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The Graduate School of Sciences and Engineering

Master of Science in
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A TRANSPORTATION APPLICATION ON ROUTE AND MODE CHOICE IN İSTANBUL BY USING DISCRETE CHOICE METHODS

by

Yasemin POLAT

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APPROVAL PAGE

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ABSTRACT

Trips take an important role of daily life which are modelled according to decisions about route choice and mode choice. The mode and route choice is a complex problem with many parameters to maximize the individual benefit, the effectiveness of a mode and route choice model depends on well-understanding of the choice behaviour. Because human behaviour is complex and diffucult to understand the underlying choice mechanism and reasoning. Identifying the human behavior, discrete choice models are commonly used. The purpose of this study is to model the mode and route choice problem of an important network defined in İstanbul with Multinominal Logit and C-logit model. So that, a consumer choice behavior model developed for İstanbul transportation by using the real data gained by survey. The aim is to decide on the transportation modes and route between the selected pilot areas in İstanbul while going from one area to the other. In this choice phase, we considered too many criteria such as transportation time, cost, traffic intensity, comfortability of the transportation mode, passenger characteristics, etc. to decide on the alternative route and mode having maximum utility. After constructing a model, we analyzed and discussed the results.

Keywords: Discrete choice models, Route choice, Mode choice

KESiKLİ SEÇİM MODELLERİ İLE İSTANBUL'DAKİ BİR PİLOT BÖLGEDE ULAŞIM ROTASI VE ARAÇ TİPİ SEÇİMİ İÇİN BİR UYGULAMA

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ÖZ

Günlük yaşamda önemli bir role sahip olan seyahatler, ulaşım türü ve rota seçimi ile ilgili verilen kararlar sonucu şekillenmektedir. Rota ve araç seçim problemi, birçok parametrenin değerlendirilerek, bireysel fayda enbüyüklemesinin sağlanabilmesine yönelik oldukça kompleks bir problem olup, oluşturulacak modelin verimliliği, bireysel araç ve rota seçimi davranışının gerçekçi olarak yakalanabilmesine bağlıdır. Çünkü insan davranışı genellikle karmaşıktır ve altında yatan seçim mekanizmalarının anlaşılması oldukça zordur. Seçim davranışının belirlenmesinde tüketici tercih modelleri yaygın olarak kullanılmaktadır. Bu çalışmanın amacı İstanbulda belirlenmiş olan bir yol ağındaki araç ve rota seçim problemini modellemektir.Böylece, anketle elde edilen gerçek veriler kullanılarak istanbul ulaşımı için bir tüketici tercih modeli geliştirilmiştir. İstanbul' da seçilen pilot bölgeler arasında bir yerden bir yere giderken hangi ulaşım aracının ve ulaşım güzergahının seçileceğine karar verilmesi amaçlanmıştır. Seçim aşamasında yolcu açısından maksimum faydayı sağlayan rota ve ulaşım araçlarının seçilmesi, yolculuk süresi, maliyet, trafik yoğunluğu, ulaşım araçlarının konforlu olması, yolcu karakteristik özellikleri, vb. birçok kriter göz önünde bulundurularak karar verilmiştir. Model oluşturulduktan sonra sonuçlar analiz edilip değerlendirilmiştir.

Anahtar kelimeler: Kesikli tercih modelleri, Rota seçimi, Araç seçimi

To my parent

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

Trips take an important role of daily life which are modelled according to decisions about route choice and mode choice. The mode and route choice is a complex problem with many parameters to maximize the individual benefit, the effectiveness of a mode and route choice model depends on well-understanding of the choice behaviour. Because human behaviour is intricate and diffucult to understand the underlying choice system and reasoning. In-depth understanding of human nature is essential to the planning, design, and operational analysis of transportation systems.

İstanbul is a metropolitan city. Many metropolitan city troubled by a proceeding increase in traffic congestion. This congestion caused by longer travel times, increased accidents, more fuel consumption and deterioration in air quality. Main reason under the congestion is awareness of passenger preference and expectations. To be aware of passenger preference and expectations depends on understanding of human behaviour. Identifying the human behavior, discrete choice models are commonly used. Discrete choice models have received widespread acceptance in transport research, being used in travel demand modelling and behavioral analysis. Discrete choice analysis is the methodology used to analyze and predict travel decisions.

There are two basic ways of modeling such aggregate (or group) behavior. One approach directly models the aggregate share of all or a segment of decision makers choosing each alternative as a function of the characteristics of the alternatives and socio-demographic attributes of the group. This approach is commonly referred to as the aggregate approach.The second approach is to recognize that aggregate behavior is the result of numerous individual decisions and to model individual choice responses as a function of the characteristics of the alternatives available to and socio-demographic attributes of each individual. This second approach is referred to as the disaggregate approach(Koppelman and Bhat, 2006).

The set of considered alternatives is called the choice set. Each alternative in the choice set is characterized by a set of attributes. The decision rule is the process used by the decision-maker to evaluate the attributes of the alternatives in the choice set and determine a choice. Most models used for travel behavior applications are based on *utility theory*, which assumes that the decision-maker's preference for an alternative is captured by a value, called utility, and the decision-maker selects the alternative in the choice set with the highest utility(Ben-akiva and Bierlaire, 2003).

1.2 OBJECTIVES

Mode and route selection process has a very complex structure, in order to simplify this complexity depends on the correct understanding of the parameters characteristics. Discrete choice models have ability to modelling these attributes. Also discrete choice models have received widespread acceptance in transport research, being used in travel demand modelling and behavioral analysis.

The purpose of this study is to model the mode and route choice problem of an important network defined in İstanbul with discrete choice models. Consumer choice behavior model developed for İstanbul transportation by using the real data gained by survey. The aimed is to decide on the transportation modes and route between the selected pilot areas in İstanbul while going from one area to the other.

In this choice phase, considered too many criteria such as transportation time, cost, traffic intensity, comfortability of the transportation mode, passenger characteristics (gender, income statue, and car ownership), peak hours, etc. to decide on the alternative route and mode having maximum utility.

1.3 SUBJECT AND SCOPE

This thesis related with road and passenger status analysis, determination of passenger preference and according to this preference determining the route and mode choice.

Thesis consist of some stages: determination of pilot area in İstanbul, accordingly determination of the mode and route alternatives, identification of route, road and mode characteristics, the preparation of a survey to measure the behavior of passengers, implementation of the survey, data analysis, construction of model, reporting of result and further research.

In this study; first of all determined Origin-Destination Points (OD) of the sixth route in Hadımköy- Yenibosna after designed a survey to determine the passenger preference about mode and route choice and demonstrate evaluations as a result of the election.

These data obtained which acts on the choice of mode and route; travel time, cost, comfort, peak hours, walking distance parameter is used as input and mode and route selection intended as output logit model has been developed. Biogeme software was used to develop a logit models. Then, we compared the result of logit models with shortest route.

CHAPTER 2

LITERATURE REVIEW

Our literature review consist of two parts. General part include human behaviour and discrete choice models research. Application part include application of discrete choice models (utility based models) and non-utility based models for transportation.

2.1 GENERAL

Human behaviour is complex and often not transparent. Nevertheless, one would like to understand human behaviour and especially the underlying choice mechanisms and reasoning. Understanding choice behavior is of utmost importance in both the private and public sector. In the business world, companies are interested in consumer choice behaviour because a better understanding of consumer choice behaviour allows them to introduce more successful products and increase their market share (Lovelock, 1975).

The Logit formula was first derived by Luce (1959); Marschak (1960) later showed that the model is consistent with utility maximization and McFadden (1973) showed that the form of the Logit formula necessarily implies the use of the type I extreme value (Gumbel) distribution for the unobserved part of the utility.

Discrete choice models describe decision makers' choices among alternatives. To fit within a discrete choice framework, the set of alternatives, called the choice set, needs to exhibit three characteristics. First, the alternatives must be mutually exclusive from the decision maker's perspective.

Choosing one alternative necessarily implies not choosing any of the other alternatives. The decision maker chooses only one alternative from the choice set. Second, the choice set must be exhaustive, in that all possible alternatives are included. The decision maker necessarily chooses one of the alternatives. Third, the number of alternatives must be finite. The researcher can count the alternatives and eventually be finished counting (Bovy, 2009).

