Innovative modeling for assessing driver behavior towards information provision: A comparison between neural networks and discrete modeling in route choice

Dr. Charalampos Petamidis (MSc, PhD) *

Department of Civil Engineering,

University of Thessaly, Volos, Greece

Prof. Eftihia Nathanail (MSc, PhD)

Department of Civil Engineering,

University of Thessaly, Volos, Greece

Maria Tsami (PhD candidate)

Department of Civil Engineering,

University of Thessaly, Volos, Greece

***** Email: mailto:chpetami@hol.gr

1 Abstract

This paper proposes a different type of travel behavior model, under the effort to formulate route choice behavior in the presence of information. Until nowadays discrete choice models and especially the multinomial logit model are the most common used. In order to encounter problems associated with these models, which are based on the theory of utility maximization, we propose the implementation of models using Artificial Neural Networks, and especially supervised feedforward neural network models, exploiting their advantages and their functional similarity to the neural structure of the brain. A case study in the outer ring road of Thessaloniki (Greece) is examined, with the assistance of traffic simulation software. The results underscore the advantages of NN models, not only by means of prediction potential but also in demonstrating limited demand of time and effort, when someone tries to simulate a complex phenomenon like human behavior in a complex environment like city road network.

2 Introduction

The increasing importance of Intelligent Transport Systems on economy, safety, and environment and especially on sustainable transport is well recognized by the White Paper of the European Commission [11]. The goal of reducing congestion by increasing capacity through traffic management, involves the use of ITS technologies to exploit imbalances between supply and demand, using information as a tool of influencing driver decisions. Advanced Traveler Information System (ATIS), as part of an ITS, is an effective way to inform drivers to about route choices and avoid traffic congestion [21]. The impact of ATIS on driver response towards route change, is modeled in numerous researches [1,18]. Usual development of models capture and analyze user behavior in the presence of information, either stating the concurrent status of the network or also by suggesting, for example, the best route to be chosen [6,7].

The evaluation of the effectiveness of such systems requires the simulation of driver behavior, through the development of driver behavior prediction models, as well as of the impact of such behavior on traffic [3]. Discrete choice models and especially the multinomial logit model are the most common methods used for modeling driver behavior [4,8,17]. Encountering problems associated with these models, which are based on the theory of utility maximization, current research aims at developing an alternative framework for drivers' behavior prediction, modeling mainly the decision of the drivers in route choice, using Artificial Neural Networks.

In this context, the objectives of our research may be phrased as follows:

• to develop a platform for collecting and processing data that affect driver behavior in route choice,

• to assess the parameters that may be used in driver behavioral models,

• to formulate and develop commonly used and alternative models to be implemented for the estimation of the probability of the effect ATIS may have on travelers,

• to validate the accuracy of the above models in predicting behavior

3 Background

Although formulating driver behavior models is a quite complicated task [12, 20], there are three main categories of models simulating driver behavior in respect of the task of route choice. The first category consists of discrete choice models, and especially logit models [5,8,10,13,19, 23]. The second category is that of models based on the theory of fuzzy logic [9,16, 25,26,27]. The third category consists of models based on the use of artificial neural networks, exploiting their advantages like Non-linearity, Input-Output Mapping, adaptivity, Evidential Response, VLSI implementability, Fault Tolerance, Uniformity of Analysis and Design and Neurobiological Analogy, for accommodating complicated problems without the requirement of giving explicit equations correlating input/output data [14,22].

In this study feedforward neural networks [2,15,24], are used as a method to produce a quick and efficient method to analyze route choice behavior, and are compared to the more traditional multinomial logit models.

4 Data collection

The required data for the models implementation was collected from commuters, mainly using the ring road of the city of Thessaloniki. The parameters affecting traveler choice were distinguished in four main categories, namely user characteristics, trip characteristics, route attributes and ATIS attributes.

Data was collected through an internet survey which required more than 400 answers for the correct implementation of the neural networks models.

5 Models formulation

As it was mentioned before, the models formulated, belong to the family of random utility models, namely the multinomial logit model and to the family of supervised artificial neural networks, namely the multilayer feedforward neural network trained using the backpropagation algorithm.

The generic formulation of the logit model is depicted as follows:

Let j E J denote the alternative choices that the driver may choose from.

Let d E D denote the drivers.

Let k E K denote the parameters which affect the driver choice.

$$p_i^d = \frac{\exp(U_i^d)}{\sum j \exp(U_j^d)}$$

where p_i^d the probability for driver d to select alternative i

U_i^d the utility for driver d of choosing alternative i

U_j^d the utility for driver d of choosing alternative j

and the utility function:

$$U_i^d = a_i + \sum_k \gamma_k x_i^{k,d} + \sum_\lambda \delta_\lambda x_i^{\lambda,d} + \sum_k \beta_k x_i^k + \sum_\pi s_\pi x_i^\pi + e_i^d$$

where U_i^d the utility to driver d of choosing alternative i

$x_i^{m,d}$ the value of variable k for driver d and the alternative i (e.g. experience)

$x^{\lambda,d}$ the value of variable λ for driver d (e.g. age)

x_i^k the value of variable k for the alternative i (e.g. traffic volume)

x_i^π the value of variable π for the alternative i (e.g. information provided)

$a_i, \gamma_k, \delta_\lambda, \beta_k, s_\pi$ parameters

e_i^d error term

The formulation of the neural network model was produced after following the steps below:

1. Splitting the survey data-set into calibration and validation data sets, and suitable transformation

2. Minimization of the Mean Square Error (error function) using the backpropagation algorithm

3. Definition of number of iterations (epochs) and of starting conditions

4. Selection of the MLFFNN architecture

5. Definition of the parameters for the selected architecture

6. Training the network through the selected cost criterion

The comparison of the models was made using the average relative variance statistical indicator and the receiver operating characteristic curve.

