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Section: Roads and Railways

Evaluating Freeway Traffic Noise Using Artificial Neural Network

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Abstract

In this paper, were conducted a study on the noise produced by traffic on the freeway. In particular, it was rated the Sound Pressure Level Equivalent, resulting from the passage of vehicles on a highway located in southern Italy. It was carried out a number of readings using five sensors Orione Cel 500 Model 573 located close to the highway. The period of data collection lasted about six months and involved a stretch of about 20 km. In addition, the following atmosphere and environmental parameters were detected: Speed and Wind Direction, Temperature, Rainfall, and Traffic Flow. The data, organized and stored in an appropriately trained GIS system, were processed using Artificial Neural Network procedures. The Artificial Neural Network has proved particularly valid in fact, in comparison with the main models in the literature it was the most reliable.

Keywords: Noise pollution; Artificial neural network; Traffic; Freeway.

Nomenclature

I	weighted sum (dimensionless);
w_i	weight (dimensionless);
x_i	input (dimensionless);
θ_j	bias unit; (dimensionless);
u_i	degree of sensitivity of *uj* when it receives an input signal from *uj* (dimensionless);
w_{ij}	weight between the connection of the neuron "*i*" with the neuron "*j*" (dimensionless);
T_{p_j}	target (dimensionless);
O_{p_j}	output (dimensionless);
$1/R$	curvature (1/m);
i	longitudinal slope (%);
$\sum_i {}^{a_i}\!/_{2}$	tortuosity (Degree/Km)
E_p	error function (dimesionless)

1. Introduction

The noise levels produced by vehicles are a problem affecting the entire globe. In all the countries of the world where there is traffic, laws and regulations for the containment and control [1] of this phenomenon have been produced.

At international level the ISO 9613-1 Acoustics − Attenuation of Sound during Propagation Outdoors – Part 1: Calculation of the Absorption of Sound by the Atmosphere represents the legal/reference standard for the evaluation of acoustic propagation resulting from vehicular traffic. In the European Union, the rules governing noise pollution are based on *Directive 2002/49/EC of the European Parliament and of the Council of 25 June 2002 relating to the assessment and management of environmental noise – Declaration by the Commission in the Conciliation Committee on the Directive relating to the assessment and management of environmental noise,* which provides guidelines and criteria for the

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containment of noise (including from vehicular traffic). The scientific community is also very interested in the problem. Several researchers and research institutions in this field have produced in recent decade templates and procedures useful for the planning of useful strategies for the control and maintenance of noise pollution caused by traffic.

The model, *National Swedish Institute of Building Research* (NSBIR- Fog H., Jonsson) [2], calibrated for motorways, measure the Equivalent Sound Level (L_{eq}), where are a reference distance (d_o) of the road axis from the receptor 5 m. From L_{eq} (d_o) is also possible to calculate L_{eq} at any distance by means of a factor that takes into account attenuation due to the absorption of the ground).

The model of *Griffiths* and *Langdon* [3] relates the Average Sound Level (where, L_{50} represents the Sound Pressure Level exceeded in the 50%). The cumulative statistical levels of correlation are calculated using formulas derived experimentally by Benedict and Spanish through an experimental investigation conducted in Turin in 1977. The model is valid for the following traffic conditions:

- 500 vph < Q < 5000 vph (vehicles per hour) and heavy traffic of less than 35%.

The model Josse, *Notions d'acoustique Paris, France, Ed. Eyrolles 1972*, applies to more closely evaluate the influence of multiple reflections due to the presence of buildings that line the street.

The model Alexandre *et al.* [4] evaluates the L_{eq} of highway traffic vehicle at a speed of just under 120 km/h under the following conditions:

- absence of absorption by the soil;
- absence of wind and thermal turbulence.

The model of *Burgess* [5], applied for the first time in Australia only in terms of traffic with free traffic flow, takes into account the parameters characterizing vehicular traffic:

- hourly flow (Q);
- percentage of heavy vehicles (p);
- distance (d) between the noise sources and the receptors.

The model CNR (National Research Council) was developed in 1983. CNR evaluates L_{eq} as a function of the following parameters:

- average speed of traffic flow (ΔLv);
- noise reflection (ΔLb);
- road surface type (ΔLs);
- longitudinal slope (ΔLg).

