

Copyright
by
Ravi Venkatraman
2013

The Thesis Committee for Ravi Venkatraman
Certifies that this is the approved version of the following thesis:

**Adaptive Routing Behavior with Real Time
Information under Multiple Travel Objectives**

**APPROVED BY
SUPERVISING COMMITTEE:**

Supervisor: _____
Stephen D. Boyles

Randy Machemehl

Adaptive Routing Behavior with Real Time Information under Multiple Travel Objectives

by

Ravi Venkatraman, B.Tech

Thesis

Presented to the Faculty of the Graduate School of
The University of Texas at Austin
in Partial Fulfillment
of the Requirements
for the Degree of

Master of Science in Engineering

The University of Texas at Austin
August 2013

Acknowledgments

I would also like to express my gratitude to Dr. Randy Machemehl, for providing useful tips on my work. My course Professors - Dr. Balakrishnan, Dr. Bhat, Dr. Bratu and Dr. Morton greatly added to my values. I would like to mention my Professors in India, Dr. Karthik Srinivasan and Dr. Gitakrishnan Ramadurai, who ignited my passion for the subject. I would like to thank Dr. Unnikrishnan and Rachel from West Virginia University in collaborating in this study, their inputs, help in publicity and preliminary analysis. This material is based upon work supported by the National Science Foundation under Grant No. 1157294.

I thank Tarun for providing useful tips all along, and providing awesome company during much needed breaks. His knowledge and experience has been a resourceful tool during my Undergraduate and Graduate studies. The amazing group at the dungeon like office at B.124 - Aria, Chrissy, Pallu, Raghu, Rajesh, Sriram and Tarun, transformed the place into the most exciting one. A special mention to the times when the basement converted into a cricket stadium - the only time in any sport when my presence is perceivable. My roommates, Dinesh and Prem, have been a great source of laughter at home, and good listeners to my words of wisdom. I would like to thank all members of AID-Austin, who have inspired me by their sheer motivation and passion, and also forced me outside to hit the running trail regularly. My first year as a newbie was welcomed by a hospitable Avni, who made me so much more comfortable. I am immensely grateful to Sucheta, for the endless hours of discussions on topics spanning the globe, and for her constant support.

Finally, I am indebted to my family - my parents, Deepa and Satish for all their love and support. Their routine skype calls complement my morning coffee, which has kept me going throughout.

Adaptive Routing Behavior with Real Time Information under Multiple Travel Objectives

Ravi Venkatraman, MSE

The University of Texas at Austin, 2013

Supervisor: Stephen D. Boyles

Real time information about traffic conditions is becoming widely available through various media, and the focus on Advanced Traveler Information Systems (ATIS) is gaining importance rapidly. In such conditions, travelers have better knowledge about the system and adapt as the system evolves dynamically during their travel. Drivers may change routes along their travel in order to optimize their own objective of travel, which can be characterized by disutility functions. The focus of this research is to study the behavior of travelers with multiple trip objectives, when provided with real time information. A web based experiment is carried out to simulate a traffic network with information provision and different travel objectives. The decision strategies of participants are analyzed and compared to the optimal policy, along with few other possible decision rules and a general model is calibrated to describe the travelers' decision strategy. This research is a step towards calibrating equilibrium models for adaptive behavior with multiple user classes.

Table of Contents

Acknowledgments	iv
Abstract	v
List of Tables	ix
List of Figures	x
Chapter 1 Introduction	1
1.1 Background	1
1.2 Motivation	2
1.3 Objectives	3
1.4 Notation	4
1.5 Organization	5
Chapter 2 Literature Review	6
2.1 Adaptive Routing	6
2.1.1 Non-Linear user behavior	8
2.2 Congestion Experiments	8
Chapter 3 Routing Policy	11
3.1 Introduction	11
3.2 Disutility Functions	11
3.3 Traveler Scenarios	14

3.3.1	Shopping Trip	15
3.3.2	Work Trip	15
3.3.3	Social Trip	16
3.3.4	Airport Trip	17
3.4	Policies	19
3.4.1	Optimal Policy	19
3.4.2	<i>A priori</i> Path Policy	22
3.4.3	Greedy Policy	22
3.4.4	Policy Simulation	24
3.4.5	Example	26
3.5	Conclusion	30
Chapter 4	Experiment Setup	31
4.1	Introduction	31
4.2	Motivation and Objectives	31
4.3	SmartDrive Interface	32
4.3.1	Scenarios	32
4.3.2	Navigation	33
4.3.3	Historical Data	35
4.4	Data Representation	35
Chapter 5	Numerical Analysis	37
5.1	Demographic descriptives	37
5.2	Use of Cell Phones for ATIS	39
5.2.1	Results	40
5.3	Game Scores	43
5.4	Route Choice Model	47
5.4.1	Methodology	48
5.4.2	Results	52

5.4.3	Validation	58
5.4.4	Summary	59
Chapter 6	Conclusion	61
6.1	Summary	61
6.2	Future Work	62
Bibliography		64

List of Tables

3.1	Travel Time Distribution: Braess's Network	26
3.2	Optimal Policy : Braess's Network	28
5.1	Cross-tabulation: Age vs Average Score	38
5.2	Cross-tabulation: Real time information use vs Average Score	39
5.3	Cross-tabulation: Real time information use vs Employment	39
5.4	Propensity to use Cell Phone for Travel Information - Binary Choice Model Results	41
5.5	Score comparisons : User vs Policies	45
5.6	Social Trip: Policy Overlap	48
5.7	Work Trip: Policy Overlap	48
5.8	Airport Trip: Policy Overlap	49
5.9	Shopping Trip: Policy Overlap	49
5.10	MNL alternatives - Notations	50
5.11	Alternatives Chosen: Frequency Distribution	51
5.12	MNL results - constants only model	53
5.13	MNL - constants from partially segmented model	54
5.14	MNL results - partially segmented model	55
5.15	Model validation	59

List of Figures

3.1	Linear Disutility	12
3.2	Deviance Disutility	13
3.3	Quadratic Disutility	14
3.4	Arrival on Time Disutility	15
3.5	Disutility for User Classes/Trips	18
3.6	Greedy Policy Network	24
3.7	Policy Illustration: Braess's Network	27
3.8	Expected Value Labels	28
3.9	Policy Comparisons	29
4.1	Game: Scoring Rules	33
4.2	Game: Network Navigation	34
4.3	Game: Historical Data	36
5.1	Number of Rounds played	43
5.2	Score Distribution	44
5.3	Average Score with #Rounds played	47

Chapter 1

Introduction

1.1 Background

Uncertainty is inherent in every transportation network, in the form of variable congestion levels, incidents, or network closure due to bad weather conditions. This stochasticity is a hindrance both to the users, who try to choose the *best* route within a transportation network, and to the planners, who try to develop an efficient transportation system. Hence, there is a continuous need to monitor the system in order to adapt to changes in it. In recent times, much effort has been devoted towards mitigating the effects of such uncertainties by providing users with real time information about the network. This information may be provided through various media, such as variable message signs (VMS), internet, smartphones, or the radio. System reliability has been a major focus of research, and in route choice, is seen equally important as general cost of travel. From the user perspective, reliability can be improved by making travelers more aware of the system conditions. Further, depending on the type of information provided, users may react differently based on personal characteristics and the purpose of their trip.

We focus our research in stochastic networks with information, keeping in mind different behavior among users. Our work is focused on validating some of the existing research practices dealing with network uncertainty and heterogeneous behavioral characteristics among users.

1.2 Motivation

With network uncertainty and information in mind, a series of immediate questions arise, which motivated us to carry out our studies. This section is structured similar to our *thought process* that led us to carry out our research.

Q. What is the cause of uncertainty in transportation networks?

Travel time uncertainty is primarily due to the stochastic nature of users' decisions in choosing routes, as well as incidents on roads, bad weather, or closures due to constructions and maintenance work. Information regarding the latter is usually readily available and can be predicted quite accurately. User decisions are much more unpredictable and require more attention to address the stochastic nature of the network. This leads us to our next question.

Q. How do *user characteristics* play a role?

The decisions of a traveler depends on various factors characteristic of the particular user, such as the purpose of his/her trip, the extent of risk-prone behavior of the user, familiarity with the network etc. These factors ultimately play a role in the route chosen.

Q. Can we incorporate user behavior in route choice models?

Yes, there is already a lot of existing research which has focused on this area. This can be done by the use of *disutility functions*, which is explained in Section 3.2. Specifically, we focus on different disutility functions depending on trip purpose.

Q. Is this actually how route choice decisions are made in practice?

This is one of the fundamental questions we try and answer in our study. We look at how users react in uncertain network conditions, given real time information and different disutility functions. It is very important to know the answer to this question for research as well as practice, as validity of such a route choice model will be the

motivation of further studies and applications in the real world.

Q. What are the benefits of providing travel information *en route*?

Providing real time information about the network partially decreases the stochastic element in the network, by eliminating the uncertainty on the immediately downstream links. Users can be more aware and make better decisions about their travel. Real time information is provided by means of VMS, internet and smartphones, text messages and radio. This leads to a class of shortest path problems (SPP) called the online shortest paths (OSP), where information is revealed *en route* and the user can make a series of *adaptive* decisions to minimize his/her expected travel cost.

1.3 Objectives

The specific objectives of this study are:

1. To study the behavior of individual travelers in a simulated environment with real time local information, under multiple travel objectives.

This is done by developing an interactive user application which simulates the above mentioned conditions. Users navigate through a network with local information with a specified travel objective, and make adaptive decisions along their route.

2. To validate the use of optimal adaptive routing policies in practice, and if different, develop a policy consistent with the user behavior.

The validation process essentially is a comparison of users' decisions to the optimal decisions. We define other plausible policies, and develop a "*hybrid*" policy which models the user behavior.

In the following section, we describe the notations used to describe the various models used, particularly in context with *Objective 2*.

1.4 Notation

Consider a network $G = (N, A)$ with n nodes and m arcs. The network is stored in an adjacency list or forward arc structure, with $\gamma(i)$ and $\gamma^{-1}(i)$ representing the downstream and upstream nodes of i . The network costs are uncertain and are represented by a known probability distribution. For our study, we assume that each arc (i, j) can exist in multiple discrete states, each represented by $s \in S_{ij}$, occurring with probability p_{ij}^s . The real time information is represented using node-states, instead of arc states. A node state is constructed based on the information received by users at crucial intersections (nodes) regarding the routes ahead, or downstream arcs. For the network G , this information includes the state of each downstream arc. Hence, the node state includes all permutations of possible downstream arc states. These are represented by $\theta \in \Theta_i$ for a node i , with $|\Theta_i| = \prod_{j \in \gamma(i)} |S_{ij}|$. We state a few assumptions for this work.

Assumption 1: Complete information regarding all downstream arcs is available at each node. This assumption can be easily relaxed in the stated models and experiments. Our primary motive is to assess the user behavior in the presence of information, and this research does not look into user decisions when partial information is provided.

Assumption 2: The arc states occur with probability p_{ij}^s independent of each other, or there is no spatial correlation between links. Hence, the probability of occurrence of each node state $\theta \in \Theta_i$ can be computed as $Pr(\theta) = \prod_{j \in \gamma(i)} p_{ij}^{s_\theta}$ where s_θ is the state of arc (i, j) in node-state θ .

Assumption 3: On subsequent arrivals at the same node, the downstream arc states are memoryless and hence, are “reset”. They are determined independent of arc states at previous arrivals.

The network is traversed in non-negative discrete time states $t = 0, 1, 2 \dots T$. This study considers different user classes, each denoted by q , and their *disutility* function of arriving at the destination v at time t is denoted by $f^q(t)$. The disutility function describes the user preferences and accounts for any non-linear behavioral patterns, as explained in Section 3.2. Let the expected disutility of arriving at node i at time t be denoted by $L(i, t)$. The optimal strategy is defined by a policy $\pi(i, t, \theta)$ that defines the route choice based on current information θ . Further information on policies is defined in Section 3.4.

1.5 Organization

The remaining part of the thesis is organized as follows. Chapter 2 describes existing research in the area of adaptive routing, route choice behavior studies and congestion experiments. We describe how we use the existing ideas to build upon our research. Chapter 3 describes the disutility functions used in the context of the web-application, and the adaptive policy. Chapter 4 describes the structure, operation, and functioning of the web-application used to study user behavior. Chapter 5 describes the analysis procedure and corresponding results obtained. This chapter contains our primary findings and forms the crux of this thesis. Chapter 6 summarizes the work done in this thesis and identifies opportunities for future research.

Chapter 2

Literature Review

In this section, we study past literature related to our research. For convenience, we divide the literature review into two main focus areas. Section 2.1 describes the developments on modeling and implementing algorithms for OSPs. We also discuss relevant literature on non-linear user behavior and use of disutility functions in this section. Section 2.2 focuses on experiments conducted to understand route choice behavior. These focus on objectives of the studies, procedure for conducting them, and results observed.

2.1 Adaptive Routing

Networks with stochastic costs have been of interest to researchers for a long time. One of the first attempts at finding paths with minimum expected travel time in a stochastic and time dependent network was by Hall [1986]. He discussed the need of an adaptive decision strategy rather than an *a priori* path. Miller-Hooks and Mahmassani [2000] discussed a polynomial algorithm to obtain the travel times of *a priori* least expected time paths in stochastic time varying networks. They also placed lower bounds on travel times of the optimal adaptive strategy. Later, Miller-Hooks [2001] proved that the labels from the algorithm are in fact, the optimal labels and discussed the same with illustrative examples and computational results. The networks were assumed to have arcs with spatially and temporally independent travel times, and waiting at nodes was not allowed.

