Processes for Noise Reduction in Urban Port Fronts

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Abstract. As part of the LIST-PORT, Report and Decibel Project (Interreg IT-FR Marittimo Programme 2014–2020), which is included in a cluster of initiatives aimed at containing port noise, a synchronized traffic - noise survey campaign involving four ports in as many cities in the upper Tyrrhenian area, is now nearing completion. This paper describes the guidelines on the basis of which the traffic-noise surveys were conducted in the four ports and the types of data collected. In a second step of the study, these data will be used to train the predictive model of the sound pressures generated by traffic in ports, based on neural networks. The database presented in this work is thus the key element for the subsequent implementation of the predictive model which is currently in an advanced phase of development as part of another project in the cluster.

Keywords: Noise reduction · Urban front ports · Artificial neural networks

1 Introduction

Several European waterfront cities are afflicted by through traffic of private and commercial vehicles generated by port activities. Residential areas and susceptible structures such as schools, hospitals, care homes etc. may be exposed, both during the day and at night, to sound pressure levels as high as or sometimes exceeding the critical limits. These values are established by environmental noise regulations for the protection of people and the environment.

The ambitious objective of the projects, named List Port, Report and Decibel, is to develop a procedure/methodology for dynamically generating prediction scenarios for the short-medium term as a function of the noise source distribution and intensity scenarios. To do so, a series of acoustic measurement campaigns was conducted simultaneously with traffic counts in four different ports, whereby all the point and nonpoint sources were monitored. The predicted scenarios can thus be implemented dynamically to define specific noise abatement actions for the benefit of those susceptible areas in port cities that are particularly exposed to acoustic climate fluctuations.

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Lastly, the adaptive learning model, inspired by artificial neural network technology for predicting noise scenarios, is described. Other researchers in [1, 2] investigated the use of a neural network model for traffic noise prediction and also in comparison with statistical methods [3]. The present model is able to correctly estimate the sound pressure level that would be generated at a given point in the presence of an assigned scenario of vehicle traffic composition and layout.

2 The ITS Information Mobility System Driven by a Neural Network Prediction Model

In this paper, we illustrate the results of the experimental campaign and the predictive traffic-noise model, based on artificial intelligence (AI) to be integrated into the Intelligent Transportation System (ITS) system.

The model defined in this research aims to analyze the levels of noise emission generated by certain traffic scenarios. Depending on the levels recorded, the ITS system suggests driving behavior and alternative routes by transmitting info-messages, through variable message signs or mobile device applications (Fig. 1). These strategies are aimed at lowering the levels of noise emission in port cities' waterfronts. The traffic and sound pressure levels constitute the input and output data of the predictive model respectively. The case study concerned the urban waterfront of the port of Olbia, with the intention to extend the methodology to other port environments, such as Piombino, Vado Ligure and Bastia.

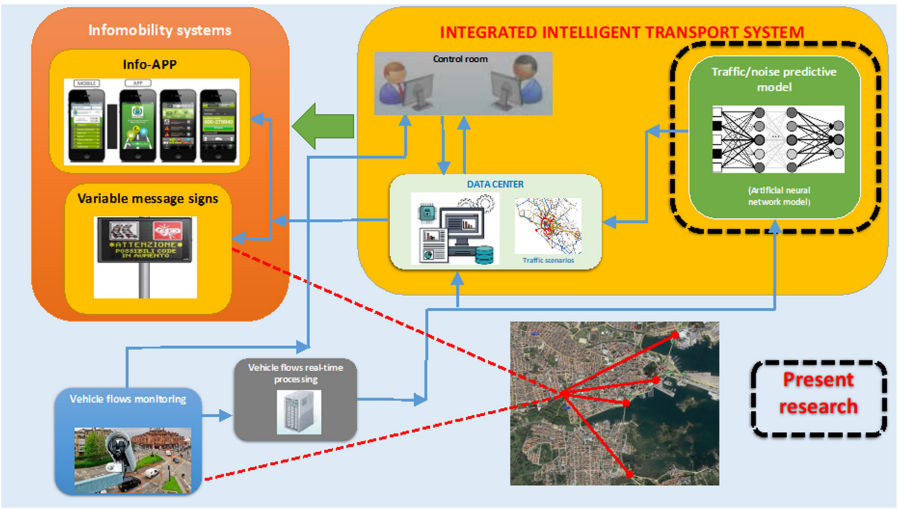

Fig. 1. ITS system diagrams.

