Application of Soft Computing Techniques in Mode Choice Analysis

Ramanuj P. S.[1*] and Varia H. R.[2]
[1] Asso. Prof., Civil Engg. Dept., S. S. Engg. College, Bhavnagar
(PhD scholar, Gujarat Technological University, Ahmedabad) India
[2] Professor and Head, civil & Infrastructure Engineering, Adani Institute of Infrastructure Engg., Ahmedabad
[1]Email: pinakramanuj@gmail.com

Abstract

Determining choice of transportation mode is an important part of transportation planning. Mode choice is behavioral and complex in nature. Various techniques are available in the literature for mode choice modeling. This paper emphasizes on statistical mode choice models such as multinomial logit, nested logit models and probit models as well as recent advanced soft computing techniques such as Artificial Neural Network models (ANN) and Fuzzy approach model that are applicable for modal split analysis.

Keywords: *Mode choice, Soft Computing Techniques*

1. Introduction

Determining choice of transportation mode is an important part of transportation planning. A proper analysis of mode choice decisions are helpful in addressing issues such as forecasting demand for new modes of transport, mitigating traffic congestion, mode shift due to improvement in existing transportation facility etc. It played key role in public transport policy making (Ortuzar & Willumsen, 2011). For attracting the users of private modes to mass transport modes, one needs to carry out the relationship between mode choice and factors affecting to it.

A major innovation in the analysis of transportation demand was the development of disaggregate travel demand models based on discrete choice analysis methods (Ben-Akiva, M;Lerman, S, 1985); the different available alternatives in a discrete choice experiment are mutually exclusive and collectively exhaustive. Since 1990, application of newly developed techniques such as Artificial Neural Network, Fuzzy sets, Neuro-fuzzy networks pattern recognition was adopted.

1. Aggregate and Disaggregate Approach

Disaggregate and Aggregate modeling, which applicable to mode choice models are critical concepts in travel demand modeling. Aggregate models refer to grouped data and patterns instead of an individual. Aggregate models were popularly used up to the late 1970s. Traditionally aggregate models are used in dealing with the travel choice behaviour of individual travelers with aggregated to zone data. Disaggregate models, which became more popular during the 1980s, offer substantial advantages over the traditional aggregate models. Disaggregate models offer advantage over aggregate models as it represents the behavior individuals. (i) Disaggregate approach has better ability to reflect changes in choice behavior due to changes in individual characteristics and attributes of alternatives. (ii) It is likely to be more transferable to a different point in time and to a different geographic context, which is a critical requirement for prediction.(iii) It is more suited for proactive policy analysis since it is causal, less tied to the estimation data and more likely to include a range of relevant policy variables. (iv) It is more efficient than the aggregate approach in terms of model reliability per unit cost of data collection (Koppleman & Bhat, 2006). While, aggregation leads to considerable loss in variability, thus requiring much more data to obtain the same level of model precision.

2. Factors Influencing Mode Choice Behavior

The significant characteristics in determining the mode choices of the trip makers can be classified into three groups: characteristics of trip makers, journey and transport facility. Mode choice of commuters is influenced by factors like travel time, travel cost, waiting time, number and ease of transfers, comfort, income, car ownership, egress and ingress time etc. Over the years mode choice models have been dealing with the general range of trade-offs individuals are willing to make among these factors (Ben-Akiva, M;Lerman, S, 1985). Almasri and Alraee (2013) have identified that the total travel time, total travel cost divided by personal income, ownership of transport means, age, distance and average family monthly income are predominant factors affecting mode choice for urban trips (Almasri & Alraee, 2013). However, Yao and Morikawa (2005) and Bhat (1995) found that service frequency also affect the mode choice decision of individual for intercity travel (Bhat, 1995) (Yao & Morikawa, 2005). Further Zhao at.el. (2018) Zhao et. al. (2018) found that better feeder accessibility is important in enhancing ridership (Tang. L.at. al. ,2018).

3. Mode Choice Models

Discrete choice models, widely used in transportation applications are based on random-utility maximization.

