Human Aspects of Route Choice Behavior: Incorporating Perceptions, Learning Trends, Latent Classes, and Personality Traits in the Modeling of Driver Heterogeneity in Route Choice Behavior

By

Aly M. Tawfik and Hesham A. Rakha
Department of Civil and Environmental Engineering
Virginia Tech

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ABSTRACT

Driver heterogeneity in travel behavior has repeatedly been cited in the literature as a limitation that needs to be addressed. In this work, driver heterogeneity is addressed from four different perspectives. First, driver heterogeneity is addressed by models of driver perceptions of travel conditions: travel distance, time, and speed. Second, it is addressed from the perspective of driver learning trends and models of driver-types. Driver type is not commonly used in the vernacular of transportation engineering. It is a term that was developed in this work to reflect driver aggressiveness in route switching behavior. It may be interpreted as analogous to the commonly known personality-types, but applied to driver behavior. Third, driver heterogeneity is addressed via latent class choice models. Last, personality traits were found significant in all estimated models. The first three adopted perspectives were modeled as functions of variables of driver demographics, personality traits, and choice situation characteristics. The work is based on three datasets: a driving simulator experiment, an in situ driving experiment in real-world conditions, and a naturalistic real-life driving experiment. In total, the results are based on three experiments, 109 drivers, 74 route choice situations, and 8,644 route choices. It is assuring that results from all three experiments were found to be highly consistent. Discrepancies between predictions of network-oriented traffic assignment models and observed route choice percentages were identified and incorporating variables of driver heterogeneity were found to improve route choice model performance. Variables from all three groups: driver demographics, personality traits, and choice situation characteristics, were found significant in all considered models for driver heterogeneity. However, it is extremely interesting that all five variables of driver personality traits were found to be, in general, as significant as, and frequently more significant than, variables of trip characteristics − such as travel time. Neuroticism, extraversion and conscientiousness were found to increase route switching behavior, and openness to experience and agreeable were found to decrease route switching behavior. In addition, as expected, travel time was found to be highly significant in the models that were developed. However, unexpectedly, travel speed was also found to be highly significant, and travel distance was not as significant as expected. Results of this work are highly promising for the future of understanding and modeling of heterogeneity of human travel behavior, as well as for identifying target markets and the future of intelligent transportation systems.

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Chapter 1

Introduction

Chapter 1
Introduction

If an alien was to hover a few hundred yards above the planet

It could be forgiven for thinking

That cars were the dominant life-form

Heathcore Williams, Autogeddon, 1991 [1]

In his book, The Life of the Automobile, Ilya Ehrenburg defended the automobile. He said "[The automobile] can't be blamed for anything. Its conscience is as clear as Monsieur Citroen's conscience. It only fulfills its destiny: it is destined to wipe out the world" [2]. These two observations are very true to the extent that Herbert Girardet wrote that today we no longer live in a civilization, but rather in a mobilization – of natural resources, people and products [3].

Climate change and the peaking of oil are probably the two most prominent life threatening challenges of the twenty first century. The term peaking of oil refers to the point in time at which maximum global extraction of oil is reached, where oil extraction starts to decline and become more expensive, and when oil wars begin [4]. Relevant to the former challenge, transportation systems are responsible for approximately 14% of global greenhouse gas emissions, and it is the second most growing source of these emissions [5]. In the US, motor vehicles alone are estimated to produce 60% of all carbon dioxide gas emissions [6]. As for the latter challenge, half of all global oil produced is used in transportation. In addition, about 95% of all transportation systems are powered with oil [7]. Rob Routs, Executive Director at Shell said that "Since the marriage of fossil fuels and the internal combustion engine some hundred years ago, the fortunes of our industries have been tied together" [8]. However, it appears that the fate of climate change too is tied with the fate of the internal combustion engine, because every gallon of petrol produces 24 pounds of heat trapping emissions [4].

The world is asking transportation researchers and engineers for solutions that could decrease the carbon footprint and the oil dependency of today's transportation systems. Especially since a significant portion of these emissions and oil consumption is unproductively and irrationally wasted in traffic jams. Adding to this the extravagant annual numbers of deaths and injuries that are related to transportation makes this a nightmare. Most of transportation emissions, oil consumption, traffic jams, and casualties are attributed to the automobile. Today, the number of automobiles roaming the world is estimated to be more than 650 million cars. With current trends it is estimated to reach 1 billion in a couple of decades [4].

Many have written about the obligatory need to significantly cut human generated greenhouse gas emissions and dependence on oil, if humans care about sustaining life on earth. Today, however, chances that humans will change their lifestyles or stop using the car to save their lives seem highly unlikely. Even more than the way it was half a century ago when science fiction author and Nobel Peace Prize Nominee Arthur C. Clarke wrote that civilization could not survive for 10 minutes without the car [9]. One of Buckminster Fuller's famous quotes states that "You

never change anything by fighting the existing reality. To change something, build a new model that makes the existing model obsolete". There are signs that the transportation industry is following this quote. It appears that the above threats will result in the tipping of transportation as we know it.

In spite of its difficulty, many have made applaudable efforts to predict the future of transportation [4, 10, 11]. Although these predictions are recent, uncertain and consequently incomprehensive, and although the predictions are very different, they all have one common solution element: Intelligent Transportation Systems (ITSs).

It is because of all the above that worldwide expectations from ITS applications are on the rise. To "enhance safety, increase mobility and sustain the environment" [12], ITS attempts to transform the transportation system to "an integrated nexus rather than a parallel series" [4]. ITS applications apply information, communication and computation technologies to all areas of the transportation industry. Although ITS applications vary significantly, the focus of this dissertation is not. This dissertation provides foundation work that demonstrates that for ITS to achieve its ultimate potential, it is imperative to consider driver heterogeneity.

Route choice models are responsible for predicting the route a driver would choose when going from a point of origin to a point of destination. Route choice models are among the most widely used models in transportation engineering. They are used in transportation planning, traffic simulation, advanced traffic signal control, and Electronic Route Guidance Systems (ERGSs). ERGS applications are the branch of Advanced Traveler Information Systems (ATISs) that provides route guidance to a traveler; whether pre-trip (e.g. Google Maps) or en-route (e.g. commercial GPS units like Garmin). ATIS, by turn, is the branch of ITS which involves providing travelers with information to aid them in making informed choices.

In general, there are two main groups of route choice models. The first group encompasses mathematical network oriented models that assume drivers to behave in a certain manner so that a certain objective function can be optimized at the network level (e.g. user equilibrium and dynamic traffic assignment) [13-15]. The second group of models includes behavioral driver oriented models which attempt to accurately describe individual driver route choice behavior and incorporate the effect of information provision on driver behavior. Examples of these models include random utility models [16, 17], random regret minimization models [18], probabilistic models [19], cognitive-psychology based models [20, 21], fuzzy models [22], and models based on data mining which are sometimes referred to as user models [23-26].

An optimally functioning ITS system would use the above models on two different sides: the driver and the system. While the driver side would improve network performance by helping drivers make better choices, the system side would enhance network performance by improving network efficiency. Two main assumptions are required for the driver side system to be successful: i) drivers are incapable of accurately acquiring the provided information on their own, and ii) the provided information is relevant to the drivers' criteria for choice preference. On the other hand, two other assumptions are needed for the system side to be efficient: i) it considers the information provided to each driver and can correctly predict drivers' choices, and ii) it is capable of using these predictions to improve system management.

Since that the violation of any one of these assumptions sacrifices half of the ITS system, it is imperative to ensure their validity. Additionally, it can be seen that all four of these assumptions: a) perceptions, b) choice criteria, c) choice prediction, and d) network management, are highly dependent on the behavior of the individual driver. Accordingly, an ITS system that incorporates factors of driver heterogeneity is destined to be more efficient. In summary, two factors are crucial: 1) assumptions validity, and 2) driver heterogeneity.

Moreover, within the context of route choice behavior, recent publications have identified four main areas of challenge: i) experiment medium, ii) processing of large datasets, iii) choice set generation, and iv) discrete choice modeling [25, 27]. In addition, driver heterogeneity has been repeatedly cited as a limitation that needs to be addressed. Example citations include: "it is desirable to develop a model which is disaggregated by a type of driver because the route choice behavior varies by individual" [28], "Drivers do not become homogeneous and rational, as equilibrium analyses presuppose; rather, there are fewer rational drivers even after a long process of learning, and heterogeneous drivers make up the system" [29], "studies that focus only on a rather rational description of day-to-day learning cover only a limited part of the way route choices are made over time" [17].

Mediums for route choice experiments include stated and revealed preference surveys, travel and driving simulator experiments, and real-world and naturalistic driving GPS-based experiments. In addition, a few experiments are based on simulation. Because of cost limitations and past technological limitations, most route choice literature is based on either stated preference surveys or travel simulator experiments. Stated preference surveys are surveys in which drivers answer questions about their behavior in hypothetical situations [30, 31]. Travel simulators are computer based programs that digitally display the choice situation and its characteristics for a participant. Then the participant makes her/his choice, which is considered a revealed preference [16, 32]. There are guidelines to make either of these methods more realistic [33]. Nonetheless, since drivers do not actually live the choice situation, it is impossible for either of these methods to capture drivers' perceptions of real-world traffic conditions. On the other hand, for about a decade now, experiments based on driving simulators [19, 34] and GPS-based surveys [24, 26] have been gaining momentum. Driving simulators are vehicle-like structures which a person drives in virtual environments. It uses a computer to display the environment exterior of the vehicle to the driver. In a driving simulator, the driver drives through a virtual network in real-time. In a travel simulator, no driving happens. Driving simulators have been extensively used for safety research. Recently, however, researchers have started to use driving simulators for travel behavior. GPS-based surveys are surveys based on actively logging the individuals' movements –usually– in a naturalistic setting. They are usually supplemented with a travel diary that is typically filled by the participant. While experiment fidelity is the main critique for driving simulator-based experiments, limitations of GPS-based route choice surveys include the inability to infer the travel conditions on the alternative routes and the inability to identify the choice set that the driver considers when making her/his route choices. Last, simulation-based experiments are generally used to investigate the performance of a specific choice theory, and not for capturing driver behavior [29].

With this in mind, the work presented here starts with an evaluation of three of the four necessary assumptions for an efficient ITS system: perceptions, choice criteria, and choice prediction. Then, the work attempts to identify sources of driver heterogeneity that can improve models of route choice behavior. Considered sources of driver heterogeneity include driver perceptions, learning trends and driver-types, latent classes, and variables of driver personality traits as captured by the NEO Personality Inventory-Revised [35]. Estimated route choice models include general, hierarchical and latent class models of route switching behavior, and models of route choice set size. In addition, this work addresses current challenges of experiment medium by estimating models using three different mediums: a driving simulator experiment supplemented with a revealed preference survey, a real-world experiment supplemented with stated and revealed preference surveys, and a naturalistic real-life experiment. In total the results presented in this work are based on a sample of 109 drivers, who collectively faced 74 choice situations and made 8,644 route choices.

It is assuring that results from all three experiments were found to be highly comparable. Discrepancies between predictions of network-oriented traffic assignment models and observed route choice percentages were identified, and incorporating variables of driver heterogeneity were found to improve route choice model performance. Variables of three natures: driver demographics, personality traits, and choice situation characteristics, were found significant in all estimated models of driver heterogeneity. However, it is extremely interesting that all five variables of driver personality traits were found to be, in general, as significant as, and frequently more significant than, variables of trip characteristics – such as travel time. Neuroticism, extraversion and conscientiousness were found to increase route switching behavior, and openness to experience and agreeable were found to decrease route switching behavior. In addition, as expected, travel time was found to be highly significant in the models estimated. However, unexpectedly, travel speed was also found to be highly significant, and travel distance was not as significant as expected.

This work is divided into three parts. The first part includes chapters 3, 4, and 5 and presents analysis and models that are based on the driving simulator experiment. The second part includes chapters 6, 7, 8, and 9 and presents analysis and models that are based on the real-word driving experiment. The last part includes chapter 10 and presents the analysis and models based on the naturalistic real-life driving experiment.

The following parts of this dissertation are organized as follows. Chapter 2 presents a thorough literature review of route choice models and their implications on network performance. Part I: Driving Simulator Experiment follows chapter 2 and is outlined as follows.

Chapter 3 contrasts drivers' perceptions and choices against their experiences of travel time, speed and distance. It identifies significant limitations of driver perceptions and highlights the importance of travel speed perceptions in route choice behavior. Chapter 4 explores the aggregate network choice evolution, and based on driver learning trends identifies four driver types. Chapter 5 explores the benefits of including the identified driver types in the route choice model, and investigates differences between driver-type choice criteria.

Part II: Real-World Driving Experiment starts with chapter 6 and is composed of the following. Chapter 6 (similar to chapter 3) contrasts drivers' perceptions and choices against their experiences of travel time, speed and distance, and it identifies significant limitations of driver perceptions and highlights the importance of travel speed in route choice behavior. In addition, the chapter includes models of driver perceptions that reveal the importance of driver personality traits. Chapter 7 identifies discrepancies between predictions of network-oriented traffic assignment models and observed route choice percentages. The same four driver-types of Chapter 4 are re-observed in Chapter 7, and are found predictable based on driver demographics and personality traits in a driver-type model. Chapter 8 presents a two-stage hierarchical model where the first stage predicts the driver type and the second stage incorporates the predicted driver type in route choice switching models. The last chapter of Part II, Chapter 9, estimates latent class choice models to overcome the limitations of the hierarchical model. Like the hierarchical model, the estimated latent class models prove that inclusion of latent driver classes improves model performance.

In the last part of this work, Part III: Naturalistic Real-Life Experiment, Chapter 10 presents two route choice behavior models: a route switching model and a model of route choice set size. Variables of personality traits are found to be highly significant in both models.

The dissertation ends with Chapter 11, which presents the conclusions of this work and suggestions for further work.

Results of this work are highly promising for the future of understanding and modeling heterogeneity of human travel behavior, as well as for identifying target markets and the future of intelligent transportation systems.

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Chapter 2

(Literature Review)
Traffic Networks: Dynamic Traffic Routing, Assignment, and Assessment

Published in the Encyclopedia of Complexity and Systems Science

Traffic Networks: Dynamic Traffic Routing, Assignment, and Assessment

Hesham Rakha[1] and Aly Tawfik[2]

ARTICLE OUTLINE

GLOSSARY

Link or Arc: A roadway segment with homogeneous traffic and roadway characteristics (e.g. same number of lanes, base lane capacity, free-flow speed, speed-at-capacity, and jam density). Typically networks are divided into links for traffic modeling purposes.

Route or Path: A sequence of roadway segments (links or arcs) used by a driver to travel from his/her point of origin to his/her destination.

Traffic Routing: The procedure that computes the sequence of roadways that minimize some utility objective function. This utility function could either be travel time or a generalized function that also includes road tolls.

Traffic Assignment: The procedure used to find the link flows from the Origin-Destination (O-D) demand. Traffic assignment involves two steps: (1) traffic routing and (2) traffic demand loading. Traffic assignment can be divided into static, time-dependent, and dynamic.

User Equilibrium Traffic Assignment: The assignment of traffic on a network such that it distributes itself in a way that the travel costs on all routes used from any origin to any destination are equal, while all unused routes have equal or greater travel costs.

System Optimum Traffic Assignment: The assignment of traffic such that the average journey travel times of all motorists is a minimum, which implies that the aggregate vehicle-hours spent in travel is also minimum.

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[1] Professor, Charles E. Via Jr. Department of Civil and Environmental Engineering. Virginia Tech Transportation Institute, 3500 Transportation Research Plaza, Blacksburg VA, 24061. E-mail: hrakha@vt.edu.

[2] Graduate Student, Teaching Fellow, Charles E. Via Jr. Department of Civil and Environmental Engineering. Virginia Tech Transportation Institute, 3500 Transportation Research Plaza, Blacksburg VA, 24061. E-mail: tawfik@vt.edu.

Static Traffic Assignment: Traffic assignment ignoring the temporal dimension of the problem.

Time-Dependent Traffic Assignment: An approximate approach to modeling the dynamic traffic assignment problem by dividing the time horizon into steady-state time intervals and applying a static assignment to each time interval.

Dynamic Traffic Assignment: Traffic assignment considering the temporal dimension of the problem.

Traffic Loading: The procedure of assigning O-D demands to routes.

Synthetic O-D Estimation: The procedure that estimates O-D demands from measured link flow counts, which includes static, time-dependent, and dynamic.

Traffic Stream Motion Model: A mathematical representation (traffic flow model) for traffic stream motion behavior.

Car-following Model: A mathematical representation (traffic flow model) for driver longitudinal motion behavior.

Marginal Link Travel Time: The increase in a link's travel time resulting from an assignment of an additional vehicle to this link.

I. DEFINITION OF THE SUBJECT AND IMPORTANCE

The dynamic nature of traffic networks is manifested in both temporal and spatial changes in traffic demand, roadway capacities, and traffic control settings. Typically, the underlying network traffic demand builds up over time at the onset of a peak period, varies stochastically during the peak period, and decays at the conclusion of the peak period. As traffic congestion builds up within a transportation network, drivers may elect to either cancel their trip altogether, alter their travel departure time, change their mode of travel, or change their route of travel. Dynamic traffic routing is defined as the process of dynamically selecting the sequence of roadway segments from a trip origin to a trip destination. Dynamic routing entails using time-dependent roadway travel times to compute this sequence of roadway segments. Consequently, the modeling of driver routing behavior requires the estimation of roadway travel times into the near future, which may entail some form of traffic modeling.

In addition to dynamic changes in traffic demand, roadway capacities are both stochastic and vary dynamically as vehicles interact with one another along roadway segments. For example, the roadway capacity at a merge section varies dynamically as the composition of on-ramp and freeway demands vary (Cassidy et al. 1995; Evans et al. 2001; Lertworawanich et al. 2001; Lorenz et al. 2001; Lertworawanich et al. 2003; Minderhoud et al. 2003; Kerner 2004; Kerner 2004; Kerner et al. 2004; Rakha et al. 2004; Cassidy et al. 2005; Elefteriadou et al. 2005; Kerner 2005; Kerner et al. 2006). To further complicate matters, traffic control settings (e.g. traffic signal timings) also vary both temporally and spatially, thus introducing another level of dynamics within transportation networks. All these factors make the dynamic assessment of traffic networks extremely complex, as shall be demonstrated in this article. The article is by no means comprehensive but does provide some insight into the various challenges and complexities that are associated with the assessment of dynamic networks.

II. INTRODUCTION

Studies have shown that even drivers familiar with a trip typically choose sub-optimal routes thus incurring extra travel time in the range of seven percent on average (Jeffery 1981). Furthermore, the occurrence of incidents and special events introduces other forms of variability that drivers are unable to anticipate and thus result in additional errors in a driver's route selection. Consequently, advanced traveler information systems (ATISs), which are an integral component of intelligent transportation systems (ITSs), can assist the public in their travel decisions by providing real-time travel information via route guidance systems; variable message signs (VMSs); the radio, or the web. It is envisioned that better travel information can enhance the efficiency of a transportation system by allowing travelers to make better decisions regarding their time of departure, mode of travel, and/or route of travel. An integral component of an ATIS is a dynamic traffic assignment (DTA) system. A DTA system predicts the transportation network state over a short time horizon (typically 15- to 60-min. time horizon) by modeling complex

demand and supply relationships through the use of sophisticated models and algorithms. The DTA requires two sets of input, namely demand and supply data. Demand represents the demand for travel and is typically in the form of mode-specific time-dependent origin-destination (O-D) matrices. Alternatively, the supply component models the movement of individual vehicles along a roadway typically using roadway specific speed-flow-density relationships together with the explicit modeling of queue buildup and decay. Figure 1 illustrates schematically that an ATIS can utilize two approaches for the estimation of future traffic conditions, namely: statistical models or a DTA framework. This article focuses on the DTA approach and thus will be described in more detail. The DTA combines a traffic router and modeler, as illustrated in the figure. The traffic router estimates the optimum travel routes while the traffic modeler models traffic to evaluate the performance of traffic after assigning motorists to their routes. A feedback loop allows for the feedback of either travel times or marginal travel times, which in turn, are used by the traffic router to compute the optimum routes. This feedback continues until the travel times are consistent with the travel routes and there is no incentive for drivers to alter their routes.
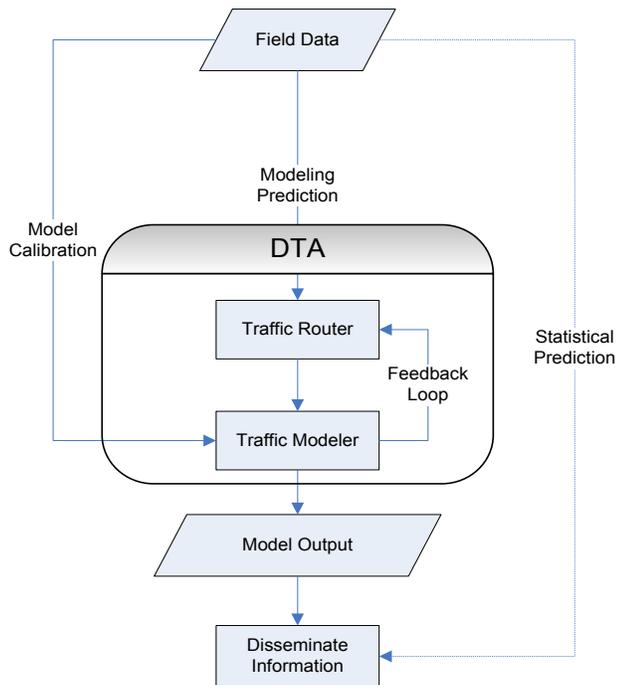
Figure 1: Schematic of an ATIS Framework

A DTA can be applied off-line (in a laboratory) or on-line (in the field). An on-line application of a DTA entails gathering traffic data in real-time at any instant t and feeding these data to the DTA to predict short-term traffic conditions Δt temporal units into the future (i.e. at time $t+\Delta t$). As was mentioned earlier, the input to the DTA includes mode specific time dependent O-D matrices. Unfortunately, current surveillance equipment does not measure O-D matrices; instead they measure traffic volumes passing a specific point. Consequently, O-D estimation tools are required to estimate the O-D matrix from observed link counts, as illustrated in Figure 2. However, the estimation of an O-D matrix requires identifying which O-D demands contribute to which roadway counts. The assigning of O-D demands to link counts involves what is commonly known in the field of traffic engineering as the traffic assignment problem. Traffic assignment in turn requires real-time O-D matrices and roadway travel times as input. Consequently, some form of feedback is required to solve this problem. A more detailed description of traffic assignment formulations and techniques is provided in Sections IV and V, while the estimation of route travel times is described in Section VII and the estimation of O-D matrices is described in Section VIII.

The dynamic assessment of traffic networks using a DTA is both data driven (trapezoidal boxes) and model based (colored rectangular boxes), as illustrated in Figure 2. This procedure involves: measuring raw field data, constructing model input data, executing a traffic model to predict future conditions, and advising a traveler in the case of control

systems. The framework starts by measuring traffic states at instant "t" (roadway travel times and link flows) and subsequently estimating these traffic states Δt in the future. Procedures for the estimation of dynamic roadway travel times are provided in Section VII of this article. Using the measured link flows and travel times, an O-D matrix is constructed using a synthetic O-D estimator. Section VIII describes the various formulations for estimating a dynamic O-D matrix together with some heuristic practical approaches to estimate this O-D matrix.

Once the O-D demands are estimated the future states are predicted using a traffic modeler. Section VI provides a brief overview of the various state-of-the-practice modeling approaches. The model also computes various measures of effectiveness (MOEs) including delay, fuel consumption, and emissions, as will be described in Section IX. The traffic modeler can either combine traffic modeling with traffic assignment or alternatively utilize the routes computed by the O-D estimator to route traffic. This closed loop optimal control framework can involve a single loop or in most cases may involve an iterative loop to attain equilibrium. The framework involves a feedback loop in which input model parameters are adjusted in real-time through the computation of an error between model predictions and actual measurements. This real-time calibration entails adjusting roadway parameters (e.g. capacity, free-flow speed, speed-at-capacity, and jam density) and traffic routes to reflect dynamic changes in traffic and network conditions. For example, the capacity of a roadway might vary because of changes in weather conditions and/or the occurrence of incidents. The system should be able to adapt itself dynamically without any user intervention.
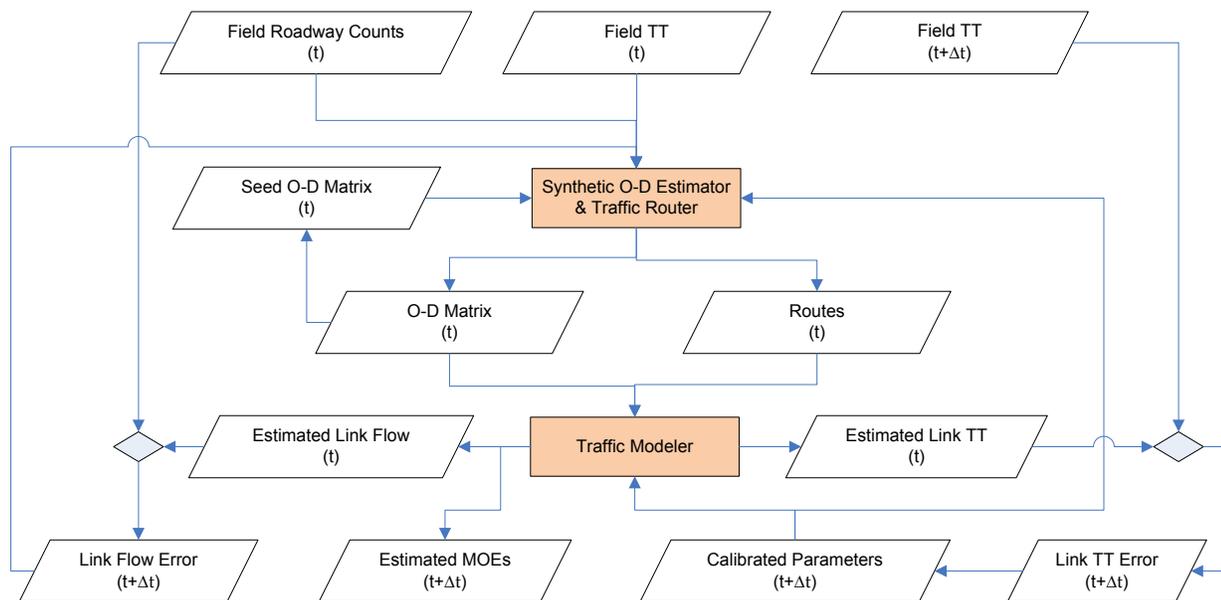
Figure 2: Dynamic Traffic Assessment and Routing Framework

This article attempts to synthesize the literature on the dynamic assessment and routing of traffic. The problem as will be demonstrated later in the paper is extremely complex because, after all, it deals with the human psychic, which not only varies from one person to another, but may also vary depending on the purpose of a trip, the level of urgency the driver has, and the psychic of the driver at the time the trip is made. This article is by no means comprehensive, given the massive literature on the topic, but does highlight some of the key aspects of the problem, how researchers have attempted to address this problem, and future research needs and directions.

The article discusses the various issues associated with the dynamic assessment of transportation systems. Initially, driver travel decision behavior modeling is presented and discussed. Subsequently, various traffic assignment formulations are presented together with the implementation issues associated with these formulations. Next, the mathematical formulations of these assignment techniques are discussed together with mathematical and numerical approaches to modeling dynamic traffic routing. Subsequently, the issues associated with the modeling of traffic stream behavior, the estimation of dynamic roadway travel times, and the estimation of dynamic O-D demands are discussed. Subsequently, the procedures for computation of various assessment measures are presented. Next, the use of technology to alter driver behavior is presented. Finally, directions for further research are presented.

III. DRIVER TRAVEL DECISION BEHAVIOR MODELING

As with the general case of modeling human behavior, modeling driver travel behavior has always been complicated, never accurate enough, and in constant demand for further research. Among the early attempts to model human choice behavior is the economic theory of the "economic man"; who in the course of being economic is also "rational" (Simon 1955). According to Simon's exact words, "*actual human rationality-striving can at best be an extremely crude and simplified approximation to the kind of global rationality that is implied, for example, by game-theoretical models*".

In general, traffic assignment (static or dynamic assignment) has undoubtedly been among the most researched transportation problems, if not the most, for more than the past half of a century. However, DTA in particular has had the bigger share for almost one third of a century now. Since the early work of Merchant and Nemhauser (Merchant 1978; Merchant 1978), researchers have attempted to improve available DTA models, hence, providing a very rich and vastly wide literature.

As a result of the rapid technological evolution over the last decade of the previous century (the 20th century); manifested in the communications, information and computational technological advances; a worldwide initiative to add information and communications technology to transport infrastructure and vehicles, termed as the intelligent transportation systems (ITS) program, was introduced to the transportation science. According to the Wikipedia Encyclopedia, among the main objectives of ITS is to "*manage factors that are typically at odds with each other such as vehicles, loads, and routes to improve safety and reduce vehicle wear, transportation times and fuel consumption*". Needless to say, the ITS impact on route selection and roadway travel times has a direct effect on a DTA.

The main effect of ITS on DTA manifests itself within the area of advanced traveler information systems (ATIS). ATIS is primarily concerned with providing people, in general, and trip makers, in particular, with pre-trip and en-route trip-related information. According to the U.S. Federal Highway Administration (FHWA), "*advanced traveler information includes static and real-time information on traffic conditions, and schedules, road and weather conditions, special events, and tourist information. ATIS is classified by how and when travelers receive their desired information (pre-trip or en-route) and is divided by user service categories. Operations essential to the success of these systems are the collection of traffic and traveler information, the processing and fusing of information - often at a central point, and the distribution of information to travelers. Important components of these systems include new technologies applied to the use and presentation of information and the communications used to effectively disseminate this information*" (J. Noonan et al. 1998).

As will be discussed later, a significant amount of DTA research is directed towards developing data dissemination standards. These standards attempt to achieve the maximum possible benefits while complying with the ITS objectives. Although the provision of pre-trip information may influence traveler departure time and route of travel (and in extreme cases, might result in a person canceling his/her trip all together), thus requiring further complicated DTA models that capture forgone and induced demand, as will be discussed later. Moreover, probably the greatest dimension for DTA model complexity was introduced to research when the disseminated ATIS information was to be designed as a control factor to change the manner by which trips are distributed over the network, for example from user equilibrium to system optimum.

Although ITS and ATIS were practically introduced a little more than a decade ago, and in spite of the significant research funds and efforts that have been devoted to the topic, current available DTA models are, at least, relatively undeveloped, which necessitates new approaches that can capture the challenges from the application domains as well as for the fundamental questions related to tractability and realism (Srinivas Peeta 2001). This will be discussed briefly in the following section.

Driver travel decision theory is a complicated research area. Research within this area encompasses a very wide range of research efforts. Before going over a brief list of these possible research areas, it should be noted that most of these research areas overlap with one another. Therefore, for a valid driver behavior model, all of the following aspects should be efficiently covered in a practical and realistic manner. This been said, the following is a brief list of some of the main research areas that are highly related to driver travel decision theory:

- Human decision theory, which can be reflected in the trip maker's decision to make or cancel a scheduled trip, route and departure time selection, compliance with the pre-trip or en-route disseminated information,

en-route path diversion and/or return, mode choice based on disseminated information, etc. Literature concerning human decision theory extends back to more than half a century ago and continues to be researched up to this date. Examples of the literature concerning the human decision theory include: administrative behavior (Simon 1947; Simon 1957), theory of choice (Arrow 1951), rational choice theory (Simon 1955), game theory, and decision field theory (Jerome R. Busemeyer 1993). Examples of the literature concerning driver decision theory include: decision field theory (Talaat 2006), approximate reasoning models (Koutsopoulos et al. 1995), route choice utility models (Hawas 2004), inductive learning (Nakayama et al. 2000), effect of age on routing decisions (Walker et al. 1997), and rational learning (Nakayama et al. 2001).

- Design of disseminated information, which encompasses the criteria governing the dissemination of information, the structure and type of information to be disseminated, when data are disseminated, and indentifying target drivers. This governs, to a large extent, the drivers' compliance rates in response to disseminated information. Hence, affecting the routes chosen by drivers, the traffic volumes on these routes and alternative routes, and different travel times, among others. Literature concerning the effect of ATIS and ATIS content on drivers behavior include: the required information that would reduce traffic congestion (Richard Arnott 1991), the effect of ATIS on drivers route choice (Abdel-Aty 1997), commuters diversion propensity (Schofer 1993), the effect of traffic information disseminated through variable message signs on driver choices (S. Peeta 2006), drivers en-route routing decisions (Asad J. Khattak 1993).

- Human perception based on experience and information provision, which is reflected in day-to-day variations in driver decisions. For example, given identical conditions on two separate days, the same person might select different routes and departure times; possibly due to different experiences on previous days. Examples of current literature include: models that include the incorporation of driver behavior dynamics under information provision (Srinivas Peeta 2004), behavioral-based consistency seeking models (Srinivas Peeta 2006), perception updating and day-to-day travel choice dynamics with information provision (Mithilesh Jha 1998), the modeling of inertia and compliance mechanisms under real-time information (Srinivasan 2000), drivers psychological deliberation while making dynamic route choices (Talaat 2006), the effect of using in-vehicle navigational systems on diver behavior (Allen et al. 1991), the effect of network familiarity on routing decisions (Lotan 1997), and the effect of varying levels of cognitive loads on driver behavior (Katsikopoulos et al. 2000).

- Among the challenges in modeling human decision theory are the possible data collection techniques. The current practice for data collection includes revealed and stated preference surveys. Research has demonstrated that surveyed stated preference results have significant biases; in comparison to real behavior. In addition to the research being performed to analyze, capture, and improve the reasons for such biases; other research directions are being performed to solve other survey problems. For example, the problems of low and slow survey participation rates, as well as under-represented groups in typical survey techniques. Examples of literature within this field include: stated preference for investigating commuters diversion propensity (Schofer 1993), using stated preference for studying the effect of advanced traffic information on drivers route choice (Abdel-Aty 1997), driver response to variable message sign-based traffic information according to stated preference data collected through three different survey administration methods, namely, an on-site survey, a mail-back survey and an internet-based survey (S. Peeta 2006), transferring insights into commuter behavior dynamics from laboratory experiments to field surveys (Hani S. Mahmassani 2000) and (Peeta 2000), and the applicability of using driving simulators for data collection (Koutsopoulos et al. 1995).

- Issues of uncertainty, which is a fundamental feature in most transportation phenomena. Research dealing with uncertainty has a wide application in DTA. It can be represented in the trip maker route travel time estimates, in the compliance rates of drivers to information, in the driver's trust in the disseminated information and its reliability, among others. Uncertainty-related research issues have been addressed through several approaches, like stochastic modeling, fuzzy control, and reliability indices. Examples of current literature include the works of Birge and Ho (Birge 1993), Peeta and Zhou (Peeta 1999; Peeta 1999), Cantarell and Cascetta (Cantarella 1995), Ziliaskopoulos and Waller (Ziliaskopoulos 2000), Waller and Ziliaskopoulos (Waller 2006), Waller (Waller 2000), Peeta and Jeong (Srinivas Peeta 2006), Jha et al. (Jha 1998), Peeta and Paz (Peeta 2006), Koutsopoulos et al. (Koutsopoulos et al. 1995), and Hawas (Hawas 2004).

IV. STATIC TRAFFIC ROUTING AND ASSIGNMENT

Prior to describing the issues associated with dynamic routing, a description of static routing issues is first presented. This section describes two formulations for static traffic assignment, namely the User Equilibrium (UE) and System Optimum (SO) assignment. Traffic assignment is defined as the basic problem of finding the link flows given an origin-destination trip matrix and a set of link or marginal link travel times, as illustrated in Figure 3. The solution of this problem can either be based on the assumption that each motorist travels on the path that minimizes his/her travel time – known as the UE assignment – or alternatively to minimize the system-wide travel time – known as the SO assignment. The traffic assignment initially computes the travel routes (paths) and then determines the unique link flows on the various network links. As will be discussed later, while the estimated link flows are unique the path flows that are derived from these link flows are not unique and thus require some computational tool to estimate the most-likely of these path flows (synthetic O-D estimator). If a time dimension is introduced to the assignment module the formulation is extended from a static to a dynamic context. However, as will be discussed later the addition of a time dimension deems the formulation non-convex and thus the mathematical program used to solve the problem becomes infeasible and thus comes the need for a simulation-based solution approach.
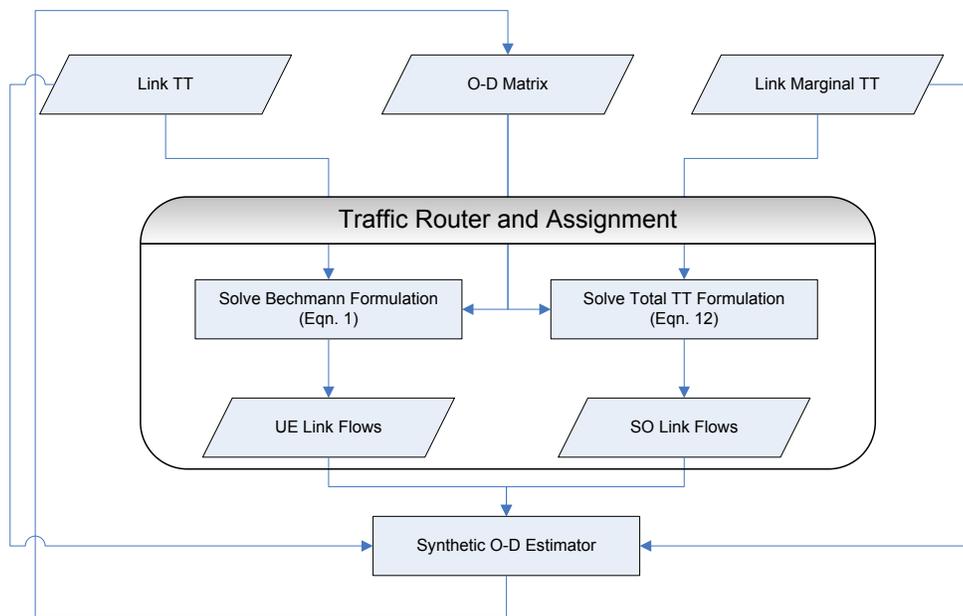
Figure 3: Traffic Assignment Framework

Wardrop (Wardrop 1952) was the first to explicitly differentiate between these two alternative traffic assignment methods or philosophies. Models based on Wardrop's first principle are referred to as UE, while those based on the second principle are deemed as SO. Wardrop's first principle states that "*traffic on a network distributes itself in such a way that the travel costs on all routes used from any origin to any destination are equal, while all unused routes have equal or greater travel costs.*" Alternatively, Wardrop's second principle states that the average journey travel times of all motorists is a minimum, which implies that the aggregate vehicle-hours spent in travel is also minimum.

One of the most spectacular examples that illustrated that the UE flow in a network is in general different from the SO flow, is the Braess network (Braess 1968). In this network the system-optimal flow was obtained by completely suppressing the flow which would normally occur, on a certain link, at equilibrium. The Braess "paradox" was studied later in more detail (LeBlanc et al. 1970; Murchland 1970; LeBlanc 1975; Fisk 1979; Stewart 1980; Frank 1981; Steinberg et al. 1983; Rilett et al. 1991). For example, Stewart (Stewart 1980) illustrated three important facts using a very simple two-link network and the Braess paradox that included: (a) the equilibrium flow does not necessarily minimize the total cost; (b) adding a new link to a network may increase the total cost at equilibrium; (c) adding a new link to a network may increase the equilibrium travel cost for each individual motorist. Stewart also illustrated that a

group of travelers having only one reasonable route may be seriously inconvenienced by another group of travelers who choose the same route in order to obtain a slight improvement in their personal cost of travel.

User Equilibrium vs. System Optimum Traffic Assignment

The differences between user and system optimum traffic assignment are best illustrated using an example illustration. The sample test network for this study is derived from an earlier study by Rakha (Rakha 1990). The network consists of two one-way routes, numbered 1 and 2, from origin A to destination B. The travel time relationship for route 1 is characterized by the relationship $10+0.010v_1$ where v_1 is the traffic volume on route 1 (veh). Alternatively, the travel time along route 2 is characterized by the relationship $15+0.005v_2$ where v_2 is the traffic volume traveling along route 2 (veh). Considering at total demand of 1000 veh traveling between zones A and B, the travel time along routes 1 and 2 vary as a function of the volume on each of the routes, as illustrated in Figure 4. The figure demonstrates that the travel times along routes 1 and 2 are equal at 16.5 min. when 667 veh travel along route 1 and 333 veh travel along route 2. Alternatively, the system-optimum traffic assignment is achieved at a volume distribution of 500 veh on routes 1 and 2, respectively. From a traffic engineering point of view, the difference in total travel time between the system and user-optimum traffic assignment (16,250 versus 16,667 veh-min.) is of interest. This difference represents the extent of possible benefits for a system versus user optimum routing for this particular network and traffic pattern. Figure 4 also illustrates how the average link travel times on routes 1 and 2 vary for the same range of possible routings of traffic between route 1 and 2. In this figure the difference between the travel times on route 1 and 2 (15.0 versus 17.5 minutes) represents the incentive that exists for vehicles on route 2 to change to route 1. When compared to the user equilibrium routing, the total difference in travel time is composed of two components, which represent the respective increases (route 1) and decreases (route 2) in average travel time that result from a shift from the system to user-optimum routing.
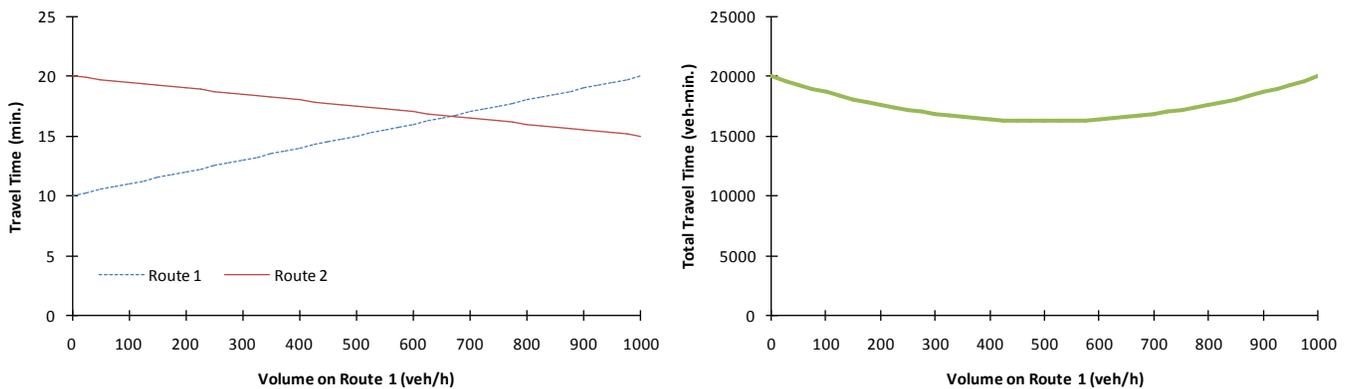
Figure 4: Variation in Route and System Travel Time for Test Network

Implementation Issues

While the simple example illustrated the potential benefits of system optimized routings and the incentive that exists for drivers to switch back to the original user equilibrium routings, it is clear that neither an exhaustive enumeration nor an analytical approach (solving the differential equations of the system travel time) are satisfactory for finding the system optimized routings when more than just a few possible routes are available.

Different static traffic assignment algorithms have been developed over the past half century. These methods are broadly divided into non-equilibrium and equilibrium methods. Non-equilibrium methods include all-or-nothing assignment, where all traffic is assigned to a single minimum path between two zones (path that incurs the minimum travel time). Example algorithms for computing minimum paths include models developed by Dantzig (Dantzig 1957) and Dijkstra (Dijkstra 1959). Other non-equilibrium methods include incremental, iterative, diversion models, multipath assignment (Dial 1971), and combined models. According to Van Vliet (Van Vliet 1976) the incremental assignment method (explained later) is capable of reaching an acceptable degree of convergence faster than an iterative method. With regards to diversion models, the most common diversion models include the California

diversion curves (Moskowitz 1956) and the Detroit diversion curves (Smock 1962). Alternatively, multipath traffic assignment methods assign traffic stochastically. For example, the Dial method (Dial 1971) stochastically diverts trips to alternate paths, but trips are not explicitly assigned to routes. Other multipath methods (Burell 1968; Burell 1976) assume that users do not know the actual travel times on each link, but a driver's estimate of link travel time is drawn randomly from a distribution of possible times. Finally, combined non-equilibrium models include combining capacity restraint models with probabilistic assignment (Randle 1979), combining iterative with incremental assignment (Yagar 1971; Yagar 1974; Yagar 1975; Yagar 1976), or combining stochastic with equilibrium assignment (Sheffi et al. 1981).

Equilibrium assignment techniques are based on Wardrop's first principle (Wardrop 1952). These were classified by Matsoukis and Michalopoulos (Matsoukis et al. 1986) into: assignments with fixed demand, assignments with elastic demands, and combined models. Only the first method will be discussed. The equilibrium assignment algorithm is a weighted combination of a sequence of all-or-nothing assignments. This produces a non-linear programming (NLP) problem which is subject to linear constraints. This NLP is very hard to solve and the approach seems to be of limited use for realistically sized equilibrium traffic assignment problems. The NLP problem can be replaced by a much simpler linear approximation and solved using the Frank-Wolfe algorithm (Frank et al. 1956). This iterative linearization procedure still involves longer computational times than the iterative procedure. LeBlanc et al. (LeBlanc et al. 1974) developed an iterative procedure solving one-dimensional searches and LP problems that minimize successively better linear approximations to the non-linear objective function. Nguyen (Nguyen 1969) converted the convex optimization problem into a set of simpler sub-problems that could be solved with the convex-simplex method.

One of the most common approaches to implement a user equilibrium traffic assignment involves the use of an incremental traffic assignment technique (Yagar 1971; Yagar 1975; Leonard et al. 1978; Van Aerde 1985; Matsoukis 1986; Van Aerde et al. 1988; Van Aerde et al. 1988). Such a technique breaks down the total traffic demand that is to be loaded onto the network into a number of increments that are each loaded onto the network in turn. Each increment is loaded onto what appears to be the shortest route, after all the previous increments have been loaded. The link travel times are then recalculated, in order to re-compute the fastest route for the next increment to be loaded. When more than one route are to be used for travel between a given origin and destination, the increments are automatically assigned alternatively to each route, when each becomes faster again after previous increments head along the other route. In the end, the extent to which the overall assignment approaches an equilibrium state depends upon the number of increments utilized, with the average final error being roughly proportional to the final increment size.

Van Aerde and Rakha (Rakha et al. 1989; Rakha 1990) demonstrated that the system-optimum traffic assignment can also be solved considering an incremental traffic assignment. Specifically, Van Aerde and Rakha (Rakha et al. 1989; Rakha 1990) recognized the fact that the increase in system travel time caused by the addition of one vehicle is composed of the additional travel time incurred by the subject vehicle and the increase in travel time that is imparted on all other vehicles which are already on the link. While the former quantity is usually already available as a direct or indirect measurement on the link, the derivation of the latter quantity is more subtle. It is a function of the rate of change of the average travel time, per additional vehicle, and the number of vehicles already on the link. In mathematical terms, this is simply the product of the derivative of the travel time versus volume relationship, with respect to volume, multiplied by the volume already present on the link. Consequently, the standard objective function that is utilized in any minimum path algorithm, which searches for the user equilibrium routes, can be replaced by a new objective function that minimizes the total travel time. This routing can be achieved using an incremental assignment of vehicles based on their marginal travel time as opposed to their actual travel time, which results in a system optimum as opposed to a user equilibrium routing, as was demonstrated earlier in Figure 3. Stated differently at dynamic system optimum, the time-dependent marginal cost on all the paths actually used are equal and less than the marginal cost on any unused paths. In the static case, the path marginal cost (PMC) is the sum of the link marginal cost (LMC). However, in the dynamic case, the PMC evaluation is much more complicated since path flows are not assigned to links on the path simultaneously. However, within the dynamic context, most researchers (Peeta 1994; Ghali et al. 1995) assume that the path flow perturbation travels along the path at the same speed as the additional flow unit. Shen et al. (Shen et al. 2006) demonstrated that this assumption is not necessarily correct.

Furthermore, they presented a solution algorithm for path-based system optimum models based on a new PMC evaluation method. The approach was then tested and validated on a simple network.

V. DYNAMIC TRAFFIC ROUTING

This section describes the mathematical formulations for the static routing problem together with some solution approaches. Subsequently, the extension of the problem for the dynamic context is presented together with state-of-the-art solution approaches.

The dynamic traffic assignment approach is summarized in Figure 5 and involves three input variables, namely: dynamic link travel times (in the case of the UE assignment), dynamic marginal travel times (in the case of the SO assignment), and dynamic O-D matrices. In the case of the UE assignment the Bechmann formulation is solved (Equation (1)) if we use a time-dependent static (or quasi static) assignment as will be discussed in detail in the following sections, while in the case of the SO assignment Equation (12) is solved. Within the static context these formulations are solved analytically using a mathematical program given that the objective function and feasible region are convex. Alternatively, in the dynamic context the objective function is non-convex and thus is more difficult to solve necessitating the use of a modeling approach to solve the problem.

After solving these two formulations the link flows are computed and input into an O-D estimator to provide an estimate of the O-D demand which is then compared to the initial solution. This feedback loop continues until the difference in either link flows or O-D flows is within a desired margin of error or the maximum number of iterations criteria is met.
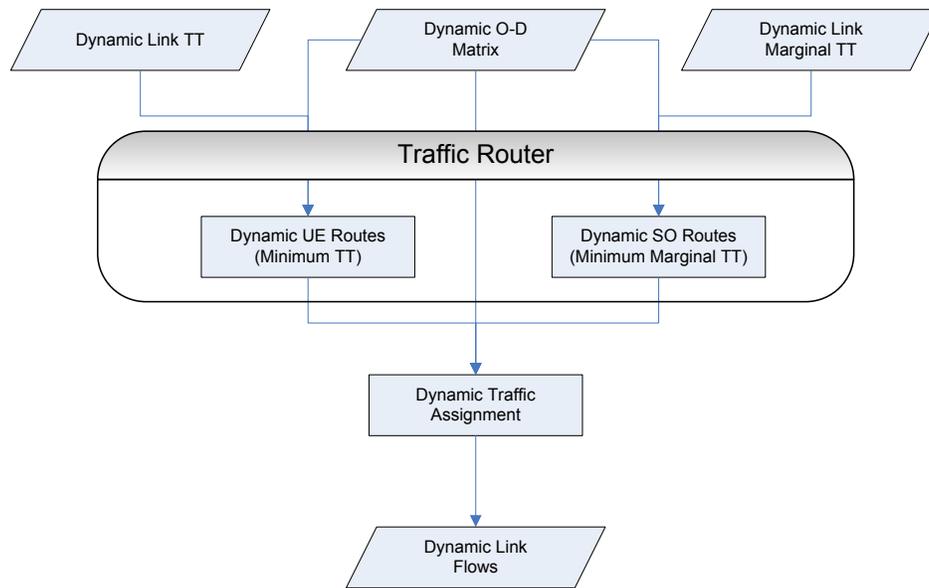
Figure 5: Dynamic Traffic Assignment Framework

Mathematical Formulations

Following the notation presented by Sheffi (Sheffi 1985) we present the network notations that are used in the mathematical formulation of a static traffic assignment problem. Initially, the variable definitions are presented followed by the vector definitions (bold variables).

N	Set of network nodes
A	Set of network arcs (links)
R	Set of origin centroids
S	Set of destination centroids
k_{rs}	Set of paths connecting O-D pair r-s; $r \in R, s \in S$
x_a	Flow on arc (a)
t_a	Travel time on arc (a)
f_k^{rs}	Flow on path (k) connecting O-D pair $(r$-$s)$
c_k^{rs}	Travel time on path (k) connecting O-D pair $(r$-$s)$
q_{rs}	Trip rate between origin (r) and destination (s)
$\delta_{a,k}^{rs}$	Indicator variable: $\delta_{a,k}^{rs} = \begin{cases} 1 & \text{if arc } (a) \text{ is on path } (k) \text{ between O-D pair } (r\text{-}s) \\ 0 & \text{otherwise} \end{cases}$

Using vector notations (bold variables) the variables are defined as,

$\mathbf{x}$	Vector of flows on all arcs, $= (..., x_a,...)$
$\mathbf{t}$	Vector of travel times on all arcs, $= (..., t_a,...)$
$\mathbf{f^{rs}}$	Vector of flows on all paths connecting O-D pair r-s, $= (..., f_k^{rs},...)$
$\mathbf{f}$	Matrix of flows on all paths connecting all O-D pairs, $= (..., \mathbf{f^{rs}},...)$
$\mathbf{c^{rs}}$	Vector of travel times on all paths connecting O-D pair r-s, $= (..., c_k^{rs},...)$
$\mathbf{c}$	Matrix of travel times on all paths connecting all O-D pairs $,= (..., \mathbf{c^{rs}},...)$
$\mathbf{q}$	Origin-destination matrix (with elements $= q_{rs}$)
$\Delta^{\mathbf{rs}}$	Link-path incidence matrix (with $\delta_{a,k}^{rs}$ elements) for O-D pair r-s, as discussed below
Δ	Matrix of link-path incidence matrices (for all O-D pairs), $= (..., \Delta^{\mathbf{rs}},...)$

The link-path incident matrix is of size equal to the number of links or arcs in the network (number of rows) and number of paths between origin (r) and destination (s). The element in the ath row, and k^{th} column of $\Delta^{\mathbf{rs}}$ is $\delta_{a,k}^{rs}$. In other words, $(\Delta^{rs})_{a,k} = \delta_{a,k}^{rs}$.

The following basic relations are fundamental to the mathematical program formulation:

- A link performance function, which is also known as the volume-delay curve or the link congestion function, represents the relationship between flow and travel time on a link (a) ($t_a=t_a(x_a)$).

- The mathematical program formulations assume that travel time on a given link is only dependent on the flow on the subject link (the model does not capture the effect of opposing flows on the delay of opposed flows), or mathematically

$$\frac{\partial t_a(x_a)}{\partial x_b} = 0 \qquad \forall \, a \neq b \text{ and } \frac{\partial t_a(x_a)}{\partial x_a} > 0 \qquad \forall \, a \text{ where, } x_b \text{ is the flow on link } (b).$$

- The travel time on a particular path equals the sum of the travel times on the links comprising that path as $c_k^{rs} = \sum_a t_a \delta_{a,k}^{rs} \quad \forall \, k \in k_{rs}, \forall \, r \in R, \forall s \in S$ or $\mathbf{c} = \mathbf{t}.\Delta$ considering the vector notation.

- The flow on each link equals the sum of the flows on all paths traversing the subject link as $x_a = \sum_r \sum_s \sum_k (f_k^{rs}.\delta_{a,k}^{rs}) \;\; \forall a \in A$ or $\mathbf{x} = \mathbf{f}.\Delta^{\text{T}}$.

- The above formula uses the incidence relationships to express link flows in term of path flows, i.e. $x = x(f)$. The incidence relationships also mean that the partial derivative of the link flow can be defined with respect to a particular path flow as follows,

$$\frac{\partial x_a(f)}{\partial f_l^{mn}} = \frac{\partial}{\partial f_l^{mn}} \sum_r \sum_s \sum_k (f_k^{rs} \delta_{a,k}^{rs}) = \delta_{a,l}^{mn}, \text{ where } \frac{\partial f_k^{rs}}{\partial f_l^{mn}} = 0 \text{ if } k \neq l \text{ or } r\text{-}s \neq m\text{-}n$$

Where, f_l^{mn} is the flow on path (*l*) connecting O-D pair (*m-n*). Since the function $x_a(f)$ includes a flow summation using the subscripts *r, s,* and *k*, the variable with respect to which the derivative is being taken is subscribed by *m, n,* and *l,* to avoid the confusion in differentiation.

User Equilibrium

As mentioned earlier, the UE model is based on the assumption that each traveler takes the path that minimizes his/her travel time from their origin to their destination, regardless of any effect this might have on the other network users. In other words, at equilibrium, none of the travelers will be able to reduce their travel times by unilaterally switching to another path. This implies that at equilibrium the link flow pattern is such that the travel times on all of the used paths connecting any given O-D pair will be equal. The travel time on all of these used paths will also be less than or equal to the travel time on any of the unused paths.

The mathematical program that represents this model can be cast using Bechmann's transformation as,

$$\text{Min. } z\ x\ = \sum_a \int_0^{x_a} t_a\ w\ dw$$

S.T.

$$\sum_k f_k^{rs} = q_{rs} \qquad \forall\ r,s \qquad \text{(Flow conservation constraints)} \qquad (1)$$

$$f_k^{rs} \geq 0 \qquad \forall\ k,r,s \qquad \text{(Non-negativety constraints)}$$

$$x_a = \sum_r \sum_s \sum_k f_k^{rs} \cdot \delta_{a,k}^{rs} \qquad \forall\ a$$

It is worth mentioning that this formulation "*has been evident in the transportation literature since the mid-1950's, but its usefulness became apparent only when solution algorithms for this program were developed in the late 1960's and early 1970's*"(Sheffi 1985).

In order to prove that the solution of Beckmann's transformation program satisfies the user-equilibrium assignment, first the equivalence conditions will be discussed followed by the uniqueness conditions. In the equivalence conditions it will be shown that the first-order conditions for the minimization program are identical to the equilibrium conditions. Whereas, in the uniqueness conditions, it will be shown that the user-equilibrium equivalent minimization program has only one solution. Hence, proving that the solution of Beckmann's transformation program satisfies the user-equilibrium assignment problem.

