

ABSTRACT

Title of dissertation: ON AGENT-BASED MODELING: MULTI-DIMENSIONAL TRAVEL BEHAVIORAL THEORY, PROCEDURAL MODELS AND SIMULATION-BASED APPLICATIONS

Chenfeng Xiong, Doctor of Philosophy, 2015

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This dissertation proposes a theoretical framework to modeling multidimensional travel behavior based on artificially intelligent agents, search theory, procedural (dynamic) models, and bounded rationality. For decades, despite the number of heuristic explanations for different results, the fact that “almost no mathematical theory exists which explains the results of the simulations” remains as one of the large drawbacks of agent-based computational process approach. This is partly the side effect of its special feature that “no analytical functions are required”. Among the rapidly growing literature devoted to the departure from rational behavior assumptions, this dissertation makes effort to embed a sound theoretical foundation for computational process approach and agent-based microsimulations for transportation system modeling and analyses. The theoretical contribution is three-fold: (1) It theorizes multidimensional knowledge updating, search start/stopping criteria, and search/decision heuristics. These components are formulated or empirically modeled and integrated in a unified and coherent approach. (2) Procedural and dynamic

agent-based decision-making is modeled. Within the model, agents make decisions. They also make decisions on how and when to make those decisions. (3) Replace conventional user equilibrium with a dynamic behavioral user equilibrium (BUE). Search start/stop criteria is defined in the way that the modeling process should eventually lead to a steady state that is structurally different to user equilibrium (UE) or dynamic user equilibrium (DUE). The theory is supported by empirical observations and the derived quantitative models are tested by agent-based simulation on a demonstration network. The model in its current form incorporates short-term behavioral dimensions: travel mode, departure time, pre-trip routing, and en-route diversion. Based on research needs and data availability, other dimensions can be added to the framework. The proposed model is successfully integrated with a dynamic traffic simulator (i.e. DTALite, a light-weight dynamic traffic assignment and simulation engine) and then applied to a mid-size study area in White Flint, Maryland. Results obtained from the integration corroborate the behavioral richness, computational efficiency, and convergence property of the proposed theoretical framework. The model is then applied to a number of applications in transportation planning, operations, and optimization, which highlights the capabilities of the proposed theory in estimating rich behavioral dynamics and the potential of large-scale implementation. Future research should experiment the integration with activity-based models, land-use development, energy consumption estimators, etc. to fully develop the potential of the agent-based model.

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APPLICATIONS

by

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Dedication

To my beloved wife and daughter, Taixi and Lucine.

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I now am able to look back to my grad-school journey. I think it is pretty much like a lotr trilogy (yes, I am a lotr fan, and lotr stands for Lord-of-the-Rings). After two-year studying M.S. and another two years spent on the M.A., now my Ph.D. work reaches its finale. At the end of the day, when I sit back, light a tobacco and revisit my long journey, I realized that there are so many vivid characters that come and make my trip a great adventure.

I must send my greatest gratitude to my advisor, Dr. Lei Zhang who dragged me out of my comfortable little wine cellar and whipped me into the wild of ignorance. Your guidance, inspiration, encouragement, and protection have always enlightened me and guided me through the misty mountain, enchanted forest, and dwarf's mine. You are my Gandolf the White. Other committee members are like the Council of Elrond. Their advices were also crucial to me. Professor Chang's constructional and sometimes bitter advices stimulate me and lead towards the correct direction. Professor Haghani is erudite in all transportation-related fields. Professor Ozbay brings his expertise in behavioral and experimental economics into my research. Professor Mi offers another out-of-the-box perspective from environment

and energy. It is always a great asset having them in the committee.

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I owe my deepest thanks to my family - my parents who have always stood by me and guided me through my life and my beloved wife and daughter who encouraged me against all impossible odds that I have encountered. Words cannot express the gratitude I owe them.

It is impossible to remember all, and I apologize to those I’ve inadvertently left out. Of course, what I learned the most from the journey is that exploration is a life-time job. As a trained Ph.D. and researcher, I will keep the pace in exploring fearless ideas and addressing emerging needs.

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Chapter 0

Related Publications

- Xiong, C., X. Chen, X. He, X. Lin, and L. Zhang. Agent-based en-route diversion simulation: Dynamic behavioral responses and network performance represented by Macroscopic Fundamental Diagram. *Transportation Research Part C*, 2015.
- Xiong, C., X. Chen, and L. Zhang. Multidimensional travel behavior: descriptive theory, agent-based modeling, and numerical experiment. In S. Rasouli and H. Timmermans Eds., *Bounded Rational Choice Behavior: Applications in Transport*, Emerald, UK. 2015.
- Xiong, C., X. Chen, X. He, W. Guo, and L. Zhang. The analysis of dynamic travel mode choice: a heterogeneous hidden Markov approach. *Transportation*, 42(6), 985–1002, 2015.
- Xiong, C., Z. Zhu, X. He, X. Chen, S. Zhu, S. Mahapatra, G.L. Chang, and L. Zhang. Developing a 24-hour large-scale microscopic traffic simulation model for the before-and-after study of a new tolled freeway in the Washington DC-Baltimore region. *ASCE Journal of Transportation Engineering*, 2015. 05015001.
- Xiong, C., P. Hetrakul, and L. Zhang. Travelers' responses to managed lanes:

- a lane and departure time model with latent carpooling preference. *ASCE Journal of Transportation Engineering*. 2014. 140(8), 04014033.
- Xiong, C. and L. Zhang. A descriptive Bayesian approach to modeling and calibrating en-route diversion behavior. *IEEE Transactions on Intelligent Transportation Systems*. 14(4): 1817–1824. 2013.
 - Xiong, C. and L. Zhang. Deciding whether and how to improve statewide travel demand models based on transportation planning application needs. *Transportation Planning and Technology*. 36(3):244–266. 2013.
 - Xiong, C. and L. Zhang. A Positive model of departure time choice under road pricing and uncertainty. *Transportation Research Record*. 2345: 117–125. 2013.
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 - Chen, X., L. Zhang, X. He, C. Xiong, Z. Li. A surrogate-based optimization of average travel time for highway toll charges in transportation network. *Computer-Aided Civil and Infrastructural Engineering*. 29: 359–381. 2014.

- Zhang, L., G.L. Chang, S. Zhu, C. Xiong, L. Du, M. Mostafa, N. Hopper, and S. Mahapatra. Integrating an agent-based travel behavior model with large-scale microscopic traffic simulation for corridor-level and sub-area transportation operations and planning applications. *ASCE Journal of Urban Planning and Development*. 139(2):94–103. 2013.

Chapter 1

Introduction

1.1 background

The study of travel demand estimation, forecasting, and adjustment has long been a vital topic in the field of transportation planning. Being an induced demand, travel demand is often regarded as the product of other activities. Individuals commute to work, drop-off family members, travel for leisure, fly to customers/suppliers, visit relatives/friends, and so forth. While these activities are often differentiated by locations and time, how these spatial/temporal details can be accounted for becomes an essential question for transportation planners and researchers. Moreover, these activities encompass interrelated travel decisions including destination, mode, departure time, and route. Therefore, the complexity arising from the mutual effects of these multidimensional decisions upon each other and from their decision timing needs to be represented.

Traditional travel demand modeling structure distinguishes four decision dimensions: deciding the frequency of travel, choosing a destination, selecting a travel mode, and traveling via a route. These decision dimensions are assumed to follow a predefined sequential manner of trip generation, trip distribution, mode choice, and trip assignment, as known as the “Four-Step” method. Travel behavior research gradually moved from aggregate demand models to more disaggregate individual-

level and activity-based models [24, 19]. While the majority of interest focuses on advancing single-dimensional (single-facet) choices and more advanced representation of activity pattern such as scheduling [58, 24], land use influence [121], and location choices [17], the linkages among different travel behavioral dimensions are largely ignored [110] and individuals' embedded behavioral processes that influence them to change certain dimension(s) of their travel behavior remain unexploited.

Besides the rigid sequential assumption, travel demand models also rely on other simple and sometimes unrealistic behavioral assumptions in order to keep themselves analytically tractable. Perfect rationality theory is one of the well-known assumptions assuming that individuals are fully rational, have perfect information, and always maximize utility [122, 132]. Being an approach with rich results, mathematical rigor, and interesting applications, perfect rationality and utility maximization allow structural insights and explain similarities and differences in travel behavior. However, if using this theory to calculate how certain variations in the situation are predicted to affect travel behavior, "these calculations obviously do not reflect or usefully model the adaptive process by which subjects have themselves arrived at the decision rules they use" [86].

The opposite holds true for the computational process models, a group of new methods that departs from rationality assumptions and implement learning, adaptations, information acquisition, and decision making efficiently by taking the advantages of computer power. These models are microsimulations relying on heuristic arguments and imitation of human behavior. A large number of real-world or benchmark problems can be analyzed by applying these models to simulate nu-

merical results in different set-ups. Examples on the rapidly growing list include FAMOS, ALBATROSS, MILATRAS, ADAPTS, etc. [108, 9, 8, 136]. On one hand, these models introduce more complex learning, adaptation, and behavioral rules instead of utility maximization. But on the other hand, multi-agent simulation cannot prove but only suggest a certain feature of travel pattern and still assumes sequential decision process. Thus it requires additional theories to conceptualize more rigorous behavioral foundation and better explain behavior adjustments along multiple choice dimensions (see [8, 110]).

1.2 Vision of Agent-Based Modeling

Agent-Based Modeling (AgBM, to differentiate from ABM which stands for Activity-Based Models) is an innovative modeling technique that describes a complex system as a collection of autonomous decision making entities dubbed as agents. It focuses on naturalistic (or descriptive) representation of individual behavior and seeks to capture emergent global (or system-wide) patterns resulting from the local interactions and decisions of individual agents. This bottom-up modeling paradigm differs significantly from the conventional equation-based modeling paradigm [102] which focuses on describing relationships between observables. These are the measurable characteristics of interest associated with either separate individuals (e.g. vehicle speed in the context of transportation), or with the aggregate measures of individuals as a whole (vehicle volume passing through one freeway link). In contrast, AgBM describes the individual agent behavior with naturalistic languages

such as if-then rules, and relies on simulation to explore system dynamics. Because of this difference in modeling paradigm, AgBM exhibits a significant advantage in the domains where system dynamics are highly non-linear and when discrete states are involved. For example, human decisions are usually driven by a series of if-then reasoning processes, which can be naturally represented in AgBM but are hard to describe through equations. This advantage of AgBM becomes even more pronounced when a complex behavior such as hysteresis (the phenomenon that the dynamics during the onset and the offset of certain patterns such as congestion is asymmetric), spatial and temporal correlation, and quasi-Markovian processes (where the dynamics of a system depends not only on its current state, but also previous states, or memory) are involved.

More importantly, AgBM differs from the more conventional modeling approach through its ability to capture complex system behavior via local interactions between agents. As Bonabeau pointed out [21], AgBM is a “mindset more than a technology”, which models a system from the perspective of its constituent units. For example, in transportation, current equation-based models have formulas, which directly forecast congestion. AgBM on the other hand never addresses congestion directly; rather it mimics the activity of individual agents, which then produce congestion. For many disciplines, this bottom-up modeling paradigm offers a better representation of the real world. Moreover, AgBM provides a way to explore the system dynamics cascading from local interactions between agents (dubbed as emergent patterns). These system dynamics are sometimes counter-intuitive and hard to capture through direct modeling of the process. Because of these advantages, signif-

icant research efforts have been dedicated to AgBM in various disciplines, including ecology, social science, economics, geography, and management science. Tesfatsion and Judd [129] listed 22 special issues on the topic of AgBM between 1992 and 2011 in various journals, including *Journal of Economics and Statistics*, *Proceedings of the National Academy of Sciences*, and *Physica A: Statistical Mechanics and its Applications*. The breadth and depth of these research works demonstrated the great potential of AgBM in modeling our complex real world. As indicated by Grimm et al. [61], the AgBM approach may one day “change our whole notion of scientific theory” by reducing various complex systems into sets of conceptually simple mechanism that can produce different dynamics in different context.

1.3 Objectives

Transportation systems are some of the most complex systems that involve millions of agents with different characteristics interacting in both temporal and spatial dimensions. At the local level, drivers maneuver their vehicles to achieve desirable speed, keep a comfortable gap with leading vehicles, and/or turn to follow a route. However, their maneuver is limited by nearby vehicles and can, in turn, influence the behavior of other vehicles. This local interaction between vehicles can form traffic jams as described by Helbing and Treiber [65]. In reaction to traffic congestion, a traveler can adjust route, departure time, mode, and/or destination to better suit personal objectives (e.g. arriving at work in time, making grocery shopping, etc.). Changes in individual travel decisions can then alter the global travel

demand pattern in a transportation system, triggering further shifts in individual decisions. In the long term, the emergent travel demand pattern can influence pricing strategies of road operators, network investment decisions of the government, and shift economic activities. The interactions between individual agents and among agents at different levels (e.g. individuals, operators, and regulators) are extremely complex. Therefore, AgBM may be the ideal tool to address many challenges in the transportation system.

Although studies on behavior of various components of the complex transportation system have a long history in each discipline (e.g. studies on driving behavior dates back to 1970s when CORSIM was first developed; simulation studies on travel behavior starts in 1980s and 1990s), application of AgBM in the field of transportation is still exploratory. Systematic modeling of interactions among various agents/components of transportation system and the complex system dynamics still remain explorative in a sense that no model based on individual behavior has matured enough to satisfactorily replicate and predict global patterns, and to be applied to support traffic management and policy making. Given the advances of agent-based modeling techniques in other disciplines and its strength in decoding the complex system pattern through intuitive description of individual behavior, further research efforts of applying AgBM in transportation is warranted. Recognizing that numerous autonomous agents operate in the transportation system and make various driving and travel decisions on dissimilar time scales that are influenced by different factors (see Table A.1.), I envision a coherent agent-based model that simulates transportation system dynamics as an evolutionary process

with an explicit clock for time tracking. Different agents rely on behavioral rule sets that can be empirically estimated to make driving and travel decisions as decision-situations emerge or are triggered by external stimuli (e.g. information, recurrent or non-recurrent congestion, toll, new travel option). Each person is tracked in the agent-based model, and his/her spatial knowledge and experiences accumulate over time as he/she makes decisions as a driver, an individual traveler, or as part of a household.

Table 1.1: Driving and Travel Decisions on Dissimilar Time Scales and Influential Factors

Decision dimension	Agents	Time Scale	Influenced by
Driving behavior	driver, vehicle	Real-time	Real-time surrounding traffic conditions
En-route diversion	driver, vehicle	Real-time	Real-time congestion, traveler information, policies
Pre-trip route choice	Person	Daily, short term	Network knowledge, experience, information, policies
Departure time	Person	Daily, short term	Schedule flexibility, dynamic tolls, traffic information
Mode choice	household person	Mid-term	Modal performance, personal attributes, inertia, # of vehicles
Destination choice	household person	Mid-term (shopping) Long-term (work)	Spatial knowledge, information, network LOS, personal attributes
Trip frequency	household person	Mid- to long-term, adjustable daily	Activity patterns, household personal attributes

1.4 Contributions

Urged by the aforementioned theoretical and modeling issues, this dissertation describes an alternative framework to modeling multidimensional aspects of travel behavior. Descriptive theory and models are built upon economics and travel

behavior research on learning [58, 7], search theory (Stigler 1961), and bounded rationality [125, 93]. The theory recognizes that there are inconveniences and risks associated with each behavior adjustment dimension, which is conceptualized as a search cost unique to each individual and each behavior dimension. On the other hand, an individual, based on his/her spatial knowledge, personal travel experiences, and beliefs, forms subjective expectations on potential gains (search gain) from behavioral adjustments along each behavioral dimension. It is the interplay of these search gains and search costs along all feasible behavioral adjustment dimensions that collectively determine when individuals start seeking behavior changes, how they initially change behavior, how they switch behavior adjustment dimensions, and when they are satisfied and stop changing behavior. The theorization of multidimensional knowledge updating, search model, and behavior process becomes a unified and coherent approach that models the activity and travel decision-making with a consistent behavioral foundation and increased rigor. The theory is supported by empirical observations and the derived quantitative models are tested by agent-based simulation.

Building on this vision, agent-based approach is broadly tested for integrated driver and traveler behavior modeling with applications for transportation systems management, capital investment evaluation, transportation planning, and beyond. The framework of agent-based models developed in this research focuses on decision dimensions including en-route diversions, pre-trip route choice, departure time choice, and mode choice; these dimensions collectively provide the crucial linkages between traditional traffic simulation, travel demand and the emerging agent-based

models. Data required for building driver and traveler agents will be collected with techniques proven in our previous research, including interactive laboratory experiments, driving simulators and traditional/web-based/GPS-based surveys. Agent behavior rules will be empirically estimated with rule-based artificial intelligence methods and possibly utility-based methods when detailed agent behavior data is not available. Findings from this research will (1) Improve our understanding of driver and traveler behavior; (2) Enhance transportation systems management; and (3) Provide new insights for capital investments. The innovative agent-based modeling and simulation approach developed in this dissertation and its applications in transportation planning and operations could also significantly improve the mobility and reliability of the transportation system.

The major contribution made by this dissertation can be viewed three-fold:

- it develops a pertinent new theory of choices with experimental observations and estimations to demonstrate agents with systematic deviations from the rationality paradigm. Modeling components including knowledge, limited memory, learning, and subjective beliefs are proposed and empirically estimated to construct adaptive agents with limited capabilities to remember, learn, evolve, and gain higher payoffs. All agent-based models are based on empirical observations collected via various different data collection efforts.
- Modeling procedural and multidimensional agent-based decision-making. Individuals choose departure time, mode, and/or route for their travel. Individuals also choose how and when to make those choices. A behaviorally sound

modeling framework should focus on modeling the procedural decision-making processes. This study seeks answers to questions that largely remain unanswered including but not limited to: (1) when do individuals start seeking behavior changes? (2) How do they initially change behavior? (3) How do they switch behavior adjustment dimensions? (4) When do they stop making changes?

- The transformation from the static user equilibrium to a dynamic behavioral equilibrium. Traditional solution concepts are based on an implicit assumption that agents have complete information and are aware of the prevailing user equilibrium. However, a more realistic behavioral assumption is that individuals have to make inferences. These inferences can either be their subjectively perceived distributions of travel time and travel cost or be the multidimensional alternatives they subjectively identified. In other word, individuals determine their choice set and the attributes of each alternative rather subjectively. It is the process of making inferences that occupies each individual in making a decision. This process is the very reason for not using static equilibrium theories or random utility maximization models to analyze behavior.

This dissertation is organized as follows:

- Chapter 2 provides a comprehensive review of existing studies of agent-based modeling approach with a focus on modeling multidimensional behavior and choices.
- Chapter 3 conceptualizes the overall modeling framework of the agent-based

modeling approaches.

- Chapter 4 develops multidimensional behavioral model and its single-dimensional agent-based model components including mode search and switching, departure time search and switching, route choice, and en-route diversion. Calibration methods for these agent-based behavioral rules are discussed.
- Chapter 5 presents a number of applications of agent-based models in transportation planning and operations.
- Chapter 6 concludes the dissertation with discussion on future research work to further enhance the agent-based models and on the ongoing research efforts to support further model development.

One major challenge for developing agent-based models in transportation is due to the fact that no general framework for designing, testing, and analyzing such models has yet been established, despite numerous successes of AgBM in various disciplines. To better benefit from earlier successful applications of AgBM, the next section provides a survey of recent advances of AgBM in both transportation and other disciplines. To better inform model development efforts, I specifically focus on the strengths and weaknesses of modeling methods adopted in previous studies and their implications to their further extension in the field of transportation.

Chapter 2

Literature Review

2.1 Agent-Based Modeling Approach

The idea of Agent-Based Modeling (AgBM) is often attributed to Von Neumann whose work laid the foundation for the construction and modeling of artificial life [55]. Although many seminal works have been done (e.g. [123]) before the advent of the personal computer, AgBM only became popular when the computational power became widely available. For example, AgBM has attracted significant interest in the communities of Computer Science and Artificial Intelligence for designing new software packages since the 1980s. Its value in social science was not widely realized until the 1990s. As more computing power became available and people's understanding of this innovative modeling tool advanced, AgBM has been applied in a wider span of disciplines. Besides AgBM, other terminologies have also been used, such as Individual-Based Models (IBM) in ecology or Agent-based Computational Modeling in economics.

Despite this broad range of applications of AgBM, there has been no consensus in literature on the precise definition of AgBM in transportation. While reviewing related transportation studies in the field, we first define the three essential elements of an agent-based model that are typically defined in AgBM studies in other fields.

Fig. 2.1 illustrates a typical framework of agent-based models.

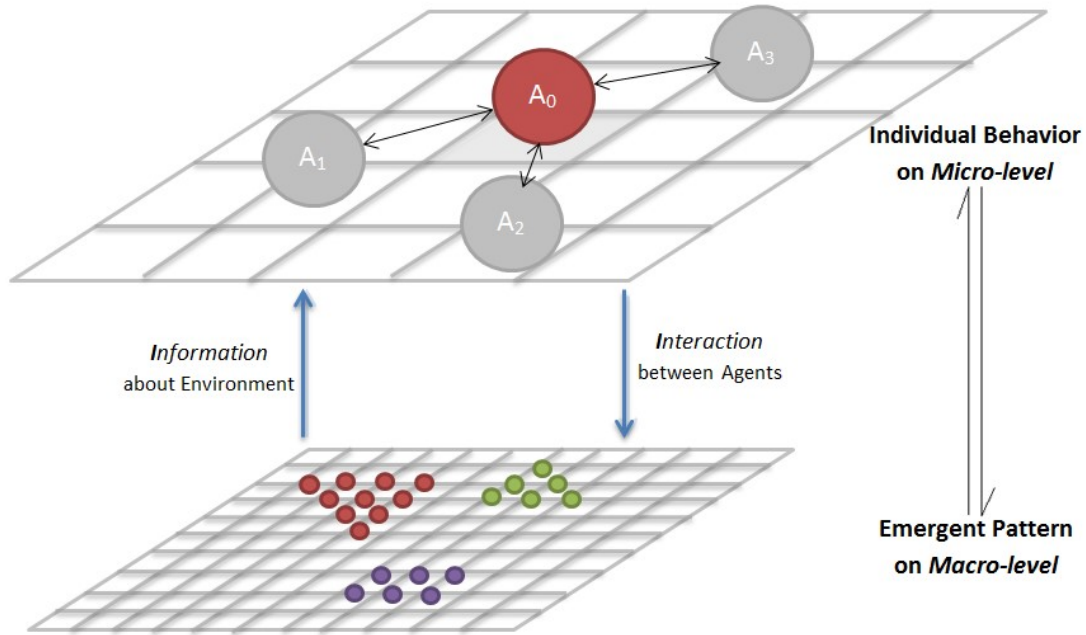


Figure 2.1: Structure of a typical agent-based model

Three elements are illustrated in Figure 2.1 explicitly:

Agents: agents ($A_0, A_1, A_2, A_3, \dots$) should have the following features: (1) agents should be able to sense the environment and change it through its action; (2) agents should act independently without centralized control; (3) agents should be able to pursue their own objectives by acting responsively to the environment changes, proactively to explore opportunities, and/or collectively through communication and cooperation with other agents. Flexibility is also interpreted as adaptive, goal-directed, and social ability by Macal and North [87]. They also argue that agents should be heterogeneous, which distinguishes agent-based modeling from particle simulation. Similar discussions of agent characteristics can also be found in many other papers such as Macy and Willer [89], O’Sullivan [99], and etc. Despite

this diversity in terminology, at the center of this modeling paradigm is the philosophy of modeling complex systems through a bottom-up process, where system-wide patterns emerge through local interactions between agents.

Behavioral Rules: A number of agent behavior rules shall be defined in an agent-based model. Firstly, adaptive agents have the capability to learn. Rather than following a fixed stimulus-response pattern, they continuously adapt to changes in their environment according to their expectations and objectives. Also, agents evaluate the results of the actions and their impacts according to their own expectations. And then agents search to identify better routines to meet their expectations. The decisions are usually made asynchronously under bounded rationale. Adaptive agents can even change their objectives and routines.

Environment: provides the playground where agents behave and interact. Agents' learning cycle of acting, evaluating, and adapting is based on the results of actions dependent on the response of the environment. Agents may exchange information with the environment through sensing or with other agents through communication, and then act to fulfill their objectives. On the macro level, the environment may evolve into different patterns, driven by the interactions between agents. Researchers may conduct a series of experiments to test different assumptions about agent behavior, interaction mechanism, and information flow, which help researchers to capture the critical causal mechanism that drives system dynamics of the environment.

Agent-based models also allow researchers to answer a series of if-what questions through these simulation-based experiments, most of which are too costly to

be conducted in the field. Answers to these hypothetical questions would then support decision-makers to take initiatives that influence the system dynamics (e.g. implement new policy in transportation, or introduce new regulation in business) and to build an efficient, fair, orderly, and robust system.

After two decades of development, agent-based models have moved from an early demonstration of ideas and qualitative analysis to a more robust quantitative analysis of system dynamics. Many modeling techniques have been applied in various disciplines. Given the variety of agent-based models, findings from these early studies could greatly inform and inspire current research efforts in the field of transportation. In the following sub-sections, applications of agent-based modeling in several disciplines will be surveyed.

2.2 Agent-Based Models in Transportation

A number of transportation related agent-based applications already exist in the literature. Most of them are still under development or at the experimental stages, but they clearly demonstrate that implementing these methods has a significant potential to improve the performance of traffic and transportation systems. Kikuchi et al. [76], Bernhardt [15], and Chen and Cheng [31] are examples of papers that review literature and examine how agent-based modeling is applied to transportation modeling. These reviews demonstrate that the most common applications of AgBM in transportation are traffic or pedestrian simulation and demand modeling efforts.

2.2.1 Agent-Based Traffic Flow Simulation

There are many problems, such as congestion and incident management, signal control optimization, public transport priority, etc. which, due to the high level of complexity, cannot be solved by analytical methods. As a result, several microscopic traffic simulation tools have been developed recently. They allow transport operators to evaluate various alternatives in order to determine the optimum solution for any traffic scenario. These tools are essentially based on microscopic driving behaviors such as car following and lane changing which have a significant impact on the accuracy of the models. Although a large number of models have been developed for driving behaviors and reported in the literature, most of them are not completely described. As a good examples in this field, can be mentioned to Gipps [57] and Fritzsche [48]. To face the difficulties of modeling congested conditions, in the last decade, agent-based simulation has received increasing attention in traffic flow simulation. Computational performance, the accuracy of models in representing the traffic flow, and the integration with advanced traffic management and traffic information systems are the main challenges in these agent-based models.

Hidas develops a lane-change model for a multi-agent simulation system called ARTEMiS (Analysis of Road Traffic and Evaluation by Micro-Simulation, previously named SITRAS) which models driver-vehicle objects as autonomous agents [67, 68]. These papers present the details of the lane changing and merging models developed using agent-based concepts. For the modeling, lane change maneuvers are classified into free, forced and cooperative. These classifications are essential in

simulating the congested traffic conditions more accurately. The lane change model was implemented in ARTEMiS and tested on several simple hypothetical road network scenarios. A number of new concepts like Lane-Change Plan are introduced in this approach to model the maneuvers. Lane-Change Plan is created when a vehicle determined that a lane change is essential, but it is not immediately feasible. Because of the close relationships between the lane changing and car following models, it should be mentioned that Hidas describes car-following model implemented in ARTEMiS [66]. This model is based on a desired spacing criterion, which is assumed to be a linear function of the speed.

Panwai and Dia [101] study a car-following model that is based on a reactive agent structure and a neural network approach. Reactive agents, unlike the cognitive agents, are based on a simple approach for mapping perceptions to actions. In this study, neural network is employed for this mapping. With application of different Artificial Neural Network (ANN) techniques, four different models are proposed in this study. After model development, all of them are interfaced to AIMSUN and validated at the microscopic and macroscopic levels. Furthermore, the performance of these models is compared to each other and to a number of existing car-following models.

2.2.2 Agent-Based Travel Demand Models

Traditionally, researchers have been using the four-step travel demand models for travel demand forecasting. As more and more research efforts move from

conventional trip-based models to activity-based models, application of AgBM in travel demand modeling attracts increasing research interest. Most existing agent-based travel demand models focus on single-dimensional (or single-faceted) travel behavior. Some researchers focused on the departure time and route choice for a specific trip (most of the time the commute trip), while others investigated the more comprehensive activity patterns and the travel demands these activities generate.

System STARCHILD models the activity and travel scheduling decision as a classification and choice process [114, 113], which is dependent on the basic concepts of utility maximization within a constrained environment, and results in observed travel/activity behavior. The key features are the detailed representation of constraints in the identification of alternatives, and the use of a classification method to generate the choice set. However, the notation that all feasible activity schedules are generated in order to select this maximum utility alternative is unrealistic.

SCHEDULER is one of the first computational process models (CPM) of activity-travel patterns [50, 58]. A CPM focuses on the process of making a decision, while the econometric approach such as utility maximization focuses on what factors affect the rational choice but not how the utility is maximized. SCHEDULER works as follows. Activities are available in the Long-Term Calendar (stored in long-term memory). Each activity has a priority and duration. A subset is retrieved for scheduling on the basis of priority and duration. Information about spatio-temporal constraints (feasible locations, open hours) is retrieved from a memory representation of the environment called the Cognitive Map (also stored in long-term memory). The SCHEDULER then makes choice of location and departure times. The result-

ing activity schedule is stored in the Short-Term Calendar (short-term memory) for later execution. Drawing on empirical observations indicating that people often use a nearest-neighbor heuristic in choosing sequences of locations, location choices are modeled accordingly. SMASH is developed following the framework of SCHEDULER and include more factors that are known to affect activity scheduling [45]. However, the model still assumes a complete knowledge of all possible alternatives in each scheduling step (inclusion, deletion, or substitution of an activity). GISICAS is another model in the SCHEDULER framework with search heuristics combined with GIS to generate feasible schedules [84].

AMOS (Activity-Mobility Simulator) is a unique system in that it predicts the switch response to a policy change from a “baseline” activity schedule, which is an input to the model [77, 79]. A neural network is used to predict an output signal for each alternative, which is a scalar function of 36 decision-maker characteristics under the policy change. A multinomial Logit model converts the output signals to probabilities by using the output signal as the only explanatory variable in the utility function. The parameters of the basic response model are estimated from data supplied by a policy specific stated preference survey. The switch decision is made with a satisficing rule, rather than utility maximization.

PCATS (Prism-Constrained Activity-Travel Simulator) is a micro-simulator of individuals’ activity engagement and travel within Hagerstrand’s prism [80]. The probability of choosing a daily activity-travel pattern is decomposed into a series of conditional probabilities, each associated with an activity episode or trip (product of conditional probabilities). These conditional probabilities are derived from utility

maximization models and thus unbounded rationality is assumed. FAMOS is an application of PCATS in Florida [107].

Zhang and Levinson propose an agent-based travel demand model [154]. In this model, three types of agents interact with one another: node, arc, and traveler. The goal of each traveler agent is to find and reach the activity with the lowest travel costs. Travelers move between nodes through the connecting arcs and decide to either accept or reject the opportunities at the nodes. During this search, they learn arc costs. They add this information to the exchangeable knowledge base as well. Similarly, node and arc agents also have specific properties and learning abilities. Along with these properties, some other interaction rules (including learning rules) complete the model. This framework enables the model to perform trip distribution and route assignment. A simple ten by ten grid network and the Chicago sketch network are the numerical examples and are used for calibration. After the calibration, resulted trip length distribution is close to the observed one and most traffic is assigned to the shortest paths.

CEMDAP (Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns) is a microsimulation model based on utility maximization econometric models at various levels of decision making (pattern, tour, and stop). It simulates both workers and non-workers along a continuous time frame [18]. ALBATROSS [8] is a fully operational CPM of activity scheduling. It is designed as a rule-based model in which situational, household, institutional and space-time constraints as well as choice heuristics of individuals are explicitly represented. Central to the approach is the use of the decision tree for representing choice heuristics and deriving

these heuristics from activity travel data. Note that although the theoretical framework describes how a decision heuristics might evolve over time, the model does not contain any dynamic element: the decision tree is generated from cross-sectional data. AURORA is an agent-based microsimulation system that uses scheduling heuristics and has elaborated learning models [4]. Congestion is the mechanism by which agents interact. Perceived utilities of scheduling options are dependent of the state of the agent, and implementing a schedule changes this state. Particularly, an agent keeps a record of the history of each activity in his activity agenda to determine the urgency of each optional activity at the time of scheduling. Long-term adaptations are based on learning processes. Each time after having implemented a schedule, an agent updates his knowledge regarding choice-sets, default settings of activities and expected values of attributes of the transportation and land-use system. Choice-set updating is relevant for choices where the choice-set is a subset of the universal choice-set and does not necessarily include the optimal choice for each possible schedule. This generally holds for location choice and route choice. Location choice-sets are dynamic and changes follow from processes of knowledge decay, reinforcement and exploration.

2.2.3 Integrated Agent-Based Models

Microscopic traffic simulation models exhibit strong advantages in capturing detailed traffic dynamics and have been approved in practice as a valuable tool for evaluating corridor capacity expansion and traffic operation improvements. Their

applications have recently been extended to address a broader range of transportation-related issues, including congestion management, multimodal corridor improvements, evacuation planning, land use and economic development. However, a comprehensive analysis of many of these issues requires models that can consider various demand responses to these traffic management strategies such as peak spreading, modal shifts, and traffic diversions at the corridor and regional levels. These travel demand dynamics can be readily addressed by agent-based travel demand models. On the other hand, agents in demand models require traffic conditions and travel experience as inputs for behavioral adjustments. Therefore, an integration of agent-based travel demand models with microscopic traffic simulation models can provide researchers with a powerful tool to simulate the complex transportation system and provide answers to many interesting policy questions. Some research efforts have been dedicated to this field.

