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A Neuro-Fuzzy Approach to Route Choice Modelling

Suji R. Chandran[1], Dr. Manju V. S.[2], Anu P. Alex[3]
[1]Former M. Tech student, College of Engineering, Trivandrum, India, sujirchandran@gmail.com
[2]Associate Professor, College of Engineering Trivandrum, India, manjusajeev@yahoo.com
[3]Assistant Professor, College of Engineering Trivandrum, India, anualex55@gmail.com

Abstract *:* The traditional methods of traffic assignments do not take into account the route choice preference of the commuters. Under such circumstance, fuzzy logic was recognized as a modelling tool for route choice. Fuzzy logic can be used effectively in capturing the variability of the traveller's appraisal of the different route attributes, as well as the variability in their perceptions to the various attribute levels. The main disadvantage of fuzzy inference system is the setting of the rules and membership functions of the variables. These limitations can be overcome by adopting hybrid soft computing technique; neuro-fuzzy logic. This study makes use of Adaptive Neuro-Fuzzy Inference System for route choice modeling by using the data set generated by Factorial Experimental Design Model (FEDM). The developed model was found to be successful in predicting the route choice with reasonable accuracy.

Key words : route choice, traffic assignment, neuro fuzzy, driver behaviour

INTRODUCTION

Route choice problem involves the selection of a path between a given origin and destination, when faced with a road network consisting of many nodes, links, origins and destinations. Route choice behaviour of drivers' has a great influence on traffic flow patterns**.** It is fundamental to the traffic assignment step in travel forecasting models and to the traffic simulation models. There are several difficulties in route choice behaviour modelling. The perception of the traveller may vary. The acceptable performance level varies with traveller. The route attributes considered and the perceived values associated with these attributes also vary. Hence the choice of the best route is not the same for all travellers. The route choice models based on random utility theory has the limitation that it cannot model the vagueness in driver behaviour. Hence they cannot predict route choice accurately.

Fuzzy logic can be used effectively in capturing the variability of the traveller's appraisal of the different route attributes as well as the variability in their perception to the various attribute levels. In complex problems, extracting the if-then rules for fuzzy logic, calibration of the membership functions and rules are difficult. These limitations encountered in developing fuzzy logic systems can be overcome by the training capabilities of the neural nets. Hence the objective of this study was to develop a neuro-fuzzy (integrated fuzzy logic and neural nets) model for route choice. The data for the model development was generated from Factorial Experimental Design Model (FEDM) which is based on a scoring technique [3].

PREVIOUS STUDIES IN ROUTE CHOICE

Many research studies had been conducted for years in modelling route choice. Different researchers used different criteria and methods in developing an efficient route choice model. Yang et al. [10] developed a model of driver route choice with advanced traveller information using neural network concepts based on data collected from learning experiments using interactive computer simulation. Mahmassani et al. [5] developed an interactive survey approach to study traveller responses to ATIS for shopping trips. According to this study, the interactive internet survey was found to be a successful tool to gather data on travel decisions.

Kuri et al. [4] modelled car route choice with non-dynamic stated preference data: a comparison between fuzzy similarity and random utility models. It deals with fuzzy and non-fuzzy car route choice modelling. Bijun et al. [1] studied the drivers' taste variation and repeated choice correlation in route choice modelling by using the mixed logit model. Hawas [2] developed a route choice utility model by neuro-fuzzy approach. Hawas [3] developed a route choice utility model by factorial experimental design approach. Ridwan [7] studied fuzzy preference based traffic assignment problem. The core of the model was FiPV, which is a choice function based on fuzzy preference relations for travel decisions. Sakda et al. [8] presented a fuzzy neural approach to modelling behavioural rules in agent-based dynamic driver behaviour models. Knoop et.al [12] investigated to what extent travelers change their route when faced with unexpected traffic situation.

Shiftan et.al [13] presented a learning-based model of route-choice behavior when information was provided in real time. Grange et.al [11] presents a route choice model for public transit networks that incorporates variables related to network topology, complementing those found in traditional models based on service levels and users' socioeconomic and demographic characteristics. Zhou et.al [14] developed a general travel decision-making rule utilizing Cumulative Prospect theory (CPT).

