EXPLORING THE BENEFITS OF INTEGRATED CORRIDOR MANAGEMENT: THE ROLE OF PRICING

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Abstract

Highway congestion is still a major problem in traffic operations and management, and the search for feasible mitigation measures continues to evolve with advancement in technology and better understanding of traveler behavior. Many congestion mitigation strategies have been implemented in the past; but they were unable to improve traffic conditions for entire transportation corridors due to lack of coordination among corridor stakeholders. These strategies were implemented on individual transportation facilities in a corridor and often ended up improving conditions on one facility at the expense of others. Therefore, coordinating the management of transportation facilities within a corridor offer an opportunity to operate and improve traffic conditions in the entire system as opposed to individual facilities. This concept of congestion management is referred to as Integrated Corridor Management (ICM).

While ICM holds the potential to mitigate highway congestion, a major problem faced by transportation agencies who intend to adopt its use is the identification and selection of the most beneficial strategies to implement in a corridor. This research proposed a five-step ICM evaluation methodology based on which strategies that will benefit the operational needs of a transportation corridor can be identified. The proposed evaluation methodology was applied to a real-world transportation corridor in northern Virginia (section of I-95/I-395) to determine the feasibility of ICM implementation in this corridor using a simulation. Based on the analysis of simulation results, variable speed limit system, increasing transit and parking capacity, HOV lanes, and HOT lanes were identified as the most beneficial strategies under both incident and non-incident conditions. As a result of ICM implementation, average corridor person flow increased by 6,860 persons per hour (+37.8%) and 3,286 persons per hour (+14.4%) under incident and non-incident conditions respectively.

The use of pricing to influence driver behavior through the HOT lane concept has been identified as a very important ICM strategy by most ICM initiatives. The evaluation of the impact of pricing in the ICM methodology developed in this research (as well as those developed for pioneer ICM sites) was based on long-term average mode and route shifts associated with pricing due to limited published knowledge on how tolls affect drivers' decision to use/not to use HOT lanes in real-time. This research investigated how drivers responded to tolls using data from four HOT lane facilities in the U.S. The purpose of this approach was to determine if there is a general pattern in driver behavior in terms of their response to tolls. Analysis results revealed that, elasticity of HOT lane demand with respect to tolls is positive and statistically significant but inelastic (below +0.2). During peak periods, the elasticity further reduced to an average of +0.07. This implies that drivers' decision to use/not to use HOT lanes is not greatly influenced by toll prices but by other factors such as travel time reliability, level of congestion, etc. The positive and inelastic relationship observed in this research goes against conventional wisdom that drives use of HOT lanes: tolls are supposed to discourage drivers from using HOT lanes. This suggests the probability that the tolls are not allowed to rise to a level where supply/demand can take place.

For ICM to be effective, it must be possible to anticipate the results of any implemented strategy. This research developed models to predict the demand for HOT lane use for each of the studied facilities based on tolls and changing traffic conditions. As expected, the performance of the model in predicting absolute demand wasn't outstanding due to the weak relationship between

HOT lane demand and tolls. However, the models fairly predict (about 70% of the time) the expected level of service conditions on HOT lanes.

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Chapter 1

Introduction

Highway congestion continues to be a major problem in traffic operations and management, and the search for feasible mitigation measures keeps evolving with advancement in technology and better understanding of traveler behavior. According to the Texas Transportation Institute's (TTI) Urban Mobility Report 2012, travel delay per commuter was 38 hours, total delay was 5.52 billion hours, and total fuel wasted was 2.88 billion gallons, amounting to $121.2 billion for the entire U.S. in 2011. Between 1982 and 2011, the cost of congestion increased by over 400% *(1)* despite investments in different congestion mitigations strategies during this time period. Demand for highway travel by Americans continues to grow as population increases, particularly in metropolitan areas *(2)*; therefore, transportation professionals must develop innovative means of realizing the full capacity benefits of existing facilities since the addition of new physical capacities alone cannot keep up with the pace of this rising demand.

Many congestion mitigation strategies have been proposed and implemented over the years. These strategies comprises both operational improvements and travel demand management. Operational improvement strategies such as incident management *(3)*, ramp metering *(4)*, variable speed limit *(5)*, real-time traveler information *(6)*, etc. have been found to lessen the impacts of highway congestion. Similarly on the demand side, some of the congestion mitigation strategies include High Occupancy Vehicle (HOV) facilities *(7)*, congestion pricing *(8)*, transit fare policies *(9)*, etc. Until recently, a disjointed approach towards congestion management in a transportation corridor has been the modus operandi. Managers of different transportation facilities (e.g. freeways, arterials, etc.) in a corridor mitigated congestion by focusing only on improving conditions of those facilities that fall under their jurisdiction. This frequently results in inefficiencies at network junctions (e.g. freeway/arterial junctions), and fails to achieve the maximum possible benefits of such mitigation measures on the entire transportation system. Integrated Corridor Management (ICM) provides an opportunity to effectively mitigate congestion by coordinating the management and operation of multimodal transportation facilities to improve traffic conditions in the entire corridor. This ensures that existing capacities on the different facilities/modes within a corridor are effectively utilized. Identifying the right combination of ICM strategies to mitigate congestion in a corridor can be quite challenging; however, this is very crucial to the success of an effective ICM.

High Occupancy Toll (HOT) lanes have been identified by most of the ICM pioneer sites as a critical congestion mitigation strategy with high benefit-cost ratio *(10,11)*. This strategy employs pricing to regulate use of the extra capacity on HOV lanes by Single/Low-Occupant vehicles (SOV/LOV) in order to prevent the HOV lanes from becoming gridlocked. Supposedly, the tolls are required to discourage SOV/LOVs from using the HOT lanes. However, there is limited published knowledge on how the tolls affect drivers' decision to use/not to use the HOT lanes. Many of the existing research efforts on this topic have focused on specific HOT lane facilities, making their findings site specific *(12–15)*. Therefore, there is the need to investigate how drivers from different locations/regions respond to tolls and changing traffic conditions; this will help to determine if there is a general pattern in driver behavior in terms of their response.

Managing highway congestion effectively requires a proactive approach. For ICM to be effective in congestion mitigation, the system must be able to anticipate how drivers/travelers will react to strategies before their implementation. Although pricing is used in HOT lanes, it only reacts to driver/traveler behavior; that is, when demand for HOT lane use increases, tolls are increased and vice versa. If the HOT lane concept is to be a critical component of ICM, then the demand for its use by drivers/travelers must be predictable. Knowing the expected level of demand on the HOT lanes will enable managers to put in place strategies to avoid traffic breakdown. Till date, HOT lane demand prediction is carried out only when the feasibility of HOT lane implementation is under consideration. The intended purpose of such prediction is to estimate the expected revenue from HOT lane use once it is built *(16)*. Predicting HOT lane demand in real-time (e.g. every 5 minutes) for operational purposes (managing demand in real-time) is not a common practice.

As a result of discussions in the preceding paragraphs, this dissertation focused on how to make ICM more effective as a congestion management tool by investigating some of its key components. These include how to identify the right strategies during the planning stages of ICM implementation, exploring the general behavior of traveler response to HOT lane tolls (pricing) and changing traffic conditions, and how to make ICM more proactive by predicting expected demand for HOT lane use.

1.1 Research Objective and Scope

The specific objectives of this research are as follows:

1. To develop an evaluation methodology based on which beneficial ICM strategies can be identified.

2. To investigate driver behavior in terms of how they respond to HOT lane tolls (pricing) and changing traffic conditions using data from multiple HOT facilities. This will help to determine if there is a general pattern in the behavior of HOT lane users' response to pricing.

3. To develop a predictive model that can be used to estimate HOT lane demand levels in real-time for effective ICM.

The scope of this research is focused on HOT lane facilities with real-time dynamic tolling capabilities. These are facilities in which the tolls charged are dynamic and not pre-determined. The tolls are based on real-time conditions on the HOT lanes and fluctuate at regular short intervals (e.g. every 5 minutes). Therefore when density on HOT lanes increases, tolls are also increased and vice versa. Drivers using corridors with HOT lanes have no prior knowledge of the actual toll amount at any point in time; they are only notified through dynamic message signs (DMS) when they approach HOT lane entry points and have a short period of time to decide whether to use it or not.

In this dissertation, the words "drivers", "users" and "travelers" will be used interchangeably. They all refer to people who travel on transportation corridors with HOT lanes and parallel

General Purpose (GP) lanes operating side by side. These people are potential users of the HOT lanes depending on their choice behaviors.

1.2 Research Motivation

ICM has gained traction in recent years as a potential congestion management tool, and as the pioneer sites continue to demonstrate its use and expected benefits, a couple of observations have been made. These observations, as explained below provided the motivation for this research.

1.2.1 ICM and the Selection of Potential Strategies

Integrated Corridor Management (ICM) can be described as the coordination of the day-to-day operation of distinct transportation networks/facilities (freeways, arterials, transit systems, etc.) within a clearly defined geographical region (corridor), with the aim of improving mobility, safety and efficiency of the existing transportation system *(17)*. Transportation corridors often contain underutilized capacity in the form of parallel routes (freeways, arterials, and HOV lanes), single-occupant vehicles, and transit systems operating below capacity that could be tapped to help reduce congestion *(18)*. ICM utilizes real-time information integration and dissemination technologies - combining fragmented traffic information together and delivering it to travelers - so that they can make sound travel decisions, by either changing their travel mode, departure time, or even destination, to avoid congestion *(19)*. Figure 1 describes a generic ICM corridor composed of freeways (managed by the State DOT), arterials (managed by individual cities), rail lines (managed by regional rail agency), and bus transit (managed by the bus company).

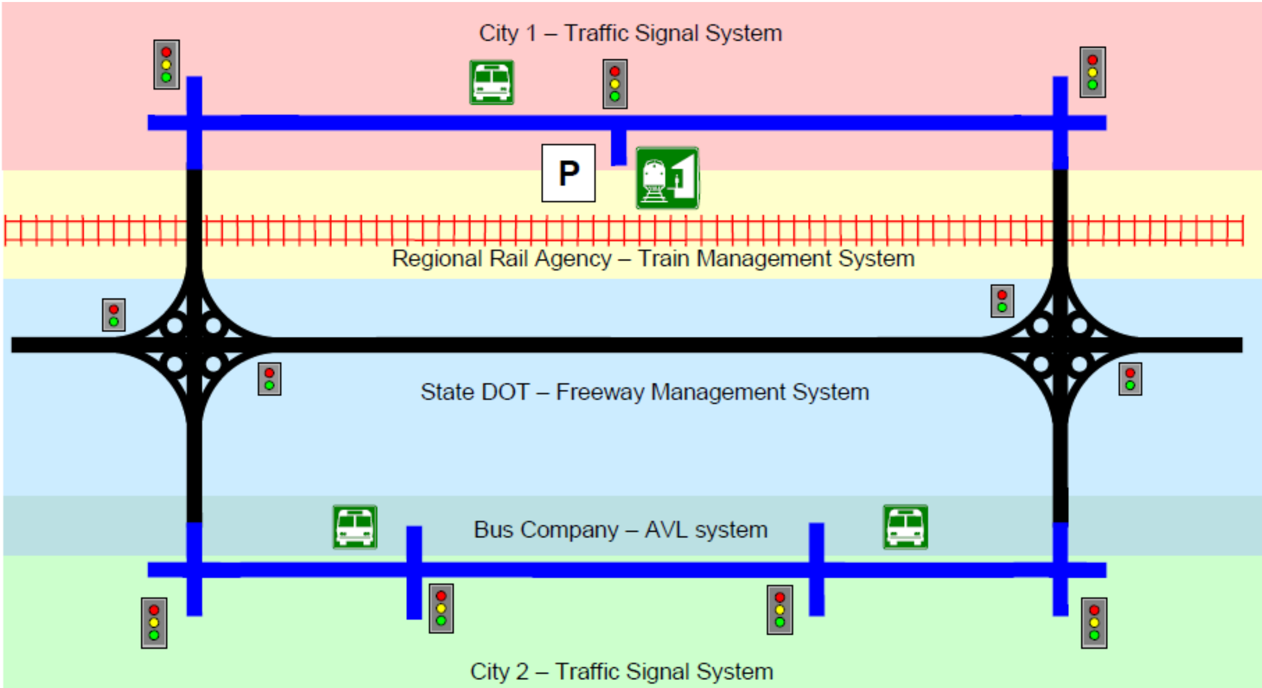


Figure 1.1: Generic ICM corridor (Source: ICM implementation Guidance, FHWA, 2006)

Selection of the most beneficial combination of strategies to implement is very critical to the success of ICM as a congestion management tool. An Analysis, Modeling and Simulation (AMS) methodology has been developed for three of the ICM pioneer sites (Dallas, TX; Minneapolis, MN; and San Diego, CA) to help identify the most beneficial ICM strategies. In *Integrated Corridor Management Analysis, Modeling, and Simulation Experimental Plan for the Test Corridor*, Alexiadis (2008) outlined details of the AMS methodology and its application to ICM sites *(20)*. A summary of the methodology is provided below.

The AMS methodology applies macroscopic trip table manipulation for the determination of overall trip patterns, mesoscopic analysis of the impact of driver behavior in reaction to ICM strategies (both within and between modes), and microscopic analysis of the impact of traffic control strategies at roadway junctions (such as arterial intersections or freeway interchanges). The methodology also includes a simple pivot-point mode shift model and a transit travel-time estimation module, the development of interfaces between different tools, and the development of a performance measurement and benefit/cost module.

In this AMS framework, macroscopic, mesoscopic, and microscopic traffic analysis tools can interface with each other, passing trip tables and travel times back and forth looking for natural stability within the system. Absolute convergence may not be achieved because of inherent differences at the various modeling levels. This methodology will seek a natural state for practical convergence between different models, and the iterative process will be terminated or truncated at a point where reasonable convergence is achieved.

The AMS methodology described above, though comprehensive, is a high level conceptual framework with little guidance on implementation. Therefore, most transportation agencies currently considering the adoption of ICM have to come up with their own methodologies to identify beneficial strategies. This dissertation presents a five-step evaluation methodology based on which the most beneficial combination of ICM strategies can be identified.

1.2.2 HOT Lane Driver Behavior

HOT lanes use electronic toll collection and traffic information systems that make it possible to provide variable, real-time toll pricing for SOVs and LOVs *(16)*. The pricing information enables potential users to decide whether or not to use the HOT or GP lanes**.** That is, the pricing is intended to influence travelers' behavior in terms of the decision to use/not to use the HOT lanes. Many of the research efforts in how HOT lane toll pricing affect the behavior of travelers have focused on specific HOT lane facilities, making their findings site specific *(12–15)*. HOT lane driver behavior has often been evaluated in two ways: in terms of their Value of Travel Time Savings (VTTS) /willingness to pay and HOT lane demand elasticity with respect to price.

Brownstone et al. (2003) investigated the behavior of drivers on the I-15 Fast Trak express lanes in San Diego for a two-month period, in October and November 1998. The study found that, the median cost of hour of travel time savings that drivers were willing to pay was $30.0 per hour *(21)*. Another study on the I-394 MnPASS HOT lanes in Minneapolis by Burris et al. (2012) examined travelers' willingness to pay for travel time savings using three years of data from 2008. The authors found that, travelers' VTTS averaged $73 per hour in the morning and $116 per hour in the afternoon *(12)*. VTTS for users of I-85 express lanes in Atlanta were also studied by Sheikh et al (2014) using 9 months of toll and travel time data. The study concluded that the median VTTS was $36 per hour in the morning peak and $26 per hour in the afternoon peak *(13)*. Although the above mentioned findings are important and contribute to the state-of-knowledge of HOT lane driver behavior, they are site specific and do not apply to driver behavior on other HOT lane facilities. Additionally, since each of the research efforts was conducted for a specific site, it is difficult to identify possible reasons for the similarities and differences in their findings. For example, the VTTS obtained for the study on 1-85 express lanes during the morning period ($36 per hour) *(13)* is almost half the VTTS reported for I-394 MnPASS HOT lanes for the same time period ($73 per hour) *(12)*. However, reasons for such a huge difference in VTTS estimates cannot be readily determined because both facilities were not examined together.

As a result of the limitations of the site specific HOT lane driver behavior findings, there is the need to investigate the behavior of drivers across multiple HOT lane facilities in different locations. Such a study will help to determine if there is a general pattern in HOT lane driver behavior in terms of their response to toll prices and changing traffic conditions. Furthermore, studying multiple HOT lane facilities together affords the opportunity to identify factors that causes users of any pair of HOT facilities to be similar or different in their behavior. Understanding the underlying causes of the observed behavior in HOT lane users will provide significant insights about the use of pricing in ICM.

1.2.3 Predicting HOT Lane Demand

Prediction of HOT lane demand has been usually done at the planning stages of HOT lane implementation where demand forecasting is done for both HOVs and SOVs. Predicting HOT lane demand at the planning stage serves a dual purpose: first, it allows the project sponsor to determine the combination of pricing and occupancy requirements that maximizes transportation benefits for all motorists traveling in the HOT lane corridor. Secondly, it allows the project sponsor to forecast revenue streams and then evaluate financing approaches *(16)*. Currently, there are no known models in the existing HOT lane literature that predict dynamically-priced HOT lane demand for operational purposes. That is, there are no known models that can help transportation professionals to determine the expected demand for dynamically-priced HOT lane use at different toll prices and traffic conditions in real-time. Many of the models found in the HOT lane literature have been developed to identify factors that influence the decision of drivers to use HOT lanes *(22,23)*. For ICM to be effective and proactive, it should be possible to anticipate the consequences of implemented strategies. For example, during peak periods, it should be possible for transportation professionals to know the expected level of HOT lane demand for a certain toll price and traffic condition in order to prevent the lanes from been gridlocked. The purpose of this dissertation is to help fill the knowledge gap in HOT lane demand models useful for real-time traffic control management.

1.3 Research Contributions

This dissertation will add to the body of knowledge of ICM and HOT lane systems. The specific contributions include the following:

1. This research provided an evaluation methodology based on which transportation agencies will select the most beneficial combination of ICM strategies to implement in their corridors.

2. Previous efforts in HOT lane driver behavior research have either focused on one or two HOT facilities, making their findings site specific and less generalizable. This dissertation used data from multiple HOT lane facilities located in different geographical regions to determine whether or not there is a general pattern in HOT lane driver behavior.

3. Prediction of HOT lane demand has traditionally been conducted at the planning stages of HOT lane implementation mainly for financial feasibility purposes. Hence, there are no known predictive models that can be used to effectively manage HOT lane demand in real-time. In this dissertation, predictive HOT lane demand models that can be used to estimate expected Level of Service (LOS) on the lanes were developed. Such predictive models will help to make ICM proactive.

1.4 Report Organization

The remaining chapters of this dissertation are organized as follows:

Chapter 2 reviews existing literature on the ICM concept, HOT lane driver behavior and the prediction of its demand. Chapter 3 presents an ICM evaluation framework based on which transportation agencies will select strategies that are beneficial to the operational needs of their corridors. Chapter 4 analyzes driver behavior across four HOT lane facilities to determine if there is a general pattern. In Chapter 5, development of HOT lane demand models for operational purposes is discussed. Chapter 6 summarizes the research and its key findings. Finally, Chapter 7 discusses the major research contributions arising from this dissertation, and identifies areas for future research.

Chapter 2

Literature Review

Literature on past research works on Integrated Corridor Management (ICM), High Occupancy Toll (HOT) lane driver behavior and HOT lane demand prediction were reviewed to understand the current state-of-knowledge in these areas. Detailed discussions on each area are presented below.

2.1 ICM Concept

The ICM concept enables transportation agencies to optimize the use of available infrastructure by providing travelers with real-time information on traffic conditions in a corridor based on which informed travel decisions can be made. The information provided to travelers may help them to change trip departure times, routes, mode of travel etc. The success of ICM hinges on three main pillars:

1. Intelligent Transportation Systems (ITS): Technology is an essential ingredient in ICM. Recent advancements in ITS technologies provide the opportunity to integrate network operations so as to manage total corridor capacity *(24)*. ITS technologies such as real-time traveler information, parking management systems, transit signal priority, and electronic tolling systems enhance holistic optimization of transportation systems. This presupposes that investment in ITS technology must precede the implementation of ICM. The ability of ICM to be proactive rather than being reactive is made possible through ITS, which facilitates the capture and rapid processing of traffic information in order to make informed decisions.

2. Stakeholders Partnership: ICM employs a collective approach to optimize the transportation system in a corridor. To accomplish the goals of ICM, all partner agency representatives must put aside their bias as they strive to operate the corridor in a true multimodal, integrated, efficient, and safe fashion where the focus is on the transportation customer. A stakeholder is a person or group with a direct interest in the integration of the corridor and the associated networks and network linkages. These include municipalities, counties, Metropolitan Planning Organizations (MPO), transit authorities, Traffic Management Centers (TMC), etc. It is important to identify all stakeholders as early as possible so as to incorporate their needs and views in the concept development phase. The number and types of corridor stakeholders depend on the transportation networks included in the corridor and the proposed ICM concepts *(25)*.

3. Information Sharing: As part of the partnership between stakeholders, there is the need to share real-time traffic and incident information within the corridor for the purpose of enhanced decision making. Comparative real-time corridor data on freeways, HOV lanes, arterials, and transit facilities need to be shared among the various operating agencies in order to determine the appropriate strategies to be implemented. Information

can be shared through voice, data, video and other media depending on the protocols adopted *(25)*.

2.1.1 ICM Implementation

A generic 2006 ICM implementation guide by Neudorff et al. outlined the steps involved in implementing ICM *(26)* .The procedure is based on the principles of systems engineering, a formal process by which quality is continuously promoted. The systems engineering process is often portrayed as a "V" so as to relate the different stages in the system life cycle to one another. The V-shaped model helps to show the relationship between the works done on each side of the "V"; for example, the testing of activities on the right side of the "V" is based on the results (e.g., concept of operations, system requirements, etc.) from the corresponding steps on the left side of the "V".

The individual components of the V-shaped systems engineering process include:

- Concept Exploration: Identifying the need for corridor management based on an existing regional ITS architecture and establishing corridor stakeholder group. Consequently, potential corridors and initial boundaries are identified.

- Systems Engineering Management Plan: Involves the development of a management plan that will be used to implement ICM.

- System Conception: This is an important stage in the systems engineering process since it explicitly defines the ICM concept. It involves inventorying existing systems, identifying existing corridor conditions, the establishment of corridor vision and goals, identifying potential ICM approaches and strategies, etc. Systems conception leads to the development of the concept of operations for ICM.

- System Requirements: This stage of the process looks into defining system level requirements (standards) that will be applicable to the already developed concept of operations. It includes high level ICM requirements, detailed ICM requirements, institutional requirements, and performance analysis. This stage results in a system requirements document.

- ICM High-Level Design: Decomposition of requirements into alternative architectures and identifying system interfaces. This results in the development of an ICM architecture that is consistent with the regional ITS architecture.

- ICM Detailed Design: Decomposition of system and subsystems into hardware, software, database, and other individual components. Subsequently, technologies and design features of each component are laid out.

- Implementation and Deployment: This stage transforms ICM designs into an operating system by verifying and integrating units and subsystems through hardware fabrication, software engineering, and coding. ICM is then deployed and verified for acceptance based on already defined requirements and standards.

- ❖ Operations and Maintenance/Evaluation: Managing effectively, the day-to-day operations of the ICM in accordance with operations and maintenance plan. The performance of the system is evaluated continuously, and changes/replacements are made when necessary.

Numerous literatures are available from the pioneer sites on the development of the concept of operations, system requirements, and analysis, modeling, and simulation methodology for ICM. The remaining stages of the systems engineering process for ICM are still in development.

2.1.2 Concept of Operations (Con Ops)

According to Neudorff et al. (2006), the concept of operations is a formal document that provides a user-oriented view of ICM, its approaches and strategies, and the associated operations *(25)*. The concept of operations answers the following questions:

- ❖ What: the known elements and the high-level capabilities of the system.
- ❖ Where: the geographical and physical extents of the system.
- ❖ When: the time-sequence of activities that will be performed.
- ❖ How: resources needed to design, build, operate, and maintain the system.
- ❖ Who: the stakeholders involved with the system and their respective responsibilities.
- ❖ Why: justification for the system, identifying what the corridor currently lacks, and what the system will provide.

The Con Ops does not delve into the technological requirements of the ICM system, but addresses the operational scenarios and objectives, information needs, and overall functionality. It must also address the institutional environment in which ICM must be deployed, operated, and maintained. Some of the benefits of Con Ops include:

- ❖ Providing a means for engaging ICM stakeholders in order to solicit their views on existing problems and possible solutions.
- ❖ Providing a means of describing stakeholders' operational needs for ICM without getting into details.
- ❖ Identifying institutional, technical, and operational environment in which ICM will function.
- ❖ Formulating definitions and descriptions for ICM and its associated operations.

The development of Con Ops is divided into the following tasks:

Identification of ICM Corridor Boundaries and Travel Characteristics

The boundaries of the proposed corridor must be clearly defined. Corridor boundary definition include its length, constituent individual transportation networks (such as freeways, arterials, railway lines, frontage roads, bus transit systems, toll roads, park-and-ride lots, etc.), any natural features such as rivers within a specified proximity, the geographical orientation (north-south or east-west), the adjoining cities and suburbs, and any other feature or infrastructure whose proximity will affect the corridor's operation.
The travel characteristics of individual transportation networks within the corridor and the areas they serve need to be identified as well. These include capacities of freeways and arterials, the kind of service they provide (commuter, local or regional traffic), economic activities that might influence travel patterns, etc.

Identification of Corridor Stakeholders and Users

By default, the operating agencies of all the individual transportation networks that constitute the corridor are stakeholders. These include State DOTs, City department of public works/transportation, railway agencies, transit agencies, etc. Another category of stakeholders provide support service and law enforcement. These stakeholders include City and State police, and Fire departments (ambulance and hazardous materials services). Administrative and federal agencies such as MPOs, the Department of Homeland Security (DHS), the Federal Emergency Management Agency (FEMA), Virginia Department of Emergency Management (VDEM), the Virginia Department of Environmental Quality (VDEQ), the Federal Transit Agency (FTA), and the Federal Highway Administration (FHWA) are also part of the corridor stakeholders.

Additionally, institutions and businesses whose activities will be impacted by the corridor's operations will have to be involved in the development of the Con Ops. Examples of such institutions and businesses are courier fleets (U.S. Postal Service, Federal Express, etc.), information service providers, and visitors bureau (representing tourists that use the corridor).

Identification of Needs and the Potential for ICM

The inefficiencies and bottlenecks affecting transportation operations within the corridor have to be outlined, and the potential for ICM to provide the necessary remedies must be demonstrated. Typical issues that undermine efficient transportation systems include congestion during peak periods, bus schedules that are not adhered to, underutilization of existing capacity, lack of coordination and information-sharing among various operating agencies, sparse and disintegrated real-time traveler information, etc. Hence, there is the need for real-time information-sharing (data, video) between all agencies, more of a "corridor-wide" and multi-modal view of ITS operations, improved operational coordination of networks in the corridor, increased transit usage, coordinated and efficient responses to incidents among all stakeholders, and improved dissemination of real-time traveler information across all networks from a single source. The needs listed are not exhaustive and must reflect the existing conditions of the corridor. ICM has the potential to address all these needs, since it focuses on the operational, institutional, and technical coordination of multiple transportation networks and cross-network connections within a corridor.

ICM Vision, Goals, and Objectives

A vision statement outlining the goals and objectives of ICM and the benefits corridor users stand to gain after its implementation must be developed by stakeholders. Using the vision statement as a starting point and taking into consideration the current operating conditions of the corridor, stakeholders will develop specific goals and objectives of the ICM project. The ICM goals and objectives generally revolve around the following:

- ❖ Corridor perspective: Corridor goals and objectives take precedence over that of individual transportation facilities.

- ❖ Corridor mobility and reliability: Improving travel time predictability and reducing travel times by enabling multi-modal travel and the utilization of spare capacity.

- ❖ Corridor traveler information: Providing accurate, reliable, and timely travel time information regarding the entire corridor to enhance traveler decision-making.

- ❖ Corridor event and incident management: Providing a corridor-wide and integrated approach to event and incident management, so as to minimize traffic disruptions and the impacts of such incidents.

ICM Operational Approaches and Strategies

After setting the goals and objectives of ICM, stakeholders must identify means of achieving those targets by enumerating specific strategies that can be used. Examples of ICM strategies and the approaches adopted to implement them are shown in Table 2.1 below.

Approach	Idea	Strategy(ies)
Information sharing/Distribution	1. Sharing of real-time information among stakeholders 2. Formation of a corridor-based advanced traveler information system that can be accessed by travelers and value-added entities	1. Pre-trip websites, 511 2. En-route Dynamic Message Signs (DMS), transit public announcement systems
Optimizing operations at network junctions and interfaces	1. Improving cross-network operations 2. Encouraging multi-modal travel 3. Improving communications and protocols among agencies	1. Transit signal priority 2. Transit hub connection protection (e.g., holding buses at rail terminals) 3. Coordinated operation between ramp meters and arterial signals

Table 2.1: Examples of ICM strategies and approaches

ICM Concept Operational Description

This explains how ICM will function operationally after its implementation. To ensure effective ICM operation, a central corridor decision-making body referred to as the Corridor Operating Panel (COP) must be established. This body will be composed of delegates from each of the stakeholders of the corridor. Second, a control center that will manage the daily operation of ICM must be put in place. This could be a physically centralized (a dedicated building facility) or virtual control center.

Any of the participating corridor agencies with available space in their building facilities can house the control center, or else a new facility should be acquired. However, as a result of high costs associated with the acquisition of new building facilities or lack of available space, a virtual ICM control center would be a cost-effective alternative.

Regardless of the type of ICM control center, there must be a well-defined communication platform based on which real-time data exchange among participating agencies can be carried out. In the event that a participating agency provides space to house the ICM control center, that agency can be the lead agency for the daily operation of ICM. Functions of the control center would include:

- ❖ Investigate and prepare response plans for various scenarios that are likely to occur in the corridor.

- ❖ Identify performance measures based on which the effectiveness of ICM strategies can be evaluated.

- ❖ Develop and deploy a decision support system for rapid response to changing corridor traffic conditions.

- ❖ Monitor corridor travel conditions, implement response plans, and inform participating corridor agencies on prevailing traffic conditions and the impacts of implemented response plans.

The ICM control center would be run by a chief corridor operating officer to be appointed by the COP and supported by either existing staff within respective participating agencies or dedicated staff. Finally, an effective communication channel between corridor traffic managers and travelers as well as among participating ICM agencies is very important to successful ICM operation. Travelers must be kept informed in real-time about prevailing traffic conditions through 511, DMS, websites, radio stations, mobile applications, etc. A real-time communication protocol and standards for information-sharing among agencies and critical support staff must also be adopted.

Required Assets and ICM Implementation Issues

This concerns the identification of ITS asset gaps and potential problems that may affect ICM implementation. The potential problems are grouped into three categories:

1. Technological issues: e.g., Adoption and implementation of ITS standards for the center-to-center (C2C) connections, integration of these standards, bandwidth requirements for C2C communications, etc.

2. Operational issues: Procedure for the shared use of resources/ shared control of ITS assets, policies for implementing demand/capacity management strategies, potential safety concerns for ICM strategies, etc.
3. Institutional issues: Establishment of a more formal institutional structure to bridge the differences between the various operating agencies, establishment of protocols among operating agencies for real-time data-sharing, decision-making and implementation, recruitment of dedicated staff for ICM operations, etc.

ICM Concept Institutional Framework

This relates to the institutional framework based on which ICM will be implemented, operated, managed, and maintained. This framework establishes the leadership of the corridor decision making body (i.e., COP), project initiation and selection, corridor operating policies and procedures, budget development, and overall administration of ICM within a corridor.
An important aspect of the institutional framework is the roles and responsibilities of participating agencies in the daily operation of ICM. This must be clearly defined in order to maximize the potential benefits of ICM. While all participating agencies in a corridor will be collaborating on the implementation of all of the proposed ICM strategies, a lead agency will be assigned for the implementation of a particular strategy. The lead agency will be responsible for the daily operation of the strategy it is in charge of and will coordinate with other agencies that are involved in the operation of such strategy. When issues occur, the lead agency will be responsible for reporting the issues to the ICM control center and will assist the center to resolve the issues.

System Requirements

This is the next step in developing an ICM after producing the Con Ops document. The system requirements describe what the system is to do (functional requirements), how well it must perform (performance requirements), and under what condition (functional or non-functional). Once the system is described in the Con Ops, and these requirements specifications are deployed and integrated among agencies, the new ICM will become fully operational. The following are the key aspects of the system requirement stage in the development of ICM (27).

Functional Requirements

Functional requirements refer to how the ICM is supposed to function once it becomes operational, especially how it functions to improve the operating conditions of the corridor. It includes the following:

- ❖ Identification of ICM Subsystems & ICM Requirements. ICM is a system of systems functioning together as a unit. It is therefore important to identify the core subsystems that are critical to its operation. According to the high-level system requirements developed for the U.S.-75 ICM project in Dallas, Texas, the core subsystems for the project were an ICM database subsystem, an evaluation model subsystem, a decision support subsystem, and a web subsystem. The ICM database subsystem will store data within the ICM system; the types of data to be stored include data coming from a data warehouse (historic data), current network data provided by the ICM agencies in the corridor, and output data from the decision support subsystem including response plans and predictive conditions of the network. The evaluation model will be used to evaluate the overall performance of the corridor. The decision support subsystem will be used as a tool for the coordination of responses to events, to evaluate current network conditions, and predict network conditions in order to proactively manage the corridor. Finally, the web subsystem will be a tool to enable the viewing, reporting, and sending of ICM data. The web subsystem will provide an "ICM web interface" for approved users to interact with the ICM data and provide a data feed of current network conditions to corridor ATIS.

- System Requirements for Individual Systems. The individual networks that comprise the corridor are operated as systems by their respective agencies. For them to function as a unit under the ICM there will be the need for some enhancements to their infrastructure and technology in order to deliver the desired benefits. This involves analyzing the current operations and conditions of the individual network assets and proposing the needed improvements required to upgrade them to the standard of an ICM component. The I-394 ICM project in Minneapolis, Minnesota, termed this as "existing systems and field devices" and "planned systems and field devices" in its high-level system requirement document *(28)*. Additionally, the daily roles of each individual network in the ICM must be specified.

- User Characteristics and Needs. The characteristics of the users of the ICM are critical to the design and development of a system that supports their needs. The main users of the ICM include agency operators, administrators, third parties (additional service providers), and the travelling public. The needs of these users are embodied in the vision, goals, and objectives developed by stakeholders during the Con Ops stage. Hence, the ICM must function in a way to address these needs as thoroughly as possible.

- Major System Constraints. This is meant to bring the challenges faced by the corridor into the development of the functional system requirements. It exposes prevailing operational, technical, and institutional obstacles that might hinder the smooth implementation and operation of an ICM. Once these difficulties are known, it is expected that stakeholders will devise strategies to fix them, and those strategies will be part of the system requirements.

- Operational Scenarios. Hypothetical operational scenarios of the corridor and how ICM will respond to these scenarios are required in the systems requirement stage. This involves identifying problematic locations within the corridor and their respective traffic conditions, as well as defining how the ICM is supposed to function. This stage is based on the experience of the stakeholders with regard to operating conditions within the corridor.

- Hardware Requirements. Hardware components of the individual networks as well as the ICM must function at certain standards. These requirements are intended to ensure that there are no frequent breakdowns in the operations of the ICM. An example of a hardware requirement could be the accommodation capacity of the message transmission hardware of the ICM traffic operations.

- Interface Requirements. ICM involves the exchange of data among subsystems and other systems by following protocols and standards established for communication. Usually, the interface of exchange follows national ITS standards; however, when necessary, additional requirements can be placed on the system depending on the uniqueness of the ICM.

- Documentation and Training Requirements. This was found only in the system requirement document for the I-394 ICM project in Minneapolis, Minnesota. It is likely that separate developers might develop different portions of the overall ICM, and, during operations, each agency will operate their system as part of the overall ICM. Therefore, there must be documentation of how the individual systems operate and how to train staff who will manage the systems.

Performance Requirements

These are target thresholds set by stakeholders to ensure that ICM is achieving the desired results. These thresholds are embodiments of the vision, goals, and objectives for the corridor. They are usually long-term targets that provide authorities the opportunity to know whether the performance of ICM is moving in the expected direction or not. For example, stakeholders of the U.S.-75 ICM project in Dallas, Texas have targeted increasing corridor throughput (persons/trips per hour) by 2% *(27)*. It must be noted that the targets must be realistic so as to avoid over-expectations.

Analysis, Modeling, and Simulation (AMS)

The purpose of this step is to design a simulation model that can replicate existing operating conditions and quantify the benefits of proposed ICM strategies. This will help in selecting the best combination of strategies to generate the most benefits. A 2008 report by Alexiadis Vassili entitled *Integrated Corridor Management Analysis, Modeling and Simulation (AMS) Methodology* laid out some general principles to be followed *(20)*.

The methodology centers on the following core values: integrating existing modeling and analysis tools, recognizing limitations in the available tools, development of AMS framework that is vendor-neutral, and development of consistent analytical approaches and performance measures. Essential details of the AMS methodology are summarized here.

Performance Measures and Analysis Approach

The AMS methodology includes the capability to convert all impact/performance measures to non-mode specific measures such as person trips. These mode-independent performance measures will be produced by an interface tool that can translate AMS model components outputs into non-mode specific performance measure output.

Since ICM is multimodal, the operational impacts need to be measured beyond the traditional network-based measures. This will help to evaluate and compare operations among the alternative paths and properly portray the corridor-wide performance. The performance measures must provide an understanding of existing traffic conditions and demonstrate the ability of ICM strategies to improve the corridor's operating conditions. When necessary, performance measures should be reported by mode (transit, single-occupancy vehicle, etc.), facility type (freeway, arterial, etc.), jurisdiction (e.g., County), and peak-periods or by hour of day. The proposed performance measures should focus on:

- Mobility: how well the corridor moves people and freight, e.g., delay, travel time.

- Reliability: predictability of travel time, e.g., buffer index.

- Safety: safety characteristics of the corridor, e.g., crash rate.

- Environment: emissions and fuel consumption, e.g., CO_2 emissions.

As part of the analysis approach, adequate data for modeling recurring and non-recurring congestion is needed to establish baseline conditions. Geometric data such as number of lanes on the freeways and parallel arterials, lane and shoulder widths, configurations of key intersections on parallel arterials, and other vital information about the physical structure of the roadway are also required.

Modeling and Limitations

The modeling and simulation step is a critical component of the ICM, since it is the only available means to justify the investments in ICM prior to implementation. It has been observed that each available simulation tool type has different advantages and limitations, and is better than other tool types in some analysis capabilities. There is no single tool type that can successfully address the analysis capabilities required by ICM. An integrated approach can support corridor management planning, design, and operations by combining the capabilities of existing tools. The existing tools are made up of three different types:

1. Macroscopic models: Models traffic from a global perspective and covers large areas compared to mesoscopic and microscopic models. Effective in estimating mode-shift, e.g., TransCAD.

2. Mesoscopic models: Models individual vehicles but their movement is based on average link speed. They are able to model larger areas compared to microscopic models, and are effective in evaluating traveler information systems (pre-trip and en-route), e.g., Dynasmart-P.

3. Microscopic models: Model and simulate individual vehicles based on theories of car-following and lane-changing. Microscopic models capture detailed driver-driver and driver-road interactions and cover less area compared to macroscopic and mesoscopic models. They are effective in evaluating operational control strategies (like ramp metering), e.g., VISSIM.

All these models vary in resolution (detail of analysis) and the geographical scope of application. Less detailed tool types (macroscopic models) are tractable for large networks, while more detailed tool types (microscopic and mesoscopic models) are restricted to smaller networks. Depending on corridor size and the types of analyses required, all tool types are potentially valuable for ICM AMS. Consequently, a proposed AMS framework that integrates all three types is recommended. Combining the strengths of all the three different models will help to better quantify the benefits of ICM.

The proposed AMS methodology includes macroscopic trip table manipulation for the determination of overall trip patterns, mesoscopic analysis of the impact of driver behavior in reaction to ICM strategies (both within and between modes), and microscopic analysis of the impact of traffic control strategies at roadway junctions (such as arterial intersections or freeway interchanges).

The proposed methodology also includes the development of a simple pivot-point mode shift model and a transit travel time estimation module, the development of interfaces between different tools, and the development of a performance measurement/benefit-cost module. In the AMS framework, macroscopic, mesoscopic, and microscopic traffic analysis tools will interface with each other, passing trip tables and travel times back and forth until convergence is achieved between consecutive iterations that produce travel times and number of trips that differ less from one iteration to the next.

Once convergence is achieved, performance measures will be calculated and benefits (such as travel time savings) will be evaluated and compared to deployment costs to produce benefit-cost ratios associated with each scenario/ alternative. With the help of benefit-cost information, alternatives can be ranked and a roadmap can be produced outlining the implementation timeline for ICM strategies. In the ICM analysis, it is important to differentiate between short-term and long-term mode shifts in order to determine if ICM has the potential to impact the choices of travelers in the long-term.

2.2 HOT Lane Driver Behavior

The review of literature on HOT lane driver behavior was grouped into four main categories based on the type of tolling system (dynamic or non-dynamic pricing) used and the type of research approach (stated preference or revealed preference) adopted. Details of each category are provided below.

2.2.1 HOT Lane Driver Behavior with Non-Dynamic Pricing: Stated Preference

Justice Appiah conducted a stated preference survey to determine the factors driving HOT lane utilization on the Katy Freeway (I-10) and Northwest Freeway (US 290), both in Houston, Texas. Both facilities have fixed toll rates which did not vary with traffic conditions on the HOT lanes. Based on the response of survey participants, the author concluded that the $2.00 toll charged on the HOT lanes was not a major deterrent to HOT lane usage. The study also found that the following factors affect HOT lane usage: driver's perception of travel time savings offered by HOT lanes, frequency of travel in the freeway corridor, trip purpose, age and level of education, occupation and hourly wage rate *(29)*.

Patil et al. (2011) used stated preference data from the Katy Freeway in Houston, Texas to determine HOT lane utilization factors as well driver willingness to pay for HOT lane use. It was shown that as travelers household income increases, their likelihood of using the HOT lanes increases. Additionally, drivers who are late for an appointment or have an important appointment tend to have the highest willingness to pay for HOT lane use *(30)*. Another study on the same facility by Devarasetty et al. (2012) examined driver willingness to pay for travel time savings and reduced travel variability. The study compared user's stated preference survey responses to real world data on the facility's usage. The stated preference results yielded a willingness to pay value of $22/hour for travel time savings and $28/hour for reduced variability. Analysis of the real world data found an average willingness to pay value of $51/hour of travel time savings on the lane — surprisingly close to the combined value for travel time savings and reduced variability *(31)*.

Sullivan (2000) conducted a stated preference survey on SR 91 express lanes in Orange County, California. The pricing system used on this facility is not completely static; it varies based on the time of day in hourly intervals and was therefore not considered as a true dynamically-priced facility. The author found that a traveler's primary reason for using the 91 express lanes was for travel time savings. However, one third of the respondents cited reasons other than simply travel time savings. Easier driving and safety ranked highly among the other reasons noted by the drivers who paid to use the lane during off-peak periods. About 58% of express lane users felt the lanes were safer than the free lanes. A very small percentage of the respondents cited reasons like enjoying passing others, feeling prestige, or a low risk of a speeding ticket. Less congestion, less aggressive driving, no large vehicles, better enforcement and better emergency response were among the reasons why respondents think the express lanes were safer than the free General Purpose (GP) lanes *(32)*.

2.2.2 HOT Lane Driver Behavior with Dynamic Pricing– Stated Preference

A panel-based stated preference survey conducted by Supernak et al (2002) on the I-15 Fast Trak express lanes in San Diego found that Fast Trak customers mainly used the facility for travel time savings. The need to be on time at their destination was a matter of concern to a significant number of commuters: 21% of respondents said that they could not be late without consequences and an additional 10% said that they had only a 10-min window or less for being on time. The study also found that Fast Trak customers were from higher income households, more highly educated (bachelor's degree or higher), mostly between 35 to 54 years, more likely to be homeowners and more likely to be middle-aged women *(33)*.

An attitudinal panel survey was designed by Zmud et al. (2007) to measure the attitudes, perceptions and travel behaviors of I-394 MnPASS lane users. Analysis of the response from participants showed a significant increase in the willingness to pay a toll for travelers who earned more than $100,000 per year. Younger travelers had a higher value of travel time savings than older travelers. The value of travel time also varied depending on the time of the day a trip is made; morning commuters were more willing to pay for time savings compared to afternoon commuters *(34)*.

2.2.3 HOT Lane Driver Behavior with Dynamic Pricing—Revealed Preference

Janson and Levinson (2013) conducted three field experiments on the I-394 and I-35W MnPASS lanes between October 2012 and January 2013 to measure drivers' response to tolls. During these experiments, drivers were not made aware of any changes in the pricing plan. In the field experiments, toll prices were deliberately altered without regards to traffic conditions on the HOT lanes. Therefore there were times during the experiment when toll prices were raised above the normal prices although traffic conditions on both the HOT and GP lanes were near free-flow. In addition, two years of toll and traffic data were analyzed to measure drivers' responses to toll prices. Results of both experimental and historic data analysis revealed that, driver elasticity to price was positive with magnitude less than 1.0. Also, drivers consistently paid between $60-$120 per hour for travel time savings, much larger than the average value of time ($15.6 per hour) often used by the Minnesota Department of Transportation (MnDOT) *(14)*.

Burris et al (2012) also used historical tolling data from 2008 for the I-394 MnPASS lanes to estimate drivers' willingness to pay for travel time savings. The research found that users of the I-394 MnPASS lanes paid an average of $73/hour in the morning and $116/hour in the afternoon commutes. Based on how large these values are, the authors concluded that it is likely travelers are paying for more than just travel time savings; possibly travel time reliability. These means that these lanes likely have an added value to travelers beyond travel time savings *(12)*.

Driver value of travel time savings on I-85 express lanes was studied by Sheikh et al (2014) using historical traffic and tolling data between September 2012 and May, 2013. The results indicate median values of travel time savings of $36/hour in the southbound morning peak and $26/hour in the northbound afternoon peak. The authors also mentioned that, the value HOT users attributed to their time saved exceeded the time-value using the average wage rate in the region *(13)*. Another study on the same facility by Wood et al (2014) using 8 months of historic traffic and tolling data found similar results. The analysis found the median value of travel time savings to be $33.17/hour for southbound morning peak and $19.45/hour across all time periods *(15)*.