6 Conclusions

The current work tried to expose the differences and the possible advantages of using NN models instead of the common used logit models, for route choice modeling, applied as a case study in the area of Thessaloniki. In the comparison the two layered feedforward neural network model seems to overcome the logit model mainly because the existence of similar alternative route choices, highlighting a common weakness of this form of logit models and the existence of noisy data which has more negative effect on logit models than on the quite robust Neural Network ones.

References

[1] Adler, L. J., Recker, W.W., McNally, G. M., (1992), Using Interactive Simulation to Model Driver Behavior under ATIS. The University of California Transportation Center, University of California, Berkley, UCTC No 126.

[2] Almeida, L., (1997), Multilayer perceptrons,in Handbook of Neural Computation, Oxford University Press and Institute of Physics, United Kingdom.

[3] Avineri, E., Prashker, N.J., (2005), Sensitivity to travel time variability: Travelers' learning perpective. Transportation Research Part C 13, 157-183.

[4] Ben-Akiva, M. and Bierlaire, M. (1999). Discrete choice models and their applications to short-term travel decisions, in R.Hall, Handbook of Transport Science, Kluwer, pp. 5-34.

[5] Ben-Akiva, M., Cyna, M., De Palma A. (1984). Dynamic model of peak period congestion. Transportation Research Part B: Methodological, Volume 18, Issues 4–5, August–October 1984, Pages 339-355

[6] Cascetta, E., Nuzzolo, A., Russo, F. and Vitetta, A., (2002). A model of route perception in urban road network. Transportation Research Part B 36, 577-592.

[7] Cascetta E., Nuzzolo, A., Russo, F. and Vitetta, A. (1996). A modified logit route choice model overcoming path overlapping problems specification and some calibration results for interurban networks. In: Proceedings of ISTTT conference, Lyon, France.

[8] Cascetta, E., Papola., Russo, F., Vitteta, A, (1998). Implicit availability/perception logit models for route choice in transportation networks. Preprint 8 WCTR, Antwerp, Belgium.

[9] Cascetta, E., Papola, A.(2001). Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand. Transportation Research Part C: Emerging Technologies, Volume 9, Issue 4, August 2001, Pages 249-263

[10] Dial, B. R., (1971) A probabilistic multipath traffic assignment model which obviates path enumeration. Transportation Research, Volume 5, Issue 2, June 1971, Pages 83-111

[11] European Commission, WHITE PAPER, Roadmap to a Single Transport Area- Towards a competitive and resource efficient transport system, Brussels, 28.3.2011.

[12] Florian, M. and Fox, B. (1976). On the probabilistic origin of Dial's multipath traffic assignment model. Transportation Research, Vol. 10, pp. 339-341

[13] Frejinger, E., Bierlaire, M., 2007. Capturing correlation with subnetworks in route choice models. Transportation Research Part B, 41(3), 363-378.

[14] Gurney, K. (1997). An introduction to neural networks, CRC Press, London.

[15] Hensher, D., and Ton, T., (2000). A comparison of the predictive potential of artificial neural networks and nested logit models for commuter mode choice, Transportation Research Part E 36, 155-172.

[16] Henn, V. and Ottomanelli, M.(2006).Handling uncertainty in route choice models: From probabilistic to possibilistic approaches . European Journal of Operational Research, Volume 175, Issue 3, 16 December 2006, Pages 1526-1538

[17] Koppelman, S.F. and Sethi V. (2000). Closed-form discrete choice models, in Handbook of Transport Modeling, Edited by D.A Henser and K.J. Button, Elsevier Science Ltd.

[18] Mahmassani, H. and Liu, Y.H., (1999). Dynamics of commuting decision behavior under advanced traveler information systems. Transportation Research Part C, 91-107.

[19] McFadden, D., Train, T., 2000. Mixed MNL models for discrete response. Journal of Applied Econometrics, 15(5), 447-470.

[20] Ridwan, M. (2004). Fuzzy preference based traffic assignment problem. Transportation Research Part C: Emerging Technologies, Volume 12, Issues 3–4, June–August 2004, Pages 209-233

[21] Rong-Chanh, J., (2000). Modeling the impact of pre-trip information on commuter departure time and route choice, Transportation Research part B 35, 887-902.

[22] Samarasinghe, S. (2006). Neural Networks for Applied Sciences and Engineering: From Fundamentals to Complex Pattern Recognition, Auerbach Publications, New York.

[23] Sheffi, Y., Daganzo F. C.,(1977). Another “paradox” of traffic flow .Transportation Research, Volume 12, Issue 1, February 1978, Pages 43-46.

[24] Shmueli, D., Salomon, I., Shefer, D., (1996). Neural network analysis of travel behaviour: evaluating tools for prediction, Transportation Research.-C, Vol. 4 No. 3, pp 151-166.

[25] Teodorovic, D., Kikuchi S. (2000). Fussy sets in Traffic and Transport systems. Fuzzy Sets and Systems, Volume 116, Issue 1, 16 November 2000.

[26] Vythoulkas, C. P., Koutsopoulos, N. H. (2003). Modeling discrete choice behavior using concepts from fuzzy set theory, approximate reasoning and neural networks. Transportation Research Part C: Emerging Technologies, Volume 11, Issue 1, February 2003, Pages 51-73

[27] Zadeh, L.A. (1975). The role of fuzzy logic in the management of uncertainty in expert systems. Fuzzy Sets and Systems, Volume 11, Issues 1–3, 1983, Pages 197-198