In the recent past, considerable emphasis has been placed on provision of real time information through ITS technologies, leading to research on OSPs. Polychronopoulos

and Tsitsiklis [1996] developed a dynamic programming strategy to find shortest paths on a time invariant network with random arc costs when information was revealed *en route*. The time invariant approach assumed the arc costs were fixed once the user traversed the arc, and resulted in an exponential dynamic programming algorithm formulation. Provan [2003] developed a label setting strategy to find the shortest paths when arc travel times were reset upon revisiting. Versions of this problem without the reset assumption are NP hard. Waller and Ziliaskopoulos [2002] studied two versions of the online shortest path problems, one with spatial dependence where downstream arc travel time probabilities were conditioned on the travel times of upstream arcs, and temporal dependence where cost of the arc was learnt on arriving at the tail of the arc. Gao and Chabini [2006] provided a general framework to develop the optimal routing policy in stochastic time dependent networks, and outlined an algorithm where arc costs display stochastic dependency and value of information provided was considered.

Given that a set of users follow an adaptive routing strategy, work has been done on proceeding towards user equilibrium. Unnikrishnan and Waller [2009] discussed a convex mathematical formulation for static user equilibrium under stochastic link travel times with information provision. They discussed two scenarios, one where all users observe the same arc states and one where users arriving at the same node observe different arc states, and solved the models using a method similar to Frank-Wolfe algorithm. Boyles and Waller [2009] built on this and found the optimal locations for providing information by constructing contracted networks. The heuristic using this procedure was applied to three cases - routing of an individual vehicle, routing of multiple vehicles in an uncongested system, and multiple vehicle equilibrium in a congested network, with the first two being special cases of the third.

2.1.1 Non-Linear user behavior

There has been some research on the benefits of incorporating non linear preferences for traveler choices. Such benefits have mostly been assessed through studies and discrete choice modeling applications. In this context, we outline a few relevant findings. Mandel et al. [1994] demonstrated that the non-linear Box-Cox logit variant was a more accurate model than a linear model to forecast demand. de Lapparent et al. [2002] also used a Box-Cox functional form and revealed non-linear user preferences for travel time. Pinjari and Bhat [2006] demonstrated the importance of non-linearity in response to travel time and reliability in choice modeling by using different coefficients for travel time in the utility function depending on the absolute travel time incurred. Their results demonstrated a clear difference in values of travel time and values of reliability as compared to a constant value of travel time.

Non linear preferences have been incorporated in routing decisions in the context of reliability and preference of robust paths. Fan et al. [2005] and Nie and Wu [2009] considered reliability by maximizing the probability of arriving earlier than a specified arrival time. Gao [2005] considered a reliability measure by minimizing variance, expected early and late schedule delay. Approximate methods were used for minimizing variance since Bellman’s optimality conditions do not hold for the problem. Our research is motivated by the work of Boyles [2009b], who developed an approach applicable for any general disutility function, yielding optimal policies in a stochastic network. Boyles and Waller [2007] observed significant differences in solutions while using a deviance disutility function from linear disutility.

2.2 Congestion Experiments

The main focus of our research is to assess traveler responses in a stochastic network environment with information under multiple travel objectives. In the past, there have been quite a few congestion experiments dealing with route choices under

the provision of information. However, many of these studies have been carried out with the objective of assessing multiplayer interaction and convergence to equilibrium. Others have carried out experiments to assess the influence of information on driving behavior. Ramadurai and Ukkusuri [2007] conducted an online multiplayer network game to check the conversion to a steady state in a dynamic network with a single bottleneck. They also studied the impact of online information on users' payoff. The decisions in the experiment were to choose departure time to arrive at the destination at a specified time. In addition to observing no convergence to equilibrium, they also observed a paradox like behavior where providing information yielded in lesser overall payoffs. However, the small sample size (players and number of rounds played) warrants further research to ascertain any such behavior. Selten et al. [2007] conducted a route choice experiment to compare different equilibrium strategies - pure equilibrium and symmetric mixed equilibrium. The results tend to portray convergence to pure equilibria with a few fluctuations. But the large number of rounds played is expected to have yielded a more stable solution to justify pure equilibrium as well. Real time information is not provided in their study. However, feedback about their past trip is provided. Morgan et al. [2009] tested for change in traffic flows in a multiplayer setting when changes were made to a network, and observed that flows did shift on changing network conditions, but more towards user equilibrium rather than system equilibrium. Users in this game were given post-trip feedback too. Srinivasan and Mahmassani [2000] modeled the route choice behavior under information provision as either complying to the ATIS information, or using the same path as before. From their experiments, they found that tendency to comply with ATIS information increases with congestion levels and travel time savings. They modeled the user behavior as a multi-nomial probit (MNP) with a binary variable indicating overlap between the two choices (inertia and compliance). Avineri and Prashker [2006] noted that provision of information does not always result in lower expected travel time, possibly because the nature of users' choices tends to

be more heterogeneous when provided with information. The users either adopted a strategy to minimize expected travel time or became risk averse by choosing the most reliable route. Dia and Panwai [2007] collected data from users and developed neural network models to ascertain the types of information provided in VMSs that are most influential. These experiments provided more insight on equilibrium and reaction to information systems. Our research looks at a more fundamental behavior at the individual level. We study route choice behavior assuming complete access to real time information with non linear preferences. Comparisons are made to the optimal behavior and other suggested decision rules (Section 3.4) and a multinomial logit (MNL) model is developed for the same. To our knowledge, no study has been conducted in the past that looks at the decision strategy of users in a stochastic network with non-linear preferences. We aim to provide useful insights about individual behavior that may be a step towards calibrating equilibrium models with adaptive routing and heterogeneous routing policies.

Chapter 3

Routing Policy

3.1 Introduction

Network travel times are a direct function of the link flows, which in turn depend on the routing decisions of the system users. Hence, we must place considerable emphasis on the *routing policies*. We define a policy as a decision making rule followed by a user, which may depend on factors like current location or node i , current time t , the current state of the node θ , and target travel objective, represented in the disutility function. Evidently, such a policy may not lead to a fixed *a priori* path. They will describe a *hyperpath*, or a path based on decision rules dependent on the current location, time and information.

This chapter places an emphasis on the concept of disutilities, the user classes and functions used for our study, and the policies considered for representing user behavior. Section 3.2 describes the use of disutility functions for representing different user behaviors. Section 3.3 describes the particular scenarios used for our web application. Finally, Section 3.4 describes the various policies that might be used by a traveler for route choice.

3.2 Disutility Functions

Traditional travel objectives mainly deal with minimizing travel time or travel cost, where the cost is an increasing function of travel time and other parameters. However, these do not capture non-linear user behavior such as preferences of a target arrival time at the destination, or risk preferences of a user when faced with uncertain travel

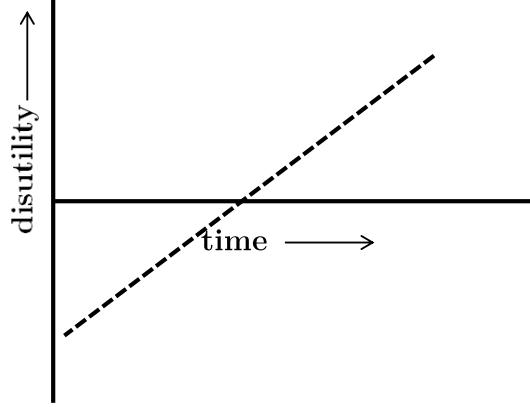


Figure 3.1: Linear Disutility

times. The disutility function $f^q(t)$, of a specific user class q describes the 'cost' of completing a trip in time t . An optimal policy minimizes the expected disutility. Possible disutility functions described by Boyles [2009b] are listed below.

Linear: Linear disutility functions describe the standard shortest path objective i.e. we wish to minimize $E[t]$. This disutility function does not incorporate any risk preferences, or target arrival times. Arriving at the destination as soon as possible is the primary concern.

Deviance: The deviance disutility is defined as $f(t) = (t - t^*)^2$, which can be seen as a variance of some mean target arrival time t^* . The optimal policy now minimizes $E[(t - t^*)^2]$.

In the above case, the 'penalty' for an early or late arrival is the same i.e. there is no difference between arriving early by Δt units or late by Δt units. In some cases, late arrival may be a heavier burden than an earlier arrival, or vice-versa. A simple modification to account for such a case would be a disutility function given below:

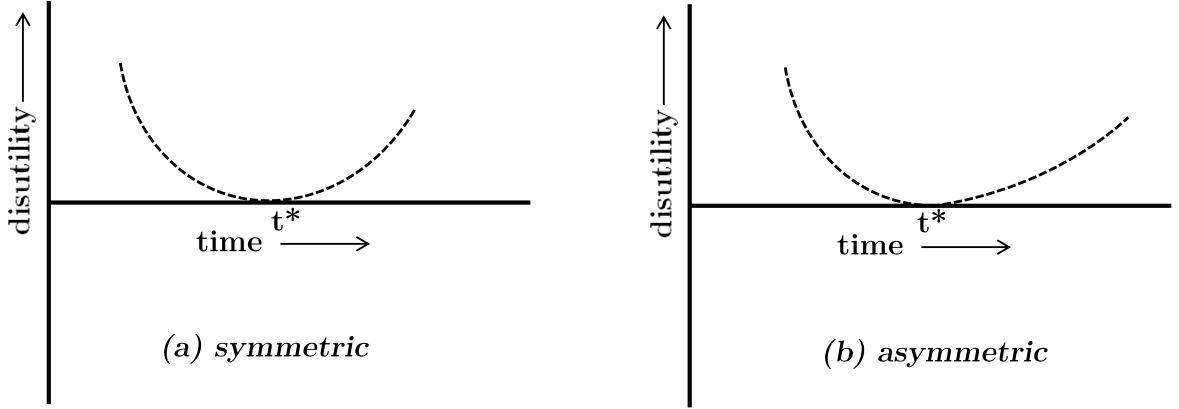


Figure 3.2: Deviance Disutility

$$f(t) = \begin{cases} (t - t^*)^2, & \text{if } t \leq t^* \\ b(t - t^*)^2, & \text{if } t > t^* \end{cases}$$

where $b > 1$ if the penalty for late arrival is greater than early arrival, $0 \leq b < 1$ if the penalty for early arrival is greater.

Quadratic: A quadratic disutility function captures the risk taking characteristics of a user class. Boyles and Waller [2007] parameterize this behavior using a single parameter k , representing the change in derivative of f between a range of possible arrival times.

For the same value of disutility, a convex function allows for a later arrival time than a concave function. A user class with such a behavior will be less prone to taking risks to arrive earlier. $k > 0$ yields a convex function, and represents a risk averse behavior, whereas $k < 0$ yields a concave function representing a risk prone behavior.

Arrival On Time: Nie and Fan [2006] and Nie and Wu [2009] address the problems to attain a given probability to arrive at a specified time or earlier. The arrival on time disutility is used to represent the scenario of a traveler wishing to arrive at the

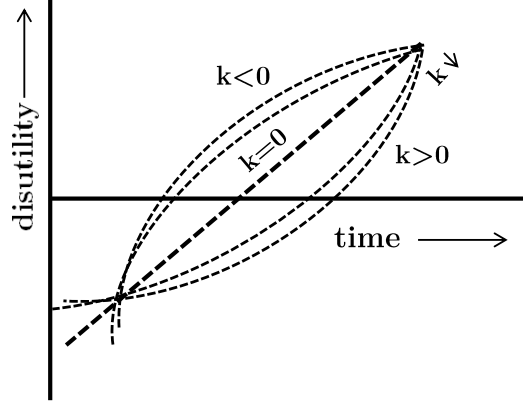


Figure 3.3: Quadratic Disutility

destination no later than a threshold time t^* . The function is represented by an indicator function,

$$f(t) = \begin{cases} 1, & \text{if } t \leq t^* \\ 0, & \text{if } t > t^* \end{cases}$$

The next section describes how these disutility functions were modified to represent different scenarios.

3.3 Traveler Scenarios

Our web application uses specific scenarios to represent different user classes and hence, different disutility functions. The specific objectives are listed later in Section 4.2. The objectives try to represent and simulate the different disutility functions mentioned in Section 3.2, as encountered during common travel routines. We consider linear disutilities and target arrival times for our study, but ignore simulating different risk preferences for a user class. The common travel objectives used are listed below.

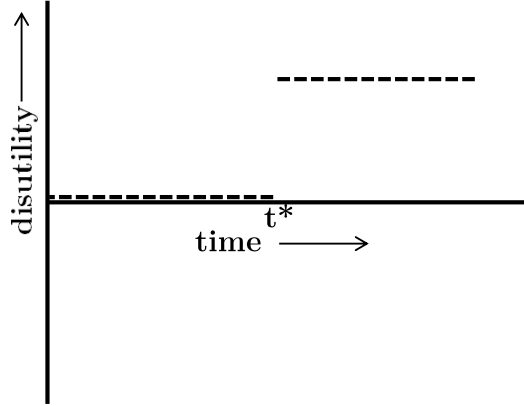


Figure 3.4: Arrival on Time Disutility

3.3.1 Shopping Trip

A class of users traveling for a shopping trip may represent a linear disutility, since they want to arrive at the destination as soon as possible, with no particular target time.

Figure 3.5 represents this scenario. In this figure, t_M represents the maximum time at which users may want to arrive at the destination, beyond which they have no incentive to arrive.

3.3.2 Work Trip

Work trips are used to describe a scenario with a target arrival time. Assume a traveler making a trip to his/her work place, with a target arrival time t^* . The user certainly does not wish to arrive late to the work place, since there is a high penalty associated with late arrival. Furthermore, one may argue that it is not beneficial to arrive early to the work place either. These may be due to several reasons concerning the work environment. For example, arriving early for collaborative meetings or other such jobs has no incentives and can be seen as unproductive time for fixed working

hours. Other outlooks include loss of time for other tasks that might have been done prior to start of work.

The mathematical motivation behind such a constraint is to obtain a disutility function similar to the deviance function explained in Section 3.2. However, this situation clearly requires the cost of late arrival to be greater than the cost of an early arrival. Furthermore, the function is approximated as a piece-wise linear function in view of making the web application and objectives user friendly. This does not cause any changes in the mathematical approach to the problem.