Burris et al (2012) used historic data from I-15 Fast Trak lanes between March 2009 and June 2010 to determine drivers' willingness to pay for travel time savings. The median value of travel time savings obtained were $49/hour in the morning and $54/hour in the afternoon. The study also found considerable variation in toll rates during the morning and afternoon peak hours with tolls ranging from $0.5 to $8.0. Conversely off-peak times showed little to no variations *(12)*.

Finally, Perk et al (2011) used five days of historic traffic and toll data from I-95 express lanes to develop a discrete choice model based on which drivers' value of travel time savings were estimated. The five days of historical data were based on responses to an online survey which asked users of when they traveled on the facility, how much they paid, and their approximate speed. The responses were compared with actual data to validate the information provided by survey respondents. The survey also asked questions related to demographics and attitude of express lane users. Results of the analysis indicated that drivers' value of travel time savings ranged from $2.27/hour $79.32/hour, with an average of $32.00/hour. The authors also concluded that the value of travel time savings was approximately 49% of drivers' average hourly wage based on annual household income *(35)*.

Song and Smith used traffic sensor and count data from March 2008 to study the factors contributing to HOT lane utilization rates on the I-394 MnPASS HOT lanes. The authors developed a decision model based on which SOV drivers decide to use/not use the HOT lanes. The elasticity analysis revealed that HOT lane drivers' response to changes in toll rate was negligible, implying that there might be other factors which contribute strongly to the decision to use the HOT lanes *(36)*.

2.2.4 HOT Lane Driver Behavior with Dynamic Pricing—Revealed/Stated Preference

The San Diego I-15 Fast Trak lanes were studied by Brownstone, et al. (2003) over a two month period, in October and November 1998. Travel time data was compared with survey data asking respondents on what days and times they traveled, and whether they used HOT lanes. The authors discovered that higher toll rates were signaling drivers, indicating increased congestion downstream. Higher tolls only served to reduce HOT lane usage when the travel time variability (measured as the 90th percentile travel time less the 50th percentile travel time) for that time period is less than 7.21 minutes. Also when drivers encountered a toll rate higher than the average for that time of day, they tended to use the HOT lanes in greater numbers. Similarly, if they encountered a toll rate lower than expected, they used the HOT lanes in lower numbers. The median cost drivers were willing to pay for travel time savings on this facility was $30 per hour *(21)*.

2.2.5 HOT Lane Driver Behavior—Other Studies

Brownstone and Small (2005) studied the value of reliability of HOT lane users using both stated and revealed preference data from SR 91 express lanes (variably-priced) and I-15 Fast Trak lanes (dynamically-priced). To better capture the significant expense of being late for work, they focused on the difference between the 90th and 50th percentile of morning travel time to capture the upper tail of the travel time distribution. Their results suggested that that travel time savings was worth about two-thirds of overall service quality of HOT lanes, while reliability made up another third *(37)*.

In an attempt to better understand whether stated preference survey estimates underestimate value of travel time savings, Brownstone and Small found that survey participants often overestimated the time savings they would get using express lanes by a value of two. The misperception of travel time savings could be a key factor in the difference between RP and SP values of time. Brownstone and Small theorized that drivers that experience ten minutes of congestion may perceive an experience of twenty minutes, and may therefore be willing to pay a higher toll to avoid congestion on the GP lanes *(37)*.

2.3 HOT Lane Demand Prediction

Demand for HOT lane use is typically predicted only at the planning stages of HOT lane implementation. The prediction includes both SOV and HOV demand. First, it allows the project sponsor to determine the combination of pricing and occupancy requirements that maximizes transportation benefits for all motorists traveling in the priced managed lane corridor. Secondly, it allows the project sponsor to forecast revenue streams and then evaluate financing approaches *(16)*. A search in the literature for research works on short-term HOT lane demand prediction proved futile. The next section provides a brief overview of how HOT lane demand is predicted at the planning stages of its implementation.

2.3.1 HOT Lane Demand Prediction at Planning Stage

Predicting demand on the priced managed lane corridor is accomplished by using a travel demand forecasting model. Travel demand models are mathematical tools that estimate roadway and transit travel based on projected population levels, land use trends, and expected roadway and transit characteristics such as cost and travel time. Forecasting travel demand for priced managed lanes is challenging because traditional travel models use simplified representations of pricing and have limited capabilities for predicting how travelers would change mode, route, departure time, destination, or trip frequency in response to pricing. In addition, forecasting demand for priced managed lanes is very sensitive to future conditions, such as land use, population growth, characteristics of alternative road and transit modes, and even macro-economic cycles. The complexity of the forecast is compounded by the sensitivity of demand for priced managed lanes to travel conditions in the general-purpose lane and to the extent to which multiple-occupant vehicle trips are made in the corridor. How well the model predicts demand for the priced managed lane and the resulting revenues depends on the structure of the model, how well it is calibrated and validated, and how it is applied to quantify the uncertainty inherent in any forecast of future economic activity. In the case of priced managed lanes, three model structural characteristics are most important: representation of relevant travel choice decisions (route choice, mode choice and travel time choice), representation of travel costs (value of travel time, cost of fuel, etc.), and representation of travelers' willingness to pay.

2.4 Summary

In this chapter, an extensive review of important research in ICM, HOT lane driver behavior, and prediction of HOT lane demand was conducted. An overview of ICM implementation as well as identification of most beneficial strategies was discussed. The behavior of HOT lane users in terms of their response to pricing (tolls) was also reviewed and gaps in the research noted. Finally, HOT lane demand, which is usually predicted only at the initial stages of HOT implementation, was reviewed, and the lack of short-term predictions for operational purposes noted. The next chapter presents a novel ICM evaluation methodology based on which the most beneficial ICM strategies can be identified.

Chapter 3

Development of ICM Evaluation Methodology

The concept of ICM revolves around the integration of multi-modal strategies to help mitigate congestion and increase person throughput. Prior to its implementation, transportation agencies are often faced with the dilemma of selecting from the plethora of available strategies, the best combination to generate the most operational benefits. Given the complexity of ICM and the required interrelationship of systems, an accurate evaluation of the effectiveness of ICM requires a detailed methodology that can help to identify those strategies that will be beneficial to the needs of a transportation corridor. Although an evaluation methodology has been developed for ICM pioneer sites, it is a high level conceptual framework with little guidance on its implementation. Therefore, transportation agencies who intend to adopt ICM are faced with the challenge of coming up with their own evaluation methodology. This research developed an evaluation methodology based on which transportation agencies can identify the most beneficial ICM strategies. The developed methodology was then used to evaluate the feasibility of ICM implementation on a test corridor in northern Virginia. The application of the proposed methodology to a real-world transportation corridor provided useful lessons on how ICM can be implemented to achieve the intended purpose of increasing person throughput.

3.1 Description of Proposed ICM Evaluation Methodology

The proposed approach is a five-step evaluation methodology that provides adequate support to evaluate and quantify the benefits of ICM strategies. The methodology includes the modeling of base conditions, the application of candidate ICM strategies to base conditions, sensitivity analysis of ICM strategies, a test of statistical significance of the effects of candidate strategies, and recommendation of combination of strategies to implement. The chart in Figure 3.1 below describes the proposed methodology.

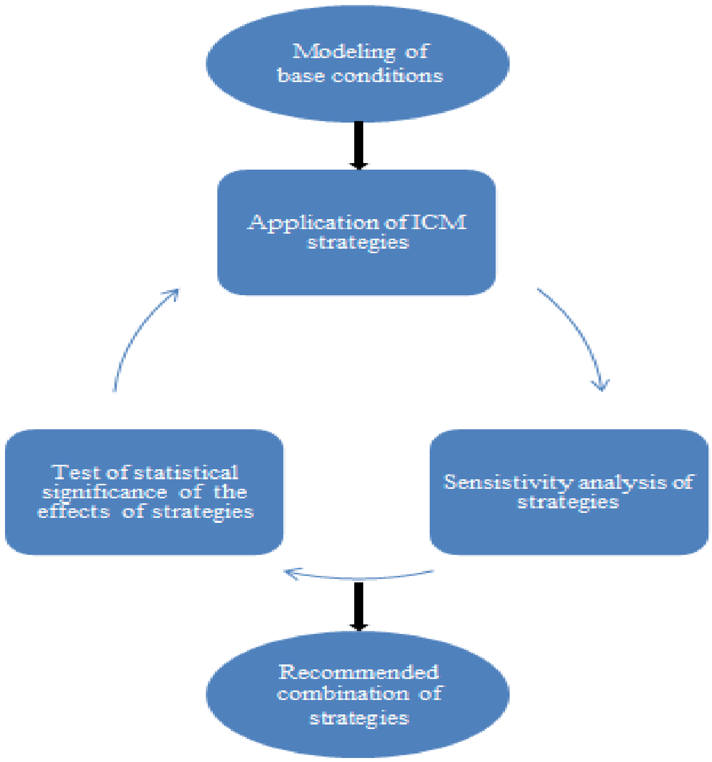


Figure 3.1 ICM evaluation methodology

ICM operates within a multidimensional framework with several candidate strategies and varying levels of application. It is therefore difficult to determine a good combination of applicable strategies based solely on expert judgment or random selection. There must be an unambiguous causal relationship between traffic improvement indicators (e.g. person throughput) and a set of ICM strategies to justify their selection; such inferences can only be drawn from an experimental design. Experimental designs provide an efficient procedure for planning experiments so that data obtained can be analyzed to give valid and objective conclusions *(38)*. The evaluation methodology described implicitly entails the experimental design process. In order to better understand the evaluation methodology, it will be explained through an illustrative example:

Consider a corridor that is made up of a 10-mile freeway and an adjacent arterial across the entire length of the freeway. The freeway has six single-lane on-ramps that are not metered, but the signals on the arterial have optimization capabilities. The corridor experiences excessive congestion during peak periods, partially due to a significant percentage of SOVs, and a small number of operating buses (two buses every hour). Stakeholders in the corridor have agreed to implement a set of ICM strategies and these are: ramp metering, Variable Speed Limit (VSL) system, provision of parking facilities, increasing transit capacity by adding more buses, and subsidizing transit and parking fees.

How will the evaluation methodology described in Figure 3.1 apply to this ICM initiative? Each of the five steps of the proposed methodology is hereby explained using the above example.

Modeling of Base Conditions

Prior to evaluating any ICM strategy, the base operating conditions of the transportation corridor must be established. The base case should include all modes and facility types in the corridor. In this example, these include transit, freeways, and arterials. The use of the micro-simulation software VISSIM (and other such as Dynasmart) enables the execution of this task. Performance metrics, which are indicative of corridor operating conditions, are determined from this step. These include average vehicle flow, person throughput, average travel times, average delays, average emissions of CO_2, NOx, etc.

Application of ICM Strategies

After determining the prevailing operating conditions of the corridor as captured by the performance metrics, the ICM strategies agreed on by the corridor's stakeholders are implemented (modeled). Each strategy in this example is modeled by the characteristic described below:

1. *Ramp metering* (X_1) – this strategy regulates the flow of vehicles onto the freeway in order to improve freeway traffic flow and safety during merging conditions. The metering rate, which is between 240 and 900 vehicles/hour for a single-lane ramp meter *(4)* is the main attribute being modeled.

2. *Variable speed limit* (X_2) – the VSL strategy seeks to promote dense traffic flow by varying speed limits across the length of the freeway to avoid traffic flow breakdown. The percentage of driver compliance with the posted speed limits will be varied to determine its impact. Therefore, driver compliance is the attribute being modeled.

3. *Increasing transit capacity* (X_3) – the corridor stakeholders want to increase transit capacity by increasing the number of buses from two to six buses every hour. This will decrease the headways from 30 minutes to 10 minutes per bus stop. The capacity of the transit system is the variable being modeled.

4. *Provision of parking facilities* (X_4). The main attribute of interest is the opportunity provided to drivers who decide to park and use the bus, and that opportunity is quantified in terms of parking capacity.

5. *Subsidized transit and parking fees* (X_5). The cost of parking and bus fares may deter potential transit users. Corridor stakeholders have decided to subsidize these costs to make transit use attractive. The attribute being modeled is how travelers respond to these financial incentives, in terms of mode shift.

It can be inferred from strategies 3, 4, and 5 (transit and parking capacity increase, financial incentives through subsidy) that traveler behavior is expected to be influenced in order to benefit the transit mode in real-time. However, the magnitude of traveler response is unknown. Therefore, assumptions of percentage shift (range of traveler responses) in mode from SOVs to buses (based on existing literature) will be made in order to continue with the modeling process.

From this, it will be possible to estimate the limit of effectiveness of influencing traveler behavior toward mode shifts.

Sensitivity Analysis of Strategies

It is worth noting that the individual effects of the five strategies on corridor performance are of less significance within the context of ICM. The underlying principle of interest is how all five strategies combine to improve the operating performance of the corridor. Additionally, there are some strategies whose effects diminish once they are combined with other strategies; such strategies are not worth investing in and must be identified. Therefore, it is necessary to identify among the five strategies those that are critical to the improvement of corridor operating performance. Also, the extent to which unknown traveler behavior (response to subsidized transit and parking fees, extra transit capacity) can improve corridor performance is an important piece of needed information. Estimating the combined effect of the five strategies, identifying those strategies that are critical to improving corridor performance and testing for the limits of effectiveness of unknown traveler behavior can be achieved through sensitivity analysis. The next logical question is how to conduct the sensitivity analysis?

As described earlier, ICM is composed of several strategies; therefore, accurate quantification of its impact requires intensive computation and large amounts of data. For example, in order to estimate the impact of the five ICM strategies (assuming each strategy has a range of 6 values), 6^5 (7,776) different combinations (trials) of these strategies will have to be tested. Additionally, each of these combinations will have to be run at least 5 times in VISSIM to reduce the effect of stochastic variability *(39)*. An experimental design technique (referred to as the Latin Hypercube Sampling [LHS]), which minimizes the amount of data and computational intensity, but enables accurate estimation of the sensitivity of corridor performance to ICM strategies can be used. This sampling technique helps to achieve the same level of accuracy in sensitivity analysis with fewer number of strategy combinations (trials).

The LHS was developed by McKay and Conover in 1979 as an alternative to simple random sampling in Monte Carlo Studies (MCS) *(40)*. In MCS, values of parameters are selected at random from their assumed probability distributions, and dynamic simulations of the system are repeated for all sampled input parameters. The accuracy of such Monte Carlo simulations depends on the number of model runs, making it less suitable for application to complex systems with many parameters.

In the LHS approach, the range of each of the five variables (strategies) X_1, X_2, X_3, X_4, and X_5 is divided into N (e.g., 6) intervals in such a way that the probability of the variable falling in any of the intervals is *1/6*. Then, one value is selected at random from each interval. The *6* values obtained for the first variable X_1 are paired randomly with the *6* values of the second variable X_2. These pairs are furthermore randomly combined with the sampled values of the third variable, and so on, which finally results in *6* combinations of five variables. This set of five tuples is the Latin hypercube sample that is used for successive execution of model runs. It is convenient to think of this sample as forming a (*6 X 5*) matrix of input where the i^{th} row contains specific values of each of the *5* input variables to be used in the i^{th} run of the micro-simulation model

(41). Thus, with LHS, a smaller number of trials achieve the same accuracy as a larger number of Monte Carlo trials.

As shown in Figure 3.2, each of the cells represents a combination of strategies that could be run in a micro-simulation model. The LHS technique helps select a smaller number of combinations (cells with yellow polygons) that will result in the same accuracy level as the maximum possible number of combinations. The LHS technique can be coded in MATLAB and statistical packages such as R and SAS.

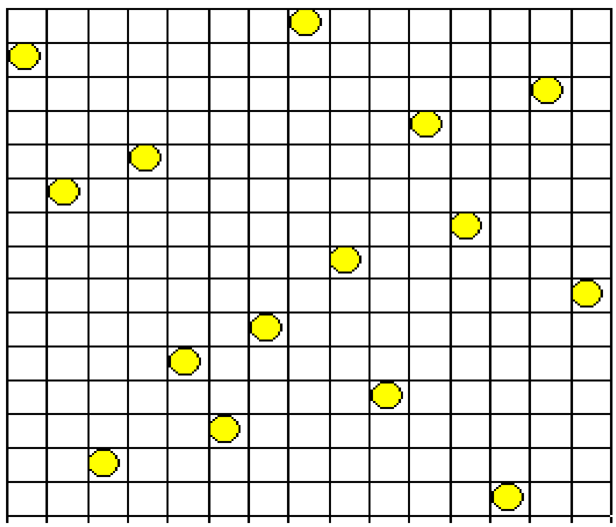


Figure 3.2 Latin hypercube sampling

Once the required feasible number of strategy combinations has been determined using LHS, they are used as inputs to run the micro-simulation model (VISSIM). The outputs and inputs of the micro-simulation runs are used to develop regression and correlation equations (sensitivity analysis techniques) based on which:

1. The combined effect of the five ICM strategies on corridor performance is estimated.
2. The limits of effectiveness of unknown traveler behavior are determined.
3. The most critical ICM strategies among the proposed five are identified.

Three sensitivity techniques are used (standardized regression coefficient, linear correlation coefficient, and semi-partial correlation coefficient) to identify the most beneficial combination of ICM strategies.

Standardized Regression Coefficient (SRC)

Multiple linear regression models are often used to determine the relationship between model parameters and model output. The coefficients of regression (b_i) of model parameters, which is interpreted as the amount of change in model output based on a unit change in a model parameter (while all other parameters are held constant) are in different units; preventing any meaningful comparison between the significance of model parameters *(42)*. To make these coefficients comparable, they must be standardized. Standardization of regression coefficients (b_s) can be achieved by multiplying ordinary regression coefficients (b_i) by the ratio between the standard deviation of the respective model parameters (s_p) and the standard deviation of model output (s_o).

Assuming an ordinary linear regression equation is developed from the micro-simulation outputs and inputs as shown in equation 3.1:

$$A = b_0 + \sum b_i(X_i) \tag{3-1}$$

Where:

A = the micro-simulation output of a performance measure (e.g. person throughput)
b_o = the regression constant
b_i = the parameter (ICM strategies) coefficients for I = {1, 2, 3, 4, 5}.

Then, the SRC will be

$$b_s = b_i\,(s_p/s_o) \tag{3-2}$$

The mathematical form of a standardized regression is as shown in equation 3-3.

$$A = b_1(X_1) + b_2(X_2) + b_3(X_3) + b_4(X_4) + b_5(X_5) \tag{3-3}$$

The standardized coefficients are interpreted as the standard deviation change in the dependent variable (corridor performance indicators) when an independent variable (ICM strategy) is changed by one standard deviation, holding all other variables constant. Instead of comparing changes by one unit, the comparison is between changes in standard deviation *(42)*.

Once the coefficients become comparable, a ranking (in terms of absolute coefficient values) of all the coefficients of the five ICM strategies is made. The accuracy level of the SRC as a relative sensitivity measure depends on how well the regression fits the parameter data, the level of correlation among parameters, and how realistic estimated parameter variance is.

A quality of fit close to 1 and a weak or zero correlation among model parameters make SRC a valid measure of sensitivity. In order to ensure that model parameters are not correlated (multicolinearity), the Variance Inflation Factor (VIF) of the standardized regression typically should be less than or equal to four or at most less than 10.

Linear Correlation Coefficient (LCC)

The LCC is the most simple and widely used measure that reflects the linear relationship between model output (A) and model parameters (X_i). It can be expressed as the ratio between the covariance of model output and parameters ($cov\ (A, X_i)$), and the product of the variances of model output ($var\ (A)$) and parameters ($var\ (X_i)$). This can be written mathematically as

$$LCC = cov\,(A, X_i)/(var\,[A]*\,var\,[X_i]) \tag{3-4}$$

The LCC is computed for each of the five ICM strategies, based on which a ranking (in terms of absolute LCC values) of the importance of these strategies to corridor performance improvement is developed.

The LCC is used as a sensitivity measure since it expresses the relative change of a quantity with relation to its standard deviation (taking into account the effects of correlation among parameters). If the relationship between X_i and A is almost linear and if the correlation between the parameters X_i is weak, then the LCC is a measure to quantify sensitivity and will be approximately equal to the SRC. LCC value ranges between 1 and -1, with the sign indicating positive or inverse correlation.

Semi-partial Correlation Coefficient (SPC)

SPC is similar to LCC, but corrects model parameters for the effects of correlation among each other. If the correlation between the corrected parameters is weak, the SPC is approximately equal to the LCC and the SRC. In case of a strong correlation between the corrected parameters, this measure can give a misleading impression of parameter sensitivity. Similarly, ranking the importance of the five ICM strategies based on SPC absolute values is developed. The SPC can be expressed mathematically as

$$SPC = SRC/\sqrt{VIF} \tag{3-5}$$

At the completion of any parameter sensitivity analysis, a ranking of the input parameters sorted by the amount of influence each has on the model output is generated. The model output of interest in this research as far as ICM strategy sensitivity analysis is concerned is corridor person throughput; this is because it is not mode-specific and measures the ultimate objective of a corridor – to transport people. The different sensitivity analysis measures (SRC, LCC, and SPC) might produce varying rankings; however, the actual position in the ranking (based on the different measures) is not as important as is the specification of which strategies consistently appear near the top of the list regardless of which measure was used *(43)*. An example of the results of model parameter (parameters for the different strategies) rankings using the different sensitivity measures is as shown in Table 3.1. The rankings and coefficients are hypothetical and meant for illustration purposes only.

ICM Strategy	**SRC**	**Ranking**	**LCC**	**Ranking**	**SPC**	**Ranking**
Ramp Metering (X_1)	155	1	0.88	1	0.74	3
VSL (X_2)	148	2	0.65	3	0.91	1
Transit Capacity (X_3)	110	3	0.35	5	0.44	5
Parking Capacity (X_4)	50	4	0.75	2	0.62	4
Subsidies (X_5)	30	5	0.55	4	0.81	2

Table 3.1 Hypothetical sensitivity rankings

It can be inferred from Table 3.1 that ramp metering (X_1) and VSL (X_2) consistently appeared near the top of the rankings regardless of which sensitivity measure was used. If the coefficients of these two strategies are statistically significant (as will be shown in the next section), then, it implies that they are the most critical among the five ICM strategies intended to be introduced in the hypothetical corridor.

Test of Statistical Significance of the Effects of Strategies

In order to ascertain that the coefficients of the ICM strategies as shown in Table 3.1 are not due to chance, they must be tested for statistical significance. Two types of t-statistic are used to test for statistical significance at 5% significance level.

Model coefficients obtained from LCC and SPC are tested for statistical significance using a t-statistic defined mathematically as

$$t = r\sqrt{(N-2)/(1-r^2)} \tag{3-6}$$

where:

r = the correlation coefficient
N = the sample size
N-2 = the degrees of freedom.

For model coefficients generated based on SRC, the t-statistic is computed by the formula

$$t = \text{Regression coefficient } (b_i)/\text{Standard error of } b_i \tag{3-7}$$

Recommended Combination of Strategies

After identifying the most critical of the five ICM strategies and testing for statistical significance, any of the strategies that were not statistically significant can be dropped so that the model can be re-run. New sets of outputs are obtained based on which sensitivity analysis and the tests of statistical significance are conducted again. This procedure will be repeated until the best set of ICM strategies that will improve the corridor operating performance is identified.

3.2 Test Corridor for Proposed ICM Evaluation Methodology

The ICM evaluation methodology described in section 3.1 was applied to a real-world transportation corridor to determine the feasibility of ICM implementation as well as identify the most beneficial strategies. The description and potential application of ICM in the corridor is discussed in the following paragraphs.

The I-95/I-395 corridor is a major north-south corridor located in the Northern region of Virginia and connects downtown Washington, D.C. to many of the suburban cities south of Washington, D.C. The corridor begins at the intersection of U.S. 1 and I-95 at Spotsylvania (Mile Marker [MM] 126), terminating at the intersection of the 14th Street Bridge and I-395 in Washington, D.C. (MM 10). The corridor is composed of three segments:

1. U.S. 1/17 to Route 610 (MM 126-144)
2. Route 610 to Interstate 495 (MM 144-170)
3. Interstate 495 to 14th Street (I-395[MM0-10]).

The corridor is composed of freeways (I-95 and I-395); a primary arterial (U.S. 1); commuter rail (Virginia Railway Express [VRE]) along the entire length of the corridor (but some segments lie far from I-95), Metrorail from Franconia to Washington, D.C.; bus services (e.g., Fairfax connector, Potomac and Rappahannock Transportation Commission [PRTC] buses); and park-and-ride facilities. The freeways are made up of six to eight General Purpose (GP) lanes and two reversible High Occupancy Vehicle (HOV) lanes (expansion to three in the future for high occupancy tolling operation). The primary arterial, U.S. 1, is a relatively convenient alternate route for transportation between Spotsylvania and Woodbridge. Additionally, the corridor operation includes transportation demand management strategies such as vanpooling, carpooling, "slugging," and real-time ride sharing (pilot). About 40,771 spaces are available at the park-and-ride facilities in the corridor and 3,000 more have been proposed for construction by 2015.

Currently, the operating conditions along the corridor deteriorate as one travels north. Volume to capacity (V/C) ratios on I-95 exceed 1:0 near and inside I-495, with operating speeds ranging from 20%-25% of free flow speeds during the morning peak (northbound) and 14%-23% of free flow speeds during the evening peak (southbound). Similarly, the number of crashes is also higher at the northern end of the corridor. Table 3.2 shows a list of hot spots along the corridor and their operating conditions.

Hot Spot Location	Volume/Capacity		% of Operating Speed to Free Flow Speed		Crashes
	AM (NB/SB)	PM (NB/SB)	AM (NB/SB)	PM (NB/SB)	
Route 17 (MM 134-136)	0.8/0.9	0.92/0.88	70/60	48/65	165
Route 619-234 (MM 151-153)	0.88/0.8	0.93/0.88	62/73	49/66	276
Route 123 (MM 157-161)	1.0/0.82	0.92/1.02	25/67	53/21	390
Route 7100 (MM 166-170)	1.1/0.93	0.94/1.04	20/30	27/23	644
I-495-Route 236 (MM 0-3)	1.04/0.8	1.05/1.15	20/56	25/14	388

Table 3.2 I-95/I-395 corridor hot spots

In order to test as many ICM strategies as possible in the simulation environment, a northbound segment of the corridor beginning at MM 152 (exit 152 on I-95N) and ending at MM 163 (intersection of I-95 N and Lorton Road) was selected as the analysis segment as shown below in Figure 3.3.

A key consideration in selecting this segment was the relative proximity of I-95N to the primary arterial, U.S. 1N, as well as the VRE commuter line. On average, the distance between the freeway and the arterial along the entire length of this segment is 1.5 miles, making it a desirable alternative route should a traveler choose to change routes. Also, a shorter segment of the entire I-95/I-395 corridor was used as a result of the computational limitations of the adopted microscopic simulation software (VISSIM).

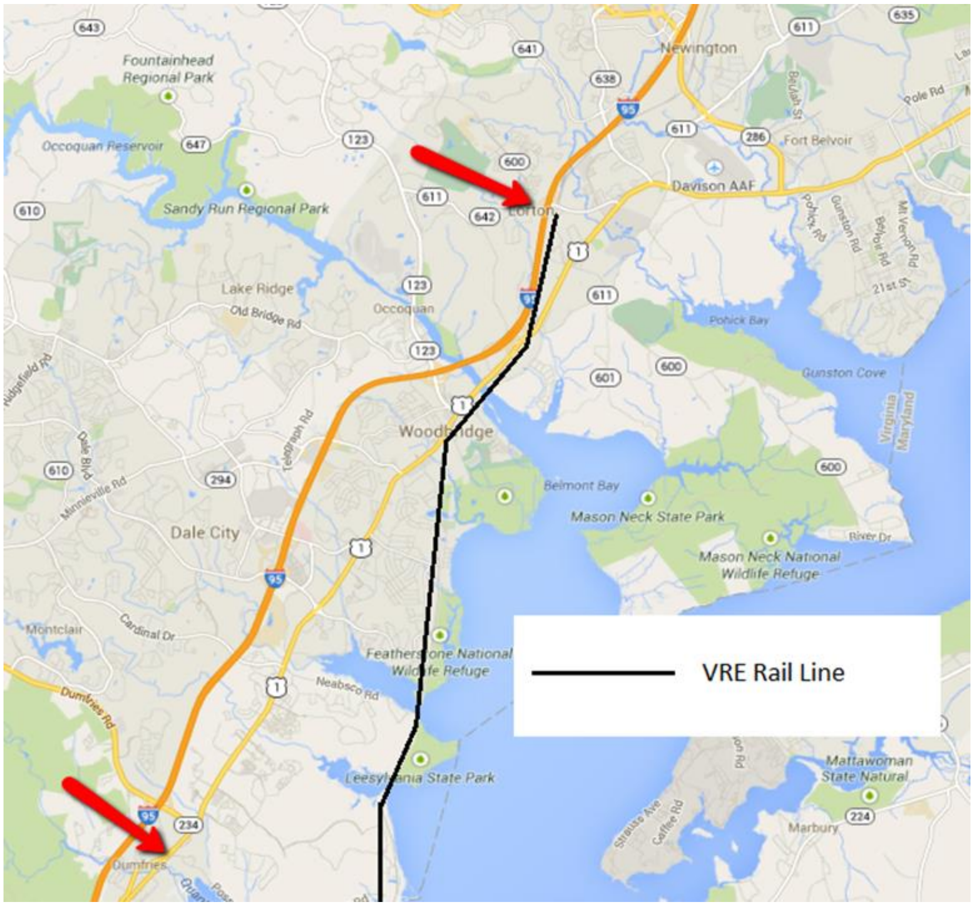


Figure 3.3: ICM test corridor

Tables 3.3 and 3.4 show the parking and transit facilities located in the analysis segment.

Commuter Lot/Park-and-Ride	Number of Spots	Filled by 8:00 AM?	Available Spots
Horner Road	2363	Yes	0
PRTC Transit Center	145	Yes	0
Telegraph Road	200	No	Unknown
Potomac Mills	275	Yes	0
SR234/SR 1	843	Yes	0
Lakeridge	638	Yes	0
Oldbridge/SR 123	580	Yes	0
SR 123/I-95 N	580	Yes	0
VRE (Rippon Station)	676	No	229
VRE (Woodbridge Station)	738	No	221
Total	**7038**	**--**	**450**

Table 3.3: Parking facilities in analysis segment (Source: PRTC and VRE websites)

Route	Number of Trips (AM Period)	Person Capacity	Capacity Used	Available Capacity
PRTC (Lakeridge-Washington)	10	570	293	277
PRTC (Lakeridge-Pentagon/Crystal City)	6	342	203	139
PRTC (Dale City-Washington)	25	1425	867	558
PRTC (Dale City-Pentagon/Crystal City)	9	513	312	201
PRTC (Dale City-Navy Yard)	6	342	220	122
PRTC (Lakeridge-Capitol Hill)	1	57	25	32
PRTC (South Route 1-Washington)	4	228	155	73
VRE (Fredericksburg Line)	7	5626	4921	705
Total	**68**	**9103**	**6996**	**2107**

Table 3.4: Transit routes in analysis segment (Source: PRTC and VRE websites)

From Table 3.4, it can be seen that there is extra passenger capacity in the transit system. In general, many factors affect transit ridership. These include transit service quality, transit fares, gas prices, proximity of bus stops to residential areas, availability of parking spots at park-and-ride facilities, etc. Using Table 3.3 as the basis of argument and without any further considerations, the unused transit capacity could be attributed to the limited availability of parking spots (a deficit of 2065 compared to transit capacity). Additionally, early transit departure times could also limit the full utilization of existing transit capacity. A careful examination at the operating schedule for PRTC buses *(44)* and VRE trains *(45)* as presented on their websites indicates that 21 of the 68 transit trips (19 buses, 2 commuter trains) start and end before 6:00 AM. Such a transit operating schedule might not be convenient for many travelers. Regardless of the reason for unused transit capacity, there is a clear potential to institute some transit-oriented ICM strategies that will take advantage of the extra capacity in order to increase corridor person throughput.

3.3 Development and Validation of Simulation Network

A comprehensive network of all the road facilities within the analysis segment described in the previous section was coded in VISSIM 5.4. In developing the network, the Google Earth application was used to collect geometric characteristics of the road facilities.

The facilities coded include I-95 N GP and HOV lanes, the primary arterial U.S. 1N, VRE rail line, the intersecting arterials (running east-west and west-east) that include Dumfries road (SR 234), Lorton road (SR 642), Dale Blvd (SR 784), Prince William Pkwy (SR 294), Gordon Blvd (SR 123), and the bus transit routes. Traffic flow data were obtained from the most recent VDOT Average Annual Daily Traffic (AADT) estimates to develop vehicle origins and destinations. Travel time data provided by INRIX was obtained from the vehicle probe suit of

Regional Integrated Transportation Information System (RITIS). The travel time and traffic flow data were used to calibrate and validate the model against actual driving conditions. The candidate ICM strategies were then incorporated into the simulation model.

A total of 50 VISSIM simulation runs were conducted to aid in the calibration process, and the results are as shown in Table 3.5. The simulation was run for a 90-minute period of the morning commute but data collection was scheduled to begin after the warm-up period of 30 minutes. For acceptable calibration results, travel times and speeds must be within 15% of the corresponding field values. The GEH, a modified chi-squared test, compared the simulated vehicle flow per hour with traffic data obtained from VDOT's AADT estimate. The GEH statistic must be less than 5 in order to be considered acceptable *(46)*.

Segment	**Average Travel Time (minutes)**			**Average Speed (mph)**			**Flow (Vehicles/Hour)**		
	Base	**Model**	**% Change**	**Base**	**Model**	**% Change**	**Base**	**Model**	**GEH Value**
I-95 N (SR234-SR123)	16.3	17	4.3	38	37	2.6	5416	5542	1.7
I-95 N (SR123-SR642)	10.6	10.1	4.7	26.5	25.3	4.5	5652	5668	0.2
I-95 N HOV(SR234-SR123)	8	7.6	5	60.3	58	3.8	2047	1901	3.3
I-95 N HOV(SR123-SR642)	4	4	0	55.8	54	3.2	3965	3759	3.3
U.S. 1N(SR234-SR123)	19.8	20.6	4	32.8	33.2	1.2	1931	2060	2.9
U.S. 1N(SR123-SR642)	9.7	10.1	4.1	28	26.8	4.3	2566	2488	1.6

Table 3.5: Model validation results

3.4 Evaluation of Candidate ICM Strategies

Eight ICM strategies were selected for evaluation in the simulation environment based on their relative ease of implementation, proven effectiveness in reducing congestion, and ability to interact and complement other congestion mitigation techniques. For those strategies that sought to influence traveler behavior in real-time/short-term, assumptions about traveler responses were made based on information from published literature. The eight strategies are VSL, ramp metering, increasing transit and parking capacity, high occupancy vehicle/toll lanes, financial incentives, ramp meter bypass/high occupancy access treatments and transit signal priority. Each of the candidate ICM strategies is briefly discussed below.

Variable Speed Limits (VSL)

VSLs have been used as a congestion mitigation measure for some time now, making it easier to have access to its implementation algorithms/codes. This research modified a publicly available VSL code, as described here *(47)*.

All VSL signs were set to display 55 mph during the first cycle in the simulation's warm-up phase. Each detector then gathered data and recorded the instantaneous speed data for every vehicle that crossed over the detector, as well as volume (which are tallied up into a cumulative volume [cum_vol] value). This instantaneous speed data is then converted into space mean speed (*speed = (1/vf)*, where vf = the instantaneous speed of a vehicle recorded over a detector), which was added up during the course of the cycle to obtain a cumulative speed value (cum_speed).

Using the cumulative data from the end of each cycle (a cycle being the time period between speed limit updates – 5 minutes in this case) space mean speed, flow, and density values were calculated for the data from each detector using the following equations:

$$space\_mean\_speed = \frac{cum\_vol}{cum\_speed} \tag{3-8}$$

Where:

space_mean_speed = the total space mean speed at a detector over the course of one 5-minute cycle
cum_vol = volumes accumulated over the course of one 5-minute cycle
cum_speed = accumulated speed values over the course of one 5-minute cycle

$$Flow = 12*cum\_vol \tag{3-9}$$

Where:

flow = The equivalent hourly flow based on a cycle's volume (in this case, 12 is used in the equation due to a 5-minute cycle time)
cum_vol = volumes accumulated over the course of one 5-minute cycle;

$$density = \frac{flow}{space\_mean\_speed} \tag{3-10}$$

Where:

density = the calculated density used to determine posted speed limits.

The next step is to determine the worst (highest) density at each VSL sign location (which is where detectors are located). As there is a detector in each mainline lane at each sign location, the worst density represents only one lane, but is used to represent the entire location.

Once the worst density has been determined for each location, the desired speed can be determined based on downstream density (for example, location 3's desired speed is based on the density at location 4, the next downstream location. This is to allow vehicles to prepare for upcoming conditions). Desired speeds to which each VSL sign is set are derived from pre-determined density ranges that are appropriate for optimal speeds. The Greenshield and Greenberg equations were used to determine an average optimal density that corresponded to five ranges of speed as shown in Table 3.6.

Density (pc/mi/lane)	Speed Range (mph)	Speed Limit (mph)
0 to 34.2	Greater than 52.5	55
34.2 to 45	Between 47.5 and 52.5	50
45 to 56.4	Between 42.5 and 47.5	45
56.4 to 68.5	Between 37.5 and 42.5	40
Greater than 68.5	Below 37.5	35

Table 3.6: Variable speed limits and density ranges

Figure 3.4 is an example of the downstream and upstream VSL system layout for a typical bottleneck location. The reason for placing the detectors immediately upstream of the bottleneck was to identify as close to the time as possible when the bottleneck was activated so that mitigation techniques might be implemented. This was done to allow sufficient time and distance for vehicles to reduce their speed in case of any downstream congestion.

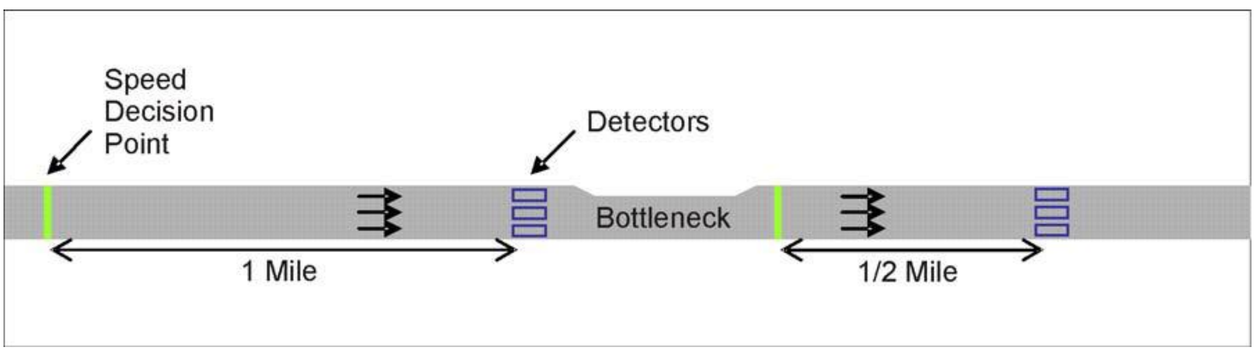


Figure 3.4 Typical VSL layout

Driver compliance rates are critical in determining the impact of VSL systems on highway traffic conditions. VISSIM offers the capability to define the percentage of the driver population who will/will not adhere to speed limits. The driver population that does not comply with VSLs was labeled Non-Compliant (NC) in the model. The compliance rates modeled ranged from 45% to 90% to evaluate the range of expected performance.

Ramp Metering (RM)

The concept of ramp metering was selected to regulate the flow of vehicles from side streets onto the freeway. The metering rate can range from 240 to 900 veh/hr for a single-lane on-ramp *(4)*.

In order to hold the metering rate constant for each scenario, a fixed ramp metering operation was used. The range of metering rates tested was between 500 and 900 veh/hr. To make the ramp metering operation more realistic, meters were turned off for the first 30 minutes of the simulation because the freeway was operating at/near free flow conditions. Similarly during the simulation of incident conditions, ramp meters were only turned on after the incident had occurred so that congestion on the freeway was not exacerbated. Ramp meters were provided at all 10 on-ramps within the analysis segment.

Transit and Parking Capacity (TPC)

Park-and-ride facilities and associated transit services along with park-and-pool facilities formalize and make readily available the option of mixed-mode travel. The combination they facilitate allows the use of a low-occupancy mode, most often driving alone, where travel densities are low and high-occupancy modes are inconvenient. It allows transfer to a high occupancy mode—rail transit, bus, vanpool, or carpool—where travel densities become higher and more supportive of high-occupancy mode efficiencies *(48)*. Since transit and parking facilities are complimentary in mixed-mode travel, the ability of available capacities to attract new transit riders was the attribute of interest. Turnbull et al. (2004) cited two studies that suggested that an added park-and-ride space attracts 0.22 new transit riders *(48)*. This traveler response does not represent decisions taken by travelers in real-time. Rather, they are indicative of long-term traveler behavior in response to the increase in parking capacity. However, this served as a guide in choosing the traveler response rate to test, taking into account the proposed addition of 3000 new parking spots within the corridor. The research team assumed an attraction between 7.5% and 23% of SOVs to transit.

A new "vehicle type" group labeled TPC in VISSIM was created to model the impact of transit and parking capacities. For the purposes of real-time/short-term application, TPC vehicles behave as SOVs during the first 30 minutes (warm up period) of the simulation, and begin to exit toward parking facilities and transit stops when congestion begins to build (after warm up period).

High Occupancy Vehicle (HOV) Lanes

HOV facilities provide preferential treatment for transit, vanpools, carpools, and other designated vehicles by providing lanes and roadways reserved for their use. HOV lanes usually carry two to five times as many persons as GP lanes, and have the potential to double the capacity of roadway to move people *(49)*. The analysis segment contains two reversible HOV lanes that operate in the analysis direction (north) during the morning peak with an occupancy requirement of three or more. The HOV lanes carry about 25% of the vehicle traffic (compared with GP lanes) and still have extra capacity to attract new users (over 1,000 veh/hr between SR 234 and SR 123; over 500 veh/hr between SR 123 and SR 642). The ability of this extra capacity to attract new users is the attribute of interest. Therefore, a new "vehicle type" group called HOV-E was created in VISSIM to model the attraction of new HOV users from the existing SOVs. The attraction of new HOV users is possible through real-time information dissemination. The assumed range of new users modeled was from 0% to 15%. Similar to TPC vehicles, HOV-E vehicles become operational after the first 30 minutes of the simulation.

High Occupancy Toll (HOT) Lanes

The use of market forces to allocate limited highway capacity among users by their need to travel and willingness to pay, usually referred to as congestion pricing in the literature is a known congestion mitigation measure. Drivers who are not willing to pay may choose not to travel or select an alternative time, route, or mode, and those who pay receive the value of being able to drive, when they choose to, with reduced congestion. The concept of HOT lanes seek to achieve better utilization of special lanes such as HOV lanes by making them accessible to low occupant vehicles (LOVs) who are willing to pay. The research team is not interested in which toll amounts result in better utilization of HOT lanes, but rather in the impact of the HOT lane concept in increasing carpools and ridesharing.

One reason for this impact is because it is believed that drivers get a tangible sense of the cost savings offered by carpooling when tolling is introduced rather than paying alone to enjoy the better services of the HOT lanes *(50)*. Therefore, the ability of HOT lanes to reduce the percentage composition of LOVs and SOVs through carpool and ridesharing formations was modeled. A reduction range of 0% to 15% was assumed. To model this, a new "vehicle type" group called HOT was created in VISSIM. This strategy was considered because of plans by VDOT to introduce HOT lanes in the corridor in future. HOT vehicles also become operational after 30 minutes (after the warm up period) of simulation.

Financial Incentives

Transit and parking pricing play an important role in transit ridership. The most common objective of transit pricing and fare changes is to increase revenues in response to actual or forecasted increases in operating costs. Such changes usually involve fare increases for most transit users. An associated objective is to minimize the ridership loss usually involved in fare increases *(51)*. Similarly, the primary objective for setting a price on parking for parking facility owners/operators is to cover cost and earn a reasonable return on investment *(52)*.

In this research, it is believed that these costs may stifle transit ridership increases. For example, if a traveler decides to park at a parking facility in order to use transit, he/she must pay for parking and transit costs, as well as a reduced level of comfort compared to driving alone. Providing financial incentives to travelers to cover parking and transit costs may help to increase transit ridership and reduce congestion in the corridor. Therefore, the power of financial incentives to reduce the percentage of SOVs was the attribute modeled. In VISSIM, a "vehicle type" group labeled Financial Incentives (FI) was created to aid in the modeling. The assumed range of reduction in SOVs modeled was between from 0% and 7.5%. FI vehicles also became operational only after 30 minutes of the simulation.

It is important at this stage to clearly outline the similarities and differences between TPC, HOV-E, HOT, and FI as modeled in this study. Both TPC and FI are strategies meant to induce mode shifts (from SOV to transit). However, they are two different strategies. According to the literature, some travelers shift to transit because of available spots at park-and-ride lots or seats in transit vehicles *(48)*. Similarly, there is another group of travelers who shift to transit because of reduction in transit *(51)* and parking *(52)* fees. It is possible there are some travelers who are induced by both strategies but the extent of intersection is unknown. Independently, each of the two strategies has been discussed in the literature, but their combined effect is also unknown; this knowledge, in conjunction with other implemented ICM strategies, is what is been sought after in this research. Similarly, HOV-E and HOT are both intended to facilitate mode shifts from SOVs to HOVs. The HOT strategy in this study catalyzes the formation of carpools/vanpools as a result of travelers getting a tangible reason for carpooling due to the tolls being charged *(50)*. On the other hand, some travelers form carpools/vanpools because of congestion on the GP lanes, the travel time reliability afforded by HOV lanes, etc., and not because of tolls *(49)*. Just as in the case of TPC and FI, there are some travelers who might be susceptible to both HOT and HOV-E. Within the framework of ICM, the desired objective is to determine the combined effect of these strategies, which have traditionally been implemented as stand-alone strategies.

Ramp Meter Bypass and HOV Access Treatments

This strategy gives HOVs priority at metered freeway entrance ramps by providing either a separate lane located adjacent to the metered GP lane or a separate HOV entrance ramp. Either way, they allow HOVs to move around the traffic queue at the meter or otherwise directly enter the freeway. These techniques may be used in combination with a freeway HOV lane or as a stand-alone measure. Direct access ramps from adjacent roadways, park-and-ride lots, and transit stations are also employed in some areas to provide buses, and sometimes vanpools and carpools, with extra travel time savings and trip time reliability *(49)*. This strategy was modeled by providing separate lanes adjacent to the metered lanes, and restricting the use of the separate lane to only HOVs and buses. The evaluation of this strategy was tied to the ability of HOV lanes to attract new HOV users because it seeks to reduce the percentage of SOVs in the analysis segment.