Dia [40] presents an agent-based approach to model dynamic driver behavior under the influence of real-time traffic information. For each form of the provided information to drivers (e.g. quantitative delay, predictive and prescriptive delay), a number of Multinomial Logit models are developed to determine the factors that affect the propensity of the drivers to adjust their travel patterns and to determine the values of these factors. This evaluation is based on a field behavioral survey in a congested real-world commuting corridor. Based on these driver behavioral models and to evaluate the impacts of providing drivers with travel information, an agent-based framework for a microscopic traffic simulation tool is presented in this study, which applies the Belief, Desire, and Intention (BDI) agent architecture.

The feasibility of this approach is demonstrated through a case study on the same corridor where the travel behavior survey was conducted.

Another study which applies the BDI concept is Rossetti et al. [117]. They propose an extension to an existing microscopic simulation model called Dynamic Route Assignment Combining user Learning and micro-simulation (DRACULA). In this extension, the traffic domain is viewed as a multi-agent world and the behavior of agents is represented in terms of mental attitudes, which allow them to make decisions about route choice and departure time. The main part of this paper is concerned with the reasoning mechanism of drivers modeled by means of BDI architecture. In addition, as the main goal of this work, a framework is presented which model and implement commuter scenarios using BDI drivers. This framework was designed in a way that influence of exogenous information on the drivers' decision making can also be assessed.

TRANSIMS has been developed by researchers at the Los Alamos National Laboratory. It is based on four primary modules: population synthesizer, activity generator, route planner, and traffic micro-simulator. The activity is generated by matching household demographic data, and therefore not as sensitive to policies as other more developed activity-based models. The multi-modal route choice is based on shortest paths assuming global and perfect knowledge of the network, and thus assumes unbounded rationality.

TRANSIMS was designed to be modular and improved by further updates. Later versions of TRANSIMS included more advanced agent based activity models such as SACSIM. Hao et al. focus on integration of an activity-based travel demand

model, TASHA [64], with a dynamic agent-based traffic simulation model, MAT-Sim. This research has two main objectives. The first is to develop an agent-based framework that includes both travel demand modeling and traffic assignment by integrating the above mentioned software. The second objective is to employ this newly integrated model in vehicle emission modeling. In this study, an iterative process is applied for the integration and a series of data conversions is proposed to make this process possible. The modeling framework is implemented to the greater Toronto area (GTA).

Flötteröd et al. [46] is another study which links the demand models to the agent-based traffic simulation. This study concentrates on the calibration of demand models in the context of dynamic traffic assignment. Calibration refers to the estimation of the models' parameters (such as the coefficients of a utility function) from time-dependent traffic counts. These parameters represent the simulated travel behavior. The calibration simultaneously adjusts the route choice, departure time choice, and mode choice (car versus no car) of individual travelers by employing a Bayesian framework. They assume that the supply simulator is to be modeled without error. Therefore, calibration of supply models is not included in this research.

2.2.4 Modeling Multimodal Traveling Agents

Current agent-based models are often limited to a single transportation mode only. As many of them are used to support analysis of the complex transportation

system comprising multiple modes, transit must be considered. Transit poses a major challenge because mode choice decisions are usually based on comparison between highway travel time and transit travel time for each traveler. The network models must therefore be able to route travelers through a transit network (which, with buses, also operates on the highway network). The network models must be capable of estimating time to access transit, time to wait for transit, the amount of time spent in the transit vehicle and the number of transfers required between transit lines. Several efforts are now underway. In demand modeling, tools like ALBATROSS and CEMDAP have some specific components for mode choice and the transit demand between OD pairs is one the main outputs of them.

On the supply side, models must be capable of route assignment, estimating time to access transit, time to wait for transit, the amount of time spent in the transit vehicle and the number of transfers required between transit routes. Wahba and Shalaby [135] develop MILATRAS, (Microsimulation Learning-Based Approach for Transit Assignment) which is an agent-based transit assignment module for PARAMICS (parallel microscopic simulation). PARAMICS is a traffic microscopic simulator. This module is capable of tracing every agent through the transit network, supporting transfers between routes, and dealing with boarding and alighting at the passenger level. Moreover, it models behavioral responses of transit passengers under information provision. Cortés et al. [37] propose a general framework to evaluate transit systems with the capabilities of commercial microsimulators. The focus of the study is more on the flexible transit and uses a bus rapid transit system and a large-scale real-time routed transit as examples of framework implementa-

tions. Framework can be applied to any agent-based microsimulator but, in this paper, it coded in PARAMICS. Rieser et al. [116] is another study in this area that presents the extensions implemented into the agent-based simulation framework of MATSim to support not only car legs, but also other modes of transport.

There are some researches in the literature which utilize the agent-based modeling to study other aspects of transit systems. For instance, Balbo and Pinson show how agent-based methodology is applied for the development of a Decision Support System (DSS) for management of urban public transportation systems [10]. Li et al. [85] propose an artificial urban transit system (AUTS) based on agent-based modeling. AUTS can dynamically model the passenger's behavior and route choice. Forecasting transit flow, setting parameters for urban transit networks, evaluating alternative modifications to the transit systems, and predicting the impact of special/emergency events are some of the most important applications of this artificial system.

Another area of study is integrating demand and supply models for transit, which poses a major challenge. Demand models estimate transit ridership by comparing highway travel time to transit travel time for each passenger and commonly work with passengers as the agent. On the other hand, the network models route travelers through a transit network (which, with buses, also operates on the highway network) and usually consider vehicles as the main agents. Even with the existing challenges, several researches are carrying out merging the transit demand and supply models. TRANSIMS is one the commercial packages which employs agent-based approach and model transit on both sides. In TRANSIMS, the transit network is

defined by transit routes, stops, fares, driver plans, and schedules. C10 projects in Strategic Highway Research Program 2 (SHRP2) are other researches on integrating demand and supply models for transit in an agent-based framework.

2.3 Multidimensional Behavioral Studies in Transportation

2.3.1 Agent Behavior in Different Dimensions

2.3.1.1 Mode choice

also attracts lots of research interests. Although mode choice is obviously an important dimension in travel decision-making process, it is usually treated as given in many practices and is not part of the individual travel demand models [105]. One reason for this treatment is that the mode decision is constrained by factors such as vehicle ownership, availability of public transit, and transit fare, all of which are relatively stable and unlikely to change in a short time period. However, as concepts such as Transit Oriented Development (TOD) and multimodal corridor management attract increasing interests from both researchers and policy makers, there is increasing need to internalize mode decisions and build a more comprehensive model to support policy analysis. In addition, as congestion in general threatens most metropolitan areas, peak-hour congestion is still the worst when people commute [115]. Policies and strategies, such as congestion pricing, parking pricing, managed lanes, enhanced transit services, among others, are commonly employed to nudge travelers to gradually switch from auto to other non-auto modes [41, 49].

Mode choice behavior has been traditionally modeled by the econometric theory of random utility maximization. It assumes that an individual's travel mode choice is determined by the indirect utilities of each alternative mode and the individual can choose the one with the highest utility level. For example, Koppelman used a multinomial logit model to predict mode share changes in response to a range of transit service improvements [82]. Later on, a great deal of advances has been done following this line of research. Mixed logit models have been applied to model mode choice and incorporate both observed and unobserved heterogeneities [95]. The assumption of independence from irrelevant alternatives (IIA) has been addressed by a series of studies on nested logit and generalized nested logit models [133, 138].

One major deficiency of most existing studies is that they model static choice and rely on cross-sectional datasets [78, 109, 105]. Increasing number of research on dynamic models have been available (e.g. [137, 107, 34]). However, far less attention has been given to modeling the dynamics of mode choice. This is partly due to longitudinal data collection difficulties [112]. Due to the challenges and budget constraints, a good and timely longitudinal travel behavior data is often lacking [109]. Meanwhile, a theoretically sound modeling framework is yet to be widely accepted. Among the limited research, Goulias proposed a generalized mixed Markov latent class model for activity pattern switching using the Puget Sound Transportation Panel (PSTP) data from 1989 to 1993 [60]. Srinivasan and Bhargavi investigated long-range commute mode choice dynamics (including exogenous variable change, state-dependence, user sensitivity, and unobserved factors) in India using a five-year

longitudinal dataset [128]. Their model captured persistent inertia which would hinder the immediate effects, as predicted by traditional cross-sectional models, of improved LOS in transit services. Research on short-term within-day [112] and day-to-day [103] variability was also seen in literature.

As an alternative, process models attract increasing research attention. Arntze and Timmermans developed an activity-based process model (ABATROSS) wherein decision trees were employed to model the mode choice process [8]. Ben-Akiva [12] proposed a planning and action choice model where the intrinsic plan of changing modes was modeled as a process. A preliminary application of this model in mode choice was a binary stated choice between auto and transit [2]. This paper seeks to further uncover the factors that contribute to the dynamics of mode choice behavior. In doing so, we first conceptualize a modeling framework which is formed by a cyclic two-stage searching and switching process. The searching process serves as a choice set generation step. At each time period, each traveler searches for one alternative mode based on her/his habitual mode and previous travel experience. Then the traveler makes a switching decision between the habitual mode and the alternative one.

2.3.1.2 Departure time choice and route choice

Departure time and route choice are traditionally connected with traffic assignment models with an explicit and detailed representation of the transportation network that is subject to congestion. Therefore travelers' choice adjustment from

day to day has been investigated since early days (see, e.g., [69, 28, 149, 36]), albeit generally to answer questions about the existence and stability of traffic equilibrium, and not in an attempt to derive more behaviorally realistic models. Route and departure time choice have largely followed the utility-maximization paradigm in these so-called day-to-day “dis-equilibrium” models (and also in equilibrium traffic assignment models), with a few exceptions including the “indifference band” theory [93] and the SILK-BUE model [151].

The learning model in route choice is first introduced to the transportation community by Horowitz in a two-link stochastic equilibrium analysis [69], with the assumption that the perceived travel time is based as the weighted average of travel times in the past. Three learning scenarios are developed based on which past travel times are available: 1) actual travel times on both routes; 2) perceived travel times (actual time plus a random disturbance) on both routes; 3) perceived travel time on the chosen routes only. It shows that the details of the route choice decision-making process determine the convergence of the link volumes to equilibrium. When link volumes converge to non-equilibrium values, the levels at which the volumes stabilize typically depend on the initial link volumes or perceptions of travel costs. Later on when the day-to-day dynamic models are applied to a general network for theoretical analysis (see, e.g., [28, 149]), the third scenario is rarely used, largely because it is difficult to derive meaningful theoretical results with such an assumption. The first two scenarios however imply global knowledge in a general network, which in general is a strong assumption.

Simulation-based dynamic traffic assignment models find it straightforward

to apply the learning processes similar to those in [69] to simulated individuals. Examples are DynaMIT [13] and Emmerink et al. [42]. Both assume that a traveler updates travel times on experienced routes only. Ben-Akiva et al. assumes utility maximization [13], and Emmerink et al. utilizes the “indifference band” theory [42], which states that a traveler does not necessarily seek the optimum, and would stay on the current route if the change in travel time from consecutive days is not larger than a threshold. However, this “bounded rationality” is incomplete, since it also assumes that if the threshold is exceeded, a shortest path is sought, which again implies global network knowledge and unlimited computational capacity. DYNASMART uses Bayesian updating to update travel time perceptions for joint departure time and route choice, and also assume utility maximization [72]. DRACULA has a similar link travel time updating mechanism and also assumes shortest path choice [117]. Ettema et al. use reinforcement learning to update perceptions and assume utility maximization in a day-to-day departure time choice simulation [44].

Nakayama et al. simulates a learning process in route choice by assuming drivers are choosing from a set of simple decision rules based on experience [96]. The four rules are: no switching, random switching, experience based on a limited number of past days, and experience based on all past experience. A reinforcement learning model is used for the rule selection. The authors conclude that drivers do not become homogeneous and rational; their attitudes toward and perceptions of each of the two routes in the tested network become bipolar. The authors then question the foundation of equilibrium analysis.

Ozbay et al. use stochastic learning automata (SLA) to analyze drivers’ day-

to-day route choice behavior [100]. This can be viewed as a variant of reinforcement learning. An internet based route choice simulator is developed to calibrate the model. The calibrated SLA model is applied to a simple transportation network to test if global user equilibrium, instantaneous equilibrium, and driver learning have occurred over a period of time. It is shown that the sample network converges to equilibrium, both in terms of global user and instantaneous equilibrium.

Arentze and Timmermans [5] and the subsequent Han et al. [63] deal with spatial knowledge learning explicitly. When making a trip, individuals make observations that may increase their knowledge about their environment. Arentze and Timmermans develop a measure of expected information gain based on a Bayesian model of mental maps and belief updating [5]. They argue that expected information gain is an element of the utility function of trip choice alternatives under conditions of limited information and learning. The simulations conducted illustrate that expected information gain tends to favor longer trips and variety seeking in terms of both route and destination choice. They argue, therefore, that individuals may perceive a positive utility of travel through environments with which they are less familiar.

Han et al. address one type of dynamics: the formation and adaptation of location choice sets under influence of dynamic relationships within social networks [63]. It extends the dynamic model developed in earlier work, which simulates habitual behavior versus exploitation and exploration as a function of discrepancies between dynamic, context-dependent aspiration levels and expected outcomes. Principles of social comparison and knowledge transfer are used in modeling the impact of so-

cial networks through information exchange, adaptations of spatial choice sets and formation of common aspiration levels. They demonstrate model properties using numerical simulation with a case study of shopping activities.

SILK-BUE is a simulation-based traffic assignment program developed by Zhang [151] where route choice is modeled without the perfect rationality assumption (i.e. complete information and utility maximization). Bayesian learning is used to update perceptions of route attributes. Expected search gain is compared to search cost to determine whether a search will be performed at all. A search process is explicitly modeled for the generation of choice set. Search rules are represented by a decision tree generated from survey data, which determine whether an alternative will be considered. If an alternative is indeed going to be considered, another decision tree is applied to decide whether the traveler will switch to the new alternative. The traffic equilibrium under the adopted positive assumptions is defined as the Behavioral User Equilibrium at which the subjective search gain is lower than the perceived search cost for all users. Results suggest that normative assumptions, such as perfect information and unlimited human abilities to maximize utility, can produce significant prediction biases.

2.3.1.3 En-route diversion

en-route route choice under information provision has been traditionally modeled by the econometric theory of random utility maximization [11]. Mahmassani and Liu [91] adopted a multinomial probit framework to model the commuters' joint

pre-trip departure time and en-route diversion behavior in response to real-time information, based on data from a laboratory interactive driving simulator. The study suggests that commuters switch routes if the expected travel time savings exceed an indifference band which varies with the remaining trip time to destination. Abdel-Aty *et al.* [1] developed logit models to capture the effect of real-time information on en-route diversion, using stated preference data. Khattack *et al.* [75] estimated a bivariate ordinal probit model of drivers' diversion and departure time choice when traffic information is available.

Limitations exist in the en-route diversion models. First of all, they are often not well-calibrated due to data limitation and other issues. The inherent bias of the stated preference data and driving simulator data has long been argued as a major deficiency of the models [22]. Koutsopoulos *et al.* [83] further assert that driving simulators, for en-route diversion analysis, can be more useful if revealed preference data collected from "actual en-route route choice behavior" and an appropriate designed calibration become available.

Moreover, unlike the decisions of departure time and pre-trip route choice, en-route diversion is a decision triggered by impulsion. When making en-route diversion decisions, a driver usually has very limited reaction time to obtain the real-time traffic information from the sources, process the information, compare the original route and the diverting route, and make a decision. Therefore, some researchers [104] emphasized the need for rule-based computational process models, since it has long been claimed that utility-maximizing models do not always reflect the true behavioral mechanisms underlying travel decisions (people may reason more

in terms of “if-then” structures than in terms of utility maximizing decisions). ALBATROSS applies CHAID decision trees to model the activity scheduling behavior [44]. Janssens *et al.* [71] developed a Bayesian network augmented tree (BNT) approach to look at multi-facet decision making processes. This approach took advantage of both the Bayesian network and decision tree/rule induction method. Zhang [152] developed a positive theoretical framework (referred to as the SILK theory) for travel decision-making analysis, which was subsequently applied to model route choices on a real-world transportation network in Twin Cities, Minnesota. Xiong and Zhang [144] further explored the SILK framework and proposed a descriptive departure time searching and switching model. This model has been successfully integrated with a large-scale microscopic traffic simulation [153]. In modeling en-route diversion behavior, few studies have been reviewed in this line of research. Paz and Peeta [104] employed aggregate behavioral if-then rules and calibrated weight vectors for these diversion rules, so as to match the estimated and actually observed network states.

Other than rules that give only a simple classification, models that give probability estimates are favored in the field of practical data mining and artificial intelligence for their flexibility in applications when combining decisions and sensitivity analysis [14]. Naive Bayes model is one of the most efficient and effective algorithms that predict probability estimates. Although its underlying conditional independence assumption is rarely true in real-world applications, the correlation among variables does not affect the performance optimality of naive Bayes model, as quantitatively proved by Zhang [150]. Except for some research in mode choice modeling

[20], few travel behavior studies have explored this promising approach.

Existing research also tried to consider en-route diversion behavior and evaluate information provision in operations applications. Xu et al. developed a probit model by employing real-world loop detector data and vehicle plate reader data to analyze the impact of dynamic message signs (DMS) [147]. Their study emphasized the significant behavioral difference between field data and stated preference data. Quantitative evaluation of the impact on network travel conditions is lacking since the network model of the study area is yet to be developed. Bustillos et al. embedded en-route diversion in a real-world regional network to evaluate the impact of incident scenarios and en-route behavior changes [27]. The en-route decision was modeled as a delay tolerance threshold. Tsubota et al. explored the impact of en-route behavior changes under information provision by employing the Macroscopic Fundamental Diagram (MFD) as a measurement [131]. Assumed network and microscopic simulation was employed to simulate difference diversion ratios. These studies all seek linkages between en-route diversion and operations applications. A complete framework to integrate agents' en-route diversion model, behavior calibration, network and simulation, and performance measures is yet to be developed and in imperative needs.

2.3.2 Multidimensional Agent Behavior

The majority of travel behavior research focuses on single-dimensional (i.e. single-faceted) choice of travel separately. However, the correlation between behav-

ioral dimensions does exist. For obvious reasons, behavioral changes in one dimension (e.g. changes in travel mode) almost always cause changes in other dimensions (e.g. departure time and/or route).

Very few studies consider more dimensions of travel behavior and responses. Pendyala et al. developed an activity-based microsimulation (AMOS) which predicted multidimensional behavior using the Neural Network approach [106]. Yamamoto et al. modeled departure time choice and route choice under congestion pricing by conducting a stated preference survey (SP) in the Osaka-Kobe metropolitan area [148]. These choice dimensions were analyzed by jointly considering the prior and posterior activities. The activity durations were incorporated as endogenous variables that influenced choices of departure time and/or route. Wen et al. investigated mode and departure time choices under time-of-day pricing of transit services using similar SP survey conducted for Taipei Metro users and using a random utility maximization approach [139].

Multi-faceted behavior adjustment rules were modeled by Arentze, Hofman, and Timmermans as response strategies to possible policy scenarios [6]. In the paper, the agent behavior rules were represented by several discrete choice models describing the multi-dimensional (multi-faceted) reactions of individuals intended for reducing the negative impact of the policy. Results indicate that agents tend to change route and departure time more frequently if their commuting trips are influenced by the policy. For non-work activities, changing route and switching to bike are the most dominant responses. This multi-faceted policy response model is linked to ALBATROSS model to predict different policy/planning sensitivities.

Vrtic et al. have developed joint choice analysis to understand political acceptability of mobility pricing, route choice, mode choice, and departure time choice behavior [134]. The study is supported by data collected from a large-scale self-administered stated preference (SP) survey conducted in Switzerland. The agent behavior is predicted by a series of multinomial logit models of the joint choices (e.g. joint departure time and mode, route and departure time, etc.). Multidimensional preferences can thus be predicted for Swiss travelers. The most significant behavior response to increased congestion level is that Swiss travelers prefer to depart earlier to make sure that they arrive on time. The study also unveils Swiss travelers' nonlinear valuing of cost and time characteristics.

More recently, Sokolov, Auld, and Hope demonstrated a flexible framework for developing integrated modeling systems using an agent-based approach named POLARIS (Planning and Operations Language for Agent-based Regional Integrated Simulation) [127]. The structure is designed in a fairly flexible way that travelers' short-term en-route behavior (lane-changing, car-following, etc.), mid-term trip behavior (route choice, departure time, etc.), and long-term life-style behavior (location choice, mode/destination choice) are all integrated within the agent-based design. It provides an architecture overview of how an AgBM framework should be constructed. Different specific behavior rules need to be filled into the framework.

To summarize the existing literature on multidimensional behavior modeling, the authors believe that a universally well-accepted behavioral theory is still lacking. Following a legacy model of Four-Step planning framework, one has to make strong assumptions about the sequential choice behavior (making a trip – destination choice

– mode choice – route choice) and accept the limited time-of-day representation. Researchers make effort in relaxing this rigid framework. The later-on developed joint choice models assume rational agent behavior and simultaneously determine agent behavior. Neural network models (AMOS), decision-tree models (ALBATROSS), and the fully agent-based framework (e.g. [127]) are the most flexible behavior representations. These microsimulation models employed complex heuristic for the output, but require additional theories to explain behavior adjustments along multiple choice dimensions.

2.4 Discussion

This section reviews traditional travel demand travel behavior models and agent-based modeling systems in Transportation. The legacy models are classical and have been widely applied in numerous applications. Being a practical approach, the traditional models often rely on rigid assumptions, including aggregate demand (e.g. direct demand models and/or aggregate modal split), fixed top-down decision-making process, and perfect rationality assumption.

Thinking out-of-the-box, AgBM constructs a completely different bottom-up approach to model travel demand. The breadth and depth of AgBM applications have clearly demonstrated the great potentials. This innovative approach, which relies on some local interaction rules between agents to explain complex system dynamics, is both powerful and adaptive. Many models, such as the segregation model by Schelling [123], exhibit a surprising beauty of simplicity and elegance. Yet

their implication for various disciplines is profound. As Epstein and Axtell argued [43], AgBM may one day fundamentally change our view towards scientific theories. People would ask questions like “Can you grow it?” instead of “Can you explain it”.

Although many research questions remain to be answered to fulfill such a vision, we do see rapid development of AgBM during last few decades. It has moved from early proof-of-idea and qualitative analysis to more rigorous quantitative analysis. The applications of AgBM in various disciplines are three-folds: 1). Improve our empirical understanding of complex systems. By capturing the salient characteristics of a complex system, it helps researchers to understand how system-wide regularities emerge and persist. 2). Improve our normative understanding of complex systems. The rapid development of AgBM has greatly benefited from advances in computing technology during the past few decades. Agent-based models allow researchers to test different scenarios within limited time and monetary budget. For example, many cities want to develop and evaluate their evacuation plan. Researchers know some local failure of transportation, communication, or electric network would cascade into system failure, which cannot be captured through equations. AgBM simulation provides a way to answer various “what-if” questions and provide insights to some unexpected events. 3). Develop heuristics to optimize our system. AgBM allows researchers to improve the system based on understandings built through experiments.

Notable efforts have been dedicated to applying AgBM approach in transportation. Transportation systems consist of numerous intelligent agents such as

travelers, drivers, and vehicles that interact with one another on various time scales in urban and regional systems, producing important and often complex system-level patterns, such as travel demand and congestion. Despite the successful applications of AgBM listed in this report, significant research work is warranted before AgBM's potential in transportation is fully explored.

One long-lasting challenge is the lack of a widely-accepted general framework for designing, testing, and analyzing agent-based models. This is true for both transportation studies and other disciplines. There is no universal definition for what constitute salient agent behaviors. As we move upward through different hierarchies, we start to apply agent behaviors that have wider impacts. In this way, we reduced the number of parameters for each hierarchy. The first objective of this research is to propose a theoretical framework for agent-based driver and traveler behavioral modeling, which could benefit from a wide spectrum of travel/activity data and push forward the current state-of-the-art and state-of-the-practice in traffic operations, management, and transportation planning.

Another challenge is modeling adaptive agent behavior along different behavioral dimensions. A substantial difference between a legacy planning model and an AgBM model is that the decision-makers in an AgBM keep evolving and make flexible and dynamic behavior changes. For instance, when a road pricing scheme is implemented on agents' normal route to work, agent behavior theory needs to explain why an agent may initially search and adjust route while someone else previously using the same route may switch to transit instead. In a fully operational AgBM, multidimensional learning and knowledge need to be modeled. Agents have

the capability to remember and forget personal past experiences wherein they form their own spatial knowledge and beliefs. From their agent-based cognitive spaces, agents form subjective expectations on potential gains (search gain) from behavioral adjustments along each behavior dimension. On the other hand, theory needs to consider bounded rationality and recognize that there are inconveniences and risks associated with each behavior adjustment dimension. The authors believe that the interplay of these gains and impedance along all feasible behavioral dimensions collectively determine when individuals start seeking changes, how they initially change behavior, how they switch behavior dimensions, and when they are satisfied and stop changing behavior.

As various agent-based models for different sub-systems are built and improved, researchers may integrate these models into one mega model that includes all major players of transportation systems: individual travelers, commercial transporter, transit operator, infrastructure provider, and regulator. We may also include other components such as agent-based land use model, regional economic model, and even international trade and immigration models to simulate the interaction between a wide-range of systems. It is also possible to gradually replace one or a few of the modules of an existing planning model with agent-based models in order to introduce AgBM capabilities that are particularly needed. For instance, implementing an AgBM departure time searching and switching model to existing planning applications can effectively enable the time-of-day sensitivity and predict peak-spreading effects for future year and for analysis of behavior response to road pricing scenarios. Being the third major objective of this research, demonstrating

AgBM application capabilities in planning, operations/control, and optimization (policy decision-making) are of essential importance.

Chapter 3

The System of the Agent-Based Models

The objective of this research study is to develop a theoretical framework for agent-based driver and traveler behavioral modeling, which could benefit from a wide spectrum of travel/activity data and push forward the current state-of-the-art and state-of-the-practice in traffic operations, management, and transportation planning. The previous section has reviewed existing research efforts on activity-based/agent-based models and their applications. As previously discussed, there has been no consensus in literature on the precise definition of Agent-Based Modeling System despite a broad range of applications of such system across multiple disciplines. Yet most researchers agree that the essence of Agent-Based Modeling paradigm is the philosophy of modeling complex systems through a bottom-up process, where system-wide patterns emerge through local interactions among agents. For example, some activity-based travel demand models capture travel demand by modeling individual choices such as activity location, scheduling, and duration. However, applications of agent-based modeling in transportation are still explorative and unsystematic. Positive/descriptive models have not been adequately explored. Many models aim at providing a good match of aggregate performance measures but not reasonable assumptions of travel behavior. The lack of high-quality behavioral data is often named as the reason that positive/descriptive approach is not usually

adopted.

To bridge these gaps, I first propose a theoretical framework for Agent-Based Modeling System in transportation based on existing data and innovative data collection effort. This modeling system emphasizes an integrated and comprehensive framework that includes both dynamic network supply models and agent-based travel demand models. A series of single-dimensional Agent-Based Modeling (AgBM) components has been covered, with each focusing on one single behavioral dimensions including travel mode choice, pre-trip routing, scheduling, and dynamic routing. Based on these modeling experiences, I am exploring innovative methods to capture how and when cumulative experiences resulting from agent decisions on these shorter time scales trigger decision-making processes on longer time scales (e.g. mode choice, destination choice). This leads to a multi-dimensional agent-based modeling system that addresses a key theoretical and modeling issue in driver and traveler behavior modeling. The proposed multi-dimensional AgBM can take the place of traditional four-step sequential modeling approach and offer a more flexible model structure regarding how agents actually behave. Meanwhile, the AgBM framework also allows the flexibility to incorporate some or all of the existing AgBM modules to enhance the current four-step modeling framework.

Fig. 3.1 provides a broad schematic of the structure of the agent-based modeling framework. It includes five primary modules: the agent synthesizer, the baseline agent behavior generator, the multidimensional behavior response model, network models, and performance measures.

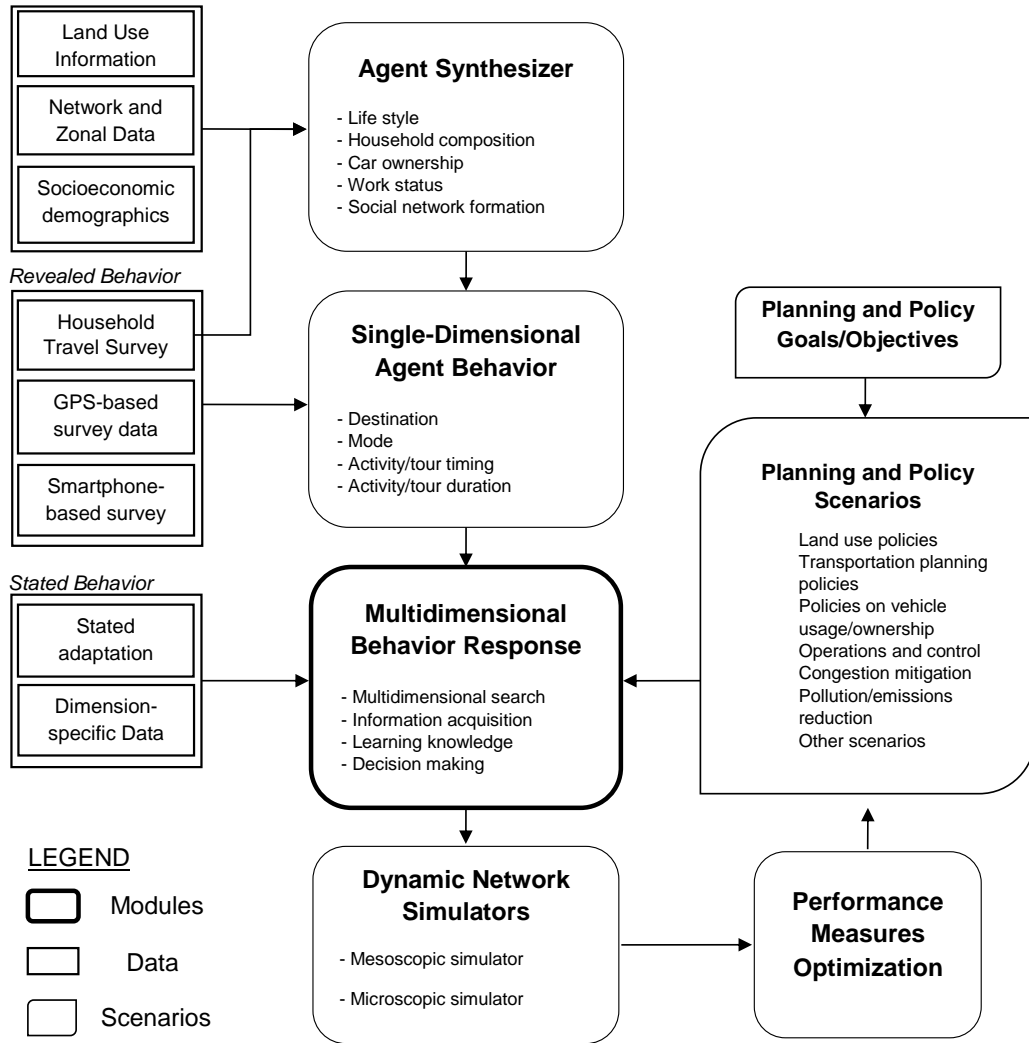


Figure 3.1: Structure of the agent based modeling (AgBM) framework

To support this innovative modeling effort, high-resolution longitudinal data of individual travel/activity patterns are needed. Most existing data such as conventional household travel survey data do not have sufficient detail to support the development of a comprehensive AgBM framework. Therefore, I also design and implement various surveys and data collection to support the modeling efforts. GPS/Smartphone-based individual travel/activity survey and a multidimensional

stated-adaptation survey have been conducted in the Washington D.C. metropolitan area.

Vision of this study has been summarized in Fig. 3.1. Various AgBM modules, and the multi-dimensional AgBM to be developed as part of this study, form the modeling engine and play a central role in the comprehensive framework. The data hub synthesizes data from existing data sources, enhances them through data filtering and integration, and then informs the modeling engine. The modeling engine can also be informed by existing models such as the conventional four-step regional planning model. Actually, if data are not sufficient, a subset of the multi-dimensional AgBM wherein data is particularly lacking can be replaced by conventional models. The AgBM modeling engine needs to be interfaced with supply-side models (most of them are developed with various commercial software packages under current practice) to provide a full picture of the transportation system dynamics. To facilitate the communication with practitioners, policy makers, and the public, a visualization module is needed to present the system performance and its dynamics. Outputs from such a system will support various applications in both traffic operations and transportation planning. They will be discussed in detail in the following sections respectively to demonstrate the potential of the current system to benefit existing practice.

In this framework, the agent synthesizer generates agent characteristics, as well as the agenda of mandatory or fixed activities (e.g. fixed work arrangement) that must be accomplished by each agent. Agents' life style such as household composition, work status, vehicle ownership, social network formation, and other long-term

decisions are also considered in this step. All the available revealed preference information supplemented by GPS-based survey and GPS-enabled smartphone survey will be employed in the baseline agent behavior generator. The generator reads individual trip records from survey data sources. The generator will correct any logical inconsistency against these criteria and supplement missing information. Then a coherent baseline agent behavior will be generated.

The multidimensional behavior response module is the focus of this deliverable. This module predicts agents' behavior response to various planning and policy scenarios. Agents' response such as multidimensional search, information acquisition, learning and knowledge, and decision making are explicitly modeled. When the scenario is introduced, the expected travel condition based on the agents' baseline travel pattern will be affected accordingly. This may motivate agents make behavior adaptation along one or multiple behavior dimensions. Agents' multidimensional behavior response will be modeled by employing stated behavior data collected from dimension-specific surveys and multidimensional stated adaptation surveys. This module yields an altered agent behavior pattern for all individual agents tracked in the model.

The modified agent behavior pattern is then fed into dynamic network models to generate measures of effectiveness (MOEs) of interest. Depending on different planning/policy analysis needs, simulators with different levels of details, as well as the MOEs, can be selected strategically. The linkage with dynamic network models enables the ABM to produce various kinds of performance measures including, but not limited to, level of service (LOS) of each link, queue length of each inter-

section, total vehicle miles traveled, total and average delay, pollution and carbon emissions, etc. In conjunction with baseline travel pattern, the dynamic network models emit measures of change in travel characteristics under each model-specified planning and policy scenario. The scenario can thus be evaluated based on various performance measures. Moreover, an optimal planning and policy strategy can be obtained through a simulation-based optimization module. This module samples through the simulation of agent behavior response and network dynamics, and optimizes planning and policy objective(s) (e.g. minimize total travel time, maximize toll revenue, etc.).

