DAY-TO-DAY DYNAMICS AND SYSTEM RELIABILITY IN URBAN TRAFFIC NETWORKS

By

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Dissertation

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

in

Civil Engineering

May, 2006

Nashville, Tennessee

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ACKNOWLEDGEMENTS

This work would not have been possible without the financial support from the Vanderbilt Graduate School, the Department of Civil and Environmental Engineering, and the National Science Foundation grant DMI-0223492.

I would like to express my sincere gratitude to my advisor and committee chair Dr. Robert E. Stammer, Jr. for his encouragement, support and guidance during my Ph.D. study. I would also like to acknowledge Dr. Karthik Srinivasan for his continuous support and guidance from his technical expertise and experience. I am also thankful to Dr. Mark Abkowitz, Dr. Malcolm Baird, Mark Ellingham, and Dr. Sankaran Mahadevan, members of my dissertation committee, for their participation and useful suggestions.

I want to thank my dear friends, especially Yusong Li and Wenying Li, who have helped me in many ways and have made my stay at Vanderbilt memorable. I thank all my colleagues in Kimley-Horn and Associates Memphis office, especially Kenny Monroe and James Collins, for their support and encouragement to the timely completion of my dissertation.

Finally, I want to express my gratitude to my wife Wenjun, my sister Zhiling and my mother Xiangguo. I could not have finished this dissertation without all your patience and support throughout my life.

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ATIS	Advanced Traveler Information Systems
BDI	Belief-Desire-Intention
BP	Best Path
CP	Current Path
DYNASMART	Name of the dynamic traffic assignment model originally developed in University of Texas at Austin
KSP	K-Shortest Path
IEFR	Integer Excess Flow Redistribution Problem
ITS	Intelligent Transportation Systems
MIP	Mixed Integer Problem
MP	Market Penetration
MSA	Method of Successive Averages
MVAP	Minimum Variance Assignment Problem
O-D	Origin-Destination
PAT	Preferred Arrival Time
RCAP	Robust Cost Assignment Problem
RSO	Robust System Optimal
SDL	Late Schedule Delay
SO	System Optimal
TCM	Transportation Control Measures
UE	User Equilibrium

CHAPTER I

INTRODUCTION

1.1 Background

The increase in congestion levels on existing traffic systems, and the limited space available for expansion have led to an increased interest in alternative congestion reduction methods. The implementation of Intelligent Transportation Systems (ITS) holds promise for meeting the challenges of more effective and efficient use of existing transportation systems by applying advanced and emerging technologies in information processing and communications. Advanced Traveler Information Systems (ATIS), a key component of ITS, provide real-time traffic information (both en-route and pre-trip) to assist users in trip planning and decision making to improve travel efficiency. Through the provision of information, ATIS attempt to achieve several system objectives including reducing system congestion, reducing uncertainty, improving mobility, safety, and convenience. To achieve these objectives, there is a need for the development of more accurate models which lead to more effective investment, design, operation and planning of urban transportation networks.

To support these decisions, dynamic traffic assignment models aim to describe network flow dynamics, and form a core component in the evaluation and operation of Intelligent Transportation Systems. Three principal time-frames are of interest in dynamic network analysis of transportation systems: real-time, within day and day-today dynamics *(Mahamassani, 1997)*. Real-time dynamics relates to dynamics that arises due to the effect of real-time traffic information on user decisions (particularly en-route) and system performance. Within-day dynamics refers to variations in trip-time due to variation in O-D patterns across different departure times. Day-to-day dynamics refers to variation in network flows from one day to the next due to various types of internal and external system perturbations *(Srinivasan and Guo, 2003)*. Such perturbations include but are not limited to: day-to-day departure time and route changes, effect of transportation control measures, activity and stop changes, weather-induced effects, incidents and accidents, construction, ramp and highway closure, special events such as concerts, etc.(*Peeta, 2001)*. These perturbations can lead to fluctuations in system performance from day-to-day as well as the travel experiences of commuters (trip-time reliability, probability of arriving late, etc.). Many dynamic network models have focused on the first two dimensions of dynamics given the interest in modeling routing decisions under information. However, investigations into day-to-day dynamics have received relatively limited research attention. Furthermore, there is increasing interest and growing recognition of the importance of travel time stability and reliability. For instance, FSHRP (Future Strategic Highway Research Program) makes travel time reliability an important priority area for research in the upcoming decade. In this context, this study focuses on the impact of day-to-day dynamics on network performance and system reliability. In this study, system reliability is investigated from the following aspects. Trip time reliability for a user is defined as the fraction of days when the experienced travel time exceeds the mean travel time by a certain threshold. Reliability of on time arrival is the fraction of days when users' arrival time fell within a threshold from the preferred arrival time.

Information reliability is measured as the fraction of good messages among total messages received by the user.

In this context, from a theoretical point of view, a robust cost network optimization algorithm to account for the randomness of trip time is proposed and its application is demonstrated for the static traffic assignment problem. Next, a day-to-day simulation framework is developed and integrated with the DYNASMART traffic simulator. The proposed day-to-day simulation framework has the capability to capture various sources of dynamics and randomness including 1) user's departure time switching behavior, 2) pre-trip and enroute route choice decisions, 3) interaction of day-to-day, within-day, and real time dynamics, and 4) simulation of incidents and its impact on day-to-day dynamics. Using this day-to-day simulation framework, the influence of several key factors including user behavior factors, demand management measures, and incidents on network evolution, trip-time reliability, and commute experience metrics (on-time arrival propensity) are analyzed. From a practical point of view, four potential trip time reliability improvement approaches are analyzed. These four approaches include transportation control measures, incident management strategies, real-time information market penetration, and reduction of departure time switching rate.

1.2 Motivation

The effectiveness of ATIS and ITS depend on their ability to monitor and predict traffic conditions (as they evolve) and the ability to influence user response favorably. Given the dynamic nature of information, to support the needs of information supply through ATIS, various types of dynamic traffic assignment models have been proposed.

These studies have sought to characterize steady state conditions and equilibrium flows, typically under the assumption of known but time dependent demand O-D distribution *(Watling, 1999)*. Fewer studies examine day-to-day dynamics in real world networks (*Watling, 1999; Peeta, 2001*), particularly dynamics that result from variation in departure time decisions of trip-makers despite significant empirical evidence of such variability (*Hatcher, 1992; Cherrett, 1997; Van Berkum, 1998; Jou, 1998; Lu, 2000*). Commuter diary studies in Texas indicate that 52% of the commuters switch their departure time from day to day, and 25% of the commuters switch their route from day to day *(Jou, 1998)*. Disregarding departure time adjustment decisions from day-to-day can lead to errors in evaluation of planning options since the time-dependent O-D matrix may not be accurate. Another common assumption in dynamic traffic assignment relates to equilibrium where users select paths such that all used paths have equal and minimal trip times. However, empirical data shows significant route switching in practice *(Cherrett, 1997; Van Berkum, 1998; Lu, 2000).* This suggests that the chosen routes are not necessarily optimal under time-varying traffic. Other studies show that equilibrium may not exist or may not be stable *(Horowitz, 1984)*, or the system may converge to a 'deluded' equilibrium state *(Nakayama,1999)*. These studies, though, have mainly focused on the day-to-day dynamics in a static network, without real-time information or a time-dependent O-D matrix. Consequently, limited insights are available on 1) how users' route and departure time decisions evolve from day-to-day in response to real-time information and system dynamics, 2) how system dynamics, reliability and stability change as a result of user response, and 3) the quality and role played by information and other supply-related factors.

The insights on the influence of real-time information on day-to-day decisions are essential for the evaluation of ATIS and ITS technologies. A clear understanding of day-to-day dynamics could be applied towards the design of information systems and for the development of guidelines to improve the stability and reliability of system performance. Furthermore, a better understanding of system performance over a longer multi-day planning horizon is also of interest for practical applications including work zone and construction planning, incident management, and more cost-effective network design and operational decisions.

The motivation for this study is threefold. First, the development of such day-to-day network models have important practical applications: 1) to identify or assess strategies to guide or steer the system towards the equilibrium (through information or other means) when substantial deviations occur, 2) to evaluate the performance of demand management strategies from a commute reliability perspective, and 3) to investigate the role of incident characteristics on travel delays and identify effective strategies to ensure smoother traffic flows from day to day. Insights and models along these lines will have important implications for congestion mitigation, improvement of travel time reliability, assessment of different travel demand management strategies, improvement of incident management strategies, and the evaluation of alternative ITS technologies. Second, several sources of day-to-day dynamics are observed and reported in real-world networks, but the underlying sources and their influence on system volatility and commute reliability are not yet well understood *(Huff et. al. 1986, Hazelton et. al. 1996a, Cherrett 1997)*. In this context, there is a need to incorporate richer, dynamic, and more behaviorally realistic models of user behavior concerning factors such as departure time and route switching while investigating network reliability. Finally, dynamic user equilibrium models currently used for network analysis are inadequate while investigating network reliability and day-to-day variability under system perturbations because of their steady state assumptions. These assumptions may not hold in the presence of system shocks and perturbations (*Cantarella, 1995; Cascetta, 1991*). Therefore, to analyze system reliability and deviations from equilibrium, a day-to-day system evolution framework is necessary.

1.3 Objectives

Given the motivating considerations discussed in the previous section, five major objectives are pursued in this study: 1) to propose a robust network assignment algorithm to account for the randomness of trip time, 2) to develop a dynamic simulation model for analyzing day-to-day dynamics under real-time information, 3) to analyze the impact of internal perturbations, particularly the role of users' route and departure time choice behavior on day-to-day network dynamics and trip-time reliability, 4) to investigate the role of transportation control measures (TCMs) on day-to-day evolution of network flow and trip time reliability, and 5) to analyze the effect of unplanned capacity reduction (in the form of incidents) on day-to-day dynamics and system reliability.

Under the first objective to develop an assignment algorithm accounting for trip time randomness, two sub-objectives are pursued. The first sub-objective aims to propose an algorithm for robust cost optimization in networks with random arc costs involve day-to-day dynamics. A new formulation and solution methodology is proposed for the robust network assignment problem that explicitly considers trip time variability. Several important variants of the robust cost assignment problem are also analyzed. The second sub-objective involves demonstrating the performance and practical use of the algorithm in an experimental traffic network.

Under the second objective investigating day-to-day dynamics, the following sub-tasks are pursued. First, an agent-based belief-desire-intention (BDI) architecture is used to model the day-to-day dynamics under the route choice and departure time adjustment decision process of commuters. Two empirically calibrated utility maximization behavior models are used as the core components of this BDI architecture. Second, the capability to simulate day-to-day evolution in traffic flows at the network level is obtained by integrating these dynamic and stochastic decision models with a dynamic network traffic simulation assignment model (DYNASMART). This integration of within-day and day-to-day network traffic assignment capabilities depicts a wider range of system performance measures at the three levels of dynamics: real-time, within-day, and day-to-day in a coherent, mutually consistent, and a co-evolving framework. Specifically, the integrated framework and simulation model enable the computation of several day-to-day related performance measures including departure time switching rate, percentage links in common, and individual level switching measures that account for each user's past traffic experience. Furthermore, the variability and reliability at the system level can be captured through several indicators including trip time reliability, trip time volatility, and on time arrival reliability. In addition the quality of information and its variation over time (within-day and from day-to-day) can also be monitored and evaluated. Thus this proposed day-to-day framework will facilitate the analysis of the impacts on information, user response, traffic management measures and system control measures, on the evolution of the network performance and its reliability from day-to-day. Third, to investigate the effects of different behavioral rules, a model depicting multiple user behavior classes (departure time only, en-route route choice only, pre-trip route choice only, and combinations of the three) is proposed. Fourth, in order to simulate the incidents from day to day, simulation procedures for random sampling incidents are developed. Incident characteristics such as the probability of occurrence, durations and incident severity are embedded in the proposed simulation framework.

The following sub-objectives are investigated for the third objective investigating internal perturbations. The first sub-objective analyzes the influence of routine perturbations induced by small changes in user behavior under real-time information. Specifically, the effect of users' route and departure time switching decisions on network evolution and its reliability are studied. Under this objective, the influence of joint switching, sequential switching, and switching in only one dimension (route only, or departure time only) are also analyzed. The second sub-objective investigates the influence of changes in users' sensitivity (responsiveness to system performance factors) on system trip-time, network reliability, and commuting performance and reliability (e.g., on-time arrival reliability). In this objective, the influence of users' responsiveness is investigated at two levels: systematic changes in user sensitivity to factors (e.g., mild, moderate, or high sensitivity to late schedule delay), and unobserved variations in sensitivity to system attributes across different users.

The fourth objective focuses on the effect of external demand side shocks in conjunction with transportation control measures (TCM). Under this objective, the effect of staggered work hours, real-time information provision, telecommuting, and work-week compression are studied on day-to-day evolution, system stability, and commute reliability measures.

The fifth and last objective is to analyze the day-to-day dynamics and system reliability under non-recurrent supply-side shocks (in the form of incidents). Under this objective, the effect of key incident characteristics including the probability, duration, and severity on system stability and reliability are investigated, and alternative measures to improve network performance and reliability (real-time information, incident management measures, and departure time switching rate reduction) are analyzed.

Through these objectives this study aims to contribute to dynamic and stochastic transportation network modeling literature in the following respects: 1) proposing a new algorithm for robust cost minimization in networks with random arc costs that explicitly takes into account correlated arc costs and trip-time variability on the arcs, 2) developing a tool for quantifying and analyzing travel time reliability and stability (an emerging thrust in network operations, 3) providing insights on the various factors that affect network reliability and day-to-day evolution, 4) identification of transportation control measures to improve network reliability and reduce congestion, and 5) analyzing incident impacts on day-to-day dynamics, with guidelines on effective incident management.

1.4 Overview of Approach

To address the first objective of developing a robust cost assignment algorithm, a robust cost network optimization formulation is proposed for networks with random and correlated arc costs. The robust cost minimization model aims to minimize a hybrid robust cost function that consists of a combination of the mean and variance of arc costs.

The associated existence, uniqueness, and optimality conditions are identified and used to develop a solution algorithm. A polynomial time algorithm is proposed and implemented for solving the robust cost optimization problem when real-valued flows are sufficient. Models for several important variants of the robust cost minimization problem are also proposed including: 1) minimum variance assignment problem, 2) robust cost minimization problem with integer constraints, and 3) robust cost problem with independent within-link flows. A two-stage heuristic is proposed when integer valued solutions are demanded by the practical application (e.g., network revenue management applications where flows represent customer acceptance decisions). The application of this general network algorithm to a robust cost traffic assignment problem is also demonstrated for a simple test network. On this network, computational experiments are used to examine the role of arc trip-time variability on the system performance. The results of the robust assignment solution are also compared to the deterministic system optimal assignment formulation.

The second objective of investigating day-to-day dynamics is addressed by developing a simulation-based framework to model day-to-day dynamics in network flows. Simulation-based models are necessitated by the complexity of the day-to-day studies (stochasticity and dynamics), which precludes the use of analytical approaches *(Nagel, 2000)* for realistic networks. The proposed framework accounts for the day-to-day variation in departure time and routing decisions through the use of empirically calibrated user behavior models and agent-based belief-desire-intention architecture as described in Chapter 3. This simulation framework provides for a joint and mutually consistent representation of within-day and day-to-day dynamics in an integrated framework by integrating a dynamic assignment model (DYNASMART) with this day-to-day user decision framework.

The following unique features are included in this simulation framework. An agent-based behavior modeling approach is proposed that incorporates empirically calibrated models of user decisions under real-time information that accounts for user's past experience, system dynamics and information quality. This agent-based architecture is used to represent within-day and day-to-day route choice dynamics and departure time adjustment decisions. In particular, this framework provides the capability of simulating all day-to-day related variables, past traffic experience and cumulative variables, and various performance measures of interest with respect to system volatility, system reliability, and information reliability that are typically disregarded in within-day dynamic network models. The simulation model also includes the capability to represent stochastic incidents that are needed to analyze the impact of incidents on system reliability and performance. The new incident simulation procedure captures the randomness of incidents from day-to-day, thus relaxing the limitation of the original incident model in DYNASMART which allows only pre-determined incidents. This integrated simulation model is used to conduct a series of computational experiments to achieve the remaining objectives.

To meet the third objective of investigating internal perturbations, two sets of experiments are conducted. The first set of experiments focuses on 1) the effect of joint switching versus separate switching, and 2) the influence of initial conditions, in the form of different recurrent congestion levels and simultaneous versus sequential switching. The second set of experiments examines the role of variations in user behavior. Six factors are considered in this set of experiments. These factors include departure time inertia, route switching inertia, sensitivity to late schedule delay, sensitivity to trip time volatility, unobserved variability in departure switching behavior, and unobserved variability in route switching behavior. The corresponding coefficients in the behavior model are varied systematically and the resulting system performance is recorded and analyzed.

The fourth objective involving external perturbations is performed by analyzing the effect of transportation control measures (staggered work hours, real-time information provision, telecommuting, and work-week compression) on day-do-day dynamics and system evolution. The staggered work hour is simulated by staggering the preferred arrival times of a fraction of users. Real-time information scenario is simulated by providing real-time information to users, as per the desired level of market penetration. Telecommuting is modeled by adjusting the demand based on the assumption that a certain fraction of users work from home once a week. Work-week compression is modeled by assuming that a fraction of commuters have a compressed work week schedule, and adjusting their departure times accordingly.

In analyzing the fifth objective involving supply side shocks, the following tasks are performed. First, the impact of the incidents is studied by systematically varying unplanned congestion levels (incident probabilities), conditional probability of different incident types, severity of the incidents, incident durations, and spatial distribution of incidents. Second, alternative measures for improving network performance and reliability (real-time information, incident management measures, and departure time switching rate reduction) are analyzed and the findings are discussed.

This study is distinct from prior studies in the following four respects. 1) The BDI agent modeling architecture with dynamic and empirically calibrated user behavior models as decision rules in network performance analysis are used, which enables the treatment of within-day and day-to-day dynamics as mutually endogenous and co-evolving stochastic processes in response to information and user behavior. 2) Various reliability metrics, such as trip-time reliability and on-time arrival fractions, are accessed together with conventional performance measures in this study. 3) Alternate TCM strategies and the sensitivity of user behavior on system dynamics are studied, with relaxation of steady state assumptions. 4) The impact of incident characteristics and the effectiveness of information and incident management approaches under incident scenarios are systematically analyzed.

1.5 Structure of This Dissertation

The rest of the dissertation is organized as follows. Chapter 2 reviews related literature on various sources of system perturbation and their impact on day-to-day network performance, and highlights critical gaps in modeling day-to-day dynamics under real-time information. In Chapter 3, the robust assignment algorithm for minimum cost network flows under random arc costs is presented. The simulation framework proposed in this study is described in detail in Chapter 4. Chapter 5 presents the experimental design, results and findings for alternative user behavior factors and transportation control measures (objective 4 and 5). Incident simulation procedures, experimental design and analysis are discussed in Chapter 6. The last chapter summarizes the research work and findings, the suggested contributions to new knowledge, and the future research directions.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

2.1 Overview

This chapter briefly reviews prior studies on within-day and day-to-day dynamics in urban transportation network flows. The purpose of this review is to 1) synthesize current knowledge on within-day and day-to-day modeling approaches, 2) to recognize the essential characteristics of the process under study, and 3) to outline the approaches adopted by various researchers and highlight their salient results and limitations with regard to the research issues of interest in this study.

The sources of day-to-day dynamics and variability in urban transportation networks are presented in the next section. In Section 2.3, the literature pertaining to ATIS and their influence on trip-maker's behavior and within day and day-to-day dynamics are reviewed. Within-day dynamic simulation models based on various equilibrium assumptions are presented in Section 2.4. In Sections 2.5 and 2.6 the literature on day-to-day route choice-based and departure time based models are reviewed. In Section 2.7, agent-based modeling approaches, from both control and user behavior point of views, are presented and critiqued briefly. Section 2.8 reviews the related research on transportation network reliability analysis. Finally, gaps in the literature are identified and the need for the current study is described in Section 2.9.

2.2 Sources of Day-to-day Dynamics and Variability

Traffic networks are routinely subjected to external and often time-varying demand and supply side shocks, which affect network performance, resulting in possible deviations from equilibrium. Examples of such shocks include changes in traffic patterns due to weather (rain/snow) related capacity reductions, planned and unplanned maintenance (*Mahmassani, 1997*), special events such as concerts, stochastic accidents and incidents, and other factors. Equilibrium-based models are not designed to address the impact of these shocks, or to evaluate alternative strategies to manage the impacts of these perturbations (*Peeta et. al., 2001*). Traffic studies routinely show the presence of daily, monthly, and seasonal variation in flows in real-world networks. A study of traffic on I-10 freeway in San Antonio, instrumented with detectors, revealed significant day-to-day variability in traffic speeds (up to 20 mph difference) during the evening peak period (*Cherrett, 1997*). Significant day-to-day variations in network flows have also been reported by observational studies of traffic in the Netherlands and England (*Van Burkum, 1998; Lu, 2000*).

Day-to-day dynamic and stochastic effects in trip-maker behavior may also lead to significant day-to-day variations observed in real-world networks *(Srinivasan and Guo, 2003)*. Departure time switching rates of 56-65% were observed in commuter behavior in the cities of Dallas and Austin over a two-week period, while route switching rates estimated to be between 23-31% (*Hatcher, 1992; Jou, 1998*). These findings suggest that users are more likely to switch departure times from day-to-day, whereas, many equilibrium models focus mainly on modeling routing decisions. The extent and significance of these switching rates call into question the existence of equilibrium traffic flows, particularly, when trip-maker choice behaviors exhibit significant switching rates. Several recent studies on the role of real-time traffic information suggest that information induces significant route switching behavior within-day and departure time and pre-trip route switching behavior from day-to-day (*Vanghn, 1995; Chen, 1999; Srinivasan, 1999*). Furthermore, there is significant evidence that users' learn dynamically about evolving traffic conditions based on information and experience, and adjust their behavior accordingly (*Nagel, 1994; Rickert, 1997; Selten, 2002; Iida, 1992; Nakayama, 1999*).

Day-to-day variations in traffic flows could also arise from variations in underlying activity patterns of individuals over time (*Huff et. al., 1986*). For instance, a commuter may not stop by the grocery store every day, but do so every few days. Empirical studies note significant variability in stop-making behavior (25% of commuters make one or more stops during morning commutes and 36% during evening commutes), and stop-duration (with average stop durations of 14.5 minutes for morning and 31.6 minutes for evening) during commuting trips (*Jou et. al., 1998*). These changes can translate into stochastic variations in O-D pattern variation from day-to-day.

Another source of perturbation is real-time information. User equilibrium (deterministic) assumes that all users select minimal trip-time paths under information. While intuitively appealing, this assumption imposes the following questionable behavioral restrictions: perfect knowledge and optimization capabilities under time-varying conditions, and identical (homogeneous) decision behavior by all users (*Garling, 1998*). In fact, in the context of real-time information, several studies have found that users do not always know the optimal paths under time-varying traffic conditions, and often select sub-optimal paths due to habit persistence and inertial considerations (*Van Berkum, 1998; Chen, 1999; Srinivasan, 1999*) or imperfections in information. Furthermore, significant heterogeneity and stochasticity has been observed in users' route and departure time choice behavior under information and experience, especially imperfect information (*Iida, 1992; Garling, 1998*). Further, users may be inclined to select paths/departure times based on multiple objectives including trip-time minimization, schedule delay, and travel time reliability (*Vanghn, 1995; Chen, 1999; Nakayama, 1999*), which may not always be mutually consistent *(Srinivasan and Guo, 2003).*

2.3 Role of ATIS on Within-day and Day-to-day Dynamics

Several studies examine the potential benefits to drivers through the supply of real-time traffic information. Advanced Traveler Information Systems provide dynamic traffic information to drivers based on prevailing or predicted traffic conditions, in contrast to static information that is based on historical or average system conditions. The supply of real-time traffic information to trip makers through various types of advanced traveler information systems (ATIS) is increasingly viewed as a means of reducing traffic congestion in urban networks *(Mobility 2000, Final Report of the Working Group on ADIS, 1990)*. Mahmassani *(1991)* analyzed the system performance and user response under various levels of market penetration of information system. Their results indicated that actions by drivers under real-time traffic information, in some cases, might result in worse conditions for themselves (individual objectives) and for the entire system. Another study on the influence of dynamic route guidance system by Hadj-Alouane et al. *(1995)* also indicated that the gains of an individual driver and the system are affected by the levels of market penetration, i.e., the fraction of drivers with access to the information. Simulation experiments suggested that the magnitude of benefits due to real-time traffic information is highly sensitive to the initial conditions in the traffic network and drivers' route choice rules *(Chen, 1991)*. Providing real-time information and route guidance through ATIS can aid drivers who are not familiar with the traffic network. However, the benefits of ATIS may decrease as drivers get more familiar with travel conditions, whereas, more experienced drivers may only benefit from ATIS during the pre-trip planning stage *(Adler, 1993)*.

From the studies cited earlier, one conclusion is that ATIS can significantly impact drivers' route choice behavior, and thus ATIS offer the potential to benefit drivers and alleviate traffic congestion in urban networks. However, the extent and magnitude of actual benefits from information varies considerably in different cases and critically depends on many factors such as route choice rule, market penetration, and traffic conditions. Furthermore, day-to-day dynamics on transportation network and the impact of information on day-to-day dynamics and network reliability are not studied. In this context, further research on the relationship between drivers' benefits from ATIS and the role of ATIS on day-to-day dynamics in the long-run are particularly desirable, and forms the focus of this thesis.

2.4 Within-day Dynamics

Within-day dynamics refers to variations in trip-time due to variation in O-D patterns across different departure times. Within-day dynamic models relax the assumption of constant trip-time and flow rates in peak period. To represent the time-varying nature of flows within the peak period, many researchers have investigated within-day dynamics in transportation networks based on the user equilibrium or system optimal frameworks

(Mahmassani, 1997; Peeta, 2001; Ran, 1996; Li, 1999). The underlying premise is that users' seek to minimize their trip-time (or related measure) that accounts for the real-time traffic conditions. Based on this premise, several types of 'dynamic' equilibria have been proposed and aim to represent various cases of practical interest including fixed and elastic demand, presence of real-time information, multiple user classes with various objectives, and the effect of various types of traffic control systems. A large body of dynamic traffic assignment literature has emerged that develop mathematical programming and variational inequality formulations and network assignment algorithms to solve for these equilibrium conditions (for a comprehensive review of these dynamic assignment and equilibrium methodologies, the interested reader is referred to Peeta and Zilliaskopoulos, 2001). One common feature among these studies is that at equilibrium no user can improve his/her cost by switching unilaterally. Thus, these equilibria are 'dynamic' in the sense that the travel times of users departing at different times vary on a given day. As such these equilibrium flows are intended to represent the time-varying nature of flows once stationarity is achieved.

However, the equilibria represent "comparative statics" in a day-to-day sense, since users have no incentive to change their routes/departure time decisions at equilibrium *(Srinivasan and Guo, 2003).* Under the equilibrium paradigm, therefore, the resulting network flows vary across departure times on a given day, but are static for the same departure time from day-to-day (*Cantarella, 1995; Ran, 1996*). Hence, the travel times and flows do not vary from day-to-day. Empirical observations of real-world traffic in several cities (*Huff, 1986; Cherrett,1997; Van BerKum, 1998; Lu, 2000; Hatcher, 1992*) and laboratory studies (*Hazelton, 1997a; Nagel, 1994; Rickert, 1997; Hu, 1997; Selten, 2002*), however, show that network flows in real-world networks may not necessarily be at or near equilibrium conditions, due to various system perturbations including the effect of information and dynamic user decisions. Several sources of perturbations can lead to significant day-to-day dynamics and variability in observed flows and trip-times.

2.5 Day-to-day Route Choice Based Models

To account for these day-to-day variations, a few researchers have investigated the evolution in network flows from day-to-day. Cantarella et al. *(1995)* used a stochastic process model and found that system flows may deviate significantly from equilibrium due to the effect of information and past experience on route choice decisions. Horowitz *(1984)*, in one of the earliest studies in this area, demonstrated that traffic flow can exhibit non-convergence, or convergence to non-equilibrium states, even when stochastic user equilibrium was unique, due to the role of learning effects on user decisions. In a related finding, Nakayama et al. *(1999)*, indicated that network may converge to a 'deluded' equilibrium state which may be considerably worse than equilibrium conditions, due to heterogeneity (differences across drivers) of perception (of trip-times and paths). More recently, Peeta et al. *(2001)* questioned whether real-world flows are at or near equilibrium conditions given the numerous sources of random shocks (demand, supply, incidents, weather, and construction). Selten et. al. *(2002)* shows that day-to-day variation can persist even for an unusually long period even in a fairly simple network where only pre-trip information is allowed.

2.6 Day-to-day Departure Time Based Models

In most studies cited above, route choice decisions have been the main source of day-to-day variability in network flows. In contrast, the role of departure time decisions on network flow evolution has received relatively less attention in network analysis, although several empirical studies have found that commuters are more likely to change their departure time than route *(Mahmassani, 1990)*. For instance, departure time switching rates of 56% and route switching rates of 23% were observed in commute trips (based on travel-diary surveys for 2 weeks) in Dallas and Austin *(Hatcher, 1992; Jou, 1998)*. Due to the focus on the effect of routing decisions in current models, the influence of departure time dynamics on network performance, stability and reliability are not yet well understood. Furthermore, due to tractability considerations, many day-to-day studies do not account for within-day dynamics (with a few exceptions, e.g., *Cantarella,1995*).

A few studies try to address the shortcomings above by combining within-day and day-to-day dynamics through an integrated framework. Among these studies, Cascetta *(1991)* used a modified version of within-day departure time choice model *(Small, 1987)* and evaluated system performance under alternative control strategies. However, the departure time adjustment process is modeled at an aggregate level by assuming that a pre-specified fraction of users will reconsider the previous day's choices. Hu and Mahmassani *(1997)* used a dynamic traffic assignment framework (DYNASMART) to evaluate day-to-day network dynamics under real-time information and responsive signal control system. The results showed that the departure time patterns converged to a peaked flow pattern which had the same mode (peak), regardless of the control strategies that were considered. Although this study uses a more disaggregate and empirically calibrated behavioral model, adjustment decisions are only partially accounted for through an empirical binary departure time switching model (switch / do not). Further, due to the focus on the role of information market penetration and on-line control in this study, few insights are obtained on day-to-day dynamics and stability. Duong and Hazelton *(2002)* proposed a new Markov traffic assignment model (MARTS) which incorporates a route choice model based on past experience and pre-trip information. The experiments showed that providing high quality pre-trip information in highly volatile systems may not be entirely beneficial in terms of system performance.

Most of the results discussed above have been reported using small networks (with few links) under simple hypothetical user behavior rules that account for learning and switching under experience, and mostly in the absence of real-time information. However, the nature and extent of system reliability under information and shocks, particularly from a users' standpoint has not received sufficient research attention and still remains to be quantified systematically.

2.7 Agent-based Simulation Approach

In recent years, many researchers are increasingly exploring the possibility of using multi-agent systems to model the intelligent traffic management systems *(Hernandez, 2002)*, which is intuitively a natural approach for the high complexity problem with multi-user and control interactions such as those present in real-world traffic networks. Multi-agent systems are systems composed of multiple interacting entities, known as agents with the ability to: make decisions, adapt, adjust and influence the environment in which they operate. Agents are systems with two important capabilities: 1) autonomous actions of deciding for themselves what they need to do in order to satisfy their objectives, and 2) the capability for interacting with other agents by engaging cooperation, coordination, and negotiation. *(Wooldridge, 2001).* In traffic systems, many different entities, such as traffic lights, drivers, and variable message signs are present with varying levels of information and decision making abilities ('intelligence'). These agents are distributed over a large area and interact with each other to achieve certain goals. Different agents may seek to fulfill different objectives even while participating in the same environment, and make their decisions based on limited and imperfect information about the future. The multi-agent approach on traffic flow models offers an alternative interpretation of the classical traffic flow models, since it relaxes the constraints associated with pre-determined outcomes (for instance, equilibrium flows). In contrast, the dynamics of the system is largely determined by mutual interactions between the various agents, and the system continues to evolve as users learn about the environment and adapt their decisions. The flexibility and the versatility of the agent-based representation enable a much richer and less restrictive description of system dynamics and evolution.

Hernandez et. al *(2002)* described the development of knowledge-based multi-agent architecture for real-time traffic control, a system capable to reason about the traffic behavior and evolution in a manner similar to an expert traffic operator, in order to achieve improved system performance. Two relevant members of the TRYS (an agent-based environment for building ITMS applications for roadway networks) family of systems are discussed and compared in Hernandez *(2002),* given that these systems are installed and tested online in traffic control centers. The two systems differ in the way the traffic agents are coordinated (centralized and decentralized control). The traffic network is divided into several problem areas, and each area is controlled by a traffic agent. The agent has knowledge regarding the underlying network, the usual behavior of vehicles, and can reason and suggest signal actions that may improve the traffic condition. The control strategies suggested by each local control agent can then be coordinated by a higher level coordinator agent. These types of knowledge-based traffic management tools, if properly designed and implemented, can significantly simplify and automate the control process by operators. However, the accuracy of the decision process is largely dependent upon the sophistication level of the knowledge base, and the decisions reached by control agents may not be globally optimal. In addition, the impact of these types of control systems on system performance is not yet well understood given the limited practical deployment of these technologies.

Agent-based approach for modeling dynamic driver behavior has also received attention from multiple researchers. The major advantage of using agents in travel behavior modeling is that they are active entities that interact with their environment (by receiving and reacting to real-time traffic information) and in concert with other agents in the system *(Dia, 2002)*. Agent-based behavior models also allow for coordination of agent tasks and actions, which can be useful for modeling the interaction between informed and un-informed drivers and co-ordination of their goals which has not been investigated adequately in conventional driver behavior modeling studies. Whale et. al. *(2002)* proposed an agent-based route choice behavior model using the Belief-Desire-Intention (BDI) architecture. The BDI architecture is simplified to a two-layer architecture: the tactical and strategic layer. The traffic information (travel time) is obtained using probe vehicles and then provided to informed vehicles. However, the switching decision is assumed to be always "comply", and only pre-trip decision is allowed. In addition, the simulation is conducted in a two-route network with a simple network flow assignment model.

In *Dia (2002)*, an agent-based route choice behavior model based on real world driver's behavioral survey is presented, and interfaced with microscopic traffic simulation. The advantage of this model is that it explicitly captures the heterogeneity of drivers in terms of socio-economic factor, driver's aggression, awareness and familiarity with the network by utilizing multinomial logit models. However, the perception of real-time information and the decision process is oversimplified, without considering the dynamic nature of the information quality, individual user's past traffic experience, and the interaction of inertia and compliance mechanisms operating in the decision-making process. In addition, the model is essentially in real-time dynamic context only. However, drivers are assumed to be memory-less from a day-to-day perspective.

Given the important role of departure time and route choice dynamics, representing user decisions from day-to-day at a sufficiently disaggregate level and rich temporal resolution is essential. In Srinivasan *(2001)*, an empirically calibrated model of dynamic departure time choice provides a richer stochastic representation of user decisions. This model explicitly accounts for the role of dynamics in network and commute performance, users' past experience, and users' departure time switching history on a user's departure time decisions. For route choice decisions under information, a disaggregate and behavioral model was developed in Srinivasan *(1999)*. This model captures two principal behavioral mechanisms observed in route choice decision process under information: compliance and inertia. These two models have been integrated with a dynamic network assignment framework (DYNASMART) in this dissertation research. The details of these models used in this research are presented in Chapter 4.

2.8 Network Reliability Research on Transportation Networks

Although reliability analysis is an integral part in design and planning of many infrastructure networks (eg., electric power systems and communication networks), reliability analysis has received relatively less attention in the context of traffic networks. Among the few reliability-related studies pertaining to transportation networks, attention is mostly focused on two aspects: travel time reliability and capacity reliability. Du et. al. *(1997)* describes approximation procedures for sensitivity and reliability analysis for a degradable transportation system. In this research work, a conventional integrated network equilibrium model with variable demand is used to describe flow on a degradable transportation network with a range of degradation on roadway capacity. The proposed reliability model involves defining the reliability of individual sub-systems (O-D pairs) as the probability that given some event, the proportional reduction of flow in the sub-system is less than some threshold value. The author argued that an exact solution is unlikely, even in a relatively simple network. Consequently, an approximation solution based on a recursive algorithm was developed to estimate the system reliability.