Transit Signal Priority (TSP)

TSP is an operational strategy that facilitates the movement of transit vehicles (usually those in-service), either buses or streetcars, through traffic signal-controlled intersections. Objectives of TSP include improved schedule adherence and improved transit travel time efficiency while minimizing impacts to normal traffic operations *(53)*. The main TSP control strategies modeled were green extension and early green (active priority). A constant extension period of 15 seconds was established to facilitate the operation of TSP in VISSIM.

Only one of the transit routes (South Route 1) is on the primary arterial (U.S. 1). This route starts from Fox Lair/Route 1, travels south, and connects to the HOV lanes through SR 234. The effect of TSP on the corridor will be implicitly captured by the number of bus trips recorded during the analysis period. Additionally, bus travel times will also be used to evaluate the effect of TSP.

3.5 Simulation Results and Analysis

The analysis of simulation results focused on highlighting the impacts of ICM in the analysis segment. Using the LHS technique, 50 scenarios of ICM strategy combinations were tested, with each scenario having different combinations of the ICM parameters (See Appendix A).

Several performance measures including individual facility average travel times, average speeds, average vehicular flow, average vehicle delay, corridor person flow, fuel economy and emissions were collected. It is important to note that the analysis was not focused on the performance of individual strategies but on how they perform as a system; therefore, no special attention was paid to any individual strategy during the analysis, unless something unusual about a strategy is observed. In selecting the most critical ICM strategies, corridor person flow per hour was the main performance measure used. This performance measure was chosen because it is not mode-specific and satisfies the performance measure requirement prescribed in the AMS framework.

The simulation model did not incorporate any information dissemination strategy. In carrying out the analysis, it was assumed that all the necessary means by which real-time traveler information is disseminated were employed. Additionally, those strategies meant to influence traveler behavior (TPC, HOV-E, FI, and HOT) were not intended for only SOVs on I-95 N GP lanes. Rather, they were meant to influence all SOVs in the corridor. For example, some of the SOVs that would have eventually ended up on the GP lanes exited to a parking facility while traveling on U.S. 1N.

ICM can be beneficial during both incident-induced and recurring congestion periods. Therefore, the ICM strategies were tested under both non-incident and incident conditions. The analyses of simulation results under both conditions are discussed next.

3.5.1 Impact of ICM in Non-Incident Conditions

Limited access facilities such as freeways are designed to operate at higher performance standards (in terms of speed, travel time, flow, etc.) than, for instance, arterials. In the absence of inter-agency coordination among corridor operating agencies, freeway operators (usually the State DOTs) will want to shift freeway traffic to any parallel arterial in order to improve its operating performance. This strategy was tested before incorporating ICM strategies into the simulation model, and the results are as shown in Table 3.7.

I-95 N				U.S. 1N		
% Diverging	**Average Travel Time (min)**	**Average Speed (mph)**	**Flow (veh/hr)**	**Average Travel Time (min)**	**Average Speed (mph)**	**Flow (veh/hr)**
0	27.1	31	5668	30.7	30	2488
5	25	36	5594	32	31	2390
10	24	39	5748	33.5	30	2380
15	22.3	40	5673	35	32	2350
20	22.5	40	5721	37	29	2156

Table 3.7: Impact of Diversion of I-95 N and U.S. 1N

from Table 3.7, it will take 15% of vehicles diverting from I-95 N to U.S. 1N in order to reduce average travel time on the freeway by about 4.8 minutes and increase corresponding average speed by 9 mph. This will adversely affect traffic conditions on U.S. 1N, resulting in corresponding increase in average travel time of 4.3 minutes. In terms of vehicular flow, neither the freeway nor arterial experience any significant changes. The ICM strategies tested under non-incident conditions showed significant improvements in most of the performance measures for the individual road facilities as well as the entire corridor.

Average Travel Times

I-95 N experienced a reduction in average travel times for all the 50 tested scenarios. The 8-mile segment between SR 234 and SR 123 experienced a travel time reduction of about 7 minutes, whereas the travel time for the 3-mile segment between SR 123 and SR 642 was reduced by 6 minutes, resulting in a combined travel time reduction of 13 minutes. For the primary arterial, U.S. 1N, average travel times between SR 234 and SR 123 were reduced by almost 6 minutes in scenarios where the percentage of vehicles parking in order to use transit (TPC and FI vehicle types) is high. This reduction in travel time is reasonable because there are less vehicles on the roadway due to those exiting U.S. 1N in order to park and use transit, enabling the remaining cars to travel at or near design speeds. The second segment of U.S. 1N (between SR 123 and SR 642) recorded an average travel time reduction of 3 minutes.

The reversible HOV lanes were not significantly impacted by the ICM strategies in any of the 50 scenarios. The average travel times were not significantly different from the base conditions. This was expected because none of the ICM strategies was directly intended to improve HOV travel times. It is likely that as the percentage of HOV-E and HOT vehicles increases, average travel times on HOV lanes might increase. Table 3.8 and Figure 3.5 show the travel time savings for the individual road facilities.

Segment	Average Travel Time Savings (min)	Condition(s)
I-95 N (SR 234-SR 123)	7	All scenarios
I-95 N (SR 123-SR 642)	6	All scenarios
I-95 N HOV (SR 234-SR 642)	0	All scenarios
U.S. 1N (SR 234-SR 123)	6	When TPC and FI % are high
U.S. 1N (SR 123-SR 642)	3	All scenarios

Table 3.8: Travel time savings due to ICM

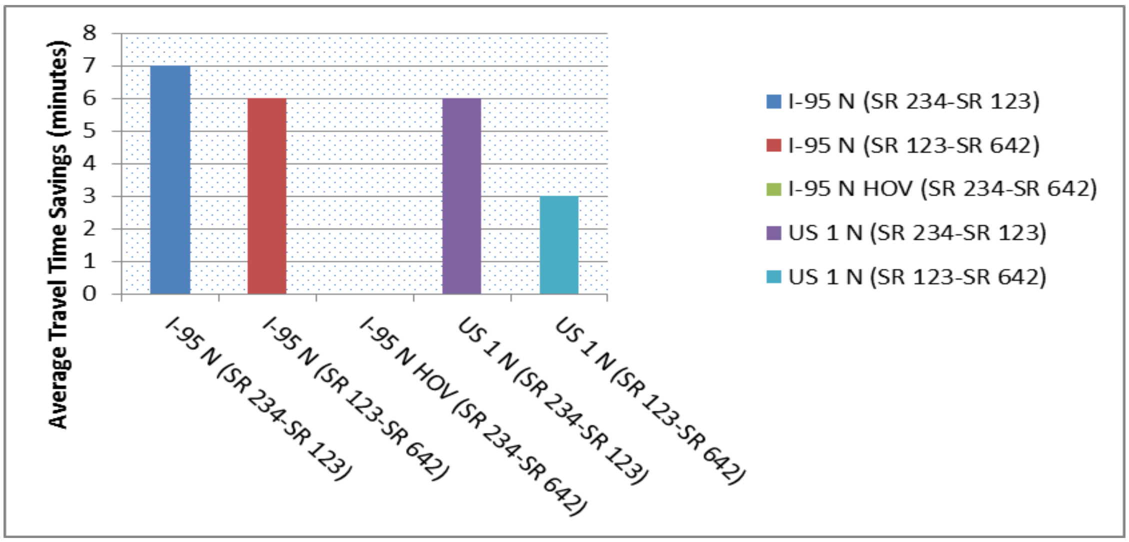


Figure 3.5: A plot of travel time savings due to ICM

Vehicular Flow and Speed

Vehicular traffic volumes generally decreased along the entire length of the I-95 N GP lanes. This is not unexpected, because most of the ICM strategies modeled are meant to reduce the percentage of SOVs in the traffic stream. Consequently, most of the vehicles exit toward a parking facility in order to use the PRTC buses or VRE commuter trains.

The 3-mile segment of the I-95 N GP lanes only experienced vehicular flow levels close to the base conditions when the percentage of TPC, HOV-E and FI are very low (that is, only a small % of LOV reduction). The HOV lanes occasionally experienced reductions in flow, especially when the percentage of vehicles exiting to parking facilities (TPC) is high. This might be due to the high level of interactions that occur when drivers decide to exit. This usually begins with a reduction in speed, followed by the search for safe gaps in order to carry out lane changes. Therefore, if there are a lot of vehicles trying to exit, it might impact flow conditions. Visual inspection of the simulation revealed that, when the % of vehicles exiting from the GP lanes to

SR 234 is large, it reduces the opportunity for HOVs, HOV-Es, and HOTs to access the HOV on-ramp south of SR 234.

Conversely, the segment along U.S. 1N between SR 234 and SR 123 experienced an average vehicular increase of about 500 veh/hr in almost all of the 50 test scenarios. The remaining segment between SR 123 and SR 642 did not experience any significant changes in vehicular flow. Table 3.9 shows a summary of the impact of ICM on vehicular flow.

Segment	Impact on Flow
I-95 N (SR 234-SR 123)	Decreased in all scenarios(17%-25%)
I-95 N (SR 123-SR 642)	Only increased when TPC, HOV-E, FI % are low
I-95 N HOV (SR 234-SR 642)	Increased when TPC % is low
U.S. 1N (SR 234-SR 123)	Increased in all scenarios (18%-29%)
U.S. 1N (SR 123-SR 642)	No significant changes

Table 3.9: Impact of ICM on vehicular flow

As a result of the reduction in vehicular flow along I-95 N GP lanes, average speed increased along its entire length. An average speed increase of 10 mph was recorded for the segment between SR 234 and SR 123 and 23.5 mph for the segment between SR 123 and SR 642.

The I-95 N HOV lanes experienced a slight speed increase of 2.9 mph, which is consistent with the corresponding travel times reported earlier. The primary arterial also recorded significant speed increases of 7.9 mph and 8.6 mph between SR 234 and SR 123, and SR 123 and SR 642, respectively. Table 3.10 and Figure 3.6 show the benefits of ICM in terms of speed increases.

Segment	Speed Increase (mph)
I-95 N (SR 234-SR 123)	10.0
I-95 N (SR 123-SR 642)	23.5
I-95 N HOV (SR 234-SR 642)	2.9
U.S. 1N (SR 234-SR 123)	7.9
U.S. 1N (SR 123-SR 642)	8.6

Table 3.10 Speed improvement due to ICM

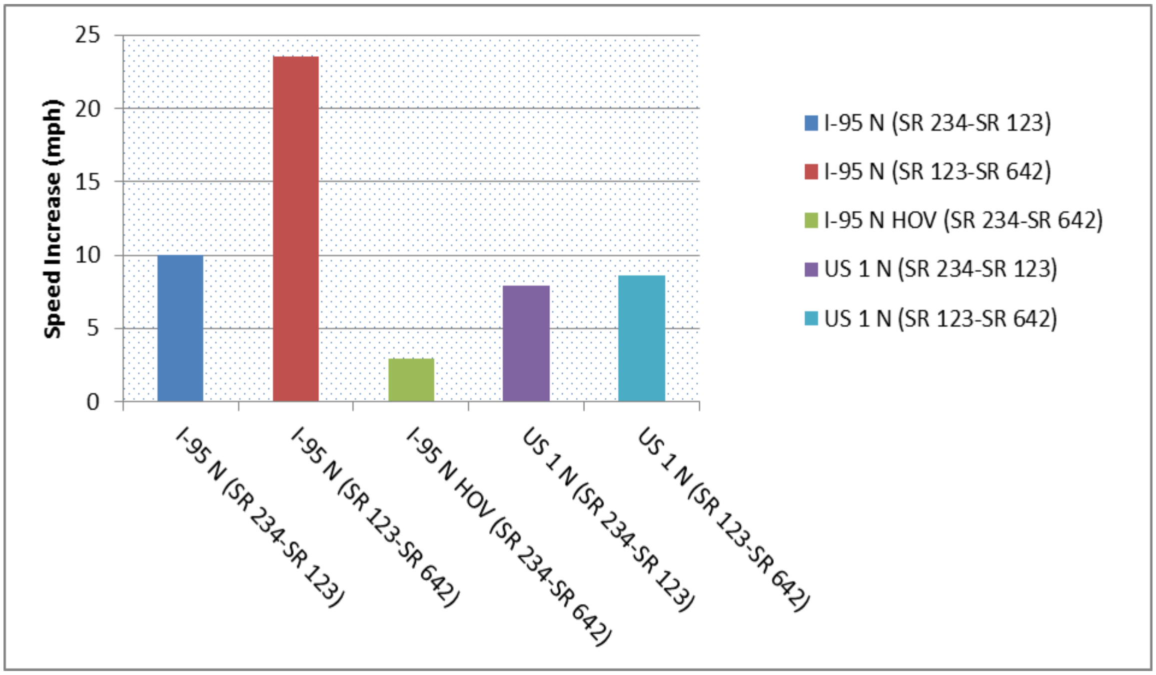


Figure 3.6: Improvement in travel speeds due to ICM

Selection of Critical ICM Strategies under Non-Incident Conditions

As described earlier, ICM consists of different congestion mitigation strategies operating together over a large geographical area. It is important to know those strategies that are most critical to the success of the ICM operation. The evaluation methodology developed in this research was used to identify the critical ICM strategies. The main performance measure used in identifying the critical ICM strategies was corridor person flow per hour. The corridor person flow obtained was as follows:

$$Corridor\ Person\ flow\ (Persons/hr) = GP_{PF} + HOV_{PF} + US1_{PF} + VRE_{PF} \qquad (3\text{-}11)$$

Where:

GP_{PF} = Total person flow on the GP lanes in 1 hour
HOV_{PF} = Total person flow on the HOV lanes in 1 hour
$US1_{PF}$ = Total person flow on U.S. 1 in 1 hour
VRE_{PF} = Total person flow on the VRE Commuter rail in 1 hour.

VISSIM enables the determination of the number of persons traveling at specific points in a network. Since the direction of travel modeled was toward Washington, D.C. (north), person flow data were collected at the end of the analysis segment, which is the intersection of SR 642 and the individual rail and road facilities. The corridor person flow under base conditions is 22,755 per hour compared with 26,041 per hour when ICM strategies are implemented, resulting in an increase of 3,286 persons per hour (14.4%).

The three sensitivity measures discussed earlier were calculated using results from the 50 test scenarios. From Table 3.11, it can be seen that HOV-E and HOT have larger coefficients than the remaining ICM strategies based on all the three sensitivity measures (SRC, LCC, and SPC). For the SRC, the R^2 value obtained was 0.985, which implies that the assumption of a linear relationship between corridor person flow and the ICM strategies is justified and that the ICM strategies adequately describe the variability in corridor person flow. Variance inflation factors for the ICM strategies were also less than 4, signifying insignificant correlation among the strategies.

Strategy	SRC	LCC	SPC
RM	0.00185	-0.0555	0.003071
TPC	30721.15	0.3687	0.243221
HOT	117623.5	0.5389	0.293893
HOV-E	142695.9	0.6567	0.394323
FI	128937.7	0.083	0.025769
VSL	17222.5	0.3867	0.206324

Table 3.11: ICM strategies sensitivity values

There is a need to test the statistical significance of the coefficients of ICM strategies before ranking them. Table 3.12 shows the t-statistic for the coefficients of ICM strategies at a significance level of 0.05. This implies that for a strategy's coefficient to be statistically significant, the t-statistic must be greater than 1.96.

Strategy	SRC	LCC	SPC
RM	*3.0	0.4	0.02
TPC	*8.7	*2.7	*1.98
HOT	*29.5	*4.4	*2.13
HOV-E	*34.2	*6.0	*2.97
FI	*7.6	0.6	0.18
VSL	*24.7	*2.9	*1.97

Table 3.12: T-statistic values for ICM strategies
*Statistically significant at 5% significance level

Finally, the ICM strategies were ranked based on the sensitivity measures and their statistical significance. Table 3.13 shows the ranking from most sensitive (rank equals 1) to least sensitive (rank equals 6) strategies based on the different sensitivity measures.

Parameter	SRC	LCC	SPC
RM	6	6	6
TPC	4	4	3
HOT	2	2	2
HOV-E	1	1	1
FI	5	5	5
VSL	3	3	4

Table 3.13: ICM strategies sensitivity rankings

From Tables 3.12 and 3.13, it was established that HOV-E and HOT were statistically significant and consistently ranked first and second, respectively, based on all three sensitivity measures. It was also evident that RM consistently ranked last in all the three rankings. The exact position of a strategy in the rankings is not as important as how consistently a strategy appears near the top. Based on all the three sensitivity measure rankings, four of the six ICM strategies were statistically significant. These strategies can be considered as the most critical among the six strategies modeled. They are TPC, HOT, HOV-E, and VSL. Note, when implemented in the field, some "shifts" from SOV's to transit or HOV's may be incentivized by more than one of these strategies. In other words, there is likely some "double-counting" in this analysis. However, given the goal of this work to explore feasibility, it can be concluded that each of these strategies does hold significant potential.

The fact that RM was not identified to be critical was not surprising. This is because; the presence of ICM strategies such as TPC and FI ensures that less vehicles get on to the freeway due to the availability of parking and transit capacity. Therefore, the need to meter entry of vehicles onto the freeway wasn't necessary.

Another phenomenon that is worth mentioning is the heavy traffic demand from the east-bound on-ramp of SR 123. From visual inspection during the calibration process, the ramp queue usually spills onto the arterial even though there was no metering. Therefore, it was expected that the queue length would grow with the introduction of ramp meters. However, there were no queues when ramp meters were in operation. Again, this might be due to the fact that the ramp meter was not operating in isolation but in conjunction with other ICM strategies such as TPC and FI.

The use of financial incentives was only statistically significant for the SRC sensitivity measure. This does not necessarily mean that this strategy has no ICM benefits. In this research, financial incentives were used to encourage travelers to park and use transit. Instead, it could have been used to influence travelers to use the HOV lanes. This strategy has been employed in Atlanta, and it proved to be beneficial *(54)*. Therefore, the final decision to discard a strategy must be taken after all practical uses of the strategy have been exhausted.

Fuel Economy and Emissions

The impact of ICM on fuel usage and vehicular emissions was very significant as shown in Table 3.14. In all 50 tested scenarios, significant reductions were experienced. Table 3.14 summarizes the impact of ICM strategies on fuel economy and emissions during non-incident conditions.

Condition	Fuel (gallons)	CO (g)	NOx (g)	VOC (g)
Without ICM	12346	863009.4	167910.3	200010.8
With ICM	8111	566988	110315	131405

Table 3.14: Impact of ICM on fuel economy and emissions

Limits of Effectiveness of Unknown Traveler Responses to ICM Strategies

As stated earlier, responses to those strategies that were meant to influence traveler behavior (TPC, HOT, HOV-E, FI) were purely based on assumptions from published literature. However, it is imperative to know the limits of effectiveness of such responses in terms of how they help improve the corridor's operating performance (increase person flow). It was difficult to establish a clear pattern for the limits of effectiveness taking into account that the modeling experiment was designed to minimize the number of trials.

3.5.2 Impact of ICM during Incident Conditions

Incident-induced congestion accounts for a significant proportion of travel delays, and it is therefore necessary to ascertain how ICM can help lessen its impact. In order to achieve this, an incident was created in the simulation by activating a red light on three of the four GP lanes on I-95 N between the west-bound off-ramp onto SR 123 and west-bound on-ramp from SR 123. This location was chosen so that all the ICM strategies could be adequately modeled.

The incident was scheduled to occur after the 30 minutes "warm-up" period. The incident lasted for one hour, and data collected during the one hour period were analyzed. Table 3.15 summarizes the impact of incidents on travel conditions on I-95 GP lanes.

Segment	Average Travel Time (min)	Average Speed (mph)	Vehicle Flow (veh/hr)	Corridor Person Flow (persons/hr)
I-95 N (SR 234-SR 123)	32	23.9	2531	--
I-95 N (SR 123-SR 642)	6.2	47.0	3468	18107

Table 3.15: Traffic conditions on I-95 corridor during modeled incident (No diversions)

From Table 3.15, corridor person flow per hour during incident conditions was 18,107; compared to non-incident conditions, corridor person flow decreased by 4,648 persons per hour. One of the most common approaches in addressing incident-induced congestion is to divert traffic onto adjacent/parallel routes. Usually, this is done without knowledge of traffic conditions on these parallel routes. In the end, corridor flow is significantly reduced. To replicate this condition, the incident was first modeled without incorporating the ICM strategies.

If traffic has to be diverted onto U.S. 1N in order to mitigate congestion on I-95 N GP lanes, what percentage of diversion will result in improved traffic operating conditions? Table 3.16 shows the impacts of different diversion percentages on both I-95 N and U.S. 1N.

I-95 N				U.S. 1N		
% Diverting	Average Travel Time (min)	Average Speed (mph)	Flow (veh/hr)	Average Travel Time (min)	Average Speed (mph)	Flow (veh/hr)
0	38.2	36	3468	30.7	30	2488
5	36.4	36	2762	30.5	28	2054
10	35.7	34	2869	33.5	27.3	2080
15	33.9	37	2813	35	26	2022
20	32.9	37.5	2876	37	24	2017

Table 3.16: Impacts of diversion on I-95 and U.S. 1N

From Table 18, 15% of the traffic has to be diverted onto U.S. 1N in order to reduce average travel time by 5 minutes coupled with no significant increase in speed. These diversions can increase average travel times on U.S. 1N up to 7 minutes and reduce average speeds by 6 mph. Regardless of the diversion percentage, there was no significant increase in the vehicular flow on I-95. In contrast, vehicular flow on U.S. 1N reduced by as much as 471 vehicles per hour. For those vehicles that do divert, their average travel times are as shown in Table 3.17.

Diversion Point	End Point	Average Travel Time (min)
I-95/SR-234	I-95/SR-642	29.9
I-95/SR-769	I-95/SR-642	29.8
I-95/SR-294	I-95/SR-642	23.2
I-95/SR-123	I-95/SR-642	18.7

Table 3.17: Average travel times for diverted vehicles

Even though there were travel time savings for those who exited onto SR 234, only a few vehicles (less than 20) recorded this travel time during the analysis period. Incorporating ICM strategies into the modeled incident resulted in the findings in Table 3.18. The next section discusses these results.

Segment	Average Travel Time (min)	Average Speed (mph)	Vehicle Flow (veh/hr)	Corridor Person Flow (persons/hr)
I-95 N (SR 234-SR 123)	15.2	47.2	2823	
I-95 N (SR 123-SR 642)	7.2	50.6	3624	20598 to 29315

Table 3.18: Impact of ICM during conditions

Average Travel Time

Average travel time between SR 234 and SR 123 was reduced by 16.8 minutes, with the second segment experiencing an insignificant increase of 1 minute as shown in Table 3.18. Overall, average travel time on I-95 was reduced by 15.8 minutes when ICM strategies were operational. Figure 3.7 shows a graphical plot of the travel time savings.

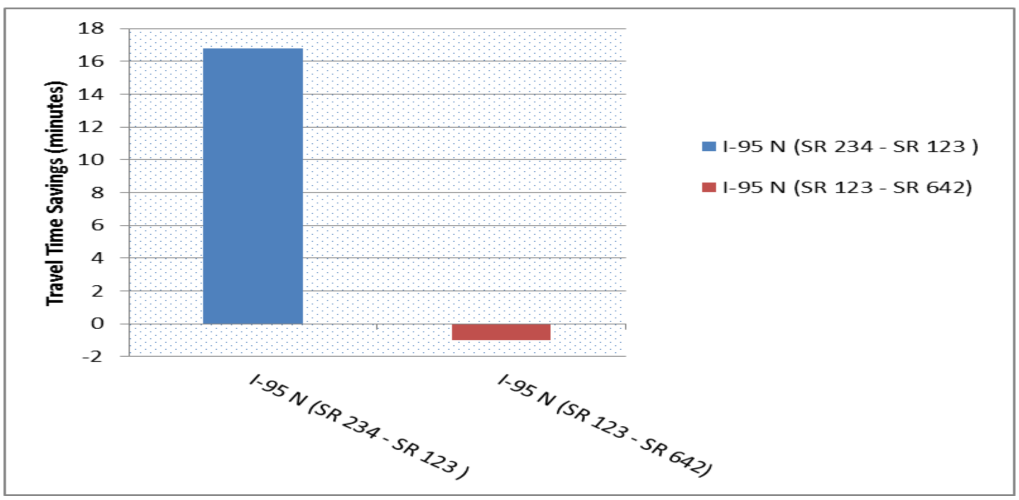


Figure 3.7: Travel time due to ICM strategies

Vehicular Flow and Speed

There was a significant increase in the vehicular flow of over 300 veh/hr between SR 234 and SR 123 and about 150 veh/hr between SR 123 and SR 642. However, there was a significant increase in average travel speeds by 23.3 mph in the first section and a reduction of 3.6 mph in the second section. Figure 3.8 shows a graphical plot of the impact of ICM strategies on travel speeds during incident conditions.

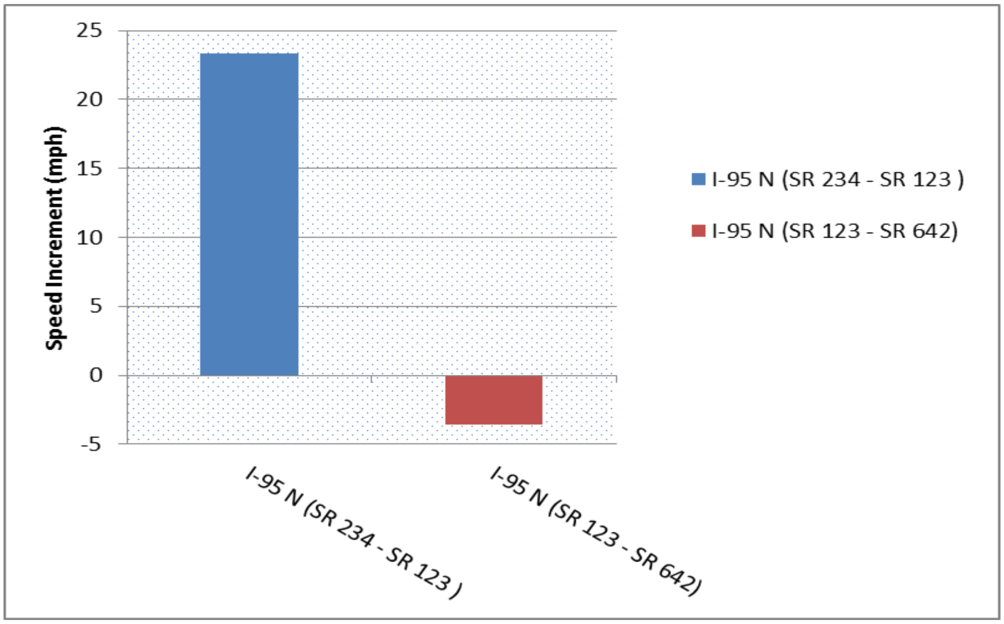


Figure 3.8: Impact of ICM strategies on speed during incident conditions

Selection of Critical ICM Strategies during Incident Conditions

The same methodology used in selecting critical ICM strategies during non-incident conditions was used in selecting that of incident conditions shown in Table 3.19. Similarly, the main performance measure used was corridor person flow per hour. The average corridor person flow experienced when ICM strategies were implemented was 24,967 persons per hour. Compared to the case where there were no ICM strategies implemented, corridor person flow increased by 6860 persons per hour (37.8%). For the SRC, it is worth noting that the R^2 value obtained was 0.97; this implies that the assumption of a linear relationship between corridor person flow and the ICM strategies is justified and that the ICM strategies adequately describe the variability in corridor person flow. Also, variance inflation factors computed for each of the variables/strategies was less than 4, implying that there were no significant correlations among the implemented ICM strategies.

Strategy	SRC	LCC	SPC
RM	0.00172	-0.1727	0.056993
TPC	26926.81	0.3352	0.234578
HOT	108109.1	0.6038	0.550437
HOV-E	146257.9	0.7716	0.712401
FI	72983.78	0.0201	0.100495
VSL	5147.182	0.2578	0.15004

Table 3.19: ICM strategies sensitivity values during incidents

Table 3.20 shows the t-statistic of the coefficients of ICM strategies at a significance level of 0.05. This implies that for a strategy's coefficient to be statistically significant, the t-statistic must be greater than 1.96.

Parameter	SRC	LCC	SPC
RM	*2.16	-1.21	0.40
TPC	*5.10	*2.46	*1.98
HOT	*20.85	*5.25	*4.57
HOV-E	*26.98	*8.40	*7.03
FI	*3.81	0.14	0.70
VSL	*5.68	*1.99	*1.97

Table 3.20: T-statistic values for ICM strategies during incidents
*Statistically significant at 5% significance level

The ICM strategy rankings are as shown in Table 3.21 below.

Parameter	SRC	LCC	SPC
RM	6	5	6
TPC	4	3	3
HOT	2	2	2
HOV-E	1	1	1
FI	3	6	5
VSL	5	4	4

Table 3.21: ICM strategy rankings

From Tables 3.20 and 3.21, the ramp metering strategy appeared to be less critical among the rest. Similarly, FI was statistically significant only under the SRC ranking criteria. The four ICM strategies that were statistically significant under all three ranking criteria are HOV-E, HOT, TPC, and VSL. Based on the ranking criteria, these four ICM strategies are the most critical.

Fuel Economy and Emissions

The impact of ICM on fuel usage and vehicular emissions was very significant as shown in Table 3.22: In all 50 test scenarios, significant reductions were experienced.

Condition	**Fuel (gallons)**	**CO (g)**	**NOx (g)**	**VOC (g)**
Without ICM	13190	922014.1	179390.4	213685.7
With ICM	8828	617079.1	120061.2	143014

Table 3.22: Impacts of ICM during incidents on fuel economy and emissions

Limits of Effectiveness of Unknown Traveler Response to ICM Strategies

As experienced during non-incident conditions, the limits of effectiveness of traveler responses to ICM strategies during incident conditions could not be clearly determined.

3.5.3 Effects of Transit Signal Priority on Bus Travel Times

The impact of the TSP strategy was evaluated by comparing average bus travel times with and without TSP. It is important to note that the impact of TSP within this context is affected by the other ICM strategies modeled. Hence, the effectiveness of TSP as a stand-alone strategy is not the sought after objective, rather it is how TSP performs within an ICM framework. The reductions in average travel time were modest for buses traveling between Dale City and the Washington, D.C. area (2.5 minutes), and between South Route 1 (Dumfries) and Washington, D.C (2.1 minutes). Conversely, the routes between Lakeridge and the Washington, D.C. area experienced an average travel time increase of 3.4 minutes. Buses using this route have stops at three park-and-ride facilities. Roads leading to these park-and-ride facilities experience heavy traffic when the % of vehicles wanting to park and use transit is high. This might slow down buses and increase their travel times. Table 3.23 shows the impact of TSP on average bus travel times.

Bus Route	Average Travel Time (min) No TSP	Average Travel Time (min) With TSP	Change in Average Travel Time (min)
Dale City-Washington	25.3	22.8	2.5
Dale City-Pentagon/Crystal City	25.3	22.8	2.5
Dale City-Navy Yard	25.3	22.8	2.5
Lakeridge-Washington	19.1	22.5	*3.4
Lakeridge-Pentagon/Crystal City	19.1	22.5	*3.4
Dale City/Lakeridge-Capitol Hill	19.1	22.5	*3.4
South Route 1-Washington	27	24.9	2.1

Table 3.23: Impact of TSP on average bus travel times
*Increase in average travel time

3.6 Summary

This chapter focused on the development of an ICM evaluation methodology based on which most beneficial ICM strategies can be selected. The proposed methodology was applied to a real-world transportation corridor in northern Virginia (I-95 corridor) to evaluate the feasibility of ICM implementation. Using a microscopic simulation tool (VISSIM), the effectiveness of ICM under both incident and non-incident conditions was evaluated for the test corridor. Also, the most beneficial ICM strategies that can help to mitigate congestion on the test corridor were identified. The analysis of simulation results revealed that implementation of ICM has the potential to mitigate highway congestion, especially during incident conditions. The next chapter uses data from multiple HOT lane facilities in the U.S. to investigate the behavior of HOT lane users in terms of their response to pricing (tolls). The purpose of the multi-facility analysis approach is to help determine if there is a general pattern in the behavior of HOT lane users.

Chapter 4

Multi-HOT Lane Driver Behavior Analysis

Among the numerous Integrated Corridor Management (ICM) strategies which can help mitigate congestion, the use of High-Occupancy Toll (HOT) lanes has gained ground in recent years. The HOT lanes use price, occupancy and access restrictions to manage the number of vehicles traveling on them, thereby maintaining free-flow traffic conditions, even during peak travel periods *(32)*. As a result of the additional travel option provided by HOT lanes, mobility is improved for all people in a corridor including transit, freight and drivers in the General Purpose (GP) lanes. HOT lanes encourage carpooling and other transit alternatives (which increases person throughput) while offering vehicles that do not meet standard occupancy requirements another option for more reliable travel times *(55)*. Although there are numerous HOT lane facilities operated currently in the U.S., the behavior of drivers who use these facilities is not completely understood. Many research efforts (stated and revealed preferences) have been conducted to identify factors that influence the decision to use/not to use HOT lanes; however, most of these investigations have focused on individual HOT lane facilities, making their findings site specific *(12–15)*. Effective ICM requires that transportation system managers take action to fully utilize available capacity in a corridor. There is a need to understand how drivers will react to options (i.e. whether to use the HOT lanes or not) and how much they are willing to pay for HOT lane use. This research seeks to understand the choice behavior of HOT lane drivers using revealed preference data from multiple HOT lane systems in the U.S. The objective of this approach is to determine if there is a general pattern in the behavior of HOT lane drivers in terms of how they respond to tolls and changing corridor traffic conditions as well as their willingness to pay for HOT lane use.

This chapter is organized into two main sections. The first section focused on HOT lane driver willingness to pay for travel time savings and explored the differences and similarities observed for the multiple HOT lane facilities considered in this research. HOT lane driver response to toll rates and changing traffic conditions on GP lanes is thoroughly examined in the second section. That is, estimation of the elasticity of HOT lane demand with respect to (w.r.t) toll rates and GP lane congestion. Consequently, differences and similarities between HOT lane demand elasticities for the different facilities were analyzed.

4.1 Economic Theory behind HOT Lanes

The primary purpose of HOT lanes is to serve High Occupant Vehicles (HOV) while regulating use of the extra capacity by non-HOVs through pricing. As supply of unused capacity on the HOT lanes becomes scarce, there will be a demand at higher price. Therefore, pricing (charging of tolls) is used as a mechanism to keep HOT lane demand at levels just enough to use the extra capacity. The demand-based tolls charged by HOT lanes vary based on prevailing traffic conditions (dynamic pricing) and are usually updated at shorter intervals (e.g. every 5 minutes). Arguably, the decision to pay for HOT lane use follows rational choice theory since drivers calculate the likely benefits and costs before making a choice between HOT and GP lanes *(56)*. Travel time savings is often cited by HOT lane users as the major benefit they derive from using

HOT lanes *(32,33)*. Therefore, the amount of money drivers are willing to pay for travel time savings is their Value of Travel Time Savings (VTTS). Willingness to pay for travel time savings tend to differ among individuals and across time for the same individual depending on prevailing conditions, trip purpose, etc. *(57,58)*. At any point in time, if tolls are set too high (above drivers' willingness to pay levels) very few drivers will use the HOT lanes (leading to loss in potential revenue and efficient use of capacity). Conversely, if tolls are set too low, too many drivers may use the lanes resulting in over-use of the extra capacity (which defeats the purpose of HOT lanes). Therefore, setting tolls to ensure that HOT lane demand is kept at optimum levels (just enough to use the extra capacity) is very critical to the success of HOT lanes.

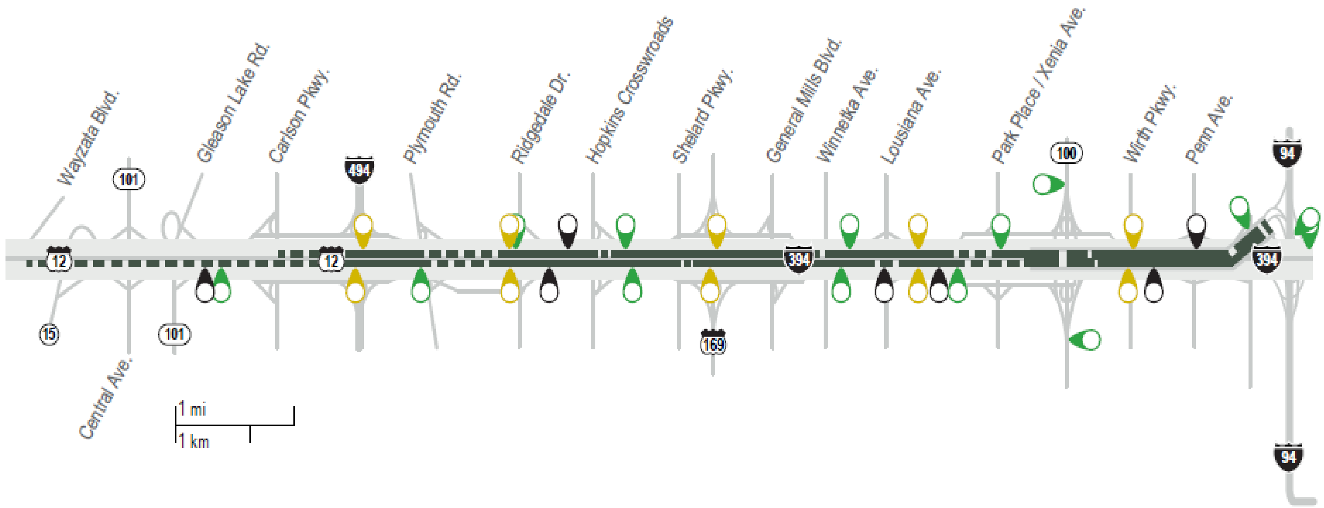
4.2 HOT Lane Facilities Studied

Four HOT lane facilities with dynamic electronic tolling systems were studied in this research. These are the I-394 MnPASS express lanes in Minneapolis, Minnesota; I-15 Fast Trak express lanes in San Diego, California; I-85 express lanes in Atlanta, Georgia; and I-95 express lanes in Miami, Florida. Each facility is briefly described below.

4.2.1 I-394 MnPASS Express Lanes – Minneapolis

The I-394 MnPASS express lane (Figure 4.1) is an 11-mile HOT facility which was opened in May 2005 by converting existing HOV lanes to HOT lanes. It runs east-west and serves as the most direct link for commuting between downtown Minneapolis and parts of the Minneapolis-Saint Paul metropolitan area. The HOT facility is made up of two distinct segments. The first segment, which runs from Wayzata Boulevard to State Highway 100 (8 miles) comprises a single HOT lane in each direction and is separated from the GP lanes by double-striped white lines. The first segment is commonly referred to as the "diamond' lane section, operating Monday through Friday, from 6:00 AM to 10:00 AM in the eastbound direction and 2:00 PM to 7:00 PM in the westbound direction.

The second segment is between State Highway 100 and I-94 (2.7 miles) and operates as a two lane barrier-separated reversible facility. The reversible section collects tolls at all times, including weekends, except when the direction is been changed. The HOT lanes are operated in the eastbound direction from 6:00 AM to 1:00 PM, and in the westbound direction from 2:00 PM to 5:00 AM. The reversible lanes remain westbound Friday afternoon and early Saturday morning. They are switched to eastbound at 8:30 AM Saturday morning, where they remain until 1 PM on Monday. This segment of the facility was used in the analysis. A map of the facility is as shown below in Figure 4.1 *(59)*.



I-394 MnPASS Express Lanes Pricing Zones

Direction	Limits	Hours
Eastbound	Wayzata Blve. to Hwy. 100	6AM - 10AM, Mon - Fri
Reversible lane Eastbound	Hwy. 100 to I-94	6AM - 1PM, Mon - Fri
Westbound	Hwy. 100 to Carlson Pkwy.	2PM - 7PM, Mon - Fri
Reversible lane Westbound	I-94 to Hwy. 100	2PM - 5AM Mon - Fri

Figure 4.1: I-394 MnPASS express lanes (Source: MnDOT)

Usage of the HOT lanes is restricted to carpools of two or more passengers, transit vehicles and SOVs which are equipped with MnPASS transponders. Carpools and transit vehicles are allowed to use the facility at no cost while SOVs are required to pay between $0.25 and $8.00 per trip *(60)*.

Dynamic Tolling Strategy

The stated goal of MnPASS's toll rates is to maintain a Level-of-Service (LOS) C in the HOT lanes based exclusively on density. To achieve this goal, the toll is automated, and will reevaluate itself every three minutes based on the traffic density in the HOT lanes and adjust if necessary. To determine its new rate, first the level-of-service in the HOT lanes is determined. For each density level-of-service A through F, the toll rate initiates at a default rate. Within any particular level-of-service, the toll rate may either increase or decrease based on the increasing or decreasing traffic density. Table 4.1 below outlines the toll rate algorithm used by MnPASS *(61)*.

LOS	Min Toll	Default Toll	Max Toll	Δ1	Δ2	Δ3	Δ4	Δ5	Δ6
A	\$0.25	\$0.25	\$0.25	\$0.25	\$0.25	\$0.25	\$0.25	\$0.25	\$0.25
B	\$0.50	\$0.50	\$1.50	\$0.00	\$0.25	\$0.50	\$0.75	\$1.00	\$1.25
C	\$1.50	\$1.50	\$2.50	\$0.00	\$0.25	\$0.50	\$0.75	\$1.00	\$1.25
D	\$2.50	\$3.00	\$3.50	\$0.25	\$0.50	\$0.75	\$1.00	\$1.25	\$1.50
E	\$3.50	\$5.00	\$6.00	\$0.25	\$0.50	\$0.75	\$1.00	\$1.25	\$1.50
F	\$6.00	\$8.00	\$8.00	\$0.00	\$1.00	\$2.00	\$2.00	\$2.00	\$2.00

Table 4.1: MnPASS toll rate algorithm

With the density in the HOT lanes at LOS D, the default toll rate begins at \$3.00. As long as the LOS remains D, the toll rate cannot go below the minimum of \$2.50 or the maximum of \$3.50. Should the traffic density increase by 2 vehicles/lane/mile, the toll rate will increase by the corresponding LOS D and Δ2 value of \$0.50, provided in Table 4.1, resulting in a total toll of \$3.50. Had the density instead decreased by 2 vehicles/lane/mile from the previous three minutes, the toll rate would have decreased by the same amount, from \$3.00 to \$2.50. The algorithm is designed to be sensitive to changes in densities, but still be a step-wise algorithm that avoids rapid fluctuations in toll rates *(61)*.

HOT Lanes Usage

Along the reversible section of the HOT facility, an average of about 4740 eastbound vehicles trips were experienced between 6:00 AM and 9:00 AM during the fourth quarter of 2013. This includes about 2,250 car/van pools, 2,065 tolled SOVs, 241 SOV violators and 184 transit buses. These vehicle trips translate to about 12,147 person trips for the same analysis period. The reverse direction (westbound) registered 4,027 vehicle trips (between 3:00 PM and 6:00 PM), comprising 2,066 car/van pool trips, 1,477 tolled SOV trips, 308 SOV violators, and 176 bus transit trips. Person trips amounted to about 10,964 *(62)*.

Revenue

MnPASS express lanes revenue mainly comes from tolls and transponder fees. The average toll paid to use the HOT lanes is between \$1.5 and \$2.0 *(63)* while the monthly lease for a transponder costs \$1.50. In 2012, total revenue of \$3 million was generated: About \$ 2.5 million from tolls and \$500,000 from transponder fees. Operations and maintenance during the same period was \$2.4 million, resulting in a surplus of \$600,000. In general, revenue in excess of operations and maintenance costs gets split evenly between the Minnesota Department of Transportation (MnDOT) and the metropolitan council for highway and transit improvements *(64)*.

4.2.2 I-15 Fast Trak Express Lanes – San Diego

The I-15 express lanes, referred to as Fast Trak lanes, run north-south from SR 163 in the south to SR 78 in Escondido for 20 miles (Figure 4.2). They are made up of four lanes (two in each direction) with a movable barrier for maximum flexibility. The Express Lanes were built in three segments. The middle segment was the first to be constructed and opened to traffic in two phases. The first phase from SR 56 to Rancho Bernardo road opened in September 2008. The second phase from Rancho Bernardo Road to Centre City Parkway opened in early 2009. The North Segment (Center City Parkway-SR 78) and the south segment (S 163-SR 78) opened to traffic in 2011 and 2012, respectively. A 4 mile stretch of the facility, specifically between Mira Mesa Boulevard and Sabre Springs transit center, was analyzed in this research. This section contains the most traveled gantry (plaza 23NB/53SB) of the express lanes. A map of I-15 express lanes is shown in Figure 4.2 *(65)*.

The HOT lanes are in operation 24 hours a day all year round in both directions. Car/Van pools (two or more people), zero-emission vehicles with an approved clean air vehicle sticker issued by the California department of motor vehicles, motorcycles, and Metropolitan Transit System (MTS) buses can use the HOT lanes at no cost (no preregistration or transponder required). In order to use the HOT lanes, SOVs are required to be equipped with electronic transponders which can be obtained by opening a prepaid Fast Trak account. Employing a dynamic distance-based electronic tolling system, the toll paid by an SOV is based on rate per mile at the time SOVs enter the lanes and the total distance travelled. The toll rates are recalculated and updated every three minutes based on the level of traffic density in the HOT lanes, ensuring that traffic flows freely in the lanes. Typical toll rates range between $0.5 and $8.0. To help drivers realize the value of the tolls paid, average travel times on the HOT lanes are provided at the entry points of the lanes) *(66)*.

HOT Lanes Usage

The I-15 express lanes experienced an average daily traffic of about 27,556 vehicles between January 2011 and December 2011. Out of this total, about 80% (22,026) of the vehicles were not tolled (mostly HOVs). Only 20% (5,530) of the total average daily traffic paid tolls. The number of Fast Trak accounts (people registering to use facility) continues to increase. For example, the total Fast Trak accounts increased by 10% (1,450) from 14,300 in January 2011 to about 15,750 in December 2011. In terms of transit usage, ridership on I-15 commuter express routes have been steadily rising and totaled approximately 300,000 one-way passenger trips in financial year 2011 (which represents approximately 1,200 daily transit trips or roughly 600 unique drivers) *(67)*.