The complex transportation systems include two inter-dependent components: the aggregate travel demand based on individual travel decisions and the network supply. To explore the dynamics of these systems, and to better inform practitioners and policy makers who rely more on aggregate system performance measures, the ABM applications need to be interfaced with supply-side models or be integrated with the existing modeling frameworks. These modeling frameworks include both traffic operations and management models that focus more on intersection and corridor level analysis and planning models that target on issues of larger scale. However, as transportation systems become more complex and inter-related, the boundary between those two types of applications diminishes. Many corridor-level measures such as road pricing, HOV/HOT lanes, and multi-modal corridor management strategies may have significant regional impacts, thus affect planning decisions. Therefore, it is helpful to analyze these two types of applications within an integrated framework.

Chapter 4

Agent-Based Models

This chapter explores a descriptive theory of multidimensional travel behavior, estimation of quantitative models, and its demonstration in an agent-based microsimulation. A descriptive theory on multidimensional travel behavior is conceptualized. It theorizes multidimensional knowledge updating, search start/stopping criteria, and search/decision heuristics. These components are formulated or empirically modeled and integrated in a unified and coherent approach. The theory is supported by empirical observations and the derived quantitative models are tested by agent-based simulation on a demonstration network. Based on artificially intelligent agents, learning and search theory, and bounded rationality, this chapter makes effort to embed a sound theoretical foundation for computational process approach and agent-based microsimulations. A pertinent new theory is proposed with experimental observations and estimations to demonstrate agents with systematic deviations from the rationality paradigm. Procedural and multidimensional decision-making is modeled. The numerical experiment highlights the capabilities of the proposed theory in estimating rich behavioral dynamics.

4.1 Multidimensional Travel Behavior

4.1.1 A Descriptive Theory of Multidimensional Behavior

The multidimensional travel decision-making theory is conceptualized in Fig.

4.1.

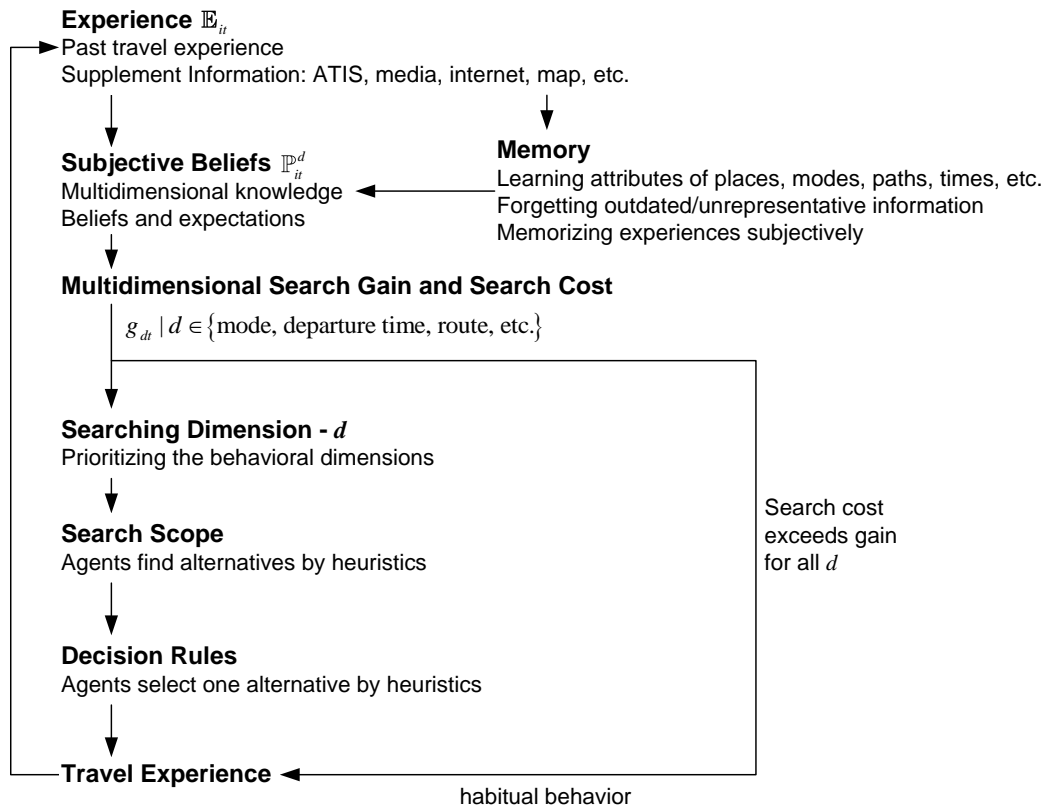


Figure 4.1: Conceptualization of multidimensional travel decision-making theory

The theory starts with the definition of artificially intelligent agents and their characteristics. Each agent i is treated differently with socio-demographic attributes, personal experience, knowledge, and subjective beliefs. At any given time, an agent has a certain level of knowledge about places, activities, and transport networks in

an urban area. This spatial/temporal knowledge can be employed to solve various spatial/temporal decision tasks such as choosing destination, departure time, and routes. This problem-solving process consists of several procedural steps in the true behavioral sense. Firstly, each agent i at a given time period t possesses experiences, denoted as \mathbb{E}_{it} . Agents acquire \mathbb{E}_{it} through past searches or through information sources such as internet, media, advanced traffic information system (ATIS), etc. \mathbb{E}_{it} is time-variant as the agent searches and accumulates a-priori experiences in the urban transportation network day-by-day. Travel experiences with similar payoffs that occur routinely may reinforce the agent's memory, while the travel experiences that are not representative may be easily forgotten. Moreover, agents are assumed to be able to search information about one behavioral adjustment dimension at a time, e.g. agents may search for an alternative route or search for an alternative travel mode. Thus each past experience can be mapped into one single dimension d and form a multidimensional memory space \mathbf{M}^d .

The memory space keeps updating, alters the aspiration level, and changes subjective beliefs \mathbb{P}_{it}^d . An agent thus determines the expected gain g_{dt} from a search for alternatives in each behavioral dimension d based on his/her subjective beliefs. Information acquisition and other mental efforts are explicitly modeled as perceived search cost sc_{di} when agents are searching for alternatives for each behavioral dimension. These search cost variables are recognized in this theory as inconveniences and risks associated with each behavior adjustment dimension. It is the interplay of these subjective search gains and costs that jointly determines when a search for alternatives in dimension d is initiated or stopped in time period t . Although the

subjective search gain is defined by individual's beliefs and therefore can be quantitatively derived, it is much more difficult to theoretically determine the magnitude of perceived search cost which should be individually different. Once the multidimensional behavioral adjustment evidences can be observed, the perceived search cost and its relations with other variables can be empirically derived.

If an agent decides not to search in a dimension, habitual behavior in that dimension is executed. Otherwise, the agent will employ a set of search rules to search from her/his knowledge and identify a new alternative. After identifying an alternative, she/he needs to determine whether or not to switch to that alternative. The decision rules constitute a mapping from spatial/temporal knowledge (especially experienced travel conditions corresponding to different alternatives) to a binary decision: switch to the alternative or retain habit. Both the search rules and the decision rules should be empirically estimated from observed search processes.

4.1.2 Modeling Imperfect Knowledge

Search, learning, and knowledge play a crucial role in making a decision. A rational person will choose the best alternative from the set of feasible alternatives. The term "rationality" would also require that this rational person holds the knowledge that is derived from coherent inferences. In contrast, more realistic models are intended to allow modelers to construct agents who systematically do not possess perfect knowledge and do not make correct inferences but make biased ones.

An agent explores decision opportunities by searching her/his feasible envi-

ronment and learns knowledge about the various payoffs related to the search and decisions. Here the spatial/temporal knowledge is generalized as multidimensional vectors with each vector corresponding to a particular dimension. Assume that each agent i at any given time period t possesses a list of past experiences, \mathbb{E}_{it} . Each experience is characterized by a generalized cost:

$$C_{E_{it}} = \sum_n \lambda_n \psi_n \quad (4.1)$$

Wherein n denotes the index of different related attributes such as travel time, cost, schedule delays, mode comfort, etc. $\boldsymbol{\psi}$ denotes the vector of attributes; $\boldsymbol{\lambda}$ denotes the coefficients to translate values into monetary costs (e.g. value of time). This generalized cost is adopted to measure the outcome of each event and to set an anchoring point for the search model. Assuming that in each behavioral dimension d , an individual's perceptual capabilities allow the separation of generalized cost into a number of categories. If C_E that falls into the generalized-cost category j has been observed m_j times in prior experiences, the memory this individual has about the generalized cost in dimension d is fully described by a vector $M^d = (m_1, \dots, m_j, \dots, m_J)$. Individuals update memory space through learning and forgetting processes. Bayesian learning relies on the premise of some prior knowledge. When new information from various sources becomes available, learning occurs and obeys the Bayes' rule. Forgetting relies on the cognitive weighting of each past experience, which can be measured as a function of the recentness and representativeness of the experience. Once the weight is lower than a certain threshold parameter, the

experience will be eliminated from \mathbb{E}_{it} .

According to Bayesian learning rules, when a new alternative in this dimension is experienced and the associated generalized cost falls into category j , the updated memory becomes $M^d = (m_1, \dots, m_j + 1, \dots, m_J)$. Let the vector $P^d = (p_1, \dots, p_j, \dots, p_J)$ represent an individual's subjective beliefs, where p_j is the subjective probability that an additional search in dimension d would lead to an alternative with j th level of generalized cost. In order to quantitatively link M^d and P^d , we assume that individuals' prior beliefs and memory follow a Dirichlet distribution, which is a J -parameter distribution. Therefore the posterior beliefs will also be Dirichlet distributed since the Dirichlet is the conjugate prior of the multinomial distribution [118]. The probability density function is defined as:

$$P = \frac{\Gamma(N)}{\prod_{j=1}^J \Gamma(m_j)} \cdot \prod_{j=1}^J p_j^{m_j-1} \quad (4.2)$$

where N denotes the total number of \mathbf{M}^d observations and Gamma function $\Gamma(m_j) = (m_j - 1)!$. According to the law of large numbers, as sample size N grows, this assumption asymptotically converges to:

$$\mathbb{E}(p_j) = \frac{m_j}{N} \quad (4.3)$$

Bayesian learning is capable of describing updates of spatial knowledge about the attributes of spatial objects, and relations between spatial objectives when repeated observations are available. Travel time on a roadway section, waiting time

at a transit station, level of congestion for a specific trip during a peak hour, attractiveness of housing unit in a neighborhood, distance between an origin and a destination, closeness of a shopping center to the route from work back home, etc.

4.1.3 Modeling Multidimensional Search

An individual, based on her/his past experience and subjective beliefs, forms expectations on potential gain (search gain) from behavioral adjustments along each dimension. The decision to search for a new alternative is based on the interplay of subjective search gain and perceived search cost. Let an agent's generalized cost on the currently used alternative be C . The subjective search gain (g_{dt}) is based on subjective beliefs, P , and defined as the expected improvement in regard to generalized cost savings per trip from an additional search:

$$g_{dt} = \sum_{j(\forall C_j < C)} p_j \cdot (C - C_j) \quad (4.4)$$

where C is actually the minimum of all experienced generalized costs because individuals can select from all tried alternatives in dimension d and pick the one with the lowest costs C_{\min}^d . We assume all individuals start with a preferred travel pattern. It can be the stabilized travel pattern with an initial generalized cost C_0 . Once a policy/congestion stimulus emerges, travel condition deteriorates. Let us further assume that individuals have the initial beliefs that search and switching to another alternative will lead to a travel condition as good as their original travel condition C_0 until they search and experience otherwise. As the search process proceeds, the

subjective probability of finding an alternative with C_0 after N searches is $1/(N+1)$.

Therefore, Eq. 4.4 can be further simplified as:

$$g_{dt} = \frac{C_{\min}^d - C_0}{N + 1} \quad (4.5)$$

While C_0 remains universal among all dimensions, C_{\min}^d , the currently best travel option(s) in dimension d , can differ in each dimension d since the search processes in different dimensions vary and result in diverse outcomes. The subjective search gain g_{dt} evolves and reflects how much value each search can gain based on subjective beliefs. Once g_{dt} is less than or equal to zero, it indicates that search along dimension d is no longer worthwhile and the search process will not initiate. A positive g_{dt} will asymptotically decrease to zero as the number of searches increases and as a better alternative is found (C_{\min}^d getting increasingly closer to C_0).

Furthermore, the theory formulates satisficing behavior that even with positive gains, individuals may stop search whence the gain is lower than the perceived search cost. The search and information acquisition is no longer free as this theory recognizes the inconveniences and risks associated with each behavior adjustment dimension. This impedance is conceptualized as a search cost for each agent and each dimension. Search cost can be perceived and inferred once individuals' searching sequence can be reconstructed using empirical observations collected from survey. The empirical data provides evidence about agents' search and decision processes. Each individual follows her/his own path along the three dimensions in reaching the final behavior decisions. When it is observed that an individual ends her/his search

in dimension d and has searched N times along that dimension for the time being, it infers that the individual satisfies after N rounds of search in d . The search cost must be lower than $g_{d,t-1}$ so that the N th search is meaningful and rewarding. Meanwhile, the search cost must be higher than so that the $(N + 1)$ th search does not occur. Let us denote individual i 's search cost along dimension d as sc_{di} , which is viewed as an innate personal characteristic for individual i . It can be estimated by using the lower and upper bounds:

$$sc_{dt} \leq g_{d,t-1} = \frac{C_{\min,t-1}^d - C_0}{N} \quad (4.6)$$

$$sc_{dt} \geq g_{dt} = \frac{C_{\min,t}^d - C_0}{N + 1} \quad (4.7)$$

$$\bar{sc}_{dt} = \frac{1}{2}(g_{d,t-1} + g_{dt}) \quad (4.8)$$

Note that for each individual, only one of the multidimensional perceived search costs can be perceived from the empirical data. A subsequent regression analysis for all survey subjects and all dimensions thus needs to be estimated in order to empirically model search cost. We specify that the search cost model in dimension d as:

$$sc_{dt} = \beta_0 + \beta_1 C_0 + \beta_2 gender + \beta_3 fixedsch + \beta_4 purpose + \beta_5 income1 + \beta_6 income2 + \beta_7 income3 + \beta_8 distance + \beta_9 peak + \beta_{10} veh + \epsilon_i \quad (4.9)$$

where C_0 is the generalized cost for the originally reported travel experience; distance measures the mileage that the subject travels; Dummy variables include

gender (equals to 1 if the subject is female), fixedsch (equals to 1 if the subject has fixed travel schedule), purpose (equals to 1 if the trip purpose is work/school), peak (equals to 1 if the travel is in peak-hour periods), and veh (equals to 1 if household number of vehicles is greater than 2). Different household annual income levels are considered in the model (income1: less than \$50,000; income2: \$50,000 - 100,000; income3: \$100,000 - \$150,000; income4: \$150,000 and above). In our model, C_0 is identified as an instrumental variable (IV) in order to better incorporate the sufficiently high correlation between C_0 and other independent variables. We employ generalized method of moments (GMM) and two-stage least-squares (2SLS) estimator. Denoting the IV as \mathbf{z} and the independent variables as \mathbf{x} , we can estimate parameters β from the population moment conditions:

$$\mathbb{E}[\mathbf{z}(\mathbf{sc}_{di} - \mathbf{x}\beta)] = \mathbf{0} \quad (4.10)$$

The estimation result is reported in Table 4.1. The search cost is positively related to the initially experienced generalized cost of the travel. Lower-income agents have higher search costs along mode dimension. Female agents are more reluctant to search departure times and routes than to search alternative modes. Fixed schedule and traveling during peak-hour increase the search cost for all dimensions. Travel distance has a negative impact on search cost meaning that the longer the travel distance, the more likely she/he will search for alternatives. The coefficients for trip purpose indicate that agents doing commute travels have more incentive to search for alternative modes and departure times. By estimating and applying

search cost models, one can make personal/household characteristics endogenous in the search process and model diversified and behaviorally rich multidimensional search. It helps explain why some travelers may adjust routes first while others may adjust departure time first in response to the same stimulus. This feature can potentially provide rich level of detail especially for policy/social equity analysis whence measuring the impacts/benefits by different socio-economic strata of society is of interest.

Table 4.1: Multidimensional Perceived Search Cost Models (Generalized Method of Moments and Instrumental Variable)

Models:	Search cost (<i>d</i> : mode)	Search cost (<i>d</i> : departure time)	Search cost (<i>d</i> : route)
Variables	Coeff. (std. err.)	Coeff. (std. err.)	Coeff. (std. err.)
Generalized cost C_0	0.023 (0.010)	0.008 (0.001)	0.001 (0.000)
gender (female)	0.014 (0.088)	0.162 (0.071)	0.098 (0.046)
fixed schedule	0.118 (0.065)	0.194 (0.080)	0.115 (0.045)
purpose (work/school)	-0.101 (0.062)	-0.091 (0.056)	0.098 (0.048)
Income (< \$50k)	0.188 (0.106)	-0.272 (0.201)	-0.299 (0.060)
Income (\$50k – \$100k)	0.085 (0.41)	-0.285 (0.203)	-0.207 (0.066)
Income (\$100k – \$150k)	-0.007 (0.007)	-0.542 (0.234)	-0.089 (0.086)
Travel distance (10 mi)	-0.020 (0.003)	-0.008 (0.001)	-0.006 (0.000)
Peak-hour travel	0.161 (0.094)	0.112 (0.062)	0.010 (0.041)
Number of Cars (i 2)	-0.088 (0.021)	0.298 (0.092)	-0.035 (0.053)
Constant	1.341 (0.148)	0.402 (0.225)	0.384 (0.068)

It is hypothesized that agents will search the most rewarding dimension with the highest search gain/cost ratio. Successive unrewarding searches along a particular behavioral adjustment dimension (e.g. route) will lead to diminishing subjective search gain for that dimension and at a later point cause the search to shift to a different behavior dimension (e.g. departure time). Once the ratios for all dimensions drop down below one, the multidimensional search process ceases. Since g_{dt} is

monotonically decreasing and converges to zero, the search is guaranteed to reach stability. The interplay of these search gains and costs along all feasible behavioral dimensions defines the bounded rationality embedded in the theory. It collectively determines the prospects for profitable searches over finite horizon and guarantees a convergence of behavioral changes. It quantitatively theorizes when individuals start seeking behavioral changes, how they initially change behavior, how they switch behavioral adjustment dimensions, and when they stop the search.

4.1.4 Search Rules and Decision Rules

An agent will keep the status quo and repeat her/his habitual behavior once she/he decides not to search in any dimension. Once determining a dimension to search, a search process is invoked to find useful alternatives to meet travel demand. Spatial/temporal search is not random and can be biased [70]. For instance, if a person currently departs at 8 am and is not satisfied with the resulting travel and/or schedule delay, the person may be more likely to try departing at 7:30 am and 8:30 am than 7 am and 9 am (i.e. an anchoring effect). Different knowledge extracting technologies can be applied to mine individuals' search rules and decision rules. I adopt production rules for more shorter-term search: departure time search and route search. For more longer-term search such as travel mode search, the search process is dynamic and is correlated to the status of the previous time period. In the following section, the mode search is conceptualized as a hidden Markov process wherein the current behavioral state is dependent to the a-priori behavioral

state. This process can be generalized to cover other behavioral dimensions such as destination choice.

After each round of search, a new alternative is identified. Agents either change behavior to use the new alternative or stay with their habitual behavior. This is determined by a set of decision rules. Even though during the multidimensional search process many alternatives may be visited, the final decision is assumed to be the outcome of a series of switching decisions. Production rules derived by various machine learning algorithms [111, 30, 35] are selected here to represent decision rules. Departing from random utility maximization, this assumption about the search-decision procedure relaxes the unrealistic assumption of human information processing and computational capabilities and incorporates individual-based historical dependencies. It also improves the computational efficiency of agent-based simulation since the execution of production rules only requires minimum computational resources. These search and decision rules are empirically derived for each behavioral dimension and are discussed in greater details in the following sections of this chapter.

4.1.5 Empirical Data Collection

The development of those quantitative models can be data intensive. This research conducts a stated adaptation experiment administered online to explore possible substitutions to the longitudinal information that is typically missing. This survey method is particularly useful when one seeks answers from respondents on

a number of what-if questions such as “what would you react if you were faced with specific constraints/conditions” [6]. It helps capture respondents’ multi-faceted behavioral responses. Furthermore, it has the capability to infer the procedural decision-making process which embeds the behavioral foundation of the proposed theory and models since respondents will naturally exhibit satisficing behavior if playing the scenarios repeatedly for a sufficient number of iterations. The survey procedure is reported in Fig 4.2.

Starting from a self-reported most recent trip, exogenous policy/congestion changes are assumed in each scenario to alter the travel condition for that trip. It is further assumed that each agent will adapt to those changes by searching new modes, departure time, and/or routes. The dimensions wherein the behavior adjustment occurs are asked explicitly in the survey for each subject. The subject then is asked to elaborate the alternative she/he would identify and search along that dimension (this data infers the determination of search rules). Once a search has been recorded by a subject, the program will feed a corresponding travel condition simulated in the back-end for the subject to consider and make a switching decision between the alternative and the habitual one (this data infers the decision rules). Another round of behavior adjustment (could be in the same dimension or in another dimension) will occur unless the subject states satisfactory about the travel experience. Iteratively repeating this process, a complete behavioral adjustment sequence of each subject can be observed. Initial samples include 110 University of Maryland staffs and students. They perform adaptations under schemes such as overall congestion increase and road-pricing scenarios.

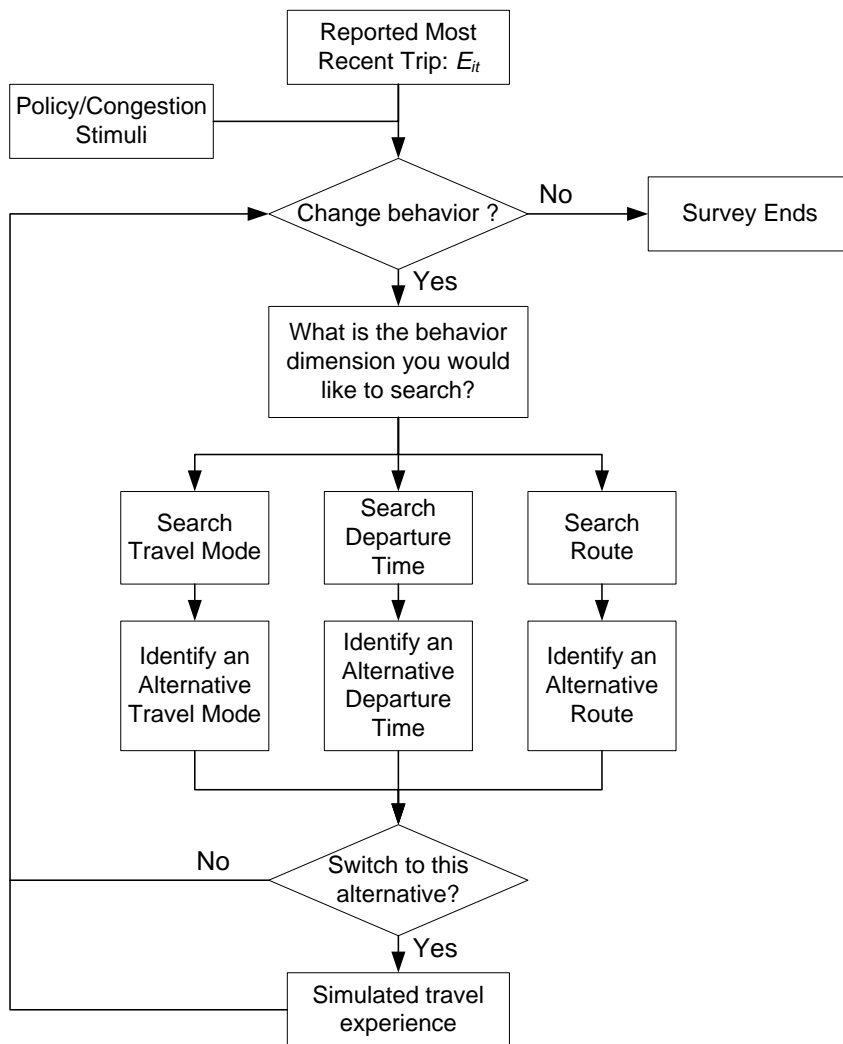


Figure 4.2: The Stated Preference Experiment Flowchart

4.1.6 Agent-Based Simulation Results

The proposed multidimensional behavioral theory and models have been estimated and implemented in an agent-based simulation to demonstrate the capability. A toy network with one origin-destination pair, three alternative routes, and three travel modes (auto, carpool, and transit) is employed. The scenario that is analyzed in this simulation is an assumed 10 percent increase in travel demand which

creates excessive travel time and cost for the simulated agents and stimulates them to start the multidimensional behavior adjustments. 90,000 agents are generated in this microsimulation of extended morning peak hours (5:00 am–10:00 am). Agents’ characteristics are synthesized based on Transportation Planning Board (TPB) Baltimore Metropolitan Council (BMC) Household Travel Survey (2007/2008) data.

In the simulation, agents travel from origin to destination, accumulate experience, make behavioral adjustment on one or multiple dimensions, dynamically update beliefs, and eventually satisfy on their decisions. The uniqueness of the model brings attention to each agent for whom the interplay of search gain and search cost is dynamically modeled in order to determine the behavioral dimension wherein the search and decision process occurs. Fig. 4.3 illustrates the evolving gain/cost ratio for a particular agent.

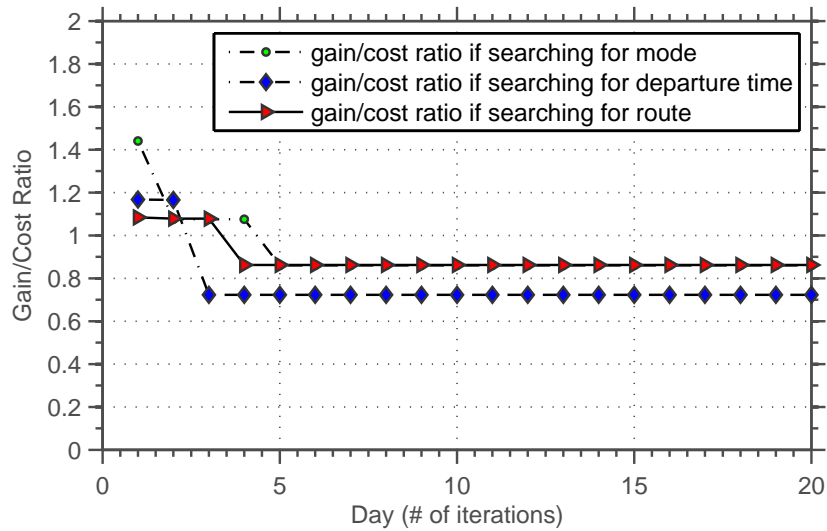


Figure 4.3: The evolving gain/cost ratios of multidimensional travel behavior

On simulation day 1, the agent initially believes that all dimensions are rewarding (with gain/cost ratios all above one) while the most profitable dimension

is the mode dimension. She/he then employs search rules and decision rules to identify and examine one alternative mode. While the subsequent search reveals further information, this agent's knowledge and subjective beliefs on the mode dimension evolve significantly. And on the second day, the departure time dimension emerges to be the one with the highest gain/cost ratio. A search for alternative departure time is therefore performed. Iterating this process, the agent forms a time-dependent search path about choosing behavioral adjustment dimensions: mode-departure time-route-mode. On the fifth day, the gain/cost ratios of all dimensions drop down below 1, which indicates that this agent subjectively believes that no more searches are necessary. The agent is thus satisfied and stays dormant afterwards. Once a new turbulence emerges in the transport system, such as new policies and booming travel demand, the agent may be influenced in the way that the gain/cost ratios in certain dimensions grow. And the agent may seek further changes.

The convergence of the multidimensional behavior is illustrated in Fig. 4.4a. Overall, the model predicts active and reasonable agent behavior along the three behavioral dimensions. The convergence processes are smooth. With the innate bounded rationality and satisficing behavior, agents reach steady state and stop search within 25 search iterations. If each agent travels five days a week and all agents start search at the same time, it would take five weeks for the traffic to stabilize and equilibrate on the network. This is an interesting finding that on one hand, it allows us to model the gradual behavior adaptation to exogenous policies (e.g. pricing policy in Stockholm gradually nudge drivers to change behavior, [23]).

On the other hand, it suggests potential applicability of the proposed theory in large-scale planning models and simulation since it embeds multidimensional behavioral response while maintaining a reasonable converging speed.

In response to the assumed demand increase, changing route and changing departure time are the most significant ways of behavioral adaptation. The initially high route searching frequency cools down rapidly since agents can hardly identify any better alternative routes under the assumed overall demand increase. Agents quickly learn the fact and update the subjective beliefs, which results in a decreasing search gain in the route dimension. Then agents turn to search alternative modes and departure times instead. Thus we can observe in the simulation an increasing number of agents searching for alternative departure times in the second and third simulation days. A few agents search for alternative modes. Agents' mode searching and switching behavior is illustrated in Fig. 4.4b. Agents' departure time changes are illustrated in Fig. 4.4c.

By aggregating the individual behavior into travel patterns, we can observe that the multidimensional learning and adaptation leads to a slight percentage decrease of auto drivers (Auto D in Fig. 4.4b). Those agents switch to auto passengers (Auto P) or transit users. The aggregate mode share of auto drivers drops from 63.4% to 58.3%. After 6 simulation days, the mode share tends to be stabilized even though from the microscopic level, there still exist some 3,000 travelers changing their travel modes. The active departure time changes lead to a significant peak spreading effect. The assumed demand increase results in more severe congestion and travel time unreliability especially during peak hours. The excessive travel time,

cost, and schedule delays make the departure time adjustments necessary in order for the agents to gain an acceptable payoff through search. The model predicts that the dominating behavioral responses to the stimulus are route changes and departure time changes, which is in line with existing research (e.g. [6]). Meanwhile, the model predicts the behavioral dynamics and adaptive process, which advances our current understanding about multidimensional travel behavior adjustments.

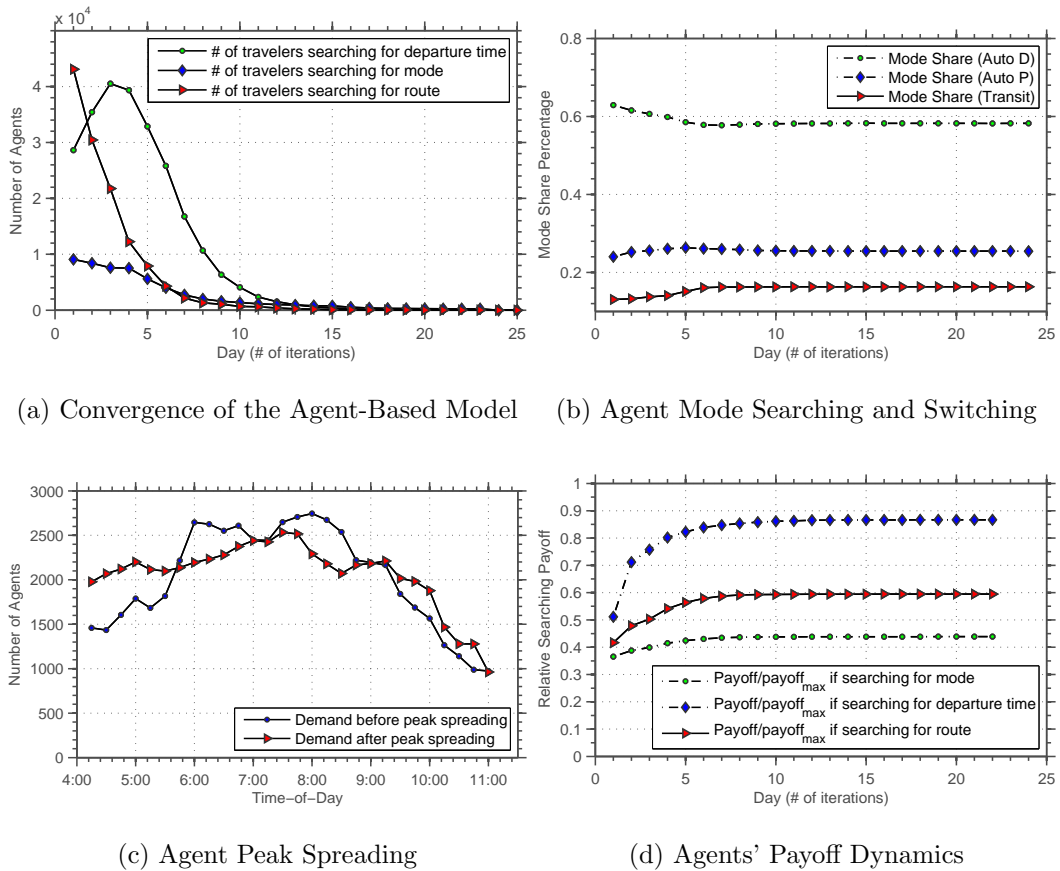


Figure 4.4: A Demonstration of the Agent-Based Model of Multidimensional Behavior

Travelers in the multidimensional agent-based model are not perfectly “rational” in that they do not maximize their utility (or payoff). Instead, they are restrained by information acquisition cost, decision cost, computational limitation,

time budget, and deadlines. They are not perfectly rational also in the way that they follow different intuitive and heuristic behavioral rules. Fig. 4.4d demonstrates that through multidimensional learning and adaptation, agents search and improve their relative searching payoff. This term is defined as the ratio of the cumulative actual search gain and the cumulative subjective search gain (i.e. subjectively believed maximum payoff from the search) for all the searchers. Judging by the curves, the departure time dimension turns out to be the most profitable dimension. Once searching in this dimension, agents are able to retrieve the highest relative searching payoff. However, this learning and adaptation does not ensure them to make decisions that result in maximum payoff. This example demonstrates the bounded rationality of the agents in search and changing their behavior.