Chen et. al. *(2002)* defined capacity reliability as the probability that the network capacity can accommodate a certain traffic demand at a required service level, while accounting for drivers' route choice behavior. A framework is proposed for evaluation of the capacity reliability. Monte Carlo simulation is used to randomly sample the capacity of links in the network. For each set of arc capacities generated, a network equilibrium algorithm is used to find the equilibrium flows. Then a sensitivity-based approach is used to compute the derivatives of the performance function, and the associated reliability measures are computed and analyzed. Besides the probabilistic assessment of network capacity, travel time reliability is also determined in the evaluation process. Numerical results are presented in terms of a simple network with five nodes and two O-D pairs to demonstrate the feasibility of the evaluation procedure. However, the drawback of this evaluation framework is that a deterministic link travel time evaluation function (BPR function) and static equilibrium state are assumed for a given set of arc capacities. Considering the internal perturbations, real-time, within-day, and day-to-day dynamics, a discrete event simulation method is warranted to evaluate the trip time and capacity reliability in transportation networks.

2.9 Research Gaps and Summary

Several gaps exist in the literature reviewed in this chapter pertaining to urban transportation network reliability analysis. Due to incidents, weathers, users' route and departure time decisions, and other day-to-day factors as highlighted earlier, link travel time can vary significantly from one day to the next. The travel times between links can also be correlated. The randomness of link cost is not considered in traditional user equilibrium (UE) and system optimal (SO) assignment models. Stochastic user equilibrium models do allow random errors on the information users received, but the system variance is not explicitly considered as part of the system objective, and the correlations between random link costs are not captured. There is a need to address this gap from methodological point of view. In the next chapter, a new system optimal formulation is proposed, with the ability to account explicitly for variance of system cost, and allow trade-off between cost and variance in the objective function. In addition, an algorithm based on the Method of Successive Assignment (MSA) is proposed to solve the formulation.

From a network modeling point of view, there is a need to incorporate behaviorally-based user decision models in network analysis, specifically pertaining to day-to-day changes in users' route and departure time decisions, in response to information, experience, and learning. These models should enable the representation of stochasticity (for instance, imperfect information quality that changes in response to user behavior over time) and heterogeneity (differences in users' propensities and perceptions to switch routes, departure times, or comply with information). To measure system stability and travel time reliability, a day-to-day dynamic assignment framework is essential wherein the day-to-day system evolution influences, and is influenced by, within-day congestion and real-time dynamics (due to information). Among the few studies that examine day-to-day dynamics, the role of either departure time switching or route switching has received attention. But the effect of joint switching behavior has not been sufficiently studied due to tractability or other confounding issues.

Furthermore, in the commuting context, jointly considering commute performance characteristics together with trip time reliability is important. In addition, there is a need to represent the influence of system perturbations (both planned and unplanned) on day-to-day system evolution. Due to these limitations, many within-day dynamic models are not entirely satisfactory in representing network flows when they deviate from equilibrium conditions.

Because of these modeling limitations, limited insights were obtained from extensive empirical analysis, especially from a day-to-day point of view. Specifically, the following research questions are not systematically analyzed: 1) What is the role of joint switching versus switching in only one dimension? 2) What is the role of user behavior factors on day-to-day evolution of network flows? 3) What is the impact of Transportation Control Measures on day-to-day dynamics? 4) Which incident characteristics have the largest impact on network performance? 5) How does the incidents influence the system stability and reliability and how to reduce these effects?

To answer these questions, experimental factors need to be carefully chosen and extensive empirical analysis is needed. To partially address these shortcomings, a simulation-based day-to-day network analysis framework is developed and implemented in this study to investigate network flow evolution and system reliability from day-to-day due to departure time and route choice dynamics. An agent-based behavior modeling approach is proposed in this study, that seeks to capture more accurate and realistic agent behavior models as decision components for both departure time adjustment decisions and route choice decisions. The details of this simulation framework are discussed in Chapter 4.

The use of simulation-based experiments for analysis is necessitated by the complexity and nonlinearity of this problem (stochasticity and dynamics), which precludes the use of analytical approaches *(Nagel 2000)* especially for real world networks. Further, the direct use of empirical real-world data for analysis is also inadequate, since controlling the experimental factors and observing user response at the desired temporal resolution is difficult. Further, the observed evolutionary path (in the real-world) is only one possible sample from a set of possible stochastic realizations.

Based on the day-to-day simulation framework developed in this research, a series of computational experiments are conducted and the results are analyzed to explore the role of user behavior factors, transportation control measures, and incidents on system performance and reliability. These empirical results are presented in Chapters 5 and 6.

CHAPTER III

ALGORITHM FOR ROBUST COST MINIMIZATION IN NETWORKS WITH RANDOM ARC COSTS

3.1 Introduction

For traffic networks, link travel time can vary from one day to the next due to accidents, weather, users' route and departure time decisions, and other day-to-day factors as discussed in chapter one. In addition, the travel times between links can also be correlated. The randomness of link cost is not considered in traditional user equilibrium (UE) and system optimal (SO) assignment models. Stochastic user equilibrium models do allow random errors on the information users received, but the system variance is not explicitly considered as part of the system objective, and the correlations between random link costs are not considered. Solving the network flow assignment exclusively by minimizing cost can lead to a solution with considerably high variance. On the other hand, the solution focused on minimizing the variance may give a high system cost. In this chapter, a new SO formulation is proposed, with the ability to explicitly account for variance of system cost, and allow trade-off between cost and variance in the objective function. In addition, an algorithm based on the Method of Successive Assignment (MSA) is proposed to solve the formulation.

Besides in a traffic network, the minimum cost network assignment problem arises in numerous other practical applications (e.g., revenue optimization problem, warehouse location, internet traffic routing). Given its importance, many efficient algorithms (including polynomial time algorithms) have been proposed to solve the minimum cost assignment problem and its variants. For instance, algorithms have been developed to address several extensions to the standard minimum cost problem including: multiple related objectives (e.g., least cost/time ratio), time-dependence (time-dependent minimum cost assignment), multiple user classes (multi-class models), and demand-supply imbalance (minimum cost with back-log). In a network formulation, arc cost refers to the cost associated with the unit flow traversing an arc (e.g., link travel time for a driver in a traffic network). In several applications above, the arc costs are deterministic, whereas, in many practical problems of interest arc costs are random. Examples of problems with random arc costs include reservation management in airline and car rental networks (due to random cancellations), project management (uncertainty of task durations), and traffic networks (due to day-to-day variation factors such as accidents and weather).

Although, the stochastic shortest path problems have been investigated in several studies, the stochastic minimum cost problem has received relatively less attention *(Hall, 1986; Miller et. al., 1994; Provan, 2003)*. When costs are random, the deterministic minimum cost assignment method can be applied with expected costs to obtain the minimum expected cost solution. However, this solution can be problematic in two respects: 1) This may lead to an unacceptably high level of risk and variability in costs, especially in cases where downside risks can have significant monetary penalties, and 2) A lower overall cost or higher revenue may be obtained through alternative strategies for some random scenarios where this solution is sub-optimal. Further, the minimum expected cost solution does not distinguish between cases when arc costs are correlated and those where costs are independent across arcs. To address these shortcomings, this chapter proposes an algorithm to find a robust minimum cost assignment when arc costs are random. Robustness in this study is defined in terms of a weighted linear combination of the mean and variance of system costs, where the relative preference weight for risk/variability can be specified by the decision-maker. This algorithm has important applications for assessing the robustness of alternative solutions, and is illustrated here in the context of a small traffic network with random and correlated link travel times.

Two objectives are pursued in this chapter: 1) To propose algorithms for robust cost optimization in networks with random arc costs, and 2) To apply the algorithm to the static traffic network assignment program and demonstrate the performance and benefit of the robust system optimal algorithm using an illustrative traffic network.

This chapter contributes to network modeling under uncertainty in the following respects. A polynomial time algorithm is proposed to solve the robust cost optimization problem when real-valued flows are sufficient. The optimal solution for this problem exists but may not be unique. Models for several important variants of the robust cost minimization problem are also proposed including: 1) minimum variance assignment problem, 2) robust cost minimization problem with integer constraints, and 3) robust cost problem with independent within-link flows. A two-stage heuristic is proposed when integer valued solutions are demanded by the practical application (e.g., rental reservations acceptance problem). At the empirical level, models are proposed to determine the network flow assignment strategies that minimize the hybrid robust cost objective for a small traffic network with random and correlated link travel times. In particular, the role of randomness (expressed in terms of the variance of link travel time) is investigated on the performance of the Robust Cost Assignment Problem (RCAP) solution relative to the expected system optimal travel time solution.

Section 3.2 defines the robustness criterion in this study, and presents the formulation and optimality conditions for the robust cost minimization problem. Section 3.3 describes an algorithm based on the Frank-Wolfe method to solve this problem, and its application is demonstrated using a numerical example. In Section 3.4, three special variants of the robust cost optimization problem are discussed. Section 3.5 discusses salient results regarding the robustness of alternative strategies based on a series of computational experiments for the traffic assignment problem, followed by a few concluding remarks in Section 3.6.

3.2. Formulation and Optimality Conditions for Robust Cost Minimization under Random Arc Costs

Robustness is defined here by a hybrid robust cost function R(x) that consists of a linear combination of the mean and variance of the system cost and is defined as:

$$R(x) = (1-\alpha)V(x) + \alpha\, E(x)^2$$

where

R(x) is the robust cost objective function,

x represents the vector of path flows on the network,

α is a preference weight reflecting the risk tolerance of the decision-maker towards cost variability.

V(x) is the variance of cost corresponding to the flow vector x,

$E(x)^2$ is the square of the expected cost resulting from the flow assignment x, A highly risk-averse decision maker ($\alpha = 0$) may seek to minimize variance of cost, whereas a highly risk seeking decision-maker ($\alpha = 1$) may choose to minimize the expected revenue.

3.2.1 Problem Statement

Consider a graph G(N,A) to be a directed network with N denoting the set of nodes and A representing the set of arcs. Each arc (i,j) has an associated cost c(i,j) and capacity u(i,j). With each node i in the node set there is an integer value associated with that node, b(i), referred to as the demand/supply of node i. The assumption is that the network is balanced, (i.e. Σ_i b(i) = 0). The arc capacity and O-D pairs are assumed to be deterministic, but the arc costs are distributed randomly according to a general multivariate distribution (C ~ Multivariate (M, Σ)). The robust cost assignment may then be formally formulated as follows:

Robust Cost Assignment Problem (RCAP)

Minimize

$$R(\mathbf{x}) = (1-\alpha)[\sum_a x_a^2 \sigma_a{}^2 + \sum_a \sum_{b \neq a} 2 x_a x_b \rho_{ab} \sigma_a \sigma_b] + \alpha[\sum_a x_a \mu_a]^2 \qquad (1)$$

Subject to:

$\sum_l f_l^{mn} = q_{mn}$ - flow balance of network

$f_l^{mn} \geq 0$ - non-negative path flow

$x_a = \sum_{mn} \sum_{l \in K_{mn}} f_l^{mn} \delta_{a,l}^{mn}$ for $\forall$a - arc-path flow relationship

$0 \le x_a \le w_a$ for $\forall$a , - capacity constraints

where:

m,n = origin or destination node name, m $\neq$ n

x_a = flow on arc a,

x = vector of arc flows$\{x_a\}$

σ_a = standard deviation of cost per unit flow on arc a

ρ_{ab} = correlation coefficient between arc a and b

μ_a = expected cost per unit flow on arc a

f_l^{mn} = flow on path l between O-D pair m-n

q^{mn} = demand on O-D (m-n)

w_a = capacity on arc a

$\delta_{a,l}^{mn}$ = 1 if path l between O-D pair m-n uses arc a, otherwise = 0

The assumption is made that the link costs are deterministic in nature for a given scenario, although they vary randomly across different scenarios.

3.2.2 Reformulation of RCAP Using Link-separable Arc Costs

The Problem RCAP is reformulated below in a separable form, where the overall hybrid cost is written as the sum of suitable arc level hybrid costs:

Minimize

$$Z(x) = (1-\alpha)\sum_a c_{1a}(x) + \alpha\sum_a c_{2a}(x) = \sum_a c_{3a}(x) \qquad (2)$$

Subject to:

$$\sum_l f_l^{mn} = q_{mn} \quad \text{-flow balance of network}$$

$$f_l^{mn} \geq 0 \qquad \text{-non-negative path flow}$$

$0 \leq x_a \leq w_a$ for $\forall$a , - capacity constraints

where

$$c_{1a}(x) = \sigma_a^2 x_a^2 + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}$$

$$c_{2a}(x) = \mu_a^2 x_a^2 + \mu_a x_a \sum_{b \neq a} \mu_b x_b$$

$$c_{3a}(x) = (1-\alpha)\ c_{1a}(x) + \alpha\ c_{2a}(x)$$

Note that the composite cost term c_{3a} denotes an arc level hybrid cost that involves a convex combination of the mean and variance of original arc costs (which are random variables). Furthermore, this arc cost is not only a function of flow on that arc, but also depends on flow on all other arcs on the network. In determining the variances as per term c_{1a} , all units of flow on a given link are assumed to experience the same but random link cost in a given instance. In other words, the units of flows are grouped together, and therefore the associated costs experienced are not mutually independent.

3.2.3 Optimality Conditions

For ease of illustration, the conditions are first derived for the case when all arc flows are unbounded ($capacity = \infty$) in this section, and extended to the case where the capacity is later finite in section 3.2.5.

To convert the constrained problem RCAP (equation 1 in section 3.2.1) to an unconstrained problem, a set of Lagrangian multipliers (u_{mn}) are applied to the constraint equations and added to the objective function as follows:

Minimize $L(f,u) = R(x) + \sum_{mn} u_{mn}(q_{mn} - \sum_{l} f_l^{mn})$

Subject to: $f_l^{mn} \geq 0$

First-order necessary conditions for optimality can then be expressed as follows:

$$f_l^{mn} \frac{\partial L(f,u)}{\partial f_l^{mn}} = 0 \quad \forall\, l, m, n \tag{3a}$$

$$\frac{\partial L(f,u)}{\partial f_l^{mn}} \geq 0 \quad \forall\, l, m, n \tag{3b}$$

$$\frac{\partial L(f,u)}{\partial u_l^{mn}} = 0 \quad \forall\, m, n \tag{3c}$$

For this problem the term $\frac{\partial L(f,u)}{\partial f_l^{mn}}$ is given by:

$$\frac{\partial L(f,u)}{\partial f_l^{mn}} = \frac{\partial R(x)}{\partial f_l^{mn}} + \frac{\partial}{\partial f_l^{mn}} \sum_{mn} u_{mn}(q_{mn} - \sum_{l} f_l^{mn}) \tag{4}$$

Simplifying the right hand side of equation 4, the first term can be rewritten as:

$$\frac{\partial R(x)}{\partial f_l^{mn}} = \sum_i \frac{\partial R(x)}{\partial x_i} \bullet \frac{\partial x_i}{\partial f_l^{mn}} = \sum_i \frac{\partial R(x)}{\partial x_i} \bullet \delta_{i,l}^{mn} \tag{5a}$$

since $\frac{\partial x_i}{\partial f_l^{mn}} = \delta_{i,l}^{mn}$ from definitional constraint in 1 that links arc flows to path flows. Note that the inner term $\frac{\partial R(x)}{\partial x_i}$ gives the marginal change in system hybrid cost given a unit change in flow on arc i and is referred to as the marginal hybrid cost ($\tilde{t}_i$) on arc i, Therefore, expression 5a simplifies as:

$$\frac{\partial R(x)}{\partial f_l^{mn}} = \sum_i \tilde{t}_i(x) \bullet \delta_{il}^{mn} = \tilde{T}_l(\mathrm{x}) \tag{5b}$$

where $\tilde{T}_l$ represents the total marginal hybrid cost on path *(l)* for the vector of flows x. This follows from the fact that link-path incidence variable is non-zero for only those arcs that belong to path *(l)*, and the marginal costs are added along all the arcs that belong to path *(l)*. In equation 5b, the marginal hybrid cost for flow on arc i $\tilde{t}_i(x)$ is obtained as:

$$\tilde{t}_i = \frac{\partial R(x)}{\partial x_i}$$

since $\quad \mathrm{R(x)} \quad = \sum_a c_{3a}(x)$

$$= \sum_a (1-\alpha)\ [\sigma_a^2 x_a^2 + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}\ ] \ + \ \alpha\ [\ \mu_a^2 x_a^2 + \mu_a x_a \sum_{b \neq a} \mu_b x_b\ ]$$

$$\tilde{t}_i(X) = \frac{\partial R(X)}{\partial x_i}$$

$$= \frac{\partial}{\partial x_i}\left((1-\alpha)\left(\sigma_i^2 x_i^2 + 2\sigma_i\, x_i \sum_{j \neq i} \sigma_j x_j \rho_{ij} \right) + \alpha \left(\mu_i^2 x_i^2 + 2\mu_i\, x_i \sum_{j \neq i} \mu_j x_j \right) \right)$$

Simplifying the terms after differentiation, the following expression is obtained for the hybrid marginal cost for arc i:

$$\tilde{t}_i(x) = (1-\alpha)\left(2\sigma_i^2 x_i + 2\sigma_i \sum_{j \neq i} \sigma_j x_j \rho_{ij} \right) + \alpha \left(2\mu_i^2 x_i + 2\mu_i \sum_{j \neq i} \mu_j x_j \right) \tag{5c}$$

The second term on the RHS of equation (4) can be simplified as:

$$\frac{\partial}{\partial f_l^{mn}} \sum_{rs} u_{rs}(q_{rs} - \sum_k f_k^{rs}) \ = \ -u_{mn} \tag{6}$$

Based on the expressions in equations 5b and 6, the optimality conditions (3a) yields:

$$f_l^{mn} \frac{\partial L(f,u)}{\partial f_l^{mn}} = f_l^{mn}(\tilde{T}_l - u_{mn}) = 0 \ for\ \forall l, m, n \tag{7a}$$

Optimality condition (3b) can be written as:

$$\frac{\partial L(f,u)}{\partial f_l^{mn}} \geq 0 \Rightarrow \tilde{T}_l - u_{mn} \geq 0 \quad for\ \forall\, l, m, n \tag{7b}$$

Optimality condition (3c) provides the flow conservation condition:

$$\frac{\partial L(f,u)}{\partial u_l^{mn}} = 0 \Rightarrow \sum_l f_l^{mn} = q_{mn}\ for\ \forall\, m, n \tag{7c}$$

In addition the non-negativity condition $f_l^{mn} \geq 0$ should also hold at optimality. The optimality conditions 7a and 7b will be satisfied under the following two cases:

a. Flow on path *(l)* connecting origin-destination pair m-n $f_l^{mn} = 0$, in which case, 7b implies that the corresponding marginal hybrid cost is at least as large as the Lagrangian multiplier for the corresponding O-D pair (u_{mn}).

b. Flow on path *(l)* connecting origin-destination pair m-n f_l^{mn} is strictly positive, in which case the corresponding marginal hybrid cost is equal to the minimum Lagrangian multiplier for the corresponding O-D pair (u_{mn}).

The conditions (7a-7c) collectively imply that at optimality, all paths that carry flow should have equal and minimal total marginal hybrid costs (=u_{mn} for each O-D pair m-n).

3.2.4 Existence and Uniqueness of Optimal Solution

Existence of the optimal solution for the unbounded capacity case, follows from the convexity of the robust cost assignment problem (RCAP), since the objective function is convex in terms of flows, and the constraints are linear. To see this, note that the functions c_{1a}, and c_{2a} are convex (since the corresponding Hessian matrices are positive semi-definite). Therefore, the function c_{3a} (for each arc) is convex since it is the convex combination of two convex functions *(Luenberger, 1984)*. The overall objective R(x) is the sum of the convex functions c_{3a} across all arcs, and is also convex. Therefore, the program is globally convex and the optimal solution exists. The solution is not necessarily unique depending on the arc cost configurations.

3.2.5 Optimality Condition for the Case When Arc Capacities Are Finite

To handle the case of finite capacity arcs, the formulation in Section 2.3 is generalized by adding a cost term $c_{4a}(x)$ that penalizes the violation of arc capacity. This penalty is set to 0 if the flow on arc a does not exceed its capacity by more than a pre-specified capacity tolerance level (e.g. capacity *(1 + tolerance)), and penalty increases with increasing deviation otherwise. Thus by adding a suitable arc penalty, a new objective function is defined: as

$$R_1(x) = \sum_a [c_{3a}(x) + c_{4a}(x)] \tag{8a}$$

where $c_{4a}(x)$ is a penalty term for capacity violation which takes the form of:

$$c_{4a}(x) = M\left(\frac{x_a}{w_a(1+\Delta)}\right)^{M_1}$$

where M, M_1 are large positive integers

x_a is the current flow on link a

w_a is the capacity of link a

Δ is the tolerance applied to capacity violation.

Repeating the formulation and optimality conditions in Section 3.2.4, with this change:

$$\text{Minimize} \qquad L(f,u) = R_1(x) + \sum_{rs} u_{rs}(q_{rs} - \sum_k f_k^{rs}) \tag{8b}$$

Subject to: $f_k^{rs} \geq 0$

The first order conditions have the same form as in equations 7a, 7b, and 7c, except that the marginal hybrid cost on an arc also includes the corresponding marginal penalty terms due to possible capacity violation on the arc.

For a penalty of the form in c_{4a} above, the contribution of the penalty term to the hybrid cost on arc a, $\tilde{t}_{p,a}$ can be computed as:

$$\tilde{t}_{p,a} = \frac{\partial c_{4a}(x)}{\partial x_a} = \frac{M2}{(1+\Delta)\times w_a}\left(\frac{x_a}{(1+\Delta)\times w_a}\right)^{M_1-1} \tag{9}$$

where $M_2 = M_1 M$

Consequently, the marginal hybrid cost on a path *(l)* includes the penalty contributions for all arcs on this path in addition to the original hybrid cost now also. The new marginal hybrid cost including capacity violation penalty ($\tilde{T}_l^p$) is given by:

$$\tilde{T}_l^p = \tilde{T}_l + \sum_i \frac{\partial c_{4a}(x)}{\partial x_i} \bullet \delta_{il}^{mn} = \tilde{T}_l + \tilde{T}_{1,l} \tag{10}$$

where the $\tilde{T}_{1,l}$ represents the marginal hybrid cost contribution of the penalty term of all arc flows to path l.

With this change, the optimality conditions can be shown as:

$$f_l^{mn} \frac{\partial L(f,u)}{\partial f_l^{mn}} = f_l^{mn}(\tilde{T}_l^p - u_{mn}) = 0 \ for \ \forall l, m, n \tag{11a}$$

Optimality condition 3b yields:

$$\frac{\partial L(f,u)}{\partial f_l^{mn}} \geq 0 \Rightarrow \tilde{T}_l^p - u_{mn} \geq 0 \quad for \ \forall l, m, n \tag{11b}$$

Optimality condition 3c yields the flow conservation condition:

$$\frac{\partial L(f,u)}{\partial u_l^{mn}} = 0 \Rightarrow \sum_l f_l^{mn} = q_{mn} \text{ for } \forall m, n \tag{11c}$$

Similar to the argument in Section 2.4, the existence of the optimal solution can be proved for the finite capacity case, by choosing the penalty term c_{4a} to be a convex function of link flows.

3.3 Algorithm Description and Implementation

3.3.1 Algorithm Overview

Given the optimality condition, and the existence of a solution to the problem RCAP, the solution to this convex non-linear program can be found using the Frank-Wolfe method *(Sheffi, 1985; Patriksson, 1998)*. Although this method is widely applied in transportation models, a brief outline is provided for unfamiliar readers. This method starts with a feasible flow, and linearizes the objective function evaluated at the feasible flow solution from the previous iteration. The smallest total marginal hybrid cost path is determined for each O-D pair using a shortest path algorithm at each iteration, which constitutes a direction of descent for the objective function. The extent of movement in the descent direction is determined using the convex combinations method. This step updates the flows for the next iteration. The steps for solving linearized sub-problems, direction search, and flow updating are repeated until convergence is achieved. The detailed algorithmic steps are outlined below, and may be skipped by familiar readers.

3.3.2 Algorithm Description

Let d^{mn} denote the total demand from m to n, and k indicates the iteration counter. Let $x_l^{mn}(k)$ represent the flow on path l between O-D pair m-n, and $y_l^{mn}(k)$ be the auxiliary flow on path l between O-D pair m-n in the k^{th} iteration. Let P(k) denote the set of paths found until the k^{th} iteration.

Step 0: initialization

Set k = 0

Set x(k) = 0 as the initial feasible flow.

Step1: update hybrid marginal cost

Compute the marginal hybrid cost on each arc based on the current feasible flow vector $ta(k) = ta(x_k)$.

Step 2: direction finding

Compute the shortest marginal hybrid cost path for each OD pair based on ta(k). The paths (one for each O-D pair) are referred to as the auxiliary paths (A_k). If some auxiliary paths are not present in the current path set P(k), then they are added to the path set for the next iteration (i.e. $P(k+1) = P(k) \cup A_k$), otherwise $P(k+1) = P(k)$.

Step 3: flow update

Perform an (implicit) all-or-nothing assignment to the auxiliary paths using $t_a(x(k))$ to find the auxiliary flows. The auxiliary flows are defined as follows:

y_l^{mn} (k) = d^{mn} if l is an auxiliary path for O-D pair m-n in iteration k

= 0 otherwise.

The flows for iteration k+1 are determined using the method of successive averages by combining the path flows from the previous iteration with the auxiliary flows from the current iteration as follows:

$$x_l^{mn}(k+1) \;= \frac{k}{k+1} x_l^{mn}(k) + \frac{1}{k+1} y_l^{mn}(k)$$

Step 4: Convergence test

Check if the marginal hybrid costs have converged (as per 7a and 7b) or equivalently if the flow difference in path flows across successive iterations falls below the convergence threshold. If yes, the algorithm is terminated. If not, set the iteration counter k = k+ 1, and repeat steps 1-4.

Note that the convex combination (Franke-Wolfe) algorithm used for solving this problem RCAP has a polynomial time complexity *(Zangwill, 1969).*

3.3.3 Numerical Example

The following example is used to demonstrate the convergence of this algorithm to the optimal solution for the special case where a minimum variance solution is sought ($\alpha = 0$). The cases ($\alpha \neq 0$) are presented later in Section 3.5. The network (see Figure 3-1) has 8 nodes, 11 links. There is one O-D pair 2-8, with 100 units of demand. The σ (i,j) in the graph represents the standard deviation of arc cost, and w (i,j) represents the capacity.

The iterations of this algorithm are shown in Table 1 and 2. The tables show that after 15 iterations the flows are close to equilibrium. Table 1 illustrates that at each iteration of the algorithm, the flow is removed from higher marginal hybrid cost paths and reassigned to paths with smaller marginal hybrid costs. This process tends to equalize the marginal hybrid cost among all used paths, thus bringing the system closer to the optimal solution, as seen from Table 2. The objective function value reduces accordingly. Note that 98% of the gap between the initial solution and optimal solution is bridged in the first three iterations, whereas the rate of convergence slows thereafter. This feature is a characteristic of the F-W algorithm whose convergence rate is linear *(Zangwill, 1969)*. The rate of convergence when the current flows are close to the optimal value may be improved by the use of methods such as Disaggregate Simplicial Decomposition, which effectively exploits the structure of the sub-problem and has good reoptimization capability.

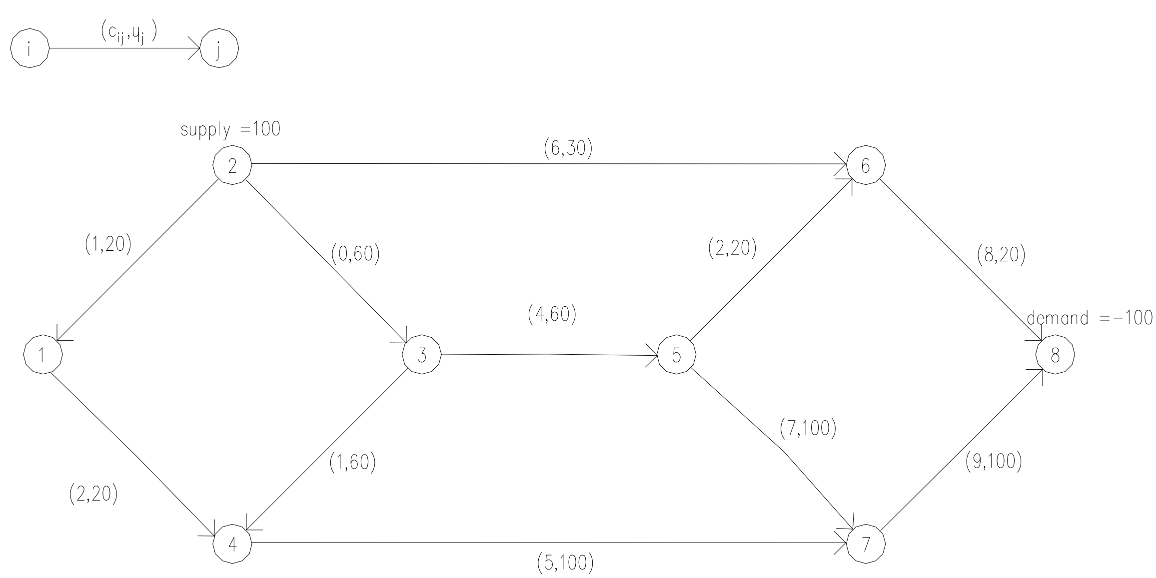


Figure 3-1 Test network

Table 3-1 Pathflows in Test Network Shown on Figure 3-1

Iteration Number	Path flows					% of Optimal Obj. Fn. Value
	2-3-4-7-8	2-6-8	2-3-5-6-8	2-3-5-7-8	2-1-4-7-8	
0	100.00	0.00	0.00	0.00	0.00	240.96
1	50.00	50.00	0.00	0.00	0.00	116.54
3	25.00	25.00	25.00	25.00	0.00	106.83
5	16.70	33.30	16.70	16.70	16.70	104.59
15	31.30	25.00	31.30	6.30	6.30	100.14
Final Solution	30.80	22.10	34.90	6.10	6.20	100.00

Table 3-2 Path Marginal Variance in Test Network Shown on Figure 3-1

Iteration Number	Path marginal hybrid cost					% of Optimal Obj. Fn. Value
	2-3-4-7-8	2-6-8	2-3-5-6-8	2-3-5-7-8	2-1-4-7-8	
0	0	0	0	0	0	240.96
1	21400	0	0	0	0	116.54
3	7133.3	10933.3	9866.7	6466.7	0	106.83
5	7520	10560	9120	9720	7480	104.59
15	9626.7	8266.7	8373.3	9493.3	9626.7	100.14
Final Solution	8881	8880.6	8881.3	8881.6	8881.1	100.00

3.4. Important Variants of the Robust Cost Assignment Problem

The Robust Cost Assignment Problem subsumes the following important class of sub-problems which may be of interest in different practical settings.

3.4.1 Minimum Variance Assignment Problem (MVAP)

The minimum variance assignment problem (MVAP) arises as a special case of the RCAP above by setting alpha = 0. The resultant formulation can be stated as follows:

Minimize

$$Z(x) = \sum_a c_{1a}(x) \tag{12}$$

Subject to:

$$\sum_l f_l^{mn} = q_{mn} \quad \text{-flow balance of network}$$

$$f_l^{mn} \geq 0 \qquad \text{-non-negative path flow}$$

where

$$c_{1a}(x) = \sigma_a^2 x_a^2 + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}$$

The optimality conditions for this problem take the same form as 3(a) to 3(c), where the marginal hybrid cost now corresponds to:

$$\tilde{t}_i(x) = 2\sigma_i^2 x_i + 2\sigma_i \sum_{j \neq i} \sigma_j x_j \rho_{ij} \tag{13}$$

At Optimality, this total marginal hybrid cost is equal and minimal across all used paths. Being a special case of the RCAP problem, the existence of the solution to the MVAP is guaranteed by arguments presented in Section 3.2.4.

3.4.2 Robust Cost Assignment with Independent within Link Flows

In the model presented previously, the assumption was that all flow units passing through a link experience the same random arc cost. In this case, with x units of flow on an arc, and if σ^2 represents the variance in arc costs per unit flow, then the link cost variance can be written as $x^2\sigma^2$. This model is referred to as the group flow model.

In contrast to the 'group flow' model, in some cases modeling link flow units as experiencing the link cost in a mutually independent manner may be appropriate. This occurs for example in cases such as car-rental and hotel reservations management problems, where costs represent revenues from individual customers, and the randomness arises from cancellation decisions which are made independently across customers. In such a case, with x units of flow on an arc, and if σ represents the variance in arc costs per unit flow, then the link cost variance can be written as $x\sigma^2$, which is much smaller than the variance from the group flow model. This model is referred to as the independent (within-link) flow model. For the independent flow model, therefore the variance term in the RCAP changes as follows:

Minimize

$$Z(x) = (1-\alpha)\sum_a c_{1a}(x) + \alpha \sum_a c_{2a}(x) = \sum_a c_{3a}(x) \tag{14}$$

Subject to:

$\sum_l f_l^{mn} = q_{mn}$ -flow balance of network

$f_l^{mn} \geq 0$ -non-negative path flow

where

$$c_{1a}'(x) = \sigma_a^2 x_a + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}$$

$$c_{2a}(x) = \mu_a^2 x_a^2 + \mu_a x_a \sum_{b \neq a} \mu_b x_b$$

$$c_{3a}(x) = (1-\alpha)\ c_{1a}(x) + \alpha\ c_{2a}(x)$$

The formulation of $c_{1a}'(x)$ is derived as follows. Assume the group size is 2, and the unit expected cost is E[x], with variance V[x]. For group arrivals case, total expected cost can be expressed as E[2x] = 2E[x], and total variance is V[x1 + x1] = V[2x] = $4\sigma^2$. For independent arrivals case, the total expected cost is the same: E[x1 +x2] = 2E[x]. However, the total variance V[x1 + x2] = V[x1] + V[x2] = $2\sigma^2$. In general group size,

$c_{1a}'(x)$ is formulated as $\sigma_a^2 x_a + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}$ in this special case, rather than $c_{1a}(x) = \sigma_a^2 x_a^2 + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}$ in the general case. The total marginal hybrid cost needs to be modified as from the expression in Equation 5(c):

$$\tilde{t}_i'(x) = (1-\alpha)\left(\sigma_i^2 + 2\sigma_i \sum_{j \neq i} \sigma_j x_j \rho_{ij}\right) + \alpha\left(2\mu_i^2 x_i + 2\mu_i \sum_{j \neq i} \mu_j x_j\right) \tag{15}$$

All other conditions including existence also hold for the modified formulation.

3.4.3 Robust Cost Assignment Problem with Integer Flow Requirements

Note that the hybrid marginal cost algorithm produces real-valued flow solutions, whereas, imposing integer constraints on feasible flows may be desirable in some contexts. For instance, in the car rental or hotel reservation problems, flows represent acceptance or rejection decisions and are therefore integer-valued in nature. The addition of the integer flow constraints to the RCAP problem makes this problem computationally difficult (NP problem, *Beasley and Chu, 1997*). A simple and computationally efficient heuristic is provided below when integer valued flows are sought for the RCAP problem.

First, the problem RCAP is solved (by relaxing the integer constraints) and the optimal path set (P_1) and path flows (X^*_k) are determined for all paths $k \in P_1$. Since the objective function is convex and quadratic and the constraint set is linear, the integer solution will be close to the real-valued solution of the relaxed problem is intuitively expected. Therefore, the proposed heuristic truncates the real-valued path flows and redistributes the excess integer flows among a set of potential least cost hybrid paths, in order to minimize the total marginal hybrid cost of redistribution, formulated as a mixed integer program (MIP), as described below.

The set of potential least marginal hybrid cost paths (P_2) is obtained by finding the K-smallest marginal cost paths, where K is the excess integral flow that must be redistributed. The marginal arc costs for this problem are computed corresponding to the hybrid marginal cost evaluated at the truncated integer flows, $x_k^{new} = floor(x_k^*)$ where floor represents the largest integer smaller than x. The set of feasible paths (P) to which the excess integer flows may be reassigned is obtained as the union of the path sets P_1 and P_2, since the optimal redistribution of excess flows may involve assignment to a path in P_1. The least marginal cost assignment of the excess flows to the paths in the path set P is obtained by solving the following Mixed Integer Program:

Integer Excess Flow Redistribution Problem (IEFR):

Minimize: $$\sum_{k \in P} C_k(x_k^{new}) y_k \tag{16}$$

Subject to:

$$\sum_{k \in P} y_k = \sum_{k \in P} y_k \, (x_k^* - x_k^{new}) = \textit{total excess flow}$$

$$\sum_{k \in P} (x_k^{new} + y_k \, \delta_{kl}) \le u_l \quad \textit{for} \ \forall\, l$$

$$y_k \ge 0 \quad \textit{for} \ \forall\, l$$

$$y_k \quad \textit{is integer}.$$

The decision variable in this problem is the excess flow y_k assigned to path k, where k belongs to the path set $P = \{P_1 \cup P_2\}$. The three constraints ensure that 1) all excess flow is assigned across the K paths, 2) the reassignment does not lead to capacity violation on any arc, and 3) the reassignment must lead to integer valued solution. The performance of this heuristic is compared against the real solution lower bound, true integer solution, and truncated solution for various test networks. This heuristic was found to perform reasonably well in terms of accuracy. The results are reported in Section 3.5.3.

