurement (Torija et al., 2010b).

N°	Input variable
1	Type of day
2	Day period
3	Commercial/leisure environment
4	Type of location
5	Presence of vegetation
6	Statilization time of the sound level
7	Type of traffic flow dynamic
8	Anomalous sound events related to traffic
9	Anomalous sound events no related to traffic
10	Ascendant light vehicles
11	Descendant light vehicles
12	Ascendant heavy vehicles
13	Descendant heavy vehicles
14	Ascendant buses
15	Descendant buses
16	Ascendant motorcycles-mopeds
17	Descendant motorcycles-mopeds
18	Vehicles with siren
19	Average speed
20	Number of upward lanes
21	Number of downward lanes
22	Street geometry
23	Street width
24	Street height

Table 2. Input variables used for the development of the prediction model

Developing an Artificial Neural Network for Modeling and Prediction of
Temporal Structure and Spectral Composition of Environmental Noise in Cities
449

5. Data sampling

To carry out this study a representative sample of locations (120 locations) of the city of Granada (Spain) was selected. Locations were selected in such a way that they included the higher variability in the value range of the input variables given in table 2. In the given subset of locations is included all the input variables (street geometry, ascendant or descendant flow, stabilization time etc) in such way that one or more elements of the subset of variables will be noteworthy or with a high change range in at least one location point.

The selection included locations where the main source of environmental noise at the time of measurement was road traffic. Some locations were affected by other noise sources as well. Overall, there were variations in traffic intensity, traffic flow dynamics, geometry of the traffic routes, types of road surface, traffic slope and speed, and situation within the city. Moreover, because urban environments do not necessarily entail the direct incidence of road traffic noise, we also selected settings with other predominant sound sources, such as pedestrian areas, locations with commercial/leisure activities, and squares or urban parks where the soundscape would principally comprise social and natural sounds.

Measurements were obtained following european procedures of reference; all microphones were mounted away from reflecting facades, at a height of 4 m above local ground level (Directive 2002/49/EC). Once all the measurements had been taken, the acoustical descriptors used in this research were calculated, so that from the different selected input variables and with 5 minutes set as the integration time period, the prediction of each one of the used acoustical indicators could be effected.

6. Artificial Neural Network structure

To undertake the goal established in this work, we chose to apply a back-propagation neural network. The ANN based prediction model involves implementation of the Levenberg-Marquardt variant with Bayesian regulation back-propagation. The internal parameters and geometry of the back-propagation neural network were carefully studied (Maier and Dandy, 1998), and the ANN structure affording major precision, minor prediction error, and low computation time was selected.

	ANN Configuration
Input Variables	24
Output Variables	30
Neurons on Hidden Layer	17
Divide Function	dividerand
Learning Function	learngdm
Performance Function	mse
Training Function	trainbr
Transfer Function	tansig + purelin
Mu Parameter	0.005

Table 3. Artificial neural network (ANN) configuration

The structure of the ANN can be seen in Table 3 and Fig. 1. The adaptation learning function is Learngdm and the performance function is MSE. The ANN has 24 input variables, 17

neurons on the hidden layer and 30 output variables. The transfer function is Tangsig (layer 1) + Purelin (layer 2) and the Marquardt adjustment parameter (mu) is 0.005.
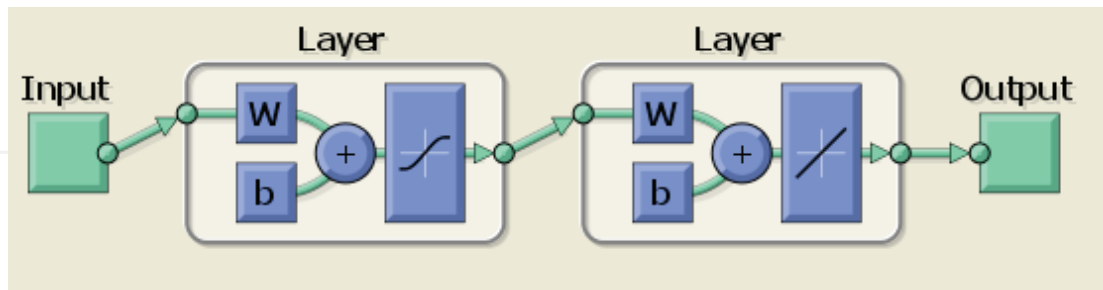

Fig. 1. Artificial neural network (ANN) structure

We have divided the available 543 input records into three data subsets (Training, validation and test) which are different from each other. The training subset contains 400 records (75% of the 543 input records), the validation subset comprises 27 records (5% of the 543 input records) and the test subset includes 116 records (20% of the 543 input records).

7. Results

Once established the structure of the artificial neural network (ANN) and to evaluate the precision of the prediction model, this ANN has been trained and tested 25 times, 5 times for each of the previously established 5 training-validation-test subsets. As we can see in Table 4, the ANN was trained with a number of epochs between 24 (data subset 3) and 51 (data subset 5). The time spent on the completion of the training phase has been between 77.77 sec (data subset 3) and 161.62 sec (data subset 5).

