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Neural based contingent valuation of road traffic noise

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A B S T R A C T

In this paper, we present a new approach to value the willingness to pay to reduce road noise annoyance using an artificial neural network ensemble. The model predicts, with precision and accuracy, a range for willingness to pay from subjective assessments of noise, a modelled noise exposure level, and both demographic and socio-economic conditions. The results were compared to an ordered probit econometric model in terms of the performance mean relative error and obtained 85.7% better accuracy. The results of this study show that the applied methodology allows the model to reach an adequate generalisation level, and can be applicable as a tool for determining the cost of transportation noise in order to obtain financial resources for action plans.

1. Introduction

Noise pollution is one of the transportation externalities in urban areas, causing discomfort, annoyance, and displeasure for the exposed population (Basner et al., 2014). The results from the first phase of the strategic noise mapping in the European Union (EU), which occurred in 2007, suggest that approximately 56 million people are exposed to environmental noise above 55 dBA during daytime from road traffic within agglomerations, while 33 million are exposed to noise from major roads outside agglomerations. Additionally, approximately 40 million people across the EU are exposed to noise above 50 dBA from roads within agglomerations during the night, and 22 million are exposed to outside agglomerations (Murphy and King, 2014). These results are very worrying from a public health perspective, given that the World Health Organisation (WHO) sets 40 dBA as the nighttime level at which health effects are noticeable (Hurtley, 2009).

In Latin American developing countries, the noise pollution issue is not very different. The daytime road traffic noise of 49.81% of Santiago de Chile has above 55 dBA (Suárez and Barros, 2014), whilst in the urban area of Medellin, Colombia, the 50% of the total noise measurements reported levels above 72 dBA during daytime, and 68 dBA during nighttime (Yépez et al., 2009). Zannin et al. (2013) found that 90% of the 58 measurement points recorded noise levels above 55 dBA in the campus of the Polytechnical Center of the *Universidade Federal do Parana* (Federal University of Parana) in Curitiba. Pinto and Mardones (2009) found that the noise levels in Copacabana were over the allowed values due to traffic.

The impact of road noise pollution can be assessed in monetary terms (Moliner et al., 2013). Economic values of road traffic noise are often evaluated using different instruments: travel costs, hedonic pricing, cost-benefit analysis, conjoint analysis, choice experiments, and contingent valuation (Istamto et al., 2014a). The well-stablished contingent valuation method

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(Wardman and Bristow, 2004; Bjørner, 2004; Arsenio et al., 2006) is a stated preference (SP) analysis that assesses the willingness to pay (WTP) or accept (WTA) compensation in order to make values for individuals' work commensurable with other market values (Brouwer, 2000). Conventional methods such as the travel cost, or the hedonic pricing are not capable of capturing the non-use values. This contrasts with the contingent valuation method which has a wide acceptance as the most effective method for estimating these values (Venkatachalam, 2004). Whereas other SP analysis such as choice models tend to ask for the order of preference, contingent valuation tends to ask for the strength of preference, and is less tedious where it involves a single question, and the information content of the single response is in principle high. Whilst choice analysis is a behavioural model from which values are implied, contingent valuation method is a direct valuation model (Wardman and Bristow, 2004).

The use of computational intelligence, and more specifically, artificial neural networks (ANN), could be an alternative approach for solving transportation issues. The literature shows increasing applications of ANNs in transportation research in the last decades. Dougherty (1995) reviewed the applications of ANNs for transport, introducing topics like driver behaviour, pavement maintenance, vehicle detection/classification, traffic pattern analysis, forecast, and control. ANNs have been used to estimate transport energy demand (Murat and Ceylan, 2006), and recently, for the management of transportation infrastructure for safety purposes (De Luca, 2015). Transportation road noise issues have also been studied through ANNs: e.g., prediction of noise caused by urban traffic (Cammarata et al., 1995; Genaro et al., 2010; Givargis and Karimi, 2010; Parbat and Nagarnaik, 2008; Nedic et al., 2014), relationships between annoyance and road noise (Botteldooren and Lercher, 2004), recognition of horn signals (Couvreur and Laniray, 2004), objective indices modelling for urban sound environments (Torija et al., 2012), predicting highway traffic noise (Kumar et al., 2014), perceptual quality of soundscapes (Yu and Kang, 2009). Recently, Torija and Ruiz (2016) proposed an expert system to classify urban locations based on their traffic composition for addressing a prompt assessment of potential road traffic noise related problems. Air noise transportation had also been studied through ANN for classification issues (Sánchez-Pérez et al., 2013; Márquez-Molina et al., 2014). Collins and Evans (1994) applied neural computing techniques to discern the effect of aircraft noise on residential properties values through a hedonic approach. However, we have not found ANN studies related to noise contingent valuation.

The costs of traffic noise are an important factor for researchers as well as policy makers to consider in order to further and justify action plans to reduce noise in cities (Barreiro et al., 2005), as well as in the vicinity of airports or railways (Lawton and Fujiwara, 2016; Wolfe et al., 2014), or inclusive in natural areas (Iglesias Merchan et al., 2014). Navrud (2002) conducted a review that indicates how relevant this topic is. His paper is considered state-of-the-art when it comes to evaluating the financial impact of noise in developed countries. Correa et al. (2011) described the costs of noise in other Latin American countries, showing the results of studies in Chile, Argentina, and Colombia.

The main objective of this paper is to validate a methodology, which allows to train an ANN model properly, in order to predict the WPT range to reduce road traffic noise annoyance within a given population. The results obtained with this methodology were compared to the econometric ordered probit model outcomes. The target variables used to adjust the model come from a socio acoustic survey that collects the WTP of the respondents. Characteristics such as: (a) environmental noise perception of the respondents, (b) modelled day-night noise exposure level (LDN) at the facade of their dwellings, and, (c) the respondents' demographic and socioeconomic status were used as the model inputs.

The paper is organized as follows: Section 2 reviews the basic operation of feedforward ANNs predictors. Section 3 deals with the methodology used for data collection, econometric modelling, and ANN architecture. In Section 4, the results of the econometric and ANN models are presented, and in Section 5, the results are discussed and commented. The conclusions of this study can be found in Section 6.