Although, this MIP model is also NP-hard in general, the problem is computationally more tractable than the original integer-valued problem in practice for two reasons. First, there are fewer variables (paths to be considered), and the amount of flows to be redistributed is small (compared to the original demand). For instance, due to the large dimensionality of the original problem, the optimal solution could not be determined when integer constraints were directly imposed on the non-linear program RCAP, whereas, the integer solution to the IEFR was always found for runs reported in Section 3.5.3. Second, since the MIP formulation is actually an integer network flow problem, it can be shown that the constraint coefficient matrix is totally unimodular by HTG (Heller & Tompkins / Gale) Theorem *(Heller and Tompkins, 1956)*. Thus solving the linear program relaxation of IEFRLP will yield an integer solution.

3.5 Assessing Cost Robustness in the Static Traffic Assignment Problem

3.5.1. Static Traffic Assignment Problem

In traditional transportation planning process, traffic assignment is an important step to assign the vehicular trips to the traffic network based on average link travel time. For each travel mode, given the trip OD matrix, the links available to assign traffic, and functions to estimate the average link travel time (e.g. a BPR function which relates link travel times as a function of the volume/capacity ratio), a unique value of time for the mode, and an assignment method (e.g., User equilibrium or system optimal), the traffic flows are assigned to the network. The average link travel time is deterministic given the volume assigned to each link. To simplify the presentation of the algorithm, only a single travel mode (passenger car) is considered.

However, due to the various reasons of day-to-day variation of network flows, as discussed in the previous chapter, the travel time is essentially a random variable. Assignment solutions without considering the uncertainty of travel time can lead to sub-optimal system cost, especially in a highly uncertain environment. Considering the path information provision to travelers, the operational management center may need to be judiciously providing path information to users, if travel time varies considerably different across links based on historical data.

3.5.2 Network Representation

To demonstrate the use of the robust cost assignment algorithm, the following network model is used, as shown in Figure 3-2. The nodes in the network represent the intersections in the traffic network. In this network, there are eight nodes. Arcs on the network represent the roadways connecting each intersection. For ease of illustration, only one origin (node 1) and one destination (node 8) are modeled in this network, although the proposed method is applicable to the case of multiple O-D pairs. Each link has associated attributes. The capacity of each link is based on the roadway characteristics. The flows on these arcs represent the number of vehicle trips assigned.

Average link travel time is given by the BPR function with the following form:

$$t_a = t_a^{ff}\left[1+\alpha\left(\frac{x_a}{w_a}\right)^{\beta}\right] = t_a^{ff}\left[1+0.15\left(\frac{x_a}{w_a}\right)^{4}\right] \quad (17)$$

Where t_a = mean travel time on arc (a) under flow x_a under normal conditions

t_{ff} = free flow travel time on link (a)

Travel time variance is expressed by $\sigma_a^{\ 2}$. The source of variance includes volume fluctuation, incident, weather and other factors discussed in chapter 1. The variance is assumed to be a known parameter that is independent of link flow and capacity, and can be obtained from historical data.

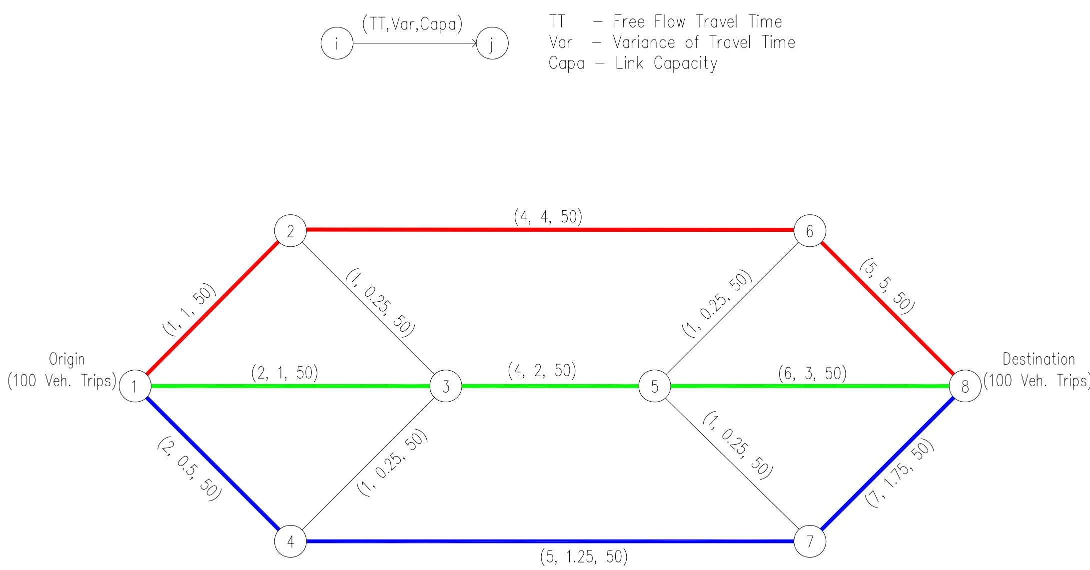


Figure 3-2 Experimental Network

To represent correlations between link travel times across arcs, the travel times are assumed to be distributed as per the multivariate normal distribution with means and variances above, and pre-specified correlations across arcs. Given that the traffic assignment decisions have to be integer valued, all the results reported here are obtained by using the integer heuristic described in section 3.4.3.

For demonstration purpose, three major paths from origin to destination are modeled. Path 1-2-6-8 is considered an arterial with highest variance, but with shortest distance and travel time from origin to destination. Path 1-3-5-8 is considered a freeway corridor with normal level of variance, and with medium travel time. Path 1-4-7-8 is modeled as a local arterial with lowest travel time variation, but with highest travel time.

3.5.3 Robust System Optimal (RSO) Assignment Formulation

For the traffic assignment problem, the assumption is that the link travel times for all users using a specific link are perfectly dependent (e.g., if incident occurs on this link, all users using this link will be affected). Therefore, the group flow model is used for computing the robust cost solution. The randomness in link travel time due to various factors is captured by the mean and variance described in section 3.5.2. The variance levels chosen in the experiments are discussed in the experimental design in next section.

The objective function for traffic assignment problem may then be modified as follows:

$$\mathrm{R}(\mathbf{x}) = (1-\alpha)[\sum_a x_a^2 \sigma_a{}^2 + \sum_a \sum_{b \neq a} 2 x_a x_b \rho_{ab} \sigma_a \sigma_b] + \alpha[\sum_a x_a t_a]^2 \qquad (18)$$

Rewrite the objective function to link separable form:

$$\mathrm{Z(x)} = (1-\alpha)\sum_a c_{1a}(x) + \alpha \sum_a c_{2a}(x) = \sum_a c_{3a}(x)$$

Where

$$c_{1a}(x) = \sigma_a^2 x_a^2 + \sigma_a x_a \sum_{b \neq a} \sigma_b x_b \rho_{ab}$$

$$c_{2a}(x) = t_a^2 x_a^2 + t_a x_a \sum_{b \neq a} t_b x_b$$

$$= x_a^2 t_a^{ff\,2} \left(1 + 0.15\left(\frac{x^a}{w_a}\right)^4\right)^2 + x_a t_a^{ff}\left(1 + 0.15\left(\frac{x^a}{w_a}\right)^4\right) \sum_{b \neq a} x_b t_b^{ff}\left(1 + 0.15\left(\frac{x^b}{w_b}\right)^4\right)$$

$$c_{3a}(x) = (1-\alpha)\ c_{1a}(x) + \alpha\ c_{2a}(x)$$

The total marginal hybrid cost needs to be modified as from the expression in Equation 5(c):

$$\tilde{t}_i\,'(x) = \ (1-\alpha)\left(2\sigma_i^2 x_i\ + 2\sigma_i \sum_{j \neq i} \sigma_j x_j \rho_{ij}\right)$$

$$+\alpha\left(x_i\, t_i^{ff\,2}\left(2 + 0.225\left(\frac{x_i}{w_i}\right)^8 + 1.8\left(\frac{x_i}{w_i}\right)^4\right) + t_i^{ff}\left(1 + 0.75\left(\frac{x_i}{w_i}\right)^4\right)\sum_{j \neq i} x_j t_j^{ff}\left(1 + 0.15\left(\frac{x_j}{w_j}\right)^4\right)\right) \tag{19}$$

All other conditions including existence also hold for the modified formulation.

The problem RSO is solved for the network described in Section 3.5.2, with free-flow travel times and variances given in figure 3-2. The performance of the robust system optimal formulation is compared against the corresponding deterministic User equilibrium (UE) and system optimal (SO) solutions based on the BPR function given. The formulations for UE and SO problems are presented next.

3.5.4 Deterministic User Equilibrium / System Optimal Benchmarks

To compare the performance and benefit of the robust system optimal assignment algorithm, two benchmark solutions for the same network are solved, namely user equilibrium (UE) and system optimal (SO). The standard deterministic UE and SO formulations are well known, and are presented for completeness below. Given the corresponding link cost function (for UE) and marginal cost function (for SO), the same successive assignment routine is applied to solve the UE/SO solution for the same network settings as benchmarks.

1) Deterministic User Equilibrium Assignment Solution

The objective for user equilibrium assignment is to minimize the path travel time for each individual users. The key user equilibrium assignment conditions are: Each user selects the shortest trip time path; all used paths for each O-D pair are minimal and equal; and any unused path for a given O-D pair has a greater travel time than any used paths for that O-D pair.

Minimize

$$\mathrm{R}(\mathbf{x}) = \sum_{a} \int_{s=0}^{x_a} t_a(s)\,ds \qquad (20)$$

Subject to:

$$\sum_{l} f_l^{mn} = q_{mn} \qquad \text{-flow balance of network}$$

$$f_l^{mn} \geq 0 \qquad \text{-non-negative path flow}$$

$$x_a = \sum_{mn} \sum_{l \in K_{mn}} f_l^{mn}\, \delta_{a,l}^{mn} \quad \text{for } \forall a \text{ -arc-path flow relationship}$$

$$0 \leq x_a \leq w_a \;\; \textit{for all a} \quad \text{for } \forall a \text{ , capacity constraints}$$

Link cost function to find the shortest path:

$$t_i(x) = t_i^{ff}\left(1+0.15\left(\frac{x_i}{w_i}\right)^4\right) \qquad (21)$$

2) Deterministic System Optimal Assignment Solution

The objective for system optimal assignment is to minimize the total system travel time. The key SO assignment conditions are: total marginal travel times on all used paths are equal and minimal.

Minimize

$$\mathrm{R}(\mathbf{x}) = \sum_a x_a t_a \qquad (22)$$

Subject to:

$$t_a = t_{ff}\left[1+0.15\left(\frac{x_a}{w_a}\right)^4\right]$$

$$\sum_l f_l^{mn} = q_{mn} \qquad \text{-flow balance of network}$$

$$f_l^{mn} \geq 0 \qquad \text{-non-negative path flow}$$

$$\mathrm{x_a} = \sum_{mn}\sum_{l\in K_{mn}} f_l^{mn}\,\delta_{a,l}^{mn} \quad \text{for } \forall \text{a -arc-path flow relationship}$$

$$0 \leq x_a \leq w_a \ \textit{for all a} \quad \text{for } \forall \text{a , capacity constraints}$$

It can be shown that for the BPR function above, the link marginal cost function to find the shortest path is given by:

$$\tilde{t}_i(x) = t_i^{ff}\left(1+0.75\left(\frac{x_i}{w_i}\right)^4\right) \qquad (23)$$

3.5.5 Experimental Design and Procedures

To explore the potential benefit of the RSO algorithm, and to investigate the performance of the algorithm under different variance levels and correlations, three set of experiments are conducted, as described as follows:

In the first set of experiments, the trade-off between average system travel time and risk (measured by variance of the system travel time) is analyzed across varying levels of risk tolerance (α). In this set of experiments, the medium level variance of travel time is assumed as shown in Figure 3-2. The free flow travel time is assigned such that the path 1-2-6-8 has the shortest travel time, but also the highest standard deviation, which has the same order of magnitude as the free flow travel time. Path 1-3-5-8 has the second best travel time with medium variance in the level of 1/2 of the travel time. The third path, path 1-4-7-8, has the highest travel time, but the lowest variance level, whose magnitude is nearly 0.25 times the free flow travel time. All other links represent side streets with only associated switching costs of 1 minute and a standard deviation of 0.25 minute on each link. The link travel time and variance settings are shown in Table 3-3 below. In this set of experiment, the correlation of variance across links is assumed to be 0 to avoid confounding.

The second set of experiments focuses on investigating the potential benefits of the robust cost assignment algorithm under different level of travel time variations. Three different variance levels (low, moderate and high) are selected, with moderate level as the baseline. The moderate level corresponds to the same variance settings used in experiment 1. For low variance case, the standard deviations of link 1-2, 2-6, and 6-8 are reduced to 1/4 of the free flow travel time, and the standard deviations of link 1-3, 3-5 and 5-8 are reduced to 3/8 of the free flow travel time. For high variance level, the standard deviations of link 1-2, 2-6, and 6-8 are increased to 2 times of the free flow travel time, and the standard deviations of link 1-3, 3-5 and 5-8 are increased to 3/4 of the free flow travel time. It's expected that the gap of travel time variation across paths increases in high variance level, and decreases in low variance level. No correlation across links is assumed for this set of experiments.

Table 3-3 Link Level Parameter Settings

Link SN	Tail	Head	Capacity	Free Flow Travel Time (min.)	Standard Deviation (Low)	Standard Deviation (Med)	Standard Deviation (High)
1	1	2	50	1	0.5	1	2
2	1	3	50	2	0.75	1	1.5
3	1	4	50	2	0.5	0.5	0.5
4	2	3	50	1	0.25	0.25	0.25
5	2	6	50	4	2	4	8
6	3	5	50	4	1.5	2	3
7	4	3	50	1	0.25	0.25	0.25
8	4	7	50	5	1.25	1.25	1.25
9	5	6	50	1	0.25	0.25	0.25
10	5	7	50	1	0.25	0.25	0.25
11	5	8	50	6	2.25	3	4.5
12	6	8	50	5	2.5	5	10
13	7	8	50	7	1.75	1.75	1.75

The third experimental factor is to investigate the performance of robust cost assignment under different correlation levels. Only the links that belong to the same path are assumed to have correlated travel times. For instance, the links 1-2, 2-6 and 6-8 are assumed to have mutually correlated travel times with a constant correlation ($\rho_{1-2,2-6} = \rho_{2-6,6-8} = \rho_{1-2,6-8}$) as noted below. However, the travel times on these links are assumed to be independent of travel times on other network links. Three levels of correlations are considered, namely negative, positively low and positively high, with correlation coefficients of -0.25, 0.25, and 0.5 correspondingly. The no correlation case is taken as the baseline for comparison in this set of experiments.

The total system wide travel time and variance of travel time are obtained as performance measures and analyzed in each experiment. The travel time increase and the variance reduction from baseline level, UE and SO assignment benchmarks are also compared and analyzed. The O-D demand is taken as 100 trips, and is fixed in all three set of experiments.

Based on the deterministic UE/SO assignment solution, Monte Carlo simulation procedures are applied to simulate the variation of travel time with 10000 random realizations, and the average system travel time and variance is obtained. In addition, the trip time reliability measure is developed as the percentage of reliable realizations. A random realization is said to be reliable if the total system travel time does not deviate +/- 10% from the mean trip time.

3.5.6 Experimental Results and Findings

1) Experiment I: Effect of risk tolerance on travel costs from the RCAP solution

The robust cost assignment algorithm proposed in section 3.3 may be used in two ways to assess the variability/risks associated with alternative assignment strategies. First, if a decision-maker's relative preference towards travel time and its variance is known, this can form the basis to determine the preference weight for cost variability (given weight by 1-α). The robust cost assignment problem may then be solved to yield the assignment strategy that minimizes the robustness of travel time for the given (α). However, the preferences towards risk are not well-formed in practice is possible, given the sole focus on travel cost minimization in current practice. In such a case, several optimal policies may be determined by repeatedly solving problem RSO corresponding to various values of (α), and the corresponding average costs and risk may be determined for each value of (α). These solutions may then be used to obtain a curve depicting the trade-off between trip time variability and average travel time, which may be used to inform decision-makers about the variability/cost trade-offs. The variability-cost trade-off curve can be used to elicit decision-maker preferences regarding the most desired variability/average travel time combination. The assignment policy corresponding to this preferred variability/cost combination may then be implemented in practice. Alternatively, the proposed solutions may be used to provide benchmark levels of variability of travel times, against which the variability in travel time with currently used practices (user equilibrium assignment) may be compared to assess the acceptability of the current travel time variability.

To test the variability versus cost trade-off, the following set of experiments were conducted. The robust cost assignment is obtained for varying levels of variability tolerance (α), and the results are compared against the UE and SO solution. The results corresponding to different levels of variability tolerance are shown in Table 3-4, and are plotted in Figure 3-3. Due to the unbalanced growth rate of variance and cost terms in the objective function, the absolute alpha values are not a truthful indication of the weight imposed on the cost term. The trade-off curve can be utilized by the decision maker to select an appropriate alpha level.

Table 3-4 Variability-cost Trade-off

Variability Tolerance Level Alpha (%)	% of Travel Time Increase (from SO)	% of Variance Reduction (from SO)	% of Travel Time Increase (from UE)	% of Variance Reduction (from UE)
0.00	14.07	35.54	9.14	54.89
1.00	7.20	33.01	2.57	53.12
2.00	5.55	31.16	1.00	51.83
3.00	3.85	28.10	-0.64	49.69
4.00	**2.91**	**25.62**	**-1.53**	**47.95**
5.00	2.45	24.15	-1.97	46.92
6.00	1.77	21.20	-2.62	44.86
7.00	1.56	20.37	-2.82	44.28
8.00	1.26	18.65	-3.11	43.07
9.00	0.84	15.72	-3.51	41.02
100.00	0.01	2.55	-4.31	31.81

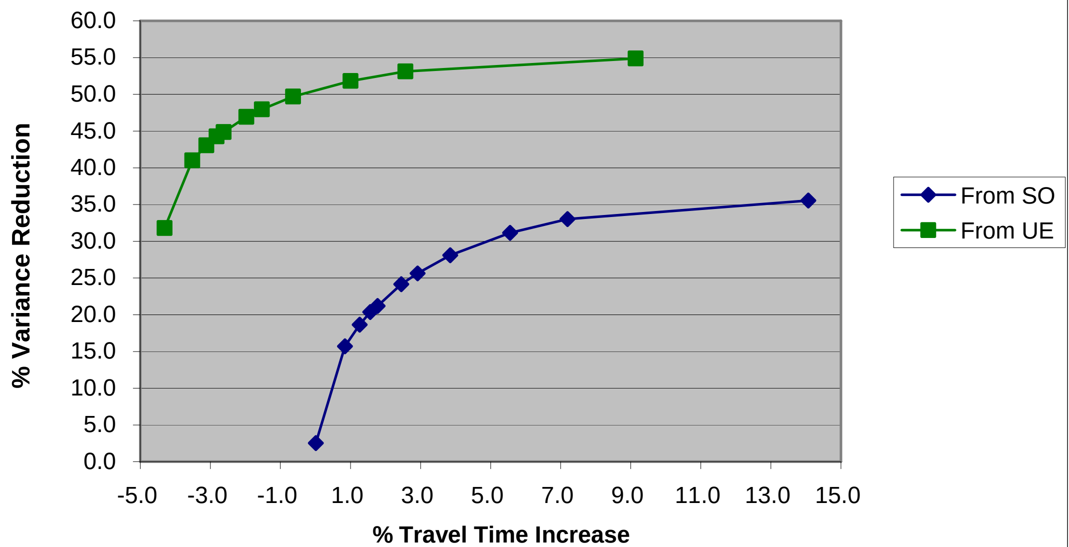


Figure 3-3 Variance-Cost Trade-off Curve

A greater alpha indicates a decision-maker with a higher variability tolerance, whereas, a low alpha indicates a risk averse decision-maker who seeks to minimize variance possibly at the expense of average travel times. The results indicate that the

RSO solution can reduce nearly 15-35% of the travel time variance while only sacrificing 1-14% of average travel time. The variance-cost trade-off curve shown in Figure 3-4 may be used by a decision-maker to select an assignment solution corresponding to his/her variability tolerance level. For instance, a decision-maker who is moderately risk averse, may prefer alpha = 4% since it provides 2.9% of the travel time increase from SO assignment solution, but is much more robust (with a variance reduction of 25.6%). This reduction in variance for the RSO compared to the SO solution was the result of difference in assignments in the two cases, as described below.

In the UE solution, path 1-2-6-8 and 1-3-5-8, the paths with shorter travel time but higher variance, are used up to their capacities. Consequently, the variance of system travel time increases. The SO solution improves the system travel time by balancing the assignment to more paths. However, both UE and SO solutions are not aware of travel time variance. RSO solution has the moderate travel time performance, but assigns more flows to path 1-4-7-8 (high travel time, but low variance) in order to reduce the travel time variation. Therefore, the robust cost assignment performs reasonably well compared to the SO and UE, when the decision-maker can make trade-offs between travel times and variances across different paths with different levels of travel time variation. The path flow comparison is shown in Table 3-5 below.

Table 3-5 Path Flow Comparison among Different Assignment Solutions

Path / Assignment type	1-2-6-8	1-3-5-8	1-4-7-8	1-2-3-5-8
RSO with alpha=4%	34	30	31	5
SO Assignment	44	34	22	0
UE Assignment	50	50	0	0

On the other hand, if the variance difference across paths is minimal, there will not be enough opportunities for the trade-off between travel time and variability (reflected by cost variability). In such a case, the robust cost assignment solution and the SO solution will be close in terms of both travel time and variances. In practice, travel time variation may depend on different roadway characteristics (such as functional classification, median type and number of lanes) and other internal and external factors. For instance, incident occurrence rate for undivided urban multilane highway can be five times higher than the rate for freeway (Traffic and Safety Policies and Procedure Manual, TN DOT, 1994). Due to these factors, therefore, opportunities for trade-off between trip time and travel time variability is likely to exist among different routes in real world networks.

Table 3-6 Travel Time Reliability Improvement

Assignment Type	Travel Time Reliability (%)
UE	48%
SO	54%
RSO	62%

Table 3-6 shows the improvement of travel time reliability obtained from 10000 draws of Monte Carlo random realization. RSO solution provides 14% increase in travel time reliability from UE solution (system will experience 14% more days with travel time variation less than 10% from the mean travel time) and 8% increase from SO solution.

2) Experiment II: Effect of Various Travel Time Variation Levels

The performance of the RSO and SO is compared for varying levels of travel time variations, as illustrated in Table 3-7. As expected, the results reveal that randomness in travel time contributes significantly to system level travel time variability in the deterministic system optimal solution, as described below. The variance trade-off curves for three levels of variance are also compared in Figure 3-4.

Table 3-7 Performance Measures for Different Travel Time Variation Levels

Assignment Type	Variance Level	% Travel Time Increase (from SO)	% Variance Reduction (from SO)
RSO with 2% - 3% travel time increase	Low variance	2.47	13.68
	Medium variance	2.91	25.62
	High variance	2.81	32.77

Notes:

1. The results in this table are based on RCAP assignment solution with corresponding travel time increase level of 2-3%. Alpha levels are 1%, 4% and 10%, corresponding to the Low, Medium and High variance levels.
2. Percentages are based on the corresponding SO assignment solution for each case.

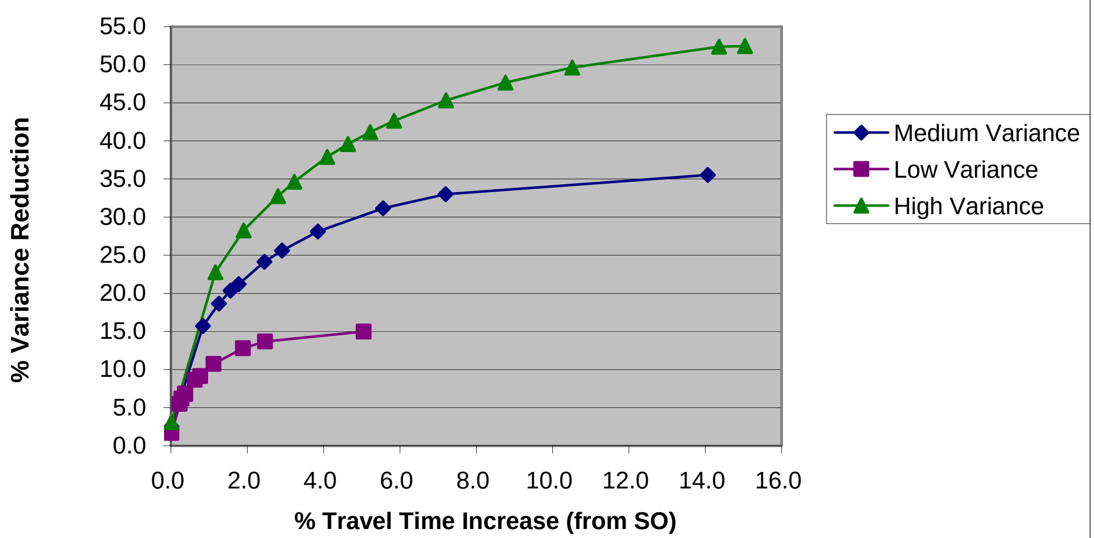


Figure 3-4 Variance-Cost Trade-off Curve for Different Variance Levels

The results shows that with increasing travel time variability, system travel time variability (16576, 27990, and 50818) increase for the deterministic system optimal solution. In the robust system optimal solution, the corresponding average trip times (1240, 1245, and 1244) and system variability (14309, 20818, and 34166) are also observed to increase. The reduction in system variability obtained by the robust solution with the deterministic solution increases with increasing level of uncertainty in the network. For instance, the variability reduces from 13.7% to 32.7% relative to the deterministic system optimal solution, and this reduction comes at the mild expense of a 2.5% to 2.9% increase in average trip times. This reduction is mainly due to more trips being assigned to low variance paths in the RSO than in the SO solution. The variance improvement of the RSO over the SO is significant with medium and high incident probabilities (25.6% and 32.7% respectively). Thus, using the RSO in highly uncertain environments may be desirable, whereas, the SO solution may be chosen for low travel time variation scenarios.

3) Experiment III: Effect of Various Variance Correlation Levels

The link travel times may be correlated for various reasons including secondary incidents, inertial behavior of roadway users, and weather effects. Under the within path correlation assumption, three levels of correlations are tested, namely negative correlation, positive low correlation, and positive high correlations. The performance measures are summarized in Table 3-8.

The results of RSO solution with alpha = 4% are compared against the SO and UE solutions in corresponding correlation levels. Since the robust SO solution with zero correlation disregards correlation in arc travel times, this solution systematically underestimates system variance in networks with positive travel time correlations, and overestimates them when the costs are negatively correlated. Thus, the assumption of independence of travel times across arcs can lead to biased solutions. When the correlation level increases, the variance reduction from corresponding SO solution increases from 21.33% (for negative correlation case) to 29.03% (at high correlation level). The travel time increase for RSO corresponds to 1.56% to 4.62% from SO solution. Notice that with a higher correlation level, the reliability of travel time decreases significantly for both the UE and SO solution, as shown in Figure 3-5. Although RSO solution has slightly higher travel time (1.56%-4.62%), RSO solution leads to more reliable travel time (7% to 9% improvement from corresponding SO solution). These results show that correlation trends may be used to select robust assignment strategies at different times (e.g., peak and off-peak times) when they can be predicted, in order to achieve more reliable system performance and to limit the extent of downside system travel time variability.

Table 3-8 Performance Measures under Different Correlation Levels

Variance Level	Assignment Type	Mean Travel Time	Mean Variance	Travel Time Reliability (%)	% Travel Time Increase (from SO)*	% Variance Increase (from SO)*
Negative Correlation (-0.25)	UE	1265.00	22120.05	60.90	4.51	42.25
	SO	1210.40	15550.50	67.07	0.00	0.00
	RSO (alpha=4%)	1229.31	12232.94	74.10	1.56	-21.33
No Correlation	UE	1265.00	40000.00	47.52	4.51	42.91
	SO	1210.40	27990.00	53.55	0.00	0.00
	RSO (alpha=4%)	1245.66	20818.25	62.28	2.91	-25.62
Low Correlation (0.25)	UE	1265.00	57879.95	40.33	4.51	43.16
	SO	1210.40	40429.50	45.74	0.00	0.00
	RSO (alpha=4%)	1253.67	29475.50	54.06	3.57	-27.09
High Correlation (0.5)	UE	1265.00	75759.90	35.15	4.51	43.30
	SO	1210.40	52869.00	40.48	0.00	0.00
	RSO (alpha=4%)	1266.30	37522.63	49.06	4.62	-29.03

Notes:

Percentage travel time and variance increases are measured from the SO solutions in corresponding correlation levels.

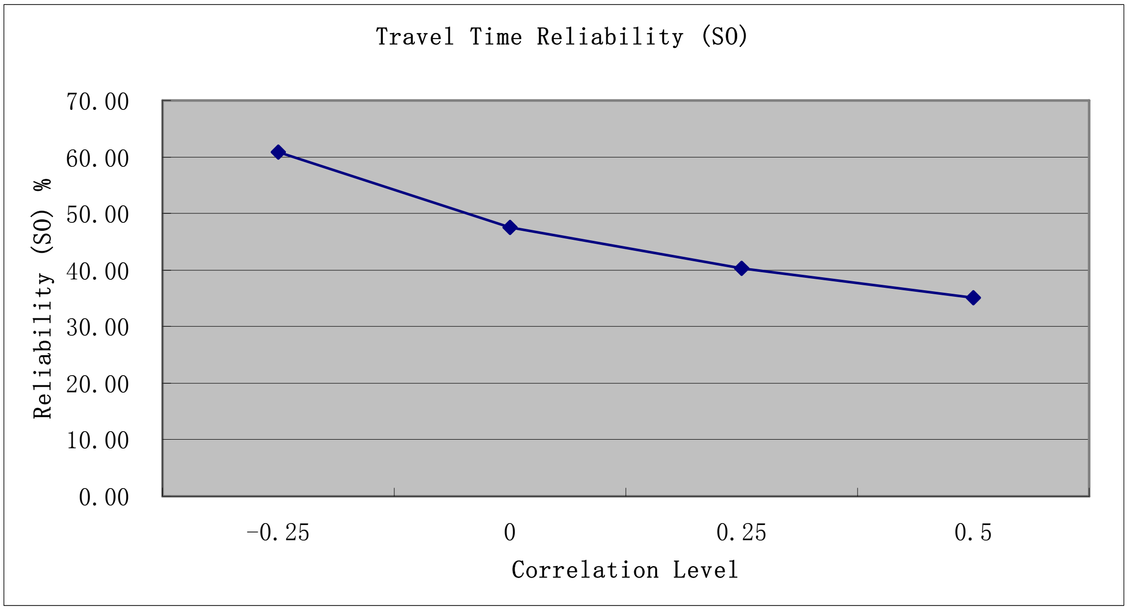


Figure 3-5 Travel Time Reliability Trends under Different Correlation Levels (SO solution)

For higher correlation scenarios, a smaller alpha is needed to achieve more reliability. This improvement in reliability comes at the expense of increasing average system trip-times, as shown in Table 3-9.

Table 3-9 Performance Measures under High Correlation Level

Scenarios under High Correlation (0.5)	Assignment Type	Travel Time Reliability (%)	% Travel Time Increase (from SO)*	% Variance Increase (from SO)*
SO (baseline)		0.40	0.00	0.00
RSO	alpha=4%	0.49	4.62	-29.03
	alpha=2%	0.51	8.34	-30.85
	alpha=1%	0.52	9.59	-33.94
	alpha=0.5%	0.53	11.39	-34.60
	alpha=0.1%	0.55	14.52	-35.10

Notes:

1. Baseline is the SO solution for high correlation case.
2. For baseline level, travel time = 1210, and variance = 52869.

Further, the results indicate that there is a limit to the extent of improvements in reliability possible purely due to reassignment of flows in robust network algorithm. To achieve further reliability improvements, systematic variance reduction techniques that aim to reduce link travel time variability such as transportation control measures or incident management measures may be necessary. The influence of transportation control measures on network reliability is examined in Chapter 5, and the effect of incident management measures on network reliability is investigated in Chapter 6.

3.5.7 Assumptions and Exceptions

In the empirical analysis above, several simplifying assumptions have been used to avoid experimental confounding and to enhance analysis tractability. The link capacity is assumed to be constant and deterministic. The O-D demand is assumed to be fixed and known. A static assignment formulation is considered. Also, free flow travel time is assumed to be constant across scenarios. A single O-D pair is used for convenience of illustration. The proposed framework can be generalized in a straightforward manner to handle the cases of elastic demand, varying free flow travel times and multiple O-D pairs. However, the development of robust assignment algorithm for time-dependent stochastic networks is beyond the scope of this study and is an important direction for future research.

3.6 Conclusions

This chapter has formulated and proposed an algorithm to solve robust cost minimization in networks with uncertain arc costs, as well as three important variants of this generic problem. The variants considered include 1) minimum variance assignment problem, 2) robust cost minimization problem with integer constraints, and 3) robust cost problem with independent within-link flows. Existence of a solution is shown for these cases, and a strongly polynomial time algorithm is proposed for their solution based on the Franke-Wolfe algorithm. In contrast to these cases, where real-valued flows were of interest, the chapter also proposes a heuristic to model the robust cost minimization problem with integer constraints. The proposed integer heuristic is computationally efficient, and reasonably accurate (in terms of deviation from a relaxed LP solution).

At the empirical level, the application of the proposed RSO model to determine robust traffic assignment policy for static traffic assignment problem was presented. The RSO model may be used to elicit and understand the relative risk propensity (trade-off between travel time and travel time variability). The experimental results indicated that the RSO solution is very sensitive to 1) the degree of risk aversion, 2) the level of travel time variation, and 3) correlations among links. These results have important implications for understanding the reliability of travel time and robustness of traffic assignment solutions. The robust cost optimization model also has important implications on perishable inventory allocation decisions such as airlines, car-rentals, resorts, and hotels. These models may also be extended to infrastructure network design and operations such as telecommunication, airline and freight transportation networks, and project scheduling networks, where arc costs may be uncertain in nature.

For future research direction, extending the basic algorithm to robust user equilibrium assignment is desirable because user equilibrium assignment may receive more attention in practice. Furthermore, the robust algorithm may be extended to time-dependent robust UE and SO algorithm, adding the ability to model time-dependent features such as departure time and route switching. From a practical point of view, exploring robust information strategies is a natural direction of future research. With regard to theoretical direction, qualification of variance as a function of flow is a challenging direction for future research.

CHAPTER IV

DAY-TO-DAY DYNAMIC SIMULATION ASSIGNMENT FRAMEWORK AND METHODOLOGY

4.1 Overview

In order to represent and analyze day-to-day dynamics and network reliability in urban transportation systems, the following components and features must be represented. First, a within-day dynamic traffic assignment model is needed to capture the time varying O-D demand, to enable users to receive real-time information and switching routes. Secondly, the user decision process must be modeled, with the ability to account for both users' past experience and anticipated congestion and trip time savings. The third and the most important component is the feedback loop from day to day, to enable consistent, and mutually co-evolving representation of three principal dimensions of dynamics: real-time, within-day and day-to-day.

Two key internal factors that influence day-to-day dynamics in network performance include departure time adjustment and variations in route choice decisions from day-to-day. Individual user decisions could vary from day to day due to the effect of information, past experience or changes in network conditions, as noted previously. Therefore, two empirically calibrated behavior models of user response are integrated into the existing within-day dynamic traffic simulator. The within-day network assignment model used in this study is based upon the well-established dynamic network assignment model (DYNASMART), which is described in section 4.2. Section 4.3

discusses how the ATIS information supply strategies are simulated in the day-to-day context. Next, the two user behavioral models used in this chapter to model day-to-day dynamics (for departure time and route choice decisions respectively) are described in section 4.4. Based on these behavior models, a day-to-day simulation assignment framework is developed, as described in section 4.5. This day-to-day dynamic simulator consists of three major components: network dynamic traffic simulation, user response (through stochastic route choice model and dynamic departure time adjustment model), and information supply through ATIS devices.