	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
Epochs	30	26	24	34	51
Training time (sec)	116.29	84.98	77.77	109.33	161.62

Table 4. Number of epochs and training time for the 5 data subsets used

Table 5 shows the mean squared error (MSE) of the 5 training subsets for the ANN based prediction model. As can be seen from the results shown in Table 5, for the case of descriptors L_{Aeq} (between $8.3 \cdot 10^{-5}$ in subset 1 and $1.2 \cdot 10^{-4}$ in subsets 2, 3) and L_{eq} ($1.2 \cdot 10^{-4}$ in subset 1 and $1.5 \cdot 10^{-4}$ in subsets 2, 3, 4 and 5), the value of the mean squared error (MSE) remains relatively stable for all the five data subsets.

Acoustical descriptors	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
L_{Aeq}	$8.3 \cdot 10^{-5}$	$1.2 \cdot 10^{-4}$	$1.2 \cdot 10^{-4}$	$1.1 \cdot 10^{-4}$	$1.0 \cdot 10^{-4}$
L_{eq}	$1.2 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$
TSLV	$5.5 \cdot 10^{-4}$	$4.9 \cdot 10^{-4}$	$5.5 \cdot 10^{-4}$	$5.9 \cdot 10^{-4}$	$5.3 \cdot 10^{-4}$
CF	$4.8 \cdot 10^{-4}$	$5.1 \cdot 10^{-4}$	$3.8 \cdot 10^{-4}$	$4.1 \cdot 10^{-4}$	$3.8 \cdot 10^{-4}$
1/3-octave bands (31.5-10000 Hz)	$4.4 \cdot 10^{-4}$	$5.6 \cdot 10^{-4}$	$5.5 \cdot 10^{-4}$	$5.3 \cdot 10^{-4}$	$5.0 \cdot 10^{-4}$

Table 5. Mean squared error (MSE) of the training subsets for the proposed ANN based prediction model

As for the descriptors for the characterization of temporal structure, that is TSLV (between $4.9 \cdot 10^{-4}$ in subset 2 and $5.9 \cdot 10^{-4}$ in subset 4) and CF (between $3.8 \cdot 10^{-4}$ in subsets 3, 5 and $5.1 \cdot 10^{-4}$ in subset 2), the MSE value fluctuates slightly in the five used data subsets. Something very

similar happens in the case of output variables related to the spectral composition (1/3-octave bands between 31.5-10000 Hz), where fluctuations in the MSE value between $4.4 \cdot 10^{-4}$ (subset 1) and $5.6 \cdot 10^{-4}$ (subset 2) are found.

Acoustical descriptors	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
L_{Aeq}	$2.3 \cdot 10^{-4}$	$2.3 \cdot 10^{-4}$	$1.9 \cdot 10^{-4}$	$1.9 \cdot 10^{-4}$	$1.8 \cdot 10^{-4}$
L_{eq}	$1.3 \cdot 10^{-4}$	$1.5 \cdot 10^{-4}$	$1.7 \cdot 10^{-4}$	$1.7 \cdot 10^{-4}$	$1.8 \cdot 10^{-4}$
TSLV	$4.0 \cdot 10^{-4}$	$4.2 \cdot 10^{-4}$	$5.0 \cdot 10^{-4}$	$3.8 \cdot 10^{-4}$	$4.5 \cdot 10^{-4}$
CF	$5.0 \cdot 10^{-4}$	$3.5 \cdot 10^{-4}$	$3.3 \cdot 10^{-4}$	$3.1 \cdot 10^{-4}$	$2.9 \cdot 10^{-4}$
1/3-octave bands (31.5-10000 Hz)	$6.4 \cdot 10^{-4}$	$8.4 \cdot 10^{-4}$	$7.2 \cdot 10^{-4}$	$7.2 \cdot 10^{-4}$	$7.6 \cdot 10^{-4}$

Table 6. Mean squared error (MSE) of the test subsets for the proposed ANN based prediction model

In Table 6 we can observe the MSE value of the 5 test subsets for the ANN based prediction model. In view of the obtained results, the MSE value follows a quite similar pattern to that observed for the case of training subsets (Table 4) with regard to the MSE value found in the different test subsets.

1/3-octave bands [Hz]	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
31.5	0.79	0.76	0.79	0.80	0.76
40	0.79	0.78	0.80	0.79	0.76
50	0.88	0.87	0.87	0.86	0.86
63	0.86	0.87	0.85	0.86	0.86
80	0.77	0.76	0.78	0.78	0.78
100	0.81	0.79	0.83	0.79	0.81
125	0.84	0.87	0.88	0.88	0.88
160	0.86	0.86	0.87	0.88	0.87
200	0.86	0.86	0.87	0.88	0.87
250	0.88	0.88	0.89	0.91	0.89
315	0.90	0.89	0.90	0.92	0.91
400	0.90	0.89	0.90	0.91	0.91
500	0.88	0.87	0.88	0.89	0.87
630	0.88	0.89	0.89	0.90	0.89
800	0.88	0.89	0.90	0.89	0.92
1000	0.87	0.88	0.88	0.88	0.90
1250	0.88	0.88	0.88	0.88	0.90
1600	0.90	0.89	0.89	0.89	0.89
2000	0.89	0.88	0.90	0.90	0.90
2500	0.88	0.87	0.88	0.89	0.89
3150	0.85	0.83	0.85	0.86	0.85
4000	0.88	0.85	0.87	0.88	0.88
5000	0.84	0.84	0.86	0.87	0.86
6300	0.82	0.80	0.83	0.84	0.83
8000	0.82	0.80	0.82	0.83	0.82
10000	0.81	0.80	0.83	0.84	0.82