Figure 3.5 depicts the piecewise linear disutility function. Note that the slope for $t > t^*$ is *steeper* than the slope for $t \leq t^*$. t_M represents the latest possible time of arrival. This is an example of “schedule delay”, which is a measure of the difference between a target arrival time and actual arrival time.

3.3.3 Social Trip

This scenario is used to describe another piece-wise linear disutility function with a target arrival time. Assume a traveler making a trip to a social occasion, with a target arrival time t^* . This may be a party, event, game etc. The user may not want to arrive too early for a social occasion, nor may he/she want to arrive late to miss the event.

Figure 3.5 represents the piece-wise linear disutility function for this case. Similar to the previous case, the penalty for arriving later is more than that of arriving early, or slope for $t > t^*$ is *steeper* than the slope for $t \leq t^*$. However, the target arrival times and penalties for late or early arrival are more relaxed than the work trip.

The disutility functions with target arrival times allow possibilities of cycling in a FIFO network or using paths other than the path yielding least expected travel time.

Another scenario where such behavior can be expected is cycling to finding an appropriate parking spot. Such a phenomenon of visiting a node multiple times was studied by Boyles [2009b] and is termed *contretemps*. Note that this may be observed with linear disutilities too, if the network is not a FIFO network i.e. it may be optimal to depart at a later time to reach the destination earlier. Boyles [2009b] places bounds on the difference in expected disutility between the optimal policy with a finite time horizon and the optimal policy with an unrestricted horizon. The bounds hold for a disutility of any functional form.

3.3.4 Airport Trip

A user traveling to the airport to catch a flight needs to be in time at the airport. There is no cost or incentive if he/she arrives before the target time. However, the target time is a very strict threshold. If the arrival time is later than the target time by any amount, the flight is missed. This is represented by the On Time Arrival disutility function described in the previous section. The same structure is used for this scenario in our web application.

Disutility functions are an important concept in practice while considering the entire system. For example, consider a hypothetical scenario where we could route everyone in the system according to their preferences and known disutility functions. Consider two individuals, one traveling to work and the other to the airport along similar paths, with disutility functions similar to the ones mentioned above. If the person traveling to work is expected to arrive late, there may be a possibility to route the individual traveling to the airport along a longer route such that s/he still makes it to the flight and reduces the travel time for the individual to work. Hence, we can increase the overall performance of the system with such knowledge.

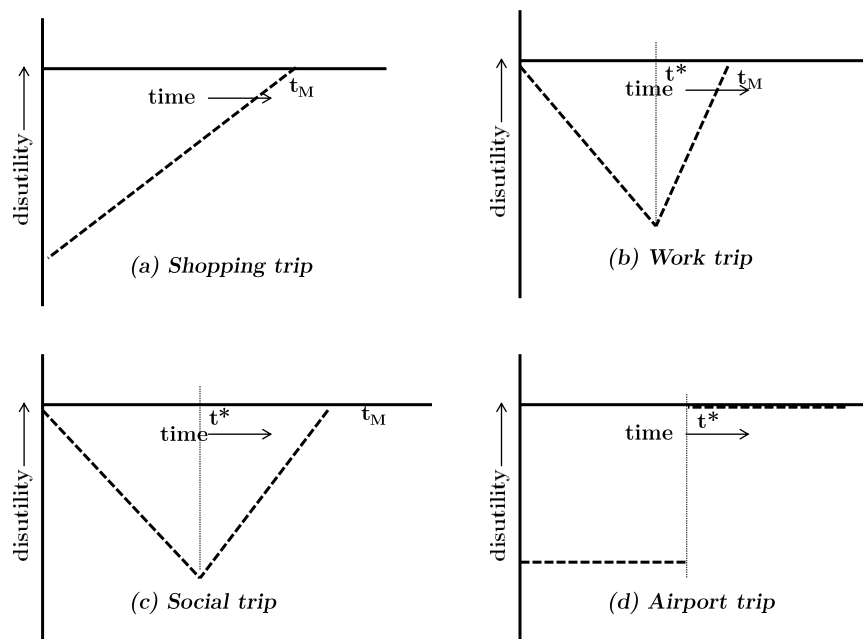


Figure 3.5: Disutility for User Classes/Trips

3.4 Policies

The disutility function of user class affects the routing policy which the user belonging to a particular class follows. This section describes the various policies that might be used to choose the path in the presence of local information.

3.4.1 Optimal Policy

The optimal strategy minimizes the expected disutility of the user class. With local information on the downstream arcs, the problem is similar to the one step temporal dependence in online shortest paths considered by Waller and Ziliaskopoulos [2002]. The TD-OSP algorithm suggested by them is based on the label correcting algorithm (Ahuja et al. [1993]).

Let $L(i, t)$ be the expected disutility of arriving at node i at time t . We start at the destination node and work backwards, till the we know the optimal labels for all nodes and time periods. Chabini [1998] suggested a decreasing order of time (DOT) algorithm that makes use of the decreasing time intervals to compute labels more efficiently. The basic idea is that if we compute labels in decreasing order of time, at any stage t_0 , we have the optimal labels of all downstream nodes which will be reached at a time $t > t_0$. With local information, a decision or policy is framed for each node state that yields a route to minimize expected disutility. Boyles [2009b] suggests an adaptive policy algorithm that computes the optimal labels and policy for the network.

The algorithm AdaptivePolicy runs in $O((n + m)T|\Theta|)$ time, where $|\Theta|$ is the maximum number of node states examined for a node. Note that $|\Theta|$ can be $O(S^m)$. However, a reduction, proposed by Waller and Ziliaskopoulos [2002] reduces the number of states scanned to $O(Sm)$. For a node with A downstream arcs with S states each, we can reduce the node states from S^A to SA . Note that this reduction is not used

Algorithm 1 AdaptivePolicy($\mathbf{t}, \mathbf{f}, v$)

```
1:  $\mathbf{t}$  contains the travel times for each link in every state.  $\mathbf{f}$  and  $v$  represent the  
   disutility function and destination, respectively.  
2: for all  $i \in N$  do  
3:   for all  $t \in T_v$  do  
4:      $L(i, t) \leftarrow \infty$  ▷ Initialization  
5:     for all  $\theta \in \Theta_i$  do  
6:        $\pi(i, t, \theta) \leftarrow \emptyset$   
7:     end for  
8:   end for  
9: end for  
10: for all  $t \in T_v$  do  
11:    $L(v, t) \leftarrow f(t)$  ▷ Destination Initialization  
12: end for  
13:  $t \leftarrow T - 1$   
14: while  $t \geq 0$  do  
15:   for all  $i \in N$  do ▷ Node Loop  
16:      $temp_L \leftarrow 0$   
17:     for all  $\theta \in \Theta_i$  do ▷ Node-State Loop  
18:        $temp^\theta \leftarrow L(i, t)$   
19:       for all  $j \in \Gamma(i)$  do ▷ Downstream Arcs Loop  
20:          $temp_j \leftarrow 0$   
21:         if  $t + t_{ij}^\theta > T$  then  
22:            $temp_j \leftarrow \infty$   
23:         else  
24:            $temp_j \leftarrow L(j, t + t_{ij}^\theta)$   
25:         end if  
26:         if  $temp_j < temp_\theta$  then ▷  $\min_j L(j, t + t_{ij}^\theta)$   
27:            $temp^\theta \leftarrow temp_j$   
28:            $\pi(i, t, \theta) \leftarrow j$   
29:         end if  
30:       end for  
31:        $temp_L \leftarrow temp_L + temp^\theta * Pr(\theta)$   
32:     end for  
33:      $L(i, t) \leftarrow temp_L$   
34:   end for  
35:    $t \leftarrow t - 1$   
36: end while
```

in our implementation, since the computational expense for smaller sized problems such as ours is not extensive.

The initialization takes place for all n nodes, T time periods and at most $|\Theta|$ node states. Hence, the initialization requires $O(nT\Theta)$ time. There are $(T-1)$ iterations of the outer *while* loop in the main algorithm. In each time period, every outgoing arc of a node is examined at most once for a particular time period. Hence, there are at most m iterations of the node and arc loops combined. The examination takes place for every node state, which can be at most $|\Theta|$ for a node. Hence, the computation of policies and labels requires $O(mT\Theta)$ time. The total computation requirement is $O((n + m)T|\Theta|)$. For sparse networks, where m is $O(n)$, the computation time is $O(nT|\Theta|)$.

Proposition: *The algorithm terminates with the optimal labels and policy.*

Proof: The algorithm is guaranteed to terminate in finite time since the computation occurs progressively for arc, corresponding state and time period.

We will prove the result by an induction like argument based on the proof of the label correcting algorithm by Ahuja et al. [1993]. At the end of an iteration of the *Node Loop*, the algorithm computes the optimal labels and policy for the node. The network is a time-expanded network and hence, is acyclic. After initialization at $t = T$, the destination label is set to the corresponding disutility value and all other labels are set to infinity and hence, the result holds after initialization.

At any stage t and node i , the algorithm examines all the node states, computing the expected disutility if each arc was traversed in the corresponding state. The policy yielding the minimum value is chosen. Due to the decreasing order of time, the labels of the downstream nodes are known and cannot change in future iterations. Further, a temporary label $temp_L$ computes the expectation of all such possibilities

$(\sum_{\theta} temp_{\theta} * Pr(\theta))$. Hence, the algorithm terminates with optimal labels and policies for each node, state and time interval.

3.4.2 *A priori* Path Policy

Another policy that might be followed by users is following an *a priori* path that yields least expected disutility. Miller-Hooks [2001] suggested an algorithm to compute adaptive least expected travel time (LET) paths in uncertain networks with links whose probability distribution varies with time. A user with this strategy does not make use of local information, but relies on past experiences to determine travel time distributions and follows the path with minimum expected disutility.

The LET algorithm computes $\min_{p \in P} E[t(p)]$, where P is the set of all paths from origin to destination and $t(p)$ denotes the travel time of path p . Irrespective of correlation between link travel times and distributions, $E[t(p)] = \sum_{(i,j) \in p} E[t_{ij}]$. In our case, the probability distributions of a link do not vary with time, hence $E[t_{ij}]$ is deterministic. We use Algorithm 1 to calculate least expected disutility paths by replacing the multiple states of each arc with a single state with travel time $E[t_{ij}]$.

Now, $|\Theta| = 1$ and the algorithm runs in $O(nT)$ time. Since, this is a special case of the optimal policy algorithm, the termination and correctness are guaranteed.

3.4.3 Greedy Policy

The greedy policy, similar to the traditional definition, represents a myopic user behavior. Though the local information readily available is used, the broader objective of minimizing expected disutility through route decisions is not taken into consideration.

In the context of routing policy with online information, a greedy strategy is defined

as choosing the arc with least travel time. In case of multiple arcs with equal, minimal travel times, the first arc in the forward star list is chosen. However, note that this may result in infinite loops and one may never reach the destination. An improved version of the greedy strategy is suggested in which the motive of the user to travel towards the destination is considered. Two main qualitative behavioral patterns are incorporated in this case. These are illustrated through an example network shown in Figure 3.6 with 9 nodes. Assume a user traveling using the greedy strategy from node 1 to 8. The double sided arrows indicate the presence of two separate links in each direction.

- The user does not traverse in a direction opposite to the destination. For example, if we are currently at node 5, we can travel to nodes 4,6 and 8, but not to node 2, which is a direction opposite to the destination. This also includes directions (or vectors) which have a component in the opposite direction. For example, the user cannot travel from node 5 to nodes 3 or 1 (if links 5–3, 5–1 existed), since the vector 5–3 (or 5–1) has a component along 5–2. Dial [1971] considers ‘reasonable paths’ for logit based traffic assignment, and bases the criteria on shortest path distance of a node to (and from) the destination (source). Our criteria is based on the geographical direction of travel with respect to the destination, while allowing shortest path distances to the destination to increase on traversal.
- *Spiral* paths are avoided. Consider a hypothetical line joining the origin and destination, node 1 and 8 in 3.6. A spiral is a path that crosses this line more than once. For example, a path 1–2–3–6–5–4–7–8 is a spiral since it crosses the hypothetical line twice, once at 1–2 and again at 5–4.

To avoid this, we define a set of *restricted nodes* from each node i , which consist of the nodes that should not be traversed to from the current location. This set can be initialized *a priori*, but additions may be made during traversal. For example, to

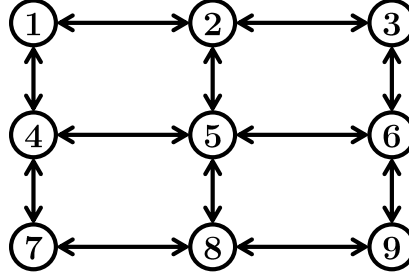


Figure 3.6: Greedy Policy Network

avoid a spiral path, once the path 1–2–3–6 has been traversed, nodes 4 and 7 may be added to the set of *restricted nodes* from node 5, if they were not already present in the set. This strategy does not consider non linear user behavior, the objective is to reach the destination minimizing the travel time.

The *GreedyPolicy* algorithm is outlined below.

GreedyPolicy runs in $O(m|\Theta|)$ time. The termination and correctness of this algorithm are trivial.

3.4.4 Policy Simulation

A simulation of all the policies is carried out on the network used for the application.

The objective of carrying out simulations are three fold:

1. Verify the optimal and *a priori* labels
2. Compare route choices in each of the above policies
3. Use results to develop other policies that match user behavior closely, and compare these with other definite policies.

