The application of a neural network on a study of noise pollution in urban transport: a case in Villa S. Giovanni

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Abstract

The forecast of the level of noise produced on and by transport infrastructures is part of an essential aspect for a compatible strategy of development of the urban texture. It is thus necessary to dispose of adequate and specific mathematical tools (models) which can reproduce and/or simulate different acoustic scenarios, to use for assessment and planning of the existing or future infrastructures.

The experimental data measured in the city of Villa S. Giovanni, which for its particular location is always subject to heavy vehicular traffic to and from Sicily, was analysed allowing us to highlight, also in numerical form, the dependence of the equivalent level of noise L_{eq} from the characteristics of the vehicular traffic flows (quantity, composition and mean speed of the vehicular flow) and the typology of the roads (in particular the width of the carriageway), with the aim of comparing the behaviour of different neural networks (of the kind MLP, Multilayer Layer Perceptions, and GRNN, General Regression Neural Network), so as to supply an instrument of dynamic and flexible evaluation for the analysis of the T.N.I. (Traffic Index Noise), also comparing among the different NN approaches the one which gives the results best fitting the data observed during the measuring campaign. The results are also compared with the outputs of the forecasting models most known and used in the literature.

1 Models to forecast noise levels related to road traffic in urban environment

The need for adequate tools for the analysis and the assessment of the levels of noise in the city areas has promoted the research which produced numerous

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mathematical models for the study of noise pollution.

The methods of forecast of the noise from road traffic can be distinguished, for various degrees of reliability and precision, in three fundamental typologies: numerical simulations on physical models in a scale size, simulations by codes for automatic calculation and models based on analytic equations [1].

In the first two cases it is necessary to realize for the first a physical model, and for the second to use hardware and dedicated software. This implies a significant cost, in time and money.

The models based on analytic equations are surely the ones of larger use, also in urban environment, for simplicity and rapidity of use. This because the calculation of the acoustic parameters is obtained through non acoustic variables. Many mathematical formulae have been proposed, of empirical kind, on the base of the results of measures from in field campaigns in different urban settings. The regression equations obtained are similar in structure and they differ for the number of the considered parameters and for the applicable conditions.

The variables that normally appear in the forecasting formulae are the main parameters that characterize the street traffic: the dimension and composition of the vehicular flow, the average speed, the geometric characteristics of the road, and the driving trends.

2 Survey campaigns

The surveys were carried out in the city of Villa San Giovanni during week days in the month of June 2002. The area object of the acoustic measures includes the historical center of Villa S. Giovanni.

The business district and the public offices are concentrated within the perimeter of the survey field.

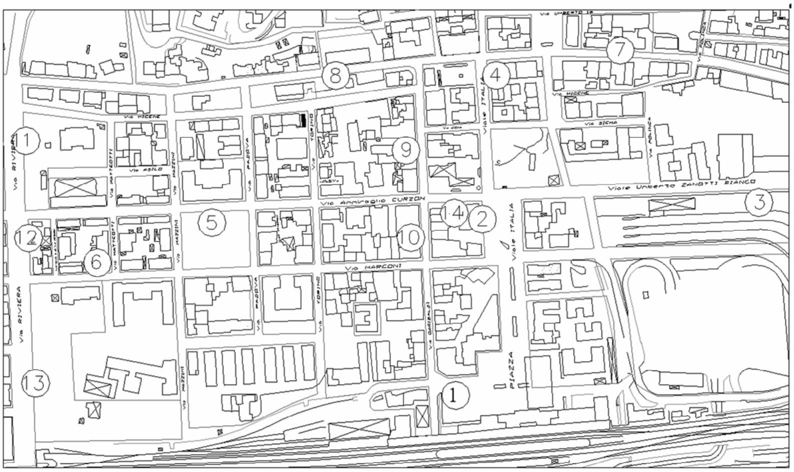

Figure 1: Location of the monitoring points on the city map.