2. Theoretical consideration

2.1. Artificial neural networks

An ANN approach is considered as a statistic machine learning procedure (Russell and Norvig, 2004). ANNs offer, among other things, a numerical technique that, similar to flexible nonlinear statistical methods, is capable of adapting to arbitrary or unknown functional forms with a specified degree of accuracy (Curry et al., 2002), and is inspired by the structure and operating principles of the human brain. The ANN, which does not require any predefined underlying relationship between dependent and independent variables, has been shown to be a powerful tool in dealing with prediction and classification problems (De Luca, 2015) by identifying functional relationships among a certain number of variables.

The biological neuron adds its input and produces an output, transmitted to subsequent neurons through the synaptic joints. Otherwise, the ANNs are useful models for problem solving and knowledge engineering in a 'humanlike' way (Kasabov, 1996).

The ANN's model preparation takes into account input and output samples of an arbitrary system (linear or nonlinear). This model (multilayer feedforward network), as shown in Fig. 1, is able to extract higher order statistics from it input-output pairs (Haykin, 2009).

The input-output relationships can be encoded in the synaptic weights during a training procedure called backpropagation (Rumelhart et al., 1986). In such training procedure, the synaptic weights are progressively adjusted in such way that the differences between the desired target functions and the network's output are gradually minimized. In other words, a neural network modifies its behaviour in response to the input-target pairs, leading to its most attractive feature, learning capacity.

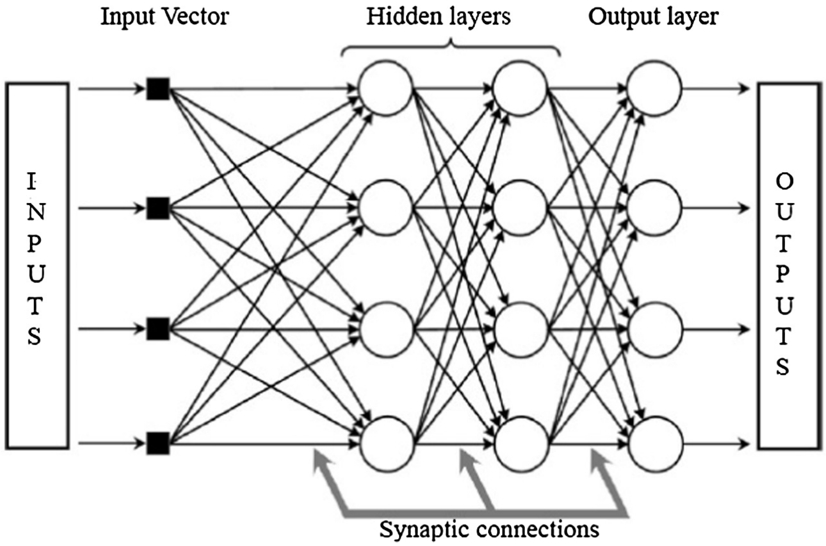

Fig. 1. Neural networks setting (Adapted from: Lucio Naranjo, 2014).

It is worth noting that even with an adequate training procedure, an ANN model still could fail in emulating an acceptable behaviour. This is generally due to a poorly dimensioned network for the problem to be modelled upon. For instance, an over-dimensioned network has excessive flexibility, which could lead to overfitting problems. On the other hand, a sub-dimensioned network will have a significant bias and will fail to learn the relevant details of the problem (Bishop, 2005). When the dimension of the network is suitable for the problem, an ANN can exploit one of its most powerful characteristics, the generalisation. This feature is shown after the neural network has been trained and a new input vector (not used during training) is presented to the network. A recall procedure is activated, which attempts to produce similar outputs from similar inputs from the training dataset (Haykin, 2009).

Another source for imprecision in ANN models may come from the lack of representativeness in the input-output pair selected for training. This discrepancy can be handled by applying the holdout method, in which, a certain amount of data pairs are reserved for testing, and the rest are saved for training. Conventionally, one third of the data is held out for testing and the remaining two-thirds are used for training. Nevertheless, when dealing with limited amount of input-output pairs the latter could not be enough. A primary safeguard against uneven representation can be applied with a procedure called stratification. It consists in randomly selecting the samples for the training and test subsets in a way that guarantees that all the problem characteristics are properly represented in both subsets, i.e. a stratified holdout (Witten et al., 2011). In this point, if the network performance is not yet satisfactory, a multifold cross-validation procedure can be applied (Haykin, 2009).

2.2. Committee of networks

A common practice in ANN approaches involves training several networks, selecting the one that presents the most accurate approximation, and discarding the rest. Nonetheless, this approach presents two disadvantages: waste of computational effort in training the non-used networks and generalisation problems caused by random components due to noise in the data. An alternative approach involves combining the networks into a committee (see Fig. 2), leading to a significant improvement in the predictions of new data (Bishop, 2005).

Committees of ANNs are desirable due to the fact that the selection of the synaptic weights is an optimisation problem with many local minima, showing a great deal of randomness stemming from different initial points and sequencing of the training examples, and forming different ways to found generalisations. As each network makes generalisation errors on different subsets of the input space, the collective decision produced by the ensemble is less likely to be in error than the decision made by any of the individual networks (Hansen and Salamon, 1990).

Committees of ANNs show improved generalisation capabilities that outperform those of single networks (Granitto et al., 2005). Bishop (2005) demonstrates mathematically the improved performance of the network ensemble compared to single ANN in terms of the average error. This is due to the reduced variance produced by averaging several results.