METHODOLOGY

The data needed for the present study was collected by conducting a questionnaire survey. The survey used a scoring technique, in which trip makers were asked to mark the levels and rate the parameters out of ten. These ratings were used for calculating the route utility. Route utilities of the individual passengers were taken for the development of FEDM. Data set generated from FEDM was used to develop a neuro-fuzzy model for determining utility of the route. Validation of neuro-fuzzy logic model was done by

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comparing the data obtained from neuro-fuzzy model and data obtained from field and of RMSE were found out.

DATA COLLECTION & ANALYSIS

Route Utility from Questionnaire Survey

On the basis of suggestions obtained from the respondents in apreliminary survey, the following parameter were included in the final questionnaire: travel time, speed, familiarity, queue time and pavement condition. Sample size of around 400 was selected. Out of these 23.5% were car users and the rest were using two wheelers. The survey used a scoring technique and it was conducted over two stages; the score stage and the numeric levels identification stage. In the score stage, participants were asked to assign scores to the factors mentioned in the questionnaire. The factor score (out of 10) represents the degree to which the participant's route choice decisions are affected by such a factor. The level score reflects the preference to undertake a route exhibiting this particular level. The modelling approach adopted is based on the assumption that the route utility perceived by the traveller is equal to the sum of the products of the factor scores and the perceived level scores. Given this assumption, the route utility can be expressed as follows:

$$U_i^{k,t} = \sum_{j=1}^{J}\sum_{l=1}^{L} S_j^k \hat{S}_{l,j}^k \delta_{i,j,l}^{k,t}, \qquad \forall i \in I,\ k \in K_n,\ n = 1,...,N \quad (1)$$

Where; t=integer time index; i=route index; $i = 1,..., I$;
j =attribute (factor) index; $j = 1,..., J$;
l = index of attribute's level perceived by the traveller;
$l = 1,..., L$; k=participant (traveller) index;
n=index of socio-demographic set (group) to which the participant belongs; K_n = set of participants in the n[th] group;
$U_i^{k,t}$ = absolute route utility assigned to route i by participant k at time t ;
S_j^k = score of factor j assigned by participant k;
$\hat{S}_{l,j}^k$ = score of level l of factor j assigned by participant k;
$\delta_{i,j,l}^{k,t}$ =binary index with value of l if level of factor j is perceived by participant k along route i at time t, and 0 otherwise.

Data Generation from FEDM

The parameters selected for developing neuro-fuzzy logic model for route utility as in the order of priority are (i) Familiarity (ii) Travel time (iii) Speed (iv) Queue time (v) Pavement condition. In order to develop a neuro-fuzzy logic model for route utility, the parameters were trained by FEDM with the software 'Design Expert'. The FEDM was done based on the assumption that the traveller assigns specific rates or ''scores'' to the various route attributes according to the level of attribute he/she perceives, and then utilises such scores to estimate an overall route utility. Table 1 shows a sample of the data structure for the FEDM development. Each data record (row) is comprised of five categorical variables (A through E) and the average route utility. A total of 162 records (with all possible factor-level combinations) were prepared. Variable 'A' refers to the travel time, B refers to the queue time, C refers to the familiarity, D refers to the speed, and E refers to the pavement condition. The last column represents the average utility of route i, [estimated by (1)] for the participants.

Table 1: Sample data for FEDM development

Sl No.	Travel time (A)	Queue Time (B)	Familiarity (C)	Speed (D)	Pavement Condition (E)	Avg. Utility
1	low	low	familiar	medium	satisfactory	243
2	low	high	familiar	medium	satisfactory	192
3	medium	high	familiar	medium	satisfactory	152
4	low	low	non familiar	medium	poor	212
5	low	medium	non familiar	medium	satisfactory	180
6	medium	high	familiar	medium	poor	132
7	medium	low	familiar	medium	Satisfactory	234
8	medium	low	familiar	medium	satisfactory	200
9	high	high	familiar	medium	good	170
10	high	medium	familiar	medium	satisfactory	249

Factorial experimental model was the developed (not reported) based on the scoring technique, which contain three levels of interactions of the parameters. The final coded form of the route utility comprises of four blocks; the mean effect, the factors' effects, the selected second-level interactions' effects and the selected third level interactions' effects.