4.2 Dynamic Travel Mode Search and Switching

In this subsection, individual dynamic mode choice behavior is conceptualized as a cyclic process of repetitively making mode search and switching decisions, as displayed in Fig. 4.5.

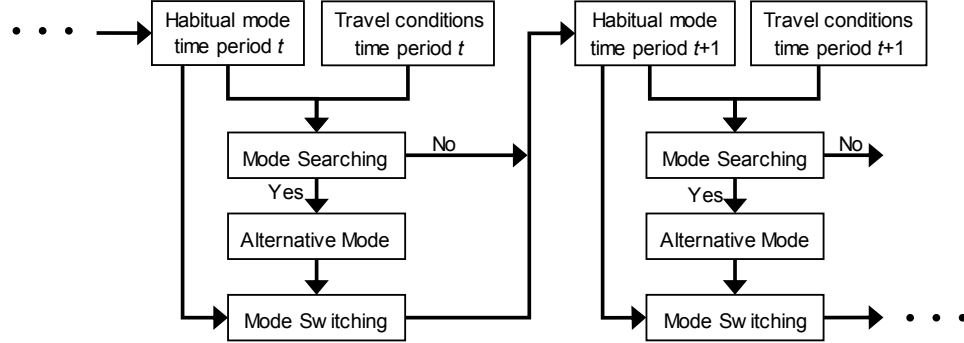


Figure 4.5: Travel mode search and switching as a dynamic procedural model

The framework represents a sequential decision of mode searching and switching. To decide the travel mode for a specific trip type, the starting point of the procedure for a given time period t is the existing habitual behavior and its associated travel conditions such as travel time and travel costs. Travelers may be satisfied with their habitual mode as long as the travel conditions remain at a certain level. Once the level-of-service changes, travelers may have the incentive to search for an alternative mode depending how significant the LOS change is. This stimulus can be attributed to policy changes and/or congestion level changes. For instance, consider the situation when road pricing policy has been implemented on a commuting corridor. The increased toll charges may effectively trigger a number of auto drivers to consider alternative modes to reduce the cost. In this case, auto drivers who initially have an innate preference towards their habitual modes now may identify transit or carpool as their alternative. After an alternative mode has been determined, travelers make a switching decision between the habitual mode and the newly identified alternative. This decision may be based on comparison

after some trial-and-error experience or externally collected information about the alternative. The selected mode will be the habitual mode for the next time period when a similar sequence of processes takes place.

Within this theoretical framework, the dissertation focuses on the empirical evidence about the first behavior stage: mode searching dynamics. This dynamic context is formulated based on hidden Markov model. Travelers' innate mode preferences have been conceptualized as different hidden states. The transitions between states are formulated as a function of the LOS variables of travelers' current habitual modes. This model can be easily linked with a mode switching model (discrete choice or rule-based). However, this is subject to be finished in the full dissertation.

4.2.1 Search Rules

Hidden Markov Model is a doubly embedded stochastic process with an underlying stochastic process that is not observable, but can only be inferred through another set of stochastic processes that produce the sequence of observations. It has been applied successfully to, e.g., speech recognition, biological sequences analysis, and many others [124, 97]. The objective of this paper is to develop an individual-level dynamic model that explicitly parameterizes the processes that travelers search and identify their alternative modes. In many situations, observed decisions on alternatives are preceded by unobserved states representing innate preferences, satisfactory levels, etc. For instance, when choosing an alternative mode, the states may represent individuals' hidden preference on one or several modes. Fig. 4.6 illustrates

a graphical representation of the model.

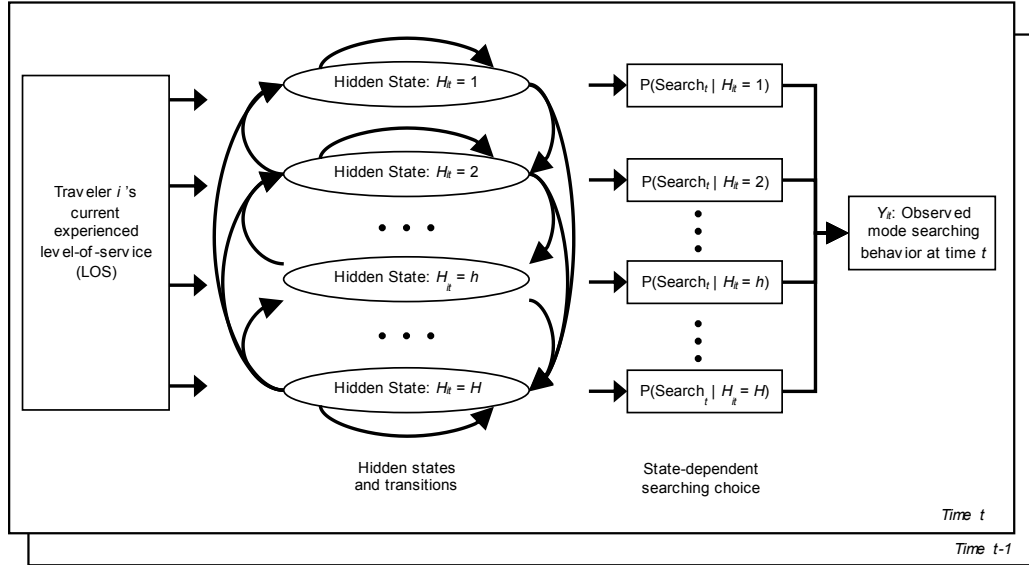


Figure 4.6: A Hidden Markov model of travel mode search dynamics [145]

As displayed in Fig. 4.6, two major components are highlighted in this model:

- Hidden states and transitions. Starting from an initial state distribution $\pi_{is} = Pr(H_{i,t=1} = s)$ (i.e. at time 1, the probability that traveler i is in state s), a sequence of Markovian transitions $Q_{i,t-1 \rightarrow t}$ is employed to express the likelihood that the LOS experiences of the habitual mode in the previous period were strong enough to transition the traveler to another hidden state.
- State-dependent mode searching decision. Given the hidden state that a traveler i is in, the probability that she/he will identify mode m as the alternative in the mode searching stage at time t is determined by $Pr(Y_{it} = m | H_{it})$. Y_{it} is the mode searching decision made by traveler i at time t .

4.2.1.1 Model observed search sequences

We assume that given individual i 's true state H_{it} in period t , the observed process of searching and identifying mode alternatives: Y_{it} are conditionally independent of the hidden state of other time period. Thus, we assume that the likelihood function of state-dependent searching of the alternative modes follows multinomial logit form:

$$Pr(Y_{it} = m | H_{it} = h) = \frac{\exp(\mathbf{Z}_{it}' \beta_{\mathbf{h},m})}{\sum_j \exp(\mathbf{Z}_{it}' \beta_{\mathbf{h},j})}; h = 1, \dots, H \quad (4.11)$$

where \mathbf{Z}_{it} is the vector of covariates measured at period t for individual i , $\beta_{h,m}$ is the corresponding regression coefficients for selecting mode m in hidden state h .

The transitions between hidden states have been modeled as a Markov process.

The transition matrix is defined as:

$$\mathbf{P}_{i,t-1 \rightarrow t} = \begin{bmatrix} p_{it}^{(1,1)} & p_{it}^{(1,2)} & \cdots & p_{it}^{(1,H)} \\ p_{it}^{(2,1)} & p_{it}^{(2,2)} & \cdots & p_{it}^{(2,H)} \\ \vdots & \vdots & \ddots & \vdots \\ p_{it}^{(H,1)} & p_{it}^{(H,2)} & \cdots & p_{it}^{(H,H)} \end{bmatrix}$$

In this formulation, $\mathbf{P}_{i,t-1 \rightarrow t}$ is the Markov chain transition matrix expressing, in probabilistic manner, the likelihood that the traveler switches hidden state which is assumed to represent hidden modal preferences. $p_{it}^{(h_1, h_2)}$ denotes the transition probability from hidden state h_1 to hidden state h_2 for individual i in period t . Unlike most homogeneous Hidden Markov model, in this model, we allow the transition

probabilities to be dependent on time-varying variables (e.g. higher auto travel cost for a habitual car lover could switch her/him to prefer transit instead). Therefore the transition probability expresses how strong the effects of habitual modal LOS in the previous period are to transition the traveler to another preference state. This assumption is found behaviorally and empirically grounded in our empirical application. Thus, we introduce the following parameterizations into the transition specification:

$$p_{it}^{(h_1, h_2)} = \frac{\exp(\mathbf{Z}_{it}' \lambda^{(h_1, h_2)})}{1 + \exp(\mathbf{Z}_{it}' \lambda^{(h_1, h_2)})} \quad (4.12)$$

$\lambda^{(h_1, h_2)}$ is the corresponding regression coefficients for the transition probability $p_{it}^{(h_1, h_2)}$. This formulation defines a heterogeneous Markov Chain since it allows the transition probabilities of the hidden states to depend on the set of observed covariates (including travel time, cost, and socio-demographical variables).

Another main component of the model is the individuals' initial hidden state. The initial state distribution is commonly defined as the stationary distribution of the transition matrix for a hidden Markov model with time homogeneous transition matrix [88]. Smith and Vounatsou [126] have specified non-informative uniform priors for initial state distribution. In this paper, because the transition matrix has been specified as a function of time-varying covariates, we calculate the stationary distribution of the transition matrix by solving the equation:

$$\boldsymbol{\pi}_{i1} = \boldsymbol{\pi}_{i1} \bar{\mathbf{P}}_i \quad (4.13)$$

Where $\bar{\mathbf{P}}_i$ is the transition matrix with the estimated coefficients $\lambda^{(\mathbf{h}_1, \mathbf{h}_2)}$. The stationary distribution $\boldsymbol{\pi}_{i1}$ satisfies $\sum_h Pr(H_{i1} = h) = 1$. Variables are set to their mean value across individuals and time periods. The transition matrix is aperiodic and irreducible due to the strictly positive transition probabilities as defined in Equation 4.12. Thus the initial state distribution is guaranteed to exist and be unique [97].

An individual's decision probabilities are correlated through the common underlying path of the hidden states, because of the Markovian properties of the model. Therefore, the joint likelihood function is given as:

$$\begin{aligned}
L(\beta, \boldsymbol{\lambda}, H_{it}) &= Pr(Y_{i1} = y_{i1}, \dots, Y_{iN} = y_{iN}) \\
&= \sum_{H_{i1}} \sum_{H_{i2}} \dots \sum_{H_{iN}} [Pr(H_{i1}) \prod_{t=2}^N Pr(H_{it}|H_{it-1})] \\
&\quad \cdot \prod_{t=1}^N Pr(Y_{it} = y_{it}|H_{it})
\end{aligned} \tag{4.14}$$

Where N denotes the total number of periods in the observations. H_{i1} denotes the initial hidden state of the individual i . Its distribution is solved using Equation 4.13. The last term on the right hand side of Equation 4.14 represents the state dependent mode searching probabilities. Therefore, the likelihood can be interpreted as that the joint likelihood of a sequence of observations of searching alternative modes is given by the sum over all possible routes that this person could take over periods from an initial state to an end period when she/he is satisfied and stops searching.

4.2.1.2 Estimation Procedure

Parameters of the transition matrix and state-dependent searching are estimated using the joint likelihood function in Equation 4.14. Estimation and maximization of the likelihood is not easy especially when the transition matrix is covariate-dependent. Here we employ Bayesian estimation and Markov Chain Monte Carlo (MCMC) simulation to sample the parameter distributions. This method follows Bayesian statistical inference. This paper assumes prior distributions for the regression coefficients β and $\lambda^{(\mathbf{h}_1, \mathbf{h}_2)}$. The Bayesian inference is based on the posterior distribution:

$$Pr(\beta, \lambda, \mathbf{H}_{it} | \mathbf{Y}) = \mathbf{L}(\beta, \lambda, \mathbf{H}_{it}) \mathbf{Pr}(\beta, \lambda, \mathbf{H}_{it}) \quad (4.15)$$

This formulation's left-hand side represents the posterior distribution of the coefficients. The right-hand side is a multiplication of the joint likelihood function and the prior distribution. To estimate the coefficients, this posterior distribution needs to be sequentially drawn. However, the equation does not have a closed form. In Bayesian theory, if it is possible to express each of the coefficients to be estimated as conditioned on the others, then we can eventually reach the true joint distribution by cycling through these conditional statements [56]. Thus we use MCMC simulation to sample the posterior. For this paper, standard MCMC technique (i.e. Gibbs sampler) is coded using R and WinBUGS package. Starting from initial values $[\beta^{[0]}, \lambda^{[0]}]$ (the superscript denotes the step), at the j th step, the

estimation method draws values from the following conditional distributions:

$$\boldsymbol{\beta}^{[j]} \sim \pi(\boldsymbol{\beta} | \boldsymbol{\beta}^{[j-1]}, \boldsymbol{\lambda}^{[j-1]}) \quad (4.16)$$

$$\boldsymbol{\lambda}^{[j]} \sim \pi(\boldsymbol{\lambda} | \boldsymbol{\beta}^{[j]}, \boldsymbol{\lambda}^{[j-1]}) \quad (4.17)$$

$\pi(\boldsymbol{\beta}, \boldsymbol{\lambda})$ denotes the limiting distribution of interest where $\boldsymbol{\beta}$ and $\boldsymbol{\lambda}$ are the vectors of coefficients whose posterior distribution we want to describe. j is incremented and repeated until convergence. By doing this, a Markov chain that cycles through these conditional statements Equations 4.16 and 4.17 moving forward and then around the true limiting distribution has been constructed. Once convergence is reached, a sufficient number of samples should be drawn to represent all areas of the target posterior. Gibbs sampling requires a full set of conditional distributions which is often not the case in hierarchical conditional relationships. The Metropolis-Hastings algorithm can be explored in future research when the model is enhanced with Bayesian hierarchical structure.

4.2.2 Empirical Application

4.2.2.1 Data description

The data used to estimate the model are collected by the authors via a memory recall survey. As a pilot study, a total number of 146 students from the University of Maryland were recruited for participation in the data collection.

During the survey, each respondent was asked to fill a questionnaire regard-

ing socio-economic and demographic characteristics, typical travel patterns, and, in particular, the travel modes that have been considered and used for her/his commuting travel. In the survey, a series of memory-recall questions were employed to gather the information of the travel modes that the respondents have tried in their commuting trips. Each respondent was asked to recall the order of alternative travel modes they had considered and actually tried, as well as the travel times and travel costs corresponding to those travel modes. In particular, for each respondent, the first travel mode was collected from a question: “please recall the situation when you just arrived at University of Maryland and planned for your school trip, what was the first travel mode that you used?” After the answer, the associated level of service information was also gathered. Assuming that the respondent kept experiencing this first reported travel mode, she/he was then asked whether she/he had considered any alternative mode after using the original travel mode. If the answer is yes, she/he was then asked to recall the alternative mode that she/he had searched along with the level of service information. This recall process ceased when the respondent stated that he/she did not consider changing travel mode any further. In this sense, the memory-recall survey has collected process data regarding the mode searching behavior, as well as time series information on travel time and cost about all the searched travel modes. One may argue that the recall process is subjective and may be biased. The paper summarizes the survey descriptive statistics for the mode-specific level-of-service variables in Table 4.2. They are compared with the school trip data collected from Washington D.C. Transportation Planning Board (TPB)/Baltimore Metropolitan Council (BMC) household travel survey. The

descriptive statistics of the memory-recall survey data reasonably conform to the representative sample.

Table 4.2: Travel Mode Memory-Recall Survey Descriptive Statistics for Level-of-Service Variables and Comparison with BMC/TPB HTS Survey

Modes	Variables	Memory-Recall Survey	BMC/TPB HTS Survey
		Mean (Std. Dev.)	Mean (Std. Dev.)
Auto	Travel cost (\$)	4.30 (8.92)	N/A
	Travel time (min.)	32.72 (19.26)	28.17 (18.28)
Carpool	Travel cost (\$)	1.13 (1.92)	N/A
	Travel time (min.)	29.83 (27.16)	24.92 (17.92)
Transit	Travel cost (\$)	2.12 (1.90)	N/A
	Travel time (min.)	44.38 (21.62)	51.81 (22.81)
Walk/Bike	Travel time (min.)	27.67 (18.10)	22.22 (10.83)

The distribution of the number of alternative modes searched by respondents is illustrated in Fig. 4.7a. About one third of the respondents only had one travel mode for their commuting trips. Around a half of the respondents had searched two different modes. About 16% of the respondents had considered more than two travel modes. As reported in Fig. 4.7b, the aggregate mode share is 35% auto, 9% carpool, 33% transit, and 22% walk/bike.

4.2.2.2 Estimating the number of hidden states

The models are estimated using a Bayesian estimation procedure wherein MCMC Gibbs sampling method has been employed and coded in R. The first 70,000 iterations have been used as a “burn-in” period. The last 10,000 iterations have been used to estimate the conditional posterior distributions. Gelman and Rubin method [51] has been adopted for convergence assessment. For each parameter, three parallel

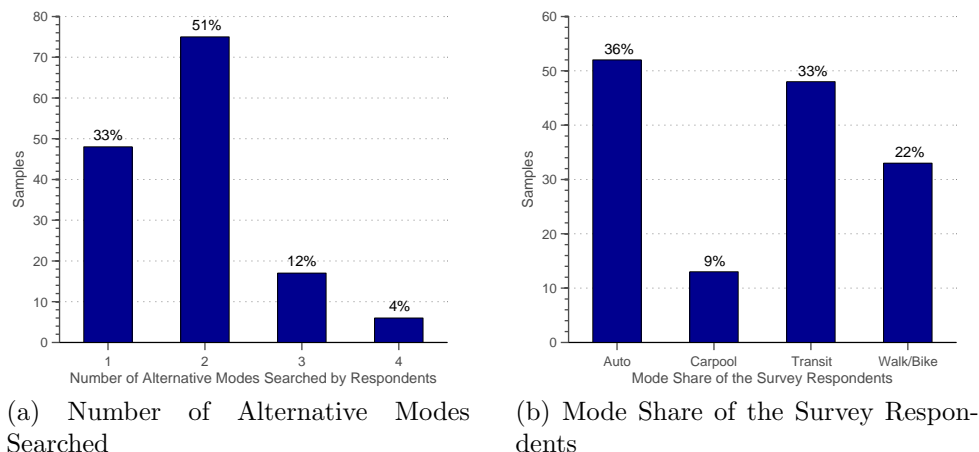


Figure 4.7: Descriptive statistics for mode searching and aggregate mode share

chains are updated in the estimation process. Within variance and between variance across these three chains are compared. The result indicates that convergence has been reached.

Determining the number of hidden states is the first task in estimating the HMM model. Various model selection criteria for Bayesian model goodness of fit have been compared, including log-likelihood, the Bayesian information criterion (BIC), the deviance information criterion (DIC), and the cross-validation hit ratio. BIC and DIC both measure the goodness of fit and penalize for the number of parameters and sample size, respectively. As shown in Table 4.3, the best fitting model is the model with two hidden states based on all performance measures. The two-state estimation maximizes the log-likelihood statistic, minimizes BIC and DIC, and shows a most accurate cross-validation result. The superiority of the 2-state model over the single-state one indicates that the underlying behavioral changes over time are significant.

Table 4.3: Performance Measures for Choosing the Number of Hidden States

# of States	Log-likelihood	BIC	DIC	Cross-Validation Hit Ratio
1	-316.1	804.0	630.3	75.6%
2	-198.0	752.7	400.5	81.3%
3	-207.8	1,019.1	411.9	79.5%

4.2.2.3 Estimating the initial states and transition

Table 4.4 reports the estimated posterior means and posterior standard deviations of the transition matrix coefficients. Dynamic covariate effects are estimated. The interpretation of the states can be derived from the intrinsic propensity to search either auto or carpool/transit (the intercepts of the state-dependent searching). State-1 travelers are thus label as car lovers and state-2 travelers are labeled carpool/transit lovers in the following text. Overall, the model suggests that level-of-service variables (travel time and travel cost) have significant effects on transition. Longer travel time for the habitual mode at time period $t1$ has a diminishing effect on the likelihood of transition at time t . A high travel cost, on the opposite, is a central incentive for individuals to switch hidden states. These two findings provide essential insights on travelers' mode searching attitude. An a-priori long travel time for the habitual mode may indicate that traveling with alternative modes must be equally time consuming. Therefore, changing the attitudes towards difference alternative modes is less likely. However, an excessive travel cost works the other way around.

The socio-demographic variables further indicate that female travelers, travelers with driver's license, and lower-income individuals are more likely to change

hidden modal preference. These variables are interacted with LOS variables [98] to reflect different effects of LOS on different population segments.

Table 4.4: Estimation Results for the Hidden Markov Transition Matrix

Variables	Interaction with	Estimates	Std. Err.
Transition from car-loving to transit-loving			
Travel time (min.)	-	-0.72	0.02
License	Travel time	0.98	0.13
Gender	Travel time	-0.28	0.03
Travel cost (\$)	-	1.51	0.38
High income	Travel cost	-2.75	0.54
Transition from transit-loving to car-loving			
Travel time (min.)	-	-0.49	0.11
License	Travel time	0.39	0.11
Gender	Travel time	-0.09	0.04
Travel cost (\$)	-	4.20	0.58
High income	Travel cost	-0.23	0.75

4.2.2.4 State-dependent search

Table 4.5 reports the posterior means and posterior standard deviations of the HMM. Insignificant socio-demographic variables are excluded. The intercepts indicate an intrinsic propensity to search different modes. The parameters that capture the effect of level of service experiences indicate that, in general, longer travel time for the habitual mode encourages travelers to search faster travel modes and excessive travel cost encourages travelers to search lower-cost travel modes.

Significant effects of socio-demographic variables are found in car-loving state. The model also indicates fairly strong mode search inertia effects. Individual are highly likely to stay with a mode they have previous used especially for carpoolers

Table 4.5: Estimation Results for the Hidden Markov Model

Variables	State 1 Estimates	State 1 Std. Err.	State 2 Estimates	State 2 Std. Err.
Intercept (Search auto)	0.393	0.153	-2.794	1.968
Intercept (Search carpool)	-1.868	1.741	2.950	1.738
Intercept (Search transit)	-3.735	1.777	2.576	2.160
Travel time (search auto)	0.028	0.011	1.375	0.079
Travel time (search carpool)	0.113	0.020	1.253	0.080
Travel time (search transit)	0.055	0.011	1.228	0.081
Cost (search auto)	-0.043	0.142	-0.957	0.373
Cost (search carpool)	-5.742	1.082	-0.712	0.375
Cost (search transit)	0.086	0.155	-0.788	0.407
License (search auto)	1.318	0.120	-	-
License (search carpool)	1.473	0.124	-	-
License (search transit)	1.057	0.479	-	-
Gender (search auto)	1.222	0.380	-	-
Gender (search carpool)	1.865	0.747	-	-
Gender (search transit)	1.101	0.388	-	-
High income (search auto)	1.394	0.437	-	-
High income (search transit)	0.947	0.424	-	-
CM ¹ is auto (search auto)	1.508	1.708	5.648	1.922
CM is auto (search carpool)	-3.551	2.206	-1.410	1.909
CM is auto (search transit)	-0.447	1.894	-4.115	2.102
CM is carpool (search auto)	0.863	1.885	0.478	2.125
CM is carpool (search carpool)	8.363	1.920	1.743	1.975
CM is carpool (search transit)	-3.012	2.386	-0.769	1.884
CM is transit (search auto)	-1.825	1.651	-5.325	2.370
CM is transit (search carpool)	0.182	1.630	-0.334	2.061
CM is transit (search transit)	1.156	1.785	4.22	1.651
CM is walk/bike (search auto)	-5.650	1.670	-3.662	2.428
CM is walk/bike (search carpool)	-10.110	1.940	1.488	2.199
CM is walk/bike (search transit)	-1.350	1.750	1.318	2.198

and walk/bike users in hidden state 1.

4.2.3 Demonstration

4.2.3.1 Individual dynamics

One of the interesting features of our model is the ability to investigate the individual-level effects of dynamic covariates on the transitions between the hidden states. It allows modelers to predict not only the outcome but also the timing of modal preference changes and searching choice changes. This unique feature is ensured by the heterogeneous transition matrix specified in our model. As a demonstration, let us consider a female traveler with driver’s license and an initial low household income. Let us further assume that her habitual travel mode at time $t - 1$ is auto with 10 minutes travel time and 1 dollar travel costs. Then the baseline transition matrix for this individual is shown as the left matrix in Table 4.6. The middle matrix in Table 5 examines the scenario when this individual’s income level increases. The auto-loving state becomes stickier since the likelihood of leaving this state drops drastically from 0.79 to 0.19. The third matrix in Table 4.6 represents the scenario when the auto travel cost increases by 1 dollar. In this case, the individual is more likely to switch to the carpool/transit-loving state.

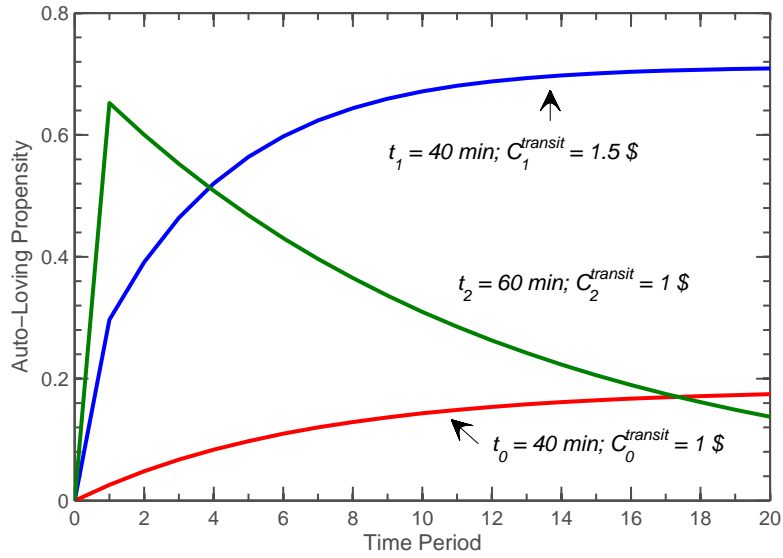
Using the heterogeneous transition matrix, the paper further demonstrates the model’s capability in capturing individual-level hidden state dynamics. Consider a licensed and high-income male traveler who originally is in carpool/transit-loving state and actually uses transit. For simplicity, let us assume that during each time period, auto travel cost remains at 1.5 dollars and that transit and auto travel times are the same (this individual does not have this information because he is

Table 4.6: The Posterior Transition Matrices Demonstrating Individual Dynamics

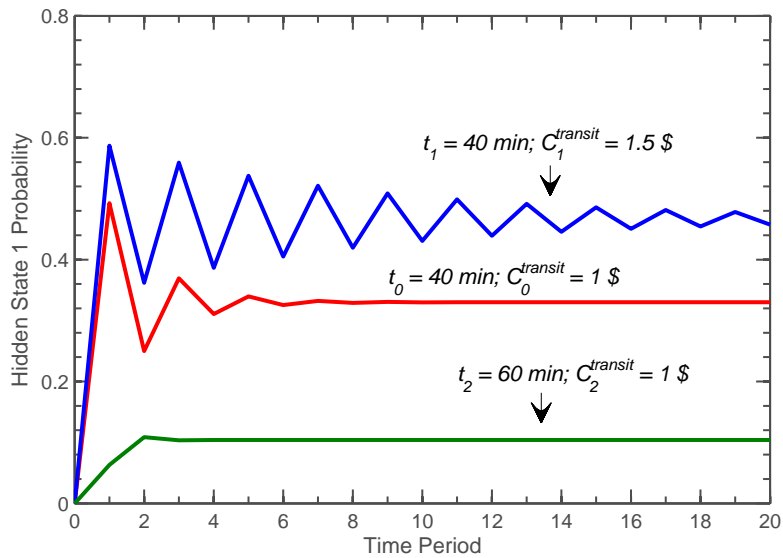
	Baseline		Income +		Cost +	
	t		t		t	
$t - 1$	Auto-Lover	Transit-Lover	Auto-Lover	Transit-Lover	Auto-Lover	Transit-Lover
Auto-Lover	0.21	0.79	0.81	0.19	0.06	0.94
Transit-Lover	0.91	0.09	0.89	0.11	0.99	0.01

using transit only right now). This example considers the impacts of travel time increase and travel cost increase on both modes separately. The model setup and the analytical results are shown in Fig. 4.8a. The red curve denotes the baseline scenario, showing that the individual gradually exhibits a slight tendency towards car-loving. When the transit fare increases to the same level as auto cost, the asymptotic propensity for this individual to be in car-loving state greatly increases to about 70% as shown by the blue curve. The green curve shows that when the travel time grows to an unpleasant level while travel cost stays the same, this traveler at the beginning is very likely to change attitude. After experiencing the same level of congestion (as we assumed), this individual gradually switch back to transit-lover state as transit has a more reasonable travel cost.

Given other conditions equal, a female individual’s behavior is predicted differently as shown in Fig. 4.8b. She hesitates and wanders between the two states even if the transit fare increases. And if the congestion gets more severe, she becomes conservative and stays being a transit-lover. This outcome suggests that excessive travel time discourages female travelers to switch hidden states (in particular, a too



(a) Male with license and high income who initially prefers and uses transit



(b) Female with license and high income who initially prefers and uses transit

Figure 4.8: Numerical examples of heterogeneous HMM and individual dynamics

long commute trip by auto could be especially unpleasant for female drivers). Table 4.5 and Figure 4.8 highlight the capability of the model in capturing short-term and long-term individual dynamics and predicting heterogeneous travel behavior

over time. It demonstrates that with the observed mode searching and switching sequences, one could dynamically segment the individuals or simulated agents in a typical agent-based/activity-based model into different habitual preference status. Future research could look at incorporation of unobserved heterogeneity in transition probability functions by specifying a hierarchical Bayesian structure [56]. Researchers could explore even further to consider some dynamic covariates as decision variables (e.g. getting a drivers' license and purchasing a vehicle).

4.2.3.2 System dynamics

The substantive policy implications can also be obtained from the estimated HMM model regarding the effect of changes in level-of-service on travelers' mode searching behavior. By altering the level-of-service variables during the peak period, most transportation management strategies, such as congestion pricing and parking pricing, tend to effect a change in mode choice [16] especially to discourage drive-alone mode. The agent-based simulation will be applied to analyze system-level travel modal changes. This model will be demonstrated as application-ready and capable tool for predicting dynamic behavior. A more rigorous demonstration on the dynamic effects can be done once the mode search dynamics are integrated with a mode switching model and a multimodal simulation model.

4.3 Departure Time Search and Switch

4.3.1 Search Rules

Once an individual decides to start searching for alternatives (i.e. subjective search gain becomes larger than perceived search cost due to either new spatial knowledge or external stimuli such as increase level of congestion and/or schedule delay associated with the current departure time choice), the individual employs a set of rules to search alternative departure times, which need to be empirically derived for the positive modeling approach. The search for alternative departure times is obviously not random due to scheduling constraints and anchoring effects. For example, an individual, whose current departure time is 7:30 a.m. with a preferred arrival time at 8:00 a.m., may adjust the departure time when congestion worsens. It is more likely that this individual will first experiment with alternative departure times closer to 7:30 a.m. (anchoring effect). In addition, it is less likely that this individual will consider departure times later than 7:30 a.m. due to scheduling constraints. To consider these factors, we define departure time alternatives that anchor at the current departure time, e.g., 0–15 min earlier, 0–15 min later, 15 – 30 min earlier, 15–30 min later, and so on. Schedule delay considerations are incorporated into the explanatory variables in the search rules.

If-then rules are selected to represent departure time search heuristics for several reasons because they are shown to be capable of replicating various types of human heuristics and decision-making processes in previous expert systems and knowledge extraction research, and because the execution of if-then rules at the

model implementation stage requires minimum computational resources which is important especially for large-scale departure time and peak spreading models involving millions of independent decision-makers.

Part 2 of the survey data on search processes are used to derive search rules. The variables used in the search rule induction model include: arrival schedule delay early ($ASDE$), arrival schedule delay late ($ASDL$), travel time (TT), and free flow travel time (TT^*). Equations 4.18, 4.19, and 4.20 define the arrival schedule delay variables (i.e. $ASDE$, $ASDL$, and $Delay$), which is consistent with the definition in previous research. PAT denotes the preferred arrival time, AT the actual arrival time, $Delay$ the difference between actual travel time (TT) and free flow travel time (TT^*).

$$ASDE = \max(0, PAT - AT) \quad (4.18)$$

$$ASDL = \max(0, AT - PAT) \quad (4.19)$$

$$Delay = (TT - TT^*)/TT^* \quad (4.20)$$

Various machine learning algorithms [140] are able to derive if-then rules from behavior process survey data. We have tested four proven algorithms including C4.5 [111], PRISM [30], PART [47], and RIPPER [35], and selected PART based on predictive accuracy of the derived search rules on a validation dataset. The complete departure time rule sets are presented below:

Search 60+ min earlier, if

$$[ASDL > 70] \quad \text{Rule 1}$$

Search 30-60 min earlier, if		
	$[45 < ASDL \leq 70]$	Rule 2
Search 0-30 min earlier, if		
	$[0 < ASDL \leq 30 \text{ AND } Delay > 0]$	Rule 3
Search 0-30 min later, if		
	$[ASDL > 30 \text{ AND } Delay > 50\%]$	Rule 4
OR	$[ASDL \leq 10 \text{ AND } ASDE \leq 40 \text{ AND } Delay \leq 50\% \text{ AND } TT \leq 65]$	Rule 5
Search 30-60 min later, if		
	$[ASDL = 0]$	Rule 6
Search 60+ min later, if		
	$[ASDE > 75]$	Rule 7
OR	$[ASDE > 45 \text{ AND } Delay > 10\%]$	Rule 8
Otherwise, search 0-30 min earlier.		Rule 9

Rule 1 states that individuals will consider shifting their departure times earlier by more than 60 if their experienced arrival schedule delay late is over 70 minutes. All other rules can be similarly interpreted. These rules collectively replicate the heuristics individuals use to identify alternative departure times based on their current experiences and knowledge. As spatial knowledge is updated during the search process, the same rule set can generate different alternatives for the same individual.

