Transportation Research Part D 50 (2017) 26–39

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Neural based contingent valuation of road traffic noise

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ARTICLE INFO

Article history:
Received 1 March 2016
Revised 19 August 2016
Accepted 29 October 2016
Available online 9 November 2016

Keywords:
Artificial neural network
Contingent valuation
Road traffic noise

ABSTRACT

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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http://dx.doi.org/10.1016/j.trd.2016.10.020
1361-9209/

(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.