In order to train the data for neuro-fuzzy approach, data set were generated from the developed FEDM model. A programme was written in MATLAB and the parameters were given as the input and the utility values were calculated. These utility values were used as input for training the data set in neural networks.

Neuro – Fuzzy Approach for Route Utility

Five input variables discussed earlier were used in this approach. The first variable familiarity had two membership functions and the remaining variables had three membership functions. So a total of 162 rules were formed by the Adaptive Neuro-Fuzzy Inference System (ANFIS). Variables and memebrship functions used are given in Table2. Fuzzification sub-network transforms the real inputs into fuzzified inputs in term of "high" and "low" ranges. Therefore, the input layer consists of 14 neurons. The output layer has only one neuron for representing membership function of compliance/delay threshold rate (Fig 1).

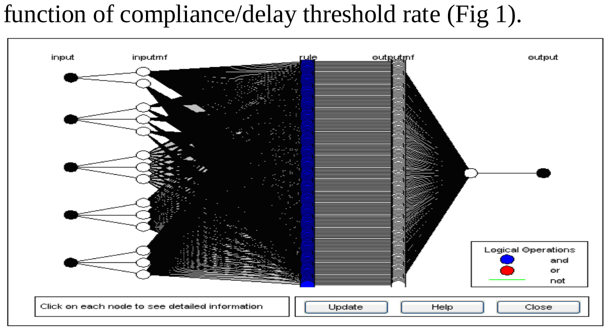

Fig1: General structure of ANFIS

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Table 2: Variables and Membership functions

Variable name	Range		Membership functions
Travel time	0	1	Low, medium, high
Queue time	0	1	Low, medium, high
Familiarity	0	1	Familiar, non familiar
Speed	0	1	Low, medium, high
Pavement condition	0	2	Poor, moderate, good
Utility	0	1	Very low, low medium, medium, medium high, high, very high

The ANFIS generated a system for route utility from the training and checking data set. Within the range of the input parameters, the membership functions and rule bases were calibrated by the system. The ANFIS already contains a fuzzy inference system. Error between the data set and the fuzzy inference system was reduced by the back propagation algorithm by selecting suitable number of epochs and error tolerance. Error tolerance was taken as zero. The error obtained was 0.046 with 500 epochs. Fig 2 shows the reduction in error of the training data and checking data. In this figure the bold line indicate the error reduction of the training data set.

Validation of Neuro – Fuzzy Model

Utility value obtained from neuro-fuzzy model was compared with the actual utility obtained from the field for the same inputs. Actual utility is the utility of the respondents based on the scoring technique using (1). Comparisons of the results are shown in Table 3. The percentage Route Mean Square Error was 5.13% which is within the permissible limits. Hence the method of route choice based on neuro-fuzzy approach is considered to be valid.