Equivalency Conditions

Beckmann's transformation program is a minimization program with linear equality and non-negativity constraints. In order to find the first-order conditions for such a program, the Lagrangian with respect to the equality constraints can be written as

$$L\ f,u\ = z\big[x\ f\ \big] + \sum_r \sum_s u_{rs}\left(q_{rs} - \sum_k f_k^{rs} \right), \qquad (2)$$

where u_{rs} denotes the dual variable associated with the flow conservation constraint for O-D pair (r-s). At the stationary point of the Lagrangian, the following first-order conditions have to hold with respect to the path-flow variables and the dual variables. First, with respect to the path-flow variables

$$f_k^{rs} \frac{\partial L\ f,u}{\partial f_k^{rs}} = 0 \qquad \forall\ k,r,s \text{ and } \frac{\partial L\ f,u}{\partial f_k^{rs}} \geq 0 \quad \forall\ k,r,s \tag{3}$$

must hold. Alternatively, with respect to the dual variables

$$\frac{\partial L\ f,u}{\partial u_{rs}} = 0 \quad \forall\ r,s \tag{4}$$

must hold. In addition to the following non-negativity constrains,

$$f_k^{rs} \geq 0 \quad \forall\ k,r,s. \tag{5}$$

Note that the formulation of this Lagrangian is given in terms of path flow by using the incidence relationships, $x_a = x_a(f)$.

The partial derivative of $L(x,u)$ with respect to the flow variables f_l^{mn} can be given by

$$\frac{\partial L\ f,y}{\partial f_l^{mn}} = \frac{\partial}{\partial f_l^{mn}} z\left[x\ f\ \right] + \frac{\partial}{\partial f_l^{mn}} \sum_r \sum_s u_{rs}\left(q_{rs} - \sum_k f_k^{rs} \right). \tag{6}$$

Using the chain rule the first term can be solved as

$$\frac{\partial}{\partial f_l^{mn}} z\left[x\ f\ \right] = \sum_{b \in A} \frac{\partial z\ x}{\partial x_b} \cdot \frac{\partial x_b}{\partial f_l^{mn}} = \sum_b \left[\left(\frac{\partial}{\partial x_b} \sum_a \int_0^{x_a} t_a(w)\,dw \right) \cdot \left(\frac{\partial x_b}{\partial f_l^{mn}} \right) \right] = \sum_b t_b \cdot \delta_{b,l}^{mn} = c_l^{mn}. \tag{7}$$

The second term can be solved as

$$\frac{\partial}{\partial f_l^{mn}} \sum_r \sum_s u_{rs}\left(q_{rs} - \sum_k f_k^{rs} \right) = -u_{mn}, \tag{8}$$

because (a) u_{rs} is not a function of f_l^{mn}; (b) q_{rs} is constant; and $\dfrac{\partial f_k^{rs}}{\partial f_l^{mn}} = \begin{cases} 1 \text{ if } r=m,\ s=n,\ \text{and } k=l \\ 0 \text{ otherwise} \end{cases}$. Consequently,

Equation (3) and (4) can be solved to derive

$$\frac{\partial L(f,u)}{\partial f_l^{mn}} = c_l^{mn} - u_{mn}.$$

Hence, we can derive the following first-order conditions,

$$\begin{aligned} f_k^{rs}(c_k^{rs} - u_{rs}) &= 0 & \forall\ k,r,s \\ c_k^{rs} - u_{rs} &\geq 0 & \forall\ k,r,s \\ \sum_k f_k^{rs} &= q_{rs} & \forall\ r,s \\ f_k^{rs} &\geq 0 & \forall\ k,r,s \end{aligned} \tag{9}$$

We can imply the following from these conditions, (1) The first two conditions, for any path (k) connecting any O-D pair (r-s), either (a) The flow on that path, f_k^{rs}, equals zero, in which case, the travel time on this path, c_k^{rs}, will have a value that is greater than or equal to the value of the O-D specific Lagrange multiplier, u_{rs}, or, (b) the flow on that path will have a value (greater than zero), in which case, the travel time on this path will have a value equal to the value of the O-D specific Lagrange multiplier, u_{rs}. In both cases, the value of the O-D specific Lagrange multiplier is always

less than or equal to the travel time on all other paths connecting the same O-D pair. Hence, this value of the Lagrange multiplier is the minimum path travel time between this O-D pair thus proving that the solution of Beckman's transformation program satisfies the user-equilibrium assignment.

The last two conditions satisfy the flow conversation and non-negativity constraints, respectively. The proof can further be explained as follows, paths connecting O-D pair (*r-s*) can be divided into two groups, (1) Paths with zero flow, and are characterized by a travel time which is either greater than or equal to the minimum travel time; and (2) Paths with non-negative flows, and are characterized by minimum travel times. Thus, confirming the user-equilibrium notion which states that no user can improve his/her travel times by unilaterally changing their routes.

The above proves that user-equilibrium conditions are satisfied at any stationary point of Beckman's transformation program. The following section proves that there is only one solution for Beckman's transformation program. It proves that Beckman's transformation program has only one stationary point, and that this point is a minimum.

Uniqueness Condition

In order to prove that Beckmann's transformation program has only one solution, it is sufficient to prove that the objective function is strictly convex in the vicinity of the solution point, convex everywhere else (within the feasible solution region), and that the feasible region (defined by the constraints) is convex.

It is known that linear equality constraints ensure a convex feasible region, and that the addition of the non-negativity constrains does not alter this fact. The convexity of the objective function, with respect to link flows, can be proven in two different ways. The fist way can be achieved by the application of the properties of convex functions, on the link-performance functions. On the other hand, the second proof is achieved by proving that the Hessian matrix of the objective function is positive definite.

Link performance functions are known to be continuously increasing functions. Hence, link-performance functions are convex functions. The objective function equals the summation of the integral of the link-performance functions of all links. Properties of convex functions state that integrals of convex functions are also convex functions, and that the summation of convex functions is also a convex function. Hence, proving that the objective function is convex everywhere. Subsequently proving that there is only one solution for Beckman's transformation program, with respect to link flows, and that solution is a minimum.

Recalling that

$$\frac{\partial^2 z(x)}{\partial x_m \partial x_n} = \frac{\partial t_m(x_m)}{\partial x_n} = \begin{cases} 1 & \text{for m=n} \\ 0 & \text{otherwise} \end{cases}, \tag{10}$$

the Hessian matrix for the objective function can be calculated to be as follows,

$$\nabla^2 z(x) = \begin{bmatrix} \dfrac{\partial^2 z(x)}{\partial x_1^2} & \dfrac{\partial^2 z(x)}{\partial x_2 \partial x_1} & \cdots & \dfrac{\partial^2 z(x)}{\partial x_A \partial x_1} \\ \dfrac{\partial^2 z(x)}{\partial x_1 \partial x_2} & \dfrac{\partial^2 z(x)}{\partial x_2^2} & \cdots & \dfrac{\partial^2 z(x)}{\partial x_A \partial x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{\partial^2 z(x)}{\partial x_1 \partial x_A} & \dfrac{\partial^2 z(x)}{\partial x_2 \partial x_A} & \cdots & \dfrac{\partial^2 z(x)}{\partial x_A^2} \end{bmatrix} = \begin{bmatrix} \dfrac{dt_1(x_1)}{dx_1} & 0 & \cdots & 0 \\ 0 & \dfrac{dt_2(x_2)}{dx_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \dfrac{dt_A(x_A)}{dx_A} \end{bmatrix}. \tag{11}$$

Obviously, the matrix is definite positive, proving that the objective function is strictly positive, and subsequently, has a unique minimum solution.

It is worth mentioning that the Beckman's transformation program is not convex with respect to path flows, and therefore, the equilibrium conditions themselves are not unique with respect to path flows. In other words, while there is actually only one unique solution for link flows, there are an infinite number of paths flows solutions that

would produce this unique link flows solution, which raises the need to compute the most likely of these solutions using a synthetic O-D estimator as was described earlier and will be discussed later in more detail.

System Optimum

As mentioned earlier, the SO model attempts to minimize the total travel time spent in the network. Hence, it might assign certain trips to a slightly longer path (in terms of travel time), in order to reduce the travel time of other user trips by a value which is greater than the value of the increased travel time, and thus achieving a reduced total network travel time. Opposite to user equilibrium, in the system optimum state, users can reduce their travel times by unilaterally switching to alternative paths, which becomes a challenge to implement such a strategy. Therefore, the solution is not stable. SO network travel time mainly serves as a yardstick that measures the performance of a network.

The mathematical program that represents this model can be written as follows,

$$\text{Min. } \tilde{z}(x) = \sum_a x_z . t_z(x_a)$$

S.T.

$$\sum_k f_k^{rs} = q_{rs} \qquad \forall r, s \qquad \text{(Flow conservation constraints)} \qquad (12)$$

$$f_k^{rs} \geq 0 \qquad \forall k, r, s \qquad \text{(Non-negativety constraints)}$$

$$x_a = \sum_r \sum_s \sum_k (f_k^{rs} . \delta_{a,k}^{rs}) \ \forall a$$

As can be seen, the only difference between user-equilibrium and system optimum programs is the objective function. The SO optimum objective function equals the summation of the products of the travel time on each link times the traffic volume assigned to this link, for all links. Hence, it works on minimizing the total travel time experienced by all vehicles traveling on all links of the networks. On the other hand, the UE objective function equaled the summation of only the travel times of all links.

It can also be seen that the constraints in the SO model are exactly the same as in the UE model. Consequently, similar to the case with the user-equilibrium equivalent program, the solution of this program can be found by solving for the first-order conditions for a stationary point of the following Lagrangian

$$\tilde{L}\ f, u\ = \tilde{z}\big[x\ f\ \big] + \sum_r \sum_s \tilde{u}_{rs} \left(q_{rs} - \sum_k f_k^{rs} \right), \qquad (13)$$

where $\tilde{u}_{rs}$ denotes the dual variable associated with the flow conservation constraint for O-D pair (r-s). At the stationary point of the Lagrangian, the following first-order conditions have to hold with respect to the path-flow variables

$$f_k^{rs} \frac{\partial \tilde{L}(f, \tilde{u})}{\partial f_k^{rs}} = 0 \ \forall\ k, r, s \ \text{ and } \frac{\partial \tilde{L}(f, \tilde{u})}{\partial f_k^{rs}} \geq 0 \qquad \forall\ k, r, s\ . \qquad (14)$$

With respect to the dual variables

$$\frac{\partial \tilde{L}(f, u)}{\partial \tilde{u}_{rs}} = 0 \qquad \forall\ r, s\ . \qquad (15)$$

In addition to the non-negativity constraints

$$f_k^{rs} \geq 0 \quad \forall\ k, r, s\ . \qquad (16)$$

Note that, the formulation of this Lagrangian is given in terms of path flow by using the incidence relationships, $x_a = x_a(f)$.

The partial derivative of $\tilde{L}(x, \tilde{u})$ with respect to the flow variables f_l^{mn} can be given by,

$$\frac{\partial \tilde{L}(f, \tilde{u})}{\partial f_l^{mn}} = \frac{\partial}{\partial f_l^{mn}} \tilde{z}\left[x\ f\ \right] + \frac{\partial}{\partial f_l^{mn}} \sum_r \sum_s \tilde{u}_{rs}\left(q_{rs} - \sum_k f_k^{rs} \right)$$

$$\frac{\partial}{\partial f_l^{mn}} \tilde{z}\left[x\ f\ \right] = \sum_{b \in A} \frac{\partial \tilde{z}\ x}{\partial x_b} \cdot \frac{\partial x_b}{\partial f_l^{mn}} = \sum_b \left[\left(\frac{\partial}{\partial x_b} \sum_a x_a . t_a\ x_a\ \right) \frac{\partial x_b}{\partial f_l^{mn}} \right] = \sum_b \left[t_b\ x_b\ + x_b \frac{dt_b\ x_b}{dx_b} \right] \delta_{b,l}^{mn} = \sum_b \tilde{t}_b \cdot \delta_{b,l}^{mn} = \tilde{c}_l^{mn}$$

Assuming $\tilde{t}_b = t_b\ x_b\ + x_b \dfrac{dt_b\ x_b}{dx_b}$ and $\dfrac{\partial}{\partial f_l^{mn}} \sum_r \sum_s \tilde{u}_{rs}\left(q_{rs} - \sum_k f_k^{rs} \right) = -\tilde{u}_{mn}$ because (a) u_{rs} is not a function of

f_l^{mn} ; (b) q_{rs} is constant; and (c) $\dfrac{\partial f_k^{rs}}{\partial f_l^{mn}} = \begin{cases} 1 & \text{if } r = m, s = n, \text{and } k = l \\ 0 & \text{otherwise} \end{cases}$.

Therefore $\dfrac{\partial \tilde{L}(f, \tilde{u})}{\partial f_l^{mn}} = \tilde{c}_l^{mn} - \tilde{u}_{mn}$.

Where, $\tilde{t}_a$ is a summation of two terms, (1) $t_a(x_a)$, which is the travel time experienced by this additional driver when the total link flow is (x_a) and (2) $\dfrac{dt_a\ x_a}{dx_a}$, which is the additional travel time burden that this driver inflicts on each one of the other (x_a) travelers already using link *a*.

In summary, it can be interpreted as the marginal contribution of an additional traveler – or an infinitesimal flow unit – on the ath link to the total travel time on that link.

Substituting the above results into Equations (14) through (16), we get the following first-order conditions

$$\begin{aligned} f_k^{rs}\left(\tilde{c}_k^{rs} - \tilde{u}_{rs} \right) &= 0 & \forall\ k, r, s \\ \tilde{c}_k^{rs} - \tilde{u}_{rs} &\geq 0 & \forall\ k, r, s \\ \sum_k f_k^{rs} &= q_{rs} & \forall\ r, s \\ f_k^{rs} &\geq 0 & \forall\ k, r, s \end{aligned}$$

Similar to the interpretation of the user equilibrium conditions, the following can be implied from the above, (1) The first two Conditions, for any path (*k*) connecting any O-D pair (r-s), either (a) the flow on that path, f_k^{rs} , equals zero whenever the marginal total travel time on this path, $\tilde{c}_k^{rs}$, will have a value that is greater than or equal to the value of the O-D specific Lagrange multiplier, $\tilde{u}_{rs}$,or, (b) the flow on that path, f_k^{rs} , will have a value (greater than zero) whenever the marginal total travel time on this path, $\tilde{c}_k^{rs}$, will have a value equal to the value of the O-D specific Lagrange multiplier, $\tilde{u}_{rs}$. In both cases, the value of the O-D specific Lagrange multiplier is always less than or equal to the marginal total travel time on all other paths connecting the same O-D pair, i.e. the value of the Lagrange multiplier is the marginal travel time on the used paths between this O-D pair. (2) The last two conditions satisfy the flow conversation and non-negativity constraints, respectively.

The proof can further be explained as follows, paths connecting O-D pair (r-s) can be divided into two groups, (1) Paths with zero flow, and are characterized by a total marginal travel time which is either greater than or equal to the marginal travel time of the used networks (or the Lagrange multiplier). (2) Paths with non-negative flows, and are characterized by equal marginal travel times.

In order to prove that the SO program has only one solution, as was the case with the user equilibrium program, it is sufficient to prove that the objective function is strictly convex in the vicinity of the solution point, convex everywhere else (within the feasible solution region), and that the feasible region (defined by the constraints) is convex.

It is known that linear equality constraints assure a convex feasible region, and that the addition of the non-negativity constrains does not alter this fact. The convexity of the objective function, with respect to link flows, can be proven if the Hessian matrix of the objective function is positive definite.

Recalling that,

$$\frac{\partial^2 \tilde{z}\ x}{\partial x_m \partial x_n} = \frac{\partial}{\partial x_n} \cdot \left[\frac{\partial}{\partial x_m} \sum_a x_a . t_a\ x_a \right] = \frac{\partial}{\partial x_n}\left[t_m\ x_m\ + x_m \frac{dt_m\ x_m}{dx_m} \right] = \begin{cases} 2\dfrac{dt_n(x_n)}{dx_n} + x_n \dfrac{d^2 t_n(x_n)}{dx_n^2} & \text{for } m = n \\ 0 & \text{Otherwise} \end{cases}.$$

As in the user equilibrium program, the Hessian matrix for the objective function can be calculated to be as

$$\nabla^2 z(x) = \begin{bmatrix} 2\dfrac{dt_1\ x_1}{dx_1} + x_1 \dfrac{d^2 t_1\ x_1}{dx_1^2} & 0 & \cdots & 0 \\ 0 & 2\dfrac{dt_2\ x_2}{dx_2} + x_n \dfrac{d^2 t_2\ x_2}{dx_2^2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 2\dfrac{dt_A\ x_A}{dx_A} + x_A \dfrac{d^2 t_A\ x_A}{dx_A^2} \end{bmatrix}.$$

This Hessian matrix is positive definite if all the diagonal terms are positive, which is manifested if the link performance functions are positive. Based on the earlier discussion in the user equilibrium section, it was demonstrated that link-performance functions are convex, and thus demonstrating that the objective function is strictly positive, and subsequently, has a unique minimum solution – with respect to link flows.

It is worth noting that user equilibrium and system optimum produce identical results in any of the following: (1) If congestion effects were ignored, i.e. $t_a(x_a) = t_a'$ (a constant value per arc) or (2) In case of minimal traffic volumes, that would have negligible effects on the arc specific travel times, $t_a(x_a)$.

Dynamic Traffic Assignment Solution Approach

The extension from a static to a dynamic formulation involves the introduction of two time indices into the formulation. The first time index identifies the time at which the path flow leaves its origin while the second time index identifies when the path flow is observed on a specific link. Unfortunately, the introduction of these time indices deems the objective function non-convex and thus two approaches are considered in solving this problem. The first approach is to divide the analysis period into time intervals while assuming that conditions are static within each time interval (time-dependent static or quasi static). The duration of these intervals are network dependent and should be sufficiently long enough to ensure that motorists can complete their trip within the time interval. The static UE and SO mathematical programs can then be solved for each time interval using the standard static formulations that were presented earlier. The mathematical solution approach requires a closed form solution using an analytical modeling approach. Analytical modeling of the network aims at finding the correct mathematical presentation of DTA models that would realistically reflect the real world problem with minimum compromises in the modeling of traffic behavior. The solution of such models should guarantee theoretical existence, uniqueness, and stability. Analytical models are valuable because theoretical insights can be analytically derived. Different analytical network modeling may include mathematical programming formulations, optimal control formulations, and variational inequality formulations (Srinivas Peeta 2001). Literature within this area of research is extensive. In general, models within the group may be classified into (Srinivas Peeta 2001): i) mathematical programming formulations, as the works of

Merchant and Nemhauser (Merchant 1978; Merchant 1978), Ho (Ho 1980), Carey (Carey 1986; Carey 1987; Carey 1992), Janson (Janson 1991; Janson 1991), Birge and Ho (Birge 1993), Ziliaskopoulos (Ziliaskopoulos 2000), Carey and Subrahmanian (Carey 2000); ii) optimal control formulations, as in the works of Friesz et al. (Terry L. Friesz 1989), Ran and Shimazaki (Ran 1989; Ran 1989), Wie (Wie 1991), Ran et al. (Ran 1993), Boyce et al. (Boyce 1995); and iii) variational inequality formulations, as with the works of Dafermos (Dafermos 1980), Friesz et al. (Terry L. Friesz 1993), Wie et al. (Byung-Wook Wie 1995), Ran and Boyce (Bin Ran 1996), Ran et al. (Bin Ran 1996), Chen and Hsueh (Huey-Kuo Chen 1998).

Alternatively, the second approach involves the use of a simulation solution approach. Simulation models on the other hand, in spite of solving the DTA problem within a simulation environment, still use some form of mathematical abstraction of the problem. According to Peeta (Srinivas Peeta 2001), "*the terminology simulation-based models may be a misnomer. This is because the mathematical abstraction of the problem is a typical analytical formulation, mostly of the mathematical programming variety in the current literature. However, the critical constraints that describe the traffic flow propagation, and the spatio-temporal interactions, such as the link-path incidence relationships, flow conservation, and vehicular movements are addressed through simulation instead of analytical evaluation while solving the problem. This is because analytical representations of traffic flows that adequately replicate traffic theoretic relationships and yield well-behaved mathematical formulations are currently unavailable. Hence, the term simulation-based primarily connotes the solution methodology rather than the problem formulation. A key issue with simulation-based models is that theoretical insights cannot be analytically derived as the complex traffic interactions are modeled using simulation. On the other hand, due to the inherently ill-behaved nature of the DTA problem, notions of convergence and uniqueness of the associated solution may not be particularly meaningful from a practical standpoint. In addition, due to their better fidelity vis-à-vis realistic traffic modeling, simulation-based models have gained greater acceptability in the context of real-world deployment*".

One of the early simulation DTA tools is the Simulation and Assignment in Urban Road Networks (SATURN) approach. The SATURN algorithm utilizes an equilibrium technique which optimally combines a succession of all-or-nothing assignments (i.e. it is an iterative equilibrium assignment based on iterative traffic loading) (Bolland et al. 1979; Hall et al. 1980; Van Vliet 1982). This model treats platoons of traffic rather than individual vehicles but delays vehicles but delays at intersections are treated in considerable detail. The model consists of two parts: a simulation component and a traffic assignment component. The traffic simulation component fits a delay-flow power curve to three points, namely: zero flow, current flow, and capacity. This delay-flow curve is used by the assignment model to route vehicles. For each traffic signal four cyclic flow profiles are considered: the IN pattern, the ARRIVE pattern, the ACCEPT pattern, and the OUT pattern. SATURN can account for delays caused by opposing flows, delays caused by vehicles on the same roadway, the shape of the arriving platoon, the effect of traffic signal phasing structure and offsets, and individual lane capacities. Arrival rates that exceed capacity are assumed to form queues that build up at constant rates. SATURN can model networks at two levels of detail, namely: inner and buffer. The model was used in studies in the U.K., Australia, and New Zealand. The limitations of the model include: (a) it assumes steady-state conditions for periods of 15-30 minutes and thus is a time-dependent dynamic assignment approach; (b) queues are modeled vertically and thus they cannot spillback to upstream intersections; (c) it is unsuitable for freeways; (d) it cannot model over-saturated conditions explicitly.

Another early simulation DTA that was developed in the late 1970s is the CONTRAM model (CONtinuous TRaffic Assignment Model). CONTRAM is similar to SATURN in that it combines traffic assignment with traffic simulation (Leonard et al. 1978). CONTRAM is a computer based time-varying assignment and queuing model. Unlike SATURN, vehicles are grouped within CONTRAM into packets where each packet is treated in the same way as a single vehicle when assigning it to its minimum path. Time varying flow conditions are modeled by dividing the simulation period into a number of consecutive time intervals, which need not be of the same length, and the packets leave each origin at a uniform rate through each such interval. The assignment is an incremental iterative technique where during the first iteration; packets are routed based on link-travel times of previous packets. However, in successive iterations, they are routed based on link travel times that reflect a weighting of travel times during previous iterations and previous packets. Prior to routing a packet, the packet volume is removed from its previously used links. An advantage of this assignment model is that it takes into account the effects of packets leaving later on the routing of packets which leave earlier. Thus, it decides upon the path based on a fully loaded network, rather than on one in which has only been loaded to the extent of any previous increments. This model is more dynamic than most models because vehicles are able to change their routing decisions while en-route, if traffic conditions alter.

Satisfactory convergence is usually achieved in 5 to 10 iterations. The limitations of the model are: (a) introduction of signal optimization makes the model unable to converge; (b) vehicles queue vertically on a link; (c) no limitation of the storage capacity of a link is introduced; (d) it is unsuitable for freeway networks; and (e) it can only assign vehicles based on Wardrop's first principle.

A number of contemporary DTA models were developed using the basic CONTRAM concept, including the INTEGRATION (Van Aerde 1985; Van Aerde et al. 1988; Van Aerde et al. 1988; Rakha et al. 1989; Van Aerde et al. 1989; Rilett et al. 1991; Rilett et al. 1991; Rilett et al. 1991; Rilett et al. 1993; Rakha et al. 1998; Van Aerde et al. 2007; Van Aerde et al. 2007), DYNASMART (Jayakrishnan et al. 1990; Jayakrishnan et al. 1991; Peeta et al. 1991; Jayakrishnan et al. 1993; Abdelghany et al. 1999; Abdelghany et al. 2000; Srinivasan et al. 2000; Abdelfatah et al. 2001; Abdelghany et al. 2001; Chiu et al. 2001) and DYNAMIT (Koutsopoulos et al. 1995; Ben-Akiva et al. 1998; Yang 2000; Balakrishna et al. 2005) modeling approaches. In this section the INTEGRATION dynamic traffic assignment and modeling framework is briefly described as an example illustration of a microscopic traffic assignment and simulation approach. The INTEGRATION model is similar to the CONTRAM model in that it models individual vehicles (packets of unit size). Unlike, other traffic assignment models, the INTEGRATION traffic simulation logic is microscopic in that it models vehicles at a deci-second level of resolution. The software combines car-following, vehicle dynamics, lane-changing, energy, and emission models. Thus, mobile source emissions can be directly estimated from instantaneous speed and acceleration levels. Furthermore, the traffic and emission modeling modules have been tested and validated extensively. For example, the software, which was developed over the past two decades, has not only been validated against standard traffic flow theory (Rakha et al. 1996; Rakha et al. 2002), but has also been utilized for the evaluation of real-life applications (Rakha et al. 1998; Rakha et al. 2000). Furthermore, the INTEGRATION software offers unique capability through the explicit modeling of vehicle dynamics by computing the tractive and resistance forces on the vehicle each deci-second (Rakha et al. 2001; Rakha et al. 2002; Rakha et al. 2004).

The INTEGRATION software uses car-following models to capture the longitudinal interaction of a vehicle and its preceding vehicle in the same lane. The process of car-following is modeled as an equation of motion for steady-state conditions (also referred to as stationary conditions in some literature) plus a number of constraints that govern the behavior of vehicles while moving from one steady-state to another (decelerating and/or accelerating). The first constraint governs the vehicle acceleration behavior, which is typically a function of the vehicle dynamics (Rakha et al. 2002; Rakha et al. 2004). The second and final constraint ensures that vehicles maintain a safe position relative to the lead vehicle in order to ensure asymptotic stability within the traffic stream. A more detailed description of the longitudinal modeling of vehicle motion is provided by (Rakha et al. 2004). Alternatively, lane-changing behavior describes the lateral behavior of vehicles along a roadway segment. Lane changing behavior affects the vehicle car-following behavior especially at high intensity lane changing locations such as merge, diverge, and weaving sections.

The INTEGRATION model provides for 7 basic traffic assignment/ routing options: (a) Time-Dependent Method of Successive Averages (MSA); (b) Time-Dependent Sub-Population Feedback Assignment (SFA); (c) Time-Dependent Individual Feedback Assignment (IFA); (d) Time-Dependent Dynamic Traffic Assignment (DTA); (e) Time-Dependent Frank-Wolf Algorithm (FWA); (f) Time-Dependent External; and (g) Distance Based Routing.

The derivation of a time series of MSA traffic assignments involves analyzing each time slice in isolation of either prior or subsequent time slices (time-dependent static or quasi static). The link travel times, upon which the route computations are based, are estimated based on the prevailing O-D pattern and an approximate macroscopic travel time relationship for each link. Multiple paths are computed in an iterative fashion, where the tree for each subsequent iteration is based on the travel times estimated during the previous iterations. The weight assigned to each new tree is $1/N$ where N is the iteration number.

In the case of the feedback assignment vehicles base their routings on the experience of previous vehicle departures (incremental traffic assignmnent). In the case of the SFA assignment all drivers of a specific type are divided into 5 sub-populations each consisting of 20% of all drivers. The paths for each of these sub-populations are then updated every *t* seconds during the simulation based on real-time measurements of the link travel times for that specific vehicle class. The value of *t* is a user-specified value. Furthermore, the minimum path updates of each vehicle sub-population are staggered in time, in order to avoid having all vehicle sub populations update their paths at the same

time. This results in 20% of the driver paths being updated every t/5 seconds. In the case of the IFA assignment all paths are customized to each individual driver and may therefore be unique relative to any other drivers. This incremental traffic assignment accounts the effect of earlier vehicle departures on the travel time of later which is very similar to the CONTRAM approach. However, unlike CONTRAM no iterations are made to re-assign all the vehicles.

The INTEGRATION DTA computes the minimum path for every scheduled vehicle departure, in view of the link travel times anticipated in the network at the time the vehicle will reach these specific links. The anticipated travel time for each link is estimated based on anticipated link traffic volumes and queue sizes. This routing involves the execution of a complete mesoscopic DTA model prior to the simulation of the traffic. During this DTA, the routes of all vehicles are computed using the above procedure. Upon completion of this DTA, the actual simulation simply implements the routings computed as per the DTA.

Clearly the validity of any of these modeling approaches hinges on the ability of the traffic simulation model to reflect real-life behavior and capture all the complexities of traffic modeling. Clearly, no modeling approach can claim that it is capable of capturing every aspect of empirical traffic flow behavior and thus the output of such models should be interpreted within the context of how they model the spatio-temporal behavior of drivers.

It should also be noted that the models that were described in this section are heuristic approaches attempting to solve the mathematical formulations that were presented earlier and thus there is no guarantee that they converge to a single (unique) solution for UE and/or SO assignment problems for a complex dynamic network. Furthermore, it is not clear if drivers actually attain such an equilibrium state in such networks. Consequently, research is needed to study and develop models on how drivers select routes, how they respond to the dissemination of traffic information, and how their routing decisions vary temporally in the short- and long-term.

VI. TRAFFIC MODELING

A key component of a DTA is the modeling of traffic stream behavior in order to predict traffic states into the near future and compute link travel times and various measures of effectiveness, as was illustrated earlier in Figure 2. This section briefly summarizes the various state-of-the-practice approaches to traffic modeling. Researchers have demonstrated that these approaches are unable to predict empirical spatio-temporal aspects (Kerner 2004) observed in the field. Conversely, others have argued that these approaches, while not perfect, capture the main aspects of empirical data. While our objective is not to argue either way, it is sufficient to note that these tools are being used by transportation professionals to assess dynamic networks and thus are presented in this section. These approaches can be classified into three categories, which include: macroscopic, mesoscopic, and microscopic approaches. Each of these approaches is briefly described in this section. Again the description is by no means comprehensive but does provide a general overview of these approaches. The interested reader should consider reading the wealth of literature on this topic.

Prior to describing the specifics of the various modeling approaches it is important to note that with the exception to research conducted by Kerner (2004), most existing approaches are based on the famous one-dimensional kinematic waves (KW) theory, which was proposed by Lighthill and Witham (Lighthill et al. 1955) and independently proposed by Richards (Richards 1956). The key postulate of the theory is that there exists a functional relationship between the traffic stream flow rate q and density k that might vary with location x but does not vary with time t (this contradicts the definition of dynamic given that within a dynamic process variables vary spatially and temporally). It should be noted that in microscopic approaches, as will be described later, the fundamental diagram various temporally as a function of the traffic composition, thus overcoming some of the drawbacks o f this approach. The fundamental hypothesis of all traffic flow theories is the existence of a site-specific unique relationship between traffic stream flow and traffic stream density, commonly known as the fundamental diagram, the traffic stream motion model, or the car-following model at the microscopic level. The assumption is that all steady-state model solutions lie on the fundamental diagram and thus are referred to as fundamental diagram approaches (Kerner 2004). Given that traffic stream space-mean speed can be related to traffic stream flow and density, a unique speed-flow-density relationship (in the macroscopic approach) is derived from the fundamental diagram for each roadway segment. This relationship can also be cast at the micro-level by relating the vehicle speed to its spacing, given that vehicle spacing is the inverse

of traffic stream density. Some researchers have argued that the fundamental diagram approach cannot capture the spontaneous traffic stream failure that is observed in the field and thus these researchers have proposed other theories.

One of these theories is the three-phase traffic flow theory proposed by Kerner (2004), which attempts to explain empirical spatiotemporal features of congested patterns. The theory divides traffic into three phases: free-flow, synchronized flow, and wide moving jams. The free-flow phase is consistent with the uncongested regime on a fundamental diagram and thus is not discussed further. The *synchronized flow* phase involves continuous traffic flow with no significant stoppage. The word "flow" reflects this feature. Within this phase there is a tendency towards synchronization of vehicle speeds and flows across the different lanes on a multilane roadway, and thus comes the name "synchronized." This synchronization of speeds is a result if the relatively low probability of passing within this phase. The third phase, *wide moving jam*, is a phase that involves traffic jams that propagate through other states of traffic flow and through any bottleneck while maintaining the velocity of the downstream jam front. The phrase *moving jam* reflects the propagation as a whole localized structure on a road. To distinguish wide moving jams from other moving jams, which do not characteristically maintain the mean velocity of the downstream jam front, Kerner uses the term wide moving jam. Kerner indicates that if a moving jam has a width (in the longitudinal direction) considerably greater than the widths of the jam fronts, and if vehicle speeds inside the jam are zero, the jam always exhibits the characteristic feature of maintaining the velocity of the downstream jam front.

Kerner distinguishes his three-phase traffic flow theory from fundamental diagram approaches in a number of aspects. He demonstrates that the fundamental diagram approach cannot capture two key empirically observed phenomena in traffic, namely: (a) the probabilistic nature of free-flow to synchronized flow transition (flow breakdown), and (b) the spontaneous formation of general patterns (GP), which include moving and wide moving jams. Alternatively, it could be hypothesized that by modeling individual driver behavior (micro or nano modeling), capturing vehicle acceleration constraints, and introducing stochastic differences between drivers that this may be sufficient to model these two key phenomena.

Macroscopic Modeling Approaches

In order to solve for the three traffic stream variables (q, k, and u) three equations are introduced. The first is the functional relationship between flow and density, or what is commonly known as the fundamental diagram. Typical functions include the Pipes triangular function (3 parameters), the Greenshields parabolic function (Greenshields 1934) (2 parameters), or the Van Aerde (Rakha et al. 2002) function (4 parameters). The second equation is the flow conservation equation (equation of continuity) that can be expressed as $\partial k(x,t)/\partial t + \partial q(x,t)/\partial x = 0$, considering

no entering or exiting traffic. The third and final equation relates the traffic stream flow rate (q) to the traffic stream density (k) and space-mean speed (u) as $q = ku$. The numerical solution of the KW problem involves partitioning the network into small cells of length Δx and discretizing time into steps of duration Δt. For numerical stability $\Delta x = u \Delta t$. The problem is solved by stepping through time and solving for the variables in every cell using the incremental transfer (IT) principle (essentially explicit finite difference method). Extensions to the standard KW solution have introduced IT solutions for each lane along a freeway where the freeway is modeled as a set of interacting streams linked by lane changes. Lane-changing vehicles can be treated as a fluid that can accelerate instantaneously, however this approach does not capture the reduction in capacity that is associated with lane changes. Consequently, further improvements have been introduced through the use of a hybrid approach (Laval et al. 2006) that combines microscopic and macroscopic models. Specifically, slow vehicles are treated as moving bottlenecks in a single KW stream, while lane changing vehicles are modeled as discrete particles with constrained motion. The model requires identifying a lane-change intensity parameter in addition to the functional relationship parameters that were described earlier. It is not clear how such a parameter is derived. The major drawbacks of this modeling approach are that it does not account for the dynamic changes in roadway capacity (e.g. the capacity of a weaving section varies as a function of the traffic composition), it cannot capture the spontaneous traffic stream failure that is observed in the field, it cannot capture the impact of opposing flows on the traffic behavior of an opposed flow (e.g. how the capacity of an opposed left turn movement is affected by the opposing through movement), and it ignores the stochastic nature of traffic.

Mesoscopic Modeling Approaches

The mesoscopic analysis tracks individual vehicles as they travel through the network along a sequence of links that are determined by the traffic assignment. The level of tracking involves computing the vehicle's travel speed on each link based upon the density on the link together with a user specified speed/density relationship. The vehicle is then held on the link for the duration of its travel time. At the vehicle's scheduled departure time, the vehicle is allowed to exit the link if the link privileges permit it to leave; otherwise, the vehicle is held on the link until the link privileges so permit. Link exit privileges may be controlled by traffic signals at the downstream end of the link or by any queues that may be present on the lane. Queues are stored for each lane separately to account for any queue length differentials that may occur (e.g., longer queues on left turn opposed lanes). The mesoscopic analysis captures the operational level of detail (e.g., the reduction in lane capacity as a result of an opposed flow) without having to track each vehicle's instantaneous speed profile. This means that the computational requirements for such a type of modeling are more than that required by a macroscopic analysis, but less than that required by a microscopic analysis. The INTEGRATION 1.50, DynaSMART, and DynaMIT models are examples of such modeling approaches. This approach suffers from similar drawbacks as identified in the macroscopic analysis procedures, namely an inability to capture correct spatiotemporal propagation of congestion, a failure to capture dynamic changes in capacity, a failure to capture for spontaneous breakdown in a traffic stream, and failure to capture the stochastic nature of traffic.

Microscopic Modeling Approaches

The third approach to modeling traffic is the microscopic analysis, which tracks each vehicle as it travels through the network on a second-by-second or deci-second level of resolution using detailed car-following and lane-changing models. Microscopic simulation software use car-following models to capture the longitudinal interaction of a vehicle and its preceding vehicle in the same lane. The process of car-following is modeled as an equation of motion for steady-state conditions (also referred to as stationary conditions in some literature) plus a number of constraints that govern the behavior of vehicles while moving from one steady-state to another (decelerating and/or accelerating). The first constraint governs the vehicle acceleration behavior, which is typically a function of the vehicle dynamics. The second and final constraint ensures that vehicles maintain a safe position relative to the lead vehicle in order to ensure asymptotic stability within the traffic stream. A more detailed description of the longitudinal modeling of vehicle motion is provided by (Rakha et al. 2004). While there are a number of commercially available software packages that simulate traffic microscopically (CORSIM, Paramics, FREEVU, VISSIM, AIMSUN2, and INTEGRATION), these approaches are computationally intensive and cannot run in real-time. The INTEGRATION software has been able to capture the stochastic nature of traffic stream capacity by randomly modeling vehicle-specific car-following models. Furthermore, the model captures the capacity loss associated with recovery from breakdown through the vehicle acceleration constraints. The stochastic nature of car-following and lane-changing behavior may allow the model to capture spontaneous breakdown in traffic stream flow.

The amount of computation and memory necessary for simulating a large transportation network at a level of detail down to an individual traveler and an individual vehicle may be extensive. Hence a microscopic massively parallel simulation approach entitled "cellular automata" (CA) is sometimes proposed to simulate large networks. The cellular automata approach essentially divides every link on the network into a finite number of cells. At a one second time step, each of these "cells" is scanned for a vehicle presence. If a vehicle is present, the vehicle position is advanced, either within the cell or to another cell, using a simple rule set (Nagel et al. 1992; Nagel et al. 1995; Nagel 1996). The rule set is made simple to increase the computational speed necessary for a large simulation. Vehicles are moved from one grid cell to another based on the available gaps ahead, with modifications to support lane changing and plan following, until they reach the end of the grid. There, they wait for an acceptable gap in the traffic or for protection at a signal before moving through the intersection onto the next grid. This continues until each vehicle reaches its destination, where it is removed from the grid. Reducing the size of the "cell", expanding the rule set, and adding vehicle attributes increases the fidelity of the simulator, but also greatly affects the computational speed. The size of 7.5 meters in length and a traffic lane in width is often chosen as a default size for the "cell" as was applied with the TRANSIMS software (Nagel et al. 1992). This approach suffers from a number of drawbacks including the inability to capture the dynamic nature of roadway capacity, the inability to capture spontaneous breakdown of traffic stream, and the inability to capture opposing flow impacts on opposed flow saturation flow rates (e.g. the impact an opposing

through movement flow has on the capacity of a permitted left turn movement that has to find a gap in this opposing flow).

VII. DYNAMIC TRAVEL TIME ESTIMATION

As was demonstrated earlier in the paper, the DTA requires arc (link) travel times in order to compute minimum paths. There are several systems commercially available that are capable of estimating real-time travel times. These can be broadly classified into spot speed measurement systems, spatial travel time systems, and probe vehicle technologies. Spot speed measurement systems, specifically inductance loop detectors, have been the main source of real-time traffic information for the past two decades. Other technologies for measuring spot speeds have also evolved, such as infrared and radar technologies. Regardless of the technology, the spot measurement approaches only measure traffic stream speeds over a short roadway segment at fixed locations along a roadway. These spot speed measurements are used to compute spatial travel times over an entire trip using space-mean-speed estimates. In addition, new approaches that match vehicles based on their lengths have also been developed (Coifman 1998; Coifman et al. 2001; Coifman et al. 2002; Coifman et al. 2003). However, these approaches require raw loop detector data as opposed to typical 20- or 30-second aggregated data. Alternatively, spatial travel time measurement systems use fixed location equipment to identify and track a subset of vehicles in the traffic stream. By matching the unique vehicle identifications at different reader locations, spatial estimates of travel times can be computed. Typical technologies include AVI and license-plate video detection systems. Finally, probe vehicle technologies track a sample of probe vehicles on a second-by-second basis as they travel within a transportation network. These emerging technologies include cellular geo-location, Global Positioning Systems (GPS), and Automatic Vehicle Location (AVL) systems.

Traffic routing strategies under recurring and non-recurring strategies should be based on forecasting of future traffic conditions rather than historical and/or current conditions. In general the traffic prediction approaches can be categorized into three broad areas: (i) statistical models, (ii) macroscopic models, and (iii) route choice models based on dynamic traffic assignment (Ben Akiva et al. 1992; Birge 1993; Peeta 1995; Moshe Ben-Akiva 1997; Moshe Ben-Akiva 1998). Time series models have been used in traffic forecasting mainly because of their strong potential for online implementation. Early examples of such approaches include (Ahmed et al. 1982) and more recently (Lee et al. 1999) and (Ishak et al. 2003). In addition, researchers have applied Artificial Neural Network (ANN) techniques for the prediction of roadway travel times (Park et al. 1998; Park et al. 1998; Abdulhai et al. 1999; Park et al. 1999; Park et al. 1999; Park 2002). These studies demonstrated that prediction errors were affected by a number of variables pertinent to traffic flow prediction such as spatial coverage of surveillance instrumentation, the extent of the loop-back interval, data resolution, and data accuracy.

An earlier publication (Dion et al. 2006) developed a low-pass adaptive filtering algorithm for predicting average roadway travel times using Automatic Vehicle Identification (AVI) data. The algorithm is unique in three aspects. First, it is designed to handle both stable (constant mean) and unstable (varying mean) traffic conditions. Second, the algorithm can be successfully applied for low levels of market penetration (less than 1 percent). Third, the algorithm works for both freeway and signalized arterial roadways. The proposed algorithm utilizes a robust data-filtering procedure that identifies valid data within a dynamically varying validity window. The size of the validity window varies as a function of the number of observations within the current sampling interval, the number of observations in the previous intervals, and the number of consecutive observations outside the validity window. Applications of the algorithm to two AVI datasets from San Antonio, one from a freeway link and the other from an arterial link, demonstrated the ability of the proposed algorithm to efficiently track typical variations in average link travel times while suppressing high frequency noise signals.

Within the filtering algorithm, the expected average travel time and travel time variance for a given sampling interval are computed using a moving average (MA) technique. As shown in Equations 17 and 18, it estimates the expected average travel time and expected travel time variance within a given sampling interval based on the set of valid travel time observations in the previous sampling interval and the corresponding previously smoothed moving average value using an adaptive exponential smoothing technique. In both equations, calculations of the smoothed average travel time and travel time variance are made using a lognormal distribution to reflect the fact that the distribution is

right skewed (skewed towards longer travel times). Field data from the San Antonio AVI system demonstrated that this assumption is reasonable.

$$\tilde{t}_{i,k} = \begin{cases} e^{\left[\alpha \cdot \ln t_{i,k-1} + 1-\alpha \cdot \ln \tilde{t}_{i,k-1} \right]}, & \text{if } n_{i,k} > 0, \\ \tilde{t}_{i,k-1}, & \text{if } n_{i,k} = 0, \end{cases} \tag{17}$$

$$\tilde{\sigma}_{i,k}^2 = \begin{cases} \alpha \cdot \sigma_{i,k-1}^2 + (1-\alpha) \cdot \tilde{\sigma}_{i,k-1}^2, & \text{if } n_{i,k} > 1, \\ \tilde{\sigma}_{i,k-1}^2, & \text{if } n_{i,k} \leq 1. \end{cases} \tag{18}$$

It should be noted that $t_{i,k}$ is the observed average travel time along link i within the kth sampling interval (s), $\tilde{t}_{i,k}$ is the smoothed average travel time along link i in the kth sampling interval (s), $\sigma_{i,k}^2$ is the variance of the observed travel times relative to the observed average travel time in the kth sampling interval (s²), $\tilde{\sigma}_{i,k}^2$ is the variance of the observed travel times relative to the smoothed travel time in the kth sampling interval (s²), $n_{i,k}$ is the number of valid travel time readings on link i in the kth sampling interval, and $\alpha=1-(1-\beta)^{n_{i,k}}$ for all i and k is an exponential smoothing factor that varies as a function of the number of observations $n_{i,k}$ within the sampling interval, where β is a constant that varies between 0 and 1.
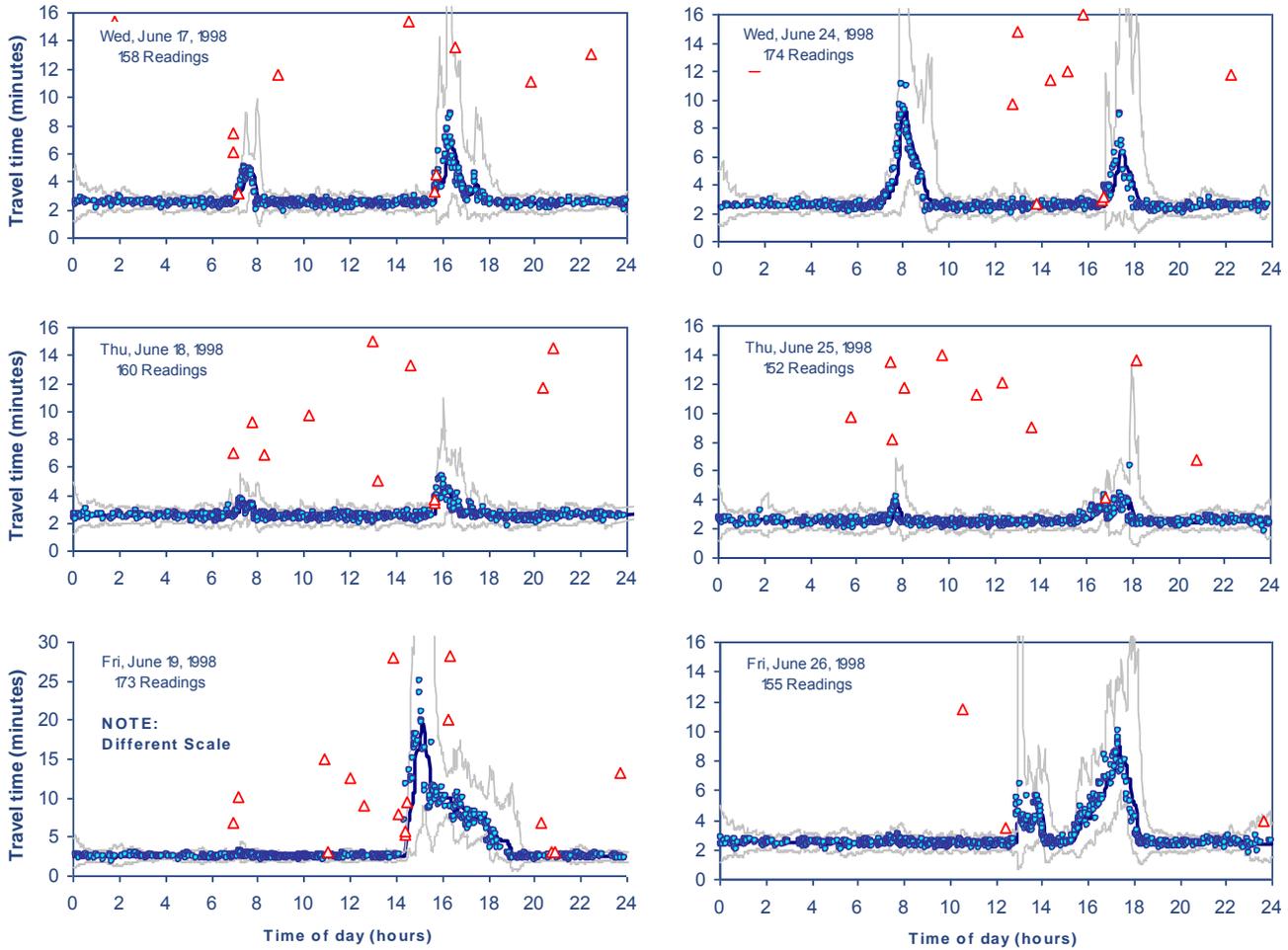
Figure 6: Sample Application of AVI Travel Time Estimation Algorithm (Dion et al. 2006)

Figure 6 shows an example application of the algorithm using AVI data along I-35 in San Antonio, TX. The figure illustrates the average travel time estimate (thick line), the validity window bounds (thin lines), what are considered to be valid data (circular), and the observations that are considered to be outliers (triangles). The figure clearly illustrates the effectiveness of the algorithm in estimating roadway travel times for low levels of market penetration of AVI tags.

Once link travel times have been estimated, the expected trip or path travel times can be computed by summing the relevant smoothed link travel times. In addition, the trip travel time reliability, which is the probability that a trip can reach its destination within a given period at a given time of day, can be computed for use in traffic routing. Travel time reliability is a measure of the stability of travel time, and therefore is subject to fluctuations in flow (Bell and Iida, 1997). Typically, when flow fluctuations are large, travel time is often longer than expected. As levels of congestion in transportation networks grow, generally the stability of travel time will have greater significance to transportation users. The trip travel time reliability can be computed as the probability $P(T<=t)$ that the trip travel time (T) is less than some arbitrary travel time (t), using the cumulative distribution function estimated from an analysis of AVI field data. The current state-of-the-art in predicting trip travel time variability is to assume that the travel times on all the links along a path are generated by statistically independent normal distributions. Consequently, the trip variance can be computed as the summation of the link travel time variances for all links along a path. As part of the proposed research effort, different statistical techniques (not assuming independent normal variates) will be devised to estimate the trip travel time variance, as discussed in the Proposed Research Tasks section. These techniques will be tested using data from the video detection system that is currently implemented in the Blacksburg Area.

In addition, research has been conducted to estimate the optimum locations of surveillance equipment for the estimation of travel times. Specifically, an earlier publication developed an algorithm for optimally locating Automatic Vehicle Identification tag readers by maximizing the benefit that would accrue from measuring travel times on a transportation network (Sherali et al. 2006). The problem is formulated as a quadratic 0-1 optimization problem where the objective function parameters represent benefit factors that capture the relevance of measuring travel times as reflected by the demand and travel time variability along specified trips. An optimization approach based on the Reformulation-Linearization Technique coupled with semi-definite programming concepts was designed to solve the formulated reader location problem. Alternatively, a Genetic Algorithm (GA) approach was developed to optimally locate the AVI readers (Arafeh et al. 2005).

VIII. DYNAMIC OR TIME-DEPENDENT ORIGIN-DESTINATION ESTIMATION

As was demonstrated earlier the Bechmann UE and the SO formulations do not provide unique path flows and thus a synthetic O-D estimator is required to estimate the path flows from the unique link flows. The techniques used to estimate O-D demands can be categorized based on different factors, as will be discussed in detail. The first categorization, of the available O-D estimation techniques, relates to whether the O-D's to be estimated are static, and apply to only one observation time period, or whether estimates are required for a series of linked dynamic time periods. The next breakdown relates to whether the estimation is based on information about the magnitude of trip ends only, or whether information is available on additional links along the route of each trip. The former problem is commonly referred to as the trip distribution problem in demand forecasting, while the latter problem is commonly referred to as the synthetic O-D generation problem. Both problems are discussed, but this section will focus on the latter synthetic O-D generation problem. The former is viewed simply as a simpler subset of the latter.

Within the overall static synthetic O-D generation problem, there are two main flavors. The first exists when the routes that vehicles take through the network are known a priori. The second arises when these routes need to be estimated concurrently while the O-D is being estimated. A priori knowledge of routes can arise automatically when there is only one feasible route between each O-D pair, or when observed traffic volumes are only provided for the zone connectors at the origins and destinations in the network. The first condition is common when O-D's are estimated for a single intersection or arterial, or a single interchange or freeway. The second condition is the default for any trip distribution analysis. This section will initially focus on situations where the routes are known a priori. Subsequently,

a solution to the more general problem which involves an iterative use of the solution approach when routes are not known a priori will be discussed.

Within the static/dynamic synthetic O-D generation problem, for scenarios where routes are known a priori (or are assumed to be known a priori) there exist two sub-problems. The first of these problems relates to situations where flow continuity exists at each node in the network, and multiple O-D matrices can be shown to match these observed flows exactly. In this case, the most likely of these multiple O-D matrices needs to be identified. The second sub-problem relates to situations where flow continuity does not exist at either the node level or at the network level. In other words, the observed traffic flows are such that no matrix exists that will match the observed flows exactly. In this case, Van Aerde *et al.* (Van Aerde et al. 2003) introduced a new set of complementary link flows that maintain flow continuity by introducing minimum alterations to the observed flows to solve the maximum likelihood problem.

The static synthetic O-D generation problem, for scenarios where flow continuity does exit, can be formulated in two different ways (Willumsen 1978; Van Zuylen et al. 1980). The first of these considers that the fundamental unit of measure is the individual trip, while the second considers that the fundamental unit of measure is the observation of a single vehicle on a particular link. The availability of a seed or target O-D matrix is implicit in the latter formulation, but can be dropped in the former formulation, as was demonstrated in an earlier publication (Van Aerde et al. 2003). However, only when a seed matrix is properly included in the former formulation is it guaranteed to yield consistent results with the latter formulation. In other words, the absence of a seed matrix in the trip based formulation can be shown to yield inconsistent results, at least for some networks in which the multiple solutions result in a different number of total trips.

An additional and related attribute, of the trip-based formulation of maximum likelihood, is the presence of a term in the objective function that is based on the total number of trips in the network. This term, referred to as *T*, is often dropped in some approximations. However, it can be shown that dropping this term can yield solutions that represent only a very poor approximation to the true solution (Rakha et al. 2005). In contrast, approximations involve the use of Stirling's approximation, for representing the logarithm of factorials, were shown to yield consistently very good approximations (Rakha et al. 2005). This finding is critical because use of Stirling's approximation is critical to being able to compute the derivatives that are needed to numerically solve the problem (it is difficult to take derivatives of terms that include factorials).

Other examples from literature include the works of Cremer and Keller (Cremer 1987), Cascetta et al. , Wu and Chang (Wu 1996), Sherali et al. (Sherali 1997), Ashok and Ben-Akiva (Ashok 2000), Hu et al. (Hu 2001) , Chang and Tao (Chang 1999), Pavlis and Papageorgiou (Pavlis 1999), Peeta and Zhou (Peeta 1999; Peeta 1999), Peeta and Yang (Peeta 2000; Peeta 2003), Yang (Yang 2001), Peeta and Bulusu (Peeta 1999).

Comparison of Synthetic O-D and Trip Distribution Formulations

Within the four-step planning process O-D matrices are estimated in the trip distribution step. Several methods are used for trip distribution including the gravity, growth factor, and intervening opportunities models. The gravity model is most utilized because it uses the attributes of the transportation system and land-use characteristics and has been calibrated and applied extensively to the modeling of numerous urban areas. The model assumes that the number of trips between two zones i and j (T_{ij}) is directly proportional to the number of trip productions from the origin zone (P_i) and the number of attractions to the destination zone (A_j) and inversely proportional to a function of travel time between the two zones (F_{ij}) as

$$T_{ij} = P_i \left(\frac{A_j F_{ij} K_{ij}}{\sum_j A_j F_{ij} K_{ij}} \right). \tag{19}$$

Typically the values of trip productions and attractions are computed based on trip generation procedures. The values of F_{ij} are computed using a calibration procedure that involves matching modeled and field trip length distributions. The socio-economic adjustment factors (K_{ij}) values are used when the estimated trip interchange must be adjusted to ensure that it agrees with observed trips by attempting to account for factors other than travel time. The values of K

are determined in the calibration process, but considered judiciously when a zone is considered to possess unique characteristics.

Because the O-D problem is under-specified, multiple O-D demands can generate identical link flows. For example, if one attempts to estimate an O-D matrix for a 100 zone network with, say 1000 links, one has more unknowns to solve for than there are constraints. In the case of the trip distribution process, there are 100x100 O-D cells to estimate, and only 2x100 trip end constraints. In the case of the synthetic O-D generation process, there are again 100x100 O-D cells to estimate, and only 1000 link constraints. Given the possibility of multiple solutions, both the trip distribution process and the synthetic O-D generation process invoke additional considerations to select a preferred matrix from among the multiple solutions.

In the case of synthetic O-D generation, the desire is to select from among all of the possible solutions, the most likely. This approach requires one to define a measure of the likelihood of each matrix. In general, there are two approaches to establish the likelihood of a matrix. One of them treats the trip as the basic unit of observation, while the other considers a volume count as the basic unit of observation. The first approach will be discussed in detail, while the interested reader might refer to the literature (Van Aerde et al. 2003) for a more detailed description of the various formulations. It suffices to indicate that for any matrix with cells T_{ij}, the likelihood of the matrix can be estimated using a function $L=f(T_{ij},t_{ij})$, where t_{ij} represents prior information. The prior information is often referred to as a seed matrix, and can be derived from a previous study or survey. In the absence of such prior information, all of the cells in this prior matrix should be set to a uniform set of values.

In the case of the trip distribution process, the additional information that is added is some form of impedance. For example, the original gravity model considered that the likelihood of trips between two zones was proportional to the inverse of the square of the distance between the two zones. Since that time, many more sophisticated forms of impedance have been considered, but for the purposes of this discussion, all of these variations can be generalized as being of the form F_{ij}, where $F_{ij} = f(c_{ij})$ or the generalized cost of inter-zonal travel. What is less obvious, however, is the fact that the use of this set of impedance factors F_{ij}, is essentially equivalent to the use of a seed matrix t_{ij}.

Van Aerde *et al*. (Van Aerde et al. 2003) demonstrated that solving the trip distribution problem, using zonal trip productions and attractions as constraints, together with a trip impedance matrix, is essentially the same as solving the synthetic O-D problem using zone connector in and out flows as constraints, and utilizing a seed matrix based on Equation (20).

$$t_{ij} = T \frac{F_{ij}}{\sum_{ij} F_{ij}} \tag{20}$$

Static Formulations

Entropy maximization and information minimization techniques have been used to solve a number of transportation problems (Wilson 1970). The application of the entropy maximization principles to the static O-D estimation problem was first introduced by Willumsen (Willumsen 1978; Van Zuylen et al. 1980). Willumsen demonstrated that by maximizing the entropy, the most likely trip matrix could be estimated subject to a set of constraints.