3. Method

3.1. Data collection

Data related to WTP, traffic noise perception, demographic and socioeconomic attributes were collected from an in-person survey consisting of three sections according to the guidelines for contingent valuations (Arrow et al., 1993). In

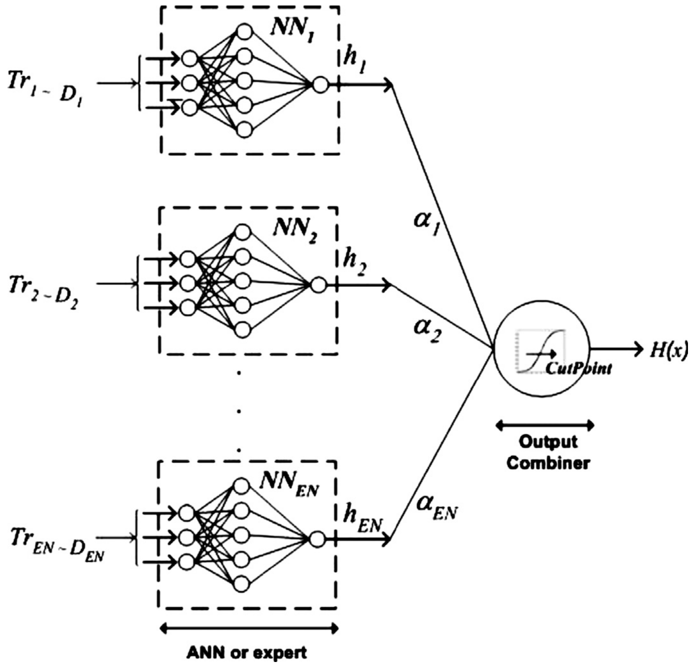

Fig. 2. Committee machine architecture. The boxes with dashed lines indicate the ANNs or experts (Silva et al., 2008).

the first Section, 9 questions were asked about the following issues: environmental quality importance (EI); the relevance of noise pollution as an environmental issue (N_P); whether silence was a factor in the decision of whether to inhabit a dwelling (S_H); the years of residence at the home (YH); the daily hours at home (H_H); the day (DA) and night (NA) road noise annoyance; the investments in the home for noise mitigation purposes (NC_H); and the perceived effects of noise on health, such as stress (S), sleep disturbance (SD), hearing loss (HL), headaches (HA), and concentration loss (CL).

The second section evaluates WTP in order to reduce road noise annoyance. It is initially explained as the need to create a hypothetical market, which shows the noise mitigation action plan investments for the next 10 years (awareness, mapping, road infrastructure, mobility, etc.) A payment method through a monthly increase in basic services was proposed. A closed-ended referendum question with bids based on a range of percentages of cost of vehicle inspection ($26) was used.

The third section deals with the socioeconomic status (SE) of the respondents according to their housing, education, occupation, technology access, health and life insurance, and consumption levels. Demographic information such as gender (G), age (A), seniors (O) and minors (MO) inhabiting the home, district (P), type of road (R) next to the dwelling, and the height (HF) or floor of the dwelling was also obtained. Finally, the geographic coordinates were acquired.

A sample of 600 respondents throughout the Municipality of Quito answered the personal questionnaire, considering a great diversity of urban scenarios, populations and road densities. Although in CV literature there is no consensus on how to treat protest responses, in this study, individuals who do not agree with the payment do not face the valuation referendum question due to the risk of bias in the estimations (Soliño et al., 2010). The results of this study excluded 14.6% protest responses and the cases with any unanswered questions (7% of the total sample), leaving 469 valid respondents from the original 600 sample.

Protest responses were related to several reasons to give a zero WTP value to reduce road noise annoyance: (a) costs should be included in transportation prices, (b) government should pay all costs to reduce noise, (c) effects of noise pollution from road traffic are negligible. The proportion of protest responses obtained in our study compare well with those of similar European multi-country study on air and noise pollution (Istamto et al., 2014b), as well as the NEEDS study in air pollution (Desaigues et al., 2011), which reported an overall 10% and 11% of protest responses, respectively.

In order to assess road traffic noise exposure for each respondent the day-night noise level (L_{DN}) was predicted through the RLS-90 model, which has produced similar results in previous studies (e.g. Suárez and Barros, 2014). The estimation of L_{DN} requires information about road traffic flow, average speed, composition of traffic flow, road setting, roundabouts, light signals, etc. Road traffic flows and compositions were collected on counting stations installed on the major roads. For streets without traffic flow information, similar roads traffic flows data were used. Velocity data were referred to speed limits for urban roads. The road's surfaces used in the model were: asphalt concrete and pavement stone road, according to an in-situ view. All the geometric data of the road and topography were available in digital format (GIS – ESRI). Buildings contours were drawn using photographs supplied by the Street View Google Maps tool. One hundred hourly noise measurements validated the model results (R^2 = 0.89) over twenty measurement points. All the variables used are reflected in Tables 1 and 2.

3.2. Econometric estimation

To estimate the impact of noise on wellbeing and living conditions (measured using WTP), the literature often focuses on stated preferences analysis (Schlereth et al., 2012). In the setup of impact evaluations, these models can be motivated directly from a setup of utility maximization. That is, individual i is willing to pay up to quantity j for noise reduction if:

$$\mathrm{U_i(pay_j)} \geqslant \mathrm{U_i(pay_k)}\ \forall\ \mathrm{pay_j} \geqslant \mathrm{pay_k}\ \text{and} \tag{1}$$

$$\mathrm{U_i(pay_j)} \geqslant \mathrm{U_i(pay_k)}\ \forall\ \mathrm{pay_j} < \mathrm{pay_k} \tag{2}$$

From this setup a stated preferences analysis estimates Prob(willingnes to pay $\geqslant \mathrm{pay_j}$). Usually available data only identifies if an individual is willing to pay a certain amount. This is a binary outcome, and in this case the choice structure collapses due to a binary problem represented by a logit or probit model. However, our survey allows for observation of a sequence of potential bids for the WTP for each individual, allowing us to exploit this additional variation in our estimations. Since the potential bids are ordered, a natural choice to estimate the WTP is the ordered probit model. For a sequence of bids $\mathrm{a_i}$ the ordered probit estimates:

$$\mathrm{Prob(a_i \leqslant y_i \leqslant a_j | X_i, noise)} \tag{3}$$

where the first bid value is \$0 and the highest is \$ 30. X_i stands for a rich vector of control variables that include characteristics of the individual, characteristics of the household, living condition indicators and health indicators. These variables are included to control for potential confounders of the effect of noise levels on WTP.