Revenue

The main sources of revenue include tolls and fines, congestion mitigation and air quality (CMAQ) funds, transit cooperative research program (TCRP) funding, etc. For the financial year 2011, the total revenue generated was $4.4 million. Similarly, the annual operating cost for the same time period was $4.4 million, so there was no surplus. The revenue generated was spent on staff salaries, benefits, and indirect expenses; TransCore system operations and maintenance; materials and equipment; and other direct costs. Additionally, an amount of $800,0001 was given out as a transit subsidy (67).

Figure 4.2: Map of I-15 express lanes

4.2.3 I-85 Express Lanes - Atlanta

The I-85 express lane (separated from GP lanes by double striped white lines) consists of a single lane in each direction (northbound and southbound) and was opened for use in October 2011. Prior to opening, the facility was a standard HOV-2 lane that routinely became congested *(13)*. The 15.5 mile HOT facility is located in the northeast Atlanta metropolitan area, stretching from Chamblee-Tucker road, just south of I-285, to old Peachtree road in Gwinnett County as shown in Figure 4.3 below *(68)*. The segment analyzed in this study was between Chamblee-Tucker road and Beaver Ruin road for the northbound section (6.8 miles) and between Old Peach road and Jimmy Carter Blvd. (9.6 miles) for the southbound section. The express lanes operate continuously for 24 hours in a day and 7 days in a week. In order to use the express lanes for free, transit buses, carpools with three or more occupants, motorcycles, emergency vehicles, and alternative fuel vehicles with proper license plates must pre-register (PeachPass account). Vehicles that do not meet occupancy requirements (less than three occupants) will be able to use the express lanes by paying a toll. The price to use the express lanes ranges from 0.01 cent per mile to 0.90 cents per mile *(69)*.

The dynamic tolling algorithm used on the I-85 express lanes continuously monitors the changes in traffic flow and speeds for vehicles to determine the appropriate toll required to maintain an average speed of 45 mph *(13)*. Depending on the prevailing conditions in the corridor, the dynamic tolling algorithm may consider changes in traffic flow and speeds on the GP lanes in the determination of tolls to be charged on the HOT lanes. The tolls are recalculated and updated every five minutes.

Figure 4.3: Map of I-85 express lanes

HOT Lane Usage

As of February 2013, the I-85 express lanes experienced about 395,744 monthly trips of which 14% were non-tolled trips. Weekday trips also averaged 17,777. Compared to February 2012, monthly and daily trips increased by 13.3% and 21.5% respectively. The total PeachPass accounts created also increased from 219,410 in February 2012 to 224,808 in February 2013 (+2.5%) *(70)*.

Revenue

Tolls charged for the use of the express lanes are the main source of revenue since the cost of opening a PeachPass account is free. Average daily toll paid by users in February 2013 was $1.49, which is a 26.2% increase compared with $1.18 paid by users in February 2012 *(70)*. At the end of the 2013 fiscal year, the I-85 express lanes took in $5.7 million in operating revenue and spent $7.4 million in operations and maintenance *(71)*. Enforcement cost has been identified as a major driving factor in the high cost of running the express lanes.

4.2.4 I-95 Express Lanes - Miami

The I-95 express lanes (Figure 4.4) were first opened for use in 2008. The first phase of the project converted a single HOV lane into two express lanes while maintaining the same number of GP lanes. Phase 1A opened on December 2008 and ran northbound from SR-112 to the Golden Glades Interchange (GGI) area just north of NW 151st street in Miami-Dade County. Phase 1B began tolling in January 2010 and runs southbound from the GGI area to I-395. Phase 1B also extended the northbound express lanes further to the south so that the northbound lanes now run from north of I-395 to the GGI area. The second phase (phase 2) which began construction in November 2011 will also create HOT lanes in both directions between the GGI area in Miami-Dade County and Davie road in Broward County. The section analyzed in this research was between SR-112 and GGI area in both directions (about 7.3 miles). A map of the I-95 express lanes is shown in Figure 4.4. The express lanes are separated from the GP lanes by flexible plastic poles *(72)*.

The express lanes are in operation at all times of the day and week. Until March 1, 2014, toll rates ranged between $0.25 and $7.0. Due to increasing driver demand for the use of the HOT lanes, new tolls ranging from $0.5 to $10.50 *(73)* are currently charged. The dynamic tolling algorithm used monitors traffic conditions exclusively on the express lanes and updates the toll rates every 15 minutes based on changes in express lane traffic density. The express lanes are open for use at no cost by pre-registered vehicles such as vanpools/carpools (3+), hybrid vehicles, Miami-Dade and Broward County buses, regular transit buses, school buses, and over-the-road buses. Motorcycles and emergency vehicles can use the express lanes without the need for pre-registration. Vehicles which do not qualify for toll exemptions must create and own a SunPass electronic transponder in order to access the express lanes. These vehicles will be charged a toll that will be deducted from the prepaid SunPass account. Trucks with three or more axles are not allowed on the express lanes *(74)*.

Figure 4.4: A map of I-95 express lanes

HOT Lane Usage

About 1,738,838 vehicle trips were recorded on the I-95 express lanes for the month of February 2013. Out of the total trips recorded, southbound and northbound directions constituted 51.3% and 48.7% respectively. Toll-exempt trips constituted approximately 1.9% of the total vehicle trips for the same time period. Average weekday volumes for southbound and northbound directions were 35,374 and 33,390 respectively *(75)*.

Revenue

Total revenue generated from tolls from the opening of the express lanes to February 2013 is $55 million. For the month of February 2013 alone, an amount of $1.72 million was realized from tolls. Average weekday peak period toll rate was $2.33 for southbound and $2.90 for northbound. In all, the southbound direction accounted for 51.7% of the total monthly revenue compared to 48.3% for the northbound direction (75).

4.3 VTTS Analysis

As mentioned in the introductory part of this chapter, HOT lanes provide a relatively faster and reliable travel alternative to SOV drivers but at a cost. It is therefore necessary for transportation professionals to be knowledgeable about how much drivers are willing to pay in order to benefit from the premium service provided by HOT lanes. SOV drivers have a choice when a HOT facility is available – they can travel for free on GP lanes and experience a delayed travel time, or pay a toll to use HOT lanes and experience a lower travel time. Based on how much drivers are willing to pay for HOT lanes access, the value they place on their travel time savings can be inferred. This metric is advantageous since it captures both the driver response to traffic conditions as well as toll rate.

4.3.1 Data Needs for VTTS Analysis

Two main types of data were needed to estimate HOT lane users' VTTS. The two data types are traffic and tolling data. Each data type and how it was obtained for the study areas are briefly discussed below.

Traffic Data

Data describing the traffic conditions on both the GP and HOT lanes enables the determination of their respective travel times. If the length of the analysis segment is known, average speed can be used to estimate the average travel time traveled on GP and HOT lanes from which travel time savings can be computed. Travel time savings for two of the facilities (I-394 MnPASS lanes and I-95 express lanes) were generated using the above-mentioned procedure. On I-394 MnPASS lanes, average speed data was obtained from MnDOT's "data extract" tool. The speed data covered the reversible section (2.7 miles) of the HOT lanes between October 2012 and February 2013. In total, speed data was obtained from 12 detector stations at three minute intervals, 6 each from GP (S1125, S1126, S1127, S1128, S1129, and S1130) and HOT lanes (S280, S281, S282, S284, S286, and S288). The speed data was used in estimating the respective travel times on GP and HOT lanes, and the resulting HOT lane travel time savings. Similarly, average speed data for I-95 express lanes was obtained from Florida department of transportation's (FDOT) central data warehouse, STEWARD, which is maintained by the University of Florida. Seven detector stations each from GP (600301, 600471, 600521, 600641, 600781, 600791, and 600851) and HOT lanes (690421, 690471, 690511, 690551, 690641, 690791, and 690841) were used to obtain the speed data at 15 minute intervals from October 2012 to February 2013. The speed data was used in estimating travel time savings experienced by users of the I-95 express lanes.

The data for both I-394 MnPASS and I-95 express lanes were screened for outliers using several key standards set by the Texas Transportation Institute (TTI) in their *Monitoring Urban Freeways in 2003* report *(76)*. About 95% of the original data was retained after screening process. The standards include:

1. Setting maximum and minimum speeds at 80 mph and 5 mph respectively;

2. Removing data points associated with controller error codes;
3. Consistency of elapsed time between records;
4. Removal of duplicate records when detector and timestamp are identical for multiple records ;
5. No more than 8 consecutive identical volume-occupancy-speed;
6. Removal of records with zero volume values when speed is non-zero; and
7. Removal of records with zero speed value when volume is non-zero.

For I-85 express lanes (Atlanta, GA) and I-15 Fast Trak express lanes (San Diego, CA), average travel times for both GP and HOT lanes were directly provided by State Road Tollway Authority (SRTA) and San Diego association of governments (SANDAG) respectively. SRTA and SANDAG are the agencies which manage I-85 express lanes and I-15 Fast Trak express lanes respectively. The travel times were provided at 5-minute intervals for I-85 express lanes and 3-minute intervals for I-15 Fast Trak express lanes. Consequently, travel time savings were calculated for each HOT facility.

Tolling Data

Toll amounts paid by users of HOT lanes were obtained for a 5-month period; between October 2012 and February 2012 excluding weekends and holidays. For I-85 express lanes, the toll data was provided at 5-minute intervals, which is the frequency at which toll rates are calculated and updated. Toll data for I-394 MnPASS lanes and I-15 Fast Trak express lanes was provided at 3-minute intervals with that of I-95 express lanes at 15-minute intervals. Time intervals during which no tolls were charged as a result of an incident or technical failures were excluded from the dataset. This constituted only 1% of the tolling data for all HOT facilities studied.

4.3.2 Methodology for VTTS Estimation

Both GP and HOT lanes generally operate at similar traffic conditions prior to congestion, with the later offering superior travel alternative during the peak and congested periods. It is possible that the VTTS for travelers might differ between congested and non-congested periods. Therefore, it was essential to estimate VTTS for the entire morning (6:00 AM to 10:00 AM) and evening (3:00 PM to 7:00 PM) periods as well as for the morning and evening peak periods (7:30 AM-8:30 AM/5:00 PM-6:00 PM). This will help to establish if travelers' VTTS changes with congestion. Data from the entire 5-month analysis period was used in calculating VTTS; however, holidays, weekends, and days with weather-related incidents (e.g. snow) were excluded.

VTTS can be expressed mathematically as:

$$VTTS = \frac{Toll\ Paid\ (\$)}{Travel\ Time\ Savings\ (hours)} \tag{4-1}$$

For each HOT facility, mean VTTS was calculated as the ratio of average toll paid ($) to average travel time savings (hours). Both average toll paid and average travel time savings were calculated by weighting the toll or travel time savings by the number of users who experienced it. Mean VTTS estimation results and discussion are presented in the section below.

4.3.3 Results and Discussions

Tables 4.2 and 4.3 display mean VTTS estimates for the four HOT lane facilities during the entire morning/evening periods and peak periods respectively.

FACILITY	DIRECTION	LOCATION	AVERAGE TOLL ($/mile)	AVERAGE TT SAVINGS (min/mile)	MEAN VTTS ($/hour)	MEDIAN VTTS ($/HOUR)
I-394	EB (AM)	Minneapolis	0.41	0.37	66.5	55.1
I-15	NB (PM)	San Diego	0.25	0.25	59.6	51.2
	SB (AM)		0.35	0.38	55	45.5
I-95	NB (PM)	Miami	0.37	0.49	45.1	41.2
	SB (AM)		0.36	0.43	49.7	43.8
I-85	NB (PM)	Atlanta	0.22	0.43	30.6	18.5
	SB (AM)		0.45	0.5	53.4	38.1

Table 4.2: VTTS for morning and evening periods

EB: Eastbound direction;
NB: Northbound direction;
SB: Southbound direction
AM: Morning period;
PM: Evening period

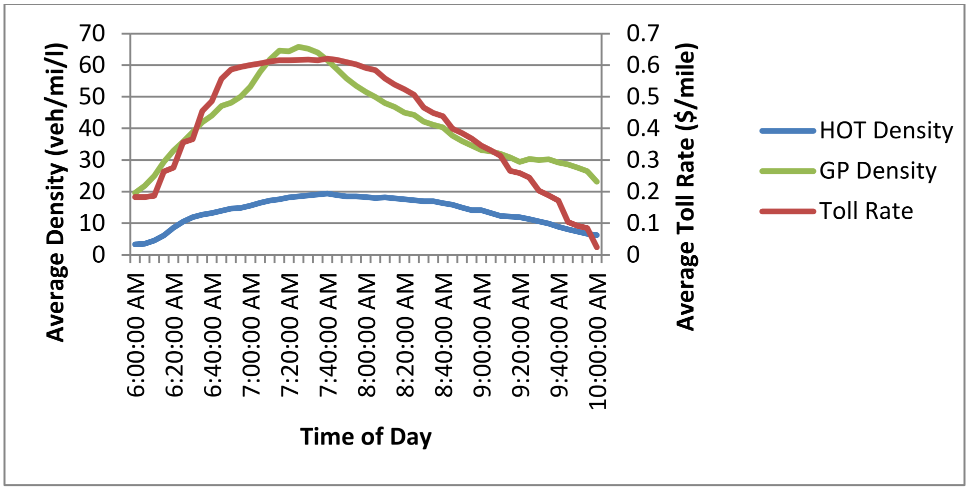
FACILITY	DIRECTION	LOCATION	AVERAGE TOLL ($/mile)	AVERAGE TT SAVINGS (min/mile)	MEAN VTTS ($/hour)	MEDIAN VTTS ($/hour)
I-394	EB (AM)	Minneapolis	0.51	0.43	71.2	60.8
I-15	NB (PM)	San Diego	0.41	0.37	66	59.7
	SB (AM)		0.54	0.41	79	72.4
I-95	NB (PM)	Miami	0.5	0.61	48.6	43.4
	SB (AM)		0.43	0.52	50.9	44.2
I-85	NB (PM)	Atlanta	0.28	0.40	42.0	34.8
	SB (AM)		0.59	0.59	59.8	42.5

Table 4.3: VTTS for morning and evening peak periods

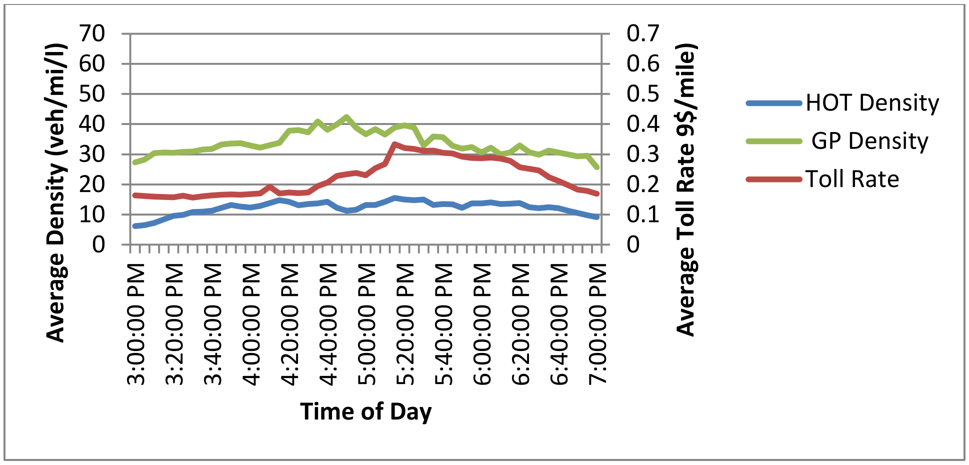
The results in Tables 4.2 and 4.3 were further analyzed to determine if there was a general trend/behavior among travelers from the various HOT facilities in terms of average tolls paid, travel time savings, and VTTS. Details of the analysis are presented below.

Trends in Average Toll Rate

In order to compare average toll rate values from the different studied HOT facilities, they were normalized by the lengths of the HOT lanes, hence the unit $/mile. With the exception of I-85 express lanes, there was no huge difference between the average tolls paid during the morning and evening (as well as their peak) periods. The average toll paid on I-85 express lanes during the morning period ($0.45 per mile) was about twice what was paid during the evening period ($0.22 per mile). A possible explanation for the uniqueness of I-85 express lanes is the stark difference between congestion levels during morning and evening commute on the parallel GP lanes as shown in Figure 4.5. Average density on GP lanes parallel to I-85 express lanes during the morning period (55 veh/mi/l) was significantly higher than that of the evening period (35 veh/mi/l). It is expected that more eligible HOT lane users will shift to the HOT lanes when the GP lane becomes congested, causing higher morning period tolls than that of the evening period. On the remaining facilities, the difference between GP lane congestion levels during morning and evening periods wasn’t as huge as that experienced on I-85 express lanes. For example, average density on GP lanes parallel to I-15 Fast Trak express lanes was similar for both morning (30 veh/mi/l) and evening (29 veh/mi/l) periods.



a) Morning Period



b) Evening Period

Figure 4.5: Toll rate variations on I-85 express lanes

Tolls paid during peak periods were found to be higher than that of entire morning/evening periods. This makes sense since the level of congestion on GP lanes during peak periods are usually high; this causes many vehicles to shift to the HOT lanes, leading to an increase in tolls in order to avoid breakdown of traffic in the HOT lanes. For example, the difference was significant for I-15 express lanes where average toll paid during the morning period was \$0.35 per mile compared with \$0.54 per mile for the peak period.

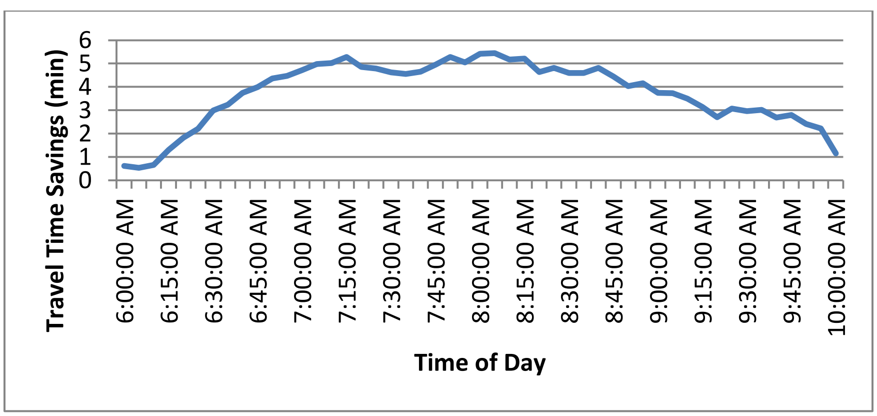
From the discussion above, it can be said that average toll paid on most facilities during morning and evening periods were almost the same as observed on I-15 Fast Trak and I-95 express lanes. However, when difference in levels of GP lanes congestion significantly differ between the morning and evening periods, the average toll paid also differs significantly between the two time periods (as observed on I-85 express lanes). Also, travelers on all the studied facilities were observed to pay higher tolls during the peak/congested periods regardless of morning or evening commute and the magnitude of the difference varied among the studied facilities. Finally, average toll paid by travelers on the different HOT facilities were generally similar in magnitude and there seem to be no trend in terms of geographical location of the HOT facilities.

Variations in Travel Time Savings

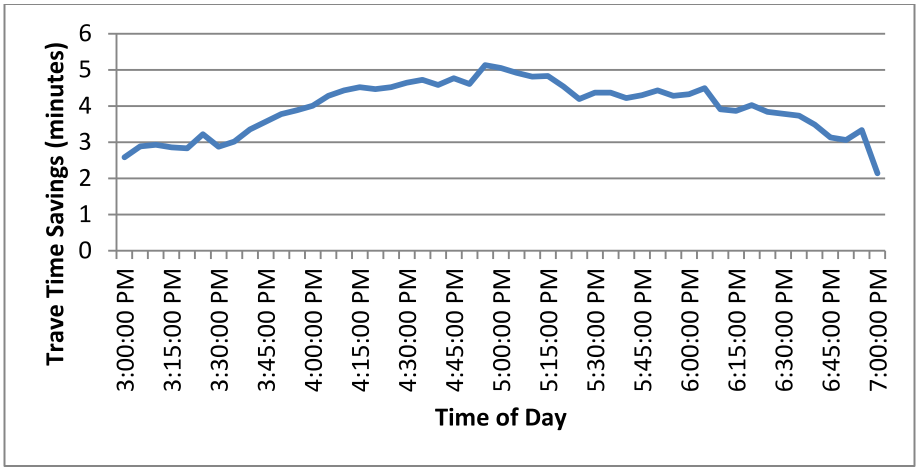
There was no significant difference in travel time savings between morning and evening period commute for all facilities studied. As shown in Figure 4.6, the difference in travel time savings on I-15 between morning and evening periods was only 0.15 minutes per mile. Therefore, total difference in travel time savings for the entire study length of 4 miles was 0.6 minutes (36 seconds). Similar insignificant directional differences in travel time savings were observed during the peak periods as well. Also, peak period travel time savings were generally higher than non-peak periods. On average travel time savings between the peak and entire/morning evening periods was 0.1 minute/mile.

Average travel time savings on I-95 (0.47 minutes/mile) and I-85 (0.46 minutes/mile) express lanes were found to be higher than corresponding average travel time savings on I-394 MnPASS (0.37 minutes/mile) and I-15 Fast Trak (0.32 minutes/mile) express lanes during the morning and evening periods. The difference in average travel time savings between the two groups of HOT facilities was about 0.1 minute/mile. Similar observation was made during the peak periods as well.

Consequently, it can be said that there is no significant directional difference in average travel time savings for the HOT facilities studied. Also, average travel time savings were higher during peak periods for all studied facilities. Finally, the range of average travel time savings for all the studied HOT facilities were generally between 0.05 and 0.65 minutes per mile.



a) Morning Period

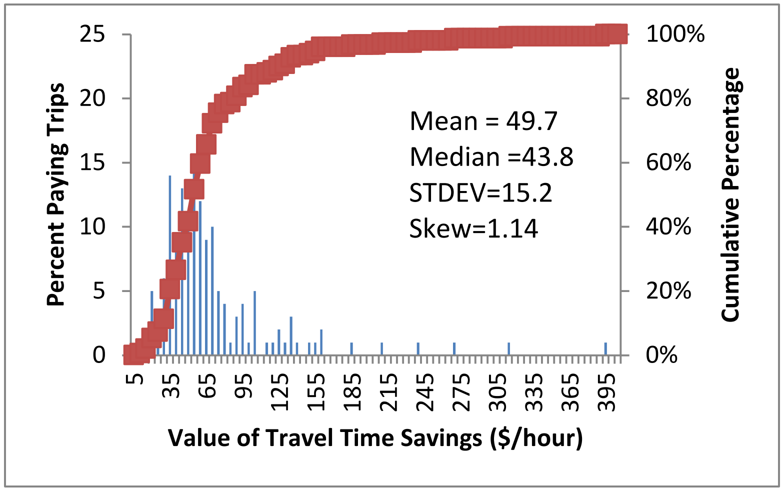


b) Evening Period

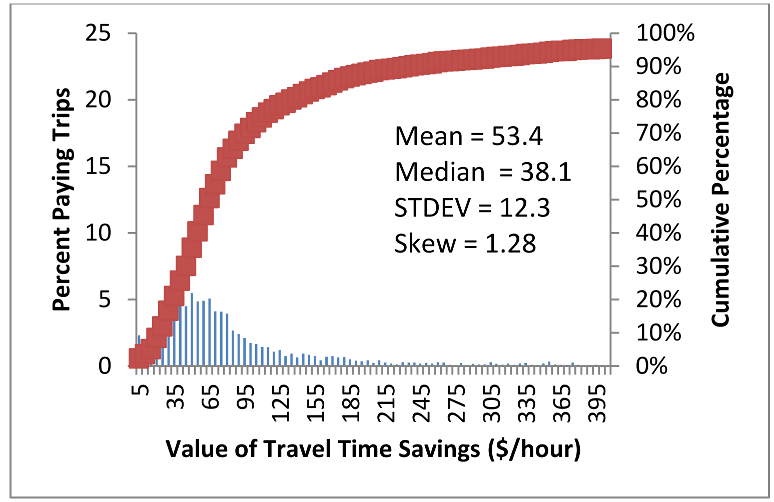
Figure 4.6: Average travel time savings on I-15 express lanes

VTTS Distribution

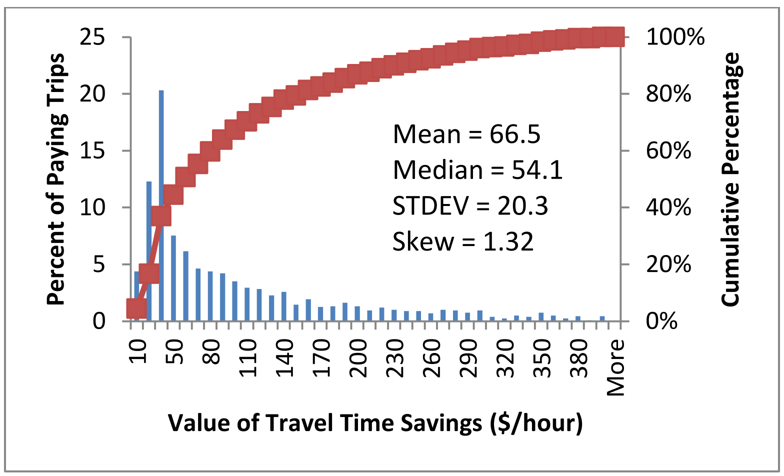
Distributions of VTTS were developed for all the studied HOT facilities. All the distributions were positively skewed (skew values between 0.9 and 1.32) regardless of direction of travel. That is, there were a few travelers with extremely high VTTS values extending the tail of the distribution farther to the right. This implied that, the mean VTSS for the studied facilities were higher than their respective median estimates. VTTS values were generally within similar ranges for each of the facilities ($0/hour to $400/hour) except for I-15 Fast Trak lanes which had a narrower range between $0/hour and $230/hour. The standard deviations of VTTS estimates for each of the facilities generally ranged between $30/hour and $50/hour. For each of the HOT facilities, about 70% of VTTS estimates were less than $100/hour and 90% were below $200 /hour. This suggests that only a few travelers had extremely high VTTS estimates. The higher VTTS estimates were as a result of travelers using the HOT lanes when travel time savings were very little (sometimes as low as 30 seconds). Figure 4.7 shows VTTS distributions for the different HOT lane facilities studied.



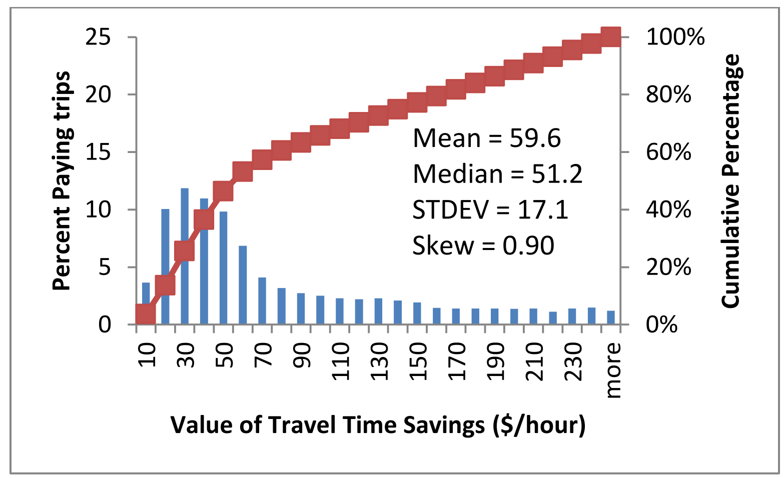
I-95 Express lanes (Evening period)



I-85 Express lanes (Morning period)



I-394 MnPASS lanes (Morning period)



I-15 Express lanes (Morning period)

Figure 4.7: VTTS distribution for studied HOT facilities

In terms of directional effects, average VTTS estimates (both mean and median) were generally higher during the morning periods than the evening periods for all the study sites except for I-15 Fast Trak express lanes. However, the directional differences in VTTS estimates were not significant for all the facilities except for I-85 express lanes where the VTTS estimate for the morning period ($53.4/hour) was almost twice the estimate for the evening period ($30.6/hour). This was mainly due to the relatively high tolls charged during the morning period when GP lane congestion caused more travelers to shift to the HOT lanes. Accordingly, I-85 express lanes had the highest ratio of mean (1.75) and median (2.0) VTTS estimates between morning and evening periods.

I-394 MnPASS lane users paid a mean and median VTTS of $66.5/hour and $55.1/hour respectively during the morning period. This value is pretty close to the $53/hour median VTTS reported by Cho et al (2011) *(77)* for the same analysis segment of the facility. For I-15 Fast Trak express lanes, the $45.5 per hour median VTTS obtained in this research during the morning period is slightly lower than the median VTTS ($49.22 per hour) reported by Burris et al (2012). The analysis period for that study was between 5:30 AM and 12:00 PM while that of this research was between 6:00 A.M. and 9:00 A.M. The evening period median VTTS ($51.2 per hour) was also slightly less than the median VTTS ($54.39 per hour) reported Burris et al (2012) *(12)* . The median VTTS estimate for I-85 express lanes ($38.1 per hour during the morning period) was not significantly different from what has been reported for this facility in existing literature. Sheikh et al (2014) reported a median VTTS estimate of $36 per hour for users of I-85 express lanes *(13)* while Wood et al (2014) reported a median VTTS estimate of $33.17 per hour for the same facility *(15)*. The only literature on VTTS estimate for users of I-95 express lanes used data from 208 individual trips which occurred between August 17th 2011 and August 21st 2011. The authors reported a mean VTTS estimate of $32/hour *(35)*. This estimate is lower than the mean VTTS estimate obtained in this research ($47.4 per hour). The small sample size (only 5 days) used by the authors may not have covered the entire spectrum of VTTS distribution on I-95 express lanes, and may be the reason for the observed disparity in the VTTS estimate.

Generally, VTTS estimates during the peak period were relatively higher than that of entire morning/evening periods for all HOT facilities analyzed. For the morning commute direction, peak mean VTTS was about $5/hour more for all HOT facilities except I-15 Fast Trak lanes where the mean peak VTTS was $24 per hour more. The higher cost of using I-15 express lanes during the morning peak period was as a result of the small travel time savings it provided despite the hike in toll price. The evening commute was similar to the morning commute in terms of difference between peak and non-peak VTTS estimates. Peak VTTS estimates were $5/hour more except for I-85 express lanes whose peak VTTS estimate was $12 per hour more than the non-peak period.

Two operational and geometric characteristics of the HOT facilities analyzed could influence the relative values of VTTS estimates. The length of analysis segments for I-394 MnPASS (2.7 mile) and I-15 Fast Trak express lanes (4 miles) were shorter than the corresponding analysis lengths of I-95 (7.3 miles) and I-85 (6.8 miles and 9.6 miles for southbound and northbound respectively). It is possible that the shorter lengths on I-394 MnPASS and I-15 Fast Trak express lanes might influence drivers to use the HOT lanes (because of the notion that short lengths cost less) even when there are no apparent travel time savings. However, considering the fact that most of the HOT facility users are commuters and might have used the facility for a longer period of time, they should be aware of the true costs for using even shorter segments. Secondly, HOV usage is relatively higher on I-394 MnPASS (51%) and I-15 Fast Trak express lanes (80%) than on I-95 (1.9%) and I-85 (14%) express. Therefore, high usage of the HOT facilities by HOVs (on I-394 MnPASS and I-15 Fast Trak express lanes) might inflate the VTTS estimates for these two facilities since aggregate data was used. However, past research efforts on I-394 MnPASS and I-15 Fast Trak express lanes using SOV only data resulted in similar VTTS estimates *(12)*. Therefore, the impact of HOV usage on the VTTS estimates calculated in this research might be less profound.

Hypothesis Testing of VTTS Distributions

VTTS tend to differ among individuals and across time *(57,58)* and may differ among different regions/localities. However, it is also possible that some different geographical regions/locations may have similar distributions of VTTS. Regardless of whether or not VTTS estimates vary across geographical regions, the most important insight is the cause of such variance/invariance. In order to achieve this purpose, hypothesis tests were conducted between VTTS distributions of all HOT facilities studied in this research. Statistical distributions are employed in hypothesis testing to estimate the probabilities of observing the sample data, given an assumption of what "should have" occurred. When observed results are extremely unlikely to have occurred under assumed conditions, then the assumed conditions are considered unlikely *(78)*. A two-tail hypothesis test investigating whether the average VTTS for a pair of HOT facilities are the same or not was used at 5% significance level.

If

μ_1 is the average VTTS for users of HOT facility in location A; and

μ_2 is the average VTTS for users of HOT facility at location B

Then the competing hypotheses are:

Null hypothesis: H_o: $\mu_1 - \mu_2 = 0$

Alternate hypothesis: H_a: $\mu_1 - \mu_2 \neq 0$

Since the sample size for each of the VTTS distribution was large (>=1000), an approximate normal distribution could be assumed; therefore, the test statistic used for the hypothesis testing was the Z-statistic. Also, the hypothesis testing was conducted assuming unequal variance. The results of the hypothesis test are as shown below in Table 4.4.

FACILITY PAIR	Z-STATISTIC (toll elasticity)	P(Z<z) two-tail	Z Critical two-tail	RESULT
I-394 VS. I-15	1.691	.071	1.96	Equal
I-394 VS. I-95	4.280	.020	1.96	Not equal
I-394 VS. I-85	2.972	.016	1.96	Not equal
I-15 VS. I-95	5.654	.034	1.96	Not equal
I-15 VS. I-85	3.176	.039	1.96	Not equal
I-85 VS. I-95	1.81	.068	1.96	Equal

Table 4.4: Results of hypothesis testing

The null hypothesis (average VTTS estimates are equal for each pair of HOT facilities) is rejected if the Z statistic is greater than the critical Z value and vice versa. Based on Table 4.4 above, there is no evidence to reject the assumption that I-394 MnPASS lanes and I-15 Fast Trak have the same average VTTS since the Z statistic (1.691) is less than the critical Z value (1.96) at 5% significance level. Similarly, there isn't enough evidence to reject the null hypothesis that the average VTTS estimates for I-85 and I-95 express lanes are equal. The remaining HOT facility pairs appear to have statistically significant differences between their respective average VTTS estimates based on the results of the hypothesis test. Having identified statistically significant differences and similarities among the studied HOT facilities in terms of their average VTTS estimates, the next logical step is to explore the factors that might have contributed to such findings. The next section discusses some of the potential factors that may directly or indirectly influence the observed differences/similarities between average VTTS estimates of the studied HOT facilities.

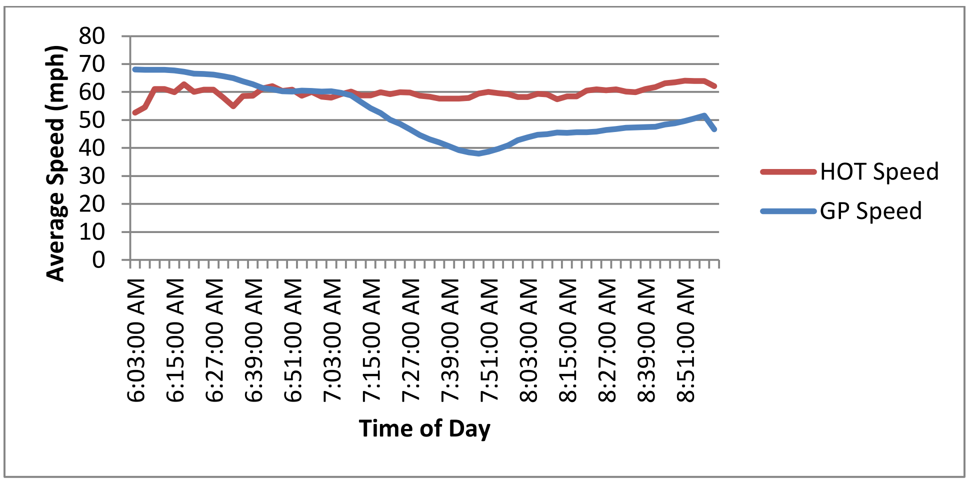
4.4.1 Possible Reasons for VTTS Similarities/Differences

A lot of factors (travel-related and socio-economic) have been identified to influence variation in VTTS. These include travel related factors such as trip purpose (commuting trips, business trips and private trips), travel time (length of journey), level of comfort during travel (e.g. weather condition during travel), travel mode (transit, automobile, etc.), travel costs and time of day trip is made. The individual socio-economic factors include income level, age and gender (which influences perception of time), household level composition and level of education. Among the numerous factors listed above, trip purpose and income level have been found to be very influential in VTTS variations *(57)*. However, the impact of travel time is worth considering alongside trip purpose and income level in this research. This is because travel time savings were found to be different for I-394 MnPASS/I-15 Fast Trak express lanes and I-95/I-85 express lanes; this implies that congestion levels on parallel GP lanes might be different for the two groups of HOT facilities. It is therefore necessary to explore how GP lane congestion levels affect VTTS for each HOT facility. Also, travel reliability (level of variation in travel conditions) could play an important role in the magnitude of VTTS estimates. If travel time variability is very high on the GP lanes, then drivers may tend to use the HOT lanes regularly in anticipation of unreliable travel conditions on the GP lanes.

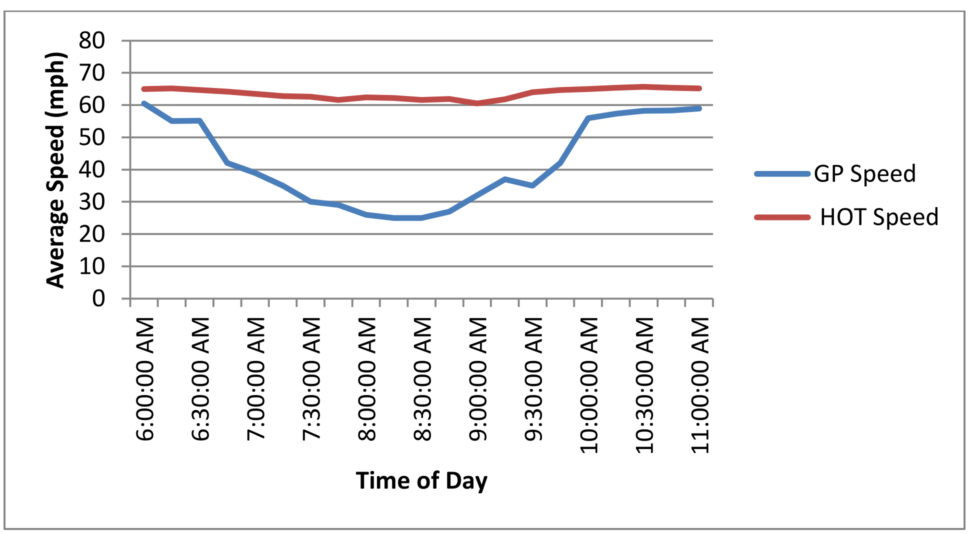
The data used in generating VTTS estimates for all the studied HOT facilities was between 6:00 AM-10: 00 AM and 3:00 PM to 7:00 PM. These are the typical time periods during which morning and evening commutes take place. Therefore, trips on all of the HOT facilities analyzed have the same purpose—commuting; this implies that trip purpose wouldn't be a differentiating factor for the observed similarities/differences between VTTS estimates of the studied HOT facilities. Therefore level of congestion on GP lanes, income level, and travel reliability were further investigated to determine their impacts on the observed similarities/differences between VTTS estimates.

Level of Congestion on GP Lanes

Travel time savings were found to be relatively higher for users of I-95 and I-85 express lanes compared to the travel time savings enjoyed by users of I-394 MnPASS and I-15 Fast Trak lanes. The difference in travel time savings arose from the relatively higher levels of congestion on the GP lanes parallel to I-95 and I-85 express lanes than those parallel to I-394 MnPASS and I-15 Fast Trak express lanes as shown in Figure 4.8 below.



a) I-394 MnPASS lanes



b) I-95 Express lanes

Figure 4.8: Comparing GP lane congestion levels

From Figure 4.8 above, the difference in speed between MnPASS and parallel GP lanes is at most 21 mph during the peak period. On the contrary, a larger speed difference of about 35 mph is observed between I-95 express lanes and the parallel GP lanes. Obviously, travel time savings will be higher for I-95 express lane users than those using I-394 MnPASS lanes; this consequently leads to a relatively lower VTTS on I-95 express lanes than I-394 MnPASS lanes.

The differences in the level of GP lane congestion between the two groups of HOT facilities could be explained by the level of highway use at each HOT facility's location. Vehicle Miles Traveled (VMT) is an indicator of the travel levels on the roadway system by motor vehicles. As the amount of vehicle travel increases, the time wasted on congested roadways increases accordingly *(79)*. According to Texas Transportation Institute's (TTI) urban mobility report 2012, VMTs for Miami (I-95 express lanes) and Atlanta (I-85 express lanes) areas were higher than those of Minneapolis-St. Paul (I-394 MnPASS) and San Diego (I-15 Fast Trak). Daily total (Freeway and principal arterials) VMTs in 2011 for Miami and Atlanta were 92,702,000 and 94,300,000 respectively. The corresponding total daily VMTs for Minneapolis-St. Paul and San Diego were 54,302,000 and 59,483,000 respectively *(1)*. Although these are not the VMTs for the studied HOT corridors, they are an indication of the level of demand for highway travel at their respective locations/regions. A lot of factors can influence VMTs (e.g. population, travel cost such as fuel, low levels of public transit, sprawl, etc.) *(79)*; however, their considerations were beyond the scope of this research.

Income Levels and Regional Economy

Income levels tend to influence the value travelers place on their travel time savings *(34,58)*. In order to ascertain if it played a role in the observed similarities/differences between VTTS estimates of the studied HOT facilities, annual income data for locations of the studied facilities were obtained from the 2012 American Community Survey (ACS). Additionally, employment data for the locations of each studied HOT facility was obtained from ACS' 5-year estimates (2008-2012). Discussions of the income levels and employment distribution for the studied locations are presented in the next sections.

I-394 MnPASS Lanes, Minneapolis

Minneapolis is part of Hennepin county, Minnesota with civilian employed population (16 years and over) of about 620, 758. Significant proportion of the jobs in the county fall into the following industries: educational, healthcare, and social assistance services (22.9%); manufacturing (11.9%); retail trade (11.7%); and finance, insurance, real estate, rental, leasing (9.9%). The mean and median incomes for the county in 2012 were \$89,008 and \$63,559 respectively. As shown in the income distribution in Figure 4.9 below, about 17.3% of the working population earned between \$50,000 and \$74,999 (modal income level). On average, about 30% of the working population earned over \$100,000 in 2012 while 28% earned below \$35,000 *(80)*. Since the mean income is higher than the median income, the income distribution appeared to be positively skewed i.e. small percentage of the population have extremely high annual incomes.

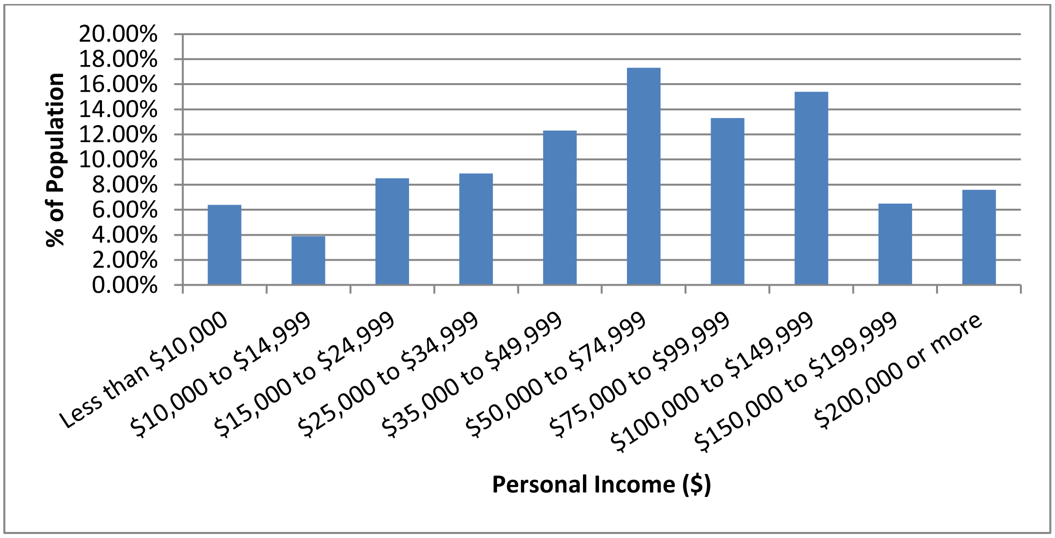


Figure 4.9: Annual income distribution for Hennepin County (Minneapolis area)

I-15 Fast Trak HOT Lanes, San Diego

The city of San Diego is located within the San Diego county, and has a working population (16 years and over) of about 1,386,825. The major sources of employment include: educational, healthcare, and social assistance services (20.9%); professional, scientific, management, administrative, and waste management services (14.2%); retail trade (11.1%); and manufacturing (9.4%). The mean and median incomes for the year 2012 were $95,806 and $73,969 respectively. The modal income (between $50,000 and $74,999) was earned by about 17.3% of the population. About 30% of the working population earned at least $100,000 while 28% earned below $35,000 *(80)*. The income distribution appeared to be positively skewed with a small percentage of the working population earning extremely high incomes. Figure 4.10 shows the 2012 income distribution for San Diego County.

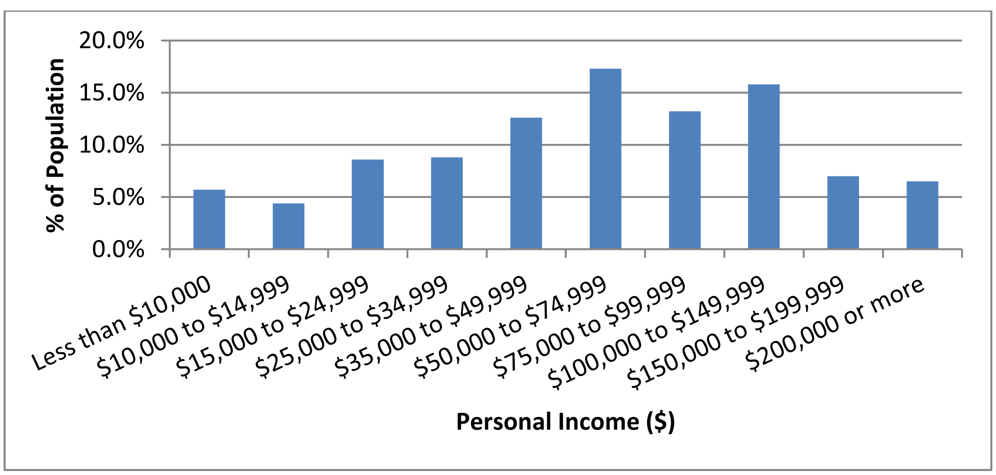


Figure 4.10: Annual income distribution for San Diego City

I-95 Express Lanes, Miami

I-95 express lanes connect cities in the northern part of Miami Dade County (as well as nearby cities in Broward County) to the downtown areas of Miami. The working population (16 years and over) in Miami-Dade county is about 1,132,783 of which 72.4% are male and 27.6% female. The major industries providing employment are: educational, healthcare, and social assistance services (20.2%); professional, scientific, management, administrative, waste management services (12.4%); retail trade (12.4%); and arts, entertainment, recreation, accommodation and food services (10.5%). The mean and median incomes for 2012 were $65,799 and $43,464 respectively. For the nearby Broward County where significant proportions of I-95 express lane users come from, the mean and median incomes were $72,122 and $51,603 respectively in 2012. The modal income range for both counties was between $50,000 and $74,999. Additionally, about 19% of the working population from both counties earned at least $100,000 while 28% earned below $35,000 *(80)*. As observed for San Diego and Hennepin counties, the income distributions for both Miami-Dade and Broward counties were positively skewed as shown below in Figure 4.11.