The first step consisted in analyzing the existing maps of the city of Olbia, satellite images and the database containing mobility and noise time series analyses. Potential measurement points were then assessed on the basis of their ability to provide a sufficiently comprehensive and representative framework of sound pressure levels, and thus exposure to noise, throughout the commercial port and neighboring area. Figure 2 provides an overview of the area of interest showing the positions of the measuring points for both acoustics and vehicle flows.



Fig. 2. Representation of the area of interest and measuring points.

2.1 Experimental Set-up: Noise and Traffic Measurements

The environmental noise recorded in the *soft* and *peak* periods constitute the database of reference for analyzing the evolution of the waterfront's acoustic climate and for the subsequent implementation of the forecast model.

Measurement campaigns were carried out on March 25–28 (soft period) and on August 23–26, 2019 (peak period).

As for instrumentation and measurement techniques, representation and processing of acoustic data, the current regulatory requirements [4–14] were taken as reference.

In order to build a useful database, average values of acoustic quantities were acquired and stored, with a time base of 100 ms. In particular, sound pressure level trends were stored according to the different frequency weighting curves and the spectrum trends with normalized 1/3 octave bands. Acoustic data was captured in sync with vehicle flow video detection for a period of 72 h. The acquired data was stored in a georeferenced database WGS84 UTM32N.

2.2 The Neural Network Model

One of the most significant scientific results of the research project is the development of a model capable of predicting the sound pressure level that would be generated at a given point of the waterfront for a given vehicle traffic layout in the investigated road sections.

The model is based on the acquisition of noise events, but without necessarily having all sound *patterns* that could occur. To achieve the goal of providing valid, or at least acceptable, predictions, for all possibilities of noise occurrence, starting with partial knowledge of the phenomenon, we implemented a model based on artificial neural networks. This recognition system was chosen because of its ability to generalize the results and thus to associate the correct response even with input signals *never seen* before, or with missing or partially damaged information [15, 16]. Figure 3 depicts a biological neural network and an artificial neural network. These learning models are used with increasing success to solve artificial intelligence problems, such as used in energy [17], building [18], speech recognition [19], etc., where it is necessary to recognize configurations or in general information belonging to a wide universe of accomplishments, both in the discrete and continuous domain.

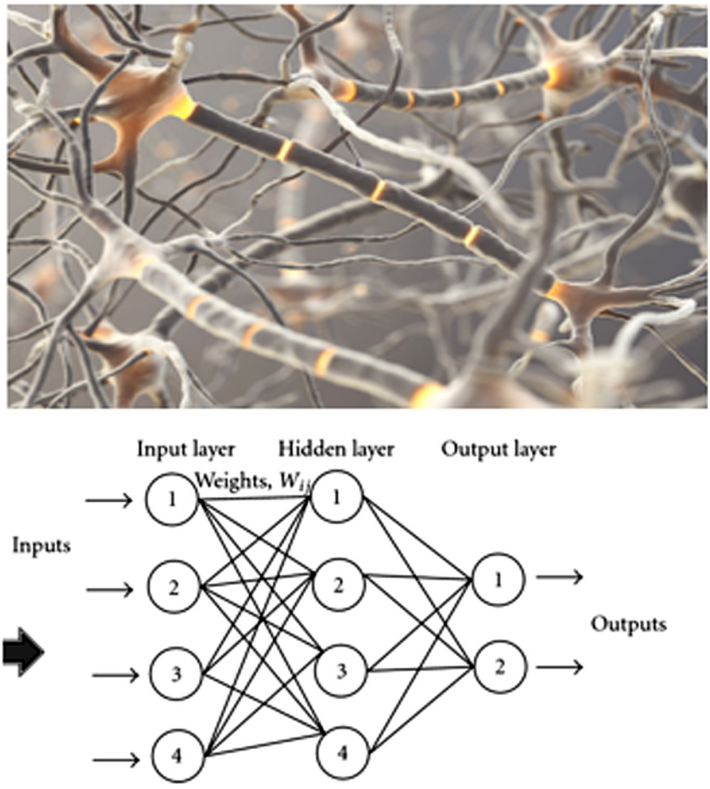

Fig. 3. Representation of a biological neural network (top) and structure of an artificial neural network (bottom).