3.3. ANN setting and training

The main goal of this study is to validate a methodology, which allows to train an ANN model properly, in order to predict the WPT range of the respondents under a wide range of each of the input variables. This is a nonlinear problem due to the subjective nature of the data. For this reason, we applied a multilayer feedforward neural network architecture with a back-propagation learning algorithm.

The structure of the ANN model consisted of an ensemble (committee) of six networks. Each one of these deals with a different set of variables of the survey (four variables for the first five networks, except the last one, which had the three remaining variables). All the networks were trained to predict the WTP range. The variable distribution in each set was done according to the gain of information of each variable (Hick, 1952). The gain of information depends on the probability of

Table 1
Input variables used in the model.

Input variables			
Module	Variable	Label	Variable Ranges - Codes
Noise perception	Environmental quality importance	EI	Not at all (1), few (2), regular (3), very (4)
	Noise pollution as relevant environmental issue	N_P	Lowest (1) - highest (8)
	Silence as a reason to inhabit	S_H	No answer (0) - first reason (5)
	Awareness of the impact of noise to health	N_H	No (0) - Yes (1)
	Years of residence at home	YH	0–61 years
	Daily hours at home	H_H	0–12 h
	Day road noise annoyance	DA	0–10
	Night road noise annoyance	NA	0–10
	Building refurbishment made for noise mitigation purposes	NC_H	No (0) - Yes (1)
Noise effects	Stress	ST	No (0) - Yes (1)
	Concentration loss	CL	No (0) - Yes (1)
	Sleep disturbance	SD	No (0) - Yes (1)
	Hearing loss	HL	No (0) - Yes (1)
	Headache	HA	No (0) - Yes (1)
Noise level	Day - Night Noise Level	L_{DN}	47–91 dBA
Demographic and socioeconomic	Gender	G	Female (0) - Male (1)
	Age	A	18–25 (1), 26–35 (2), 36–45 (3), 46–55 (4), 56–65 (5), >65 (6)
	District	P	Categorical
	Type of road	R	Local (1), secondary (2), main (3), arterial (4), semi-expressway (5), expressway (6)
	Senior occupants	O	1–10 inhabits
	Minor occupants	MO	0–7 inhabits
	Floor height	HF	1–12 floors
	Socioeconomic status	SE	A(1), B(2), C+(3), C−(4), D (5)

Table 2
Output variables used in the model.

Output variables		
Variable	Economic values	Model Range
WTP	=\$0	1
	(\$0 – \$2.6]	2
	(\$2.6 – \$5.2]	3
	(\$5.2 – \$10.4]	4
	(\$10.4 - \$20.8]	5
	(\$20.8 - \$26]	6
	(\$26 - \$30]	7
	>\$30	8

occurrence of the possible alternatives (in this case the WTP range), and should be that which changes expectation into certainty. The gain of information is given by:

$$Gain\ of\ information = 1 - \sum_{i=1}^{n} p_i I_i [bits] \tag{4}$$

where n is the number of events, p_i is the probability of occurrence of the ith event, and I_i is defined by

$$I_i = -\sum_{i=1}^{n} p_i \cdot log_n(p_i) \tag{5}$$

The outputs of each network of the ensemble are the inputs of the consolidated ANN. For all cases, the training procedure required a training dataset for synaptical weight optimisation, a validation dataset for early stopping purposes, and a test dataset to evaluate the performance of the model (Mennis and Guo, 2009). In order to guarantee that the holdout stratification is conducted properly, it was applied a Kohonen self-organizing map (SOM) approach to perform a cluster classification on the data sets, which is based on similarities in the samples of the same group (which can even be difficult to identify for the naked eye). Next, a random distribution was applied to each cluster using the MatLab *dividerand* function, taking 70% of the samples for training, 15% for validation and 15% for testing. This procedure ensured that all the problem characteristics were taken into account.

The protest responses were not considered for the training procedure due to its evident lack of representativeness in a WTP range prediction model. Moreover, such responses have a significant number of occurrences if compared to the total sample (14.6%).

The input variables were preprocessed using a normalizing algorithm (*mapminmax* Matlab function) in order to present homogenous inputs to the networks and facilitate training. Since most of the employed artificial neurons use a tansigmoid activation function, this normalizing procedure comes in handy since it allows to present in a defined range $[-1;\ 1]$ all the variables involved, regardless its nature (dichotomic, categorical and numerical). All the ANNs use the *resilient backpropagation* algorithm (*trainrp*). To establish the ANN architecture, it was assessed the mean squared error (MSE) and the generalisation performance of a single hidden layer structure, in an iterative procedure which tested the number of neurons in this layer from 5 to 350 elements. In order to avoid inconsistencies due to random nature of the synaptical weight initialisation, the iterative procedure was conducted eight times. Fig. 3 shows average results of the procedure in terms of the MSE. All the networks of the ensemble had one hidden layer with 230 neurons.

All the ANN of the committee uses in their hidden layers a *hyperbolic tangent sigmoid* (*tansig*) activation function, whilst the output layer used a *linear* (*purelin*) activation function (Fig. 4).

The training, validation and test performance for WTP range prediction in the consolidated ANN are shown in Fig. 5. In order to identify the instant when the model began to lose the capacity of generalisation, the early stopping approach was applied. The three curves in the figure have similar decays, showing evidence that overfitting problems were avoided. The best validation performance in terms of MSE (0.531) occurs at epoch 84, whilst the test MSE was 0.4614.

In order to assess the learning procedure of each network, Table 3 indicates the MSE values obtained from the training, validation and test datasets. It is noteworthy that there is a reduction of the MSE in the consolidated network (7) for the three processes compared to the individual networks.

It is worth noting that Table 3 shows the model preparation errors (training phase). Although this gives a general idea, it does not precisely represent the errors in the performance of the ANN model (execution phase), which is discussed in the next section.