The trip-based approach to defining maximum likelihood considers that the overall trip matrix is made up of uniquely identifiable individual trip makers. The most likely matrix is one where the likelihood function is maximized as

$$\text{Max.} \quad Z_1 \ T_{ij} \ = \ \frac{T!}{\prod_{ij} T_{ij}!} . \tag{21}$$

The above formulation does not take into account any prior information, from for example a previous survey. While the seed matrix does not necessarily have to satisfy the observed link flows, the seed matrix can be utilized to expand the maximum likelihood function to

$$\text{Max.} \quad Z_2 \left(T_{ij}, t_{ij} \right) = \frac{T!}{\prod_{ij} T_{ij}!} \prod_{ij} \left(\frac{t_{ij}}{\sum_{ij} t_{ij}} \right)^{T_{ij}}. \tag{22}$$

It can be noted that the likelihood of an individual trip from *i* to *j* is $t_{ij}/\Sigma\Sigma t_{ij}$, based on the above seed matrix. Consequently, the probability of T_{ij} trips being drawn is $(t_{ij}/\Sigma\Sigma t_{ij})^{T_{ij}}$.

The above formulations of objective functions for expressing likelihood require additional constraints in order to be complete (Willumsen 1978; Van Zuylen et al. 1980). The simplest of these constraints indicate that the sum of all trips crossing a given link must be equal to the link flow on that link as

$$V_a = \sum_{ij} T_{ij} p_{ij}^a \qquad \forall\, a\,. \tag{23}$$

As will be shown later, the simplest mechanism, for including the above constraints in the earlier objective functions, is to utilize Lagrange multipliers. These multipliers permit an objective function with equality constraints to be transformed into an equivalent unconstrained objective function.

This simple set of equality constraints, while making the formulation complete, may at times also render the problem infeasible. A more general formulation that was proposed in the literature (Van Aerde et al. 2003) is to minimize the link flow error, rather than eliminate the error. In other words, rather than finding the most likely O-D that exactly replicates the observed link flows, the problem is re-formulated as finding the most likely O-D matrix from among all of those that come equally close to matching the link flows. One expression that is proposed to capture the error to be minimized is shown in Equation (24), and is subject to the flow continuity constraints in Equation (25). The constraints in Equation (25) can be introduced in Equation (25) to yield an unconstrained objective function, yielding a set of complementary link flows V'_a. These complementary flows are those which deviate the least from the observed link flows, while satisfying link flow continuity. Given that these complementary link flows do satisfy flow continuity, they can now be added in as rigid equality constraints to the objective function (21) or (22), and be guaranteed to yield a feasible solution.

$$\text{Min.} \quad Z_3 \left(T_{ij} \right) = \sum_a \left(V_a - V'_a \right)^2 \tag{24}$$

$$V'_a = \sum_{ij} T_{ij} p_{ij}^a \qquad \forall\, a \tag{25}$$

Alternatively, one can incorporate Equations (25) into Equation (24) to yield

$$\text{Min.} \quad Z_4 \left(T_{ij} \right) = \sum_a \left(V_a - \sum_{ij} T_{ij} p_{ij}^a \right)^2. \tag{26}$$

This equation should be minimized concurrently to maximizing the objective function (21) or (22). Unfortunately, it is not easy to combine one expression that desires to maximize likelihood with another that desires to minimize link flow error, as a Lagrangian can only add equality constraints to a constrained objective function. Van Aerde *et al.* proposed a solution to this problem which involves taking the partial derivatives of Equation (26) with respect to each of the trip cells that are to be estimated as

$$\frac{\partial}{\partial T_{ij}} Z_4 \left(T_{ij} \right) = \frac{\partial}{\partial T_{ij}} \sum_a \left(V_a - \sum_{ij} T_{ij} p_{ij}^a \right)^2 = 0 \qquad \forall\, i,j\,. \tag{27}$$

$$0 = 2 \left(\sum_a V_a \cdot p_{ij}^a - \left(\sum_a p_{ij}^a \left(\sum_{xy} T_{xy} p_{xy}^a \right) \right) \right) \qquad \forall\, i,j \tag{28}$$

This yields as many equations as there are trip cells, as shown in Equation (27). Furthermore, setting these derivatives equal to 0 is equivalent to minimizing Equation (27). However, while equation (24) could not be added to the maximum likelihood objective function, the equalities in Equation (28) can. This produces an unconstrained objective function that always yields a feasible solution computed as

$$\text{Max.} \quad \frac{T!}{\prod_{ij} T_{ij}} \prod_{ij} \left(\frac{t_{ij}}{t}\right)^{T_{ij}} - \sum_{ij}\left(\lambda_{ij} \cdot 2\left(\sum_a V_a \cdot p_{ij}^a - \left(\sum_a p_{ij}^a\left(\sum_{xy}T_{xy}p_{xy}^a\right)\right)\right)\right), \tag{29}$$

where: $T = \sum_{ij} T_{ij}$ and $t = \sum_{ij} t_{ij}$.

The net result, of the above process, is to suggest that most synthetic O-D generation problems consist of two sub-problems. One of these involves finding a new set of complementary link flows that do produce link flow continuity, at which point the maximum likelihood problem can be solved as before. Alternatively, one can compute the partial derivatives, that will yield link flow continuity, while deviating by the least amount from the observed link flows, and then utilize them directly in the maximum likelihood formulation using Lagrange multipliers. Both solutions can be shown to yield identical results.

A first challenge with maximizing Equation (29) is that it yields very large numbers that are difficult to work with. Further more, as it is common to maximize objective functions by taking their derivatives, and as it is more difficult to contemplate the derivative of a discontinuous expression, such as those including factorials, a simple approximation is made. This approximation involves taking the natural logarithm of either objective function Equation (21) or (22). Taking the natural logarithm of the objective function both makes the output easier to handle and permits the use of Stirling's approximation as a convenient continuous equivalent to the term ln(x!) as

$$\ln(T!) = T\ln T - T \tag{30}$$

The resulting converted objective function using the Stirling approximation on the original objective function of Equation (22) is computed as

$$\text{Max.} \quad T\ln\left(\frac{T}{t}\right) - T - \sum_{ij}\left(T_{ij}\ln\left(\frac{T_{ij}}{t_{ij}}\right) - T_{ij}\right) - \sum_{ij}\left(\lambda_{ij} \cdot 2\left(\sum_a V_a \cdot p_{ij}^a - \left(\sum_a p_{ij}^a\left(\sum_{xy}T_{xy}p_{xy}^a\right)\right)\right)\right). \tag{31}$$

Expanding and simplifying the various terms we derive

$$T\ln\left(\frac{T}{t}\right) - T - \sum_{ij}\left(T_{ij}\ln\left(\frac{T_{ij}}{t_{ij}}\right) - T_{ij}\right) = T\ln\left(\frac{T}{t}\right) - \sum_{ij}T_{ij}\ln\left(\frac{T_{ij}}{t_{ij}}\right). \tag{32}$$

When Equation (32) is augmented with the previously mentioned partial derivatives that minimize the link flow error we derive

$$\text{Max.} \quad T\ln\left(\frac{T}{t}\right) - \sum_{ij}T_{ij}\ln\left(\frac{T_{ij}}{t_{ij}}\right) - \sum_{ij}\left(\lambda_{ij} \cdot 2\left(\sum_a V_a \cdot p_{ij}^a - \left(\sum_a p_{ij}^a\left(\sum_{xy}T_{xy}p_{xy}^a\right)\right)\right)\right). \tag{33}$$

This equation, when solved, yields the most likely O-D matrix of all of those matrices that come equally close to matching the observed link flows.

It should be noted that the objective function of Equation (33) is composed of two components. The first being the error between the field observed flows and the flows that satisfy flow continuity with minimum difference from observed flows. The second component represents the likelihood of an O-D matrix table. The objective is to find the O-D matrix with the maximum likelihood. In the case that the seed matrix is the optimum matrix the likelihood component resolves to zero.

Dynamic Formulations

The above formulations assume that the vehicles are assigned to all links simultaneously (i.e. a vehicle is present on all links along its path simultaneously). In order to address the dynamic nature of traffic, the analysis period can be divided into equally spaced time slices. Origin-destination demands are then indexed by the time slice they depart and the time slice they are observed on a link, as

$$\text{Max.} \quad T_r \ln\left(\frac{T_r}{t_r}\right) - \sum_{rij} T_{rij} \ln\left(\frac{T_{rij}}{t_{rij}}\right) - \sum_{rij}\left(\lambda_{rij} \cdot 2\left(\sum_{sa} V_{sa} \cdot p^{sa}_{rij} - \left(\sum_{sa} p^{sa}_{rij}\left(\sum_{rxy} T_{rxy} p^{sa}_{rxy}\right)\right)\right)\right). \tag{34}$$

Where T_r is the total demand departing during time-slice r, t_r is the total seed matrix demand departing during time-slice r, T_{rij} is the traffic demand departing during time-slice r traveling between origin i and destination j, t_{rij} is the seed traffic demand departing during time-slice r traveling between origin i and destination j, λ_{rij} is the Lagrange multiplier for departure time-slice, origin, and destination combination rij, V_{sa} is the observed volume on link a during time slice s, and p^{sa}_{rij} is the probability of a demand between origin i and destination j during time-slice r is observed on link a during time-slice s. The solution of Equation (34) is computationally extensive and has been demonstrated to not produce significantly better results than generating time-dependent O-D demands, as will be discussed.

Alternatively, the more common approach is to generate time-dependent O-D demands by solving Equation (33) for each time-slice independently assuming that O-D demands can travel from the origin to destination zone within a time-slice (i.e. the trip travel time is less than the time-slice duration) without considering the interaction between time slices. This approach is computationally simpler and easier to implement and thus will be discussed in more detail. The formulation can written as

$$\text{Max.} \quad T_r \ln\left(\frac{T_r}{t_r}\right) - \sum_{ij} T_{rij} \ln\left(\frac{T_{rij}}{t_{rij}}\right) - \sum_{ij}\left(\lambda_{rij} \cdot 2\left(\sum_{a} V_a \cdot p^{a}_{rij} - \left(\sum_{a} p^{a}_{rij}\left(\sum_{xy} T_{rxy} p^{a}_{rxy}\right)\right)\right)\right) \quad \forall r. \tag{35}$$

Here the T_{rij} are solved for independent of other time-slices. It should be noted, that the approach ignores the interaction of demands across various time-slices which is a valid assumption if the network is not over-saturated. However, if the network is oversaturated the assumption of time slice independence may not be valid. The duration of the time-slice should be selected such that steady-state conditions are achieved within a time-slice.

Solution Algorithms

The solution of the set of equations presented in (35) is hard given that the objective function is nonconvex and that in many cases the p^a_{rij} are not available and thus the problem becomes to solve for T_{rij} and p^a_{rij} that maximize the objective function.

Here we present a numerical heuristic that solves the above formulation for large networks when the number of equations and unknowns becomes extremely computationally intensive. This special purpose equation solver has been developed and implemented in the QUEENSOD software. This solver fully optimizes the objective function of Equation (35). The software has been shown to produce errors less than 1% for the range of values and derivatives being typically considered in the problem. A sample application of the QUEENSOD software is presented later in the paper, however, initially the heuristic approach is described.

The numerical solution begins by building a minimum path tree and performing an all-or-nothing traffic assignment of the seed matrix, as illustrated in Figure 7. A relative or absolute link flow error is computed depending on user input. Using the link flow errors O-D adjustment factors are computed and utilized to modify the seed O-D matrix. The adjustment of the O-D matrix continues until one of two criteria are met, namely the change in O-D error reaches a user-specified minimum or the number of iterations criterion is met. If additional trees are to be considered, the model builds a new set of minimum path trees (loop 2) and shifts traffic gradually to the second minimum path tree. The minimum objective function for two trees is computed in a similar fashion as described for the single tree scenario. The process of building trees and finding the optimum solution continues until all possible trees have been explored. The proposed numerical solution ensures that in the case that the seed matrix is optimum no changes are

made to the matrix. In addition, the use of the seed matrix as a starting point for the search algorithm ensures that the optimum solution resembles the seed matrix as closely as possible while minimizing the link flow error. In other words, the seed matrix biases the solution towards the seed matrix.
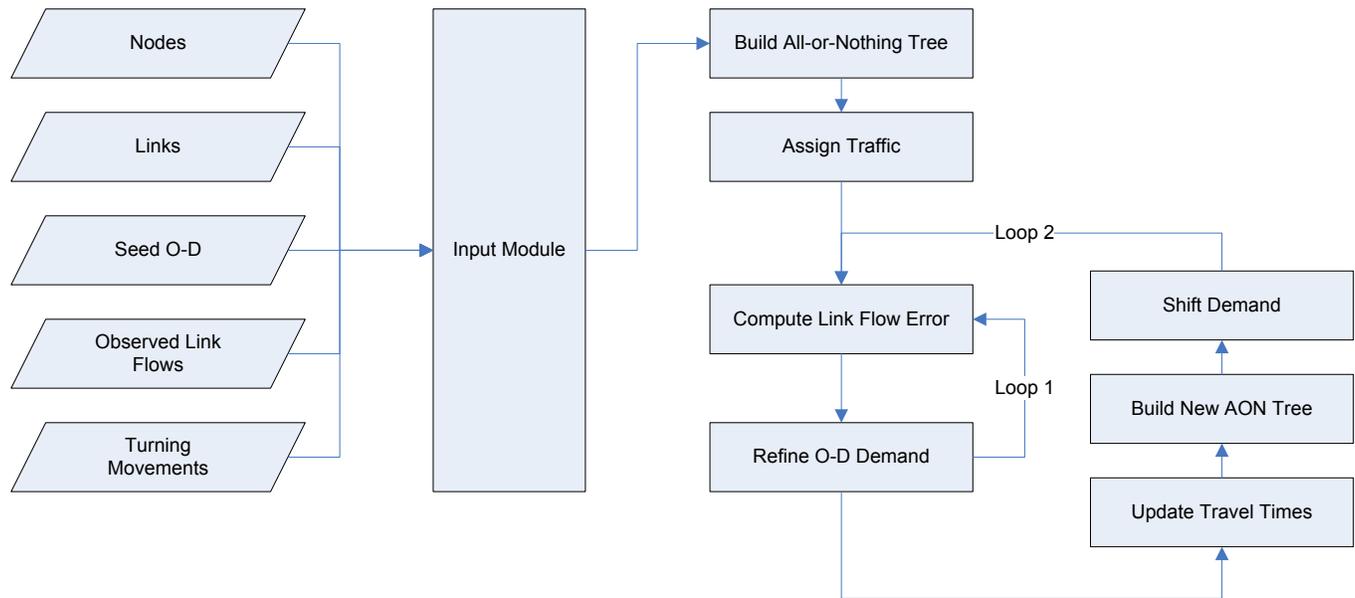
Figure 7: QueensOD Heuristic O-D Estimation Approach (Synthetic O-D Estimator)

In order to demonstrate the applicability of the QUEENSOD software, a sample application to a 3500-link network of the Bellevue area in Seattle is presented. Other applications of the QUEENSOD software are described in detail in the literature (Rakha et al. 1998; Dion et al. 2004). The O-D demand for the Bellevue network was calibrated to AM peak Single Occupancy Vehicle (SOV) and High Occupancy Vehicle (HOV) flows. The seed matrix was created using the standard four-step transportation planning process by applying the EMME/2 model. The Seattle network was converted from EMME/2 format to INTEGRATION format.

The calibration of the O-D demand to tube and turning movement counts was conducted using the QUEENSOD software using the planning trip distribution O-D matrix as the seed solution. The calibration resulted in a high level of consistency between estimated and field observed link flow counts (coefficient of determination of 0.98 between the estimated and observed flows), as illustrated in Figure 8. Figure 8 demonstrates that in calibrating the O-D matrix to observed traffic counts, the trip distribution O-D matrix (seed matrix) was modified significantly (coefficient of determination of 0.56 between trip distribution and synthetic O-D matrix). Consequently, it is evident that a modification of the trip distribution matrix was required in order to better match observed link and turning movement counts. It should be noted however, that the total number of trips was increased by only 4 percent as a result of the synthetic O-D calibration effort. Consequently, the illustrated calibration effort resulted in a significant modification of the trip table with minor modification to the total number of trips.
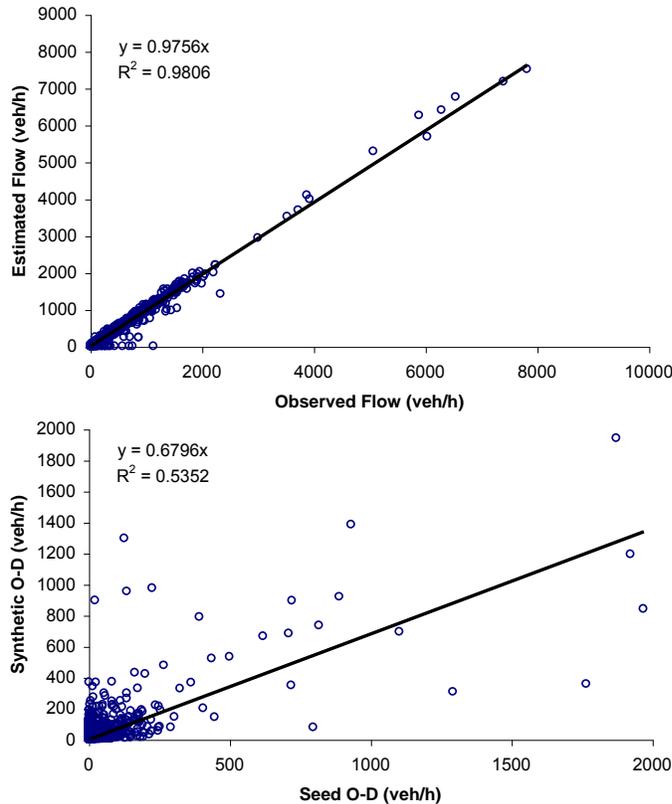
Figure 8: Example Application of QUEENSOD to the Bellevue Network in Seattle

In addition to the above mentioned research, a significant number of problem formulations and applications have been documented in the literature. To name a few (in chronological order) Cascetta et al (Cascetta et al. 1993) tested a method based on two generalized least squares estimators on the Brescia-Verona-Vicenza-Padua motorway in Italy. They found that the accuracy of their model depended heavily on the number of links with observed traffic counts. Van Aerde et al. (Van Aerde et al. 1993) introduced the QUEENSOD method and demonstrated its applicability on a 35-km section of Highway 401 in Toronto, Canada. Ashok (Ashok 1996) evaluated the use of a Kalman filtering-based method, which was first presented by Okutani (Okutani 1987) and estimates unobserved link traffic counts from observed link traffic counts. The method used was formulated by Ashok and Ben Akiva (Ashok et al. 1993) and Ashok (Ashok 1996) and was evaluated using actual data from the Massachusetts Turnpike, Massachusetts, a stretch of I-880 near Hayward, California and a freeway encircling the city of Amsterdam, Netherlands. Later, Hellinga and Van Aerde (Hellinga et al. 1998) compared a least square error model and a least relative error model on a 35-km section of Highway 401 in Toronto, Canada. Zhou and Sachse (Zhou et al. 1997) compared the use of three different O-D estimators and on a motorway network in Europe. They concluded that the models, although characterized by different computational loads, produced satisfactory results. They also commented on the need to decide on locations of detectors and aggregation time intervals. Van Der Zijpp and Romph (Van Der Zijpp et al. 1997) experimented their model on the Amsterdam Beltway. They tested their model using two different days worth of data and compared their model results with real and historical average data. While their model performed better in cases of accidents, the historical average data did, at least as good, in normal traffic. They stressed on the importance of correct modeling of the network and traffic flow characteristics for the production of good results. Kim et al. (Kim et al. 2001) introduced a genetic algorithm based method to overcome the shortcoming of the bi-level programming method when there is a significant difference between target and true O-D matrices. They tested their model on a small network of 9 nodes. Bierlaire and Crittin (Bierlaire et al. 2004) formulated a least-square based method to overcome some of the shortcomings of the Kalman filter approach. They tested their method on a simple network as well as two real

networks: a medium scale network, Central Artery Network, Boston, MA, and a large scale network, Irvine Network, Irvine, CA. Yun and Park developed a genetic algorithm based method with the purpose of solving dynamic O-D matrices for large networks. They compared their model's results with the results of QUEENSOD, and they tested their method on the City of Hampton network using the PARAMICS microscopic traffic simulation software. Nie et al. (Nie et al. 2005) developed a formulation that incorporates a decoupled path flow estimator in a generalized least squares framework with the objective of developing an efficient, simplified solution algorithm for realistic size networks. They tested their method on a small (9-node) and mid-size (100 nodes) network. Zhou and Mahmassani (Zhou et al. 2006) developed a multi-objective optimization framework for the estimation of the O-D matrices using automatic vehicle identification data. They tested their method on a simplified Irvine testbed network (31 nodes). Finally, Castillo et al. (Castillo et al.) developed a method for the reconstruction and estimation of the trip matrix and path flows based on plate scanning and link observations. They tested their method on the Nguyen-Dupius Network, and concluded the superiority of plate scanning on link counts.

It should be noted at this point that the O-D estimation formulations and techniques that were presented and described in this section are heuristics and thus there is no mathematical proof that the algorithms converge to the unique optimum solution either in the static or dynamic context. While we have demonstrated that the solution matches the observed link flows for complex networks (Figure 8), unfortunately the actual O-D demand is typically not available for real-life applications and thus it is not possible to measure how good the solution compares to the unique optimum O-D matrix.

IX. DYNAMIC ESTIMATION OF MEASURES OF EFFECTIVENESS

Dynamic assessment of traffic network performance requires the estimation of various measures of effectiveness in a dynamic context. This section provides a brief overview of the procedures for estimating delay, vehicle stops, and vehicle energy consumption and emissions.

Estimation of Delay

A key parameter in the dynamic assessment of traffic networks is the estimation of vehicle delay. The computation of delay requires the computation of travel times. Significant research has been conducted to develop analytical models for estimating delay especially at signalized intersections. Examples of such research efforts are provided for the interested reader (Catling 1977; Cronje 1983; Cronje 1983; Cronje 1986; Rouphail 1988; Brilon et al. 1990; Rouphail et al. 1992; Cassidy et al. 1993; Tarko et al. 1993; Akcelik et al. 1994; Cassidy et al. 1994; Li et al. 1994; Brilon 1995; Daniel et al. 1996; Engelbrecht et al. 1996; Fambro et al. 1996; Lawson et al. 1996; Newell 1999; Colyar et al. 2003; Fang et al. 2003; Hagring et al. 2003; Krishnamurthy et al. 2004; Daganzo et al. 2005; Flannery et al. 2005).

Roadway travel times can be computed for any given vehicle by providing that vehicle with a *time card* upon its entry to any roadway or link. Subsequently, this *time card* is retrieved when the vehicle leaves the roadway. The difference between these entry and exit times provides a direct measure of the roadway travel time experienced by each vehicle. The delay can then be computed as the difference between the actual and free-flow travel time.

Alternatively, vehicle delay can be computed microscopically every deci-second as the difference in travel time between travel at the vehicle's instantaneous speed and travel at free-flow speed, as

$$d\ t_i\ = \Delta t \left(1 - \frac{u\ t_i}{u_f} \right) \quad \forall\ i\,. \tag{36}$$

The summation of these instantaneous delay estimates over the entire trip provides an estimate of the total delay. This model has been validated against analytical time-dependent queuing models, shockwave analysis, the Canadian Capacity Guide, the Highway Capacity Manual (HCM), and the Australian Capacity Guide procedures (Dion et al. 2004). The procedure has also been incorporated in the INTEGRATION traffic simulation software (Van Aerde et al. 2007; Van Aerde et al. 2007) and utilized with second-by-second Global Positioning System (GPS) data (Rakha et al. 2000; Dion et al. 2004).

Estimation of Vehicle Stops

Numerous researchers have dealt with the problem of estimating vehicle stops especially at signalized intersections. An important early contribution is attributed to Webster (Webster 1958), who generated stop and delay relationships by simulating uniform traffic flows on a single-lane approach to an isolated intersection. In particular, the equations that Webster derived have been fundamental to traffic signal setting procedures since their development. Later, Webster and Cobbe (Webster et al. 1966) developed a formula for estimating vehicle stops at under-saturated intersections assuming random vehicle arrivals. Other models were developed by Newell (Newell 1965) and Catling (Catling 1977). Catling adapted equations of classical queuing theory to over-saturated traffic conditions and developed a comprehensive queue length estimation procedure that captured the time-dependent nature of queues to be applied to both under-saturated and over-saturated conditions. In addition, Cronje (Cronje 1983; Cronje 1983; Cronje 1983; Cronje 1986) developed stop and delay equations by treating traffic flow through a fixed-time signal as a Markov process. The approach assumed that the number of queued vehicles at the beginning of a cycle could be expressed by a geometric distribution. These models, however, were not designed to account for the partial stops that vehicles may incur. Furthermore, the models that account for partial stops do not estimate vehicle partial and full stops for over-saturated conditions. A study by Rakha et al. (Rakha et al. 2001) developed a procedure for estimating vehicle stops while accounting for partial stops, as

$$ S\ t_i\ = \frac{u\ t_i\ -\ u\ t_{i-1}}{u_f} \quad \forall\ i \quad \ni u\ t_i\ < u\ t_{i-1}\ . \tag{37} $$

The sum of these partial stops is also recorded. This sum, in turn, provides a very accurate explicit estimate of the total number of stops that are encountered along a roadway. Again the model can be implemented within a microscopic traffic simulation software or applied to second-by-second speed measurements using a GPS system.

Estimation of Vehicle Energy Consumption and Emissions

Estimating accurate mobile source emissions has gained interest among transportation professionals as a result of increasing environmental problems in large metropolitan urban areas. While current emission inventory models in the U.S., such as MOBILE and EMPAC, are capable of estimating large scale inventories, they are unable to estimate accurate vehicle emissions that result from operational-level projects. Alternatively, microscopic emission models are capable of assessing the impact of transportation projects on the environment and performing project-level analyses. Consequently, the focus of this discussion will be on these microscopic and also mesoscopic models. Two models that are emerging include the Comprehensive Modal Emissions Model (CMEM) and the Virginia Tech Microscopic (VT-Micro) model. These models are briefly described in terms of their structure, logic, and validity.

Comprehensive Modal Emission Model

The Comprehensive Modal Emissions Model (CMEM), which is one of the newest power demand-based emission models, was developed by researchers at the University of California, Riverside (Barth et al. 2000). The CMEM model estimates LDV and LDT emissions as a function of the vehicle's operating mode. The term "comprehensive" is utilized to reflect the ability of the model to predict emissions for a wide variety of LDVs and LDTs in various operating states (e.g., properly functioning, deteriorated, malfunctioning).

The development of the CMEM model involved extensive data collection for both engine-out and tailpipe emissions of over 300 vehicles, including more than 30 high emitters. These data were measured at a second-by-second level of resolution on three driving cycles, namely: the Federal Test Procedure (FTP), US06, and the Modal Emission Cycle (MEC). The MEC cycle was developed by the UC Riverside researchers in order to determine the load at which a specific vehicle enters into fuel enrichment mode. CMEM predicts second-by-second tailpipe emissions and fuel consumption rates for a wide range of vehicle/technology categories. The model is based on a simple parameterized physical approach that decomposes the entire emission process into components corresponding to the physical phenomena associated with vehicle operation and emission production. The model consists of six modules that predict engine power, engine speed, air-to-fuel ratio, fuel use, engine-out emissions, and catalyst pass fraction. Vehicle

and operation variables (such as speed, acceleration, and road grade) and model calibrated parameters (such as cold start coefficients, engine friction factor) are utilized as input data to the model.

Vehicles were categorized in the CMEM model based on a vehicle's total emission contribution. Twenty-eight vehicle categories were constructed based on a number of vehicle variables. These vehicle variables included the vehicle's fuel and emission control technology (e.g. catalyst and fuel injection), accumulated mileage, power-to-weight ratio, emission certification level (tier0 and tier1), and emitter level category (high and normal emitter). In total 24 normal vehicle and 4 high emitter categories were considered (Barth et al. 2000).

The Virginia Tech Microscopic Energy and Emission Model (VT-Micro Model)

The VT-Micro emission models were developed from experimentation with numerous polynomial combinations of speed and acceleration levels. Specifically, linear, quadratic, cubic, and fourth degree combinations of speed and acceleration levels were tested using chassis dynamometer data collected at the Oak Ridge National Laboratory (ORNL). The final regression model included a combination of linear, quadratic, and cubic speed and acceleration terms because it provided the least number of terms with a relatively good fit to the original data (R^2 in excess of 0.92 for all measures of effectiveness [MOE]). The ORNL data consisted of nine normal-emitting vehicles including six light-duty automobiles and three light-duty trucks. These vehicles were selected in order to produce an average vehicle that was consistent with average vehicle sales in terms of engine displacement, vehicle curb weight, and vehicle type. The data collected at ORNL contained between 1,300 to 1,600 individual measurements for each vehicle and MOE combination depending on the vehicle's envelope of operation (Ahn et al. 2002).

This method has a significant advantage over emission data collected from a few driving cycles because it is difficult to cover the entire vehicle operational regime with only a few driving cycles. Typically, vehicle acceleration values ranged from -1.5 to $3.7 \, m/s^2$ at increments of $0.3 \, m/s^2$ (-5 to $12 \, ft/s^2$ at 1-ft/s^2 increments). Vehicle speeds varied from 0 to $33.5 \, m/s$ (0 to $121 \, km/h$ or 0 to $110 \, ft/s$) at in increments of $0.3 \, m/s$ (Ahn et al. 2002).

The model had the problem of overestimating HC and CO emissions especially for high acceleration levels. Since this problem arose from the fact that the sensitivity of the dependent variables to the positive acceleration levels is significantly different from that for the negative acceleration levels, a two-regime model for positive and negative acceleration regimes was developed as (Ahn et al. 2002; Rakha et al. 2004)

$$
\ln(MOE_e) = \begin{cases} \sum_{i=0}^{3}\sum_{j=0}^{3} (L_{i,j}^e \times u^i \times a^j) & \text{for } a \geq 0 \\ \sum_{i=0}^{3}\sum_{j=0}^{3} (M_{i,j}^e \times u^i \times a^j) & \text{for } a < 0 \end{cases}.
\tag{38}
$$

Where MOE_e is the instantaneous fuel consumption or emission rate (ml/s or mg/s); $K_{i,j}^e$ is the model regression coefficient for MOE "*e*" at speed power "*i*" and acceleration power "*j*"; $L_{i,j}^e$ is the model regression coefficient for MOE "*e*" at speed power "*i*" and acceleration power "*j*" for positive accelerations; $M_{i,j}^e$ is the model regression coefficient for MOE "*e*" at speed power "*i*" and acceleration power "*j*" for negative accelerations; u is the instantaneous speed (km/h); and a is the instantaneous acceleration rate (km/h/s).

Additionally, the VT-Micro model was expanded by including data from 60 light-duty vehicles (LDVs) and trucks (LDTs). Statistical clustering techniques were applied to group vehicles into homogenous categories using classification and regression tree (CART) algorithms. The 60 vehicles were classified into five LDV and two LDT categories (Rakha et al. 2004). In addition, HE vehicle emission models were constructed using second-by-second emission data. In constructing the models, HEVs are classified into four categories for modeling purposes. The employed HEV categorization was based on the comprehensive modal emission model (CMEM) categorization. The first type of HEVs has a chronically lean fuel-to-air ratio at moderate power or transient operation, which results in high emissions in NO. The second type has a chronically rich fuel-to-air ratio at moderate power, which results in high emissions in CO. The third type is high in HC and CO. The fourth type has a chronically or transiently poor catalyst performance, which results in high emissions in HC, CO, and NO. Each model for each category was constructed within the VT-Micro modeling framework. The HE vehicle model was found to estimate vehicle

emissions with a margin of error of 10% when compared to in-laboratory bag measurements (Ahn et al. 2004). Furthermore, all the models were incorporated into the INTEGRATION software, and made it possible to evaluate the environmental impacts of operational level transportation projects (Park et al. 2006).

X. USE OF TECHNOLOGY TO ENHANCE SYSTEM PERFORMANCE

Due to the recent extensive developments within the fields of artificial intelligence, communications, and computation algorithms, transportation and traffic engineers' goals have evolved. As mentioned earlier in the paper, current spatio-temporal distribution of trips is far from being optimum, either with respect to driver satisfaction and/or network performance. A part of the contemporary DTA research is directed towards influencing, as opposed to modeling, dynamic spatio-temporal trip distributions. Advanced Traveler Information Systems (ATISs) are definitely the main tool for such influence, and understanding driver behavior is critical to the design and implementation of such systems. Research with is directly related to the possibility of enhancing system performance through the use of technology may be categorized in the following main areas of research:

- Validation of models, lab experiments and real world behavior, which is the area concerned with verifying the different theories and their implicit assumptions with regards to real-life situations. Due to the extreme complexity and questionable possibility of this task, several attempts have been made to verify the models with respect to lab experiments rather than the real world behavior. Moreover, comparison and verification of spatial and temporal transferability of the models might as well fall within this area. Examples of current literature include the works of Chang and Mahmassani (Chang 1988) and Mahmassani and Jou (Mahmassani 2000).

- Calibration of algorithms and models, which as the name suggests, is the area related to the calibration of the algorithms and model parameters. This also entails spatial and temporal calibration, for certain models and/or parameters might only be valid for certain locations and time periods rather than others. Examples of current literature include the works of Chang and Mahmassani (Chang 1988) and Rakha and Arafeh (Rakha et al. 2007).

- Real time deployment, which focuses on the possibility of deploying DTA models into the real world. This area of research is concerned with developing deployable DTA algorithms. Current literature states that although "a mathematically tractable analytical model that is adequately sensitive to traffic realism vis-à-vis real-time operation is still elusive", yet even with currently available models there is a tradeoff between solution accuracy and computational efficiency. Other real-time deployment issues include computational tractability; consistency checking; model robustness, stability, and error and fault tolerance; and demand estimation and prediction (Srinivas Peeta 2001). Examples of current literature include the works of Mahmassani et al. (Mahmassani 1993; Mahmassani 1998; Mahmassani 1998; Mahmassani 1998), Ben-Akiva et al. (Moshe Ben-Akiva 1997; Moshe Ben-Akiva 1998), Mahmassani and Peeta (Mahmassani 1992; Mahmassani 1993; Mahmassani 1995), Peeta and Mahmassani (Peeta 1995), Hawas (Hawas 1995), Hawas et al. (Hawas 1997), Hawas and Mahmassani (Hawas 1995; Hawas 1997), Cantarell and Cascetta (Cantarella 1995), Anastassopoulos (Anastassopoulos 2000), and Jha et al. (Jha 1998).

- Issues of uncertainty, which is, as mentioned earlier, a fundamental feature in most transportation phenomena. Uncertainty can be represented in trip makers' knowledge of different route travel times, in the compliance rates of drivers to information, in the accuracy of the disseminated control information, in the driver's perception of disseminated information reliability, in the controller's predicted and/or refined dynamic travel times and/or O-D matrices, among others. Uncertainty-related research issues have been addressed through several approaches, like stochastic modeling, fuzzy control, and reliability indices. Examples of current literature include the works of: Birge and Ho (Birge 1993), Peeta and Zhou (Peeta 1999; Peeta 1999), Cantarell and Cascetta (Cantarella 1995), Ziliaskopoulos and Waller (Ziliaskopoulos 2000), Waller and Ziliaskopoulos (Waller 2006), Waller (Waller 2000), Peeata and Jeong (Srinivas Peeta 2006), Jha et al. (Jha 1998), Peeta and Paz (Peeta 2006).

- DTA control, which is the area of research concerned with modifying how trips are distributed on the network. Research within this area focuses on capturing current network performance, and works on modifying the system elements, such as drivers route, and/or departure time selection, as well as mode choice (possibly through pricing and information dissemination); and traffic management (primarily through signal operation), in order to optimize system performance. Examples of current literature include the works of Peeta and Paz (Peeta 2006).

- Realism of other system characteristics, which is the research area concerned with capturing other system realities that are not considered in current available literature. Examples of such realities may include (Srinivas Peeta 2001),

  o Person rather than driver assignment. It is an undeniable fact that many people tend to make their mode choices based on daily, real-time decisions, i.e. this is a dynamic and not a static process. It is further anticipated that with the current (and predicted) maturity of information technology within the transportation arena, would require explicit modeling within DTA models.

  o The effect of interaction between the different vehicle classes and road infrastructure. It is beyond doubt that certain vehicle classes (such as trucks and busses for example) will not be able to comply with certain diversion-requesting disseminated information, due to road infrastructure constraints. However, in other occasions, these vehicle classes might be able to divert routes, yet with travel time penalties (example if the turning radius was inadequate) that might not only affect these vehicle classes, but all other diverting vehicles as well.

  o Capturing latest traffic control technology and strategies. Traffic control technology and strategies have been rapidly developing during the past couple of decades. Examples of this include transit signal preemption, real-time adaptive signal traffic control, electronic toll collection, etc. For efficient DTA control, DTA algorithms should be able to sufficiently capture and consider them.

Examples of current literature include the works of Ran And Boyce (Ran 1996), Peeta et al. (Peeta 2000), Ziliaskopoulos and Waller (Ziliaskopoulos 2000), Dion and Rakha (Dion et al. 2004), Sivananden et al. (Sivanandan et al. 2003), Rakha et al. (Rakha et al. 2000; Rakha et al. 2005), Rakha and Zhang (Rakha et al. 2004).

XI. RELATED TRANSPORTATION AREAS

Research within the following two transportation areas definitely precedes DTA research. However, their significance to the DTA field is based on the fact that DTA theories are mostly dependent on older theories stemming from these two areas. Hence, advances within these two areas could probably significantly affect the advances within the DTA arena.

- Traffic flow models encompass the mathematical representation, or perhaps simulation of the traffic flow characteristics, such as modeling traffic flow propagation, queue spillbacks, lane-changing, signal operation, travel time computation, etc. are crucial in determining driver expectations and behavior. In addition, these are also fundamental in the calculations of travel times, which are vital in the combined problem of departure time and route choice. The quantity of research available in this area is probably as big as the quantity of research done in the area of DTA all together, if not even more. However, as mentioned earlier, all of the research done within this area has direct influence on the realization of the traffic flow models, which are also used within the DTA models.

- Planning applications, which in spite of being a quite under-researched area at the moment, is a vitally important one. There is no doubt DTA models are superior to static models, hence, it is probably only a matter of time before the industry abandons static models for dynamic models. "Dynamic models are simply the natural evolution in the transportation field that like any other new effort suffers from early development shortcomings" (Srinivas Peeta 2001). Examples of current literature within this area of research include the

works of Li (Li 2001), Friesz et al., Waller (Waller 2000), Waller and Ziliaskopoulos (Waller 2006), Ziliaskopoulos and Waller (Ziliaskopoulos 2000), Ziliaskopoulos and Wardell (Ziliaskopoulos 2000).

XII. FUTURE DIRECTIONS

Future research challenges and directions include:

- Enhance traffic flow modeling and driver behavior modeling. These include the modeling of person as opposed vehicle route choices, the separation of driver and vehicle within the traffic modeling framework, the explicit modeling of vehicle dynamics, enhancing car-following, lane-changing, and routing behavior.

- Develop more efficient algorithms that would be suitable for real-time deployment, without making any compromises in the computational accuracy, i.e. without trading-off the solution accuracy for the computational efficiency. In precise, without compromising any dimension of the traffic flow theory, nor driver behavior assumptions. As a matter of fact, further research should be done to capture more of the traffic, as well as the driver behavior theory. Hence, this should help in improving the realism of the available DTA models.

- Conduct more research on the driver behavior theory. Especially, since human factors cognitive research has significantly improved in the previous couple of decades, then modeling driver behavior from this perspective might lead to valuable outcomes.

- Critical examination of the validity of network equilibrium as a framework for network flow analysis (Nakayama et al. 2001). Many of the current algorithms are based on the assumption that drivers become rational and homogeneous with learning. Hence, resulting in network equilibrium. A number of recent research efforts suggest that some drivers remain less rational, and heterogeneous drivers make up the system; drivers' attitudes toward uncertainty become bipolar; and some drivers are sometimes deluded. Further research is required to characterize and model such behavior.

- Validate current models by comparing current model outputs with real world experiments, and possibly with controlled lab experiments (as mid-way experiments before conducting real world evaluations).

- Enhance traffic modeling tools within DTA models to capture the effect of diversion compliance of different vehicle modes (especially heavy vehicles) to more geometrically restrictive highways.

- Possibly calibrating hybrid fuzzy-stochastic models and comparing results to traditional models. According to the work done by Chen (Chen 2000), probabilistic methods are better than possibility-based methods if sufficient information is available, on the other hand, possibility-based methods can be better if little information is available. However, when there is little information available about uncertainties, a hybrid method may be optimum.

- Conduct further research on the dynamic synthetic O-D estimation from link flow measurements and vehicle probe data. Further research is required to quantify the impact of erroneous or missing data on the accuracy of O-D estimates.

- Conduct further research on the temporal distribution of demand, analyzing and modeling it. Then, including the estimation and forecast of time-dependent demand within the planning process, in addition to the dynamic traffic management and control processes. This should, hopefully, help to fill-in the gap between the three mentioned processes.

- Incorporating person assignment, rather than mode assignment in the DTA and planning models, for as mentioned earlier, mode split is currently more of a daily real-time dynamic, rather than a static decision.

- Research is needed to develop models for driver behavior to different ATIS systems: (types and/or scenarios). Current literature is mainly based on stated preference surveys, which are known for their lack of accuracy. Before the deployment of ATIS systems, stated preference surveys were the best approach for prediction and

modeling drivers' reactions. However now, after the deployment of many ATIS systems, more research is needed to capture the actual (possibly revealed) drivers' behavior, rather than the stated behavior.

- Develop approaches that are capable of realistically capturing traffic flow, traffic control, and their interactions; and simultaneously optimizing traffic flow routing and control. In other words, developing algorithms that are actually capable of capturing real-time driver behavior, and are able to control it, in order to improve network performance.

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Appendix

TERM ABBREVIATIONS

ANN   Artificial Neural Networks

ATIS   Advanced Traveler Information System

AVI   Automatic Vehicle Identification

AVL   Automatic Vehicle Location

DTA   Dynamic Traffic Assignment

FHWA Federal Highway Administration

GA   Genetic Algorithm

GPS   Global Positioning System

HCM   Highway Capacity Manual

HOV   High Occupancy Vehicle

ITS   Intelligent Transportation Systems

LDV   Light Duty Vehicle

LMC   Link Marginal Cost

LP   Linear Programming

MOE   Measure of Effectiveness

NLP   Non-Linear Programming

O-D   Origin – Destination

PMC   Path Marginal Cost

SO   System Optimum

SOV   Single Occupancy Vehicle

TT   Travel Time

UE   User Equilibrium

VMS   Variable Message Sign

VARIABLE DEFINITIONS

v_i	Traffic volume on route i
N	Set of network nodes
A	Set of network arcs (links)
R	Set of origin centroids
S	Set of destination centroids
k_{rs}	Set of paths connecting O-D pair $(r\text{-}s)$; $r \in R, s \in S$
x_a	Flow on arc (a)
x_b	Flow on arc (b)
t_a	Travel time on arc (a)
t_b	Travel time on arc (b)
f_k^{rs}	Flow on path (k) connecting O-D pair (r-s)
f_l^{mn}	Flow on path (l) connecting O-D pair (m-n)
c_k^{rs}	Travel time on path (k) connecting O-D pair (r-s)
q_{rs}	Trip rate between origin (r) and destination (s)
$\delta_{a,k}^{rs}$	Indicator variable, =1 if arc (a) is on path (k) between O-D pair (r-s), and 0 otherwise
$\mathbf{x}$	Vector of flows on all arcs, $= (..., x_a, ...)$
$\mathbf{t}$	Vector of travel times on all arcs, $= (..., t_a, ...)$
$\mathbf{f^{rs}}$	Vector of flows on all paths connecting O-D pair r-s, $= (..., f_k^{rs}, ...)$
$\mathbf{f}$	Matrix of flows on all paths connecting all O-D pairs, $= (..., \mathbf{f^{rs}}, ...)$
$\mathbf{c^{rs}}$	Vector of travel times on all paths connecting O-D pair r-s, $= (..., c_k^{rs}, ...)$
$\mathbf{c}$	Matrix of travel times on all paths connecting all O-D pairs , $= (..., \mathbf{c^{rs}}, ...)$
$\mathbf{q}$	Origin-destination matrix (with elements $= q_{rs}$)
$\Delta^{\mathbf{rs}}$	Link-path incidence matrix (with $\delta_{a,k}^{rs}$ elements) for O-D pair r-s, as discussed below
Δ	Matrix of link-path incidence matrices (for all O-D pairs), $= (..., \Delta^{\mathbf{rs}}, ...)$
z	Objective function
L	Lagrange (transformation of the) objective function
u_{rs}	Dual variable associated with the flow conservation constraint for O-D pair (r-s)
$t_{i,k}$	Observed average travel time along link i within the kth sampling interval
$\tilde{t}_{i,k}$	Smoothed average travel time along link i in the kth sampling interval
$s_{i,k}^2$	Variance of the observed travel times relative to the observed average travel time in the kth sampling interval
$\tilde{s}_{i,k}^2$	Variance of the observed travel times relative to the smoothed travel time in the kth sampling interval
$n_{i,k}$	Number of valid travel time readings on link i in the kth sampling interval
α	Exponential smoothing factor that varies as a function of the number of observations $n_{i,k}$ within the sampling interval
β	Constant that varies between 0 and 1
T_{ij}	Number of trips between production zone i and attraction zone j
P_i	Number of trip productions from the origin zone
A_j	Number of trip attractions to the destination zone
F_{ij}	Impedance factor between production zone i and attraction zone j
K_{ij}	Socio-economic adjustment factor for trips between production zone i and attraction zone j

c_{ij} Generalized cost of inter-zonal travel between production zone i and attraction zone j

t_{ij} Prior information on the number of trips between production zone i and attraction zone j

V_a Traffic flow on link (a)

V_a' Complementary traffic flow on link (a)

p_{ij}^a Probability of traffic flow between origin (i) and destination (j) to use link (a)

T_r Total demand departing during time-slice (r)

t_r Total seed matrix demand departing during time-slice (r)

T_{rij} Traffic demand departing during time-slice (r) traveling between origin (i) and destination (j)

t_{rij} Seed traffic demand departing during time-slice (r) traveling between origin (i) and destination (j)

l_{rij} Lagrange multiplier for departure time-slice, origin, and destination combination (rij)

V_{sa} Observed volume on link (a) during time-slice (s)

p^{sa}_{rij} Probability of (a) demand between origin (i) and destination (j) during time-slice (r) is observed on link (a) during time-slice (s)

$d(t_i)$ Vehicle delay at time (t_i)

$u(t_i)$ Vehicle instantaneous speed at time (t_i)

u_f Free-flow speed

$S(t_i)$ Vehicle full and partial stops at time (t_i)

MOE_e Instantaneous fuel consumption or emission rate

$K_{i,j}^e$ Model regression coefficient for MOE(e) at speed power (i) and acceleration power (j)

$L_{i,j}^e$ Model regression coefficient for MOE (e) at speed power (i) and acceleration power (j) for positive accelerations

$M_{i,j}^e$ Model regression coefficient for MOE (e) at speed power (i) and acceleration power (j) for negative accelerations

u Vehicle instantaneous speed

a Vehicle instantaneous acceleration rate

q Traffic stream flow (veh/h)

k Traffic stream density (veh/km)

u Traffic stream space-mean speed (km/h)

u_f Expected traffic stream free-flow speed (km/h)

u_c Expected traffic stream speed-at-capacity (km/h)

k_j Expected traffic stream jam density (veh/km)

q_c Expected traffic stream capacity (veh/km)

c_1 Model coefficient (km/veh)

c_3 Model constant (h/km^2-veh)

c_2 Model constant (h^{-1})

Part I

Driving Simulator Experiment

Part I: Driving Simulator Experiment

Chapter 3

Driver Route Choice Behavior: Experiences, Perceptions, and Choices

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Driver Route Choice Behavior: Experiences, Perceptions, and Choices

Aly M. Tawfik, Hesham A. Rakha, *Member, IEEE*, and Shadeequa D. Miller

Abstract— **Within the context of transportation modeling, driver route choice is typically captured using mathematical programming approaches, which assume that drivers, in attempting to minimize some objective function, have full knowledge of the transportation network state. Typically, drivers are assumed to either minimize their travel time (user equilibrium) or minimize the total system travel time (system optimum). Given the dynamic and stochastic nature of the transportation system, the assumption of a driver's perfect knowledge is at best questionable. While it is well documented in psychological sciences that humans tend to minimize their cognitive efforts and follow simple heuristics to reach their decisions, especially under uncertainty and time constraints, current models assume that drivers have perfect or close to perfect knowledge of their choice set, as well as the travel characteristics associated with each of the choice elements. Only a few of the many route choice models that are described in the literature are based on observed human behavior. With this in mind the research presented in this paper monitors and analyzes actual human route choice behavior. It compares actual drivers experiences, perceptions and choices, and demonstrates that (a) drivers perceptions are significantly different from their actual experiences, and that drivers' choices are better explained by their perceptions than their experiences; (b) drivers perceive travel speeds better than travel times (c) perceived travel speeds seem to influence route choice more than perceived travel times, and (d) drivers' route choice behavior differs across different driver groups.**

I. INTRODUCTION

In an effort to mitigate the impacts of traffic congestion, transportation engineering research is rich in literature directed towards understanding driver travel behavior. Because to the wide application of driver route choice models in transportation engineering and planning, dynamic traffic assignment, advanced area-wide signal control, advanced traveler information and electronic route guidance systems, among others, driver route choice models probably rank among the most influential models [1, 2]. This paper attempts to extend this wealth of research by observing actual driver route choices and evaluate the interactions between drivers' experiences, perceptions and choices.

Some studies show that most commuters use only one route to get to work or school [3], other research efforts show that most drivers select more than one route to get to their destination to avoid congestion and minimize travel time. A recent study concluded that 40 percent of the commuters used only one route for their commute and the remaining 60 percent of commuters used at least two routes [4]. Accordingly, assuming that around half of the drivers use only one route for their commute seems a reasonable assumption.

Modeling human route choice can be complicated. The number of available alternative routes from an origin to a destination can be vast, and the cognitive task of route choice is not easy and requires decisions about how to reach a destination while satisfying various limitations and obligations. Also, the experience of earlier route choices can affect the probability of the route being selected again. Furthermore, the characteristics of each alternative route do not have the same importance in a driver's final decision [4]; how commuters select their routes may be affected by many other factors such as age, gender, time, distance, special events, bad weather, and the behavior of other drivers [5].

Although in all route choice models drivers are assumed to behave rationally and to have a certain level of knowledge about their travel network, little has been done to investigate the actual cognitive abilities and rational behavior of drivers. Studies performed to measure route choice and driving performance can be categorized into different groups, such as: mathematical network models [2, 6] and evolving psychological driver behavior models [7, 8]; simulator-based, closed-course, and on-road studies [9, 10]; time-of-day, day, and trip purpose models; survey-, simulation-, and GPS- based studies [11-13], and with and without information provision [14]. Yet, there remains no perfect model available to explain the way drivers make route choice decisions. All techniques are characterized with strengths and weaknesses. Data collection and real-life validation of proposed models, nonetheless, significantly add to the challenge.

Most route choice models assume that drivers constantly evaluate and remember the travel times on the routes they travel, and use this information to select the travel route that maximizes some utility function. It assumes that drivers are

constantly conscious and rational of their route choices. According to the HOT cognition theories, however, human behavior and decisions are highly dependent on humans' personal perceptions. For example, it is rather common for humans to behave irrationally based on erroneous personal perceptions, or beliefs. It is well documented in human psychological behavior that humans tend to minimize their cognitive efforts, and follow simple heuristics to reach their decisions, especially under uncertainty and time constraints, and with repetition, cognitive activities become habitual and could reach automaticity. Hence, minimizing the required cognitive resources [15].

Unlike most route choice research that is based on rational behavior assumptions, and is primarily focused on the end product of route choice, this research attempts to investigate the validity of these assumptions. It explores the accuracy of drivers' perceptions and examines the reasons for route choice based on drivers' perceptions. Drivers' perceptions are compared to their choices, In an attempt to weigh the fidelity of drivers' perceptions, this work also captures the drivers' actual experiences and cross examines them with their perceptions. To the best of the authors' knowledge, no previous research has examined the extent of validity of rational route choice behavior. The authors anticipate that this work could provide insights into driver route choice behavior and that more unexplained variation in modeling driver route choice behavior can be uncovered. For example, drivers' compliance to disseminated traffic information has been reported to vary according to age, gender, driving experience, and other factors [16, 17]. Although unexplained variation still exists, the authors believe that incorporating drivers' cognitive characteristics can improve route choice models [18].

In the following sections, the authors present the objectives of the study, followed by a detailed explanation of the study approach: participants, instruments and materials, procedures, and limitations. In the third section, the authors present the experimental results and discussion, and in the fourth section the paper ends with the conclusions of the study and recommendations for further research.

II. OBJECTIVES

The objectives of this study are to demonstrate that: (a) drivers perceptions can be significantly different from their actual experiences, and that drivers' choices are better explained by their perceptions than their experiences; (b) drivers can perceive travel speeds better than travel times (c) perceived travel speeds seem to influence route choice more than perceived travel times, and (d) drivers' route choice behavior differs across different driver groups.

III. METHODOLOGY

A. Participants

The research involved a total of fifty participants. All participants had valid driver's licenses, a normal or corrected-to-normal vision and perfect color vision. As presented in Table 1, participants were selected from different groups to ensure variability in their personal attributes.

TABLE I
BREAKDOWN OF PARTICIPANTS BY GROUP

Criteria	Groups	Count
Age	Age1: 17 – 25 years	32
	Age2: 26 – 56 years	18
Gender	Gen1: Males	33
	Gen2: Females	17
Ethnicity	Eth1: European/American (White)	28
	Eth2: Non European/American (Non-White)	22
Education	Ed1: Bachelor Degrees	26
	Ed2: Graduate Degrees	24
Driving Years	Yrs1: < 4 years	25
	Yrs2: > 4 years	25
Annual Miles*	Mil1: <12,000 miles/year	31
	Mil2: >12,000 miles/year	18

* One participant did not report his/her annual driven miles.

B. Instruments and Materials

Driving Performance: The experiment was conducted using the STISIM driver simulator software that was developed by Systems Technology Inc. (STI). STISIM Drive is an interactive program that is capable of recording numerous performance measures. The program offers the investigator control over development of driving scenarios, ensuring that all participants encounter the same events and conditions while driving. It also offers the investigator with possible partial randomization in the simulated scenario and events. The simulated driving program operates on a vehicle-similar structure with a 48 cm (19 in.) monitor. The vehicle-similar structure is equipped with a vehicle chair, a steering wheel, and gas and brake pedals. Software limitations are discussed in the limitations section.

Driving Network: As depicted in Figure 1, the research used a network composed of two geometrically-identical routes with nearly identical (but statistically biased) routes, with mean travel times of 3 to 4 minutes with an average speed of approximately 56 to 40 km/h (35 to 25 mph), respectively. Although all intersections were priority controlled by four-way stop signs, for clearer presentation the stop signs are not shown on Figure 1. As discussed later in the limitations, no landmarks were placed at any location.

Initial Questionnaire: Participants were asked to fill a short questionnaire before performing the driving tasks. The questionnaire collected information about their age, gender, ethnicity, education, vision problems, driving years, and average number of miles driven per year.

Final Questionnaire: Participants were asked to fill a short questionnaire after performing all the driving runs. The questionnaire was designed to capture the participants' cognition of the different sections of this study. The questionnaire collected information about their perceptions of differences in travel characteristics between the two routes, and reasons for their route choice.

C. Experiment Procedure

After participants read and signed the consent forms, they were asked to fill an initial questionnaire, which collected their general information (as described earlier). Then, participants were given a 15-minute drive on practice routes. The practice routes were characterized by different terrains and driving schemes, with the objective of allowing the drivers to be familiar with the simulator driving motor skills.
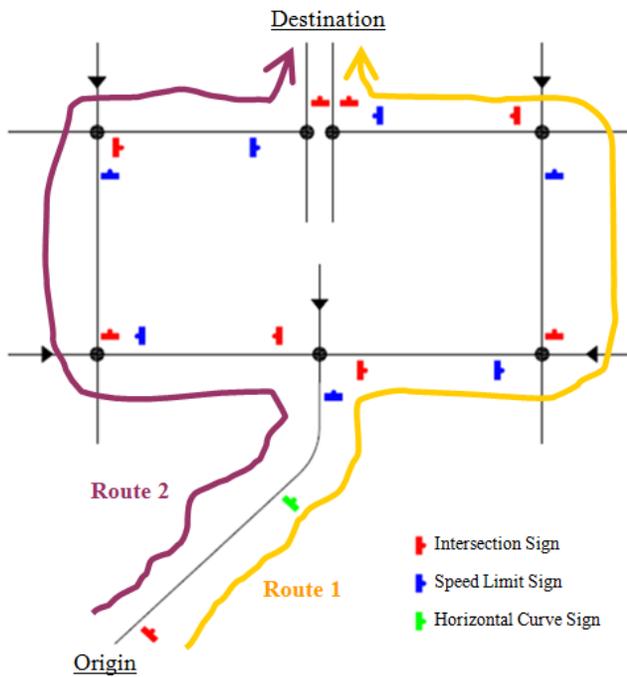
Fig. 1. Sketch of the simulated network

Afterwards, participants were introduced to the research route. They were handed a draft sketch showing the network and the points of origin and destination. The participants were asked to drive from the point of origin to the point of destination. They were asked to imagine moving to a new city, where the origin point was home, and the destination point was work/school. They were asked to drive similar to how they would drive in the real world. Participants were asked to repeat driving from home to work many times, and most participants ended up driving twenty times from origin to destination. Participants were allowed as many intermediate breaks as they liked, and were instructed to report any signs of nausea or fatigue.