The framework for a discrete choice model can be presented by a set of general assumptions Ben-Akiva and Lerman (1985):

1. Decision-maker -- defining the decision-making entity and its characteristics;

2. Alternatives -- determining the options available to the decision-maker;

3. Attributes -- measuring the benefits and costs of an alternative to the decision maker; and

4. Decision rule -- describing the process used by the decision-maker to choose an alternative.

The traditional four-step planning procedure has four main steps involved- Trip Generation, Trip Distribution, Mode Choice, and Trip Assignment. In the trip generation, the number of trips generating from all the zones are modeled. Once the total trips generated by each zone are estimated, the trip distribution procedure calculates the trip interchanges between the zones. In the mode choice step, mode specific trip interchanges are estimated. Trip assignment is the last stage of the model, dealing with the allocation of a given set of trip interchanges to a specific transport network.

In general the utility is expressed in a cost function, with travel time as the most important component. Basically, the random utility based models can be divided into two groups: deterministic and stochastic route choice models. Deterministic route choice models always generate the same set of paths for an OD-pair. Most of the deterministic models can be made stochastic by using random generalized cost for the shortest path computations (Frejinger at al.. 2009). Stochastic methods generate an individual (or observation) specific subset.

Stochastic route choice models based on the random utility theory are: Multinomial logit, C-logit, Nested logit, and Cross Nested Logit (Telgen, 2010).

Since McFadden (1973) pioneered disaggregate discrete choice modeling of travel behavior in the 1970s researchers have been concerned about the Independence from Irrelevant Alternatives property implied by the conditional logit model. Of course, the property is also implied by any discrete choice model with independent and identically distributed unobserved utility terms.

The Generalized Extreme Value family of models, introduced by McFadden (1978), is a set of closed form discrete choice models that are all based on the use of the extreme-value distribution, and which allow for various levels of correlation among the unobserved part of utility across alternatives.

A first version of the Nested Logit model was proposed by Domencich & McFadden (1975). A very general version of a two-level GEV model is given by the Generalized Nested Logit (GNL) model of Wen & Koppelman (2001), which allows alternatives to belong to different nests, with different degrees of allocation for different nests, and differential levels of correlation in different nests.

Non-utility based models cope with the disadvantages of the random utility based models. Tversky and Kahneman (1986) have shown conflicts of the random utility theory with actual decision situation, therefore they developed the Prospect theory.

McFadden's Nested Logit (1978) model provided a generalization that could handle the types of unobserved error correlations frequently encountered in transportation applications. Nested Logit is the most popular 3 member of the wider class of generalized extreme value models. Small (1987) derived the ordered generalized extreme value model, and Chu (1981) derived the paired combinatorial logit model (Koppelman and Wen, 2000).

None of these generalized extreme value models are flexible enough to approximate arbitrary discrete choice models, and recent work by Bhat (1999) and Brownstone and Train (1999) have demonstrated cases where Nested Logit is not sufficiently flexible to model travel behavior. The only models that are flexible enough to approximate any discrete choice model are Multinomial Probit and Mixed Logit.

2.2 APPLICATIONS

Henn and Ottomanelli (2006) show that the consideration of randomness of traffic by drivers is hardly ever represented in random utility route choice models. These randomness of traffic by drivers is incorporated in Fuzzy logic. They also discuss that Possibility theory is more accurate in representing decision behavior under uncertainty than Probability theory which is used in the random utility theory. Game theory considers the traffic assignment from a totally different point of view. This theory considers the assignment as a game with multiple players.

Although Bayesian methods are attracting increasing attention (Malakoff, 1999), there have been very few Bayesian discrete choice models in transportation. Applied researchers in other disciplines are adopting Bayesian techniques because they provide a principled approach for incorporating non-sample prior information, and they avoid asymptotic approximations.

(Bekhor at al., 2007) applied a Stochastic User Equilibrium assignment based on the cross-nested logit (CNL) route choice model. They developed path-based algorithms to solve the Cross Nested Logit - Stochastic User Equilibrium problem based on adaptation of the disaggregate simplified decomposition method.

Murat and Uludağ (2008) modeled route choice of transportation network in Denizli using fuzzy logic model and logistic regression model. Four important parameters (traffic safety, travel time, congestion and environmental effects) were used in models.

Abdel-Aty and Abdelwahab (2001) developed mode choice models for Florida. The mode choice model was estimated as a three level nested logit structure. There were three separate trip purposes calibrated. These purposes were: home based work trips, home based non-work trips, and non-home-based trips.

Bovy, Uges, Lanser (2003) analyzed the influence of multi-modal trip attributes on the quality and competitiveness of regional multi-modal train alternatives. Hierarchical Nested Logit models are estimated to take account of unobserved similarities between alternatives at the home end and the activity end of the trip respectively, resulting in two level nesting structures which differentiate between intercity and non-intercity railway station types at the upper level and between transit and private access modes at the lower level. In order to reflect the multidimensional structure of the data a more advanced so-called Multi- Nested general extreme value model according to the Principles of Differentiation has been estimated which significantly improves the explanatory power and stresses the importance of the home side of the multi-modal trip.

Murat and Kulak (2005) used Information Axiom for route selection in transportation networks. Travel time, congestion, safety and environmental effects are the important criteria that should be taken in to account in route choice. The Information axiom, the second axiom of Axiomatic Design principles, proposes the selection of the proper alternative that has minimum information content. Axiomatic approach including crisp information axiom for complete information and fuzzy information axiom for incomplete information is used as a tool for the evaluation of alternative routes in Denizli.

Chen, Tzeng (1999) used fuzzy integral for evaluating subjectively perceived travel cost in a traffic assignment model. They constructed nontraditional traffic assignment model.

Haldenbilen, Başkan (2011) developed Ant Colony Optimization and Harmony Search model to solve the stochastic traffic assignment problem. Furthermore, the results of Stochastic User Equilibrium assignment are compared with the Deterministic User Equilibrium.

Eluru, Chakour and El-Geneidy (2012) analyzed the travel mode choice component and transit route choice component using classical multinomial logit model for Montreal.

Yang (2010) investigated the impact of service quality on travelling airline choice by integrating the Multinomial Logit model and fuzzy integral. This study focused on the airline choice behaviour of four domestic airlines in Taiwan.

CHAPTER 3

DISCRETE CHOICE MODELS

Discrete choice modeling, sometimes called qualitative choice modeling or consumer choice behaviour model is an interesting new statistical technique common in the market research. They are called discrete because they deal with the modeling of discrete choices, we either choose one option or the other, and you can't choose both. By identifying patterns in these choices, discrete choice models help to understand consumer's choice mechanism. Discrete choice models allows marketers to examine the share impact of product configuration, pricing and promotion on different classes of customers.

Discrete choice model has a widespread acceptance in many sectors. For example; automotive manufacturers use discrete choice model to forecast demand for new models. Telephone companies use discrete choice model to configure new products. For transportation discrete choice model have been used in demand analysis.

The first step in a discrete choice models is to establish focus groups to determine the preference factors. The second step involves conducting survey from the focus groups. Once data have been collected, the final step is to build a computer model using complicated statistical techniques.

The framework for a discrete choice model can be presented by a set of general assumptions Ben-Akiva and Lerman (1985):

1. Decision-maker -- defining the decision-making entity and its characteristics;

2. Alternatives -- determining the options available to the decision-maker;

3. Attributes -- measuring the benefits and costs of an alternative to the decision maker; and

4. Decision rule -- describing the process used by the decision-maker to choose an alternative.

Decision-maker: Discrete choice models are also referred to as disaggregate models, meaning that the decision-maker is assumed to be an individual. To explain the heterogeneity of preferences among decision-makers, a disaggregate model must include their characteristics such as the socio-economic variables of age, gender, education and income.

Alternatives: Analyzing individual decision making requires not only knowledge of what has been chosen, but also of what has not been chosen. Therefore, assumptions must be made about available options, or alternatives, that an individual considers during a choice process. The set of considered alternatives is called the choice set. The choice of a travel mode is a typical example of a choice from a discrete choice set.

