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Alternative approach for valuing road traffic noise: Case study of Quito, Ecuador.

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Abstract

This study reports the results of a contingent valuation of road traffic noise in Quito, Ecuador. Two approaches were evaluated: an ordered probit econometric model and a committee of artificial neural networks. The input variables were obtained through a social survey that assess the respondent's noise perception and socio economic status as well as the modelled noise exposure level. A comparison indicates that the ANN model can predict the willingness to pay to reduce road noise annoyance with 85.7% better accuracy than the econometric model. The proposed approach reaches an adequate generalisation level, becoming a tool for determining the cost of transportation noise in a policy-making context.

Keywords: contingent valuation, road noise, artificial neural networks, willingness to pay, Quito.

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1 Introduction

Transportation noise has been a source of discomfort due to the population growth in urban areas. Scientific evidences reveal that noise pollution causes many health problems, such as: cardiovascular effects [1], cognitive impairment in children [2], or atrial fibrillation [3]. The first phase of strategic noise mapping across the EU estimates that over 56 million urban population are exposed to noise above 55 dBA during daytime, and 40 million people are exposed to night noise above 50 dBA [4]. These results are worrying given the WHO guidelines that suggest a 40-dBA noise level for night-time as the threshold at which noise effects are noticeable [5].

Noise pollution in Latin American countries is not different. Recent studies in Chile, Colombia and Brazil estimated that over 50% of the main urban cities recorded noise level above the WHO recommendation [6], [7] y [8].

Noise pollution incidence can be assessed in economic terms through different methods such as contingent valuation (CV) or hedonic pricing (HP). CV is a stated preference method that estimates the willingness to pay (WTP) in order to modify a welfare status. On the other hand, HP is a revealed preference method that estimates an economic value of any externality in the real state market [9].

Artificial intelligence techniques such as artificial neural networks (ANN) could be an alternative approach for solving transportation issues, specifically noise related problems, such as: predictions of noise levels [10,11,12,13,14], road noise annoyance relationships [15], or even soundscapes quality [16]. Nonetheless, contingent valuations of road traffic noise using ANNs have not been founded in the literature.

The costs of noise are relevant for policy makers in order to compare and justify actions plans to reduce noise pollution. Navrud [17] conducted a literature review of transportation noise valuation in developed countries, confirming the pertinence of this topic.

In this study we aim to value road traffic noise with a CV method using artificial neural network, and compare its prediction capacity to an econometric ordered probit model. This was realised through a personal survey and noise prediction model data inputs including: individual´s noise perception, demographics and socioeconomic status, and day-night noise exposure level Ldn.

2 Intelligent forecasters and classifiers

ANNs are one of the numerical techniques of artificial intelligence that are capable of adapting unknown functional forms with an specified degree of accuracy, intending to operate in a similar fashion to the human brain, and have shown to be a relevant tool for forecasting and classification issues.

Figure 1 indicates a common structure of ANNs that is formed by the input data vector, the hidden layer(s), and the output (target) layer. Each layer contains neurons fully connected to the other neurons in adjacent layers.

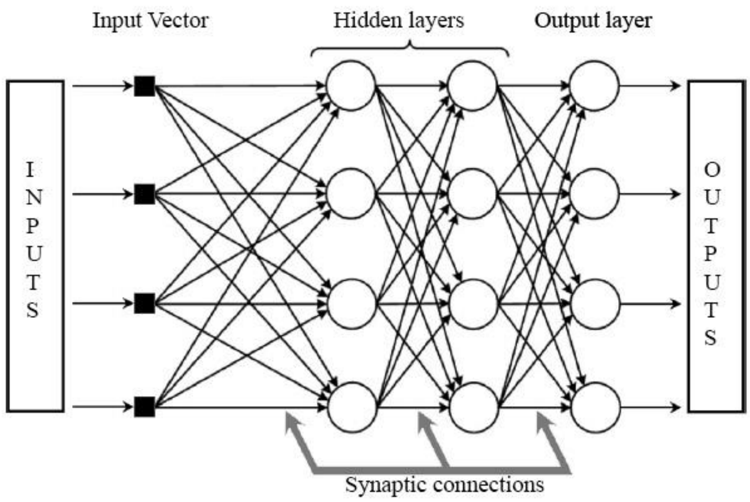

Figure 1: Neural network structure

In the hidden and output layers occur two processes: the synaptic weighted summation, which represents the "memory" of the system, and the activation function, which calculates the activation level of the neuron.

In feed-forward networks, the synaptic weights of all the neurons on each layer are multiplied by the input vector and evaluated by an activation function before proceeding into the next layer. In mathematical terms, neural processing is defined by (1) and (2):

$$sum_k = \sum_{i=1}^{n} w_{ki} x_i \tag{1}$$

$$out_k = f(sum_k) \tag{2}$$

where out_k refers to the output of the k_{th} neuron and w_{ki} is the synaptic weight associated with the i_{th} input x_i. The input-output relations can be encoded in the synaptic weights during a training procedure called backpropagation [18].