Finally, it must be taken into account that the training process requires a significant computational effort. Some of these procedures even involve human intervention for adjusting some architecture configurations. Nonetheless, this complexity has not any relevance when the model is all set. The computer cost of the ANN model in execution phase (in temporal complexity terms) is not meaningful for this particular study, given an impression of instantaneity from the human point of view.

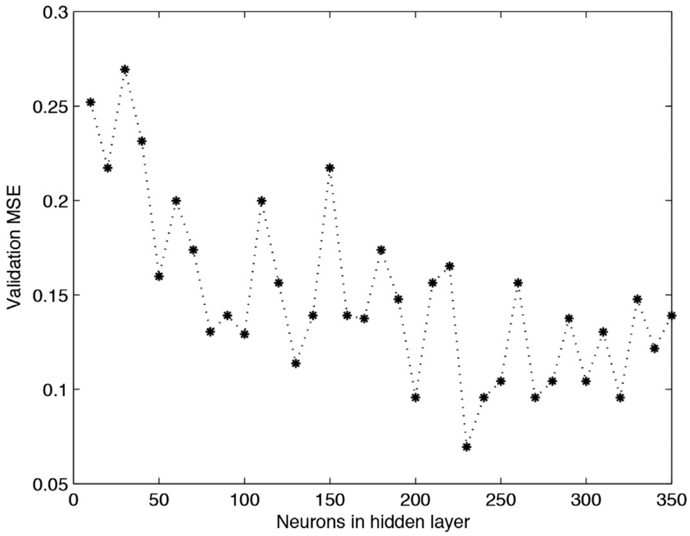

Fig. 3. ANN performance as function of the number of neurons in hidden layer.

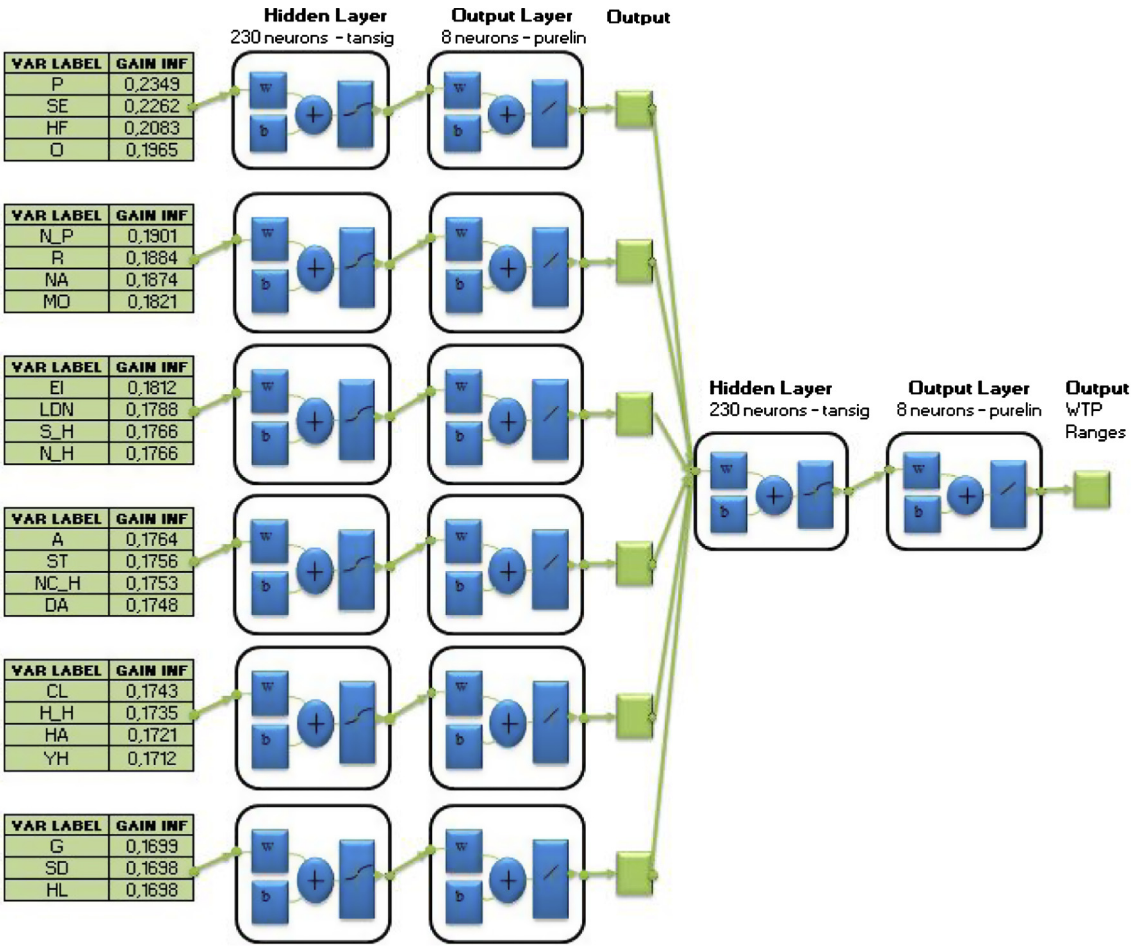

Fig. 4. Architecture of the ensemble of networks used in the model.

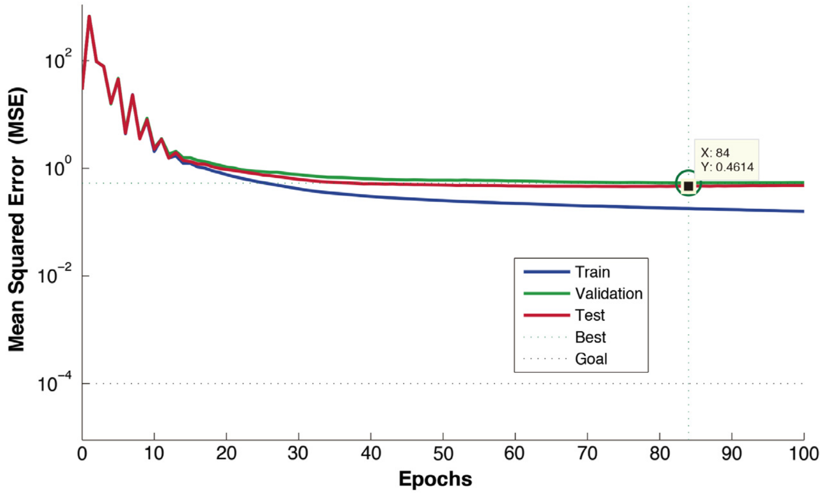

Fig. 5. MSE of the training, validation and test datasets for the WTP ranges of the consolidated ANN.

