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Modelling Short Distance Intra-Town user Mode Choice: An Artificial Neural Network Approach

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Abstract—*Application of artificial intelligence is growing rapidly in many diverse fields of engineering and transportation engineering is no exception to that. In recent years, neural networks and fuzzy systems are being experimented in analyzing travel demand as well as for the purpose of forecasting travel demand. It has been found that Artificial Neural Networks (ANN) can be used as an effective tool in travel demand analysis. The basic reason lies in the fact that neural networks are able to capture complex relationships and learn from examples and also able to adapt to the new data when they become available. Transportation mode choice analysis has been a subject with regard to the Artificial Neural Networks approach in recent times. It is seen that most of the researches deal with extra urban (inter-city or intra regional) trips to calibrate the mode choice model. The present research aims to develop mode choice models using artificial neural networks (feedforward backpropagation algorithm) taking the short distance intra-town trips (<3 km) in case of a small developing Indian town namely Hailakandi in the state of Assam,where multiple types of modes are available, and allows to investigate the user mode choices. The results obtained can be interpreted to show that artificial neural network approach can be an effective tool in predicting user mode choice in small distance trips.*

1. INTRODUCTION

The traditional four-step travel demand analysis procedure has four main steps involved- Trip Generation, Trip Distribution, Mode Choice, and Traffic Assignment. Mode choice can be defined as that aspect of the demand analysis process that determines the number (or percentage) of trips between zones that are made by different types of available modes (Garber and Hoel, 2002). The selection of one mode or another is a complex process that depends on factors such as the traveller's income, the availability of transit service or auto ownership, and the relative advantages of each mode in terms of travel time, cost, comfort, convenience, safety etc. Usually, mode choice analysis as regards a transportation system is handled as a discrete choice problem and conventional tools such as multinomial logit model, nested logit model, probit model etc. are used (Domencich and McFadden, 1975; Ben Akiva and Lerman, 1985; Hensher et al, 1999; Cascetta, 2001). But recently, modelling discrete choice behaviour associated with transportation has been in the context of soft computing applications like artificial neural networks. Neural networks have been used in the transportation demand forecasting by Chin et al (1992), Teodorović and Vukadinovic (1998), and forecasting intercity flows by Nijkamp et al (1996). Celikoglu (2006) shows that application of ANN as simple Multi Layer Perceptron(MLP) may outperform the utility function calibration in travel choice modeling, while Rao et al. (1998), Xie et al. (2003), Adrande et al. (2006), Zhang and Xie (2008) and Hensher and Ton (2000) reported MLP's predictive capability as superior over multinomial and nested logit models. Cantarella and de Luca (2005) found that multilayer feedforward networks (MLFFNs) can be a feasible tool for travel demand analysis. According to Tortum et al (2009) Modeling of mode choices of intercity freight transportation with the ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) shows that the almost every value predicted in all the models and the distribution of the errors is very close to the zero line. In addition, the error histograms are not widely open to the right and left directions, the zero error frequency is high and also in the model the predicted values together with the observed values are in good agreement. Recently, Gazder and Ratrout (2015) developed a new technique of ensembling Logit model with ANN which showed consistently high accuracies for overall predictions as well as individual mode predictions for all multinomial problems. The proposed ensemble was more beneficial for multinomial choice problems as compared with binomial choice problems. However, most of the researches are found to deal with long distance inter-city or intra-regional trips to calibrate the mode choice model where the available modes are rather limited.

The present study is done in case of small distance intra-town trips in an Indian town namely Hailakandi in the state of Assam where the available modes of travel are diverse which makes the prediction problem rather complex compared to extra urban mode choice modelling problems.

The aim of this paper is to show that application of artificial neural network can be more fruitful than conventional multinomial logit model in predicting the user mode choice in case of small distance intra-town trips where multiple modes are available to the user. The proposed approach is based on the feedforward backpropagation algorithm, as in the cited papers.