The model Ontario Ministry of Transportation and Communication (OMTC) – Ministry of the Environment (MOE) - Ontario Road Noise Analysis Method for Environment and Transportation (ORNAMENT) − Technical Document (*https://archive.org/stream/ornamentontarior00schruoft#page/n1/mode/2up*) was developed in 1989. OMTC estimates L_{eq} up to a distance of 200 m from the infrastructure; assuming there are no obstacles between source and receiver. The model estimates L_{eq} as a function of the following parameters:

- flow light vehicles (QVL);
- flow heavy vehicles (QVh);
- average speed of all vehicles (v).

The model *Conseil National de Recherches/Central Society of hypothèques et de Logement* (CNR/SCHL) was developed in 1986. CNR/SCHL calculates the L_{eq} 24 hours through the following parameters:

- additional attenuation due to absorption of the equivalent continuous level of the ground (Am);
- reference distance (do), usually equal to 30 m;
- average speed of the traffic flow (v);
- slope of the road (S);
- any breakpoints traffic flow (F).

In this paper, were conducted an analysis on the noise produced by traffic on the freeway using ANN.

2. Technique used: the Artificial Neural Network multilayer approach

Inspiration for the structure of the Artificial Neural Network (ANN) is taken from the structure and operating principles of the human brain. It is made of interconnected artificial neurons that mimic some properties of biological neurons. The function of a biological neuron is to add its input and produce an output. This output is transmitted to subsequent neurons, through the synoptic joints, only if the transmitted signal is high (i.e. greater than a predetermined value), otherwise, the signal is not transmitted to the next neuron. In the network, therefore, a neuron calculates the weighted sum, using Eqn. (1) (considering the input x_i and weights w_i) and compares it with a threshold value; if the sum is greater than the threshold value, the neuron lights up and the signal is transmitted. Otherwise, the neuron does not turn on and the flow stops.

$$I = \sum_{i=1}^{n} w_i x_i \ , \tag{1}$$

where: I is the weighted sum (dimensionless); w_i is the weight (dimensionless); x_i, is the input (dimensionless).

The activation value U_j rather than U_j, connected to weight w_{ij}, is a function of the weighted sum of the input. This function may take various forms. In this study, a function of type Eqn. (2) was used:

$$u_j = \frac{1}{1+e^{-(\sum(i) w_{ij} \cdot u_i + \theta_j)}}, \tag{2}$$

where: θ_j is the bias unit (dimensionless); u_i is the degree of sensitivity of u_j when it receives an input signal from u_j; (dimensionless); w_{ij} is the weight between the connection of the neuron "i" with the neuron "j" (dimensionless).

Multi-Layer Perceptron (MLP) and the Back Propagation (BP) algorithm

In this study, a neural network with Multi-Layer Perceptron (MLP) architecture was used. Training was carried out using the Back Propagation (BP) algorithm. The neurons (or units) that comprise this type of network are organized into layers: an input layer, an output and a number of intermediate layers between input and output referred to as hidden, defined by the user. Initially, the weights values are assigned random (normalized in the range [0,1] or [–0.5, +0.5]); moreover, there is input vector $X_p = (X_0, X_1, X_2, ..., X_{n\text{-}1})$ with $X_0 = 1$ and an output vector $T_p = (T_0, T_1, T_2, ... , T_{m\text{-}1})$.

In this way, the network will consist of n-1 input neurons and m-1 output neurons. The weighted sum of the inputs for each layer is calculated using Eqn. (1) and its value of activation, i.e. output using Eqn. (2). Then, the weights must be changed so that the output of the network (i.e. the output of the last layer of neurons) increasingly approximates the target set by the user. It was defined a function error Eqn. (3) proportional to the square of the difference between the output and target for all output neurons:

$$E_p = \frac{1}{2}\sum_j \left(T_{p_j} - O_{p_j}\right)^2, \tag{3}$$

where: T_{p_j} is the Target (dimensionless); O_{p_j} is the output (dimensionless).