Algorithm 2 GreedyPolicy($\mathbf{t}, v$)

```
1:  $\mathbf{t}$  contains the travel times for each link in every state and  $v$  represents destination.
2: for all  $i \in N$  do
3:    $RestrictedNodes(i) \leftarrow \emptyset$ 
4:    $updateRestrictedNodes(i)$  ▷ Initialize restricted nodes
5:   for all  $\theta \in \Theta_i$  do
6:      $\pi(i, \theta) \leftarrow \emptyset$  ▷ Policy Initialization
7:   end for
8: end for
9: for all  $i \in N$  do ▷ Node Loop
10:  for all  $\theta \in \Theta_i$  do ▷ Node-State Loop
11:     $temp^\theta \leftarrow \infty$ 
12:    for all  $j \in \Gamma(i)$  do ▷ Downstream Arcs Loop
13:       $temp_j \leftarrow 0$ 
14:      if  $temp_j > t_{ij}^\theta$  AND  $j \notin RestrictedNodes(i)$  then
15:         $temp_j \leftarrow t_{ij}^\theta$ 
16:         $\pi(i, \theta) \leftarrow j$ 
17:      end if
18:    end for
19:  end for
20: end for
```

We iteratively simulate each of the policies for each specified disutility function, as shown in algorithm *SimulatePolicy*.

Algorithm 3 *SimulatePolicy*($\mathbf{t}, \mathbf{f}, startTime, s, v$)

```

1:  $\mathbf{t}$  contains the travel times for each link in every state,  $\mathbf{f}$  contains the disutility
   function,  $startTime$ ,  $s$ ,  $v$  represents the starting time, origin and destination,
   respectively.
2:  $i \leftarrow s$ 
3:  $t \leftarrow startTime$ 
4:  $\theta \leftarrow randomStateGenerator(i)$  ▷ generates random states
5: while  $i \neq v$  AND  $\pi(i, t, \theta) \neq \emptyset$  do ▷
6:    $updateRestrictedNodes(i)$  ▷ For greedy policy, see algorithm GreedyPolicy
7:    $i \leftarrow \pi(i, t, \theta)$ 
8:    $t \leftarrow t + t_{i, \pi(i, t, \theta)}^{s_\theta}$ 
9:    $\theta \leftarrow randomStateGenerator(i)$ 
10: end while
11:  $disutility = f(t)$ 

```

3.4.5 Example

A simple example is demonstrated to compare and contrast the three policies stated previously. Consider the familiar 4-node Braess network. The network, associated states and their costs are shown in Figure 3.7 and Table 3.1 respectively.

Table 3.1: Travel Time Distribution: Braess's Network

Arc	State 1		State 1	
	Cost	Probability	Cost	Probability
1-2	3	0.5	5	0.5
1-3	3	0.5	9	0.5
2-4	2	0.5	6	0.5
3-2	2	1.0	—	0.0
3-4	3	0.5	5	0.5

Consider a user class with a linear disutility function traveling from node 1 to node 4, i.e. the objective is to minimize expected travel time. We evaluate different policies

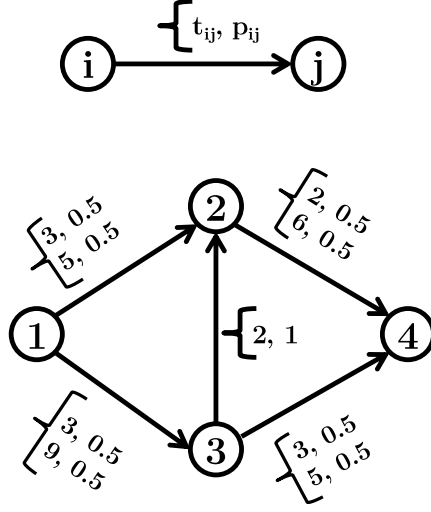


Figure 3.7: Policy Illustration: Braess's Network

and demonstrate an instance using the same.

The *a priori* path can be obtained by simply enumerating the three possible paths and choosing the one with least expected travel time. The *a priori* path is path 1–2–4 with expected travel time of 8. The optimal policy is a set of decisions to minimize expected travel time, using the observed downstream information. The labels with least expected values of travel time are shown in Figure 3.8, and the corresponding policy is constructed in Table 3.2.

We construct an instance of this problem, and demonstrate the progression using the three policies. The simulation, as outlined in Algorithm 3 is show below in Figure 3.9. The highlighted nodes in each stage represent the current location. At node 1, information regarding travel times of downstream links to nodes 2 and 3 are obtained, as 4 and 3, respectively. The *a priori* strategy follows the least expected path and chooses node 2. The greedy strategy chooses node 3 since the immediate travel time node 3 is less than node 4, without any information regarding the travel

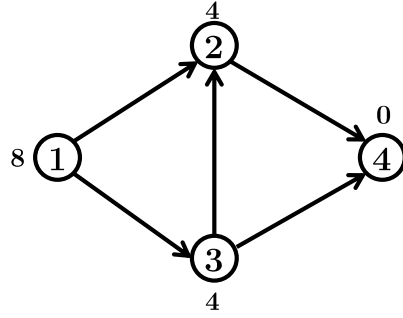


Figure 3.8: Expected Value Labels

Table 3.2: Optimal Policy : Braess's Network

Node	Downstream Arc	State/Cost	Optimal Policy
1	1-2	3	2
	1-3	3	
	1-2	3	2
	1-3	9	
	1-2	5	3
	1-3	3	
	1-2	5	2
	1-3	9	
2	2-4	2	4
	2-4	6	4
3	3-2	2	4
	3-4	3	
	3-2	2	4
	3-4	5	

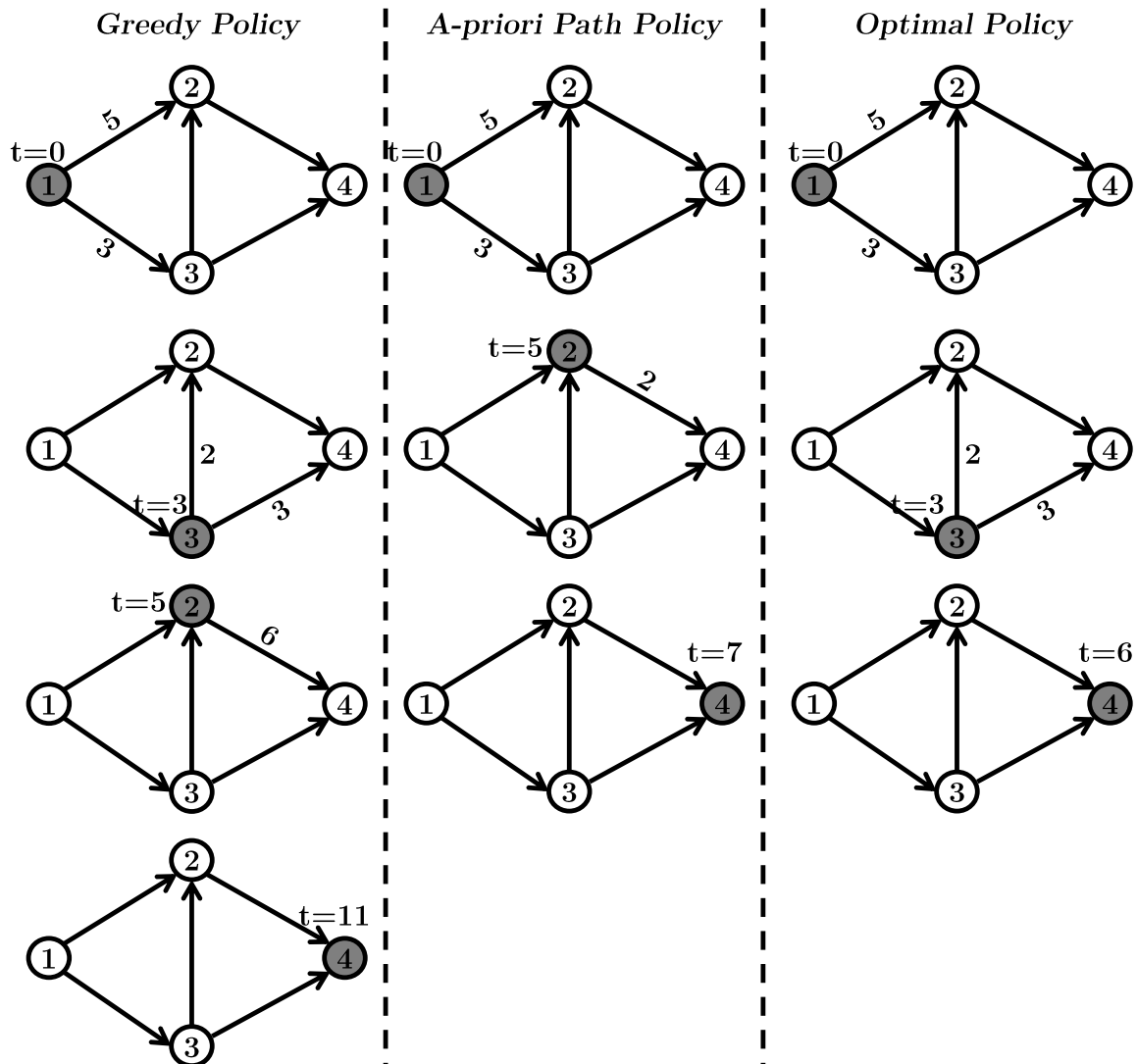


Figure 3.9: Policy Comparisons

time distributions of arcs downstream of 2 and 3. The optimal strategy is to observe the current information, and choose the node which minimizes the expected travel time from node 2 or 3 i.e. choosing node 2 would yield an expected travel time of $9(5 + 4)$, whereas choosing node 3 would yield an expected travel time of $7(3 + 4)$. At the next stage, the *a priori* strategy continues from node 2 to the destination 4, yielding a travel time of 7 (less than the expected travel time of 8). At node 3, the deterministic link to 2 with travel time of 2 is observed, and the link to 4 is observed with travel time 3. Now, the optimal policy chooses the minimum of paths $3 - 2 - 4$ (with expected travel time 6) and $3 - 4$ (with deterministic travel time 3), and chooses to reach the destination. The total travel time in this case is 6 (less than the initial expected travel time of 10). However, the greedy policy chooses to reach node 2, since the travel time on link $3-2$ is less than that of $3-4$. At the next stage, the observed travel time on link $2 - 4$ is 6 and the same is followed. The total travel time for this strategy is 11. Here, $T_{optimal} < T_{apriori} < T_{greedy}$.

This trend is specific to this problem instance, and may be different for other instances.

3.5 Conclusion

This chapter described how different user classes and non-linear user behavior can be represented using appropriate disutility functions. Different objectives such as arriving at the earliest possible time, or pursuing a target arrival time, or a threshold time are modeled. The disutility functions form a critical part of the route choice decision. The algorithm for computing optimal adaptive policies or decisions is listed, along with other plausible user policies such as following an *a priori* path or making myopic decisions. The disutility functions will be implemented in the web application for users emulate, and data will be collected to assess their route choice decisions. The next chapter describes the construction and implementation of the web application.

Chapter 4

Experiment Setup

4.1 Introduction

A web application was created to assess the route choice decisions of users under the presence of local information, and multiple travel objectives. In order to make the experience of using the interface stimulating and enjoyable, the study is designed as a game with the objective of maximizing a score and monetary incentives were provided. The details of game design and the process of conducting it are explained further in this chapter. The study was publicized through the web, University mailing lists, social networks, and fliers.

The rest of the chapter is organized as follows. The next section describes the motivation and objectives, stated in the game. Section 4.3 demonstrates the game through snippets and instructions. Section 4.4 discusses the data stored during the the game.

4.2 Motivation and Objectives

The motivation of the online application is primarily based on our research objectives stated in Section 1.3, which include:

- Validating the adaptive routing behavior of users,
- If the user behavior deviates from that of the optimal policy, develop mathematical models to replicate the user strategy.

Using the data collected during the survey, a number of parameters could be assessed for our modeling purposes. Specific objectives that we focus on are:

1. Analyze users’ performance with time, or over successive iterations, to evaluate any apparent ‘learning’ trends.
2. Compare the users’ decisions at each node with the policies stated in Section 3.4.
3. Develop a new decision model based on the above results, if needed. This model will try to describe the observed behavioral patterns.
4. Finally, compile user feedback regarding the application for future use.

Based on their relative scores, the top 80 performers were eligible for an incentive ranging from \$10–\$50. These incentives were used to motivate people to use the application with a clear goal of achieving the stated objectives. We strongly believed that the absence of any incentives would not draw as many people towards the survey, and would result in more random responses. An iteration without an optimal performance from the users’ perspective would result in a loss of performance and hence, loss of incentive. This can be represented as the cost of not achieving such a goal in daily trips.

4.3 SmartDrive Interface

The game, titled “*SmartDrive*”, is demonstrated through instructions and snippets in this section.

4.3.1 Scenarios

Users run through different iterations of the game, with multiple travel objectives. These objectives are defined by the disutility functions described in Section 3.3. However, the objective had earlier been that of disutility minimization. In order to make it more comprehensible to the users, the disutility minimization objective is converted to a score maximization objective. Hence, the scoring scheme is defined as

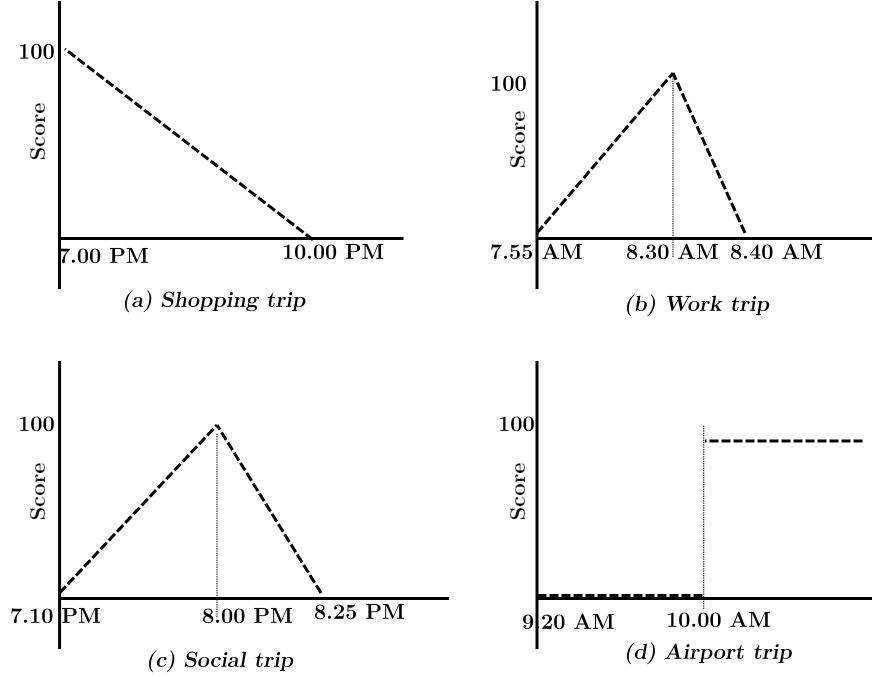


Figure 4.1: Game: Scoring Rules

$score(t) = -f(t) + score_{max}$, where $score_{max}$ is the maximum achievable score and is set to 100. The revised scoring graphs are shown in Figure 4.1, with t^* being the target time of arrival, if any, and t_M being the latest allowable time of arrival, beyond which there is no loss of incentive to arrive at the destination. The average score for a user is the average score obtained over all scenarios.

