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Critical Appraisal of Commuter's Mode Choice behavior Model Analysis

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Abstract—*Transportation modeling plays an important role in supporting transportation planning. Work trips are centre of focus of urban transportation planning and policy analysis. This may causes congestion in peak hours in the urban transportation network. One of the important aspects of transportation modeling is to predict the travel choice behavior. The travel choice behavior is also referred to as traveler mode choice, which is the most frequently modeled travel decision. It involves a specific aspect of human behavior dedicated to choice decision. This paper discusses the behaviors for making decisions of a particular trip mode are largely depend upon the sociodemo graphic characteristics and the purpose of the trip. It means it depends on whether it is a work trip or non work trip or shopping trip or recreational and family visit trip.*

1. INTRODUCTION

Transportation modeling plays an important role in supporting transportation planning. One of the major roles of transportation modeling is to forecast travel demand based on changes in the transportation system. There are different types of models that have been developed to create actual travel patterns of people and existing demand conditions. The models are used to predict changes in travel pattern and utilization of the transportation system in response to changes in land-use, demographics and socioeconomic conditions [1]. Work trips are centre of focus of urban transportation planning and policy analysis. This may causes congestion in peak hours in the urban transportation network. One of the important aspects of transportation modeling is to predict the travel choice behavior. The travel choice behavior is also referred to as traveler mode choice, which is the most frequently modeled travel decision. It involves a specific aspect of human behavior dedicated to choice decisions. With a model, as simplified representation of a part of ealityprovides a better understanding and interpreting of these complex systems.

2. OBJECTIVES OF THE PAPER

To identify the various variables that influences the mode choice behaviour of commuters for different types of destination.

To examine the methods used for the evaluation of the models using statistical and artificial intelligent techniques.

3. LITERATURE REVIEW

In recent years, growing attention has been given to destination choice models and in particular to the relation between the spatial layout of urban land use and destination choice behaviour.McFadden [16] initiated the idea that turned the economic theory of choice behaviour into the practical model to analyze the suitable residential zones. South worth [23] calibrated threedestination choice models for social/recreation, shopping and work trips, respectively, using in-vehicle, out-of vehicle travel time, monetary expenditure, and number of trip destinations included in each alternative as specifications. Daly applied improved Newton-Raphson algorithm to calibrate choice models containing attraction variables.

Bhat et al. [3] developed zones location indicator, zonal spatial structure measure (SSM), and sociodemo graphic variables in addition to travel impedance to estimate an attraction-end choice model for home-based work and shopping trips in Boston. Furthermore, Kitamura et al. [13]provided statistical evidence that destination choice was influenced by time of day, activity duration, and home location in South California. Chow et al. and Li et al. [7]built the destination choice models, respectively, for three income groups (high, middle, and low) of residents in Broward, Palm Beach,Volusia towns of Florida. Apart from the above destination choice models of home-based work and home-based shopping, Pozsgay and Bhat [19] presented an attraction-end choice model for urban recreational trips in Dallas-Fort Worth, and the effects of level-of-service, retail acreage, zonal spatial measurement were examined.

Generally, destination choice is often combined with travel mode choice, which has demonstrated to improve the traditional travel demand model. For instance, Ben- Akiva and Lerman [1] estimated joint mode and destination choice models for personal business and shopping trips in Paris by using the theory of samples of alternatives. Among the current hot research topic of activity-based travel demand models, the tour-based joint model of destination choice model and travel mode choice model has become a critical module. Bowman and Ben-Akiva [5]put the tour destination and mode choice model as the base module in the whole activity-based travel demand model, with time of day and activity pattern as the upper level of the model. Calibrations of this model are made using data from the travel survey in Boston.

Stopher and Wilmot [24] suggested that data has to be collected by considering the issues like type of activities,tradeoffs between in-home and out-of home activities, locations of an activity and interaction betweenhousehold members. Hence, extreme care should be given to the design of survey instrument and method of administration. Arentze et.al. [2] stated that diaries, Interactive computer experiments and conjoint experiments are the most viable methods to collect data for activity behaviour research..