This set of rules is in a full disjunctive normal form [140], a form of closed-world assumption. In the rule set, each of its variables appears exactly once in every clause. In another word, in each round of searching, any particular searcher can only be classified into one class and follow one of those derived search rules at

a time. Therefore, in the set, rules cannot conflict and there is no ambiguity in rule interpretation.

4.3.2 Decision Rules under Uncertainty

Once an individual found a new departure time alternative, the individual after experimenting with the new alternative will either change or not change departure time. This adjustment decision-making process can be modeled with a set of decision rules. The dataset employed here is collected from a stated-preference departure time survey, where seven different scenarios with various travel time duration and toll cost specifications are given to each respondent. The empirically derived decision rule set consists of 13 rules, presented below. RIPPER is chosen for its superior predictive performance on validation dataset, and the clear physical meaning of the derived behavioral rules.

The travel time uncertainty (RANGE) is specified here as the 95% confidence interval of the travel time duration. Other explanatory variables in the decision rules include: travel time (TIME), arrival schedule delay early (ASDE), arrival schedule delay late (ASDL), monetary cost (COST), household income (INCOME), gender (GENDER). The variable flex is a dummy variable that is equal to one if the trip maker's preferred arrival schedule is flexible, and 0 otherwise. denotes percentage changes of the alternative departure time attributes from the attributes of current departure time choice.

Switch to the alternative departure time, if

- [$\Delta RANGE \leq -16.7\%$ AND $\Delta TIME \leq -15.4\%$] Rule 1
- [$\Delta TIME \leq -25\%$ AND $\Delta RANGE \geq 0\%$] Rule 2
- [$\Delta RANGE \geq 0\%$ AND $\Delta COST \leq -35.2\%$ AND $flex = 1$] Rule 3
- [$\Delta RANGE \leq 0\%$ AND $-8.3\% \leq \Delta COST \leq -35.2\%$ AND $INCOME < \$150K$ AND $\Delta TIME \leq 10\%$] Rule 4
- [$\Delta RANGE \leq 0\%$ AND $\Delta COST \leq -8.3\%$ AND $\Delta ASDL \leq 35\%$ AND $INCOME < \$150K$] Rule 5
- [$-16.7\% \leq \Delta RANGE \leq 0\%$ AND $INCOME \leq \$50K$] Rule 6
- [$\Delta ASDL \leq -38\%$ AND $\Delta RANGE \geq 0\%$ AND $\Delta TIME \geq 17\%$] Rule 7
- [$-66.7\% \leq \Delta RANGE \leq 16.7\%$ AND $-4.2\% \leq \Delta COST \leq -35.2\%$] Rule 8
- [$INCOME \leq \$50K$ AND $flex = 1$ AND $-22.7\% \Delta TIME \leq 16.6\%$ AND $\Delta COST \leq 20\%$] Rule 9
- [$INCOME \leq \$50K$ AND $GENDER = female$ AND $\Delta RANGE \leq -70\%$] Rule 10
- [$INCOME \leq \$100K$ AND $GENDER = female$ AND $\Delta TIME \leq 8.3\%$ AND $\Delta RANGE \leq -44.4\%$] Rule 11
- [$-21\% \leq \Delta TIME \leq -10\%$ AND $\Delta ASDL \geq 33\%$ AND $\Delta RANGE \leq -40\%$] Rule 12
- Otherwise, continue to use the current departure time. Rule 13

There apparently exist perception thresholds in travel time uncertainty. In general, the rules imply individuals are more likely to change departure times as long as the travel time uncertainty is lower. This risk aversion behavior is especially significant for certain travelers, such as those who are with lower income (Rule 6)

and whose gender is female (Rule 9 and 11). While strongly risk-loving behavior (i.e. choose the riskier alternative given all other things equal) is not directly captured in the rule set, some travelers are implicitly risk-neutral or risk-loving and are willing to try more risky departure time alternatives as long as they are better off in other attribute(s). As shown by the Rule 2, 3, and 7, for instance, the travelers tend to sacrifice the travel time reliability for the improved travel condition, i.e. shorter expected travel time, lower travel cost, and less arrival schedule delay, respectively. These different attitudes toward risk and travel time uncertainty are thereby simulated in the agent-based system. Drivers' heterogeneity towards pricing is also explicitly modeled (Rule 3 and 10). Rule 8 further suggests that drivers are willing to pay up to an extra 10% of the original travel cost for a more reliable alternative. These sensitivities potentially allow the model to analyze time-varying/dynamic pricing, flexible work hours, and other peak spreading incentives. While the following section presents a numerical example with natural peak spreading incentives, we leave the simulation of various pricing scenarios and peak spreading effects for future research.

4.3.3 Model Validation

Validating the rule sets is an important process proving the model's credibility. A within-sample validation is conducted for each of the model developed. In particular, ten-fold cross-validation has been employed in the validation, which is typically seen in most practical limited-data situations [81]. Future research may explore

how innovative data collection and advanced survey methods, such as web-based interactive games, simulation-based group dynamics, GPS surveys, and smart-phone applications, can support and improve the validation.

In the ten-fold cross-validation, the original data sample is first randomly partitioned into ten sub-groups. One sub-group is retained as the test set. The rest nine sub-groups are used as the training set. Then the estimation and validation process is repeated ten times so that each data sample is used exactly once for validation. The aggregate cross-validation accuracy for the search scope modeling is 93.3%, while six search scopes have been specified in the rules set. And the validation of the decision rules can get 96.5% correctly classified instances.

4.3.4 Agent-Based Simulation

4.3.4.1 Baseline scenario

The computational feasibility to combine departure time model with various macro-, meso- and microscopic network traffic models for peak spreading analysis has been demonstrated in the author's Master Thesis and other published papers [141, 153, 146]. In this section, I enhance the numerical test with supply- and demand-side uncertainty and demonstrate how the travelers' actual departure time decision-making process under various uncertainty scenarios. Since a large number of uncertainty scenarios are specified and at this moment only the departure time changes are considered in the model, a one-link highway commuting corridor with one OD pair and two lanes is selected here as the test example for simplicity. Other

setups of the numerical example are listed as follows:

- Link capacity is 1,600 vehicles per lane per hour.
- Link length is 33 miles, with two lanes.
- The base-case scenario is characterized by an initial demand in 15-minute intervals from 4 a.m. to 11 a.m. A total number of 21,648 trips per day are simulated in each iteration.
- The testing policy assumes a uniform 10% increase in OD demand across all time intervals, which is expected to cause significant increase in congestion (especially during the peak hours of the study period) and subsequently adjustment of departure times for certain commuters.
- Commuters' arrival times in the base case are assumed to be their preferred arrival times.

4.3.4.2 Demand and supply-side uncertainty scenarios

In order to examine how travelers' make departure time decisions under uncertainty, a number of demand-side uncertainty scenarios and a number of supply-side uncertainty scenarios are defined and simulated in this paper. In each run of the simulation, each traveler learns, makes departure time search, and adapts behavior under certain demand-side and/or supply-side uncertainty.

On the demand side, the uncertainty is introduced by randomness of the total travel demand from day to day. For instance, consider the case when a student

commutes to campus on a daily base. She/he may encounter higher congestion caused by day-to-day demand fluctuation such as special events, graduation, etc. The coefficient of variation (CV, defined as the demand standard deviation divided by the mean travel demand) can be used to measure the demand-side fluctuation. In this study, 50 demand-side uncertainty scenarios are specified. The CV value varies from 0 to 0.3 in a uniform step size.

On the supply side, the uncertainty is defined by lane failure rate. It is defined as the probability that one lane loses the capacity due to certain events such as work zone and traffic incidents, etc. Since we only define one link in the numerical example for simplicity, the occasion that all the lanes on the same link fail at the same time is neglected. 50 supply-side uncertainty scenarios are specified. The lane failure rate varies from 0 to 0.0002 in a uniform step size.

Thus, a total number of 2,500 combinations of demand- and supply-side uncertainty scenarios is produced and tested in this agent-based simulation setup. 100 random seeds are selected in order to varying the simulation results. And in each uncertainty scenario, 100 iterations (simulated days) at maximum are conducted to allow system-level performance measures to converge to their true values for that particular scenario.

Fig. 4.9 verifies that as simulated by the numerical example, travelers actually experience worse travel time reliability as the level of uncertainty increases. The reliability is measured by the coefficient of experienced travel time variation (i.e. the standard deviation of the experienced travel time divided by the mean travel time). As shown in Figure 4.9, the reliability is approximately monotone with respect to

both the supply-side and the demand-side uncertainty. A reasonable interpretation is that individuals are making one-dimensional departure time decisions. More dramatic reliability variation can be introduced by simultaneously considering together the routing and changing departure time in a more sophisticated and realistic road network.

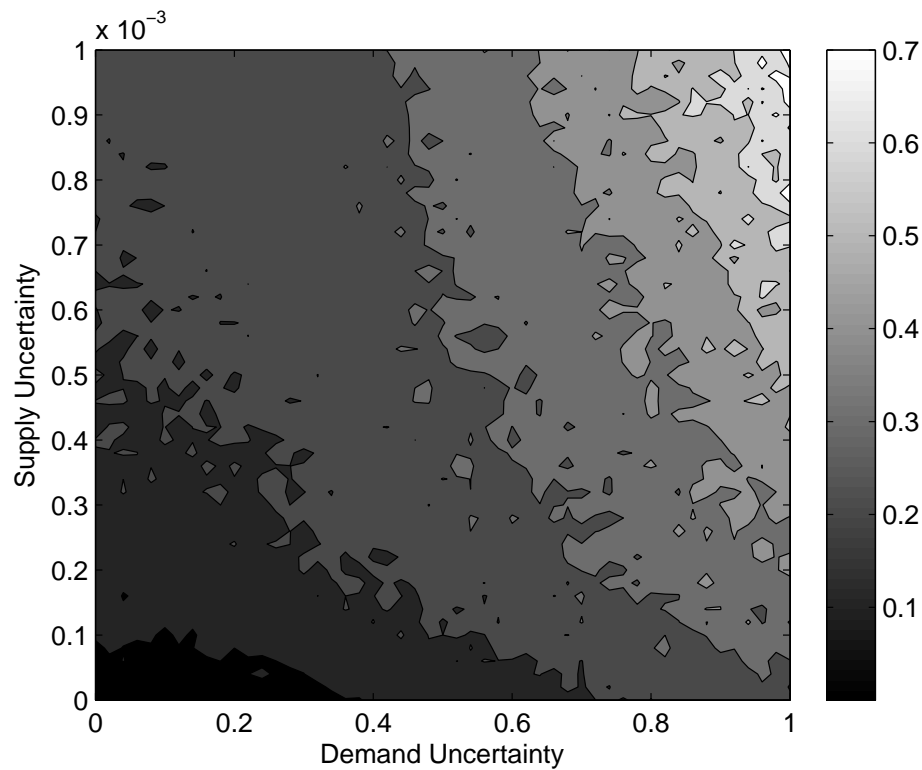
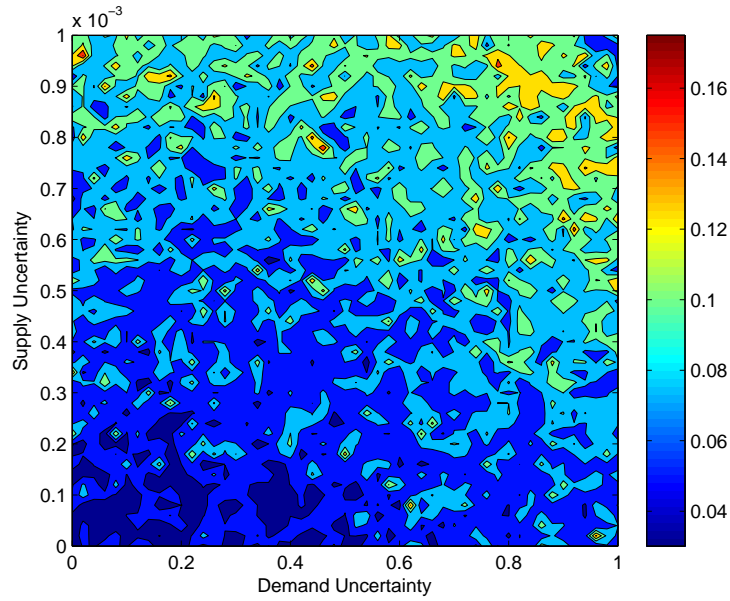


Figure 4.9: Experienced travel time reliability (measured by coefficient of travel time variation)

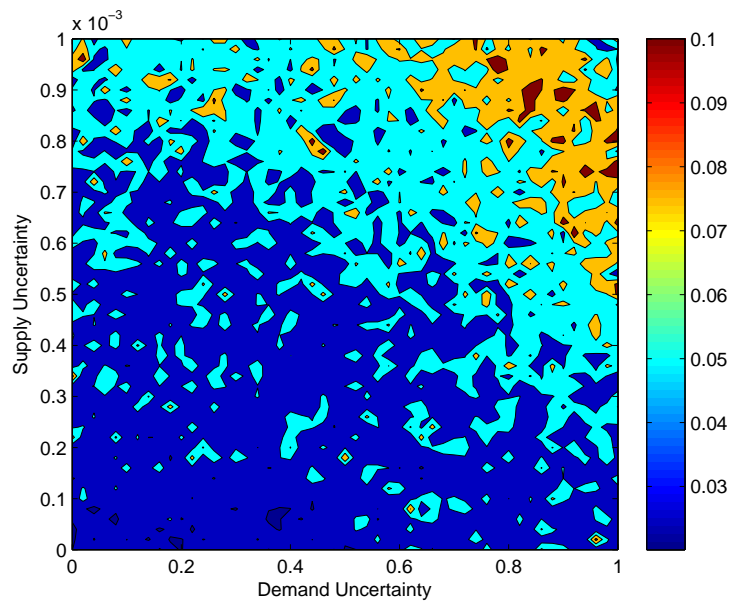
Departure time search and switching behavior under uncertainty is illustrated in Fig. 4.10. Overall, it agrees with the hypothesis that more travelers search for alternatives in response to non-recurrent congestion due to increasing uncertainty (contour color turns darker from the bottom-left to the upper-right). At the highest uncertainty level, about 16% of the travelers have searched for alternatives. In-

terestingly, we can observe that when both the supply-side and the demand-side uncertainty reach peak (the upper-right corner in Figs. 4.10a and 4.10b, the average percentage of travelers who have searched/changed departure time drops to the level of moderate uncertainty scenarios. This is because when the uncertainty level is too high, a small amount of travelers keeps searching and changing due to their extremely high subjective search gain. While most scenarios under low and normal uncertainty level take some 30 simulated days to converge, under the high-uncertainty scenario it takes significantly more iterations (about 90 iterations) for the travelers to satisfy and for the model to converge given the uncertain situation. Thus, the average percentage of travelers who have changed their behavior decreases in this occasion.

Fig. 4.11 plots the ratio of travelers who have chosen more reliable departure alternatives among all travelers who have searched. This ratio is defined as the total number of travelers who have switched to or stayed in the less risky departure times (i.e. of lower coefficient of experienced travel time variation) divided by the total number of travelers who have searched for departure time alternatives. As aforementioned, we observe a general trend of increased departure time searching and changing propensities with increased system uncertainty (see Fig. 4.10). Here we further explore travelers' decision under uncertainty by calculating the percentage of travelers who have chosen the less risky departure time alternatives when they are making the switching decision. As depicted in Fig. 4.11, when the uncertainty level is relatively low, about 60% to 65% of the travelers are able to choose more certain alternatives. As the uncertainty grows to a certain level, as highlighted



(a) % of travelers who have searched for alternatives



(b) % of travelers who have changed departure time

Figure 4.10: Daily departure time search and switching behavior under uncertainty by the dash line, travelers become less successful in decreasing their experienced uncertainty and this percentage of choosing lower risk decreases to about 50%. In other word, travelers are almost indifferent between choosing riskier alternatives and

choosing more reliable alternatives when uncertainty level grows to a certain level. When the system becomes even more unreliable, travelers' decisions are strongly against more risky alternatives. Under the highest level of uncertainty scenario, about 75% travelers in the system prefers alternatives associated with lower travel time uncertainty.

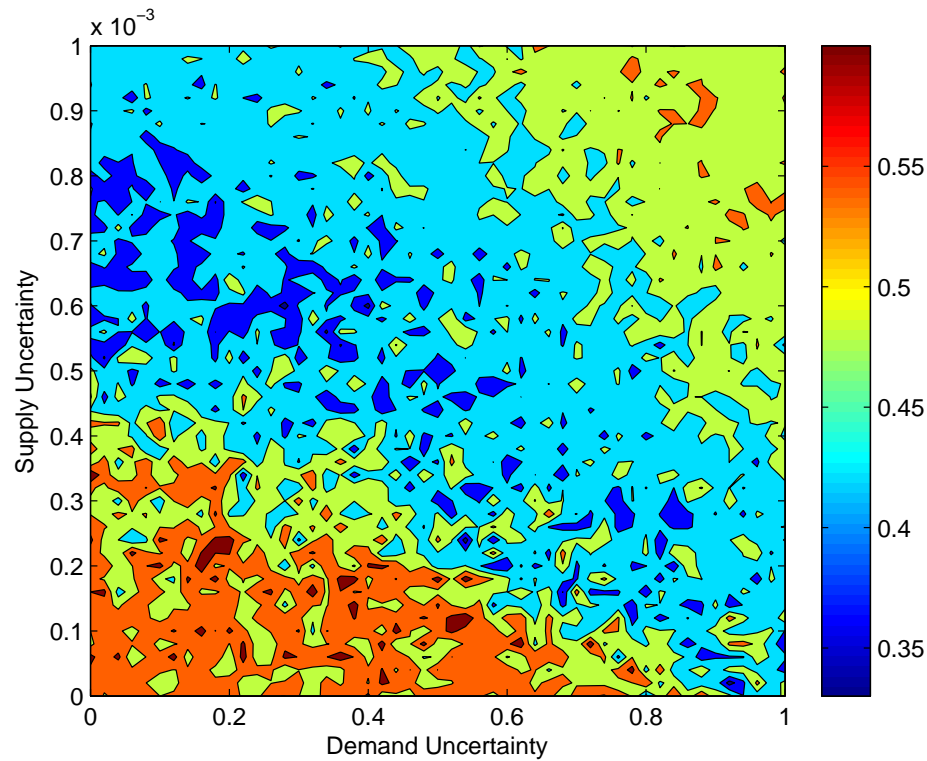


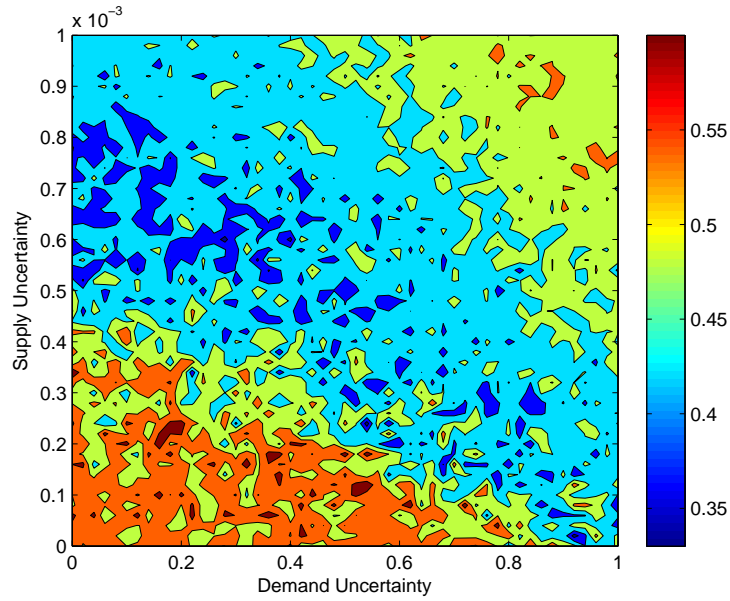
Figure 4.11: The percentage of travelers who choose the less risky departure time

Another interesting comparison when studying departure time searching and switching behavior is between searching/switching to earlier time alternatives or searching/switching to later time alternative. The ratio of travelers who searched for earlier departure times (calculated as the total number of people who have employed search rules to investigate earlier departure alternatives divided by the total number of people who have searched for alternatives) is presented in Fig. 4.12a. Similarly,

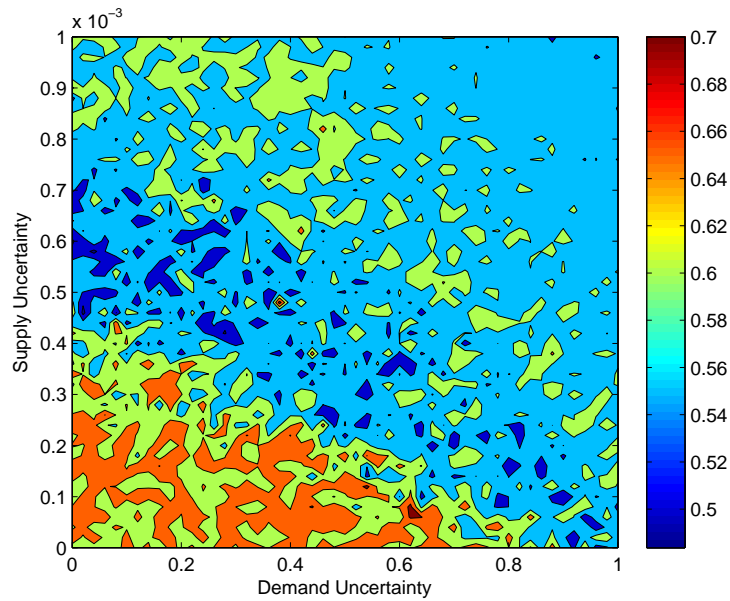
the ratio of travelers who switched to earlier departure times is calculated as the total number of travelers who have decided to choose the earlier departure alternatives divided by the total number of travelers who have decided to change their departure time). And this ratio is presented in Fig. 4.12b.

As the system becomes more congested due to the demand growth, travelers generally arrive at their destinations later than their preferred schedule (ASDL ≤ 0) and this dissatisfaction encourages them to search (often biased towards earlier alternatives). Interestingly, the numerical result suggests significant behavioral heterogeneity in this regard. Travelers are interested in earlier alternatives only when the system-level uncertainty is relatively lower. As depicted by the dark grey zone in the bottom-left corner of Fig. 4.12a and 4.12b, about 55% to 60% of the travelers try earlier departure times when the supply- and demand-side uncertainty is low. And under these circumstances, about 65% eventually decide to depart earlier among those who have decided to change departure times.

Again, we observe a ribbon area in Fig. 4.12a and 4.12b, showing that when the uncertainty increases to a certain level, the ratio of searching for earlier alternatives and the ratio of switching to earlier alternatives drop drastically to below 40% and below 55%, respectively. In other word, travelers in general are more likely to look into later departure times under these uncertainty scenarios, even when they have experienced schedule delay under the policy scenario that the total demand grows by 10%. This uncertainty zone is very consistent with the bounded dash line shown in Fig. 4.12, which together indicates that travelers are somewhat indifferent between earlier departures and later departures, and between lower risk and higher risk.



(a) The ratio of searching for earlier alternatives



(b) The ratio of switching to earlier alternatives

Figure 4.12: The ratio of travelers who searched/switched to earlier alternatives

4.4 En-Route Diversion with Information Provision

4.4.1 Training Data from Driving Simulator Experiment

The data for developing the en-route diversion classifier is collected from a driving simulator experiment designed by the Human Performance Laboratory at the

University of Massachusetts Amherst (see [130] for more details about the data). 63 effective subjects were recruited in this driving simulator survey. Subjects were shown three types of route maps in the tests, shown in Fig. 4.13. Each type of the maps appeared six times with different assigned travel times. Some social demographic information (i.e. gender, age, and years holding a driver’s license) has also been collected.

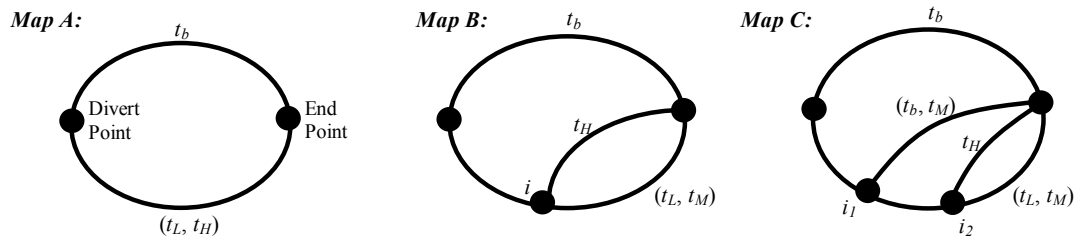


Figure 4.13: Three types of maps in the driving simulator experiment

In Fig. 4.13, each map contains one routine route with deterministic travel time t_b and one risky diverting route using (m, n) to denote a random travel time with two ordered outcomes m or n ($m < n$), each with probability 50%. The risky diverting branch gets more complicated in topology from Map A through C. Map A contains one simple-risk diversion, with a possible low travel time t_L and high travel time t_H . In Map B, a bifurcation is added to the diverting route, where the safe detour has a deterministic travel time t_H . The risky route has a low travel time t_L and a prohibitively long delay t_M , which could be due to an incident. At Node i , a subject will receive real-time information on the realized travel time on the diverting route. Map C adds another bifurcation to the diverting route, upstream of the one in Map B, with two possible outcomes t_b and t_M . Again, real-time information is

available at Node i_1 and i_2 on the realized travel time. Similarly the information at either node could help drivers avoid the extremely high travel time t_M on the diverting route. A driver, while driving, takes into account the real-time traffic information to some extent in making en-route diversion choice at the Divert Point.

4.4.2 A Logit Model

A binary logit model is first specified and estimated. There are two alternatives denoted by: + (i.e. not-divert) or - (i.e. divert). In this model, expected travel time (*Time*) and travel time unreliability (*UNR*) are employed as two major explanatory variables. *UNR* Thus, individual n 's systematic utility function of choosing the routine route (i.e. not divert) is formulated as:

$$V_n(+) = \beta_0 + \beta_1 \cdot Time_n \quad (4.21)$$

The utility of choosing the alternative route (i.e. divert) is formulated as:

$$V_n(-) = \beta_1 \cdot Time_n + \beta_2 \cdot UNR_n + \beta_3 \cdot Gender_n + \beta_4 \cdot Risk_n \quad (4.22)$$

The utilities are applied within the logit form to yield the probability of a given diversion observation that individual n chooses alternative C .

$$P_n(C) = \frac{\exp(V_n(C))}{\sum_{C_n=\{+,-\}} \exp(V_n(C_n))} \quad (4.23)$$

The explanatory variables are defined as:

- *Time*: the expected travel time. $Time = t_b$ in “not divert” alternative and $Time = \frac{t_L+t_H}{2}$ in “divert” alternative.
- *UNR* is specified as the 95% confidence interval of the random travel time duration.
- *Gender*: a dummy variable which equals one if the subject is male, zero otherwise.
- *Risk*: a dummy variable which equals one for Scenario Map B and C, zero otherwise.

Risk is a dummy variable reflecting the complexity (or risk) of the alternative route. Consider the situation when the diverting route involves bifurcation and possible huge delay t_M (the situation in Map B and C shown in Fig. 4.13). Even if theoretically the drivers can make the correct and strategic en-route decision to avoid the huge delay penalty t_M with the guidance of the real-time information at the information point i (or i_1 and i_2 in Map C), drivers are less likely to divert considering the little reaction time in making this decision. Choosing this type of alternative route is considered as a diversion of high risk.

The logit model estimates are presented in Table 4.7. The estimated coefficients of the variables are all significant and with the correct signs. The negative alternative specific constant β_0 indicates that under the driving simulation scenarios, the likelihood of diversion from the routine route has been positively affected

by certain factors, e.g. the provision of travel time information. Travel time and travel time unreliability negatively affect drivers' choice. Male drivers were more likely to divert from their routine routes. This finding conforms to previous en-route diversion research [94, 90, 3, 74]. The model estimates also showed that when the alternative route consists of more complex network topology and therefore represents higher risk, the drivers were less likely to divert.

Table 4.7: A Binary Logit Model for En-Route Diversion

Variables	Coefficients	Estimates	Std. Err.	T-test
Const. (not divert)	β_0	-0.358	0.189	-1.90
<i>Time</i> (min.)	β_1	-0.119	0.009	-13.72
<i>UNR</i> (min.)	β_2	-0.041	0.008	-5.09
<i>Alt. = diverting</i>				
<i>Gender</i>	β_3	0.433	0.103	4.20
<i>Risk</i>	β_4	-1.22	0.107	-11.43
# obs.	2095			
Initial Log Likelihood	-1452.2			
Log Likelihood	-1130.3			
ρ^2	0.222			

In this paper, evaluating the predicted response v.s. the actual responses was used to compare between models. A within-sample ten-fold cross-validation is conducted for validating the en-route diversion model. This validation technique is typically seen in most practical limited-data situations [81]. The aggregate cross-validation accuracy for the binary logit model is 91.3%.

4.4.3 A Naive Bayesian Classifier

This paper then proposes a naive Bayesian classifier (see Fig. 4.14) to model the en-route diversion behavior based on the same dataset. In Fig. 4.14, nodes represent a tuple of stochastic attributes (F_1, F_2, \dots, F_n) and a behavioral classification variable denoted by C . There are two behavioral classes denoted by: + (i.e. the not-diverting class) or - (i.e. the diverting class). The directed arcs represent conditional dependencies between variables.

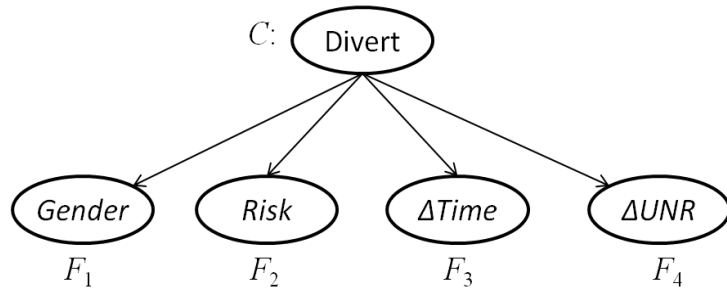


Figure 4.14: the Naive Bayes model structure

Variables F_i used in this model include expected travel time ($Time$), travel time unreliability (UNR), gender ($Gender$), and diverting risk ($Risk$). Δ denotes percentage changes of the alternative route's attributes from the attributes of the routine route.

For each training observation \mathbf{F} , the naive Bayesian classifier is a function that assigns a class label to it. This method learns the conditional probability of each variable F_i given the class C . According to Bayes' Rule, the probability of the

example $\mathbf{F}a = (F_1, F_2, \dots, F_n)$ being class + is:

$$p(+|\mathbf{F}) = \frac{p(+)\prod_{i=1}^n p(F_i|+)}{p(\mathbf{F})} \quad (4.24)$$

For a training observation, naive Bayes classifier assumes conditional independence of every other attribute, given the value of the classification variable:

$$\begin{aligned} p(\mathbf{F}|+) &= p(F_1, F_2, \dots, F_n|+) \\ &= \prod_{i=1}^n p(F_i|+) \end{aligned} \quad (4.25)$$

Thus, the equation 4.26 shows the functional form of naive Bayesian classifier.

The empirical observation is classified as + if and only if $f_{nb}(\mathbf{F}) \geq 1$.

$$f_{nb}(\mathbf{F}) = \frac{p(+)}{p(-)} \prod_{i=1}^n \frac{p(F_i|+)}{p(F_i|-)} \quad (4.26)$$

The estimated naive Bayes classifier model using the full training dataset is presented in Table 4.8.

In the model, $\Delta Time$ and ΔUNR are estimated as normal distributed random variables. Their conditional prior probabilities are thus calculated as:

$$p(x|C) = \frac{1}{\sigma_{x,C}\sqrt{2\pi}} \exp\left(-\frac{(x - \mu_{x,C})^2}{2\sigma_{x,C}^2}\right) \quad (4.27)$$

Where C represents the classification; $\mu_{x,C}$ denotes the estimated mean of x given class C ; and $\sigma_{x,C}$ denotes the estimated standard error of x given class C .

Table 4.8: Conditional Prior Probability Estimates for the Naive Bayes Classifier

Class and Class Prior	Variables	Mean	Standard Deviation
Class: + $p(+)=0.53$	<i>Gender</i> = male	$p(\text{male} +) = 0.403$	N/A
	<i>Gender</i> = female	$p(\text{female} +) = 0.597$	N/A
	<i>Risk</i> = low	$p(\text{low} +) = 0.504$	N/A
	<i>Risk</i> = high	$p(\text{high} +) = 0.496$	N/A
	$\Delta Time$	0.022	0.262
	ΔUNR	0.452	0.242
Class: - $p(-)=0.47$	<i>Gender</i> = male	$p(\text{male} -) = 0.532$	N/A
	<i>Gender</i> = female	$p(\text{female} -) = 0.468$	N/A
	<i>Risk</i> = low	$p(\text{low} -) = 0.548$	N/A
	<i>Risk</i> = high	$p(\text{high} -) = 0.452$	N/A
	$\Delta Time$	-0.163	0.066
	ΔUNR	0.304	0.270

The estimates have similar model interpretation as the binary logit estimates. Conditioned on the behavioral class -, the probability estimates of $\Delta Time$ (i.e. mean value of -0.163 and standard deviation of 0.066) suggests that lower expected travel time is one major incentive that motivates drivers to divert. On the other hand, the probability estimates of $\Delta Time$ conditioned on behavioral class + has mean value that is close to zero and has larger standard deviation, which indicates that not-diverting class is almost indifferent to expected travel time. The conditional probability estimate of ΔUNR for the diverting class has positive mean value, which indicates that drivers take risk to some extent when making en-route diversion decision. When travel time unreliability increases to a high level, drivers are more likely to stay with their routine route as $p(\Delta UNR|+)$ has higher mean than $p(\Delta UNR|-)$. The estimates on discrete variables (i.e. *Gender* and *Risk*) are also consistent with the estimates of binary logit model, suggesting that drivers that are male and/or in

lower-risk diversion situations are more likely to divert to the alternative routes.