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Once the monitoring points were specified, in order to obtain a precise knowledge and assessmentof the environmental noise, apart from the equivalent level L_{eq} (that represents the level of continuous noise which, in the interval of considered time, would distribute an amount of sonorous energy equal to that effectively distributed from the fluctuating noise in the same interval of time), an adeguate number of percentile levels have been used, as representative parameters, and in particular: L_{10}, L_{50} and L_{90} (representing the levels of noise that are introduced respective for 10%, 50%, 90% of the sampling time [2]).

2.1 Surveys carried out in the city of Villa S. Giovanni

The sound level measures consisted in measures articulated on the perimeter of the area interested by significant levels of noise pollution, with an overlapping of residential and business building areas.

Table 1: Statistical analysis of the measured levels of noise.

	L_{10}	L_{50}	L_{90}	L_{eq}
Sampling rate	154	154	154	154
Mean	74.36	66.42	60.77	69.40
Median	73.70	66.40	60.75	69.30
Mode	73.10	67.60	59.10	69.50
Geometric Mean	74.25	66.34	60.67	69.35
Variance	17.69	10.31	12.47	7.23
Standard deviation	4.21	3.21	3.53	2.69
Min	66.40	56.40	50.60	63.60
Max	88.20	73.90	68.20	75.90
Range	21.80	17.50	17.60	12.30
Lower quartile	66.40	56.40	50.60	63.60
Upper quartile	88.20	73.90	68.20	75.90
Interquartile range	21.80	17.50	17.60	12.30

It was chosen to carry out the measures during day hours, in an interval of time between 8:00 a.m. and 7:00 p.m. and altogether the data is divided in 9 hour slots. The sampling interval inside the hourly slots has been of 15 minutes.
For the 14 monitoring sites, they have been finds to you:

- geometry;
- the composition of the traffic flow;
- the levels of noise;
- width of the carriage way;
- width of the sidewalks on the monitoring side and the opposite side;
- number of lanes available for the vehicular traffic;
- marching directions;
- parking;
- height of the buildings on the monitoring side and the opposite side;

For the kind and composition of the traffic flow the mobile sources of noise have been classified, subdivided in the following categories:

1) motorcycles and mopeds
2) motor vehicles
3) light industrial vehicles (LGV)
4) heavy industrial vehicles (HGV)
5) bus

In table 1 the most significant statistics relatively to the measured levels of noise are given.

3 References to literature models

For an acoustic forecasting analysis, among the numerous existing models, hereafter are shown some which best adapt to the conformation of the urban environment and planning of the city of Villa S. Giovanni [4,5,6,8]. The models are briefly described.

Model CSTB. It calculates the equivalent sound levels L_{eq} at the edge of city roads with the relation in function of the vehicular flow Q. In the formula the value of Q_e holds in account the presence of heavy vehicles assuming an equivalence of one Heavy Vehicle = six Light Vehicles.

Model of Benedict Spanolo and Burgess**.** holds in account the characterizing parameters of the vehicular traffic (veic/hour, percentage of heavy vehicles), and the distance of noise sources. In the formula p is the percentage of heavy vehicles and d the width of the roadway.

Model OMTC and of Garcia and Bernal. The models holds in account, the composition of the traffic flow, and the average speed of vehicles V.

Table 2: Formulae of the considered models.

Model		
M_1	*CSTB*	$L_{eq} = 7.735 \cdot \log(Q_e) + 48.410$
M_2	*Benedict - Spanish*	$L_{eq} = 10.762 \cdot \log Q + 0.12 \cdot p - 9.64 \cdot \log d + 45.194$
M_3	*Burgess*	$L_{eq} = 10.2 \cdot \log(Q) + 0.3 \cdot p - 19.3 \cdot \log(d) + 55.5$
M_4	*OMTC*	$L_{eq} = 10.21 \cdot \log(Q_L + 6 \cdot Q_P) - 13.9 \cdot \log(d) + 0.21 \cdot V + 49.5$
M_5	*Garcia and Bernal*	$L_{eq} = 11.2 \cdot \log(Q) + 0.4 \cdot p - 12.7 \cdot \log(2d) - 0.05V + 55.7$

4 Analysis of the data with the regressive models

The results of the application of the data of the survey to the models M_1, M_2, M_3, M_4 and M_5 are illustrated in Table 4, confronting the equivalent level measured during the survey with that one estimated with the four models, for every of them it is described the relative coefficient of correlation.