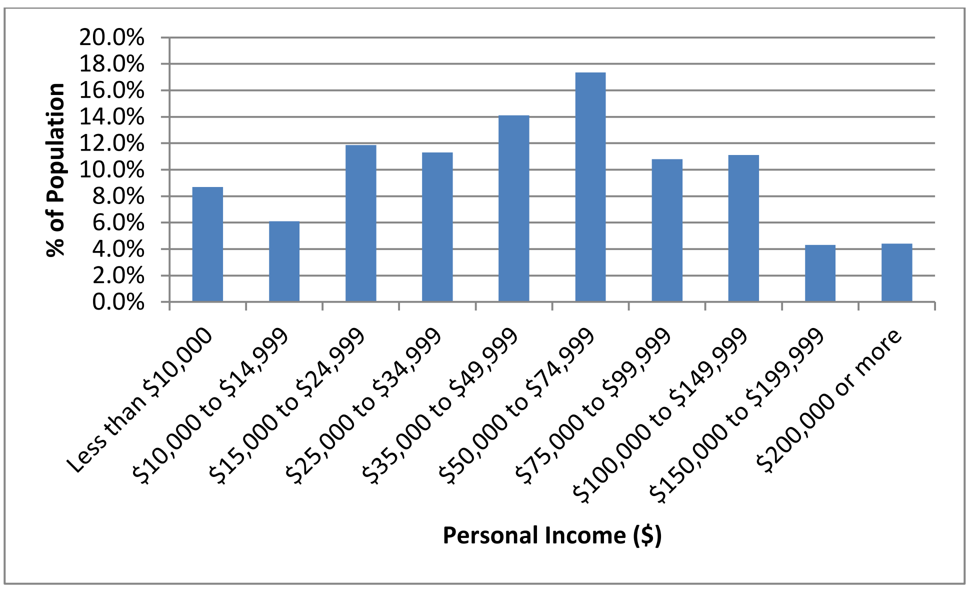


Figure 4.11: Annual income distribution for Miami Dade County

I-85 HOT Lanes, Atlanta

The I-85 express lanes in Atlanta is located within the Gwinnet County which has a working population (16 years and over) of about 388,595. The main employment industries include: educational, healthcare, and social assistance services (17.3%); professional, scientific, management, administrative, and waste management services (13.9%); retail trade (13.1%); and manufacturing (9.2%). The median and mean incomes for 2012 were $61,944 and $78,204 respectively. On average, about 27% of the working population earned at least $100,000 while 26% earned below $35,000. About 19.4% of the working population earned between $50,000 and $74,999 (modal income) *(80)*. Figure 4.12 shows the 2012 income distribution for Gwinnet County.

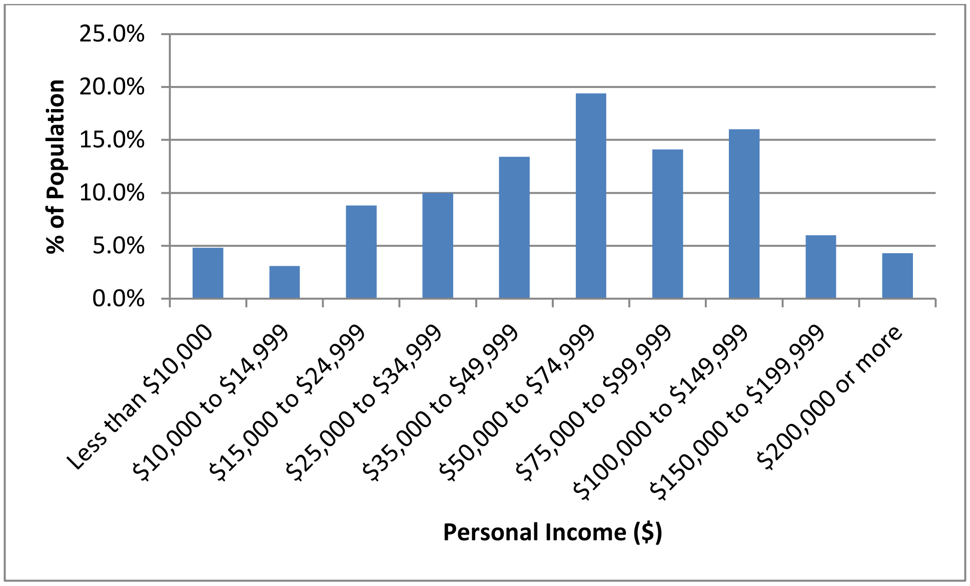


Figure 4.12: Annual income distribution for Atlanta area

Table 4.5 provides a summary of the annual average income of all the regions/locations under study. It also compares the mean and median incomes with VTTS estimates of HOT facilities.

FACILITY	LOCATION (COUNTY)	2012 MEAN INCOME ($)	2012 MEDIAN INCOME ($)	PEAK MEAN VTTS ($/hour)	PEAK MEDIAN VTTS ($/hour)	INCOME DISTRIBUTION
I-394	Minneapolis (Hennepin)	89,008	63,559	71.0	60.8	Positive-skewed
I-15	San Diego (San Diego)	95,806	73,969	72.5	65.9	Positive-skewed
I-95	Miami/Broward Counties	68,960	47,534	49.5	43.8	Positive-skewed
I-85	Atlanta (Gwinnett)	78,204	61,944	50.9	38.7	Positive-skewed

Table 4.5: Comparing average annual incomes with peak VTTS estimates

Generally, the annual income distribution for all HOT facilities analyzed appeared to be positively skewed; implying the tail of the distribution is extended far to the right as a result of high annual incomes earned by a small percentage of the population. Another commonality between all the studied locations was the sources of employment for the population. Educational, healthcare, and social assistance industry was consistently the first or second major source of employment in all of the four locations. The retail trade industry was also among the top four sources of employment at all the studied locations. Although the percentage distributions of these jobs are not uniform across the studied locations, there appear to be no stark difference between the respective local economies of all HOT facilities analyzed.

In terms of annual average income earnings, Miami-Dade is ranked lowest while the San Diego area is ranked highest. There is about 16.3% difference in annual median income between San Diego and Hennepin County/Minneapolis (second highest annual income) as well as 19.4% difference between San Diego and Gwinnet County (Atlanta area). Before any meaningful comparisons could be made between income levels, it was necessary to consider variations in the purchasing power of money across geographical locations. If the income data in Table 4.5 is to be analyzed as it is, an implicit assumption has to be made; the assumption is that a dollar in San Diego and Minneapolis (or Atlanta and Miami) can buy the same quantity of a particular good. In reality however, price levels vary across geographical locations; therefore it is necessary to correct for these price disparities before any meaningful comparison of annual average income levels could be made. Regional Price Parities (RPPs) help to account for the differences in price levels in personal incomes across geographical locations. RPPs measure the differences in the price levels of goods and services across states and metropolitan areas for a given year. They are expressed as a percentage of the overall national price level for each year, which is equal to 100.0 *(81)*. Mathematically, RPPs can be expressed as:

$$RPP = (P_i / P_{US}) * 100 \qquad (4\text{-}2)$$

Where:

P_i is the price level for location i

P_{US} is the national average price level for the entire U.S.

The RPPs are constructed in two stages. The first stage uses price and expenditure inputs collected for the Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) program and the BLS Consumer Expenditure Survey (CE). CPI price data are available for 38 urban areas, while CPI expenditure weights, derived from CE survey data, are available for the 38 urban areas plus four additional rural regions. In this stage, price levels are estimated for CPI areas. In the second stage, the price levels and expenditure weights are allocated from CPI areas to all counties in the United States. They are then recombined for regions, such as states and metropolitan areas, for which final RPPs, including an all item RPP, are estimated. This stage incorporates data for housing from the Census Bureau's ACS. The ACS provides snapshots of the entire U.S. population, with a focus on demographic and housing conditions.

To account for price differences in personal incomes, the personal income must be divided by the RPP for a given year and region. If the RPP for area A is 140 and for area B is 90, then on average, prices are 40% higher and 10% lower than U.S. average for A and B respectively. Therefore, if the personal income for area A is $14,000 and for area B is $10,000, then the RPP-adjusted incomes are $10,000 ($14,000/1.4) and $11,111 ($10,000/0.9) respectively. Although area A has a higher personal income than area B, the purchasing power for area B's income is higher than that of area A's income.

The RPPs for all the study locations were obtained from the Bureau of Economic Analysis (BEA) and used to adjust their respective personal annual average incomes. The adjusted-personal annual average incomes can now be compared because they have been corrected for the differences in price levels. Table 4.6 shows the RPP-adjusted incomes.

FACILITY	LOCATION (COUNTY)	2012 MEAN INCOME ($)	RPP	RPP-ADJUSTED MEAN INCOME ($)	RPP-ADJUSTED MEDIAN INCOME ($)	PEAK MEAN VTTS ($/hour)	PEAK MEDIAN VTTS ($/hour)
I-394	Minneapolis (Hennepin)	89,008	1.022	87,092	62, 190	71.0	60.8
I-15	San Diego (San Diego)	95,806	1.143	83,820	64,715	72.5	65.9
I-95	Miami-Dade/Broward Counties	68,960	1.045	65,990	45,487	49.5	43.8
I-85	Gwinnett (Atlanta)	78,204	0.978	79,963	63,337	50.9	38.7

Table 4.6: RPP-adjusted annual incomes and VTTS estimates

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From Table 4.6 above, Minneapolis and San Diego areas have almost the same RPP-adjusted mean (difference of 3.9%) and median (difference of 4.1%) annual incomes. The insignificant difference between the annual incomes of the two locations (Minneapolis and San Diego areas) might be a contributing factor to the similarity in their high VTTS estimates. The RPP-adjusted mean incomes of $87,092 and $83,820 for Minneapolis and San Diego areas suggest that residents of these locations are likely to have enough income to pay for HOT lane use even when there are no significant travel time savings. As a result, their average VTTS estimates were found to be relatively high especially during peak periods ($71/hour for MnPASS users and $72.5/hour for I-15 Fast Trak users). Although Miami and Gwinnet (Atlanta) County areas both have RPP-adjusted annual incomes below $80,000, the difference between their average annual incomes (21%) is higher than that observed between Minneapolis and San Diego areas (about 4%). Notwithstanding the above observation, the annual income level of both locations is still a causal factor in their relatively low VTTS estimates. However, the magnitude of the impact of annual income on VTTS estimates might be higher for Minneapolis/San Diego areas than for the Miami/Gwinnet (Atlanta) County areas. The impact of income levels on VTTS is well documented in literature, reaffirming the findings in this research. Zmud et al (2007) conducted a stated preference survey of I-394 MnPASS users and found that VTTS estimates increase sharply with income above $100,000 levels *(34)*. Patil et al (2011) also conducted a stated preference survey of users of the Katy managed lanes in Houston, Texas. The authors concluded that the likelihood of using the managed lanes increases as a traveler’s household income increases *(30)*.

It can therefore be concluded that the high income levels of Minneapolis and San Diego areas contributed to the high VTTS estimates of I-394 MnPASS and I-15 Fast Trak users respectively. Users of these facilities have high income levels and are likely to pay for HOT lane use even when the travel time savings were insignificant. Similarly, the relatively low income levels of the Miami and Atlanta areas contributed to the low VTTS estimates. In this instance, users of I-95 and I-85 express lanes usually paid for HOT lane use when travel time savings were relatively significant.

Travel Reliability

The level of variability in travel conditions on the GP lanes has the potential to influence HOT lane usage. Commuters are usually aware of the average levels of congestion on routes they use, and tend to account for it in travel time estimation or change departure times in order to avoid it. However, if the GP congestion levels have high variability (less reliable) then the possible alternative is regular use of the HOT lanes which guarantee reliable travel times at least 95% of the time. Three reliability measures were calculated for parallel GP lanes on each HOT facility analyzed. They include Planning Time Index (PTI: ratio of 95th percentile travel time to free-flow travel time), Travel Time Index (TTI: ratio of peak travel time to free-flow travel time) and Coefficient of Variation (CV: ratio of travel time standard deviation to average travel time). High values of these reliability measures indicate high travel variability on the GP lanes and vice versa. The results are as shown below in Table 4.7.

FACILITY	PTI	TTI	CV
I-394 MnPASS Lanes	2.82	1.72	0.50
I-15 Express Lanes	2.11	1.63	0.64
I-85 Express Lanes	1.65	1.26	0.21
I-95 Express Lanes	1.75	1.33	0.26

Table 4.7: Travel time reliability measures

From Table 4.7, the magnitudes of the reliability measures for GP lanes parallel to I-95 and I-85 express lanes are relatively smaller than those found on GP lanes parallel to I-394 MnPASS and I-15 express lanes. Based on CV values for example, standard deviation of travel times on GP lanes parallel to I-394 MnPASS and I-15 express lanes is at least 50% of the average travel time compared with 21% on corresponding GP lanes parallel to I-85 express and I-95 express lanes. This suggests that, travel conditions on GP lanes parallel to I-95 and I-85 express lanes have less variability (high reliability) than what is experienced on GP lanes parallel to I-394 MnPASS and I-15 express lanes. With low travel reliability (high variability) on GP lanes parallel to I-394 MnPASS and I-15 express lanes, drivers may tend to use the HOT lanes even when the GP lanes are less congested in order to be guaranteed reliable travel conditions (less variability). That is, although congestion levels on GP lanes parallel to I-394 MnPASS and I-15 express lanes maybe relatively low, travel conditions are less reliable; therefore travelers may shift to HOT lanes even when there are no apparent travel time savings, leading to high VTTS estimates.

4.4.2 Comparing VTTS Estimates with Hourly Wages

An important piece of information often used by transportation agencies to gauge driver willingness to pay values /VTTS is the average wage rate. A research by Small et al. (2005) suggested that value of time for work trips is about 93% of average wage *(82)*. That is, average wage is often used as a surrogate for how much drivers are willing to pay for travel time savings, and the toll rates on HOT lanes are likely to be set based on these values. However, the average wage is only an indication of the earnings of average residents; it does not capture completely, the high income earners at the far right tail of the income distribution. The VTTS estimates obtained in this research were compared with 2012 Bureau of Labor Statistics (BLS) average hourly wages for each HOT facility's location. This approach was adopted to determine if average VTTS of HOT lane users is the same as the hourly wage of an average resident. Table 4.8 shows the results of the comparison.

FACILITY	LOCATION	MEAN VTTS ($/hour)	BLS HOURLY WAGE ($/hour)	% MORE
I-394	Minneapolis	71.0	24.2	193
I-15	San Diego	72.5	24.4	197
I-95	Miami	49.5	20.6	139
I-85	Atlanta	50.9	22.8	123

Table 4.8: Mean VTTS vs. BLS hourly wages

As evident in Table 4.7 above, HOT lane users' VTTS estimates was at least more than twice the average hourly wages. For Minneapolis and San Diego, VTTS estimates were almost a triple of the average hourly wages. The stark difference between VTTS estimates and average hourly wages imply that HOT lane users are likely to earn more income than the average resident. As a result, they value their travel time savings more than the average resident. Therefore, transportation agencies must design tolls that are indicative of the true driver willingness to pay and not based on average hourly wages.

4.5 Driver Elasticity

The analyses in the previous sections have shed light on the behavior of HOT lane users in terms of their willingness to pay for travel time savings (i.e. VTTS differences/similarities across different facilities). However, it does not provide any insight into how the demand for HOT lane use will vary with changes in tolls and traffic conditions. Although it has been established (from previous section) that HOT lane users generally have higher VTTS (i.e. willing to pay more in order to use HOT lanes), it is not known how this behavior influences the drivers' real-time decision to use/not to use the HOT lanes. Elasticity enables the determination of the responsiveness of HOT lane users (i.e. demand for HOT lane use) to changes in toll prices and traffic conditions. An additional factor which hasn't been explored so far is how the level of congestion on parallel GP lanes affects HOT lane demand. Some of the relevant questions which this section seeks to answer include 1) whether HOT lane users have the same sensitivity to tolls and GP lane congestion, and 2) whether HOT lane users are sensitive to high toll rates even when the level of congestion on GP lanes is high. Details of the elasticity analysis are hereby presented.

4.5.1 Data Needs for Driver Elasticity Determination

Three different types of data were used to estimate HOT lane driver elasticity. These include HOT lane volume/demand, toll rates, and GP congestion levels. Average density was selected as the surrogate for GP lane congestion since it is the most stable variable among the three traffic state variables *(83)*. The data types are described below.

HOT Lane Volume/Demand

For the reversible I-394 MnPASS lanes and I-15 Fast Trak express lanes, volume was obtained at three minute intervals from the same detectors used in the VTTS analysis. Similarly, volume data for I-95 and I-85 express lanes were also obtained at 15-minute and 5-minute intervals respectively from the same detectors used in the VTTS analysis. All data were screened for outliers using the data processing standards outlined in the VTTS analysis.

GP Congestion (Density)

Average density on the GP lanes was obtained using detector occupancy data. For I-394 and I-95 express lanes, detector occupancy data were obtained from the same GP detectors used in the VTTS analysis. For I-85 and I-15 express lanes, detector occupancy data were obtained from Georgia's Remote Traffic Microwave Sensor (RTMS) database and California's freeway performance management system (PeMS) respectively. The occupancy data was converted to density using average field length of traffic sensors. It is important to note that, the densities used in this research were provided by the managing agencies of the studied HOT facilities. All data were screened for outliers using the same procedure employed in the VTTS analysis.

Tolling Data

Toll rates used in the elasticity analysis were the same as those used in the VTTS analysis in terms of both duration (October 2012 to February 2013) and intervals for each HOT facility.

4.5.2 Methodology

HOT lane driver elasticity was estimated for two factors: changes in toll rates and changes in GP congestion level (density). For elasticity with respect to price (toll rates), it was calculated in such a way that the effect of traffic fluctuations in the GP lanes can be accounted for. Therefore, HOT lane demand was obtained by normalizing HOT lane volume by the total volume on both HOT and GP lanes to obtain the percentage of HOT lane use in the corridor as shown below in equation 4-3.

$$\%\ of\ HOT\ Use\ (HOT_D) = \frac{HOT\ Lane\ Volume}{HOT\ Lane\ Volume + GP\ Volume} \tag{4-3}$$

The driver elasticity of demand (ε_T) was subsequently calculated as:

$$\varepsilon_T = \frac{(HOT_{Di+2} - HOT_{Di+1}) / 0.5*(HOT_{Di+1} + HOT_{Di+2})}{(TR_{i+1} - TR_i) / 0.5*(TR_i + TR_{i+1})} \quad (4\text{-}4)$$

Where:

HOT_{Di+1} = % of HOT use at time i+1

HOT_{Di+2} = % of HOT use at time i+2

TR_i = Toll rate been charged at time i

TR_{i+1} = Toll rate been charged at time i+1

As seen in equation 4-4, the elasticities were calculated as midpoint arc elasticities instead of point elasticities. This is because; point elasticities are sensitive to which of the two points is chosen as the new point. This results in different elasticity values depending on whether the value at time *i* or *i+1* is chosen as the new point. Midpoint arc elasticities account for this problem by using the midpoint of the values at *i* and *i+1*. This ensures that, the same elasticity value is obtained regardless of which point is chosen as the new/old point. Additionally, it is important to note that the elasticities are intended to measure changes in HOT lane demand as a result of changes in toll prices and not vice versa.

Similarly, driver elasticity of demand w.r.t GP congestion level (density) was calculated as shown below in equation4-5.

$$\varepsilon_{GP} = \frac{(HOT_{Vi+2} - HOT_{Vi+1}) / 0.5*(HOT_{Vi+2} + HOT_{Vi+1})}{(GP_{DEN\,i+1} - GP_{DENi}) / 0.5*(GP_{DENi+1} + GP_{DENi})} \quad (4\text{-}5)$$

Where:

ε_{GP} = HOT lane driver elasticity w.r.t to GP congestion (density)

HOT_{Vi} = HOT lane volume at time i

HOT_{Vi+1} = HOT lane volume at time i+1

HOT_{Vi+2} = HOT lane volume at time i+2

GP_{DENi} = GP lane density at time i

GP_{DENi+1} = GP lane density at time i+1

Finally, the elasticity values were computed for the entire morning and evening periods as well as their respective peak periods. This helps to ascertain HOT lane driver reaction to the two factors under varying traffic conditions.

4.5.3 Results and Discussions

The results of HOT lane driver elasticity w.r.t prices (toll rates) and GP congestion level (density) is shown below in Tables 4.9 and 4.10.

FACILITY	DIRECTION	LOCATION	AVEAGE PRICE ELASTICITY OF DEMAND	AVERAGE ELASTICITY W.R.T GP DENSITY
I-394	EB (AM)	Minneapolis	0.11*	0.10*
I-15	NB (PM)	San Diego	0.16*	0.19*
	SB (AM)		0.17*	0.21*
I-95	NB (PM)	Miami	0.09*	0.40*
	SB (AM)		0.15*	0.48*
I-85	NB (PM)	Atlanta	0.08*	0.45*
	SB (AM)		0.12*	0.50*
AVERAGE			0.13	0.34

Table 4.9: Elasticity for morning and evening periods
* Statistically significant

FACILITY	DIRECTION	LOCATION	AVERAGE PRICE ELASTICITY OF DEMAND	AVERAGE ELASTICITY W.R.T GP DENSITY
I-394	EB (AM)	Minneapolis	0.10*	0.12*
I-15	NB (PM)	San Diego	0.09*	0.23*
	SB (AM)		0.08*	0.22*
I-95	NB (PM)	Miami	0.03	0.53*
	SB (AM)		0.07*	0.68*
I-85	NB (PM)	Atlanta	0.06*	0.61*
	SB (AM)		0.04*	0.72*
AVERAGE			0.07	0.45

Table 4.10: Peak period elasticity (7:30 AM – 8:30 AM/5:00 PM – 6:00 PM)

An important finding revealed by this analysis is the magnitude and direction of the impacts of tolls on HOT lane demand. During the morning and evening periods, HOT lane demand elasticity w.r.t toll was positive for all HOT facilities analyzed. This implies that, an increase in tolls tend to increase the use of the HOT lanes. Under the HOT lane concept, tolls are supposed to discourage SOVs from using the HOT lanes. In other words, tolls are meant to have a negative impact on HOT lane demand, by disincentivizing SOVs from using it. A positive relationship between tolls and HOT lane demand defeats this purpose. The magnitude of the elasticity estimates was very low, depicting a highly inelastic relationship with HOT lane demand. Evidence from Table 4.9 shows that none of the HOT facilities analyzed had a price elasticity of demand that exceeded +0.2. The range of HOT lane demand elasticities w.r.t tolls across all studied facilities was between +0.08 and +0.17, with an average of +0.13. Therefore a 10% increase in HOT lane toll will increase its demand by only 1.3%. The impact of tolls on HOT lane demand diminished further during peak conditions with an average elasticity value of +0.07 as shown in Table 4.10. This observation was consistent across all studied HOT facilities and presents a unique challenge to transportation policy makers. It is apparent that, the current pricing structure/levels do not discourage drivers from using the HOT lanes. Therefore, to make the concept of pricing serve its intended purpose in HOT lanes (discourage drivers), toll prices must be set in such a way that it accounts for the low demand elasticities found in this research. The impacts of GP lane congestion on HOT lane demand was also studied; it was found that GP lane congestion has a positive relationship with HOT lane demand, with increasing impact during peak periods. Average HOT lane demand elasticity w.r.t GP congestion was +0.34 during morning/evening periods and +0.45 during peak periods. The range of the elasticities was between +0.1 and +0.5 during morning/evening periods and between +0.12 and +0.72 during peak periods. The elasticities w.r.t GP density appeared to be relatively higher for I-95 and I-85 express lanes (which have relatively higher congestion levels) with values ranging between 0.4 and 0.72.

In conclusion, HOT lane demand exhibited a positive but inelastic relationship with tolls and GP congestion. The next sections provide detailed discussions of the relative impacts of tolls and GP lane congestion on HOT lane demand. Additionally, similarities and differences between the studied HOT facilities in terms of their elasticities were explored, and the possible factors behind such similarities/differences investigated.

4.5.3.1 Relative Impacts of Tolls and GP Density on HOT Lane Demand

In all HOT facilities analyzed, it was observed that the impact of GP lanes congestion (density) on HOT lane demand was either higher than that of tolls charged (I-15 Fast Trak express lanes, I-85 express lanes, I-95 express lanes) or approximately equal (I-394 MnPASS express lanes). As shown in Table 4.9 above, the elasticity of HOT lane demand w.r.t tolls was statistically significant at 5% significance level for each of the HOT facilities for the entire morning and evening periods, indicating that tolls charged do affect HOT lane demand. However, the size of the effect, as depicted by the elasticities is very small. Similarly, HOT lane demand elasticity w.r.t GP lane congestion was statistically significant at 5% significance level for all facilities and both directions of travel. Across the four studied facilities and both directions of travel, average elasticity of HOT lane demand w.r.t tolls was +0.13 compared to +0.34 for elasticity w.r.t GP density (160% difference). This implies that on average, a 10% change in tolls charged will change HOT lane demand by 1.3% while a similar percentage change in GP density will result in a change of 3.4% in HOT lane demand. The magnitudes of both elasticities are less than one which indicates that HOT lane demand has an inelastic relationship with tolls charged and GP density; however, the level of inelasticity is very high w.r.t tolls charged. This implies that, among the two factors, toll is the least predictor of HOT lane usage.

The magnitude of the difference between the relative impacts of tolls and GP lane congestion on HOT lane demand even gets bigger during peak periods. As shown above in Table 4.10, the impact of tolls on HOT lane demand further diminishes during the peak periods; resulting in relatively smaller elasticity estimates (average elasticity of +0.07). This suggests that, most drivers tend to be even less sensitive to the tolls been charged during peak/congested periods, and may use the HOT lanes to enjoy travel time savings as shown in the peak period (7:30 AM – 8:30 AM) of I-85 express lanes in Figure 4.13.

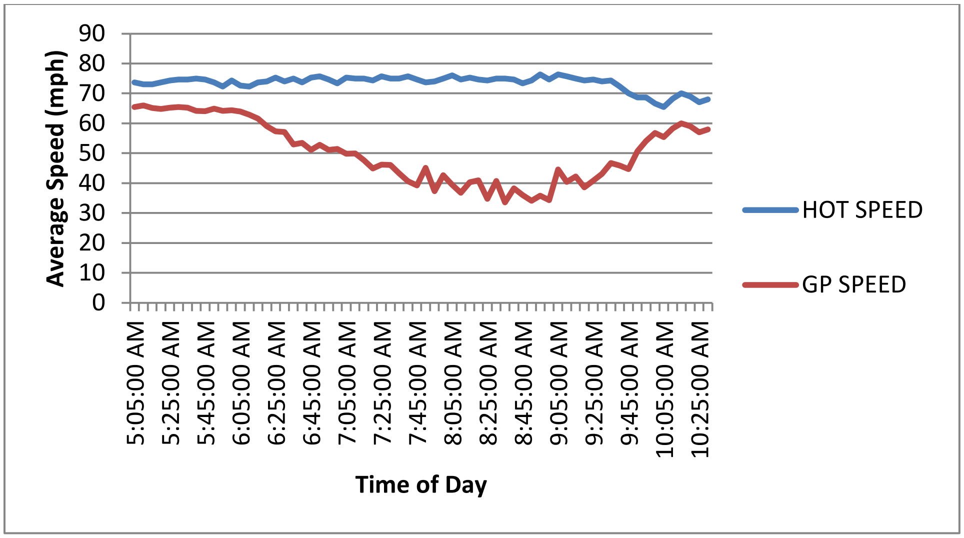
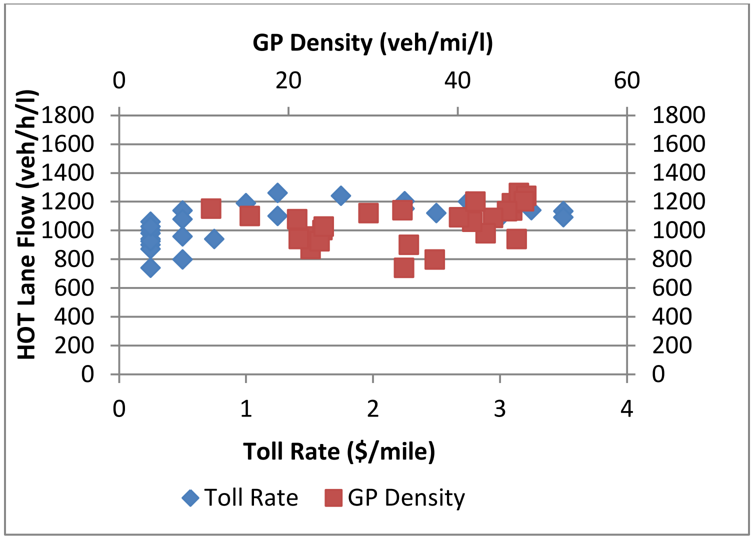
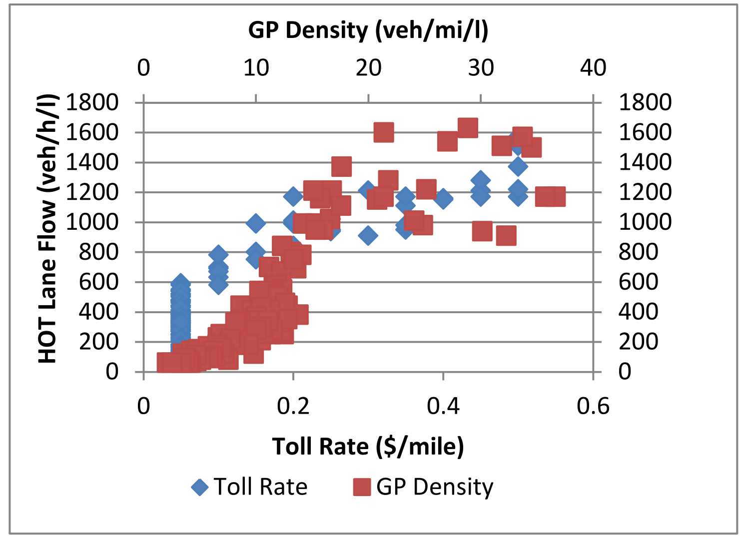


Figure 4.13: Comparison between HOT and GP lane speeds on I-85 SB

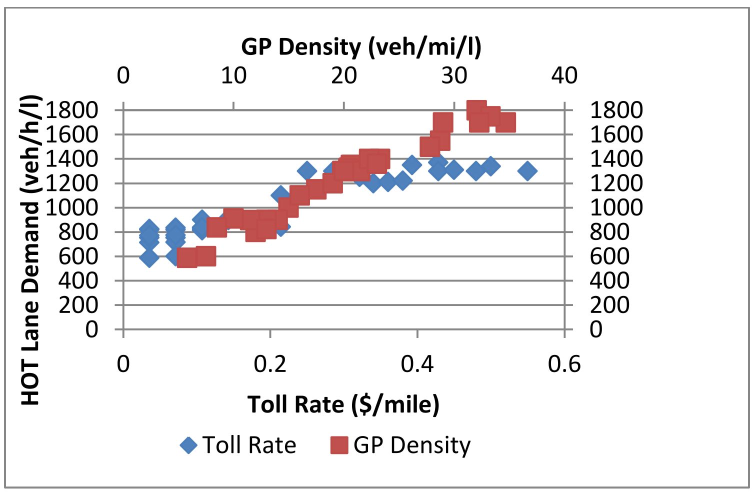
Figure 4.14 displays plots of the relationships between HOT lane demand and toll rates/GP lane density for all studied HOT facilities.



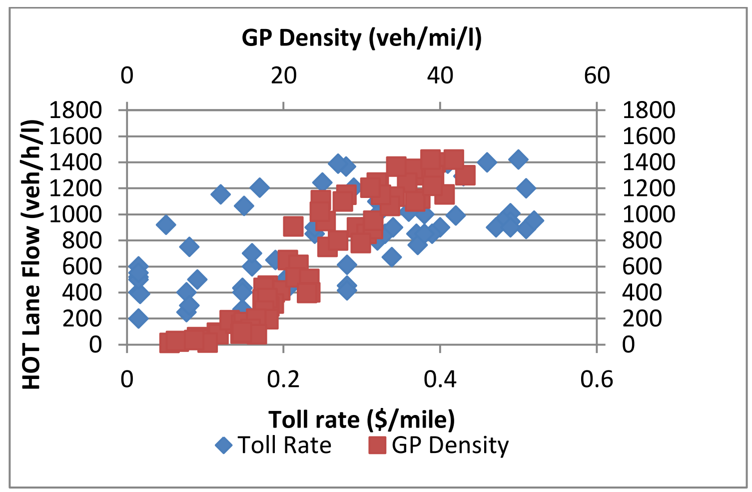
I-394 MnPASS Lanes



I-15 Fast Trak Express Lanes



I-95 Express Lanes



I-85 Express Lanes

Figure 4.14: Relative impacts of tolls and GP congestion on HOT lane demand

Figure 4.14 above shows that, the relative impacts of tolls and GP lane congestion on HOT lane demand is approximately equal on I-394 MnPASS lanes. The flat nature of the plots for both variables suggest their influence on HOT lane demand is small (inelastic relationship); hence the elasticity values of +0.11 (w.r.t tolls) and +0.10 (w.r.t GP density). The plot of I-15 Fast Trak express lanes is similar to I-394 MnPASS lanes; especially the inelastic behavior between tolls/GP congestion and HOT lane demand during high tolls (data appoints appear scattered without a trend). However, I-85 and I-95 express lanes appear to be different from the other two HOT facilities in terms of the impacts of GP congestion on HOT lane demand. As shown in Figure 4.14, the relationship between GP density and HOT lane demand for I-85 and I-95 express lanes appear to have a relatively steeper slope than those observed for I-15 Fast Trak and I-394 MnPASS lanes. This suggests that, the impact of GP congestion on HOT lane demand for I-85 and I-95 express lanes is relatively higher than the corresponding impacts on I-394 MnPASS and I-15 Fast Trak lanes.

Although differences and similarities (among studied HOT facilities) about the relative impacts of tolls and GP lane congestion have been mentioned, accurate conclusions about these observations can only be made after statistical analysis of the elasticity distributions of all HOT facilities has been conducted. Therefore, comparisons were made between HOT lane demand elasticity distribution w.r.t tolls and HOT lane demand elasticity distribution w.r.t GP density for each HOT facility using hypothesis testing. The hypothesis test is used to assess the evidence on whether a population parameter (e.g. mean) between two or more groups is likely to have arisen by chance or whether some other factors is responsible for the difference *(78)*. For each HOT facility, the following competing hypotheses were formulated:

If

μ_1 is the average HOT lane elasticity of demand w.r.t tolls in location A; and

μ_2 is the average HOT lane elasticity of demand w.r.t GP congestion at location A

Then the competing hypotheses are:

Null hypothesis: H_o: $\mu_2 > \mu_1$

Alternate hypothesis: H_a: $\mu_2 \leq \mu_1$

The specific goal here is to determine if the relative impact of GP congestion on HOT lane demand is greater than the impact of tolls on HOT lane demand. Consequently, a hypothesis test assuming unequal variances was used to examine the statistical significance of the differences between the average elasticity of HOT lane demand w.r.t tolls and GP congestion. The result of the hypothesis testing is shown below in Table 4.11.

Facility	**Z-STATISTIC**	**P(Z<=z) one-tail**	**Z Critical one-tail**
I-394	2.12	.035	1.644
I-15	3.34	.028	1.644
I-95	1.25	.059	1.644
I-85	1.14	.068	1.644

Table 4.11: Results of hypothesis testing (toll elasticity vs GP congestion elasticity)

The null hypothesis (HOT lane demand elasticity w.r.t GP congestion is greater than HOT lane demand elasticity w.r.t tolls) is rejected if the Z statistic is greater than the critical Z value and vice versa at 5% significance level. From Table 4.11 above, the null hypothesis was rejected for I-394 MnPASS lanes and I-15 Fast Trak express lanes. This implies that, the HOT lane demand elasticity w.r.t GP congestion was not greater than the corresponding elasticity w.r.t tolls for those two facilities (the difference in impacts on HOT lane demand is statistically insignificant). On the contrary, the null hypothesis couldn't be rejected for I-95 and I-85 express lanes; suggesting the relative dominance of HOT lane demand elasticity w.r.t GP congestion over that w.r.t tolls.

As observed from the results of the hypothesis test, I-394 MnPASS lanes and I-15 Fast Trak Lanes appear to be alike in terms of the relative impacts of tolls and GP congestion on HOT lane demand (equal impacts) but different from the remaining two facilities (I-95 and I-85 express lanes) which were also similar to each other. It is possible that I-394 MnPASS lanes and I-15 Fast Trak lanes might have something in common (e.g. driver behavior, local economy, etc.) which makes them different from I-95 and I-85 express lanes. Based on this assumption, it is necessary that the individual facilities are compared with each other and the possible reasons for similarities/differences explored. The next section discusses the comparison between the individual HOT facilities.

4.5.3.2 Comparison between HOT Facilities

A hypothesis test, comparing the individual HOT facilities in terms of the impacts of tolls and GP congestion on HOT lane demand (elasticity) was conducted at 5% significance level. This test will help to establish if HOT lane demand elasticity w.r.t tolls and GP lanes is consistent or different across multiple HOT facilities. Comparisons in terms of HOT lane demand elasticity w.r.t tolls and GP congestion were carried out separately. The competing hypotheses for each pair of HOT facilities (A and B) were:

H_o: Average HOT elasticity w.r.t tolls for A = Average HOT elasticity w.r.t tolls for B

H_a: Average HOT elasticity w.r.t tolls for A ≠ Average HOT elasticity w.r.t tolls for B

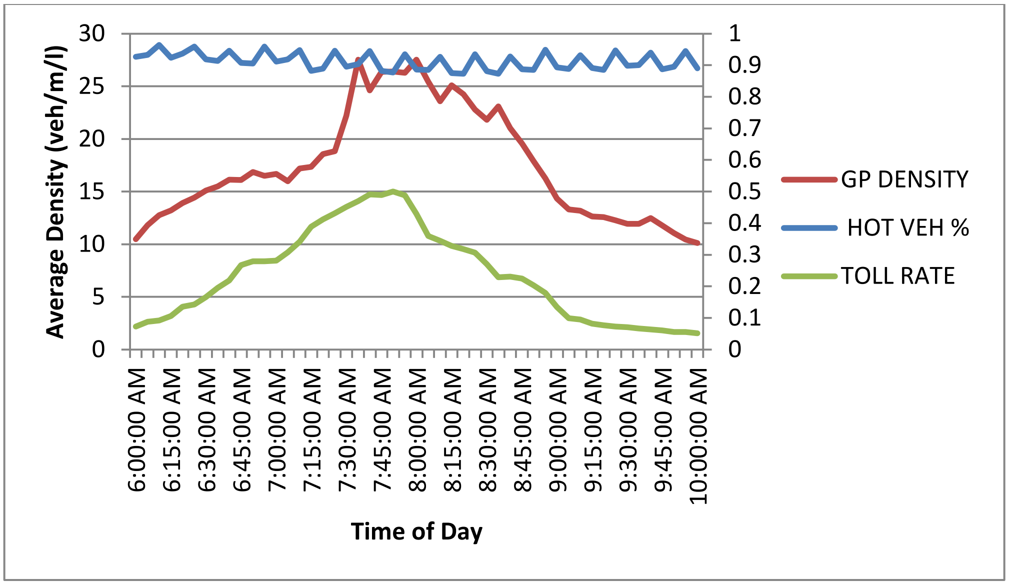
The same set of hypotheses was used for HOT lane demand elasticity w.r.t GP congestion. The test was conducted assuming unequal variances and approximate normal distribution because of the large sample size (>= 1000). Results of the test are shown below in Table 4.12.

FACILITY PAIR	Z-STATISTIC (Toll elasticity)	Z-STATISTIC (GP congestion elasticity)	P(Z<z) two-tail	Z Critical two-tail	RESULT
I-394 VS I-15	1.082	1.309	.083	1.96	Similar
I-394 VS I-95	2.834	3.824	.021	1.96	Different
I-394 VS I-85	3.562	2.991	.032	1.96	Different
I-15 VS I-95	2.329	4.804	.015	1.96	Different
I-15 VS I-85	5.963	3.615	.044	1.96	Different
I-85 VS I-95	1.481	1.230	.069	1.96	Similar

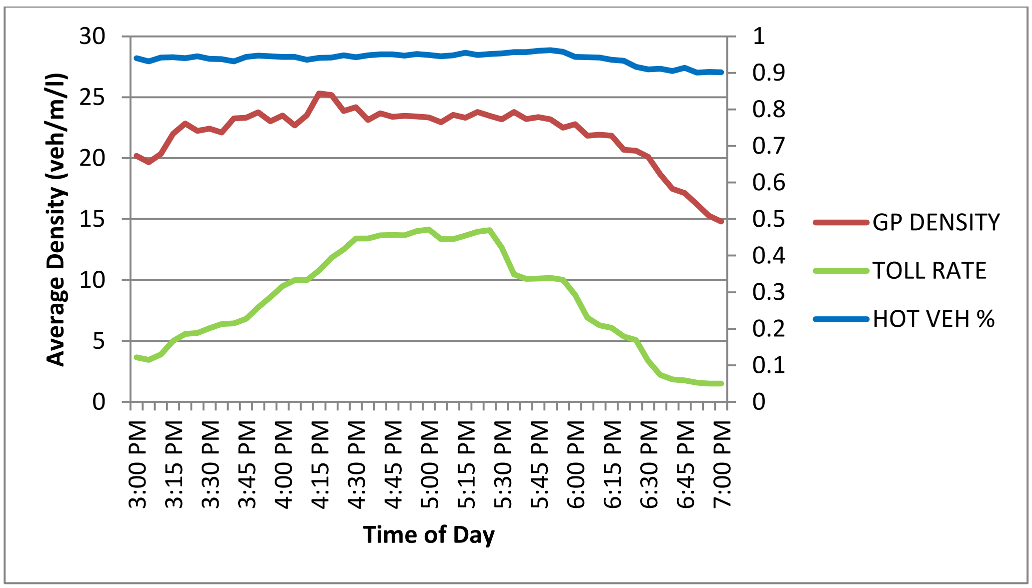
Table 4.12: Results of hypothesis testing (facility-pairs comparison)

The null hypothesis (that two HOT facilities are equal in terms of average HOT lane demand elasticity w.r.t tolls and GP congestion) is rejected if the Z statistic is greater than the critical Z value at 5% significance level or otherwise. From Table 4.12, I-394 MnPASS lanes and I-15 Fast Trak lanes appear to have equal average HOT lane demand elasticity w.r.t to tolls and GP congestion since the Z statistic was less than the critical Z value (i.e. failure to reject the null hypothesis). The same could be said of I-85 and I-95 express lanes where the null hypothesis of equality couldn't be rejected. The remaining HOT facility-pairs were found to be different in terms of their average HOT lane demand elasticity w.r.t tolls and GP congestion.

The similarity in average HOT lane demand elasticities for I-15 Fast Trak express lanes and I-394 MnPASS lanes was not surprising. For both HOT facilities, demand elasticity w.r.t tolls and GP lane congestion was highly inelastic, with elasticities not exceeding +0.17 and +0.21 respectively during morning and evening periods. The inelastic behavior did not change during peak periods where elasticities (w.r.t tolls and GP congestion) fell below +0.1 and +0.23 respectively. The lack of significant changes in elasticities (w.r.t tolls and GP lane congestion) between off-peak and peak periods suggest that travelers used the HOT lanes with little or no regards to tolls and changing congestion levels on GP lanes. In order to test this assumption, data describing the distribution of eligible HOT lane users (SOVs and zero emission vehicles with transponders) was obtained for I-15 Fast Trak lanes. This data provides the percentage split of eligible HOT lane users between GP and HOT lanes at any point in time. For example, at 6:30 AM on a HOT facility, 70% of eligible HOT lane users may be on the HOT lanes while the remaining 30% use the GP lanes. The data covered the 5-month analysis period and was used to develop plots as shown in Figure 4.15 below.



a) Morning period



b) Evening period

Figure 4.15: Relative distribution of HOT lane users on I-15 express lanes

From Figure 4.15 above, about 90% of eligible HOT lane users consistently patronized the lanes even when the GP lanes were operating at LOS A regardless of direction of travel. It appears the HOT lane users were not responding to changes in tolls and level of congestion on GP lanes during both peak and non-peak periods. The constant usage of the HOT lanes with high insensitivity towards tolls and GP lane congestion explains the low demand elasticities observed on this HOT facility.

Goodall and Smith (2008) conducted a research which investigated the behavior of SOVs using the reversible section of I-394 MnPASS lanes (same segment of MnPASS facility used in this research). The authors developed a two-component model to predict the percentage of SOVs using the HOT lanes in time interval *t* at cost per hour of travel time saved *c*. When the model was applied to dataset obtained from the 2.7 mile reversible section of MnPASS, it was revealed that about 87.5% of HOT lane users were not sensitive to tolls been charged. The non-sensitive drivers used the HOT lanes even when the GP lanes were operating above the speed limit of 55 mph. The authors concluded that under the congestion levels experienced on the MnPASS system, pricing has negligible influence on behavior. This finding on the I-394 MnPASS lanes is similar to what was found on the I-15 Fast Trak express lanes in this research. It is therefore not surprising that, the two were found not to be statistically different from each other in terms of their elasticities w.r.t tolls and GP lane congestion. The common factors behind the similarities of the two HOT facilities will deepen our understanding of HOT lane user behavior. An important commonality between the two facilities is their average annual incomes. As mentioned earlier, the locations of both HOT facilities have high RPP-adjusted annual average incomes of $87,092 (I-394 MnPASS, Minneapolis) and $83,820 (I-15 Fast Trak, San Diego). As a result the current price levels of the HOT lanes might not influence the choice behavior of such high income HOT lane users. Consequently, it was found in the VTTS analysis that users of these two HOT facilities have high mean VTTS estimates during morning/evening periods ($65 for I-394 MnPASS, $57.5 for I-15 Fast Trak). This implies that, they use the HOT lanes even when there are no significant travel time savings. Looking at these commonalities in unison, it is likely that the high VTTS estimates are due to the high annual average incomes, and this eventually may lead to HOT lane users not been sensitive to tolls and changing GP congestion (low elasticities w.r.t tolls and GP congestion).