With these prior probability estimates, the model predicts diversion probability for each empirical observation. For instance, consider the case that a male driver is in low-risk diversion scenario with $\Delta Time = -10\%$ (i.e. alternative route improves expected travel time by 10%) and $\Delta UNR = -10\%$ (i.e. alternative route improves travel time unreliability by 10%). By employing Equation 4.24, the model predicts that his diversion probability is 92.53%.

A within-sample ten-fold cross-validation is conducted for validating this model. The aggregate cross-validation accuracy is 97.7%, which is slightly better than the binary logit model. When applied to predict diversion behavior, the predictive performance could differ dramatically from the actual observation. For planning and operational application purposes, this model needs to be further calibrated, as more field data becomes readily available. This issue is further discussed and studied in the next section of the paper.

4.5 Calibration Methods

The survey-based data collection is often criticized to be biased [83]. The discrepancy between survey respondents' stated behavior and their actual behavior can be significant. Taking driving simulator experiment as an example, certain features of the simulation experiment may reinforce the subjects' perception of the simulator as artificial, although realism is clearly a goal when designing the scenarios. Secondly, drivers' knowledge and behavioral propensity differ on a case-specific basis

and the transferability of the models may be an issue when the planning and operational application of the model to a specific region is of interest. Taking en-route diversion as an example, more drivers will choose to divert in the cases where a number of parallel routes can serve effectively as alternative routes than in those cases with only one or two not-so-good alternative routes. Collectively, these facts emphasize the need of a stand-alone calibration process in order to map the models (designed using stated behavioral data) to field observations.

I here in this section compare actual en-route diversion behavior from field observation with our model's prediction. Even though our rule-based diversion model can explain the driving simulator data pretty well (over 90 percent accuracy of cross-validation), it performs poorly if employed to predict actual behavior in two real-world diversion scenarios. Therefore, to supplement the driving simulator data, real-world field observations on an often-congested commuting corridor are collected as the testing dataset, in order to re-calibrate the en-route diversion model. Then, a Bayesian calibration is performed to transform the naive Bayes classifier scores into more accurate probability estimates on local observations.

4.5.1 The Discrepancy between Stated Behavior and Actual Behavior

As shown in Fig. 4.15, I-95 and I-895 are two alternative routes that pass through the tunnels under the Baltimore Harbor and eventually rejoin at east Baltimore. They split approximately five miles prior to Baltimore City. The DMS

device has been installed prior to the split and is often used for displaying actual travel time, delay, and diversion messages regarding these two alternative routes [62]. A number of Bluetooth sensors are deployed along these two routes to detect the actual travel time as well as the en-route diversion behavior [62], as shown in Fig. 4.15.

While enormous traffic-related ground truth information was collected during the two-week Bluetooth sampling period, two real-world en-route diversion scenarios were observed and extracted for the analysis. Scenario 1 is shown in Fig. 4.15a. In this case, the DMS device posted travel time messages about the congestion on I-95 and suggested drivers to divert to I-895. Scenario 2 is shown in Fig 3b, where the DMS device reported major delays on I-895 and diverted drivers to the I-95/I-695 corridor. The date, duration, and traffic diversion rate of these two scenarios are reported in Table 4.9.

Table 4.9: En-Route Diversion Percentage between I-95 and I-895

	Scenario 1	Scenario 2	Base Case
DMS	Divert to I-895 and travel time	Divert to I-95 and travel time	Free-flow travel time
Date and (Time Periods)	3/31: (16:50–17:16) 4/6: (9:48–10.04) (10:07–10:21) (16:05–16:21)	4/2: (7:31–7:46) (9:32–12:23) (12:32–18:23)	N/A
Avg. I-95 %	78.5	93.9	88.7
Avg. I-895 %	21.5	6.1	11.3
Std. Dev.	12.03	7.54	6.04

During the time periods when diversion messages were posted, the diversion behavior is significant. For instance, in Scenario 1, approximately 10% of I-95 users



(a) Scenario 1: simple-risk diversion



(b) Scenario 2: high-risk diversion

Figure 4.15: I-95/I-895 En-route diversion scenarios and bluetooth sensor locations decided to switch to the I-895 corridor. A total number of 39191 Bluetooth devices have been detected during this two-week study period. Then the data has been processed as follows.

By matching the Bluetooth Machine ID, 1186 Bluetooth devices that have been observed during the time periods of Scenario 1 and 2 were also recorded at

least twice in other time periods. Thus the testing dataset consists of 1186 effective Bluetooth samples, with the routine route information and the actual en-route diversion decisions during Scenario 1 and 2 successfully observed. The expected travel time and travel time reliability associated with the routine route and the alternative route have been derived using the exact time information recorded by the Bluetooth detectors at the time when the devices passed by.

When trying to apply the en-route diversion behavioral model to this field data, information on variables *Gender* and *Risk* was also needed for model prediction. *Gender* has been generated by using Monte Carlo simulation. For variable *Risk*, Scenario 1 represented the low-risk diversion case defined in the driving simulator experiment (Map A in Fig. 4.13). Scenario 2, wherein the downstream of the alternative route has a further bifurcation (i.e. I-695), represented the high-risk diversion case.

4.5.2 A Bayesian Approach to Calibrating the Naive Bayesian Classifier

Then the Naive Bayes model has been applied to the Bluetooth samples. The model assigned each testing example a score between 0 and 1 that can be interpreted, in principle, as a class membership probability estimate. However, it is well known that these scores are not well-calibrated [140]. In this subsection, the paper demonstrated the relatively low predicting capability of the model on the field data and proposed a Bayesian calibration approach which significantly improved the accuracy

of the prediction. Various quantitative performance measures are summarized in the next subsection.

In Fig. 4.16 we show the receiver operating characteristic (ROC) estimated for the en-route diversion testing dataset. ROC curve is typically employed for evaluating data mining schemes [140]. The true positive (i.e. the predicted class and the actual class are the diverting class +) rate is plotted on the vertical axis against the false positive (i.e. the predicted class is – but the actual class is +) rate on the horizontal axis. The perfect classification would yield a point in the upper left corner, representing 100% accuracy. The diagonal line represents a completely random guess. If the classifier is well-calibrated, the ROC curve should be above the diagonal line. The figure demonstrates the effect of overoptimistic probability estimation. The model’s prediction is too optimistic, predicting very high diversion probabilities and thus yields a high false positive rate. In actuality, the diversion percentage is much lower than the estimated value. As depicted in Table 4.9, the reported average I-95/I-895 percentages suggest that roughly 1 out of 9 vehicles decide to use the diverting route in Scenario 1 and roughly half of the vehicles decide to divert in Scenario 2.

The Bayesian approach to calibrating the naive Bayes classifier is illustrated in Fig. 4.17.

To differentiate from the training observations \mathbf{F} , testing data points are denoted as \mathbf{E} . The en-route diversion classifier produces a prediction about an empirical data point \mathbf{E} in the testing dataset. Also, it gives some confidence score $s(\mathbf{E})$, indicating the strength of its decision that the empirical observation belongs

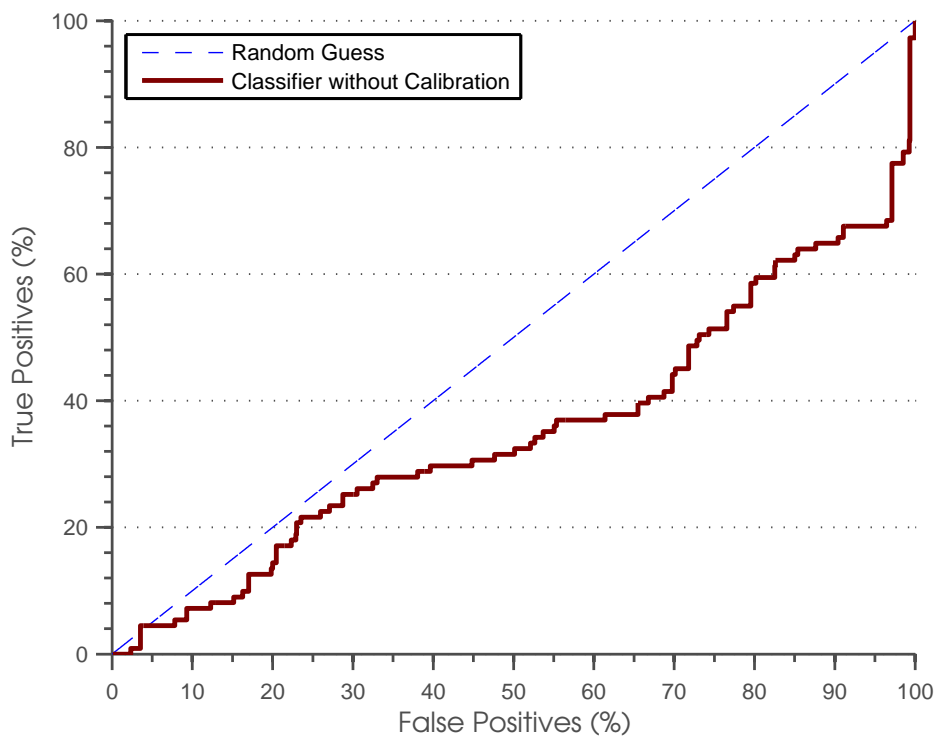


Figure 4.16: ROC curve for the naive Bayes en-route diversion classifier.

to the “not divert” class. The log-odds (equation 4.28) of the classifier’s estimate are usually defined as $s(\mathbf{E})$ for recalibrating a typical data mining classifier. This measurement is useful because it scales the outputs from $[0, 1]$ to a space $[-\infty, +\infty]$ where Gaussian and other distributions are applicable.

$$s(\mathbf{E}) = \log \frac{p(+|\mathbf{E})}{p(-|\mathbf{E})} \quad (4.28)$$

The confidence scores (i.e. the log-odds) and predicted diverting probabilities may not necessarily match the empirically observed probabilities. For recalibrating the classifier, a certain posterior function performing a mapping of the score s to the probability $p(+|s(\mathbf{E}))$ is needed, in order to obtain a better predicting accuracy.

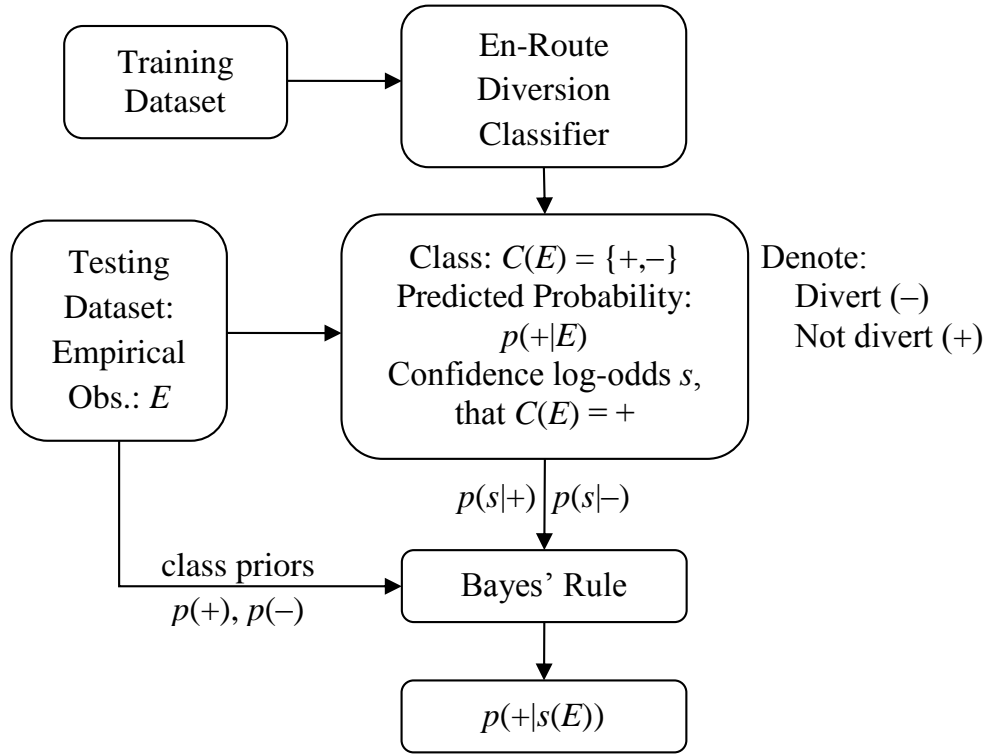


Figure 4.17: A Bayesian approach to calibrating the naive Bayes classifier.

Here the paper breaks down the problem to the two specific classes. An estimator for each of the class-conditional densities (i.e. $p(s|+)$ and $p(s|-)$) is produced for the diversion class and the not-divert class. Then, Bayes' Rule and the class priors are used to obtain the estimate for $p(+|s(\mathbf{E}))$:

$$p(+|s) = \frac{p(+)\cdot p(s|+)}{\sum_{C=\{+,-\}} p(C)\cdot (s|C)} \quad (4.29)$$

For the calibration function of the class-conditional densities, a Gaussian and a generalized extreme value (GEV) are fit to each of the class-conditional densities using the usual maximum likelihood estimates. The fits of these two functions represent a qualitative comparison between using symmetric distributions and using

asymmetric distributions to approximate the class-conditional densities. Fig. 4.18 shows the calibration function fits produced by these methods, versus the actual testing data. The actual testing data behaviors are illustrated as nonparametric fixed-width kernels. Quantitative performance measures of these calibration functions are offered in the next subsection.

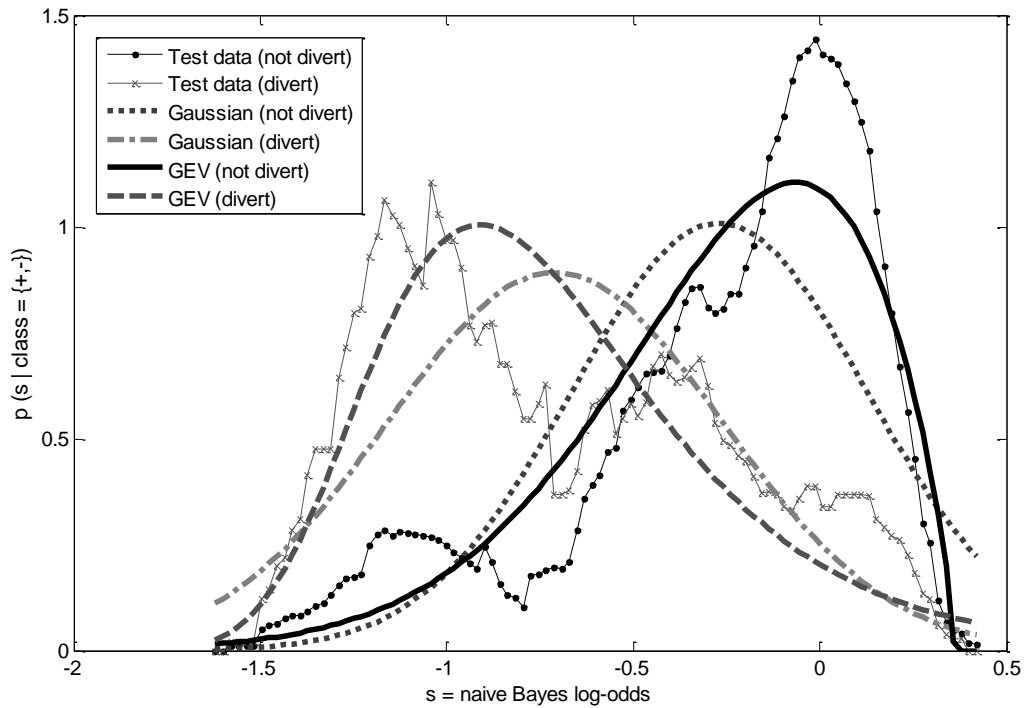


Figure 4.18: Estimated class conditional score densities versus the actual densities of the testing dataset.

In general, the calibration results agree with the empirical observation. The average value for the naive Bayes log-odds is approximately -0.5, which is consistent with the low diversion rates empirically perceived from the testing dataset. In other words, the optimistic prediction estimated by the en-route diversion model is well captured and recalibrated by this Bayesian calibration process. For the diversion class (-), the test data curve plotted in Fig. 4.18 skews towards the left side, as

the en-route diversion model gives these observations higher probability estimates to divert. This is the opposite for the not-divert class (+).

4.5.3 Performance Measures

The calibration function maps the estimated probabilities (i.e. log-odd scores) to the actually observed diversion rates. Now the evaluation of the calibration results is of concern. There are at least two types of performance measures that have been typically used in data mining to assess the quality of the probability estimates: i.e. log-loss [59] and squared error [25, 39]. While actually meaning an overall improved prediction quality, a better score according to these rules, sometimes has been loosely termed improving “calibration” [14].

The actual classification for an empirical observation \mathbf{E} (with class $C(\mathbf{E}) \in \{+, -\}$) in the testing dataset is observed. Let δ denote the Kronecker delta function which equals 1 if the two arguments are equal to each other and 0 otherwise. The log-loss and the squared error (*Error*²) are defined in Equations 4.30 and 4.31, respectively.

$$\begin{aligned} \log loss = & \delta(C(\mathbf{E}), +) \log p(+|\mathbf{E}) \\ & + \delta(C(\mathbf{E}), -) \log p(-|\mathbf{E}) \end{aligned} \tag{4.30}$$

$$\begin{aligned} Error^2 = & \delta(C(\mathbf{E}), +)(1 - p(+|\mathbf{E}))^2 \\ & + \delta(C(\mathbf{E}), -)(1 - p(-|\mathbf{E}))^2 \end{aligned} \tag{4.31}$$

This paper first reports the average log-loss and mean squared error (*MSE*)

for the performance measure of the calibration. The results are given in Table 4.10. Both calibration functions result in significant improvement for the model’s prediction accuracy, as the average log-loss statistic has been improved from -1.9909 to -0.9750 and -0.4792 respectively. The *MSE* has been reduced from 0.2855 to 0.0921 and 0.0767 respectively. Overall, asymmetric distributions (for instance, GEV in this case) tend to be empirically preferable and outperform symmetric distributions in terms of prediction accuracy. After the calibration, the receiver operating characteristic curves for Gaussian and GEV functions are plotted again in Fig. 4.19 to visualize the enhanced calibration results. Area under the curve (AUC) statistics are summarized in Table 4.10 for a direct interpretation of the ROC curves.

Table 4.10: Results for Calibrating Naive Bayes Model

Performance Measures	Naive Bayes	Gaussian	GEV
Total Log-loss	-2361.3	-1156.4	-568.34
Avg. Log-loss	-1.9909	-0.9750	0.4792
Total Squared Error	338.66	109.34	90.947
Mean Squared Error	0.2855	0.0921	0.0767
Predicting Accuracy	0.5877	0.9039	0.9182
Area Under Curve	0.3514	0.6442	0.6449

This section has developed and demonstrated a Bayesian approach which can be employed to calibrate the naive Bayes probability estimates predicted by the naive Bayes en-route diversion model. This approach is a consistent and theoretically sound parametric method to transform the predicted diversion probabilities to the actually observed probabilities. This approach is very flexible and thus can be easily transferred to other study areas to analyze diversion-related operations and

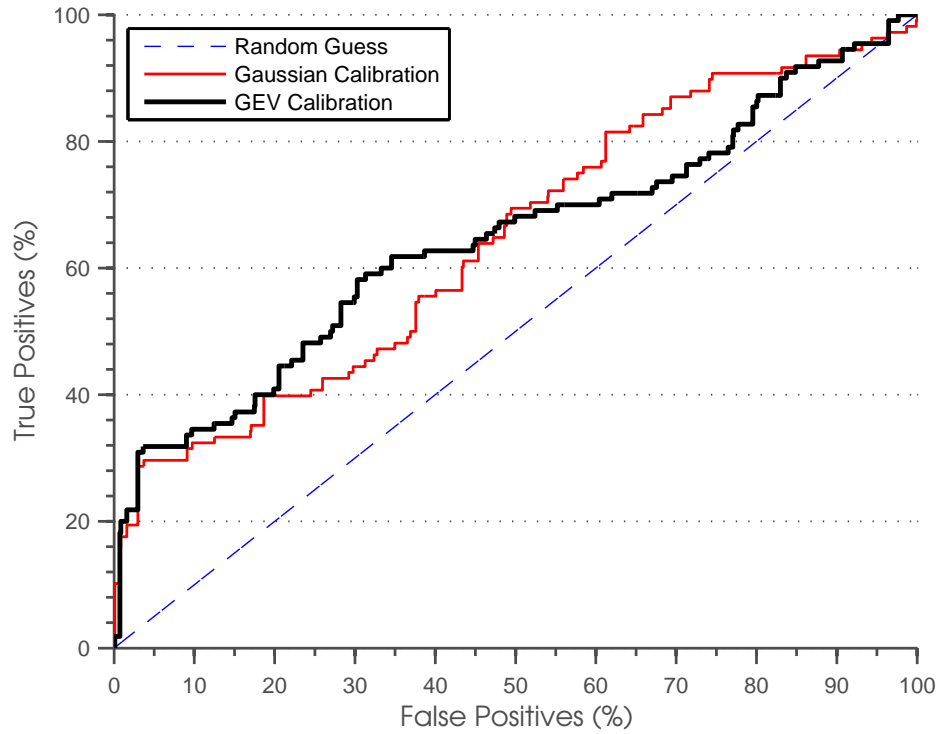


Figure 4.19: ROC curves for the Bayesian calibration.

management strategies, such as ATIS, DMS, the provision of real-time information, etc. It has the practical value that researchers and practitioners may potentially apply the en-route diversion model to other regions based on recalibration using locally collected field observations.

4.6 Summary

This chapter introduces a theoretical framework to modeling multidimensional travel behavior based on artificially intelligent agents, search theory, and bounded rationality. For decades, despite the number of heuristic explanations for different results, the fact that “almost no mathematical theory exists which explains the results of the simulations” [38] remains as one of the large drawbacks of agent-based

computational process approach. This is partly the side effect of its special feature that “no analytical functions are required”. Among the rapidly growing literature devoted to the departure from rational behavior assumptions, this theoretical framework makes effort to embed a sound theoretical foundation for computational process approach and agent-based microsimulations. The theoretical contribution is three-fold:

- A pertinent new theory of choices with experimental observations and estimations to demonstrate agents with systematic deviations from the rationality paradigm. Modeling components including knowledge, limited memory, learning, and subjective beliefs are proposed and empirically estimated to construct adaptive agents with limited capabilities to remember, learn, evolve, and gain higher payoffs. All agent-based models are based on empirical observations collected via various data collection efforts.
- Modeling procedural and multidimensional agent-based decision-making. Individuals choose departure time, mode, and/or route for their travel. Individuals also choose how and when to make those choices. A behaviorally sound modeling framework should focus on modeling the procedural decision-making processes. This study seeks answers to questions that largely remain unanswered including but not limited to: (1) when do individuals start seeking behavior changes? (2) How do they initially change behavior? (3) How do they switch behavior adjustment dimensions? (4) When do they stop making changes?

- The transformation from the static user equilibrium to a dynamic behavioral equilibrium. Traditional solution concepts are based on an implicit assumption that agents have complete information and are aware of the prevailing user equilibrium. However, a more realistic behavioral assumption is that individuals have to make inferences. These inferences can be their subjectively believed search gain (or perceived distributions of travel time and travel cost), the multidimensional alternatives they subjectively identify, and the heuristics they employ to evaluate alternatives. It is the process of making inferences that occupies each individual in making a decision. With search start/stop criteria explicitly specified, this process should eventually lead to a steady state that is structurally different to user equilibrium.

The estimation of the proposed agent-based models usually needs additional behavior process data. Whether or not the increased data needs can be justified by improved model realism and model performance in applications can be a subject for further examination. This chapter empirically estimates the models using data collected from a stated adaptation survey, a similar but different survey structure compared to stated preference experiments. This survey method effectively captures adaptations in response to changing attributes or context and can record behavior process if implemented in an iterative manner (see e.g. [73]). The observed behavior process actually is a search path possessed by each respondent. This historical information can be applied to further calibrate the knowledge model or the search cost models. Another future research direction may explore how advanced data

collection technologies such as GPS-surveys, smartphone applications, and social network data can improve the affordability and quality of behavior process data and further support the proposed modeling framework.

The numerical example presented in the paper highlights the capabilities of the proposed theory and models in estimating rich behavioral dynamics, such as multidimensional behavioral responses, day-to-day evolution of travel patterns, and individual-level learning, search, and decision-making processes. The computational efficiency of the proposed models needs further exploration through real-world implementations using agent-based simulation techniques. It is believed that the flexible framework, computational efficiency, and more realistic assumptions can make the proposed modeling tool extremely suitable for integrated large-scale multimodal planning/operations studies which typically have to cope with millions of agents. This work is primarily exploratory in its conceptualization of a descriptive theory, estimation of quantitative models, and demonstration in an agent-based microsimulation. In an era of big-data access, multi-core processors, and cloud computing, the ambition of transportation demand modelers has never been greater. The hope is that the preliminary findings in this chapter could raise interest in the behavioral foundation of multidimensional travel behavior as well as in microsimulating people's complex travel patterns in the time-space continuum. Extensive examination of the proposed tool on a larger and more representative survey sample and for real-world studies is necessary before we can conclude that the tool is fully practice-ready.

Chapter 5

Integrating Agent-Based Models with DTA and Applications

As demonstrated in Chapter 4, rule-based models and artificially intelligent agents can improve the behavioral realism by mimicking travelers' actual behavior. At the same time, these models can potentially make disaggregated models more computationally efficient. In order to demonstrate the capability, this chapter presents an integration plan of agent-based models and dynamic traffic assignment (DTA) models. The proposed integration is then applied in various real-world applications. Applications in planning, operations, and optimization are developed and analyzed.

5.1 Integration of Agent-Based Models and DTA

A transportation system typically has two major components: the transportation network and its users (potentially, decision-makers can also be considered). Agent-based models have the capability of mimicking and simulating travel behavior changes of each user in the system. Once integrated with a traffic simulator, the system can thus be complete given that all traffic conditions in the transportation network can be simulated by the simulator. This motivates the proposed integration of agent-based models and DTA simulator, as illustrated by the following flowchart (Fig. 5.1). The traffic simulator used in the dissertation is the DTALite model

(i.e. an open-source Light-weight Dynamic Traffic Assignment and Simulation Engine, <https://code.google.com/p/nexta/>). Therefore the integrated model is named AgBM-DTALite for short.

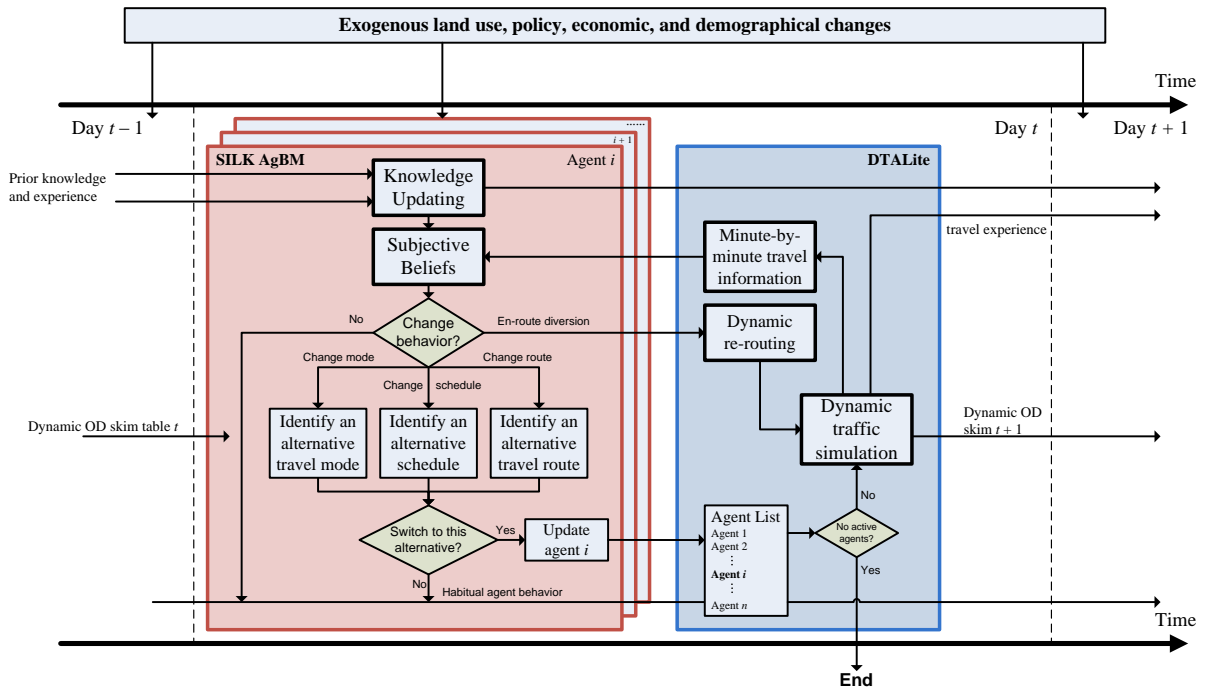


Figure 5.1: The Integration of Agent Based Models and DTALite Traffic Simulation Engine (AgBM-DTALite)

Travelers arrange their daily or recreational itinerary based on knowledge and various information sources: previous experience, social network, mass media, real-time traffic data sources (e.g. Google and INRIX), etc. Exogenous changes may result in different adjustment to the travel itinerary. AgBM models the travel behavior with the full consideration of information, learning, knowledge and searching, as elaborated in Chapter 4. Here the emphasis is given to the integration and, in particular, the information exchange between AgBM and DTALite. DTA models

are capable of simulating traffic in greater detail and producing various time-varying traffic information. A successful integration can provide fairly useful analysis tool to predict travel behavior in higher fidelity and accuracy and to evaluate various exogenous changes. The changes include relatively shorter-term real-time information provision via advanced traffic information system (ATIS), as well as more longer-term vehicular technology advances (e.g. ride-sharing, connected/autonomous vehicles). In the proposed AgBM-DTALite, two levels of integration are developed:

- **Between-Day Integration.** On Day t , agents are able to acquire information from Day $t - 1$ and accumulate knowledge about the transportation system. For instance, when an autonomous vehicle is introduced to a household in a future year, members of the household will respond and rearrange their trips. Seniors and juveniles who previously rely on non-auto modes now may consider riding the vehicle. Working adults may need to readjust departure time to accommodate foreseeable increasing vehicle usage. These changes to each agent are modeled and outcomes are fed into DTALite to simulate dynamic traffic conditions, based on which agents will adapt their behaviors again on the Day $t + 1$.
- **Within-Day Integration.** In the same day t , information is conveyed between AgBM and DTALite. Real-time information on congestion and different non-recurrent incidents has been made available to a certain percentage of agents, which reflects the fact that ATIS subscribers and Google/INRIX users have the access to timely estimates of traffic congestion. This type of information

exchange would trigger dynamic behavior adaptation. En-route diversion is a likely reaction and is incorporated in this integration. Future study may also internalize dynamic modal shifts (park-and-ride options along major freeways, ride-sharing, etc.).

The proposed integration is tested in a real-world case study using a mid-size transportation network. The study area is the White Flint region in the Montgomery County, Maryland. Mixed land development and transit-oriented development are on-going in White Flint, reshaping a dense and multi-functional urban region. Multiple bus lines and the Metro of Washington D.C. also serve the area. The transportation network is illustrated in Fig. 5.2. 24 traffic analysis zones, 55 roadway links, and 136 nodes are included in this network. A total number of 40,140 traveling agents are generated to represent travel demand pattern in the morning peak hours in a typical work day.

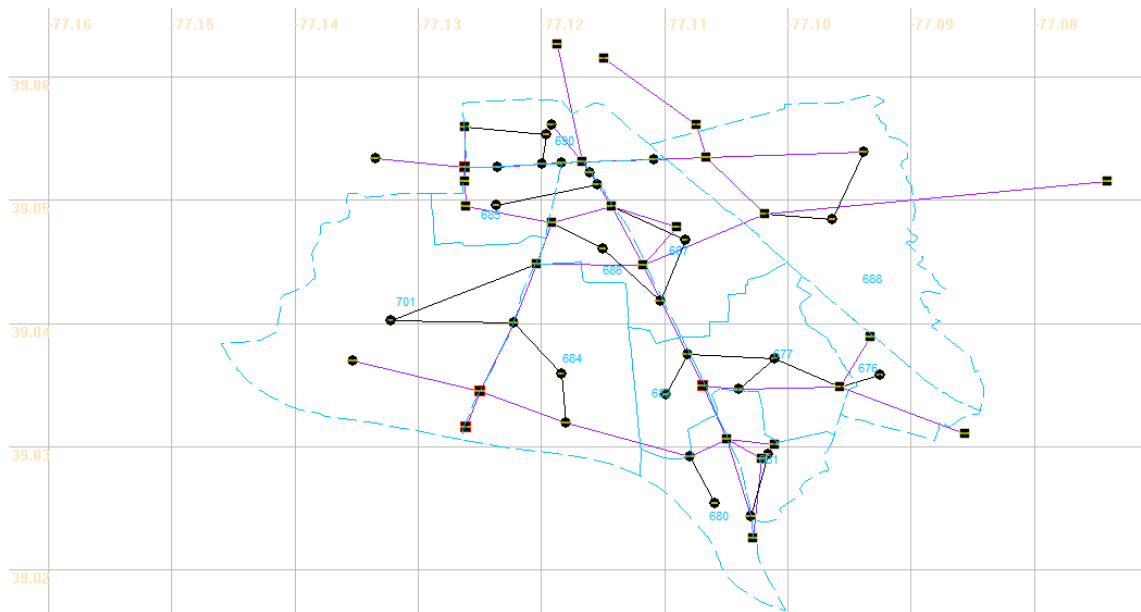
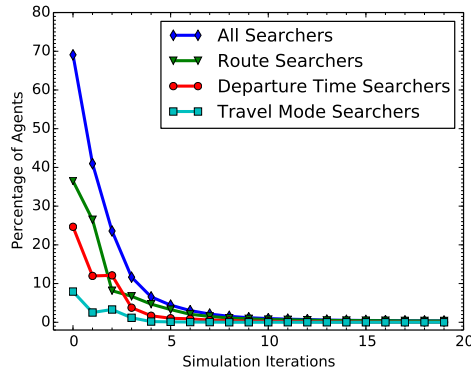
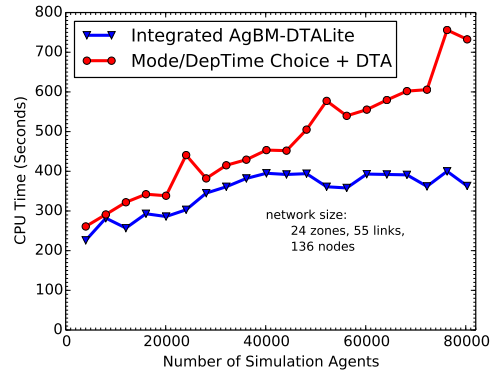


Figure 5.2: AgBM-DTALite Study Area: White Flint

If running a typical DTA using this network and demand files, the dynamic user equilibrium cannot be achieved within 50 iterations. In fact, the larger size the network, the much greater number of iterations it requires to reach DTA convergence. Based on the proposed AgBM, another equilibrium, Behavioral User Equilibrium (BUE), has been defined in this research as the situation where all agents stop making behavioral adjustments. Initially, travelers will follow their travel option that yields the lowest generalized cost. Congestion during the a.m. peak hours results in the discrepancy between the expected and realized travel conditions. And thus over 70% of travelers decide to search, learn and adapt to the network by adjusting modes, departure times, and/or routes. Among these travelers, more than half are searching routes. As time goes by, agents reach satisfaction either because a more promising travel alternative has been identified or because of the decreasing expectation on travel condition after excessive searching. Therefore, the number of searchers decreases, as shown in Fig. 5.3a. After ten iterations, only a very small amount of users are still actively searching for alternatives. The integrated model reaches convergence after twenty simulation iterations. Defined by the bounded rationality, BUE convergence is guaranteed regardless the size of the network and the scale of the study.