2.3 Training and Testing Procedure

The development of a learning model based on artificial neural networks starts with a preliminary stage, called training procedure, whereby the network is guided to adapt its internal parameters to the goal of learning a number of instances of noise events related to traffic flows scenario comprising the training set.

Once training is completed, a second phase, namely the testing procedure, is conducted. This is a verification activity and accounts for the learning capacity achieved by the neural network during the training phase.

Learning capacity is measured and evaluated in terms of the network's ability to correctly recognize the largest number of noise event configurations belonging to the training set and also in terms of its ability to extend a valid recognition to cases belonging to the whole test set, i.e. cases that have not been previously included in the training set.

Traffic flows and acoustic measurements recorded during the periods March 25–28, and August 23–26, produced a time series of acoustic data and vehicle traffic. Figure 4 gives an example, both in the time and frequency domain.

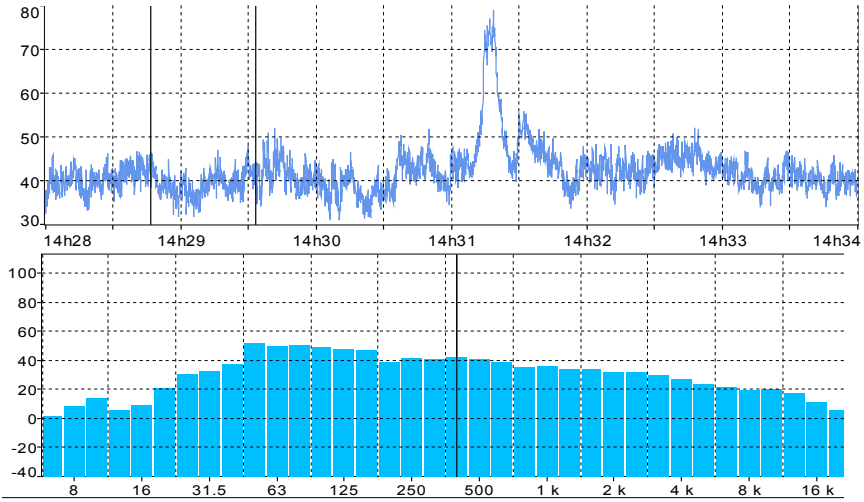

Fig. 4. Leq equivalent level and corresponding spectrum

Figure 5 shows the sound pressure level trend throughout the entire measurement period (March 25 to 28, 2019). We can recognize the typical dynamics that alternate between daytime, evening and nighttime.

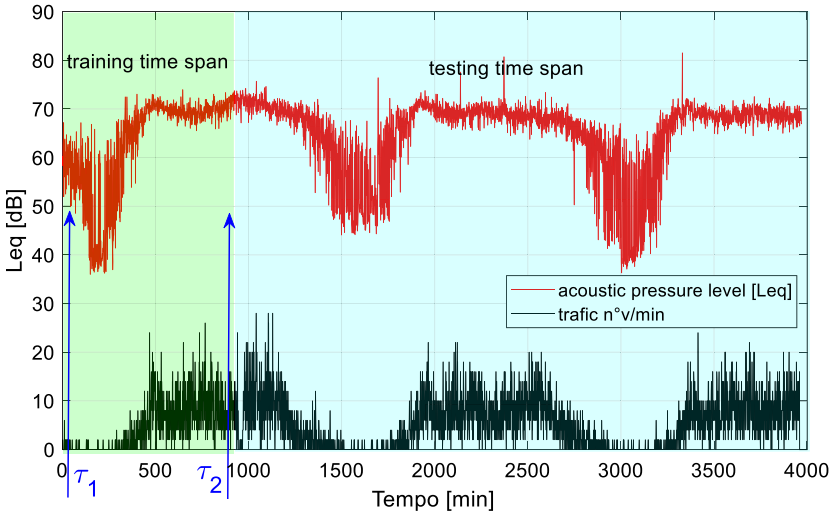

Fig. 5. Trend of vehicle traffic and noise detected. The periods referred to by the data considered for the training and test set are highlighted. Measuring position B.