Random Utility Theory: The utility is mathematically represented as a linear function of the attributes of the journey weighted by the coefficients which attempt to represent their relative importance as perceived by the traveler. It may further assume that the utility associated by individual n to alternative i, denoted by U_{in} can be represented by two components:

i. V_{in} - A measurable systematic part, which is the function of the measured attributes; and

ii. ε_{in} - A random part, which reflects the measurement or observational error along with the taste of the individual.

The utility U_{in} is a random variable such that

$$U_{in} = V_{in} + \epsilon_{in} \tag{1}$$

Where, $V_{in} \in R$ is the deterministic or systematic component of the utility, and ε_{in} is a random term. If Z_{in} is a vector of attributes of alternative i for individuals n, and S_n is a vector of socio-economical characteristics for individual n, then,

$$V_{in} = V_{in}(\beta, Z_{in}, S_{in}) \tag{2}$$

Where, β is a vector of unknown parameters which are to be estimated. For simplification, it is a common practice to merge Z_{in} and S_n into a vector of attributes, denoted by X_{in}. Therefore, a simpler formulation is

$$V_{in} = V_{in}(\beta, X_{in}) \tag{3}$$

The probability that individual n selects alternative i is given by,

$$P(i \backslash C_n = P(U_{in} \geq U_{in} \forall_j \in C_n) \tag{4}$$

Based on the functional form of the error term distribution, there are three different families of models namely Logit models, Probit models and General Extreme Value (GEV) Models. In case of random residuals Independently and Identically Distributed (IID) Gumbel distributed, the probability expression reduce to Multinomial Logit Model (MNL), if it is normally distributed then the expression reduce to Probit model. Logit model has the ability to model complex travel behaviors of any population with simple mathematical techniques and thus proves to be the most widely used tool for mode choice modeling.

3.1 Logit Analysis Models

The logit model is obtained by assuming that random component ε_{in} is distributed independently, identically extreme value. The critical part of the assumption is that the unobserved factors are uncorrelated over alternatives, as well as having the same variance for all alternatives. Its popularity is due to the fact that the formula for the choice probabilities takes a closed form. It may be binomial logit or multinomial logit model depends on alternative under consideration.

3.2 Multinomial Logit model

Multinomial Logit Model (MNL) is widely used model due to its simplicity, can be represented as shown in Fig. 1. There are three basic assumptions regarding the error components which underline the MNL formulation. (i) The error components are extreme value (Gumbel) distributed, (ii) The error components are identically and indecently distributed across alternatives and (iii) The error components are identically and independently distributed across observation/ individuals.

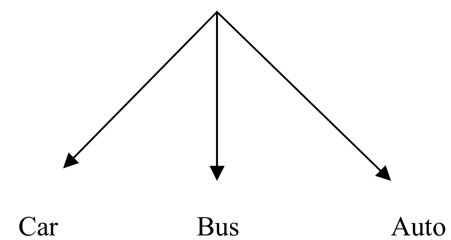

Figure 1: Simple Multinomial Logit Model

However, these assumptions also leave the MNL model laden with Independence of Irrelevant Alternatives (IIA) property at the individual level which has proven to be the greatest drawback of MNL model (Bhat, 1995). Ashalatha et al. (2013) modeled the mode choice preference of commuters of Thiruvananthapuram city by MNL model for predicting Bus, Car and Two wheeler modes. The findings from the study revealed that as age increases, preference to the two wheelers decreases and car increases in comparison with public transport (Ashalatha, Manju, & Zacharia, 2013). Subbarao and Rao (2013) have developed Multinomial Logit Regression model for Mumbai Metropolitan region. The study results indicated that travel time, travel cost, household income, vehicle ownership, accompanied household members played the major role in the decision related to urban trips (Subbarao, 2013). Logit model also usefull for developing mode choice models for goods transportation. Sayed and Razavi (2000) have developed binary logit model for U. S. freight transport market using information on individual shipper and individual shipments (Sayed & Razavi, January, 2000). In the Logit models importance of variables and its significance interpreted using the value of its multiplying constant and t-statistic respectively which is as shown in Table 1 (Subbarao, 2013).