Attributes: Each alternative in the choice set is characterized by a set of attributes. Note that some attributes may be generic to all alternatives, and some may be alternative-specific. An attribute is not necessarily a directly measurable quantity.

Decision rule: The decision rule is the process used by the decision-maker to evaluate the attributes of the alternatives in the choice set and determine a choice. Most models used for travel behavior applications are based on *utility theory*, which assumes that the decision-maker's preference for an alternative is captured by a value, called utility, and the decision-maker selects the alternative in the choice set with the highest utility.

3.1 RANDOM UTILITY THEORY

Random utility theory is based on hypothesis that every individual is a rational decision –maker, maximizing utility relative to his or her choice.

The utility is modeled as a random variable in order to reflect this uncertainty. More specifically, the utility that individual n associates with alternative i in the choice set C_n is given by Eq (3.1):

$$U_{in} = V_{in} + \varepsilon_{in}, \tag{3.1}$$

where V_{in} is the deterministic (or systematic) part of the utility, and ε_{in} is the random term, capturing the uncertainty. According to the random utility theory the traveler choose his route from the choice set based on the net utility Uin. The deterministic term V_{in} of each alternative is a function of the attributes of the alternative itself and the characteristics of the decision-maker(Bierlaire, 2003).

The random part of the utility: Among the many potential models that can be derived for the random parts of the utility functions. The models within the Logit family are based on a probability distribution function of the maximum of a series of random variables, introduced by Gumbel (1958). Probit and Probit like models are based on the Normal distribution motivated by the Central Limit Theorem(Telgen, 2010).

Basically, the random utility based models can be divided into two groups: **Deterministic** and **Stochastic** route choice models.

3.2 DETERMINISTIC MODELS

Deterministic route choice models always generate the same set of paths for an OD-pair. Deterministic route choice models assume that the travelers have full knowledge about the links and their ’costs’ in the network (Telgen, 2010).

3.2.1 Shortest Path

Most models of the deterministic group are based on the shortest path principle. In the shortest path principle, travelers are assumed to minimize on one variable or a mix of variables, for instance travel time or distance (Telgen, 2010).

3.2.2 Labeling Approach

The labeling approach assumes that different travelers minimize different attributes. Some travelers may wish to minimize travel time, while other travelers feel uncomfortable driving on dangerous roads and avoid curvy roads. Each of these criteria may correspond to a different road being preferred, and thus, each route can be labeled with a different criterion for which it is the optimum. Examples of labels are: time, distance, fuel, scenery, traffic lights and congested travel. The labeling approach is used in combination with the Nested logit model when paths have multiple labels (Ramming, 2009).

3.3 STOCHASTIC MODELS

Stochastic methods generate an individual (or observation) specific subset. Stochastic route choice model assumes reasonably that travelers have imperfect information about path costs and choose the route that minimizes their perceived travel costs given a set of routes.

Most stochastic route choice models are a member of the Generalized Extreme Value family. Generalized Extreme Value members described in this section are: Multinomial logit model, the C-logit, the Path Size logit, the Nested logit, and the Cross Nested logit. Mc Fadden derived the basic Generalized Extreme Value model from the random utility theory. The Generalized Extreme Value model assumes that the random term in the utility function follows the Gumbel distribution. In the Generalized Extreme Value models a choice set is defined. The choice set consists of all available alternative routes for individual n (Ben-Akiva and Bierlaire, 2003).

3.3.1 The Multinomial Logit

The Multinomial logit model is the most widely used choice model, due to its simple mathematical structure and ease of estimation. Its generalization to more than two alternatives is referred to as the Multinomial Logit Model. According to the random utility theory the traveler choose his route from the choice set based on the net utility Uin. We as modelers do not have complete information about this net utility and try to describe the net utility by a deterministic part Vin and a random part ε_{in}.

In the Multinomial logit is assumed that the random part can be described by the exponential Gumbel distribution. The exponential in the probability distribution ensures that large differences in travel times are highly recharged in the route choice probabilities (Wenn and Koppelman, 2001).

The probability that a given individual *n* chooses alternative *i* within the choice set C_n and θ is a scale parameter is given by Eq (3.2):

$$P((i|Cn) = \frac{e^{\theta(Vin-CFi)}}{\sum j\epsilon\, Cn\ \ e^{\theta(Vjn-CFj)}} \tag{3.2}$$

A special property of the Multinomial logit is the Independent of Irrelevant Alternatives property. Independent of Irrelevant Alternatives means that the ratio of the probabilities of any two alternatives is independent of other alternatives, so $\frac{P(i|C_1)}{P(j|C_1)} = \frac{P(i|C_2)}{P(j|C_2)}$. This property was considered as an advantage of the model, due to the property it is possible to forecast the share of a new alternative that is not present at the calibration stage if the attributes are known. However this property has also a disadvantages, one of the disadvantage is unsuitable for solving essentially nonlinear problems, and another disadvantage is explained below.

Somebody is traveling from O (Origin) to D (Destination). This person utility depends on travel time. This network described of figure 3.1.

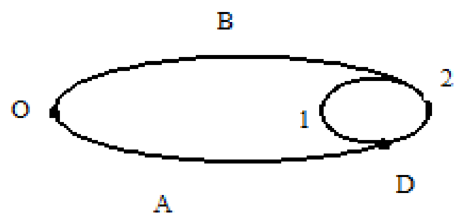

Figure 3.1 Origin Destination Network.

First suppose that only two paths are exist (B1 not exist yet) so, path alternatives is [A, B2]. All paths have a same travel time t. And probabilities of choosing each path according to MNL Logit $\frac{e^t}{2e^t} = {}^1\!/_2$. If new route added to network, choices are [A, B1, B2] and probabilities are changed to 1/3 (depends on the IIA property). We expect the probabilities for B1 and B2 are 0.25, for A 0,5. The Multinomial Logit Model is not consistent with this intuitive result.

This situation appears in choice problems with significantly correlated random utilities, as it is clearly the case in the path choice example. Indeed, alternatives 2a and 2b are so similar that their utilities share many unobserved attributes of the path and, therefore, the assumption of independence of the random parts is not valid in this context.

3.3.2 The C-logit

The basic idea of the C-logit is to deal with similarities among overlapping paths Cascetta, Nuzzolo, Russo and Vitetta (1996) proposed the C-logit model, to maintain the computational simplicity of the logit form but produce more intuitive forecasts of route shares especially when path overlapping occurs. The C-Logit model, proposed by Cascetta *et al.* (1996) in the context of route choice. They add to the deterministic part of the utility function a term, called "commonality factor" that captures the degree of similarity between the alternative and all other alternatives in the choice set.

In contrary to the Multinomial logit consists the deterministic part of the net utility of two elements Vin-CFi instead of one Vin. The probability that an individual n chooses route i is formulated in the C-logit model by Eq (3.3):

$$P((i|Cn) = \frac{e^{\theta(Vin-CFi)}}{\sum j\epsilon\ Cn\ \ e^{\theta(Vjn-CFj)}} \tag{3.3}$$

The scale factor, scales the effect that differences in systematic utilities (Vjn -CFj) have on the traveler's decision, the larger the more influence of the differences (Telgen, 2010).

The commonality factor (CFi) of individual n for route i is proportional to the path overlap. Heavily overlapping paths have larger commonality factors and thus a smaller systematic utility with respect to similar, but independent paths. If path i is made up of links belonging exclusively to that path, then CFi is equal to zero (Cascetta et al., 1996).