The adopted models were recalibrated, by applying a regression based on the data of the measures, using the least-squares method.

The mathematical expressions of the recalibrated models are shown in the following table:

Table 3: Mathematical formulae of the recalibrated models.

Model		
M_6	*CSTB*	$L_{eq} = 10.00 \cdot \log(Q_e) + 42.71$
M_7	*Benedict – Spagnolo & Burgess**	$L_{eq} = 11.082 \cdot \log Q + 0.124 \cdot p + 40.059$
M_8	*OMTC**	$L_{eq} = 9.46 \cdot \log(Q_L + 6 \cdot Q_P) - 0.47 \cdot \log(d) + 44.62$
M_9	*Garcia & Berna*l*	$L_{eq} = 9.93 \cdot \log(Q) + 0.16 \cdot p - 0.05V + 43.96$

In the formulae earmarked with a (*) the coefficient relative to the distance *d* is negligible in regards to the others. In figure 3 the equivalent level measured during the survey is put in relation with those estimated with the recalibrated models.

Table 4: Relative coefficient of correlation for the considered models.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9
R	0.76	0.55	0.35	0.18	0.60	0.77	0.77	0.76	0.78

5 Analysis of the data with neural networks

On the base of the collected data various forecasting models are developed based on the neural networks.

A neural network (ANN) can be seen as a system which can answer a question or supply an output in reply to an input and is defined from a certain number of interconnected units of calculation, which operate as a parallel calculation structure and that acquire their knowledge from the experience supplied, that is, the transfer function of the network is not programmed, but is obtained through a process of training with empirical data. In other terms the network learns the function that ties the output with the input by means of the presentation of correct examples of input/output pairs [3,7].

Effectively, for every input introduced to the network, in the learning process, the network supplies an output that differs of a given δ amount from the desired output: the training algorithm modifies some parameters of the network in the desired direction. Every time that an example is introduced, therefore, the algorithm fits slightly the parameters of the network to the values optimal for the solution of the example: in this way the algorithm tries to please all the examples a little at a time.

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5.1 Construction of the neural network

As illustrated, the independent variables assumed in the regression formulas are generally the vehicular flow, the average speed of the flow, the composition of the flow and in particular the percentage of the heavy vehicles and the width of the roadway, these same indicators are, therefore, been used as input data for the achievement of the network [9]. Altogether the variables (of input and output) characterizing the problem are:

Indicators	Variable	
Motorcycles	M [veic./h]	INPUT
Car	A [veic./h]	
LGV	ML [veic./h]	
HGV	MP [veic./h]	
Bus	B [veic./h]	
Average speed	V [km/h]	
Width of the track	d [m]	
Level of acoustic pressure	L_{10} [dB(A)]	OUTPUT
Level of acoustic pressure	L_{90} [dB(A)]	

The output are the statistical levels of the acoustic pressure L_{10} and L_{90}, that is, the parameters that define the character of the noise produced from vehicular traffic in urban environment by the use of the T.N.I. (Traffic Noise Index). The disturbance due to the noisiness of urban traffic is, matter of fact, closely correlated not only to the level of background noisiness L_{90}, but also to the amplitude of the fluctuations between trough and peaks, the latter index called noise climate and defined from the difference between the parameters L_{10} and L_{90}.

The network typology chosen in order to better analyze the problem, is the General Regression Neural Network (from here on GRNN). The GRNN approximates any function between input and output and is based on the theory of the not linear regression for the estimation of the function.

In order to realize models for the identification of the examined system in it is necessary, following a classic methodology of regression, to assume some functional shape that will assume the relation between the variables, choosing a set of parameters to determine based on the experimental data. The values of these unknown parameters are determined as to supply the best possible adaptation between the assumed function and the registered values in the reality.

The model of neural network GRNN exceeds the necessity of such hypotheses on the functional shape, and allows to gain it directly without the necessity of some preliminary assumption.