Table 7. R^2-value for the 1/3-octave bands (31.5-10000 Hz) of the ANN test subsets

As for descriptors L_{Aeq} and L_{eq} MSE values between $1.8 \cdot 10^{-4}$ (subset 5) - $2.3 \cdot 10^{-4}$ (subsets 1 and 2) and between $1.3 \cdot 10^{-4}$ (subset 1) - $1.8 \cdot 10^{-4}$ (subset 5) are found respectively. The variability of the MSE value in the different test subsets for the descriptors TSLV ($3.8 \cdot 10^{-4}$ in subset 4 and $5.0 \cdot 10^{-4}$ in subset 3), CF ($2.9 \cdot 10^{-4}$ in subset 5 and $5.0 \cdot 10^{-4}$ in subset 1) and 1/3-octave bands between 31.5-10000 Hz ($6.4 \cdot 10^{-4}$ in subset 1 and $8.4 \cdot 10^{-4}$ in subset 2) is greater than that observed for the two previous descriptors.

Regarding the R^2-value of the third octave bands for all the used test subset (Table 7), it can be observed that the correlation factor of prediction varies depending on the frequency band considered. We found that the frequency band with a lower correlation factor corresponds to the third octave band of 80 Hz ($R^2 = 0.76$-0.78). On the other hand, the 1/3-octave band of 315 Hz has the highest value of R^2 factor ($R^2 = 0.89$-0.92).
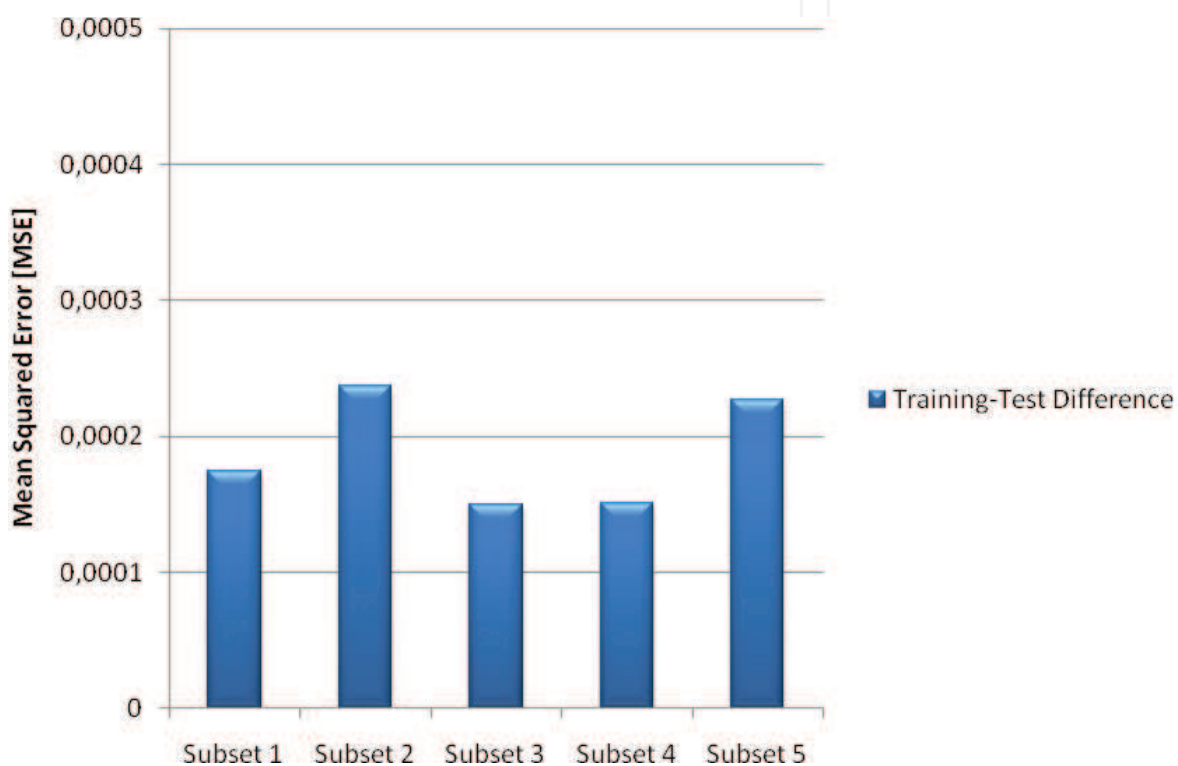
Fig. 2. Mean Squared Error (MSE) differences between training and test subsets

In view of the results shown in Tables 5 and 6, we can check that the magnitude of the MSE value is practically similar between the training and test data subsets. This finding is confirmed by the results reflected in Fig. 2. This figure represents the difference in the MSE value between the training and test subsets for all used data subsets (1-5). According to the Fig. 2, the MSE value decreases slightly from the training to the test subsets in a value between $2.2 \cdot 10^{-4}$ and $1.5 \cdot 10^{-4}$.