I-85 and I-95 express lanes which were also found to be similar from the results of the hypothesis test were also analyzed. Both HOT facilities appear to have relatively high HOT lane demand elasticity w.r.t GP lane congestion (around +0.5 during morning/evening periods) than w.r.t tolls (less than +0.12 during morning evening period). For both facilities, HOT lane demand elasticity w.r.t GP lane congestion appears to increase during peak period (around +0.7) while the corresponding elasticity w.r.t tolls decreases (average elasticity of +0.06). In addition, users of both HOT facilities have relatively low mean VTTS estimates ($49.5/hour and $50.9/hour for I-95 and I-85 express lanes users respectively) compared to what was observed for I-394 MnPASS and I-15 Fast Trak lanes. Also, their income levels were relatively low; RPP-adjusted annual incomes of $65,900 and $79,963 for Miami (I-95 express lanes) and Atlanta (I-85 express lanes) respectively. Congestion levels on GP lanes may also be a significant contributing factor to the similarities between I-95 and I-85 express lanes. For the segments analyzed in this research, congestion levels on GP lanes parallel to I-85 and I-95 express lanes were generally higher (average density of 50 veh/mi/l) than what was experienced on I-15 Fast Trak/I-394 MnPASS lanes (average density of 30 veh/mi/l). As a result of the low operating speeds on GP lanes (due to high congestion levels), eligible users of I-85 and I-95 HOT facilities tend to shift to the HOT lanes; hence the relatively higher elasticities w.r.t GP lane congestion for both facilities.

In order to further understand the difference in user behavior between I-394 MnPASS/I-15 Fast Trak lanes and I-85/I-95 express lanes, data on eligible HOT lane user distribution was also obtained for I-85 express lanes. As shown in Figure 4.16, use of the I-85 express lanes was not consistent as observed on I-15 Fast Trak lanes; rather, percentage of eligible users on I-85 express lanes fluctuated with changing traffic conditions on the GP lanes and tolls. Although data was not available for I-95 express lanes in terms of eligible user distribution, it is likely that users may exhibit a similar choice behavior.

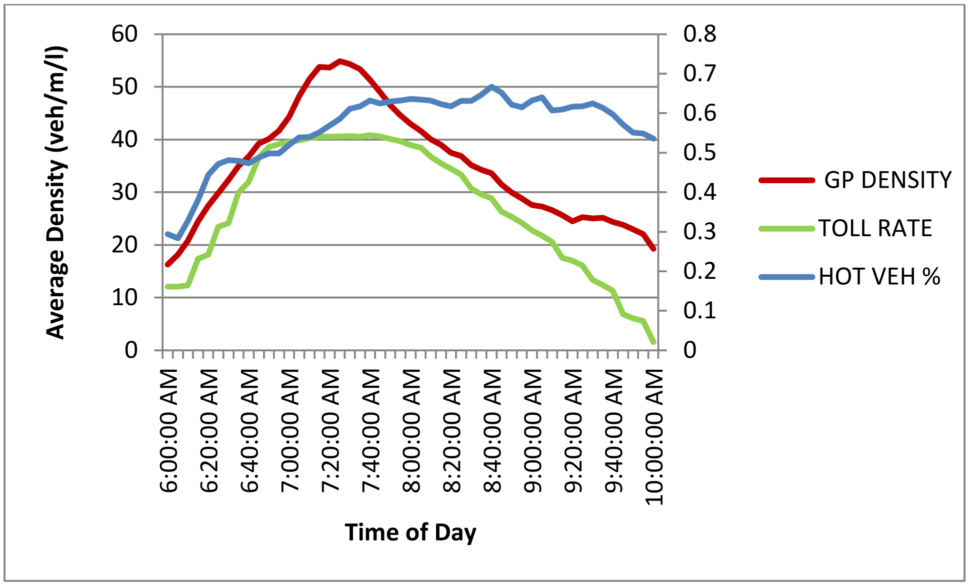


Figure 4.16: Relative distribution of HOT lane users on I-85 express lanes

4.6 Summary

This chapter was focused on behavior of HOT lane users across multiple HOT lane facilities in the U.S. The purpose was to determine if there was a general pattern in the behavior of HOT lane users in terms of their response to pricing (tolls) and changing traffic conditions. Using 5 months of toll and traffic data from four different HOT lane facilities, VTTS and elasticity estimates were obtained for each HOT facility. Statistical comparison of these estimates resulted in two different groups of HOT lane facilities, with members of each group having similarities in how drivers responded to tolls and changing traffic conditions. Three important factors which were found to differentiate between the two groups of HOT facilities were income levels of where these facilities are located, the level of congestion in the HOT corridor and travel reliability on GP lanes. The next chapter presents the development of models that could be used to predict the expected level of demand on HOT lanes.

Chapter 5

HOT Lane Demand Prediction

For Integrated Corridor Management (ICM) to be very effective in mitigating highway congestion and ensuring efficient use of transportation facilities, it must be proactive rather than reactive. The ICM system should be able to anticipate the impacts of any implemented strategy on traffic conditions in a corridor. This valuable piece of information can then be shared in real-time with ICM partner agencies as well as with the traveling public. Currently, High Occupancy Toll (HOT) lane systems do not predict into the future, the expected levels of demand on the lanes based on tolls and changing traffic conditions. Instead, the effects of tolls are evaluated in retrospect. This chapter is intended to develop short-term HOT lane demand/flow predictive models using tolls and the level of congestion on the General Purpose (GP) lanes (density) as explanatory variables. The developed model will help to predict the expected Level of Service (LOS) or demand on HOT lanes in real-time (e.g. every 5-minute period).

5.1 Candidate Modeling Approaches

An important step in the development of any predictive model is the selection of modeling approach. The choice of modeling approach often depends on the desired purpose of the predictive model and the type of data to be used. Over the years, a lot of different modeling approaches have been used in highway traffic prediction. The three main types of modeling approaches identified in the literature include parametric techniques, non-parametric techniques, and hybrid methods. Brief discussions of the different modeling approaches and the criteria for selecting the approach to be used in this research are discussed below.

Parametric models are models whose functional forms (established based on theoretical considerations) are known prior to model development *(84)*. Some of the common parametric models used in traffic prediction include smoothing techniques *(85)*, autoregressive linear processes such as the auto-regressive integrated moving average (ARIMA) family of models *(86)*, state-space (Kalman filter) models *(87)*, linear and non-linear regression models *(78)*, etc. Although smoothing techniques (linear and exponential filters) are generally used to eliminate the unwanted effects of randomness in a time series data, these filters can also be used for predictive purposes. ARIMA models describe the behavior of a phenomenon in terms of its past values and are useful for traffic prediction even in the absence of explanatory variables *(78)*. According to Smith and Demetsky (1997), ARIMA models rely on an uninterrupted series of data ; making it less useful for datasets with missing values *(88)*. State-space (Kalman filter) models allow the selected state variable to be updated continuously and sometimes show superiority over simple ARIMA formulations when modeling traffic data from different periods of the day *(89)*. Parametric regression (e.g. linear regression) is a widely used technique, and is often the first modeling approach to be tested in the model selection process *(78)*. Depending on whether the regression model is linear or non-linear, parameter estimation is respectively based on methods from linear algebra and search methods that minimize the magnitude of residual errors.

Non-parametric modeling approaches do not assume any specific functional form that explains the relationship between the dependent and independent variables. Instead, the phenomenon of interest is modeled by allowing it to have a general form which is gradually approximated with a certain precision using a growing dataset. Non-parametric models are data driven; hence, their successful implementation is strongly related to the quality of available data *(84)*. Notable examples of this modeling approach are non-parametric regression, neural networks, classification and regression trees (CART), etc. In non-parametric regression, the approach locates the state of the system (defined by independent variables) in a “neighborhood” of past, similar states. The past cases in the neighborhood are used to estimate the future value of the dependent variable. This implies that, the quality of this procedure is dependent on the ability of past datasets to represent the spectrum of all possible future conditions *(85)*. Neural networks are extremely popular in traffic forecasting and transportation research as a whole. They are mainly used to forecast complex, mostly non-linear, and non-stationary phenomena. Neural network models are data-driven and are based on the principles of artificial intelligence with exceptional pattern classification and recognition abilities *(84)*. A major issue with models developed by neural networks is the interpretation of its parameter because of the so-called “black box” phenomenon *(90)*. CART models identify optimum break points within predictor variables, separating them into groups inside which the values of the dependent variable are as homogeneous as possible. The main disadvantage of CART models is the subjectivity involved in choosing the optimum tree size *(91)*.

Hybrid models offer an alternative to traffic prediction by combining different methods to produce more efficient models. An example of a hybrid model in traffic prediction include the combination of clustering technique and linear regression in developing the ATHENA model *(92)*. Fuzzy logic and genetic algorithms also provide an opportunity for the development of hybrid models *(84)*.

Although most of the modeling techniques described above can be used to develop HOT lane demand/flow predictive models, the final choice was based on two main criteria.

1. The objective of this research is to explicitly model the impacts of toll rates on HOT lane demand/flow taking into account congestion on GP lanes. As a result, the model must not include any lagged variables (i.e. time effects are not considered).

2. The desired model must be simple enough so that it can be clearly understood and its parameter estimates clearly interpreted.

Based on the first criterion, parametric models such as the smoothing and ARIMA family of models will not be used. This is because, the ARIMA models are usually based on lagged variables of the dependent variable while the smoothing techniques do not make use of explanatory variables. Non-parametric (e.g. neural network models) and hybrid models tend to have superior predictive capabilities than parametric models; however, they are relatively more complex and data intensive. As a result, their parameter estimates (especially neural networks) are very difficult to interpret. Therefore, non-parametric and hybrid models were excluded from consideration.

Multiple linear regression was finally settled on as the choice of modeling approach for this research effort for many reasons. To begin with, linear regression is suitable for modelling a wide variety of relationships between variables and its assumptions are often satisfied in many applications. Secondly, linear regression model outputs are relatively easy to interpret and communicate to others. Thirdly, numerical estimation of linear regression models is relatively easy (and well understood) and softwares are readily available to carry out the estimation task *(78)*. Lastly, it is always useful to begin the model building process with simple models; increasing the level of complexity as and when the need arises. Hence, it is a step in the right direction to begin the model development with a linear regression method.

5.2 Data Needs

In order to predict HOT lane demand/flow, traffic data from the GP and HOT lanes as well as data on tolls charged for the use of the HOT lanes were gathered. The traffic data included GP lanes average density and HOT lanes average traffic flow. These traffic data were the same as those used in VTTS and elasticity analysis in Chapter four. The traffic data were obtained at the same time intervals used to update tolls charged on the HOT lanes (e.g. every three minutes on I-394 MnPASS lanes, every 5 minutes on I-85 express lanes in Atlanta, etc.). Both traffic and toll data used in the model development covered a 5-month period; that is from October 2012 to February 2013. Data during inclement weather and other suspicious data were removed using the same procedure employed in the VTTS and elasticity analysis in Chapter four.

5.3 Data Preparation

The 5-month data for both the response (HOT lane demand/flow) and explanatory (GP density and toll rate) variables were obtained at regular time intervals (e.g. every three minutes for I-394 MnPASS lanes) and can therefore be considered as a time series data. In order to use time series data to develop linear regression models, some technical concerns must first be addressed. These concerns are described in the next sections.

5.3.1 Spurious Regression

Regression models built using time series data are seriously hampered when non-stationary variables are used. When non-stationary independent variables are used in linear regression models, the statistical significance of parameters tends to be overestimated. As a result, one may obtain apparently significant relationships from unrelated variables. This phenomenon is referred to as spurious regression *(78)*. A stationary process is one whose statistical properties do not change over time. There are two types of stationarity in time series. For a strictly stationary stochastic process, the joint statistical distribution of a time series at times t_1 and t_2 is the same as the joint statistical distribution at times t_6 and t_7. On the other hand, a weak stationary process has the property that the mean, variance, and autocovariance do not change over time *(93)*. This implies a flat looking series without trend, with constant variance over time and with no periodic fluctuations. The condition of stationarity must be achieved before a time series data can be used in a linear regression. Figure 5.1 below differentiates between a stationary and non-stationary time series data.

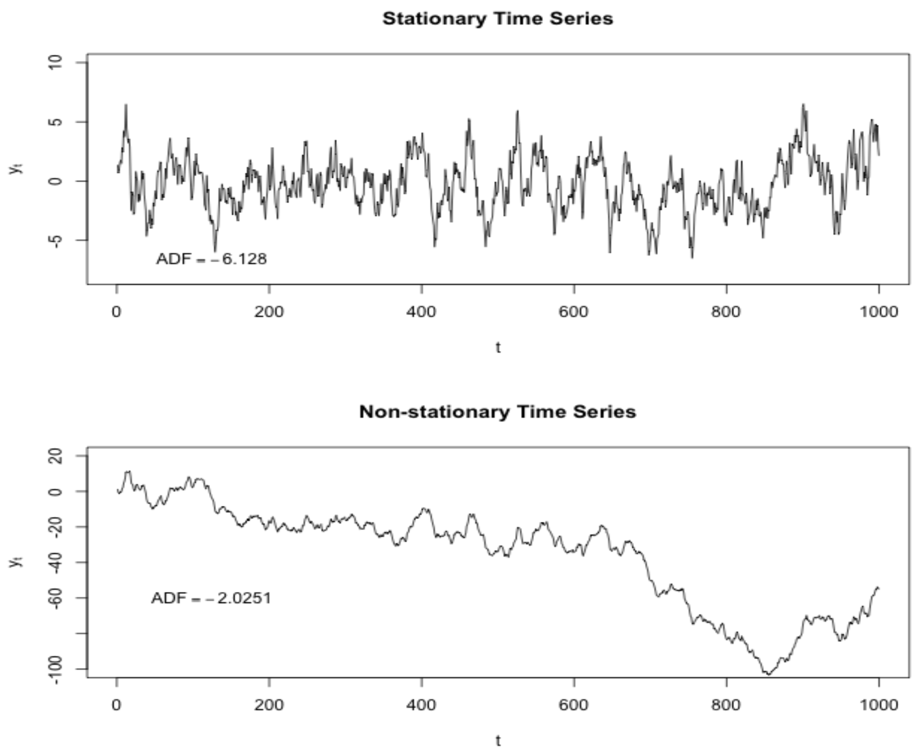


Figure 5.1: Differentiating between stationary and non-stationary time series

There are many tests that can be conducted to determine whether a time series is stationary or not. These include Elliot-Rothenberg test, Philips-Perron test, Schmidt-Phillips test, Augmented Dickey-Fuller (ADF) test, etc. However, the ADF test is more popular and widely used. The ADF statistic used in the test is a negative number. If the test statistic is more negative than the critical value at a certain confidence level, then the null hypothesis that there is a unit root (non-stationarity) in the time series can be rejected *(93)*.

If a time series is found to be non-stationary, it must be corrected before it can be used for regression analysis. A common approach to achieving stationarity is to difference the series between time intervals. Mostly the first difference (i.e. difference between the time series at successive time intervals) of a time series tends to be stationary *(94)*.

5.3.2 Autocorrelation (Serial Correlation)

An important assumption in linear regression models is the independence of residuals/disturbances across observations .The correlation of a series with its past observations results in serial or autocorrelation. This implies that the errors associated with a given time period carry over into future time periods *(78)*. For example, an overestimate in traffic flow in one time period is likely to lead to overestimates in subsequent time periods. Serial correlation does not affect the unbiasedness or consistency of ordinary least square (OLS) estimates but it does affect their efficiency *(78)*. With positive serial correlation, the OLS estimates of the standard errors will be smaller than they really are; resulting in inflated t values of parameter estimates. This will lead to the conclusion that the parameter estimates are more precise than they really are and often result in rejecting the null hypothesis when it should not be rejected. The most used test statistic for detecting serially-correlated errors is the Durbin-Watson (DW) statistic *(95)*. This statistic can be expressed mathematically as shown below in equation 5.1.

$$DW = [\sum (e_t - e_{t-1})^2]/\sum e_t^2 \qquad (5.1)$$

Where:

e_t is the residual at time t
e_{t-1} is the residual at time t-1

The DW statistic usually lies between 0 and 4. If it is substantially less than 2, there is evidence of positive serial correlation (successive residuals are close in value to each other). However, if DW statistic is greater than 2, successive error terms are much different in value from each other (negative serial correlation). To test for serial correlation at a certain level of statistical significance, the DW statistic must be compared with the critical upper and lower values for that significance level provided by the DW statistic look up table *(78)*. Positive and negative serial correlations are explained in Figure 5.2 below.

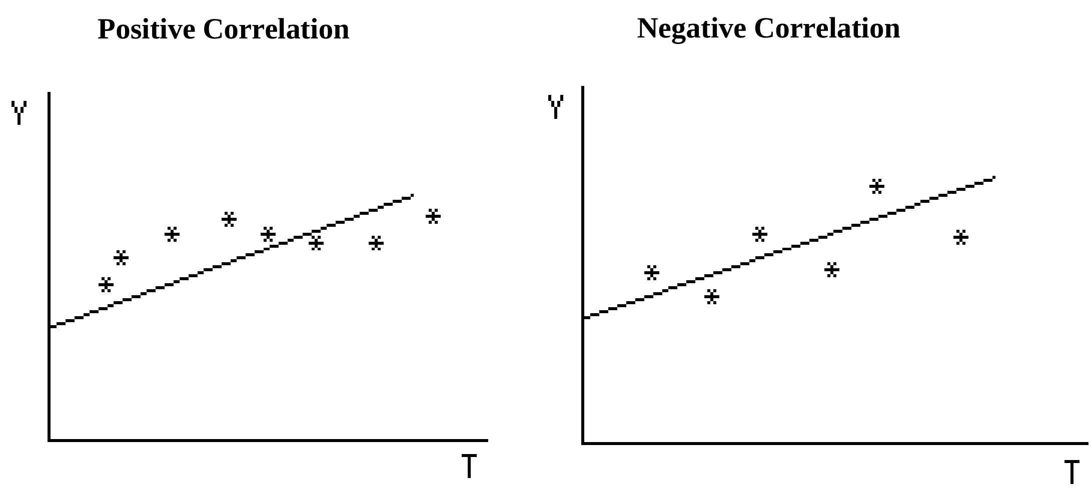


Figure 5.2: A plot of positive and negative serial correlations

There are various procedures for correcting serially correlated time series data. These include generalized differencing, the Cochrane-Orcutt procedure, the Hildreth-Lu procedure, the Prais-Winsten estimation, etc. *(95)*.

5.4 Methodology for Model Development

The procedure used in developing and testing the HOT lane demand/flow predictive model is as shown below:

1. For each HOT lane facility, 70% of the dataset was set aside to develop (train) the predictive model while the remaining 30% was held back to test its performance. Both the training and "hold back" data were selected in such a way that they are truly representative of general traffic conditions on each HOT lane facility. Therefore both training and validation data were comprised of data from all months, weekdays, and time of day.

2. The traffic and toll rate data were tested for stationarity using the ADF test. If a variable was found to be non-stationary, the appropriate corrective/transformative procedure was applied.

3. The data was also tested for serial correlation using the DW test. When serial correlation was found to be present in the data, the Prais-Winsten estimation was employed to provide the necessary corrections to the data. After corrections have been applied, the DW statistic is calculated again and compared with critical values at 5% significance level in order to reject the null hypothesis that serial correlation is zero or otherwise.

4. After the data have been tested for both stationarity and serial correlation, scatter plots of the response (HOT lane demand/flow) and explanatory (toll rate and GP density) variables were developed. This helped to identify if there is any relationship between the response and explanatory variables as well as the functional form (linear, exponential, etc.) of the relationship.

5. In order to use the linear regression technique, non-linear relationships were linearized through logarithmic transformations. This ensured that the basic assumptions of linear regression were not violated.

6. A forward stepwise regression method was used to select the "best" HOT lane demand/flow predictive model. This procedure allows the inclusion of explanatory variables in the model through a stepwise manner. In the end, only explanatory variables that improve the model will be included.

7. Finally, the predictive performance of the "best" model was evaluated using the "hold back" data.

Detailed explanations of the Prais-Winsten estimation, forward stepwise regression procedure, and performance evaluation procedure of the HOT lane demand/flow predictive models are covered in the next sections.

5.4.1 Correcting for Serial Correlation (Prais-Winsten estimation)

Prais-Winsten estimation is a procedure meant to take care of the serial correlation of type AR (1) in a linear model. This estimator improves on the Cochrane-Orcutt method in that the first observation is preserved in the estimation routine *(96)*. Consider the linear model

$$Y_t = \alpha + X_t\beta + \mathcal{E}_t \tag{5.2}$$

Where:

Y_t is the time series of interest at time t
β is a vector of coefficients
X_t is a matrix of explanatory variables
ε_t is the error term

The error term can be serially correlated over time, that is: $\varepsilon_t = \rho\varepsilon_{t-1} + e_t$ where e_t is a white noise and ρ is the autocorrelation coefficient (between 0 and 1). The Cochrane-Orcutt transformation can be used to correct for the serial correlation as shown in equation 5-3 below.

$$Y_t - \rho Y_{t-1} = \alpha\,(1-\rho) + \beta\,(X_t - \rho X_{t-1}) + e_t \tag{5-3}$$

For t = 2,3,….,T.

From the Cochrane-Orcutt transformation equation above, it can be seen that the differencing occurs between successive time intervals; hence, the first observation is always excluded since it has no observation before it. The Prais-Winsten procedure makes a reasonable transformation for t=1 (first observation) as shown in equation 5-4 below.

$$\sqrt{1-\rho^2}Y_1 = \alpha\sqrt{1-\rho^2} + (\sqrt{1-\rho^2}X_1)\beta + \sqrt{1-\rho^2}\mathcal{E}_1 \tag{5-4}$$

The impact of preserving the first observation can be advantageous when regression is carried out on small samples. Both Cochrane-Orcutt and Prais-Winsten transformations use an initial ρ (autocorrelation coefficient) value (e.g. 0) to correct for serial correlation. An iterative process is then initiated in which the values of ρ and regression parameters are recalculated at each iteration. Least squares estimation is employed in the iterative process. The Prais-Winsten estimation procedure in STATA software was used to correct for serial correlation *(96)*.

5.4.2 Forward Stepwise Regression

Stepwise regression is a procedure that relies on a user-defined criterion, such as R-squared, F-ratio, or other goodness of fit measures to select a “best” model among competing models generated by the procedure. Stepwise regression procedures can either be backward or forward. Backward stepwise regression starts by comparing models with large numbers of independent variables and sequentially removing one independent variable at each step. The variable removed is the one that contributes least to the goodness of fit criterion. The procedure iterates until a regression model is obtained in the final step. The user can then compare “best” models of different sizes. On the other hand, forward stepwise begins with a simple regression model and sequentially grows the regression by adding the variable with the largest contribution to the goodness of fit criterion *(78)*. The forward stepwise regression procedure in SPSS software was used in this research. A description of forward stepwise regression procedure is as follows *(97)*:

1. Set a significance level for deciding when to enter a predictor into the stepwise model; this is called alpha-to-enter (α_E). The significance level in this research was set at 0.05.

2. Fit each of the one-predictor models; that is regress the dependent variable (y) on each of the independent variables ($x_1, x_2, x_3, x_4, \ldots, x_n$) separately.

3. Of those predictors whose *t*-test *P*-value is less than α_E = 0.05, the first predictor put in the stepwise model is the predictor that has the smallest *t*-test *P*-value. If no predictor has a *t*-test *P*-value less than α_E = 0.05, the procedure stops.

4. Suppose x_1 had the smallest *t*-test *P*-value below α_E = 0.05 and therefore was deemed the "best" one predictor arising from the second step; now, fit each of the two-predictor models that include x_1 as a predictor. That is regress y on x_1 and x_2 , y on x_1 and x_3, etc.

5. Of those predictors whose *t*-test *P*-value is less than α_E = 0.05, the second predictor put in the stepwise model is the predictor that has the smallest *t*-test *P*-value.

6. If no predictor has a *t*-test *P*-value less than α_E = 0.05, the procedure stops. The model with the one predictor obtained from the third step becomes the final model.

7. But, suppose instead that x_2 was deemed the "best" second predictor and it is therefore entered into the stepwise model; now, fit each of the three-predictor models that include x_1 and x_2 as predictors.

8. Continue the steps as described above until adding an additional predictor does not yield a *t*-test *P*-value below α_E = 0.05.

5.4.3 Model Performance Evaluation

The performances of the predictive models developed were tested against the “hold back” data for each HOT lane facility. Using the “hold back” data, the expected HOT lane demand/flow was estimated. These estimates were then used to determine the expected LOS of the HOT lane facility. Finally, the predicted LOS was compared with the actual LOS experienced on the HOT lane facility for a given time period.

In chapter four, it was established that there was a weak causal relationship between HOT lane demand/flow and the explanatory variables (toll rate and GP congestion) based on the elasticity analysis. Therefore, the predictive model developed in this research was highly inaccurate in terms of predicting absolute HOT lane demand/flow. However, the LOS measure has broad intervals and was better suited to the predictive capabilities of the developed model. Hence, LOS was chosen as the performance measure in the evaluation process. Most HOT lane systems are mandated under federal regulations not to operate below 45 mph (i.e. LOS C for 95% of the time) *(98)*. Therefore the use of LOS as the performance evaluation measure will help transportation professionals to easily monitor compliance of their HOT systems with this federal requirement. The highway capacity manual (HCM 2010) provides guidance on the range of per lane flow rates for each LOS as shown in Table 5.1 *(99)*. These ranges of values were used as a basis to evaluate the performance of the predictive model in determining the expected LOS of a HOT facility.

Level of Service	**Range of Flow Rates (veh/hr/l)**	
	Lower Value	**Upper Value**
A	0	820
B	821	1310
C	1311	1750
D	1751	2110
E &F	2111	2400

Table 5.1: Level of service and corresponding flow rates

The performance of HOT lane demand/flow in predicting LOS was also compared with a naïve model. The naïve model did not contain any explanatory variables; however, it predicts the expected LOS for a time period based on the historic average HOT lane demand/flow for that time period.

5.5 Results and Analysis

The methodology described for this research effort was used to develop and evaluate predictive models for each HOT lane facility studied. The results of the model development as well analysis of predictive performance for each HOT lane facility is discussed below.

5.5.1 I-394 MnPASS Lanes, Minneapolis

Out of 80 days of data, 70% (56 days) was used to develop the predictive model for the 2.7 mile reversible section of I-394 MnPASS lanes. A test for stationarity was conducted for all the variables involved in the model using the ADF test. Using a critical value of -1.950 at 5% significance level, the null hypothesis of the presence of a unit root in the data was rejected. Hence, all the variables were found to be stationary. Additionally, the presence of serial correlation was also tested. A DW statistic of 0.74 indicated the presence of positive serial correlation among the error terms. Consequently, the Prais-Winsten estimation procedure was used to correct for the serially correlated data, resulting in a new DW statistic of 2.28. At 5% significance level, the critical DW lower and upper statistic values are 1.92447 and 1.92847 respectively. Since the DW statistic value of 2.28 is bigger than the critical upper value, the null hypothesis ($\rho = 0$) cannot be rejected.

Scatter plot of the response (HOT lane demand/flow) and explanatory (toll rate and GP lane density) variables was constructed as shown in Figure 5.3. Both toll rate and GP lane density appeared to have a positive correlation with HOT lane demand/flow; indicating an increase in HOT lane demand/flow as both toll rates and GP density increases. Additionally, it was observed from the scatter plots that both explanatory variables appear to have a second-order polynomial (quadratic) relationship with HOT lane demand/flow.

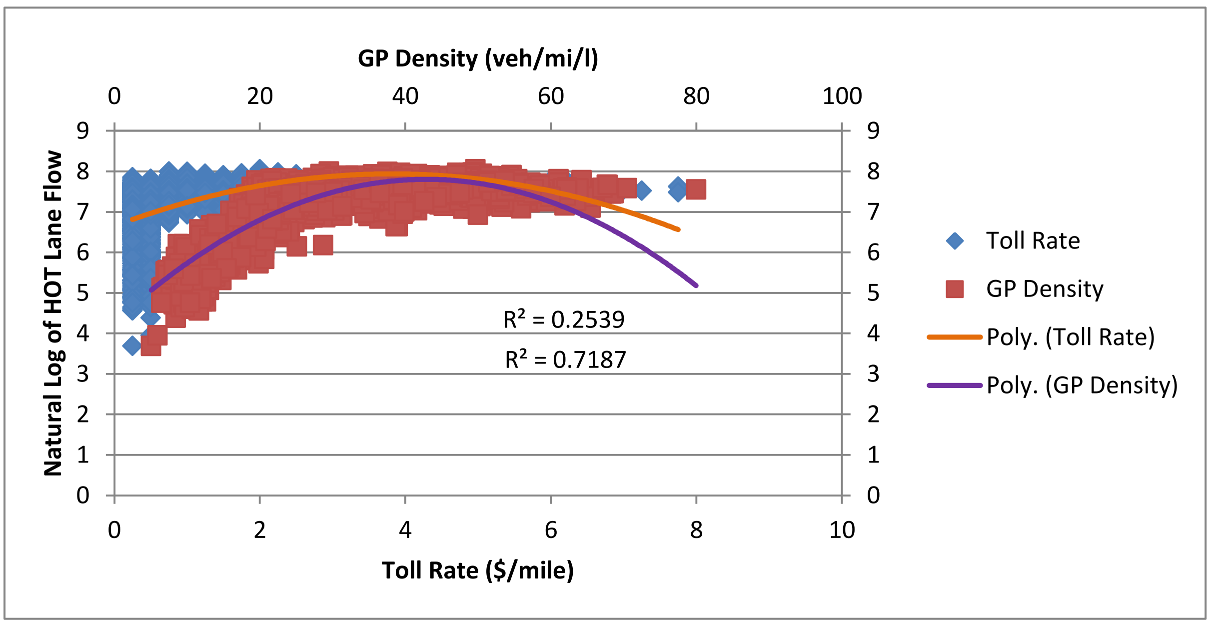


Figure 5.3: Scatter plot of response and explanatory variable (I-394 MnPASS lanes)

Model Building

A forward stepwise regression method was used to develop a HOT lane demand/flow predictive model for this facility. Since both explanatory variables appeared to have a quadratic relationship with HOT lane demand/flow, squared terms of toll rates and GP density were also considered in the model. Additionally, the possibility of an interaction between toll rates and GP density was also tested by considering an interaction term in the model. The dependent variable (HOT lane demand/flow) was log-transformed in order to satisfy the assumptions of linear regression. Using SPSS statistical package, the stepwise building of the predictive model is as shown below in Table 5.2.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GPDEN		Forward (Criterion: Probability-of-F-to-enter <= .050)
2	GPDEN2		Forward (Criterion: Probability-of-F-to-enter <= .050)
3	TR		Forward (Criterion: Probability-of-F-to-enter <= .050)
4	TR2		Forward (Criterion: Probability-of-F-to-enter <= .050)

a. Dependent Variable: LNHOTF

Table 5.2: Stepwise regression procedure (I-394 MnPASS lanes)

Where:

GPDEN= GP density
GPDEN2= GP density squared
TR= Toll rate
TR2= Toll rate squared
LNHOTF= natural log of HOT lane demand/flow

As evident in Table 5.2, all the explanatory variables except the interaction term (between toll rate and GP density) were included in the predictive model at 5% significance level. GP density been the first explanatory variable to be included in the model implies that it has the most statistically significant correlation with the dependent variable (HOT lane demand/flow). In the same vein, the squared toll rate term has the least statistically significant correlation with HOT lane demand/flow. Table 5.3 below shows the model summary.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.516[a]	.266	.266	.254
2	.542[b]	.294	.294	.226
3	.735[c]	.540	.540	.220
4	.736[d]	.542	.542	.219

a. Predictors: (Constant), GPDEN

b. Predictors: (Constant), GPDEN, GPDEN2

c. Predictors: (Constant), GPDEN, GPDEN2, TR

d. Predictors: (Constant), GPDEN, GPDEN2, TR, TR2

NB: Adjusted R^2 values reducing at the fourth decimal place

Table 5.3: Model summary statistics (I-394 MnPASS lanes)

The "best" model based on the adjusted R^2 values is model four which includes a constant term, GP density, GP density squared, toll rate, and toll rate squared. This model explains about 54.2% of the variance in HOT lane demand/flow. The second "best" model which does not include a squared toll rate term almost explains the same percentage of the variance (54%) in HOT lane demand/flow as the "best" model. Although addition of the squared toll rate term only increased the explanatory power of the model by 0.2%, it was still retained in the model. This is because, its exclusion is inconsistent with the quadratic relationship observed in the scatter plots in Figure 5.3. Additionally, despite its infinitesimal improvement in the model's explanatory power (adjusted R^2), it is statistically significant at 5% significance level. Consequently, model four was chosen as the HOT lane demand/flow predictive model for this HOT facility. This model had an F-statistic of 1512.6 which is greater than the critical F value (2.61) at 5% significance level.

Another important observation from the model summary statistics in Table 5.3 is the individual contributions of toll rate (and its squared term) and GP density (and its squared term). GP density and its squared term alone accounts for about 29.4% of the variance in HOT lane demand/flow while toll rate and its squared term account for the remaining 24.8%. This implies that, the decision by drivers to use/not to use HOT lanes appears to be equally influenced by the level of congestion on GP lanes and toll rates since the difference is only 4.6%. This observation confirms earlier findings in Chapter four in which the elasticity of HOT lane demand with respect to GP density (+0.11) was similar in value to the elasticity of HOT lane demand to toll rates (+0.10).

The coefficients of the explanatory variables and their corresponding statistical significance are as shown below in Table 5.4. Each of the explanatory variables in the selected model (model four) was found to be statistically significant at 5% significance level. Also, the variance inflation factors (VIF) for all the explanatory variables in the selected model were less than 5; implying little or no multicollinearity *(78)*.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	1.860	.022		84.545	.000	1.817	1.903		
	GPDEN	0.056	.023	.005	2.435	.000	.011	.101	1.000	1.000
2	(Constant)	2.380	.057		41.754	.000	2.267	2.492		
	GPDEN	.075	.135	.002	15.000	.000	.065	.085	.320	3.125
	GPDEN2	-.002	.022	-8.8E-06	-2.000	.000	-.004	-4E-05	.340	2.941
3	(Constant)	2.890	.056		51.607	.000	2.780	3.000		
	GPDEN	.096	.133	.013	3.200	.000	.037	.155	.352	2.841
	GPDEN2	-.0001	.022	-4.5E-09	-10.000	.000	-1.2E-04	-8E-05	.350	2.857
	TR	.022	.013	3E-04	7.333	.000	.016	.028	.899	1.112
4	(Constant)	3.410	.056		60.893	.000	3.300	3.520		
	GPDEN	.096	.132	8.7E-04	48.808	.000	.092	.099	.251	3.984
	GPDEN2	-.0001	.022	-4.6E-09	-10.000	.000	-1.2E-04	-8E-05	.242	4.132
	TR	.012	.016	1.1E-04	6.000	.000	.008	.016	.221	4.524
	TR2	-.001	.010	-1.4E-06	-3.330	.000	-.002	-4.1E-04	.230	4.348

a. Dependent Variable: LNHOTF

Table 5.4: Model coefficients and summary statistics (I-394 MnPASS lanes)

Using the coefficients from Table 5.4, model four (which was selected as the HOT lane demand/flow predictive model for this HOT facility) can be expressed mathematically as:

$$LN\ (HOTF) = 3.410 + 0.096*GPDEN - 0.0001*GPDEN2 + 0.012*TR - 0.001*TR2 \qquad (5\text{-}5)$$

Since the dependent variable was log-transformed, the interpretation of above equation is different from the usual regression output interpretation. The general interpretation is that the dependent variable changes by 100*(coefficient) percent when an independent variable changes by a unit while all other variables in the model are held constant. For example, it can be stated from equation 5-5 that if GP density increases/decreases by 1 veh/mile/l then HOT lane demand/flow will increase/decrease by about 9.6%. Similarly, if toll rate increases/decreases by $1, HOT lane demand/flow will increase/decrease by about 1.2%. In order to obtain the predicted HOT lane demand/flow in vehicles per hour using the above model, an exponential of the dependent variable must be taken ($e^{LN\ (HOTF}$).

The above predictive model makes sense even though the squared GP density term has a negative coefficient. The magnitude of the coefficients of GP density and GP density squared are such that the net impact of GP lane congestion on HOT lane demand/flow remains positive. For example if GP density is 100 vehicles per mile per lane, then based on the model, GPDEN will yield a value of 9.6 (0.096*100) while the squared term GPDEN2 will yield -1 (-0.0001*10000). The net value will be 8.6. Therefore, for all practically possible density values, the impact of GP density on HOT lane demand/flow will be positive. The same can be said of toll rates.

It is worth noting that the variable “toll rate” had a positive sign in the predictive model, implying toll rate increase leads to an increase in HOT lane demand/flow. This observation is contrary to how toll rates are expected to influence HOT lane driver behavior. In the HOT lane concept, the tolls charged are supposed to deter drivers from using the HOT lanes; therefore it was expected that toll rate will have a negative sign in the predictive model. However, the reality is that most drivers see high tolls as a sign of congestion in the GP lanes *(14,21)* and will use the HOT lanes in order to experience reliable travel conditions. Hence, the positive sign in the predictive model. This brings into question whether the current toll levels are high enough to deter drivers from using the HOT lanes.

Since linear regression modeling technique was used, it was necessary to check if the key assumptions have been met. Figures 5.4 and 5.5 show a histogram and P-P plots of model residuals. Both plots appear to suggest that the linear regression assumption of normally distributed residuals was fairly satisfied.

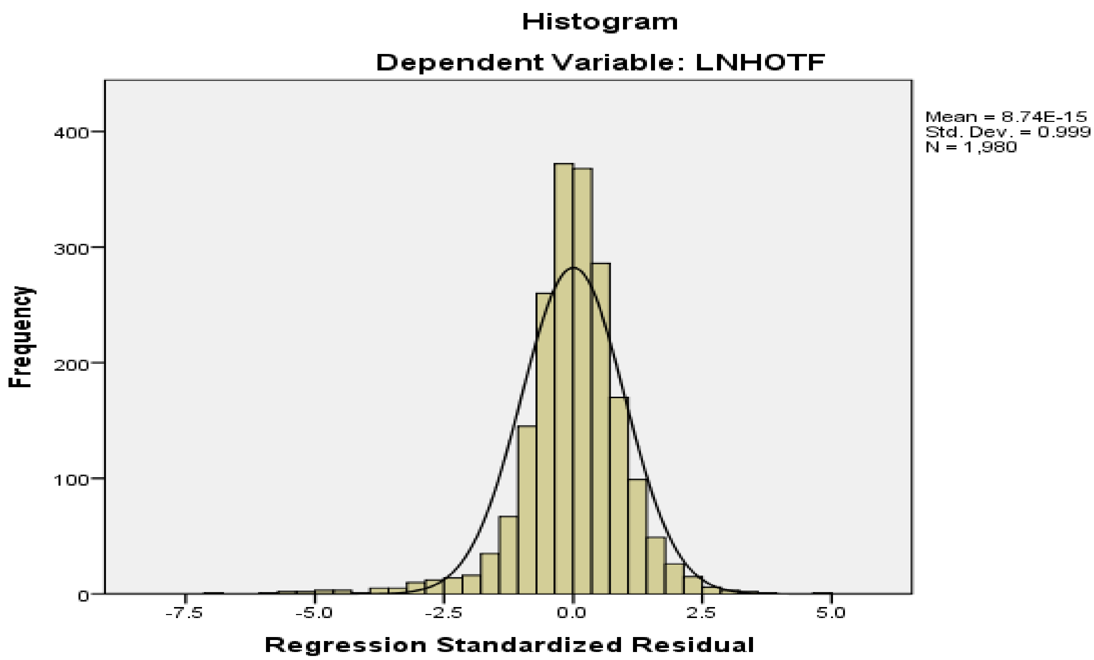


Figure 5.4: A histogram of regression residuals (I-394 MnPASS lanes)

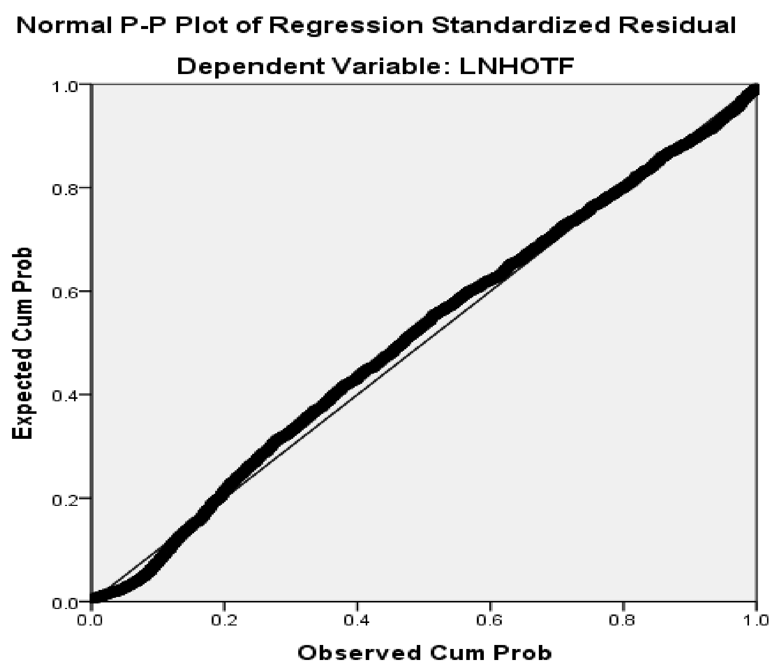


Figure 5.5: P-P plot of regression residuals (I-394 MnPASS lanes)

Also, a plot of standardized residuals against standardized predicted values (Figure 5.6) shows that the residuals are generally around zero. This implies that the linearity assumption in the regression was not considerably violated.

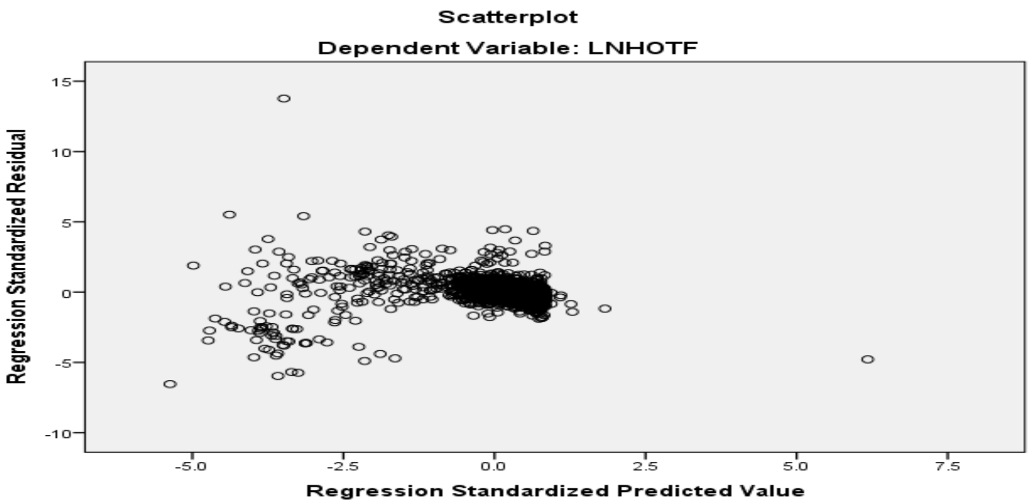


Figure 5.6: A scatter plot of regression residuals/predicted values (I-394 MnPASS lanes)

Model Performance Evaluation

The developed model was used to predict expected HOT lane demand/flow using the "hold back" data (24 days). The predicted demand was then used to determine the expected LOS for the HOT facility. As mentioned earlier, the relationship between HOT lane demand/flow and the explanatory variables was not very strong (especially for toll rate); therefore, the model's performance in predicting absolute HOT lane demand/flow was not encouraging, often over/under-predicting by as much as 25% of the true HOT lane demand/flow. However, the performance in terms of predicting the expected HOT lane LOS was relatively better. A comparison was made between performances of the predictive model and a naïve model which uses only average time-based HOT lane demand/flow values to predict expected HOT lane LOS. Table 5.5 shows results of the performance evaluation for both models.

DAY	% CLASSIFIED CORRECTLY (NAÏVE)	% CLASSIFIED CORRECTLY (PREDICTED)
10/23/2012	90	55
10/24/2012	85.7	52.4
10/25/2012	86.2	93.1
10/29/2012	77.8	66.6
10/30/2012	72	75.9
10/31/2012	81.4	82
11/27/2012	94.2	85.7
11/28/2012	96.7	70
11/29/2012	87.5	79.1
11/30/2012	85.7	82.9
12/10/2012	81	74
12/27/2012	44	100
12/28/2012	32	100
01/17/2013	68	77
01/23/2013	54.5	51.5
01/24/2013	91.3	78.3
01/25/2013	76	92
02/5/2013	79	82
02/11/2013	81	85
02/13/2013	65	75
02/22/2013	56.1	69.4
02/26/2013	80	86.7
02/27/2013	90.3	83.4
02/28/2013	93.1	82.8
AVERAGE	**77**	**78.3**

Table 5.5: Model performance evaluation (I-394 MnPASS lanes)

The performance of the predictive model in terms of predicting expected LOS was almost the same as that of the naïve model as shown in Figure 5.7 below. The average accuracy rate for both the predictive and naïve models were 78.3% and 77% respectively. The predictive model was only superior to the naïve model when traffic conditions deviated considerably from average conditions (e.g. days after holiday periods or days with unexpectedly high HOT lane demand). During such atypical traffic conditions (i.e. extremely low or high HOT lane demands), the performance of the predictive model is about 89% accuracy rate compared with 50% of the naïve model. The performance of the predictive model was consistent and did not show any systematic bias in terms of time of day, day of week, or month of year.