If we knew the density of combined probability between the variables x and y, that is of the probability density that to a given value x it corresponds a given one y, the expected value of y could be calculated in correspondence to any x.

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The expected value of y, given X will be:

$$E[y/X] = \frac{\int_{-\infty}^{+\infty} y\, f(X,y)\, dy}{\int_{-\infty}^{+\infty} f(X,y)\, dy} \tag{1}$$

The density function $\hat{f}(X,Y)$ can be estimated on the base of a set of values X_i, Yi of random variables x and y:

$$\hat{f}(X,Y) = \frac{1}{(2\pi)^{\frac{p+1}{2}}\, h^{p+1}} \cdot \frac{1}{n} \sum_{i=1}^{n} \exp\left[-\frac{D_i^2}{2h^2}\right] \exp\left[-\frac{\left(Y-Y_i\right)^2}{2h^2}\right]$$

having indicated with n the number of observations available, with p the dimension of vector x and being defined the following scalar function:

$$D_i^2 = \left(X - X_i\right)^T \left(X - X_i\right) \tag{2}$$

Replacing in (1) the esteem of the expected value is obtained:

$$\hat{Y} = \frac{\sum_{i=1}^{n} Y_i \exp\left(-\frac{D_i^2}{2h^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2h^2}\right)} \tag{3}$$

that can also be expressed as:

$$\hat{Y} = \frac{\sum_{i=1}^{n} Y_i w_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

with:

$$w_i = \exp\left(-\frac{D_i^2}{2h^2}\right) \tag{5}$$

w_i can be considered as the weight of the i-th parameter for the esteem of $\hat{Y}$, therefore, the value $\hat{Y}$ can be seen as the weighed average of all the Y_i observations, where each of them is weighed exponentially function of the distance D_i from X; h it is a constant that controls the amplitude of the receptive zone (radial function); advanced GRNN models can use anisotropic parameters h.

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The used value of h in the examined case in the one that minimizes RMS (root mean squared error) in the verification phase. In figure 4 the trend of RMS with the variation of the coefficient h of smoothing is shown.

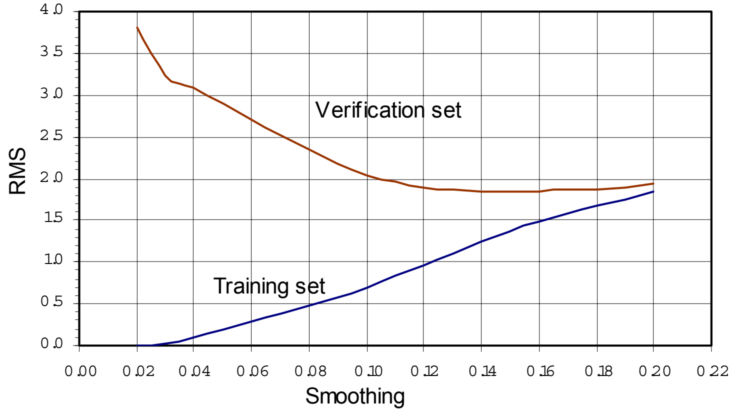


Figure 2: Trend of the RMS.

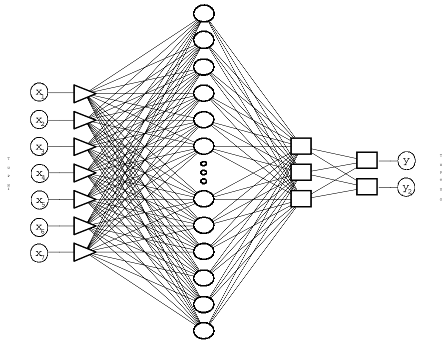


Figure 3: GRNN neural network.

The input units supply to the network the elements of vector X of which we want to calculate the correspondent expected value $\hat{Y}(X)$. Such values are sent to the neurons of the second layer (pattern units). Every node of the second layer corresponds to an available set and all together constitute a kind of memory of the network.