These results inform us about the great ability of generalization of the developed prediction model, since not only accurately predicts the output variables of the training subsets but also the output variables of the test subsets, which correspond to the blind data for the neural network (not used in the training phase).

In order to certify the good results obtained with the developed ANN based prediction model in Figs. 3-7 (a), are shown as an example the correlation values between measured and estimated by the model output variables for the case of data subset 5. In addition, as an

example in Figures 3-7 (b) display the evolution of measured and estimated value of the output variables (L_{Aeq}, L_{eq}, TSLV, CF and 800 Hz sound level) for all records used for the test phase (in the case of the data subset 5).
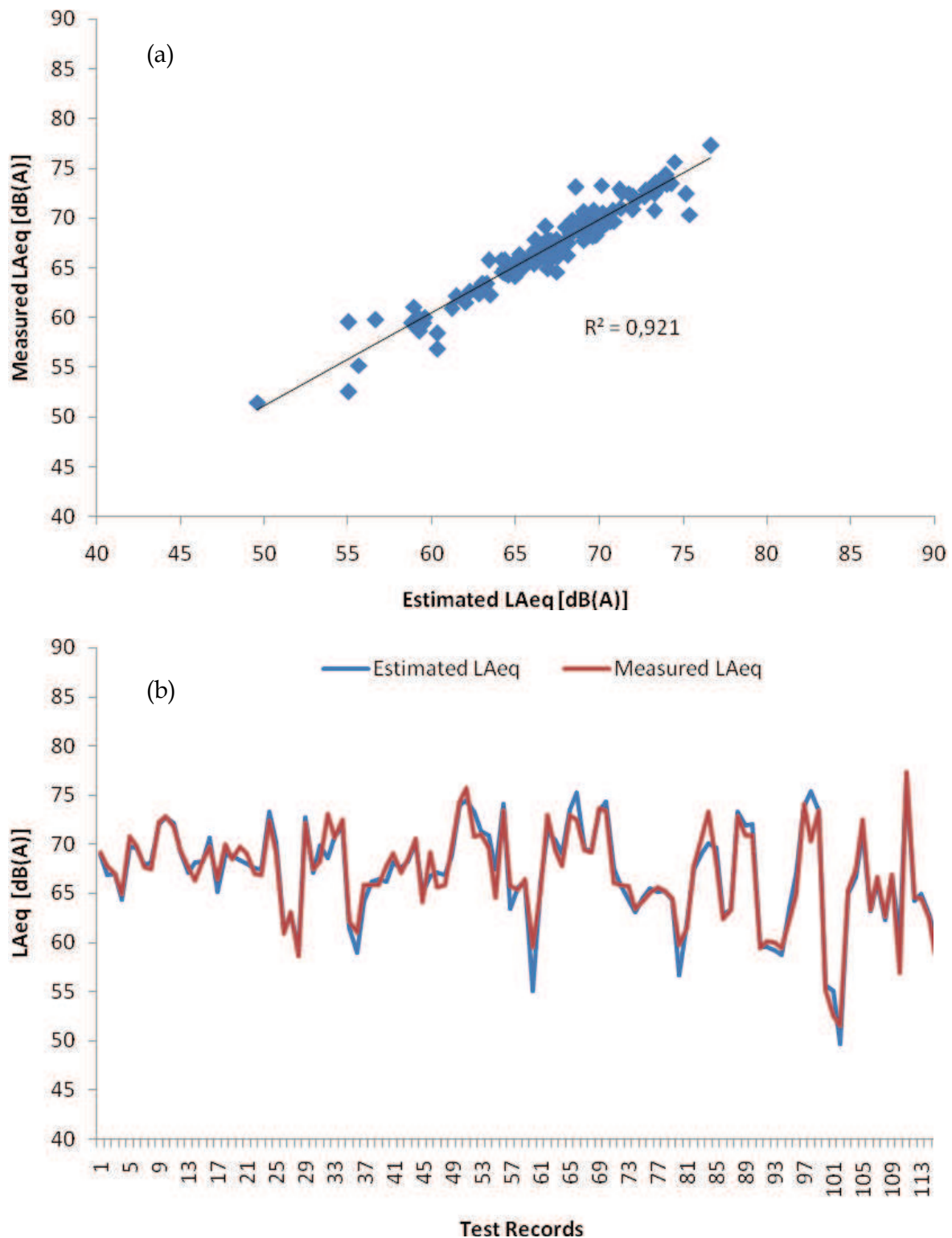