At the end, participants were asked to fill a post-task questionnaire where they were asked to report their route choices and network perceptions (as described earlier).

D. Study Limitations

To place the results of this study in context, the limitations of this research effort are summarized. The STISIM driver simulator dynamics lacked some realism. A noticeable difference was observed between real-life steering and breaking, and in the simulator experience. As an example, Modeling of T-intersections was not possible using the STISIM software; so, construction cones were placed to prevent participants from continuing through at the 4-leg intersections. However, although participants' vehicles would crash if driven into a construction cone, other simulated vehicles were not smart enough to recognize construction cones and drove into the cones with no harm.

Also, the STISIM software does not support "If, Then" logic. Accordingly, it was not possible to build a different scenario based on "If" the participant turned right or left at the different intersections, and as a result, no landmarks were added to the network. Due to lack of landmarks, a

small number of participants made wrong turns and got lost a few times. The total number of trials that involved crashes or missed turns, however, was less than 10% of total runs.

IV. RESULTS

A. Drivers Experiences

Figure 2 presents a cumulative distribution of experienced travel times by the fifty participants. On average, the right route was 5% shorter in travel time than the left one. Based on a t-test and an F-test, both travel time means and standard deviations, respectively, were significantly different (p-value<0.01). Based on a Monte-Carlo simulation, probability of the right route having a shorter travel time was 60%.

	Right Route	Left Route
Mean TT	208	216
SD of TT	22	26
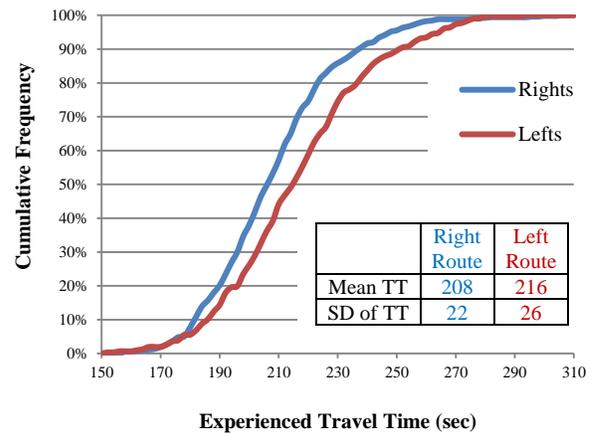
Fig. 2: Cumulative Frequency Distributions of Experienced Travel Times on Each Route

Table 2 shows the average experienced values of traffic conditions encountered by drivers on both routes. Three measures were selected to reflect experienced traffic conditions; namely, the number of vehicles encountered, the closest experienced car-following distance, and the average car-following distance experienced per trial. T-tests and F-tests indicated significant mean and variance differences for all three measures. As presented in Table 2, although, on average, the left route was characterized with slightly lighter traffic, vehicles were following at closer distances than the right route. Due to this discrepancy, drivers' perceptions of traffic volumes were more erroneous than their travel time and speed perceptions. Therefore, in the following sections less focus is placed on drivers' traffic volume perceptions.

TABLE 2
DRIVERS' EXPERIENCED TRAFFIC VOLUMES ON THE TWO ROUTES

Route	Average Number of Vehicles Encountered	Average Min. Experienced Car Following Distance (m)	Average Avg. Experienced Car Following Distance (m)
Left	8.5	23	237
Right	9.0	27	296

B. Drivers Perceptions

Figures 3.a and 3.b show drivers' perceptions of travel times, and travel speeds, respectively. Differences between drivers' travel time and travel speed perceptions are

particularly interesting, because since distances were equal, perceptions of travel times and speeds should have been the same. Given that humans allocate more attention to more important events [19], this difference in perception can be useful in identifying the more important route choice factor.

Two possible alternative explanations for the obvious bias in travel speed perceptions favoring the left route over the right route are the primacy effect and the short gains strategy; because in order to choose the left route, drivers had to cross oncoming traffic at the first intersection.

Perception differences between driver groups, observable from Figures 3.a, and 3.b, should be noted. Although differences between driver groups have been repeatedly reported in many driving related areas, they still have not been fully incorporated in route choice models.
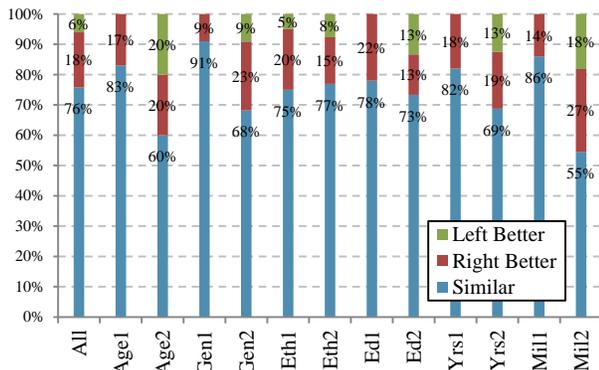

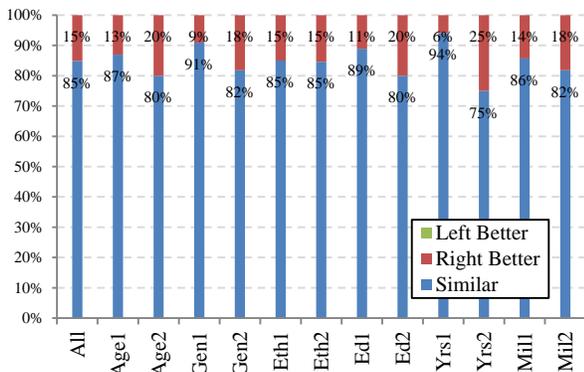Fig. 3.a: Drivers Perceptions of Experienced Travel Times on Both Routes; Broken Down by Driver Groups

Fig. 3.b: Drivers Perceptions of Experienced Travel Speeds on Both Routes; Broken Down by Driver Groups

Table 3 shows drivers perceptions of the three traffic parameters on both routes. It is noted that while perceptions of travel time and speed were close, traffic perceptions were a little different. Because several research efforts concluded that travel speed could be a better indicator of route choice than travel time, the difference between travel time and travel speed perceptions are studied further.

TABLE 3
DRIVERS' PERCEPTION OF TRAFFIC CONDITIONS
ON THE TWO ALTERNATIVE ROUTES

Perception	Travel Time	Speed	Traffic
No Difference	76%	85%	55%
Right Better	18%	15%	30%
Left Better	6%	0%	15%

C. Drivers Experiences vs. Perceptions

Table 4 shows a comparison between drivers' perceptions and experiences. It can be seen that while 76% of the drivers were unable to perceive travel time differences, only 12% of the drivers were able to correctly perceive their experienced travel times, and conversely, 12% perceived the opposite of their experience. While this result signifies the usefulness of traveler information systems, the small difference between the two travel times should be noted. The experienced travel time was calculated as the average travel time per participant on all trials. Table 4 also shows that, as expected, average signal strength (experienced travel time difference) was stronger for correct than for opposite perceptions.

TABLE 4
BREAKDOWN OF PARTICIPANTS' TRAVEL TIME PERCEPTIONS BASED ON
THEIR ACTUAL EXPERIENCES

			Travel Time Experiences		
			Left Faster	Right Faster	All Drivers
Travel Time Perceptions	Left Faster	% of Drivers	*0%*	6%	6%
		% Avg. $Left_{TT} - Right_{TT}$	*N/A*	5%	5%
	Right Faster	% of Drivers	6%	*12%*	18%
		% Avg. $Left_{TT} - Right_{TT}$	-5%	*8%*	4%
	No Differ.	% of Drivers	33%	43%	76%
		% Avg. $Left_{TT} - Right_{TT}$	-4%	8%	3%

* Bold Italic Cells: Correct Perception, Underline Cells: Incorrect Perception, Highlighted Cells: Opposite Perception.

D. Drivers Choices

Two different measures of choices were observed. First the drivers' reported choices in the post-task questionnaire, referred to as declared choices, and second, the observed choices on each individual trial, referred to as trial choices. Results of both measures were the same; therefore, only declared choices are presented in Figure 4.
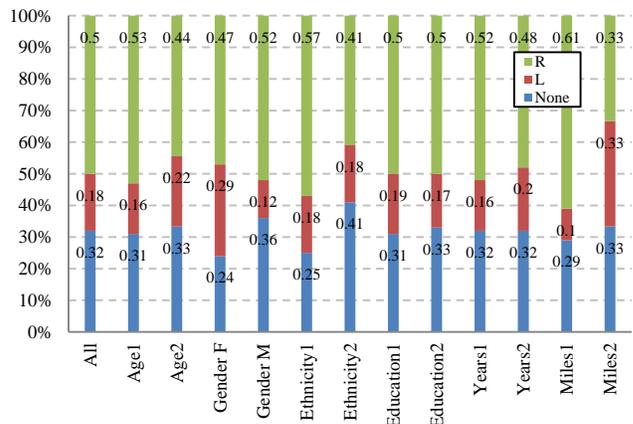
Fig. 4: Percentage of Drivers Choosing Right Route, Left Route and not Making a Decision; Broken Down by Driver Groups

E. Drivers' Experiences vs. Choices

Table 5 compares trial choices (Table 5.a) and declared choices (Table 5.b) to experienced travel times. It is shown that in either case about 50% of the drivers did not choose the minimum experienced travel time route. Again, this result demonstrates the potential benefits of traveler information systems.

TABLE 5
DRIVERS EXPERIENCES VERSUS CHOICES*

TABLE 5.A
ROUTE TRIAL CHOICES VERSUS
TRIAL EXPERIENCES

Trial Choices	Left Driven	Right Driven
Right Faster	66%	67%
Left Faster	34%	33%

TABLE 5.B
ROUTE REPORTED CHOICES VERSUS
ROUTE EXPERIENCES**

Reported Choices	Left Chosen	Right Chosen
Right Faster	60%	64%
Left Faster	40%	36%

* Highlighted Cells: drivers choosing longer travel time routes.
** Driver experience calculated as average travel time of all trials per driver.

F. Drivers' Perceptions vs. Choices:

Table 6 compares perceptions of travel time (Table 5.a), travel speed (Table 5.b), and traffic volume (Table 5.c) to reported choices. Three types of behaviors were identified in the table: logical behavior reflects drivers choosing better perceived routes, cognitive behavior reflecting drivers choosing a route in spite of not perceiving a difference between both routes, and irrational behavior reflecting drivers choosing worse perceived routes. Cognitive behavior is in line with human psychology hypotheses postulating that humans always minimize their cognitive loads.

TABLE 6: DRIVERS PERCEPTIONS VERSUS REPORTED CHOICES*

TABLE 6.A: REPORTED CHOICES VS. TRAVEL TIME PERCEPTIONS

Choice	Perception of Travel Time			Sum
	No Differ.	Right Faster	Left Faster	
None	33%	6%	3%	42%
R	36%	12%	0%	48%
L	6%	0%	3%	9%
Sum	76%	18%	6%	100

TABLE 6.B: REPORTED CHOICES VS. TRAVEL SPEED PERCEPTIONS

Choice	Perception of Travel Speed			Sum
	No Differ.	Right Faster	Left Faster	
None	39%	3%	0%	42%
R	36%	12%	0%	48%
L	9%	0%	3%	9%
Sum	85%	15%	0%	100

TABLE 6.C: REPORTED CHOICES VS. TRAFFIC VOLUME PERCEPTIONS

Choice	Perception of Traffic Volume			Sum
	No Differ.	Right Lower	Left Lower	
None	30%	6%	6%	42%
R	21%	24%	3%	48%
L	3%	0%	6%	9%
Sum	55%	30%	15%	100

* Italic Cells: Logical Behavior, Underlined Cells: Cognitive Behavior, Highlighted Cells: Irrational Behavior

Figures 5.a and 5.b show the breakdown of drivers reported choices versus perceptions of travel time, and travel speed, respectively, by driver group. Again, differences between driver groups are evident and incorporating these differences in route choice models seems a promising arena.

Figure 5 implies that travel speed is a better variable in predicting driver choices in comparison to travel time, since it is characterized with a clear reduction in the percentage of irrational decisions; in total and across all driver groups.
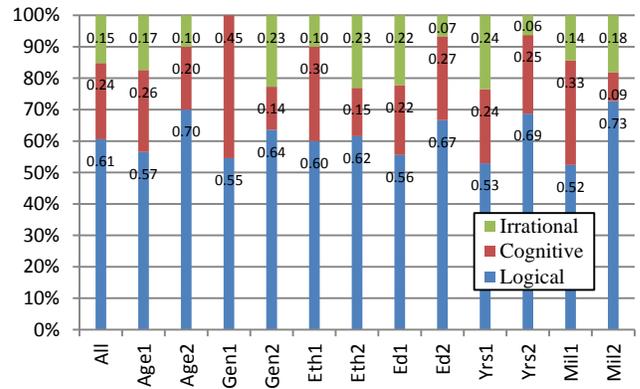

Figure 5.a: Percentage of Drivers Making Logical, Cognitive, and Irrational Choices Based on Travel Time Perceptions; Broken Down by Driver Groups
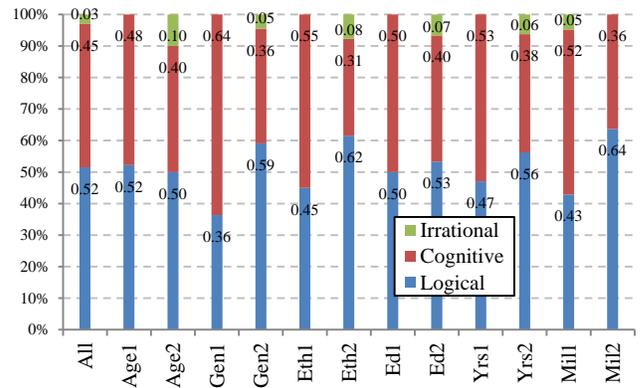
Figure 5.b: Percentage of Drivers Making Logical, Cognitive, and Irrational Choices Based on Travel Speed Perceptions; Broken Down by Driver Groups

V. CONCLUSIONS AND FURTHER WORK

While the results of this experiment should not be considered conclusive for all driver populations; because of limitations in the sample size and experiments, the results do demonstrate that driver choices are not necessarily identical to their perceptions and that modeling route choice based on driver experiences invokes errors in route choice models. Accordingly, incorporating drivers' perceptions to route choice models rather than experiences, if possible, could improve model accuracy.

About half of the drivers did not choose their minimum experienced travel time routes. This finding may be attributed to the small travel time difference between both routes (5%) and the high travel time variance. This difference, however, could reflect real life situations; even in longer trips where on many occasions as part of a longer trip drivers may be faced with the option of choosing between two short alternative travel legs. It is documented in wayfinding literature that drivers may consider short segments sequentially, instead of the entire travel route [20].

It appears that drivers can perceive travel speeds better than travel times and route choice decisions are more influenced by travel speeds than travel times. Hence, it might be useful to include travel speed variables including the number of stop signs and traffic signals along a route in

route choice models. Nevertheless, even when considering both travel speed and travel time perceptions, irrational route choice behavior, although small, continues to exist. This implies the existence of other unidentified variables (e.g. reliability).

In accordance with current research standings, in this work, differences between driver groups were observable, and incorporating these differences in route choice models could improve model accuracy.

Finally, a few possible future research directions include: modeling route choice with different signal strengths and in more complicated networks and analyzing the effect of each variable on the driver route choice task; investigating the possible effects of primacy and recency on route choice behavior, use of better driving simulators with higher fidelity levels to overcome the earlier mentioned limitations; examining route choice behavior in real environments; and comparing the differences between simulator and real-life results, with respect to drivers' experiences, perceptions and route choices.

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Part I: Driving Simulator Experiment

Chapter 4

An Experimental Exploration of Route Choice: Identifying Drivers Choices and Choice Patterns, and Capturing Network Evolution

An Experimental Exploration of Route Choice: Identifying Drivers Choices and Choice Patterns, and Capturing Network Evolution

Aly M. Tawfik, Hesham A. Rakha, and Shadeequa D. Miller, *Member, IEEE*

Abstract— **Most driver route choice is typically captured using mathematical programming approaches which assume that drivers choose their routes to minimize some objective function, and in the late stages of typical route choice models, drivers are assumed to have perfect, or close to perfect, knowledge of their choice set, as well as the travel characteristics associated with each of the choice elements. It is, however, well documented in human psychological behavior that human perceptions are often different from actual reality, and that humans tend to minimize their cognitive efforts, and follow simple heuristics to reach their decisions; especially under uncertainty and time constraints. In addition, while only a few of the many route choice models are based on observed human behavior, the quality of route choice models is usually judged based on some simulation-based conversion criteria whose fidelity has not been comprehensively established. With this in mind, unlike most route choice research that is primarily focused on the end result of the route choice task, this research effort traces the evolution of route choices with driving experience and network knowledge. The research presented in this paper monitors and traces actual human route choice, and demonstrates that (a) drivers' route choice evolution varies; while some drivers do not evaluate the various alternative routes others do not decide on a specific route, (b) although there appears to be possible evidence to conclude that drivers learn the network conditions by experience, it appears that drivers perceptions over estimate the benefits, (c) drivers' route choice behavior differs between different driver groups, and (d) soliciting drivers' route choice based on observing choices over a period of time with reasonable accuracy is possible.**

I. INTRODUCTION

The number of available alternative routes from an origin to a destination can be vast and because of the social nature of traffic, most traffic decisions are not independent [1]. Hence, the cognitive task of route choice is not easy requiring decisions about how to reach a destination while satisfying various requirements. In addition, the experience of earlier route choices can affect the probability of the route being selected again. Furthermore, the characteristics of each alternative route do not have the same importance in a driver's final decision [2]; how a commuter selects which route to take may be affected by many other factors such as age, gender, driving experience, time, distance, special events, bad weather, and the behavior of other drivers [3].

While some commuters switch back and forth between routes, others consistently take one route until some external factor forces them to alter their route of travel. Route choice is a main concern that commuters face and make a decision about on a daily basis [2]. While some studies show that most commuters use only one route to get to work or school [4], other research efforts show that most drivers select more than one route to travel to work or school to avoid congestion and minimize travel time. On average, assuming that approximately 50 percent of the drivers use only one route for their commute seems to be a reasonable assumption.

Unlike most route choice research that is primarily focused on the end product of route choice, this research explores the development of route choice from being a conscious to a subconscious task. Conscious route choice assumes that drivers constantly evaluate and remember their travel times on the routes they travel, and use this information to select the travel route that maximizes some utility function [5, 6]. However, it is well documented in human psychological behavior that human perceptions are often different from actual reality [7], and that humans tend to minimize their cognitive efforts, and follow simple heuristics to reach their decisions, especially under uncertainty and time constraints. In addition, with repetition, cognitive activities become habitual and could reach automaticity. Hence, minimizing the required cognitive resources [8].

It is hypothesized that subconscious route choice constitutes a significant percentage of commuter travel; especially during under-saturated traffic conditions, and in the absence of information provision. This paper suggests that the activity of route choice starts as a conscious cognitive task, during which drivers consciously evaluate the different alternative travel routes. However, at a certain point in time, the route choice activity becomes habitual and possibly descends to the subconscious domain; where drivers choose only one route and seize to consciously evaluate the different alternatives, unless something

Aly M. Tawfik is a PhD Candidate in Virginia Tech Via Department of Civil and Environmental Engineering, Blacksburg, VA, 24061 (phone: 540-577-0462; fax: 540-951-7532; e-mail: tawfik@vt.edu).

Hesham A. Rakha is a Professor in Virginia Tech Via Department of Civil and Environmental Engineering and Director of the Center for Sustainable Mobility at Virginia Tech Transportation Institute, Blacksburg, VA, 24061 (e-mail: hrakha@vtti.vt.edu).

Shadeequa D. Miller was a graduate student in Virginia Tech Grado Department of Industrial and Systems Engineering. Now she is a graduate student in the University of Wisconsin-Madison, Madison, WI 53706 (e-mail: sdmiller@vt.edu).

significant happens (such as an accident) that raises the route choice activity back to the conscious level.

To the best of the authors' knowledge, no previous research has examined the evolution of route choice from being conscious to subconscious level. Drivers' compliance to disseminated traffic information has been reported to vary according to age, gender, driving experience, and other factors [9, 10]. Still, though, unexplained variation continues to exist. The authors hope that by exploring the evolution process of the route choice process, some explanation for the remaining unexplained variability may be addressed. For example, the authors believe that a driver would probably comply with disseminated information if s/he was driving a certain route for the first time, i.e. route decision process is still conscious. On the other hand, if a driver has been driving on the same route and never switched for years, then this person's route choice process is undoubtedly highly subconscious, and the chances that s/he would comply to the disseminated information is highly unlikely. In addition, route choice models typically include simulation-based convergence criteria that have not been comprehensively evaluated against actual observed human behavior. The authors hope that the findings of this research could add to such criteria.

There remains no perfect model available to explain the way drivers make route choice decisions, and although all techniques are characterized with strengths and limitations, data collection and real life validation of proposed models significantly add to the challenge. Studies performed to measure route choice and driving performance can, however, be categorized into different groups, such as: mathematical network models [6, 11] and evolving psychological driver behavior models [12, 13]; simulator-based, closed-course, and on-road studies [14, 15]; time-of-day, day, and trip purpose models; with and without information provision [16], and survey-, simulation-, and GPS- based studies [17, 18]. Stated preference studies, nonetheless, have been specifically overly criticized, and GPS-based ones seem very promising. With the increasing usage of GPS-based studies, algorithms capable of identifying drivers' route choice preference based on GPS observed data seem potentially useful.

In the following sections, objectives of the study are presented, followed by a detailed explanation of the study approach: participants, instruments and materials, procedure, and limitations. The third section presents the experiment results and discussion, and in the fourth section the paper ends with conclusions of the study and recommendations for further research.

II. OBJECTIVES

The objectives of this study are to investigate (a) the possibility of identifying patterns of drivers' route choice evolution, (b) the possibility of soliciting drivers' route choice based on observing choices over a period of time (or GPS data), (c) the evolution of network performance with drivers' learning, , and (d) any differences in route choice behavior between different driver groups.

III. METHODOLOGY

A. Participants

The research involved a total of fifty participants. All participants had valid driving licenses, a normal or corrected-to-normal vision and perfect color vision. As presented in Table 1, participants were selected to ensure variability in their personal attributes.

TABLE I
BREAKDOWN OF PARTICIPANTS BY GROUP

Criteria	Groups	Count
Age	Age1: 17 – 25 years	32
	Age2: 26 – 56 years	18
Gender	Gen1: Males	33
	Gen2: Females	17
Ethnicity	Eth1: European/American (White)	28
	Eth2: Non European/American (Non-White)	22
Education	Ed1: Bachelor Degrees	26
	Ed2: Graduate Degrees	24
Driving Years	Yrs1: < 4 years	25
	Yrs2: > 4 years	25
Annual Miles	Mil1: <12,000 miles/year	31
	Mil2: >12,000 miles/year	18

B. Instruments and Materials

Driving Performance: The experiment was conducted using the STISIM driver simulator software that was developed by Systems Technology Inc. (STI). STISIM Drive is an interactive program that is capable of recording numerous performance measures. The program offers the investigator control over development of driving scenarios, ensuring that all participants encounter the same events and conditions while driving. It also offers the investigator with possible partial randomization in the simulated scenario and events. The simulated driving program operates on a vehicle-similar structure with a 48 cm (19 in.) Dell monitor. The vehicle-similar structure is equipped with a vehicle chair, a steering wheel (with a horn and a turning signal arm), and gas and brake pedals. Software limitations are discussed in the limitations section.

Driving Network: As depicted in Figure 1, the research used a network composed of two routes with a total of 7 nodes and 9 links. Each route was composed of 5 links and 4 intersection nodes, and of a total length of 2,804 m (9,200 ft), i.e. a travel time of 3 to 4 minutes with an average speed of around 56 to 40 km/h (35 to 25 mph), respectively. All links were two-lane two-way links, with passing restricted at all sites due to the short lengths of links between intersections. With the exception of the first link which was around 1,067 m (3,500 ft) in length and the last link which was approximately 91 m (300 ft) long, all links were approximately 518 m (1,700 ft) in length. All links had 64 km/h (40 mph) speed limit signs, and "intersection ahead" warning signs. All intersections were priority controlled by four-way stop signs. For clearer presentation, the stop signs are not shown on Figure 1.

Both routes were identical: having equal distances and speed limits. Both routes were characterized by an equal number of right and left turning movements (2 lefts and 2 rights), so that participants wouldn't choose a route based on turning preference. Both routes were also characterized by

equal traffic volumes in all directions: with-flow, contra-flow, as well as in intersecting directions. However, the exact times and distances where the other traffic were to appear were randomized. This randomization resulted in the right route being 5% shorter (significant difference of 8 seconds), on average, when compared to the left route. Also the shapes, colors and types of the other traffic were randomized. As discussed later in the limitations section, no landmarks were placed at any location.
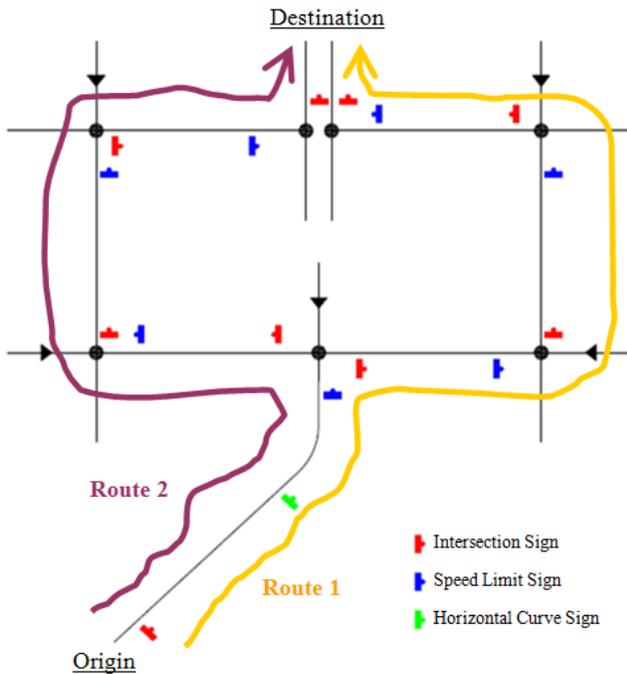

Fig. 1. Sketch of the simulated network

Initial Questionnaire: Participants were asked to fill-in a short questionnaire before performing the driving tasks. The questionnaire collected information about their age, gender, ethnicity, education, vision problems, driving experience, driving frequency, average number of miles driven per year, and use of cellular phones while driving.

Final Questionnaire: Participants were asked to fill a short questionnaire after performing all the driving runs. The questionnaire was designed to capture the participants' cognition of the different sections of this study. The questionnaire collected information about the number of repetitions the participants believed they would need before deciding on a preferred route from home to work/school in a new city and the number of repetitions they needed in the performed experiment, about their perception of differences in travel characteristics between the two routes, about their route choice, and reasons for their route choice.

C. Experiment Procedure

After participants read and signed the consent forms, they were first asked to fill an initial questionnaire, which collected their general information (as described earlier). Then, the participants were given a 15-minute drive on several practice routes. The practice routes were characterized by different terrains and driving schemes and

scenarios, with the objective of allowing the drivers to be familiar with the simulator driving motor skills.

Afterwards, participants were introduced to the research route. They were handed a draft sketch of the network showing the network and the points of origin and destination. The participants were asked to drive from the point of origin to the point of destination. They were asked to imagine that they moved to a new city, and that the origin point was home, while the destination point was work/school. They were asked to drive similar to how they would drive in the real world. Participants were asked to repeat driving from home to work many times, and most participants ended up driving twenty times from origin to destination. Participants were allowed as many intermediate breaks as they liked, and were instructed to report any signs of nausea or fatigue.

At the end of the experiment, participants were asked to fill a post-task questionnaire where they were asked to report their route choices and network perceptions (as mentioned earlier).

D. Study Limitations

To place the results of this study in context, the limitations of this research effort are summarized. The STISIM driver simulator dynamics lacked some realism. A noticeable difference was observed between real-life steering and breaking and the simulator experience. As an example, Modeling of T-intersections was not possible using the STISIM software. So, construction cones were placed to prevent participants from continuing through at the 4-leg intersections. However, although participants' vehicles would crash if driven into a construction cone, other simulated vehicles were not smart enough to recognize construction cones and drove into the cones with no harm.

Also, the STISIM software does not support "If, Then" logic. Accordingly, it was not possible to build a different scenario based on "If" the participant turned right or left at the different intersections, and as a result, no landmarks were added to the network. Due to lack of landmarks, a small number of participants made wrong turns and got lost a couple of times. The total number of trials that involved crashes or missed turns, however, was less than 10% of the total runs.

IV. RESULTS

A. Drivers Route Choice Evolution

Observing the drivers' individual evolution of route choice, four patterns were identified. Table 2 presents sample figures demonstrating each of the four patterns together with the percentage frequency of each pattern. On the figures a 0 represents a driver choosing one of the routes while a 1 represents a choice of the other route.

In the first pattern drivers make no route choice switches. These drivers select one of the routes, are satisfied with their experience, and repeat the same choice over and over again while never investigating alternative routes (14% of the total sample). In the second pattern, drivers start by arbitrarily picking one of the routes, repeat their choice a

few times and are not satisfied with their experience. These drivers switch to the other route, and either feel satisfied with their new choice or switch back to their initial choice, and never switch again. These drivers account for 16% of the sample. The third group is drivers who alternate their route choices continuously but have a preference for one of the routes. These drivers account for 38% of the sample size. The last group of drivers alternate between routes with no preference for a specific route.

TABLE 2
INDIVIDUAL PATTERNS OF ROUTE CHOICE EVOLUTION

Pattern	Sample Figure	Frequency Percentage and Description
1		Frequency = 14% A driver starting by arbitrarily picking a route, is apparently satisfied with the experience, and continues making the same choice for the entire 20 trials; till the end of the experiment.
2		Frequency = 16% A driver starting by arbitrarily picking a route, is apparently not satisfied with the experience, tries the other route, and decides that the first route was better. So, switches back to the first choice, and continues with this choice till the end of the experiment.
3		Frequency = 36% A driver switching between the two alternative routes till the end of the experiment. The driver, however, drives on route 1 much more than s/her drives on route 0. This reflects his/her preference for route 1.
4		Frequency = 32% A driver switching between the two alternative routes during the entire time of the experiment. The driver drives both routes with approximately equal percentages. This reflects the lack of preference towards any of the alternatives.

These results can be useful in identifying driver tendencies to comply with a route guidance system. For example, drivers that have established preferences for a certain route – as in patterns one, two, and three – would probably be more willing to comply with information that favors their preferred choice – especially when compared to drivers of pattern four. Alternatively, it would be more challenging to encourage drivers to use a route other than their preferred choice. The same challenge can be true for drivers of pattern four. Probably depending on their perception of the reliability of the provided information, they might decide to comply with the information, or depend on their personal experience-based knowledge.

B. Eliciting Drivers Route Choice

In an attempt to investigate the possibility of identifying choice preference based solely on observing drivers choices, two simple choice criteria were examined. The first criterion assumed that if a driver repeats the same choice for a certain number of consecutive trials, this may be used as an indication of a choice preference. The second criterion, on the other hand, is based on the percentage a single route is chosen in a certain number of trials. It assumes that if in a certain number of trials a driver chooses a route for more than a certain percentage this could reflect a preference for that route. For example, it assumes that if (in a certain number of trials) a driver chooses the right route more than a certain percentage, X (which has to logically be greater than 50%), then this driver has established preference towards that route. In order to optimize the models, different values of X were examined, and only the results based on the optimum X are shown in Table 3. The process for obtaining the optimum X values is demonstrated in Figure 2.

Table 3 shows that three different values were examined for the first criterion, namely, 3, 4 and 5 consecutive trials. The second criterion, however, examined the percentage of times the right route is chosen in the first 10, 15, and 20 trials. The values in the table reflect the number of times the adopted model is correct and the number of times the model is incorrect. Being correct involves two cases. The first case is when both the stated choice and the model indicate the same choice for the driver (case 1 in Table 3), i.e. the model predicted a correct choice. The second case is when both the stated choice and the model indicate that the driver did not reach a decision (case 4 in Table 3). Being incorrect, on the other hand, involves three cases. The first case is when the driver states making a choice while the model predicts that the driver did not make a choice (case 2 in Table 3). The second case is the opposite of the first one: when the driver states not making a choice while the model predicts that the driver made a choice (case 3 in Table 3). Finally, the third error results when both the model and the driver state that the driver made a choice; however, the driver states choosing a certain route, and the model predicts that the driver chose the other route (case 5 in Table 3).

Table 3 shows that the best performance is achieved using the sixth model (84% correct predictions), which is based on the second criterion. The other two second criterion models produce correct predictions of 72% and 42%; however, perform worse than the three first criteria models

(correct predictions of 78%, 76%, and 78%).

TABLE 3
CRITERIA AND PERFORMANCE OF MODELS FOR PREDICTING DRIVERS' ROUTE CHOICE

Model #	Criteria	Limit	% Correct			% Incorrect				Rank
			Total	1	4	Total	2	3	5	
1	Consecutive Trials	3	0.78	0.64	0.02	0.22	0.18	0.14	0.02	3
2		4	0.76	0.58	0.10	0.24	0.14	0.18	0.00	4
3		5	0.78	0.58	0.10	0.22	0.12	0.20	0.00	2
4	Number of Trials	10*	0.42	0.30	0.32	0.58	0.20	0.12	0.06	6
5		15*	0.72	0.50	0.18	0.28	0.10	0.22	0.00	5
6		20*	0.84	0.68	0.00	0.16	0.16	0.16	0.00	1

 * Based on optimum limit: for 10 (L<0.20, R>0.80), for 15 (L<0.40, R>0.60), and for 20 (L<0.44, R>0.56) (See Figure 5)

Figure 2 shows the process used to derive the percentage limits that optimize the predictions of the second criteria models. The figure depicts the performance of the models versus the different percentage values, X. The figure shows that the best performance of the 20 trials model is when X (a person is assumed to choose the right route when the percentage of times this driver selects the right route) is greater than 56%. The figure also shows that the best performance of 15 and 20 trials models is any value between 57% and 63%, and at the value of 80%, respectively.
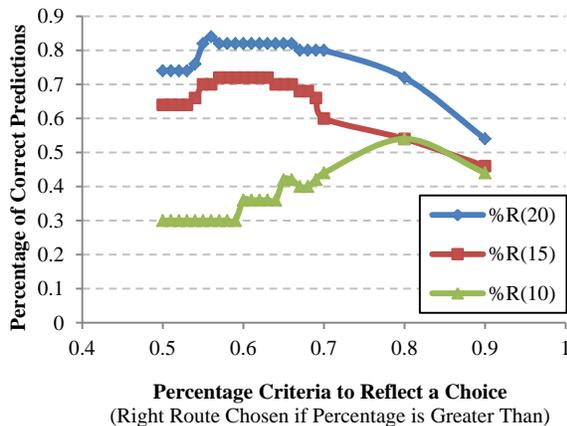

Fig. 2. Performance of Second Criteria, Number of Trials, Models According to Percentage Limit to Reflect Choice

C. Network Evolution

While validation of route choice models and traffic simulation runs have been usually dependent on model convergence as the primary factor, the analyses presented in this paper can be used as additional validation criteria. Furthermore, such models for predicting route choice and preference based on observance of drivers' route choice behavior can be significantly useful in GPS-based data collection methods.

Figure 3 depicts the aggregate evolution of drivers' route choice over trials. This evolution reflects the aggregate learning curve of all drivers at the network level. Statistical analysis of the slope of the curve with respect to the trial number shows that the trial number is significant (p-value = 3.5%) for the determination of the percentage of drivers choosing the right, faster, route. The regression formula reflects that, on average, an increase of 0.5% of drivers choosing the right route is achieved with every new experience. Although this possibly proves that drivers aggregately learn and change their behavior according to system evolution, the learning curve is relatively shallow. This may be attributed to the difficulty in observing the small difference in travel time between the two alternative routes. Surprisingly, however, the aggregate percentage of drivers choosing the right route on the first trial was almost 70%, which is significantly higher than 50%. This may be due to drivers avoiding turning through oncoming traffic at the first intersection, which was repeatedly reported as the reason for choosing the right route in the post-task questionnaire. Regardless, this high percentage of drivers choosing the shorter travel time route on the first trial could be contributing to the relatively shallow learning curve. As mentioned in the suggested future work section, it would be interesting to observe the system's learning curve if the situation had been reversed, i.e. if the left route was the shorter travel time route.

$$y = 0.0057x + 0.573$$
$$R^2 = 0.2241$$
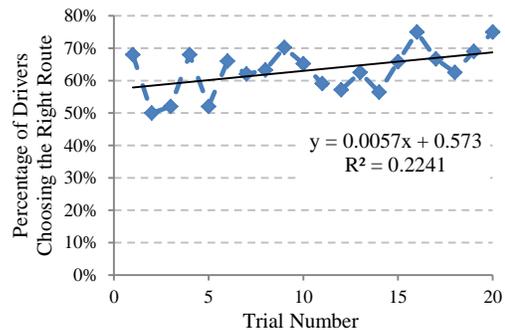
Fig. 3: Aggregate Evolution of Route Choice over Trials

Comparing the percentage of drivers choosing the right route over the left route to the probability of the right route being shorter than the left route reveals other intriguing results. Based on a Monte Carlo simulation of all experienced travel times, the right route was shorter than the left one 60% of the time; hence, implying an aggregate drivers' route choice evolution curve that is asymptotic with 60% of drivers choosing the right route. Interestingly, however, based on the 20 experiment trials, the aggregate evolution curve in Figure 3 does not follow such a trend, and overshoots the 60% line. Again, as mentioned above, this might be explained by the drivers' reported reason of choosing the right route to avoid turning through traffic at the first intersection. However, while this could be a rational reason on the first trial, where drivers lack any knowledge regarding the network, it does not seem rational in later trials, where drivers would have arguably established perfect knowledge of the system. Hence, such behavior could alternatively be explained as drivers basing their decisions

on short-term gains; possibly due to the small average travel time difference between both routes.

D. Driver Group Differences

In order to characterize the effects, if any, of the independent variables on the evolution of route choice, the aggregate evolution was computed per driver group (age, gender, ethnicity, driving years, and annual driven miles), as presented in Figure 4 (Figures 4.a thru 4.f, respectively).
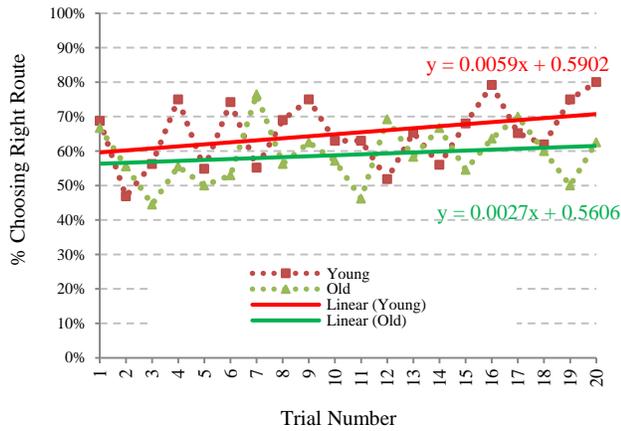
Fig. 4.a: Choice Evolution by Age
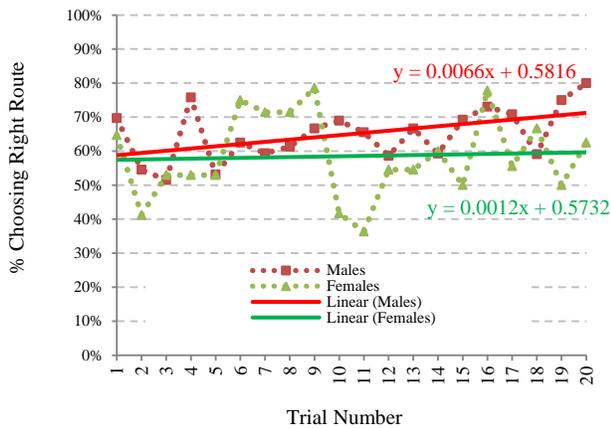
Fig. 4.b: Choice Evolution by Gender
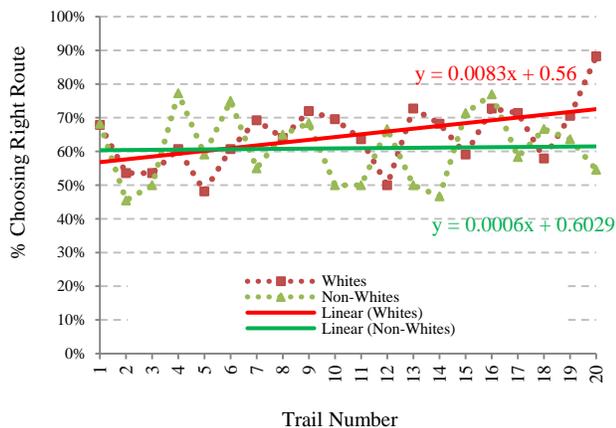
Fig. 4.c: Choice Evolution by Ethnicity
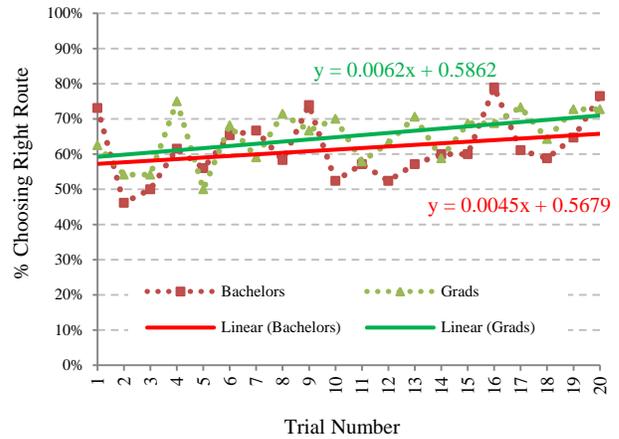
Fig. 4.d: Choice Evolution by Education
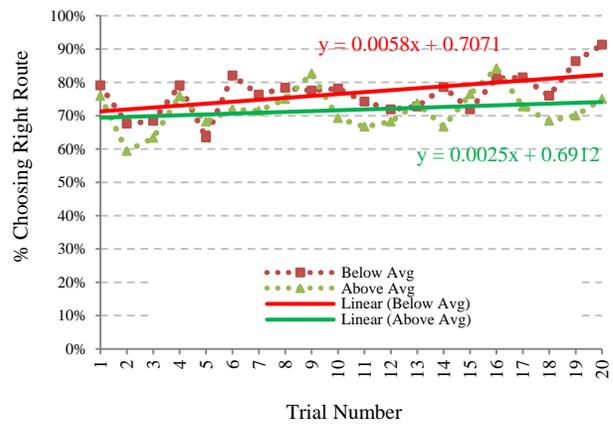
Fig. 4.e: Choice Evolution by Driving Years
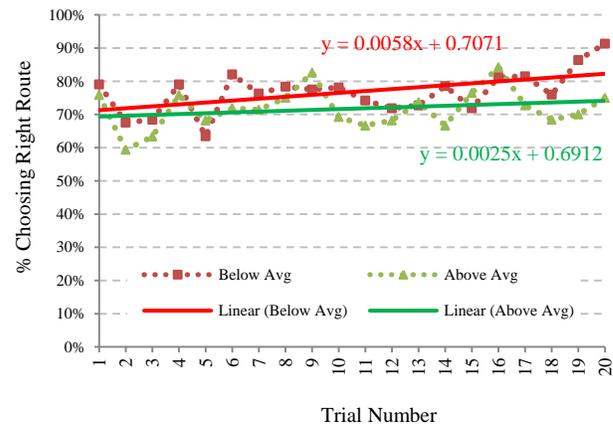
Fig. 4.f: Choice Evolution by Annual Driven Miles

Fig. 4: Aggregate Effect of Independent Variables on Route Choice Evolution

Figure 4 shows that the percentage of drivers choosing the right, shorter travel time route increases for drivers of all groups. Figure 4.a shows that young drivers are more inclined to adapt and choose the minimum travel time route (a slope of 0.0059), in comparison to older ones (a slope of 0.0027). Similarly, Figure 4.b shows that males are more

inclined to adapt and choose the minimum travel time route (a slope of 0.0066), in comparison to females (a slope of 0.0012); Figure 4.c shows that European/American (white) are more inclined to adapt and choose the minimum travel time route (a slope of 0.0083) in comparison to non-European/American (a slope of 0.0006); and likewise, Figure 4.d shows graduate students are more adaptive (a slope of 0.0062) in comparison to undergraduate students (a slope of 0.0045), Figure 4.e shows drivers with short driving experience (a slope of 0.0071) are more adaptive than drivers with longer experience (a slope of 0.0031), and Figure 4.f shows drivers driving less annual miles (a slope of 0.0058) are more adaptive in comparison to those driving more annual miles (a slope of 0.0025).

Figure 4 also shows that the group that is most adaptive to learning evolution is the European/American (white) drivers (a slope of 0.0083), followed by drivers with short driving experience (a slope of 0.0071). Alternatively, the non-European/American (non-whites) drivers are characterized with least learning evolution towards choosing the minimum travel time routes (a slope of 0.0006) followed by the female drivers (a slope of 0.0012). Interestingly, though, since the probability of the right route to be shorter is 60% (Monte Carlo simulation) these two groups are the same groups that are not significantly over estimating the benefits of the right route.

V. CONCLUSIONS AND FURTHER WORK

While the results of this experiment should not be considered conclusive for all driver populations; due to the small sample size, from the results of the experiments it can be concluded that drivers' route choice evolution is not identical. It has been observed that while some drivers do not explore other alternative routes, others are unable to select a specific route. The research identified four major route choice evolution patterns. These identified patterns could have a multitude of benefits. For example, inclusion of these different patterns in route choice models can help improve the models by decreasing unexplained variation. Also, the possible identification of drivers following these different patterns and their compliance to travel information can be extremely useful in identifying target groups for marketing dynamic electronic route guidance systems.

With respect to the possibility of eliciting route choice based on route choice observations, high percentages of correct predictions were obtained based on the simple criteria used in the experiment. Although these values could significantly improve by incorporating more advanced data mining techniques, it should be noted that these values were descriptive and not predictive. In case of a predictive model, model performance would probably be less.

There appears to be some evidence to support aggregate learning evolution of systems, possibly towards choice of minimum travel time routes; however, the process seems to be imperfect, relatively slow and is definitely affected by other factors that require further investigation. Drivers' route choice behavior seems to be influenced by short-term gains,

more than strategic evaluations, and it appears that drivers' route choice might be overestimating the benefits of shorter travel time routes.

These results of drivers' route choice evolution and network learning can be very useful if considered as criteria for models validation. While most route choice model validation has been primarily based on convergence of the solution, results of this research could be incorporated into the validation process. Again, to reiterate, there is no doubt that these findings are only preliminary, and that more research needs to be done before considering these results conclusive.

From observing the aggregate evolution trends of the different driver groups, it appears that drivers' route choice behavior is also affected by the demographic factors. The extent of the effect of these factors on aggregate route choice behavior, undoubtedly, necessitates further investigation.

Finally, a few possible future research directions include: modeling route choice with different signal strengths and in more complicated networks and analyzing the effect of each on drivers' route choice patterns and network evolution, use of better driving simulators with higher fidelity levels and that overcome the earlier mentioned limitations, examining route choice patterns in real environments, examining the effect of route guidance systems on the compliance of drivers with different evolution patterns as well as on the aggregate system evolution, incorporating the differences between drivers with different route choice patterns in a hierarchical route choice model and evaluating the benefits, and comparing the differences between simulator and real-life results, with respect to drivers' route choice patterns and network evolution.

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Part I: Driving Simulator Experiment

Chapter 5

Disaggregate Route Choice Models Based on Driver Learning Patterns and Network Experience

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Disaggregate Route Choice Models Based on Driver Learning Patterns and Network Experience

Aly M. Tawfik, *Member, IEEE*, John Szarka, Leanna House, and Hesham A. Rakha, *Member, IEEE*

Abstract— **Since their emergence, route choice models have been continuously evolving; particularly because of their wide application and consequent influence in the transportation engineering arena. Although early versions of route choice models were based on theories of rational behavior and neglected limitations of human cognition, later closer observance of human behavior resulted in better modeling frameworks such as Bounded Rationality and Prospect Theory. Nonetheless, recent developments in Intelligent Transportation Systems have increased the demand for more exploration, modeling and validation of behavioral route choice models. This work presents statistical models of route switching based on a real-time driving simulator study of 50 drivers. The research presented in this paper demonstrates that (a) different driver learning patterns have significant route choice effects, (b) driver route choice behavior significantly changes with driver network experience, and (c) disaggregate route choice models based on either driver learning patterns or network experience outperform aggregate route choice models.**

I. INTRODUCTION

Route choice models are extremely important in transportation engineering. For example, these models are used in transportation planning, dynamic traffic assignment, advanced traffic signal control, advanced traveler information systems, and electronic route guidance systems [1, 2]. With increased advancements in Intelligent Transportation Systems (ITSs), the importance of route choice models seems to only increase. This is especially evident by the increased interest in developing behavioral and user-specific route choice models.

Earlier models of route choice were based on assumptions of rational behavior and resulted in an extensive literature of deterministic and stochastic equilibrium models. Recent work explored the possibility of attaining system optimum via alternating cooperation strategies [3]. Research, however, succeeded in uncovering significant limitations in

rational human behavior theories and highlighted the need for further empirical research that bases its findings on theories from behavioral science. Furthermore, recent developments in ITS and disappointing rates of user satisfaction with navigation systems underpinned the heterogeneity of drivers and increased the need for personalization of route guidance systems via the incorporation of user specific parameters [4].

In the past few years, several empirical route choice studies were conducted and developments in route choice models in the direction of behavioral sciences are becoming a norm. For example, Bogers et al. [5] developed a framework for the joint modeling of learning, risk attitude under uncertainty, habit, and the impacts of advanced traveller information on route choice. In another study, based on travel simulator data, an empirical model was developed that incorporates parameters that represent both implicit and explicit learning [6]. Talaat and Abdulhai [7] explored the suitability of using Decision Field Theory (DFT) (which is a significantly advanced development of Random Utility Models) in route choice, based on empirical travel simulator experiment data. Iida et al. [8] performed an empirical route choice experiment on a travel simulator and concluded that "it is desirable to develop a model which is disaggregated by a type of driver because the route choice behavior varies by individual". Similarly, in a series of publications based on micro-simulation, Nakayama et al. [9-11] concluded that drivers are not homogeneous, may use different strategies at different times, and that even after a long process of learning drivers do not become homogenous or rational.

In an attempt to better understand heterogeneity of route choice behavior, this research effort does not assume rational behavior and does not focus on the final outcome of route choices. The work attempts to investigate the validity of these assumptions by monitoring and tracking actual human route choices performed on a driving simulator. In an earlier publication the authors contrasted and presented discrepancies between driver experiences, perceptions and choices [12]. In another earlier publication, the authors investigated drivers learning behavior and identified four different driver learning patterns [13]. In this paper, the authors build on the previous work and examine differences in route switching models.

In the following sections, the authors present the objectives of the study, followed by a brief explanation of the study approach: participants, instruments and materials, procedures, and limitations. In the third section, the authors present the experimental results and discussion, and in the fourth section the paper ends with the conclusions of the study and recommendations for further research.

II. OBJECTIVES

The objectives of this study are to demonstrate that (a) different driver learning patterns have significant route choice effects, (b) drivers route choice behavior significantly changes with driver experience, and (c) disaggregate route choice models based on either driver learning patterns or network experience outperform aggregate route choice models.

III. METHODOLOGY

This section explains the methodology briefly. For more information readers are referenced to earlier publications [12, 13].

A. Participants

A total of 50 participants were selected with variable personal attributes (age, gender, ethnicity, education, driving years, and annual driving miles).

B. Instruments and Materials

Driving Performance: The experiment was conducted using a low fidelity driving simulator.

Driving Network: The research network was composed of two alternative geometrically-identical routes with nearly identical (but statistically biased) traffic. The mean travel times were 3 to 4 minutes based on average speeds of approximately 56 to 40 km/h (35 to 25 mph), respectively.

Initial Questionnaire: Participants were asked about their age, gender, ethnicity, education, vision problems, driving years, and average number of miles driven per year.

Final Questionnaire: Participants were asked about their perceptions of differences in travel characteristics between the two routes, and reasons of their route choice.

C. Experiment Procedure

Participants were asked to fill an initial questionnaire and were given a 15-minute practice drive. Then, participants were handed a draft sketch of the network and asked to drive from the point of origin to the point of destination. They were asked to imagine moving to a new city, where the origin point was home, and the destination point was work/school. Participants were asked to repeat driving from home to work many times, and most participants ended up driving twenty times from origin to destination. At the end, participants were asked to fill a final questionnaire.

D. Study Limitations

The low fidelity driving simulator was characterized with a number of limitations that are discussed in the earlier publications [12, 13].

IV. RESULTS AND DISCUSSION

A. Drivers Experiences

On average, the right route was 5% shorter in travel time than the left one. Based on a t-test and an F-test, both travel time means and standard deviations, respectively, were significantly different (p-value<0.01). Based on a Monte-Carlo simulation, the probability of the right route having a shorter travel time was 60%.

Discrepancies between driver experiences, perceptions and choices were observed and investigated in an earlier publication [12] and thus are not discussed further.

B. Choice Evolution Patterns

In an earlier publication, Tawfik et al. [13] categorized driver route choice evolution into four patterns; presented in Table 1. In addition to this categorization, the models presented below are based on four more categorizations.

C. Route Choice Models

Response Variable: the modeled response is the probability that driver i will switch his/her route choice on trial t.

Independent Variables: The independent variables investigated in this work are presented in Table 2. Although the previous categorization of learning patterns was based on all observed trials, Cat4R20, the added four categorizations are based on fewer numbers of trials. The rational is to limit the dependence between the independent categorization variables and the modeled error terms.

Model Data: in total there were 823 observations. However, all observations with missing data were dropped. This included all trials where drivers were not aware of the travel time on the alternative route. Hence, all observations of learning pattern 1 (in Cat4R20 and Cat4R10) were not considered in the following models. Because categorizations that are based on 5 runs cannot be as accurate as those based on more runs, some drivers were mistakenly categorized under learning pattern 1 in Cat3R5, and 0 number of switches in Cat5R5. As a result these two categories were not dropped from the data. A total of 605 observations were included in all the following models. All numeric variables used in the presented models were scaled; so that the magnitude of one (or more) variables would not over shadow other variable(s) and affect the solution.

Model Structure: the route choice model proposed here is a mixed effects generalized linear model with a logit link function. Because each driver was asked to repeat his/her choice several times, one random parameter, the intercept, is estimated over all individuals instead of all observations. The model has the following structure.

$$y_{it} \sim Bern(p_{it})$$
$$logit(p_{it}) = x_{it}'\beta + \theta_i$$
$$\theta_i \sim N(0, \varphi)$$

where,

$y_{it} = 1$ if person i switches his/her route choice at trial t
$y_{it} = 0$ if person i does not switch at trial t
$Bern$ is the Bernoulli distribution
p_{it} is the probability that person i switches at trial t
$logit(p_{it}) = \dfrac{p_{it}}{1 - p_{it}}$
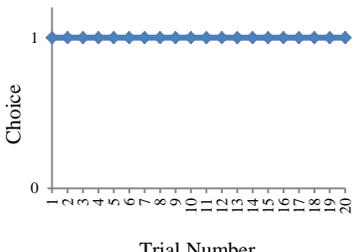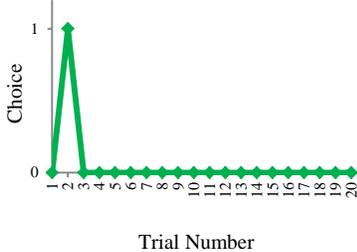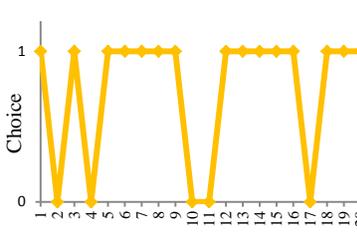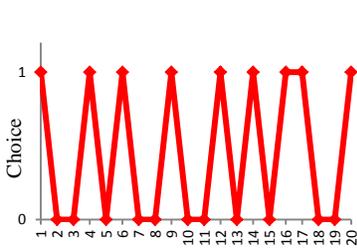x_{it} is the vector of covariates for person i at time t
β is a vector of the parameters
θ_i is the random component of person i
N is the Normal distribution
φ is the variance

TABLE 1
INDIVIDUAL PATTERNS OF ROUTE CHOICE EVOLUTION

Pattern	Sample Figure	Frequency Percentage and Description
1	 Trial Number	Frequency = 14% A driver starts by arbitrarily picking a route, is apparently satisfied with the experience, and continues making the same choice for the entire 20 trials.
2	 Trial Number	Frequency = 16% A driver starts by arbitrarily picking a route, is apparently not satisfied with the experience, tries the other route, and decides that the first route was better. The driver makes a choice after trying both routes and does not change afterwards.
3	 Trial Number	Frequency = 36% A driver switches between the two alternative routes till the end of the experiment. The driver, however, drives on route 1 much more than s/her drives on route 0. This reflects his/her preference for route 1.
4	 Trial Number	Frequency = 32% A driver switches between the two alternative routes during the entire time of the experiment. The driver drives both routes with approximately equal percentages. This reflects the lack of preference towards any of the alternatives.

Three models were developed and are presented here. Model 1 explores the benefit of including the categorization as an independent variable in the general route switching model. Model 2 investigates the benefits of having a separate route switching model (disaggregate models) for each learning pattern. Model 3 as was the case with Model 1 examines the entire population but develops separate models for early and later stages of driving. It examines whether

drivers' route switching behavior changes with driver experience and the benefits of having disaggregate models based on driver network experience.