Subsequently, BP is applied i.e. the weights are varied so that error E_p tends towards zero (starting from the last layer to the first). It is define, for the current pattern p, a variation Δw_{ij} of weight w_{ij} between the neuron i and j that given by Eqn. (4).

$$\Delta_{pw_{ij}} = -\alpha \frac{\partial E_p}{\partial w_{ijp}} + \beta(\Delta_{p-1}) w_{ij}, \tag{4}$$

where α – learning coefficient (learning rate); β – momentum and $\Delta_{p\text{-}1} w_{ij}$ is the variation of the same weight calculated according to the previous model. The new weights are given by Eqn. (5):

$$w_{ij}^{new} = w_{ij}^{old} + \Delta_p w_{ij}. \tag{5}$$

The variation of the weights is calculated starting from the layer of output neurons and backward toward the first hidden layer. The derivatives is calculated using Eqn. (6).

$$\Delta_p w = \alpha A_i \delta_j + \beta \Delta_{p-1} w_{ij}, \tag{6}$$

where A_i is the value of the i^{th} *neuron* of the layer being considered; δ_j is given by Eqn. (7) if considering the output layer.

$$\delta_j = (T_j - O_j) O_j (1 - O_j). \tag{7}$$

It is given by Eqn. (8) for all other intermediate layers:

$$\delta_j = I_j (1 - I_j) \sum_k w_{jk} \delta_k. \tag{8}$$

To train a network, this process must be run many times (at least 1000) with different patterns, each of which features a different weight. This process is performed until the error is less than a predetermined value (the value is set by the user). When the process converges, the network is ready to classify a new input with an unknown target. The parameters α and β are chosen by the user (range between 0 and d 1); in the present study $\alpha = 0.5$ and $\beta = 0.4$. In particular, α is linked to the convergence of the network.

3. Data collection

Stretch analyzed and instrumentation used in monitoring

The characteristics of the freeway analyzed are shown in Fig. 1. Table 1 shows the location (geo-referenced) of five stations Sound Level meter used in the study.

Fig. 1. Stretch analyzed

Table 1. Location of Sound Level Meter

Label Sound Level Meter station	Latitude	Longitude
*S*1	39° 09’ 47.8”	16° 23’ 34.5"
*S*2	39° 03’ 71.1”	16° 13’ 72.9”
*S*3	39° 02’ 18.1”	16° 12’ 10.1”
*S*4	39° 01’ 72.2”	16° 11’ 98.8”
*S*5	39° 00’ 05.8”	16° 08’ 00.0”

The instrumentation used for monitoring activities (Fig. 2.) is composed of a Sound Level Meter integrator *Orione Cel 500 Model 573*, and related accessories. Were performed a series of survey in five different locations whose coordinates are given in Table 2.

The surveys were made continuously for 24 h a day for a total period of 6 months. The monitoring measurements of L_{eq} were made in according with *Directive 2002/CE/49*.

Data collection in a Geographic Information System environment

The data [6] were stored in a suitably trained Geographic Information System (GIS) [7]. The road axis was constructed. A data were stored in a suitably trained GIS. The road axis was constructed in a *Computer-Aided Design* (CAD) environment, in an appropriate layer, considering each plan metric element of the road separately. Cross sections were inserted into another layer (at known points, i.e. curve centre, curve end, etc.). Next, a file in *.dxf format, containing the road axis and sections, was imported into ArcGIS, geo-referenced according to the *Universal Transverse Mercator* (UTM) coordinates, and converted into the format used in ArcGIS (i.e. *.shp file format). Finally, (Fig. 3) the results of each monitoring station (indicated wit acronym *S*1, *S*2, *S*3, *S*4 and *S*5), were loaded into the GIS environment. or each monitoring station was recorded L_{eq} for the whole day (24 h) for the entire observation period (6 months).

The data were aggregated into classes of vehicular flow with amplitude equal to 100 veh/h. Also has been determined, at around the monitoring station (range of influence equal to 1 km), the operating speed of the vehicles [8] through the relationship (9):

$$V_{85} = 154.8 - 2015\left(\frac{1}{R}\right) - 0.42\left(\sum_i {a_i}/{2}\right) - 4.2\left|i\right|, \tag{9}$$

where: 1/R, is the curvature (1/m); i, is the longitudinal slope (%); $\sum_i {a_i}/{2}$, is the tortuosity (degree/km).