In literature, there are five different forms of the commonality factor:

$$CFi = \beta \ln \sum_{j \epsilon Cn} (\frac{Lij}{\sqrt{Li\,Lj}})^{\gamma} \tag{3.4}$$

$$CFi = \beta \ln \sum_{a \epsilon \Gamma_i} \frac{l_a}{Li} N_a \tag{3.5}$$

$$CFi = \beta \sum_{a \epsilon \Gamma_i} \frac{l_a}{Li} \ln N_a \tag{3.6}$$

$$CFi = \beta \ln \left(1 + \sum_{j \,\epsilon\, C_{n,j \neq i}} \frac{L_{ij}}{\sqrt{Li\,Lj}} \frac{L_i - L_{ij}}{L_j - L_{ij}}\right) \tag{3.7}$$

$$CFin = \beta \ln \sum_{a \epsilon\, i} \omega_{ai} N_a \tag{3.8}$$

Where β and γ are coefficients that weight the commonality factor, L_{ij} is the common length of path i and path j, Γ_i is the set of arcs in path i, and l_a the length of link a. N_a is the number of paths connecting the same OD pair which share link a, with N_a = 1 for centroid connectors (Ramming, 2002), and ω_{ai} is the proportional weight of link a for path i. Formulation (3.8) is similar to formulation (3.5) if ω_{ai} is chosen according to the distances. Larger values of β causes higher influence of the overlapping constant with respect to the utility. The influence of γ is smaller than β and has the opposite effect. The parameter is usually taken in the range [0,2] (Cascetta et al., 1996). Formulation (3.4) is the only symmetric formulation. Symmetric means that the order in which routes i and j are considered, does not influence the value of the commonality factor. In the other formulations, differences in route length will lead to an asymmetry (Bovy et al., 2005).

In literature is not described which form of the commonality factor is the best formulation. There is a lack of theory or guidance to which form of commonality factor should be used.

3.3.3 Path Size Logit

The Path Size logit also copes with overlapping paths. Like the C-logit, PS logit adds a correction term, the path size PS, to the utility function. The probability function is of the Path Size logit model is:

$$P(i|C_n) = \frac{PS_{in}\, e^{V_{in}}}{\sum_{j \epsilon C_n} PS_{jn} e^{V_{jn}}} \tag{3.9}$$

Where PSin is the size of path i for individual n. Path-Size logit was introduced by Ben-Akiva and Ramming (1998), who presented the following formulation for the path size:

$$PS_{in} = \sum_{a \epsilon \Gamma_i} \frac{l_a}{L_i} \frac{1}{N_{an}} \tag{3.10}$$

The term (l_a/Li) is a weight corresponding to the fraction of path impedance coming from a specific link. The term Na is like at the C-logit the amount of paths using link a. This term is not affected by the length or impedance of the paths using it.

3.3.4 The (Cross) Nested Logit

The Nested logit is an extension of the MNL to deal with correlations between alternatives. The Nested logit is most often used in mode choice and in multi-dimensional choice, such as combined destination and mode choice. Additional to the nested logit model the Cross Nested logit is developed. Nested logit models divide the choice set into m nests. It is based on the partitioning of the choice set C_n into M nests C_{mn}. The Cross Nested logit differs from the nested logit in that lower-level alternatives may belong to more than one nest (Ramming, 2002). The probability that individual n chooses alternative i consists of two parts:

$$P(i|G_n) = P(C_{mn}|C_n)P(i|C_{mn}) \tag{3.11}$$

The choice probabilities of the Cross Nested logit are:

$$P(i|C_{mn}) = \frac{\alpha_{mi}e^{V_{in}}}{\sum_{j\in Cmn}\alpha_{mj}e^{V_{jn}}} \tag{3.12}$$

$$P(C_{mn}|C_n) = \frac{e^{V_{Cmn}+\mu_m I_{Cmn}}}{\sum_{l=1}^{M} e^{V_{Cln}+\mu_m I_{Cln}}} \tag{3.13}$$

Where $I_{Cmn}=ln\sum_{j\,\epsilon\,Cmn}(\alpha mje^{Vjn})^{\frac{1}{\mu m}}$ and α_{mi} represents the membership of alternative i in nest m. The Cross Nested logit model is difficult to estimate because of the large number of nesting parameters (Ben-Akiva et al., 2009), this reduces the usage of the Cross Nested logit. The Cross Nested logit is used for route choice modeling in small networks.

3.3.5 The Probit Model

The Probit model is not a member of the Generalized Extreme Value family. The error terms in the Probit model follow a multivariate normal distribution. The Probit model incorporates the correlation among alternatives (Telgen, 2010). Therefore, the Probit model uses a vector notation for the utility function:

$$U_n = V_n + \varepsilon_n \tag{3.14}$$

where Un,Vn, and ε_n are (Jnx1) vectors. The probability function of the Probit model is:

$$P\ (i \mid Cn) = P\ (U_{jn} - U_{in} \leq 0;\ \forall_j \in C_n) \tag{3.15}$$

The main advantage of the Probit model is its ability to capture all correlations among alternatives. However, due to the high complexity of its formulation, very few applications have been developed. The difficulty in implementing the Probit model is that no closed form exists for the multivariate normal distribution, so numerical techniques must be used. Numerical integration techniques are computationally feasible when the number of Gaussian variables (generally the number of alternatives less one) is small (Ramming, 2002).

3.3.6 Mixed Logit Models

Models with error terms distributed as a combination of normal and Gumbel distribution are: Mixed logit, Hybrid logit and Kernell logit. The general form of the Kernell logit model, in vector notation is:

$$U = X\beta + FT\xi + \nu \tag{3.16}$$

Where U is a Jn by 1 vector of utilities, β is a column vector of K unknown parameters; X is a Jn by K matrix of explanatory variables; ξ is a column vector of M independent and identically distributed standard Normal variables, which represent unobservable factors; F is a Jn by M factor loading matrix; T is an M by M lower triangular matrix of unknown parameters; and ν is a Jn by 1 vector of independent and identically distributed. Gumbel variables with scale parameter μ. The Logit Kernel model suffers from the same computational difficulties as pure Probit(Ramming, 2002).

CHAPTER 4

METHODOLOGY

The route choice and mode choice model is an important step of the transport model. We decided to construct model for University personnel and students so we selected pilot area as a Hadımköy-Yenibosna. We wanted to analyze route and mode choice behaviour. We found several route and mode choice models. We selected the most promising mode and route choice models on the basis of: reality, computational time, ease of use and dealing with overlapping. The C-logit and the MNL logit mode and route choice models are the best models for us. Because in our pilot area we have many overlapping and also C-logit cope with overlapping paths. MNL logit has a simple mathematical structure and ease of use. We used Biogeme Software for maximum likelihood estimation we mentioned below the details of this software.

We found many attributes of choice alternatives which are the common in the literature. We referred the common attributes and our model attributes in this chapter. Also we explained the details of our models and pilot area. To understand the background of this problem we gave introduction about the our methodology. We didn't mention about MNL logit and C- logit in this chapter because we described in chapter 3.

We used real data which is gained by survey and our survey in appendix A. The survey is designed to identify the relevant individual socioeconomic attributes, route and mode characteristics. The socio economic and personal attributes consist of gender, occupation, monthly income, car ownership. Route characteristics, such as, distance of travel, congestion, etc… Other details include mode characteristics i.e. waiting time, travel cost, travel time, etc... The survey was conducted in May 2013. The samples were collected by internet based survey.

4.1 BIOGEME SOFTWARE

Biogeme Software has been created by Prof. Michel Bierlaire for estimation of discrete choice models. This software has some advantages such as free downloaded, state of the art software for estimating models in the field of discrete choice.

Biogeme software helps to estimate utility functions. These utility functions indicate the perceived value of the feature and how sensitive consumer perceptions and preferences are to changes in product features. Maximum is typically used (Orme, 2010).

4.2 ATTRIBUTES

Attribute is a characteristic of an object such as route and mode characteristics. Each alternative in the choice set is characterized by a set of attributes. Note that some attributes may be generic to all alternatives, and some may be alternative-specific. An attribute is not necessarily a directly measurable quantity.

In the literature we found different attributes for mode and route choice. For example; travel time, travel cost, time waiting for public transport, time inside the automobile, cost of parking in destination, paid toll, congestion, safety (number of accident), environmental effects (landscape, shopping mall…), comfort.

The socio economic and personal attributes consist of gender, age, occupation, monthly income, car ownership, possession of driving license and private car use.

Our model consist of mode and route choice. After making some research and brainstorming we decide that passenger should make mode choice first. Because if the passenger select public transportation it is not possible to change the route.