(a) The Convergence of the Integrated AgBM-DTALite (Number of Searchers on Different Behavioral Dimensions)



(b) The Comparison of Computational CPU Time (in seconds) between AgBM-DTALite and DTA with Mode and Departure Time Choices

Figure 5.3: The Convergence and Computational Properties of the Integrated AgBM-DTALite Model

Other than the behavioral foundation and the convergence property, another merit of the proposed AgBM-DTALite lies in its superior computational efficiency when compared to typical disaggregated travel demand models. Two unique characteristics of the integrated model ensure the promising computational performance:

- Without the time-consuming log-sum calculation, learning, searching and decision rules can be executed within relatively shorter CPU time.
- BUE changes the way of defining relative gaps and thereby reduces the number of simulation iterations.

Importantly, the second characteristic does not differ with respect to the size or the scale of the system. Unlike DTA models that have exponentially increasing number of alternative paths w.r.t. network size, AgBM-DTALite assumes agents neither

have the capability nor are willing to consider every alternative. BUE only relies on each individual's travel experience and information gathered to determine the starting and stopping of each search. Thus, it is believed that AgBM-DTALite can maintain its computing performance even if applied to a very large-scale transportation analysis. In Fig. 5.3b, the computing CPU time of AgBM-DTALite and that of discrete-choice-DTA travel demand models are compared. Twenty scenarios with varying number of simulation agents are analyzed on a PC with 2.33GHz CPU and 16 GB RAM. Again, the White-Flint project is employed as the study area. The network is kept the same while the number of agents vary from 10% to 200% of the total demand. The results corroborate that the simulation time remains manageable when the number of agents increases from 0 to 200%.

5.2 Corridor Active Management and Behavior

5.2.1 Implementation Framework

The framework of modeling agents' en-route diversion behavior under information provision is illustrated in Fig. 5.4.

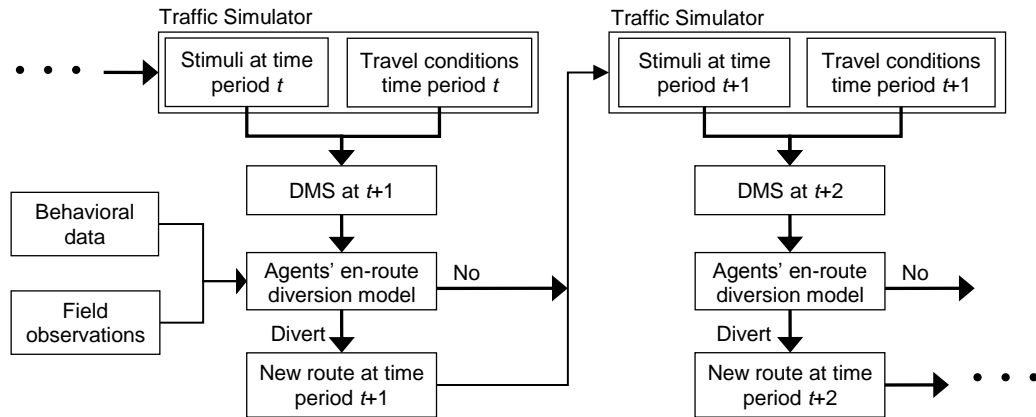


Figure 5.4: Structure of agent-based en-route diversion model [142]

Routinely, travelers form a relatively stable travel pattern and route choice, especially for their daily commute travels. A user equilibrium condition well represents this situation. When en-route traffic conditions change at time period t due to, for instance, recurrent/non-recurrent congestion, incidents, and work zones, stimuli for the agents to make en-route behavior changes, as well as the stimuli for the operations strategy makers to encourage diversion, becomes more significant. Various ATIS strategies can be employed here to provide real-time traffic information. DMS is the one typically seen in Maryland and is thus chosen here for a demonstration purpose. The real-time information is updated dynamically. The travel conditions at time t for both the congested route and the diverting route will be displayed on the DMS platform during the period $t + 1$. While the response to DMS can be modeled by a myriad of methods, we employ an innovative Bayesian approach to empirically model and re-calibrate the agents' en-route diversion by using behavior data collected from the driving simulator and field observations col-

lected by Bluetooth sensors deployed at two real-world diversion scenarios. This agent-based model predicts the diversion decision for each individual simulated in the model. Then the agent behavior is aggregated and fed back into the network traffic simulator to obtain the traffic conditions for the next time period. The use of simulation modeling allows examination of the agents' en-route diversion under real or simulated ATIS scenarios. The process will be operational according to a predefined DMS functioning duration. In future work, the functioning duration of DMS can be optimized through a simulation-based optimization approach.

Agents' en-route diversion behavior is modeled from these two aspects: (1) the Naive Bayes model is employed to represent behavioral rules; (2) The Bayesian calibration is employed to re-calibrate the model based on local observations.

5.2.2 Calibrating the Behavioral Rules Using Field Observations

Agents' behavioral rules are represented by the Naive Bayes model developed in [143]. This method is based on the more general Bayes' Rule and data mining techniques, which is believed to embed more reasonable behavioral foundation without assuming random utility maximization. Employing stated preference data collected from carefully designed driving simulator scenarios, drivers' diversion decision has been denoted as two agent classes, being the divert class and the not-divert class. A tuple of stochastic attributes (F_1, F_2, \dots, F_n) affects the classification variable denoted by C , including travel time ($Time$) and travel time unreliability (UNR) of the normal route and the diverting route, travelers' gender ($Gender$), and

diverting risk (*Risk*). *UNR* is specified as the 95% confidence interval of the travel time duration. *Risk* is a dummy variable reflecting the complexity (or risk) of the diverting route. If the diverting route involves bifurcation and possible huge delay, even if theoretically the drivers can make the correct en-route decision to avoid the delay penalty with the guidance of the real-time information at the DMS, drivers are less likely to divert. This type of diverting routes is considered as a diversion of high risk.

For each training observation F , the naive Bayesian classifier is a function that assigns a class label to it. This method learns the conditional probability of each variable F_i given the class C . According to Bayes' Rule, the probability of the example $\mathbf{F} = (F_1, F_2, \dots, F_n)$ being not-diverting class (denoted by $+$) is:

$$p(+|\mathbf{F}) = \frac{p(+)p(\mathbf{F}|+)}{p(\mathbf{F})} \quad (5.1)$$

For a training observation, naive Bayes classifier assumes conditional independence of every other attributes given the value of the classification variable. Equation 5.2 shows the functional form of naive Bayes classifier. The empirical observation is classified as $+$ if and only if $f_{nb}(\mathbf{F}) \geq 1$.

$$f_{nb}(\mathbf{F}) = \frac{p(+)p(\mathbf{F}|+)}{p(-)p(\mathbf{F}|-)} = \frac{p(+)}{p(-)} \prod_{i=1}^n \frac{p(F_i|+)}{p(F_i|-)} \quad (5.2)$$

The estimated naive Bayes model using the SP data as the full training dataset is revisited here in Table 5.1. These conditional priors $p(F_i|C)$ can be used to calculate the classifier (Equation 5.2) and thus constitute the agent behavioral rules.

Table 5.1: En-Route Diversion Model’s Conditional Prior Probability Estimates

Class Model:	Not Divert		Divert	
Variables	Conditional Priors	Mean (Std. Dev.)	Conditional Priors	Mean (Std. Dev.)
Class Prior	$p(+)$	0.53	$p(-)$	0.47
<i>Gender</i> = male	$p(\text{male} +)$	0.403	$p(\text{male} -)$	0.532
<i>Gender</i> = female	$p(\text{female} +)$	0.597	$p(\text{female} -)$	0.468
<i>Risk</i> = low	$p(\text{low} +)$	0.504	$p(\text{low} -)$	0.548
<i>Risk</i> = high	$p(\text{high} +)$	0.496	$p(\text{high} -)$	0.452
$\Delta Time$	$p(\Delta Time +)$	0.022 (0.262)	$p(\Delta Time -)$	-0.163 (0.066)
ΔUNR	$p(\Delta UNR +)$	0.452 (0.242)	$p(\Delta UNR -)$	0.304 (0.270)

In the model, Δ denotes percentage changes of the alternative route’s attributes from the attributes of the routine route. The high class prior for divert class (almost as high as the class prior for not divert class) indicates that the likelihood of diversion from the routine route has been positively affected by certain factors, e.g. the provision of travel time information. Conditioned on the divert class, the probability estimates of $\Delta Time$ suggests that lower expected travel time is one major incentive that shifts individuals off their routine routes. On the other hand, the probability estimates of $\Delta Time$ conditioned on not-divert class has mean value that is close to zero and has a relatively larger standard deviation. It indicates that not-divert class is almost indifferent to expected travel time. While generally being risk averse (i.e. positive and higher value for $p(\Delta UNR|+)$), individuals take risk to some extent when making en-route diversion ($p(\Delta UNR|-)$ has positive mean). The estimates on discrete variables (i.e. *Gender* and *Risk*) suggest that male drivers and drivers in lower-risk diversion situations are more likely to divert. These empirical findings conform to previous research [94, 74].

From the estimated class priors (0.53 for not-divert class v.s. 0.47 for divert class), one can draw the conclusion that individuals (in the driving simulator, of course) are almost indifferent between their routine route and the alternative one, given other conditions equal. However, this may be greatly different in real-world cases [83]. Drivers may react differently when actually provided with real-time information. Drivers may have a greater preference towards their routines due to the inertia. Before applying the agent-based model to evaluate any real-world cases, a recalibration process is necessary. A separate field observation data source collected from Bluetooth detectors deployed in a real-world DMS scenario in Maryland is employed here as calibration evidences. Fig. 5.5 illustrates the scenario. Bluetooth detectors are deployed to penetrate vehicles in routine traffic flow and re-routing flow (denoted as the red arrows) during normal traffic conditions as well as the periods whence an incident occurs. If an incident is identified, DMS in the upstream will be functioning and displaying dynamic information about travel times and travel time ranges for the routine route and the alternative route. The Bluetooth detectors actively collect data for two weeks and thus can penetrate sufficient vehicles that are repeatedly using the routes. And the vehicles captured during incidents are identified as the real-world agents who are making diversion choices. Let us denote the vector of these data points as \mathbf{E} .

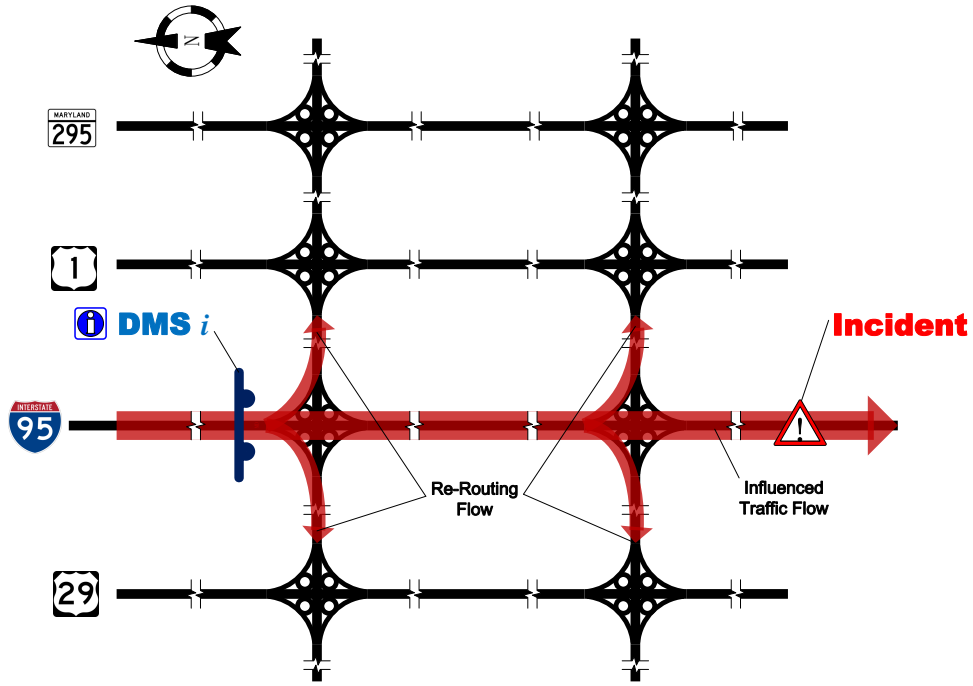
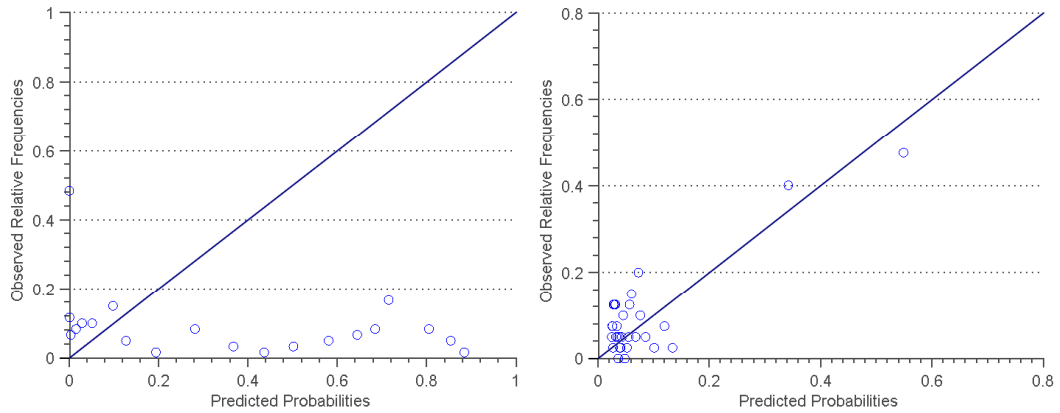


Figure 5.5: Mesoscopic traffic simulation network

The recalibration process employed here is developed by [143]. It offers a mapping from the real-world behavioral data to a set of more accurate behavioral rules. By directly applying the uncalibrated Naive Bayes model to \mathbf{E} , one can predict divert probabilities ranging on $[0, 1]$. If we translate the probabilities using log-odds: $s(\mathbf{E}) = \log(p(+|\mathbf{E})) - \log(p(-|\mathbf{E}))$, this measurement can range on a space $[-\infty, +\infty]$. Thus, we can model the probability density function (PDF) of the prediction score $s(\mathbf{E})$ (conditioned on the actually observed class) as a function of the log-odd score. This PDF $p(s|class = \{+, -\})$ is then applied as the recalibration function and plugged into Equation 5.4 using Bayes' Rule and the class priors.

$$p(+|s) = \frac{p(+)p(s|+)}{\sum_{C=\{+,-\}} p(C) \cdot p(s|C)} \quad (5.3)$$

More details of this Bayesian calibration method is given in [143]. Applying this method to analyze the actual observations \mathbf{E} , we can correct the dramatically higher diversion propensity predicted by the uncalibrated model and match the predictions to the low diversion rate. In Fig. 5.6a we show the reliability diagram estimated for the en-route diversion calibration dataset. The x-axis shows the predicted probability of the naive Bayesian classifier for the divert class. The y-axis shows the empirically observed relative frequency of the divert class. If the classifier is well-calibrated, all points should coincide with the diagonal line, which indicates that the predicted diverting probability are equal to the empirical probability. The model's prediction is too optimistic, predicting diversion probabilities that are too close to 1. In actuality, the diversion percentage is much lower than the estimated value. After performing the calibration, the reliability diagram is illustrated in Fig. 5.6b. The Bayesian calibration successfully readjusts the model prediction to match the low diversion rate observed by the Bluetooth detectors. As shown in Fig. 5.6b, most of the predicted probabilities are in line with the observed relative frequencies.



(a) Reliability diagram for the uncalibrated Naive Bayes en-route diversion model (b) Reliability diagram for the calibrated Naive Bayes en-route diversion model

Figure 5.6: Reliability diagrams for the behavioral model calibration

This section has revisited the Naive Bayes model of en-route diversion and its Bayesian calibration approach. This set of models is then applied to predict agent behavior based on empirical observations collected from real-world Bluetooth sensors. The behavioral model departs from the utility-based models in the way that it employs Naive Bayes rules to predict behavior. The calibration approach is a practical and powerful tool to take the advantage of any types of real-world diversion data. Data sources that are as aggregate as diversion rates or as microscopic as individual-level Bluetooth/GPS/Smartphone data can provide useful prior information for this approach to produce more accurate posterior probabilities. This approach is a consistent and theoretically sound parametric method to model agents' en-route diversion behavior. It is flexible and thus can be easily transferred to other study areas to analyze diversion-related operations and management strategies, such as ATIS, DMS, the provision of real-time information, etc. It has

the practical value that researchers and practitioners may potentially apply the en-route diversion model to other regions based on recalibration using locally collected field observations. This unique advantage is demonstrated in this paper through the construction of an integrated agent-based simulation model. The traffic simulator, network performance measures, and the integrated modeling outcomes are presented in the following sections.

5.2.3 Simulation Model and Network Performance

5.2.3.1 Mesoscopic traffic simulation model

To test the effectiveness of applying agents' en-route diversion model to improve transportation system performance, a case study of an assumed incident scenario during extended a.m. peak hours in Maryland and D.C. metropolitan area has been conducted. A mesoscopic traffic simulation model DynusT for the regional network is developed as the evaluation tool of system performance. The network includes around 2000 links, 500 nodes, over 300 signalized intersections, 201 TAZ, three major freeway corridors, and one tolling highway (denoted as the light blue corridor in Fig. 5.7). DynusT is a simulation based DTA model, which takes account of the dynamic interaction between network supply and user demand. As one of the latest DTA, DynusT is chosen as the simulator for the current study. It simulates individual vehicle's movement based on a mesoscopic traffic simulation model, Anisotropic Mesoscopic Simulation (AMS), which reveals its agent-based nature [33]. Moreover, as DynusT is capable of simulating each individual vehicle,

it is suitable to be integrated with agent-based behavior model to evaluate system performance more comprehensively.

The baseline scenario represents the original demand pattern and user equilibrium (UE) condition, which is calibrated using D.C. regional demand model's extended morning peak (5:00 a.m. to 10:00 a.m.) origin-destination (OD) demand as the base matrices and over 60 traffic count stations as calibration evidence. The calibration is documented in [153].

The incident (denoted as the red triangle in Fig. 5.7) is assumed to occur at 5:30 a.m. and last until 6:30 a.m. on a major commuting corridor, I-95 South Bound (SB), between Washington D.C. and Baltimore. In the incident scenario, simulated agents are not provided real-time information. In the diversion scenario, four DMS devices (denoted by the four blue rectangles along the freeway corridor in Fig. 5.7) deployed on the upstream links are assumed to be responsive to the incident. Incident message, travel time and travel time range on I-95, and the corresponding travel condition on the alternative corridor (US-29) are displayed to agents. The DMS devices are assumed to be active between 5:30 a.m. and 7:30 a.m. (one hour after the clearance of the incident). Real-time information is updated in each time period based on time-varying link travel time retrieved from the AMS model [33]. AMS is a vehicle-based mesoscopic traffic simulation approach that explicitly considers the anisotropic property of traffic flow into the vehicle state update at each simulation period. In Section 5, the incident scenario without real-time information provision and the incident scenario considering en-route diversion under ATIS are quantitatively compared using various performance measures. In

particular, MFD, defined in Section 4.2, is employed to investigate the before-and-after performance of the I-95 SB corridor links.

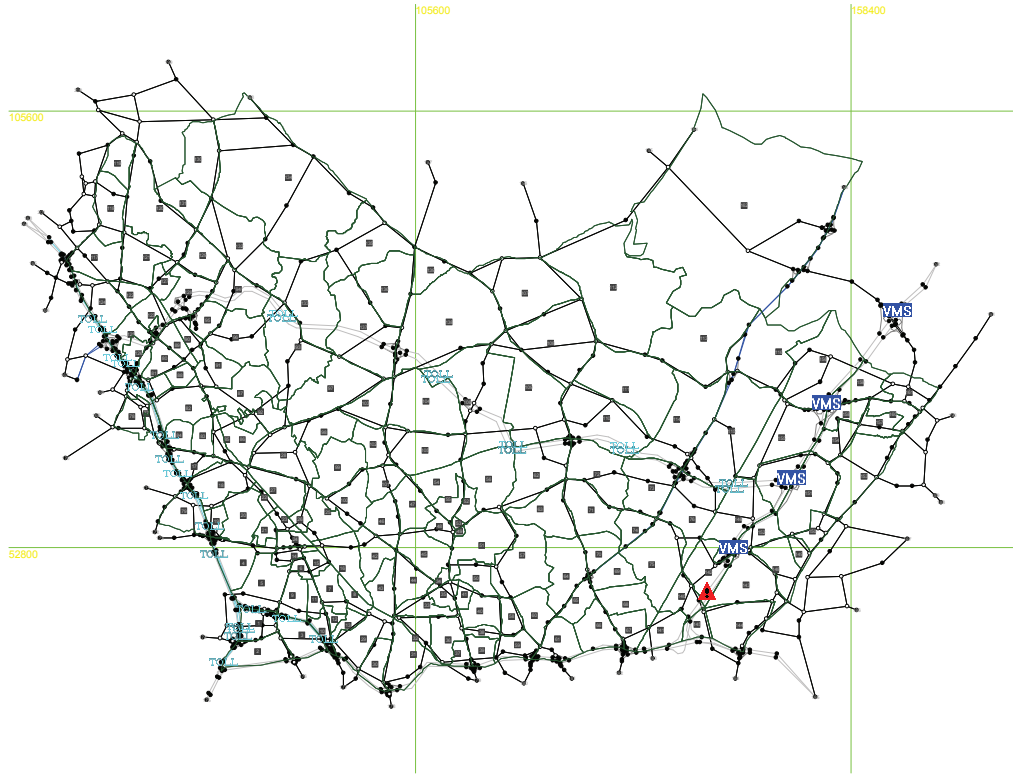


Figure 5.7: Mesoscopic traffic simulation network

5.2.3.2 Network performance: macroscopic fundamental diagram (MFD)

To implement the macroscopic traffic analysis on the corridor level, we may investigate the relationship of the accumulation of vehicles in a network with the exit outflows, and the equivalent relationship of the network-wide weighted average density and flow rate.

We have:

$$N_t = \sum_{a \in \mathbb{A}} k_{a,t} l_a \lambda_a \quad (5.4)$$

where N_t is the time varying number of vehicles in a network denoted by \mathbb{A} , each individual link is $a \in \mathbb{A}$; $k_{a,t}$ denotes the traffic density of link a at time t ; l_a and λ_a denote the length and the number of lanes of link a .

$$K_t = \frac{N_t}{L} = \frac{\sum_{a \in \mathbb{A}} k_{a,t} l_a \lambda_a}{\sum_{a \in \mathbb{A}} l_a \lambda_a} \quad (5.5)$$

where K_t is the space mean density (vehicle per mile per lane) at time t , L is the total length (lane-miles) of the network. Analogously, we have Eq. 5.6.

$$Q_t = \frac{\sum_{a \in \mathbb{A}} q_{a,t} l_a \lambda_a}{\sum_{a \in \mathbb{A}} l_a \lambda_a} \quad (5.6)$$

where Q_t is the space mean flow rate (vehicle per hour per lane) of the network, $q_{a,t}$ is the traffic flow rate of link a at time t . Both empirical observations [52] and dynamic traffic assignment experiments on a real large-scale urban network [92] concluded that Q_t was robust linear with the trip completion rate that was the sum of finished and exiting trips for the whole network. The network-wide weighted average speed is given by:

$$V_t = \frac{\sum_{a \in \mathbb{A}} v_{a,t} k_{a,t} l_a \lambda_a}{\sum_{a \in \mathbb{A}} k_{a,t} l_a \lambda_a} \quad (5.7)$$

where the weighted quantity is the number of vehicles on an arbitrary link a at time t .

According to the traffic variables relationship in the MFD, as well as Equations (5.4–5.7), the network average speed is estimated by:

$$V_t = \frac{Q_t}{K_t} \quad (5.8)$$

The spatial standard deviation of densities in the network is formulated by:

$$\sigma_t = \sqrt{\frac{\sum_{a \in \mathbb{A}} l_a \lambda_a (k_{a,t} - K_t)^2}{\sum_{a \in \mathbb{A}} l_a \lambda_a}} \quad (5.9)$$

5.2.4 Integrated Agent-Based Simulation and Results

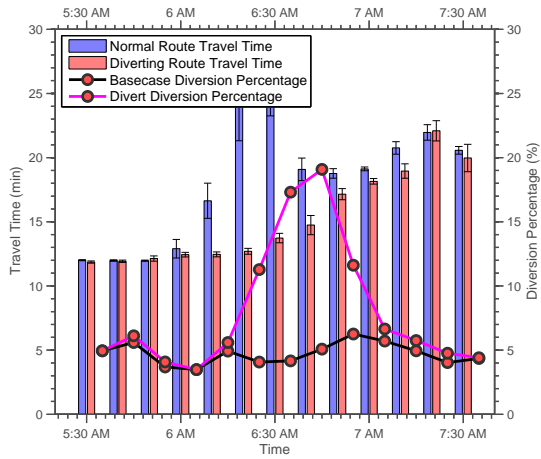
5.2.4.1 Agent-based en-route diversion response

In this section, the empirically estimated and calibrated en-route diversion model is integrated with DynusT network model and MFD post-processing analysis. Agents commuting into the D.C. area via I-95 corridor are diverted at the four active DMS points deployed along that corridor. During each time period, the travel conditions of the previous time period on the incident route and the alternative route are provided to the simulated agents for them to make an en-route diversion decision.

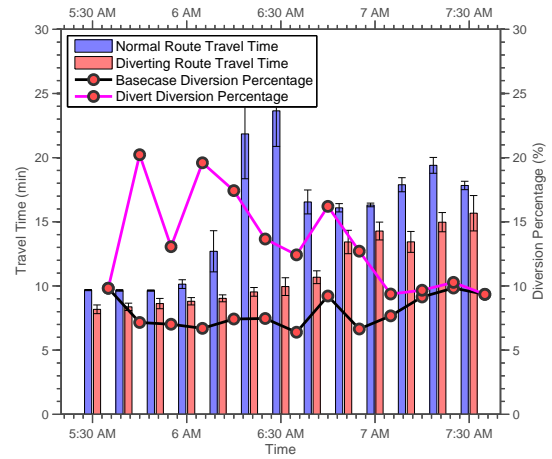
Agents' diversion behavior response to the assumed incident and DMS scenario is predicted using the behavior model. The complete agent decisions are aggregated and the diversion percentage at each diverting point is dynamically provided to the DynusT model wherein the diversion scenario is simulated. In order to reflect the dynamic nature of this operational applications while retaining the simulation in a manageable computational time, the time period length is set to be 10 minutes. Fig. 5.8a, 5.8b, 5.8c, and 5.8d illustrate, by DMS points, the integration results of

the time-varying travel time (the bar charts) and travel time range (error bars) on the normal route and the diverting route, as well as the agents' aggregated diversion percentage for each time period and each DMS points. The DMS devices are active between 5:30 a.m. and 7:30 a.m. to provide real-time information. The results indicate that the integrated model well captures the agents' behavior response dynamically and at different upstream diverting points. During the incident duration, significant diversion is predicted to happen, especially at DMS 1 and DMS 3. Over 20% agents divert between 5:50 a.m. and 6 a.m. in response to the higher congestion on the normal route (I-95 SB). The aggregate diversion percentage is highly fluctuating, as the road traffic evolves dynamically and a higher diversion percentage during one period is likely to improve the traffic condition on the normal route and thereby results in a relatively lower diversion percentage for the next time period. It is worth noting that the travel time reliability also plays an important role in en-route diversion, since DMS typically displays travel time range. If the diverting route's travel time is more uncertain, risk-averse agents are less likely to divert and the integrated model yields a lower diversion percentage.

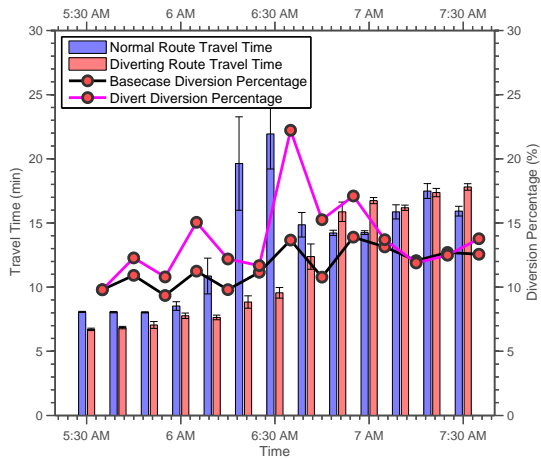
On the network level, the proposed model predicts that over all simulated agents, the average travel time per trip increases from 16.30 minutes in the base-case scenario to 17.83 minutes (8.1% increase) in the incident scenario, since agents traveling southbound on I-95 during the incident duration will encounter severe congestion. The provision of real-time information and en-route diversion can effectively mitigate the network-wide average travel time to 17.07 minutes. More detailed performance measures for the I-95 SB corridor, including time-space diagrams and



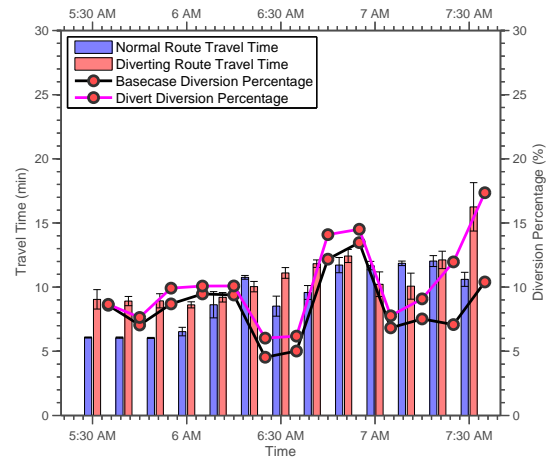
(a) Agent diversion at DMS 1 (the northmost)



(b) Agent diversion at DMS 2



(c) Agent diversion at DMS 3



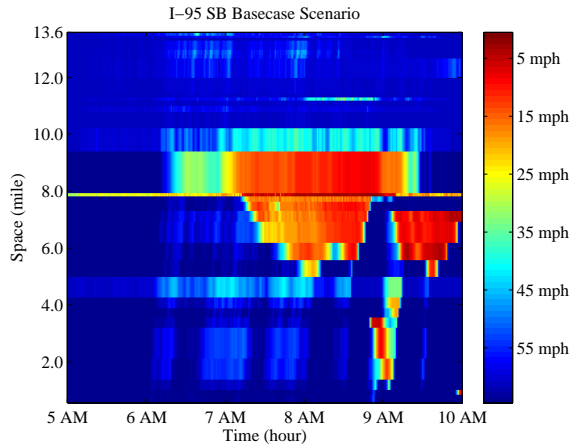
(d) Agent diversion at DMS 4

Figure 5.8: Travel time and travel time variance for normal route and diverting route and the agents' diversion percentages for the Basecase and the Divert Scenarios

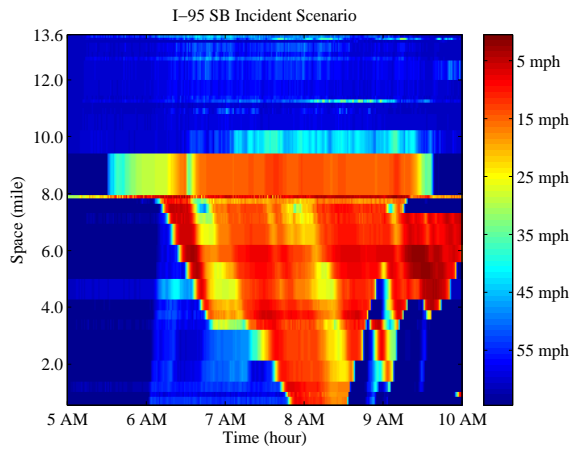
macroscopic fundamental diagrams, are presented in the next subsection.