Fig. 2. Sound Level Meter Orione Cel 500 Model 573

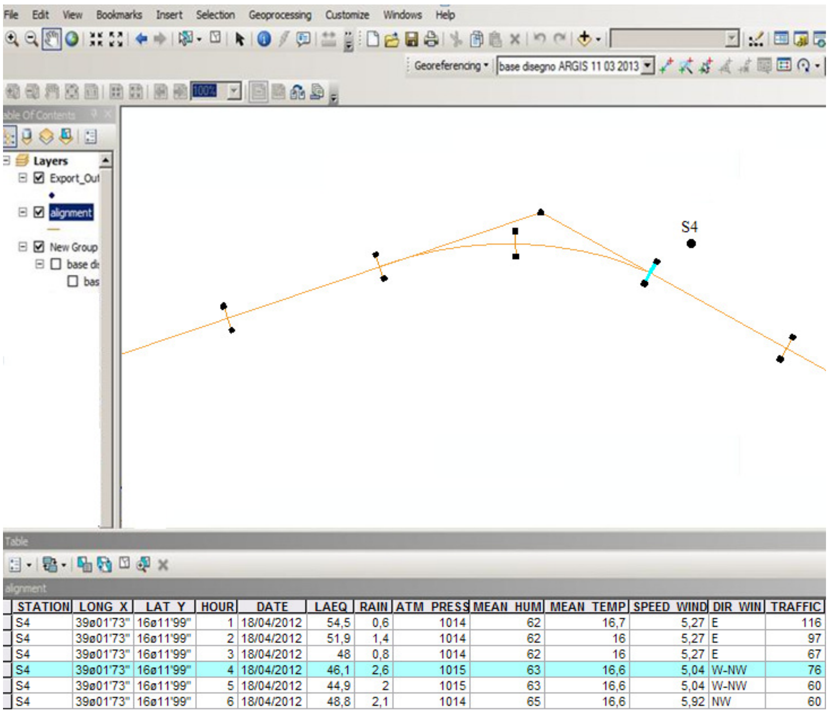

Fig. 3. Data Collection in GIS environment

Finally for each monitoring station [9] was determined by the distance *d*, i.e. distance between survey sections and vehicular flow [10], considering an influence range equal to 1 km (Fig. 4.).

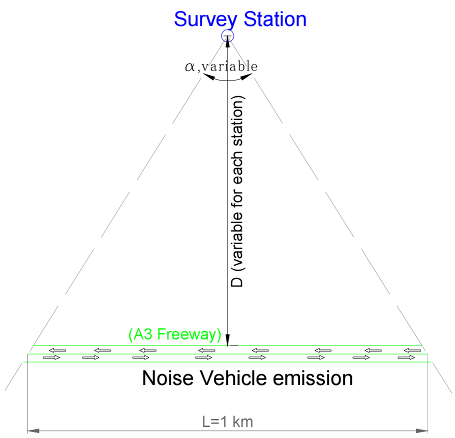

Fig. 4. Range of influence for each survey station

4. 4. Data analysis and results

The Artificial Neural Network application

The model ANN was obtained using the Artificial Neural Network technique shown in section 2.1. The variables used for the ANN shown in the Table 2 were considered. 70% of the data was used to train the network and the remaining part for verification. Different configurations were considered for the architecture of the neural network. The best architecture for the network is shown in Fig. 5 and Table 3 shows the parameters of the ANN.

Table 2. Variables used in the ANN analysis

Variables	Label	Variable types	Units
Operative Speed	V_{85}	Numeric	km/h
Distance	d	Numeric	km
Traffic Flow	Q	Numeric	veh/h