TABLE 2
MODEL INDEPENDENT VARIABLES

#	Variable Name	Variable Description	Variable Values
Variables of Driver Demographics			
1	Age_i	Age of participant i	17 to 56
2	$Gender_i$	Gender of participant i	M or F
3	$Ethnicity_i$	Ethnicity of participant i	1 or 2
4	$Educ_i$	Education level of participant i	3, 4, 5, or 6
5	$DrYears_i$	Number of years participant i has been a licensed driver	0.33 to 36
6	$Dr\ Miles_i$	Annual number of miles participant i drives	1 or 2
Variables of Driver Learning Patterns			
1	$Cat4R20_i$	Pattern type (as presented in Table 1) of driver i based on 20 trials	1[*], 2, 3, or 4
2	$Cat4R10_i$	Similar to Cat4R20, but categorization based on only 10 trials.	1[*], 2, 3, or 4
3	$Cat3R5_i$	Similar to Cat4R20, but categorization based on only 5 trials, and patterns 3 and 4 are combined into a single pattern.	1[**], 2, or 3
4	$Cat2R5_i$	Similar to Cat3R5, but patterns 1 and 2 are combined into a single pattern.	2 or 3
5	$Cat5R5_i$	Five categories based on five trials. The categories are based on the number of switches driver i makes in the first 5 trials.	0[**], 1, 2, 3, or 4
6	$Cat\#R\#\text{-}X_i$	Indicator variable indicating whether person i belongs to pattern X, according the Cat#R# category	0 or 1
Variables of Route Experience			
1	Trial Number (t)	The route choice trial number of the participant	1 to 22
2	TT_{it}	The travel time experienced by participant i on trial t	151 to 337
3	$Cars_{it}$	The number of vehicles encountered by participant i on trial t	4 to 11
4	$MinD_{it}$	The closest car-following distance experienced by participant i on trial t	0.1 to 580.6
5	$AvgD_{it}$	The average car-following distance experienced by participant i on trial t	335 to 1767
6	$TTavgOther\text{-}OverCurrent_{it}$	The ratio of the average travel times (of the other route over the current chosen route) experienced by participant i up till trial t	0.79 to 1.31
7	$Inertia_{it}$	The number of successive identical choices participant i has made right before trial t	0 to 19
8	$PrefOther\text{-}OverCurrent_{it}$	The ratio of the number of times (participant i has chosen the other route over the current chosen route) in all trials up till trial t	0.14 to 7.47

[*] Because of missing data, all observations dropped out from analysis
[**] Drivers incorrectly classified in this category and, as a result, category not dropped out from analysis.

Model1: Table 3 presents the results of 5 route choice switching models based on 5 different driver learning patterns, where Table 3A presents the significant factors and

Table 3B presents the performance of the models according to the BIC and Deviance performance measures.

Table3A shows logical model parameters. The negative sign of inertia indicates that as the inertia increases, the probability of a switch decreases. The positive sign of PrefOther-OverCurrent implies that as a driver drives one route more than the other, the probability of the driver switching back to that preferred route increases. It can also be seen that including the category variable in the model improves the BIC and deviance, and that drivers with learning patterns 3 and 4 (in Cat4R20 and Cat4R10) and learning pattern 3 (in Cat2R5) have a higher probability of switching than drivers of learning patterns 2 and 1, respectively. Since drivers of learning pattern 4 seem indifferent between both routes, it is logical that the parameters of Cat4R20-4 and Cat4R10-4 are greater than the parameters of Cat4R20-3 and Cat4R10-3, respectively, i.e. drivers of learning pattern 4 have a higher probability of switching than those of learning pattern 3.

It is not surprising that Cat5R5 was not significant. On one hand, a possible explanation of the former can be attributed to the difficulty in differentiating between learning patterns 3 and 4 in only 5 trials. On the other hand, a possible explanation of the latter is the random categorization that is not based on behavioral reasoning. The drivers that were incorrectly categorized in leaning pattern 1 provide a plausible explanation that Cat3R5 was not significant; since their behavior is not significantly different from the drivers in the other two categories.

TABLE 3A
SIGNIFICANT VARIABLES IN ROUTE CHOICE SWITCHING MODELS BASED ON DRIVER LEARNING PATTERNS

Significant Variables[*]	Cat4R20	Cat4R10	Cat2R5	Cat3R5 and Cat5R5
Intercept	-2.9894	-2.3501	-1.0491	-0.4294
Trial	-0.2760	n/s	n/s	n/s
Inertia	n/s	-0.5206	-0.6117	-0.6613
PrefOther-OverCurrent	0.6621	0.6242	0.6038	0.5889
Cat4R20-3 Cat4R20-4	2.3373 3.6850	-	-	-
Cat4R10-3 Cat4R10-4	-	1.9289 2.5144	-	-
Cat2R5-3	-	-	0.9159	-
Cat3R5	-	-	-	-
Cat5R5	-	-	-	-

[*] all variables are significant at 1%

TABLE 3B
PERFORMANCE OF ROUTE CHOICE SWITCHING MODELS

Model Performance	Cat4R20	Cat4R10	Cat2R5	Cat3R5 and Cat5R5
BIC	685.1	708.6	727.7	729.5
Deviance	646.6	670.2	695.7	703.9

It is interesting that travel time was not significant in any of the models presented in Table 3A. A possible reason could be that the travel time difference between the two routes was not big enough to be perceivable, which is explored in an earlier publication [12]. Another possible explanation could be that travel time was not important to all the drivers. A third possible explanation could be that travel time was not important at all the experience stages. While the second explanation is further explored in model 2, the third explanation is explored in model 3.

It is also interesting that none of the demographic variables was found to be significant in the route choice models. This is further explored in three other models: first, in model 2 to see if the demographic variables would appear within the learning pattern category route choice models; second, in model 3 to see if demographic variables could affect route choice at different learning stages, and last in Section D to see if it is possible to use the demographic variables to predict driver learning pattern memberships.

The BIC and deviance measures presented in Table 3B show that the models that include learning pattern variables (Cat4R20, Cat4R10, and Cat2R5) outperform those that do not include learning pattern variables (Cat3R5 and Cat5R5).

Model2a: Table 4 presents the results of modeling route switching based on disaggregate learning patterns of Cat4R20.

Again, the results in Table 4A seem logical. It is specifically interesting that travel time turned out to be significant for drivers of learning pattern 3 and not for the other two learning patterns (especially learning pattern 2). It was hypothesized that drivers of learning pattern 3 are those who are continuously evaluating the alternative routes and choosing the best one; hence, it is appropriate that travel time is important for them. On the other hand, although it was hypothesized that drivers of learning pattern 2 were also evaluating the alternative routes and choosing the best route, since they made their choices very early, their evaluation accuracy is questionable. The insignificance of the travel time variable seems in line with this reasoning.

Unlike the insignificance of the demographic variables in model 1, in this model a few demographic variables seem to affect the route choice switching behavior of drivers belonging to learning patterns 3 and 4. This is consistent with the conclusions of an earlier publication [12].

TABLE 4A
SIGNIFICANT VARIABLES IN ROUTE CHOICE SWITCHING MODELS

Significant Variables[*]	Cat4R20	Cat4R20-2	Cat4R20-3	Cat4R20-4
Intercept	-2.9894	-3.2790	-1.0170	1.0042
Ethnicity-2	n/s	n/s	0.5275[**]	n/s
DrMiles-2	n/s	n/s	n/s	-0.6678
Trial	-0.2760	n/s	-0.6761	n/s
TTavgOther-OverCurrent	n/s	n/s	-0.2824[**]	n/s
PrefOther-OverCurrent	0.6621	1.4589	0.7277	n/s
Cat4R20-3 Cat4R20-4	2.3373 3.6850	-	-	-

[*] unless otherwise stated, all variables are significant at 1%
[**] significant at 10%

TABLE 4B
PERFORMANCE OF ROUTE CHOICE SWITCHING MODELS

Model Performance	Cat4R20	Cat4R20-2	Cat4R20-3	Cat4R20-4
BIC	685.1	39.25	298.6	340.1
Deviance	646.6	25.92	265.2	323.5

The BIC and deviance measures presented in Table 4B are lower than those presented in Table 3B. This could be a result of the smaller number of observations.

Model2b: Table 5 presents the results of modeling route choice switching based on disaggregate learning patterns of Cat4R10.

As in models 1 and 2a, the signs of the parameters presented in Table5A seem logical. In addition, as in the case of model 2a, a couple demographic variables seem to affect the route choice switching behavior of drivers belonging to the disaggregate models. Travel time, on the other hand, did not appear to be significant in this model. The differences between models 2a and 2b are explainable by the fact that drivers belonging to the learning pattern categories of Cat4R20 and Cat4R10 are not the same. It is reasonable to assume that categorization of drivers based on more trial observations should make more sense.

Again, the BIC and deviance measures presented in Table 5B are lower than those presented in Table 3B. This, too, could be a result of the smaller number of observations.

TABLE 5A
SIGNIFICANT VARIABLES IN ROUTE CHOICE SWITCHING MODELS

Significant Variables[*]	Cat4R10	Cat4R10-2	Cat4R10-3	Cat4R10-4
Intercept	-2.3501	-2.8935	-0.3168[**]	0.7022
Ethnicity-2	n/s	n/s	n/s	-0.6822
Trial	n/s	n/s	n/s	-0.4210
Inertia	-0.5206	n/s	n/s	n/s
PrefOther-OverCurrent	0.6242	1.3974	0.9272	n/s
Cat4R20-3 Cat4R20-4	1.9289 2.5144	-	-	-

[*] unless otherwise stated, all variables are significant at 1%
[**] significant at 10%

TABLE 5B
PERFORMANCE OF ROUTE CHOICE SWITCHING MODELS

Model Performance	Cat4R10	Cat4R10-2	Cat4R10-3	Cat4R10-4
BIC	708.6	50.23	254.3	395.1
Deviance	670.2	36.36	238.2	372.4

Model2c: Table 6 presents the results of modeling route switching based on disaggregate learning patterns of Cat2R5.

As in models 1, 2a and 2b, the signs of the parameters presented in Table6A seem logical, and, as in the case of models 2a and 2b, a couple demographic variables seem to affect the route choice switching behavior of drivers belonging to the disaggregate models, but travel time, as in model 2b, did not appear to be significant in this model. The differences between models 2a, 2b and 2c, are explainable by the fact that drivers assigned to the disaggregate learning

pattern categories of these models are not the same. In addition, the insignificance of travel time can be attributed to the pooling of the drivers of learning patterns 3 and 4 into one category, where it seems that while drivers of learning pattern 3 might be affected by travel time, those of learning pattern 4 are not.

TABLE 6A
SIGNIFICANT VARIABLES IN ROUTE CHOICE SWITCHING MODELS

Significant Variables[*]	Cat2R5	Cat2R5-2	Cat2R5-3
Intercept	-1.0491	-1.9797	0.6580
Gender-2	n/s	n/s	-0.8450
Ethnicity-2	n/s	2.0028	n/s
Educ-2	n/s	n/s	-0.8605
DrYears	n/s	-0.3848	n/s
Trial	n/s	n/s	-0.3256
Inertia	-0.6117	-0.5301[**]	n/s
PrefOther-OverCurrent	0.6038	0.6964	0.5467
Cat2R5-3	0.9159	-	-

[*] unless otherwise stated, all variables are significant at 1%
[**] significant at 10%

TABLE 6B
PERFORMANCE OF ROUTE CHOICE SWITCHING MODELS

Model Performance	Cat2R5	Cat2R5-1	Cat2R5-2
BIC	727.7	196.2	541
Deviance	695.7	164.5	505

As in all the previous models, the BIC and deviance measures presented in Table 6B are lower than those presented in Table 3B. Again, this could be due to the smaller number of observations.

Model3: Table 7 presents the results of modeling route choice switching based on early and late learning stages.

As in all previous models, the signs of the parameters presented in Table7A seem logical. However, the results present further intriguing insights. Travel time appears to be significant at the early trials and insignificant at the mid and late stage trials. Inertia is significant at all stages, yet its effect decreases by experience. Preference, too, is significant at all trials, but its effect increases with experience.

This possibly means that at the early learning stages drivers pick minimum travel time routes and their choices are also driven by inertia and preference. However, as drivers make subsequent choices their choices are no longer driven by travel time and are less driven with inertia; instead both factors are replaced with preference. In this case, preference may be described as habit.

As in previous models, demographic variables seems to have a role in drivers route choices at the different learning stages, and the BIC and deviance measures presented in Table 7B are lower than those presented in Table 3B.

D. Driver Learning Pattern Models

None of the driver demographic variables was found to be significant in predicting the drivers learning pattern.

V. CONCLUSIONS AND FURTHER WORK

While the results of this work should not be considered conclusive for all driver populations and for all route choice conditions, due to the limitations in the sample size and the experiment and route conditions, the results seem to highlight some important and promising route choice dimensions.

As has been concluded in many earlier publications, it appears that driver demographics might play a role in route choice. This role still needs to be explored further.

In accordance with current research standings, inertia and route preference have a significant role in route choice behavior. However, unlike the main stream of route choice models, in this experiment travel time was not an all-time major factor influencing route choices. This may be attributable to the small travel time difference between the alternative routes. Nevertheless, it is a plausible that in a real-world situations that travel time may not be important, and thus models need to reflect this behavior.

The identified driver learning patters had a significant effect on route choices. Such factors were not explored in earlier studies. Hence, they need to be further investigated. It is unfortunate that this work was not able to identify significant factors that can successfully predict driver learning patterns. However, this is certainly a future direction that is worth exploring.

It is interesting that route choice models changed significantly according to the driver learning stage. This too is a direction that could provide useful route choice insights if proven to be generalizable.

Finally, all the formulated disaggregate route choice models; whether based on learning pattern groups or stage of learning, had lower BIC and deviance performance measures. Because the decrease in these measures is probably due to the smaller number of observations, further

investigation is required to reach conclusive judgments about the benefits of disaggregating route choice models.

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Part II

Real-World Driving Experiment

Part II: Real-World Driving Experiment

Chapter 6

A Real-World Route Choice Experiment to Investigate and Model Driver Perceptions

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A Real-World Route Choice Experiment to Investigate and Model Driver Perceptions

Aly M. Tawfik, MS
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 577-0462
FAX: (540) 231-7532
tawfik@vt.edu

Hesham A. Rakha, PhD., P.Eng.
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 231-1505
FAX: (540) 231-1555
hrakha@vt.edu

ABSTRACT

The value of traveler information systems depends on two major assumptions: i) drivers are incapable of accurately acquiring information on their own, and ii) the provided information is relevant to the drivers' choice rules. None of these two assumptions has ever been examined in a real-world experiment. In addition, although the second of the two assumptions has been addressed in numerous publications, the first assumption remains under-researched. Drivers' perceptions of traffic conditions are undoubtedly an important factor in transportation engineering. Yet, little attention has been given to the capability of drivers to accurately perceive traffic conditions; such as travel distance, travel time, travel speed, and traffic levels. Because of cost and past technological limitations, most travel research is based on either stated preference surveys or travel simulators; both of which are characterized with serious limitations due to their inability to address the accuracy of travelers' perceptions. To address this point this work is based on a real-world route choice experiment of a sample of 20 drivers and more than 2,000 real-world choices. Each of the drivers' experiences, perceptions, and choices were recorded, analyzed and cross examined. The results of the experiment indicate that: a) correct perceptions were about only 60% accurate and drivers' perceptions of travel speeds were more accurate than their perceptions of travel times; b) while drivers' travel time perceptions was the most important factor in explaining driver choices, travel distance perceptions was the least important; c) there are significant discrepancies between stochastic user equilibrium and real-world route choices; d) drivers' personality traits and demographic factors were found significant in predicting correctness of driver perceptions; and e) driver personality traits were found to be as important for correct perceptions as variables of travel experiences.

INTRODUCTION

Researchers and travelers worldwide have great expectations for Intelligent Transportation Systems (ITSs). Intelligent Transportation Systems refer to transportation systems that make use of information technology and communication to tackle negative transportation impacts, such as to mitigate traffic congestion and to reduce accidents. Advanced Traveler Information Systems (ATISs) are the ITS branch that entail providing travelers with information to help them make informed decisions.

The value of traveler information systems depends on two major assumptions: i) drivers are incapable of accurately acquiring the provided information on their own, and ii) the provided information is relevant to the drivers' criteria of choice preference. None of these two assumptions has been examined in a real-world experiment. In addition, although the second of the two assumptions has been addressed in numerous publications [1], the first assumption remains under-researched; particularly when dealing with car drivers. Papinski and Scott [2] provide a good review of recent publications that have collectively explored more than twenty different variables to identify their relevance to drivers in route choice situations. On the other hand, in spite of the fact that driver perceptions of travel conditions is an important factor, it has not been given the same attention. Little attention has been given to the capability of drivers to accurately perceive traffic conditions; such as travel distance, time, speed, and traffic congestion levels.

Because of cost and past technological limitations, most travel research, in general, and route choice, in particular, is based on either stated preference surveys [3, 4] or travel simulators [5, 6]; both of which are characterized with serious limitations due to their inability to address the accuracy of travelers' perceptions. Stated preference surveys are surveys in which drivers answer questions about their behavior in hypothetical situations. Travel simulators are computer based programs that digitally display the choice situation and its characteristics for a participant. Then the participant makes his/her choice. There are guidelines to make these methods more realistic [7]. Nonetheless, since drivers do not actually live the choice situation, it is impossible for either of the two methods to capture drivers' perceptions of real-world traffic conditions.

Two other methods that have been gaining momentum for about a decade are driving simulators [8, 9] and GPS-based travel surveys [10, 11]. Driving simulators are vehicle-like structures that a person drives in a virtual environment. It uses a computer to display the environment exterior of the vehicle to the driver. In a driving simulator, the driver does actually drive through a virtual network in real-time. Alternatively, in a travel simulator, no driving happens. Driving simulators have been extensively used for safety research. Recently, however, researchers have started to use driving simulators for travel behavior analysis and research. GPS-based surveys are surveys based on actively logging the individuals' movements –usually– in a naturalistic setting. They are usually supplemented with a travel diary that is typically written by the participant. Limitations of GPS-based route choice surveys include the inability to infer the travel conditions on the alternative routes, nor to identify the choice set that the driver considers when making the route choice.

It is interesting that different experiments lead to different conclusions about the importance of the different variables considered [2]. One possible explanation for this lack of consensus is the level of reality of these experiments. Humans have been repeatedly found to behave irrationally; partly because of human perceptions which are never as accurate as reality. Human time perceptions have been extensively studied in other branches of transportation engineering; particularly public transportation. For example Moreau has found that perceptions of

wait time can significantly differ from actual times [12]. Other studies have shown that travel time perceptions can vary according to whether the time is spent traveling or waiting [13], whether the waiting time is expected or not [14], and whether the traveler experiences time drag [12]. Another recent study showed that travel time perceptions can vary according to the drivers' familiarity with the destination [15].

Surprisingly, although the capability of drivers to correctly perceive traffic conditions is critical in the value of traveler information systems, it remains an under-researched area. In a previous publication the authors analyzed driver experiences, perceptions, and choices in a driving simulator experiment [16] and identified four types of drivers [17]. However, no work exists that is based on a real-world experiment. This research effort was done with the intention of bridging this gap. This work is based on a real-world driving experiment where 20 drivers were asked to make more than 2,000 route choices in an actual in-situ experiment in real-world conditions. The drivers' choices and the prevailing traffic conditions were recorded. Additionally, at the end of the experiment the drivers were asked to report their choices and their perceptions of travel distances, travel times, travel speeds, and traffic levels.

In the following sections, the authors present the objectives of the study, followed by a detailed explanation of the study approach: study description, network and questionnaires. In the third section, the authors present the experimental results, perception models, and discussion. The fourth section ends the paper with the study conclusions and recommendations for further research.

STUDY OBJECTIVES

The main objectives of this study are to use actual real-world driving data to (a) evaluate the accuracy of driver perceptions of travel distance, travel time, and travel speed; (b) identify the factors affecting driver route choices; (c) compare between the expectations of stochastic user equilibrium and actual route choices; (d) explore whether correctness of driver perceptions can be predicted based on driver demographics, personality traits, and choice situation characteristics; and (e) identify factors that influence correctness of driver perceptions.

STUDY APPROACH

Study Description

A total of 20 participants were involved in this study. Each participant was asked to complete 20 experimental runs over 20 days during regular school week days of the academic spring semester of 2011. Experimental runs were scheduled only during one of three traffic peak hours: morning (7-8 am), noon (12-1 pm), and evening (5-6 pm). It should be noted that the 20 runs for a driver were done at the same time each day. During each experiment the participants were asked to drive research vehicles on the road network of the New River Valley. All participants were given the same five Google Map print outs. Each map representing one trip: one point of origin, one point of destination, and two alternative routes. For each experimental run, participants were asked to make these five trips assuming that the provided alternative routes were the only routes available between the points of origin and destination. The trips and the alternative routes were selected to ensure differences in the five choice situations (Table 1). All driver choices as well as the experienced travel conditions were recorded via a GPS unit placed on board of the vehicle and a research escort that always accompanied the participants. Participants were instructed to behave in the same manner they behave in real life. After completion of the 20 experiment runs, participants were asked to complete a post-task questionnaire.

It should be noted that in this experiment, each trip represented a choice situation for the participants. Hence, in many occasions in this paper the terms "trips" and "choices" have the same meaning and are used interchangeably.

Incentives

Since route choice behavior is documented to vary with trip purpose, a couple of measures were designed to ensure that participants will not consider the experiment as leisure. First, participants' compensation was not a function of the time spent in the experiment; participants were provided a flat monetary amount per experiment regardless of how long it took them. Second, the experiment was not entertaining (experimental routes were not scenic, and participants were not allowed to listen to any entertainment, use their cellphone, or chat with the research escort). Hence, if any, participants had stealth incentives to reduce their experiment (and travel) times.

Network

Table 1 demonstrates the origin, destination, and alternative routes specific to each of the five choice situations. It also shows a brief description of each of the routes. More information about the routes can be seen in Figure 1 and are provided in Table 2. Figure 1 shows a map depicting all five points of trip origins and destinations as well as the ten alternative routes provided.

Table 1: Description of the Five Trips

Trip #	Trip Origin	Trip Destination	Alternative Routes		Route Description (and speed limits)
			Route #	Route Name	
1	Point 1 (VTTI)	Point 2 (Walmart)	Route 1	US460 Bypass	Mostly a high speed (65 mph) freeway
			Route 2	US460 Business	High speed (45 mph) urban highway
2	Point 2 (Walmart)	Point 3 (Foodlion1)	Route 3	Merrimac	Mostly a shorter, low speed (30 mph) back road with a lot of curves
			Route 4	Peppers Ferry	Mostly a longer, high speed (55 mph) rural highway
3	Point 3 (Foodlion1)	Point 4 (Foodlion2)	Route 5	US460 Bypass	A longer high speed (65 mph) freeway followed by a low speed (25 mph) urban road
			Route 6	N. Main St.	A shorter urban route (40 and 35 mph)
4	Point 4 (Foodlion2)	Point 5 (Stadium)	Route 7	Toms Creek	A short urban route that passes through campus (25 and 35 mph)
			Route 8	US460 Bypass	Primarily a long high speed (65 mph) freeway and low speed (25 mph) urban roads
5	Point 5 (Stadium)	Point 1 (VTTI)	Route 9	S. Main St.	A long urban road that passes through town (35 mph)
			Route 10	Ramble St.	A short unpopular low speed (25 and 35 mph) back road that passes by a small airport.

Pre-task Questionnaire

The pre-task questionnaire collected information about the participants' demographics (age, gender, ethnicity, education level, etc.) and driving experiences (number of driving years, annual driven miles, etc.).

Post-task Questionnaire

The post-task questionnaire was divided into two sections. The first section collected information about the participants' perceptions of the traffic conditions on the alternative routes (distance,

travel time, travel speed, and traffic level), as well as the participants preference levels of the routes. In the second section the participants were asked to fill in a personality inventory, the NEO Personality Inventory-Revised [18], which measures five personality traits: Neuroticism Extraversion, Openness to Experience, Agreeableness, and Conscientiousness.

Figure 1: Map of the Experiment Network (Source: Google Maps)

RESULTS AND ANALYSIS

This section starts with presenting the travel conditions that were experienced by the drivers during the experiment, followed by the drivers' perceptions and choices. Next, the accuracy of the driver perceptions is evaluated by contrasting them against their experiences. After that the driver choices are matched against their experiences and their perceptions of the study travel variables. Lastly, models of travel perceptions are developed and presented.

Driver Experiences

In this section the characteristics of the alternative routes as well as the recorded driver experiences of travel time and travel speed are presented.

General Route Characteristics

Table 2 presents the characteristics of the ten routes. As mentioned earlier and can be seen from the table, the trips and alternative routes were selected so that the characteristics of the alternatives were to vary across the five choice situations.

Travel Times and Travel Speeds

Table 3 presents the cumulative frequency distributions of the experienced travel times and travel speeds during the study. Table 3 also presents the probability, based on a Monte Carlo simulation, that the odd-number route is a better choice than the even-number route, either by being shorter in travel time (TT) or faster in travel speed (TS). It is worth noting that by design the shorter travel time routes were not necessarily the faster travel speed routes.

Table 2: Characteristics of the Alternative Routes Per Trip

Trip #	Route #	Distance (km)	Avg. Travel Time (min)	Avg. Travel Speed (kph)	Number of Intersections		Number of Left Turns	Number of Merges and Diverges	Number of Horizontal Curves
					Signalized	Unsignalized			
1	1	5.1*	8.5	36.4	10	3*	3*	1*	2*
	2	6.0	8.4*	43.3*	5*	4	4	5	3
2	3	11.1*	15.2*	42.6	5	2	3	1*	30
	4	17.4	16.7	63.2*	2*	2	2*	2	11*
3	5	5.8	7.7*	44.5*	5*	3	3	2	2
	6	5.5*	9.3	37.8	8	3	2*	1*	2
4	7	5.0*	10.2	29.5	5*	3	4	1*	0*
	8	7.7	9.6*	48.2*	6	2*	2*	4	1
5	9	5.8	10.5	33.3	8	4	4	1*	1*
	10	4.7*	8.0*	34.0*	3*	1*	3*	2	6

* Better route

Table 3: Experienced Route Travel Times (TT) and Travel Speeds (TS) Per Trip

Trip	Travel Time		Travel Speed	
	Cumulative Distribution	Monte Carlo Simulation	Cumulative Distribution	Monte Carlo Simulation
1		Prob. $(TT_{R1} < TT_{R2})$ = 48.3%		Prob. $(TS_{R1} > TS_{R2})$ = 26.6%
2		Prob. $(TT_{R3} < TT_{R4})$ = 78.5%		Prob. $(TS_{R3} > TS_{R4})$ = 0.1%
3		Prob. $(TT_{R5} < TT_{R6})$ = 85.4%		Prob. $(TS_{R5} > TS_{R6})$ = 91.8%
4		Prob. $(TT_{R7} < TT_{R8})$ = 35.2%		Prob. $(TS_{R7} > TS_{R8})$ = 0.2%
5		Prob. $(TT_{R9} < TT_{R10})$ = 5.0%		Prob. $(TS_{R9} > TS_{R10})$ = 40.0%
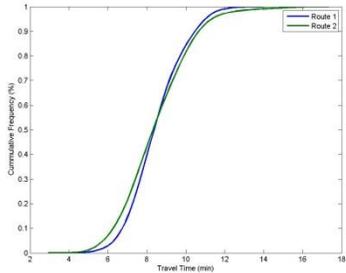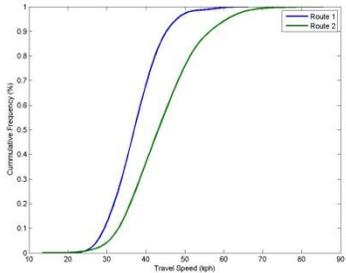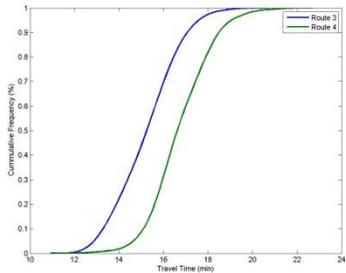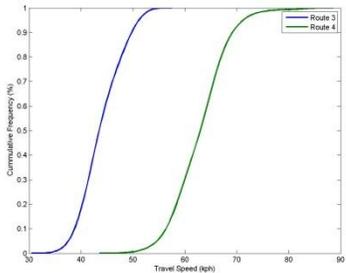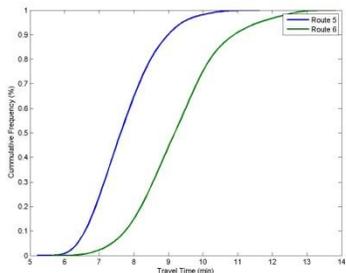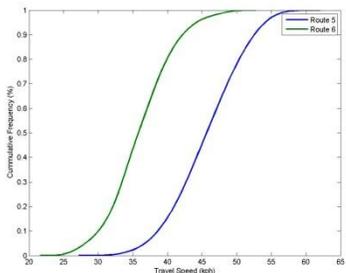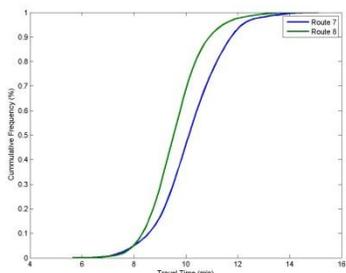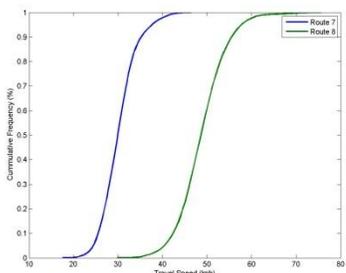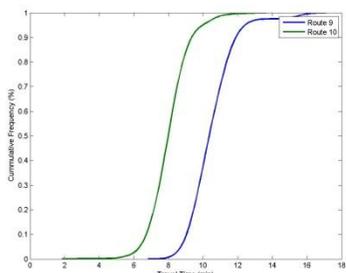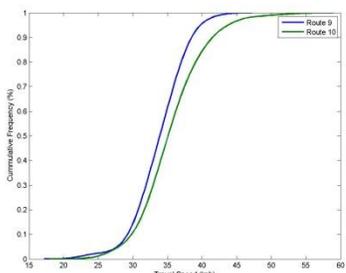
Driver Perceptions

Driver perceptions of route distances, travel times, travel speeds, and traffic levels are presented in Figure 2. The correctness of these perceptions is investigated later in this section.

Driver Choices

Driver choices were captured by two different measures: first, the choices that the drivers reported in the post-task questionnaire, and second, the choices that were made and recorded during the 20 runs of the experiment. Figure 3 presents both measures. The latter measure, however, is presented in two figures: one for the recorded driver choices on all 20 trials and another for the recorded choices in only the last 5 trials. It can be seen that the recorded choices on the last 5 trials are closer to the declared choices in the post-task questionnaire, than the choices made throughout the entire experiment. This is reasonable because a good percentage of the choices made early in the experiment were for exploratory rather than preference reasons.

Experiences vs. Perceptions

Comparing driver experiences to their perceptions is based on two groups of experiences and three groups of perceptions. The two groups of experiences are: i) drivers who tried both routes and as a result have recorded experiences on both routes, and ii) drivers who tried only one of the two alternative routes (they never tried the other route) and thus have recorded experiences for only one of the two alternatives. On the other hand, the three groups of driver perceptions are: i) drivers whose perceptions match their recorded experiences, ii) drivers whose perceptions contradict their recorded experiences, and iii) drivers who do not perceive a difference between the alternative routes. Figure 4a, 4b and 4c present the results of cross examining these two groups of experiences and three groups of perceptions over the entire experiment. It should be noted that it is not possible to judge the correctness of the perceptions of the drivers who have experienced only one of the two routes; because they have no recorded experiences on the other route. Figures 4d, 4e and 4f present the results for only the drives that experienced both alternatives in our experiment, broken down by choice situation.

It is particularly surprising that driver perceptions of distance, which is a deterministic value, are the least accurate, and driver perceptions of travel time and travel speed, which are both stochastic variables, are more accurate. This, however, may be explainable by hypothesizing that distance was not an important factor in the study choice alternatives. Hence, drivers did not pay much attention to their travel distance perceptions. Nonetheless, it is worth noting that the percentage of opposite distance perceptions is lower than the corresponding percentages in travel time and travel speed.

It is quite interesting that driver perceptions of travel speed were more accurate than their perceptions of travel time. Following the same explanation provided for the inaccuracy of distance perceptions: this could imply that travel speed was a more important factor than travel time in this study choice situations. Hence, the drivers paid more attention to their perceptions of travel speed than to travel time. In a different paper [19], both travel time and travel speed were found to be significant in explaining the probability of route switching.

As expected, looking at the driver perceptions of the travel conditions per trip shows that the higher the difference between the two alternative routes is, the more accurate are the driver perceptions. In other words, the more salient the signal, the more likely it is to be correctly perceived. This is a well-established theory in human factors.
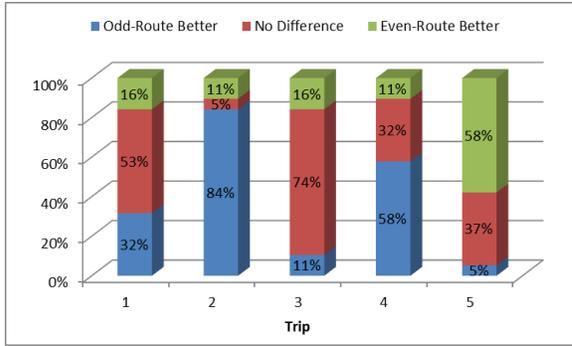
Figure 2a: Travel Distance Perceptions
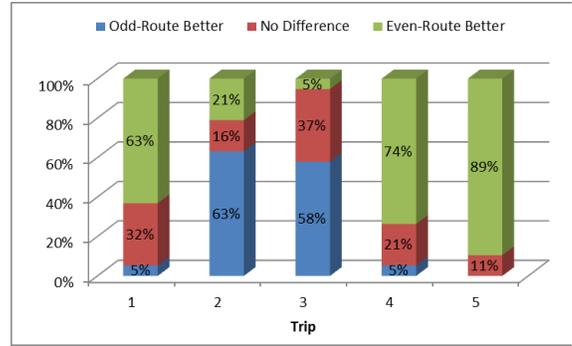
Figure 2b: Travel Time Perceptions
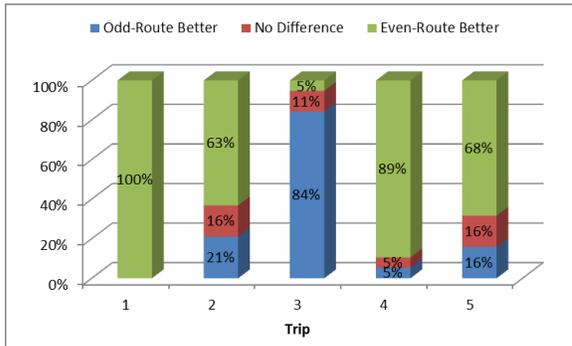
Figure 2c: Travel Speed Perceptions
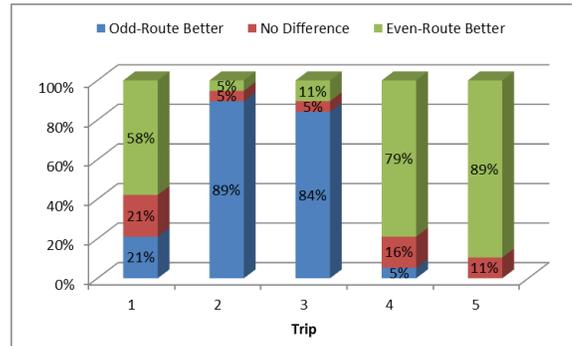
Figure 2d: Traffic Level Perceptions

Figure 2: Drivers Perceptions of Travel Distance, Travel Time, Travel Speed, and Traffic
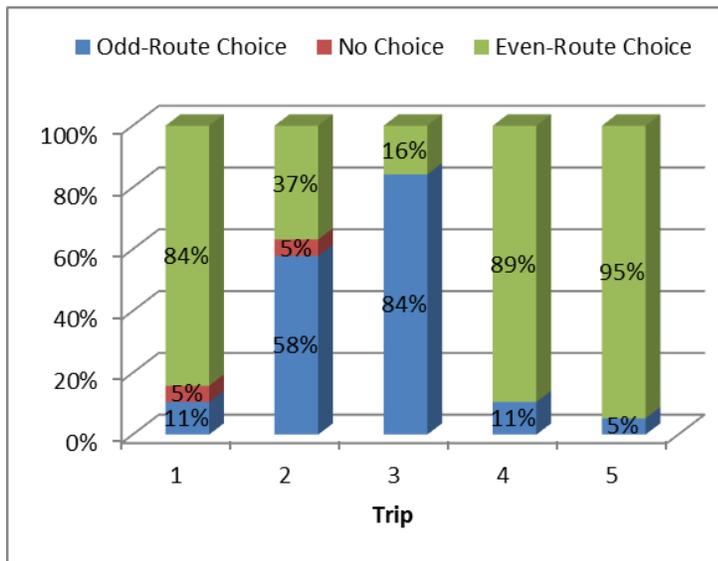
Figure 3a: Stated Route Choices in the Post-task Questionnaire
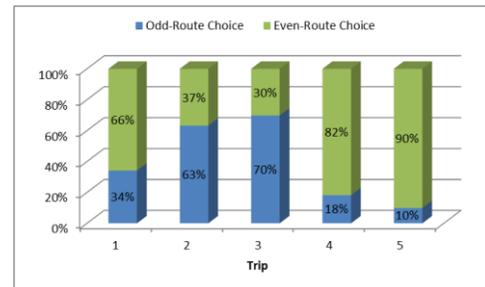
Figure 3b: Recorded Choices in All Trials
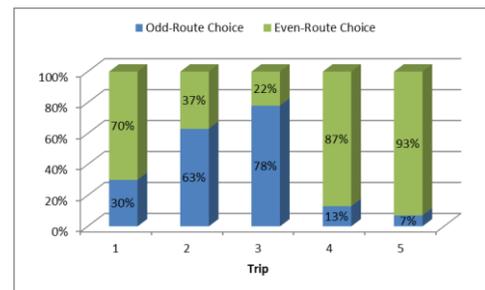
Figure 3c: Recorded Choices in Trials 16-20

Figure 3: Driver Route Choices

Experiences vs. Choices

Contrasting the driver experiences against their choices on an aggregate level reveals a rather interesting and important finding. According to the stochastic user equilibrium (SUE) theory, trips are distributed on the network in such a manner that the resulting probability of choosing a route over an alternative route equals the expected probability that the travel time on the chosen route is lower than the travel time on the alternative route. According to SUE, the travel time percentages based on a Monte Carlo simulation, presented in Table 3, are expected to equal the percentages of the choices presented in Figure 3. For convenience, the values of the Monte Carlo simulation (Table 3) and the choice percentages (Figure 3) are compiled and presented in Table 4. Analyzing Table 4 reveals that the SUE expectations seem to hold for trips 3 and 5, but do not hold for Trips 1, 2, and 4. This could be attributed to the fact that the difference in travel times between the alternative routes was high for trips 3 and 5 and thus drivers were able to perceive travel time differences between the two routes. For trip 4, although the travel time difference was also high, the difference between SUE expectations and actual choices could be attributed to travel time reliability. In the post-task questionnaire many of the drivers said they did not want to risk being caught in campus traffic.
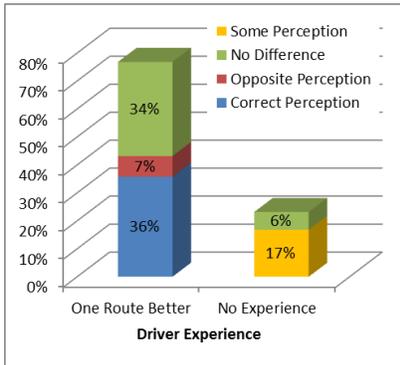
Figure 4a: Travel Distance   Figure 4b: Travel Time   Figure 4c: Travel Speed
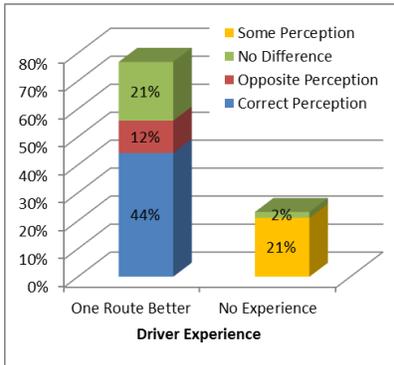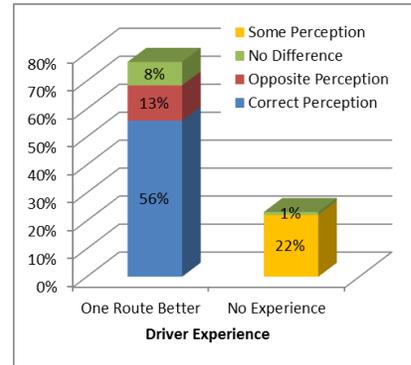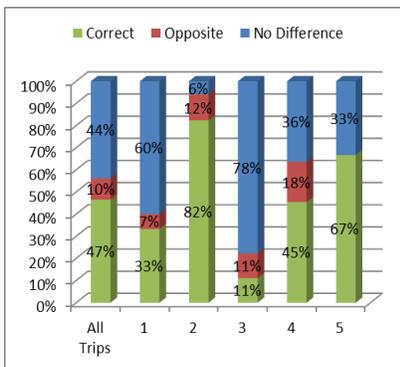
Figure 4d: Travel Distance Per Trip   Figure 4e: Travel Time Per Trip   Figure 4f: Travel Speed Per Trip
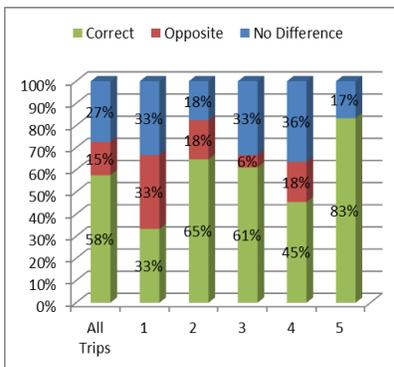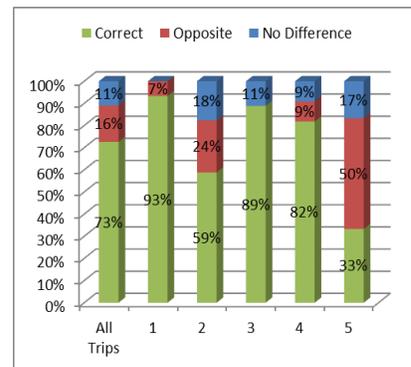
Figure 4: Cross Examining Experiences and Perceptions of Drivers Travel Time, Travel Speed and Distance

Table 4: Difference Between SUE Expected Probabilities and Actual Choice Percentages

Measure / Trip #	1	2	3	4	5
SUE: Prob. ($TT_{Odd-Route} < TT_{Even-Route}$) based on Monte Carlo Simulation	48%	79%	85%	35%	5%
Percentage of drivers choosing odd-route based on reported choices in the post-task questionnaire	11%	58%	84%	11%	5%
Difference between SUE probability and actual choice percentages	37%	21%	1%	24%	0%

In an attempt to better understand the reasons behind the difference between SUE expectations and aggregate choice percentages, driver experiences are compared against their choices on a disaggregate level (as presented in Figure 5). This comparison reveals other interesting findings. Figure 5 shows that the driver reported choices in the post-task questionnaire are better explained by their travel time experiences than by their travel distance or travel speed experiences. This can imply that travel time may be a better explanatory variable in the study's choice situations than the travel distance and travel speed. This implication contradicts the earlier explanation provided for the more accurate perceptions of travel speed, in comparison to the perceptions of travel time and travel distance.
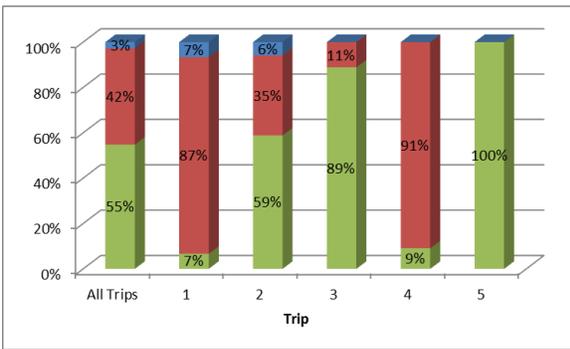
Figure 5a: Distance Experiences vs. Choices
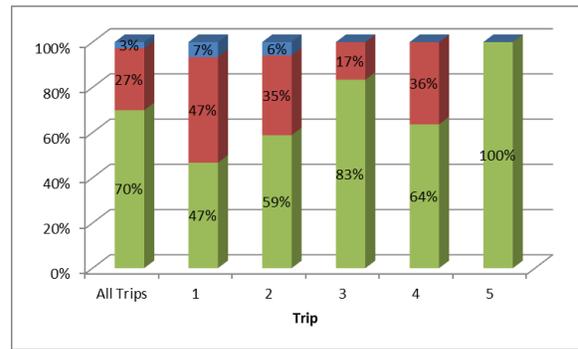
Figure 5b: Travel Time Experiences vs. Choices
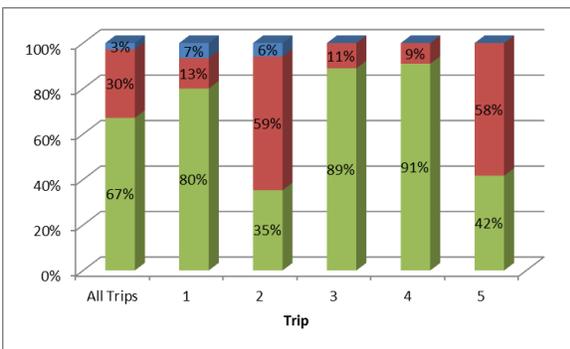
Figure 5c: Travel Speed Experiences vs. Choices

Figure 5: Driver Disaggregate Experiences versus Reported Choices

It is expected that if all drivers were to perceive travel times correctly, and to choose the minimum travel time routes, then the expectations of the SUE should coincide with the route choice percentages. It is interesting to note that this may in fact be observed from the results. Trips 3 and 5 (where the expectations of the SUE coincide with the percentage of actual choices) exhibit the least percentage of choices that are opposite to the driver travel time experiences. On the other hand, Trip 1 (where the expectation of the SUE is farthest from the percentage of actual choices) demonstrates the highest percentage of choices that are opposite to the travel time experiences. Furthermore, the last two trips (Trips 2 and 4) are almost equal in terms of the difference between: i) SUE expectations and actual choice percentages, and ii) percentage of choices that are opposite to travel time experiences. As mentioned earlier, a possible explanation for trips 3 and 5 is the relatively high difference in travel time between the alternative routes. In the case of trip 4, travel time reliability could provide a reasonable explanation.

Figure 6 shows a comparison between drivers travel time experiences and their recorded choices during the experiment (not the reported choices in the post task questionnaire). As in Figure 4, the recorded choices are considered during the entire experiment (Figure 6a), and also considered in only the last five trials (Figure 6b) which reflects more network experience. As was noticed in Figure 4, the percentages of the last five trials are closer to those that are reported in the post task questionnaire (Figure 5b). This shows evidence of driver learning.
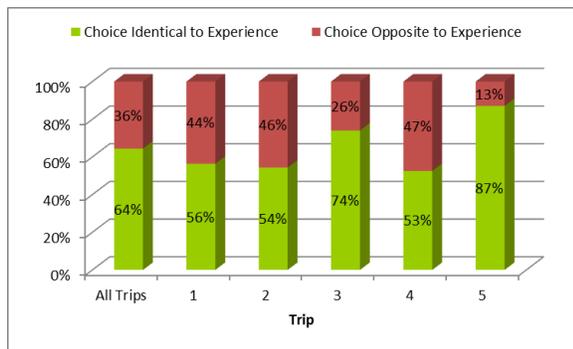
Figure 6a: Travel Time Experiences vs. Recorded Choices in all Trials
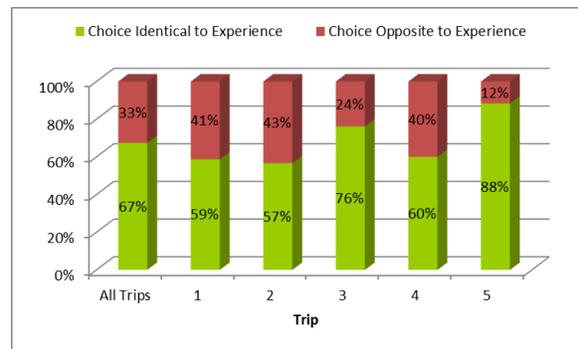
Figure 6b: Travel Time Experiences vs. Recorded Choices in Trials 16 to 20

Figure 6: Driver Disaggregate Travel Time Experiences versus Recorded Choices

It is worth noting that up till this point all driver experiences were based on the average of all previous trials. The following equation was used for the calculation of the average experienced travel time. The average experienced travel speed was calculated similarly.

$$AETT_{irt} = \frac{\sum_{t=1}^{t-1} \delta_{irt} \cdot TT_{it}}{\sum_{t=1}^{t-1} \delta_{irt}}$$

where,

$AETT_{irt}$ is the average experienced travel time of person i on route r up till trial t
δ_{irt}=1 if person i chooses route r at trial t, and 0 otherwise
TT_{it} is the travel time experienced by person i at trial t

In a recent publication, Bogers et al. [5] found that 20% of driver perceptions of travel time came from their latest route experience. Calculating the experienced travel time as a Markov process according to the following equation results in percentages of identical and opposite

choices that are slightly different from the ones presented in Figures 5 and 6. Figure 7a presents the percentage of choices that are identical to the drivers' (Markov-process) experienced travel times in the entire experiment based on different values of Lambda (Markov factor). It can be seen that in this study, the maximum percentage of identical experiences and choices is based on a Markov factor of 0.25. It is worth noting that comparing Figures 6a and 7b reveals that the usage of the Markov process experienced travel times improved the overall percentage of identical experiences and choices by only 1%. Furthermore, this improvement was not sustained across all choice situations. This implies that the Markov process updating of experienced travel times was not different from the average-based calculations.

$$ETT_{irt} = \lambda \cdot \delta_{ir[t-1]} \cdot TT_{i[t-1]} + \lambda \cdot \left(1 - \delta_{ir[t-1]}\right) \cdot ETT_{ir[t-1]} + (1 - \lambda) \cdot ETT_{ir[t-1]}$$

where,

ETT_{irt} is the experienced travel time of person i on route r up till trial t

λ is the Markov process factor

δ_{irt}=1 if person i chooses route r at trial t, and 0 otherwise

TT_{it} is the travel time experienced by person i at trial t
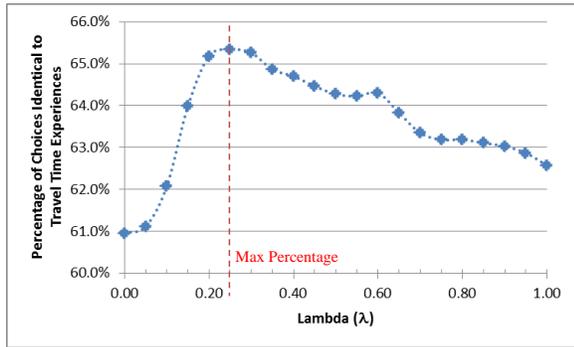
Figure 7a: Percentage of Identical Choices and Travel Time Experiences as a Function of Lambda
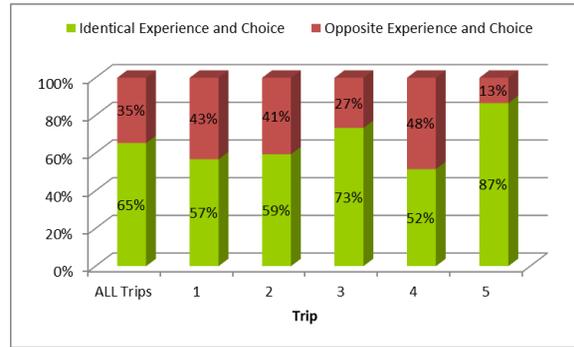
Figure 7b: Markov Process Travel Time Experiences vs. Recorded Choices in All Trials

Figure 7: Driver Disaggregate (Markov Process) Travel Time Experiences versus Recorded Choices

The percentage of choices that are opposite to the experiences in all cases explored in this section was always high and greater than one third of all choices; regardless of the measure used (aggregate or disaggregate; distance, travel time, or travel speed; and average-based or Markov process based travel time). Two possible explanations for such a behavior are either: i) drivers were unable to perceive the travel conditions correctly, or ii) drivers are not making their route decisions based on any of the above explored factors. To investigate the possibility of the first explanation, the following section compares driver choices to their perceptions.

Perceptions vs. Choices

Analyzing driver perceptions with their choices gives rise to three types of behavior: rational, irrational, and heuristic. Rational behavior connotes drivers who choose the route they perceive to be better, or perceive no difference between the alternative routes and make no choice. Irrational behavior signifies drivers who choose a route that they perceive to be worse, or who do not choose any of the routes in spite of perceiving one of the routes to be better. Last, heuristic behavior reflects drivers who perceive no difference between the routes, yet make a choice.

Figure 8 presents the percentages of these three types of behavior when contrasting driver choices against their distance, travel time, travel speed, and traffic perceptions. The figure demonstrates that driver choices can be best explained by their travel time perceptions; since it is characterized with the minimal percentage of irrational behavior. It also shows that while travel speed and traffic perceptions come second in explaining driver choices (after travel time), distance perceptions come last and are characterized with the highest percentage of irrational behavior.
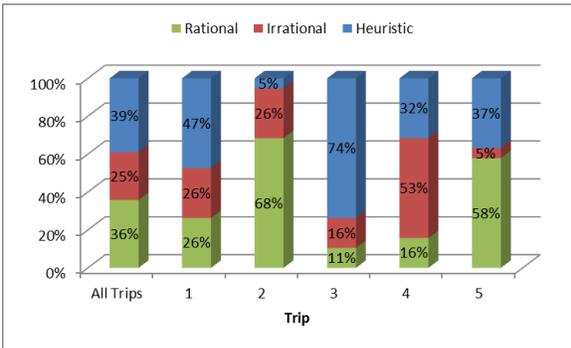
Figure 8a: Travel Distance Perceptions versus Choices
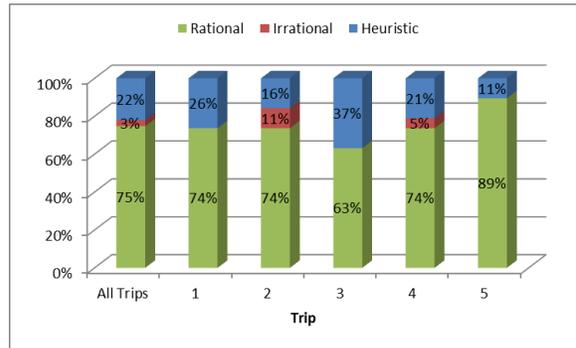
Figure 8b: Travel Time Perceptions versus Choices
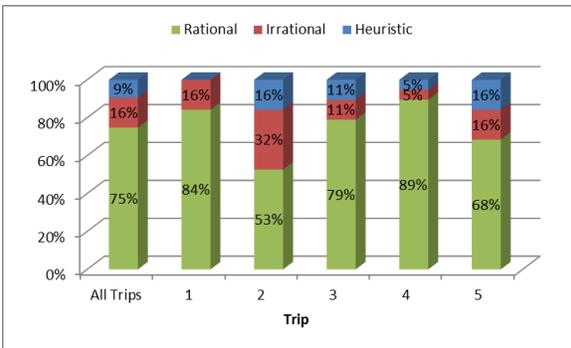
Figure 8c: Travel Speed Perceptions versus Choices
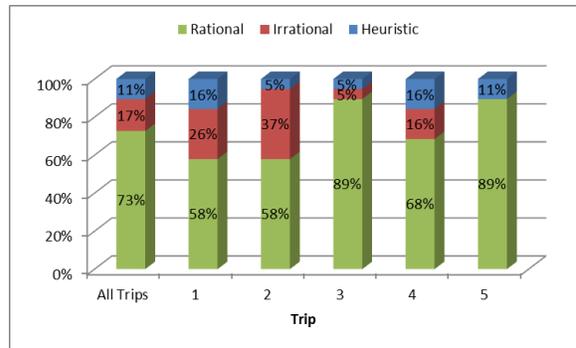
Figure 8d: Traffic Level Perceptions versus Choices

Figure 8: Driver Choices versus Perceptions of Travel Distance, Time, Speed, and Traffic

It is interesting that none of the drivers made any irrational choices in trips 1, 3, and 5 (based on travel time perceptions). Irrational behavior was identified only for trips 2 and 4. For trip 2 it is possible that the drivers –correctly – perceived route 3 to be the lower travel time route, yet for safety reasons (because route 3 has many vertical and horizontal curves) they decided to choose the longer travel time route. A possible explanation for the irrational behavior of trip 4, on the other hand, may be attributed to travel time reliability. It is possible that the drivers perceived route 8 to be the shorter travel time route. Yet, because route 8 passed through the school campus they were reluctant to choose this route and risk being caught in campus traffic.

It is interesting to note that while travel time perception was, in general, the best explanatory variable of driver choices, other variables were better at explaining the choices for trips 1, 3, and 4. For example, in the case of trips 1 and 4, travel speed perceptions provide a better explanation for driver choices, and on trip 3, traffic perceptions provide a better explanation for drivers choices. In addition, for trip 5, traffic perceptions are at least as good as travel time perceptions. Examining the mean travel times of the alternative routes of trips 1 and 4 reveals that they are the closest in comparison to the other three trips. This suggests the

possibility that in case of close travel time routes, drivers prefer the faster speed route. The traffic perception observation for trip 3 reinforces the reasoning given in the previous paragraph: drivers were choosing the other route to avoid campus traffic, or in other words drivers were picking the more reliable route. The same reasoning can partially apply to trip 5 where drivers were choosing the lower travel time route that also had less traffic.

Recalling that driver perceptions of travel speeds were more accurate than their perceptions of travel times, and keeping this in mind while exerting a closer look at Figure 8 reveals a number of intriguing findings. It could explain the lower percentage of heuristic behavior (drivers who perceived no difference and made a choice) and higher percentage of rational behavior in trips 1, 2 and 4 of Figure 8c (travel speed) as compared to those of Figure 8b (travel time).

Perception Models

According to the previous sections, travel perceptions seem to be a much better predictor for driver choices than travel experiences. Accordingly, identifying factors that influence travel perceptions could be very beneficial from two different perspectives. From the modeling perspective, incorporating models of driver perceptions in transportation models can improve the fidelity of the model outcomes. On the other hand, from the perspective of Intelligent Transportation Systems (ITS), identifying drivers that are less capable of achieving correct travel perceptions highlights a target market for ITS services. This section presents perception models for three travel variables: travel distance, travel time, and travel speed.