5.2.5 Network performance results

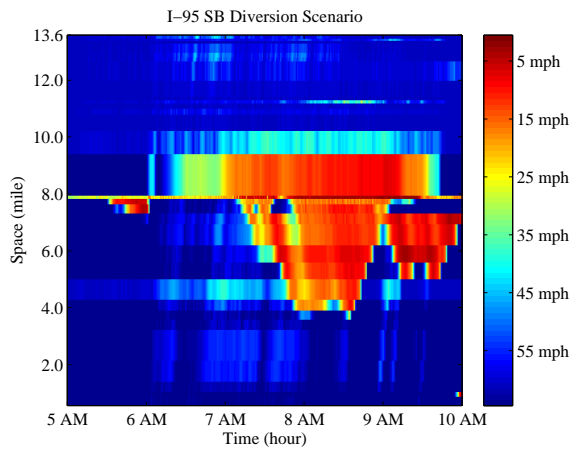
Fig. 5.9 shows the average speeds across all lanes of I-95 SB for each 1-minute interval in the time-space plot. The warmer shades indicate lower speeds and more congested traffic flows, while the cooler shades represent higher speeds and free-flow



(a) I-95 SB Baseline Scenario



(b) I-95 SB Incident Scenario



(c) I-95 SB Diversion Scenario

Figure 5.9: Comparison of time-space diagrams of I-95 SB

states.

Fig. 5.9a shows the southbound traffic flow evolutions on a 13.6-mile highway segment wherein the four DMS are implemented (see the detailed layout in Fig. 5.5 and 5.7). The period analyzed is the morning peak hours under the baseline scenario. The segment of mileposts 8.0 mile through 9.5 mile formed a traffic bottleneck that triggered a heavy congestion at around 7 a.m.. The traffic jam propagated upstream to the location of 5.0 mile. Till 9:15 a.m., the downstream queues began to dissipate and subsequently regained the free flow speed. It is worthy to point out that a local congestion state was formed at the location of 7.5 mile and continued to the end the simulation time. This was caused by an increasing on-ramp demands merging into the I-95 SB mainline. Fig. 5.9b shows the mainline heavy congestion caused by the downstream incident that lasted from 5:30 a.m. through 8:30 a.m.. In the scenario without any en-route information provision, the serious incident occurring in the 8.0–9.5-mile bottleneck reduced the highway capacity by 50% and induced a spill-over congestion propagating to the most upstream of the study highway segment. Distinguishing with the baseline scenario, the incident induced jam queue propagated backwards in a faster speed indicated by the larger slope during 6 a.m. through 6:45 a.m. from the mileposts 8.0 mile to 3.5 mile. It was also found that the speeds suddenly dropped from the approximate free-flow speed of 55 mph to the oscillating speed between 5 mph and 20 mph at the beginning of the incident occurrence. Though the congestion dissipated at around 9:30 a.m. in the bottleneck, a two-mile length of congested queue was still present at the end of the simulation, i.e. 10 a.m. The spatial impact length of the incident was larger than 9.5 miles in the study corridor, and the duration of congested states was as long as 4 hours.

Fig. 5.9c shows the effect of the en-route diversion scenario on the congestion mitigation, which reduced the incident-induced delays. Both the spatial and temporal impacts of the incident were significantly decreased by the en-route diversion and information provision. Compared with Fig. 5.9b, the spatial impact length of the incident was 6.0 miles in the study corridor, and the duration of congested states was 3 hours. In addition, drivers' diversion behaviors also smoothed the transition from the free-flow state to the congested state for the segment of 3.5 mile through 8.0 mile. The speed breakdowns were relieved and the jam propagation was slowed down, e.g. the propagating time period was from 7 AM to 8 AM which is longer than 45 min shown in Fig. 5.9b.

Numerous studies in the literature have verified the existence of MFD using both field measurements and simulated traffic data [52, 53, 54, 119, 120]. In a freeway network, if traffic is distributed heterogeneously, characteristics with regard to the hysteresis and capacity drop phenomena could be observed. In this study, we plot the 1-minute interval space mean flow rate versus the space mean density and the space mean speed vs. the space mean density for the corridor I-95 SB that includes 35 links in the simulation model, as presented in Fig. 5.10a and Fig. 5.10c, respectively.

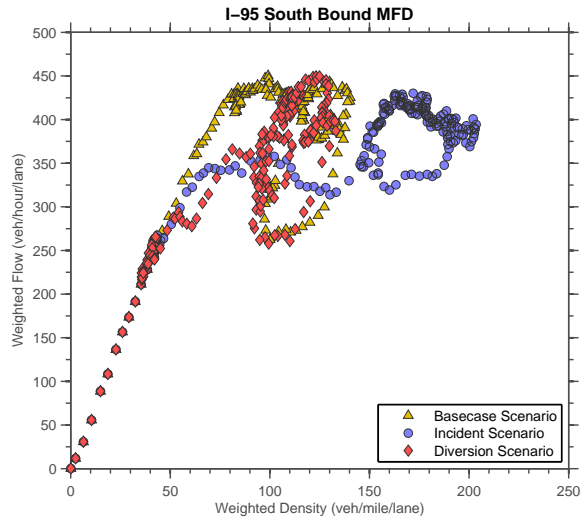
It can be seen that the MFDs of three scenarios exhibit smooth curves when the weighed density is low, which satisfies homogeneity conditions. It is observed from Fig. 5.10a that a sudden transition point exists in the incident scenario when the weighted average density reaches 40 veh/mile/lane. Compared with the baseline scenario and the en-route diversion information provision scenario, the weighted

average flow rate of the incident scenario decreases approximate 100 veh/hour/lane given the same weighted average densities in the range of 40–85 veh/mile/lane before the corridor reaches its capacity of 450 veh/hour/lane. In the free-flow regime of the MFD, the diversion scenario clearly prevents the network flow rate from a sudden declining due to the incident. In the congested regime of the MFD, scattering features can be observed for the three scenarios because the spatial density heterogeneity increases. No consistent well-defined relationship appears to exist due to the hysteresis phenomena, which indicate that the weighted average flow rate is higher during the travel demand loading period compared to the recovery period. Though the hysteresis loops do not follow a consistent pattern for different scenarios, we can still observe that the weighted densities are successfully reduced when the en-route information is available after the incident. More importantly, the MFDs of the baseline and diversion scenarios are more likely to exhibit a consistent pattern, maintaining the similar critical weighted average density which, however, does not clearly exist in the incident scenario. More detailed MFDs for different time periods is shown in Fig. 5.10b.

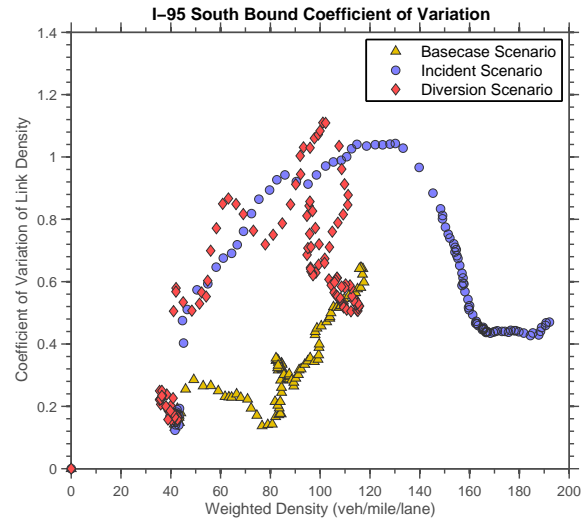
Alternatively, we can plot the vehicle accumulation (the number of vehicles in the corridor at each time step) vs. outputs (the hourly rate of exiting flows from the corridor, including all off-ramp flows and the mainline flow of the end link in the corridor) using 1-minute interval statistics. Fig. 5.10c analogously shows that the baseline and diversion scenarios exhibit a consistent MFD pattern, the slight difference exists in the scattering regime where the diversion scenario performs a little higher weighted density when the corridor is in the most congested state. However,

the incident MFD does not show an obvious two-regime feature as the existing flow rate declines after the vehicle accumulation exceeds 3,000. Its maximum weighted average density is much larger than other two scenarios.

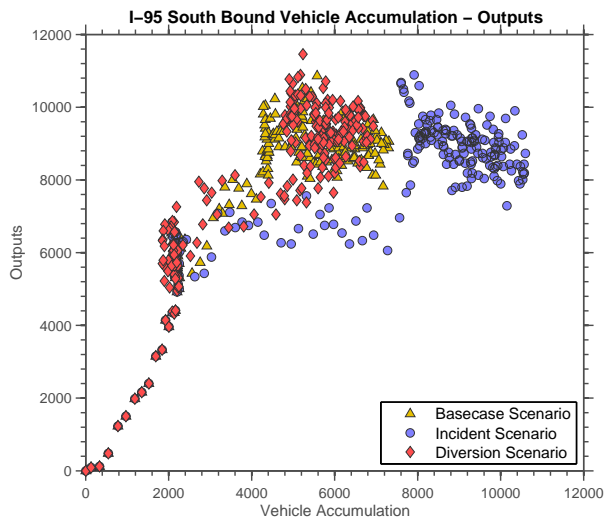
Fig. 5.10d shows the speed-based MFDs. The corridor-wide average speeds are consistent and closely predicted. The en-route diversion prevents the weighted average speed from decreasing below 40 mph, while the incident scenario suffers a weighted average speed as low as 35 mph (the corresponding maximum density reaches 190 veh/mile/lane). The information provision and en-route diversion benefits to maintain a higher level-of-service and lower density of the whole corridor after the incident.



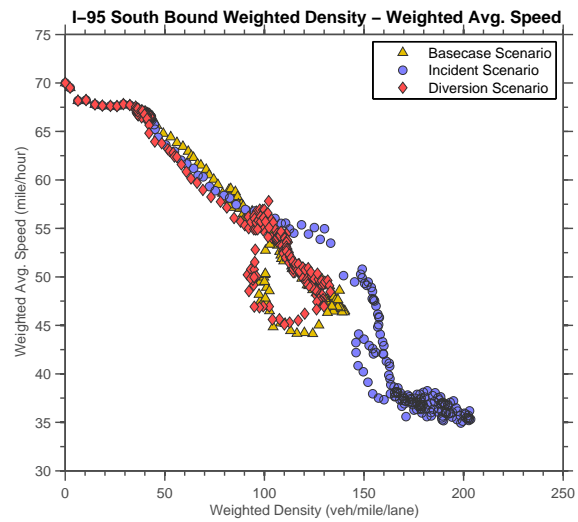
(a) Weighted Density Weighted Avg. Flow



(b) Coefficient of Variation



(c) Vehicle Accumulation Outputs



(d) Weighted Density Weighted Avg. Speed

Figure 5.10: Macroscopic Fundamental Diagrams of three scenarios

5.2.6 Summary

The objective of this paper has been to study the en-route diversion responses of agents under real-time information and to quantitatively analyze their impact on the network performance. In order to achieve this objective, a naive Bayes classifier is developed for this binary en-route diversion decision (i.e. switch to the diverting route or stay on the normal route). Stated preference data collected from driving simulator scenarios have been employed in the model estimation. Bluetooth-based field observations have been employed in the model re-calibration. This behavior model is then integrated with network model and simulation analysis. A real-world large-scale mesoscopic traffic simulation model coupled with simulation-based dynamic traffic assignment has been developed to simulate dynamic traffic conditions and reveal interesting traffic dynamics.

The first contribution of this paper lies in the originality and completeness of the proposed modeling framework. The demonstrated naive Bayes classifier serves as an effective alternative to the typical discrete choice models. This computational process model predicts agent behavior probabilities, which is highly efficient when millions of agents are simulated in the system. The model's operational application also represents a first attempt to link agents' en-route diversion behavior with large-scale network model. The proposed framework is comprehensive. It models the agent behavior, calibrates the model, simulate network conditions, dynamically applies the behavior model, deploys the diversion strategy in the simulation, and obtains various performance measures.

This paper also remains as a first research effort that uses MFD measurements to quantitatively evaluate the integration of information provision and en-route diversion in an assumed corridor incident scenario. The MFD of the studied corridor has confirmed that agents' en-route diversion has an impact on network throughput, average flow, average speed, and average density. Most importantly, the MFDs of the baseline and diversion scenarios exhibit a consistent pattern, maintaining the similar critical weighted average density. Compared to the incident (without real-time information and diversion) scenario, the diversion scenario shows fewer drops and recoveries in the average flow. This is an important finding. Without real-time information provision, an incident has the potential to make the network much more vulnerable and suffering from severe breakdown. En-route diversion, though in a low level of diversion percentage, can help avoid the breakdown and maintain a consistent traffic pattern to the corridor's normal traffic pattern.

As demonstrated in this paper, the agents' en-route diversion model is easy to be estimated and applied in computational processes and agent-based simulation. The model is transferable by applying calibration functions to available ground truth data. The proposed framework is operational and can be applied in operations analysis (e.g. to evaluate ATIS strategies) and demand models (e.g. to indicate more realistic en-route diversion behaviors). This approach meets the imperative needs in modeling en-route diversion and real-time information provision in demand modeling and operational applications, especially when most commuting corridors in contemporary metropolitan areas get increasingly congested and ATIS, such as DMS, becomes readily available.

5.3 Integrated Corridor Planning and Operational Optimization

This dissertation propose to develop a new surrogate approach for system optimization based on the proposed behaviorally-rich agent-based simulation models and mathematical optimization principles. It incorporates a Bayesian stochastic Kriging metamodel to optimize integrated Active Traffic Management (ATM) for corridors utilizing a simulation-based dynamic traffic assignment model. The new approach's merits include to (I) jointly optimize decisions that traditionally cannot be considered separately due to limitation of theory and tools, by producing a continuously updating sequence of approximations to the stochastic objective function as surrogates for optimization; (II) account for model uncertainties and their induced heteroscedasticity errors given different design strategies. As an application illustration of a freeway work zone, we jointly optimize high-occupancy/toll (HOT) rates [26] and freeway diversion rates [32] under the congestion warning information via dynamic message signs (DMS), to achieve minimization of the network-wide average trip travel time.

The study freeway/arterial corridor is along a 15.50-mile freeway segment of I-270. The left lane on each side is used as a high-occupancy vehicle (HOV) lane in the northbound direction between 15:30 and 18:30 and in the southbound direction between 6:00 AM and 9:00 AM. The network includes 61 traffic analysis zones, 435 nodes and 766 links; see Fig. 5.11. Three modals of dynamic OD matrices, i.e. single-occupancy vehicles (SOV), HOV and trucks, were estimated based on demand data from the regional planning model [153]. Field collections of urban street signal

timing are also included in the network.

The optimization problem is

$$\min_{\mathbf{x} \in \mathbb{R}^3} \mathbb{E}[f(\mathbf{x})] = \mathbb{E}[f(x_1, x_2, x_3)] \quad (5.10)$$

$$\text{s.t. } \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{x}_{\max} \quad (5.11)$$

where $f(\mathbf{x})$ represents the unknown true average trip travel time given an input \mathbf{x} , x_1 is the HOT toll rate, x_2 is the diversion rate of the DMS next to the work zone, x_3 is the diversion rate of the DMS at the off-ramp to MD 187. The box constraints are $\mathbf{x}_{\min} = [0, 0, 0]^T$ and $\mathbf{x}_{\max} = [\text{US\$ } 5.00, 100\%, 100\%]^T$.

We use 6-month (January 1 through June 30, 2013) empirical loop/microwave data of 35 fixed detector stations [29] at a time interval of 15 minutes. Fig. 5.12a compares the calibrated traffic flow model with default settings. Fig.5.12b shows the simulation matches well with historical measurements.

We simulate the PM peak from 14:00 to 19:00, and search for the optimal solution of joint HOT toll rate and freeway diversion rates utilizing the proposed Bayesian stochastic Kriging approach. To further compare the baseline and the optimal case, we run the simulations for 5 replications, respectively. Predictive distributions of the baseline $[\infty, 0, 0]^T$ and the optimal solution $\hat{\mathbf{x}}^* = [\text{US\$ } 1.42, 100\%, 0]^T$ belong to $\mathcal{N}_{\text{Baseline}}(12.32, 0.08^2)$ and $\mathcal{N}_{\text{Optima}}(12.01, 0.03^2)$, respectively. The SOV is allowed to use the HOT lane by paying US\$ 1.42 in the optima case, while SOV is restricted in the baseline. The mean optimal objective function is 11.97 min that

is close to the predictive mean value. Table 5.2 compares the baseline and optima in terms of locally impacted vehicles and the system-wide performance. Vehicles that passed through the work-zone links in the normal scenario without work zones were extracted as the locally impacted vehicles, i.e. approximately 12.42% of all demands. We can see that the integrated optimization reduces the average travel time of work-zone impacted vehicles by 4.79%. More corridor-level statistics show that these impacts may look small but such system-wide improvement can be achieved with better demand and traffic management in one single work zone.

Table 5.2: Comparison of the baseline and optima for PM peak simulation results.

Scope	Statistics	Baseline	Optima	Improvement
Locally impacted vehicles (40,763 vehicles, 12.42%)	Average trip time of impact vehicles (min)	26.11	24.86	4.79% ^a
	Complete trips	302,475	302,918	0.15%
System-wide impacts (328,314 vehicles, 100%)	Avg overall trip time (min)	12.32	11.97	2.84% ^b
	Avg trip distance (mile)	4.94	4.95	-0.20%
	Avg travel speed (mph)	24.07	24.82	3.12%

^aIndicating 12.74 thousand dollars saved for 5-hour PM peak given VOT = US\$ 15/hour

^bIndicating 26.51 thousand dollars saved for 5-hour PM peak given VOT = US\$ 15/hour

Fig. 5.13 illustrates the average trip travel time and throughput in every 5 minutes for vehicles that complete trips. The network average travel time of the optimal case is smaller than the baseline. The optimal HOT rate together with DMS implementations successfully help alleviate network congestion.

Surrogate models can intelligently mimic simulation based objective function evaluations and reduce computational times. It is a perfect fit to our agent-based model and simulation in order for optimization and policy decision-making support. This chapter proposes to evaluate the transportation system performance under inte-

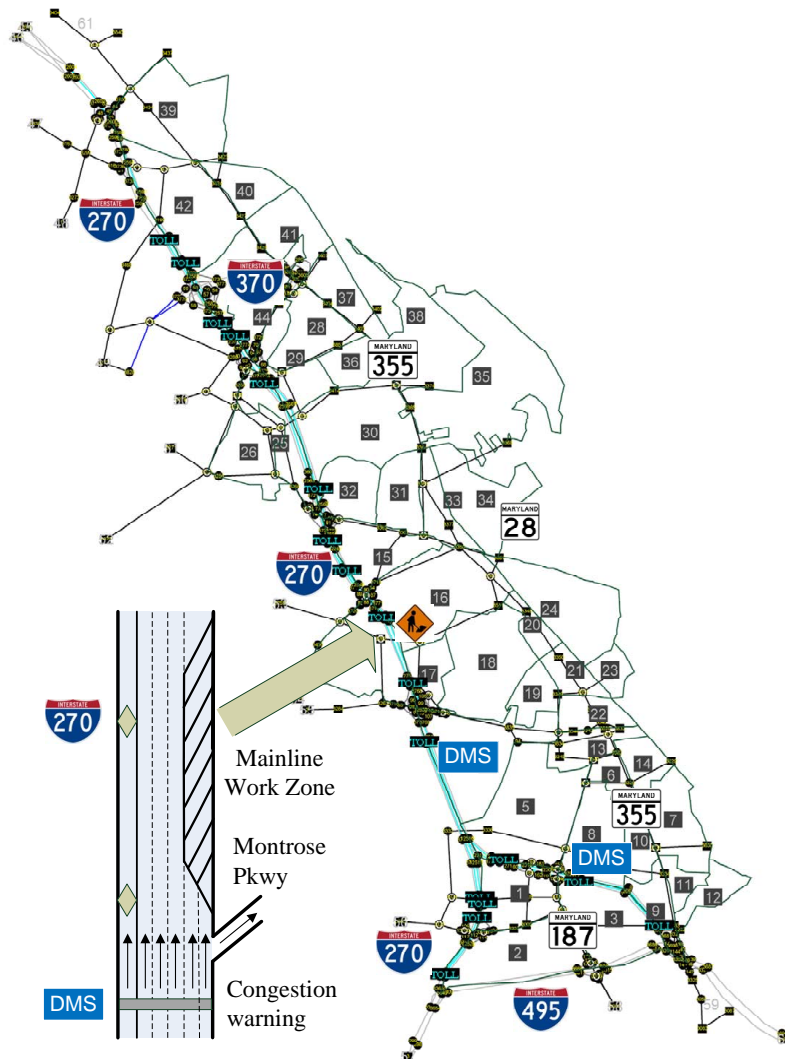
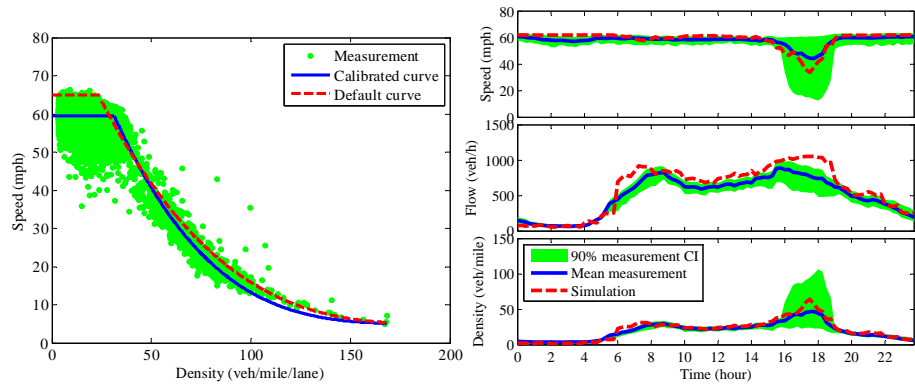
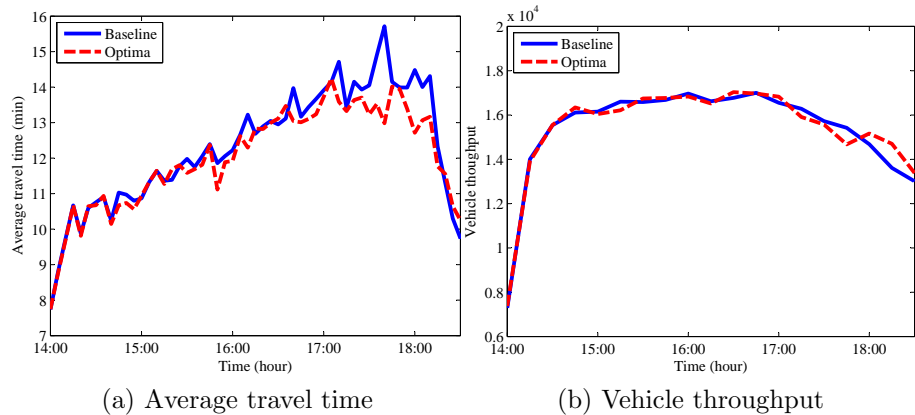


Figure 5.11: Simulation network of I-270 freeway/arterial corridor.



(a) Modified Greenshields model calibration (b) Comparison of measured confidence interval (CI) and simulated traffic on general-purpose lanes.

Figure 5.12: Demand and supply calibration results.



(a) Average travel time (b) Vehicle throughput

Figure 5.13: System-wide comparison of baseline and optima.

grated applications of travel demand management and traffic control measures with simulation. The major methodological contribution is that the heteroscedasticity of stochastic simulation outputs is taken into account by developing the Bayesian stochastic Kriging metamodel. A synthetic network is built in DynusT and used to test the performance of the proposed Bayesian stochastic Kriging model, which outperforms the other three models in estimating mean values and standard errors for heteroscedastic data. The model will be applied for joint optimization of the

HOT toll rate and freeway diversion rates in a work zone scenario of a real-world corridor.

5.4 Summary

This chapter aims at applying the proposed behavioral model and agent-based simulation to address different planning, policy, operations, and decision-making needs. An operational application applies en-route diversion model to evaluate a real-world dynamic message sign scenario. Other applications, such as employing departure time model to analyze peak spreading effect, employing mode choice model to analyze multimodal corridor management, are still on-going. This chapter also proposes to use simulation-based optimization technique to optimize certain planning/operational decisions based on the agent-based simulation results. It is believed that this integrated optimization and agent-based simulation will produce behaviorally realistic optima for decision-makers to justify a policy conclusion.

Chapter 6

Conclusion

Starting from von Neumann’s seminal work on self-reproducing automata in the 1960s, modern agent-based models have drawn increasing attention in research and practice. Agent-based modeling (AgBM) system has the potential to lead to transformational changes and truly revolutionary advances in transportation engineering and especially multimodal surface transportation in the United States. This dissertation addresses this emerging research need by developing a theoretical framework for agent-based driver and traveler behavioral modeling and analysis, which benefits from a wide spectrum of travel/activity data and innovate current practice in traffic operations, management, and transportation planning.

6.1 Contributions

Dissatisfaction with classical theory and legacy models is not new. Being one of the major assumptions of the classical theory, the perfect rationality assumption governs the literature for many years. The author reviewed previous research efforts on travel behavior models and their applications aimed at replace or revise the basic model of rationality and utility maximization with alternative decision models. However, it is difficult to pinpoint any work not based on fully rational behavior that “yields results as rich, deep, and interesting as those achieved by standard

models assuming full rationality” (Rubinstein 1998). Primarily aimed at advancing the embedded behavioral theory for travelers’ decision-making processes, this study theorizes the multi-dimensional behavior with the following three main objectives:

A pertinent new theory of choices with experimental observations and estimations to demonstrate agents with systematic deviations from the rationality paradigm. Modeling components including knowledge, limited memory, learning, and subjective beliefs are proposed and empirically estimated to construct adaptive agents with limited capabilities to remember, learn, evolve, and gain higher payoffs. All agent-based models are based on empirical observations collected via various different data collection efforts.

Modeling **procedural agent-based decision-making**. Individuals choose departure time, mode, and/or route for their travel. Individuals also choose how and when to make those choices. A behavioral sound modeling framework should focus on modeling procedural decision-making processes. This study seeks answers to questions that largely remain unanswered including but not limited to: (1) When do individuals start seeking behavior changes? (2) How do they initially change behavior? (3) How do they switch behavior adjustment dimensions? (4) When do they stop making changes?

The transformation from the static user equilibrium to a **dynamic behavioral equilibrium**. Current solution concepts are based on an implicit assumption that agents are aware of the prevailing user equilibrium. However, a more realistic behavioral assumption is that individuals have to make inferences. These inferences can either be their subjectively perceived distributions of travel time and travel cost

or be the multidimensional alternatives they subjectively identified. In other word, individuals determine their choice set and the attributes of each alternative rather subjectively. It is the process of making inferences that occupies each individual in making a decision.

The theorization of multidimensional knowledge updating, search model, and behavior process becomes a unified and coherent approach that models the activity and travel decision-making with a consistent behavioral foundation and increased rigor. For each behavioral adjustment dimension, this study proposes single dimensional AgBM models with the goal to address the important gap in modeling capability to support existing models and practices. Four standalone versions of single-dimensional AgBM have been presented in this study, including a departure time searching and switching AgBM, a pre-trip routing AgBM, a dynamic mode searching and switching AgBM, and an en-route diversion AgBM. These models can be applied directly as a supplement to existing travel demand and planning models especially when these models need additional capabilities in modeling any of those four agent behavioral dimensions.

The departure time model dynamically models the departure time decision-making under uncertainty. This study attempts to gain insights into travelers' behavior variation in uncertain and dynamic environments. The implementation of the quantitative models indicates its capability to simulate travelers' day-to-day departure time adjustment. The travel time reliability plays a crucial role in the individuals' decision-making processes as well as for the system to converge. The agent-based simulation confirms that more travelers search for alternative departure

times in response to non-recurrent congestion caused by increasing uncertainty. And under extremely high uncertainty level, travelers need more iterations (simulated days) to exhibit satisficing behavior. Another interesting result obtained in this study is that travelers exhibit risk-neutral and slightly risk-loving behavior when the system-level uncertainty increases to a moderate level and become extreme risk averters when the uncertainty reaches a very high level. When the uncertainty level is extremely low and extremely high, the majority of users choose a particular departure time with lower variability in travel time. When the uncertainty level is moderate, an increasing number of travelers choose the alternative with lower expected travel time but higher variability in travel time.

The study conceptualizes individual travel mode choice as a hidden Markov model with individual latent modal preference. This method is believed to embed more reasonable behavioral foundation without assuming random utility maximization. While longitudinal mode choice process data is often lacking, this research develops an easy-to-implement memory-recall survey to observe behavioral decision processes and empirically estimate the model. The model empirically suggests an interesting two-state transition in travelers' hidden modal preference, with the two states interpreted as car-loving and carpool/transit loving respectively. LOS variables of the habitual modes are the dominating factors in reversing individual attitudes, according to the time-varying covariates in the transition matrix. This study remains as a first research effort that uses process data to empirically model dynamic behavior. The study also opens the opportunity to explore which policies are most effective in encouraging more transit/carpool lovers and shifting more pri-

vate vehicles off the road. At a first glance at the demonstration section, reducing transit fares seem to work soundly. A careful policy analysis in the future is necessary to reach a rigorous conclusion in this regard. Future work can also focus on the theoretical part, e.g. taking into account the individual unobserved heterogeneity in the HMM model. Random-effect parameters can be incorporated into the transition matrix and estimated with a hierarchical Bayesian structure, allowing for unobserved heterogeneity in the stickiness to different states. Another promising direction can explore practical applications of this model. The authors see a potential integration of the HMM and a one-day traffic simulation model to simulate day-to-day behavior changes. Interesting results on multimodal behavior responses can be captured.

The study models en-route diversion using naive Bayes rules which serve as an effective alternative to the typical discrete choice models. This computational process model predicts agent behavior probabilities, which is highly efficient when millions of agents are simulated in the system. The model's operations application also represents a first attempt to link agents' en-route diversion behavior with large-scale network model. The proposed framework is comprehensive. It models the agent en-route diversion behavior, calibrates the model, simulates network conditions, dynamically applies the behavior model, deploys the diversion strategy in the simulation, and obtains various performance measures. The study also remains as a first research effort that uses MFD measurements to quantitatively evaluate the effect of information provision and en-route diversion in an assumed operations scenario. The MFD of the studied corridor has confirmed that agents' en-route

diversion has an impact on network throughput, average flow, and average speed. Most importantly, the MFDs of the baseline and diversion scenarios exhibit a consistent pattern, maintaining the similar critical weighted average density. Compared to the incident (without real-time information and diversion) scenario, the diversion scenario shows less drops and recovery in the average flow. This is an important finding. Without real-time information provision, an incident has the potential to make the network much more vulnerable and suffering from severe breakdown. En-route diversion, though in a low level of diversion percentage, can help avoid the breakdown and maintain a consistent traffic pattern to the corridor's normal traffic pattern.

6.2 Future Research Directions

As an on-going work, the author continues to test application potential of the proposed agent-based models in various applications in transportation planning and traffic operations. It is believed that with the proposed calibration method, the model transferability is no longer an issue. After being calibrated and validated with locally collected data, it can be applied to either replace existing models in current practice, or to inform and enrich existing models as a complementary module. This study discusses these possibilities in the context of transportation planning and traffic operations with greater details. The flexibility of agent-based models allows researchers and practitioners to benefit from this innovative modeling framework by developing and implementing agent-based models for certain dimensions of travel

decisions whenever the current data availability allows.

A full-fledged, multidimensional agent-based model obviously requires a large amount of behavioral data. To address this data challenge, the research team designed, tested, and is conducting a Smartphone-based travel survey in the Maryland/Northern Virginia/Washington D.C. area. It collects the individual travel and activity patterns over an extended time period with high resolution. The survey is conducted to collect respondents' travel behavior before-and-after the operation of Washington D.C.'s Silver-Line Metro. The Smartphone survey is supplemented by online travel diary and stated preference surveys to capture attitudinal and individual preference information that is crucial for modeling. The multidimensional agent-based behavior model developed in Section 4 is based on the preliminary data collected from a pilot study. More data collected from this survey will be applied to further develop the multi-dimensional agent-based driving and travel behavior models and calibrate more advanced modeling components.

The numerical examples presented in the dissertation highlight the capabilities of the proposed theory and models in estimating rich behavioral dynamics, such as multidimensional behavioral responses, day-to-day evolution of travel patterns, and individual-level learning, search, and decision-making processes. The computational efficiency of the proposed models needs further exploration through real-world implementations using agent-based simulation techniques. It is believed that the flexible framework, computational efficiency, and more realistic assumptions can make the proposed modeling tool extremely suitable for integrated large-scale multimodal planning/operations studies which typically have to cope with millions of agents.

This work is primarily exploratory in its conceptualization of a descriptive theory, estimation of quantitative models, and demonstration in an agent-based microsimulation. In an era of big-data access, multi-core processors, and cloud computing, the ambition of transportation demand modelers has never been greater. The hope is that the preliminary findings in this dissertation could raise interest in the behavioral foundation of multidimensional travel behavior as well as in microsimulating people's complex travel patterns in the time-space continuum. Extensive examination of the proposed tool on a larger and more representative survey sample and for real-world studies is necessary before we can conclude that the tool is fully practice-ready.

6.3 Summary

To summarize, this dissertation aims at developing multidimensional and standalone single-dimensional agent-based models (AgBM) through theoretical modeling, data collection, empirical testing, recalibration/validation, and real-world applications. I demonstrate and hold the belief that AgBM approach is a promising approach with more realistic behavioral assumptions departing from traditionally assumed perfect rationality, dynamic representations of multidimensional behavioral changes, and highly flexible structure for applications. We hope this research would inform future researchers in the field of AgBM and inspire fruitful research work towards such a vision.

Regarding the future research directions, as various agent-based models for

different sub-systems are built and improved, I plan to integrate these models into one mega model that includes all major players of transportation systems: individual travelers, commercial transporter, transit operator, infrastructure provider, and regulator. We may also include other components such as agent-based land use model, regional economic model, and even international trade and immigration models to simulate the interaction between a wide-range of systems. It is also possible to gradually replace one or a few of the modules of an existing planning model with agent-based models in order to introduce AgBM capabilities that are particularly needed. On modeling agent behavior, previous studies have demonstrated that the communication field does not necessarily overlap with the physical world. Although people may interact with their neighbors more frequently, they can communicate with physically remote agents through communication network. This is especially important as new social media emerges. As information flow is largely invisible, how to truly capture its generation and spreading will remain a big challenge for modelers.

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