Table 1. Parameter Estimates and Goodness of Fit Statistics (Sample)

Variables	Parameter	t-statistic
Generic Variables		
TT- (Travel time)	-0.0058	-0.0038
TC- (travel cost)	-0.0038	-5.71
Alternative specific variables		
h20(BUS)-(Income more than 20000/month)	0.6792	10.35
edu (Bus)- (Education Level)	-0.5144	-22.60

comfort (Rail)	-0.2608	-2.47

3.3 Generalized extreme value models (GEV)

Often it is unable to capture all sources of correlation explicitly, such that the unobserved portions of utility are correlated and IIA does not hold. In these cases, a more general model than standard logit is needed. The unifying attribute of GEV models is that the unobserved portions of utility for all alternatives are jointly distributed as a generalized extreme value. When all correlations are zero, the generalized extreme value distribution becomes the product of independent extreme value distributions and the GEV model becomes standard logit model.

3.4 Nested Logit Model:

The most widely used member of the GEV family is called nested logit model. A nested logit model, represented as shown in Fig. 2 is appropriate when the set of alternatives faced by a decision-maker can be partitioned into subsets or nests in such a way that the following properties hold. (1) For any two alternatives of the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives. That is, IIA holds within each nest. (2) For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. IIA does not hold in general for alternatives in different nests.

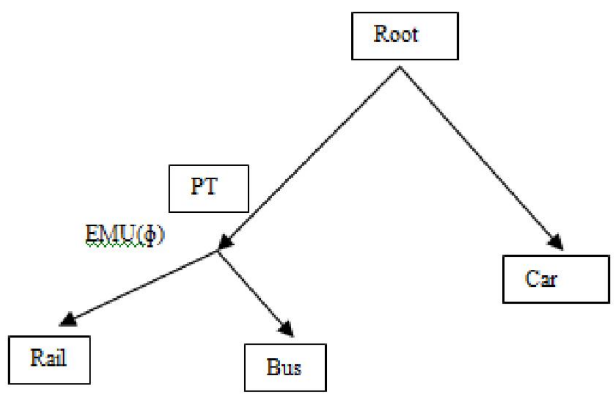

Figure 2. Structure of Nested Logit Model

Yao and Morikawa (2005) have developed the model utilizes combined estimation across multiple data sources such as SP, RP and aggregate data. Intercity travel decisions are represented by a nested model structure, and an accessibility measure is introduced to capture short term induced travel (Yao & Morikawa, 2005). Wen and Koppelman have developed Generalized Nested Logit (GNL) model which includes the two level nested logit (NL) model as a special case and can approximate closely multi level nested logit model (Wen & Koppelmal, 2001)

3.5 Mixed Logit Model:

The model contains both probit-like disturbances and an additive Independently and Identically Distributed (IID) extreme value (or Gumbel) disturbance within the multinomial logit model. It is a highly flexible model that can approximate any random utility model. Gong and Wang (2011) have developed Markov Chain Monte Carlo (MCMC) Bayes-Mixed Logit model with survey of intercity travel behavior information, taking occupation and income into the utility function using Matlab language. The experiment result shows that the fitting accuracy of Bayed- Mixed Logit is improved by 18.2 % comparing with conventional method (Gong & Wang, 2011).

3.6 Probit Model

The underlying assumption of probit models is that the error components follow a joint normal distribution with zero mean and covariance matrix with no priori restrictions on the correlation structure in the distribution. The probit model can handle random taste variation, it allows any pattern of substitution, and it is applicable to panel data with temporally correlated errors. The limitation of probit models is that they require normal distributions for all unobserved components of utility. In most of situations, normal distribution provides an adequate representation of random components. But in few situations, they are inappropriate and can lead to perverse forecasts. However, the Multinomial Probit Model does not allow to write the model in a simple closed form as in the MNL model; therefore to solve it numerically is difficult. Ghareib (1996) has compared and evaluated the predictive ability of logit and probit models when applied in mode choice context. Two transit modes operating in different cities of the Saudi Kingdom were analyzed. Based on the findings, the author recommends not to apply complicated models such as probit when analyzing the situation of a binary mode choice because it does not compensate for its analytical complexity by offering more accurate results (Ghareib, 1995) .