4.2 Within-day Dynamic Traffic Simulation

The within-day network assignment model used in this study is based upon the well-established dynamic network assignment model (DYNASMART) developed at the University of Texas at Austin *(Mahmassani,1991)*. The framework underlying this simulation model is presented below. The basic components of this simulation model and associated input and output of DYNASMART are also discussed.

4.2.1 Introduction to DYNASMART

DYNASMART was developed at University of Texas, Austin and contains a core simulation-assignment model that includes traffic flow models, path processing methodologies, drivers' behavior rules, and information supply strategies which are described below. The input data include a time-dependent O-D (origin-destination) matrix, traffic control, user class details, and physical properties and spatial/temporal constraints of the network. In a given network configuration, the simulation component will take the time-dependent loading pattern of vehicles as an input and process the movement of vehicles on the links according to theoretic traffic flow-density relationships (e.g., Greenshield's and speed-density relationships). The resulting system performance measures, including time varying speed, density, queue length, and queue formation, are modeled and recorded in various outputs as described below.

4.2.2 Within-day Traffic Simulation Components

The network simulation assignment model consists of three main components: the traffic simulator, the network path processing component, and the user decision-making components, as illustrated in Figure 4-1. The description of the DYNASMART simulator in this section is abstracted from Mahmassani et. al *(1991)*.

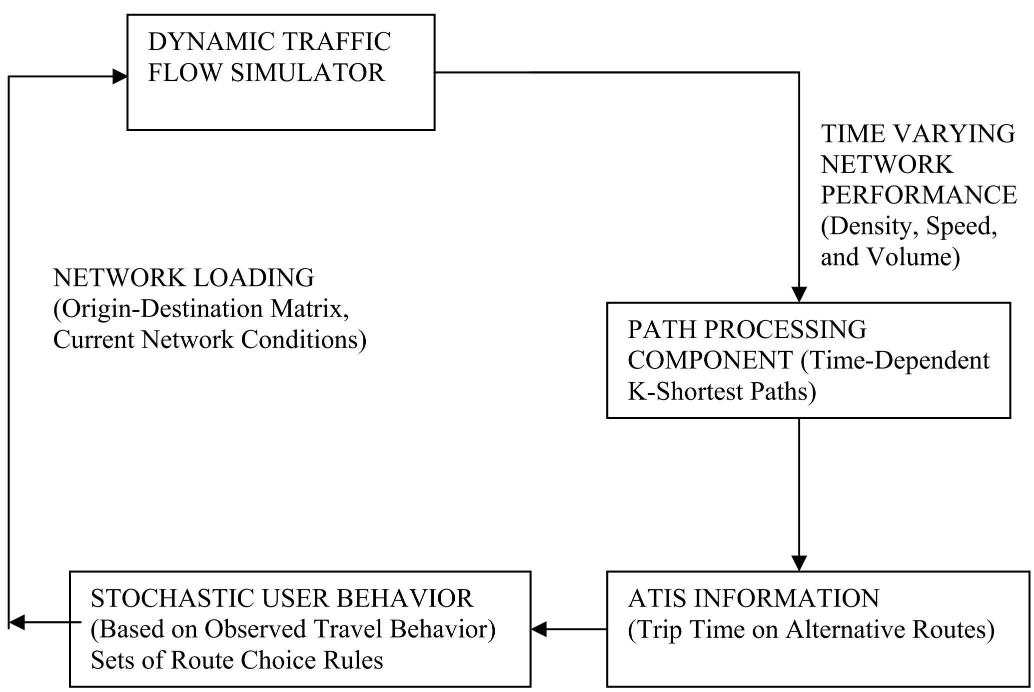


Figure 4-1 Structure of DYNASMART Simulation Assignment model

The first component, dynamic traffic flow simulator uses established traffic flow models to define the movement of vehicles through the network. The simulated vehicles on a link are moved individually at prevailing speeds consistent with macroscopic speed-density relations. At the beginning of a simulation run, DYNASMART loads input data from a series of input files. At that time, network data, a time-dependent origin-destination matrix and data associated with market penetration, congestion level, route choice rules, and incidents are loaded in a specific order. Vehicles are assigned to the network by specifying a time-dependent origin-destination matrix among zones for various departure time intervals. The network demand for a 90-minute (considered in this study) morning peak period is loaded over a period of 35 minutes. The traffic flow simulator consists of two main modules: link movement and node transfer. The link movement module processes the movement of vehicles on links during each scanning time unit in the simulation. The node transfer module performs the link-to-link transfer of vehicles at nodes. The initial movements of simulated vehicles will yield density, travel time and estimated delay of each link. These are the input to the second component, path processing.

The path processing component determines the route attributes such as travel time for use in the ATIS information supply strategies to informed drivers. For each vehicle with access to ATIS information, the K-shortest paths from the vehicle's current link to its desired destination are calculated. The travel times on the K-shortest paths are updated by using the prevailing link travel times at each simulation time.

ATIS information strategies provide information to drivers based on the travel times on K-shortest paths. This information could be based upon various forecasting models such as historical averages, real-time prevailing information or predicted travel times. In this study, real-time information in the format of prevailing trip time is provided to drivers, unless otherwise specified.

The user behavior component is intended to simulate drivers' responses to the available information according to various sets of plausible drivers' behavior rules governing route-choice decisions. Through these stochastic route choice rules, drivers can choose a suitable route from a set of available routes. The drivers' route selections are then reflected as time-varying link flows on links of the network.

In each time step (6 seconds resolution), the simulator also updates the time-dependent network performance measures including link and path trip times, density, and queue lengths, thus affecting user decisions and experience. These capabilities are adapted in this study to compute measures affecting departure time and route choice utilities such as schedule delay, and trip-time volatility, and the cycle is repeated for each day.

4.3 Simulation of ATIS Information Supply Strategies

To provide information to network users, data on prevailing traffic conditions must be obtained for each time interval, and the corresponding real-time information that is provided to drivers (prescriptive or descriptive) must be generated (e.g., VMS messages, or best path between specific OD information). An essential input to the model is the fraction of users with access to information.

In each time step (6 seconds resolution), the within-day traffic simulator described above collects and computes the time-dependent network performance measures including link trip times, density, and queue lengths. The time-dependent all pair K-shortest path (KSP) algorithm is used to compute the K-best path from each origin zone to each destination zone at discrete time steps (every 3 minutes in this study). The KSP pathset update frequency can be adjusted to increase or decrease the temporal resolution of real-time information. The proportion of informed drivers can also be adjusted, and is used to vary information market penetration in the empirical experiments described in Chapter 6. The ATIS information based on the shortest path algorithm can then be provided to users as autonomous driver information (route guidance) to in-vehicle navigation systems. In the simulation, both informed and uninformed vehicles can respond to dynamic messages from variable message signs (VMS) as well. In addition to enroute information, the within-day simulation also provides the capability to supply pre-trip information to drivers. Pre-trip information may be based on: 1) best prevailing path, 2) random path chosen from a path set consisting of three least trip time paths (also referred to as 'best' paths), or 3) guidance based on system optimal (SO) and user equilibrium (UE) assignment policy.

4.4 User Response to Information

In the proposed simulation framework, user decisions are made at the individual level. Each individual driver, with his/her own knowledge, preference and perceptions on the traffic network is modeled using an agent. A belief-desire-intention (BDI) architecture can be used to represent the driver's behavior, preferences and goals. The BDI architectures originated in the work of the Rational Agency project at Stanford Research Institute in the mid-1980s, and the conceptual framework of the BDI model is described in Bratman et. al. (1988). The primary advantage of implementing the BDI approach in modeling driver behavior is 1) allowing dynamic adjustment of behavior and 2) updating knowledge in real time. Figure 4-2 shows the BDI model in a driver behavior context.

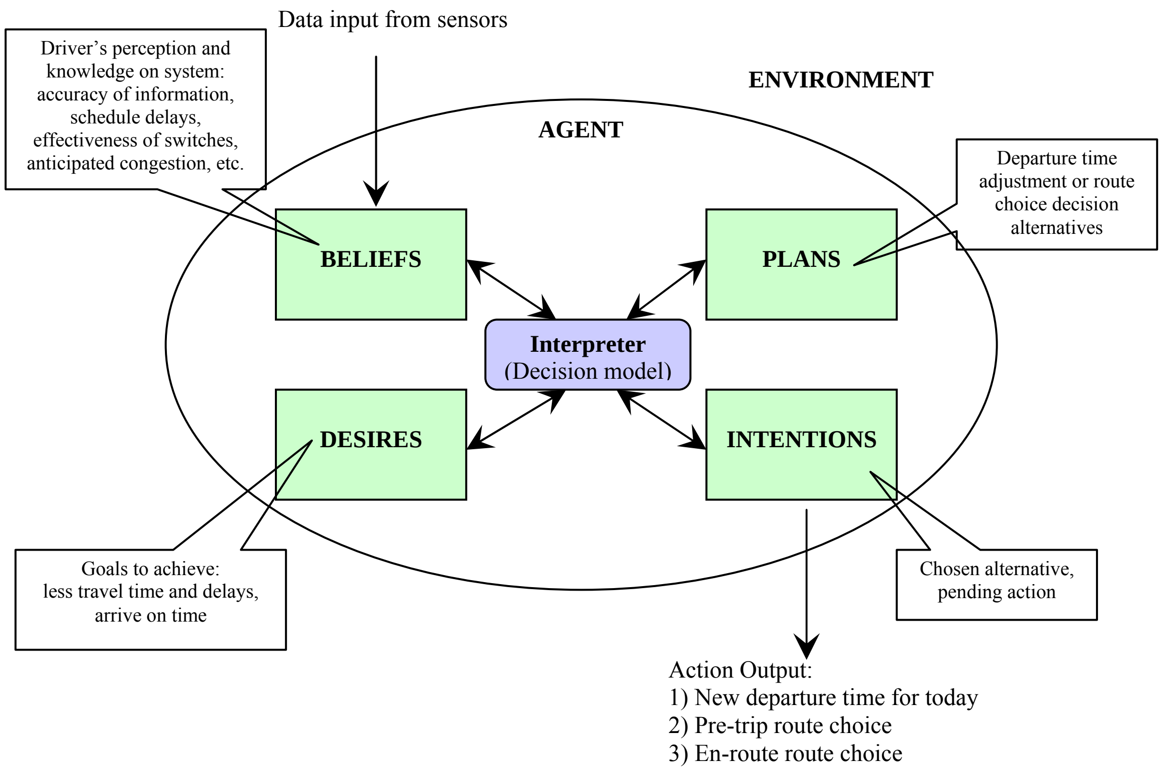


Figure 4-2 BDI Structure for Agent-based Behavior Model

Two empirically calibrated behavior models are used as the core component (interpreter) to model day-to-day dynamics are integrated into the day-to-day simulation framework (for departure time adjustment and route choice decisions respectively), as described in the following section.

4.4.1 Departure Time Decision Model

Given the important role of departure time dynamics, representing departure time adjustment decisions from day-to-day at a sufficiently disaggregate level and rich temporal resolution is essential. Toward this end, an empirically calibrated model of dynamic departure time choice *(Srinivasan, 2001)* has been integrated with a dynamic network assignment framework (DYNASMART) in this study. The empirical model used here provides a richer stochastic representation of user decisions, and provided a significantly better fit to empirical data than alternative static departure time choice models *(Srinivasan, 2001).* This model explicitly accounts for the role of dynamics in network and commute performance, users' past experience, and users' departure time switching history on a user's departure time decisions *(Srinivasan, 2000)*.

In this model, to represent commuting constraints, each commuter is assumed to have a target or preferred arrival time (PAT) at the work place, and the user selects departure times to reach his/her workplace by this time. The departure time adjustment is assumed to take place in two stages. First, a user 'reviews' whether the current departure time is satisfactory for the next day's commute (based on current and past traffic experience). In the second stage, the current choice is retained if satisfactory. Otherwise, the user determines the magnitude of departure time switch based on past experience, network performance, and failure to meet arrival time goals. Empirical results *(Srinivasan, 2001)* indicate that the alternatives are considered in aggregate intervals (bins) of five-minutes, and alternatives closer to current choices are evaluated preferentially ahead of farther alternatives. In other words, a user is more likely to consider adjustment by five minutes first before considering a switch by over fifteen minutes. In this model, the user continues to evaluate alternatives sequentially until a satisfactory and sufficient alternative is found *(Srinivasan, 2001)*.

Accordingly, the adjustment process is represented as a sequence of binary decisions. This model is operationalized through a set of corresponding binary alternatives and utilities shown in Figure 4-3. The utility values $U_{1\ldots}$ U_5, correspond to the utility of no adjustment, adjustment by more than 1 minute, adjustment by more than 5 minutes and so on. The specification of these random utilities, $U_{1,\ldots}$ U_5, are given below, and the coefficients and parameters of the error-terms are based upon the empirical model reported in Srinivasan *(Srinivasan, 2001)*.

$U_1 = 0$

$U_2 = 0 + 0.176\ \text{Dtratio} + \varepsilon_1$

$U_3 = -1.36 - 0.16\ \text{Dtratio} + 0.058\ \text{Sde} + 0.06\ \text{Sdl} + \varepsilon_2$

$U_4 = 0 + 0.31\ \text{Dtratio} + 0.046\ \text{Sdl} + \varepsilon_3$

$U_5 = 1.51 - 2.79\ \text{Dtratio} + 0.071\ \text{Sdl} + 0.78\ \text{Nsep} + -1.84\ \text{Nslp} - 0.237\ \text{Triptime} + \varepsilon_4$

where:

U_i = total utility for i-th switching alternative

ε_i = correlated random error for each switching alternatives

Dtratio = trip-time volatility ratio

Sde = early schedule delay on previous day

Sdl = later schedule delay on previous day

Nsep = cumulative percentage of switching to early departure times

Nslp = cumulative percentage of switching to late departure times

Triptime = trip time for previous day

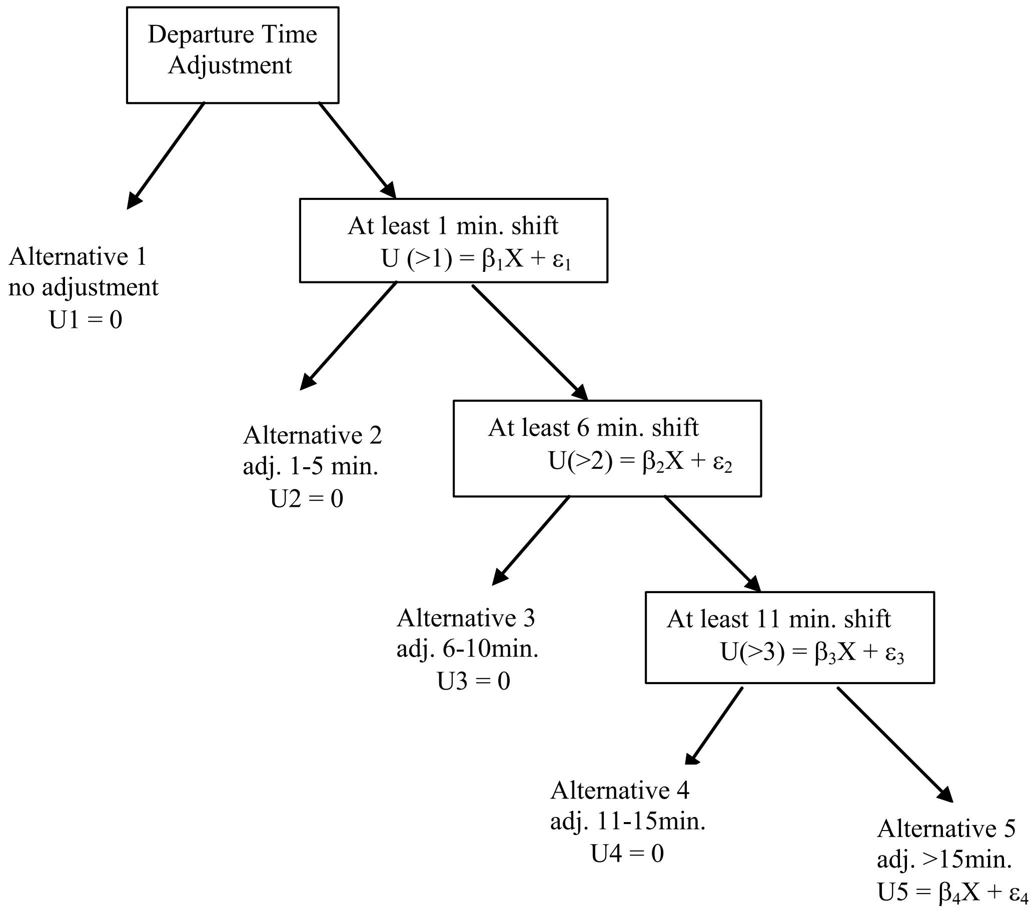


Figure 4-3
Sequential greedy search adjustment model of departure times

The variance-covariance structure of error-terms is shown below. In the structure shown, the following variance-covariance parameters are used based on Srinivasan (*22*): $\sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = 1$, $\rho_1 = 0.09$, $\rho_2 = 0.28$.

$$\Sigma = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ & \sigma_1^2 & 0 & 0 & 0 \\ & & \sigma_2^2 & \rho_1\sigma_2\sigma_3 & \rho_1\sigma_2\sigma_4 \\ & \mathit{Sym.} & & \sigma_3^2 & \rho_2\sigma_3\sigma_4 \\ & & & & \sigma_4^2 \end{pmatrix}$$

This model emphasizes the role of empirical factors on departure time adjustment decisions. Among the variables, triptime volatility ratio experienced by trip-makers significantly influences departure time adjustment behavior. As the trip time variability increases, users are more likely to switch departure times. The model also suggests that trip time does not significantly influence departure time adjustment decisions but schedule delay does. Users departure time adjustments are also sensitive to past experiences in the system. Following a late arrival episode on the previous day, users tend to select a larger departure time shift alternative at all binary decisions. Following early schedule delay, however, users tend to prefer a moderate adjustment of more than five minutes compared to a 1-5 minute shift to larger adjustments, but no differences are observed in other sequential decisions. Users with a greater cumulative proportion of departure switches to earlier departure times on the preceding days, exhibit a disposition to shift departure time significantly.

Based on the departure time choice model, for each day and each user, the utility of each alternative is computed based on the previous day's schedule delay, and experience (trip-time volatility ratio and cumulative early and late switches). The random errors are generated according to the distribution above using Monte-Carlo simulation. The total utilities are compared sequentially according to the greedy departure time search model shown in Figure 4-2. For instance, in this model, a user will change departure times if $U_1 < U_2$, and by 6-10 minutes if $U_2 > U_3$ and $U_1 < U_2$. Thus the departure time adjustment alternative for each individual is determined according to this model on each day. (The actual adjustments are assumed to be uniformly distributed within the chosen bin, i.e., the departure time shift could be 7 minutes for a 6-10 minute adjustment bin). Users are assumed to adjust their departure times according to the previous day's schedule delay towards the opposite direction (early switch following late schedule delay and vice-versa, since 95% of users in empirical data exhibited this behavior). These individual departure time adjustment decisions are aggregated to form the time-dependent O-D matrix for the following day.

4.4.2 Route Choice Decision Model

For route choice decisions under information, a disaggregate and behavioral model *(Srinivasan 1999)* was used. This model captures two principal behavioral mechanisms observed in route choice decision process under information: compliance and inertia. Inertia is defined as the mechanism underlying a decision maker's tendency to retain the current path. Compliance is the mechanism related to the tendency of a trip maker to comply with the best path recommended by ATIS. Route choice instances may be classified into two cases. Case 1 corresponds to instances where a user's current path is also the best path. In this case, both mechanisms may favor same alternative (BP=CP). In case 2, however, the current path is distinct from the best reported path. In this case, inertia favors the current path, whereas compliance favors the best path. In general, therefore, the two mechanisms can operate simultaneously and the observed choice results from a trade-off between them. The details of this empirical model are abstracted and presented below.

In each route choice instance (every time a user receives ATIS information), a user is assumed to select the alternative path with the highest total utility (consistent with random utility maximization framework). The total utility of alternative p (U_p) accounts for the utilities of U_a and U_c, associated with inertial and compliance mechanisms, respectively, in addition to a path-specific utility (U_p). These mechanism-specific utilities are unobserved and can vary across individuals and choice instances. They are expressed as:

$$U_a\,(i,t) = f\,[Z(i), X_a(i,t), \beta_a] + \varepsilon_a(i,t)$$

$$U_c\,(i,t) = f\,[Z(i), X_c(i,t), \beta_c] + \varepsilon_c(i,t)$$

Where

i = user,

t = choice instance,

Z(i) = trip-maker attributes,

$X_a(i,t)$ and $X_c(i,t)$ = vectors of attributes related to the inertia and compliance utilities,

$\varepsilon_a(i,t)$ and $\varepsilon_c(i,t)$ = corresponding error components, and

β_a and β_c = vectors of parameters associated with inertia and compliance.

The total utility of the path alternatives in each case is constructed from the path specific components and the mechanism-related utilities, as illustrated in figure 4-4.

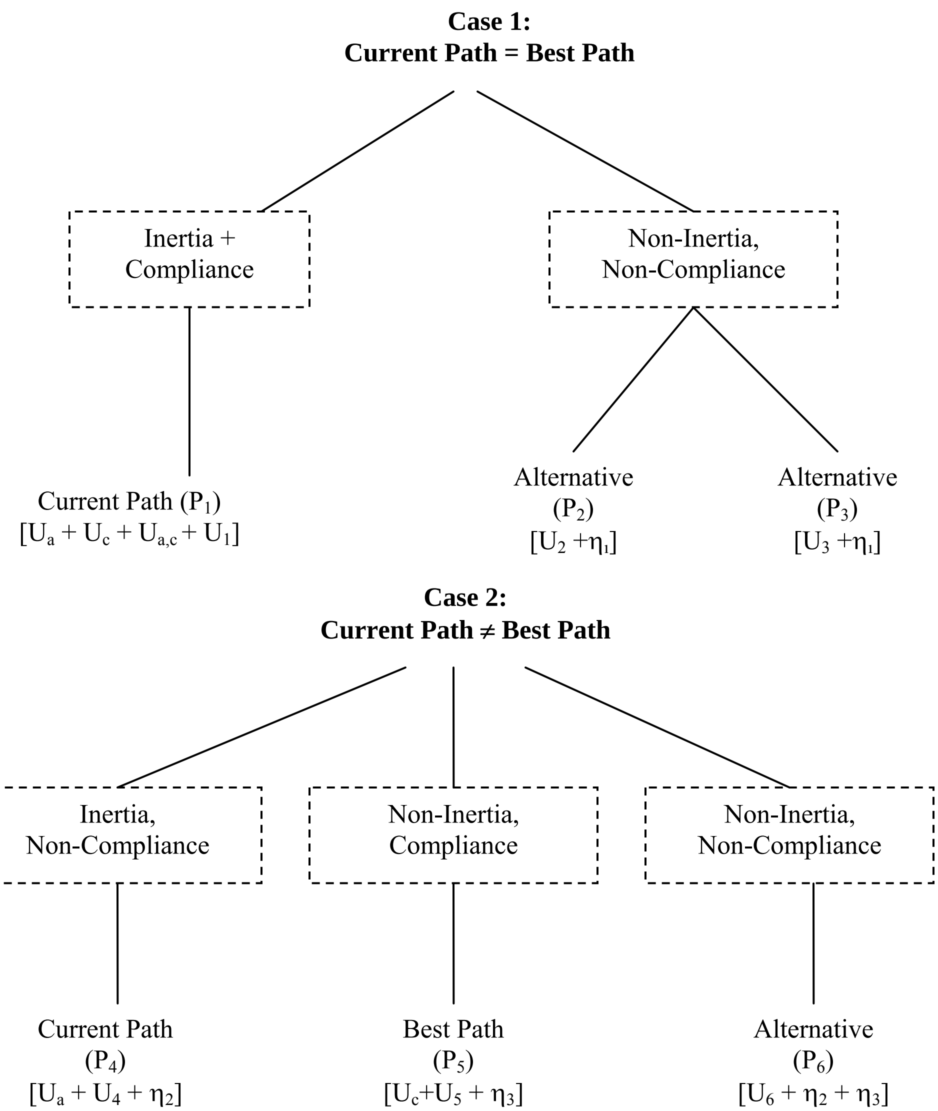


Figure 4-4
Route Choice Structure Incorporating Both Inertia and Compliance

In case 1, current path is the best reported path. In this case, following the current path is consistent with both compliance and inertia. Therefore, the utility of current path consists of U_a, U_c and a path-specific component. An interaction component $U_{a,c} = f(\beta_{a,c}, Z, X_{a,c}) + \varepsilon_{a,c}$ is introduced to capture the interaction effect between compliance and inertia in this case. For the choice of the remaining alternatives, there is no contribution of the mechanism utilities to the total utilities. Therefore, their utilities consist only of path-specific components and the error term. In case 2, the current path is distinct from the best reported path. In this case, the compliance utility is associated with the best path and the inertial utility with the current path. The utility for the third alternative (non-inertia, non-compliance) consists of only path-specific utilities and error terms. The empirical calibrated utilities may be expressed as:

$$U_c = 1.50 + 1.83\ \text{Ttratio} - 1.72\ \text{Switchcost} - 0.8\ \text{Erro} + 0.02\ \text{Sdl} + 1.01\ \text{Nsep}$$

$$U_a = 3.63 - 1.17\ \text{PretripL}_2 - 1.17\ \text{PretripL}_3 - 0.45\ \text{EnrouteL}_{23} - 2.35\ \text{Ttratio}$$
$$- 0.73\ \text{Erro} - 0.17\ \text{Erru} - 0.04\ \text{Sde} - 1.00\ \text{Nslp} - 0.99\ \text{Nsep}$$

$$U_{a,c} = -2.11 + 1.22\ \text{Erro} + 1.65\ \text{Nslp}$$

$$U_p = -0.05\ \text{Prevailtime} - 0.61\ \text{Congestion}$$

where:

U_c = Utility for compliance

U_a = Utility for inertia

$U_{a,c}$ = Utility for interaction

U_p = Utility for specific path

Ttratio = trip-time saving ratio

Switchcost = distance difference between CP and destination path

Sde = early schedule delay on previous day

Sdl = later schedule delay on previous day

Nsep = cumulative percentage of switching to early departure times

Nslp = cumulative percentage of switching to late departure times

$PretripL_2$ = 1 if current information is pretrip information and network congestion level is low

$PretripL_2$ = 1 if current information is pretrip information and network congestion level is high

$EnrouteL_{23}$ = 1 if current information is enroute information and network congestion level is high

Erro = Information over estimation error

Erru = Information under estimation error

Congestion = Anticipated congestion level measured in terms of path densities and converted to a continuous scale of between 1 and 4

Prevailtime = Prevailing travel time for this path.

According to the model, the magnitude of network loads influences both the compliance and inertial mechanisms. Increased network loads on both the current and previous day result in a decreased inertial effect. Trip makers with more frequent switches to later departure times tend to retain their current paths. With more switches to earlier departure times, decreased inertial tendency and increased compliance are observed. Increased relative trip time savings and increased switching cost decrease the propensity to retain the current path. Increased overestimation errors lead to reduced inertia and compliance. However, underestimation error merely reduces the tendency to continue on the current path.

Using the time-dependent O-D matrix aggregated by users' departure time adjustment decisions, within-day traffic flows can then be simulated on the network according to the route choice model. On a given day t, trip makers are assumed to start with their actual paths selected on the previous day t-1. Pre-trip information quality on day t is taken as the cumulative information quality experienced up to day t-1. Enroute information quality is taken as the information quality experienced in the previous decision instance on the current day. In each decision instance, path-specific utilities are computed according to the current congestion levels on the network and the prevailing travel times. Inertia and compliance utilities are computed based on the experience of current traffic experience (e.g., anticipated congestion level, over/under estimation of information in previous link) and past traffic experiences (e.g., schedule delay of yesterday, trip time saving ratio, and cumulative early and late switches). In addition, a random error term is modeled to account for difference in decisions across individuals. According to the route choice structure depicted in Figure 4-3, the systematic utility and random error for each alternative path is computed and the path utilities are compared. In this model, users are assumed to choose the path that maximizes their utility. Each individual user's route choice decisions are made at the beginning of each day (when pre-trip information is given) and at each en-route decision node (every link, unless otherwise specified).

4.5 Day-to-day Simulation Framework

Day-to-day dynamics refers to the variation in network flows from one day to the next due to internal and external system perturbations. Sources of day-to-day variation include departure time adjustment of commuters, different route choice decisions in each day, incidents, capacity reduction, weather, seasons, and others.

The departure time adjustment can affect day-to-day dynamics. For each day, trip-makers decide their departure time according to past traffic experience, cumulative switching experience and effectiveness of previous departure time adjustment. The model described in section 4.4.1 can be used to estimate both the probability that a user will switch and the magnitude of departure time shift from the previous day for each commuter. By aggregating the departure time switching decisions made by all trip-makers, the time-dependent network loading pattern (O-D matrix) is formed. Thus, if all users switch to earlier departure times, the loading profile will shift earlier in the peak period. Of course, in practice, some commuters will start earlier, and some will retain their current departure time, while some will shift to a later departure time. Consequently, due to the time-varying departure times across different O-D pairs, the within-day distribution of traffic, congestion, and queuing patterns on the network in the peak period will be affected.

When commuters are on the road, route choice decisions made by commuters are affected by the real-time information provided by ATIS, experienced information quality, perceived network congestion levels, switching cost, and past traffic experience. The route choice dynamics can affect day-to-day dynamics as follows: For each user, today's pre-trip path is based on yesterday's enroute experience, and today's pre-trip information is based on within-day dynamics of the current day. Further, these within-day dynamics will be significantly influenced by the departure time adjustment dynamics as noted above.

Another noticeable effect is the non-linear dynamic and interactive effect of information quality. Information quality is defined in terms of the error of reported travel time with respect to experienced travel time. Both the route choice and departure time dynamics will affect the within-day and day-to-day dynamics significantly as described above. Consequently, both reported travel time and experienced travel time will vary as a function of both within-day and day-to-day network performance. Thus information quality depends on the within-day and day-to-day dynamics. On the other hand, the time-varying information quality will also affect individual departure time and route choice decision process through utilities described previously.

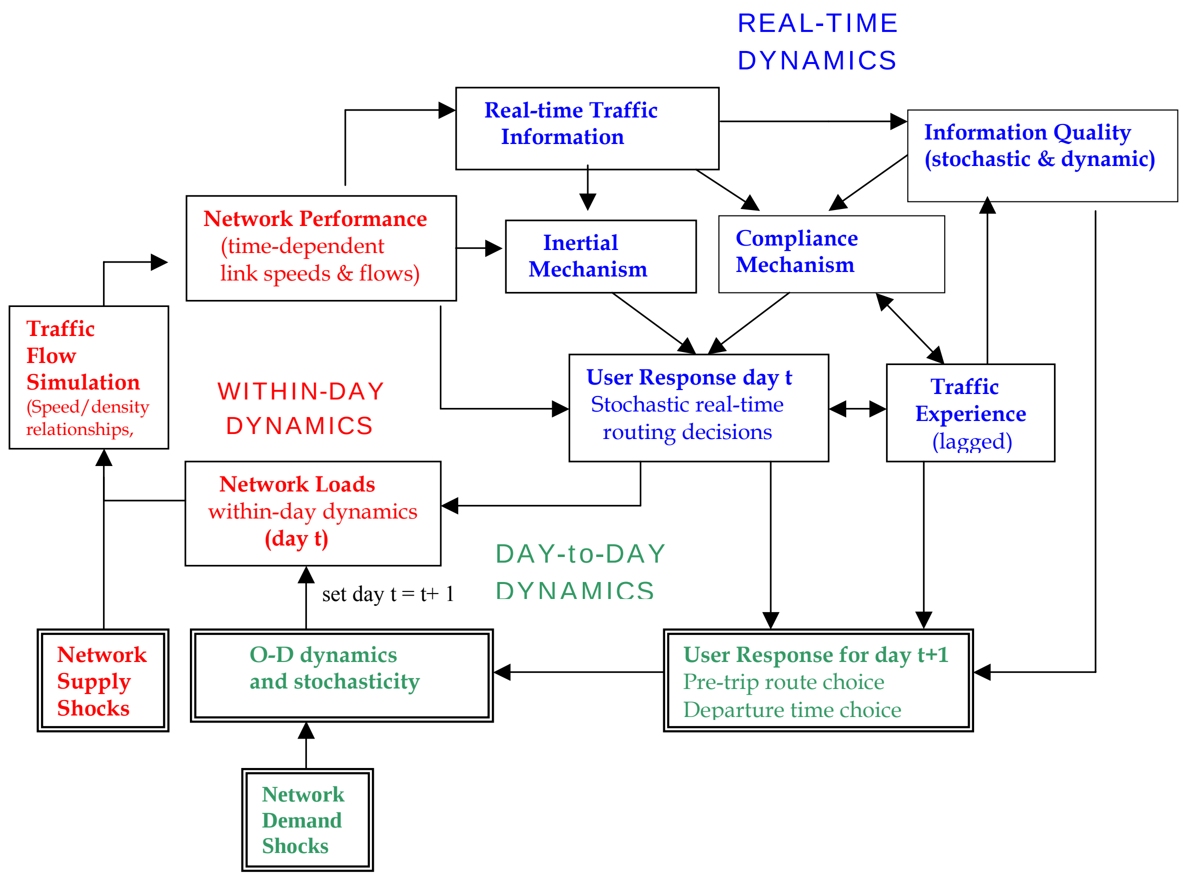


Figure 4-5 Simulation Framework for Day-to-day Dynamics

The interactions between information, information quality, user decision dynamics, and network flows occur over three inter-related timescales of real-time, within-day, and day-to-day, and can be captured in the proposed day-to-day simulation framework as shown in Figure 4-5. The framework and models are described in Srinivasan and Guo, 2003 and the interactions can be modeled as follows: 1) Stochasticity in user decisions can be simulated based on dynamic input variables from the network simulation model. 2) These stochastic decisions can be implemented on network and traffic models resulting in further network dynamics (within-day and real-time). 3) The uncertainty in information quality over time can be computed by comparing reported information and actual experience of individual drivers, which is a key input to stochastic real-time route choice decisions. 4) The dynamic network impacts in terms of experienced trip time, congestion, and uncertain information quality can be used as inputs to the stochastic departure time decision model, whose outcome yields time-varying O-D demands from day-to-day. 5) The time-varying O-D demands in turn affect network dynamics, which affects stochastic pre-trip route choice decisions of informed users.

The system evolution modeled in the proposed framework can be summarized by the following system of endogenous non-linear dynamic equations (Srinivasan and Guo, 2003). Within-day dynamics and real-time dynamics are captured in equations 1-6, and day-to-day dynamics is represented generically by equation 7. Within-day dynamics refer to departure time varying flows, under fixed O-D demand and when users do not switch routes at en-route decision locations. In contrast, real-time dynamics represent network flows when en-route switching occurs based on traffic information and user's experience. In the equations that follow, I, h, P, C, Z, and S refer to information, flow, user choice decisions, path cost, user experience, and system control (signal) vectors, respectively. The functions ϕ , r, and Γ represent time-varying link-path flow indicator function, link performance vector, and time-varying path cost function, respectively, and f_{1-11} represent functions capturing appropriate dynamics and stochasticity. Subscript 1 on a vector refers to purely within-day flows and real-time dynamics, while subscript 2 on a vector refers to within-day dynamics.