Table 3
Results of the ensemble of neural networks.

Network	1	2	3	4	5	6	7
Performance	0.390	0.43	0.361	0.335	0.352	0.399	0.158
Training error (MSE)	0.3899	0.4302	0.3634	0.3353	0.3781	0.4346	0.1779
Validation error (MSE)	0.877	2.028	0.7865	0.876	0.5669	0.4346	0.5310
Test error (MSE)	1.372	1.173	0.515	0.494	0.5669	0.4346	0.4614

Note: All the networks in the ensemble used 230 neurons in the hidden layer, 100 epochs for the training phase, a learning rate of 0.1, and a performance goal of $1 * 10^{-4}$.

4. Results

In order to classify the WTP of the respondents Table 4 shows a comparison between the results obtained with econometric and ANN models. The MSE of the econometric model is 0.88 and 0.87 for the estimation and validation subsets, respectively, whilst for the ANN model, the MSE is 79.88% less than the econometric model for the estimation subset and 42.98% less for the validation and test subsets.

The data used for estimation/training, and validation (and test) in both econometric and ANN models were 329 and 140, respectively. In the validation and test subsets, the econometric model predicted 89.3% of the WTP > 0, whilst in the ANN model predicted percentage was 95.9%. Comparing the last values the ANN model presents 7.4% better accuracy in predictive performance. However, for the cases where WTP = 0, the econometric model fails in 78.4% of the 37 cases (corresponding to

Table 4
Predictive power of the models.

Estimation/Training Subset	Econometric model MSE 0.88			ANN model MSE 0.177		
	WTP > 0	WTP = 0	Total cases	WTP > 0	WTP = 0	Total cases
Survey WTP > 0	91.4%	8.6%	243	92.2%	7.8%	247
Survey WTP = 0	64.0%	36.0%	86	13.4%	86.6%	82
Total			329			329
Validation & test subsets	Econometric model MSE 0.87			ANN model MSE 0.461		
	WTP > 0	WTP = 0	Total Cases	WTP > 0	WTP = 0	Total Cases
Survey WTP > 0	89.3%	10.7%	103	95.9%	4.1%	99
Survey WTP = 0	78.4%	21.6%	37	8.6%	91.4%	41
Total			140			140

The predictive power of the models is assessed through a comparison between its results and the survey answers. For example, the present information shows that for WTP > 0, in the validation and test subsets, 89.3% and 95.9% of the results are the same as the survey answers in the econometric model and ANN model, respectively. On the other hand, for WTP = 0 in the same subset, the econometric model presents differences in 78.4% of the cases if compared to the survey answers. This contrasts with the ANN model, which disagrees with the survey in only 8.6% of the cases.

Table 5
Percentage error values comparison for econometric and ANN models for each range of WTP.

Ranges	Mean variance (Input)	Weight [%]	Econometric model		ANN model		
			Estimation MSE 0.88	Validation MSE 0.87	Training MSE 0.177	Validation MSE 0.531	Test MSE 0.461
1	18.08	26.23	16.28	20.72	13.40	11.40	8.57
2	11.76	0.85	0.00	100.00	1,52	0.00	0.00
3	28.52	7.47	8.00	10.00	16.4	2.86	0.00
4	14.53	12.58	12.20	16.67	9.73	2.86	2.86
5	13.31	18.76	19.05	16.00	10.00	7.14	12.90
6	20.34	8.96	10.34	7.69	5.47	4.29	5.71
7	14.43	4.69	6.67	42.86	4.26	2.86	2.86
8	17.96	20.46	19.40	17.24	7.29	5.71	4.29
Weighted average			15.20	18.57	8.69	6.37	2.65

Table 6
Percentage difference between the predictive powers of the initial ANN and a setting excluding each input variable.

Excluded input variable	Percentage difference %
NA	9.0
SE	7.9
H_H	7.1
L_{DN}	6.9
P	6.4
HF	6.4
N_P	6.2
A	6.2
YH	6.2
ST	5.8
N_H	5.4
G	4.9
S_H	4.7
NC_H	4.5
EI	4.3
R	3.9
O	3.2
DA	3.2
HA	3.2
HL	3.0
MO	2.8
CL	2.8
SD	1.3

20.72% of all the cases in the validation subset), whilst the ANN model present 91.4% of the 41 cases the same results of the survey.

Table 5 indicates the percentage errors of each WTP range for the econometric and ANN models, showing the portion of results that are not agree with the target vector (survey answers). These results were obtained using a cutoff value (0.5) to approximate the output of the econometric model. In the ANN model the range was defined by selecting the highest value of the eight options present in the output vector.

A weighted average (last row in Table 5) based in the number of cases present in each range (according to the survey) was applied to obtain the global prediction performance results of each model. Comparing the weighted average for estimation and training subsets in both econometric and ANN model, the ANN model presents 42.83% better accuracy. These results are even better for the validation and test subsets, which show 85.72% better performance in the ANN model. A reading considering each range by separate also shows a better performance in the ANN model (test subset) compared to the econometric model (validation subset). The highest error in the ANN model (12.9%) was found in range five.