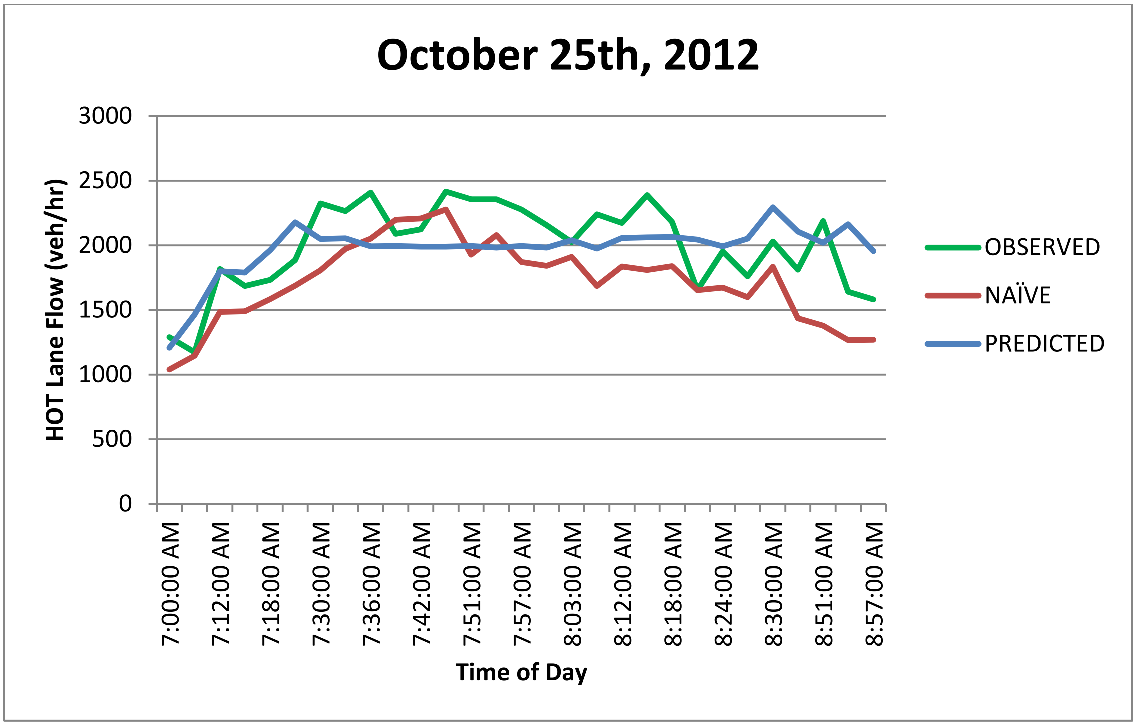


Figure 5.7: Model performance evaluation (I-394 MnPASS lanes)

5.5.2 I-15 Fast Trak Lanes, San Diego

Data from 42 out of the 60 days was used as training dataset. Test for stationarity using the ADF test was conducted on all the variables to be used for model development. At 5% significance level, all variables had ADF statistic values which were more negative than the critical value of -1.95. This implies that none of the variables had unit roots and therefore all had stationary properties. The data was also tested and corrected for serial correlation using Prais-Winsten estimation. After correction, the DW statistic changed from 1.039 to 2.32 (indicating the absence of serial correlation at 5% significance level).

In order to examine the relationships between the response and explanatory variables, the scatter plot shown in Figure 5.8 was developed. Both toll rate and GP density exhibited a moderate positive correlation with HOT lane demand/flow. This implies that HOT lane demand/flow increases as toll rates and GP density also increase. The nature of the correlation exhibited appeared to follow a polynomial distribution of second order (quadratic).

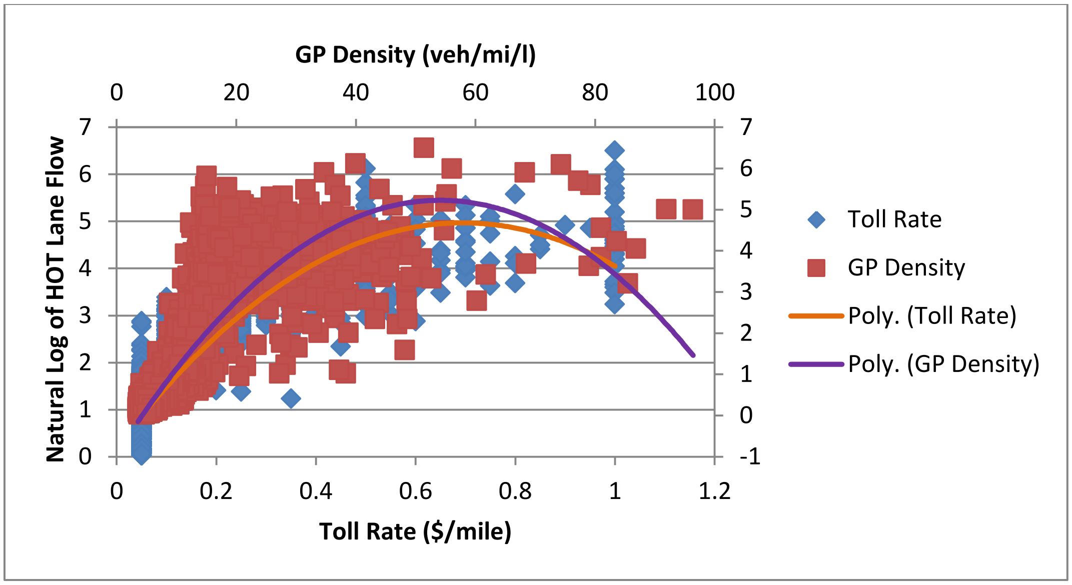


Figure 5.8: Scatter plot of response and explanatory variables (I-15 Fast Trak lanes)

Model Building

Five explanatory variables were considered for the forward stepwise regression model development. Based on the quadratic relationship revealed in the scatter plots, toll rate and GP density as well as their squared terms were tested for inclusion in the model. The fifth explanatory variable was an interaction term of toll rate and GP density. The dependent variable (HOT lane demand/flow) was log-transformed so that the model could satisfy the linear regression assumptions. The stepwise addition of the explanatory variables is as shown in Table 5.6 below.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GPDEN		Forward (Criterion: Probability-of-F-to-enter <= .050)
2	GPDEN2		Forward (Criterion: Probability-of-F-to-enter <= .050)
3	TR2		Forward (Criterion: Probability-of-F-to-enter <= .050)
4	TR		Forward (Criterion: Probability-of-F-to-enter <= .050)

a. Dependent Variable: LNHOTF

Table 5.6: Stepwise regression variable selection (I-15 Fast Trak lanes)

With the exception of the interaction term, all variables were included in the model. GP density and its squared term were selected as the first and second variables while toll rate squared and toll rate followed in that order. The order of selection of variables in stepwise regression is very important because it signifies the relative significance of each variable in the model. According to the order of variable selection in this model, the influence of GP density and its squared term on HOT lane demand/flow is more than the influence of toll rate/toll rate squared. Summary statistics for the various models is as shown below in Table 5.7.

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.452[a]	.204	.204	.951
2	.547[b]	.300	.300	.761
3	.751[c]	.564	.564	.751
4	.762[d]	.681	.681	.748

a. Predictors: (Constant), GPDEN
b. Predictors: (Constant), GPDEN, GPDEN2
c. Predictors: (Constant), GPDEN, GPDEN2, TR2
d. Predictors: (Constant), GPDEN, GPDEN2, TR2, TR
e. Dependent Variable: LNHOTF
NB: Adjusted R^2 values reducing at the fourth decimal place

Table 5.7: Model summary statistics (I-15 Fast Trak lanes)

About 68.1% of the variance in HOT lane demand/flow was explained by model four, which is made up of a constant term, GP density and its squared term, and toll rate and its squared term. However, model three (similar to model four with the exclusion of toll rate) explains nearly the same percentage of the variance (56.4%) in HOT lane demand/flow as that explained by model four. However, model four was selected for this HOT facility because it is consistent with the quadratic relationship observed in the scatter plot in Figure 5.8 and the toll rate term is statistically significant as well.

Additionally, from the model summary statistics in Table 5.7, both GP density (and its squared term) and toll rate (and its squared term) appear to equally explain the variance in HOT lane demand/flow. Prior to the inclusion of toll rate, GP density (and its squared term) alone explained about 30% of the variance in HOT lane demand/flow. Subsequently, toll rate (and its squared term) improved the model's explanatory power by 38.1%. This may suggest that the effect of GP lane congestion (GP density) on the demand for HOT lane use is almost the same as the effect of tolls. This finding is consistent with earlier findings in Chapter four where the elasticity of HOT lane demand w.r.t GP density (0.14) was similar to the toll elasticity of HOT lane demand (0.12).

Coefficients for all the four models that resulted from the stepwise regression models are as shown below in Table 5.8. All coefficients for the variables in model three were found to be statistically significant at 5% significance level.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	2.804	.018		155.778	.000	2.768	2.834		
	GPDEN	.117	.001	1.2E-04	117.000	.000	.115	.119	1.000	1.000
2	(Constant)	2.226	.017		130.941	.000	2.192	2.259		
	GPDEN	.195	.002	5.1E-04	97.500	.000	.191	.199	.461	2.167
	GPDEN2	-.001	.000	-1.3E-07	-10.000	.000	-.001	-8E-04	.461	2.167
3	(Constant)	2.194	.018		121.889	.000	2.159	2.229		
	GPDEN	.207	.002	5.5E-04	103.500	.000	.203	.211	.370	2.702
	GPDEN2	-.001	.000	-1.3E-07	-10.000	.000	-.001	-8E-04	.453	2.208
	TR2	.002	.000	2.6E-07	-20.000	.000	-.002	-.001	.642	1.558
4	(Constant)	2.152	.018		119.556	.000	2.117	2.187		
	GPDEN	.120	.002	3.2E-04	60.000	.000	.116	.124	.284	3.525
	GPDEN2	-.001	.000	-1.3E-07	-10.000	.000	-.001	-8E-04	.409	2.446
	TR2	-.001	.000	-5.3E-07	-2.500	.000	-1.7E-03	-2.2E-04	.280	3.571
	TR	.009	.000	6E-06	18.000	.000	.008	.010	.390	2.564

a. Dependent Variable: LNHOTF

Table 5.8: Model coefficients and summary statistics (I-15 Fast Trak lanes)

The predictive model can be expressed mathematically as shown in equation 5-6 below:

$$LN(HOTF) = 2.152 + 0.12*GPDEN - 0.001*GPDEN2 + 0.009*TR - 0.001*TR2 \qquad (5\text{-}6)$$

The above model implies that if GPDEN increases/decreases by 1 veh/mi/l, HOT lane demand/flow will increase or decrease by 12% (100*0.12). Similarly, if the toll rate increases/decreases by a $1, HOT lane demand/flow increases/decreases by 0.9%. Both GP density (including squared term) and toll rate have a positive sign in the model, implying any increments in the two variables may increase HOT lane demand/flow. The positive sign associated with toll rate contradicts the fundamental assumption that tolls discourage drivers from using HOT lanes (i.e. toll rate is supposed to have a negative sign). The selected model (model four) did not experience any significant multicollinearity as demonstrated by the low VIF values (generally <5).

Model Performance Evaluation

Using the "hold back" data (17 days), the performances of the predictive and naïve models were evaluated. Table 5.9 and Figure 5.9 show the performance of both models in terms of predicting HOT lane LOS.

DAY	**% CLASSIFIED CORRECTLY (NAÏVE)**	**% CLASSIFIED CORRECTLY (PREDICTED)**
10/19/2012	82.6	87.0
10/25/2012	80.0	77.7
11/07/2012	79.0	80.0
11/15/2012	85.6	84.7
11/16/2012	74.7	80.0
12/21/2012	84.4	82.0
12/27/2012	70.4	90.0
01/4/2013	79.2	84.6
01/12/2013	76.4	78.8
01/20/2013	86.1	84.6
01/26/2013	78.4	78.2
02/15/2013	80.0	82.6
02/19/2013	80.0	80.0
02/20/2013	87.2	81.7
02/22/2012	80	77.6
02/26/2013	76.1	75.0
02/27/2013	85.9	80.0
AVERAGE	**80.4**	**81.4**

Table 5.9: Model performance evaluation (I-15 Fast Trak lanes)

The performances of both the predictive and naïve models were similar. On average, both models correctly predicted the expected HOT lane LOS about 80% of the time. Figure 5.9 shows the performance of both models on a typical weekday. The performance of the predictive model was however superior during atypical traffic conditions (extremely low or high HOT lane demand) with classification accuracy of 90% compared with 73% for the naïve model. In terms of absolute numbers, the developed model expectedly over/under-predicted by as much as 20% of the true HOT lane demand/flow.

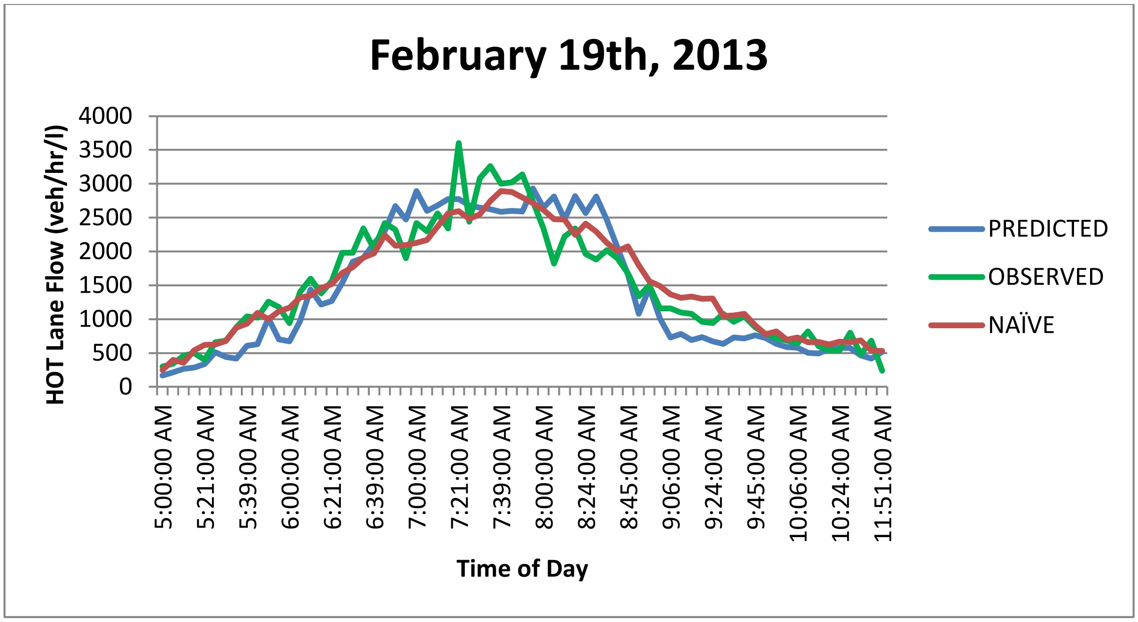


Figure 5.9: Model performance evaluation (I-15 Fast Trak lanes)

The assumption of normally distributed residuals was fairly satisfied as shown in Figures 5.10 and 5.11.

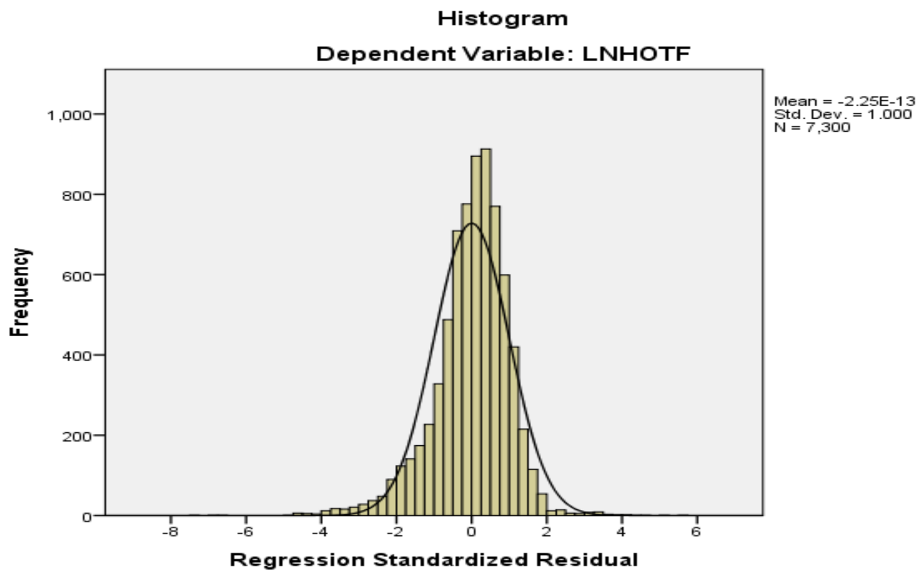


Figure 5.10: Histogram of regression residuals (I-15 Fast Trak lanes)

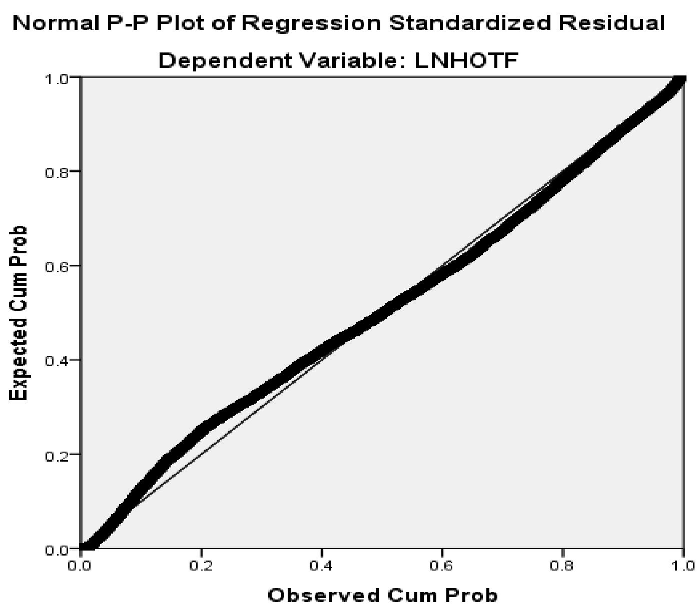


Figure 5.11: P-P plot of regression residuals (I-15 Fast Trak lanes)

Also, a plot of standardized residuals against standardized predicted values was used to test the assumption of linearity between dependent and explanatory variables. As shown in Figure 5.12, the residuals are fairly randomly distributed around the zero line.

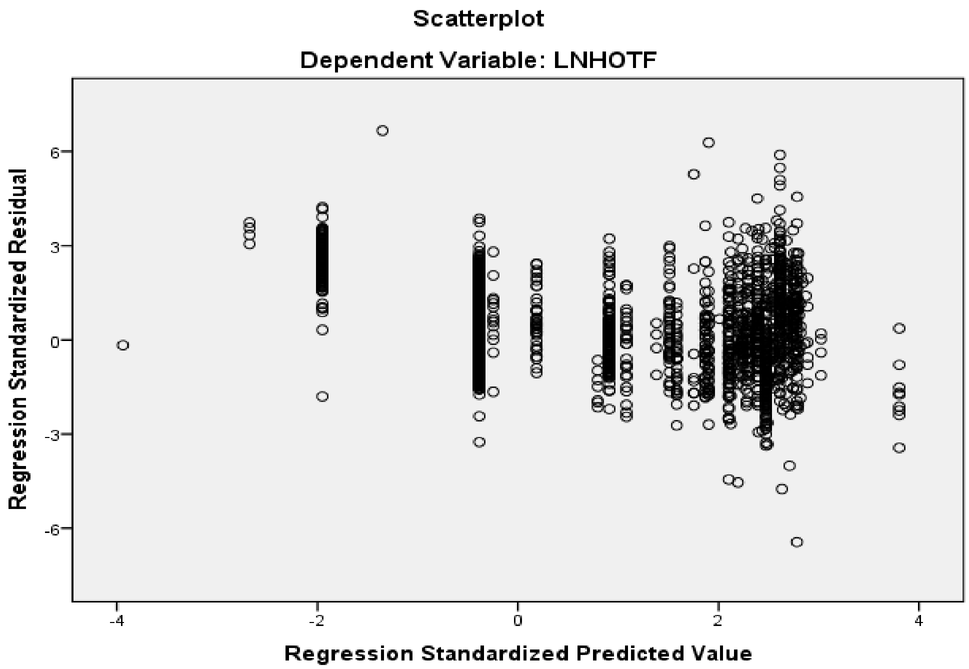


Figure 5.12: A scatter plot of regression residuals and predicted values (I-15 Fast Trak)

5.5.3 I-85 HOT Lanes, Atlanta

Data from I-85 HOT lanes covering 54 out of the total 77 days was used as training dataset in the model development. ADF stationarity test was conducted on all variables of interest. At 5% significance level, all variables were found to be stationary. The DW statistic calculated showed that serial correlation was present in the data. The Prais-Winsten estimation procedure was used to correct for it. The DW statistic after correction increased from 0.61 to 2.38 (signifying the removal of serial correlation at 5% significance level).

Scatter plot of the HOT lane demand/flow against the explanatory variables (toll rate and GP density) showed a positive relationship, implying that increases in toll rate and GP density results in HOT lane demand/flow increase. As shown below in Figure 5.13, both explanatory variables exhibited a quadratic relationship with HOT lane demand/flow.

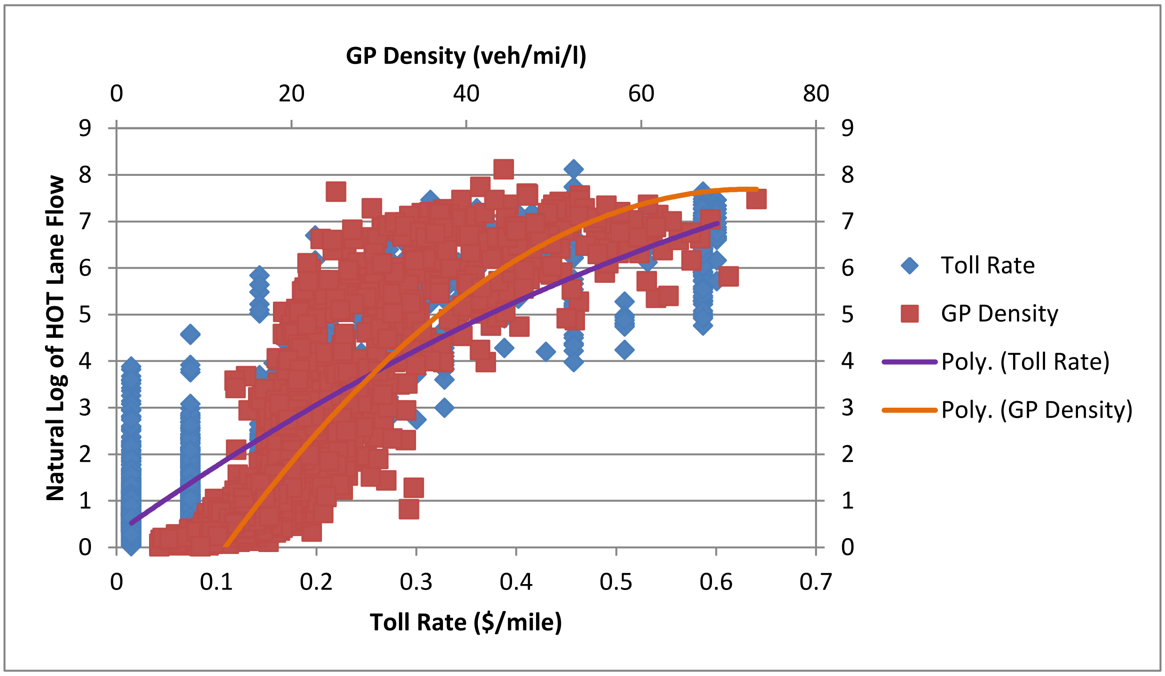


Figure 5.13: Scatter plots of response and explanatory variables (I-85 express lanes)

Model Building

A forward stepwise regression model approach which considered the two explanatory variables, their squared terms as well as their interaction effect was constructed. The explanatory variables were required to be statistically significant at 5% significance level in order to enter the model. The dependent variable (HOT lane demand/flow) was log-transformed in order to satisfy linear regression assumptions. The result of the stepwise addition of explanatory variables is as shown below in Table 5.10. All explanatory variables except the interaction term were accepted into the model. Since explanatory variables enter a stepwise regression model in order of relative statistical significance, it can be said that GP density and its squared term relatively influence HOT lane demand/flow more than the influence of toll rate and its squared term.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GPDEN		Forward (Criterion: Probability-of-F-to-enter <= .050)
2	GPDEN2		Forward (Criterion: Probability-of-F-to-enter <= .050)
3	TR		Forward (Criterion: Probability-of-F-to-enter <= .050)
4	TR2		Forward (Criterion: Probability-of-F-to-enter <= .050)

a. Dependent Variable: LNHOTF

Table 5.10: Stepwise variable selection (I-85 express lanes)

Summary statistics of the ability of each model to explain the variance in HOT lane demand/flow is shown in Table 5.11 below.

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.751[a]	.564	. 564	.587
2	.784[b]	.615	. 615	.496
3	.796[c]	.634	. 634	.472
4	.798[d]	.637	. 637	.469

a. Predictors: (Constant), GPDEN

b. Predictors: (Constant), GPDEN, GPDEN2

c. Predictors: (Constant), GPDEN, GPDEN2, TR

d. Predictors: (Constant), GPDEN, GPDEN2, TR, TR2

e. Dependent Variable: LNHOTF
Adjusted R^2 reducing at the fourth decimal

Table 5.11: Model summary statistics (I-85 express lanes)

From Table 5.11, only 63.7% of the variance in HOT lane demand/flow could be explained by the 'best' model which is made up of a constant and four explanatory variables (toll rate, GP density and their squared terms). Out of the 63.7%, GP density variable (and its squared term) contributed about 61.5% while the remaining 2.2 % came from toll rate (and its squared term). Consequently, HOT lane demand/flow is likely to be relatively sensitive to GP lane congestion than toll rates. In model building, the desire is to build a good model with as few variables as possible. Models three and four are almost the same in terms of their ability to explain the variance in HOT lane/demand flow. However, model four was selected in order to preserve the observed quadratic relationship between HOT lane demand and toll rates.

Table 5.12 provides details of model coefficients and multicollinearity statistics. Parameter estimates of all the variables in model four were found to be statistically significant at 5% significance level. Also, multicollinearity did not appear to hamper the accuracy of the selected model due to the low VIF values, generally below 5.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	3.524	.019		185.474	.000	3.487	3.561		
	GPDEN	.091	.001	1.5E-04	91.021	.000	.090	.093	1.000	1.000
2	(Constant)	1.575	.042		37.500	.000	1.493	1.658		
	GPDEN	.258	.003	1.6E-03	86.212	.000	.251	.264	.450	2.222
	GPDEN2	-.003	.001	-6E-06	-30.941	.000	-.003	-.003	.450	2.222
3	(Constant)	1.754	.041		42.789	.000	1.675	1.834		
	GPDEN	.192	.003	1.2E-03	64.549	.000	.188	.221	.440	2.273
	GPDEN2	-.0005	.000	-9.5E-09	-56.749	.000	-.0005	-.0004	.440	2.273
	TR	.006	.001	1.27E-05	6.108	.000	.004	.008	.105	3.992
4	(Constant)	1.704	.042		40.571	.000	1.621	1.786		
	GPDEN	.190	.004	1.6E-03	47.521	.000	.182	.199	.350	2.857
	GPDEN2	-.0004	.000	-7.7E-09	-43.967	.000	-.0004	-.003	.320	3.125
	TR	.004	.001	.8.5E-06	4.307	.000	.002	.006	.270	3.703
	TR2	-.0002	.007	-3E-06	-2.114	.000	-.0004	-.0003	.367	2.724

a. Dependent Variable: LNHOTF

Table 5.12: Model coefficients and summary statistics (I-85 express lanes)

The selected model (model four) can be expressed mathematically as shown below in equation 5-7:

$$LN(HOTF) = 1.704 + 0.190{*}GPDEN - 0.0004{*}GPDEN2 + 0.004{*}\ TR - 0.0002{*}TR2 \tag{5-7}$$

The above model can be interpreted as: if GP density increases/decreases by 1 veh/mi/l, HOT lane demand/flow will increase/decrease by 19.0%. Similarly, an increase/decrease in toll rate by $1 will increase/decrease HOT lane demand/flow by 0.4%. Although, the squared GP density term has a negative sign, the net effect of GP density on HOT lane demand will still be positive even when density is 200 veh/mi/l. The same can be said of toll rates

Regression assumptions of normally distributed residuals as well as a linear relationship between dependent and explanatory variables were also tested. Figures 5.14 and 5.15 show that the residuals were fairly normally distributed. Similarly, a plot of standardized residuals and standardized predicted values (Figure 5.16) shows the approximate linear relationship between HOT lane demand/flow and the explanatory variables (toll rate and GP density).

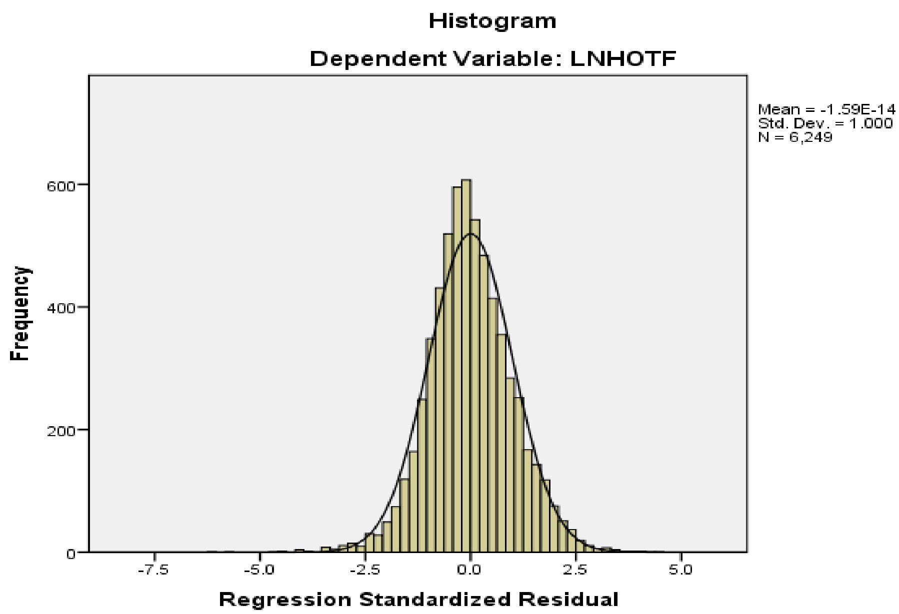


Figure 5.14: Histogram of regression residuals (I-85 express lanes)

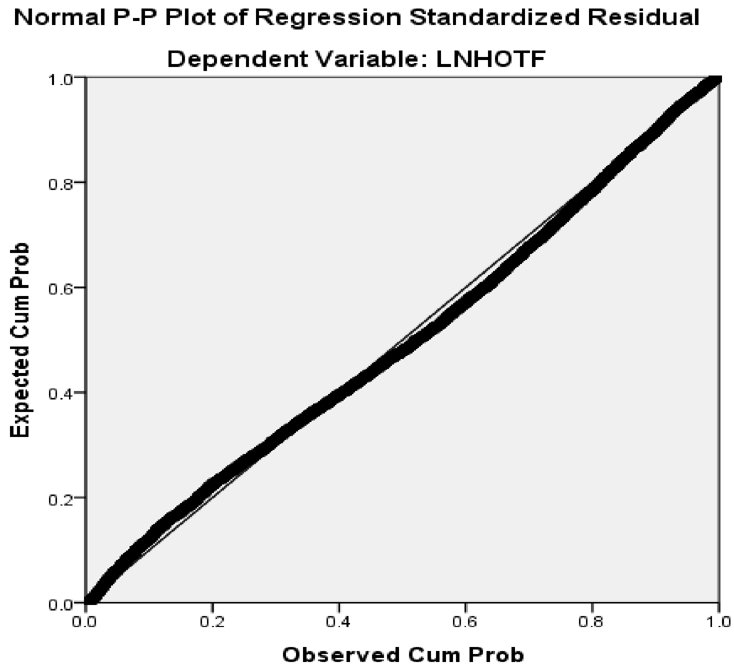


Figure 5.15: P-P plot of regression residual (I-85 express lanes)

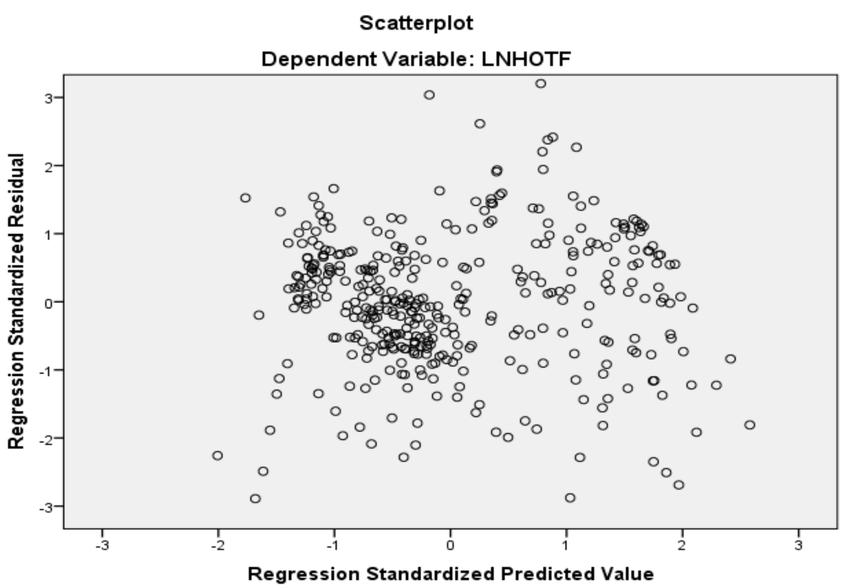


Figure 5.16: Scatter plot of regression residuals and predicted values (I-85 express lanes)

Model Predictive Performance

The "hold back" data (23 days) was used to evaluate the performance of the developed predictive model as well the naïve model in terms of predicting expected HOT lane LOS. Table 5.13 shows the performance evaluations of the naïve and predictive models.

DAY	% CLASSIFIED CORRECTLY (NAÏVE)	% CLASSIFIED CORRECTLY (PREDICTED)
10/8/2012	84.6	86.5
10/15/2012	83.9	83
10/16/2012	79.3	72.2
10/18/2012	81.1	71.3
10/19/2012	85.2	74.3
10/23/2012	79.7	81.8
10/29/2012	81.1	82.3
11/5/2012	80.4	81.8
11/9/2012	83.8	79.5
11/14/2012	77	80.0
11/15/2012	81.1	81.8
11/21/2012	60.8	90.0
11/28/2012	78.5	80.1
11/30/2012	73.8	83.8
12/5/2012	75.8	88.0
12/13/2012	77.1	85.1
12/18/2012	81.5	86.6
12/21/2012	73.1	88.8
1/7/2013	91.2	84.1
1/8/2013	83	82.3
1/18/2013	811.2	84.5
02/4/2013	76.4	76.0
02/20/2013	81.2	85.8
AVERAGE	**79.6**	**82.2**

Table 5.13: Model performance evaluation (I-85 express lanes)

On average, the naïve model was able to predict correctly the HOT lane LOS about 80% of the time compared with about 82% for the predictive model. Both models had almost the same predictive performance except on days with atypical traffic conditions (extremely low or high HOT lane demand) such as November 21st, 2012 when the predictive model (90% classification accuracy) outperformed the naïve model (60.8% classification accuracy). The performance of the predictive model was consistent for all of the time periods, days and months evaluated. Figure

5.17 below shows a plot of the performance of both naïve and predictive model on November 21st, 2012.

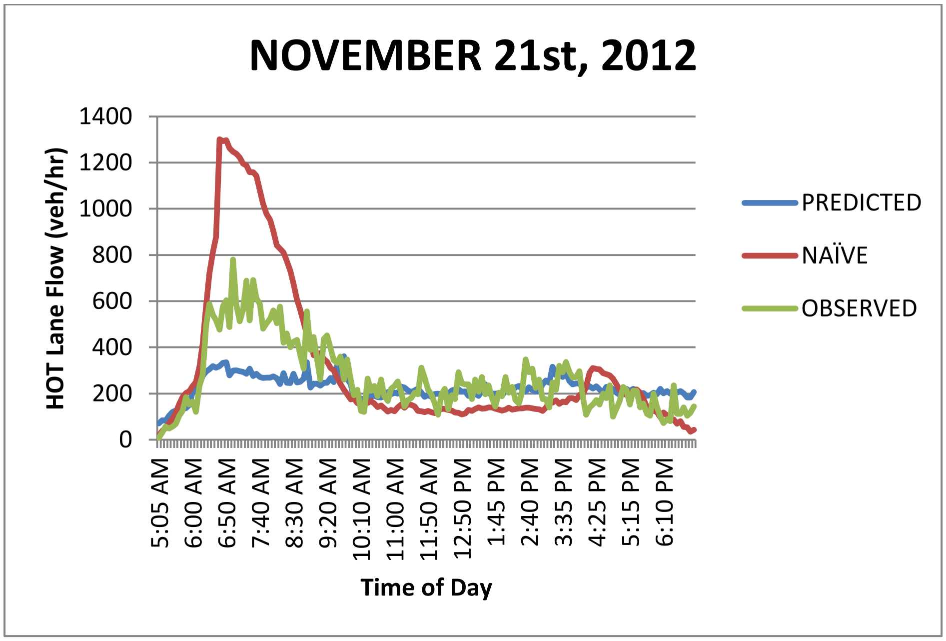


Figure 5.17: Performance of naïve and predictive models (I-85 express lanes)

5.5.4 I-95 HOT Lanes, Miami

About 70% of the total dataset was used to train the predictive model to be developed. All variables were tested for stationarity using the ADF test. At 5% significance level, none of the variables was found to have a unit root, hence all were considered to have stationary properties. Additionally, serial correlation was corrected for using Prais-Winsten estimation procedure. At 5% significance level, the corrected data had a DW statistic of 2.06.

Scatter plots demonstrating the supposed relationship between the response and explanatory variables were developed as shown in Figure 5.18 below. Both explanatory variables exhibited a positive relationship with HOT lane demand/flow. This implies that, as toll rate/GP density increases/decreases, HOT lane demand/flow increases/decreases. In terms of functional form, both explanatory variables exhibited a second order polynomial (quadratic) relationship with the dependent variable.

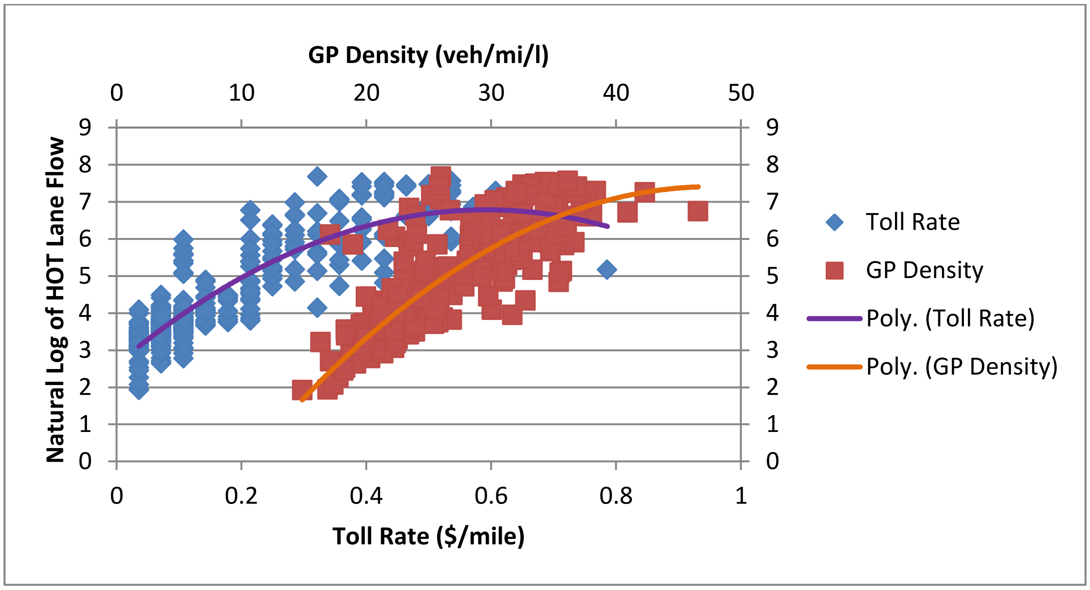


Figure 5.18: Scatter plots of response and explanatory variables (I-95 express lanes)

Model Building

Five explanatory variables were considered for development of the predictive model using forward stepwise regression method. The dependent variable (HOT lane demand) was log-transformed in order to ensure that the assumptions of linear regression were satisfied. The variables included toll rate and GP density as well as their squared terms and the interaction between the two variables. The squared terms were included because of the quadratic relationship revealed by the scatter plot of the dependent and explanatory variables. The explanatory variables were required to be statistically significant at 5% significance level in order to enter the model. Results of the forward stepwise regression procedure are as shown below in Table 5.14.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GPDEN		Forward (Criterion: Probability-of-F-to-enter <= .050)
2	GPDEN2		Forward (Criterion: Probability-of-F-to-enter <= .050)
3	TR		Forward (Criterion: Probability-of-F-to-enter <= .050)
4	TR2		Forward (Criterion: Probability-of-F-to-enter <= .050)

a. Dependent Variable: LNHOTF

Table 5.14: Stepwise selection of variables (I-95 express lanes)

The order of selection of variables indicates that GP density and GP density squared have greater impact on HOT lane demand/flow than toll rate and its squared term. A summary of model statistics is as shown below in Table 5.15.

Model Summary[e]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.772[a]	.596	.596	.153
2	.794[b]	.630	.630	.132
3	.803[c]	.644	.644	.117
4	.805[d]	.648	.648	.111

a. Predictors: (Constant), GPDEN

b. Predictors: (Constant), GPDEN,GPDEN2

c. Predictors: (Constant), GPDEN, GPDEN2, TR

d. Predictors: (Constant), GPDEN, GPDEN2, TR, TR2

e. Dependent Variable: LNHOTF
Adjusted R^2 reducing at the fourth decimal place

Table 5.15: Model summary statistics (I-95 express lanes)

As observed in all of the three previous HOT facilities analyzed, GP density and its squared term tend to have relatively greater influence on HOT lane demand/flow than toll rate (and its squared term). For this facility, GP density and its squared term were able to explain about 63% of the variance in HOT lane demand/flow. The subsequent addition of toll rate and its squared term only added an extra explanatory power of 1.8%. Although model three has fewer variables (three) than model four, and explains almost the same amount of variance (64.4%) in HOT lane demand as model four (64.8%), the latter was chosen as the predictive model for this HOT facility. This choice is consistent with the observed quadratic relationship between toll rates and HOT lane demand.

The model coefficients and associated statistics are shown in Table 5.16 below. All the coefficients for the selected predictive model (model four) were statistically significant at 5% significance level. Also, the low VIF value (less than 5) also suggests that the severity of multicollinearity in the model was low.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	5.272	.012		439.333	.000	5.248	5.296		
	GPDEN	0.094	.005	.003	18.800	.000	.084	.104	1.000	1.000
2	(Constant)	4.786	.043		111.302	.000	4.702	4.870		
	GPDEN	.089	.013	.009	6.846	.000	.064	.114	.346	2.889
	GPDEN2	-.009	.002	-1.4E-04	-4.500	.000	-.012	-.005	.346	2.889
3	(Constant)	4.765	.038		125.395	.000	4.691	4.839		
	GPDEN	.086	.159	.007	9.556	.000	.068	.104	.570	1.758
	GPDEN2	-.0004	.000	-6.8E-07	-2.002	.000	-7.9E-04	-8E-06	.330	3.030
	TR	.003	.239	2.56E-05	3.100	.000	.001	.005	.250	4.000
4	(Constant)	3.870	.144		26.875	.000	3.588	4.152		
	GPDEN	.085	.012	.009	7.083	.000	.062	.109	.490	2.040
	GPDEN2	-.0003	.000	-2.7E-07	-3.000	.000	-5E-04	-1E-04	.290	3.450
	TR	.002	.000	1.8E-05	2.010	.000	4E-05	.004	.630	1.587
	TR2	-.0001	.000	-9E-09	-10.000	.000	-1.2E-04	-8E-05	.310	3.226

a. Dependent Variable: LNHOTF

Table 5.16: Model coefficients and summary statistics (I-95 express lanes)

Using the coefficients of model four, the HOT lane demand/flow predictive model can be expressed mathematically as:

$$LN\ (HOTF) = 3.870 + 0.085*GPDEN - 0.0003*GPDEN2 + 0.002*TR - 0.0001*TR2 \qquad (5\text{-}8)$$

This model implies that, if GP density is increased/decreased by 1 veh/mi/l, HOT lane demand/flow will increase by 8.5% .Similarly, if toll rate increases/decreases by $1, HOT lane demand/flow will increase/decrease by 0.2%. Both GP density (net effect) and toll rate have positive signs in the model, implying that increases in both will increase HOT lane demand/flow. While the positive sign for GP density is expected (because drivers will use HOT lanes to avoid congestion), the positive sign associated with the coefficient of toll rate is counterintuitive since toll rate is expected to deter drivers from using HOT lanes; hence, a negative sign was expected.

The model was tested for the normality assumption in linear regression to determine if the residuals were normally distributed. Based on a histogram (Figure 5.19) and P-P (Figure 5.20) plots of the residuals, it can be stated the residuals were fairly normally distributed.