4.3.2 Navigation

The network used for the application was the familiar Sioux Falls network, with 24 nodes and 76 links. The origin and destination for each scenario was the same. Figure 4.2 shows an instant in the game in the ‘airport’ scenario.

Navigating through the network is straightforward. The white circle indicates the user’s current position and the objective is to get to the destination, marked by ‘X’ while maximizing the score. The user could choose his/her route at every intersection

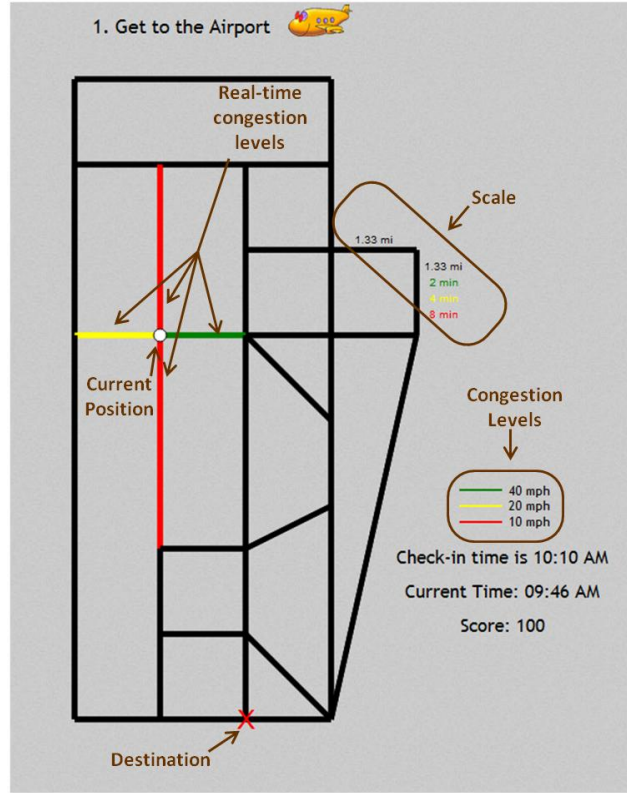


Figure 4.2: Game: Network Navigation

by clicking on the respective downstream arc. The current time, target arrival time and the score are also displayed on the screen.

As the user proceeds through the network, real-time traffic information was be provided. Congestion levels on all the downstream links was shown through color codes, which were an indication of the average speed on that road. The distance scale is highlighted in Figure 4.2 and times taken to travel the same are given below. For example, it would take 2 minutes to travel through the corresponding distance in uncongested (green) conditions. When the destination is reached, users were given the option to end the trip or continue driving (which may be chosen in cases with a target arrival time). If the user chose to end the trip, the path they followed was

highlighted temporarily before beginning the next round, to give them a recap of their trip and reassess the travel conditions.

To get familiarized with the navigation procedures, users were given three trial runs before beginning the simulations.

4.3.3 Historical Data

Though live information was available on all the downstream links, no information on any of the other links was available. Using a drop down menu, users were allowed to see the daily congestion levels on the entire network for the past 30 days. Each day's congestion level was formed by sampling the link travel time distribution. An example instance is shown in Figure 4.3. This is a tool to help users navigate through the network, and enhance the process of learning the network conditions, similar to a real network they might make their daily trips on. The main purpose behind this option is to replicate the knowledge drivers have from accumulated experience.

4.4 Data Representation

The personal information collected was based on the significant user characteristics obtained through the MNL model discussed in Section 5.2. This model assessed a marketing strategy to promote real time information usage through cell phones. These included socio-demographic details such as age, employment, education, details related to driving experience, and familiarity with usage of internet and cell phones. Detailed discussion of these is available in Section 5.2.1.

For each user, the following details were stored in each of their simulation runs, which were used for analysis and model development:

- Specific scenario type (disutility function)

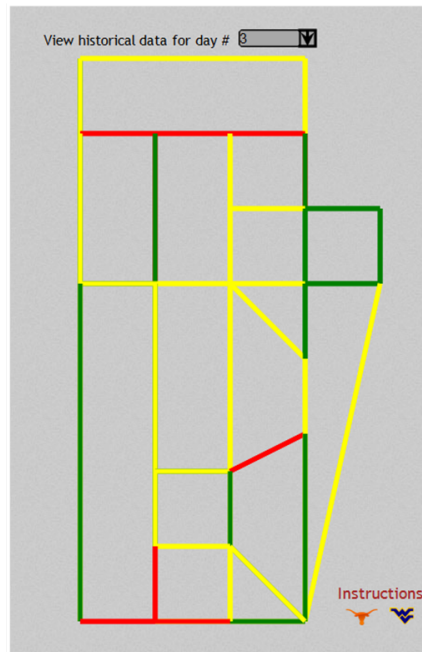


Figure 4.3: Game: Historical Data

- Local information observed at each node
- Decision made at each node

All other information could be regenerated through the above data. The next chapter discusses the findings of the web application, and provides useful insights.

Chapter 5

Numerical Analysis

This chapter outlines the findings of the study. The application was circulated through the web for a period of 2 months from November 2012 through December 2012. Users were allowed to play any number of rounds upto a maximum of 100. However, they were eligible for incentives only if they played a minimum of 10 rounds. On conclusion, the game had 267 registered users. For all our analysis, we used data from users who had played more than 10 rounds to derive consistency and trends in their decision making process. This reduced the number of users to 131, who played a total of 5203 scenarios with over 40,000 individual decision points.

5.1 Demographic descriptives

Of the 131 respondents to the game, 67% were male. 57% were aged 18–25, 26% were aged 26–32, and the rest (17%) above 32. 45% of the respondents were students and 40% were working in full time positions. The US census 2010 data states a male composition of 48% and only 25% of the population under the age 32. The numbers show that our sample does not represent the general US population. Since the application was web based and propagation was through web referrals, the control over the sample composition was minimal. However, it was not our intention to collect a sample representing the population. We intend to study the decision making process of users in a stochastic network with access to real time information, subject to parameters specific to a transportation network (trip purpose, information observed, learning trends) and not trends dependent on demographics of the population. Demographic and socio-economic characteristics may certainly impact the decision making

process, but the main motive of our research focuses on a different set of parameters. However, we outline a few interesting trends between average performance (score) in the game and these parameters. We also develop a model intended to target people likely to use cell phones as a medium of travel information in Section 5.2.

Table 5.1: Cross-tabulation: Age vs Average Score

Average Score	Age		
	18–25	26–40	>40
≤ 59.99	9.33%	11.91%	16.67%
60.00–69.99	36.00%	54.76%	50.00%
> 70.00	54.67%	33.33%	33.33%

The trends in Table 5.1 show a better score as age decreases, possibly because of younger people being more acclimatized to computer simulations and games, which may also translate into better use of ATIS in practice. 31% of the sample had driving experience of more than 10 years. This mostly constituted respondents aged 30 and higher. 32% and 26% of the sample had experience of 3–6 years and 7–10 years, respectively. Hence, over 90% of the sample had driving experience of over 3 years. Driving experience exhibits trends similar to age, where the average score is a bit lower for the category with experience of over 10 years. 70% of the respondents said they have used real time information for travel, but 62% said they use it very rarely. Only 10% of the respondents said they use real time information for travel on a daily basis. Table 5.2 shows the trend related to real time information usage. The average score for those who use such technology is less. This counter intuitive result has a possible explanation in Table 5.3. The student population might not use ATIS technology as expected, but has performed better in the web-application as compared to the employed segment of the sample, who have more access to real time information.

Table 5.2: Cross-tabulation: Real time information use vs Average Score

Total Score	Real Time Information Use	
	No	Yes
< 59.99	7.69%	12.22%
60.00–69.99	35.90%	46.67%
> 70.00	56.41%	41.11%

Table 5.3: Cross-tabulation: Real time information use vs Employment

Real Time Information Use	Employment Status	
	Employed	Student
No	27.14%	33.90%
Yes	72.86%	66.10%

5.2 Use of Cell Phones for ATIS

We emphasize use of cellphones or smartphones for ATIS applications, since we see smartphone apps as a huge potential market for ATIS. 86% of the respondents use smartphones, while only 46% have used cell phones in the past as a source of real time information. We have stated earlier it is not the prime objective of this research to dwell on user characteristics, but we perceive practical advantage in studying the characteristics of users who are more likely to be influenced by traveler information systems. An analysis of the characteristics of such users will prove to be helpful in determining the effects of a newly implemented information system, such as information through cell phones, on the entire transportation system. Hence, a comprehensive analysis of persons using travel information systems is required to assess the possible impacts on network behavior. This assessment is also necessary from a marketing point of view, to target the right audience initially to use the service and to develop aggressive strategies to influence the group of users who are not inclined to use the service. Experience creates an individual perception of the reliability of each information source. These perceptions are also influenced by social, cultural, and

psychological factors. Hence, knowledge of user demographics helps to successfully disseminate useful information. With these motivations in mind, we present results which focus on examining the characteristics of users who are likely to use cell phones as a medium of obtaining traveler information.

The data for this model was used from a survey conducted by Princeton Survey Research Associates for The Pew Research Center's Internet and American Life Project. The main purpose of the survey was to analyze mobile phone usage and profile management on social networking sites in the United States. The survey was conducted from April 26, 2011 through May 22, 2011. The entire survey was carried out through telephonic communication (landline or cell phone). Respondents were asked questions regarding their socio-demographic characteristics such as gender, age, race, employment status, income and education levels. Only adults were contacted for the survey. Respondents were asked questions to analyze the extent of mobile phone usage. The dataset consisted of 2277 responses, of which 48% of the respondents were male and 52% were female. According to the US Census 2010 data, 49% of the US population was male. The age distribution resembled the US Census 2010 data very closely as well. 23% of the respondents said they have used their cell phone for obtaining travel information, which is our dependent variable. We develop a standard multinomial logit model to understand the characteristics of users who use ATIS technologies from their cell phone.

5.2.1 Results

Table 5.4 shows the results of the estimated model. The employment status of the individual is a significant parameter in determining the propensity to use cell phones for obtaining travel information. Those who are employed full time or are self employed are more likely to make use of the cell phone for obtaining travel information. This is expected since these set of people are likely to travel more than the part time employed or retired people. In most cases, the employed people would also overlap

Table 5.4: Propensity to use Cell Phone for Travel Information - Binary Choice
Model Results

Log-likelihood Values			
At Convergence:		-1578.3	
Constant Only		-673.55	
ρ^2		0.573	
Variable	Coefficient	t-stat	
Constant	-4.510	-19.48	
Individual Characteristics			
Employed(Full-Time)	0.323	2.10	
Employed(Self)	0.745	1.94	
Internet/Social Networking Characteristics			
Internet Searches	0.456	3.02	
Wireless Internet User	0.918	3.59	
Social Network Profiles	0.112	1.88	
Cell Phone Activity			
Smartphone	0.982	5.05	
Pay for an app	1.170	5.30	
Dataplan	0.504	2.59	
Information Search	1.320	7.37	
Regular Internet Access	0.699	3.49	
Internet Tool	0.483	2.42	

with the higher income and education groups of people. This is in sync with the findings in previous research projects that persons with higher income or education level are more likely to be influenced by ATIS.

The extent of activities on the internet have a positive effect on use of cell phones for travel information. People who use the internet frequently are usually more likely to use cell phones for travel information. Among internet users, wireless internet users are very likely to use ATIS on cell phones. Most of the information is available through websites or “app” on smartphones. Hence, wireless internet users, who are probably more likely to access internet through the cell phone as well, have more access to such information en route. The number of profiles on different social networking sites is one indicator of the ‘sociability factor’ of an individual. This variable has a positive impact on the use of cell phones for travel information. This could be due to a number of reasons. The people who are more social are the people who are more likely to travel more frequently. They are also well informed of the updated technology and services available in the market. There are few applications on the social networking sites related to sharing travel information with friends. The use of such applications through these sites would prompt users to use other applications on cell phones to obtain travel information as well.

A major source of travel information, other than directly accessing websites, are “apps” that can be downloaded on smartphones. The effect of smartphones and applications is shown by the highly positive coefficient on the variable indicating use of smartphones by individuals and past history of payment to download an app. Another set of individuals who are likely to use cell phones for our stated purpose are those who have used cell phones for obtaining any general information, either through calls or texts or the web. This increases the reliability and effectiveness of the cell phone in the individuals’ perception and prompts them to use the cell phone for extended purposes as well, such as obtaining traffic information.

Most of the variables that are significant in the final specification are related to use of internet in some way. Hence, there is clear correlation between the independent variables. The use of cell phones as a medium of communication for ATIS implementation can be increased by certain changes, such as easier access to wireless internet or cheaper rates for dataplans. In the future, we would expect an increase in the number of smartphone users and online social networking activities, which would result in an increase in cell phone use for ATIS.