Table 6 shows the relative significance of each input variable in the ANN model, which means its contribution for the estimation of WTP. This analysis consisted in conduct 23 new training procedures excluding one input variable from the ANN model. Then the predictive power results of each simplified setting were compared to the one obtained with the complete setting. A higher difference between the results indicates that the variable excluded has a higher influence in the ANN model. All the results of the simplified setting were consistent in delivering a lower performance of the original setting, which varied from 1.3 to 9%. For instance, night annoyance is the most relevant variable in the ANN model (9.0%), followed by socioeconomic status (7.9%) and the daily hours at home (7.1%). On the other hand, noise effects on health such as: headache, hearing

Table 7
Cochran's Q Test for training and testing subsets in each WTP range.

Range	Training		Test		Cochran's Q	df	Asymp. Sig.
	Mean	Std. Dev.	Mean	Std. Dev.			
1	0.11	0.309	0.1	0.302	2.00	1	0.368
2	0.02	0.134	0	0	2.00	1	0.157
3	0.036	0.187	0.028	0.167	0.2	1	0.655
4	0.063	0.244	0.042	0.204	0.5	1	0.480
5	0.112	0.316	0.157	0.366	0.59	1	0.808
6	0.051	0.221	0.057	0.233	0.667	1	0.414
7	0.039	0195	0.042	0.204	0.2	1	0.655
8	0.094	0.292	0.057	0.233	0.818	1	0.366

Table 8
Estimated mean WTP.

Model	WTP ($)	Empirical confidence interval (95%)
Ordered probit	12.19	(11.01–13.36)
ANN	15.70	(14.60–16.81)

loss, lack of concentration or sleep disturbance, and junior inhabitants at home were the less relevant variables in the ANN model.

In order to ensure the ability to generalise of the ANN model, and due to the nature of the dependent variable (dichotomous categorical), it was applied the Cochran's Q test (Higgins et al., 2003) for equality of means between the MSE of the training and testing datasets. The results in Table 7 indicate that there is insufficient statistical evidence to reject the equality of means, i.e. it can be assumed that the average value of residuals (MSE) is similar in the training and test subsets (two-tailed significance > 0.05), which means that the model has a great capacity for generalisation, due to the similarity between the residuals in the training and the testing subsets.

Another relevant result of the monetisation of this study is shown in Table 8, which indicates the estimated mean WTP to reduce road traffic annoyance using both ordered probit and ANN models. Despite being not completely correct, this offers adequate estimations of the WTP (Álvarez Díaz et al., 2010) since it is the welfare measure that policy makers would consider to develop a scheme for noise mitigation action plans. Comparing the results obtained for the two approaches, the mean WTP for el ANN model is 28.8% higher than the ordered probit model. However both values are in the same WTP range (10.4–20.8) equivalent to the median WTP range for both approaches.

5. Discussion

In this study, although the MSE obtained in the two approaches is a good indicator that the model preparation was carried out correctly (estimating and training), it is not a useful estimator of the models performance. This is due to the rounding procedures applied in both outputs (econometric and ANN models) before the actual prediction of the WTP. Therefore, the predictive power of the models can be effectively assessed by quantifying the number of correctly prognosticated WTP ranges, i.e. the performance percentage error for each range, or the global performance described in the weighted average. Compared to the econometric model, the main advantage of this approach is that it presents 85.72% accuracy improvement in terms of the weighted average percentage error.

The results obtained for the first WTP range (WTP = 0) are 26.23% of the survey answers (Table 5). This represents respondents who cannot afford to pay or did not have enough information. In this case, the lack of awareness constitutes a particular subjective matter not related to the other inputs. That is the reason why the econometric model, based in the significance of the input variables and the likelihood of producing a result, fails in the majority of the cases. On the other hand, it is widely known that ANNs deal with nonlinear problems, and model with better accuracy the related subjective issues. This is shown in the ANN committee results, which indicate that the ANN model can predict with 89% better accuracy than the econometric model for the WTP = 0 cases. It was observed that for each WTP range the ANN model shows lower values of percentage errors than the econometric model. It was also perceived that, in general terms, the percentage error presents a direct relation with the number of survey cases for each range. This is due to the variance measures related to the variables present in the input vector for each case. It can be observed that the ranges with more cases present a higher variance in the input vector. In ranges 3 and 5 the last do not apply, probably due to several categorical variables in the input vector, which could not be considered for variance calculation.

Evaluating the contribution of each variable in the ANN setting, it is observed that all variables were relevant. The performance in the simplified settings shows that the model relies in all the information provided by the 23 variables. Moreover, leaving one variable out affects the predictive capacity in different levels, depending on the variable. It was also observed that socioeconomic status, road noise night annoyance, district, and the height or floor of the dwelling presented similar significance using the gain of information classification. Despite noise exposure level is not considered a relevant variable in the gain of information classification (Fig. 4), it is really significant in the contribution of the ANN setting, as well as the awareness of the effects of noise in health according to Table 6.

It is worth emphasizing the results in Table 7, which indicate that the average value of the statistical MSE will be similar in the training and testing datasets. This shows the great potential of the generalisation of the model with an ANNs committee, which not only can learn and predict responses in the training phase, but can also predict samples of the same nature not used in the model setting.

The collected evidence states that the ANN model is capable of predicting the WTP of the people living in Quito to reduce the road noise annoyance from diverse conditions presented to the network. These conditions involve heterogeneous and complex noisy environment scenarios, as well as diverse demographic and socioeconomic characteristics of individuals. This indicates that the methodology presented here is suitable for determining the cost of road noise and can be applied in the same way in other geographic, social and cultural scenarios in order to contrast the obtained results.

The presented results estimate the median WTP to reduce road traffic noise annoyance in the range of 10.4–20.8 $/year. A recent comparable study is the 6th EU Framework study INTARESE (Istamto et al., 2014a) which conducted an open ended web-based contingent valuation to estimate the perceived economic values of traffic related air pollution and noise health risks over five European countries. The median WTP estimates to avoid a 13% increase in severe annoyance by road traffic noise were: 10 €/year in Netherlands and UK, 20 €/year in Germany, 30 €/year in Spain, and 50 €/year in Finland. Another study in Latin-American country suggests that the median WTP for reducing noise levels in Santiago de Chile is 25.4 $/year (Galilea and Ortúzar, 2005). These results show the high sensitivity of the models with respect to the variables used and its specific economic conditions.