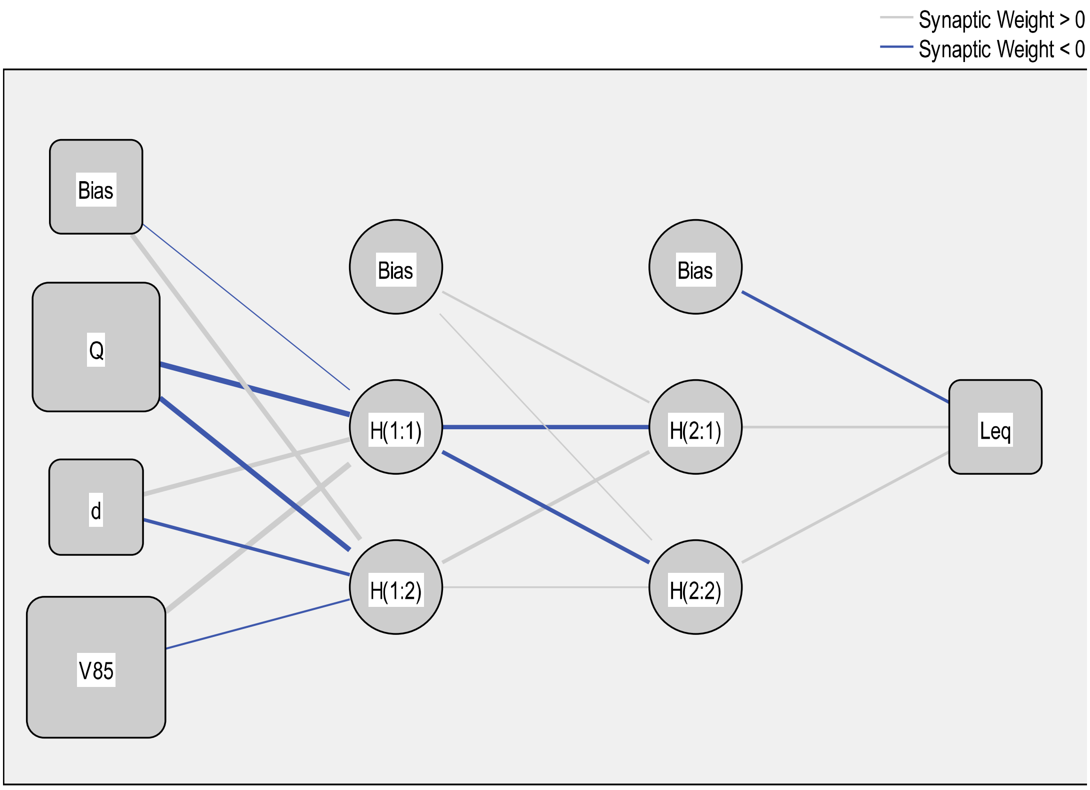

Fig. 5. Artificial Neural Network architecture

Artificial Neural Network and literature model comparison

The reliability of the model obtained through ANN was compared with the main models in the literature and reported in Table 4.

Table 3. Parameters of the ANN estimates

Predictor		Predicted				
		Hidden Layer 1		Hidden Layer 2		Output Layer
		H (1:1)	H (1:2)	H (2:1)	H (2:2)	L_{eq}
Input Layer	(Bias)	–0.004	4.283			
	Q	–4.935	–4.651			
	d	3.387	–2.143			
	V_{85}	6.394	–0.937			

Hidden Layer 1	(Bias)	1.502	0.387	
	H (1:1)	–3.284	–3.079	
	H (1:2)	2.160	0.663	
Hidden Layer 2	(Bias)			–2.058
	H (2:1)			1.710
	H (2:2)			1.884