The training process adjusts the synaptic weights as a function of the error between the desired target functions and the network's output such that the differences between them 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.

The other characteristic of ANN is generalisation. After the neural network has been trained, a new input vector (not used during training) is presented to the network, and a recall procedure is activated, which attempts to produce similar outputs from similar inputs from the training dataset and attempts to avoid overfitting phenomena. The network should become well trained so that it learns enough about the past to generalise to the future [19].

An improved generalisation capacity can be reach with an approach that combines the networks into an ANN committee, leading to a significant improvement in the predictions of new data [20]. This is due to the reduced variance produced by averaging several results.

3 Methodology

3.1 Data collection

An in-person survey applied to 600 subjects across the Quito dwellings was conducted according to the NOOA panel report guidelines for CV [21]. The first section of the survey deals with noise perception of the respondents in the following variables: 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).

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 the bids was used ($2.6, $5.2, $10.4, $20.8, $26, and $30).

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), years of residence at home (YH), hours of daytime permanence at home (H_H), seniors (O) and minors (MO) inhabiting the home, parish (P), type of road (R) next to the dwelling, and the height (H) or floor of the dwelling was also obtained. Finally, the geographic coordinates were acquired.

In order to assess road traffic noise exposure for each respondent the Ldn was predicted through the RLS-90 model.

3.2 Econometric estimation

For this study, the utility function (3) was assumed:

$$y_i^* = \beta x_i + e_i \tag{3}$$

where y_i* is the WTP ranges, β are the coefficients of the independent variables x_i, and e_i is a vector of not observed attributes equivalent to the error in the model. The WPT bids values y_i* were: \$0, \$2.6, \$5.2, \$10.4, \$20.8, \$26, and \$30. The econometric model uses a maximum likelihood method, where the probability that an observation is in any of the WTP ranges is calculated.

The WTP likelihood density is defined as (4):

$$L_i = \prod_{i=1}^{8} P(y_i)^{I(y_i)} \tag{4}$$

where $P(y_i)$ is the WTP probability for bid range, and $I(y_i)$ is a dichotomous index for the occurrence or not of the WTP in each range. Numerical analysis allows us to obtain the values of β in terms of the WTP and not in terms of the likelihood density.

3.3 ANN setting and training

The prediction of the WTP ranges is a nonlinear issue due to the subjective nature of the data. For this reason we applied a feed-forward neural network with backpropagation algorithm in its training process.

The input information of the model are 23 variables took from the first and third section of the survey. The target functions are arrays of 8 binary elements, each one representing a WTP range, and were set with the information of the second section of the survey.

The optimal architecture was defined in several empirical tests of trial and error. The best performance was reached by a committee of six networks, each one trained to predict target functions but operating with a different fraction of the input information (4 or 3 variables from the original 23). These fractions of input information were defined according to its gain of information given by Eq. 5.

$$Gain\ of\ information = 1 - \sum_{i=1}^{n} p_i \,.(- \sum_{i=1}^{n} p_i\, log_n(p_i)) \tag{5}$$

where n is the number of events, p_i is the probability of occurrence of the i_{th} event.

The outputs of each individual network are the inputs of the consolidated network.

Dataset was randomly divided in training (70%) for synaptical weight optimisation, validating (15%) for early stopping purposes, and testing (15%) for evaluating the performance of the model.

The input variables were normalized in order to present homogeneous data to the networks, and all the networks used in their hidden layer the *tansigmoid* a transfer function, whilst in the output layer the linear transfer function was used, as show the fig. 2.