Within-Day and Real-time Dynamics:

Path Flow Equations: (Traffic Flow and Supply Model)

Flows: $h_1^{t,\tau} = f_2(D_1^{t,\tau}, P_1^{t,\tau'})$,

$$h_2^{t,\tau} = f_7(D_2^{t,\tau}, P_1^{t,\tau'}, P_2^{t,\tau'}) \qquad (1)$$

Trip-maker Choice Equations: (Within-day Trip-maker Decision Model)

User Choice Probability: $P_1^{t,\tau} = f_3(I_1^{t,\tau}, C_1^{t,\tau}, Z_1^{t,\tau})$

$$P_2^{t,\tau} = f_8(I_2^{t,\tau}, C_2^{t,\tau}, Z_2^{t,\tau}) \qquad (2)$$

System Performance Equations: (Traffic Flow and Supply Model)

Path Costs: $C_1^{t,\tau} = f_4(h_1^{t,\tau}, S^t) = \Gamma(r(\phi(h_1^{t,\tau})))$ (3)

$$C_2^{t,\tau} = f_9(h_1^{t,\tau}, h_2^{t,\tau}\ S^t) = \Gamma(r(\phi(h_1^{t,\tau}, h_2^{t,\tau}))) \qquad (4)$$

Information Supply Equations: (Supply Model and Trip-Maker Decision Model)

Information: $I_1^{t,\tau} = f_1(h_1^{t,\tau-k}, C_1^{t,\tau})$

$$I_2^{t,\tau} = f_6(h_1^{t,\tau-k}, h_2^{t,\tau-k}, C_2^{t,\tau}) \qquad (5)$$

Endogenous Experience Equations: (Information, Decision, and Supply Models)

Experience: $Z_1^{t,\tau} = f_5(X_i, C_1^{t-k,\tau})$

$$Z_2^{t,\tau} = f_{10}(X_i, C_1^{t-k,\tau}, C_2^{t,\tau-k}) \qquad (6)$$

Day-to-day Dynamics

$$D^{t,\tau} = f_{11}(DT_{adj}, \overline{Z}_{t\tau}) \qquad (7)$$

where DT_{adj} refers to day-to-day departure time adjustment model, and $\overline{Z}_{t\tau}$ reflects a perceived cost updating model. The three dimensions of dynamics in this non-linear dynamic system stem from the stochastic and dynamic decisions of trip-makers represented by the following disaggregate equations.

Departure Time Choice: $$\delta_{it\tau} = f^{d}(X_i, Z_{it\tau}, I_{it\tau} \mid \theta_{d0}) \quad (8)$$

Pre-trip Route Choice: $$\delta_{itk0} = f^{ro}(X_i, Z_{it\tau}(k), I_{it\tau}(k) \mid \theta_{r0}) \quad (9)$$

Enroute Choice: $$\delta_{itkr} = f^{r}(X_i, Z_{it\tau}(k), I_{it\tau}(k) \mid \theta_{r}) \quad (10)$$

From an individual commuter's point of view, the day-to-day simulation cycle is as follows: A fixed preferred arrival time is assumed for each user. On the first day, a pre-specified path and departure time are assumed for each user. Users corresponding to different O-D pairs are loaded onto the network as per the pre-specified departure time and route distribution, and the link travel time and congestion levels are recorded by the simulator. The K-shortest paths between all O-D zone pairs are computed at pre-specified time intervals. When an informed user reaches an intersection, information regarding the prevailing travel time for the current path, the best path (with least reported travel time), and other alternative paths are provided to the user by the in-vehicle devices. The commuter then compares the utility of each path according to it's switching cost, anticipated congestion level, anticipated trip time savings, information quality, and his/her past traffic experience such as schedule delay on previous day and the cumulative switching history. The utility varies across individuals, and therefore consists of a random error term, which reflects this perception differences across users. The assumption is that the user will then select the path with the maximum utility. For uninformed users, no real-time information is received. Uninformed users will stay in their original paths. This process of route selection is repeated at each decision node until this user reaches the destination. Upon the completion of today's commuting trip, performance variables related to the most recent commute (such as schedule delay, cumulative information error of one day) are computed, and the cumulative variables related to day-to-day (e.g., cumulative information errors across days, Nsep/Nslp) are also computed. Based on these variables, the user will determine the departure time for the next day. A sequential greedy search process is conducted as described in section 4.4.1, the decision of switching and the magnitude of adjustment is determined. Based on the departure time adjustment decisions of all commuters, a new demand loading pattern is formed for tomorrow. The simulation cycle is continued for the desired planning horizon (nearly two months - 55 days is used in this study) and performance measures are recorded for analysis as described in the following section.

4.6 Performance Measures

In all experiments described in chapter 5 and 6, network flow evolution is characterized by recording and analyzing the following performance measures on each day. The effect of the experimental factors is assessed by comparing these performance measures across various levels of each factor. All the performance measures discussed below have been initially computed at a disaggregate level (i.e. for each vehicle) and then averaged across users and days to obtain aggregate system-level measures. Only aggregate measures are reported in the results in remaining chapters unless noted otherwise.

4.6.1 Performance Measures on System Dynamics

- Within-day travel time is represented by the average trip time of all vehicles on a given day.
- Within-day trip time volatility ratio (on day t) is defined by the change in trip time per unit change in departure time, averaged across users who changed departure times between days t-1 and t. A greater volatility ratio implies that a small departure time shift can lead to large trip-time changes.
- Network trip time stability is measured by the standard deviation of mean trip times (from day to day).
- Deviation of mean day-to-day trip time from user equilibrium (obtained for initial day's time-dependent O-D demand) is measured in percentage terms.

4.6.2 Commute Performance Measures

- Late/early schedule delay represents the discrepancy between the actual arrival time and the users' preferred arrival time on the late/early sides respectively.
- Trip time reliability: measured for each commuter as the fraction of days when the individual's experienced trip time exceeds his/her mean trip time +/- a triptime threshold; the threshold is taken as 5 minutes, or 30% of mean trip time, whichever is larger to reflect tolerance of at least 5 minutes, and a greater degree of tolerance on longer trips. The individual reliabilities are then averaged across users.
- On-time arrival reliability, and probability of early and late schedule delay: These are determined by observing the fraction of days when a given user arrived within

a desired preferred arrival time window (PAT- threshold, PAT + threshold), ahead of the window (arrival time < PAT – threshold), and beyond the window (arrival after PAT + threshold), respectively. The threshold is taken as 5 minutes which is reasonably intuitive and consistent with indifference bands reported in other empirical studies *(Liu, 1998; Mahamassani and Chang, 1999)*.

4.6.3 Information Quality

Information error is defined in terms of discrepancy between the reported and experienced travel times. Two types of information errors are used to measure information quality: overestimation error and underestimation error. Overestimation error occurs if the experienced travel time is less than the reported travel time and underestimation error occurs when the experienced travel time is more than the reported travel time. Based on these notions, the following measures are defined:

a) Cumulative over and underestimation errors

The error is measured as the fraction between the travel time difference (experienced time – reported time) and the experienced travel time for each vehicle for the entire path traversed and then aggregated for all the vehicles with information. The error is considered as zero if the absolute difference in the reported and the actual travel time is less than 0.25 minutes or if the actual travel time of the vehicle is less than 1 minute. Cumulative overestimation error for an individual for a given day is the ratio of total overestimation error divided by the total number of ATIS messages received. Cumulative underestimation is also defined similarly, but based on information underestimation errors. The variables are then averaged over all days and across all individuals with information. Cumulative information errors provide an indication of magnitude of over and underestimation errors in the system.

$$Error_i = \frac{Experienced\ travel\ time_i - Reported\ travel\ time_i}{Experienced\ travel\ time_i}$$

$$Cumulative\ Overestimation\ Error_i = \frac{Total\ overestimation\ error_i}{Total\ no.\ of\ messages\ received_i}$$

$$Cumulative\ Underestimation\ Error_i = \frac{Total\ underestimation\ error_i}{Total\ no.\ of\ messages\ received_i}$$

i is for each decision point.

b) Average over and underestimation errors

Average overestimation error for an individual for a given day is the ratio of total overestimation error divided by the number of overestimated ATIS messages received by him/her. Average underestimation is also defined similarly for each individual, but for information underestimation errors. The individual average errors are then aggregated and averaged across all individuals and days to obtain system level average over and underestimation errors. Unlike the cumulative accuracy metrics above, the average estimation errors here provide information on both the magnitude and the relative frequency of over and underestimation errors.

$$Average\ Overestimation\ Error_i = \frac{Total\ overestimation\ error_i}{No.\ of\ overestimated\ messages\ received_i}$$

$$Average\ Underestimation\ Error_i = \frac{Total\ underestimation\ error_i}{No.\ of\ underestimated\ messages\ received_i}$$

c) Information reliability

Another metric that also combines magnitude of error and relative frequency is information reliability. In this study, information reliability is defined as the fraction of good messages. A message is said to be "good" (reliable) if the absolute value of overestimation or underestimation error is less than 30%. The variables are then averaged over all days and individuals.

$$Information \quad Reliability_i = \frac{No.\ of \ \ good\ messages \ \ received_i}{Total \ \ no.\ of \ \ messages \ \ received_i}$$

4.6.4 Route Choice and Switching Response Measures

a) Percentage links in common:

To analyze the day-to-day switching behavior, the extent of differences in paths across consecutive days is analyzed. In comparing the actual paths between two consecutive days, a link is considered to be common to both paths if the link was present in both paths, regardless of its position in the two paths. Only paths with 7 or more links are considered in this computation to avoid significant discontinuities in this metric. Note that percentage of users with paths less than 7 links is small (< 9%). Therefore, this metric represents the extent of path changes made by users from day-to-day.

b) Route choice fractions:

For case one in the route choice model (the best path is not the current path), the fraction of users choosing to stay on the current path, alternative path one, and alternative path two are computed. For case two (the best path is distinct from current path), the fraction of users choosing to stay on the current path, best path, or the first alternative path are recorded. This metric provides an index of within-day switching and compliance. For case one, the switching rate is the fraction of users choosing alternative paths. For alternative two, the switching rate is the fraction of users choosing the best path or the alternative path. In both cases, the compliance rate is given by the fraction of users choosing the best path.

4.6.5 Individual Level Switching Behaviors

a) The fraction of users switching departure times:

In this measure, a departure time shift of at least 3 minutes is considered a switch. It is used as a measure of day-to-day departure time switching, for both informed and uninformed users.

b) Switching rate for informed users:

Users are characterized in terms of switching as: those who switch neither route nor departure time, only departure time, only route, or those that switch both dimensions from day-to-day. The fraction of users in each of the four categories are recorded and reported in the various experiments. Compliance rate is measured as the fraction of informed users who switch from the current path to the reported best path. The fraction of links common from day-to-day for a given user is taken as an important measure of day-to-day route switching.

4.6.6 Spatial Rerouting Opportunity Measures

a) Threshold of relative and absolute trip time saving obtained by switching

These two metrics are only relevant to cases where users switched routes. Threshold of absolute trip time saving is the trip time difference (magnitude in minutes) between the reported current path and the path chosen by the user. Threshold of relative trip time saving is measured as the ratio of absolute trip time saving divided by the reported trip time on the current path. The two performance measures are first computed at the individual level for each day for users who switched routes. The individual metric is then aggregated across users (who switched) and across days to obtain a system level aggregate measure of the two thresholds. The magnitude of absolute trip time indicates the average trip time difference between the current path and the path chosen by user, which is a measure of the extent of loading imbalance and rerouting opportunity available on the network. The threshold of relative trip time saving, on the other hand, gives the ratio of trip-time difference to the reported time on the current path. Thus, this provides a measure of the extent of inefficiency of current paths.

b) Congestion difference

Congestion difference is defined in terms of the difference in reported congestion levels between best (reported) path and worst (reported) path from among the K shortest paths. In this study, congestion levels are computed on each link based on the link density and converted to a standardized scale of 0-4 (0 indicates uncongested condition and 4 represents severely congested links) to facilitate congestion color coding. The average path level congestion for each reported path is computed by averaging the link level standardized congestion levels for all links that belong to that path.

4.7 Unique Features and Capabilities of the Simulator

The day-to-day dynamic simulation framework has the following unique features and capabilities compared to the existing within-day dynamic simulators.

1) Day-to-day simulation capability is added, which provides a consistent, and mutually co-evolving representation of three principal dimensions of network dynamics: real-time, within-day and day-to-day dynamics.
2) The day-to-day framework provides richer disaggregate dynamic and stochastic representation of user behaviors. Two empirically calibrated departure time

adjustment and route choice models are integrated into the simulation framework that represent an agent-based approach: User decisions are made in individual user level and can be viewed as being based on a belief-desire-intention (BDI) architecture.

3) The framework has the ability to quantify system performance in non-equilibrium states and measurement of network level and individual vehicle level reliability and travel time stability.

4) Capability to model and study the influence of system shocks including transportation control measures such as staggered work hours, telecommuting, compressed work week, and supply side shocks such as incidents are provided by the simulation framework. Monte Carlo random sampling procedures are proposed to simulate incident scenarios and capture its impact on system dynamics from day to day.

5) Richer representation of user behavior including capability of modeling heterogeneity of user behavioral strategies by allowing multi-user switching behavior classes. Users' sensitivities to behavioral factors can be simulated on the network by modifying the coefficients of the two behavior models.

6) Real-time information can be provided to users with variable update frequency (every k links in general), whereas in the original simulator, information is updated for each user on every link. This capability can be used to analyze the trade-off between too frequent and too slow information update on day-to-day dynamics.

7) The framework provides a wider array of system performance measures including all day-to-day related variables, past traffic experience and cumulative variables, and various categories of performance measures that enable assessment of reliability and trip time jointly.

4.8 Network Characteristics

The traffic network, shown in Figure 4-4, represents a part of the urban traffic network from the Fort-Worth area near Dallas. The central corridor that connects node 116 and 117 represents Interstate 35 passing through this area. Main arterials and a portion of local streets are also modeled in the network. This network contains 13 zones and consists of 178 nodes and 441 links. All 13 zones are considered to be origin and destination zones. In this study, all simulation runs were conducted on this network. In these experiments, the preferred arrival time (PAT) for each commuter is drawn (using Monte-Carlo simulation) from a PAT distribution obtained from an empirical commuter survey *(Srinivasan, 2001)*. The PAT for each commuter is assumed to be fixed for the duration of the study.

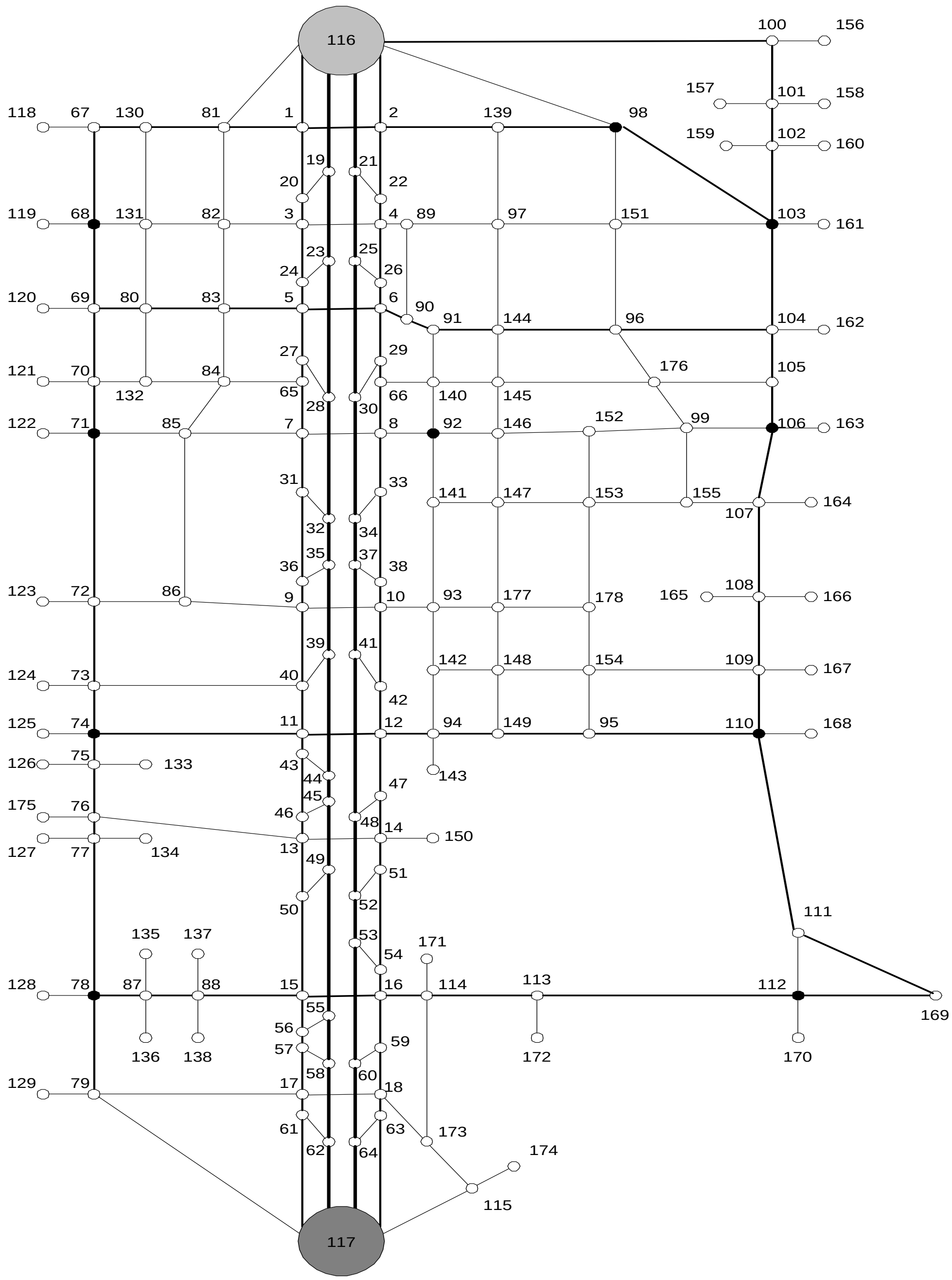


Figure 4-6 Representation of Fort-Worth Traffic Network

4.9 Summary

This chapter has discussed the structure of day-to-day dynamic simulation framework used in this study. A well-established dynamic within-day traffic simulator, DYNASMART, was introduced. Information supply and simulation strategies were discussed and user response to information was modeled by agent-based BDI architecture, using two utility maximization models (departure time adjustment and route choice respectively) as the reasoning component. The sources of day-to-day dynamics were presented and their role in the day-to-day simulation was described in section 4.5. Performance measures used for empirical experiments were described in section 4.6. The unique features of simulator were discussed next. Finally, the experimental network used in this study was presented. This simulation framework was used as the observational basis for the empirical experiments described in the following two chapters.

CHAPTER V

EFFECT OF ALTERNATIVE USER BEHAVIOR FACTORS AND TRANSPORTATION CONTROL MEASURES

5.1 Overview

This chapter describes a series of computational experiments conducted to investigate the effect of user behavior factors and transportation control measures on day-to-day evolution of network flows. The objectives of this chapter are: 1) to analyze the influence of routine perturbations in the form of route and departure time switching decisions on network reliability and evolution, 2) to investigate the influence of changes in users' sensitivity (responsiveness to system performance factors) on trip-time and commuter's on-time arrival reliability, and 3) to analyze the role of external shocks in the form of transportation control measures (TCM).

By examining the effect of route and departure time switching behavior on system performance and reliability from day-to-day, the first objective seeks insights for developing congestion control and network reliability improvement strategies. For the second objective, the role of variation in user behavior is studied, and is of interest in understanding how users' responsiveness affects system evolution. Finally, the last set of experiments focuses on analyzing the effect of five travel demand management strategies on system performance and commute reliability.

This chapter is organized as follows: In Sections 5.2, three experimental factors (routine switching behavior, variation of user behavior parameters, and travel demand management strategies) and the associated experimental procedures are described. In section 5.3, experimental results are presented and the significance of findings is described, followed by a discussion of assumptions and validation in Section 5.4.

5.2 Experimental Factors

Three sets of experiments are conducted in this chapter to achieve the aforementioned objectives. The first set of experiments investigates the influence of internal system perturbations (in the form of routine switching behavior) on day-to-day network evolution and system reliability. In the second set, the role of systematic and random variation in user behavior parameters on system evolution is explored. The final set of experiments analyzes the effect of external shocks, particularly of travel demand management strategies, on network performance and commute reliability. In each experiment, the experimental factors described below are varied systematically, one at a time to avoid confounding changes, and the corresponding system performance measures (noted in Section 3.4) are recorded and analyzed. In each experiment, the day-to-day simulation was performed for 55 days, and the first five days were excluded from the analysis to minimize initialization and simulation bias. Three levels are considered for each experimental factor (low, medium, and high) with the medium level corresponding to empirically calibrated levels of the factor, unless noted otherwise.

5.2.1 Internal System Perturbations

The first set of experiments focuses on the role of internal sources of system perturbation. Specifically, the effect of route and departure time switching behavior is investigated on system evolution and reliability. This objective is motivated by the following research issues: what is the role of joint switching versus switching in only one dimension? Is there evidence of state and sequence dependence in joint switching? Insights into these questions have important implications for congestion mitigation and network analysis. To address these questions, two experimental factors are considered: 1) The effect of joint switching versus separate switching (route only and departure time switching only); 2) The influence of initial conditions: a) analysis of system evolution under high and severe congestion with joint switching, and b) the effect of simultaneous versus sequential switching (route switching followed by departure time switching and vice-versa).

In case 1), the network evolution is simulated as per the day-to-day network assignment model, and performance measures are recorded for a period of fifty-five days under three levels: users are permitted to switch both routes and departure times, only route switches are permissible, and only departure time switches are allowed. In case 2), the network evolution is observed for two levels of recurrent congestion corresponding to network loadings of about 16000 and 19100 vehicles over a period of 1 hour. To simulate sequential (route first) switching, the network evolution is simulated by permitting only route switching for the first fifty-five days, followed by a set of another fifty-five days where only departure time switching is permitted. The sequential (departure first) case is simulated by reversing the order of switching noted above.

5.2.2 User Behavior Rules

In the second set of experiments, the role of variation in user behavior is examined. In particular, the effect of users' sensitivity to system performance and experience attributes are investigated under this objective. Six factors are considered: departure time inertia, route switching inertia, sensitivity to late schedule delay, sensitivity to trip time volatility, unobserved variability in departure switching behavior, and unobserved variability in route switching behavior. These factors are chosen to obtain insights on how users' responsiveness affects system evolution. To examine the effect of these factors, the corresponding user behavior coefficient is perturbed systematically and the effect noted. For instance, to simulate the effect of changing behavioral inertia to route and departure time switching, the coefficients a1, and a2 are perturbed from the empirically calibrated values noted in Section 3. With regard to each factor, system evolution is observed and recorded under three levels of user sensitivity: low, medium, and high (where medium corresponds to empirically calibrated values of the corresponding coefficient). The high and low levels were obtained by perturbing the baseline coefficient by +/- 50%, unless noted otherwise (+/- 0.5 if baseline level = 0). Similarly the coefficients of trip-time volatility ratio and late schedule delay in departure switching utility are also varied from the baseline levels in this set of experiments. The effect of unobserved variation is captured by examining the role of variance in a) departure time switching and b) route switching utilities on system performance (which are also perturbed from baseline levels in the manner noted above). A greater variability suggests more heterogeneous behavior among users. The system evolution and performance metrics are measured and compared by systematically varying each of the six factors above systematically.

5.2.3 Transportation Control Measures

The third set of experiments investigates the role of planned external shocks on day-to-day dynamics and system evolution. In particular, this set aims to analyze the effect of four transportation control measures on system performance and commute reliability compared to the do-nothing scenario. A severe recurrent congestion level is assumed to identify the potential of such strategies in contexts that require urgent attention. The transportation control measures that were considered include: a) effect of staggering work time, b) effect of providing real-time information to larger fraction of users, c) effect of telecommuting, and d) effect of compressed work-week.

To analyze the influence of staggered work hours, the preferred arrival times of a fixed fraction of users (adoption fraction) was staggered from their usual preferred arrival times. For instance, in the small shift (15 min.) and low adoption (5%) scenario, the assumption is that the arrival times of 5% of the users will be staggered by 15 minutes on the late side, with a corresponding fraction of users whose departure time will be staggered earlier. Similarly, the influence of staggering by large shifts (30 min.) and moderate adoption levels (15%) are also modeled. To simulate wider access to real-time information, the market penetration in the network is increased from 20% to 50%. The effect of telecommuting is modeled by assuming that a certain fraction (of adopters, say 10% selected at random from among commuters) telecommute once a week (work from home). The assumption is made that telecommuters pick the day when they work at home at random in the work week, but the day of telecommuting is not changed from week-to-week for a given user. Accordingly, the O-D loading is adjusted on the network, depending on the randomly selected telecommuting day for each user (who will telecommute). Of course, second order telecommuting effects such as changes in O-D patterns may also be included in the model, but are not considered to avoid confounding. Two levels of adoption are considered for telecommuting (low = 10% of users telecommute every week and the telecommuting is evenly spread over five days, high = 25% of users telecommute each week). In contrast, the work week compression strategy is modeled by assuming that a certain fraction of commuters (say 10% for low adoption) have a compressed work week. In other words, their work week consists of four days per week and 10 hours per day. The assumption here is that the arrival time in the morning peak remains unchanged on the four days, but the departure time from work gets extended by two hours (simulating an increase of 1 hour each in the morning and evening is also possible). The network evolution considered here pertains only to the morning peak, in view of the influence of schedule delay constraints. The noteworthy feature regarding compressed work-week is the cyclic nature of network loading in this case. In other words, every fifth day, the network loading decreases significantly (assuming that the additional day off is the fifth day), but rebounds the following Monday. Using the proposed framework, modeling memorylessness associated with Friday's commute by modifying the coefficients suitably is possible. However, this has not been modeled in the current study, given the primary focus on first-order effects. The effect of system evolution and reliability metrics are compared across strategies. Further, the effect of level of adoption of various strategies is also assessed under this set of experiments. The findings from this set of experiments assume significance in the context of effective demand management and network analysis and management under external shocks.

5.3 Experimental Results and Discussion

The results corresponding to experiment 1 to 3 are shown in Tables 5-1 to 5-3, respectively. In each experiment, the experimental factors described below are varied systematically, one at a time, to avoid confounding, and the corresponding system performance measures are recorded and analyzed. The results are described in detail below.

Table 5-1: Effect of Joint Switching, and Sequence of Switching on System Performance

Experimental Scenarios \ Performance Measures	Average Trip Time (min.)	Day-to-day variance (min.)	Within-day volatility ratio (min./min.)	Trip-time Reliability (%)	Late Arrival Rate (%)	On-time Arrival Rate (%)	Early Arrival Rate (%)
1. High Congestion							
Route Switching Only	14.19	0.43	N/A	90.4	16	23	61
Departure Time Switching Only	18.06	0.67	1.3	71.4	25	48	27
Joint Route and Departure Time Switching	15.69	0.49	1.04	74.3	22	51	27
Route Switching Followed by Departure Time Switching	15.93	0.84	1.09	69.7	31	49	20
Departure Time Switching Followed by Route Switching	15.32	1.97	N/A	89.1	18	46	36
2. Severe Congestion							
Joint Switching	23.97	2.01	1.54	58.9	32	36	31

UE-high congestion:	13.97
UE-severe congestion:	19.09

5.3.1 Effect of Switching Route Only, Departure Time Only and Joint Switching

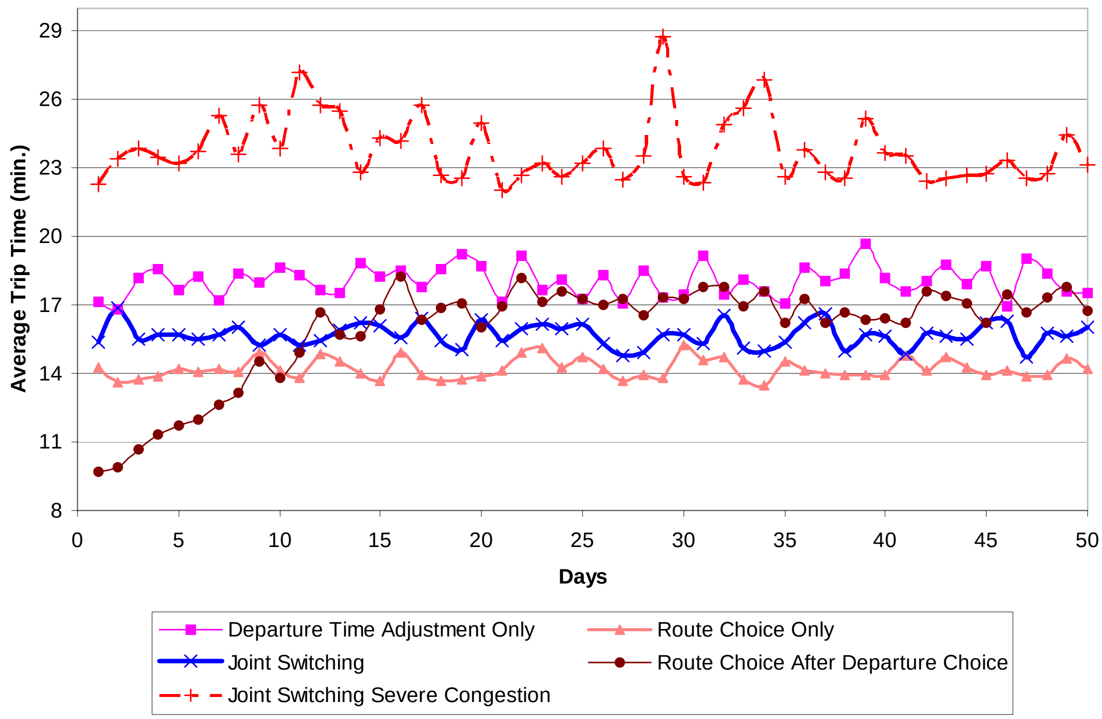
The results in Table 5-1 revealed that the best performance is obtained when only route switching (trip time = 14.19 min., and trip time reliability = 90% min) is permitted, and the worst performance occurs when there is no route-switching (trip-time = 18.06

min, and reliability = 71%). Joint switching leads to a performance in between these extreme cases (trip-time = 15.04 min, and reliability = 74%). But, the highest rate of on-time arrivals correspond to the joint switching case (on-time rate of 51%, compared to 48% in the departure switching only, and 23% in the route switching case), suggesting that much of the departure time switching behavior is aimed at reducing the cost of excessive early or late schedule delay. In contrast, the early arrival rates are at a maximum when only route switching is permitted (61% versus 27% for the other two cases). This is also reflected in the magnitudes of schedule delays. Early and late switching delays are in the range of 3.6-4.25 minutes for joint and departure time switching cases, whereas, the average early schedule delay is around 12.3 minutes under the route-switching case. When departure time shifts of 3 or more minutes are considered, the behavior of informed users also varies across the three cases. For instance, users who switch neither route nor departure time is only 19% for the route switching scenario, whereas nearly 69% of the users do not switching for the joint switching case.

The results also show that system evolution is highly non-linear and sensitive to initial conditions (Figure 5-1). To test the influence of initial conditions, the impact of joint switching was represented at two levels: i) under varying levels of network congestion (high and severe congestion levels were tested by increasing the network load from 16000 to 19100 vehicles), and ii) considering the influence of sequential versus simultaneous switching behavior. With an increasing level of recurrent congestion, the system volatility increases drastically and reliability measures reduce considerably (from 74% under high congestion to around 59% under severe congestion). In other words, under high congestion, nearly 26% of the days (nearly 1.25 times every 5 days or a work week), a user is likely to encounter trip-time values that deviate from his mean experienced trip time by over 5 minutes. Under severe congestion this trip-time unreliability increases to around 41% (nearly twice every work week, a user may expect deviations of over 5 minutes).

The system states also differ considerably depending on whether the switching behavior is simultaneous or sequential in nature (mean trip-times are 15.69, 15.93, 15.32 for simultaneous, route first, and departure time first switching behavior). In modeling sequential behavior (departure time first case), the system evolution was modeled for a period of 50 days where departure time switching was allowed, followed by a period of 50 days when only route switching was permitted. The route first case is also analogously defined. Significant differences are also seen in trip-time reliability, early, and late arrival rates across the three cases. Thus, the system does not converge to the same state and the evolution varies significantly depending on the interactions between route and departure time switching and their sequence. Figure 5-1 illustrates this sensitive dependence graphically, particularly for the sequential switching case with departure time switches occurring prior to route switching decisions. These results suggest that real-world network flows may exhibit non-unique average states under joint route and departure switching.

Figure 5-1: Effect of Joint Switching and Route/Departure Time Switching Alone



5.3.2 Effect of User Behavior Factors on System Reliability and Performance

The influence of salient behavioral factors is depicted in Table 5-2 and discussed subsequently. The variables in the table represent users sensitivity to the associated attributes (e.g., sensitivity to late schedule delay, and volatility ratio). The variance in departure time column indicates the variability in the departure switching utility for U1+, U6+ alternatives compared to the no-switch alternatives. The high and low cases represent a 50% increase/decrease relative to the baseline level consists of the empirically calibrated model reported in Chapter 4.

Table 5-2: Effect of User Sensitivity Factors on System Evolution under Joint Switching Decisions

Network and User Performance Measures (averaged over 50 days)	Baseline (Joint Choice 50 Days)	Departure Time Inertia (Low)	Departure Time Inertia (High)	Trip-time Volatility Ratio (Low)	Trip-time Volatility Ratio (High)	Late Schedule Delay (Low)	Late Schedule Delay (High)	Departure Time Variance (Low)	Departure Time Variance (high)
System Performance									
Trip time (min.)	23.97	23.82	22.56	23.27	24.14	26.26	22.07	25.30	22.77
TT volatility ratio (min. / min.)	2.01	2.77	0.91	1.74	2.14	2.39	1.65	2.45	1.76
Reliability (fraction)	0.59	0.59	0.64	0.60	0.60	0.58	0.62	0.59	0.60
Day-to-day std. deviation	1.55	1.00	1.04	1.07	1.06	1.39	1.05	1.33	0.87
Commute Performance									
Late schedule delay (min.)	5.78	5.42	5.44	5.40	5.85	7.25	4.62	5.91	5.52
Early schedule delay (min.)	5.36	5.37	5.49	5.54	5.20	4.56	5.92	5.10	5.41
Early arrival (fraction)	0.31	0.31	0.33	0.32	0.30	0.27	0.34	0.30	0.32
Ontime arrival (fraction)	0.36	0.38	0.35	0.37	0.37	0.34	0.38	0.37	0.37
Late arrival (fraction)	0.33	0.31	0.32	0.31	0.33	0.38	0.28	0.33	0.32
Departure Time Response									
Switching Magnitude to Later(min.)	4.81	4.68	5.05	4.92	4.76	4.61	4.97	4.26	5.11
Switching Magnitude to Early(min.)	4.98	4.80	5.13	5.13	4.87	4.14	5.76	4.42	5.25
Switching Rate (%)	0.55	0.77	0.29	0.52	0.58	0.57	0.55	0.59	0.54
Route Choice & Switching									
Percentage links in common (fraction)	0.56	0.55	0.60	0.57	0.57	0.55	0.58	0.55	0.57
Threshold of relative TT saving(fraction)	0.13	0.13	0.13	0.13	0.12	0.12	0.13	0.13	0.12
Threshold of absolute TT saving(min)	1.15	1.15	1.13	1.14	1.16	1.21	1.10	1.19	1.14
Individual Level Switching Behaviors									
Uninformed users									
DT switch percentage (days/maxdays)	29.00	39.55	15.60	27.70	30.00	27.80	29.90	28.60	29.50
Informed Users									
Non-switching rate (%)	60.00	54.00	71.00	61.00	60.00	61.00	60.00	60.00	60.00
Route only switch (%)	12.00	10.00	14.00	12.00	12.00	12.00	12.00	12.00	12.00
Departure time only switch fraction (%)	23.00	30.00	12.00	22.00	24.00	22.00	24.00	23.00	23.00
Users switching both (%)	5.00	6.00	3.00	5.00	5.00	5.00	4.00	5.00	5.00

5.3.2.1 Effect of behavioral inertia

With increasing departure switching inertia, the system performance improves (trip time reduces by about 5.8%, and trip time reliability increases by 6%), whereas reducing route switching inertia leads to system improvement. Route switching inertia however has a much smaller effect (trip time saving < 2%, relative reliability increases by 2%). The effect of inertia in departure time and route switching however has a negligible impact on early, and late arrival propensities (< 1% change). The influence on switching rates however is marked with departure time switching rates ranging from 29, 55, and 77% as inertial coefficients (resistance to departure time switching) change from 0.5 to 0, and -0.5. In contrast, the influence of route switching inertia is seen on compliance rates (compliance rates varying from 5%, 25%, and 62% for high to low inertial coefficients). However, the underlying switching dynamics and behavior varies depending on the magnitude of inertial effects, although trip-time differences are only marginal. In the baseline case (both inertia are moderate), 60% of users switch neither route nor departure time, 23% switch departure time only (by 3+ minutes), 12% switch routes only, and nearly 5% switch both dimensions. Under the low departure time inertia case, among switchers, departure time switches only (29%) are nearly three times more likely than route only switches (10%). In contrast, when departure time switching inertia is high, route switching rate is higher (14%) than departure time switching only rate (12%), suggesting a compensatory influence. The non-switching rates also increases from 54% to 71% when departure time inertia increases, whereas, a much smaller effect is seen when route switching inertia is increased (60-64%). These results suggest that departure time switching appears to exert a greater influence on day-to-day dynamics than route switching.