2. ARTIFICIAL NEURAL NETWORK (ANN)

Neural networks are capable of learning from examples, generalizing the knowledge learnt and apply to new data, and above all they are able to capture complex relationships in a relatively easier way than other computational methods. Conceptually, feedforward neural networks approximate unknown functions to a good level of accuracy, i.e., they can be considered as "universal approximators". The theorem proved by Hornik et al (1989) and Cybenko (1989) states that a multilayered feedforward neural network with one hidden layer can approximate any continuous function up to a desired degree of accuracy provided it contains a sufficient number of nodes in the hidden layer.

Artificial Neural Networks can be divided into several types depending upon the functional algorithm and network architecture. For prediction purposes in various fields, Feedforward Multi-layer Perceptrons (MLPs) or Feedforward backpropagation algorithm are generally being used because of their inherent capability of input-output mapping. In this paper, Feedforward ANNs are used for developing user mode choice prediction models in context to transportation.

All ANNs have some processing units known as neurons. Each neuron uses some mathematical functions which transfer the summation of inputs, carried through links of specific strength or weight, to outputs and these functions are called transfer function or activation function. An ANN may consist of several layer of neurons of which 1st layer of nodes is known as input layer and last layer of neuron is known as output layer. The layers in-between the input and output layer are called hidden layers. The nodes of the adjacent layers are connected by acyclic arcs from a lower layer to a higher layer in a feedforward network. Designing of feedforwrd network means deciding the following points-

- The number of nodes of input layer.
- The number of hidden layers and number of nodes in each layer.
- The number of nodes in output layer.
- The transfer function to be used in hidden and output layer.

3. STUDY AREA AND DATA COLLECTION

Hailakandi town is the district headquarter of Hailakandi district in the Indian state of Assam. The Hailakandi district is one of the three districts of Southern Assam which is commonly known as Barak Valley. The transportation scenario of Barak Valley region is suggestible of its lack of proper and researched planning as well as engineered application. The low density development, coupled with narrow and irregular roads, limits the feasibility of conventional public transit systems in this region. In all of the three major towns, which in turn are the district headquarters also, namely Silchar, Karimganj and Hailakandi, various paratransit modes have become the dominating mode of public transportation. Out of these three towns, Hailakandi is the most growing one in terms of road network as well as modes of transportation. With the recent introduction of e-rickshaw and autorickshaw, the traffic scene of the town has seen a sudden drastic change within a year which can either lead to a healthy and sustainable traffic system or an uncontrollably problematic situation depending on the planning of the urban transportation. Thus, the present scenario of the town provides great scope of research and applications from the viewpoint of transportation engineering.

For developing the mode choice model of the selected place, i.e. Hailakandi town, travel data of the last trip was collected from 350 users through household survey. Modes of travel considered are e rickshaw, cycle rickshaw, auto rickshaw, motorized two wheeler, private car and bicycle. Attributes selected for feeding the network as input variables are travel cost, travel time, distance and comfort level. The first three are quantitative attributes. The qualitative attribute, i.e. comfort level, is measured on a psychometric scale of 1 to 4 which represents four comfort levels as bad, average, good and very good respectively. All the trips considered are limited to 3 km distance.

4. MODEL DEVELOPMENT

The architecture of the ANN model is selected after several iterations by varying the number of hidden layers, the number of nodes or processing units (PUs) per layer, and the activation function in the layers (e.g. linear, hyperbolic tangent and sigmoid functions, usually common to all processing units in the same layer). Generally, an architecture should be preferred when it shows: (a) good reproducibility, which is measured by the error between observations and simulated values for the calibration data-set, (b) good predictability, which is measured by the error between observations and simulated values for the validation data-set.

As regard split of survey data-set into calibration and validation data-sets, 25% of the survey data has been used for calibration of the ANN model and the remaining 75% has been used for validation purpose.

Table 1: Main characteristics of the ANN model selected

Survey data-set	350
Attributes	Cost, Distance, Time, Comfort
Input PUs	4
Output PUs	6
Hidden layers	1
Hidden PUs	20
Activation function in hidden layer	hyperbolic tangent (tansig)
Activation function in output layer	sigmoid function (logsig)

Training function	Levenberg–Marquardt algorithm (trainlm)
Calibration set (25%)	88
Validation set (75%)	262

As regards weights and biases initialization, Nguyen and Widrow (1990) technique is usually used for ANNs with non-linear activation functions.