Response Variable

The modeled response is an ordinal three-level perception. The lowest level is an opposite perception, the middle level is a no-difference perception, and the highest level is a correct perception. Three different models were estimated: travel distance perceptions, travel time perceptions, and travel speed perceptions.

Independent Variables

The independent variables investigated in this work are presented in Table 5. As can be seen in the table, four groups of covariates are considered: driver demographics, driver personality traits, driver experiences, and driver stated familiarity with the choice situations prior to the experiment.

Model Structure

The model used is an ordered mixed effects generalized linear model with a probit link function. Because each driver was asked about his/her perception on five different choice situations, one random parameter, the intercept, is estimated over all individuals instead of all observations. This takes into account the average dependence effects between observations of the same driver. The model has the following structure.

$$y_{ic} \sim Multin(p_{ic1}, p_{ic2}, p_{ic3})$$
$$p_{icm} = \Phi\{\zeta_m - (x'_{ic}\beta + \theta_i)\} - \Phi\{\zeta_{m-1} - (x'_{ic}\beta + \theta_i)\}$$
$$\theta_i \sim N(0, \varphi)$$

where,
$y_{ic} = 1$ if person i's perception at choice situation c is correct
$y_{ic} = 0$ if person i perceives no difference at choice situation c
$y_{ic} = -1$ if person i's perception at choice situation c is opposite
Multin is the Multinomial distribution

p_{icm} is the probability that person i's perception at choice situation c will be of level m

m is the responce level {1: opposite, 2: no difference, 3: correct}

Φ is the cumulative Normal distribution function

ζ_m is the break point for response level m $(-\infty = \zeta_0 < \zeta_1 = 0 < \zeta_2 < \zeta_3 = \infty)$

x_{ic} is the vector of covariates for person i at choice situation c

β is a vector of the parameters

θ_i is the random component of person i

N is the Normal distribution

φ is the variance

Model Results

Table 6 presents the results of the estimated models. It is satisfying that variables belonging to three of the investigated variable groups were found significant. The only group of variables that was not found significant is the driver stated familiarity with the choice situation prior to the experiment. This too is satisfying because it could imply that the twenty experiment runs were sufficient for the drivers to construct adequate experience with the choice situations. Furthermore, the number of switches seems to have a positive effect on constructing correct perceptions on travel distances; implying that the more times a driver experiences the alternative routes, the more accurate are the driver's perceptions of the differences between the two routes. The same variable was possibly not found significant in travel time and speed perceptions because of the stochastic nature of these variables, which makes correct perceptions more difficult.

None of the estimated model parameters seems to be illogical. In general as the signal strength for travel distance, time, or speed increased (i.e. became more salient), the more accurate were the drivers perceptions of travel distance, time, and speed, respectively. As the age of the drivers increased and as the number of driving years increased, drivers' perceptions of travel time and distance decreased, respectively. Three possible explanations for this are: a) older drivers cognitive abilities are lower than those of younger drivers; b) older drivers have more to think about than younger drivers, therefore have less attention resources to assign to travel conditions; or c) as a driver becomes more accustomed to driving, the driver becomes less sensitive about driving a few extra minutes or miles and loses some interest in continuously trying to evaluate differences in travel conditions.

The signs of the personality trait variables also seem logical. First it is probably expected that correct perceptions are positively related to conscientiousness. Similarly, agreeableness was found to be positively related to correct perceptions. Of all variables, this is probably the least intuitive relation. A possible explanation for this is that: as presented in Figures 4d, 4e and 4f, driver perceptions were generally more correct than not. Hence, if a driver relies more on the collective judgments of others, this driver is more likely to construct correct perceptions. On the other hand, driver perceptions seem to be inversely related to their openness to experience. Although this might not seem intuitive for a reader that is unfamiliar with the personality traits, the authors believe it is logical. Openness to experience measures six facets. These are: fantasy, aesthetics, feelings, actions, ideas and values. It seems logical that when a driver that is more open to experience switches and tries alternative routes, this driver will be focusing on other aspects that are more closely related to the six listed facets than focusing on comparing the travel conditions. In addition, in another article, openness to experience was found to be inversely related to the probability of route choice switching. Decreased switching implies decreased experience of the alternative routes, which in turn, can result in a decrease in the probability of correct perceptions.

Table 5: Perception Model Independent Variables

#	Variable Names	Variable Description	Variable Values
Variables of Driver Demographics			
1	Age_i[*]	Age of participant i	18 to 68
2	$Gender_i$	Gender of participant i	M or F[**]
3	$Ethnicity_i$	Ethnicity of participant i	W or NW[**]
4	$Education_i$	Education level of participant i	G or NG[**]
5	$DrYears_i$[*]	Number of years participant i has been a licensed driver	2 to 57
6	$Dr\,Miles_i$	Annual number of miles participant i drives (thousands)	2 to 35
7	$Residency_i$	Number of years participant i has been residing in the area	1 to 56
Variables of Driver Personality Traits			
1	N_i	Neuroticism of participant i	7 to 30
2	E_i	Extraversion of participant i	19 to 43
3	O_i	Openness to experience of participant i	20 to 31
4	A_i	Agreeableness of participant i	22 to 42
5	C_i	Conscientiousness of participant i	26 to 47
Variables of Driver Experience [***]			
1	$TDPrc_c$	Percentage difference in experienced distance between the two alternative routes of choice situation c	5.7 to 44.8
2	$TTPrc_{ic}$[****]	Percentage difference in mean experienced travel times by driver i between the two alternatives of choice situation c	0.2 to 46.1
3	$TTVPrc_{ic}$[****]	Percentage difference in mean experienced travel time variances by driver i between the two alternatives of choice situation c	2.9 to 180.5
4	$TSPrc_{ic}$[****]	Percentage difference in mean experienced travel speeds by driver i between the two alternatives of choice situation c	0.1 to 49.0
5	$TSVPrc_{ic}$[****]	Percentage difference in mean experienced travel speed variances by driver i between the two alternatives of choice situation c	0.9 to 188.9
6	$Switches_{ic}$	Number of switches driver i made during his/her 20 experiment runs of situation c	1 to 13[*****]
Variables of Driver-Choice Combination			
1	$PriorAvgFam_{ic}$	Stated average familiarity of driver i with the two routes of choice c prior to experiment	1 to 5
2	$PriorMaxFam_{ic}$	Stated maximum familiarity of driver i with the two routes of choice c prior to experiment	1 to 5

[*] Because of the high correlation between Age and DrYears, the two variables were not allowed to be in the same model at the same time

[**] M: male, F: female, W: white, NW: non-white, NG: no post-graduate degree, G: post-graduate degree

[***] Percentage difference calculated as difference between experiences on the two routes divided by the average of the two routes

[****] All travel time and travel speed calculations are based on actual driver experiences; collected GPS data

[*****] Drivers that have not experienced both routes were dropped from the analysis because of missing experience data

The effect of travel speed and travel distance experiences seem to be inversely related to the correct perceptions of travel distance and travel speed perceptions, respectively. This seems logical given that in a previous section travel time was found to be the best variable that explains

route choices. Since travel time is directly proportional to distance and inversely proportional to speed, it seems logical that the effects of drivers travel distance and speed experiences are inversely related. Last, as differences in travel speed were more salient, drivers were more capable of perceiving travel time differences correctly. This finding might be specific to this experiment, because in this experiment faster speed routes were in aggregate also characterized with lower travel times, as presented in Table 3.

To be able to compare the importance of the different variables on driver perceptions, all variable values were normalized (with the exception of nominal variables). Hence, the absolute values of the estimated model parameters can reasonably reflect the relative importance of these variables in the estimated models. With this in mind, it is extremely interesting that variables of personality traits seem to be as important as – and sometimes more important than – variables of travel experience. This finding underscores the possible benefits of incorporating variables of personality traits in travel behavior models.

Table 6: Significant Variables of the Driver Perception Models[*]

Variables	Perception Models					
	Travel Distance		Travel Time		Travel Speed	
	Beta	p-value	Beta	p-value	Beta	p-value
(Intercept)	1.927	0.000	1.258	0.000	1.938	0.000
Age	n/s	n/s	-0.544	0.011	n/s	n/s
EducationG	2.090	0.001	n/s	n/s	n/s	n/s
DrYears	-0.711	0.004	n/s	n/s	n/s	n/s
O	-0.716	0.015	n/s	n/s	-0.950	0.008
A	0.503	0.077	n/s	n/s	0.577	0.096
C	n/s	n/s	0.733	0.003	n/s	n/s
Switches	0.597	0.024	n/s	n/s	n/s	n/s
TDPrc	0.981	0.002	n/s	n/s	-1.285	0.001
TTPrc	n/s	n/s	0.669	0.009	n/s	n/s
TSPrc	-0.590	0.045	0.409	0.043	0.858	0.009
ζ_2	2.984	0.000	1.199	0.000	0.769	0.003

[*] n/s stands for not significant

STUDY CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

In this work, a real-world route choice experiment was conducted with the objective of investigating the capability of drivers to accurately perceive travel conditions (travel distance, time, and speed) and to explore the real-world reasons that govern driver route choice decisions. Route choice literature is dense with studies about reasons of route choices; however, only a few of these studies are based on a real-world experiment and, particularly in route choice, very little attention has been given to the accuracy of driver perceptions. This work was conducted on a sample of 20 drivers that were each faced with 5 route choice situations and who collectively made more than 2,000 real-world choices. All the driver choices and the prevailing conditions

were recorded, and in this work the drivers experienced travel conditions, reported perceptions, and recorded choices were contrasted and analyzed.

It was found that driver perceptions were, in general, around only 60% accurate. The drivers were able to perceive travel speeds best and travel distances least; with travel time perceptions being in between. It was also observed that the greater the difference in a characteristic between the alternative routes, the more accurate was the driver perceptions.

Comparing the aggregate distributions of experienced travel times to the actual choice percentages showed that the differences between expectations of the stochastic user equilibrium and reality ranged between 0% and 37%, with an average difference of approximately 15%,. On the other hand, comparing the experiences to the choices on a disaggregate level showed that travel times were, in general, the best factor to explain choices with a success rate of 70%, followed by travel speed. Travel distance was the worst of the three.

Contrasting driver perceptions to their choices revealed that, in general, travel time was the best factor in explaining route choices, followed by travel speed, then traffic and lastly distance. However, the results indicated instances where travel speed and traffic perceptions explained driver choices better than travel time. These findings indicate that route choice should not be modeled based on travel time only. Although all travel times explored were based on the average of all previous trials, a Markov-process-based travel time was also explored. It was not found to represent driver experiences or perceptions any better than the use of average travel times.

Finally, models of driver perceptions were estimated. Variables belonging to driver demographics, personality traits, and route experiences were found significant in predicting correct predictions of travel conditions. As expected, the salience of signal strength was found significant for correct predictions. However, it is extremely interesting that for correct predictions, variables of personality traits were found to be as important as variables of travel experiences.

The findings of this work could be insightful; especially if successfully replicated. A number of further research directions include: the investigation of possible events that could result in the change of driver preference; examining if the same results could be replicated in a travel or a driving simulator; and examining the compliance of drivers to information in a real-world experiment.

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Part II: Real-World Driving Experiment

Chapter 7

Network Route-Choice Evolution in a Real-World Experiment: A Necessary Shift from Network to Driver Oriented Modeling

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Network Route-Choice Evolution in a Real-World Experiment: A Necessary Shift from Network to Driver Oriented Modeling

Aly M. Tawfik, MS
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 577-0462
FAX: (540) 231-7532
tawfik@vt.edu

Hesham A. Rakha, PhD., P.Eng.
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 231-1505
FAX: (540) 231-1555
hrakha@vt.edu

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ABSTRACT

Route choice models are a corner stone in many transportation engineering applications. Two main types of route choice models can be found in the literature: first, mathematical network oriented models such as stochastic user equilibrium, and second, behavioral driver oriented ones like random utility models. While the former models are much more widely used in the transportation engineering realm, evidence of its inadequacy is growing continuously. The degree of its inadequacy, however, remains debatable. Two major critiques for the theory are its unrealistic assumptions of human perceptions and its inability to incorporate driver heterogeneity. On the other hand, attempts to incorporate driver heterogeneity in the behavioral driver oriented route choice models, too, are still short. Another major limitation in all literature is that due to cost limitations, only few studies are based on real-life experiments. Most studies are based on either stated preference surveys or travel simulators. With this in mind, this work is done based on a real-world route choice experiment of a sample of 20 drivers who made more than 2,000 real-world choices. Network and driver learning evolutions were recorded and analyzed. The findings of the experiment include the following: a) with learning and network experience, real-world route choice percentages seem to be converging to specific values; however, these values are mostly very different than those derived using stochastic user equilibrium expectations; b) four types of heterogeneous driver- learning and choice evolution patterns are identified, and, c) the identified learning patterns are modeled and found predictable based on driver and choice situation variables.

INTRODUCTION

With increased proof of the negative impacts of climate change and the peaking of oil prices, worldwide expectations from Intelligent Transportation Systems (ITS) are on the rise. These heightened expectations have resulted in a necessary move towards improving the accuracy of predicting driver behavior and developing more realistic driver oriented models. Route choice models are a corner stone in many transportation engineering applications. They are a part of all transportation planning models, traffic simulation software, area-wide traffic control, and also electronic route guidance systems.

Two main groups of route choice models can be found in the literature. The first group encompasses mathematical network-oriented models such as deterministic and stochastic user equilibrium, system optimum, and dynamic traffic assignment models. In this group of models drivers are assumed to behave in a certain manner so that a certain objective function can be optimized at the network level. Comprehensive reviews of these kinds of models can be found in a number of publications [1-3]. The second group of models includes behavioral driver-oriented models. The main objective of these models is to accurately describe individual driver route choice behavior. As a result of the move towards developing more realistic driver oriented models, the second group of models has been recently gaining significant momentum. Examples of these models include random utility models [4, 5], random regret minimization models [6], probabilistic models [7], cognitive-psychology based models [8, 9], fuzzy models [10], and models based on data mining; sometimes referred to as user models [11-14].

While the models of the first group are much more widely used in the transportation engineering realm, evidence of its inadequacy is growing continuously [12, 13, 15]. The degree of its inadequacy, however, remains debatable. Two major critiques for the theory are its unrealistic assumptions of human perceptions [16, 17] and its lack of incorporation of driver heterogeneity [13]. On the other hand, attempts to incorporate driver heterogeneity in the behavioral driver oriented route choice models, too, are still short [18-20]. Another major limitation in the route choice literature is that due to cost limitations most studies are based on either stated preference surveys or travel simulators [13]. Studies based on real-life experiments such as [12, 13] are not many and are characterized with the limitations of identifying the drivers' choice sets and estimating the prevailing traffic conditions on the alternative routes – which were not chosen.

With these limitations in mind, this work is conducted by administering a real-world route choice experiment on a sample of 20 drivers who, in 20 trials, collectively made more than 2,000 real-world choices. Both the aggregate evolution of the network as well as the individual evolution of each driver's learning and choices were recorded throughout the experiment. In the following sections an analytical comparison between the drivers' experiences and the network and driver evolution patterns is presented. In addition, a model of driver heterogeneity is also presented. Before proceeding with the paper, it is interesting and probably insightful to note an analogy between route choice and household location choice models.

Reviewing the history of household location choice models reveals a rather interesting insight. A recent publication provides a good review of the history [21]. Apparently when these models were first started they, too, assumed that household decision makers were homogenous. Later, variables to incorporate the heterogeneity of the decision makers were introduced. The most common of these variables is "lifestyle". However, other variables were also used, like "personality type". At the beginning these variables were incorporated in a two stage approach, where models of the first stage were responsible for predicting the personality type and models of

the second stage used the predicted personality type to predict household location choice. Nowadays, however, both stages can be modeled simultaneously (as in the referenced paper). This notice is interesting because it appears that the authors have until this point been, unknowingly, following the same historical path. The authors are identifying driver types in one stage then using these identified types in the next stage in route choice models [7, 22].

In the following sections, the authors present the objectives of the study, followed by an explanation of the study approach: study description, network and questionnaires. In the third section, the authors present the experimental results and discussion, and in the fourth section the paper ends with conclusions of the study and recommendations for further research.

STUDY OBJECTIVES

The main objectives of this study are to use actual real-world driving data to (a) evaluate the adequacy of the expectations of the stochastic user equilibrium theory (b) identify disaggregate patterns of individual driver learning and choice evolution, and (c) examine the possibility of predicting these patterns based on driver- and choice- specific variables.

STUDY APPROACH

Experiment Description

This experiment is based on real-world GPS-recorded data of 20 participants; each making 100 choices. It is also supplemented with a pre-experiment stated preference survey and a post-experiment stated preference survey.

Each participant was asked to complete 20 trials during regular school days of the academic spring semester of the year 2011. Trials were scheduled only during one of three traffic peak hours: morning (7-8 am), noon (12-1 pm), and evening (5-6 pm). During each trial each participant was asked to drive a research vehicle on the road network of the New River Valley and was required to make 5 route choices. At the beginning of the experiment, participants were given 5 Google Map print outs. Each map representing 1 trip: 1 point of origin, 1 point of destination, and two alternative routes. These maps were the same for all participants. On each trial, participants were asked to make these 5 trips assuming that the provided alternative routes were the only routes available between the points of origin and destination. The trips and the alternative routes were pre-selected by the researchers to ensure differences in the 5 choice situations (Table 1). All drivers' choices as well as the travel conditions were recorded via a GPS unit placed onboard of the vehicle and a research escort that always accompanied the participants. Participants were instructed to behave in the same manner they behave in the real life.

It should be noted that in this experiment, each trip represented a choice situation for the participants. Hence, in many occasions in this paper the terms "trips" and "choices" refer to the same thing and are used exchangeably.

Participants and Incentives

Experiment participants were selected to ensure variability over their demographic, and study network and route experiences (ranges of experiment variables can be seen in the third column of Table 7).

Since route choice behavior is documented to vary with trip purpose, a couple of measures were designed to ensure that participants will not consider experiment time as leisure. First, participants' compensation was not a function of the time spent in the experiment; participants were provided a flat monetary amount per trial. Second, the experiment was not entertaining

(experiment routes were not scenic, and participants were not allowed to listen to any entertainment, use their cellphone, or chat with the research escort). Hence, if any, participants had stealth incentives to reduce their travel times.

Network

Table 1 demonstrates the origin, destination, and alternative routes specific to each of the 5 trips. It also shows a brief description of each of the routes. More information about the routes can be seen in Figure 1 and are provided in Table 2. Figure 1 shows a map depicting all 5 points of trip origins and destinations as well as the 10 alternative routes provided.

Table 1: Description of the Five Trips

Trip #	Trip Origin	Trip Destination	Alternative Routes		Route Description (and speed limits)
			Route #	Route Name	
1	Point 1 (VTTI)	Point 2 (Walmart)	Route 1	US460 Business	Mostly a high speed (65 mph) freeway
			Route 2	US460 Bypass	High speed (45 mph) urban highway
2	Point 2 (Walmart)	Point 3 (Foodlion1)	Route 3	Merrimac	Mostly a shorter, low speed (30 mph) back road with a lot of curves
			Route 4	Peppers Ferry	Mostly a longer, high speed (55 mph) rural highway
3	Point 3 (Foodlion1)	Point 4 (Foodlion2)	Route 5	US460 Bypass	A longer high speed (65 mph) freeway followed by a low speed (25 mph) urban road
			Route 6	N.Main	A shorter urban route (40 and 35 mph)
4	Point 4 (Foodlion2)	Point 5 (Stadium)	Route 7	Toms Creek	A short urban route that passes through campus (25 and 35 mph)
			Route 8	US460 Bypass	Primarily a long high speed (65 mph) freeway and low speed (25 mph) urban roads
5	Point 5 (Stadium)	Point 1 (VTTI)	Route 9	S.Main	A long urban road that passes through town (35 mph)
			Route 10	Ramble	A short unpopular low speed (25 and 35 mph) back road that passes by a small airport.

Pre-experiment Questionnaire

The pre-experiment questionnaire collected information about the participants' demographics (age, gender, ethnicity, education, level, etc), driving experiences (number of driving years, annual driven miles, etc.), and familiarity with the area (length of residency), and experiment routes (Likert Scale: 1 = never been there, 2 = used it once or twice, up to 5 = very familiar).

Post- experiment Questionnaire

The post- experiment questionnaire was divided into two sections. The first sections collected information about the participants' perceptions of the traffic conditions on the alternative routes

(distance, travel time, travel speed, and traffic level), as well as participants' preference of the routes. In the second section the participants were asked to fill in a personality inventory, the NEO Personality Inventory-Revised [23]. This is a psychological personality inventory that is based on the Five Factor Model. It measures five personality traits: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. In addition, each personality trait measures six subordinate dimensions (sometimes referred to as facets).
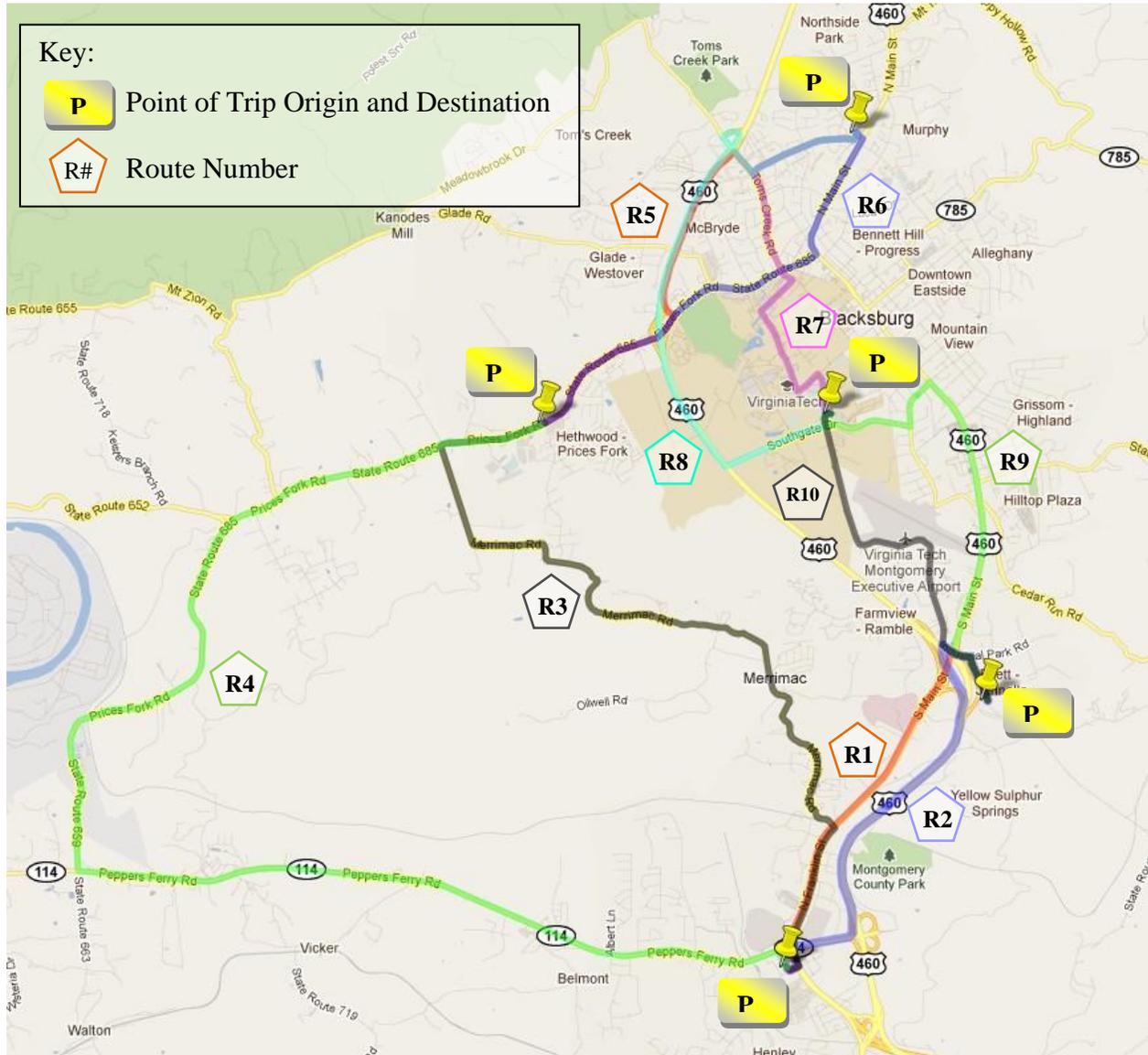
Figure 1: Map of the Experiment Network (Source: Google Maps)

RESULTS AND ANALYSIS

This section starts with presenting the characteristics of the choice alternatives. After that, the aggregate evolution of route choice with experience is explored and the results of the expected stochastic user equilibrium theory are compared to the actual evolution of choice percentages. Next, a disaggregate evaluation of the evolution of the percentage of non-TT-minimal choices is

examined. Following, an investigation of the individual evolution of learning and choice is performed where four types of heterogeneous driver behavior are identified. This section ends with a model capable of predicting the identified driver types based on personal, choice situation, and person-choice combination factors.

Table 2: Characteristics of the Alternative Routes Per Trip

Trip #	Route #	Dist-ance (km)	Avg. Travel Time (min)	Avg. Travel Speed (kph)	Number of Intersections		Number of Turns		Number of Merges and Diverges[**]	Number of Horizontal Curves[**]
					Signal-ized	Unsignal-ized[**]	Lefts	Rights		
1	1	5.1[*]	8.5	36.4	10	3[*]	3[*]	3[*]	1[*]	2[*]
	2	6.0	8.4[*]	43.3[*]	5[*]	4	4	4	5	3
2	3	11.1[*]	15.2[*]	42.6	5	2	3	2	1[*]	30
	4	17.4	16.7	63.2[*]	2[*]	2	2[*]	2	2	11[*]
3	5	5.8	7.7[*]	44.5[*]	5[*]	3	3	2	2	2
	6	5.5[*]	9.3	37.8	8	3	2[*]	2	1[*]	2
4	7	5.0[*]	10.2	29.5	5[*]	3	4	3	1[*]	0[*]
	8	7.7	9.6[*]	48.2[*]	6	2[*]	2[*]	3	4	1
5	9	5.8	10.5	33.3	8	4	4	3	1[*]	1[*]
	10	4.7[*]	8.0[*]	34.0[*]	3[*]	1[*]	3[*]	1[*]	2	6

[*] Better route
[**] Number of unsignalized intersections, number of merges and diverges and diverges, and number horizontal curves are potential indicators for route easiness and safety

Network Characteristics

In this section the characteristics of the alternative routes as well as the recorded drivers' experiences of travel time are presented.

General Route Characteristics

Table 2 presents the characteristics of the 10 routes. As mentioned earlier and can be seen from the table, the trips and alternative routes were selected so that the characteristics of the alternatives were to vary across the 5 choice situations.

Experienced Travel Times

Table 3 presents the cumulative frequency distributions of the experienced travel times during the study. Table 3 also presents the probability, based on a Monte Carlo simulation, that the odd-number route is a better choice than the even-number route, by being shorter in travel time (TT).

Aggregate Choice Evolution

This section starts by exploring the network evolution; represented by the aggregate evolution of drivers' choices. Next in this section is an evaluation of the evolution of the drivers' non-TT-minimal choices; as determined by their experienced travel times.

Table 3: Route Travel Times (TT) and Aggregate Route Choice Evolution

Trip	Travel Time Cumulative Distribution	Monte Carlo Simulation (SUE)	Choice Evolution (and a log-fit)
1		Prob. ($TT_{R1} < TT_{R2}$) = 48.3%	
2		Prob. ($TT_{R3} < TT_{R4}$) = 78.5%	
3		Prob. ($TT_{R5} < TT_{R6}$) = 85.4%	
4		Prob. ($TT_{R7} < TT_{R8}$) = 35.2%	
5		Prob. ($TT_{R9} < TT_{R10}$) = 5.0%	

Aggregate Evolution of Choice Percentages

The third column of Table 3 presents the aggregate evolution of choice percentages on each of the five trips. A logarithmic curve is fitted to the choice percentages of each trip. The expected choice percentage according to the SUE theory is also shown on each graph. It can be clearly seen that the expectations of the SUE theory can be very different from the actual reality of choice percentages. The graphs show that while the evolution of choice percentages seem to be converging to the SUE expectations on trips 3 and 5 (where the travel time difference is high), they are way off in trips 1, 2 and 4. In fact, for trips 1 and 4, the actual choice evolutions seem to be heading away from (in the opposite direction of) the SUE expectations. This trend could be attributed to the small difference in travel time between the two routes.

On each graph, the choice percentage trends seem to be converging, yet it could be argued that the 20 trials were not long enough for a complete convergence. Accordingly, the following section examines whether drivers' learning has converged or whether changes were to be expected had the drivers made more trials. Alternatively, it may be rationally argued that the observed differences (between choice percentages and SUE expectations) could be a result of the aggregation of three different travel conditions (morning, noon, and evening peaks). However, results of investigation of these differences during each peak period, separately, were not different from the results presented here.

Aggregate Evolution of Individual Non-TT-Minimal Choices

Figure 2 presents the aggregate evolution of individual non-TT-minimal choices; in all trips (Figure 2a) and on each trip separately (Figures 2b thru 2f). Disaggregate travel time experiences and choices of each driver, on each trial are evaluated separately. Each decision by each driver is compared to the minimum experienced TT route by that driver in all previous trials, then all the non-TT-minimal decisions are summed together to find the aggregate evolution of individual non-TT-minimal choices. A non-TT-minimal choice is assumed to occur if a driver chooses a longer travel time route; based on this driver's personal travel time experiences in the previous trials. The personal travel time experiences were calculated as the average travel times experienced in all previous trials, per the following equation.

$$AETT_{irt} = \frac{\sum_{t=1}^{t-1} \delta_{irt} \cdot TT_{it}}{\sum_{t=1}^{t-1} \delta_{irt}}$$

where,

$AETT_{irt}$ is the average experienced travel time of person i on route r up till trial t
δ_{irt}=1 if person i chooses route r at trial t, and 0 otherwise
TT_{it} is the travel time experience by person i at trial t

Because a good percentage of the choices made early in the experiment were for exploratory rather than preference reasons, the figures show the percentage of non-TT-minimal choices made only in the last 10 trials of the experiment. Inspecting Figure 2 shows that, collectively (Figure 2a), it appears that the percentage of non-TT-minimal choices seem to be slowly continuing to decline with experience; even until the last trial. This trend, however, cannot be observed from the figures of the individual trips (Figures 2b thru 2f). On each individual trip it appears that the percentage of non-TT-minimal decisions has stopped improving and is randomly oscillating around some value. Based on these two contradicting observations, it appears reasonable to assume that the aggregate percentage of non-TT-minimal decisions could slightly

improve with more driver experience, but only slightly. Hence, it appears that given more experience, the observed discrepancies between the expectations of the SUE theory and the actual percentages of route choices would have continued and not gotten any different. Accordingly, for a better, more comprehensive understanding of network evolution the disaggregate evolution of driver learning and choice is explored in the next section.

Figure 2a: Percentage of Non-TT-Minimal Decisions in All Trips
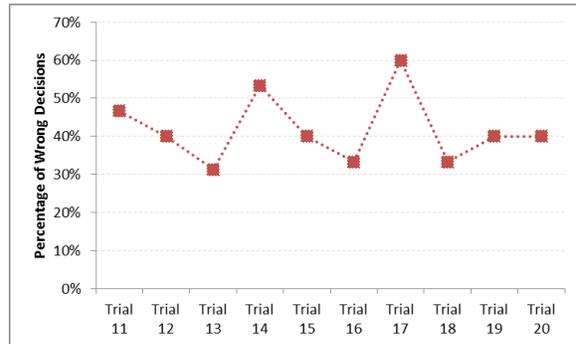
Figure 2b: Percentage of Non-TT-Minimal Decisions in Trip 1
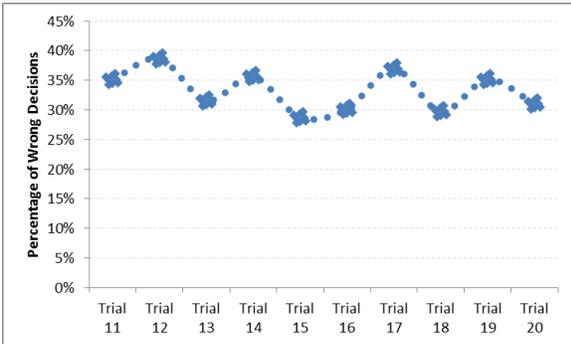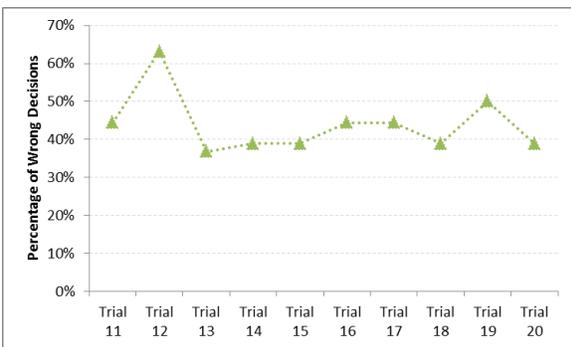

Figure 2c: Percentage of Non-TT-Minimal Decisions in Trip 2
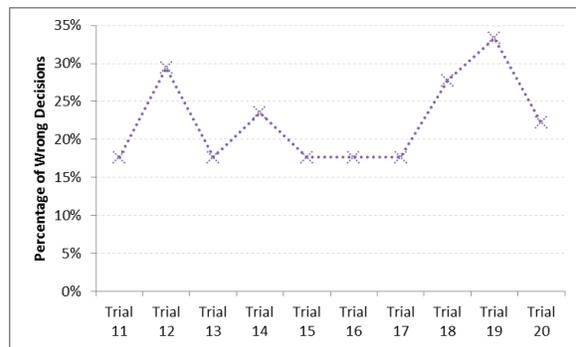
Figure 2d: Percentage of Non-TT-Minimal Decisions in Trip 3
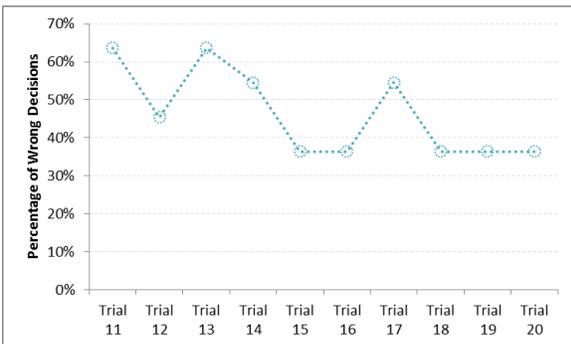
Figure 2e: Percentage of Non-TT-Minimal Decisions in Trip 4
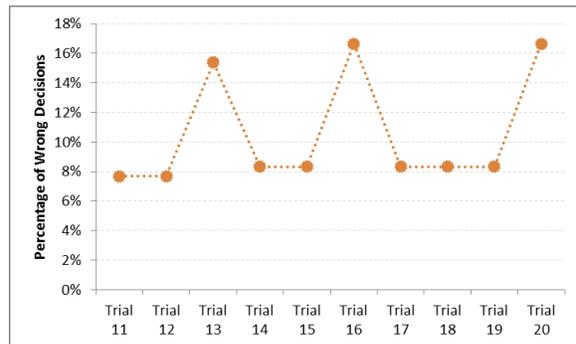
Figure 2f: Percentage of Non-TT-Minimal Decisions in Trip 5

Figure 2: Percentages of Non-TT-Minimal Decisions in the Last 10 Trials Based on Disaggregate Average Experienced Travel Time

Disaggregate Evolution

The first part of this section explores drivers' heterogeneity by investigating the individual evolution of drivers' learning and choices. Four types of drivers are identified. The second part of this section presents a model to predict the identified driver types based on driver and choice situation variables.

Driver Type

In an earlier route choice study that was based on a driving simulator, four types of driver learning evolution patterns were identified [22], and in another study these patterns were found significant in predicting route choice switching [7]. These four patterns of driver learning and choice evolution are presented in Table 4. Whether these four identified patterns were a function of the driving simulator experiment or a legitimate real-life behavior was questionable. Interestingly, these same four patterns of driver learning and choice evolution were identified in this real-world experiment. Nonetheless, it was observed that these evolution patterns are not driver specific.

In this paper these four identified learning and choice evolution patterns will sometimes be referred to as driver types. It will also be metaphorically assumed that driver aggressiveness in route switching behavior increases as a function of driver type, i.e. driver type IV is more aggressive than driver type III, and driver type III is more aggressive than driver type II, etc.

In this experiment, it was observed that some drivers were obviously on the less aggressive side, and some other drivers were obviously on the more aggressive side. However, less aggressive drivers were not always of type I and more aggressive drivers were not always of type IV. Each driver's behavior was a mixture of the different types. This discussion can probably be more obvious by checking Table 5. Table 5 presents four examples of observed driver evolution behavior. Each example represents the learning evolution behavior of a certain driver on each of the 5 trips. It can be seen that although the first driver seems to be less aggressive than the other drivers and the second driver seems to be less aggressive than the third and fourth drivers and so on, each driver's behavior is a mixture of driver types. The first driver, for example, behaves as type I on all trips except trip 2. A possible explanation for this, which is explored in the next section, is that the learning evolution patterns are a function of both: a driver aggressiveness tendency as well as choice situation factors.

Table 6 shows the percentage of driver types identified on each trip. Since the percentages are not constant across all trips, this too implies that the choice situation has an effect on the driver applied learning evolution pattern. To test this theory, the drivers' learning evolution patterns are modeled against a number of personal, choice-situation, and person-choice combination factors in the following section.

Model

Response Variable

The modeled response is the probability that driver i will adopt a type III-IV over a type I-II learning evolution pattern. Types I and II were consolidated into a single group (type I-II) and types III and IV were consolidated to one group (type III-IV) for two reasons. The first reason is to increase the number of observations per group and increase the power of the model. The second reason is to eliminate any possible classification arguments. While it is straightforward to classify a pattern as either a type I or a type II pattern, differentiating between types III and IV can sometimes be trickier.

Independent Variables

The independent variables investigated in this work are presented in Table 7. As mentioned earlier and presented in Table 7, three main groups of variables were used: personal variables (demographic and personality), choice-situation variables, and person-choice combination variables.

Table 4: Four Identified Driver Types Based on Learning and Choice Evolution

Driver Type	Typical Behavior	Type Description
I		A driver starts by arbitrarily picking a route, is apparently satisfied with the experience, and continues making the same choice for the entire 20 trials.
II		A driver starts by arbitrarily picking a route, is apparently not satisfied with the experience, tries the other route, and decides that the first route was better. The driver makes a choice after trying both routes and does not change afterwards.
III		A driver switches between the two alternative routes till the end of the experiment. The driver, however, drives on route 1 much more than s/her drives on route 0. This reflects his/her preference for route 1.
IV		A driver switches between the two alternative routes during the entire time of the experiment. The driver drives both routes with approximately equal percentages. This reflects the lack of preference towards any of the alternatives.

Table 5: Examples of Driver Behavior Varying Within Driver Across Trips

#	Observed Choice Evolution	Description
1		Driver mostly behaves as type I: driver behaves as type I in all trips except trip 2 where his/her behavior is characteristic of a type II.
2		Driver's behavior appears to be a mixture between type I, type II and a mild type III: driver behaves as type I in trip 5, as type 2 in trip 3, and as a mild type III in trips 1, 2, and 4. The reason s/he is described as a mild type 3 is beacause s/he makes her/his mind and does not revisit her/his choice after trial number 4, 4 and 9 on trips 1, 2 and 4, respectively.
3		Driver's behavior seems to be typical of type III: the driver has a clear route preference in all 5 trips; however, the driver revisits his/her choice by switching to the other route once in a while on all 5 trips.
4		The driver's behavior appears to be a mixture between types III and IV: the driver behaves as a typical type III on trips 1 and 5; arguably either type III or IV on trips 2 and 3, and as a typical type IV on trip 4.

Table 6: Percentage of Driver Behavior Type per Trip

Trip	Percentage of Type I Behavior	Percentage of Type II Behavior	Percentage of Type III Behavior	Percentage of Type IV Behavior
1	24%	5%	48%	24%
2	10%	24%	48%	19%
3	14%	29%	38%	19%
4	48%*	14%	14%	24%
5	38%	14%	43%	5%
Σ	100%	100%	100%	100%

Model Data

As explained earlier in the paper, 20 drivers were recruited for the experiment and each driver was faced with 5 trips, i.e. in total there are around 100 observations of driver-choice combinations. All numeric variables used in the presented models were scaled so that the magnitude of one (or more) variables would not over shadow other variable(s), and the modeled coefficients can indicate the importance of the covariates.

Model Structure

The driver type model proposed here is a mixed effects generalized linear model with a logit link function [24]. Because each driver was asked to repeat his/her choice several times, one mixed parameter, the intercept, is estimated over all individuals instead of all observations. The model has the following structure.

$$y_{ic} \sim Bern(p_{ic})$$
$$logit(p_{ic}) = x'_{ic}\beta + \theta_i$$
$$\theta_i \sim N(0, \varphi)$$

where,
$y_{ic} = 1$ if person i belongs to driver type III-IV at choice situation c
$y_{ic} = 0$ if person i belongs to driver type I-II at choice situation c
Bern is the Bernoulli distribution
p_{ic} is the probability that person i belongs to driver type III-IV
$logit(p_{ic}) = \dfrac{p_{ic}}{1 - p_{ic}}$
x_{ic} is the vector of covariates for person i and/or choice situation c
β is a vector of the parameters
θ_i is the random component of person i
N is the Normal distribution
φ is the variance

Table 7: Model Independent Variables

#	Variable Names	Variable Description	Variable Values
Variables of Driver Demographics			
1	Age$_i$	Age of participant i	18 to 68
2	Gender$_i$	Gender of participant i	M or F[*]
3	Ethnicity$_i$	Ethnicity of participant i	W or NW[*]
4	Educ$_i$	Education level of participant i	G or NG[*]
5	DrYears$_i$	Number of years participant i has been a licensed driver	2 to 57
6	Dr Miles$_i$	Annual number of miles participant i drives (thousands)	2 to 35
7	Residency$_i$	Number of years participant i has been residing in the area	1 to 56
Variables of Driver Personality Traits			
1	N$_i$	Neuroticism of participant i	7 to 30
2	E$_i$	Extraversion of participant i	19 to 43
3	O$_i$	Openness to experience of participant i	20 to 31
4	A$_i$	Agreeableness of participant i	22 to 42
5	C$_i$	Conscientiousness of participant i	26 to 47
Variables of Choice Situation[**]			
1	dTimePrc$_c$[***]	Percentage difference in mean TT between the two alternatives of choice c	2.8 to 24.5
2	dTimeVPrc$_c$[***]	Percentage difference in TT variance between the two alternatives of choice c	7.4 to 56.7
3	dDistPrc$_c$	Percentage difference in distance between the two alternative routes of choice c	5.7 to 44.8
4	dSpdPrc$_c$[***]	Percentage difference in mean travel speed between the two alternatives of choice c	2.1 to 48.1
5	dSpdVPrc$_c$[***]	Percentage difference in travel speed variance between the two alternatives of choice c	21.0 to 73.0
6	dLinksPrc$_c$	Percentage difference in number of links between the two alternatives of choice c	0.0 to 54.5
7	dSigPrc$_c$	Percentage difference in number of signalized intersections between the two alternatives of choice c	18.2 to 90.9
8	dUnsigPrc$_c$	Percentage difference in number of unsignalized intersections between the two alternatives of choice c	0.0 to 120.0
9	dTurnsPrc$_c$	Percentage difference in number of uncontrolled intersections between the two alternative routes of choice c	66.7 to 133.3
10	dLeftsPrc$_c$	Percentage difference in number of left turns between the two alternative of choice c	28.6 to 66.7
11	dRightsPrc$_c$	Percentage difference in number of right turns between the two alternative of choice c	0.0 to 100.0
12	dCurvPrc$_c$	Percentage difference in number of curves between the two alternatives of choice c	0.0 to 200.0
Variables of Driver-Choice Combination			
1	AvgFam$_{ic}$	Average familiarity of driver i with the two routes of choice c	1 to 5
2	MaxFam$_{ic}$	Maximum familiarity of driver i with the two routes of choice c	1 to 5
3	dFamPrc$_{ic}$	Percentage difference of the familiarity of driver i with the two alternative routes of choice c	0.0 to 133.3

[*] M: male, F: female, W: white, NW: non-white, NG: not graduate, G: graduate

[**] Percentage difference calculated as difference between the two routes divided by the average of the two routes

[***] All travel time and travel speed calculations are based on actual driver experiences; collected GPS data

Model Results

Table 8 presents the results of the estimated model. It is satisfying that variables belonging to both the driver (both demographic and personality) as well as the choice situation were found to be significant. This reinforces the reasoning that was given in an earlier section. In addition, the signs of the significant variables seem to be logical. The model proposes that drivers from a white ethnicity are more likely to exhibit a type III or type IV learning pattern, and that the higher the number of annual miles a driver makes, the lower the chances that this driver will exhibit a type III or IV behavior. This can be explained by a couple of different reasoning. It can be explained by assuming that drivers who drive a lot are more confident in their judgments or are more experienced. Consequently, they can identify the better route from just a single driving trial or even by just looking at the map and without making any trials. Alternatively, it may be that experienced drivers do not care that much about driving a few extra minutes (or miles) as long as they are comfortable with their choice. Consequently, they do not really care that much about finding the minimum travel time route as much as they care about their comfort with the route. Accordingly, they do not need to try a route several times to evaluate the stochastic travel time. What they care about is comfort and one trial is enough for them to evaluate the comfort level of a route.

Three out of the five explored personality traits were found to be significant. It was found that both extraversion and conscientiousness increased the drivers' probabilities to exhibit a type III or a type IV pattern. Openness to experience, on the other hand, was found to decrease the drivers' probabilities to exhibit a type III or a type IV pattern.

Among the reasons that were given in the earlier driving simulator route choice study [22] and in this study for a driver to continuously switch, or to switch every now and then, between the alternative routes are: boredom and to explore what is happening around the town. Two of the personality dimensions that are measured by the extraversion trait are "activity" and "excitement seeking". These dimensions clearly align with the two reasons given here. Hence, it seems logical that extraversion should increase the probability that a driver would exhibit a type III or a type IV behavior.

Among the personality dimensions that are measured by the conscientiousness, on the other hand, are "achievement striving", "self-discipline", and "deliberation". These three dimensions could imply that a driver with high conscientiousness could be more inclined to consciously deliberate the characteristics (travel times) of the alternative routes and strive to always make the best choice decision. Hence, implying that a driver would be inclined to always revisit and re-evaluate his/her perceptions of the travel characteristics on the alternative routes and, thus, trying the alternatives every now and then.

On first sight, the sign of the openness to experience variable could seem illogical. Nonetheless, reviewing the personality dimensions that are measured by this trait helps clear the picture. The six personality dimensions measured by this trait are "fantasy", "aesthetics", "feelings", "actions", "ideas", and "values". All of these traits require active cognitive capacities. For a driver to fantasize about an idea or reflect on a certain feeling or dream of aesthetics requires cognitive capacities. Hence, it is probably logical that a driver that is high on these dimensions would seek to reduce his/her cognitive capacities that are dedicated to finding the best route choice and reallocate these cognitive capacities for other liberating thoughts. Hence, such a driver could be inclined to make an early route choice judgment, stick with it, and not revisit it again. Thus, such a driver would be more inclined to exhibit a type I or a type II learning pattern.

Table 8: Significant Variables of the Driver Learning Pattern Model[*]

Significant Variables	Estimate	Std. Error	z-value	Pr(>|z|)
(Intercept)	0.92	0.384	2.401	0.016
EthNW	-2.98	1.292	-2.303	0.021
DrMls	-0.97	0.443	-2.182	0.029
E	1.14	0.437	2.619	0.009
O	-1.18	0.456	-2.589	0.010
C	1.22	0.459	2.650	0.008
dTimePrc	-0.59	0.292	-2.005	0.045
dSigPrc	0.62	0.292	2.117	0.034

[*] Variables description is presented in Table 7

Last, the choice-situation variables: difference in travel time and difference in number of signalized intersections. Logic would assume that the higher the difference in travel times between two alternative routes, the higher the degree of preference a driver would have for a certain route. The sign of the choice travel time variable agrees with this logic. Thus, the higher the difference in travel time, the higher the probability that a driver would exhibit a type I or a type II learning pattern. In contrast, the sign of the difference in the number of signals might not seem intuitive. Nonetheless, following are two possible explanations; the second of which is particularly relevant to this experiment. The first explanation is that the more traffic signals there are the more stochastic travel time is going to be. Hence, this necessitates that a driver travel the route several times before being able to get a feel of the travel time and its fluctuation. Furthermore, particularly relevant to this experiment (and many life choice situations) is that most routes that had many signals were more direct to the destination. Therefore, only by checking the map, drivers are inclined to these routes, yet upon trying them they may be disappointed with the number of signalized intersections. This tension between desire for directness and against signalized intersections inclines drivers to try the alternatives a number of times before making a decision and to revisit their choices every now and then.

It is worth noting that although the two considered measures of travel reliability (TT and travel speed variances) were not statistically significant, their signs were negative. This agrees with the logic that when one route is more reliable than the other, drivers are more likely to have a route preference; indicated by the lower probability to exhibit a type III or IV behavior. On the other hand, a possible reason that none of these measures was significant is that as seen from the distributions presented in Table 3, except for Trip 3, variances of the alternative routes are not very different.

STUDY CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

In this work, a real-world route choice experiment was conducted with the objective of investigating the degree of inadequacy of the expectations of the stochastic user equilibrium, and to explore the possibility of identifying predictable patterns of driver learning and choice evolution. Route choice literature is packed with studies; however, only a few of these studies are based on real-life experiments and very little attention has been given to differences between drives' learning types. This work was done based on a sample of 20 drivers that were each faced with 5 different route choice situations and who collectively made more than 2,000 real-world choices. All drivers' experiences and choices were recorded. In this work: the aggregate

evolutions of real-world choice percentages were compared to the expectations of the stochastic user equilibrium theory, the disaggregate evolutions of individual driver learning and choices were explored where 4 driver types were identified; and the possibility of predicting the identified driver learning types based on driver and choice variables was investigated.

On the exploration of the aggregate evolution of choice percentages, it was found that the percentages of real-world route choices were converging to certain values. However, in 3 out of the 5 cases, these values were very different from the expectations of the stochastic user equilibrium theory (SUE). In addition, in 2 out of the 5 cases, the actual choice percentages were converging away from the SUE expectations.

On analyzing the disaggregate evolution of individual learning and choices, four patterns were identified: drivers who repeated the same choice in all 20 trials, drivers who tried each alternative only once then made a decision which they never revisited, drivers who had an obvious preference but kept switching to the other route every once in a while, and drivers who were switching during the entire experiment and did not seem to have a clear preference. In a previous driving simulator experiment, it was hypothesized that these patterns are individual specific. In this experiment, however, it was found that these patterns depended on both the individual and the choice situation.

A model was developed to predict the driver learning pattern based on driver-specific and choice-specific variables. Several driver-specific and choice-specific variables were found to be significant, but none of the explored driver-choice combination variables was found to be significant. Among the significant driver-specific variables were driver demographic variables (ethnicity and annual driven miles) as well as personal trait variables (extraversion, openness to experience, and conscientiousness). The significant choice-specific variables were the percentage travel time difference between the choice alternatives and the number of signalized intersections percentage difference between the choice alternatives.

The findings of this work could be insightful; especially if successfully replicated. A number of further research directions include: incorporating the identified driver types in a route choice model; examining if the identified driver types have different compliance rates to information in a real-world experiment; and examining if the same results could be replicated in a travel or a driving simulator.

ACKNOWLEDGEMENTS

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Part II: Real-World Driving Experiment

Chapter 8

A Real-World Hierarchical Route Choice Model of Heterogeneous Drivers

A Real-World Hierarchical Route Choice Model of Heterogeneous Drivers

Aly M. Tawfik, MS
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 577-0462
FAX: (540) 231-7532
tawfik@vt.edu

Hesham A. Rakha, PhD., P.Eng.
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 231-1505
FAX: (540) 231-1555
hrakha@vt.edu

ABSTRACT

The research presented in this paper develops a hierarchical two-level heterogeneous route choice model that is developed using real-world experimental data. Experiment reality and driver heterogeneity are two limitations in route choice literature. On the one hand, aside from random error components, almost all route choice models being used in transportation engineering practice assume that drivers are homogeneous in the way they make their route choices and in the way they respond to information. Although this paper is based on only the way drivers make route choices, the proposed framework is capable of incorporating the heterogeneity of driver responses to information. On the other hand, the models developed in this paper are based on a sample of 20 drivers who collectively made more than 2,000 real-world route choices. In the proposed model, the first level presents a model that uses driver demographic and personality traits, and the characteristics of the choice situation to predict a driver type. Within the context of this paper, a driver type connotes a metaphoric measure of driver aggressiveness in route switching behavior, and captures driver heterogeneity. The second level of the model uses the predicted driver type and the travel experiences of the driver to predict the driver's route choice. The results of the developed models indicate that in general: 1) driver types can be predicted from driver demographics, personality traits, and choice situation characteristics, 2) the predicted driver types are significant in route choice models, and 3) route choice models based on the proposed framework demonstrate better fits than the general model.

INTRODUCTION

Over half a century ago, world famous science fiction author and Nobel Peace Prize Nominee, Arthur C. Clarke wrote that "the automobile of the day-after-tomorrow will not be driven by its owner, but by itself; indeed, it may one day be a serious offence to drive an automobile on a public highway" [1]. One day, this dream may become a reality; however, it is likely to happen only if we can develop intelligent systems that are capable of making choices in the same way we do them. This necessitates full understanding of how drivers make their choices.

Route choice literature can be classified into two main groups. The first group encompasses mathematical network oriented models such as deterministic and stochastic user equilibrium, system optimum, and dynamic traffic assignment models. In this group of models drivers are assumed to behave in a certain manner so that a certain objective function can be optimized at the network level. Comprehensive reviews of these kinds of models can be found in a number of publications [2-4]. The second group of models includes behavioral driver oriented models. The main objective of these models is to accurately describe individual driver route choice behavior. As a result of a move towards developing more realistic driver oriented models, the second group of models has been recently gaining momentum. Examples of these models include random utility models [5, 6], random regret minimization models [7], probabilistic models [8], cognitive-psychology based models [9, 10], artificial intelligence models like fuzzy models [11] and artificial neural network models [12], and models based on data mining (sometimes referred to as user models) [13-16].

Experiment reality and driver heterogeneity are two limitations in route choice literature [15, 17]. On the one hand, aside from random error components, almost all route choice models being used in transportation engineering practice assume that drivers are homogeneous in the way they make their route choices and in the way they respond to information. On the other hand, due to cost and past technological limitations most route choice literature is based on either stated preference surveys or travel simulators. Travel simulators are PC-based systems that simulate the conditions of the choice situation and record the choice of the user. The user, however, does not drive and does not experience the travel conditions in real-time [18, 19]. Experiments based on driving simulators and GPS data, however, have been gaining momentum and seem promising. Limitations of the former include environment fidelity, and limitations of the latter include lack of information on the non-chosen routes and the necessity for assumptions about the drivers' choice sets.

With these limitations in mind, this paper presents a hierarchical two-level heterogeneous route choice model that is based on an in situ experiment in real-world conditions. Although this paper is based on only the way drivers make their route choices, the proposed framework is capable of incorporating the heterogeneity of driver responses to information. The models developed in this paper are based on a sample of 20 drivers that collectively made more than 2,000 real life route choices. In the proposed model, the first level presents a model that uses drivers' demographics and personality traits, and the characteristics of the choice situation to predict a driver's type. Within the context of this paper, a driver type connotes a metaphoric measure of driver aggressiveness in route switching behavior, and represents driver heterogeneity [20]. The second level of the model uses the predicted driver type and the driver travel experiences to predict driver route choice.

It is interesting and probably beneficial to note the similarity between route choice and household location choice literature. A recent publication provides a good review of the history of household location choice models [21]. Apparently, similar to the modeling framework proposed

by the authors in this work, when household choice location models first moved to incorporate individual heterogeneity, it, too, was based on two-stage models. Today, however, both stages can be modeled simultaneously (as in the referenced paper). This fact is interesting because it appears that the authors have until this point been, unknowingly, following the same historical path.

In the following sections, the authors present the objectives of the study, followed by an explanation of the study approach: study description, network and questionnaires. In the third section, the authors present the experiment's results, models, and discussion, and in the fourth section the paper ends with conclusions of the study and recommendations for further research.

STUDY OBJECTIVES

The main objectives of this study are to: (a) identify predictable measures that can reflect driver heterogeneity in a route choice context, (b) use the identified measures to propose a framework capable of incorporating driver heterogeneity in route choice models, (c) evaluate the performance of the proposed framework using real-world data.

STUDY APPROACH

Study Description

Twenty participants were selected to participate in this study. The participants were first health-screened via a phone conversation. Once the participants passed the health screening questionnaire, a time was scheduled for them to complete their pre-task questionnaire and to make their first experiment run. Each participant was asked to complete 20 experiment runs during regular school days of the academic spring semester of the year 2011. Experiment runs were scheduled only during one of three traffic peak hours: morning (7-8 am), noon (12-1 pm), and evening (5-6 pm). During each experiment run, participants were asked to drive research vehicles on the road network of the New River Valley. Participants were given 5 Google Map print outs. Each map representing one trip: one point of origin, one point of destination, and two alternative routes. All participants were given identical maps and were asked to make the same 5 trips. On each experiment run, participants were asked to make these five trips assuming that the provided alternative routes were the only routes available between the points of origin and destination. The trips and the alternative routes were selected to ensure differences in the 5 choice situations (Table 1). All drivers' choices as well as the travel conditions were recorded via a GPS unit placed on board of the vehicle and a research escort that always accompanied the participants. Participants were instructed to behave in the same manner they behave in the real life. After completion of the 20 trials, participants were asked to complete a post-task questionnaire.

It should be noted that in this experiment, each trip represented a choice situation for the participants. Hence, in many occasions in this paper the terms "trips" and "choices" refer to the same thing and are used exchangeably. Similarly, "experiment runs" and "experiment trials" are also used exchangeably.