5.3.2.2 Sensitivity to within-day volatility

User sensitivity to within-day trip-time volatility has a strong impact on network dynamics from day-to-day. When users are highly sensitive to within-day trip-time volatility (measured by volatility ratio – change in trip time per minute of change in departure time on average), both trip-time unreliability and within-day volatility increase significantly. Interestingly, when users are more sensitive to volatility and are more responsive to volatility (by switching departure times more aggressively), the volatility is in fact amplified rather than dampened. Further, the travel time reliability is the highest when users are only mildly sensitive to within-day volatility, and deteriorates as the sensitivity to volatility increases. As responsiveness to volatility increases, so does the average late schedule delay. But the departure time adjustments tend to be smaller on an average (also reflective of the larger volatility), which is also reflective of larger within-day volatility.

5.3.2.3 Sensitivity to Late Schedule Delay

As users sensitivity to lateness increases, travel time performance improves substantially. Further, all reliability and volatility measures also improve significantly. For instance, information reliability increases from 86% to 89%. Within day volatility ratio drops from 2.4 min/min to 1.65 min/min., and day-to-day fluctuations in trip time reduces nearly two-fold (standard deviation decreases from 1.39 min to 1.05 min.). In addition, as the sensitivity increases, a regime shift is also observed in the form of larger schedule delay accepted by commuters. For low sensitivity, the accepted lateness (earliness) is 7.25 min. (4.56 min.) reflecting greater lateness tolerance. In contrast, for high sensitivity to late arrivals, the average late (early) schedule delay decreases and is 4.62 min. (5.92 min.). The greater tolerance to lateness than earliness, seen in the low sensitivity case, appears to be a typical response to highly congested commuting traffic, whereas, under moderate congestion levels the asymmetry is skewed in favor of larger early schedule delay due to risk-averse late arrival behavior among commuters (Liu, 2001). The findings have some interesting and important implications. First, under empirically calibrated levels of users' sensitivity to late schedule delay, day-to-day stability and reliability is poor (compared to high sensitivity). Second, while implementing measures such as flexible work hours, caution must be exercised and the influence of users sensitivity to late schedule delay should be accounted. Low sensitivity to late schedule delay due to certain travel demand measures may more than offset the short-term benefits due to departure time staggering of certain users.

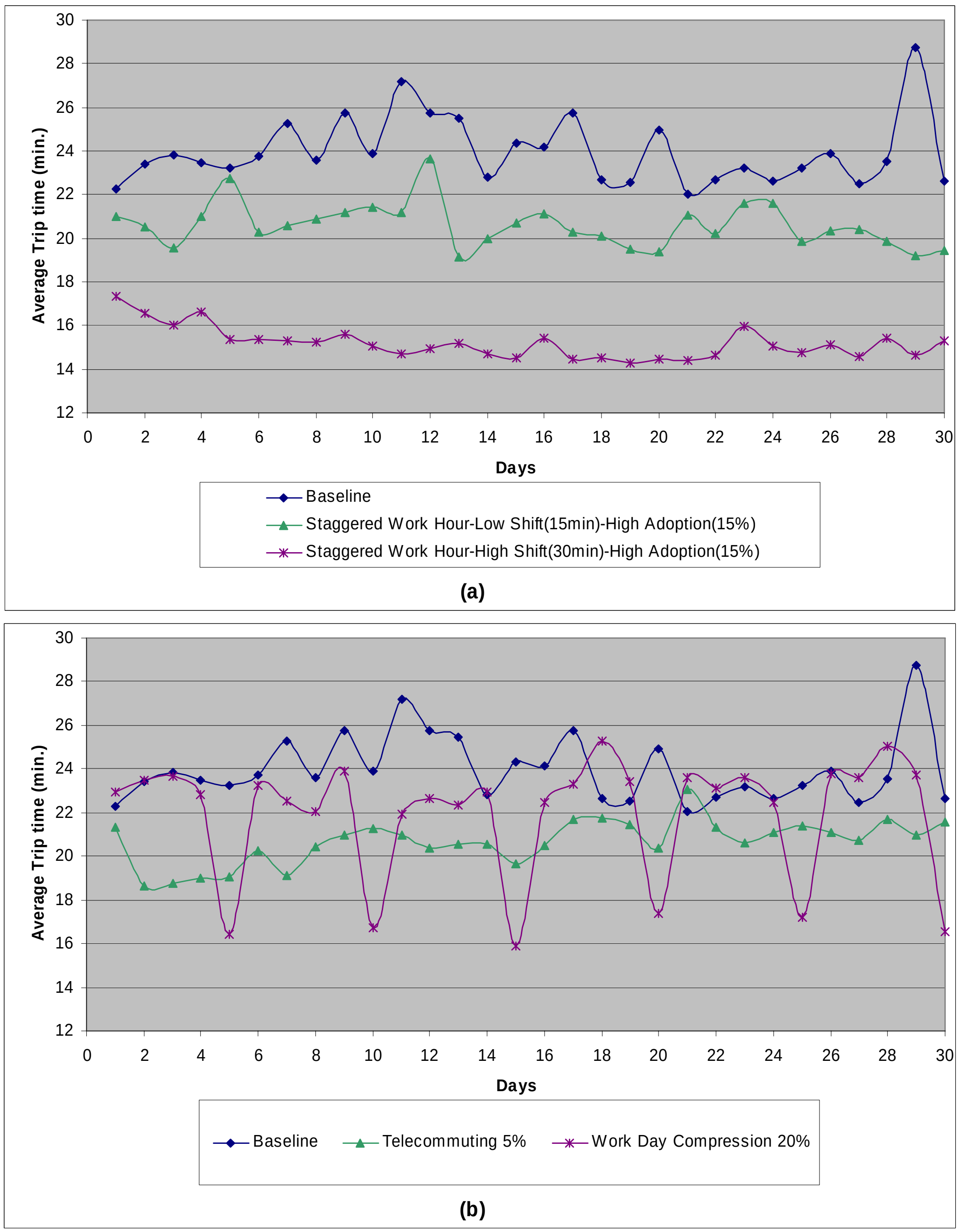
5.3.2.4. Effect of Unobserved Variability in Departure Time and Route Switching

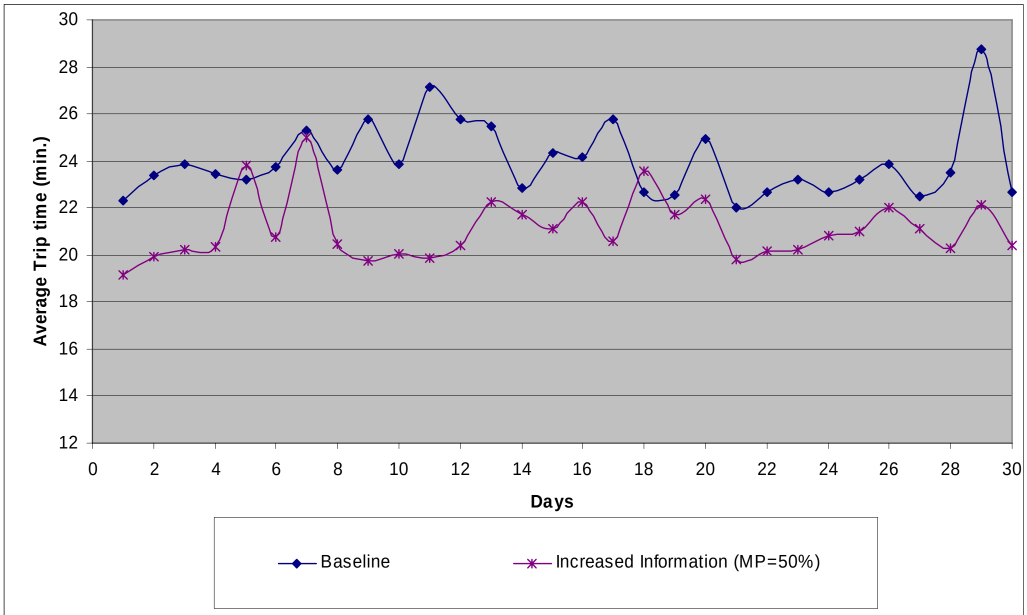
As the variability in departure time utility decreases across users, all performance measures deteriorate considerably (trip-time, within-day volatility, and day-to-day reliability). This lower variability (more homogeneous switching behavior) leads to an increase in uncoordinated switching, resulting in more departure time switching (up from 54% to 59% (1+ min shift), as well as a slightly increased day-to-day route switching (2% decrease in day-to-day common links). Consequently, an increase (decrease) in late schedule delay (early schedule delay) is observed as homogeneity in departure switching behavior increases. The within-day system volatility also increases by nearly 40% (1.75 to 2.44 min) and trip time reliability increases by about 2% as departure time switching variance decreases. Furthermore, the magnitude of shifts in departure time decreases as variance decreases, suggesting that the system evolution follows some kind of equivalent adjustment process (of the type reported in Friesz et al. *1996*). Unlike in that study, the system evolution however fails to reach user equilibrium here, but the departure time and route switching rates appear to reach a steady-state.

5.3.3 Evaluation of Transportation Control Measures (TCM)

The average travel time performance for different transportation control strategies is plotted as a function of time (over days) in Figure 5-2 (a, b, and c). This graph highlights the presence of several interesting nonlinear system dynamic features especially under the influence of travel demand management measures. First, the travel times can vary substantially from day-to-day even in the baseline case (Figure 5-2 (a)), indicating the high degree of trip-time fluctuations inherent in severely congested systems. Other salient non-linear and non-stationary effects include: the presence of trends (decline in mean trip time as a function of days for staggered work hours case indicating possible non-stationarity (Figure 5-2 (a))), oscillatory and periodic behavior (for the work-week compression strategy (Figure 5-2 (b))), aperiodic behavior and non-convergence (e.g., telecommuting, increased information (Figure 5-2 (b))), sensitive dependence on initial conditions (the patterns of evolution for the 15 min. and 30 min. stagger exhibit qualitative differences in patterns (Figure 5-2 (a))). These results suggest that trip-time performance alone is not a good indicator as several of these control strategies lead to similar average performance measures. Furthermore, real-world networks can exist in a variety of states that may deviate significantly from equilibrium for substantially long-periods of time.

Figure 5-2: Day-to-day Dynamics under Transportation Control Measures





(c)

The TCM's contribute positively to average trip time performance (Table 5-3). Both within-day and day-to-day variability also decrease except in one case. The transportation control measures tend to improve travel time reliability in all cases. On-time arrival rates also improve significantly under many but not all strategies. Note that four strategies produce similar trip-time improvements of nearly 11-13% (small shift with high adoption, large shift with low adoption, telecommute with high adoption, and increased real-time information supply). But the benefits in terms of trip-time reliability differ considerably across these strategies (15.9% for staggered work hour strategy with small shift and high adoption, 14.9% for staggered work hour strategy with large shift and low adoption, 9.3% for telecommute with high adoption, and 4.75% for increased real-time information). Thus, there is a need to jointly consider the effect of trip-time and system reliability metrics while evaluating alternative strategies. The effectiveness of demand management strategies appears to be sensitive to the nature of the strategy and the level of implementation/adoption.

Table 5-3: Day-to-day Evolution in System Performance under Transportation Control Measures

Performance Measures / Demand Management Measure	Relative triptime Improvement (%)	Relative within-day volatility reduction(%)	Relative day-to-day Variance Reduction(%)	Trip Time Reliability Increase (%)	On-time arrival rate(%)	Early arrival rate (%)
Stagger a: small shift (15 min.), low (5%)	5.34	6.86	20.83	4.92	37	32
Stagger b: small shift(15 min.), high (15%)	13.45	22.55	30.56	15.93	40	29
Stagger c: large shift (30 min.), low (5%)	13.57	20.59	33.33	14.92	44	25
Stagger d: large shift (30 min.), high (15%)	36.22	58.82	49.31	36.61	43	26
Real-time Information (MP = 50%)	11.30	3.43	6.94	4.75	51	17
Telecommute - Low adoption (2% per day, 1day/week)	4.96	5.88	34.72	4.92	41	29
Telecommute - Medium (5% per day, 1 day/week)	13.15	19.12	29.17	9.32	39	30
Work week compression - Low (10%, 1 day off)	3.95	1.47	-23.61	3.31	42	28
Work week compression - med (20%, 1 day off)	7.82	4.41	-92.36	3.36	39	30
Baseline Performance (Absolute Measures)	23.08 (min.)	2.04 (min./min.)	1.44 (min.)	59%	39%	30%

Note: UE solution had a trip-time of 19.09 min.

The results indicate that the staggered work hour strategy is likely to be more successful than other strategies in terms of congestion mitigation. Furthermore, increasing the level of adoption appears to produce a larger benefit than increasing the amount of departure time shift/stagger. Two other strategies where the performance is level sensitive are telecommuting and work week compression. At moderate levels of adoption for these strategies, the benefits are found to be relatively small. However, significant trip-time and reliability benefits accrue when the adoption level is high. The results from the work-week compression strategy indicate that in some cases, trip-time reduction may occur but at the expense of increasing day-to-day variability. The results also highlight the fact that real-time information can lead to significantly improved on-time arrival rate (up from 39% to 51%), but significant trip-time variability is found in the system (trip time reliability only increases 4.75% compared to 9%-36% in other strategies).

Despite the improvement in trip-time, significant gaps remain with respect to user equilibrium (7.5%-16.75%) even after the TCM strategy is implemented. The gaps between TCMs and user equilibrium solutions suggest still further scope for system improvement. The only exception is the case of large stagger with high adoption rate, where the system performance is better than the user equilibrium flows (corresponding to the initial departure time pattern). Thus, significant system improvement may be achieved through significant changes in departure time patterns, but such changes must be carefully coordinated. Nevertheless, the TDM strategies appear to be effective in steering the system performance closer to equilibrium travel times, but not necessarily towards the equilibrium state (i.e., high switching and volatility is still present).

5.4 Significance of Findings

The findings from the three sets of experiments have several important implications for dynamic network analysis, design of transportation control strategies to enhance system performance, and travel time reliability.

Findings from the first set of experiments regarding system dynamics are also noteworthy. First, the high trip-time reliability observed in the severe congestion case, in turn, lead to high lateness arrival rates (nearly 32% of users arrive late at the workplace after accounting for the PAT + tolerance threshold (5 min.)). Poor reliability, large system volatility and high lateness risk, in turn, induced a high degree of departure time switching (nearly 55% shift by 1+ minutes, and around 29% shift by more than 3 minutes), which further accentuated system dynamics. Second, substantial inefficiency and gaps existed even after the system evolves for a period of 50 days between average system trip time and equilibrium trip times. The gap increased as the level of congestion increased (from 12.3% for the high congestion case, and 20.3% for the severe congestion case). Thus, severe congestion makes the system intrinsically unstable due to greater departure time switching and appears to be only moderately influenced by route switching decisions (through ITS etc.). Third, the data appeared to suggest the possibility of a non-stationary and non-ergodic stochastic process driving system dynamics and variability. The ensemble average of trip times from twenty different simulations (with varying random seeds) was observed to be 15.06 minutes, which differed significantly (statistically) from the time-average over days (mean was 15.69 minutes).

In the second set of experiments, the deterioration in system performance as departure time switching variance reduced, suggests that some degree of heterogeneity in departure time switching is beneficial to system stability. In contrast, variability in route-choice across users had little influence on system performance or variability, and was not discussed further. In addition, deterministic models or models that assume more homogeneous user behavior may tend to underestimate system reliability metrics. In fact, there is greater variability in user behavior. Therefore, in the context of modeling travel time reliability and stability, richer and more disaggregate models of user behavior and associated variability are needed.

Findings in experiment 3 have important implications for the evaluation of transportation control measures. First, the use of very short-term (e.g., in the telecommuting and work-stagger cases, the first two-weeks of data tend to overestimate) or very long-term (due to non-stationarity and significant deviations exist from user equilibrium models for significant periods of time) horizons for analysis methods can lead to erroneous system state predictions, especially due to the presence of trends and oscillatory behavior. Second, care must be exercised in evaluating demand control measures since several of the effectiveness of some of these strategies are sensitive to the level of adoption/deployment (system exhibits very different evolution patterns depending on the level). Third, the dynamic evolution and the non-linear features observed empirically along with the deviation from short-term and long-term predictive models, underscore the need for the collection of richer empirical field data (including switching behavior) over reasonably long-periods of time (at least several months) while evaluating transportation control measures. While this study provides preliminary evidence of highly non-linear system evolution from day-to-day, new modeling tools and insights may be needed to uncover the nature and causes of the observed transient states (e.g., chaotic, stability, and stationarity), particularly in order to understand the limits and uncertainty associated with model-based predictions.

5.5 Assumptions and Validations

Caution is advised in interpreting these findings due to the nature of the experiments, simulated conditions, and the assumptions regarding experimental factors used in this study. Note that the findings will depend on other exogenous factors including magnitude of OD flows, network structure and route choice model structure and specification. The trends noted here were robust with increasing magnitudes of OD flows. However, given the complex and non-linear dynamics in the system, the role played by network structure and alternative choice models on network evolution remain interesting directions for further research. The effect of supply side shocks and perturbations have also not been considered in this study. Further, the deployment of TCM's may be phased over time (steady growth in contrast to the point process assumed here).

Despite these assumptions, the results appear to be robust with real-world empirical data and consistent with other simulation-based studies. Based on the simulated model using the Fort-Worth network departure switching rate of around 50-60% (≥1 minute shift) and route switching rate of nearly 25% (when the current path is not the best) are observed. These results are consistent with empirical data from Dallas and Austin (Jou et. al., 1998) based on a two week survey of nearly 900 commuters (switching rates of 52% and 23%, respectively). The compliance rates in this study range from 20-30% in most cases, and are consistent with real-world compliance rates of 20-

50% in many European and U.S. cities (Chatterjee et. al., 2002). The minimum and relative trip-time saving corresponding to a route switch were observed to be 1-2.5 minutes, and 14-24% respectively, which are corroborated by the indifference bands reported by other studies using both survey and experimental data (Liu et. al., 1991). Further, the average early and late schedule delays obtained in the model are of the order of 5-10 minutes which is intuitive and consistent with schedule delay bands noted by Hatcher et al.(1992) and Mahmassani et. al (1991). Information reliability was observed to be around 85-95% in this study whereas information reliability of about 91% were reported by real-world experimental data (Tudor et. al., 2002). Wunderlich et al. (2001) reported lateness risk of about 15% using Washington D.C. data, whereas, this probability is of the order of 16-25% for moderate congestion in this study.

5.6 Summary

This chapter investigated the effect of user behavior factors and transportation control measures on day-to-day evolution in network flows and trip-time reliability. The results suggest that modeling both route and departure time switching response jointly when analyzing the day-to-day system evolution is essential. In particular, departure time switching appears to be a stronger determinant of system dynamics than route switching with respect to many performance measures. System performance and reliability of commuter travel (trip-time, on-time reliability) are found to be affected by user behavior parameters, particularly sensitivity to system and experience variables. Among these factors, sensitivity to late schedule delay and departure time switching inertia were more influential than other factors (route switching inertia, travel time, congestion, one more).

The results also indicated that unobserved heterogeneity in commuter choice behavior can lead to significant differences in system evolution and reliability compared to more homogeneous behavior. Travel demand management measures were found to be generally conducive in improving trip-time performance, but the efficacy in terms of commute reliability metrics varied depending on the nature of strategy, and the extent of adoption by users (more so true for trip time). These findings may have important implications for evaluation of TDM strategies, improving system stability and reliability, and deployment and assessment of ITS strategies for congestion mitigation.

The following research issues arise naturally in the context of day-to-day system evolution. At the theoretical level, the nature of stochastic process underlying day-to-day dynamics, the extent of possible non-ergodicity and its implications for network planning and design warrant further inquiry. With regard to dynamics, examining the role of lagged effects, possible asymmetries in evolution and their persistence over time, particularly in the context of supply shocks (such as planned constructions or workzones, and unplanned incidents) remains an interesting direction for further research. From a policy and planning standpoint, investigating the short-term and longer-term impacts of pricing based (congestion pricing, or gas price increase) and vehicle occupancy increase measures (such as HOV/HOT) may also be of interest.

CHAPTER VI

EFFECT OF INCIDENTS ON DAY-TO-DAY DYNAMICS

6.1 Overview

Existing incident literature mainly focused on the within-day effect of incidents on system performance. In most day-to-day research literature, incidents receive limited attention due to the complexity of introducing incidents into a closed form mathematic formulation. With the new day-to-day simulation framework developed in this study, this chapter focuses on investigating the effect of incidents on day-to-day dynamics and network performance. Toward this objective, a day-to-day incident simulation procedure is developed. Incident simulation parameters are chosen from historical data reported in practice. Performance measures for congestion level and travel time reliability are added. Five sets of experiments are conducted with incident enabled simulation in this chapter. The first set of experiments focuses on comparing the difference in system evolution between with-incident and no-incident simulations. This set of experiments seeks insights into the role of incidents on system performance and reliability. The second set of experiment then systematically investigates the effect of important incident characteristics on system performance, including incident probability, distribution, severity and duration. To the extent of the researcher's knowledge, the incident characteristic and its impact on system performance is missing. The third objective is to analyze the effectiveness of three ways of improving network performance and reliability (experiment 3-5, real-time information, incident management measures, and departure time switching rate reduction). The results from this set of experiments could provide insights on design and evaluation of incident management approaches. The results are then analyzed and the findings are discussed.

The rest of this chapter consists of the following sections. Section 6.2 describes the motivation and objectives for simulating incidents, as well as the simulation procedures and adopted levels of incident characteristics. Section 6.3 discusses the experimental procedures and settings for the five set of experiments, and the new performance measures used in these experiments. The experimental results are discussed in detail in section 6.4 and the significance of the findings is discussed in section 6.5. The assumptions underlying this investigation and validation efforts for the experiments are discussed in section 6.6.

6.2 Incident Simulation

6.2.1 Motivation

According to FHWA traffic incident management handbook (2000), in most US metropolitan areas, incident-related delay accounts for between 50 and 60 percent of total congestion delay. In smaller urban areas, an even larger proportion of delays can be attributed to incidents (Cambridge Systematics, 1997). ATIS technologies can be applied with greater degree of success towards managing non-recurrent congestion, since these are able to detect and broadcast the occurrence of incidents in real-time.

Emmerink et. al *(1995b)* analyzed the potential of ATIS in the case of non-recurrent congestion. In particular, the role of ATIS under road users' route choice behavior responses was investigated. A testing network with only one O-D pair and nine decision points was used in this study. Incidents are simulated using Binomial distribution, and the duration and capacity reduction are assumed fixed. Other researchers also included the system performance analysis under incident scenarios, but mainly in within-day context (*Pal, 1999*). In contrast, there is less attention on the effect of incidents on day-to-day dynamics and system reliability. A better understanding and systematical investigation are needed given the limited amount of prior research.

Understanding how network flow evolves from day to day and the impact of system reliability under non-recurrent supply shocks is essential for transportation planning, evaluation of ITS information and management strategies, and evaluating and improving effectiveness of incident management programs and freeway service patrol programs.

6.2.2 Objectives and Approach

Given the motivation described in the previous section, three sub-objectives are proposed in this section. The first objective is to analyze the impact of incidents on network performance and system reliability by comparing the results with the no incident case reported from the previous chapter. Understanding the difference of system evolution between incident and no-incident scenario will help validate the no-incident results presented in the previous chapter, and better understand the role of incident on traffic system evolution. The second sub-objective is to analyze the impact of different incident characteristics. Specifically, the probability of incident occurrence, incident type distribution, severity (capacity reduction) and the incident durations are analyzed systematically. Understanding the effect of these incident characteristics can help develop more effective incident management strategies. The third sub-objective is to investigate the effectiveness of real-time information and incident management approaches on congestion reduction and system reliability. The simulation results from this sub-objective can provide guidance on design and evaluation of the current information and incident management practices.

The objectives are addressed using the Monte Carlo random sampling procedures for incident simulation, based on realistic distribution assumptions and parameter settings from real world data. The procedure and parameter setting of this simulation procedure is described in detail in the next section. The simulation procedure then is integrated into the day-to-day simulation framework proposed in Chapter 4.

6.2.3 Day-to-day Incident Simulation Procedures

In DYNASMART simulator, incident is implemented as capacity reduction on the specified link during a specified time window. For each peak hour simulation, the number of incidents, incident location, start and end time, and severity (specified as a capacity reduction ratio) are pre-specified. If a link is closed, all the vehicles will be rerouted after reaching the switching point (i.e. the upstream node of the link).

For day-to-day incident simulation, at the beginning of each day, the incident simulation procedures are applied to randomly generate the number of incidents based on the assumed distribution. When number of incidents are known, they are then be allocated to locations randomly picked from a super set. This super location set is predefined based on the link characteristics, peak volume and functional classification.

Knowing the locations where the incident will occur, the incident type, cross-sectional location, and its duration are then realized based on the corresponding distribution. After all the incident parameters are generated, all the incidents are then feed to the DYNASMART within-day simulator. The incident generation procedures and distribution assumptions are discussed as follows.

Using Monte Carlo simulation techniques, incident occurrences are simulated each day using a Poisson arrival process. Skabardonis et. al (1999) shows that Poisson distribution provided an adequate fit for the incident frequency, suggesting that the number of incidents at any time period is random and independent of the number of incidents in any other time interval. In addition, incident types, cross-sectional location, and its severity are simulated by multinomial distribution. Incident duration, detection, response, and clearance times are simulated by random sampling from a log-normal distribution. Skabardonis et. al (1999) shows that the log-normal distribution fits well in the incident duration distribution based on the Los-Angeles I-10 field data. All parameters used in the simulation procedures are based on 1) FHWA Traffic Incident Management Handbook (2001), 2) Los-Angeles I-10 dataset (Skabardonis, 1999), and 3) 1996 accident data in Atlanta, GA (Persley, 1999).

The simulation procedures and the distribution parameters are described as follows:

1) Incident occurrence simulation on different type of highway facilities

Based on Los-Angeles I-10 incident data (Skabardonis, 1999), average incident occurrence rate is 1.3 incidents/dir/mile/3-hour peak period. For the experimental network in the study (Dallas-FW network), the average length of freeway links is 0.44 mile, and arterial links is 0.25 mile. The assumption is that in the simulated peak period no multiple incidents could happen on the same link. For this study, the simulated morning peak is 1.5 hours. Linear factor is calculated based on the total length of the possible incident location super set and the peak hour duration. This linear factor then is applied to the original rate to obtain the rate of 0.286 incidents/mile/dir/peak for the Dallas experimental network. For a low and high level of occurrence rate, 10 percentile and 90 percentile values based on the mean value and Poisson demand distribution are chosen. The intent for choosing these extreme values is to reduce the bias on the simulated occurrence of severe incidents induced by random sampling errors and for ease of comparison.

Based on given incident occurrence rate, random sampling based on the poisson distribution is made to generate number of incidents occurred in each link for each day.

2) Conditional probability of different incident types

Incident types are divided into accident, breakdown (disablement) and Debris/Peds/Others. Given the occurrence of an incident, the conditional probabilities of three types in peak hour are 10%, 80%, and 10%, respectively, as per the guidelines in the Incident Management Handbook (2001). Using these conditional probabilities, the incident type for each incident is determined by two successive random trials using binomial distribution.

3) Incident cross-sectional locations

For the Dallas experimental network, all arterial links are of urban type. The shoulders of arterial links are 2" curb and gutter only, so incidents occurred on arterial links are always blocking lanes. For freeway links, the conditional probability values for locations given the type of the incident are listed in Table 6-1, and are determined by a binomial random trial.

Table 6-1 Conditional Probability of Incident Cross-sectional Locations

Incident Types	On Shoulder	Blocking lane
Accident	60%	40%
Breakdown	80%	20%
Debris/Peds/Others	70%	30%

4) Incident severity

Based on the type of the incidents and number of lanes blocked, the capacity reduction ratios are listed in Table 6-2 based on Highway Capacity Manual (2000). The number of lanes blocked is assumed to be equally likely, and is determined by a uniform distribution. Based on the number of lanes blocked, the capacity reduction ratio is found in Table 6-2. This capacity reduction ratio is then applied in the simulation.

Table 6-2 Capacity Reduction Ratio by Facility Type

Facility type	On Shoulder (Non-accident)	On Shoulder (Accident)	Blocking 1 Lane	Blocking 2 Lanes	Blocking 3 Lanes
1 lane	0.1	0.3	1	1	1
2 lanes	0.05	0.19	0.65	1	1
3 lanes	0.01	0.17	0.51	0.83	1
4 lanes	0.01	0.15	0.42	0.75	0.87
5 lanes	0.01	0.13	0.35	0.6	0.8

5) Incident duration

There are three components on incident durations: detection, response, and clearance times. Incident detection time refers to the time period from occurrence to the time when the incident is reported to the reacting agency and the incident is verified. The response time starts from verification and ends when the response arrives at the incident scene. The clearance time refers to the time period from response arrival to the time when incident being completely removed from the freeway and not remaining on the shoulder. To simplify the simulation process, incident durations are considered as a whole, and a log-normal distribution is assumed. The log-normal distribution parameters are estimated given the upper and lower bounds from the incident management handbook. The estimated parameters are shown in Table 6-3.

The total incident duration then can be simulated by a Log-Normal random variable generation given the mean and standard deviation.

Table 6-3 Incident Duration Parameters

Location	Incident Type	Lower Bound	Upper Bound	Mean of LN(x)**	Standard Deviation of LN(X)
On Shoulder	Accident	45	60	3.95	0.06
	Breakdown	15	30	3.05	0.13
	Others	15	30	3.05	0.13
Blocking Lane	Accident	45	90	4.15	0.13
	Breakdown	15	30	3.05	0.13
	Others	30	45	3.60	0.08

**Mean and Standard deviation for LN(X) are estimated based on the assumption of symmetric error level of 1%.

6) Incident occurrence time

In this chapter, only morning peak hours (from 7:00 AM to 8:30 AM, 1.5 hours in duration) are simulated, given that the significant delay is involved in peak hour commuting context. Incident can occur at any time during the peak hour, but is also correlated to the link volume. However, in the existing literature, there is no statistical analysis and justification on this correlation. If we simulate the incident start time as a random or normal distribution, some of the incidents will occur when the network loading is low, and the effect of capacity reduction is minimal given the relatively short peak hour horizon. For experimental control purpose, a set of fixed start time values (7:20, 7:25, 7:30, and 7:40)are tried for baseline level and the results are similar. For brevity, only the results from fixed incident start time at 7:25 (corresponds to the start time of the peak loading during the morning peak period) is reported.

6.3 Experimental Design and Procedures

Based on the simulation framework with incident procedure enabled, five set of experiments are conducted in this chapter to achieve the aforementioned objectives. The first set of experiments focuses on the effect of incident on system evolution under different recurrent congestion levels. The objective is to compare against the no-incident results presented in previous chapter to discover differences in system evolution. In addition, experiment set 2 focuses on the impact of incident characteristics. The purpose of experiment 3 to 5 is to explore the effectiveness of potential ways to improve system performance and reliability. Specifically, experiment 3 evaluates the system performance under different real time information market penetration levels. Experiment 4 focuses on the effectiveness of incident management strategies. Experiment 5 is to explore the effectiveness of reducing the uncoordinated departure time adjustment behavior of users as a control measure from traveler behavioral point of view. Details of the factors and levels are provided in Sections 6.3.1 to 6.3.3. The corresponding treatment levels described next are varied systematically in a series of computational experiments, while other experimental factors are held fixed to avoid confounding. Performance measures pertaining to system dynamics and reliability, commute performance, information quality, route choice and departure-time response metrics are recorded in the experiments and analyzed, as described in section 6.4. This set of experiments is also conducted on the same Dallas Fort Worth network as in the previous chapter.

6.3.1 Impact of Incidents under Different Recurrent Congestion Level

Three levels of recurrent congestion are selected corresponding to the loading level of 12596 (mild), 15861(high), and 19098(severe) vehicles. The baseline is the mild congestion level, with an average travel speed of 18 mph, which corresponds to an average travel time of 12.9 min on the network used in this study. For each recurrent congestion level, both no-incident and with-incident experiments are conducted. The focus on this experimental factor is on the difference of system evolution under incident scenarios under different network congestion levels. This experiment seeks insights to understanding the impact of incidents on day-to-day dynamics and system reliability under different level of network congestion.

6.3.2 Impact of Incident Characteristics:

This set of experiments attempts to examine the effect of incident levels on the system performance and stability from day-to-day. Four incident characteristics are varied systematically in this set of experiments: Incident occurrence rate, incident type distribution, incident severity, and incident durations. For each factor, three levels are considered: low, moderate, and high. The baseline level is set to the normal incident characteristic scenario, with all four factors in the medium level. Under each sub-experimental factor, the factor under investigation is varied from low to high, with all other factors held at the baseline level. Insights on how each of these incident characteristics affect system dynamics and network reliability can help evaluate various congestion mitigation strategies aimed to reduce congestion induced by incidents and developing more effective incident management strategies. Details of parameter settings are described as follows:

1) Incident Probability of Occurrence

Poisson distribution of incident occurrences is assumed. The expected value of the Poisson distribution is calculated from the LA I-10 dataset, which corresponds to the medium level, with occurrence rate of 0.65 incident per mile per peak hour. For low level of incident occurrence rate, 10 percentile value (0.557 incident per mile per peak hour) is used. 90 percentile value (0.743 incident per mile per peak hour) of the distribution is used for high incident rate level. The percentile values of occurrence counts then converted to probability of occurrence in each link.

2) Distribution of Incident Types

For this experimental factor, the conditional probability of accidents is varied by +/- 50% from the baseline level for low and high levels respectively, as listed below:

Table 6-4 Experimental Levels for Distribution of Incident Types

Levels	Conditional Probability of Incident Types (%)		
	Accident	Break Down	Others
Low Accident (-50%)	5	85	10
Medium Accident (mean)	10	80	10
High Accident (+50%)	20	70	10

3) Incident Severity

In this experimental factor, given incident occurrence and type, the capacity reduction values are varied in three levels: Low (25% lower than baseline), Medium (baseline capacity reduction), and High (25% higher than baseline level).

4) Incident duration

For this experimental factor, given other parameters in baseline level, the incident duration bounds are scaled up and down 25% to obtain the low and high level. Based on the scaled lower and upper bounds, the log normal distribution parameters are recalculated and used for incident duration simulation.

6.3.3. Evaluation of Corrective Control Measures to Improve System Performance and Reliability

From a practical level, this set of experiments investigates the effectiveness of different ITS alternatives on day-to-day system performance under non-recurrent congestion. Specifically, two types of ITS strategies are analyzed in this sub-objective: Real-time information market penetration and Incident management strategies. In addition, from traveler behavioral point of view, another control measure simulated is the coordination of commuters' departure time adjustment behavior. The details of each experimental factor are explained as follows:

1) Information Market Penetration

The first strategy under investigation is the real-time information strategy. By providing real-time pre-trip and enroute traveler information to informed users via in-vehicle devices, this strategy is commonly used and identified in the ITS strategic plans for various U.S. cities. Under this experimental factor, various levels of market penetration of real-time information are examined, from 10% to 90% with incremental of 20%. The baseline level is set to 0.1% market penetration, which is intended to represent a system with very few informed users (corresponding to early stage of in-vehicle device adoption). Understanding the impact of market penetration of informed users, user's response characteristics and day-to-day system dynamics may help in developing guidelines for more efficient and reliable ATIS products and services.

2) Incident Management Approaches

The primary components of the freeway management system consist of a fiber-optically linked closed loop system with surveillance cameras (CCTV), Dynamic Message Signs and ramp meters connected to a set of traffic management centers (TMCs). Utilizing the CCTV cameras, incident detection and verification time can be significantly shortened (by half, Presley 1999). Incident response software systems can also provide immediate response or contact list for each incident, thus reducing the incident identification/dispatch time significantly. In addition, a city or state wide emergency response team and metro-wide incident management task force can also minimize the disruption of the normal traffic flow at an incident.

To test the effectiveness of incident management approaches on system performance and reliability, three experimental scenarios are designed. The incident management programs are simulated by applying an incident duration reduction factor. The first scenario represents the early stage of adoption, by assuming that only a CCTV system is installed to help detect and verify the incident occurrence. The corresponding incident duration reduction for the first scenario is 10%. The second scenario then represents the full adoption of the typical incident management program, along with Highway Patrol Services being deployed. In this scenario, a 36% percent incident duration reduction is simulated (36% incident duration reduction is adopted from the benefit of Atlanta's NAVIGATOR system). The last scenario assumes an additional 10% incident duration reduction (thus a total reduction of 46%). This scenario takes into consideration possible further improvements by the coordination of emergency response units and additional emergency vehicle dispatch measures such as dedicated emergency vehicle signals and lanes.