Our model attributes for mode choice:

- ✓ Travel time: Total time of trip
- ✓ Cost: Cost of trip
- ✓ Comfort: Comfortability of each mode

- ✓ Walking distance: Distance or time for reaching mode
- ✓ Rush hour: Times end of the working day
- ✓ Time waiting for public transport: Sequence of movement
- ✓ Transfer discount
- ✓ Income
- ✓ Car ownership
- ✓ Occupancy rate

Possible modes for transportation between Hadımköy- Yenibosna are:

- ✓ Automobile
- ✓ Shuttle
- ✓ Minibus
- ✓ Metrobus
- ✓ Bus
- ✓ Taxi

Our model attributes for route choice:

- ✓ Distance: Total kilometer between Hadımköy- Yenibosna
- ✓ Congestion: Traffic intensity
- ✓ Number of traffic lights

Possible routes for transportation between Hadımköy- Yenibosna are:

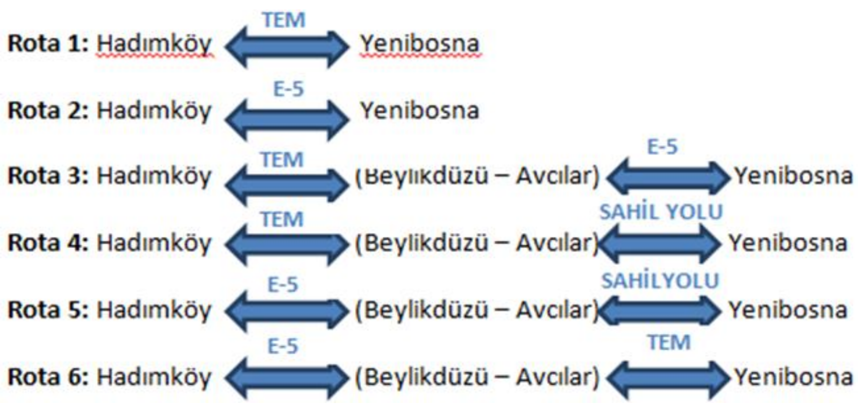

Figure 4.1 Routes between Hadımköy- Yenibosna.

CHAPTER 5

APPLICATION AND RESULTS

The aim of this thesis; route and mode choice modelling for our pilot area. We used real data which is gained by survey. The survey was conducted in May 2013. The samples were collected by internet based survey. At the end of the application two models derived. The first model described how passenger's mode preferences vary with perceived mode attributes such as travel time, travel cost, comfort, walking distance, sequence of movement, travel discount and demographics (e.g., income, gender, car ownership). The second model described how driver's route preferences vary with perceived route attributes such as distance, traffic intensity, number of traffic lights and demographics (e.g., income, gender, occupation).

Some descriptive statistics information mentioned below. This survey conducted of 211 people (72 female 139 male). Figure 5.1 represent the gender rates of survey.

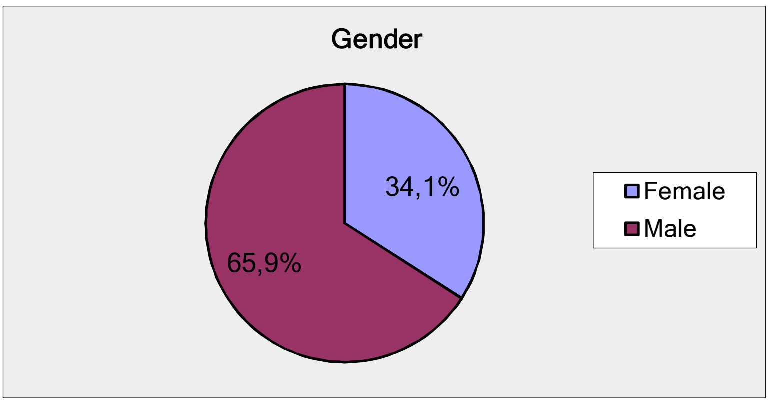

Figure 5.1 Gender distribution of survey.

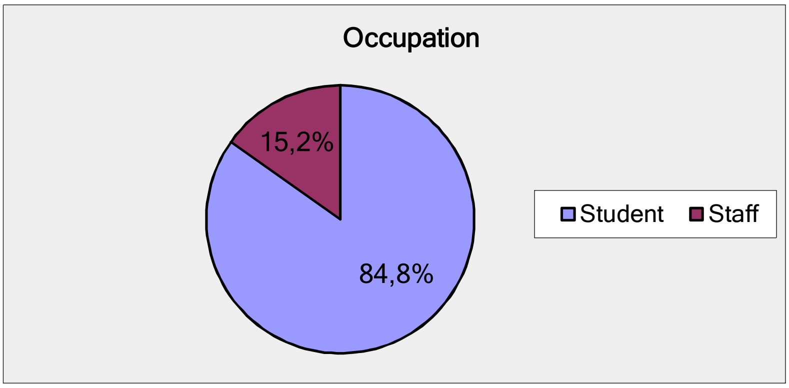

Figure 5.2 Occupation rate.

Above figure shows the student and staff distribution. Respondents consist of 179 students and 32 staff

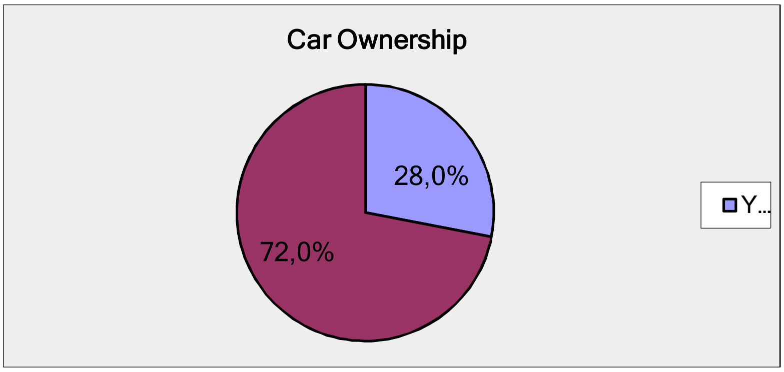

Figure 5.3 Car Ownership.

Above figure demonstrates the car ownership of respondents. Although 59 respondents have car, 152 respondents don’t have a car.

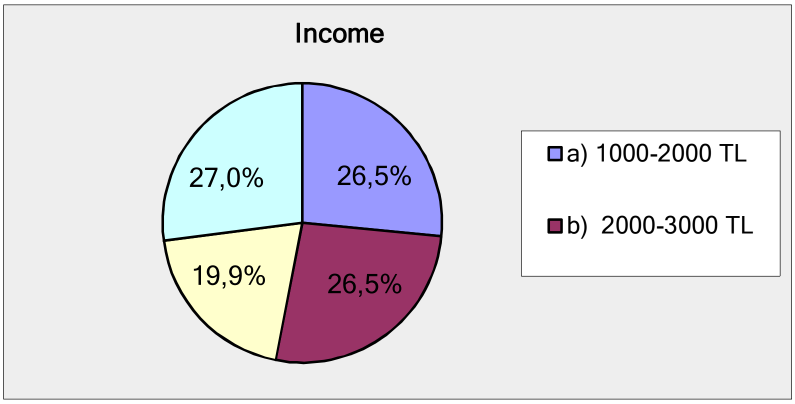

Figure 5.4 Income.

Above figure represents the income distribution. 56 respondents income are 1000-2000 TL, 56 respondents income are 2000-3000 TL, 42 respondents income are 3000-4000 TL, 57 respondent income are 4000 and upper TL. We can say that income almost equally distributed.

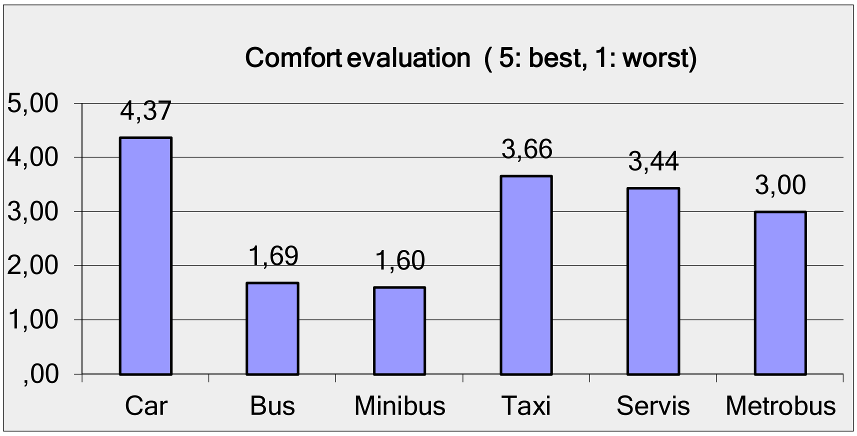

Figure 5.5 Comfort Evaluation.