5.3 Game Scores

In this section, we discuss the performance trends of users and look at preliminary comparisons with various policies. Figure 5.1 shows that close to 25% of the respondents have played more than 50 rounds, and over 60% have played more than 25 rounds. This is encouraging for further analysis and indicates a positive user experience.

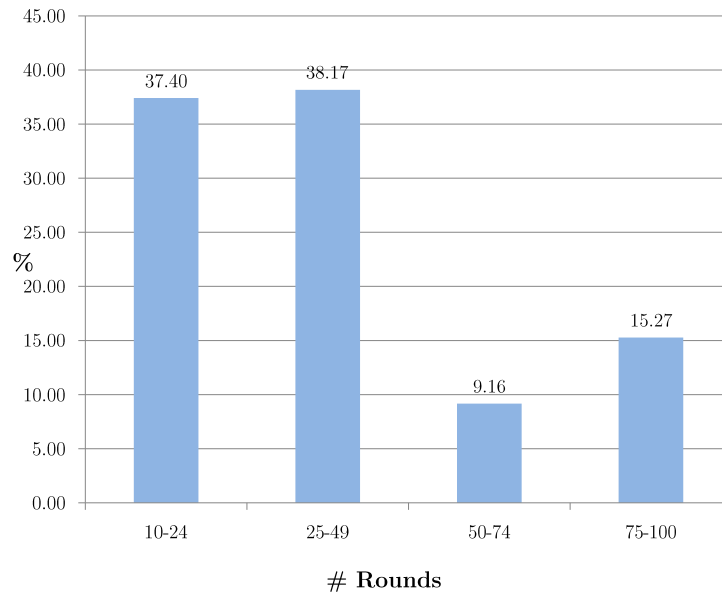


Figure 5.1: Number of Rounds played

The scores are distributed similar to a normal distribution, with majority (80%) of the respondents scoring an average of 60–80, with close to 10% of respondents each on the higher end, greater than 80 and lower end, less than 60. Interestingly, the distributions, shown in Figure 5.2, are not similar when broken up by scenario. By absolute value of score, the ‘social’ trip and ‘work’ trip are the best and worst among the four, respectively. These two have a similar piece-wise disutility function, but the social trip has a more relaxed gradient, which makes the scenario easier to perform. The shopping trip, with a linear disutility has a more consistent performance with close to 90% of the users scoring between 70–80 in it. The airport trip, with a threshold arrival time and all or nothing score, has a more spread out distribution, with a higher composition (63%) of respondents scoring below 70. However, a good percentage (22.90) of respondents have scored above 80 in this scenario, which is equivalent to stating that they make the trip on time 8 out of 10 times.

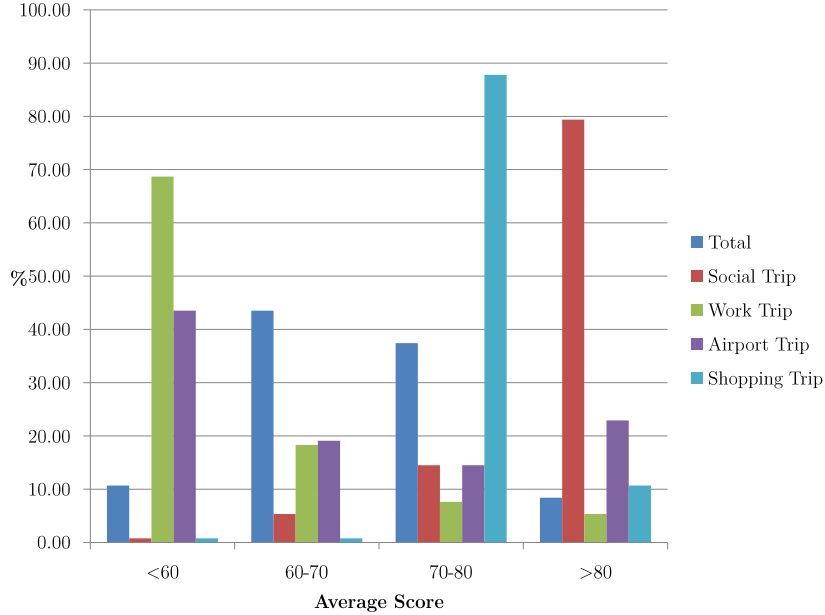


Figure 5.2: Score Distribution

The three policies discussed in Section 3.4, the Optimal policy, Greedy policy and

A priori path policy, are used for comparing with users' decisions. For each of the policies, we carried out 10000 simulation runs with each of the four disutility functions to compare average scores from the policy. These are documented in Table 5.5. The labels from the optimal policy ('Expected Disutility') are compared with the simulation results, and the scores coincide with each other. As expected, the results show that the optimal policy performs better in each case. However, it is interesting to note that the average score from the greedy strategy is better than following a fixed *a priori* path for the social and shopping trips. The greedy strategy performs very poorly for the work and airport trips. In these two scenarios, late arrival is penalized more heavily than the other two scenarios and the greedy strategy overshoots the target arrival time more often as there is no foresight while choosing the next node. From a practical perspective, it is evident to not follow a myopic decision rule while embarking on trips with strict time constraints. The users' average scores are interesting and encouraging. For all trips, the user scores are less than the optimal values as expected, but higher than the average scores from the other two strategies. This implies users are definitely following a strategy which is not completely myopic or following a fixed path, and there is a clear indication of an attempt to follow an optimal policy. Their strategy might be a combination of the three strategies and may depend on various other parameters, which we investigate further in Section 5.4.

Table 5.5: Score comparisons : User vs Policies

Scenario	Social	Work	Airport	Shopping
User Average	83.72	54.46	60.54	76.77
Expected Score (from Optimal Policy)	95.78	65.76	73.56	79.85
Average Score (from Optimal Policy)	95.58	64.41	71.26	79.55
Average Score (from Greedy Policy)	79.45	20.79	21.03	73.46
Average Score (from <i>A priori</i> Path Policy)	70.38	61.53	72.20	60.19

We are also interested in studying the 'learning' process of users. Figure 5.3 shows the learning curve with number of rounds played. The scores of each user were calculated

as a moving average with a fixed time period of 10 rounds. Let $S_i(n)$ be the score of user i in n^{th} round of the specific trip, and let $S_i^A(n)$ denote the average score of user i in the n^{th} round. The moving average over a fixed T ($=5$) periods for each user was computed as

$$S_i^A(n) = \sum_{t=n-T}^{t=n} S_i(t) / \min \{t, T\} \quad (5.1)$$

The average score over all users, $AvgScore(n)$ was computed as

$$AvgScore(n) = \sum_{i_n} S_{i_n}(n) / |i_n| \quad (5.2)$$

where i_n is the index of a user in the n^{th} round, and $|i_n|$ is the number of people who have played n rounds of the specific scenario. Figure 5.3 shows the plot of $AvgScore(n)$ with number of rounds played.

There is a steep increase in average scores with number of rounds for the social trip, and an indication of a learning trend for the shopping trip. There is a increasing trend for the airport trip as well, with ‘noise’ in the curve. This can be attributed to the all or nothing scoring pattern of this trip, which might lead to drastic fluctuations in the average scores. There is no apparent learning trend demonstrated in the work trip. This might be due to the strict time constraint and heavy penalty for late arrival in this scenario. It is possible that users are inhibited from trying out different strategies in this scenario. However, we must be cautious while studying these trends, particularly for numbers of rounds greater than 25. As the number of rounds increases, the number of users that participated, $|i_n|$ decreases. Hence, the average scores towards the end of the curve are based on relatively lesser numbers of participants.

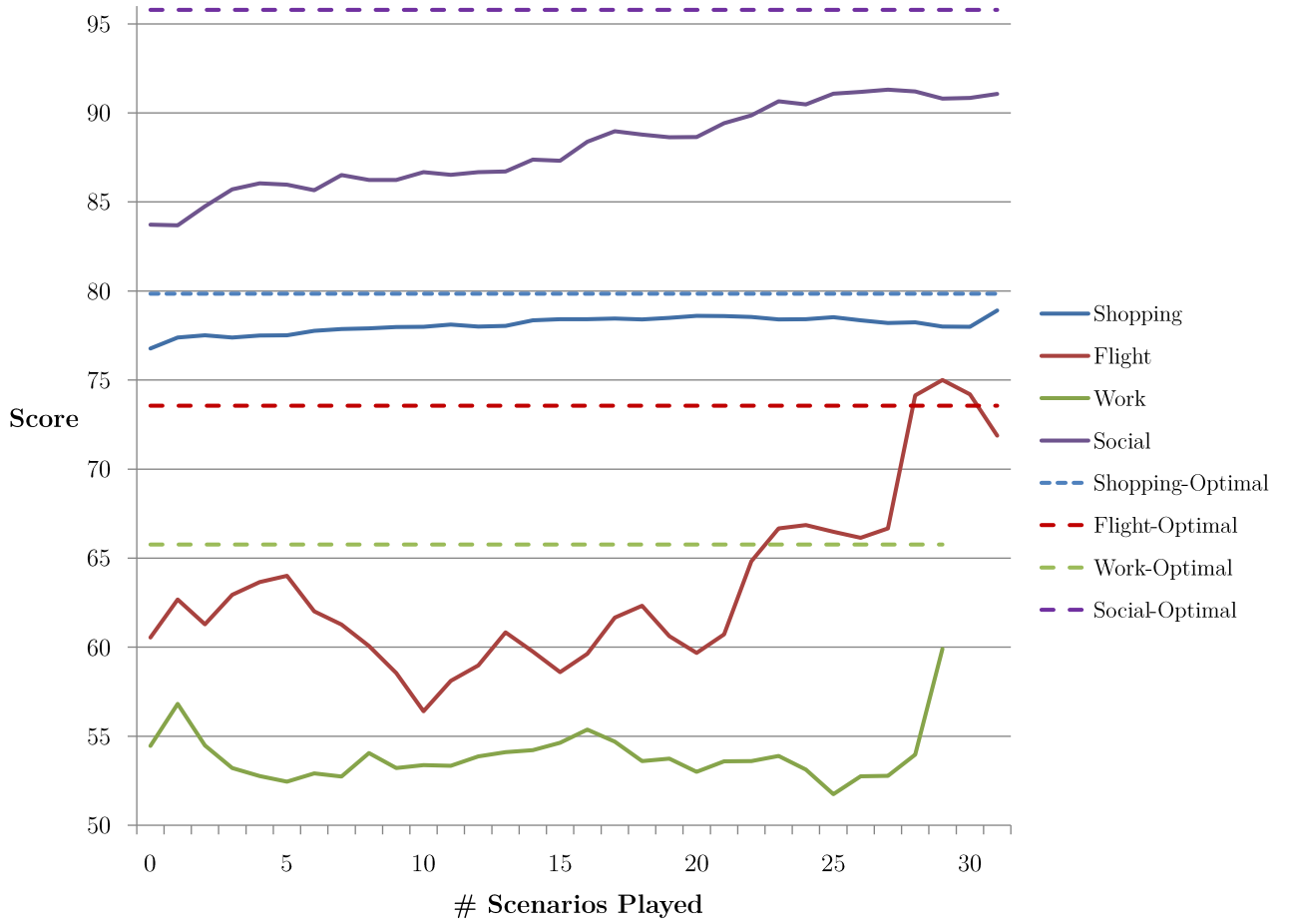


Figure 5.3: Average Score with #Rounds played

5.4 Route Choice Model

The trends show that users tend to follow a decision strategy, which is dependent on the disutility function. The objective of this section and our research, is to try and capture this decision making process into a mathematical model. Further examination of the data reveals trends with respect to other parameters like distance from the destination and number of nodes to choose from (outdegree of the current node). However, these trends do not justify a single deterministic strategy that captures the

decisions of all users, and even the same user at different stages. Hence, we develop a random utility based discrete choice model to determine the policy adopted by the users.

5.4.1 Methodology

We consider the alternatives as the distinct policies themselves. Hence, we have three immediate alternatives as the optimal policy, greedy policy or *a priori* path policy. Another factor of interest is to see how much these three policies overlap with each other. Tables 5.6-5.9 show the overlap of policies. The numbers indicate the percentage overlap between any two policies for a specific scenario. For example, for a social trip, of all decisions that are optimal, 39.56% of them are greedy strategy decisions. We can see that 35–40% of the decisions overlap for each pair of policies for each scenario. Out of those, there are significant cases for which all three overlap simultaneously. These statistics are reported for the entire network over all time periods and node states. However, only some of them are feasible from an analysis perspective. For example, users will not have made decisions at nodes near the origin at late (high) time periods.

Table 5.6: Social Trip: Policy Overlap

Social Trip	Optimal	<i>A priori</i>	Greedy
Optimal	100.00	35.85	36.47
<i>A priori</i>	35.17	100.00	38.65
Greedy	39.56	33.10	100.00

Table 5.7: Work Trip: Policy Overlap

Work Trip	Optimal	<i>A priori</i>	Greedy
Optimal	100.00	42.84	38.92
<i>A priori</i>	41.27	100.00	34.52
Greedy	40.51	32.72	100.00

Table 5.8: Airport Trip: Policy Overlap

Airport Trip	Optimal	<i>A priori</i>	Greedy
Optimal	100.00	45.23	43.26
<i>A priori</i>	47.05	100.00	37.47
Greedy	42.45	32.91	100.00

Table 5.9: Shopping Trip: Policy Overlap

Shopping Trip	Optimal	<i>A priori</i>	Greedy
Optimal	100.00	48.21	38.72
<i>A priori</i>	53.63	100.00	36.37
Greedy	36.20	32.99	100.00

There are many instances where users made decisions which did not coincide with any of these policies. The statistics with respect to these are shown in Table 5.11. Thus, we introduce two additional alternatives which correspond to choices which do not fall under either policy under consideration. These alternatives are chosen as the nodes j whose shortest length to the destination (SP_j) is least and do not fall under any of the policies (refer Table 5.10).