Fig. 3. (a) R^2-value between estimated and measured L_{Aeq} and (b) Evolution of the estimated and measured L_{Aeq} for the used test records (subset 5)
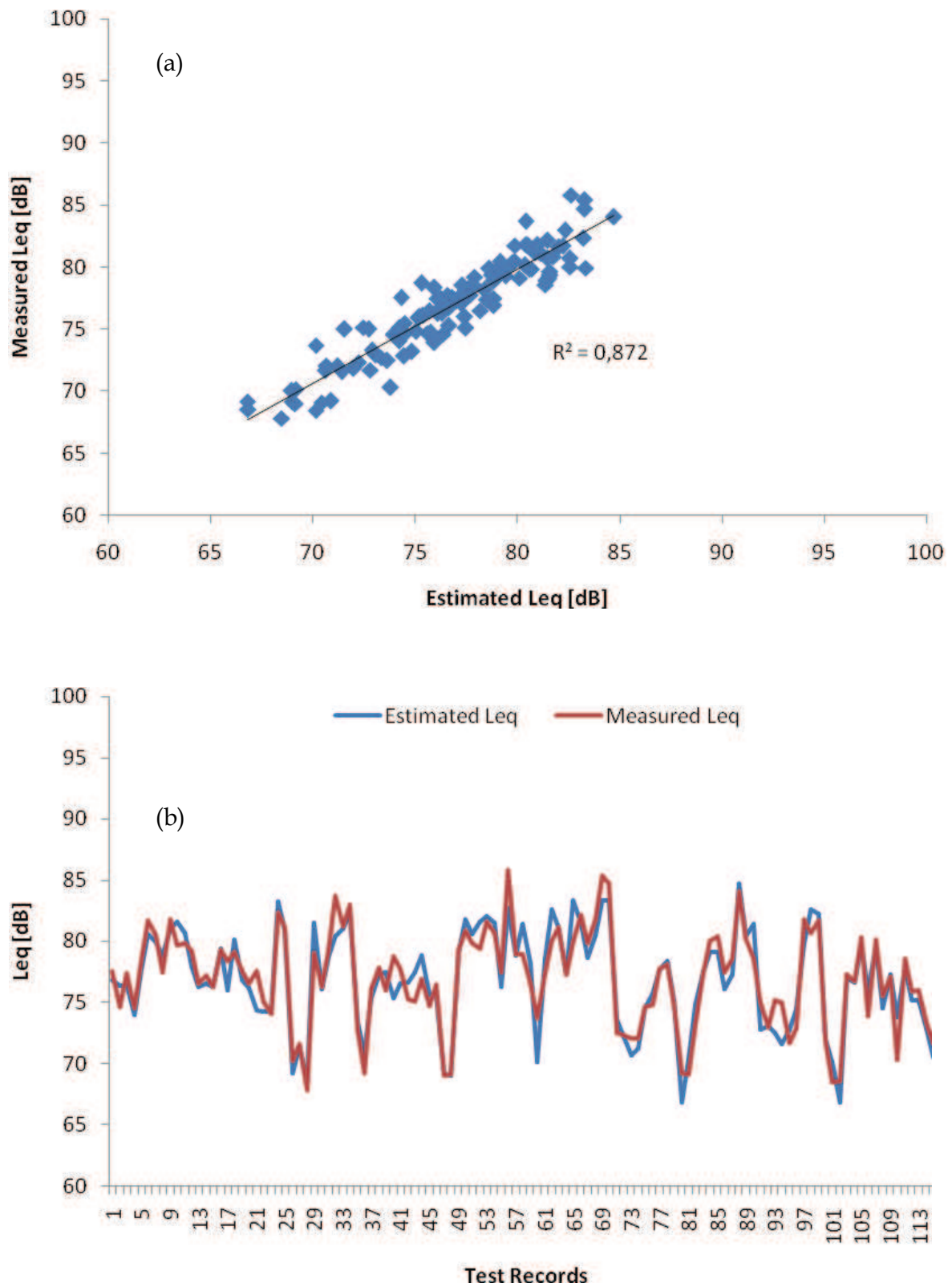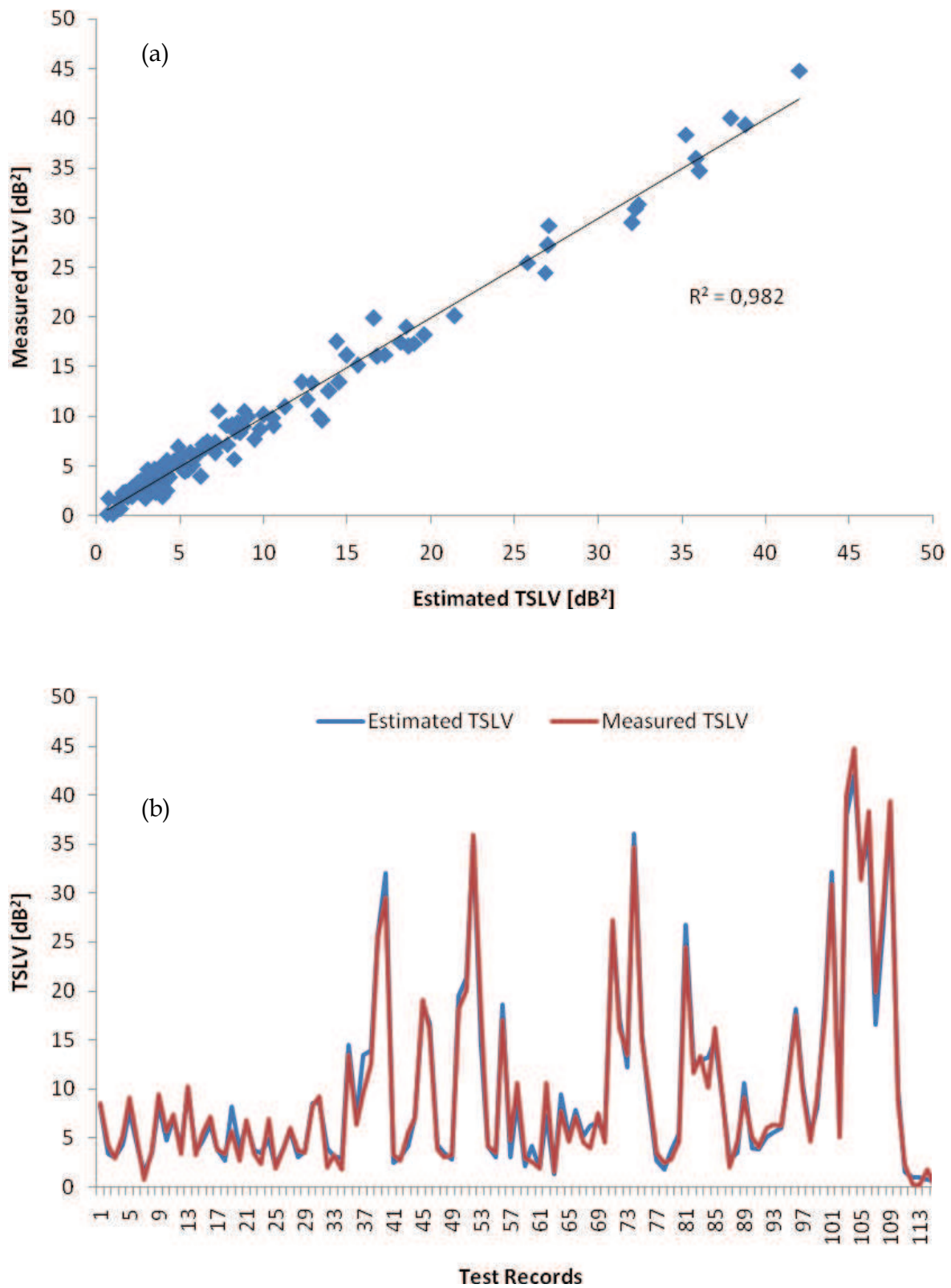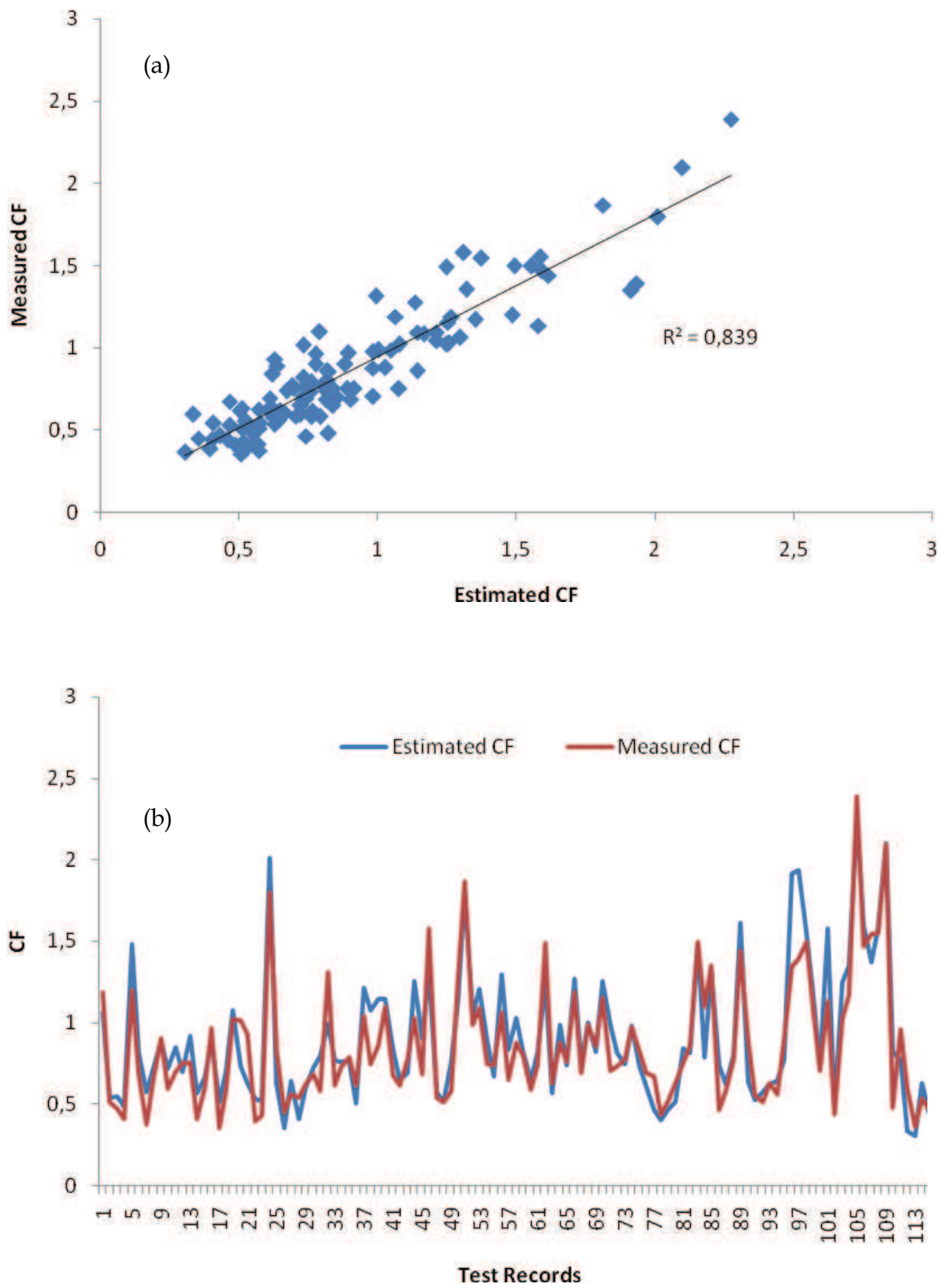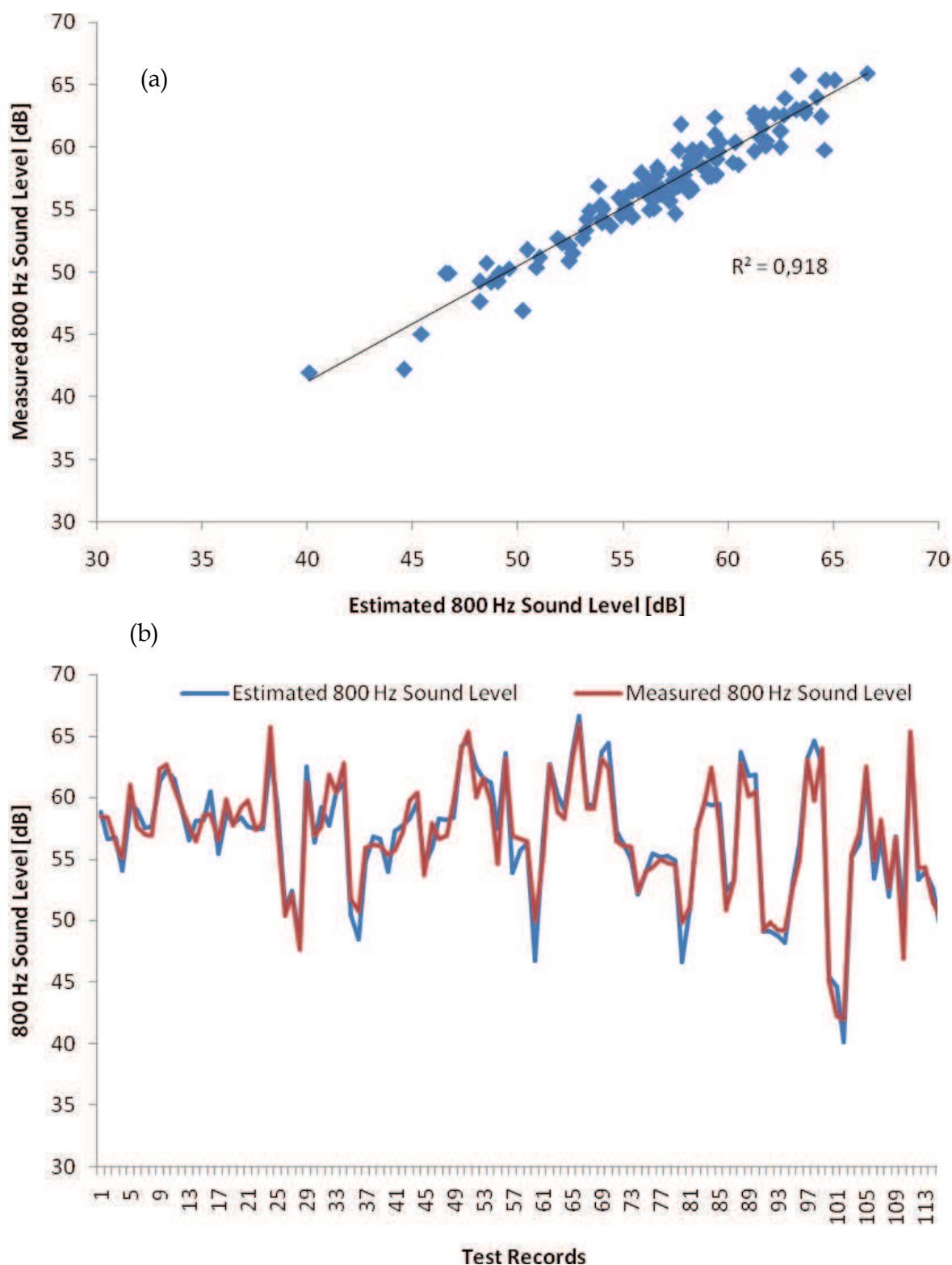
Fig. 4. (a) R²-value between estimated and measured L_{eq} and (b) Evolution of the estimated and measured L_{eq} for the used test records (subset 5)