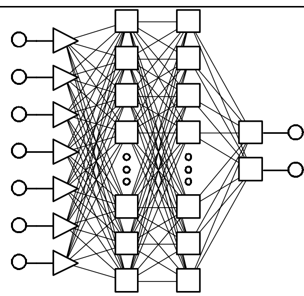
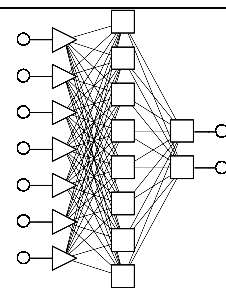
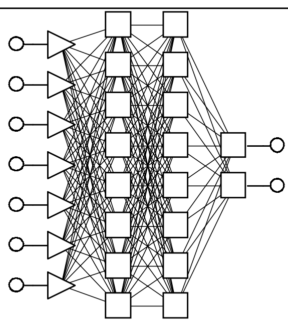
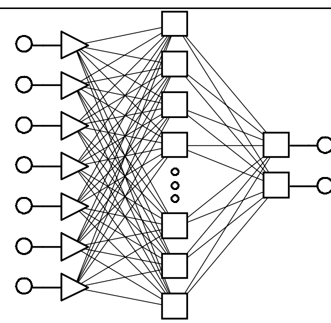
When a new vector X is introduced in order to estimate $\hat{Y}(X)$, its distance (2) from every Xi present in the pattern units is calculated, and the result is passed through an exponential function of activation $\exp\left[-\frac{D_i^2}{2h^2}\right]$, to obtain a vector of equal dimension to the number of examples available, that constitutes the input for the successive layer (summation units). In correspondence to this layer it is calculated the scalar product between this vector and the weights of the connections and the result is therefore transmitted to the output units that supply the required estimate.

The creation of example patterns, which enclose the case type of the chosen data, is the most delicate passage in order to obtain reliable results from the neural elaboration.

The available data is grouped by mostly random criteria in three sets: training-set, verification-set and test-set.

The first, preponderant in regards to the other two, serves to the network to be trained in respect to the problem and, therefore, for the determination of the weights, the verification examples are used in order to estimate the performance of the network and for the definition of the best architecture, lastly, the test data serves for one final verification of the efficiency of the network once the construction procedure is completed.

Table 5: Various network architectures of MLP.

 MLP1 (n. 2 hidden layers with 13 neurons for layer)	 MLP2 (n. 1 hidden layer with 8 neurons)
 MLP3 (n. 2 hidden layers with 8 neurons for layer)	 MLP4 (n. 1 hidden layer with 13 neurons)

6 Comparison between GR and MLP architecture of Neural networks

In the examined case the results obtained with a GRNN network type have been confronts with those obtained from 4 different network architectures of type MLP (Multilayer Layer Perceptions) implemented with the well known learning

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technique of back-propagation, chosen on a total of 32 on the base of the best achieved performance.

Completed the phase of training of the 5 considered the results were analysed, in particular the different models were compared in function of the parameters: absolute mean error, standard deviation of error, standard Pearson-R correlation coefficient and root mean square error (RMS). It can be observed that all the considered networks succeed to describe the problem in adequate way, in fact, the error of estimate of the results is nearly always contained within acceptable values, however, the GRN network apart from having the smallest RMS in the phase of verification, it introduces an elevated learning speed and converges to the surface of optimal answer as the available data increases.

These are considerable advantages if compared with the Back Propagation networks (BP) as the latter can request times of convergence of an order of magnitude up to 3 times greater than those required the GRNN, and furthermore BP does not introduce the same ability to adaptation to new data, in fact, BP requires a new training process in order to adapt itself to new information.

Table 6: Comparison between results obtained with the 5 neural networks.