4. Soft Computing Techniques

For better result, researchers have sought out to more recent soft computing techniques like A rtificial Neural Network, Fuzzy Logic and hybrid models resulting from its combinations. This section describes these recent techniques.

4.1 Artificial Neural Network Models

Artificial neural network is an information processing paradigm which is inspired by the way in biological nervous systems work. ANN models have become more popular in recent years and are being used in diversified fields like financial analysis, cognitive science, decision making problems and pattern recognition. The network is composed of a large number of highly interconnected processing elements working in parallel to solve a specific problem. The processing elements called neurons. A schematic diagram of a typical neural network with neuron is shown in Fig.3. A typical calculation of ANN can be mathematically represented as, if X_1, X_2, …. X_n are the input values and synaptic weight values are W_{ji}, the summing part is the product of the incoming neuron's activation and the synaptic weight of the connection expressed as $\sum X_i W_{ji}$. A threshold value b_j is incorporated into the output, can be expressed as

$$u_i = \sum_{j=1}^{n} (W_{ij} X_{ij} - b_j) \tag{5}$$

The purpose of the activation function expressed as f (net) is to ensure that the neuron response is bounded, i.e. actual response of the neuron is conditioned, or damped, in response to a large or small activity stimuli and thus, is controllable. The most popular activation functions are hard limiter and sigmoid. The proper activation function can be selected by experience or by trial and error in such a way that it can correlate input output relation efficiently.

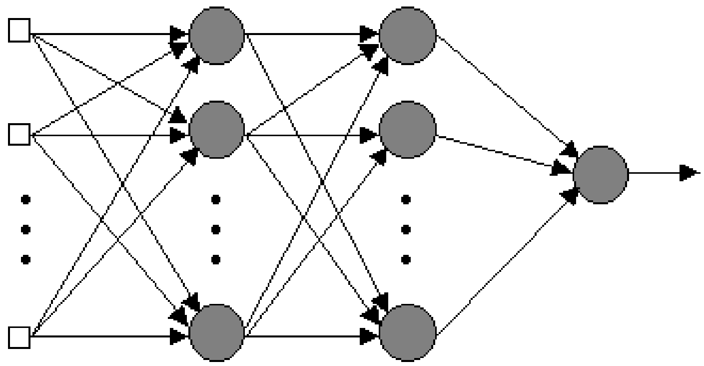

Figure 3: Artificial Neural Network

ANN can also be applied to dynamic traffic pattern classifications as was done by Jiuyi and Faghri (1993) (Hua & Faghri, 1993). Evaluation of applications developed on neural network theory in the field of transportation engineering is presented by Faghri and Hua (1992) (Faghri & Hua, 1992). Sikdar and Sekhar (2005) have analyzed mode-choice behaviour of commuters in Nagpur. In this study, mode choice behaviour has been modeled using ANN techniques. The relative importance of input variables is found by the portioning of weight algorithm (Sikdar & Sekhar, 2005). While Sayed and Razavi (2000) examine the importance of each input variable by looking at the weights between the input nodes and hidden layer (Sayed & Razavi, January, 2000).Ramanuj and Gundaliya (2013) have developed mode choice model for commuters of Ahmedbad City using ANN techniques. The ANN model when compared with conventional linear regression, the ANN model is found highly compatible (Ramanuj, 2013). which deduced from the table 2 showing ANN prediction success.

Table 2. Prediction Success in Testing

Actual Mode	Predicted Mode Choice(Testing)						Individual Match(%)
	Car	Bus	TW	Auto	Bicycle	Walk	
Car (23)	21	1	1	0	0	0	91
Bus (30)	1	28	1	0	0	0	93
TW (143)	0	3	140	0	0	0	98
Auto (15)	0	3	4	8	0	0	53
Bicycle(37)	0	1	0	1	32	3	86
Walk (21)	0	0	1	0	7	13	62
Total (269)	Correctly classified-242 ; Missed classified-27; Accuracy(%)-90						

4.2 Fuzzy Logic Based Models

Fuzzy logic is another area of the artificial intelligence which has been successfully applied to an increasing number of applications. The fuzzy set theory firstly introduced by Zadeh (1665) deals with proposition as that can be true to a certain degree (between 0 to 1) (Zadeh, 1965). The fundamentals of the concept are shown in Figure 4.