As mentioned above, the literature review does not reflect the use of ANN for predicting the WTP for road noise mitigations using contingent valuations. Nonetheless, Selim (2009) conducted a comparison between a hedonic regression and ANN model for housing attributes in Turkey, which confirmed that the ANN model performs 82.2% better prediction in terms of MSE.

6. Conclusions

It was presented an alternative approach to value traffic noise impact by means of WTP prediction conducted with an ANN committee. This committee was trained with a contingent valuation survey conducted on the Quito Metropolitan District, which showed WTP to reduce road traffic noise annoyance.

By examining which parameters influence WTP, we determinate the high significance of the district, socioeconomic status, the junior and senior inhabits at home, the day and night road noise annoyance perceived and the noise exposure levels, compared to other inputs variables (demographics and perceived noise experiences). The variable distribution on the ANN committee (shown in Fig. 3) was determined by the impact level of such variables, defined by the gain of information. The structure of the committee consisted of six neural networks with four input variables each, except one network, which had the three last inputs. In all the networks, one hidden layer with 230 neurons was used. The outputs of each individual ANN feed a consolidating network that provides the model result (WTP range).

The proposed model presents considerable improvements on accuracy in predicting WTP ranges (85.7% in terms of the weighted average percentage error), if compared to an ordered probit econometric model.

As mentioned in theoretical consideration section, an ANN approach is considered as a statistic machine learning procedure. This kind of procedure produces results based on the previously learned experience from a certain quantity of samples (modelled or experimental), which are considered as representative of the problem. This is the reason why an ANN model is quite sensible to the quantity and quality of the training dataset used for synaptic weight optimisation. The network architecture and the data amount necessary for conducting a successful training process are problem dependent and are set in an empirical process of trial and error. In this particular study, all datasets come from an empirical source (personal survey). Nonetheless, the accuracy in the results shows that the ANN architecture was correctly set and the core problem was properly represented by the quantity and quality of the input-output pairs used for training. Moreover, the predictive capacity of the model is reaffirmed considering that the generalisation ability is validated by the accuracy of the test dataset results. In general terms, the WTP is highly dependent of the wealth and cultural characteristics of the society. Therefore, if the model is to be applied for other scenarios, new surveys must be done in that particular scenario in order to have related information to conduct new training procedures to adjust the model to that new reality, following the methodology described in this work.

The prediction and modelling of the WTP ranges constitute a complex and nonlinear issue given the nature of variables involved. The results obtained in this work suggest that an implementation of a committee of ANN (due to its intrinsic strengths) can approximate a satisfactory solution. This certifies ANN as a useful tool to policy makers, seeking to know the value of noise in order to get financial resources to develop action plans.

Appendix A. Perception and WTP survey

Part I Noise perception

1. How relevant is for you the environmental quality of your city?

Very ☐ Regular ☐ Few ☐ Not at all ☐

2. In your opinion, how do you prioritize the following environmental issues?

Air pollution ☐ Noise pollution ☐ Water/river pollution ☐
Waste management ☐ Species extinction ☐ Forest fires ☐

3. How do you prioritize the main 5 reasons to choose your house?

Location ☐ Nearness to job ☐ Nearness to school ☐ Price ☐ Neighbourhood ☐
Sight ☐ Size/Volume ☐ Public transport access ☐ Silence ☐ Property quality ☐
Safety ☐ Absence of industries ☐

4. Do you know that noise has impacts on human health? Yes ☐ No ☐
5. How long have you live in your current house? (years)
6. How much time do you spent at home in daytime? (hours)
7. How do you describe the environmental noise that you perceive indoors during daytime?

Silent ☐ moderate noisy ☐ noisy ☐ very noisy ☐

8. How do you describe the environmental noise that you perceive indoors during night-time?

Silent ☐ moderate noisy ☐ noisy ☐ very noisy ☐

9. Taking account the last 12 months, when you are at home how much does noise from road traffic annoy you in daytime?

Not at all ☐ slightly ☐ moderately ☐ very ☐ extremely ☐

10. In a 0 -10 scale, how much road traffic noise annoys you when you are at home in daytime?
11. Taking account the last 12 months, when you are at home how much does noise from road traffic annoy you in night-time?

Not at all ☐ slightly ☐ moderately ☐ very ☐ extremely ☐

12. In a 0 -10 scale, how much road traffic noise annoys you when you are at home in night-time?
13. Which are the 3 most audible noise sources that you perceived at home?

Traffic noise ☐ Aircraft noise ☐ Construction noise ☐ Leisure noise ☐ Community Noise ☐

14. Have you ever invested a refurbishment at your house for noise mitigation purposes? Yes ☐ No ☐
15. Have you ever felt any of the following noise effects on your health?

Stress ☐ Lack of concentration ☐ Headache ☐ Sleep disturbance ☐ Hearing loss ☐

Part II Willingness to pay

Suppose that the City Hall conducts a noise reduction plan to be run during the next ten years, aimed at mitigating noise pollution and reducing road noise annoyance. The action plan will target the following issues: awareness and educational programs about noise and the responsible use of vehicles, traffic noise mapping, improvement of acoustic isolation in high sensitive dwellings, control and sanctions of infractions, installation of acoustical barriers, massive transport, infrastructural enhancement, etc. In order to finance this project it will require public funding levied from fees applied to basic utilities.

16. Are you willing to pay an annual fee to reduce road noise annoyance? Yes ☐ No ☐
17. If NO, why?

Costs should be included in transportation prices ☐ Government should pay all costs to reduce noise ☐
Effects of noise pollution from road traffic are negligible ☐ I cannot afford the fee ☐

18. Considering the required cost for vehicle inspection ($26). Are you willing to pay annually to reduce road noise annoyance

Yes		No	Yes		No	Yes		No
☐	$2.6	☐	☐	$5.2	☐	☐	$10.4	☐
☐	$20.8	☐	☐	$26.0	☐	☐	$30.0	☐

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