M. Manoja, Ashish Vermab [15] analyzed activitytravel behaviour of non-workers from Bangalore city in India. Using a primary activity-travel survey data, this study modelled the out-of-home activity participation behaviour of non-workers. Travel behaviour was analysed in the context of stop generation (for maintenance and discretionary activities). The core objective of this analysis was to identity the sociodemographic attributes affecting the activity participation of individuals. Due to count data type, Negative Exponential model (as observed from the data) was considered for modelling the behaviour.

In case of maintenance stop frequency model, age was found to be negatively related to the stop frequency. Similar case was observed with being female, head of household, education status, and number of non-workers in the household. In-home maintenance activity duration also had negative bearing with number of maintenance stops. Similar was the case if an individual had participated in other out-of-home activity type. Other variables like household income, vehicle ownership, number of children in the household, number of workers in the household etc. have showed positive relation with stop frequency. In case of discretionary stop frequency model, individuals in age groups <50 years showed a positive relation with stop making. Similar trend was observed for individual in age group 50-65. Apart from this, vehicle ownership, gender (male), household income, head of household, education etc. have also showed a positive relation with stop frequency.

Individual in age group >65 years, married individuals and homemakers showed a negative relation with stop frequency. Subbarao SSV and Krishna Rao KV [25] focused on designing a new survey instrument called activity-travel diary, method of administration, and analysis of activity travel behaviour in the context of developing countries.

Mumbai Metropolitan Region (MMR), India was selected as the study area. With the aim of understanding the activities of each individual over a period of time, pilot survey was conducted in a continuous time frame for a period of 15 days, followed by main survey.

The analysis of data collected by the instrument revealed some interesting facts regarding the relationship between socioeconomic attributes and their activity and tripmaking behaviour. Further, a multinomial logit model has been developed for understanding the mode choice behaviour of individual.

Essam Almasri, Sadi Alraee [10] developed a model for GAZA city. The results of this research showed that thefactors that significantly affect the choice of transport modes are: total travel time, total cost divided by personal income, ownership of means of transport, distance, age, and average family monthly income. The developed model is able to predict the choice behaviour of employed pe- ople in Gaza city as it is valid at 95% confidence level.

Ori Rubin et al [18] found the determinants of mode choice for family visits. we find that living with a partner and having a child under six years old is negatively associated with the likelihood of using public transport for family visits. Number of children is not associated linearly with mode choice. Walking and cycling is mainly associated with distance between family members: the shorter the distance the higher the likelihood of using slow-modes instead of a car. Those travelling between areas of high degree of urbanization have a higher likelihood of using public transport relative to using cars. Car ownership is negatively associated with all other modes. Using a car for commuting is also found to be negatively associated with other modes for family visits.

4. METHODS OF COLLECTING TRAVEL BEHAVIOUR DATA

The data required for modelling is collected through surveys like household survey, workplace survey, destination survey, and intercept survey. Sampling from the data set is also a critical step and should be attempted with caution. Paper and pencil interviewing (PAPI) is an orthodox method for data collecting. It represents a process of personal interviewing where the pollster holds a printed-out questionnaire, reads the question to the respondent and fills the answers into the questionnaire. It has higher chances of error compared to Computer Assisted Interviewing (CAPI).. CAPI is a computer assisted data collection method for replacing paper-and-pen methods of survey data collection and usually conducted at the home or business of the respondent using a portable personal computer. It allows interviewers to conduct face-to-face interview using the computer. After the interviews, the interviewers send the data to a central computer. CAPI can also include Computer Assisted Self-Interview (CASI) session where the interviewer hands over the computer to the respondent for a short period, but he/she remains available for instructions and assistance. Computer Assisted Telephone surveys and Commuter Assisted mail surveys are increasingly being replaced by web based online (internet) surveys. Online surveys are becoming an essential research tool for a variety of research fields, including marketing, social and official statistics research. Wang et al. [27] stated from their study based on web-based travel survey that although this type of survey method is highly capable in handling complex tasks as stated preference experiments, it can be highly unreliable.