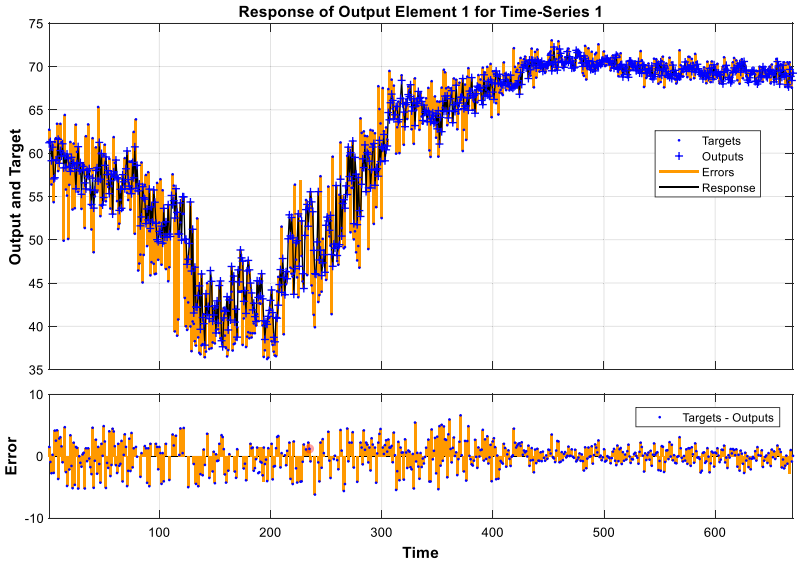

Fig. 6. Experimental trend and prediction of test set noise. Measuring position B.

Figure 6 summarizes the results of a generic network learning process, having used a single training interval containing 800 min.

2.4 Measuring Station C Underpass Exit (August 2019)

To render effective the neural network learning process for estimating the response from the measuring point C, the optimized set of traffic acquisition sections shown in Fig. 7, i.e. Sects. 3A, 3B, 3C, were considered.



Fig. 7. Sound level meter C location and road sections involved

2.5 Results of the Neural Network Applied to Traffic – Noise Prediction

This section presents the results of the neural network model's simulation phase following completion of the training procedure.

Figures 8 and 9 show respectively the performance parameters of the neural network training process and the comparison of the time evolution of sound pressure levels measured experimentally with the neural network model predictions. Each diagram also includes the absolute error between the two trends.

Figure 8 box (a) gives the average quadratic error versus the progress of the training periods; box (b) the output/target regression; box (c) the histogram of errors and frequency distributions in, box (d) the trend of gradient parameters, μ, and the number of validation checks; box (e) the simulated response of the network during training, and box (f) error autocorrelation.

For the sake of brevity, only the network response for a single measurement point (C) is reported. This point is located in via Principe Umberto, above the exit from the underpass. The site is quite complex in terms of the road sections involved and is characterized by different vehicle flow dynamics and sound pressure levels.

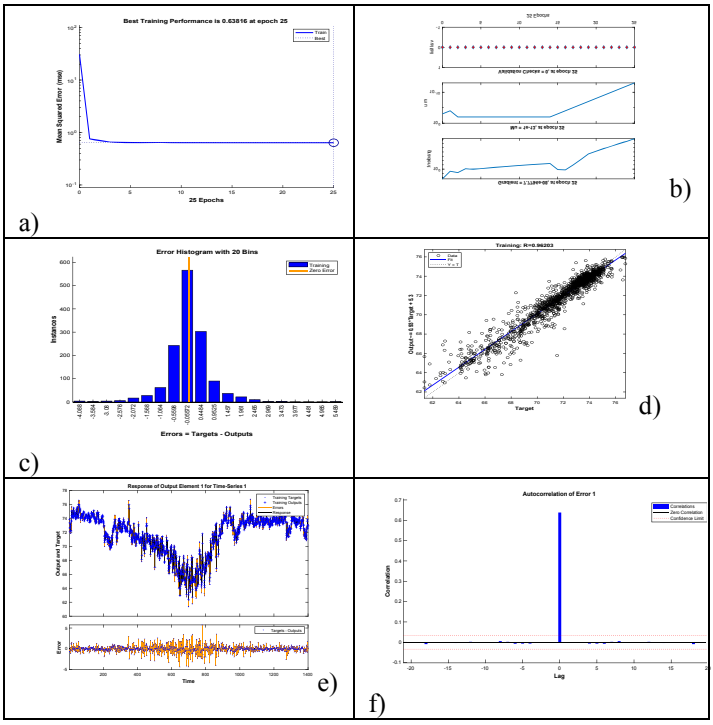

Fig. 8. Diagrams of network performance during the training phase, for C-station (road underpass).