By examining the effect of varying information and incident management approaches on the system performance and stability from day-to-day, this set of experiment seeks insights on the design and evaluation of effective incident mitigation strategies.

3) Reduction of Uncoordinated Departure Time Switching Rate

One important finding in chapter 5 was that departure time switching appears to exert a greater influence on day-to-day dynamics than route switching. Results shown later in section 6.4.3 will also indicate that the response from non-informed users has a large impact on system dynamics. These findings suggest that reduction of departure time switching rate is a promising way to influence non-informed users and reduce system congestion and unreliability.

To test this approach, a set of departure time switching rate reduction levels (namely 32%, 17%, 11% and 7%) are selected. The levels selected are based on 60 days average values observed in the simulations, and thus are not exactly equal intervals. These scenarios are simulated by adjusting the departure time inertia coefficient in the departure time adjustment model (described in chapter 5, section 5.3.2) in the range of 0 to -1.5 until a desired value within a 2% range is observed.

6.3.4 Additional Performance Measures

Recall that six categories of performance measures used in previous chapters (described in detail in Chapter 4) are: 1) system dynamics, 2) commuter performance, 3) information quality, 4) route choice and switching response, 5) individual level switching behaviors, and 6) spatial rerouting opportunity measures. These measures are also used in this chapter. In addition, two additional performance measures are developed and used for travel time reliability: travel time index and buffer index. These measures are adopted from the Urban Mobility Report (Texas Transportation Institute, 2005). The basic definitions are explained as follows.

1) **Travel Time Index:**

Travel Time Index is defined as the ratio of the peak period travel time to the free flow travel time. For example, a value of 1.20 means that average peak travel times are 20% longer than free flow travel times. Travel time index is a measure of network congestion level.

$$\text{Travel Time Index} = \frac{Peak\ \ period\ travel\ time}{Free\ \ flow\ travel\ time}$$

2) Buffer Index

Buffer index is the extra time (or buffer) needed to ensure on-time arrival for most trips. For example, a value of 40% means that a traveler should budget an additional 8 minute buffer for a 20-minute average peak trip time to ensure 95% on-time arrival.

$$\text{Buffer Index} = \frac{95^{th}\ \ percentile\ travel\ time - average\ travel\ time}{average\ travel\ time}$$

The difference in this study compared to the TTI study is that instead of an aggregate measure (e.g., average travel time for all vehicles traveled, estimated by the prevailing speed within a certain interval), these measures are computed at a disaggregate level for each individual vehicle, and then aggregated to the system level average.

To avoid the impact of the randomness of incidents, the same set of random numbers are used for the incident generation module for each scenario under comparison (with the exception of the incident characteristic experiments, in which case they are incident specific across scenarios). The results and findings from these sets of experiments are presented in the next section.

6.4 Experimental Results and Discussion

The results corresponding to experiment 1 to 5 are shown in Tables 6-5 to 6-9 respectively. As noted in chapter 5, the results corresponding to each experimental treatment level are presented in terms of percentage deviation from the baseline case (indicated in each experiment), unless noted otherwise. The evolution of a few key performance metrics are displayed in Figures 6-1 to 6-7. The results are discussed in detail below for each set of experiments.

6.4.1 Experiment 1: System Performance under Incidents for Different Recurrent Congestion Level (Table 6-5)

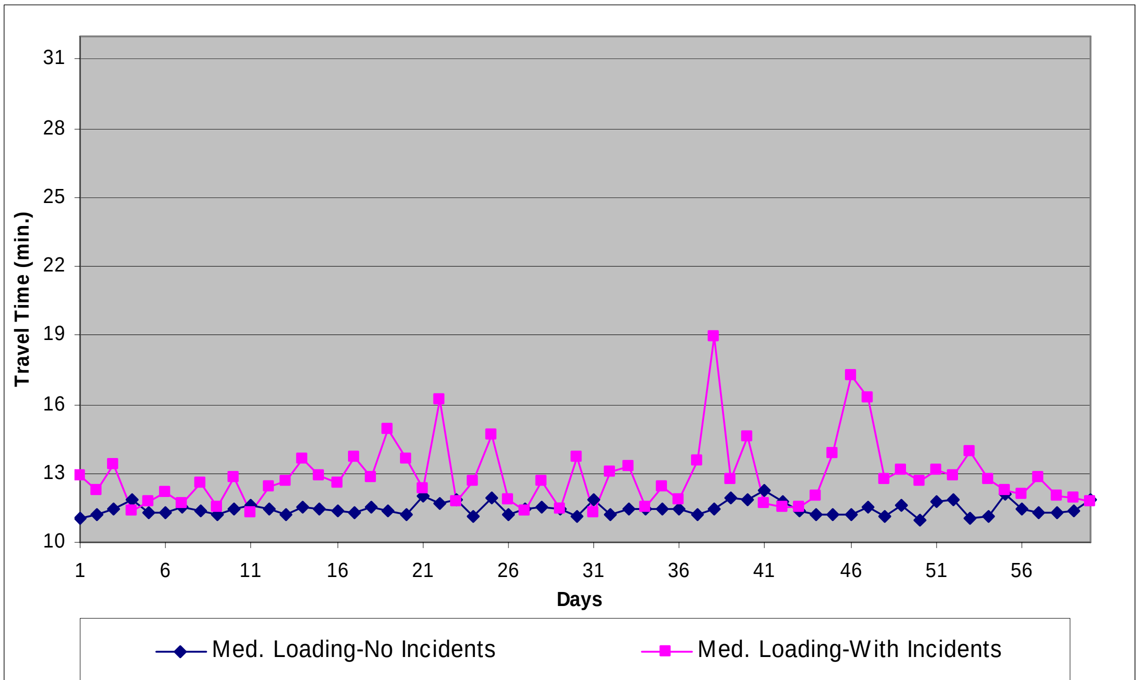
Under the no-incident scenarios, with increasing network congestion, the average network travel time increases significantly (by 42% from moderate to high, and another 42% from high to severe congestion). The trip time variation from day to day (measured as the standard deviation of average trip time across 60 days) also increases dramatically (by 163% from moderate to high, and another 36% from high to severe). Furthermore, trip time reliability decreases with increasing congestion level (decreases 12.7% from moderate to high level, and an additional 11.9% decrease from high to severe congestion level). With high and severe congestion levels, average trip time varies considerably from day-to-day (trip time reliability is 73% for high congestion level and 61% for severe congestion). These observations indicate the importance of travel time reliability and variability particularly under highly congested conditions.

Table 6-5 Performance Measures under Different Recurrent Congestion Level under Incidents

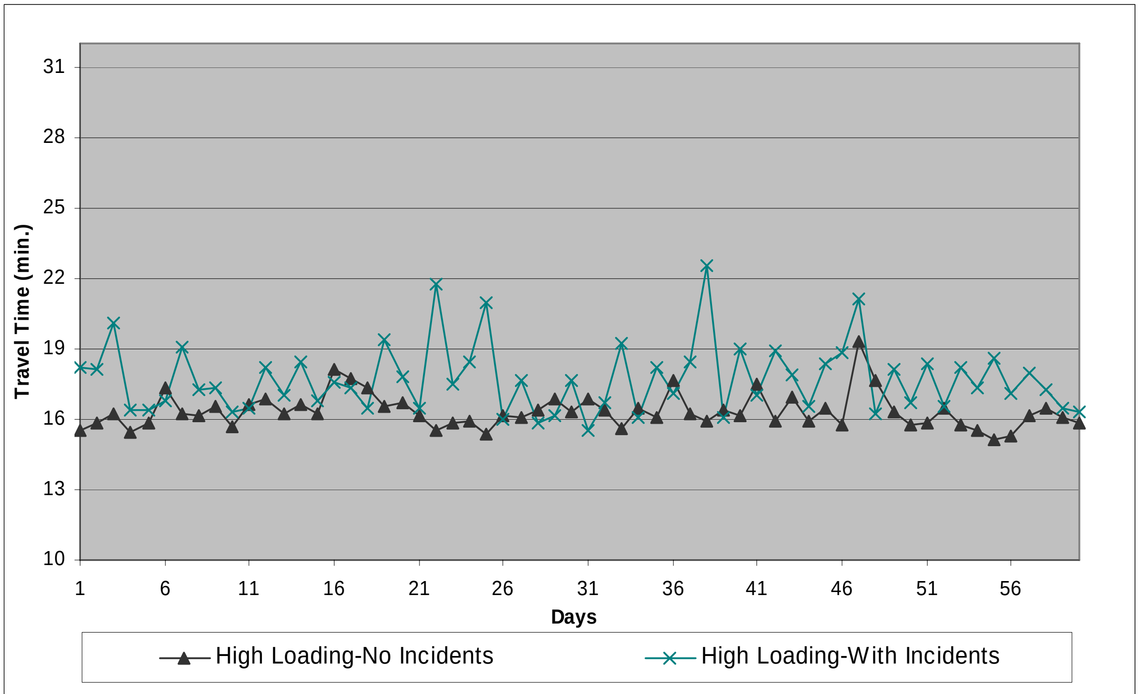
Network and User Performance Measures (averaged over 60 days)	Mild congestion (NO incident)		Mild congestion (With incident)		High congestion (NO incident)		High congestion (With incident)		Severe congestion (NO incident)		Severe congestion (With incident)	
	Average	*Std Dev*	Average	*Std Dev*	Average	*Std Dev*	Average	*Std Dev*	Average	*Std Dev*	Average	*Std Dev*
System Performance												
Trip time (min.)	11.47	0.29	12.89	1.47	16.34	0.75	17.71	1.47	23.18	1.0142	24.97	2.00
TT volatility ratio (min. / min.)	0.60	0.10	1.03	0.33	1.18	0.21	1.62	0.33	1.95	0.2248	2.30	0.35
Reliability (fraction)	0.86	0.22	0.76	0.23	0.73	0.26	0.64	0.26	0.61	0.262	0.54	0.25
Travel time index	1.15	1.20	1.40	1.21	2.03	2.11	2.27	2.09	2.96	2.5146	3.25	2.54
Buffer index (fraction)	0.51	0.42	0.95	0.62	0.70	0.48	0.95	0.53	0.81	0.4467	0.91	0.46
Commute Performance												
Late schedule delay (min.)	2.50	0.25	3.45	1.32	3.79	0.61	4.66	1.28	5.33	0.8812	6.24	1.74
Early schedule delay (min.)	3.33	0.58	3.69	0.61	4.18	0.38	4.55	0.46	5.25	0.2808	5.77	0.47
Early arrival (fraction)	0.23	0.19	0.26	0.17	0.27	0.17	0.30	0.16	0.31	0.1545	0.33	0.14
Ontime arrival (fraction)	0.61	0.24	0.53	0.21	0.50	0.25	0.44	0.23	0.39	0.2388	0.34	0.22
Late arrival (fraction)	0.16	0.14	0.21	0.13	0.23	0.16	0.27	0.14	0.30	0.1579	0.33	0.15
Departure Time Response												
Switching Magnitude to Later(min.)	4.49	0.21	4.49	0.20	4.60	0.16	4.65	0.17	4.74	0.1195	4.83	0.11
Switching Magnitude to Early(min.)	4.65	0.12	4.80	0.24	4.78	0.14	4.85	0.22	4.87	0.1801	5.03	0.28
Switching Rate (%)	0.49	0.01	0.50	0.01	0.52	0.01	0.53	0.01	0.55	0.0085	0.56	0.01
Information Quality (Fraction)												
Ave. over estimation	0.01	0.00	0.01	0.00	0.03	0.01	0.03	0.01	0.06	0.0068	0.06	0.01
Ave. under estimation	0.02	0.00	0.02	0.00	0.03	0.00	0.03	0.00	0.04	0.0032	0.04	0.00
Information reliability	0.95	0.00	0.95	0.01	0.92	0.01	0.92	0.01	0.89	0.0082	0.88	0.01
Route Choice & Switching												
Percentage links in common (fraction)	0.65	0.01	0.60	0.03	0.60	0.02	0.55	0.03	0.57	0.0193	0.54	0.02
Threshold of relative TT saving(fraction)	0.13	0.00	0.14	0.01	0.14	0.00	0.14	0.01	0.13	0.0047	0.13	0.01
Threshold of absolute TT saving(min.)	0.71	0.04	0.85	0.11	0.97	0.04	1.06	0.09	1.14	0.0539	1.17	0.06
Individual Level Switching Behaviors												
Uninformed users												
DT switch percentage (fraction)	0.24		0.25		0.26		0.27		0.29		0.30	
Informed users												
Non-switching rate (%)	65.45		64.56		62.98		62.01		60.72		59.70	
Route only switch (%)	11.42		11.72		12.15		12.44		12.03		12.16	
Departure Time only switch (%)	19.64		19.91		20.74		21.14		22.56		23.26	
Users switching both (%)	3.50		3.82		4.13		4.40		4.67		4.88	

Comparing the incident scenario with corresponding no-incident scenario, the average trip time increases from the no-incident case but with a decreasing rate (by 12.4% under moderate congestion, 8.4% under high congestion, and 7.7% under severe congestion). Under incident scenarios, the day-to-day variation of trip time increases significantly (with standard deviation doubled under both high and severe congestion level). The largest impact on trip time variability occurs under moderate congestion level (standard deviation increases by a factor of 4.2). Day-to-day trip time variation trends between incident and non-incident scenarios under different congestion levels are shown in Figure 6-1. Trip time reliability is also consistently lower under incident scenarios (by 8-10%).

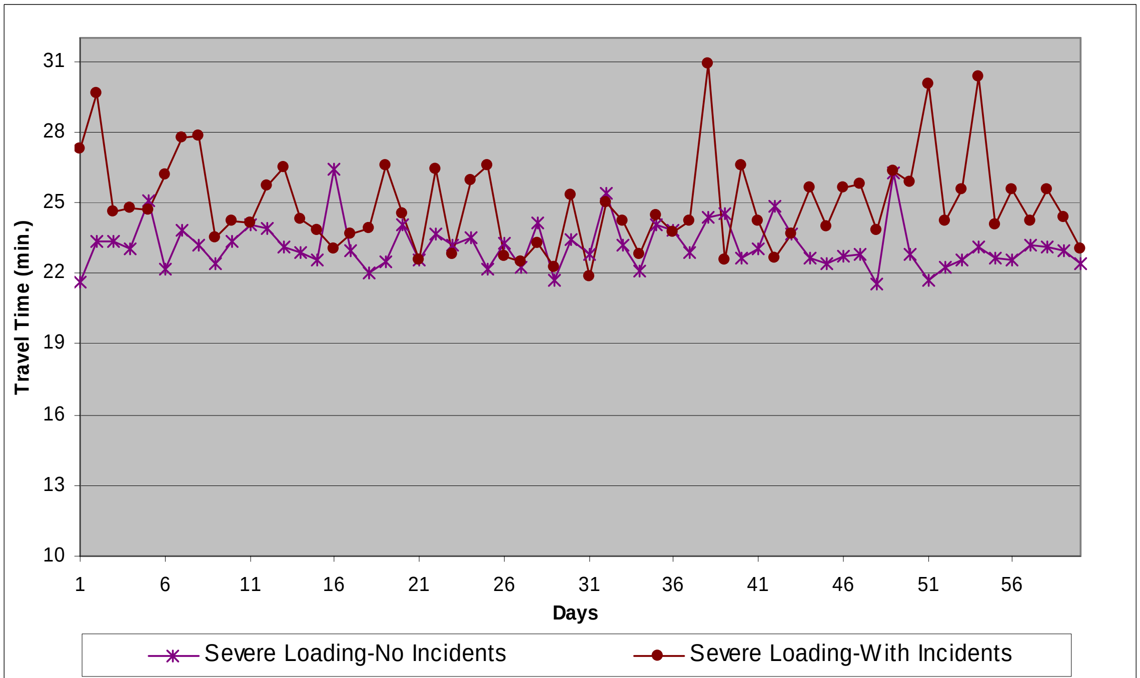
Figure 6-1 Average travel time under different recurrent congestion



(a)



(b)



(c)

In terms of commute performance measures, with increasing network congestion under no-incident, both the late schedule delay and early schedule delay increase significantly, with lower increase rate on early schedule delay. Under moderate congestion, late schedule delay experienced on the network is 2.5 min. and early schedule delay is 3.3 min. Under high congestion, 5.3 min. of late schedule delay and 5.3 min. of early schedule delay is observed. Furthermore, the volatility of late schedule delay increases by a factor of 2.47. These trends can be explained by the increase in travel time with increasing congestion. Under incident scenario, the late schedule delay increases by only 23% under high congestion and 17% under severe congestion. However, the volatility of late schedule delay is nearly doubled for both cases. A comparison of the SDL trends under severe congestion with both incident and no-incident scenarios is shown on Figure 6-2. Under incident scenarios, both the late and early arrival rates increase by 3-5%, and on-time arrival rate decreases by 3-5% comparing with the corresponding no-incident cases. These results show that under the impact of incident, commuters will experience much less stable travel in terms of delays from day-to-day.

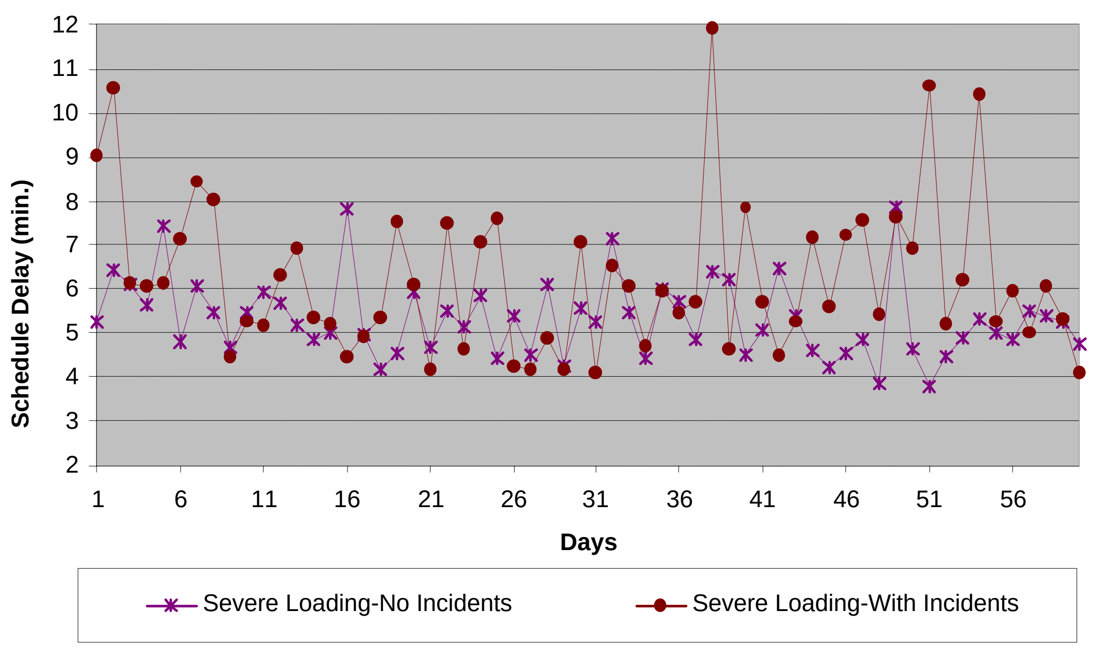


Figure 6-2 Schedule delay under severe congestion

The unstable travel experience can also be explained by user's behavioral response on both departure time adjustment and route choice decisions. Users' departure time adjustment decisions under day-to-day network dynamics is captured through the switching rate and the switching magnitude to both earlier and later sides. For departure time adjustment behavior under the influence of incidents, the switching rate increases by 1% consistently for all congestion levels, with 1.5%-3.3% increase in early side switching magnitude. The route choice decisions are captured by two related performance measures: 1) average percentage links in common, which reflects the degree of day-to-day route switching, and 2) threshold of relative and absolute trip time saving for users choosing the best paths. With incidents, the percentage of links in common decreases by 5% percent for both moderate and high congestion levels, and 3% for the severe congestion level. This suggests a greater degree of route switching from day to day under incidents. The variability of percentage links in common is also consistently higher (by 1-2%) under incidents. A comparison of percentage links in common for both incident and no-incident scenarios under moderate congestion level is given in Figure 6-3. Note that even at a moderate congestion level, the percentage of links in common does not converge to a certain level, and is bounded by a range of nearly 5% deviation from the mean under the incident scenario. This suggests that the route assignment from day–to-day may not reach steady state. Furthermore, the system performance may also deviate from user equilibrium assignment.

The results from this set of experiments show the significant impacts of incidents on day-to-day system performance and reliability. This suggests that considering the incident impact for system analysis and evaluation is necessary, and some form of coordination of user information may be needed to steer the system to more desirable states.

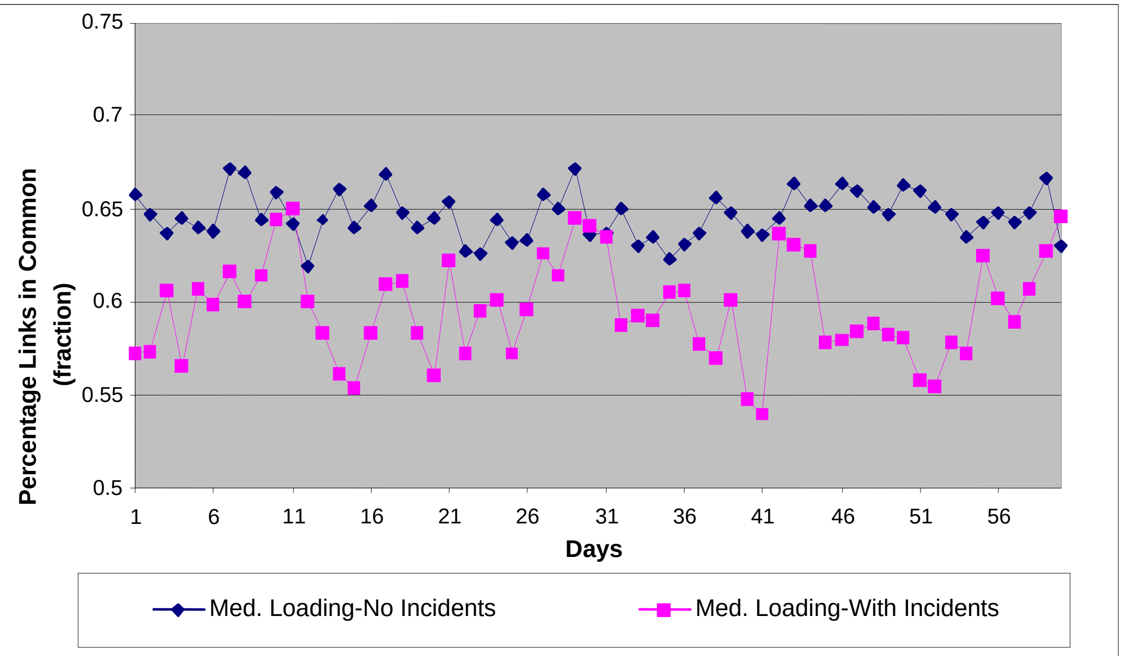


Figure 6-3 Percentage Links in Common under moderate congestion

6.4.2 Experiment 2: Impact of Incident Characteristics

As shown in Table 6-6, the performance measure is compared from low to high level for each incident characteristic in this section, unless otherwise specified.

Table 6-6 Performance Measures under Different Levels of Incident Characteristics

Network and User Performance Measures (averaged over 60 days)	Baseline	Low Incident Rate (10%ile)	High Incident Rate (90%ile)	Low Probability of Accidents	High Probability of Accidents	Low Incident Severity	High Incident Severity	Low Duration	High Duration
System Performance									
Trip time (min.)	12.89	12.39	13.11	12.74	13.50	12.30	13.98	12.78	13.64
TT volatility ratio (min. / min.)	1.03	0.91	1.03	0.92	1.18	0.80	1.34	0.95	1.20
Reliability (fraction)	0.76	0.80	0.74	0.78	0.72	0.82	0.66	0.78	0.71
Travel time index	1.40	1.31	1.43	1.38	1.51	1.31	1.59	1.38	1.54
Buffer index (fraction)	0.95	0.82	0.93	0.85	1.15	0.69	1.23	0.87	1.01
Commute Performance									
Late schedule delay (min.)	3.45	3.11	3.46	3.15	3.86	2.83	4.18	3.23	3.88
Early schedule delay (min.)	3.69	3.54	3.75	3.61	3.83	3.47	3.96	3.65	3.77
Early arrival (fraction)	0.26	0.25	0.26	0.25	0.27	0.24	0.28	0.26	0.27
Ontime arrival (fraction)	0.53	0.56	0.52	0.54	0.53	0.57	0.50	0.54	0.51
Late arrival (fraction)	0.21	0.19	0.21	0.21	0.21	0.19	0.22	0.20	0.22
Departure Time Response									
Switching Magnitude to Later(min.)	4.49	4.45	4.50	4.51	4.51	4.49	4.55	4.49	4.51
Switching Magnitude to Early(min.)	4.80	4.72	4.77	4.73	4.89	4.69	4.93	4.75	4.83
Switching Rate (%)	0.50	0.50	0.50	0.50	0.51	0.50	0.51	0.50	0.51
Information Quality (Fraction)									
Ave. over estimation	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Ave. under estimation	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Information reliability	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Route Choice & Switching									
Percentage links in common (fraction)	0.60	0.60	0.59	0.60	0.59	0.61	0.58	0.60	0.59
Threshold of relative TT saving(fraction)	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Threshold of absolute TT saving(min.)	0.85	0.81	0.87	0.86	0.86	0.80	0.88	0.85	0.87
Individual Level Switching Behaviors									
Uninformed users									
DT switch percentage (fraction)	0.25	0.25	0.25	0.25	0.25	0.25	0.26	0.25	0.26
Informed users									
Non-switching rate (%)	64.56	64.72	64.06	64.36	64.11	64.62	63.91	64.65	64.09
Route only switch (%)	11.72	11.92	11.96	11.73	11.89	11.69	11.96	11.72	11.88
Departure Time only switch (%)	19.91	19.71	20.11	20.08	20.12	19.88	20.24	19.80	20.13
Users switching both (%)	3.82	3.65	3.87	3.83	3.88	3.81	3.89	3.83	3.90

For system performance, incident severity has the most significant impact on average travel time. The average trip time increases by 13.7% under high incident severity (from 12.3 min. to 14 min.). The increase of average travel time for incident duration, probability of accidents, and incident rates are 6.7%, 6%, and 5.8%, respectively. For within-day dynamics, trip time volatility ratio increases by 67.5% under incident severity, which is consistent with the change in travel time. Other factors have less prominent impact on trip time volatility ratio, with around 26% increase in this performance measure. Changes of travel time index values are also consistent with the average travel time trends. In terms of system reliability, reliability measure decreases by 16% and buffer index increases by 54% under high incident severity. Incident duration also shows large impact on trip time reliability, with 7% decrease in reliability and 16% increase in buffer index. For probability of accident, the decrease of reliability is 6% and the increase of buffer index is 35%. One general observation is that the impact under low and high level is not symmetric when comparing to the baseline level. The high level has a much larger impact on system performance. This unsymmetrical effect indicates that the flow is much more unstable and can deteriorate very quickly when the congestion level is high.

For commute performance, under high incident severity, late schedule delay increases by 47.7% (from 2.83 min. to 4.18 min.). Similarly, the on-time arrival rate decreases from 57% to 50%. Incident rate and duration also have large impact on the on-time arrival rate, with a 4% and 3% decrease, respectively, from the low to high level. The impact of probability of accident on on-time arrival rates is minimal with only a 1% decrease.

Under high incident severity, duration, and probability of accidents, users who adjusted their departure time are slightly higher by 1% when comparing with a corresponding low level. Switching magnitude for departure time is also higher under a high level for all cases, with the largest impact occurring under high incident duration (with 5% increase). Route choice responses have the same trends as departure time responses, with a 3% decrease in percentage links in common under the high incident severity case as the largest impact.

In summary, the incident severity has the largest impact on system performance, and incident frequency has the least impact. As a general observation, the influence of incident characteristics on system reliability is much larger than on travel time. From a control measure point of view, the duration is probably the most obvious and direct results one can expect from incident management strategies, and the duration reduction does have significant impact on system performance and reliability. The incident duration reductions are further analyzed in section 6.4.4 (incident management strategies).

6.4.3 Experiment 3: Role of Information Market Penetration on Day-to-day Dynamics

The results for this set of experiments are shown on Table 6-7.

Table 6-7 Performance Measures under Different Information Market Penetration

Network and User Performance Measures (averaged over 60 days)	No Information (0.1% MP)	10% MP	20%MP	30% MP	40% MP	50% MP	60% MP	70% MP	80% MP	90% MP
System Performance										
Trip time (min.)	14.36	13.67	12.89	12.56	12.25	11.85	11.82	11.61	11.57	11.61
Trip time (informed)	10.34	10.55	10.72	10.72	10.91	10.86	11.10	11.16	11.28	11.47
Trip time (non-informed)	14.37	14.02	13.42	13.37	13.15	12.86	12.91	12.68	12.76	12.86
TT volatility ratio (min. / min.)	1.18	1.12	1.03	0.99	0.95	0.88	0.88	0.86	0.87	0.87
Reliability (fraction)	0.72	0.74	0.76	0.78	0.79	0.81	0.81	0.81	0.81	0.80
Travel time index	1.64	1.52	1.40	1.32	1.27	1.20	1.20	1.17	1.18	1.19
Buffer index	0.98	0.97	0.95	0.91	0.90	0.87	0.84	0.85	0.84	0.83
Commute Performance										
Late schedule delay (min.)	3.78	3.62	3.45	3.29	3.19	3.07	3.05	2.94	2.94	2.92
Early schedule delay (min.)	3.83	3.75	3.69	3.62	3.61	3.55	3.54	3.51	3.53	3.56
Early arrival (total)	0.27	0.26	0.26	0.26	0.26	0.25	0.25	0.25	0.25	0.25
Ontime arrival (total)	0.51	0.52	0.53	0.55	0.55	0.56	0.56	0.56	0.56	0.55
Late arrival (total)	0.22	0.22	0.21	0.20	0.20	0.19	0.19	0.19	0.19	0.20
Departure Time Response										
Switching Rate (%)	0.51	0.51	0.50	0.50	0.50	0.49	0.49	0.50	0.50	0.50
Information Quality (Fraction)										
Ave. over estimation	0.00	0.01	0.01	0.03	0.04	0.05	0.06	0.07	0.09	0.10
Ave. under estimation	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
Information reliability	0.97	0.95	0.95	0.95	0.95	0.94	0.94	0.94	0.94	0.93
Route Choice & Switching										
Percentage links in common (fraction)	0.56	0.60	0.60	0.59	0.59	0.59	0.59	0.59	0.58	0.58
Individual Level Switching Behaviors										
Uninformed users										
DT switch percentage (fraction)	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.24	0.24
Informed users										
Non-switching rate (%)	78.72	70.26	64.56	57.55	51.60	45.28	39.24	33.07	26.94	20.99
Route only switch (%)	0.13	6.09	11.72	18.50	24.56	30.77	36.71	42.83	48.86	54.65
Departure Time only switch (%)	21.15	21.72	19.91	18.08	15.88	14.07	12.13	10.15	8.24	6.31
Users switching both (%)	0.00	1.94	3.82	5.88	7.97	9.88	11.92	13.95	15.97	18.06

As the information market penetration (MP) increases, the average trip time decreases at a decreasing rate, and stops decreasing when MP is larger than 70% (see Figure 6-4). Figure 6-4 also shows the trends of average trip time for both informed and uninformed users separately. An important observation is that the benefit of increasing information market penetration is largely contributed by non-informed users, rather than informed users. This suggests that more accurately modeling the behavior of non-informed users is equally important to modeling informed users, and the day-to-day dynamics induced by the response from non-informed users are also worthy of attention.

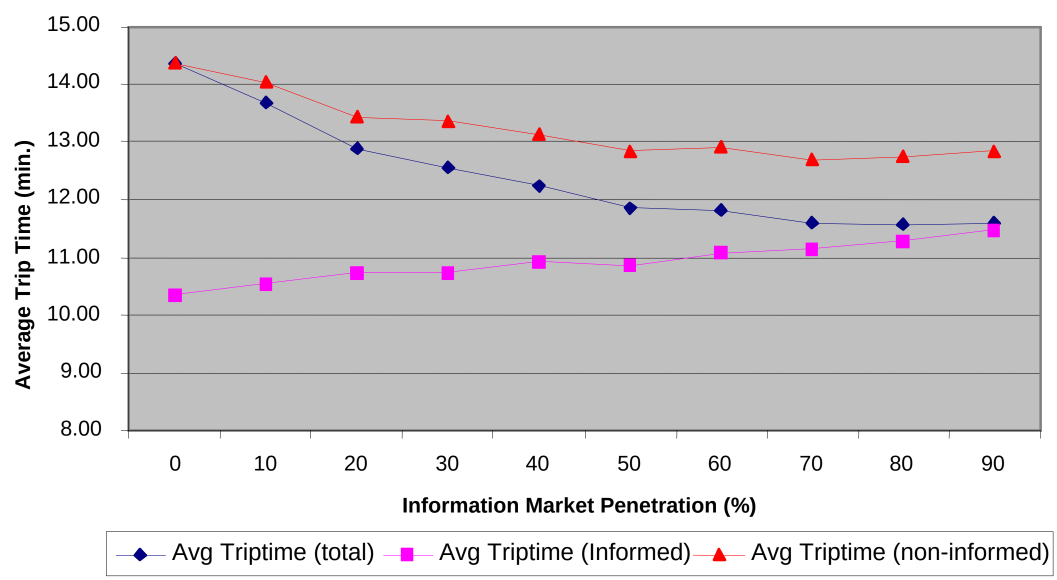


Figure 6-4 Average triptime under different information market penetration

With increasing market penetration, trip time reliability increases from 72% (under no information case) to 81% (with MP = 50%). With further increase in market penetration, the travel time reliability remains stable and slightly decreases. These trends are also consistent with the system congestion levels, as the travel time index decreases steadily, and then increases after market penetration reaches 70%. Similarly, although significant reduction of buffer index is seen in the low to medium level MP (6% from 10% to 30%), the buffer index measure stops decreasing and converges to 84% under high market penetration. The trip time volatility (standard deviation of average trip time) keeps decreasing significantly (by 0.34 minutes from 50% to 70%, and 0.24 minutes from 70% MP to 90% MP). The results imply that the benefit of larger market penetration decreases as the MP increases, though the system can still perform slightly better. Figure 6-5 shows the trends of trip time reliability, travel time index, and buffer index from day to day. These results show that a careful benefit – cost analysis is necessary when design and implementing information strategies.

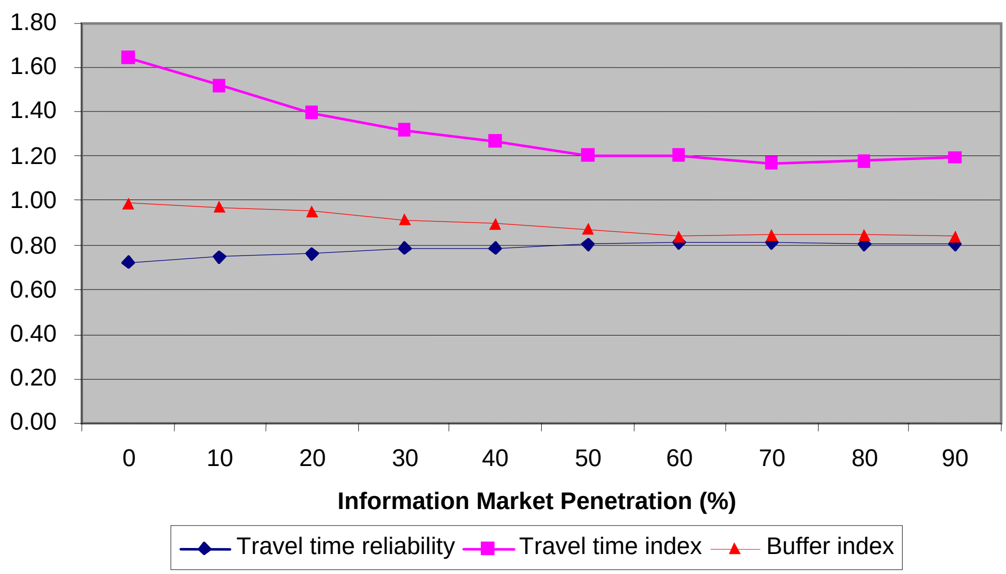


Figure 6-5 Reliability and congestion measures under different information market penetration

The results can be explained by the information quality measures. From 10% to 40% market penetration level, information quality remains reasonably good (information errors remain stable from 10% to 20% MP, and increase slightly from 20% to 40% MP). The information reliability also remains stable from 10% to 30% MP. However, as the

MP increases further (past 50% MP level), both overestimation and underestimation errors increase by a larger rate, and information reliability decreases by 1% with each 10% step of MP increase. In addition, with the increasing market penetration, more travelers are capable of switching routes because of information. For informed users, non-switching rate decreases from 70% (10% MP) to 21% (90% MP), and route only switching rate increases from 6% (10% MP) to 55% (90% MP). These aggressive switching behaviors indicate that the quality and reliability of prevailing information deteriorates quickly with increasing market penetration. This trend is also shown on the increasing average trip time of informed users under high market penetration (from 50% to 70% then to 90% MP, the travel time of informed users increased by 0.3 minutes).