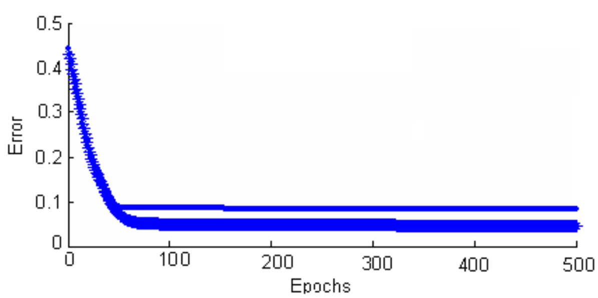

Fig1: Error plot of training and checking data

Table 3: Comparison of the result

Sl No.	Familiarity	Pavement Condition	Queue Time	Speed	Travel time	Actual	Model
1	1	0	0.6	0.7	0.9	0.66	0.64
2	1	0	0.8	0.6	0.8	0.63	0.59
3	1	1	0.6	0.7	0.7	0.58	0.57
4	1	1	0.6	0.6	0.7	0.43	0.42
5	1	0	0.4	0.6	0.5	0.28	0.32
6	1	0	0.6	0.5	0.6	0.48	0.42
7	0	2	0.5	0.6	0.8	0.42	0.39
8	1	2	0.5	0.6	0.8	0.54	0.51
9	1	1	0.6	0.7	0.7	0.39	0.39
10	1	1	0.6	0.7	0.7	0.46	0.43

CONCLUSION

Route choice behaviour is a very complex phenomenon, which changes randomly depending upon the various combinations of scenarios encountered, it is found to be difficult to model mathematically. The traditional methods of traffic assignments do not take into account the route choice preference of the commuters. Under such circumstances, fuzzy inference system is found to be highly efficient in solving these. But the main disadvantage of fuzzy inference system is the setting of the rules and membership functions of the variables. Neuro-fuzzy model overcomes the limitations of fuzzy logic model. Hence the present study made an attempt to model the route utility using ANFIS. The utility for any route can be quantified using the developed neuro-fuzzy model. The model was validated with actual field data and the percentage route mean square error obtained was 5.13%. The developed model was found to be successful in predicting the route choice with reasonable accuracy.

REFERENCES

[1] Bijun, H., Algers, S., Engelson, L.,(2001), "Accommodating drivers' taste variation and repeated choice correlation in route choice modelling by using the mixed logit model ", Transportation Research Board, 80th annual meeting,Washington, D. C, No. 01-2954.

[2] Hawas, Y.E., (2004a), "Development and calibration of route choice utility model: Neuro-fuzzy approach", Journal of Transportation Engineering, Vol. 130, No. 2, pp. 171-182.

[3] Hawas, Y.E., (2004b), "Development and calibration of route choice utility model: Factorial experimental design approach", Journal of Transportation Engineering, Vol. 130, No. 2, pp. 159-170.

[4] Kurri, J., Pursula, M., (2000), "Modelling car route choice with non-dynamic stated preference data: a comparison between fuzzy similarity and random utility models", Transportation Research Record, 80th annual meeting.

[5] Mahmassani H.S., Kraan, M., Huynh, N., (1999), "Interactive survey approach to study traveler responses to ATIS for shopping trips", Transportation Research Board, 79th annual meeting, No.00-0195.

[6] Ortuzar, J.D., (1996), "Modelling Transport", Second edition, John Wiley & Sons, Newyork.

[7] Ridwan, M., (2004), "Fuzzy preference based traffic assignment problem", Transportation research Part C, No.12, pp. 209-233.

[8] Sakda, P. and Dia, H. (2006), "A fuzzy neural approach to modelling behavioural rules in agent based route choice models", Transportation Research Part A: Policy and Practice 33(5), 337-364.

[9] State-Ease. (2007).Design expert software: Version 7.1 user's guide, State-Ease, Inc.

[10] Yang, H., Kitamura, R., Jovanis, P., (1992), "Exploration of driver route choice with advanced traveller information using neural network concepts", Institute of Transportation Studies, University of California at Davis, USA.

[11] Grange L.D., Munoz J.C. and Raveau S. (2011) "A topological route choice model for metro" Transportation Research, Vol 45, pp. 138–147.

[12] Knoop V.L. and Zuylena H.V. (2010) "Rerouting behaviour of travellers under exceptional traffic conditions – an empirical analysis of route choice" Procedia Engineering 3, pp. 113–128.

[13] Shiftan Y. and Ben – Elia E. (2010) "Which road do I take? A learning-based model of route-choice behavior with real-time information", Transportation Research Part A, Vol 44 pp. 249 - 264.

[14] Zhou J., Xu H. and Xu W. (2011) "A decision-making rule for modeling travelers' route choice behavior based on cumulative prospect theory" Transportation Research, Vol 19, pp. 218–228.