Fig. 5. (a) R²-value between estimated and measured TSLV and (b) Evolution of the
estimated and measured TSLV for the used test records (subset 5)

Fig. 6. (a) R²-value between estimated and measured CF and (b) Evolution of the estimated and measured CF for the used test records (subset 5)

Fig. 7. (a) R²-value between estimated and measured 800 Hz Sound Level and (b) Evolution
of the estimated and measured 800 Hz Sound Level for the used test records (subset 5). *The
results with respect to the output variable 800 Hz Sound Level are shown as an example of
the ANN behavior to predict the 1/3-octave Sound Level between 31.5-10000 Hz. The
correlation value for all the other frequency bands is shown in Table 7.

In view of the obtained results, where the proposed ANN based model achieves prediction with a reasonably low mean squared error (MSE), and shows a great capacity for generalization, we may affirm that the proposed neural network is capable of predicting, with considerable precision and accuracy, both the sound pressure level (A-weighted and not weighted) and the temporal and spectral composition of the different types of situations presented to the network.

8. Discussion and conclusions

It has been widely recognized that noise pollution is one of the most important environmental problems in urban agglomerations (Miedema & Vos, 1998). It is fully assumed and research studies in various countries have shown that noise affects daily activities and causes sleep disturbance as well as a poorer life quality (Lercher, 1996).

Undertake a proper modeling and prediction of environmental noise in urban environments is a challenging task. This is due to several reasons but mainly to the great variability (temporal and spatial) of sound sources. Road traffic is the main source of environmental noise in urban areas, nevertheless, road traffic is not the only noisy source in urban settings; we also encounter noise coming from construction works, commercial activities, recreation, etc. At the same time, we can find urban locations in which road traffic does not have a direct incidence, e.g. green urban areas, in which natural and social sounds predominate. This latter aspect is indicative of the great urban heterogeneity. In this sense, one of the most salient characteristics of urban agglomerations is the great heterogeneity of situations that can arise in them. From the perspective of environmental modelling, this heterogeneity is a serious problem since this situational diversity must be accounted for in any well-designed environmental model. Regarding the characterization of sound environments, something similar occurs because the number of variables that influence both the sound emission and the sound spread is very high (Torija et al., 2010a).

For these reasons, to undertake the problem of noise modelling in cities, it is more effective to fully characterize the sound space of a given urban area. To carry out an adequate characterization of a sound space is necessary to address not only the evaluation of sound pressure level but is also necessary to consider the temporal structure and spectral composition of the sound (Torija et al., 2010b). We choose these variables as defining of the given sound space, going beyond the classical noise level prediction.

Once the problem is established, a critical step is to select the variables that affect the sound space. Based on a deep study of the problem, several variables are selected, together with the output variables we need to define the sound space. The tool selected for performing the modeling, due to the reasons stated above, are neural networks. Due to their well-known characteristics, the use of artificial neural networks to approach the complex problem of modeling and prediction of urban noise seemed highly recommended. In this paper, this hypothesis is certified in view of the obtained results. The developed ANN based prediction model is able to predict, with great accuracy, the short-term level and both temporal and spectral composition of the sound pressure in urban agglomerations. In the cases studied, the proposed model is not only able to learn and predict those records presented during the training phase, but also it is able, with a high success degree, to predict those records used for the testing phase, which inform about its great capacity of generalization. This fact reports that the proposed methodology will not only be very useful for the measured situations/locations, but it may be of great usefulness in any situation/location of other Southern Europe medium-sized cities.

9. Future research work

As future work, there are several proposals that have emerged from this research.

Firstly, it would be of great interest to implement the proposed ANN based prediction model in a GIS tool, so that we could represent the spatial distribution of the obtained results. This will allow obtaining mapping with the value of each one of the different used descriptors, being this information of great value for the urban planner, as for decision making in the management of a sound space.

Secondly it will be very useful to test the model in other cities. Although the methodology describes here is fully applicable to any urban areas, the model should be refined to take into account new sound spaces arising in other cities. This would increase the applicability and generality of the model.

Finally, another aspect of great interest to consider for future work is to use another data mining techniques or new algorithms to improve the above described model. In the latter case, we are considering the use of genetic algorithms to optimize an artificial neural network, in order to evaluate their potential pros and cons regarding the development of an urban noise prediction model. The principal goal would be to analyze the main differences found between the use of backpropagation algorithms and genetic algorithms to carry out the training of an artificial neural network.

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