Above figure shows the comfort evaluation of each mode. Car has a maximum comfort value. Taxi and shuttle value is almost same. Bus and minibus have a worst comfort score. Metrobus has a middle comfort value.

Table 5.1 Type of mode used according to the time intervals.

Type of mode used according to the time intervals						
Answer Options	Car	Bus	Minibus	Taxi	Shuttle	Metrobus
Morning Arrival(8-11):	49	71	4	3	76	46
Noon Arrival(11-14):	43	110	9	0	40	22
Evening Arrival(14-17):	47	104	9	2	34	27
Morning Return(9-12):	46	102	5	3	45	26
Noon Return(12-15):	44	92	8	3	60	32
Evening Return(15-18):	49	76	11	3	71	32

Above table demonstrates the mode type preference for time intervals. Bus is a most preferable mode, taxi is a least preferable mode. Time intervals not affect the mode choice significantly. Generally passengers prefer same mode for travelling.

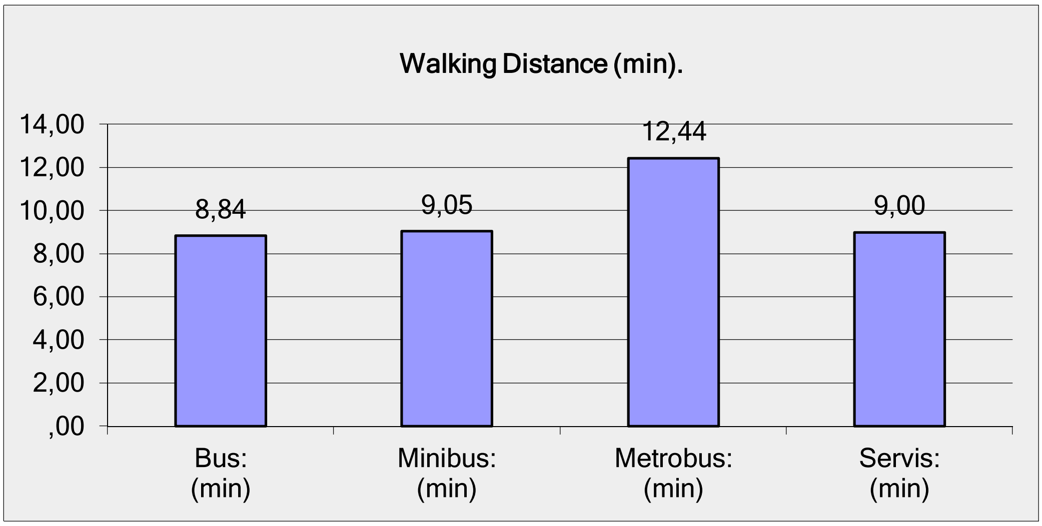

Figure 5.6 Walking Distance.

Above figure represents the walking distance time for each mode. Metrobus has a longer distance time than others.

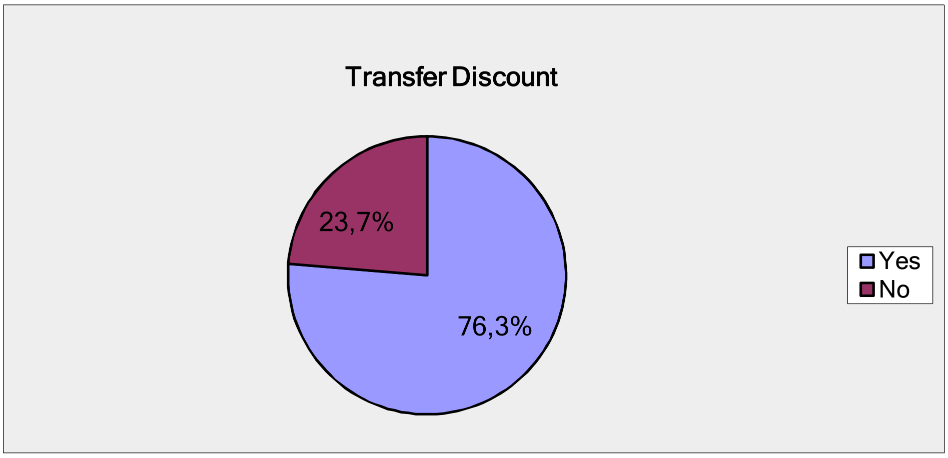

Figure 5.7 Transfer Discount.

Above figure shows the percentage of respondent who used transfer discount.

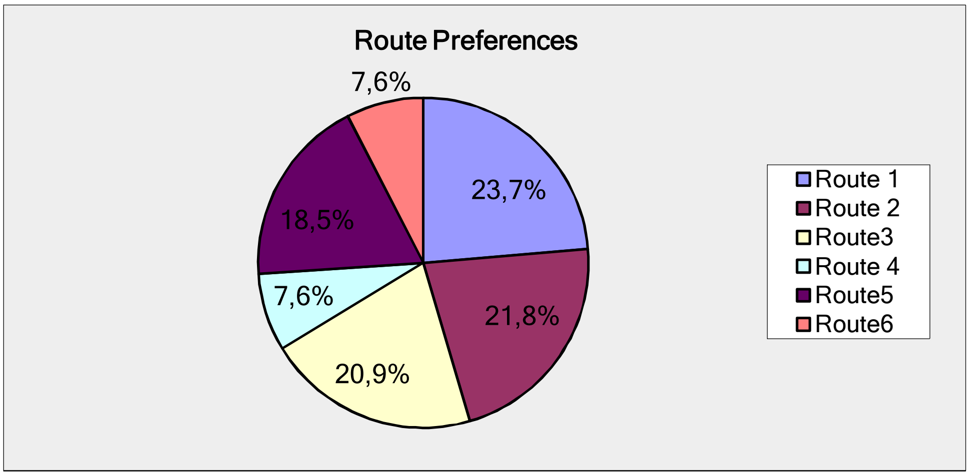

Figure 5.8 Route Preferences.

Above figure represents the route preferences. 50 respondent prefer route 1, 46 respondent prefer route 2, 44 respondent prefer route 3, 16 respondent prefer route 4, 39 respondent prefer route 5, 16 respondent prefer route 6. Route 1 is the most preferable route.

5.1 MODE CHOICE

Choice behavior in the transportation literature is often depicted as a two-stage process. First, a choice set generation process determines the feasible alternatives known and considered by the decision maker for a choice situation. Then a choice criterion is assumed that eliminates inferior alternatives until the best alternative is identified. Dominance, satisfaction, lexicographic rules, elimination by aspects, heuristic production rules (if . . . , then . . .), and utility maximization are the most common decision protocols (Svenson 1979). The analysis of mode choice behavior in this research assumed that travelers were utility maximizers.

McFadden applied the logit model to prediction of individual mode choice (McFadden 1973). Also we applied MNL model to prediction of mode choice. We mentioned the attributes for mode choice in the methodology chapter. The statistical models described previously can identify the importance of various factors on mode preference. We analyzed the models in a different time of day such as morning arrival's morning returns. Because we want to see effect of this attribute.

Table 5.2 Overall mode choice table for morning arrivals and returns.

OVERALL TABLE FOR MODE CHOICE			
	MODE TYPE	**Number of respondent who prefer the mode i**	**Probability of being selected mode**
MORNING ARRIVAL	***Bus***	69	24,477
	Car	44	55,015
	Metrobus	31	6,668
	Shuttle	60	12,333
	Minibus	4	0,860
	Taxi	3	0,647
MORNING RETURN	***Bus***	98	29,198
	Car	45	64,451
	Metrobus	24	2,324
	Shuttle	38	3,484
	Minibus	4	0,389
	Taxi	2	0,154

Above table represents the overall (students and staff) mode choice preference and choice probability for morning arrivals and returns. Findings show that car has a biggest utility. Respondent preference positively affects the choice probability. Taxi and minibus have least utility value. Bus is a most preferable mode but utility value is not very high. Shuttle users' amount is also high. We can say that some shuttle users move the bus in the morning arrivals.