Network

Table 1 demonstrates the origin, destination, and alternative routes specific to each of the five trips. It also shows a brief description of each of the routes. More information about the routes can be seen in Figure 1 and are provided in Table 2. Figure 1 shows a map depicting all five points of trip origins and destinations as well as the ten alternative routes provided.

Table 1: Description of the Five Trips

Trip #	Trip Origin	Trip Destination	Alternative Routes		Route Description (and speed limits)
			Route #	Route Name	
1	Point 1 (VTTI)	Point 2 (Walmart)	Route 1	US460 Business	Mostly a high speed (65 mph) freeway
			Route 2	US460 Bypass	High speed (45 mph) urban highway
2	Point 2 (Walmart)	Point 3 (Foodlion1)	Route 3	Merrimac	Mostly a shorter, low speed (30 mph) back road with a lot of curves
			Route 4	Peppers Ferry	Mostly a longer, high speed (55 mph) rural highway
3	Point 3 (Foodlion1)	Point 4 (Foodlion2)	Route 5	US460 Bypass	Longer fast (65 mph) freeway followed by a low speed (25 mph) urban road
			Route 6	N.Main	A shorter urban route (40 and 35 mph)
4	Point 4 (Foodlion2)	Point 5 (Stadium)	Route 7	Toms Creek	A short urban route that passes through campus (25 and 35 mph)
			Route 8	US460 Bypass	A long high speed (65 mph) freeway and low speed (25 mph) urban roads
5	Point 5 (Stadium)	Point 1 (VTTI)	Route 9	S.Main	A long urban road that passes through town (35 mph)
			Route 10	Ramble	A short unpopular slow (25 and 35 mph) back road that passes by a small airport.

Pre-task Questionnaire

The pre-task questionnaire collected information about the participants' demographics (age, gender, ethnicity, education level, etc.) and driving experiences (number of driving years, annual driven miles, etc.).

Post-task Questionnaire

The post-task questionnaire was divided into two sections. The first section collected information about the participants' perceptions of the traffic conditions on the alternative routes (distance, travel time, travel speed, and traffic level), as well as the participants preference levels of the routes. In the second section the participants were asked to fill in a personality inventory, the NEO Personality Inventory-Revised [22]. This is a psychological personality inventory that is based on the Five Factor Model. It measures five personality traits: neuroticism extraversion, openness to experience, agreeableness, and conscientiousness. In addition, each personality trait measures six subordinate dimensions (sometimes referred to as facets).

Neuroticism measures the tendency of a person to experience negative emotions such as anxiety, guilt, frustration, and depression. Persons who score high on neuroticism are usually self-conscious, and are associated with low self-esteem and irrational thinking. The six subordinate dimensions of neuroticism are: anxiety, hostility, depression, self-consciousness, impulsiveness, and vulnerability to stress. Extraversion measures the tendency towards positive

emotionality. The six subordinate dimensions of extraversion are: warmth, gregariousness, assertiveness, activity, excitement seeking, and positive emotion. Openness to Experiences measures the imaginative tendency of individuals, their attentiveness to inner emotions, and their sensitiveness towards art and beauty. The six subordinate dimensions of openness to experience are: fantasy, aesthetics, feelings, actions, ideas, and values. Agreeableness measures the more humane aspects of the personality. The six subordinate dimensions of agreeableness are: trust, straightforwardness, altruism, compliance, modesty, and tendermindedness. Last, Conscientiousness measures personality tendencies towards being diligence, thoroughness and being governed by conscience. The six subordinate dimensions of conscientiousness are: competence, order, dutifulness, achievement striving, self-discipline, and deliberation. For further details about these personality traits, or about the Five Factor Model or the NEO Personality traits, the reader is referred to Wikipedia for general information, and to other publications for thorough theoretical discussions [22-24]

Figure 1: Map of the Experiment Network (Source: Google Maps)

RESULTS AND ANALYSIS

This section starts by describing the real world experiment and presenting the characteristics of the choice alternatives. After that, driver types are presented as variables that reflect driver heterogeneity in route choice situations. Next, the two-level hierarchical modeling framework is explained. Then, the first level of the hierarchical model which models driver types is presented. This section ends with the second level of the hierarchical model which is the route choice model.

Real-World Experiment

In this section the characteristics of the alternative routes as well as the recorded drivers' experiences of travel time are presented.

General Route Characteristics

Table 2 presents the characteristics of the 10 routes. As can be seen from the table, the trips and alternative routes were selected so that the characteristics of the alternatives were to vary across the 5 choice situations.

Table 2: Characteristics of the Alternative Routes Per Trip

Trip #	Route #	Distance (km)	Avg. Travel Time (min)	Avg. Travel Speed (kph)	Number of Intersections		Number of Left Turns	Number of Merges and Diverges	Number of Horizontal Curves
					Signalized	Unsignalized			
1	1	5.1*	8.5	36.4	10	3*	3*	1*	2*
	2	6.0	8.4*	43.3*	5*	4	4	5	3
2	3	11.1*	15.2*	42.6	5	2	3	1*	30
	4	17.4	16.7	63.2*	2*	2	2*	2	11*
3	5	5.8	7.7*	44.5*	5*	3	3	2	2
	6	5.5*	9.3	37.8	8	3	2*	1*	2
4	7	5.0*	10.2	29.5	5*	3	4	1*	0*
	8	7.7	9.6*	48.2*	6	2*	2*	4	1
5	9	5.8	10.5	33.3	8	4	4	1*	1*
	10	4.7*	8.0*	34.0*	3*	1*	3*	2	6

* Better route

Experienced Travel Times

Table 3 presents the cumulative frequency distributions of the experienced travel times during the study. Table 3 also presents the probability, based on a Monte Carlo simulation, that the odd-number route is a better choice than the even-number route, by being shorter in travel time (TT).

Stochastic User Equilibrium

In another publication it was found that the expectations of the stochastic user equilibrium (SUE) theory did not match with the observed percentages of route choices [25, 26]. This is presented in the third column of Table 3. A possible reason is that SUE does not consider driver heterogeneity.

Accordingly, this paper proposes a modeling framework where driver heterogeneity is modeled and incorporated in the route choice model.

Table 3: Route Travel Times (TT) and Aggregate Route Choice Evolution
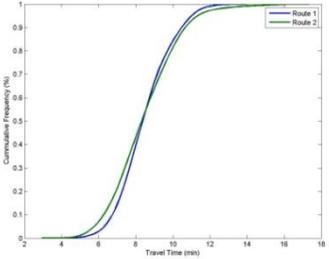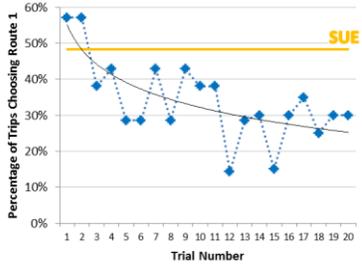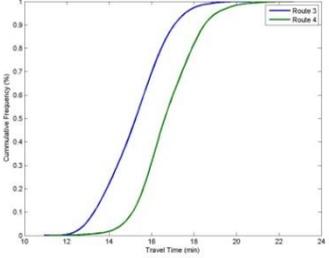
Trip	Travel Time Cumulative Distribution	Monte Carlo Simulation (SUE)	Choice Evolution (and a log-fit)
1		Prob. $(TT_{R1} < TT_{R2}) = 48.3\%$	
2		Prob. $(TT_{R3} < TT_{R4}) = 78.5\%$	
3		Prob. $(TT_{R5} < TT_{R6}) = 85.4\%$	
4		Prob. $(TT_{R7} < TT_{R8}) = 35.2\%$	
5		Prob. $(TT_{R9} < TT_{R10}) = 5.0\%$	

Driver Type

In a recent driving simulator route choice study, four different types of drivers were identified, based on the evolution trends of their learning reflected by their choices [20]. Metaphorically, these types could be taken to represent a level of aggressiveness in route switching behavior, or alternatively a level of route preference. The four types are presented in Table 4. The same four driver types were also observed in the current route choice experiment. It was found that the identified types were a function of both driver characteristics as well as choice situation characteristics [25]. The following section presents a framework showing how it is proposed to use these driver types in a hierarchical two-level route choice model.

Table 4: Four Identified Driver Types Based on Learning and Choice Evolution

Driver Type	Typical Behavior	Type Description
I		A driver starts by arbitrarily picking a route, is apparently satisfied with the experience, and continues making the same choice for the entire 20 trials.
II		A driver starts by arbitrarily picking a route, is apparently not satisfied with the experience, tries the other route, and decides that the first route was better. The driver makes a choice after trying both routes and does not change afterwards.
III		A driver switches between the two alternative routes till the end of the experiment. The driver, however, drives on route 1 much more than s/her drives on route 0. This reflects his/her preference for route 1.
IV		A driver switches between the two alternative routes during the entire time of the experiment. The driver drives both routes with approximately equal percentages. This reflects the lack of preference towards any of the alternatives.

Model Framework

Figure 2 presents a flowchart of the model framework. The flowchart shows that the proposed model is a hierarchical two-level model, where the first level of the model predicts the driver type, and the second level incorporates the predicted driver type in modeling driver route choices. Predictions of driver type (level 1) are a function of both individual characteristics (demographics and personality traits) as well as choice situation characteristics. The individual and choice situation characteristics considered in the proposed model are presented later in the paper (Table 5). Predictions of the route choices (level 2) are a function of both driver types (predicted from level 1) and the experiences the drivers had in previous trials (ex. dTT: travel time difference between alternative routes, and dTS: travel speed difference between alternative routes, etc.). Driver type and route experience covariates considered in the route choice model are presented later in the paper (Table 7). Details of the driver type and route choice models are discussed in the following sections.
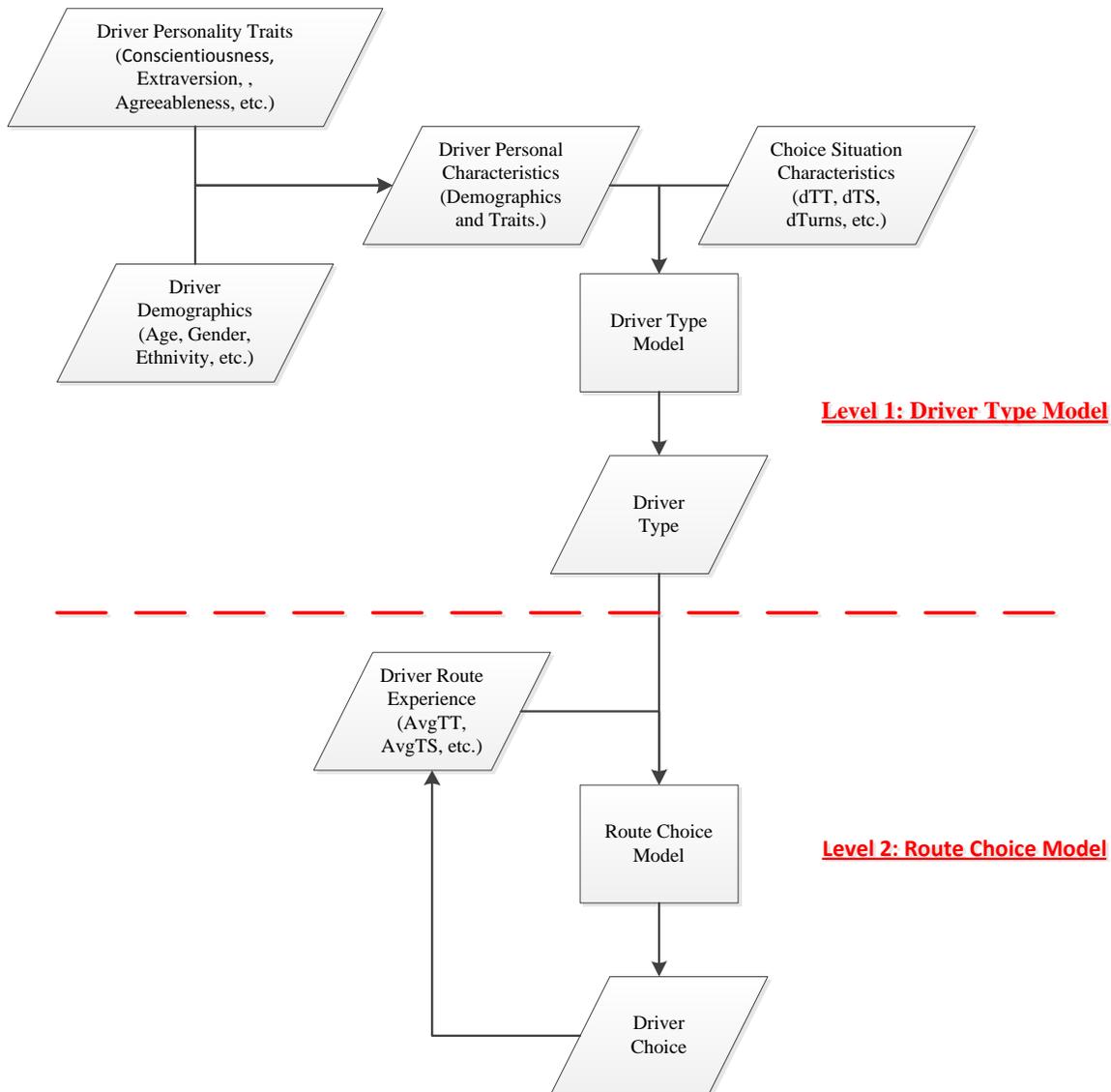
Figure 2: Flowchart of Hierarchical Route Choice Model

Hierarchical Model Level 1: Model of Driver Type

This section presents the first level of the hierarchical model. At this level variables of driver demographics and personality traits, and variables of the choice situation are used to predict driver types.

Driver Types

The four driver types presented in Table 4 are based on observing the driver route choices over a total of 20 trials. Hence, this classification is referred to as C4R20. The 'C' standards for the number of identified driver categories (types) and the 'R' stands for the number of experiment runs (trials) that were used to identify these categories (types). So, C4R20 connotes 4 "C"ategories and 20 "R"uns. In addition, C4R20-3, for example, connotes drivers that exhibit a type-III behavior under a C4R20 classification, per Table 4.

In this paper, a number of other driver type classification methods were used. C4R10 is based on classifying drivers into the same 4 categories presented in Table 4; however, based on observing driver choice evolutions in only the first 10 trials. C3R5 is based on classifying the drivers into 3 categories by observing their choice evolutions in only the first 5 trials. Classification of drivers into the first two categories of C3R5 is identical to their classification in C4R20 and C4R10. However, differentiating between a type-III behavior and type-IV behavior in only 5 trials was controversial. Therefore, both types were classified into a single category; C3R5-3.

Another classification used in this paper is C5R5. In this classification, drivers were classified according to the number of choice switches they made in the first 5 trials: minimum 0 and maximum 4; hence, 5 categories. Identical to the classification method used in C5R5 is C5R5L. The only difference is that drivers were classified according to the number of choice switches they made in the last 5 trials, instead of the first 5 trials. If the C5R5L classification is found to be significant in predicting route choices, it can be easily compared against real-life data. Since it is easy to observe or survey the last 5 route choices a driver makes in real-life. C5R5L-1 identifies drivers who made no switches in the last 5 trials and C5R5L-5 identifies drivers who made 4 switches in the last 5 trials.

Three main reasons could serve as rationale behind using classifications that are based on less number of runs. A first reason is to reduce dependency between the independent variable (driver type) and the response (route switching) in the route choice model. Driver type is an independent variable in the route choice model and is based on observing the evolution of driver route choices. On the other hand, the response of the model is to predict tendencies in route switching aggressiveness. Accordingly, to reduce this dependency, all added classifications are based on observing choice evolution in a fewer number of trials.

Another reason for using the additional classification methods is to investigate the degree of robustness of the concept of driver types in route choice prediction. If, for example, all the used driver type covariates (regardless of the classification method) turned out to be significant in predicting route choices, then this would reinforce the legitimacy of using driver types as covariates in route choice models. On the other hand, if for instance only one of these different methods turned out to be significant, then this could signify a mere coincidence.

One last reason for using the additional classification methods is to explore whether some classification methods are better than others. For example, whether three driver types can explain route choices better than five types or whether driver behavior with little experience at the

beginning of the experiment reflects driver types more than the behavior with more experience – at the last trials.

It should be stressed that these driver types should be thought of as measures of driver personality, which is what qualifies them to be independent variables. They should be thought of as measures of how easy a driver gets convinced or bored with a route, or alternatively measures of a driver's route switching aggressiveness. Since the objective is to measure a characteristic of the driver personality, it doesn't matter whether the measure is based on the first or the last trials, or whether the routes are new or familiar to the driver. The following section supports this point by showing that it is possible to predict these driver types based on driver individual characteristics (demographics and personality traits) and characteristics of the choice situation.

Response Variable

The response is an ordinal variable of *M* levels. Levels of the response variable reflect levels of driver aggressiveness in route switching behavior. The lowest level reflects a driver that is least aggressive and rarely makes route switches. On the other end, the highest level reflects a driver that is always switching between alternative routes. Five different models were estimated: C4R20, C4R10, C3R5, C5R5, and C5R5L. The modeled response is the probability that driver *i* will exhibit a route switching behavior of level *m*, when faced with choice situation *c*.

Independent Variables

The independent variables investigated in this work are presented in Table 5. As presented in the table, four main groups of variables were used: driver demographics, personality traits, choice-situation variables, and person-choice combination variables.

Response Data

As explained earlier, 20 drivers were recruited for the experiment and each driver was faced with 5 trips, i.e. in total there are around 100 observations of driver-choice combinations. All numeric variables used in the presented models were standardized; so that the magnitude of one (or more) variables would not over shadow other variable(s) and affect the solution. In addition, this scaling allows for the identification of important model variables by comparison between absolute values of estimated parameters.

Model Structure

The model used is an ordered mixed effects generalized linear model with a logit link function. Because each driver exhibited a driver-type in five different choice situations, one random parameter, the intercept, is estimated over all individuals instead of all observations. This takes into account the average dependence effects between observations of the same driver. The model has the following structure.

$$y_{ic} \sim Multin(p_{ic1}, p_{ic2}, \ldots, p_{icM})$$
$$p_{icm} = \Lambda\{\zeta_m - (x'_{ic}\beta + \theta_i)\} - \Lambda\{\zeta_{m-1} - (x'_{ic}\beta + \theta_i)\}$$
$$\theta_i \sim N(0, \varphi)$$

where,
y_{ic} is the predicted driver type level exhibited by driver *i* when faced with choice situation *c*
Multin is the Multinomial distribution
p_{icm} is the probability that driver *i* exhibits driver type level *m* at choice situation *c*
m is the responce level $\{1, 2, \ldots, M\}$

Λ is the cumulative Logistic distribution function

ζ_m is the break point for response level m $(-\infty = \zeta_0 < \zeta_1 = 0 < \zeta_2 < ... < \zeta_M = \infty)$

x_{ic} is the vector of covariates for person i at choice situation c

β is a vector of the parameters

θ_i is the random component of person i

N is the Normal distribution

φ is the variance

Table 5: Independent Variables of Driver Type Model

#	Variable Name	Variable Description	Variable Values
Variables of Driver Demographics			
1	Age_i	Age of participant i	18 to 68
2	$Gender_i$	Gender of participant i	M or F[*]
3	$Ethnicity_i$	Ethnicity of participant i	W or NW[*]
4	$Education_i$	Education level of participant i	G or NG[*]
6	$Dr\ Miles_i$	Annual number of miles participant i drives (in thousands)	2 to 35
7	$Residency_i$	Number of years participant i has been residing in the area	1 to 56
Variables of Driver Personality Traits			
1	N_i	Neuroticism of participant i	7 to 30
2	E_i	Extraversion of participant i	19 to 43
3	O_i	Openness to experience of participant i	20 to 31
4	A_i	Agreeableness of participant i	22 to 42
5	C_i	Conscientiousness of participant i	26 to 47
Variables of Choice Situation[**]			
1	$dTTTp_{ic}$	Percentage difference in mean travel time between the alternatives of choice c	2.8 to 24.5
2	$dDistPrc_c$	Percentage difference in distance between the alternative routes of choice c	5.7 to 44.8
3	$dSpdPrc_c$	Percentage difference in mean travel speed between the alternatives of choice c	2.1 to 48.1
4	$dLinksPrc_c$	Percentage difference in number of links between the two alternatives of choice c	0.0 to 54.5
5	$dSigPrc_c$	Percentage difference in number of signalized intersections between the two alternative routes of choice c	18.2 to 90.9
6	$dUnsigPrc_c$	Percentage difference in number of unsignalized intersections between the two alternative routes of choice c	0.0 to 120.0
7	$dTurnsPrc_c$	Percentage difference in number of uncontrolled intersections between the two alternative routes of choice c	66.7 to 133.3
8	$dLeftsPrc_c$	Percentage difference in number of left turns between the two alternatives of choice c	28.6 to 66.7
9	$dCurvPrc_c$	Percentage difference in number of curves between two alternatives of choice c	0.0 to 200.0
Variables of Driver-Choice Combination			
1	$AvgFam_{ic}$	Average familiarity of driver i with the two routes of choice c	1 to 5
2	$MaxFam_{ic}$	Maximum familiarity of driver i with the two routes of choice c	1 to 5
3	$dFamPrc_{ic}$	Percentage difference of the familiarity of driver i with the two routes of choice c	0.0 to 133.3

Model Results

Table 6 presents the results of the estimated models. It is satisfying that variables belonging to both the driver (both demographic and personality) as well as the choice situation were found to be significant. In addition, the signs of the variables are satisfying: first, they are consistent with a similar model that is discussed in another article [25]; and second, they are consistent across the five driver type categorization methods used. It is interesting that all modeled driver type classifications were found predictable. However, what is most interesting is the high importance of driver personal factors (demographics and personality traits), compared to variables of the choice situations. As explained earlier, since all variables (except nominal ones) were standardized, deduction about variable importance can be reasonably deduced from respective parameter estimates.

The models suggest that drivers of a white ethnicity and drivers without post-graduate degrees are more likely to switch routes than their counterparts. On the other hand, it appears that the more miles a person drives per year, the less likely that person is going to be aggressive in route switching behavior. There are three possible explanations for this. It is possible that these drivers develop cognitive mechanisms that enable them to enjoy the drives they make, and therefore, a few extra miles or minutes do not bother them much. Another explanation could be that these drivers get used to driving to the extent that driving a few extra miles or waiting a few extra minutes does not bother them. One last explanation could be that these drivers get very experienced in driving that they can identify their preferred routes from only a few trials. Therefore, do not need to switch much.

Table 6: Significant Variables of the Driver Type Model [*]

Significant Variables	Driver Type Categorization Methods									
	C4R20		C4R10		C3R5		C5R5		C5R5L	
	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value
(Intercept)	-2.362	0.117	-1.150	0.337	0.039	0.897	-5.332	0.000	-1.952	0.000
EthnicityW	3.729	0.021	2.643	0.037	n/s	n/s	6.423	0.000	n/s	n/s
EducationNG	1.701	0.052	n/s	n/s	1.570	0.005	n/s	n/s	1.663	0.037
DrMiles	-0.723	0.087	-0.753	0.032	n/s	n/s	-1.375	0.000	n/s	n/s
N	n/s	n/s	n/s	n/s	n/s	n/s	1.357	0.001	n/s	n/s
E	1.186	0.022	0.879	0.025	0.705	0.019	1.112	0.003	n/s	n/s
O	n/s	n/s	n/s	n/s	n/s	n/s	-1.389	0.000	n/s	n/s
A	-1.175	0.025	-1.158	0.008	-0.680	0.032	n/s	n/s	n/s	n/s
C	0.715	0.099	n/s	n/s	0.516	0.054	1.304	0.000	0.620	0.088
dTT	-0.798	0.041	n/s	n/s	-0.403	0.073	n/s	n/s	-0.663	0.059
dTS	-1.022	0.030	-0.756	0.054	-0.554	0.067	-0.474	0.083	n/s	n/s
dCurves	-0.405	0.060	n/s	n/s	n/s	n/s	n/s	n/s	n/s	n/s
ζ_2	1.215	0.000	1.049	0.000	1.174	0.000	0.858	0.000	0.695	0.004
ζ_3	4.314	0.000	3.467	0.000	n/a	n/a	2.540	0.000	1.763	0.000
ζ_4	n/a	n/a	n/a	n/a	n/a	n/a	4.487	0.000	3.962	0.000

[*] n/s means not significant, n/a means not applicable

It is interesting that all of the five measured personality traits were significant. It appears that drivers that are characterized with higher measures of neuroticism, extraversion, and conscientiousness are more likely to switch between alternative routes. Four of the six facets measured by neuroticism are: anxiety, self-consciousness, and impulsiveness, and vulnerability to stress. Similarly, activity and excitement seeking are two of the six facets measures by extraversion. Last, three of the six facets measured by conscientiousness are: competence, achievement striving, and deliberation. It seems logical that these three variables imply higher aggressiveness in route switching behavior. On the other hand, openness to experience and agreeableness seem to be inversely related to route switching aggressiveness. Following a similar analysis: fantasy, feelings and ideas are three of the facets measured by openness to experience, and straightforwardness, compliance and modesty are three of the facets measured by agreeableness. It seems logical that drivers with increased levels of these characteristics will be less likely to pay attention to traffic conditions and accordingly less likely to switch routes.

Finally, it seems logical that drivers are less likely to switch between alternative routes as differences in travel time and travel speed between the alternative routes increase. As an extreme example: in a scenario where the travel times on two alternative routes are 5 minutes and 50 minutes, it is highly unlikely that drivers will voluntarily switch between these two alternatives.

Hierarchical Model Level 2: Model of Route Choice

This section presents the second level of the model. After predicting driver types in the first level of the hierarchical model, the predicted driver types are used in the second level to predict driver route switching behavior.

Response Variable

The modeled response is the probability that driver *i* will switch his/her route choice at trial *t*.

Independent Variables

The independent variables investigated in this work are presented in Table 7. As can be seen in the table, two groups of covariates are considered: variables of driver type and variables of previous route experience. Driver specific variables were not included because they were used to predict driver types. It is worth mentioning that travel time and speed experiences are calculated as the arithmetic mean of all previous experiences. The following formula demonstrates how average previous travel time is calculated.

$$AETT_{irt} = \frac{\sum_{t=1}^{t-1} \delta_{irt} \cdot TT_{it}}{\sum_{t=1}^{t-1} \delta_{irt}}$$

where,

$AETT_{irt}$ is the average experienced travel time of person i on route r up till trial t
δ_{irt}=1 if person i chooses route r at trial t, and 0 otherwise
TT_{it} is the travel time experience by person i at trial t

Response Variable

In total there were more than 2,000 choice observations. However, all observations with missing data were dropped. This included all trials where drivers were not aware of the travel time on the alternative route. Hence, for example, all observations of driver type I in C4R20 were not considered in the following models. Because categorizations that are based on fewer runs cannot be as accurate as those based on more runs, some C4R20-1 drivers were categorized under type I in

C4R10 and type I in C3R5, for example. As a result these two categories were not dropped from the data. A total of 1255 observations were included in all the following models. All numeric variables used in the presented models were standardized. This helps avoid singular values in calculations for matrix inversion, and helps prevent that the magnitude of one (or more) variables would over shadow other variable(s) and affect the solution. However, as mentioned in the previous model, one big advantage of normalizing numerical variables is to be able to deduce variable importance from comparison of estimated parameters.

Table 7: Independent Variables of the Route Choice Switching Model

		Variables of Driver Type	
1	$C4R20_{ic}$	Type (as presented in Table 4) of driver i in choice situation c based on 20 trials	1[*], 2, 3, or 4
2	$C4R10_{ic}$	Similar to C4R20, but categorization is based on only 10 trials	1, 2, 3, or 4
3	$C3R5_{ic}$	Similar to C4R20, but categorization is based on only 5 trials, and patterns 3 and 4 are combined into a single type.	1, 2, or 3
4	$C5R5_{ic}$	Five categories based on five trials. The categories are based on the number of switches driver i makes in the first 5 trials.	1, 2, 3, 4, or 5
5	$C5R5L_{ic}$	Similar to C5R5, but categorization is based on the last 5 trials	1, 2, 3, 4, or 5
6	C#R#(L)-X_{ic}	Indicator variable indicating whether person i belongs to driver type X in choice situation c, according the C#R#(L) category	-
		Variables of Route Experience	
1	$Trial_t$	The route choice trial number of the participant	1 to 20
2	$Inertia_{it}$	The number of successive identical choices participant i has made right before trial t	0 to 19
3	$PrefOOC_{it}$	The ratio of the number of times (participant i has chosen the other route over the current chosen route) in all trials up till trial t	0.06 to 16.00
4	$TTOOC_{it}$	The ratio of the average travel times (of the other route over the current chosen route) experienced by participant i up till trial t	0.50 to 1.99
5	$TTVOOC_{it}$	The ratio of the travel time variances (of the other route over the current chosen route) experienced by participant i up till trial t	0.05 to 10.89
5	$TSOOC_{it}$	The ratio of the average travel speeds (of the other route over the current chosen route) experienced by participant i up till trial t	0.47 to 1.97
6	$TSVOOC_{it}$	The ratio of the travel speed variances (of the other route over the current chosen route) experienced by participant i up till trial t	0.03 to 13.92

[*] all records of C4R20 driver-type I were dropped out due to missing data about the other route. Because categories of the other classification methods were based on less number of trials, they were not as accurate and some C4R20-1 drivers were classified into the equivalent driver-type of the other methods (example: C4R10-1 and C3R5-1).

Model Structure

The route choice model proposed here is a mixed effects generalized linear model with a logit link function. Similar to the driver type model: because each driver was asked to repeat his/her choice several times, one random parameter, the intercept, is estimated over all individuals instead of all observations. This takes into account the average dependence effects between observations of the same driver. The model has the following structure.

$$y_{ict} \sim Bern(p_{ict})$$
$$logit(p_{ict}) = x'_{ict}\beta + \theta_i$$
$$\theta_i \sim N(0, \varphi)$$

where,

$y_{ict} = 1$ if person i switches his/her route choice at trial t of choice situation c

$y_{ict} = 0$ if person i does not switch at trial t of choice situation c

Bern is the Bernoulli distribution

p_{ict} is the probability that person i switches at trial t of choice situation c

$logit(p_{ict}) = \dfrac{p_{ict}}{1 - p_{ict}}$

x_{ict} is the vector of covariates for person i in choice situation c at time t

β is a vector of the parameters

θ_i is the random component of person i

N is the Normal distribution

φ is the variance

Model Results

Table 8a presents the results of the estimated models. It is appealing that almost all the driver types were found to be highly significant. The only variables that were not found significant are the indicator variables of C4R10-2, C3R5-2 and C5R5-2. The probable reason these three variables did not turn out to be significant is that based on the first 10, 5, and 5 observations, respectively, some drivers belonging to C4R20-3 were mistakenly classified as types C4R10-1 and C4R10-2, C3R5-1 and C3R5-2, and C5R5-1 and C5R5-2, respectively. This is further demonstrated by the negative sign of C4R10-2 which incorrectly implies that C4R10-2 driver are less aggressive then C4R10-1 drivers.

It is very pleasing that all driver types of the C5R5L classification were found to be significant. As mentioned earlier this is especially pleasing because it signifies that this hierarchical model can be estimated by observing naturalistic driver choices in real lives. This finding can be interpreted as proof that driver types reflect an actual truth about inherent aggressiveness in driver personalities for route switching behavior. The fact that the values of the estimated parameters for the 5 driver type levels of C5R5L increased as the driver type level increased reflects that the probability of switching consistently increased as the driver type level increased.

The signs of all variables seem logical. It is logical that an increase in inertia (consecutive identical choices), reflects an increase in route preference. Hence, implies a lower probability of switching; reflected by the negative sign of the estimated parameter. Similarly, a high percentage of choice for a certain route reflects a high route preference. Therefore, if a driver switches to an alternative route of a lower choice percentage, the probability that this driver will switch back to his/her initial preferred route should be high; reflected by the positive sign of the PrefOOC parameter. On the other hand, signs of TTOOC and TSOOC reflect that drivers prefer lower travel time and higher travel speed routes.

One finding that needs to be stressed upon is the significance of previous experienced travel speeds. As mentioned in the introduction, travel time and travel distance have typically received the highest attention in route choice models. It is interesting that while travel distance was not found significant in any of these models, travel speed was found significant in all of them. Although travel speed has not received as much attention in the literature, its significance is

not a surprise since there is a significant number of models in the literature that incorporate variables that are related to travel speed, such as the number of signalized intersections.

Last, there is strong evidence in the literature about the significance of travel time reliability in route choice models. A possible reason why neither travel time nor travel speed variances were significant in the estimated models may be explained by the minor differences in travel time and travel speed variances between the alternative routes. Differences between travel time variances of the alternative routes can be observed Table 3.

Comparing model performances (presented in Table 8b) reveals that driver-type route choice models outperform the general model (which does not include driver-type variables). All deviance measures are lower than in the general model. However, the deviance measure does not penalize for reduced model parsimony. Two statistics that penalize for reduced model parsimony are considered: AIC and BIC. The AIC statistic, like the deviance measures indicates that all driver-type route choice models outperform the general model. However, the BIC statistic which penalizes for reduced model parsimony more than the AIC measure indicates that the C5R5 and the C5R5L models do not outperform the general model. Formulas of the Deviance, AIC and BIC statistics are presented below. The formulas demonstrate that while the AIC measure penalizes reduced model parsimony with an increase of two AIC units for every model parameter, the BIC measure penalizes reduced model parsimony with an increase of BIC units that equal the natural logarithm of the number of observations, for each model parameter. In the present case the natural logarithm of 1255 observations equals 7.13. Hence, in the present case, the BIC statistic penalization for reduced model parsimony is more than triple that of the AIC statistic.

$$Deviance = -2 \times \log\big(LH(M) - LH(S)\big)$$
$$AIC = Deviance + 2 \times p$$
$$BIC = Deviance + ln(n) \times p$$

where,

LH is the log-likelihood
M is the estimated model
S is the saturated model; which includes a parameter for each observation
p is the number of model parameters
n is the number of model data points

STUDY CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

While experiment reality and driver homogeneity are two limitations in route choice models, this work addresses both limitations. This work proposes a two-level hierarchical model as a modeling framework for incorporating driver heterogeneity in route choice models. This work is based on a real-life route choice experiment where a sample of 20 drivers, faced 5 choice situations, and made a total of more than 2,000 real-world choices. The first level of the hierarchical model used driver individual characteristics (demographic and personality traits) and characteristics of the choice situation to categorize drivers into driver types. A driver type is assumed to be a metaphoric measure of driver aggressiveness in route switching behavior, or alternatively a measure of the ease by which a driver gets bored of (or used to) a route. The second level of the hierarchical model uses the identified driver type and the experiences a driver faces in the previous trials to predict driver route choices.

Table 8a: Significant Variables of the Route Choice Model

Significant Variables	Route Choice Models Based on Different Driver Type Categorizations											
	Without Driver Type		C4R20		C4R10		C3R5		C5R5		C5R5L	
	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value
(Intercept)	-1.779	< 2e-16	-3.610	< 2e-16	-2.787	0.000	-2.230	0.000	-2.352	0.000	-2.067	< 2e-16
Inertia	-1.149	0.000	-0.911	0.000	-1.003	0.000	-1.090	0.000	-1.093	0.000	-1.058	0.000
PrefOOC	0.374	0.000	0.325	0.000	0.375	0.000	0.425	0.000	0.443	0.000	0.366	0.000
TTOOC	-0.342	0.000	-0.307	0.000	-0.331	0.000	-0.330	0.000	-0.313	0.000	-0.301	0.001
TSOOC	0.159	0.040	0.204	0.010	0.201	0.010	0.171	0.028	0.183	0.018	0.155	0.047
C4R20-3	-		2.068	0.000	-		-		-		-	
C4R20-4	-		2.832	0.000	-		-		-		-	
C4R10-2	-		-		-0.429	n/s	-		-		-	
C4R10-3	-		-		1.366	0.086	-		-		-	
C4R10-4	-		-		1.733	0.030	-		-		-	
C3R5-2	-		-		-		0.036	n/s	-		-	
C3R5-3	-		-		-		0.861	0.006	-		-	
C5R5-2	-		-		-		-		0.077	n/s	-	
C5R5-3	-		-		-		-		0.619	0.053	-	
C5R5-4	-		-		-		-		1.189	0.000	-	
C5R5-5	-		-		-		-		1.512	0.001	-	
C5R5L-2	-		-		-		-		-		0.525	0.047
C5R5L-3	-		-		-		-		-		0.871	0.000
C5R5L-4	-		-		-		-		-		1.126	0.000
C5R5L-5	-		-		-		-		-		1.376	0.018

Table 8b: Performance of the Route Choice Models

Variables	General	C4R20	C4R10	C3R5	C5R5	C5R5L
Deviance	1100	1042[*]	1057[*]	1077[*]	1076[*]	1078[*]
AIC	1112	1058[*]	1075[*]	1093[*]	1096[*]	1098[*]
BIC	1143	1100[*]	1122[*]	1134[*]	1147	1149

[*] Driver type model performs better than the general model

Based on observing the trends of evolution of driver choices over a specific number of trials, a number of evolution trends were identified. Drivers belonging to each of the identified evolution trends were branded as drivers of a certain type. This defines a certain classification method. Observing the evolution of the driver choices over a different number of trials resulted in identifying different trends and in drivers being classified into different groups; hence, defining a different classification method. In this article, five different classification methods were defined and used. It was found possible to predict the identified driver types of all five classification

methods based on driver and choice situation characteristics. It was found that drivers with white ethnicities and drivers with lower levels of education exhibit a more aggressive route switching behavior. Similarly, increased levels of neuroticism, extraversion, and conscientiousness increased the probability of exhibiting a more aggressive route switching behavior. On the other hand, drivers who drive more miles per year, drivers with higher levels of agreeableness, and drivers with higher levels of openness to experiences exhibited lower tendencies to aggressiveness in route switching behavior. In addition, an increased difference between the mean travel times or travel speeds of the alternative routes decreased the probability of exhibiting an aggressive route switching behavior.

In the second level of the hierarchical model the identified driver types were used along with the drivers' previous travel experiences to predict route choices. The identified categories were found to be highly significant in route choice predictions (along with inertia, route preference, average experienced travel time, and average experienced travel speed). The models that included driver category were characterized with a better data fit than the general model that did not include driver type variables; even with the AIC performance measure which penalizes for decreased model parsimony.

In conclusion, the proposed hierarchical two-level framework for incorporating driver heterogeneity seems to be promising, and successful replications of this work could be very beneficial for the future modeling of driver heterogeneity in route choice models. A number of further research directions include: identifying other measures of driver heterogeneity; comparing the predictive rather than the descriptive abilities of the models; incorporating the effect of driver heterogeneity on the compliance rates to information; examining if the same results could be replicated in a travel or a driving simulator; and exploring whether the identified driver-types represent latent driver classes.

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Chapter 9

A Latent Class Choice Model of Heterogeneous Drivers Route Choice Behavior Based on a Real-World Experiment

Extended Abstract Submitted for Presentation at the 20th International Symposium on Transportation and Traffic Theory (ISTTT20)

A Latent Class Choice Model of Heterogeneous Drivers Route Choice Behavior Based on a Real-World Experiment

Aly M. Tawfik, MS
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 577-0462
FAX: (540) 231-7532
tawfik@vt.edu

Hesham A. Rakha, PhD., P.Eng.
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 231-1505
FAX: (540) 231-1555
hrakha@vt.edu

ABSTRACT

This paper presents a route choice model of latent class heterogeneous drivers that is based on a real-world experiment. In previous publications the authors had presented findings about driver personal differences in route switching aggressiveness. These differences were described by "driver types", which is a term developed by the authors to reflect aggressiveness in route switching behavior. Driver types were found predictable from driver demographics and personality traits, as well as choice situation characteristics. In addition, the identified driver types were found significant in predicting route choice behavior. Instead of a hierarchical model that models driver type on one level then uses the identified driver type to model route choice at a second level, this paper estimates both models simultaneously. In the estimated latent class choice models, the latent classes represent the driver types and the choice model is the route switching behavior. The models developed in this paper are based on a sample of 20 drivers who made more than 2,000 real world route choices. The results of the developed models indicate that: 1) driver classes exist and seem to be very similar to the driver-types identified in the earlier publications, 2) latent driver classes depend on driver demographics, personality traits and choice situation characteristics, 3) different driver classes follow different route choice criteria, and 4) incorporating driver types or latent classes improves route choice model performance, but latent class models perform better than hierarchical driver-type models.

INTRODUCTION

In order the increase the efficiency of our transportation systems, it is important to improve our understanding and prediction of human travel behavior. This article presents example work for improving our understanding and prediction of route choice behavior via the incorporation of variables of driver heterogeneity.

Driver heterogeneity is a limitation that has been repeatedly cited in route choice literature [1]. Example citations include: "it is desirable to develop a model which is disaggregated by a type of driver because the route choice behavior varies by individual" [2], "Drivers do not become homogeneous and rational, as equilibrium analyses presuppose; rather, there are fewer rational drivers even after a long process of learning, and heterogeneous drivers make up the system" [3], "studies that focus only on a rather rational description of day-to-day learning cover only a limited part of the way route choices are made over time" [4], and "The first [challenge facing route choice research] is to understand the underlying behavioral patterns exhibited in individual preferences" [5].

In general, the body of literature on travel behavior research has, until recently, been largely neglecting differences in human personality. Although personality differences like personal characteristics [6], attitude [7], and cognitive abilities [8] have often been cited in travel behavior research, quantifying their effect in general models of travel behavior has been challenging. Accordingly, almost all route choice and network assignment models that are used in practice do not incorporate these factors. More recent examples of personality differences that are incorporated in travel behavior literature include: *personal traits* in safety research [9, 10], *lifestyle* in household location choice models [11, 12], *driver type* in traffic gap acceptance models [13], and *driver type* in route choice models [14-19].

This work comes as an extension to the *driver-type*-based route choice models mentioned above [14-19]. In earlier publications, based on two separate route choice experiments with two different experiment mediums, the authors identified four types of drivers. One of the experiments was based on a driving simulator, and the other was an in situ experiment in real-world conditions. Within the context of this work, driver type is used as a metaphoric expression to reflect driver aggressive tendencies in route switching behavior. The four identified driver types were found predictable from driver demographics, personality traits, and were found to be significant in route choice models. In an earlier article, the authors developed a two-stage hierarchical model, where the first stage predicted the driver-type, and the second stage used the predicted driver type to model driver route choice behavior. Driver types were incorporated in the route choice models via two alternative methods [14, 19].

In the first method, driver types were included in the route switching models as additional indicator variables. Higher driver types increased the probability of route switching [14, 19]. In the second method, separate route switching models were estimated for each driver type [19]. Different variables were found significant in the driver-type-specific route switching models [19]. This indicated the possibility of existing latent driver classes.

One of the limitations of using driver types and the hierarchical model presented in the earlier work is that the researcher has to use personal judgment to classify drivers into a specific number of driver types and according to specific classification criteria. However, there is no guarantee that the chosen number of driver-types and classification criteria are optimum for explaining the modeled response. To address this limitation, latent class choice models are estimated in this paper.

It is interesting and probably beneficial to notice the developing similarity between route choice and household location choice literature. A recent publication provides a good review of the history of household location choice models [11]. Apparently, similar to the modeling framework proposed by the authors in the hierarchical model, when household choice location models first moved to incorporate individual heterogeneity, it, too, was based on two stage models. Today, however, both stages can be modeled simultaneously. This is interesting because it appears that the authors have been following the same historical path.

In the following sections, the authors present the objectives of the study, followed by an explanation of the study approach: study description, network and questionnaires. In the third section, the authors present and discuss the results of estimating hierarchical and latent class route choice models, and in the fourth section the paper ends with conclusions of the study and recommendations for further research.

STUDY OBJECTIVES

The main objectives of this study are to: (a) investigate the existence and the number of latent driver classes that can improve route choice predications, (b) identify variables that are significant in defining these latent classes, and (c) evaluate and compare the performance of hierarchical and latent class route choice models.

STUDY APPROACH

Study Description

Twenty participants were selected to participate in this study. Each participant was asked to complete 20 experiment runs during regular school days of the academic Spring semester of the year 2011. Experiment runs were scheduled only during one of three traffic peak hours: morning (7-8 am), noon (12-1 pm), and evening (5-6 pm). During each experiment run, participants were asked to drive research vehicles on the road network of the New River Valley. Participants were given 5 Google Map print outs. Each map representing one trip: one point of origin, one point of destination, and two alternative routes. All participants were given identical maps and were asked to make the same 5 trips. On each experiment run, participants were asked to make these five trips assuming that the provided alternative routes were the only routes available between the points of origin and destination. The trips and the alternative routes were selected to ensure differences in the 5 choice situations (Table 1). All driver choices as well as the travel conditions were recorded via a GPS unit placed on board of the vehicle and a research escort that always accompanied the participants. Participants were instructed to behave in the same manner they behave in the real life. After completion of the 20 trials, participants were asked to complete a post-task questionnaire.

It should be noted that in this experiment, each trip represented a choice situation for the participants. Hence, in many occasions in this paper the terms "trips" and "choices" refer to the same thing and are used exchangeably. Similarly, "experiment runs" and "experiment trials" are also used exchangeably.

Network

Table 1 demonstrates the origin, destination, and alternative routes specific to each of the five trips. It also shows a brief description of each of the routes. More information about the routes can be seen in Figure 1 and are provided in Table 2. Figure 1 shows a map depicting all five points of trip origins and destinations as well as the ten alternative routes provided.

Table 1: Description of the Five Trips

Trip #	Trip Origin	Trip Destination	Alternative Routes		Route Description (and speed limits)
			Route #	Route Name	
1	Point 1 (VTTI)	Point 2 (Walmart)	Route 1	US460 Business	Mostly a high speed (65 mph) freeway
			Route 2	US460 Bypass	High speed (45 mph) urban highway
2	Point 2 (Walmart)	Point 3 (Foodlion1)	Route 3	Merrimac	Mostly a shorter, low speed (30 mph) back road with a lot of curves
			Route 4	Peppers Ferry	Mostly a longer, high speed (55 mph) rural highway
3	Point 3 (Foodlion1)	Point 4 (Foodlion2)	Route 5	US460 Bypass	A longer high speed (65 mph) freeway followed by a low speed (25 mph) urban road
			Route 6	N.Main	A shorter urban route (40 and 35 mph)
4	Point 4 (Foodlion2)	Point 5 (Stadium)	Route 7	Toms Creek	A short urban route that passes through campus (25 and 35 mph)
			Route 8	US460 Bypass	Primarily a long high speed (65 mph) freeway and low speed (25 mph) urban roads
5	Point 5 (Stadium)	Point 1 (VTTI)	Route 9	S.Main	A long urban road that passes through town (35 mph)
			Route 10	Ramble	A short unpopular low speed (25 and 35 mph) back road that passes by a small airport.

Pre-task Questionnaire

The pre-task questionnaire collected information about the participants' demographics (age, gender, ethnicity, education level, etc.) and driving experiences (number of driving years, annual driven miles, etc.).

Post-task Questionnaire

The post-task questionnaire was divided into two sections. The first section collected information about the participants' perceptions of the traffic conditions on the alternative routes (distance, travel time, travel speed, and traffic level), as well as the participants preference levels of the routes. In the second section the participants were asked to fill in a personality inventory, the NEO Personality Inventory-Revised [20]. This is a psychological personality inventory that is based on the Five Factor Model. It measures five personality traits: neuroticism extraversion, openness to experience, agreeableness, and conscientiousness. In addition, each personality trait measures six subordinate dimensions (sometimes referred to as facets).

Neuroticism measures the tendency of a person to experience negative emotions such as anxiety, guilt, frustration, and depression. Persons who score high on neuroticism are usually self-conscious, and are associated with low self-esteem and irrational thinking. The six subordinate dimensions of neuroticism are: anxiety, hostility, depression, self-consciousness, impulsiveness, and vulnerability to stress. Extraversion measures the tendency towards positive emotionality. The six subordinate dimensions of extraversion are: warmth, gregariousness,

assertiveness, activity, excitement seeking, and positive emotion. Openness to Experiences measures the imaginative tendency of individuals, their attentiveness to inner emotions, and their sensitiveness towards art and beauty. The six subordinate dimensions of openness to experience are: fantasy, aesthetics, feelings, actions, ideas, and values. Agreeableness measures the more humane aspects of the personality. The six subordinate dimensions of agreeableness are: trust, straightforwardness, altruism, compliance, modesty, and tendermindedness. Last, Conscientiousness measures personality tendencies towards being diligence, thoroughness and being governed by conscience. The six subordinate dimensions of conscientiousness are: competence, order, dutifulness, achievement striving, self-discipline, and deliberation. For further details about these personality traits, or about the Five Factor Model or the NEO Personality traits, the reader is referred to Wikipedia for general information, and to other publications for thorough theoretical discussions [20-22]

Figure 1: Map of the Experiment Network (Source: Google Maps)

Table 2: Characteristics of the Alternative Routes Per Trip

Trip #	Route #	Distance (km)	Avg. Travel Time (min)	Avg. Travel Speed (kph)	Number of Intersections		Number of Left Turns	Number of Merges and Diverges	Number of Horizontal Curves
					Signalized	Unsignalized			
1	1	5.1*	8.5	36.4	10	3*	3*	1*	2*
	2	6.0	8.4*	43.3*	5*	4	4	5	3
2	3	11.1*	15.2*	42.6	5	2	3	1*	30
	4	17.4	16.7	63.2*	2*	2	2*	2	11*
3	5	5.8	7.7*	44.5*	5*	3	3	2	2
	6	5.5*	9.3	37.8	8	3	2*	1*	2
4	7	5.0*	10.2	29.5	5*	3	4	1*	0*
	8	7.7	9.6*	48.2*	6	2*	2*	4	1
5	9	5.8	10.5	33.3	8	4	4	1*	1*
	10	4.7*	8.0*	34.0*	3*	1*	3*	2	6

* Better route

RESULTS AND ANALYSIS

This sections starts by presenting the four driver types that were identified in the earlier publications. Then, a hierarchical model with driver-type-specific route choice models is estimated. Next, the authors present a short description of the latent models used, and the estimated latent class models are presented and discussed.

Driver Type

In two recent studies, four different types of drivers were identified, based on the evolution trends of their learning which is reflected by their choices [18]. Metaphorically, these types are taken to represent a level of aggressiveness in route switching behavior, or alternatively a level of route preference. The four types are presented in Table 3. These four driver types were observed in a driving simulator experiment and in a real-world experiment [14, 19]. It was found that the identified types were a function of both driver characteristics (demographics and personality traits) as well as choice situation characteristics [14] and are significant in route switching predications. The reader is strongly advised to recognize these four driver types because they are repeatedly referenced throughout this article. The following section presents a hierarchical route choice model that is based on these four types.

Hierarchical Model

Table 4 presents the results of an ordered multinomial generalized linear model with a logit link function. This model predicts the probability that a driver i will exhibit a driver type m at choice situation c. This presents the first stage in a hierarchical 2-stage model. For more discussion of this model, the reader is referred to an earlier publication [16]. However, these results are included in this article to be compared with the results of the latent class model which is presented in a following section.

Table 3: Four Identified Driver Types Based on Learning and Choice Evolution

Driver Type	Typical Behavior	Type Description
I C4R20-1	 Trial Number	A driver starts by arbitrarily picking a route, is apparently satisfied with the experience, and continues making the same choice for the entire 20 trials.
II C4R20-2	 Trial Number	A driver starts by arbitrarily picking a route, is apparently not satisfied with the experience, tries the other route, and decides that the first route was better. The driver makes a choice after trying both routes and does not change afterwards.
III C4R20-3	 Trial Number	A driver switches between the two alternative routes till the end of the experiment. The driver, however, drives on route 1 much more than s/her drives on route 0. This reflects his/her preference for route 1.
IV C4R20-4	 Trial Number	A driver switches between the two alternative routes during the entire time of the experiment. The driver drives both routes with approximately equal percentages. This reflects the lack of preference towards any of the alternatives.
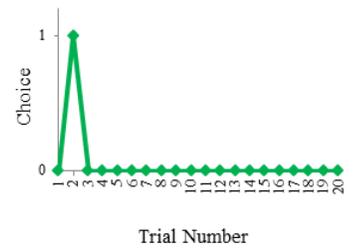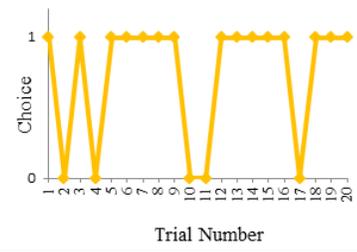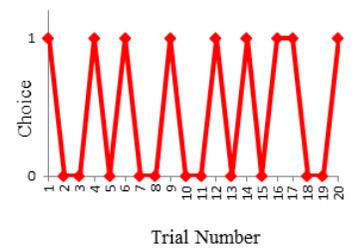
Once driver types are inferred from the 1st stage of the hierarchical model, the modeler has two options for using the identified driver types in the 2nd stage of the hierarchical model, the route choice model. The first option would be to add the driver type as an additional indicator variable in the general route choice model, as presented by the third column of Table 5a. The second option would be to use a different route choice model for each driver type, as indicated by columns 4, 5 and 6 of Table 5a. Table 5b presents four performance measures for the estimated models: log-likelihood, deviance, AIC and BIC. It can be seen that adding driver type covariate improves model performance, which can be deduced from comparing columns 2 and 3 of Table 5b. Unfortunately, the same comparison cannot be applied to the driver type specific choice models; due to the difference in number of observations.

It should be noted that all numeric variables were standardized, in order to be able to compare variable importance in the estimated models based on values of the estimated

parameters. Description of the variables explored in the hierarchical model are presented in Table 6, where Table 6a presents the variables explored in the driver type model (1st stage) and Table 6b presents the variables explored in the route choice model (2nd stage).

Unlike earlier publications, the independent variables used in the hierarchical route choice model presented here are based on differences in experienced travel conditions. They are not based on ratios of experienced travel conditions, which is what was done in the earlier publications. The reason the route choice model presented here is based on differences rather than ratios, is to allow for comparability between the estimated hierarchical choice models and the latent class choice models. The estimated latent class choice models are based on the Random Utility Model, where each choice alternative is characterized with a utility function. As can be seen from the following derivation, probability calculations are based on differences and not ratios.

The probability of choosing action a over action b equals,

$$Pr(a > b) = Pr(u_a > u_b)$$
$$= Pr(v_a + \epsilon_a > v_b + \epsilon_b)$$
$$= Pr(\epsilon_a - \epsilon_b > v_b - v_a)$$
$$= Pr(\varepsilon > \zeta)$$
$$= CFD(\varepsilon)$$

$where,$

u_j is the utility of choosing action j
$$= v_j + \epsilon_j$$
$$= X_j^T \beta_j + \varepsilon_j$$
v_j is the deterministic (measurable) part of the utility of action j
$$= X_j^T \beta_j$$
ϵ_j is the random (un-measurable) part of the utility of action j
X_j^T are the covariates of action j
β_j are the estimated parameters of action j
ε is the random variable
ζ is a deterministic value
CFD is the cumulative frequency distribution

One of the limitations of the hierarchical model is that the researcher has to decide on the classification method for driver types based on personal judgment. There is no guarantee that the researcher's chosen classification method guarantees a better performance over a route choice model that does not include driver types. Furthermore, even if the classification method was found to improve model performance, there is no guarantee that it is the best classification method. The authors had elaborated on this in an earlier publication, where they classified drivers into driver types based on different classification criteria. In the earlier publication, performance of the C4R20 classification produced the best results. Therefore, it is the method the authors chose to include in the current work [16].

This limitation does not exist in latent class choice models. The following section explains the framework of latent class choice models.