In order to incorporate the fact that policies may overlap with each other and this might possibly increase the probability of that node being chosen, we introduce each overlapping policy as a separate alternative. We refer to each of the 9 alternatives by notations indicated in Table 5.10. A similar model is developed by Srinivasan and Mahmassani [2000] to model route choice from their experiments, when distinguishing between users who do not switch route and users who comply with the VMS message. It is easy to see that each alternative will not be available at each decision point. For example, when the first alternative, $O \equiv G \equiv A$ is available, the three policies coincide, and none of the other alternatives except *Oth1* and *Oth2* can be available. Table 5.11 shows the frequency distribution for each of the alternatives chosen. Considering every users' decision points independently, we have 42,961 observations. Interestingly, over 50% of the decisions involve the first two alternatives,

which include both an optimal strategy and a greedy strategy. Hence, it is difficult to differentiate between the two. However, there is an apparent difference in the number of people choosing alternative O and alternative G or $G \equiv A$. Note that when O is an available alternative, the other available alternatives can only be G or $G \equiv A$ (apart from $Oth1$ and $Oth2$). Close to 20% of the decisions are an optimal strategy, which did not coincide with any other policy. This provides further support to a hypothesis that user decisions are more ‘inclined’ towards an optimal decision, and is in line with the scores observed in Table 5.5.

Table 5.10: MNL alternatives - Notations

Notation	Policy
$O \equiv G \equiv A$	Optimal, Greedy and <i>A priori</i> path policies overlap
$O \equiv G$	Optimal and Greedy policies overlap, <i>A priori</i> path policy is different
$O \equiv A$	Optimal and <i>A priori</i> path policies overlap, Greedy policy is different
O	Optimal policy is different from Greedy and <i>A priori</i> path policies
G	Greedy policy is different from Optimal and <i>A priori</i> path policies
$G \equiv A$	Greedy and <i>A priori</i> path policies overlap, <i>A priori</i> policy is different
A	<i>A priori</i> path policy is different from Optimal and Greedy policies
$Oth1$	Neither Optimal, Greedy or <i>A priori</i> path policy, and $SP_{j^*} = \min_j SP_j, j$ is an adjacent node
$Oth2$	Neither Optimal, Greedy or <i>A priori</i> path policy, and $SP_{j^{**}} = \min_{j \neq j^*} SP_j, j$ is an adjacent node

The decision is made when a user at a node at a particular time, observes the downstream arc states and has to make a decision with respect to the disutility function. Hence, there are certain parameters specific to the alternatives (policies) and few parameters independent of alternatives and specific to the user’s location and time, which may play a role in making the route choice decision. The following independent variables are hypothesized to explain the data:

- Outdegree (*OutDegree*): The outdegree of a node is the number of alternatives to choose from, since complete information is available in the experiment. This may affect the way in which users make decisions.

Table 5.11: Alternatives Chosen: Frequency Distribution

Policy	Frequency	Percent
O≡G≡A	11144	25.94
O≡G	12905	30.04
O≡A	1051	2.45
O	8405	19.56
G	2266	5.27
G≡A	947	2.20
A	725	1.69
Oth1	4801	11.18
Oth2	717	1.67
Total	42961	100.00

- Distance from destination (*distanceDest*): This represents the current location of the node - the distance is represented as the length of the shortest path to the destination (with respect to arc lengths).
- Experience/Network familiarity (*NumScenarios*) - The number of scenarios played by the user till that point is an indication of knowledge gained about the network. This variable can be used to demonstrate a learning experience.
- Relative arc state (*relativeArcState*) - We hypothesize that users make a decision based on the relative congestion levels on each of their route choices. For this purpose, we construct a parameter which quantifies the relative congestion level. In our experiment, arcs may have three discrete congestion levels at 40 mph, 20 mph and 10 mph. For each arc (i, j) , we denote these by their state, $ArcState_{ij}$, which takes values 1, 2, and 3, respectively. For any arc (i, j) , we define the relative congestion levels by

$$relativeArcState_{ij} = \sum_{k \in \Gamma(i)} (ArcState_{ik} - ArcState_{ij}) \quad (5.3)$$

Thus, higher the relative arc state, lower the congestion level on the arc relative

to the other downstream arcs. Note that this may not be an accurate measure of relative state, but we are interested in quantifying a parameter only to study possible trends while choosing policies. Another important point to note is that the arc with the lowest relative state need not be the greedy policy. The greedy policy is defined with respect to the travel time, whereas the relative arc states are defined with respect to the speed.

- Probability distribution of arc states(*arcReliability*)- The probability distribution on downstream links is a measure of the reliability. It is learnt through experience or looking at historical data. We categorize the arcs into three divisions based on probability distribution, with category 1 representing a deterministic arc and 3 representing high variability or equal probability of all states.

We do not consider user characteristics in our model. As discussed in Section 5.1, our motive is to understand how the route choice decisions depend on other parameters mentioned above. Ignoring individual characteristics is a limitation of the model, as trends discussed in Section 5.1 show some correlation between the individual characteristics and game performance. In a sense, the individual decision maker is not the user of the game, but the current ‘state’ in the network (location, experience gained, number of alternatives available).

One of our research objectives is to assess the decision making process under multiple trip objectives or disutility functions. Hence, we develop a model by segmenting the data by trip scenario. The results of the model are described in the next section.

5.4.2 Results

The choice of alternatives in our models is most critical for our understanding. Hence, we develop a model with no parameters to begin. This is to understand the relative

distribution of alternatives chosen, briefly shown in Table 5.11. Table 5.12 shows the results of the model with only constants. Since segmentation is carried out on 4 scenarios, there are a total of 32 $((9(\#alternatives) - 1(fixed)) * 4(scenarios))$ constants. Except for the alternatives $O \equiv G \equiv A$ and $O \equiv G$, all the other alternatives have negative constants. The important result to take away from these values is that when the optimal policy overlaps with the greedy policy, it is very highly preferred. Further, the values of the constants of the optimal policy alternative (O) are less negative than other alternatives. In fact, the value of the constant in the airport scenario is positive. This indicates that when the optimal policy is different from other strategies, it is still a more preferred alternative rather than the greedy or *a priori* strategies.

The specification of the partially segmented model, including network specific parameters and respective coefficients, is tabulated in Table 5.14. The table does not include the constants, which are tabulated separately in Table 5.13.

Table 5.12: MNL results - constants only model

Policy	Social Trip		Work Trip		Airport Trip		Shopping Trip	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
$O \equiv G \equiv A$	0.00	—	0.00	—	0.00	—	0.00	—
$O \equiv G$	0.67	7.84	-0.49	-4.97	0.53	6.47	-0.14	-1.68
$O \equiv A$	-4.63	-4.65	-2.66	-9.46	-1.30	-7.13	-2.73	-7.92
O	-0.06	-0.65	-0.50	-4.72	0.09	1.03	-0.36	-3.77
G	-1.27	-9.99	-3.10	-14.82	-0.43	-4.37	-2.27	-14.77
$G \equiv A$	-1.75	-9.33	-3.04	-14.26	-1.99	-10.46	-2.31	-12.22
A	-2.88	-19.91	-3.93	-20.13	-1.88	-18.39	-2.79	-22.45
Oth1	-0.48	-6.63	-1.55	-25.99	-0.17	-2.46	-1.18	-19.31
Oth2	-1.85	-18.55	-4.18	-23.08	-2.25	-18.87	-3.04	-25.74
Log-likelihood (Initial)	-10105.08							
Log-likelihood (Final)	-10105.08							
ρ^2	0.32							

Table 5.13: MNL - constants from partially segmented model

Policy	Social Trip		Work Trip		Airport Trip		Shopping Trip	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
O $\equiv$ G $\equiv$ A	0.00	–	0.00	–	0.00	–	0.00	–
O $\equiv$ G	-0.34	-0.84	-1.24	-3.49	0.89	4.67	1.25	2.71
O $\equiv$ A	-2.87	-3.32	0.23	0.62	3.76	6.63	1.05	1.75
O	-0.21	-0.99	-0.68	-2.67	0.85	5.23	-0.55	-2.31
G	4.36	5.94	3.79	5.19	1.06	2.59	5.43	4.96
G $\equiv$ A	0.91	2.12	-1.14	-2.80	0.49	1.37	0.54	1.38
A	-0.48	-1.13	-0.75	-2.03	0.64	2.28	1.52	4.05
Oth1	-1.19	-3.75	-3.79	-9.95	-0.33	-1.90	-0.44	-1.37
Oth2	-1.40	-4.79	-3.74	-11.37	-1.90	-8.53	-0.94	-3.04
Log-likelihood (Initial)	-10105.08							
Log-likelihood (Final)	-4882.57							
ρ^2	0.52							

Discussion

We discuss how each of the parameters influence the likelihood of a policy being chosen, drawing suitable inferences and suggesting possible explanations for the trends and behavior patterns. We place emphasis on the trip-wise segmentation carried out in the model. It is interesting to see that many parameters have different and sometimes opposite impacts in different trip types. We note that the work and airport trips have strict time constraints, and high penalty for violating the target arrival time. The shopping trip has a time constraint in the sense that the disutility function is continuously increasing with time, and there is no incentive for a user to delay the arrival time. Relative to other trips, the social trip has a more lenient time constraint and the penalty for late arrival is smaller. With these in mind, we look at the impacts of each of the parameters on the decision making process.

Table 5.14: MNL results - partially segmented model

Variables	Coeff.	t-stat
O$\equiv$G$\equiv$A		
Link Parameters		
relativeArcState (Work, Airport)	0.11	3.45
relativeArcState (Shopping)	0.27	4.99
O$\equiv$G		
Current Location		
OutDegree (Work)	0.24	1.88
OutDegree (Airport, Shopping)	0.54	5.25
O$\equiv$A		
Current Location		
distanceDest (Social)	-2.18	-5.93
distanceDest (Work)	0.60	1.97
distanceDest (Airport)	1.24	1.99
O		
Learning		
NumScenarios (Social)	0.13	2.31
NumScenarios (Work, Airport, Shopping)	0.09	2.48
Link Parameters		
relativeArcState (Work, Airport)	0.11	3.45
relativeArcState (Shopping)	0.27	4.99
G		
Current Location		
OutDegree (Social)	-0.23	-2.14
OutDegree (Work)	-2.14	-6.73
OutDegree (Airport, Shopping)	-1.72	-8.61
Link Parameters		
relativeArcState (Work, Airport)	0.11	3.45
relativeArcState (Shopping)	0.27	4.99
arcReliability (Social, Shopping)	0.35	5.49
arcReliability (Work)	1.38	10.46
arcReliability (Airport)	0.91	7.68
G$\equiv$A		
Current Location		
distanceDest (Social, Shopping)	-0.72	-3.63
distanceDest (Work, Airport)	-1.12	-5.04
Link Parameters		
arcReliability (Social, Shopping)	0.35	5.49
arcReliability (Work)	1.38	10.46
arcReliability (Airport)	0.91	7.68
A		
Current Location		
distanceDest	-1.39	-10.37
Oth1		
Current Location		
distanceDest (Work, Airport)	0.31	4.65
distanceDest (Shopping)	0.84	6.32

Out-degree

The out-degree represents the number of alternatives to choose from, since complete information is available at all nodes in the experiment. Interestingly, a higher number of alternatives negatively impacts the preference to choose a greedy policy relative to the case when all three policies overlap. Intuitively, we would expect an increase in the number of choices to result in users following a more myopic strategy. In case of a higher number of alternatives, users look at strategies other than a greedy strategy and work towards that. Moreover, the impact is highest in airport, work, and shopping trips. A plausible reason for this is that the three scenarios have higher constraints on time (strict time constraints or continuously increasing disutility), therefore users look to optimize their route more effectively. The social trip is more relaxed which leads users to choose myopic strategies to explore other routes. When the optimal and greedy policies coincide, the likelihood of the alternative being chosen in fact, increases with number of alternatives. This may be because this alternative is usually the more ‘easy’ or ‘obvious’ choice to minimize disutility.

Distance from destination

We can see that the distance from the destination has a negative impact on the greedy and *a priori* strategies, and a positive impact on the optimal policy alternative when it overlaps with the *a priori* strategy, relative to the case where all three policies overlap. It is interesting to note the highly positive impact of distance on choosing a policy (*Oth1*) which is neither of the policies. We can conclude that users are trying to optimize their routes closer to the origin when they start navigating. As they get closer to the destination, they prefer greedy strategies as they get them nearer to the destination in less time. In the process of optimizing their route when they start, they are neither following a myopic strategy, nor an optimal strategy, resulting in a choice which is not defined by any of the three policies. Further, the impact is higher for the work and airport trips for the greedy strategy. These trips, with strict time constraints and heavier penalty discourage the user from following a purely myopic or *a priori*

decision strategy and they try to use information and experience to optimize their route. Given this outcome, we would expect the tendency to use an alternative policy in the work and airport trips to be higher for other alternative policies. However, the results show that distance from destination has a lesser impact on these scenarios than a shopping trip while choosing other policies, *Oth1*. Interestingly, the location in the network affects the likelihood to choose an optimal decision (overlapping with an *a priori* strategy) in opposite ways depending on the scenario. For social trips, users are more likely to make optimal decisions closer to the destination while the trend is opposite for airport and work trips. A possible explanation is that users tend to follow optimal strategies with respect to the time constrained work and airport scenarios (which may be similar), and follow the same path for social trips as well, even though the optimal strategy for the social trip may be to take a different route.

Experience/Network familiarity

A learning process is demonstrated to choose the optimal policy, when the optimal decision is different from other policies. Further, knowledge about the optimal policy is gained more in the social trip than other trips. This may be due to a phenomenon discussed previously. It may be that users follow optimal decisions with respect to the more time constrained trips initially, and later learn optimal decisions with respect to social trips. These findings are in sync with the moving averages (of scores) plotted in Figure 5.3.