Table 5.3 Overall mode choice table for noon arrivals and returns.

OVERALL TABLE FOR MODE CHOICE			
	MODE TYPE	Number of respondent who prefer the mode i	Probability of being selected mode
NOON ARRIVAL	***Bus***	104	34,943
	Car	43	52,546
	Metrobus	20	4,242
	Shuttle	36	6,566
	Minibus	8	1,702
	Taxi	0	0,000
NOON RETURN	***Bus***	90	32,779
	Car	42	49,396
	Metrobus	25	4,106
	Shuttle	46	12,416
	Minibus	5	0,817
	Taxi	3	0,486

Above table represents the overall (students and staff) mode choice preference and choice probability for noon arrivals and returns. Car has a maximum utility. Generally preference and choice probability of noon arrivals-returns and morning arrivals-returns are similar. Table 5.4 demonstrates the represent the overall (students and staff) mode choice preference and choice probability for evening arrivals and returns. Evening arrival and return results are similar to morning and noon arrival-return results. Time interval does not significantly affect the mode choice behavior.

Table 5.4 Overall mode choice table for evening arrivals and returns.

OVERALL TABLE FOR MODE CHOICE			
	MODE TYPE	**Number of respondent who prefer the mode i**	**Probability of being selected mode**
EVENING ARRIVAL	***Bus***	105	25,707
	Car	43	59,008
	Metrobus	26	6,317
	Shuttle	26	6,269
	Minibus	9	2,207
	Taxi	2	0,492
EVENING RETURN	***Bus***	70	17,294
	Car	46	60,051
	Metrobus	27	5,243
	Shuttle	56	14,042
	Minibus	9	1,763
	Taxi	3	0,607

Also analysis was performed to understand the occupation impact on the mode choice.

Table 5.5 Staff mode choice table for morning arrivals and returns.

MODE CHOICE TABLE FOR STAFF			
	MODE TYPE	Number of respondent who prefer the mode i	Probability of being selected mode
MORNING ARRIVAL	***Bus***	9	21,202
	Car	8	45,843
	Metrobus	2	4,315
	Shuttle	12	24,302
	Minibus	1	2,162
	Taxi	1	2,176
MORNING RETURN	***Bus***	10	25,808
	Car	8	50,045
	Metrobus	2	3,335
	Shuttle	12	19,121
	Minibus	1	0,002
	Taxi	0	1,688

Above table is related with stuff mode choice preference for morning arrivals and returns. Car has a maximum utility. Shuttle is most preferred mode. Arrivals and returns results are similar. We can say that passenger generally prefer same mode for arrivals and returns.

Table 5.6 Staff mode choice table for noon arrivals and returns.

MODE CHOICE TABLE FOR STAFF			
	MODE TYPE	**Number of respondent who prefer the mode i**	**Probability of being selected mode**
NOON ARRIVAL	***Bus***	11	30,633
	Car	7	41,174
	Metrobus	3	6,275
	Shuttle	10	19,791
	Minibus	1	2,127
	Taxi	0	0,000
NOON RETURN	***Bus***	8	17,702
	Car	8	46,588
	Metrobus	3	5,944
	Shuttle	11	24,934
	Minibus	1	2,259
	Taxi	1	2,573

Table 5.7 Staff mode choice table for evening arrivals and returns.

MODE CHOICE TABLE FOR STAFF			
	MODE TYPE	**Number of respondent who prefer the mode i**	**Probability of being selected mode**
EVENING ARRIVAL	***Bus***	14	35,381
	Car	6	37,450
	Metrobus	5	11,306
	Shuttle	6	11,255
	Minibus	2	4,607
	Taxi	0	0,001
EVENING RETURN	***Bus***	9	17,341
	Car	9	58,474
	Metrobus	2	3,246
	Shuttle	11	15,434
	Minibus	1	1,839
	Taxi	0	3,666

Above table 5.6 and 5.7 represent the stuff mode choice preference for noon and evening arrivals-returns. Shuttle is a most preferred mode.

Table 5.8 Student mode choice table for morning arrivals and returns.

MODE CHOICE TABLE FOR STUDENTS			
	MODE TYPE	Number of respondent who prefer the mode i	Probability of being selected mode
MORNING ARRIVAL	***Bus***	60	19,083
	Car	36	61,654
	Metrobus	29	6,893
	Shuttle	49	11,178
	Minibus	3	0,712
	Taxi	2	0,481
MORNING RETURN	***Bus***	89	25,833
	Car	37	63,498
	Metrobus	22	4,435
	Shuttle	26	5,210
	Minibus	4	0,824
	Taxi	1	0,199

Table 5.9 Student mode choice table for noon arrivals and returns.

MODE CHOICE TABLE FOR STUDENTS			
	MODE TYPE	Number of respondent who prefer the mode i	Probability of being selected mode
NOON ARRIVAL	***Bus***	93	34,263
	Car	36	55,848
	Metrobus	17	3,636
	Shuttle	26	4,735
	Minibus	7	1,518
	Taxi	0	0,000
NOON RETURN	***Bus***	81	25,577
	Car	34	60,104
	Metrobus	22	5,021
	Shuttle	35	7,926
	Minibus	4	0,925
	Taxi	2	0,446

Above tables 5.8, 5.9 and 5.10 show the mode choice preference and choice probability of students. Car has a maximum utility. Bus is a most preferred mode. Arrivals and returns results are similar. We can say that passenger generally prefer same mode for arrivals and returns.

Table 5.10 Student mode choice table for evening arrivals and returns.

MODE CHOICE TABLE FOR STUDENTS			
	MODE TYPE	Number of respondent who prefer the mode i	Probability of being selected mode
EVENING ARRIVAL	***Bus***	92	27,884
	Car	37	61,228
	Metrobus	21	4,550
	Shuttle	20	4,364
	Minibus	7	1,541
	Taxi	2	0,434
EVENINGRETURN	***Bus***	61	18,348
	Car	37	63,402
	Metrobus	25	5,664
	Shuttle	47	10,561
	Minibus	8	1,799
	Taxi	1	0,227

Findings in this research clearly show that mode choice is a complex spatial behavior sensitive to a number of attributes (travel time, cost, comfort, walking distance, time waiting for public transport, transfer discount, ıncome, car ownership, occupancy rate) of the environment and the decision maker. Time intervals are not significantly affect the mode choice behavior. Car has maximum utility mode. Most preferable mode is a bus for students. University staff mostly used shuttle.

5.2 ROUTE CHOICE

Random utility route choice models play a central role in assignment, to road networks (Cascetta et al., 1996). The method most widely used to operationalize random utility theory is discrete choice modeling. In this research a modified specification of the Logit model, named C-Logit, is proposed. The C-Logit overcomes the main shortcoming of MNL, unrealistic choice probabilities for paths sharing a number of links, while keeping a closed analytical structure allowing calibration on disaggregate data and efficient path flow computations when paths are explicitly enumerated (Cascetta et al., 1996).

The basic idea is to deal with similarities among overlapping paths through an additional “cost” attribute, named commonality factor (Cascetta et al., 1996). The probability that an individual n chooses route i is formulated in the C-logit model by:

$$P((i|Cn) = \frac{e^{\theta(Vin-CFi)}}{\sum j\epsilon\ Cn\ \ e^{\theta(Vjn-CFj)}} \tag{5.1}$$

where θ is a scale parameter. The scale parameter θ will be assumed equal to one as it cannot be estimated independently from coefficient β. The term CF_i denoted as “commonality factor” of route i, is directly proportional to the degree of similarity (or overlapping) of route i with other routes belonging to origin-destination (Cascetta et al., 1996). Formulation of commonality factor to be used:

$$CFin = \beta \ln \sum_{a\epsilon\, i} \omega_{ai}\, N_a \tag{5.2}$$

where β is coefficient that weight the commonality factor N_a is the number of paths connecting the same OD pair which share link a and ω_{ai} is the proportional weight of link a for path i.

Figure 5.9 demonstrate the schematic form of network. Node H represents the Hadımköy, node B represents the Beylikdüzü-Avcılar and node Y represents the Yenibosna.