Table 4. Literature model used

No	Model	Equation	Label
1.	*NSIBR*	$L_{eq}\left(d_0\right)=10log_{10}\left(Q\right)+20log_{10}\left(V\right)$	(10)
		$L_{eq}=L_{eq}\left(d_0\right)-10log_{10}\left(\frac{d}{d_0}\right)-A_m$	(11)
		$L_{10}=61+8,4\cdot log_{10}(Q)+0,15\cdot p-11,5\cdot log_{10}(d)$	(12)
2.	*GRIFFITHS E LANGDON*	$L_{50}=44,8+10,8\cdot log_{10}(Q)+0,12\cdot p-9,6\cdot log_{10}(d)$	(13)
		$L_{90}=39,1+10,5\cdot log_{10}(Q)+0,06\cdot p-9,3\cdot log_{10}(d)$	(14)
		$L_{eq}=L_{50}+0,018\cdot(L_{10}-L_{90})^2$	(15)
3.	*JOSSE*	$L_{eq}=15\cdot log_{10}\left(Q\right)-10\cdot log_{10}\left(L\right)+38$	(18)
4.	*ALEXANDRE*	$L_{eq}=10\cdot log_{10}\left(\frac{Q}{d}\right)+52$	(17)
5.	*CNR*	$L_{eq}=55,5+10.2\cdot log_{10}\left(Q\right)+0.3\cdot p-19,3\cdot log_{10}\left(d\right)$	(18)
6	*OMTC*	$L_{eq}=\alpha+10\cdot log_{10}\left(Q_{vl}+8\cdot Q_{vp}\right)+10\cdot log_{10}\left(\frac{25}{d}\right)+\Delta L_v+\Delta L_f+\Delta L_b+\Delta L_s+\Delta L_g+\Delta L_{vb}$	(19)
7	*CNR/SCHL*	$L_{eq}=10,21\cdot log_{10}\left(Q_{vl}+6\cdot Q_{vp}\right)-13,9\cdot log_{10}\left(d\right)+0,21\cdot V+49,5$	(20)
8	*ISO 9613*	$L_{eq}=L_{eq}\left(d_0\right)-10\cdot log_{10}\left(d/d_0\right)-A_m$	(21)
9	*CNR*	$L_{eq}=10\cdot log_{10}\left(\sum_{i=1}^{n}\left(\sum_{j=1}^{8}10^{0,1(L_{AT}(ij)+A_f(j))}\right)\right)$	(22)

Table 5 and Fig. 6 show the comparison between the models. In particular the estimated values with ANN model are close to the values observed.