Relative arc state

The relative arc state influences the decision of four alternatives, which can primarily be classified as an optimal strategy and a greedy strategy. The higher the relative state of the arc, or lower it's relative congestion level, higher the likelihood of it being preferred. The relative state in shopping trips has a greater influence than in the 'stricter' work and airport trips.

Probability distribution of arc states

A higher value for this parameter indicates more variability in the arc states. The parameter positively impacts the greedy strategy. Lesser arc reliability increases the possibility of a greedy strategy being adopted. That is, given an option between two greedy strategies at different instances, users prefer a greedy strategy where the arc reliability is lower. This may be due to a behavioral instinct to explore a new route when it has lesser travel time than usual, but an intuitive explanation is not clear. Further, the influence is higher on the work and airport trips than on the social and shopping trips. It may be more insightful to study this simultaneously with the experience gained in a network (number of scenarios played) and to examine reliability at the path level rather than at the link level.

5.4.3 Validation

The model was developed using a random sample of 9,000 data points drawn from the dataset of close to 43,000. We validate the model using the remaining data points. For each observation i , the probability of choosing policy π , $P_i(\pi)$, is calculated as $e^{V_\pi} / \sum_j e^{V_j} * av_j$, where av_j indicates if alternative j is available. V_j is the utility of the alternative computed using the specification mentioned in Table 5.14. The total estimates over all observations, $\sum_i P_i(\pi)$ are reported in Table 5.15 for the developed model and the model with constants only. The model with constants only gives estimates of policy preferences when they overlap with each other. The model with specifications further builds on these preferences with network parameters. The results show that the model estimates trends in the entire dataset fairly accurately, given the number of uncertainties in user decisions. Specifically, all the estimates involving the optimal policy have estimates within 13% (except $O \equiv A$). On comparing with the constants only model, higher improvements can be noted in the greedy strategy. In the estimate of the alternative being chosen when $G \equiv A$, the model with specifications overestimates the preference - a high transfer of alternative preferences

from the underestimated count in the model with constants only. We also observe the drastic improvement in forecasts in the policy *Oth1*, which signifies choosing none of the three policies, as well as the alternative $O \equiv A$. Note that the three alternatives discussed now have *distanceDest* in their specification. Traveler’s relative location along their path seems to be a factor which strongly influences their driving behavior. Overall, the model gives a good description of the drivers’ route choices.

Table 5.15: Model validation

Policy	Data	Constants only model		Full specification	
		Estimate	%age difference	Estimate	%age difference
$O \equiv G \equiv A$	11144	8694	21.98	9743	12.58
$O \equiv G$	12905	11531	10.65	13761	6.63
$O \equiv A$	1051	235	77.62	829	21.17
O	8405	7150	14.93	7587	9.73
G	2266	1611	28.90	1908	15.79
$G \equiv A$	947	393	58.54	1353	42.86
A	725	910	25.48	852	17.55
Oth1	4801	11455	138.59	6018	25.34
Oth2	717	983	37.03	911	27.02

5.4.4 Summary

We developed an MNL model to explain the choice of policies adopted by users in the experiment. We compared user decisions to three policies discussed in Section 3.4 and noted that locations where the optimal and greedy strategies coincided with each other were the most preferred option. In cases where the policies were different, the optimal strategy was preferred more than a greedy or *a priori path* strategy. Some of the other findings included that users optimize their route closer to the origin when they start their trip, and a higher number of downstream links results in less preference for the greedy strategy. There were trends of learning portrayed as users played more scenarios. Further, the congestion levels of a downstream arc relative to other arcs is a factor in choosing the policy. Links with less congestion relative to adjacent

links are preferred.

The most interesting finding was the influence on different trip types in different ways, and sometimes in opposite trends (distance from destination had opposite impacts on social and work trips in optimal strategies). This demonstrates different behavior with different disutility functions, which was one of our main motives of carrying out this study.

Chapter 6

Conclusion

6.1 Summary

The research efforts in this thesis have studied individual travel behavior in response to real time information under multiple travel objectives. The class of problems studied for this purpose is the OSP (online shortest paths), where one can observe and adapt to the information gained *en route*. We use different functional forms to represent disutility for the travel objectives, defined in Section 3.3. In order to study the behavior of travelers in such conditions, we developed a web based application to simulate an environment with multiple travel objectives and real time information. Responses from 131 participants are analyzed in detail. In order to compare user decision strategies to well defined mathematical policies (or decision rules), we compare their decisions to three policies defined in Section 3.4. The optimal policy minimizes expected disutility, the greedy strategy is a myopic behavior in response to the observed information, and the third is to follow an *a priori* path. Preliminary analysis shows that there is no trend to indicate one single policy followed by users, but a significant composition of the decisions involve optimal and greedy strategies. Further, the decisions have a common trend with respect to location in the network, specific information on downstream congestion levels gained, and familiarity gained with the network. In order to incorporate all such possibilities and uncertainty in strategy followed, an MNL model is developed to determine the preference for each policy. The methodology and parameters of the models are outlined in Section 5.4. The results, discussed in Section 5.4.2, show that users decision strategies vary with travel objectives. Apart from the differences or overlap in the policy itself, other

parameters also influence the policy chosen dependent on the travel objective. We then validate this model to demonstrate it's description of the user decision making process. Hence, the outcome of this research is an insight into the traveler decision strategy in response to real time information under multiple travel objectives.

6.2 Future Work

The immense volume of data collected during the experiment permits the possibility of dwelling further into it to gain insights into routing strategies. We suggest further analysis that could be carried out using the same data or data from other such experiments. In Section 5.4.1, we discussed that the demographics of the participants was ignored for the model. There is evidence of some relation between the participants' demographic characteristics and their performance. Incorporating these into the model specification would enhance it's ability to describe the data. Further, there might be useful outcomes in studying the individual responses over time. Each decision in the game is considered as an independent data point. Studying these in relation to previous decisions during the same trip and previous trips may uncover certain trends as well. It may be useful to study the trends of the entire paths, in addition to modeling the routing at link level. However, we can represent the same link level decisions in our experiment as a choice of different paths with the downstream node representing the next information location point along the chosen route. Another point of interest may be to study if and when users have revisited nodes, or cycled along their route. This can lead to relevant insights on *contretemps* (Boyles [2009b]), discussed in Section 3.3.3.

The immediate step is to move from individual routing strategies towards equilibrium. Results obtained here or may be useful in calibrating hyperpath equilibrium models. This is necessary for such models to be used in practice. Similar experiments may be carried out involving interaction between participants to study convergence

to an equilibrium, if any. A dynamic description of the system is necessary to make the equilibrium model(s) more realistic. The adaptive routing strategy and the experiments assume that the arc states are independent of time and space, or they do not depend on the state of the arc in previous time intervals or states of adjacent links in current and previous time intervals. However, a truly dynamic system would incorporate effects of changes in a link throughout the system.

Bibliography

- R.K. Ahuja, T.L. Magnanti, and J.B. Orlin. *Network flows: theory, algorithms, and applications*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1993. ISBN 0-13-617549-X.
- E. Avineri and J.N. Prashker. The impact of travel time information on travelers learning under uncertainty. *Transportation*, 33:393–408, 2006.
- S.D. Boyles. Reliable routing with recourse in stochastic, time-dependent transportation networks. Master’s thesis, The University of Texas at Austin, 2006.
- S.D. Boyles. Online routing and equilibrium with nonlinear disutility functions. 2007.
- S.D. Boyles. An exact label-correcting algorithm for the online shortest path problem in cyclic graphs. 2009a.
- S.D. Boyles. *Operational, Supply-Side Uncertainty in Transportation Networks: Causes, Effects, and Mitigation Strategies*. PhD thesis, The University of Texas at Austin, 2009b.
- S.D. Boyles and S.T. Waller. The impact of nonlinear objective functions in online shortest paths. In *86th Annual Meeting of the Transportation Research Board, Washington, DC.*, 2007.
- S.D. Boyles and S.T. Waller. Optimal information location for adaptive routing. 2009.
- I. Chabini. Discrete dynamic shortest path problems in transportation applications: Complexity and algorithms with optimal run time. *Transportation Research Record*, 1645:170–175, 1998.

- M. de Lapparent, A. de Palma, and C. Fontan. Nonlinearities in the valuations of time estimates. In *Professional Transportation Research Part Conference, London*, Cambridge, United Kingdom, 2002.
- H. Dia and S. Panwai. Modelling drivers compliance and route choice behaviour in response to travel information. *Nonlinear Dynamics*, 49:493–509, 2007.
- R.B. Dial. A probabilistic multi-path traffic assignment model which obviates path enumeration. *Transportation Research*, 5:83–111, 1971.
- Y. Fan, R. Kalaba, and J. E. Moore II. Arriving on time. *Journal of Optimization Theory and Applications*, 127(3):497–513, 2005.
- L. Fu and L. R. Rilett. Expected shortest paths in dynamic and stochastic traffic networks. *Transportation Research Part B*, 32:499–516, 1998.
- S. Gao. *Optimal Adaptive Routing and Traffic Assignment in Stochastic Time-Dependent Networks*. PhD thesis, Massachusetts Institute of Technology, 2005.
- S. Gao. Modeling strategic route choice and real-time information impacts in stochastic and time-dependent networks. *IEEE Transactions on Intelligent Transportation Systems*, 13:1298–1311, 2012.
- S. Gao and I. Chabini. Optimal routing policy problems in stochastic time-dependent networks. *Transportation Research Part B*, 40:93–122, 2006.
- S. Gao and H. Huang. Real-time traveler information for optimal adaptive routing in stochastic time-dependent networks. *Transportation Research Part C*, 21:196–213, 2012.
- R.W. Hall. The fastest path through a network with random time-dependent travel times. *Transportation Science*, 20(3):182–188, 1986.

- D. Helbing. Dynamic decision behavior and optimal guidance through information services: Models and experiments. *Human Behaviour and Traffic Networks*, pages 47–95, Springer, Berlin, 2004.
- H.H. Hochmair and V. Karlsson. Investigation of preference between the least-angle strategy and the initial segment strategy for route selection in unknown environments. *Spatial Cognition IV*, LNAI 3343:79–97, 2005.
- RC Jou, SH Lam, YH Liu, and KH Chen. Route switching behavior on freeways with the provision of different types of real-time traffic information. *Transportation Research Part A*, 39:445–461, 2005.
- H.N. Koutsopoulos, A. Polydoropoulou, and M. Ben-Akiva. Travel simulators for data collection on driver behavior in the presence of information. *Transportation Research Part C*, 3:143–159, 1995.
- C. Lee, B. Ran, F. Yang, and WY Loh. A hybrid tree approach to modeling alternate route choice behavior with online information. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, 14(4):209–219, 2010.
- X. Lu, S. Gao, E. Ben-Elia, and R. Pothering. Information impacts on travelers route choice behavior in a congested risky network. In *TRB 2012 Annual Meeting*, 2011.
- B. Mandel, M. Gaudry, and W. Rothengatter. Linear or nonlinear utility functions in logit models? the impact on german high speed rail demand forecasts. *Transportation Research Part B*, 28, No 2.:91–101, 1994.
- E.D. Miller-Hooks. Adaptive least-expected time paths in stochastic, time-varying transportation and data networks. *Networks*, 37:35–52, 2001.
- E.D. Miller-Hooks and H.S. Mahmassani. Least expected time paths in stochastic, time-varying transportation networks. *Transportation Science*, 34(2):198–215, 2000. ISSN 00411655.

- E.D. Miller-Hooks and H.S. Mahmassani. Path comparisons for a priori and time-adaptive decisions in stochastic, time-varying networks. *European Journal of Operational Research*, 146:67–82, 2003.
- J. Morgan, H. Orzen, and M. Sefton. Network architecture and traffic flows: Experiments on the pigouknightdowns and braess paradoxes. *Games and Economic Behavior*, 66:348–372, 2009.
- Y. Nie and Y. Fan. Arriving-on-time problem: discrete algorithm that ensures convergence. *Transportation Research Record*, 1964:193–200, 2006.
- Y. Nie and X. Wu. Shortest path problem considering on-time arrival probability. *Transportation Research Part B*, 43:597–613, 2009.
- A.R. Pinjari and C.R. Bhat. Nonlinearity of response to level-of-service variables in travel mode choice models. *Transportation Research Record: Journal of the Transportation Research Board*, 1977:67–74, 2006.
- G.H. Polychronopoulos and J.N. Tsitsiklis. Stochastic shortest path problems with recourse. *Networks*, 27:133–143, 1996.
- J.S. Provan. A polynomial-time algorithm to find shortest paths with recourse. *Networks*, 41(2):115–125, 2003. ISSN 1097-0037.
- G. Ramadurai and S.V. Ukkusuri. Dynamic traffic equilibrium: Theoretical and experimental network game results in single-bottleneck model. *Transportation Research Record*, 2029:1–13, 2007.
- R. Selten, T. Chmura, T. Pitz, S. Kube, and M. Schreckenberg. Commuters route choice behaviour. *Games and Economic Behavior*, 58:394–406, 2007.
- K.K. Srinivasan and H.S. Mahmassani. Role of congestion and information in trip-makers dynamic decision processes: An experimental investigation. *Transportation Research Record*, 1676:44–52, 1999.

- K.K Srinivasan and H.S. Mahmassani. Modeling inertia and compliance mechanisms in route choice behavior under real-time information. *Transportation Research Record*, 1725:45–53, 2000.
- A. Unnikrishnan and S.T. Waller. User equilibrium with recourse. *Networks and Spatial Economics*, 9:575–593, 2009.
- S.T. Waller and A.K. Ziliaskopoulos. On the online shortest path problem with limited arc cost dependencies. *Networks*, 40(4):216–227, 2002. ISSN 1097-0037.
- A.K. Ziliaskopoulos and H.S. Mahmassani. Time-dependent, shortest-path algorithm for real-time intelligent vehicle highway system applications. *Transportation Research Record*, 1408:94–100, 1993.