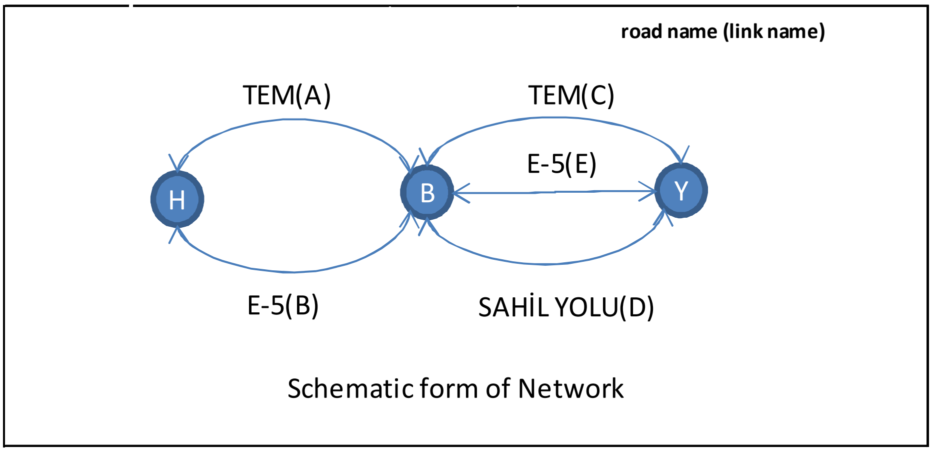

Figure 5.9 schematic form of network.

Table 5.11 link route incidence matrix and coefficient of Na.

	Route (path)						
Link	**1**	**2**	**3**	**4**	**5**	**6**	**N_a**
A	1	0	1	1	0	0	3
B	0	1	0	0	1	1	3
C	1	0	0	0	0	1	2
D	0	0	0	1	1	0	2
E	0	1	1	0	0	0	2

Below table illustrates link route incidence matrix and coefficient of N_a for all links.

Table 5.12 Route choice results.

OVERALL TABLE FOR ROUTE CHOICE		
Routes	Number of respondent who prefer the route i	Probability of being selected route
Route 1	50	21,143
Route 2	46	20,861
Route 3	44	19,445
Route 4	16	8,261
Route 5	39	20,153
Route 6	16	10,137

The results show that choice probability of route 1, 2, 3 and 5 are very similar. Generally routes are same degree of overlapping for this reason CF_i values are similar. Number of route preference also similar amount. This factor affects the choice probability. Route 1 has maximum utility and maximum choice preference.

Our results make clear that C-logit based route choice models can produce more realistic route choices than the shortest route principle. Because, Route 2 is a shortest route. Our best route is Route 1. Route 1 and Route 2 have a very similar choice probability we can say that distance is important attribute for route choice.

CHAPTER 6

CONCLUSION

Choice behavior in the transportation literature is often depicted as a two-stage process. First, a choice set generation process determines the feasible alternatives known and considered by the decision maker for a choice situation. Then a choice criterion is assumed that eliminates inferior alternatives until the best alternative is identified. Dominance, satisfaction, lexicographic rules, elimination by aspects, heuristic production rules (if . . . , then . . .), and utility maximization are the most common decision protocols (Svenson, 1979).

The purpose of this study is to model the mode and route choice problem of an important network defined in İstanbul with Multinominal Logit and C-logit model. In this choice phase, we considered too many criteria such as; travel time, cost, comfort, walking distance, time waiting for public transport, transfer discount, ıncome, car ownership, occupancy rate for mode choice and distance, congestion and number of traffic lights attributes for route choice to decide on the alternative route and mode having maximum utility.

The analysis method of mode choice behavior in this research is MNL logit model. We assumed that travelers were utility maximizers. We analyzed the models in a different time of day such as morning arrival's morning returns. Findings in this research clearly show that mode choice is a complex spatial behavior sensitive to a number of attributes (travel time, cost, comfort, walking distance, time waiting for public transport, transfer discount, ıncome, car ownership, occupancy rate) of the environment and the decision maker. Time intervals are not significantly affect the mode choice behavior. Car has maximum utility mode. Respondent preference positively affects the choice probability. Taxi and minibus have least utility value.

Also analysis was performed to understand the occupation impact on the mode choice. Arrivals and returns results are similar. We can say that passenger generally prefer same mode for arrivals and returns. Most preferable mode is a bus for students. University staff mostly used shuttle.

In this research a modified specification of the Logit model, named C-Logit, is proposed. The C-Logit overcomes the main shortcoming of MNL, ie unrealistic choice probabilities for paths sharing a number of links, while keeping a closed analytical structure allowing calibration on disaggregate data and efficient path flow computations when paths are explicitly enumerated (Cascetta et al.,1996). The results show that choice probability of route 1, 2, 3 and 5 are very similar. Generally routes are same degree of overlapping for this reason CF_i values are similar. Number of route preference also similar amount. This factor affects the choice probability. Route 1 has maximum utility and maximum choice preference.

Our results make clear that C-logit based route choice result and the shortest route result correspond to each other. We can say that distance is important attribute for route choice. Finally, it is also evident from the analysis that a number of attributes affect route choice behavior, and distance is just one of them.

Future studies should seek to incorporate more mode and route attributes in mode and route choice models and develop spatial behavioral theories and different type of methods such as non-utility based approaches that can be applied to study route and mode choice.

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APPENDIX A

Route and Mode Choice Behaviour Model Survey Form

This survey is made in order to modeling route and mode choice between Hadımköy-Yenibosna with Fatih University students and staff. Please read the questions carefully and select/ give the answer that is reasonable for you. Thank you for your time and participation. **Yrd. Doç. Dr. Özlem Coşgun, Yasemin Polat**

QUESTIONS

1) Gender?

Women **Man**

2) Occupation?

Student **Staff**

3) Do you have your own automobile?

Yes **No**

4) What is your income? (Students should consider the family situation)

a) 1000-2000 tl **b) 2000-3000 tl** **c) 3000-4000 tl** **d) 4000 and upper**

5) Evaluate the modes which have provide transportation between Hadımköy-Yenibosna in terms of comfort. (5: very good, 1: very bad)

Automobile: ……. **Bus:**…………

Minibus: ……. **Taxi:** …………

Shuffle: ……. **Metrobus:** …….

6) According to the following time intervals which type of car are prefer for transportation between Hadımköy-Yenibosna? [For example, the arrival in the morning (8-11): Bus]

Arrival **Return**

Morning(8-11): **Morning (9-12):**

Noon(11-14): **Noon(12-15):**

Evening(14-17): **Evening(15-18):**

7) Specify the number of minutes walking distance of the following transport modes.

Bus: **(dk)**

Minibus: **(dk)**

Metrobus: **(dk)**

Shuffle: **(dk)**

8) Transfers with public transport (for IETT buses and metrobuses) the transfer of discount is applied. Are you benefit from this discount?

Yes **No**

[Answer the questions 9 and 10 according to the routes mentioned below.]

[Suppose that you are traveling with your own vehicle or a taxi while the assessment of routes.]

Route 1: Hadımköy $\xleftrightarrow{\text{TEM}}$ Yenibosna

Route 2: Hadımköy $\xleftrightarrow{\text{E-5}}$ Yenibosna

Route 3: Hadımköy $\xleftrightarrow{\text{TEM}}$ (Beylikdüzü – Avcılar) $\xleftrightarrow{\text{E-5}}$ Yenibosna

Route 4: Hadımköy $\xleftrightarrow{\text{TEM}}$ (Beylikdüzü – Avcılar) $\xleftrightarrow{\text{SAHİL YOLU}}$ Yenibosna

Route 5: Hadımköy $\xleftrightarrow{\text{E-5}}$ (Beylikdüzü – Avcılar) $\xleftrightarrow{\text{SAHİLYOLU}}$ Yenibosna

Route 6: Hadımköy $\xleftrightarrow{\text{E-5}}$ (Beylikdüzü – Avcılar) $\xleftrightarrow{\text{TEM}}$ Yenibosna

9) Which do you prefer most in a defined routes?

Route…………

10) What is/are the reason of your choice? (You can choose more than one reason)

a) Distance **b) Congestion** **c) Rush Hour**

d) Travel Time **e) Cost** **f) Mode Type**

THANKS…..