5. AGGREGATE AND DISAGGREGATE MODE CHOICE MODELS

Aggregate models attempt to represent the average behavior of a group of travelers instead of a single individual. Different aggregate models devised and used over past decades are a) Trend analysis where past trends were extrapolated to estimate future travel; b) Mathematical models like the direct demand models and sequential models are usually more difficult to implement, more time-consuming and more costly but provide more accuracy; c) Trip-end modal split, applied immediately after trip generation, and d) Trip- Interchange modal split models when modal split is applied after the trip distribution. While the former preserves the various socio-economic characteristic of the commuters the latter includes the characteristics of the journey and that of the alternative modes available to user. The aggregate transportation planning models have been severely criticized for their inflexibility and inaccuracy. These models at base attempt to represent the average behavior of a group of travelers instead of a single individual. Disaggregate models which appeared in 1980s offer substantial advantage over its aggregate counterparts as it represents the behavior of individuals. In disaggregate approach individual choice responses as a function of the characteristics of the alternatives available and socio-demographic attributes of each individual.

It has a more causal nature and is thus more transferable to a different point in time and to a different geographic context, very well suited for proactive policy analysis.

Efficiency of disaggregate approach is more than the aggregate approach in terms of model reliability per unit cost of data collection.

6. MULTINOMIAL LOGIT MODEL

Multinomial logit model is also called MNL model, and it is based on utility maximization theory. That is, under specified conditions, a decision-maker always chooses the scheme with maximal utility he perceives. Utility can be divided into deterministic utility composed of observable factors and random utility composed of unobservable factors, which is:

$$U_{in} = V_{in} + \varepsilon_{in} (i \in C_n) \tag{1}$$

In this formula, in U is the utility of the ith scheme chosen by the nth decision maker, in V is the deterministic utility of the ith scheme chosen by the nth decision maker, in E is the random error of the ith scheme chosen by the nth decisionmaker, n C is the set of all schemes that can be chosen by the nth decision maker. According to utility maximization theory, the condition that the nth decision maker chooses the jth scheme from n C is:

$$U_{jn} > U_{in} (i \neq j, i \in C_n) \tag{2.}$$

Suppose random terms *e1, e2, e3* are independently and identically distributed, and the distribution function is a Gumbel distribution with parameters (0,1). Then, MNL model of the nth decision maker choosing the jth scheme can be shown as below:

$$P_{jn} = \exp(V_{jn}) / \sum_{i=1}^{k} \exp(V_{in}) \tag{3}$$

Generally, the deterministic term of utility function *jn V* is assumed to be a linear function of attributes *x* (*l* 1,2,...*L*) *jnl*

$$V_{jn} = \sum_{l=1}^{L} \beta_l x_{jnl} + \gamma_j \tag{4.}$$

The model parameters can be obtained from maximum likelihood estimation of log likelihood function. The assumption of independent random utility term makes the model have characteristics of IIA (mutual independence between noncorrelation schemes), which means that the probability ratio of any two schemes will not be influenced by the deterministic utility term of other schemes.

7. NESTED LOGIT MODELS

Nested Logit (NL) structure al lows estimation of proportions among selected sub-modes, prior to the estimation of proportions between modes. The nested log it model have their random component identically, non-independently distributed with type I extreme value distribution allowing partial relaxation of the assumption of independence among random components of alternatives (McFadden, 1978). It has a closed form solution, is relatively simple to estimate and is more parsimonious than the multinomial probit model. The major drawbacks of NL models are first, the number of different structures in search for the best structure increases rapidly as the number of alternatives increases.

Second, the actual competitive structure among alternatives may be a continuum which cannot be accurately represented by partitioning the alternatives into mutually exclusive subsets. Abdel-Aty and Abdelwahab [1] developed mode choice models for Florida, USA. The mode choice model was estimated as three level Nested Logit structure. The overall model utilized full information maximum likelihood estimation.

Among the significant variables that entered into model are transit access time, transit waiting time, number of transfer, in-vehicle travel time, fare and household car ownership. Khan [12] designed Nested logit models for different trip length and trip purpose for Redland Shire. Data was collected through a Stated Preference survey in which an entirely a new virtual travel environment was created and the result of this study indicated that trip length affects the perception of alternatives to work for longer trips.