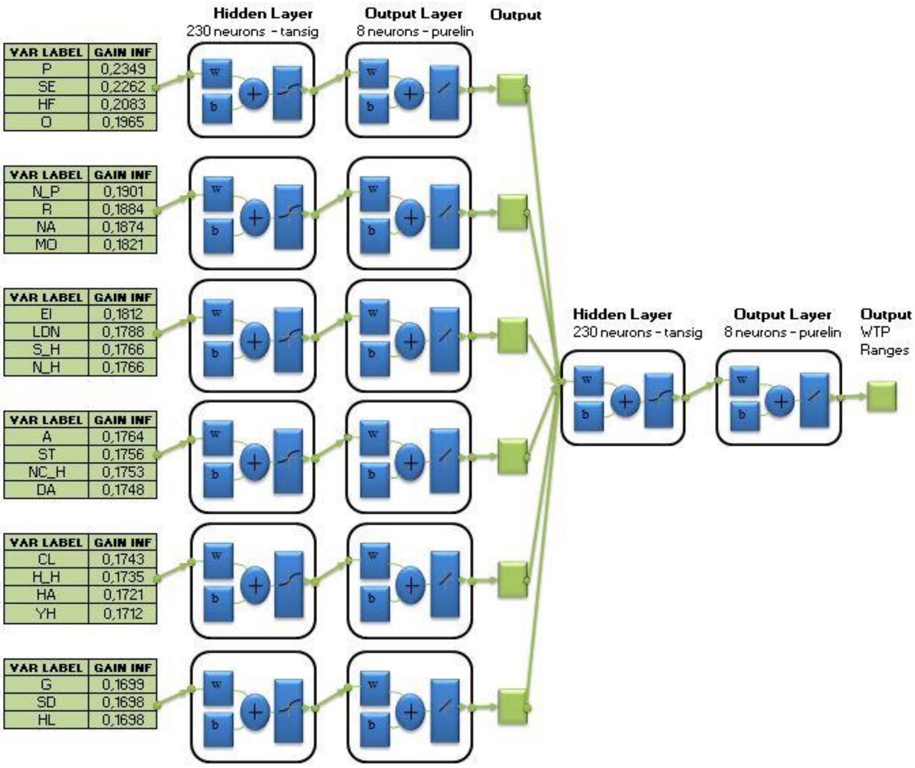

Figure 2. Ensemble of ANN used in the model.

Fig. 3 specifies the mean squared error (MSE) during the training procedure. All the curves present similar decays showing evidence that overfitting was avoided. The early stopping occurs on 84th epoch where the difference between training and validation MSE has a minimal.

Table 1 indicates the MSE values obtained for the training, validation and test datasets of the consolidated network.

Table 1. Consolidates network performance

Performance	0.158
Training error (MSE)	0.1779
Validation error (MSE)	0.5310
Test error (MSE)	0.4614

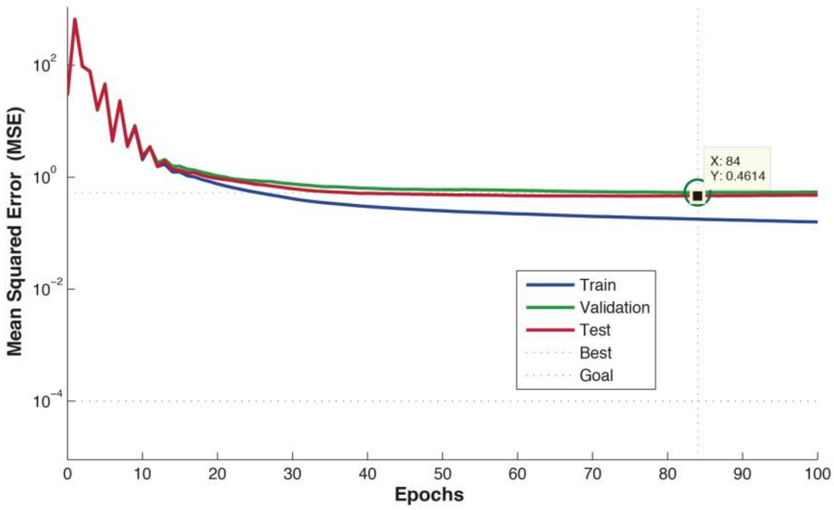

Figure 3. MSE of the training, validation and test datasets for the WTP ranges of the consolidated ANN.

4 Results

Table 2 shows the percentage errors of each WTP range for both econometric and ANN models, indicating the portion of results that are not agree with the target vector (survey answers). These results were obtained using a cut-off 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.

Table 2. Percentage error values comparison for econometric and ANN models for each range of WTP.

Ranges	Weight [%]	Econometric Model Error [%]		ANN Model Error [%]		
		Estimation MSE 0.88	Validation MSE 0.87	Training MSE 0.177	Validation MSE 0.531	Test MSE 0.461
1	26.23	16.28	20.72	13.40	11.40	8.57
2	0.85	0.00	100.00	1,52	0.00	0.00
3	7.47	8.00	10.00	16.4	2.86	0.00
4	12.58	12.20	16.67	9.73	2.86	2.86
5	18.76	19.05	16.00	10.00	7.14	12.90
6	8.96	10.34	7.69	5.47	4.29	5.71
7	4.69	6.67	42.86	4.26	2.86	2.86
8	20.46	19.40	17.24	7.29	5.71	4.29
Weighted Average Error		15.20	18.57	8.69	6.37	2.65

A weighted average (last row in Tab. 2) 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).

Another relevant result of the monetisation of this study is shown in Table 3, indicating 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 [22] 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.

Table 3. Estimated mean WTP.

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

5 Conclusions

It was presented an alternative approach (not found in the literature) 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 parish, 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, if compared to an ordered probit econometric model. Compared to the econometric model, this structure presents 85.72% accuracy improvement in terms of the average percentage error.

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 research.

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 study 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.

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