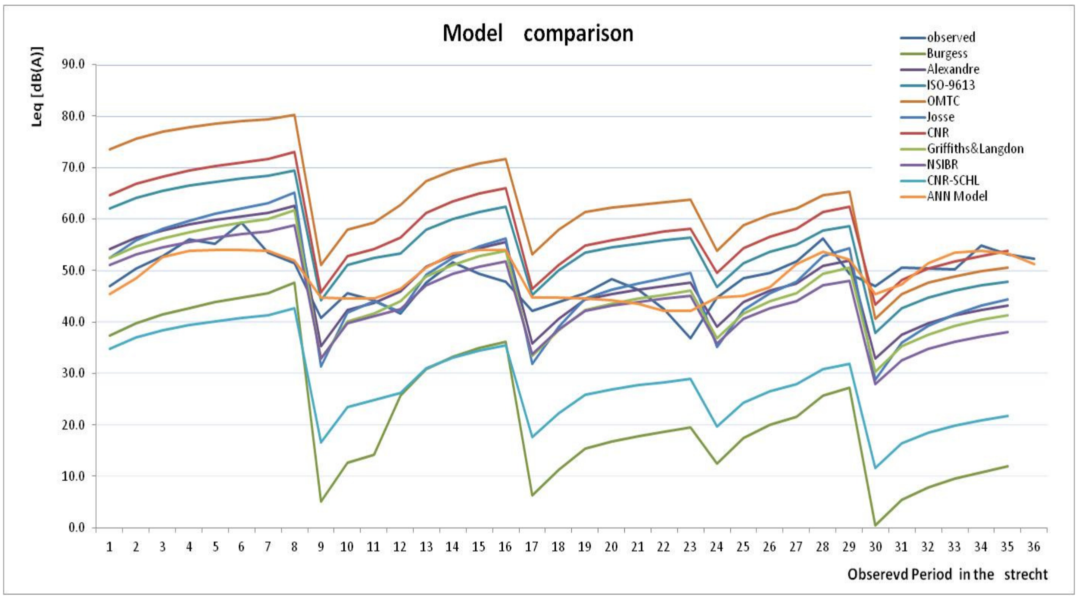

Fig. 6. Comparing models

Table 5. ANN and literature model comparison

Observed Value	NSIBR	Grif. & Lang.	Josse	Alexan.	Burgess	CNR	OMTC	Europ. ISO-9613-1	CNR-SCHL	**ANN Model**
47.0	51.0	52.4	52.5	54.1	37.3	64.6	73.6	62.0	34.8	45.5
50.3	53.2	54.7	55.8	56.3	39.8	66.8	75.6	64.2	37.0	48.5
52.8	54.6	56.3	58.0	57.8	41.4	68.3	76.9	65.5	38.4	52.6
56.0	55.6	57.4	59.7	58.9	42.7	69.4	77.8	66.5	39.4	53.8
55.2	56.4	58.4	61.0	59.8	43.8	70.3	78.5	67.2	40.2	54.0
59.3	57.0	59.2	62.1	60.5	44.7	71.0	79.0	67.9	40.8	54.0
53.5	57.6	59.9	63.0	61.1	45.5	71.6	79.4	68.4	41.4	53.9
51.4	58.8	61.7	65.2	62.6	47.6	73.1	80.3	69.5	42.6	51.9
40.8	32.8	32.9	31.3	35.3	5.1	45.8	51.1	44.1	16.6	44.6
45.5	39.7	40.1	41.8	42.3	12.6	52.8	58.0	51.0	23.5	44.6
44.2	41.1	41.7	44.0	43.7	14.3	54.2	59.3	52.4	24.9	44.5
41.7	42.4	44.0	41.9	45.9	25.7	56.4	62.7	53.2	26.2	46.4
47.7	47.1	48.8	49.1	50.7	30.7	61.2	67.4	57.9	30.9	50.5
51.6	49.3	51.1	52.4	52.9	33.2	63.4	69.4	60.0	33.1	53.4
49.4	50.7	52.7	54.6	54.4	34.9	64.9	70.7	61.3	34.4	53.9
47.8	51.7	53.9	56.3	55.5	36.2	66.0	71.6	62.3	35.5	54.0
42.1	33.8	33.5	31.9	35.9	6.3	46.4	53.1	45.3	17.6	44.6
43.8	38.5	38.4	39.0	40.6	11.3	51.1	58.0	50.0	22.3	44.6
45.6	42.1	42.3	44.5	44.3	15.4	54.8	61.3	53.5	25.9	44.5
48.4	43.1	43.5	46.2	45.4	16.7	55.9	62.2	54.5	26.9	44.3
46.3	43.9	44.5	47.5	46.3	17.8	56.8	62.8	55.3	27.7	43.5
42.5	44.6	45.3	48.6	47.0	18.7	57.5	63.3	55.9	28.3	42.2
36.8	45.1	46.0	49.5	47.6	19.5	58.1	63.7	56.4	28.9	42.2
44.8	35.8	36.8	35.1	39.1	12.5	49.6	53.9	46.7	19.6	44.7
48.5	40.6	41.7	42.2	43.9	17.5	54.4	58.7	51.5	24.4	45.0
49.6	42.7	44.0	45.6	46.1	20.0	56.6	60.8	53.6	26.5	46.8
51.7	44.1	45.6	47.8	47.5	21.6	58.0	62.1	54.9	27.9	51.2
56.3	47.1	49.3	52.7	50.9	25.7	61.3	64.6	57.8	30.9	53.6
49.3	48.0	50.5	54.3	51.9	27.1	62.4	65.2	58.6	31.8	52.0
46.9	27.8	30.3	28.8	32.8	0.4	43.3	40.6	37.9	11.6	45.4
50.5	32.6	35.3	36.0	37.6	5.4	48.1	45.5	42.7	16.4	47.2
50.4	34.8	37.6	39.3	39.8	7.9	50.3	47.6	44.8	18.5	51.5
50.2	36.2	39.2	41.5	41.3	9.5	51.8	48.9	46.1	19.9	53.5
54.8	37.2	40.4	43.1	42.4	10.8	52.9	49.8	47.1	20.9	53.8
53.2	38.0	41.4	44.4	43.2	11.9	53.7	50.5	47.9	21.7	53.4
52.3	41.3	46.1	50.3	47.1	17.3	57.6	53.2	50.9	25.1	51.3

5. Conclusions

This study used the Geographic Information System for noise produced by traffic on the freeway. In particular, the data were organized into a Geographic Information System. The data stored in the Geographic Information System were aggregated into Flow Rate classes, and were processed through an Artificial Neural Network. The Artificial Neural Network obtained proved to be very reliable, because the estimation error compared with the subsequently, the simulation capability of the Artificial Neural Network model was compared with the main models in the literature. The comparison showed that the Artificial Neural Network model has the lowest residual and is therefore the most reliable model in comparison with the other models.

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