	RMS		Mean error (μ)				Correlation (R)				Standard deviation			
			L_{10}		L_{90}		L_{10}		L_{90}		L_{10}		L_{90}	
	TR	*VE*	*TR*	*VE*	*TR*	*VE*	*TR*	*VE*	*TR*	*VE*	*TR*	*VE*	*TR*	*VE*
GRNN	1.36	1.83	0.86	1.29	0.96	1.41	0.96	0.93	0.93	0.82	1.19	1.63	1.41	1.92
MLP1	1.14	1.90	0.89	1.55	0.84	1.55	0.96	0.88	0.95	0.86	1.12	1.98	1.12	1.89
MLP2	1.57	2.07	1.34	2.20	1.18	1.45	0.92	0.79	0.91	0.86	1.67	2.53	1.47	1.72
MLP3	1.26	1.99	1.09	1.77	0.91	1.52	0.95	0.87	0.94	0.85	1.31	2.07	1.19	1.93
MLP4	1.39	1.85	1.11	1.72	1.06	1.45	0.95	0.88	0.92	0.87	1.34	1.95	1.37	1.71

The main characteristics that make the model GRNN more suitable for the considered forecasting analysis are summoned:

- the network learns in a single step (one pass learning algorithm) and is immediately in a position to generalize as soon as the available data is stored;
- the obtained regression surface converges to the optimal proportionally to the available data;
- the carried out estimate is limited from the maximum and minimum values present in the used data;
- there are no convergence problems to solutions correspondent to local minimums of the error surface (as it happens instead in the case of the Back Propagation);
- the version that uses the clustering technique of the data allows to reduce the calculation times and realize models that adapt in real time to eventual variations of the system that they represent.

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7 Comparison between regressive models and GR neural networks

In the examined case the results obtained from the application of the GRN network have been compared with those obtained from the 9 models, and in particular the different models are compared in function of the following parameters: absolute mean error, standard deviation, Pearson-R standard correlation coefficient and root mean square error (RMS).

Table 7: Statistics of the applied models.

	RMS	Mean error (μ)	Correlation (R)	Standard deviation
GRNN	1.254	1.030	0.904	1.249
M1	2.036	1. 536	0.7 67	1.7 29
M2	5.481	4.957	0.553	2.247
M3	5.908	4.930	0.347	2.530
M4	3.896	3.094	0.180	2.653
M5	2.534	2.114	0.599	2.159
M6	1.7 18	1.4 19	0.7 67	1.7 29
M7	1.711	1.400	0.770	1.722
M8	1.732	1.443	0.764	1.740
M9	1.668	1.365	0.783	1.679

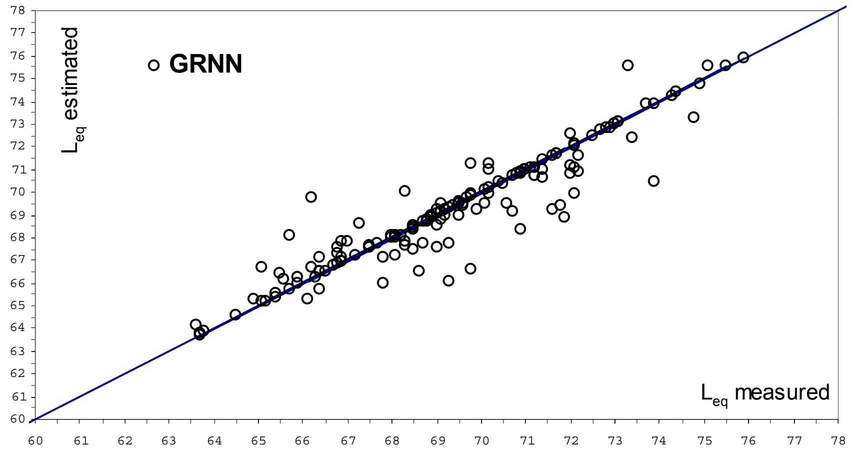

Figure 4: Measured and estimated L_{eq} with the neural model.

It can be observed as the considered neural network succeeds to describe the problem in adequate way, in fact, the estimate error of the results is contained within acceptable values, moreover guaranteeing always a greater precision than all the regressive models considered.

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8 Conclusions

From the comparison of the results from the measured data obtained during the survey, and the data forecasted adopting two different architectures of neural network, General Regression Neural Network (GRNN) and Multilayer Layer Perceptions (MLP), the analysis which involved different architectures of network, and a further comparison to reference regressive models present in literature and recalibrated with the survey data, the study has evidenced the greater reliability and computation simplicity of the General Regression Neural Network (GRNN).

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