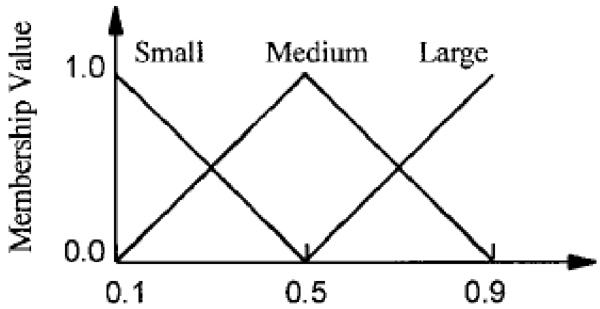

Figure 4: Fundamentals of Fuzzy Logic

In fuzzy logic, variables are fuzzy field through use of membership functions that define the membership degree to fuzzy sets, as they are often called "linguistic variables." Fuzzy rules are formed after deciding the membership function, then through Fuzzy Inference System (FIS) the input is mapped to output by using fuzzy set theory. The Fuzzy Inference System is usually designed by Fuzzification, fuzzy inference using fuzzy rules and Defuzzification. Many of the influencing variables used as input to mode choice modeling do not follow definition of crisp set. Crisp set allow either no membership of full membership, while fuzzy sets allow partial membership. Kedia and Katti (2014) have used the Fuzzy Rule Base System (FRBS) for the work trips to address the uncertainty prevailing in human linguistic expressions for the attributes in the mode choice modeling of Surat city. It is considered as the better option to address the shortcomings in crisp based modelling (Kedia & Katti, 2014). Kedia and Katti (2014) have used Matlab toolbox for the model development of the Surat city.Observed and model predicted results have Accuracy level of 91% and 94% while calibrating and validating the dataset respectively which are presented in Table 3 and Table 4.

Table 3. Cross classification table for calibration dataset

	Predicted (No. of Trips)				
Observed (No. of Trips)		2W	Auto	Car	Total
	2W	199	8	5	212
	Auto	12	35	0	47
	Car	4	0	86	90
	Total	215	43	91	349

Table 4: Cross classification table for Validation dataset

	Predicted (No. of Trips)				
Observed (No. of Trips)		2W	Auto	Car	Total
	2W	81	2	1	84
	Auto	4	15	0	19
	Car	1	0	33	34
	Total	86	17	34	137

4.3 Hybrid Mode Choice Model

Hybrid models using ANN and Fuzzy set theory were experimented to obtain the advantages of both the techniques. The Artificial Neural Network has a very good learning capacity and can capture the complex relationship between the variables if good amount of data are available. While Fuzzy set theory can capture the linguistic and vague expressions that are more close to human behavior but no learning abilities. The Neuro-fuzzy approach used by Sayed and Razavi (2000) on the U. S. freight transport market using information on individual shipper and individual shipments. Results obtained from the model are comparable with conventional logit model and ANN model. The proposed approach uses least amount of data and automates the selection of the input variables whose contribution is significant (Sayed & Razavi, January, 2000).

Lewe et al. (2014) have explored the multi-paradigm methodology and created a model of multimodal intercity transportation system. The model is calibrated using Agent Based Modeling and Simulation (ABM &S), useful for more complex condition (Lewe, Hivin, & Mavris, 2014).

5. Conclusions

- There are two modeling approaches used for modeling mode choice. Aggregate modeling and Disaggregate modeling. Disaggregate approach is widely used because it can capture individual characteristics in a better way compared to aggregated approach.
- Among three conventional disaggregated approach models namely Logit model, Probit model and General extreme value model, Logit models have found more popular and applicable due its simplicity and comparative reasonable accuracy.
- Artificial Neural Network models and hybrid model such as Neuro-fuzzy models give better result than conventional model because higher complexity involves in the travel characteristics.
- The Artificial Neural Network has a very good learning capacity to capture the complex relationship. While Fuzzy set theory can capture the linguistic expressions that are closer to human behavior.

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