8. SOFT COMPUTING MODE CHOICE MODELS

Multinomial Logit (MNL) model is a traditional model adopted for mode choice analysis which has majorlimitation that the input variables need to have crisp values and hence should be measured accurately which consumes lot of time and resources. Moreover, decision of trip maker for choosing a mode involves human approximations which are not precisely captured by MNL model. This can be overcome by using artificial intelligence techniques like fuzzy logic and neural networks.

8.1 Artificial Neural Network Models

Cantarella and De Luca [6] compared MNL and ANN models for mode choice modeling using disaggregate discrete choice data. Two types of neural networks were trained and the results compared to the logit model. The results revealed that ANN model adopted in this study outperformed the MNL model. Xie et al. [26] in their mode choice studies used Decision tree (DT) and Artificial neural network (ANN). Datasets from the San Francisco Bay Area Travel Survey (BATS) 2000 were used. They compared the results obtained by these techniques with a traditional multinomial logit (MNL) model. Prediction results show that the two data mining models offer comparable but slightly better performance than the MNL model in terms of the modeling results, while the DT model demonstrates highest estimation efficiency and most explicit interpretability and the ANN model gives a superior prediction performance in most cases. Ravi Sekhar [21] carried out a mode choice study for Delhi. In this study mode choice models based on ANN and MNL were formulated and a comparative analysis was done between both. The ANN model different models were developed based on the vehicle ownership and the choice set available to the commuters.A back propagation algorithm was used for the ANN architecture. The relative importance of input parameters was found out and Object Oriented Programming (OOP) was used to implement ANN network. ANN models outperformed the MNL models.

8.2 Fuzzy Logic Based Mode Choice Models

Deb [9] used Fuzzy set theory to study the Mass transit mode choice pattern for Calcutta. Different Mass transit alternatives like Bus, Car, Surface Railway, Metro and Water Transport were taken into account and fuzzy set theoretic approach was employed to select the more preferable set of alternatives. Aggregate matrix was used to compare the various alternatives included in this matrix to select the best alternative(s). An alternative was taken as superior to a second alternative if it dominated the second-alternative in more number of factors than the number of factors in which the second dominates the first. Sey edabrishami and Shafahi [22] carried out a Trip destination and Mode choice joint model analysis by using Fuzzy set theory. The model is structured as a decision tree in which the fuzzy and non-fuzzy classification of influential variables regarding destination selection and mode choice expand the tree for Shiraz, a large city in Iran. When compared with a multinomial logit (MNL) model, the suggested models' estimates are more accurate than the traditional MNL model. Rao and Sikdar [20] carried out urban mode choice analysis by calibration of Fuzzy functions from revealed preference survey in Mumbai. They used ANN forthe calibration of Fuzzy membership function. The membership function was modified by the back propagation of error. Modification was in proportion to the error signal. The model gave performance of 99.73% in calibration and 98.64% in validation suggesting accurate result.

9. CONCLUSION

Review on Mode choice studies carried out in this paper shed light on various aspects of mode choice analysis as a transportation planning process. Mode choice modelling directly deals with the behavioral aspect of human nature thus it needs to closely monitor and understand the factors that affect this decision making procedure. Modeling of mode choice can be approached in two ways: aggregate modeling and disaggregate modeling. Disaggregate approach is widely used as it can capture the individual characteristics in a much better way compared to aggregate models that depend on zonal characteristics.

Amongst all the three models, Logit models have found the most application in choice models because of simplicity and easy interpretation of results. It also has comparatively reasonable accuracy. The data required for modeling is collected through surveys like household survey, workplace survey, destination survey, and intercept survey. Sampling from the data set is also a crucial step and should be done diligently. Due to the complexity involved in the Indian travel characteristics a model highly flexible as well as compatible to handle such heterogeneity should be used. Artificial intelligent modelssuch as Neuro- Fuzzy models and neural networks gives better results than the statistical models.

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