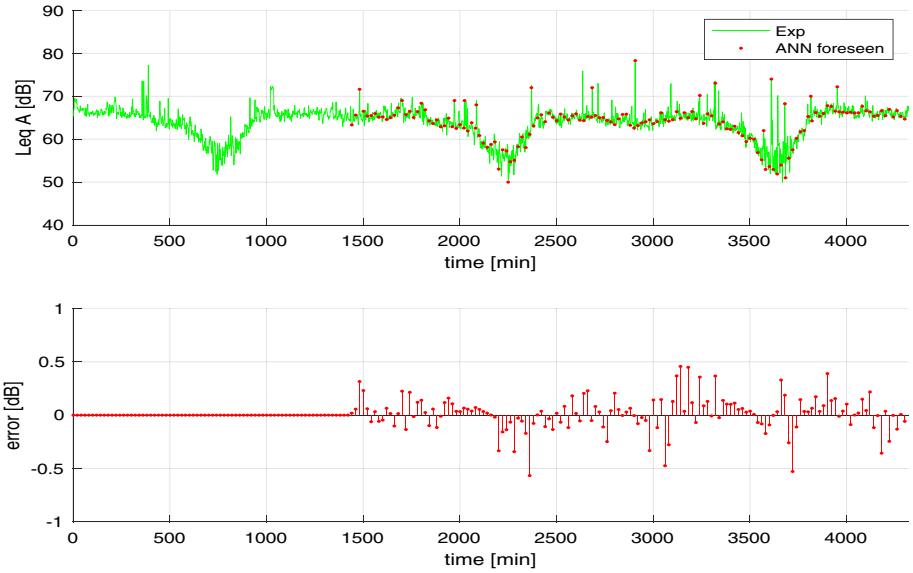

Fig. 9. Top: Leq_A measured experimentally (green) and predicted by the ANN (red pellets). Bottom - difference between calculated and experimental values. Station C peak period August 23–26, 2019 (Color figure online)

2.6 Considerations

As can be seen from the graphs in Fig. 9, the traffic-noise model shows an excellent forecast capacity for the acoustic climate generated by vehicle traffic at the considered points. Neural network model training was based on a time series consisting of the first 1400 min, while the remaining 2600 min were excluded from the training procedure and were therefore reserved for verifying network performance under generalization.

This generalization phase allows one to check whether the network is able to provide correct noise level values only when it receives *"already seen"* traffic configurations or is capable, as is desirable, of extending this ability to recognize brand-new (*"never seen"*) traffic scenarios. As can be observed, the model exhibits excellent generalization ability for all three periods: daytime, evening and nighttime. The absolute error is always below 0.5 dB for the entire "time line" of the measurement campaign. In particular, the following results can be summarized for the measurement station at position C:

Time segment during the training phase: the deviation between the experimental data and the simulated values is near to zero.

Time segment during the test-generalization phase: the deviation between experimental data and simulated values is in all cases below 0.5 dB. Note that excluding nighttime, the error would be confined to values of less than 0.3 dB.

In different environmental, traffic and background noise conditions, for all noise monitoring stations and for the two periods (*soft* and *peak*) the model is able to predict $L_{eq,A}$ values comparable to experimental values, both in quasi-stationary and under highly variable conditions.

3 Conclusions

We have constructed a traffic-noise model based on artificial neural networks for the waterfront of the port city of Olbia. The model is able to predict noise levels in three representative positions along the waterfront with a deviation from the experimental values of less than 0.5 dB. Extensions of the model to the other partner cities involved in the project, are currently being developed. The performance of different models implemented for different cities will be compared so as to identify those elements that can define and characterize a general methodology for implementation in different contexts. The research developed suggests interesting aspects and developments. In fact the results of this first phase are very comforting and provide a good basis on which to develop further studies.

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