This set of experiments suggests that moderate market penetration level (40%-50%) is desirable from both an average trip time and a day-to-day trip time reliability perspective, whereas higher market penetration levels may be considered if a lower benefit – cost ratio is acceptable.

6.4.4 Experiment 4: Effectiveness of Incident Management Strategies

Recall that in experiment 2, the incident duration reduction levels were assumed differently than in this experiment. In experiment 2, the major focus was on the effect of duration on system performance, and the low and high levels were assumed symmetric (+/- 25%). However, in this set of experiments, the capacity reduction ratio is estimated from the reported statistics from the literature. The results are summarized in Table 6-8.

Table 6-8 Performance Measures under Different Incident Management Scenarios

Network and User Performance Measures (averaged over 60 days)	Baseline (No Incident Management)		Incident Management Scenario 1 (10% duration reduction)		Incident Management Scenario 2 (36% duration reduction)		Incident Management Scenario 3 (46% duration reduction)	
	Average	*Std Dev*	Average	*Std Dev*	Average	*Std Dev*	Average	*Std Dev*
System Performance								
Trip time (min.)	12.89	1.47	13.14	1.31	12.78	0.98	12.62	0.86
TT volatility ratio (min. / min.)	1.03	0.33	1.03	0.31	0.92	0.23	0.88	0.19
Reliability (fraction)	0.76	0.23	0.76	0.23	0.79	0.22	0.80	0.22
Travel time index	1.40	1.21	1.45	1.26	1.39	1.29	1.36	1.30
Buffer index	0.95	0.62	0.91	0.58	0.81	0.50	0.77	0.47
Commute Performance								
Late schedule delay (min.)	3.45	1.32	3.44	1.16	3.11	0.86	3.02	0.72
Early schedule delay (min.)	3.69	0.61	3.69	0.56	3.61	0.57	3.56	0.58
Early arrival (total)	0.26	0.17	0.26	0.17	0.25	0.17	0.25	0.17
Ontime arrival (total)	0.53	0.21	0.53	0.22	0.55	0.22	0.55	0.22
Late arrival (total)	0.21	0.13	0.21	0.13	0.20	0.13	0.20	0.14
Departure Time Response								
Switching Rate (%)	0.50	0.01	0.51	0.01	0.50	0.01	0.50	0.01
Information Quality (Fraction)								
Ave. over estimation	0.01	0.00	0.02	0.00	0.02	0.00	0.02	0.00
Ave. under estimation	0.02	0.00	0.02	0.00	0.02	0.00	0.02	0.00
Information reliability	0.95	0.01	0.95	0.01	0.95	0.01	0.95	0.00
Route Choice & Switching								
Percentage links in common (fraction)	0.60	0.03	0.59	0.03	0.60	0.03	0.60	0.03
Threshold of relative TT saving(fraction)	0.14	0.01	0.14	0.01	0.14	0.01	0.14	0.01
Threshold of absolute TT saving(min)	0.85	0.11	0.86	0.11	0.84	0.11	0.84	0.09
Individual Level Switching Behaviors								
Uninformed users								
DT switch percentage (fraction)	0.25	0.08	0.25	0.08	0.25	0.08	0.25	0.08
Informed users								
Non-switching rate (%)	64.56	12.29	64.36	12.35	64.43	12.74	64.65	12.60
Route only switch (%)	11.72	11.37	11.72	11.36	11.88	11.52	11.73	11.36
Departure Time only switch (%)	19.91	9.11	19.98	9.14	19.96	9.18	19.88	9.22
Users switching both (%)	3.82	4.03	3.95	4.14	3.73	3.94	3.74	3.95

In the first scenario of the incident management strategy, the deployment of CCTV cameras is assumed to bring 10% incident duration reduction by helping the incident detection and verification. Interestingly to see, both the average travel cost and the trip time reliability measures are not significantly affected in this scenario (the system cost increases slightly by 2% on average, which might due to the dynamics of a particular simulation scenario. Trip time reliability does not change). However, the reliability improvement is observed in terms of trip time volatility where the standard deviation of trip times decreases by 11% from 1.47 to 1.31, and the buffer time index decreases by 4% from 95% to 91%. Note that the trip time reliability is a disaggregate measure on an individual level, which describes the level of stability of individual user's trip time from one day to the next. However, the trip time volatility is an aggregate measure, which gives the standard deviation of average trip times for each day. Buffer index measures the budget level one can expect greater than the average trip time. Under nonlinear system dynamics, these measures can show different trends. Changes in other categories of performance measures are also marginal.

The second scenario simulates the benefit of a relatively complete deployment of the incident management strategy, with improved incident response team deployment to reduce the duration of an incident. Under a simulated duration reduction of 36%, system benefits are observed for both commute performance and day-to-day travel reliability, although the average travel time is reduced by only 1%. The trip time variability is reduced by 33% (from 1.47 to 0.98 min.) and trip time reliability increases by 3% (from 76% to 79%). Buffer time index decreases from 95% to 81%. Trip time volatility ratio is also significantly reduced by 10.7%. In terms of commute performance, average on-time arrival rate increases by 2% (from 53% to 55%), and late schedule delay is improved by 9.6%. Users are obviously better off in their commuting experience.

The purpose of the third scenario is to evaluate the benefit of further increasing the effectiveness of the incident management strategy by achieving additional 10% incident duration reduction. The results show that with this further improvement, another 1.3% of the average travel time reduction is observed. Trip time volatility ratio is also further decreased further by 4.3%. In terms of travel time reliability, 1% further improved is seen in trip time reliability, and another 5% of reduction is observed for buffer index. Although on-time arrival rate does not decrease further, the late schedule delay is reduced further by another 3%. A comparison of travel time evolution trends for three different incident management scenarios are shown in Figure 6-6.

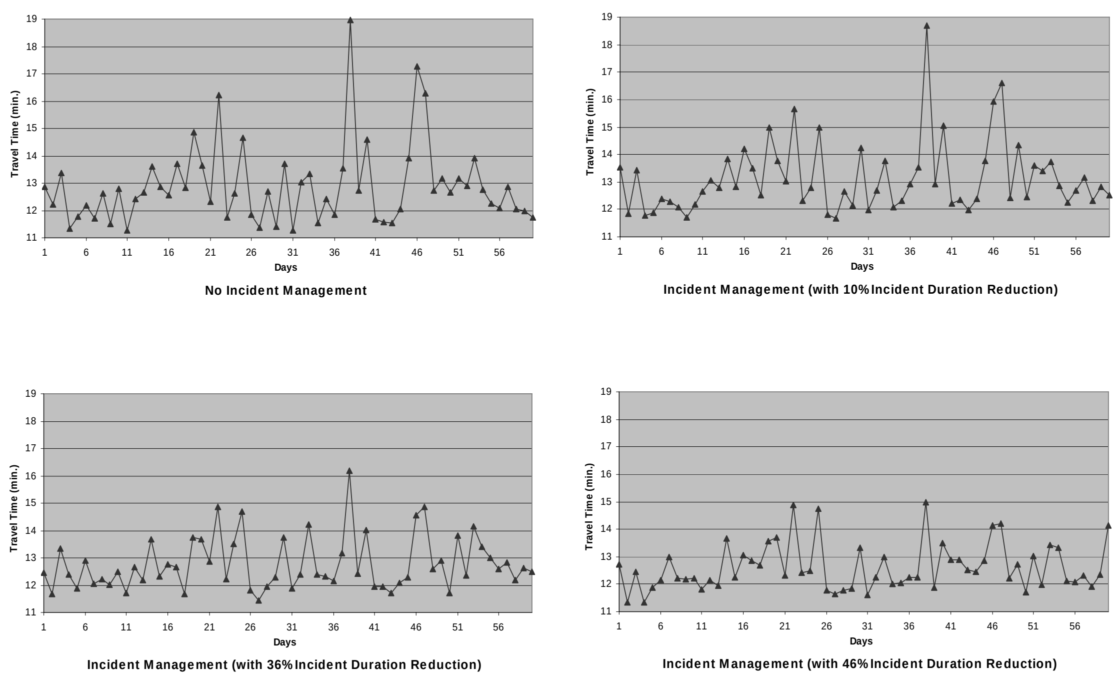


Figure 6-6 Day-to-day travel time trends under different incident management scenarios

The results from this section show that the incident management programs are effective ways to reduce congestion, improve travel experience, and increase the reliability of travel time. However, there are some interesting observations which need attention when evaluating the benefits and effectiveness of the incident management program. First, the results from the first incident management scenario indicate that the system benefit of this type of ITS deployment only (with limited incident duration reductions) is rather limited in terms of system cost benefit and day-to-day reliability. Secondly, the results in scenario 2 also show that the incident management programs are much more effective in improving travel time reliability than improving average travel cost. With further improvement of the effectiveness of incident management, as shown in scenario 3, still important improvement of system and reliability of performance can be achieved, but perhaps with a lower benefit – cost ratio. The third noteworthy finding is that under different incident duration reduction scenarios, the user behavioral measures do not change significantly. This observation might imply that the quicker release of highway capacities by the incident management strategies might not be fully utilized by commuters. The results also imply that opportunities exist to further improve the benefit introduced by the incident management strategies. More effective information provision strategies might be used to improve the information dissemination and user's responsiveness, thus further increasing the benefit of the incident management program.

6.4.5 Experiment 5: The Effectiveness of Reducing Commuters Departure Time Switching Rates

Five different levels of departure time switching rates from 32% to 7% are tested under this set of experiments, as shown in Table 6-9. The results in this set of experiments are consistent with the trends observed in Chapter 5. Although coordinating departure time behavior among users is hard to achieve in practice, this set of experiments evaluates the potential of this type of approach, and seek insights on how the system performs with underestimated departure time switching behavior. Under low departure time switching rate, the system performance improves significantly (trip time reduces by up to 7% under 7% departure time switching rate from the baseline level, and trip time reliability increases by up to 6%). However, the rate of system performance improvement is non-linear as shown in Figure 6-7. Only when the departure time switching rate is reduced to a very low level (around 10%) does the higher rate of reduction on the average trip time occur. Before this low rate level occurs, the impact of departure time switching rate reduction is not significant (<1% per 5% reduction on both average trip time and trip time reliability). Under low departure time switching rate (7%), the buffer index decreases by 12% and travel time reliability shows improvement. The travel time index decreases by 15% from a baseline level (normal departure time switching rate), which means the system is less congested. With a decreasing departure time switching rate, the early arrival fraction keeps increasing, and both the on-time arrival rate and late arrival rate continue to decrease. Under a low switching rate (7%), the on-time arrival rate decreases by 16%, but the late arrival rate decreases by 6% and the early arrival rate increases by 22%. Late schedule delay improved by about 1 minute (from 3.45 min. to 2.51 min.). Percentage of links in common increases from 60% to 63%

under a low switching rate (7% and 11%), and thus indicates a more substantial route switching behavior. However, the percentage informed users who switch route is not increased (i.e., remains stable at the 15.5% level for both 7% and baseline cases). These results show that a low departure time switching rate can lead to more effective route switching. Although it is highly impractical to restrict the departure time switching rate down to 7%, the results imply that models ignoring or over-simplifying the departure time switching behavior can be misleading and overestimate the system performance.

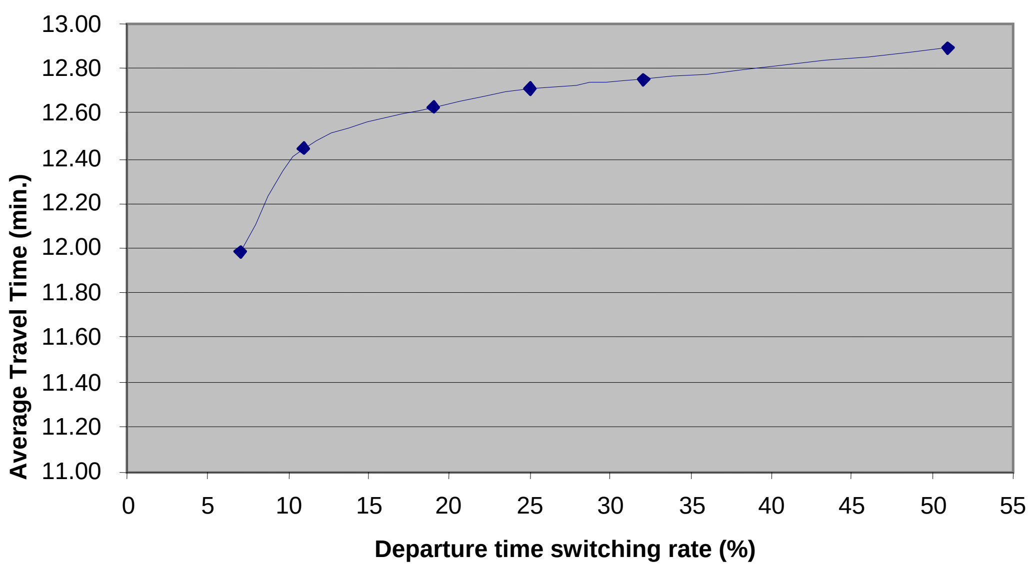


Figure 6-7 Average trip time under different departure time adjustment rate

Table 6-9 Performance Measures under Different Departure Time Switching Rate

Network and User Performance Measures (averaged over 60 days)	Baseline (DT switching rate 51%)	DT switching rate 32%	DT switching rate 25%	DT switching rate 19%	DT switching rate 11%	DT switching rate 7%
System Performance						
Trip time (min.)	12.89	12.75	12.71	12.63	12.44	11.98
Trip time (informed)	10.72	10.66	10.62	10.55	10.38	9.92
Trip time (non-informed)	13.42	13.25	13.21	13.14	12.94	12.48
TT volatility ratio (min. / min.)	1.03	0.67	0.51	0.37	0.21	0.12
Reliability (fraction)	0.76	0.77	0.77	0.78	0.79	0.82
Travel time index	1.40	1.37	1.35	1.34	1.29	1.19
Buffer index	0.95	0.95	0.93	0.94	0.90	0.84
Commute Performance						
Late schedule delay (min.)	3.45	3.32	3.29	3.18	2.89	2.51
Early schedule delay (min.)	3.69	4.09	4.45	4.90	6.39	8.10
Early arrival (total)	0.26	0.29	0.30	0.33	0.40	0.48
Ontime arrival (total)	0.53	0.51	0.50	0.48	0.42	0.37
Late arrival (total)	0.21	0.20	0.20	0.19	0.18	0.15
Departure Time Response						
Cum. Pctg of Switches to Later(%)	0.26	0.17	0.14	0.11	0.07	0.05
Cum. Pctg of Switches to Early(%)	0.18	0.11	0.08	0.06	0.03	0.02
Switching Magnitude to Later(min.)	4.49	4.60	4.73	4.86	5.23	5.56
Switching Magnitude to Early(min.)	4.80	4.82	4.86	4.89	4.96	4.93
Switching Rate (%)	0.50	0.32	0.25	0.19	0.11	0.07
Route Choice & Switching						
Percentage links in common (fraction)	0.60	0.60	0.61	0.61	0.63	0.63
Threshold of relative TT saving(fraction)	0.14	0.14	0.14	0.14	0.14	0.14
Threshold of absolute TT saving(min)	0.85	0.86	0.85	0.84	0.83	0.81
Individual Level Switching Behaviors						
Uninformed users						
DT switch percentage (fraction)	0.25	0.16	0.13	0.10	0.06	0.04
Informed users						
Non-switching rate (%)	64.56	71.75	74.38	76.95	80.21	81.88
Route only switch (%)	11.72	13.15	13.62	13.81	14.21	14.45
Departure Time only switch (%)	19.91	12.73	10.10	7.76	4.68	3.08
Users switching both (%)	3.82	2.38	1.92	1.47	0.91	0.60

6.5 Significance of Findings

The findings in this chapter are quite important for the following reasons. First, experiment 1 and 2 show that incidents have a very significant impact on day-to-day dynamics of system evolution, especially on trip time reliability. But these results also show that, at least at some level of system configuration, the current assumption of only significant within-day impact from incidents may be misleading. Secondly, the impact of uninformed user behavior is generally neglected in previous analyses, but is shown to be very important in this research. Uninformed user behavior can introduce very significant system performance benefits, as shown in experiment 3 and 5. Furthermore, the impact of departure time variations on system performance is generally not addressed in previous research, but is shown to have significant impact on system dynamics, especially under incident conditions in experiment 5. Lastly, experiment 4 shows that the benefit of incident management strategies most contribute to the system reliability and volatility, rather than on system cost. These findings can help develop more appropriate guidelines for future network analyses and evaluations.

6.6 Assumptions and Validations

As stated in the previous chapter, caution is advised in explicitly interpreting these findings due to the nature of the experiments, simulated conditions, and the assumptions regarding experimental factors used in this chapter. Due to certain computational limitations, the sample size of the Monte-Carlo simulation used for the incident simulation is rather small and thus might deviate from the underlying distribution. In addition, the incident rate is not a consistent rate when reviewing current literature. This is likely due to the close relation between incidents and the specific network conditions for each network. Incident start times are assumed fixed in this study due to the relatively short peak hour loading. In experiment 4, the full range of multi-dimensional benefits from incident management strategies might not be captured by the simulation results. Benefits such as visual identification and verification of the incident scene, and many management cost saving aspects may escape detection and a more complete understanding in this particular series of simulations.

Despite these restrictions, the results are robust with empirical data and consistent with statistics observed in real world and other previous empirical studies. The observed thresholds of relative trip time savings, departure and route choice rates, percentage of links in common, information reliability, and average late and early schedule delays are consistent with the ranges observed in Chapter 5. In addition, the observed travel time index value in the range of 1.4 – 1.5 is consistent with the 1.33 level from the 2003 Dallas Area Annual Mobility Report on Freeway Mobility and Reliability (Texas Transportation Institute, 2004). The buffer index of 0.5 – 0.9 coincides with the buffer index values of 0.57-0.96 for I-35 evening peak hours in the same report.

6.7 Summary

This chapter investigated day-to-day evolution in network flows under the impact of incidents. Five sets of experiments were conducted and analyzed. The first experiment (recurrent congestion level) focused on the comparison of the impact with and without incidents. The second experiment was to investigate the impact of incident characteristics. The last three experimental factors (information, incident management strategies, and reduction of uncoordinated departure time switching rate) explored the potential ways to improve system performance and reliability. The major findings from this chapter include: 1) The network performance deviates significantly from equilibrium under incidents, 2) Significant impacts of incident on day-to-day system performance and reliability are observed, 3) Incident severity has the largest impact on system performance, 4) 40-50% information market penetration level is desirable under real-time information supply strategy, 5) Incident management strategies have more benefit in travel time reliability rather than average trip time, 6) departure time switching behavior has significant impact on system evolution, and 7) non-informed users behavior is important in system evaluation and design. The results indicate that the impact of incidents on day-to-day dynamics and trip time reliability, the departure time dimension, and the response from non-informed users must be considered in network analysis and design. These results have some important implications for design of traffic control strategies, more effective ATIS implementation guidelines, and incident management strategies.

Future research on the impact of workzones on day-to-day dynamics is an interesting direction to find valuable practical insights to improve system cost and reliability. Furthermore, understanding the role of information strategies such as Dynamic Message Signs on incident and workzone management may also lead to insights to improve ITS strategic design.

CHAPTER VII

CONCLUSIONS

7.1 Overview

The goal of this research was primarily to achieve five major objectives. These five objectives have been achieved and each is summarized in the following paragraphs.

The first objective was to propose a robust network assignment algorithm to account for the randomness of trip time. This objective was achieved by developing a robust cost network assignment formulation with hybrid robust cost function that consists of a linear combination of the mean and variance of costs. A polynomial time algorithm was proposed to solve the robust cost optimization problem and models for several important variants of the robust cost minimization problem were proposed. The algorithm was then applied to a deterministic traffic assignment problem that minimized the hybrid robust cost objective for an experimental traffic network. The role of randomness (expressed in terms of the variance of link travel time) was investigated on the performance of the robust assignment solution relative to the expected system optimal travel time solution.

The second objective was to develop a dynamic simulation model for analyzing day-to-day dynamics under real-time information. The proposed framework accounts for the day-to-day variation in departure time and routing decisions through the use of empirically calibrated user behavior models and an agent-based belief-desire-intention architecture. This simulation framework provided a joint and mutually consistent representation of within-day and day-to-day dynamics in an integrated framework by integrating a dynamic assignment model (DYNASMART) with this day-to-day user decision framework.

With the simulation framework developed in objective 2, objective 3 thought to analyze the impact of internal perturbations, particularly the role of users' route and departure time choice behavior on day-to-day network dynamics and trip-time reliability. Two sets of experiments are conducted in objective 3. These experiments studied the effects of joint switching versus separate switching, and the influences exerted upon the initial conditions, in the form of different recurrent congestion levels and simultaneous versus sequential switching.

As a natural extension from objective 3, the fourth objective focused on investigating the role of transportation control measures (TCMs) on day-to-day evolution of network flow and trip time reliability. This objective involved analyzing the effects of staggered work hours, real-time information provision, telecommuting, and work-week compression on day-do-day dynamics and system evolution.

The fifth and last objective sought to analyze the effect of unplanned supply shocks (in the form of incidents) on day-to-day dynamics and system reliability. Specifically, two tasks were accomplished in this objective. First, the impact of the incidents was studied by systematically varying unplanned congestion levels (incident probabilities), conditional probability of different incident types, severity of the incidents, incident durations, and spatial distribution of incidents. Second, three ways of improving network performance and reliability (real-time information, incident management measures, and departure time switching rate reduction) were analyzed.

This chapter presents a summary of the key findings of this research and discusses the significance of the findings, and the future research needs in the area of day-to-day dynamics. Section 7.2 provides the summary of contributions from this research. Section 7.3 summarizes the key findings from the major objectives. The significance of findings and possible applications are discussed in section 7.4. The last section highlights possible future research directions.

7.2 Research Contributions

The major contributions emerging from this research can be classified as either methodological or empirical. Both are described in the following sections.

7.2.1 Methodological Contributions

In this dissertation research, a new network cost minimization formulation explicitly considering the robustness of the solution was proposed and an MSA based algorithm was developed to solve the problem. This research contributes new knowledge to network modeling under uncertainty in the following respects. A polynomial time algorithm was proposed to solve the robust cost optimization problem when real-valued flows are sufficient. The results showed that the optimal solution for this problem exists and is unique. Models for several important variants of the robust cost minimization problem were also proposed including: 1) minimum variance assignment problem, 2) robust cost minimization problem with integer constraints, and 3) robust cost problem with independent within-link flows. A two-stage heuristic was developed when integer valued solutions were demanded by the practical application (e.g. rental reservations acceptance problem). The robust cost optimization model has important implications for perishable inventory allocation decisions such as airlines, car-rentals, resorts, and hotels. These models may also be extended to infrastructure network design and operations such as telecommunication, airline and freight transportation networks, and project scheduling networks, where arc costs may be uncertain in nature.

The second significant methodological contribution is the day-to-day simulation framework development. To the researcher's knowledge, this framework is the first of its kind. The proposed framework accounts for the day-to-day variation in departure time and routing decisions through the use of empirically calibrated user behavior models and an agent-based belief-desire-intention architecture that was described in chapter 3. This simulation framework provides for a joint and mutually consistent representation of within-day and day-to-day dynamics in an integrated framework by integrating a dynamic assignment model (DYNASMART) with this day-to-day user decision framework.

The unique features of this simulator include: 1) an agent-based behavior modeling approach that incorporates empirically calibrated utility maximization models under information that accounts for user's past decisions, system dynamics and information quality. This agent-based architecture was used to represent within-day and day-to-day route choice dynamics and departure time adjustment decisions. In particular, this framework provides the capability of simulating all day-to-day related variables, past traffic experience and cumulative variables, and various performance measures of interest with respect to system volatility, system reliability, and information reliability that are often disregarded in within-day dynamic network models. 2) Multiple user classes with different switching behavior rules were explicitly modeled. 3) Day-to-day incident simulation procedure was developed to evaluate the impact of incidents on system reliability and performance. The development of this integrated simulation framework has important applications to modeling and forecasting network flow evolution over time, dynamic traffic assignment methodologies, and decision support for traffic management. This framework is also valuable for the design and implementation of ATIS information strategies and the evaluation of alternative traffic control strategies aimed at achieving desired system objectives. This framework can also have significant applications in supporting strategic and operational planning analysis.

7.2.2 Empirical Contributions

In Chapter 3, at the empirical level, the application of the proposed Robust System Optimal (RSO) assignment model to determine robust traffic assignment policy for static traffic assignment problem was presented. The RSO model was then used to elicit and understand the relative risk propensity (trade-off between travel time and travel time variability). The experimental results indicated that the RSO solution is very sensitive to 1) the degree of risk aversion, 2) the level of travel time variation, and 3) correlations among links. These results have important implications for understanding the reliability of travel time and robustness of traffic assignment solutions.

In Chapters 5 and 6, extensive experiments were conducted and analyzed to explore the role of user behavior factors, transportation control measures, and incidents on system performance and reliability. The findings from these experiments provided important insights on network modeling, design and developing congestion control and network reliability improvement strategies, understanding the impact of incidents within a day-to-day context and evaluation of effective incident management strategies. Significant findings and the significance of these findings are summarized in the next two sections.

7.3 Significant Findings

The major empirical findings from the research in this dissertation are presented in this section and their implications discussed in the next section.

In Chapter 3, the RSO model was used to elicit and understand the relative risk propensity (trade-off between travel time and travel time variability). The results indicated that the RSO solution can reduce nearly 15-35% of the travel time variance while only sacrificing 1-14% of average travel time. Another finding was that system variance gap increases rapidly with an increase of variation in travel time. The variance improvement of the RSO over the SO is significant with medium and high incident probabilities. Thus, using the RSO for highly uncertain environments may be more desirable, while the SO solution may a more logical choice for low travel time variation scenarios. The correlation scenarios showed that when correlation trends can be predicted, these may then be used to select robust assignment strategies at different times (e.g., peak and off-peak times). The selected strategy then applied to achieve more reliable system performance and to limit the extent of downside system travel time risk. Further, the results indicated that there is a limit to the extent of improvements in reliability possible purely due to reassignment of flows in a robust network algorithm. To achieve further reliability improvements, systematic variance reduction techniques that aim to reduce link travel time variability such as transportation control measures or incident management measures may be necessary.

In Chapter 5, the results revealed that the best performance was obtained when only route switching was permitted, and the worst performance occurred when there was no route-switching. The results also showed that system evolution is highly non-linear and sensitive to initial conditions. The system states differed considerably depending on whether the switching behavior was simultaneous or sequential in nature. The system did not converge to the same state and the evolution varied significantly depending on the interactions between route and departure time switching and their sequence. These results suggested that real-world network flows may exhibit non-unique average states under joint route and departure switching.

The following findings from the first set of experiments regarding system dynamics are also noteworthy. First, the high trip-time reliability observed in the severe congestion case, in turn, leads to high lateness arrival rates. Poor reliability, large system volatility and high lateness risk, in turn, induce a high degree of departure time switching, which further aggravates system dynamics. Second, substantial inefficiency and gap exists even after the system evolves for a period of 50 days between average system trip time and equilibrium trip times, and the gap increases as the level of congestion increases. Thus, severe congestion makes the system intrinsically unstable due to greater departure time switching and appears to be only moderately influenced by route switching decisions (through ITS etc.). Third, the data appear to suggest the possibility of a non-stationary and non-ergodic stochastic process driving system dynamics and variability.

In the user behavior experiments, the results suggested that departure time switching appears to exert a greater influence on day-to-day dynamics than route switching. When users were more sensitive to volatility and were more responsive to volatility (by switching departure times more aggressively), the volatility was in fact amplified rather than dampened. As users sensitivity to lateness increased, travel time performance improved substantially. Further, all reliability and volatility measures also improved significantly. The deterioration in system performance as departure time switching variance reduced, suggested that some degree of heterogeneity in departure time switching was beneficial to system stability. Deterministic models or models that assume more homogeneous user behavior may tend to underestimate system reliability metrics, if in fact, there is greater variability in user behavior. Therefore, in the context of modeling travel time reliability and stability, richer and more disaggregate models of user behavior and associated variability are needed.

The results in evaluating transportation control measures suggested that trip-time performance alone is not a good indicator as several of these control strategies lead to similar average performance measures. Furthermore, real-world networks can exist in a variety of states that may deviate significantly from equilibrium for substantially long-periods of time. There is a need to jointly consider the effect of trip-time and system reliability metrics while evaluating alternative strategies. The effectiveness of demand management strategies appears to be sensitive to the nature of the strategy and the level of implementation/adoption. The results indicated that the staggered work hour strategy is likely to be more successful than other strategies in terms of congestion mitigation. Furthermore, increasing the level of adoption appeared to produce a larger benefit than increasing the amount of departure time shift/stagger. The results also highlighted the fact that real-time information can lead to significantly improved on-time arrival rate (up from 39 to 51%), but significant trip-time variability is found in the system. Significant system improvement may be achieved through significant changes in departure time patterns, but such changes must be carefully coordinated. Nevertheless, the Transportation Control Measure (TDM) strategies appeared to be effective in steering the system performance closer to equilibrium travel times, but not necessarily towards the equilibrium state (i.e., high switching and volatility is still present).

In Chapter 6, the incident results showed that under incident scenarios, the day-to-day variation of trip time increased significantly, and the largest impact on trip time variability occurred under moderate congestion level. Significant impact of incident on day-to-day system performance and reliability was seen in this set of experiments. This suggests that considering the incident impact for system analysis and evaluation is necessary, and some form of coordination through information supply may be needed to users to steer the system to more desirable states. In the incident characteristic scenarios, the incident severity had the largest impact on system performance, and incident frequency had the least impact. The influence of incident characteristics on system reliability was much larger than on travel time. The duration reduction did have significant impact on system performance and reliability.

The results from real-time information market penetration experiments implied that the benefit of larger market penetration decreased as the MP increased, though the system can still perform slightly better. This set of experiments suggested that moderate market penetration level (40%-50%) is desirable from both average trip time and day-to-day trip time reliability perspective, whereas higher market penetration levels maybe considered if a lower benefit – cost ratio is acceptable. In the incident management experiments, the results showed that the incident management programs were much more effective in improving travel time reliability than was improving average travel cost. With further incident management improvements, additional improvements to the system and its reliability of performance may occur but with a lower benefit – cost ratio. Under different incident duration reduction scenarios, the user behavioral measures did not change significantly. This implied that the quicker restoration of highway capacities by better incident management strategies might not be fully utilized by commuters. There are opportunities exist to further improve the benefits introduced by the incident management strategies. More effective information provision strategies might be used to improve the information dissemination and user's responsiveness, thus further increasing the benefit of the incident management program. In the last set of experiments, the results indicated that a low departure time switching rate can lead to more effective route switching. The results implied that models ignoring or over-simplifying the departure time switching behavior can be misleading and tend to overestimate the system performance.

7.4 Significance of Findings

The robust cost assignment algorithm proposed in Chapter 3 can be used in two ways to assess the variability/risks associated with alternative assignment strategies. First, if a decision-maker's relative preference towards travel time and its variance is well-formed, this can form the basis to determine the preference weight for cost variability.

The robust cost assignment problem may then be solved to yield the assignment strategy that minimizes the robustness of travel time for the given risk tolerance level. However, the preferences towards risk are not well-formed in practice due to the heavy focus on travel cost minimization in current practice. In such a case, several optimal policies can be determined by repeated solving of the RSO problem corresponding to various values of alpha. The corresponding average costs and risk can be determined for each value of alpha. These solutions can then be used to obtain a risk and average travel time trade-off curve that is used to inform decision-makers about the risk/cost trade-offs. The risk-cost trade-off curve can be used to elicit decision-maker preferences regarding the most desired risk/average travel time combination. The assignment policy corresponding to this preferred risk/cost combination can then be implemented in practice. Alternatively, the proposed solutions can be used to provide benchmark levels of variability of travel times, against which the variability in travel time with currently used practices (user equilibrium assignment, etc.) is compared to assess the acceptability of current travel time risk.

The results from Chapter 3 have important implications for understanding the reliability of travel time and robustness of traffic assignment solutions. The robust cost optimization model also has important implications on perishable inventory allocation decisions such as airlines, car-rentals, resorts, and hotels. These models may also be extended to infrastructure network design and operations such as telecommunication, airline and freight transportation networks, and project scheduling networks, where arc costs may be uncertain in nature.

The findings from Chapter 5 have several important implications for dynamic network analysis, design of transportation control strategies to enhance system performance, and travel time reliability. First, empirically calibrated levels of users' sensitivity to late schedule delay, day-to-day stability and reliability were poor (compared to high sensitivity). Second, while implementing measures such as flexible work hours, caution must be exercised and the influence of users sensitivity to late schedule delay should be recognized. Low sensitivity to late schedule delay due to certain travel demand measures may more than offset the short-term benefits due to departure time staggering of certain users.

Findings in TCM experiments have important implications for the evaluation of transportation control measures. First, the use of both very short-term and very long-term horizons for analysis methods can lead to erroneous system state predictions, especially due to the presence of trends and oscillatory behavior. For example, in the telecommuting and staggered work hour cases, the first two-weeks of data tended to overestimate the system benefits. On the other hand, using very long-term horizon was also misleading due to non-stationarity and significant deviations existed from user equilibrium models for significant periods of time. Second, care must be exercised in evaluating demand control measures since several of the effectiveness of some of these strategies were sensitive to the level of adoption/deployment (system exhibits very different evolution patterns depending on the level). Third, the dynamic evolution and the non-linear features observed empirically along with the deviation from short-term and long-term predictive models, underscored the need for the collection of richer empirical field data (including switching behavior) over reasonably long-periods of time (at least several months) while evaluating transportation control measures. While this study provided preliminary evidence of highly non-linear system evolution from day-to-day, new modeling tools and insights may be needed to uncover the nature and causes of the observed transient states (e.g., chaotic, stability, stationarity), particularly in order to understand the limits and uncertainty associated with model-based predictions.

The findings in chapter 6 are important for the following reasons. First, experimental results showed that incidents had very significant impact on day-to-day dynamics of system evolution, especially on trip time reliability. These results showed that at least at some level of system configuration, the current assumption of primary within-day impact from incidents in practice is misleading. Secondly, the impact of uninformed user behavior had been generally neglected in previous analyses, but was shown to be very important as a means of introducing very significant system performance benefits. Furthermore, the impact of departure time dimension on system performance had been generally neglected in previous research that was shown to have a significant impact on system dynamics especially under incidents. Lastly, the benefits of incident management strategies mostly impacted system reliability and volatility, rather than system cost. These findings should help develop more appropriate guidelines for future network analyses and evaluations.

7.5 Directions for Future Research

Regarding future research directions, further expansion of the basic algorithm described in Chapter 3 to robust user equilibrium assignment algorithm is desirable. User equilibrium assignment received more attention in practice, and certainly much more can be studied. Furthermore, the robust algorithm may be extended to a time-dependent robust UE and SO algorithm, and would add the ability to model time-dependent features such as departure time and route switching. From a practical point of view, exploring robust information strategies is a natural direction of future research. With regard to theoretical direction, qualification of variance as a function of flow is another challenging direction for future research.

The following research issues arise naturally in the context of day-to-day system evolution. At the theoretical level, the nature of stochastic process underlying day-to-day dynamics and the extent of possible non-ergodicity and its implications for network planning and design warrants further inquiry. A final theoretical direction worth considering for future research involves the idiosyncrasies of particular networks.

With regard to dynamics, examining the role of lagged effects, possible asymmetries in evolution and their persistence over time need to be examined. Future research on the impact of workzones on day-to-day dynamics is an interesting direction to find valuable practical insights to improve system cost and reliability. Understanding the role of information strategies such as Dynamic Message Signs on incident and workzone management may also lead to insights on improvement of ITS strategic design. From a policy and planning standpoint, investigating the short-term and longer-term impacts of pricing based strategies (congestion pricing, or gas price increases) and vehicle occupancy increasing measures (such as HOV/HOT) may also be of interest.

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