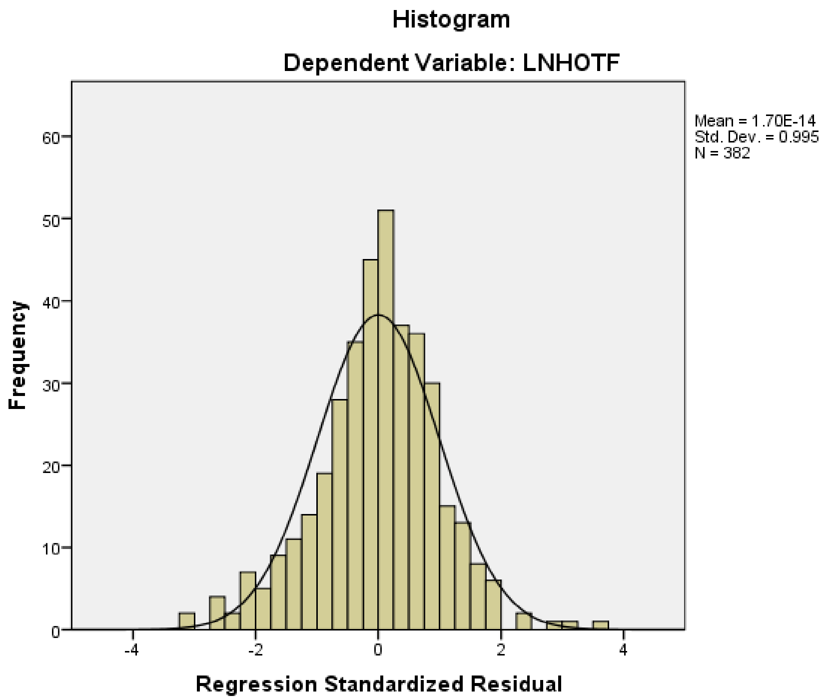


Figure 5.19: Histogram of regression residuals (I-95 express lanes)

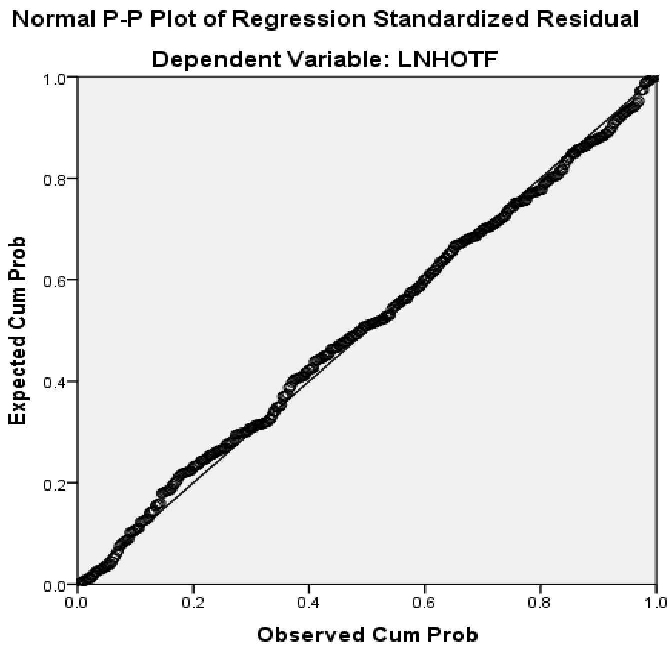


Figure 5.20: P-P plot of regression residuals (I-95 express lanes)

Also, a plot of standardized regression residuals against standardized predicted values (Figure 5.21) show that, the linearity assumption (linear relationship between dependent and explanatory variables) was fairly satisfied.

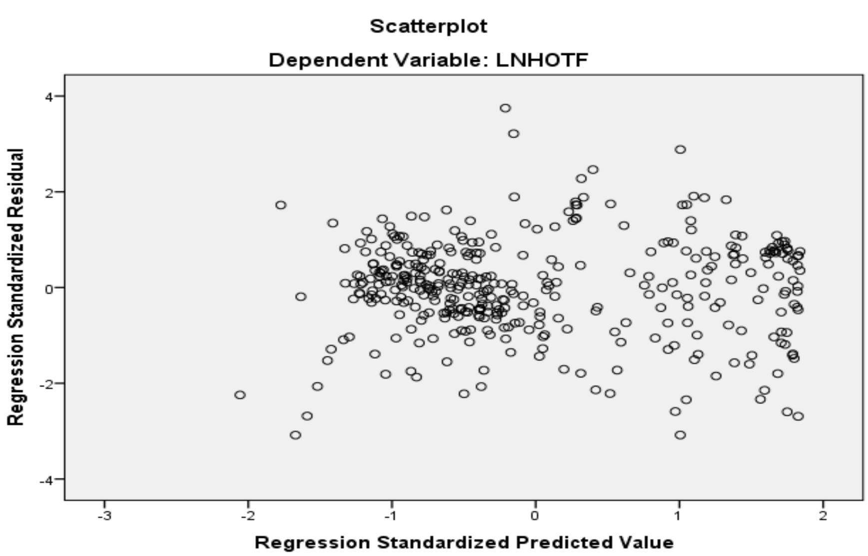


Figure 5.21: Regression residuals against predicted values (I-95 express lanes)

Model Predictive Performance

Evaluation of the predictive performance of the developed model in predicting HOT lane LOS was conducted using the "hold back" data (16 days). The performance of the predictive model was compared with the performance of a naïve model which was also tested using the same "hold back" data. Table 5.17 and Figure 5.22 show the performance of the two models.

DAY	% CLASSIFIED CORRECTLY (NAÏVE)	% CLASSIFIED CORRECTLY (PREDICTED)
10/17/2012	56.4	82.1
10/26/2012	67.9	78.6
11/09/2012	66.7	79.2
11/10/2012	60.5	79.0
11/15/2012	66.5	82.0
11/21/2012	81.8	80.0
11/28/2012	88.5	80.2
11/30/2012	83.8	93.8
12/5/2012	85.8	81.3
12/13/2012	87.1	83.2
12/18/2012	86.5	80.5
12/21/2012	83.1	98.8
1/7/2013	91.2	80.3
1/8/2013	83	73.3
1/18/2013	91.2	93.3
02/26/2013	96.1	96.3
AVERAGE	**79.8**	**83.8**

Table 5.17: Model performance evaluation (I-95 express lanes)

The naïve and predicted models were able to predict correctly HOT lane LOS for 79% and 83% of the time respectively. Accuracy level of the predictive model (80.2%) superseded that of the naïve model (63.6%) during periods when HOT lane demand was extremely low or high. Apart from that, the performance of the predictive model was consistent and did not exhibit any systematic trend due to time of day, day of week, or month of year. Figure 5.22 below shows the performance of both models on October 17th, 2012.

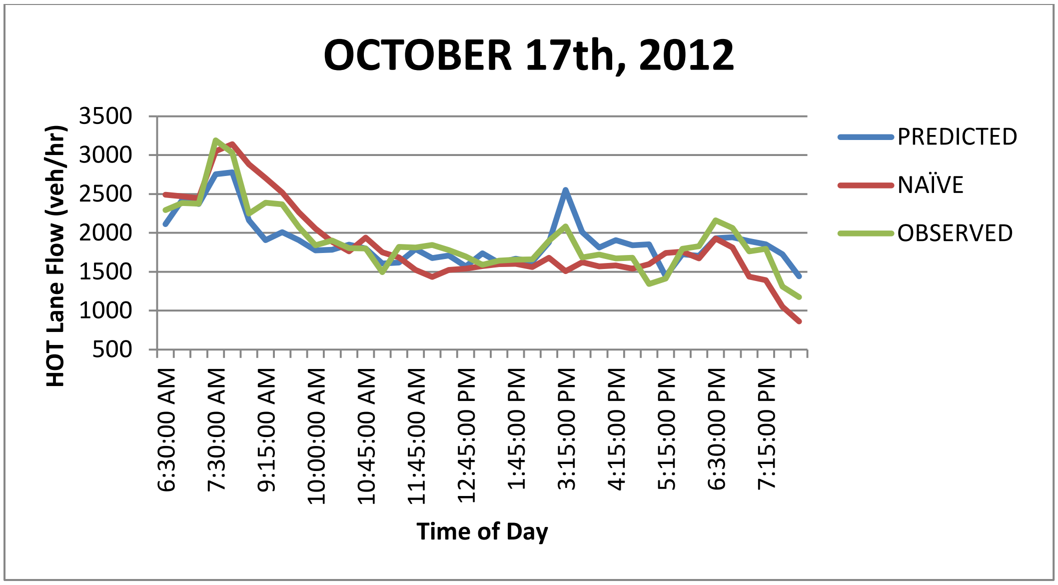


Figure 5.22: Model performance evaluation (I-95 express lanes)

5.6 Summary

This chapter focused on the development of short-term predictive models for HOT lane demand. These models will help to predict the expected LOS of HOT facilities based on tolls and GP lane congestion (density). As a result of the weak relationship between HOT lane demand and tolls/GP lane density, the developed models were not well suited for predicting absolute HOT lane demand (high prediction errors). However, the models were able to fairly predict the expected levels of demand on the HOT lanes. The next chapter presents the general conclusions arrived at for the different research areas in this dissertation.

Chapter 6

Conclusions

This research led to a number of conclusions pertaining to selection of beneficial Integrated Corridor Management (ICM) strategies as well as the general pattern of High Occupancy Toll (HOT) lane driver behavior. Major conclusions regarding the prediction of HOT lane demand using tolls and General Purpose (GP) lane congestion are also discussed. The conclusions are presented below.

6.1 Evaluation Methodology for Selecting Beneficial ICM Strategies

A five-step evaluation methodology based on which beneficial ICM strategies can be selected was developed in this research. The methodology included modeling of base case traffic conditions in a corridor, implementing candidate ICM strategies in the model, conducting sensitivity analysis, testing for statistical significance of the impacts of candidate strategies, and selection of beneficial strategies. The methodology was applied to a real-world transportation corridor in northern Virginia (11 mile section of I-95/I-395 corridor) and the following conclusions were reached:

1. The ability to "shift" demand from automobiles to transit will be very critical to the success of ICM implementation. However, this shift is dependent on the parking capacity at transit access locations and operating schedule of transit systems. In the test corridor, it was discovered that transit capacity exceeded parking capacity significantly (a deficit of approximately 2,000 parking spaces). Additionally, 21 of the 68 possible transit trips (19 bus trips and two train trips) available during the A.M period start and end before 6:00 A.M. Such early transit trips indicate that demand shifting is most practical during early portions of the peak period.

2. By examining different diversion percentages during non-incident conditions, it was discovered that it will require 15% of vehicles diverting from I-95 N (freeway) to U.S. 1N (a parallel arterial) in order to reduce average travel time (27.1 minutes) on the freeway by 5 minutes, and increase corresponding average speed (31 mph) by 9 mph. However, this adversely affected traffic conditions on U.S. 1N, resulting in a corresponding increase in average travel time (30.7 minutes) of 4.3 minutes. This illustrates that the extra capacity on U.S. 1N (principal arterial) is not adequate to accommodate significant traffic shifts from I-95 N.

3. During incident conditions on I-95 N, 15% of the traffic has to be diverted onto U.S. 1N in order to reduce average travel time (38.2 minutes) by 5 minutes coupled with no significant increase in speed. These diversions can increase average travel times (30.7 minutes) on U.S. 1N up to 7 minutes and reduce average speeds (30 mph) by 6 mph. Regardless of the diversion percentage, there was no significant increase in the vehicular flow on the I-95 N. In contrast, vehicular flow on U.S. 1N was reduced by as much as 471 vehicles per hour. Again, this illustrates that freeway/arterial ICM strategies devoid

of modal shifts are of limited effectiveness on heavily traveled corridors where demand nears or surpasses capacity.

4. This research demonstrated the need to implement comprehensive ICM as a congestion mitigation measure in Virginia, as opposed to the traditional approach of diverting vehicles to parallel routes. Overall, there was significant improvement in the performance of the individual transportation facilities (excluding the VRE commuter line, whose performance was not assessed) as well as the entire corridor.

5. The benefits of ICM were more significant under incident conditions than non-incident conditions. In terms of corridor person flow (the non-mode specific performance measure used in selecting critical ICM strategies), an average increase of 6,860 persons per hour (+38%) was experienced when ICM strategies were implemented during incident conditions. During non-incident conditions, the improvement in average corridor person flow was 3,286 persons per hour (+14%). Under incident conditions, modal shifts between 16%-21% are required to achieve the 38% increase in corridor person throughput. Similarly under non-incident conditions, modal shifts between 15% - 23% are needed in order to experience the 14% increase in corridor person throughput.

6. HOT lanes, High occupancy Vehicle (HOV) lanes, and increasing transit and parking capacity are the ICM strategies that will bring about the mode shifts under both incident and non-incident conditions. Additionally, driver compliance rate to Variable Speed Limit (VSL) must be above 70%. Unused transit and parking capacity of over 2000 seats and 450 spots respectively were identified in the analysis segment. Therefore, it appears there is adequate transit capacity to accommodate the mode shifts but vice versa when it comes to parking. Also the HOV lanes in the corridor currently has excess capacity of about 1,000 veh/hr between SR 234 and SR 123, as well as about 500 veh/hr between SR 123 and SR 642. Hence mode shifts due to HOT/HOV can also be accommodated.

7. The ICM strategies identified as critical under non-incident conditions included VSL, increasing the use of HOV lanes/HOV bypass, the impact of HOT lanes in motivating the formation of carpools and ridesharing programs, and the provision of adequate parking and transit capacities. Similar strategies were observed under incident conditions as well.

8. Transportation agencies must make it a point to identify redundant strategies in order to cut down cost. Ramp metering was the least critical among the six strategies implemented. Also the usual formation of queues on on-ramps as a result of metering operations was not experienced at any of the metered on-ramps. This implies that, some strategies lose their operational benefits when combined with other strategies. Ramp metering as a stand-alone strategy might be beneficial but within the context the ICM application in this corridor, it appeared to be redundant.

9. In terms of the impacts of TSP within an ICM framework, the reductions in average travel time were modest for buses traveling between Dale City and the Washington, D.C. area (2.5 minutes), and between South Route 1 (Dumfries) and Washington, D.C. (2.1 minutes). Conversely, the routes between Lakeridge and the Washington, D.C. area

experienced average travel time increment of 3.4 minutes. Buses using this route have stops at three park-and-ride facilities. Roads leading to these park-and-ride facilities experienced heavy traffic when the percentage of vehicles wanting to park (and use transit) is high. This can potentially delay buses and increase their travel times.

10. The ICM strategies modeled had a positive impact on the environment. Under both incident and non-incident conditions, the amount of fuel usage was significantly decreased by 33.1% and 34.3%, respectively, leading to subsequent reductions in the emissions of CO, NOx, and VOC.

6.2 HOT Lane Driver Behavior

The behavior of HOT lane users across four HOT lane facilities in different regional locations was analyzed in this research. The purpose was to determine if there was a general pattern in how users from different HOT lane facilities respond to tolls and congestion on GP lanes. Using 5 months of toll and traffic data (revealed preference), the following conclusions were reached:

1. There was no significant difference in travel time savings or toll rates between morning and evening directions of travel. On average, the difference in tolls paid between morning and evening periods was about $0.13 per mile with corresponding travel time savings difference of about 0.11 minutes per mile.

2. Across all studied HOT facilities, VTTS estimates increased during peak periods. This was due to congestion build up on the GP lanes during the peak period, causing the demand for HOT lane use by eligible users to increase. The increased demand caused toll rates to increase resulting in high VTTS. On average, VTTS estimates during peak period were about $5/hour more than that of entire morning/evening periods. However, the magnitude of the difference varied among the studied HOT facilities. For example, mean VTTS increased from $55/hour during the entire morning period to $79/hour during the morning peak period on I-15 Fast Trak lanes (morning commute). On the other hand, VTTS for 1-95 express lanes (morning commute) increased from $49.7/hour during the entire morning period to $50.9 during the morning peak period.

3. Mean VTTS estimates calculated for all the studied HOT facilities were significantly higher than the respective BLS average hourly wages. The estimates were at least more than twice the BLS average hourly wages. This suggests that HOT lane users are likely to earn more income than average residents in their locations since VTTS is known to increase with increasing income/wage rate *(100–102)*. Therefore HOT lane users may value their travel time savings more than average residents of the same location/region. Conclusions from other research efforts confirm this finding. For example, research by Khoeini and Guensler (2014) on the household incomes of HOT lane users and non-users in Atlanta concluded that the average household incomes of HOT lane users exceeded those of non-users by over $10,000 per year *(103)*. A survey of Quickride HOT lane users in Houston conducted by Burris et al (2006) revealed that about 79% of HOT lane users have household incomes greater $75,000 in 2003. The authors concluded that,

Quickride HOT lane users generally have higher household incomes than the average incomes of residents*(104)*.

4. A hypothesis test was conducted to investigate the difference between means of VTTS distributions for the HOT facilities studied. The null hypothesis was that means of VTTS distributions for a facility pair were equal. It was found that mean VTTS estimates for I-15 Fast Trak and I-394 MnPASS lanes were not statistically different from each other. Also, mean VTTS estimates between I-85 and I-95 express lanes were found to be statistically similar. I-15 Fast Trak and I-394 MnPASS lanes had a relatively higher mean peak VTTS of $72.5/hour and $71/hour respectively compared with $50/hour for I-95 express lanes and $51/hour for I-85 express lanes. For the remaining facility pairs, there was not enough evidence to suggest that the null hypothesis was true; hence they were rejected. A common denominator among the two groups of HOT facilities that emerged was annual average income of their regions/locations. The San Diego (I-15 Fast Trak) and Minneapolis (I-394 MnPASS) areas had a relatively higher annual Regional Price Parity (RPP)-adjusted respective average incomes of $83,820 and $87,092 compared with $65,990 and $79,963 for Miami-Dade (I-95 express lanes) and Gwinnet/Atlanta (I-85 express lanes) areas respectively. This suggests that regions with high annual incomes are likely to have relatively high VTTS estimates and vice versa. However, the impact was not proportional.

5. It was also found that the facilities with high mean VTTS estimates appear to have relatively lower levels of congestion in the HOT corridor. I-15 Fast Trak and I-394 MnPASS lanes had relatively high VTTS estimates but congestion levels on their parallel GP lanes was relatively low (average GP density of around 30 veh/mi/l) compared with I-95 and I-85 express lanes (average GP density of about 50 veh/mi/l) which recorded low mean VTTS estimates.

6. The elasticity of HOT lane demand w.r.t toll prices was positive for all HOT lane facilities analyzed. However, the magnitude of the estimates demonstrated an inelastic relationship, generally below +0.2. Furthermore, the toll elasticity of HOT lane demand reduced in magnitude during peak periods, generally below +0.08. The concept of HOT lanes is based on a negative relationship between tolls and HOT lane demand in order to keep the HOT lanes from becoming gridlocked. The fact that elasticity w.r.t tolls across all the studied HOT facilities was positive and sometimes statistically insignificant points to the probability that the toll rates are not allowed to rise to a level for supply/demand to take effect. Therefore tolls charged appeared not to have an impact on HOT lane demand. The tolls charged were generally between $0.22 per mile and $0.6 per mile. Depending on the distance traveled, this translates to a range between $1.5 and $8. A recent study on the diamond segment of I-394 MnPASS confirms the positive relationship between HOT lane demand and toll rates *(14)*.

7. The elasticity of HOT lane demand w.r.t GP congestion level (density) was consistently positive and greater in magnitude than the elasticity w.r.t toll rates for all the HOT facilities studied except I-394 MnPASS. The estimated values did not exceed +0.5 during the morning and evening periods, and increased to about +0.72 during peak periods.

8. A hypothesis test conducted to investigate if the impact of GP congestion was the largest motivator of HOT lane demand yielded mixed results. On I-394 MnPASS and I-15 Fast Trak lanes, the impacts of both tolls and GP lane congestion were found not to be statistically different. However, the impact of GP congestion on HOT lane demand was statistically greater than corresponding impacts of tolls on I-85 and I-95 express lanes. The possible underlying factor for this observation is the level of congestion in segments of the HOT corridors analyzed. GP lane congestion on I-394 MnPASS and I-15 Fast Trak were significantly lower (average of 30 veh/mi/l) than those of I-85 and I-95 express lanes (average of 50 veh/mi/l). This suggests that GP congestion is a larger motivator of HOT lane usage in corridors with high level of congestion.

9. A hypothesis test was also conducted to investigate the differences between the studied HOT facilities in terms of elasticity w.r.t both tolls and GP congestion. Mean elasticities were compared for each facility pair. The result indicated that I-394 MnPASS and I-15 Fast Trak were alike as well as I-85 and I-95 express lanes. The remaining facility pairs were found to be statistically different. Further probe into these facilities revealed that, about 90% of eligible I-15 Fast Trak users were not sensitive to changing toll rates and GP lane travel conditions. These users consistently traveled on the HOT lanes even when there were no significant travel time savings and had relatively high VTTS. However, travel on I-85 express lanes by eligible users appeared to fluctuate with changes in the level of congestion on parallel GP lanes and toll rates. Therefore, their VTTS were relatively lower. A possible reason for the difference in elasticity between the two groups is the high average income levels for I-394 MnPASS/I-15 Fast Trak users and a relatively low income levels for I-95/I-85 express lanes users as explained above in the fourth conclusion.

10. In addition to income and level of congestion on GP lanes, travel time reliability on parallel GP lanes also influenced the differences in average VTTS estimates observed between I-394 MnPASS/I-15 Fast Trak express lanes and I-95/I-85 express lanes. Measures of travel time reliability such as Planning Time Index (PTI), Travel Time Index (TTI) and Coefficient of Variation were calculated for GP lanes parallel to the studied HOT facilities. The results indicated that there was relatively high variability in travel times on GP lanes parallel to I-394 MnPASS (CV of 0.5) and I-15 Fast Trak express lanes (CV of 0.64) than corresponding GP lanes parallel to I-95 (CV of 0.26) and I-85 (CV of 0.21) express lanes. Lack of reliable travel conditions on the GP lanes will cause drivers to shift to the HOT lanes even where there are no significant travel time savings in order to be guaranteed on-time arrival. Paying for HOT lane use when there are no significant travel time savings will result in high VTTS estimates (as observed on I-394 MnPASS and I-15 Fast Trak express lanes).

6.3 Predicting HOT Lane Demand

In this research, models were developed to predict HOT lane demand using toll rates and GP congestion levels in real-time. The purpose was to help transportation professionals determine the expected level of service conditions on the HOT lanes based on tolls and changing traffic conditions. This was achieved by using the predicted HOT lane demand to obtain the expected LOS as described in the Highway Capacity Manual (HCM) 2010. Some of the specific conclusions include:

1. For all HOT lane facilities studied, GP density and toll rate (explanatory variables) exhibited a positive correlation with HOT lane demand/flow (dependent variable) with R^2 values ranging from 0.3 to 0.7. However, the positive correlation was generally stronger for GP density/HOT lane demand relationship than that of toll rate/HOT lane demand. Additionally, both explanatory variables had a second-order polynomial (quadratic) relationship with the dependent variable. The graphs of the quadratic functions resulted in an "n" shaped parabola because the coefficients of the squared terms were negative.

2. The order of selection of variables into the predictive model using forward stepwise regression was ubiquitous across all studied HOT lane facilities. GP density and its squared term always entered the model before toll rate (and its squared term). This implies that, GP density and its squared term appear to have greater influence on HOT lane demand than toll rate and its squared term. However, the impact of the influence varied among HOT facilities. For example, GP density and its squared term explained about 63% of the variance in HOT lane demand/flow on I-95 express lanes. The addition of toll rate and its squared term to the model only improved the explanatory power of the model by 1.8% (resulting in a total adjusted R^2 value of 64.8%). On the contrary, GP density (29.4%) and toll rate (24.8%) almost explained the same amount of the variance in HOT lane demand for I-394 MnPASS lanes.

3. The general form of the predictive models for all the studied HOT lane facilities was

$$LN\ (HOTF) = k + a*GPDEN - b*GPDEN2 + c*\ TR - d*TR2$$

   Where:

   LN (HOTF)—natural log of HOT lane demand/flow
   GPDEN—GP density
   GPDEN2—GP density squared
   TR—toll rate
   TR2 — toll rate squared
   k—model constant
   a—coefficient of GP density
   b—coefficient of GP density squared
   c—coefficient of toll rate
   d —coefficient of toll rate squared

4. Both GP density and toll rate had positive coefficients in the predictive model. This implies HOT lane demand/flow increased/decreased when GP density and toll rate increased/decreased. The preceding explanation is reasonable for GP density because eligible drivers are likely to shift to HOT lanes when the GP lanes get congested. However, the positive coefficient of toll rate is contrary to the expected negative effect of tolls on HOT lane demand (i.e. to discourage drivers from using HOT lanes). The

positive coefficient of toll rate confirms findings in chapter four in which tolls had a positive elasticity relationship with HOT lane demand/flow.

5. The predictive models developed for each HOT facility was able to fairly predict the expected LOS on the HOT lanes. On average, they were able to correctly predict the expected LOS on the HOT lanes at least 75% of the time. However, the models performed poorly in terms of predicting absolute HOT lane demand, often over-predicting/under-predicting by as much as 25% of the true demand. This demonstrates that absolute or actual demand on the HOT lanes is very difficult to predict using tolls and GP lane congestion.

6. The predictive models developed in this research did not outperform the naïve models in terms of predicting expected LOS on HOT lanes. This is an indication of the weak causal relationship between HOT lane demand and the explanatory variables (tolls and GP density) as well as less variability in traffic conditions on the HOT lanes. The predictive model only performed better than the naïve model during atypical traffic conditions (extremely low or high HOT lane demand) .This calls for more research into other factors that may affect real-time HOT lane use. Once these factors are identified, relatively highly accurate predictive models can be developed.

6.4 Summary

This chapter reviewed the major conclusions made in this research. The next chapter discusses the research's major contributions to the current state-of-knowledge in ICM evaluation and HOT lane driver behavior, and identifies several areas for expansion and possible future research.

Chapter 7

Contributions and Future Research

As demand for highway travel continues to rise, the need for efficient use of existing transportation infrastructure has become very essential. Integrated Corridor Management (ICM) offers the potential to leverage relevant technologies and underutilized capacity on all surface transportation modes in a corridor to meet this rising demand. This research developed an evaluation methodology to determine the feasibility of ICM implementation in a corridor as well as identify the most beneficial strategies. Notable among the most beneficial ICM strategies that this evaluation methodology identified was the use of pricing to influence traveler behavior in order to prevent High Occupancy Toll (HOT) lanes from becoming congested. In the evaluation methodology developed in this research (and those developed for pioneer ICM sites), the impacts of pricing on traveler behavior were mainly based on long-term average mode and route shifts associated with pricing due to limited published knowledge on how tolls affect drivers' decision to use/not to use HOT lanes in real-time. This research is the first to conduct analysis of HOT lane driver behavior using four HOT lane facilities in the U.S. with real-time dynamic tolling capabilities. Knowledge of the HOT lane driver behavior was then used to develop predictive HOT lane demand models that could be used to make ICM proactive rather than reactive. Several areas of future research that can further deepen the understanding of HOT lane driver behavior and make ICM more effective are also presented.

7.1 Research Contributions

This dissertation provided several contributions to the state-of-knowledge in HOT lane driver behavior and ICM implementation. The main and other contributions are presented below.

7.1.1 Main Contributions

The main contributions are as follows:

1. This research developed an analysis and evaluation methodology that can be used at the planning stages to determine the feasibility of ICM implementation in a transportation corridor. The five-step methodology will enable transportation agencies to identify which ICM strategies best fit the transportation needs of their corridors. Prior to this, there was only one high level evaluation methodology developed for the ICM pioneer sites with less details on its implementation. Therefore, the detailed methodology developed in this research adds to the body of knowledge of ICM and provides an alternative evaluation approach to transportation agencies.

2. This research revealed that, elasticity of HOT lane demand with respect to tolls is positive and statistically significant but inelastic (average elasticity below +0.2). Furthermore, the impact of tolls on HOT lane demand further diminished during peak

periods where average elasticity of HOT lane demand with respect to tolls fell below +0.08. This implies the lack of impact of tolls (pricing) on HOT lane demand and that the decision to use HOT lanes are driven by factors other than tolls (such as level of congestion on GP lanes, travel time reliability, etc.). The concept of HOT lanes is based on a negative relationship between HOT lane demand and tolls; that is, tolls are expected to discourage drivers from using the HOT lanes. Therefore, the positive and inelastic relationship observed in this dissertation goes against the conventional wisdom that drives use of HOT lanes. This suggests the probability that the tolls are not allowed to rise to a level for supply/demand to take effect. This situation can be likened to the effects of government control/limits on prices which prevent market forces from working correctly. A notable example of government control of prices is the price cap on rental accommodation in New York during World War II *(105)*. As a result of high demand for accommodation due to the inflow of ship builders to New York, the City set price caps on the maximum amounts Landlords could charge. This was intended to make housing affordable to ship builders who moved to the City in order to increase the production of ships for the war. The action disincentivized real estate developers from building new homes, leading to acute shortage of housing. That is, because the prices were artificially set low, people moving to New York at the time were not discouraged by accommodation cost. Similarly, when the federal government restricted gasoline price increases in the 1970s, long lines formed at gas stations and only those motorists who waited long hours in line received the scarce gasoline *(106)*. The bottom line is whenever prices are set below equilibrium level, it causes consumers to want more of the product than producers have available. In the case of HOT lanes, setting toll prices below the equilibrium level increases the demand for its use by eligible HOT lane users. This implies that, drivers' decision to use/not to use the HOT lanes will not be greatly influenced by the toll price because it is below the equilibrium level. If toll prices are not allowed to rise as dictated by market forces, then the HOT lanes will sooner or later become congested as the general demand for highway travel continues to increase. This finding will help transportation professionals to reconsider current pricing levels in order to ensure an effective ICM through pricing. Currently, some HOT lane systems have started acting in this regard. For example, the Florida Department of Transportation (FDOT) increased the minimum and maximum toll prices on I-95 express lanes in Miami from \$0.25/mile to \$0.50/mile and from \$1.0/mile to \$1.50 respectively on March 1st, 2014. According to FDOT, increasing the rate is necessary to keep traffic moving at 45 mph or higher in the express lanes for at least 90 percent of the time *(107)*.

3. This research conducted a hypothesis test to investigate the relative impacts of tolls and GP lane congestion on HOT lane demand (i.e. demand elasticity w.r.t tolls vs. w.r.t GP congestion) for each HOT facility. The results were mixed; equal impacts were observed on two of the facilities while dominant impact of GP lane congestion was recorded for the remaining two. An underlying factor for the observed groupings was the level of congestion on parallel GP lanes in a HOT corridor. The impact of GP lane congestion on HOT lane demand is not dominant when the level of congestion on GP lanes is relatively low and vice versa. For example, on I-394 MnPASS and I-15 Fast Trak lanes, the impacts of tolls and GP lane congestion on HOT lane demand were found not to be statistically different for both facilities. GP lane congestion on these two HOT facilities was found to

be significantly low, with average densities of about 30 veh/mi/l during the morning period. On the contrary, the impact of GP congestion on HOT lane demand was found to be greater than corresponding impacts of tolls for I-85 and I-95 express lanes; and as expected, both facilities had relatively high GP lane congestion with average densities of 50 veh/mi/l. This suggests that GP congestion is a larger motivator of HOT lane use in HOT corridors with high level of congestion.

4. This research represents one of the first attempt to predict HOT lane demand from the perspective of real-time traffic management in ICM. Prior efforts focused on predicting long term HOT lane demand during the planning stages of HOT lane implementation. Based on the estimated demand, operational benefits, expected revenue and benefit/cost analysis are made. None of the past research efforts have looked at predicting short-term HOT lane demand for traffic management purposes. In this dissertation, HOT lane demand predictive models were developed using tolls and GP lane congestion as explanatory variables for each facility. The intended purpose of the model was to predict the expected Level of Service (LOS) of HOT lanes based on estimated number of potential users. This model will help transportation professionals to estimate the level of demand expected in order to manage the overall HOT lane system. As expected, the performance of the predictive model wasn't outstanding because of the weak relationship between the explanatory variables (tolls and GP lane congestion) and HOT lane demand as observed in chapter four. This research demonstrated that, real-time HOT lane demand is not a predictable value using toll prices and GP lane congestion.

7.1.2 Other Contributions

The other contributions are:

1. Implementation of the developed evaluation methodology on an 11mile section of I-95/1-395 corridor in northern Virginia provided significant insights into the effectiveness of ICM as a congestion mitigation tool. These insights include:

    a. The main purpose of ICM is to increase person throughput in a transportation corridor. In order to increase person throughput, transportation agencies must find a way to utilize existing capacity on all transportation modes as well as spread travel demand across mode and time. Although there are a plethora of ICM strategies (such as queue warning and lane departure systems, signal optimization, en-route traveler information through dynamic message signs, pre-trip traveler information through text messages and websites, etc.) at the disposal of transportation agencies, care must be taken in selecting the right combination of strategies to spread demand as well as utilize capacity. On the I-95/I-395 corridor where the ICM evaluation methodology was implemented, it was discovered that the effectiveness of ICM became significant only when strategies such as HOT lanes (which provide route choice options, thereby spreading demand), variable speed limit (which helps to utilize capacity by delaying traffic flow breakdowns) and increasing transit and parking capacities (which promote mode shifts, eventually helping to spread travel demand) were combined. Therefore, ICM can only be effective when the implemented strategies help to spread demand as well utilize existing capacity.

b. The underlying concept of ICM is to combine different strategies in order to increase person throughput and reduce congestion in a transportation corridor. Hence, the effectiveness of ICM lies in how the different strategies combine to collectively achieve the above-mentioned purpose. There are some strategies whose effects diminish once they are combined with other strategies; such strategies are not worth investing in and must be identified. On the I-95/I-395 corridor, implementation of the evaluation methodology led to the discovery that the ramp metering strategy was redundant and less beneficial to the transportation needs of the corridor. This was due to the fact that ramp metering was evaluated alongside two other ICM strategies (increasing transit capacity and financial incentives) that ensured that fewer vehicles got onto the freeway due to the availability of parking and transit capacities at reduced prices. Although the ramp metering strategy can be very beneficial when operated in isolation, it was of less operational significance in this instance of ICM application. Therefore, transportation agencies who intend to adopt ICM must make it a mission to identify such redundant strategies in order to minimize cost.

2. This research represents the first attempt to compare HOT lane user VTTS (value of travel time savings) across four HOT lane facilities in different parts of the U.S. with dynamic tolling capabilities. A hypothesis test comparing VTTS distributions of each HOT facility revealed that some HOT facilities are similar in terms of their VTTS (though at different locations) while others are dissimilar. A commonality between HOT facilities found to be similar in terms of VTTS is the average annual income of the respective regions where these HOT facilities are located. Users of HOT facilities located in regions with high average RPP (Regional Price Parity)-adjusted annual incomes tend to have high mean VTTS and vice versa. I-394 MnPASS located in Minneapolis and I-15 Fast Trak express lanes located in San Diego were found to have similar mean VTTS estimates. Users of these two HOT facilities had mean VTTS estimates of $71/hour (I-394 MnPASS, Minneapolis) and $72.5/hour (I-15 Fast Trak, San Diego) lanes during peak periods. Additionally, both facilities are located in regions with relatively high average RPP (regional price parity)-adjusted incomes of $87,092 (Minneapolis) and $83,820 (San Diego) in 2012. Similarly, I-95 and I-85 express lanes in Miami and Atlanta respectively were found to have almost the same peak mean VTTS estimates of $49.2/hour (I-95 express lanes) and $50.9/hour (I-85 express lanes). Their RPP-adjusted incomes for 2012 were $65,990 (Miami) and $79,963 (Atlanta). Although the RPP-adjusted annual income of Atlanta ($79,963) appeared to be close to that of San Diego ($83,820), results of the hypothesis test indicated that their mean VTTS were statistically different.

3. VTTS analysis in this research was also used to make a general inference about the income levels of HOT lane users by comparing average VTTS estimates with Bureau of

Labor Statistics (BLS) average hourly wages for each location/region. It is known from past research that traveler VTTS increases as income or wage rate increase, but less than proportional *(100–102)*. For all HOT facilities analyzed, it was found that HOT lane users' mean VTTS was substantially higher than average hourly wages (at least more than twice) of local residents. This suggests that, HOT lane users are likely to earn more income than the average residents of HOT facility locations.

4. This research represents one of the first attempts to determine if there is a general pattern in driver behavior in terms of their demand for HOT lane use. A hypothesis test was used to compare demand elasticity distributions (w.r.t tolls and GP lane congestion) of all HOT facilities studied. It was found that, users of facilities with high mean VTTS estimates were indifferent to tolls and GP lane congestion and consistently used the HOT lanes. Conversely, users of facilities with relatively low VTTS, tend to respond fairly to changing traffic conditions (GP lane congestion) and do not use the HOT lanes at all times. I-394 MnPASS and I-15 Fast Trak lanes, which were found to have statistically similar mean elasticities recorded high mean VTTS estimates of $71/hour and $72.5/hour respectively during peak periods. Furthermore, it was found that about 90% of eligible HOT lane drivers used the I-15 Fast Trak lanes regardless of the level of congestion or toll prices during both morning and evening periods (remaining 10% used the GP lanes), while earlier research by Goodall and Smith (2010) showed that about 87.5% of I-394 MnPASS lane drivers used the facility even when its usage did not offer any travel time benefits *(23)*. For I-95 and I-85 express lanes which recorded relatively low VTTS estimates of $49.2/hour and $50.9/hour respectively, their elasticity distributions were found to be alike. HOT lane usage data from I-85 express lanes revealed that, only about 20% of eligible HOT lane drivers used the HOT lanes at the start of the morning period when there is little or no congestion on the GP lanes (remaining 80% used the GP lanes). The level of usage increased as GP lane congestion increased, peaking at 50% during the peak period (remaining 50% used the GP lanes).

7.2 Future Research

A lot of topics were identified in the course of this research as areas of possible future research. These areas are listed below.

7.2.1 HOT Lane VTTS and Elasticity

1. Timely information on traffic conditions enables drivers to make informed decisions about route choice. It was found in this research that, the studied HOT facilities either do not provide any information on travel times (for HOT lanes and parallel GP lanes) or provide travel time information for only HOT lanes. This leaves drivers to come up with their own estimation of travel time savings if they decide to use the HOT lanes. Although some travel information may be provided by radio stations and other third party services, such information are intermittent, and may not be available when the driver needs it most. As a result of lack of adequate travel time information, drivers tend to overestimate the perceived travel time savings they are likely to enjoy when they use the HOT lanes. The information vacuum may lead drivers to make route choice decisions which do not reflect prevailing traffic conditions in a transportation corridor. VTTS estimated from such

uninformed decisions by drivers may not reflect their true VTTS. Therefore, there is the need for a research in which explicit information on travel times for HOT and parallel GP lanes are provided to drivers. VTTS estimates calculated from such a research may better reflect drivers' true VTTS; helping transportation professionals to come up with better tolling schemes which can be used to really influence traveler behavior.

2. In the absence of comparative travel time information (for HOT and GP lanes), it has been reported in the transportation literature that drivers tend to interpret high toll prices as a sign of downstream congestion on the GP lanes *(14,21)*. Consequently, they shift from GP lanes to HOT lanes in order to avoid the supposed congestion. However, tolls on HOT lanes only account for traffic conditions on the HOT lanes and do not consider prevailing traffic conditions on the GP lanes. In order to test this assumption, there is the need for experiments on HOT lanes to see how drivers react to high tolls under different traffic conditions on GP lanes. This will help in designing the appropriate travel information for dissemination to drivers.

3. The elasticities and VTTS calculated in this research were for a 5-month period between October 2012, and February 2013. They provide a snapshot of HOT lane driver behavior for the specified time period. For each of the facilities analyzed, what is not known is whether the estimated behavior changes from time to time or is stable. When HOT lanes are first introduced, drivers understanding of how it works may be low. As drivers continue to use the facility for a while, they may develop a better understanding of its operation and may change their behavior as well. It is not known whether the general driver behavior becomes consistent after a certain amount of time. It is therefore necessary that a longitudinal study of HOT lane driver behavior be conducted. Such a study will help with the understanding of how driver behavior changes with time and provide us with reliable estimates of elasticity (short vs long-term elasticity).

4. ICM involves multiple modes in which timely information and pricing can be employed to utilize unused capacities in a transportation corridor. As a result, travelers may change modes in the course of their travel based on available information and necessary incentives. In this research, the impact of pricing (in the form of tolls) was investigated for only HOT lane driver behavior. In the future, it will be necessary to extend this analysis to include pricing effect on mode choice. That is, to investigate the impacts of integrated pricing (HOT lane tolls, transit fares, parking fees) on traveler behavior in a transportation corridor.

5. The airline industry has been using seat reservation systems and dynamic pricing to effectively manage air travel demand for some time now and transportation engineers have begun looking into how to apply reservation systems to highways *(108)*.Since the current pricing levels on HOT lanes do not significantly impact traveler behavior, it is necessary to investigate the possibility of incorporating reservation systems into HOT lane operations in order to prevent them from becoming gridlocked in the near future.

7.2.3 Summary

This research developed an evaluation methodology based on which beneficial ICM strategies can be selected at the planning stages of ICM implementation. Using data from four different HOT lane facilities in the U.S., this research investigated HOT lane driver behavior in terms of how they respond to tolls and GP congestion. It was found that, pricing (tolls) had little or no impacts on the decision by drivers to use/ not to use the HOT lanes. Additionally, mean VTTS estimates were higher on facilities located in regions with high RPP-adjusted annual incomes than those located in relatively low RPP-adjusted annual income regions. The elasticity of HOT lane demand w.r.t GP congestion was also studied. It was observed that the influence of GP congestion on HOT lane demand was positive and relatively higher than that of tolls but inelastic. The observed HOT lane driver behavior was used to develop a model that predicts expected level of demand for HOT lane use in real-time. The developed model has the potential to make ICM proactive and more efficient.

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Appendix A

Simulation Test Scenarios

The following represents the different simulation scenarios that were run in VISSIM. For each scenario, different combinations of ICM strategies were tested. In all, 50 different scenarios were considered, and each scenario ran five times to reduce the effects of stochastic variability. The definitions of the different strategies as used in this research are provided below:

RM—Number of vehicles allowed by the ramp meter to enter the freeway in an hour
TPC—% of vehicles that will shift to transit as a result of increase in transit and parking capacity
HOT—% of vehicles which will shift to HOT lanes as carpools as a result of tolls charged
HOV-E—% of vehicles which will form carpools to use the HOV lanes due to extra capacity
FI—% of vehicles which will use transit as a result of reduction in transit and parking fees
VSL—% of vehicles complying and not complying with variable speed limits
HGV—% of Heavy vehicles
HOV-3—Regular HOV usage %

Please note that HGV and HOV-3 are not strategies. They represent the % of heavy vehicles in traffic mix and regular HOV lane usage %. As can be seen in the appendix, their values do not change from scenario to scenario. For VSL strategy, the compliant and non-compliant % shown in the appendix represents only single-occupant vehicles traveling on the general purpose lanes. All other vehicles (those which eventually shift to transit or HOV) comply with the variable speed limit as long as they remain on the freeway.

Scenario	RM	TPC	HOT	HOV-E	FI	VSL		HGV	HOV-3
						COMPLIANT	NON-COMPLIANT		
1	608	0.218	0.045	0.131	0.053	0.263	0.034	0.0075	0.25
2	773	0.158	0.105	0	0.03	0.398	0.052	0.0075	0.25
3	758	0.15	0.098	0.068	0.053	0.075	0.306	0.0075	0.25
4	560	0.105	0.083	0.06	0.053	0.06	0.389	0.0075	0.25
5	541	0.143	0.113	0.075	0.03	0.225	0.164	0.0075	0.25
6	706	0.173	0.098	0.113	0	0.218	0.147	0.0075	0.25
7	890	0.18	0.023	0.045	0.023	0.293	0.182	0.0075	0.25
8	643	0.128	0.015	0.12	0.03	0.083	0.368	0.0075	0.25
9	733	0.12	0.15	0.068	0.023	0.278	0.113	0.0075	0.25
10	596	0.225	0.03	0.008	0.015	0.368	0.106	0.0075	0.25
11	812	0.083	0.008	0.03	0.068	0.12	0.435	0.0075	0.25
12	604	0.203	0.083	0.113	0.038	0.27	0.038	0.0075	0.25
13	714	0.188	0.12	0.075	0.068	0.3	0	0.0075	0.25
14	794	0.188	0.105	0.023	0.03	0.248	0.15	0.0075	0.25
15	864	0.09	0.03	0.053	0.06	0.383	0.137	0.0075	0.25
16	881	0.113	0.053	0.098	0.023	0.353	0.105	0.0075	0.25
17	697	0.12	0.068	0.03	0.06	0.053	0.412	0.0075	0.25
18	537	0.173	0.143	0.105	0.06	0.068	0.201	0.0075	0.25
19	550	0.098	0.023	0.038	0.023	0.188	0.382	0.0075	0.25
20	618	0.173	0.128	0.135	0.015	0.308	0	0.0075	0.25
21	842	0.09	0.09	0.045	0.06	0.308	0.153	0.0075	0.25
22	621	0.165	0.053	0.12	0.075	0.248	0.085	0.0075	0.25
23	824	0.143	0.038	0.023	0.023	0.12	0.398	0.0075	0.25
24	581	0.18	0.06	0.045	0.045	0.413	0.002	0.0075	0.25
25	872	0.18	0.075	0.015	0.038	0.368	0.067	0.0075	0.25
26	660	0.21	0.015	0.098	0.068	0.323	0.03	0.0075	0.25
27	572	0.203	0.105	0.105	0.053	0.158	0.128	0.0075	0.25
28	631	0.113	0.038	0.09	0.008	0.135	0.362	0.0075	0.25
29	748	0.165	0.06	0.083	0.068	0.165	0.203	0.0075	0.25

30	691	0.098	0.113	0.105	0.075	0.21	0.142	0.0075	0.25
31	668	0.075	0.045	0.105	0.038	0.188	0.299	0.0075	0.25
32	831	0.188	0.053	0.113	0.06	0.285	0.053	0.0075	0.25
33	746	0.143	0.12	0.09	0.038	0.105	0.253	0.0075	0.25
34	729	0.135	0.038	0.15	0.008	0.338	0.075	0.0075	0.25
35	853	0.218	0.135	0.023	0.008	0.15	0.219	0.0075	0.25
36	580	0.15	0.128	0.113	0.023	0.338	0	0.0075	0.25
37	799	0.15	0.12	0.038	0.045	0.218	0.179	0.0075	0.25
38	787	0.203	0.06	0.008	0.053	0.128	0.292	0.0075	0.25
39	650	0.173	0.09	0.083	0.045	0.098	0.255	0.0075	0.25
40	719	0.128	0.008	0.06	0.015	0.383	0.159	0.0075	0.25
41	507	0.083	0.143	0.068	0.03	0.045	0.375	0.0075	0.25
42	515	0.105	0.128	0.135	0	0.173	0.203	0.0075	0.25
43	764	0.218	0.113	0.143	0.008	0.233	0.038	0.0075	0.25
44	850	0.083	0.008	0.045	0.008	0.203	0.407	0.0075	0.25
45	898	0.12	0.075	0.083	0.068	0.278	0.125	0.0075	0.25
46	517	0.098	0	0.053	0.045	0.308	0.249	0.0075	0.25
47	683	0.195	0.075	0.143	0.015	0.098	0.222	0.0075	0.25
48	665	0.158	0.023	0.135	0.045	0.173	0.21	0.0075	0.25
49	531	0.135	0.083	0	0.015	0.083	0.43	0.0075	0.25
50	812	0.113	0.128	0.015	0.068	0.345	0.075	0.0075	0.25