5. INDICES FOR MODEL VALIDATION

The indices used for the validation of the model developed are described below. The first seven indices are the same ones as used by Cantarella and de Luca (2005). They can be computed with reference to the calibration and validation data sets.

1. **calMSE** = $\Sigma_{user}\Sigma_{mode}(p^{sim}_{mode,user} - p^{obs}_{mode,user})^2/ N_{users}$, is the (calibration) mean square error between the user observed mode choice fractions, $p^{obs}_{mode,user}$ = 0/1, and the simulated ones, $p^{sim}_{mode,user} \in [0,1]$;

2. **valMSE:** as calMSE, but over the users in the validation data-set

3. **MSE** = $\Sigma_{user}\Sigma_{mode}(p^{sim}_{mode,user} - p^{obs}_{mode,user})^2/ N_{users}$, is the root mean square error between the user observed mode choice fractions, $p^{obs}_{mode,user}$ = 0/1, and $p^{sim}_{mode,user} \in [0,1]$, over the total number of users in the sample (N users).

4. **%clearly right** is the percentage of users in the sample whose observed choices are given a probability greater than 0.90 (or any given threshold not less than 50%) by the model. (It is always not greater than %right.)

5. **%clearly wrong** is the percentage of users in the sample for whom the model gives a probability greater than 0.90 (or any given threshold not less than 50%) to a choice different from the observed one.

6. **%unclear** = 100 - (%clearly right + %clearly wrong) the percentage of users for whom the model does not give a probability greater than 0.90 (or any given threshold not less than 50%) to any choice.

7. **Fitting factor (FF)** = $\Sigma_{user}\, p^{sim}_{users}/ N_{users} \in [0, 1]$, with FF = 1, meaning that the model perfectly simulates the choice actually made by each user, say with p^{sim}_{users} = 1.

8. Another indicator, often used in the literature on Neural Networks, is the Average Relative Variance (ARV). It is defined as below:

$$\text{ARV} = \frac{\Sigma\text{user}\Sigma\text{mode}(p^{sim}_{mode,user} - p^{obs}_{mode,user})2}{\Sigma\text{user}\Sigma\text{mode}(p^{obs}_{mode,user} - p^{avg})2}$$

where p^{avg} is the average of the observed values belonging to the set of data N.

6. MODEL PERFORMANCE

The calibration and validation mean square errors obtained are:

calMSE = 0.036
valMSE = 0.095

The following tables show the different indices of the ANN model prepared.

Table 2: Main validation indices for ANN model

MSE	0.134
%clearly right	87.5
%unclear	2.3
%clearly wrong	10.2
[Psim – Preal]e rickshaw (%)	+0.7
[Psim – Preal]rickshaw (%)	+0.4
[Psim – Preal]autorickshaw (%)	-0.8
[Psim – Preal]motor.2wheeler (%)	-1.3
[Psim – Preal]car (%)	+1.4
[Psim – Preal]bicycle (%)	+1.6
Fitting Factor (%)	85

Table 3: Mean Square Error(MSE) and Average Relative Variance (ARV) between observed and simulated user choices for different modes

Mode	Criteria	
	MSE	ARV
E-rickshaw	0.0014	0.020
Rickshaw	0.0004	0.045
Autorickshaw	0.0018	0.0144
Motorised two wheeler	0.0048	0.189
Car	0.0056	0.909
Bicycle	0.0073	0.153

From the relative indices as shown in Table 2 and Table 3, it can be seen that the model predicts the user mode choice satisfactorily when applied to the validation data set. Both the % clearly right and the fitting factor (FF) are greater than 80%. The low calMSE and valMSE values indicate very good reproducibility as well as predictability. This implies that though multiple modes of travel are available in the study area, the network is capable of capturing the mode choice pattern of the users very accurately.

7. CONCLUSION

The results obtained in the present study show that Artificial Neural Network (ANN) can be an effective tool for modeling intra-town short distance transportation user mode choice even when multiple types of modes are available to the user. The proposed procedure is quite satisfactory and consistent with existing literature. Still, the model can possibly be improved by using a larger number of inputs which may again require some changes in the network architecture. Further research can be done by developing neural networks for more number of modes as well as longer travel distances.

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