Table 4: Significant Variables of the 1st Stage of the Hierarchical Model (C4R20 Driver Type Model)

Significant Variables	Beta	p-value
Intercept	-2.362	0.117
EthnicityW	3.729	0.021
EducationNG	1.701	0.052
DrMiles	-0.723	0.087
E	1.186	0.022
A	-1.175	0.025
C	0.715	0.099
dTT	-0.798	0.041
dTS	-1.022	0.030
dCurves	-0.405	0.060
ζ_2	1.215	0.000
ζ_3	4.314	0.000

Table 5a: Significant Variables of the 2nd Stage of the Hierarchical Model Based on Different Route Switching Models of the C4R20 Driver Type Classification

Significant Variables	Route Choice Model Without Categories		With C4R20 driver types as indicator variables		Route Choice Model for C4R20-2 Drivers Only		Route Choice Model for C4R20-3 Drivers Only		Route Choice Model for C4R20-4 Drivers Only	
	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value
Intercept	-2.26	< 2e-16	-3.93	< 2e-16	-10.904	0.019	-1.95	< 2e-16	-0.25	0.270
InertiaC	-0.98	0.000	-0.85	0.000	-9.965	0.044	-0.77	0.002	n/s	
PrefOMC	0.63	0.000	0.50	0.000	n/s		0.47	0.001	0.31	0.083
TTOMC	-0.31	0.000	-0.32	0.000	n/s		-0.55	0.000	n/s	
TSOMC	0.19	0.017	0.23	0.005	n/s		0.41	0.001	n/s	
C4R203	-		1.96	0.000	-		-		-	
C4R204			2.64	0.000						

 * 'n/s' means not significant and '-' means not applicable

Table 5b: Model Performance of the 2nd Stage of the Hierarchical Model Based on Different Route Switching Models of the C4R20 Driver Type Classification

Performance Measures	General	C4R20	C4R20-2	C4R20-3	C4R20-4
Log-Likelih.	-523.5	-501.1	-15.77	-273.1	-201.3
Deviance	1047	1002	31.53	546.2	402.6
AIC	1059	1018	37.53	558.2	408.6
BIC	1090	1059	48.49	584.8	419.6

Table 6a: Independent Variables of Driver Type Model

#	Variable Name	Variable Description	Variable Values
Variables of Driver Demographics			
1	Age_i	Age of participant i	18 to 68
2	$Gender_i$	Gender of participant i	M or F[*]
3	$Ethnicity_i$	Ethnicity of participant i	W or NW[*]
4	$Education_i$	Education level of participant i	G or NG[*]
6	$Dr\ Miles_i$	Annual number of miles participant i drives (in thousands)	2 to 35
7	$Residency_i$	Number of years participant i has been residing in the area	1 to 56
Variables of Driver Personality Traits			
1	N_i	Neuroticism of participant i	7 to 30
2	E_i	Extraversion of participant i	19 to 43
3	O_i	Openness to experience of participant i	20 to 31
4	A_i	Agreeableness of participant i	22 to 42
5	C_i	Conscientiousness of participant i	26 to 47
Variables of Choice Situation			
1	dTT_{ic}	Percentage difference in mean travel time between the alternatives of choice c	2.8 to 24.5
2	dTD_c	Percentage difference in distance between the alternative routes of choice c	5.7 to 44.8
3	dTS_{ic}	Percentage difference in mean travel speed between the alternatives of choice c	2.1 to 48.1
4	$dLinks_c$	Percentage difference in number of links between the two alternatives of choice c	0.0 to 54.5
5	$dSig_c$	Percentage difference in number of signalized intersections between the two alternative routes of choice c	18.2 to 90.9
6	$dUnsig_c$	Percentage difference in number of unsignalized intersections between the two alternative routes of choice c	0.0 to 120.0
7	$dTurns_c$	Percentage difference in number of uncontrolled intersections between the two alternative routes of choice c	66.7 to 133.3
8	$dLefts_c$	Percentage difference in number of left turns between the two alternatives of choice c	28.6 to 66.7
9	$dCurves_c$	Percentage difference in number of curves between two alternatives of choice c	0.0 to 200.0
Variables of Driver-Choice Combination			
1	$AvgFam_{ic}$	Average familiarity of driver i with the two routes of choice c	1 to 5
2	$MaxFam_{ic}$	Maximum familiarity of driver i with the two routes of choice c	1 to 5
3	$dFamPrc_{ic}$	Percentage difference of the familiarity of driver i with the two routes of choice c	0.0 to 133.3

[*] M: male, F: female, W: white, NW: non-white, NG: no post-graduate degree, G: have a post-graduate degree

Table 6b: Independent Variables of the Route Choice Switching Model

		Variables of Driver Type	
1	C4R20$_{ic}$	Type (as presented in Table 4) of driver i in choice situation c based on 20 trials	1[*], 2, 3, or 4
2	C#R#(L)-X$_{ic}$	Indicator variable indicating whether person i belongs to driver type X in choice situation c, according the C#R#(L) category	-
		Variables of Route Experience	
1	Trial$_t$	The route choice trial number of the participant	1 to 20
2	Inertia$_{it}$	The number of successive identical choices participant i has made right before trial t	0 to 19
3	PrefOMC$_{it}$	The difference between the number of times (participant i has chosen the other route minus the current chosen route) in all trials up till trial t	0.06 to 16.00
4	TTOMC$_{it}$	The difference between the average travel times (of the other route minus the current chosen route) experienced by participant i up till trial t	0.50 to 1.99
5	TTVOMC$_{it}$	The difference between the travel time variances (of the other route minus the current chosen route) experienced by participant i up till trial t	0.05 to 10.89
5	TSOMC$_{it}$	The difference between the average travel speeds (of the other route minus the current chosen route) experienced by participant i up till trial t	0.47 to 1.97
6	TSVOMC$_{it}$	The difference between the travel speed variances (of the other route minus the current chosen route) experienced by participant i up till trial t	0.03 to 13.92

[*] all records of C4R20 driver type 1 were dropped out due to missing data about the other route.

Framework of the Latent Class Choice Model

Figure 2 presents a flowchart of the latent class choice model framework. The latent class choice model is based on the assumption that drivers inherently belong to a number of different classes (driver types) and that these different driver classes make choices according to different functions. A possible example would be that some drivers belonging to a specific class choose routes that have lower travel times, and that another group of drivers (another class) choose routes that have shorter travel distances. Hence, a latent class model estimates class-specific choice functions.

The biggest advantage of the latent class choice model over the hierarchical model is that the modeler does not need to make assumptions about the underlying driver types. Latent class models simultaneously estimate class membership functions and class-specific choice functions. It simultaneously breaks down drivers into classes and estimates the class-specific choice functions in the manner that maximizes model performance.

Class membership functions estimate the probability that a certain driver i belongs to a certain class s (P$_{is}$), where the total number of classes equals S. Then, class specific choice functions estimate the probability that a driver belonging to a certain class s, faced with choice situation c, would choose action a (P$_{sca}$). Finally the probability that driver i faced with choice situation c chooses action a equals an average of the probabilities of all the classes to make choice a weighted by the probabilities that driver i belongs to each of the classes, i.e. sum of the probability that driver i belongs to each class multiplied by the probability that a driver from this class makes choice a, as presented by the following equation. This is demonstrated further in the following section of the latent class choice models.

$$P_{ica} = \sum_{s=1}^{S}(P_{is} \cdot P_{sca})$$
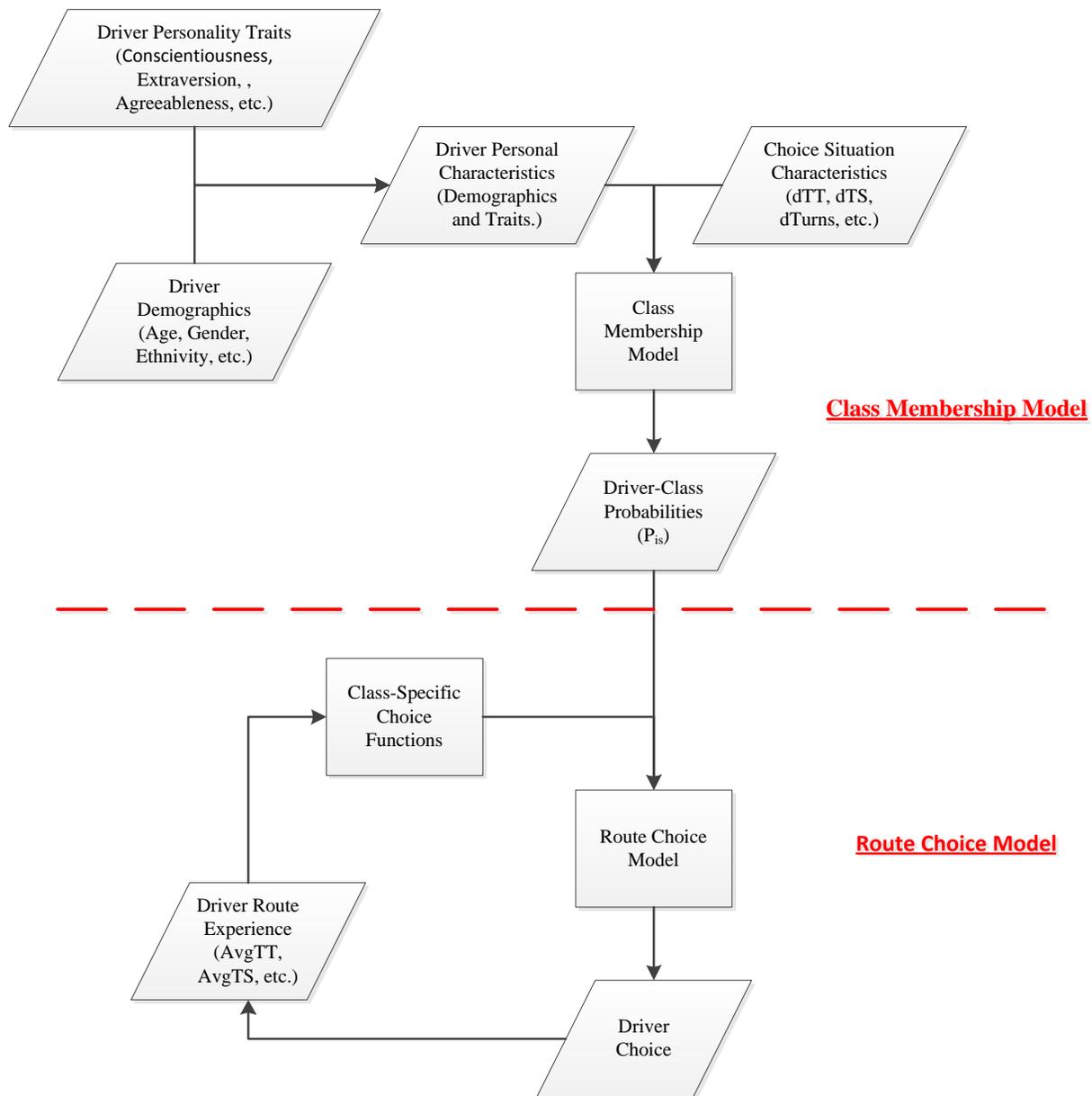
Figure 2: Flowchart of Latent Class Model Framework

One of the limitations of latent class choice models is that the researcher has to decide on the number of latent classes. The model cannot determine the number of latent classes (driver types) automatically. This limitation is addressed via systematic estimation of latent class choice models based on different numbers of classes and choosing the model that performs best. This approach requires a performance statistic that penalizes for decreased model parsimony. The statistic chosen in this work is the rho-bar.

Table 7 presents the rho-bar values of three estimated models: one model with no latent classes (i.e. all drivers belong to 1 class), one model with 2 latent classes and one model with 3 latent classes. According the rho-bar statistic, the model with 3 latent classes performs best. It

should be noted that the data used for these models does not include drivers who did not experience traveling on both alternative routes (i.e. C4R20-1 drivers are not included in this analysis), due to missing data (experiences) on the alternative route. This is identical to the analysis of the hierarchical model presented earlier in this article.

The reason that the log-likelihood statistic of the model without latent classes is lower than the corresponding statistic of the general model presented in Table 5b is the added variables of driver demographics and personality traits, as can be seen in Table 9. As expected, due to the earlier explained limitations of the hierarchical model which are addressed by the latent class choice model, the log-likelihood statistics of the latent class choice model with 3 latent driver classes is lower than the corresponding statistic of the hierarchical model. A discussion of the estimated models and their significant variables is presented in the following section.

Table 7: Performance Measures of the Latent Class Choice Models

	Without Latent Classes	With 2 Latent Classes	With 3 Latent Classes
Number of Estimated Parameters	14	13	16
Log-Likelihood	-513.7	-506.5	-487.9
Rho-bar	0.369	0.379	0.397

Latent Class Models

Probabilities of class membership functions and class-specific choice functions are multinomial logit models. This section presents the latent class models estimated for models with: a) no latent classes – 1 class, b) 2 latent classes, and c) 3 latent classes.

The investigated variables are the same variables presented in Tables 6a and 6b. However, due to notation difference, the explored variables are re-presented in Table 8. The significant variables of the three estimated latent choice models are presented in Table 9. Model formulations are presented in the following sections, where models estimations were done with the Biogeme2.1 software package [23, 24].

Model without Latent Classes (1 Class)

This model is based on the assumption that all drivers belong to 1 latent class. The probability that driver i makes action a (not switch=0, or switch=1) at trial t is based on the multinomial logit framework where the probabilities and utilities of the two possible actions are as follows.

$$P_{ita} = \frac{e^{u_{it,a}}}{1 + e^{u_{it,a}}}$$

$where$

$$u_{it,0} = ASC_0 + (B^T X_C)^{Ex} + \varepsilon$$

$$u_{it,1} = ASC_1 + (B^T X_O)^{Ex} + (B^T X)^{NEx} + \varepsilon$$

$(B^T X_{O/C})^{Ex}$ represents all route experience variables (inertia, preference, travel time, travel time variance, travel speed, and travel speed variance) on the current or other route.

$(B^T X)^{NEx}$ represents all variables of non-route experience variables (demographics, personality traits, choice situation, and driver-choice combination variables).

Table 8: Description of Latent Class Choice Model Variables

#	Variable Name	Variable Description	Variable Values
		Variables of Route Experience $(B^T X)^{Ex}$	
1	ASC_a	Alternative Specific Constant for Action a (0: no switching, 1: switching)	-
		Variables of Route Experience	
1	$Inertia_{it}$	The number of successive identical choices participant i has made right before trial t	0 to 19
2	$Pref_{it}$	The number of times participant i has chosen a route minus	0.06 to 16.00
3	TT_{it}	The average travel time experienced by participant i on a route up till trial t	0.50 to 1.99
4	TTV_{it}	The travel time variance experienced by participant i on a route up till trial t	0.05 to 10.89
5	TS_{it}	The average travel speed experienced by participant i on a route up till trial t	0.47 to 1.97
6	TSV_{it}	The travel speed variance experienced by participant i on a route up till trial t	0.03 to 13.92
7	$[Var]_{Subscript}$	The subscript after the route experience variables refer to current, C, or other, O, route	C or O
		Variables of Non-Route Experience $(B^T X)^{NEx}$	
1	CSC	Class Specific Constant	-
		Variables of Driver Demographics	
1	Age_i	Age of participant i	18 to 68
2	$Gender_i$	Gender of participant i	M or F[*]
3	$Ethnicity_i$	Ethnicity of participant i	W or NW[*]
4	$Education_i$	Education level of participant i	G or NG[*]
6	$Dr\ Miles_i$	Annual number of miles participant i drives (in thousands)	2 to 35
7	$Residency_i$	Number of years participant i has been residing in the area	1 to 56
		Variables of Driver Personality Traits	
1	N_i	Neuroticism of participant i	7 to 30
2	E_i	Extraversion of participant i	19 to 43
3	O_i	Openness to experience of participant i	20 to 31
4	A_i	Agreeableness of participant i	22 to 42
5	C_i	Conscientiousness of participant i	26 to 47
		Variables of Choice Situation[**]	
1	$dTTTp_{ic}$	Percentage difference in mean travel time between the alternatives of choice c	2.8 to 24.5
2	$dDistPrc_c$	Percentage difference in distance between the alternative routes of choice c	5.7 to 44.8
3	$dSpdPrc_c$	Percentage difference in mean travel speed between the alternatives of choice c	2.1 to 48.1
4	$dLinksPrc_c$	Percentage difference in number of links between the two alternatives of choice c	0.0 to 54.5
5	$dSigPrc_c$	Percentage difference in number of signalized intersections between the two alternative routes of choice c	18.2 to 90.9
8	$dLeftsPrc_c$	Percentage difference in number of left turns between the two alternatives of choice c	28.6 to 66.7
9	$dCurvPrc_c$	Percentage difference in number of curves between two alternatives of choice c	0.0 to 200.0
		Variables of Driver-Choice Combination	
1	$AvgFam_{ic}$	Average familiarity of driver i with the two routes of choice c	1 to 5

Checking the estimated model which is presented in columns 2 and 3 of Table 9 demonstrates that route utility increases with the increase in inertia, preference and travel speed, and with the decrease in travel time. It also shows that drivers of white ethnicities exhibited more route

switching tendencies than others, and that undergraduate students and drivers who drove more miles per year exhibited less route switching tendencies. Finally, drivers characterized with higher levels of neuroticism, extraversion and conscientiousness exhibited more switching tendencies and drivers who are more agreeable exhibited lower switching tendencies. In general, all of these findings are in line with the findings of the hierarchical model published earlier [14, 16].

Model with 2 Latent Classes

This model is based on the assumption that there are 2 different types of drivers: 2 latent classes. As explained earlier, the probability that driver *i* makes action *a* (not switch=0, or switch=1) at trial *t* is based on the sum product of the class membership probabilities and the class-specific choice probabilities. The framework of both probabilities is the multinomial logit framework, where the probabilities and utilities of the two possible classes and the two possible actions are as follows.

$$P_{it,a} = \sum_{s=1}^{2} \left(P_{is} \cdot P_{st,a} \right)$$

$$P_{is} = \frac{e^{u_{is}}}{1 + e^{u_{is}}}$$

$$P_{st,a} = \frac{e^{u_{st,a}}}{1 + e^{u_{st,a}}}$$

$$where$$

$$u_{is} = CSC_s + (B_s^T X)^{NEx} + \varepsilon$$

$$u_{st,a} = ASC_a + \left(B_s^T X_{C/O} \right)^{Ex} + \varepsilon$$

Description of the variables is as explained earlier and in Table 8

Checking the estimated model which is presented in columns 4 through 7 of Table 9 demonstrates that there are two classes of drivers. While drivers of the first class make their route choices based on inertia, travel time, and travel speed, drivers of the second class are only driven by route preference (which is reflected by the number of times a certain route has been chosen).

In general, the former class seems to reflect driver types C4R20-2 and C4R20-3 combined, and the latter class seems to reflect driver type C4R20-4. However, a few drivers seem to have apparently been differently classified. In general, parameter estimates of the class membership functions seem to be in line with the parameters of the class type model presented in Table 4. It appears that drivers of white ethnicities have higher route switching tendencies. Similarly drivers characterized with high extraversion and high conscientiousness have higher route switching tendencies. On the other hand, drivers who drive more miles per year and drivers with high openness to experience and high agreeableness have lower route switching tendencies. The only parameter that is different from the driver type model presented in Table 4 is education. While, in the driver type models, drivers with graduate degrees were found to exhibit higher route switching behavior, the current model (and the 1 class model) estimate lower route switching tendencies for driver with graduate degrees. There are two possible explanations for this. The first explanation, which is supported by the findings of the next section, is that a few drivers might have been differently classified between C4R20-3 and C4R20-4, which is highly possible due to the difficulty in classifying the behavior of some drivers as C4R20-3 or C4R20-4. The second

explanation is that this difference is a result of combining driver types C4R20-2 and C4R20-3 in a single class.

Model with 3 Latent Classes

This model is based on the assumption that there are 3 different types of drivers: 3 latent classes. As explained earlier, the framework of both probabilities is the multinomial logit framework, where the probabilities and utilities of the two possible classes and the two possible actions are as follows.

$$P_{it,a} = \sum_{s=1}^{3} \left(P_{is} \cdot P_{st,a} \right)$$

$$P_{is} = \frac{e^{u_{is}}}{\sum_{s=1}^{3} e^{u_{is}}}$$

$$P_{st,a} = \frac{e^{u_{st,a}}}{1 + e^{u_{st,a}}}$$

where

$$u_{is} = CSC_s + (B_s^T X)^{NEx} + \varepsilon$$

$$u_{st,a} = ASC_a + \left(B_s^T X_{C/O} \right)^{Ex} + \varepsilon$$

Description of the variables is as explained earlier and in Table 8

Table 9: Significant Variables of the Latent Class Choice Models

Significant Variables	Without Latent Classes		With 2 Latent Classes				With 3 Latent Classes					
			Class 1		Class 2		Class 1		Class 2		Class 3	
	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value	Beta	p-value
CSC	-		-		-1.69	0.67	0.00	-	-22.60	0.01	9.96	0.02
Ethnicity	1.98	0.00	-		4.46	0.01	-3.17	0.00	n/s		n/s	
Education	-0.82	0.00	-		-4.55	0.00	0.74	0.06	n/s		n/s	
DrMiles	-0.04	0.00	-		-0.39	0.00	n/s		-0.22	0.00	n/s	
N	0.05	0.04	-		n/s		n/s		n/s		n/s	
E	0.15	0.00	-		0.99	0.00	n/s		0.35	0.00	n/s	
O	n/s	n/s	-		-0.37	0.06	-0.29	0.08	n/s		-1.02	0.00
A	-0.10	0.01	-		-0.65	0.00	n/s		n/s		n/s	
C	0.07	0.00	-		0.22	0.00	-0.08	0.01	n/s		n/s	
dTTV	7.95	0.00	-		n/s		-5.09	0.02	n/s		n/s	
dTSV	2.07	0.00	-		n/s		n/s		n/s		n/s	
ASC$_{NSwitch}$	0.00	-	0.00	-	n/s		0.00	-	0.00	-	0.00	-
ASC$_{Switch}$	-7.90	0.00	0.27	0.03	0.27	0.03	0.61	0.00	0.61	0.00	0.61	0.00
B$_{Inertia}$	0.20	0.00	0.74	0.00	n/s		0.47	0.00	1.45	0.01	n/s	
B$_{Pref}$	1.41	0.00	n/s		2.83	0.00	n/s		n/s		2.67	0.00
B$_{TT}$	-0.20	0.00	-0.45	0.00	n/s		n/s		-1.16	0.00	n/s	
B$_{TS}$	0.02	0.02	0.07	0.01	n/s		n/s		0.12	0.06	n/s	

The estimated model, which is presented in columns 8 through 13 of Table 9, demonstrates that there are three classes of drivers. The first class of drivers makes their route choices based on inertia only. The second class makes their choices based on inertia, travel time, and travel speed. The last class includes drivers who are driven by route preference only. It appears that these three classes represent driver types C4R20-2, C4R20-3, and C4R20-4, respectively. This observation is further evident by contrasting the estimated parameters of the class membership functions against those of the driver type model presented earlier.

It appears that while drivers of white ethnicities are less likely to exhibit a type C4R20-2 behavior, drivers with graduate degrees are more likely to exhibit a type C4R20-2 behavior. In addition drivers with high levels of openness to experience and conscientiousness are less likely to exhibit a type C4R20-2 behavior. Furthermore, as the difference between TTV of alternative routes increases, drivers become more inclined to follow a C4R20-2 behavior. For the second class, it appears the drivers who drive less miles per year and drivers with high levels of extraversion exhibit higher probabilities of following a C4R20-3 behavior. Last, drivers with high levels of agreeableness are less likely to exhibit a C4R20-4 behavior. In general, these findings seem to align with the earlier ones.

STUDY CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

This work is based on a real-world route choice experiment where a sample of 20 drivers, faced with 5 choice situations, made a total of more than 2,000 real-world choices. This work is an extension on earlier publications that attempted to improve driver route choice models via incorporating measures of driver heterogeneity that are based on driver personal demographics and personality traits. These earlier publications identified four driver types that were observed in two different experiments: a driving simulator and a real-world route choice experiment. The identified driver types represent a metaphoric description of driver aggressiveness in route switching behavior. Using a two-stage hierarchical model, these identified driver types were found predictable from driver personal characteristics (demographics and personality traits) and choice situation characteristics. In addition the identified driver types were found significant in route choice predilections; either by including the driver types as additional indicator variables in a general model of route choice, or by estimating a separate route choice model for each driver type.

One limitation of the hierarchical model is that the classification of drivers into driver types is based on the modeler judgment. In addition to having different alternative classification methods and different possible numbers of classified driver types, there is no guarantee that any of these classifications is best in explaining driver route switching behavior. Accordingly, this work presented latent class choice models, as an alternative modeling framework that overcomes this limitation.

Latent class route choice models assume that drivers belong to a number of classes, where each class places different weights on different variables in making their route choices, i.e. each driver class has a class-specific choice model. The advantage of the presented latent class route choice models is that models of driver classes (types) and the class-specific choice models are estimated simultaneously, in a manner that maximizes route choice predictions. One limitation of this framework, however, is that it does not inherently determine the optimum number of classes. This limitation was overcome by estimating latent class choice models for different numbers of classes and comparing models performance.

This work presented a hierarchical model that is based on the previously four identified driver types and presented three different latent class route choice models: one with no driver

classes, one with 2 driver classes, and one with three driver classes. The results of the work provide proof that drivers do not follow the same principles in making their route choices. All models that included driver classes performed better than models that assumed all drivers were homogeneous. Evidence of driver differences that are attributable to driver demographics and personality traits were observed in the estimated parameters of all models. In addition, results of all the estimated models were highly conformable. Finally, similar to the findings of the hierarchical model, the latent class choice model with three classes (not including drivers that had no experiences on the alternative route, i.e. C4R20-I drivers) performed better than the two other models.

In conclusion, the proposed latent class route choice framework for incorporating driver heterogeneity seems to be promising, and successful replications of this work could be very beneficial for future modeling of driver heterogeneity in route choice models. A number of further research directions include: identifying other measures of driver heterogeneity; comparing the predictive rather than the descriptive abilities of the models; incorporating the effect of driver heterogeneity on the compliance rates to information; and examining if the same results could be replicated in a travel or a driving simulator.

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Part III

Real-Life Naturalistic Driving Experiment

Part III: Naturalistic Driving Experiment

Chapter 10

Modeling Driver Heterogeneity in Route Choice Behavior Based on a Real-Life Naturalistic Driving Experiment

Abstract Submitted for Presentation at the 19th ITS World Congress

Modeling Driver Heterogeneity in Route Choice Behavior Based on a Real-Life Naturalistic Driving Experiment

Aly M. Tawfik, MS
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 577-0462
FAX: (540) 231-7532
tawfik@vt.edu

Hesham A. Rakha, PhD., P.Eng.
Charles E. Via, Jr. Department of Civil and Environmental Engineering
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 231-1505
FAX: (540) 231-1555
hrakha@vt.edu

Jianhe Du, PhD
Center for Sustainable Mobility
Virginia Tech Transportation Institute
3500 Transportation Research Plaza
Blacksburg, VA 24061
Phone: (540) 231-2673
FAX: (540) 231-1555
JDu@vtti.vt.edu

ABSTRACT

This work uses data from a naturalistic real-life experiment to explore factors of driver route choice heterogeneity that can be attributable to variables of driver demographics, personality traits, and route choice characteristics. In a number of recent publications, the authors were able to identify significant relations between these variables and route choice behavior; both in a driving simulator experiment and in a real-world route choice experiment. In this work the authors explore the effects of the same variables on driver route switching behavior and driver choice set size, in a naturalistic real-life experiment. This work is based on more than 5,750 route choices made by 39 drivers in 68 choice situations. Most trips were commute trips. The results of the developed models are in accordance with the earlier publications and present evidence that driver demographics, personality traits and choice situation characteristics are significant in predicting route switching behavior and choice set size.

INTRODUCTION

Since world transportation systems are responsible for 14% of global greenhouse gas emissions (and 60% of carbon dioxide emissions in the US) [1] and the consumption of 50% of global oil production, and given the heightening criticality of the challenges of climate change and the peaking of oil, it is imperative to improve the efficiency of our transportation systems. This can be achieved via better understanding and modeling of human travel behavior. Since the introduction of the technologies of global position systems (GPS) and geographic information systems (GIS), research on travel behavior has been making continual progress.

Route choice models represent the foundation of traffic assignment models. They are widely used in many transportation engineering applications. Examples include transportation planning, traffic management, and intelligent transportation systems. Literature of route choice models can be classified into two primary groups: network-oriented models, and driver- oriented ones. The former group is older and much more widely used in transportation engineering practice. These models assign traffic in a manner that optimizes a certain objective function at the network level. Examples of these models include deterministic and stochastic user equilibrium, system optimum, and dynamic traffic assignment. Detailed reviews of these models can be found in several publications [2-4]. However, because of the unrealistic assumptions of these models, primarily assumptions about human rationality and driver homogeneity, research has been shifting towards the latter group, driver-oriented models. Real-world GPS-based studies, in particular, have been repeatedly identifying discrepancies between actual human behavior and predictions of this group of models [5, 6].

Driver-oriented models follow a wide variety of modeling classes. Random utility models (RUM) are probably the biggest class in this group [7]. Other examples of driver-oriented models include random regret minimization models [8], probabilistic models [9-11], cognitive-psychology based models [12, 13], fuzzy models [14], and models based on data mining; sometimes referred to as user models [5, 6, 15, 16]. Driver-oriented models try to replicate actual driver behavior and incorporate a variety of variables to improve model explanation of driver behavior. Examples of these variables include personal characteristics [17], attitude [18], and cognitive abilities [19]; in addition to variables of driver travel experiences like travel distance, average travel time, and inertia. However, probably because of challenges of quantifying the effects of the former groups of variables, only variables of travel experience seem to be used in practice. As a result, driver heterogeneity remains to be a limitation that requires further attention in route choice models [2, 20-23].

Recent examples in travel behavior literature that attempted to incorporate variables of driver heterogeneity include: *personal traits* in safety research [24, 25], *lifestyle* in household location choice models [26, 27], *driver type* in traffic gap acceptance models [28], and *driver type* in route choice models [9-11, 29-31]. Findings of these attempts indicate that incorporating factors of driver heterogeneity improves model performance.

Similarly, this work attempts to explore the possibility of improving models of route choice behavior via incorporating variables that can reflect driver heterogeneity. This work is an extension of a series of articles that are based on three different experiment mediums. The first experiment is a driving simulator experiment [9, 30, 31], the second is an in situ experiment in real-world conditions [10, 11, 29, 32], and this experiment is based on a real-life naturalistic study.

In the following sections, the authors present the objectives of the study, followed by an explanation of the study approach: study description, questionnaires and terminology used. In the

third section, the authors present and discuss the results of estimating the route switching and choice set size models, and in the fourth section the paper ends with conclusions of the study and recommendations for further research.

STUDY OBJECTIVES

The main objectives of this study are to investigate the effect of driver demographics and personality traits on route choice behavior and choice set size, in a naturalistic real-life experiment.

STUDY APPROACH

Study Description

The data used in this work is from the 100-Car Naturalistic Driving Study. This study "is the first instrumented-vehicle study undertaken with the primary purpose of collecting large-scale, naturalistic driving data. Drivers were given no special instructions, no experimenter was present, and the data collection instrumentation was unobtrusive". "There is every indication that the drivers rapidly disregarded the presence of the instrumentation". "The data set includes approximately 2,000,000 vehicle miles, almost 43,000 hours of data, 241 primary and secondary drivers, 12 to 13 months of data collection for each vehicle, and data from a highly capable instrumentation system including 5 channels of video and many vehicle state and kinematic sensors" [25]. The experiment site was limited to the Washington DC / Northern Virginia area. However, other sites that are distributed over the continental US are planned for the following phase of the project.

Although safety was the primary objective for this study, other attempts have been made to use the data for research in other areas of travel behavior. In addition, this work uses this data to identify factors affecting route switching and choice set size in the travel behavior area.

Questionnaires

Participants of this study were required to answer two groups of questions that are relevant to the presented work. In the first group, participants were asked questions about their general demographic and driving information, like age, gender, ethnicity, level of education, number of years driving, and number of miles driven per year. In the second group, participants were asked to fill in a personality inventory, the NEO-FFI-3[33]. This is a psychological personality inventory that is based on the Five Factor Model. It measures five personality traits: neuroticism extraversion, openness to experience, agreeableness, and conscientiousness. In addition, each personality trait measures six subordinate dimensions (sometimes referred to as facets).

Neuroticism measures the tendency of a person to experience negative emotions such as anxiety, guilt, frustration, and depression. Persons who score high on neuroticism are usually self-conscious, and are associated with low self-esteem and irrational thinking. The six subordinate dimensions of neuroticism are: anxiety, hostility, depression, self-consciousness, impulsiveness, and vulnerability to stress. Extraversion measures the tendency towards positive emotionality. The six subordinate dimensions of extraversion are: warmth, gregariousness, assertiveness, activity, excitement seeking, and positive emotion. Openness to Experiences measures the imaginative tendency of individuals, their attentiveness to inner emotions, and their sensitiveness towards art and beauty. The six subordinate dimensions of openness to experience are: fantasy, aesthetics, feelings, actions, ideas, and values. Agreeableness measures the more humane aspects of the personality. The six subordinate dimensions of agreeableness are: trust,

straightforwardness, altruism, compliance, modesty, and tendermindedness. Last, Conscientiousness measures personality tendencies towards being diligence, thoroughness and being governed by conscience. The six subordinate dimensions of conscientiousness are: competence, order, dutifulness, achievement striving, self-discipline, and deliberation. For further details about these personality traits, or about the Five Factor Model or the NEO Personality traits, the reader is referred to Wikipedia for general information, and to other publications for thorough theoretical discussions [34-36]

Terminology

In this article, a choice situation refers to a specific pair of origin and destination that are linked with a number of possible alternative routes. For example, going from home to work and going from work to home are considered two different choice situations. The main reason for splitting choice situation incidents by direction of travel (home to work versus work to home) is due to differences in the directional route choice sets as dictated by traffic management. Examples of traffic management schemes that would result in different choice sets include one way routes, freeway exists that do not include both an off-ramp and an on-ramp, and traffic lights with different directional delays. As long as dependencies between choice situations with common origins and destinations are taken into consideration, this should not be a concern.

On the other hand, a trip refers to the act of choosing one of the alternative routes in a choice situation. For instance, for each choice situation considered in this work, there are many observed trips. The analysis presented in the following sections of this article is based on a sample of 39 drivers, 68 choice situations, and more than 5,750 trips. The average number of observed trips per choice situation is 85 trips, i.e. about four working months.

RESULTS AND ANALYSIS

This sections starts by defining the response variables modeled in this work. Then, the considered independent variables are presented. Last, the authors present and discuss the findings of the estimated models.

Response Variables

The two response variables modeled in this work are a route switching model and a model of the size of the choice set. All routes chosen by each driver in each choice situation were first identified. Then the route that was chosen most in each choice situation was defined as the driver's preferred route. The definition of the first response, route choice, is the probability that the driver chooses a route other than that driver's preferred route. Obviously, the probability of choosing the preferred route plus the probability of choosing an alternative route equals one. The second response, choice set size, is defined as the number of alternative routes observed for a certain driver in a specific choice situation.

It should be noted that given the high overlap and dependency between alternative routes of a certain choice situation, different route classification methods could arise that would result in different choice set sizes. For the work presented here, two routes were considered different if they did not overlap for as little as 10% of the total route length. Contrarily, routes with less than a difference of 10% were considered as one route. While the choice of a 10% difference was somewhat arbitrary, further analysis is being considered using different thresholds.

Obviously, some level of positive correlation exists between the two modeled response variables. This correlation can be demonstrated by two extreme examples. In the first example, if

the size of the choice set of a certain driver is composed of a single route (minimum), then the probability of choosing an alternative route is zero (minimum). On the other hand, as the size of the choice set increases, the probability of choosing an alternative route also increases; because the maximum probability of choosing the preferred route decreases. In this case the max probability of choosing the preferred route decreases and equals to the following

$$Max\ Probability\ of\ Choosing\ Preferred\ Route =$$
$$= \frac{Total\ Number\ of\ Observed\ Trips - (Choice\ Set\ Size - 1)}{Total\ Number\ of\ Observed\ Trips}$$

This probability would be true in the case that the driver chooses each of the alternative routes for only a single time.

The distributions of the two response variables are presented in Figures 1a and 1b. Although the correlation between the two modeled responses equals 0.64, the joint distribution presented in Figure 1c, shows discrepancies between the two modeled variables. Furthermore, Figure 2 demonstrates different cases where drivers with large and small choice set sizes exhibited similar (high) and opposite (low) probabilities of route switching.
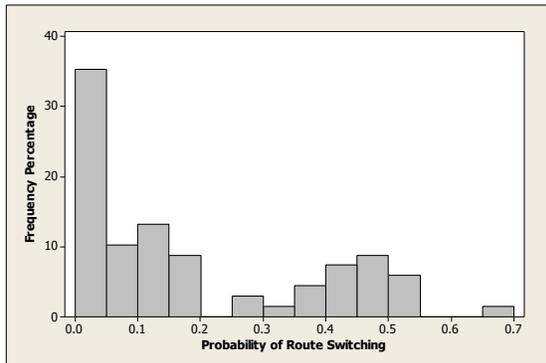
Figure 1a: Frequency Distribution of Route Switching Probabilities

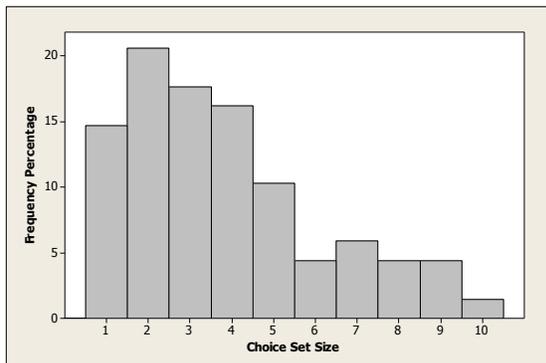Figure 1c: Joint Distribution of Probability of Route Switching and Choice Set Size
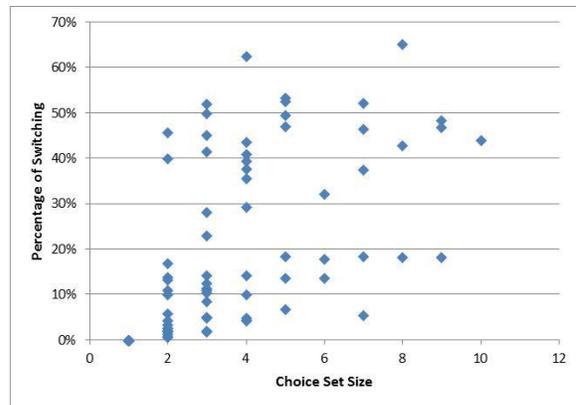

Figure 1b: Frequency Distribution of Choice Set Size

Figure 1: Marginal and Joint Distributions of the Response Variables (Probability of Route Switching and Size of Choice Set)

The frequency distribution of the route switching probabilities, Figure 1a, can imply a possibility of two types of drivers. There appears to be some drivers who have low route switching tendencies, within the range of 0 to 35%, and appear to follow a negative exponential trend. On the other hand, there appears to be another group of drivers who have higher route switching tendencies, within the range of 25% to 70%, and appear to follow a normal distribution kind of a trend. However, this could be false implication because of the small sample size. Accordingly, the models presented in this work assume all drivers belong to one group. The following section presents the independent variables considered in the models.

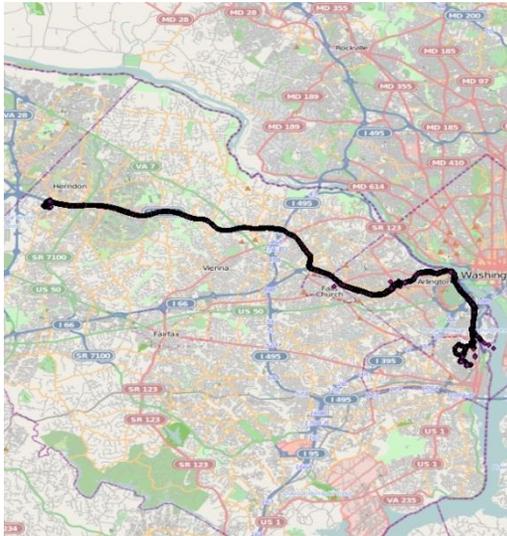Figure 2a: Low Switching Percentage (0%) and Small Choice Set Size (1)

Figure 2b: Low Switching Percentage (5%) and Large Choice Set Size (7)

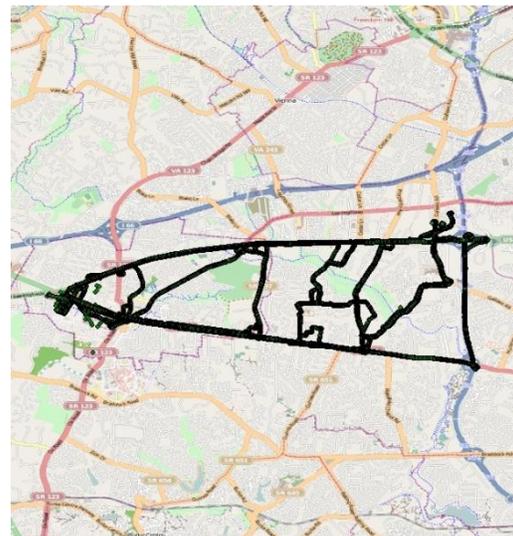Figure 2c: High Switching Percentage (42%) and Small Choice Set Size (3)

Figure 2d: High Switching Percentage (45%) and Large Choice Set Size (10)

Figure 2: Sample Images of Drivers with Low and High Switching Probability and Small and Large Choice Set Sizes

Independent variables

Table 1 presents the independent variables considered in this work. The chosen independent variables belong to four groups: demographic variables, variables of personality traits, variables specific to the choice-situation, and variables of driver-choice combination. It should be noted that all numeric variables were normalized, so that the magnitude of the estimated parameters can reasonably reflect the importance of their respective variables in the model. This scaling has an additional computational benefit because it helps to avoid singularities when inverting matrices.

Table 1: Models Independent Variables

#	Variable Name	Variable Description	Variable Values
Variables of Driver Demographics			
1	Age_i	Age of driver i	19 to 57
2	$Gender_i$	Gender of driver i	F or M[*]
3	$Ethnicity_i$	Ethnicity of driver i	W or NW[*]
4	$Education_i$	Education level of driver i	G or NG[*]
7	$Dr\ Years_i$	Number of years driver i has been licensed to driver	2 to 42
6	$Dr\ Miles_i$	Number of miles driver i drives per year (in thousands)	15 to 40
Variables of Driver Personality Traits			
1	N_i	Neuroticism of driver i	7 to 75
2	E_i	Extraversion of driver i	17 to 66
3	O_i	Openness to experience of driver i	14 to 53
4	A_i	Agreeableness of driver i	12 to 66
5	C_i	Conscientiousness of driver i	19 to 62
Variables of Choice Situation			
1	TT_c	Expected travel time of choice situation c (in minutes)	8 to 95
2	TS_c	Expected travel speed of choice situation c (in km/hr)	24 to 90
3	TD_c	Expected travel distance of choice situation c (in kilometers)	6 to 108
Variables of Driver-Choice Combination			
4	Obs_{ic}	Number of trips observed for driver i in choice situation c	25 to 216

[*] M: male, F: female, W: white, NW: non-white, NG: no post-graduate degree, G: have a post-graduate degree

Route Switching Model

Because the response is a percentage with a support range of [0,1], the chosen model is the Beta regression model. However, because the support range of the Beta distribution is (0,1), response values of 0 and 1 were increased and decreased by 1×10^{-15}, respectively. The significant variables of the Beta regression model are presented in columns 2 and 3 of Table 2.

The signs of the estimated variables seem logical and are in accordance with the results found from the previous real-world route choice experiment [10, 11]. The presented results indicate that drivers without post-graduate degrees and drivers who drive more miles per year are less likely to use alternative routes; they seem inclined to use their preferred routes more than other drivers. Similarly, drivers who are more open to experience seem to have the same

tendency. On the other hand, drivers who have higher scores of extraversion and conscientiousness seem to switch and use alternative routes more. Finally, it appears that as travel times and travel speeds increase and decrease, respectively, drivers seem to switch to alternative routes more. This seems reasonable, as drivers try to identify routes that have lower travel times or higher travel speeds.

It is extremely interesting that magnitudes of the driver and personality trait variables seem to be at least as important as variables of travel experience (travel time and travel speed). It appears that drivers' openness to experience is the most important variable in this model.

Choice Set Size Model

Because the response is the size of the choice set, which has a support range of the integers in the range $[1,\infty)$, the chosen model is a Gamma distribution generalized linear model with an inverse link function. The significant variables of the model are presented below; however, to avoid confusion about the relation between the response and the estimated parameters (as a result of using the inverse link function), the estimated parameter signs reported in Table 2 are negated. The significant variables of the Beta regression model are presented in columns 4 and 5 of Table 2.

As with the results of the route switching model, the results of this model seem logical and are in accordance with the results of the previous model and the earlier results found from the real-world route choice experiment [10, 11]. Signs of the estimated parameters indicate that drivers without post-graduate degrees and drivers with higher scores of openness to experience seem to have smaller route choice set sizes. On the other hand, drivers with higher values of neuroticism and conscientiousness seem to have larger choice sets. In addition, as the travel speeds decreases, drivers seem inclined to seek more alternative routes – presumably with higher travel speeds. Finally, it is satisfying that the number of observations was found to marginally increase the choice set size. This could imply that as drivers are faced with the same choice situation over and over again, they will tend to face some probably unforeseen circumstances that would entice them to seek new alternative routes.

Table 2: Models Significant Variables

Significant Variables	Route Switching Model		Choice Set Size Model	
	Beta	p-value	$-$ (Beta)[*]	p-value
(Intercept)	-1.38	0.000	$-$ 0.284	0.000
EducationU	-0.81	0.022	$-$ 0.098	0.026
DrMiles	-0.30	0.033	n/s	
N	n/s		0.049	0.084
E	0.56	0.013	n/s	
O	-0.97	0.000	$-$ 0.25	0.000
C	0.46	0.014	0.079	0.000
TT	0.35	0.049	n/s	
TS	-0.55	0.000	$-$ 0.058	0.001
Obs	n/s		0.001	0.030

[*] To avoid confusion about the relation between the response and the estimated parameters (as a result of using the inverse link function), the estimated parameter signs are negated

As was the case in the route choice switching model, it is extremely interesting that magnitudes of the driver and personality trait variables seem to be at least as important as variables of travel experience (travel speed). It appears that drivers' openness to experience is the most important variable in this model

STUDY CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

This work is an extension of two earlier experiments that explored driver heterogeneity in route choice behavior [9-11, 29-32]. One of the two earlier experiments was based on a driving simulator [9, 30, 31]and the other based on an in situ driving experiment in real-world conditions [10, 11, 29, 32]. In this work, significance of driver demographics and personality traits were investigated in route switching and choice set size models. The presented analysis is based on a naturalistic driving study that was performed in the Northern Virginia and Washington DC area, where the vehicles of more than 100 drivers were equipped with non-intrusive vehicle and driver tracking devises. The movement and driving behavior of these drivers were tracked for more than 12 months, resulting in approximately 2,000,000 vehicle miles, almost 43,000 hours of data. The analysis presented in this paper is based on observing the route choices of 39 drivers, who collectively faced 68 route choice situations and made more than 5,750 route choices, i.e. an average of 85 trips per driver-choice situation.

Two models of route choice behavior were estimated: a model of route switching behavior and a model of choice set size. In this work, route switching is defined as the probability that a driver selects a route other than her/his most preferred route. Although the two modeled responses (probability of route switching and choice set size) are correlated, discrepancies between drivers' behavior were observed. The estimated models shared some of the same estimated significant variables. However, the significant variables were not identical.

The results of the estimated models indicate that driver demographics, personality traits and trip characteristics are significant in predicting route choice behavior. The models indicate that route switching is positively related to driver education, extraversion, conscientiousness and travel time, and inversely related to driver annual driven miles, openness to experience and travel speed. On the other hand, choice set size is positively related to driver education, neuroticism, conscientiousness, and number of observations, and negatively related to driver openness to experience and trip travel time. It is very interesting that variables of driver characteristics and personality traits were found to be as important as variables of trip characteristics. In addition, it is assuring that the results of the estimated models are in accordance with the earlier models estimated in the two earlier experiments [9-11, 31].

In conclusion, the proposed framework for incorporating driver heterogeneity seems to be promising, and successful replications of this work could be very beneficial for the future modeling of driver heterogeneity in route choice models. A number of further research directions include: exploring differences that can be attributed to trip purpose, identifying other measures of driver heterogeneity; comparing the predictive rather than the descriptive abilities of the models; incorporating the effect of driver heterogeneity on the compliance rates to information; and examining if the same results could be replicated in a travel or a driving simulator.

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Chapter 11

Conclusions

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Conclusions

11.1 Summary of Conclusions

As a general summary, driver perceptions were found to be significantly different from driver experiences, and driver perceptions were found to be a much better predictor of driver route choices than driver experiences. Discrepancies were observed between the predictions of the stochastic user equilibrium expectations and the actual driver choice percentages. Accordingly, research was geared towards driver- rather than network- oriented route choice models. Four measure of driver heterogeneity were investigated in the driver-oriented choice models: driver perceptions, learning trends and driver types, latent driver classes, and driver personality traits. All four of the investigated measures of driver heterogeneity were found significant in predicting driver route choice behavior. In addition, incorporating measures of driver heterogeneity in the route choice behavior models improved model performance, in spite of the decreased model parsimony and in spite of using statistics that penalize for decreased model parsimony. Evidence of the existence of latent driver classes that follow different rules of route choice were identified. All five personality traits of the NEO test were found to be highly significant in the route choice behavior models, and were found at least as important as variables of route experience (like travel time). Driver aggressiveness in route switching behavior was found to be positively related with neuroticism, extraversion and conscientiousness, and inversely related with agreeableness and openness to experience. Variables of route experience that were found significant in route choice behavior are inertia, route preference, travel time and travel speed. However, not all of these variables were significant for the different driver types and latent driver classes. Models estimated for each of the three different experiments are much in accordance. The three experiments are based on a driving simulator experiment, an in situ driving experiment in real-world conditions, and a real-life naturalistic driving study. In total, this work is based on a sample of 109 drivers, who faced 74 choice situations and made 8,644 route choices. Results of this work seem highly promising for the future of understanding and modeling heterogeneity of human travel behavior, as well as for identifying target markets and the future of intelligent transportation systems.

11.2 Detailed Conclusions

This work attempted to address driver heterogeneity in route choice behavior. Driver heterogeneity has repeatedly been cited as a limitation that needs to be addresses in models of travel behavior. The presented work addressed driver heterogeneity from four different perspectives: driver perceptions, learning trends and driver types, latent driver classes, and variables of personality traits as captured by the NEO Personality Inventory-Revised (NEO PI-R). No other work has attempted to address driver heterogeneity in the way that was addressed in this work.

To address the different limitations of the different route choice experiment mediums, the work presented in this dissertation was based on three different experiments. The first experiment is a driving simulator experiment that is supplemented with a revealed preference survey. This experiment included 50 test subjects that faced one choice situation and collectively made 823

route choices. The second experiment is an in-situ driving experiment performed in real-world conditions that is supplemented with a revealed preference survey and a NEO PI-R personality questionnaire. It involved 20 test subjects that faced five choice situations and collectively made 2,065 route choices. The last experiment is a real-life naturalistic driving study that was performed in the Northern Virginia – Washington DC area and tracker driver behavior for a span of 12 to 13 months. It is supplemented with several questionnaires, out of which only a few were used in this work. These are the NEO personality questionnaire and questionnaires that collected driver demographics and driving information. The used data reflects the behavior of 39 test subjects who collectively faced 68 choice situations and made 5,756 route choices. In total, the results presented in this dissertation are based on a sample of 109 drivers, who faced 74 choice situations and made 8,644 route choices.

It is assuring that results of the models estimated for the different datasets were highly conformable. The results indicated significant contributions of all four of the considered measures of driver heterogeneity: perceptions, learning trends and driver types, latent driver classes and personality traits. The following paragraphs present the major findings of these heterogeneity measures in the three adopted experiments.

The first measure considered for driver heterogeneity is driver perceptions. Findings of the first experiment, the driving simulator, are presented in Chapter 3. The results revealed that driver perceptions were significantly different from their experiences, and that driver experiences reflected only 50% of driver route choices. In addition, analysis demonstrated that driver perceptions of travel speeds were the most accurate, followed by travel time perceptions. It is surprising that although travel distance is a deterministic measure (unlike travel time and travel speed), travel distance perceptions were the least accurate. It was also surprising that travel speed perceptions were more accurate than travel time perceptions. This is surprising because according to theories of human cognition, humans tend to assign more attention resources to events that are more meaningful to them. This finding implied that drivers route choice decisions were influenced by travel speed more than travel time. This implication was proven correct when driver choices were contrasted against their perceptions. A possible explanation for this behavior is that the travel time difference between the two alternative routes was low. Moreover, it was observed that drivers belonging to different demographic groups demonstrated different percentages of correct perceptions. Models of driver perceptions were estimated for the results of the second experiment.

The same analysis was performed for the results of the second experiment, the real-world driving experiment. This analysis is presented in Chapter 6. Contrasting drivers' experiences, perceptions and choices in this experiment revealed that in general driver perceptions were only 60% correct, and, again, driver perceptions of travel speed were more accurate than their travel time perceptions. In addition, travel distance perceptions were again the least accurate, in spite of being deterministic. However, in this experiment, drivers were faced with five different choice situations. Accuracy of driver perceptions were not consistent across the different choice situations. Contrarily to the findings of the previous experiment, travel time perceptions in general reflected driver choices more than travel speed, but by only 3%. This too was not consistent across all five choice situations. For some trips, travel speed and also traffic levels and travel distance perceptions reflected driver choices more than travel time. This finding implied

that depending on the choice situation, drivers placed different weights on these four measures, and probably on other measures that were not considered, such as measures of route comfort and legibility.

Models of driver perceptions were estimated. These models indicated that driver perceptions improved as the signal strength of the parameter being measure increased. This finding is in accordance with a long standing theory of human cognition which states that perceptions are expected to improve as the signal becomes more salient. In addition, demographic variables such as age, level of education, and number of driving years, were found significant in determining the probabilities of correct perceptions. Finally, three of the five personality traits of the NEO PI-R were found to significantly affect travel perceptions. These are openness to experience, agreeableness and conscientiousness. As explained in the following paragraphs, driver perceptions were not found significant in predicting driver type behavior or in route switching models. However, as mentioned above, driver perceptions reflected route choices much better than driver experiences. It is expected that driver perceptions will turn to be highly significant if included in route choice rather than route switching models.

The second considered measure of driver heterogeneity is driver learning and personality traits. Significant discrepancies were observed upon comparison of the expectations of the stochastic user equilibrium theory against the driver choice percentages observed in the first and second experiment, Chapters 4 and 7, respectively. Accordingly, analysis was geared towards identifying reasons for these observed discrepancies. With closer analysis of the driver choice trends when repeatedly faced with the same choice situation (which reflect trends of driver learning), four driver types were identified. Driver type is not commonly used in the vernacular of transportation engineering. It is a term that was developed in this work to reflect driver aggressiveness in route switching behavior, as demonstrated in the following paragraph. It may be interpreted as analogous to the common known personality-types (such as Myers-Briggs) but specifically applied to driver behavior.

The first type of drivers represents those who tried one of the alternative routes on the first trial of a choice situation, where satisfied with their experience and repeated the same choice in all 20 trials of this choice situation. The second type of drivers represents drivers who on the first two trials tried each alternative route once, then made a choice, and from the third till the last trial repeated the same choice without ever thinking of revisiting it. The third type represents drivers who had an obvious route preference but revisited their choice every now and then by switching and re-evaluating the alternative route. The last type represents drivers who kept switching between the alternative routes during the whole experiment and had no obvious route preference. These four identified driver types were observed in both the first and second experiments (Chapters 4 and 6, respectively). Because the data structure of the third experiment is different, no attempt was made to identify these four driver types. However, similar route switching tendencies were also identified in the third experiment (Chapter 10).

Although drivers did not exhibit the same driver-type in the five choice situations of the third experiment, drivers seemed to have an inherent tendency towards following a less aggressive route switching behavior (as in driver-types I and II) or a more aggressive one (as in driver-types III and IV), Chapter 6. It seemed logical to imply that the exhibited driver types where influence

by driver as well as choice situation characteristics. For example, no matter how aggressive a driver is, it is highly unlikely that a driver will exhibit a type IV behavior if the travel times on the alternative routes were extremely different (for example if they were 5 and 50 minutes). This hypothesis was verified by the driver type models that were estimated. The significant variables indicated that driver demographics, personality traits, and choice situation characteristics influenced the adopted driver types (Chapter 7).

Driver types were found to be highly significant in predicting route switching behavior, both in the first and the second experiment, Chapter 5 and 8, respectively. In addition, incorporating driver types improved the performance of the estimated route switching models (Chapters, 5, 8 and 9). The effect of driver types on route switching behavior was examined through two alternative methods. In the first method, driver types were included in the route switching models as additional indicator variables. Higher driver types increased the probability of route switching behavior. In the second method, separate route switching models were estimated for each specific driver type. Different variables were found significant in the driver-type-specific route switching models. This indicated the possibility of existing latent driver class.

A hierarchical two-stage route switching model was estimated in Chapter 8. The first stage used variables of driver demographics, personality traits and choice situation characteristics to predict driver types. In this model, different driver-type classification methods were adopted. They were all found predictable from variables of driver demographics, personality traits, and choice situation characteristics. The second stage used the predicted driver types and variables of driver previous route choice experiences to predict the probability of route switching. Almost all driver type classifications were found significant and improved the performance of the route switching model; in spite of the increase of the number of estimated parameters and of using performance measures that penalize for decreased model parsimony.

Variables of driver experience that were found significant in route switching behavior are inertia, route preference, travel time and travel speed. Type II drivers were found to be driven with inertia; type III drivers are driven by inertia, route preference, travel time and travel speed; and type IV drivers are driven by route preference. It was surprising that travel speed (and not travel distance) was found to be highly significant, because in route choice literature, travel distance is given more attention than travel speed.

The third considered measure of driver heterogeneity is latent driver classes, which is presented in Chapter 9. One of the limitations of using driver types and the hierarchical model presented in Chapter 8 is that the researcher has to use personal judgment to classify drivers into a specific number of driver types and according to specific classification criteria. However, there is no guarantee that the adopted specific number of types and classification criteria are optimum in maximizing model performance. To address this limitation, a latent class choice model was estimated. Findings of the estimated latent class choice model were in accordance with the findings of the hierarchical model. The findings enforced the implication of existing latent driver classes with different significant variables in the different class-specific route switching models. These models were very similar to the driver-type-specific route switching models estimated in the hierarchical model. However, as expected minor differences between these two groups of models were observed, which reflects that a few drivers were classified into classes different

from the classes that they were categorized into in the driver-type models of the hierarchical model. This was expected because differentiating between driver types III and IV depended on researcher judgment. Almost all of the significant parameters of the hierarchical model were found significant in the latent class choice model and had the same directional relation with the response.

Variables of driver experience that were found significant in route switching behavior are inertia, route preference, travel time and travel speed. Class II drivers were found to be driven with inertia; class III drivers are driven by inertia, travel time and travel speed; and class IV drivers are driven by route preference.

The fourth and last measure considered for driver heterogeneity is personality traits. It is very promising that all five factors of the personality traits were found significant in all estimated models in the second and third experiments. Unfortunately, personality traits were not measured in the first experiment. Personality traits were found significant in driver perception models (Chapter 6), in driver type models (Chapter 7, 8, 9 and 10), in route switching models (Chapters 8, 9 and 10), and in choice set size models (Chapter 10). In addition, it is very intriguing that the personality traits variables were found to be at least as important as, and often more important than, variables of choice experience; like travel time, travel speed, inertia and route preference. In general, driver type, driver route switching behavior and choice set sizes were positively related to driver neuroticism, extraversion and conscientiousness, and negatively related to driver openness to experience and driver agreeableness. On the other hand, driver perceptions were found to be positively related to driver agreeableness and conscientiousness and negatively related with driver openness to experience.

11.3 Possible Research Extensions

Possible extensions of this work include investigating possibilities of successful replication of the findings of this work, exploring driver behavior in cases of larger choice set sizes; investigating the effect of driver heterogeneity in driver compliance to information; exploring driver heterogeneity in other models of travel behavior such as trip generation, departure time choice, travel mode choice, and dilemma zone decisions; and investigating effects of driver heterogeneity in different trip purposes.