Incorporating Incident Impacts into Travel Demand Forecasting Modeling for Transportation Planning Process

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I dedicate this dissertation to

my parents Yeobum Lee and Yeonsil Kim

and parents-in-law Dukhan Chung and Yongsook Shin

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ABSTRACT

The traditional Travel Demand Forecasting Model (TDFM), used within the Long Range Transportation Planning (LRTP) process, has mainly focused on the evaluation of transportation system effectiveness and environmental impact with various performance measures to assess transportation investment alternatives. However, TDFM does not explicitly account for delays due to incidents that contribute non-recurrent urban congestion. Previous studies have developed ad-hoc techniques to consider incident impacts (e.g., safety studies that identify crash hotspots or pre-defined incident scenarios at the subarea level).

This dissertation research developed an approach to integrate the large amount of increasingly available incident data with a region's TDFM. This dissertation research has explored incident data and their impacts (the number of blocked lanes, duration, etc.) on the network and shown how incident data should be prepared to be integrated into traditional TDFM networks. Known as a Travel Demand Forecasting Model with Incidents (TDFMI), the approach incorporates historical incident information (the duration and reduced capacity due to the incidents) into the corresponding links and nodes of the traditional TDFM network.

Incident impacts were accommodated in the traffic assignment step by modifying the functional form of volume delay functions (VDFs) to consider incident duration and capacity reduction. Field traffic data and crash data in Virginia DOT's database were explored to find crash-involved traffic data by using common temporal

and spatial information. The prepared crash-involved traffic data were split into subgroups by facility types to calibrate VDFs separately. The Bureau of Public Roads (*BPR*) and Akcelik VDFs were modified with additional variables for considering incident impacts (duration and reduced capacity) at link segments and intersections. The parameters of modified VDFs were calibrated using crash involved traffic data and application results showed better performance measures compared to the TDFM results.

The approach is demonstrated in the Hampton Roads, Virginia region. Prepared incident data were successfully matched with corresponding segments and intersections on the networks of traditional TDFM. For the base year comparisons, TDFMI offers better percent root mean square error (%RMSE) than TDFM for all facility types even without the calibration and validation of TDFMI; with larger improvements in %RMSE for higher volume groups (over 40,000 vehicles per day). Especially, TDFMI results for interstate freeways and principal arterials, and rural area showed improvements in both %RMSE and volume/count ratio.

For the future year evaluation of scenario investment, TDFMI results were evaluated by three major criteria: project utility, economic vitality, and project viability. From the three criteria, six quantitative sub-criteria, contributing 85 points out of a total 300 points, were evaluated and scored. Relative to TDFM, the applications of TDFMI to nine candidate major investments show that the TDFMI notably affected the prioritization of investments by explicitly considering each investment's impact on incidents. While the top ranked project is unaffected, three projects changed their ranking by one position and another three projects changed their ranking by three positions. The paired t-Tests for the nine projects showed that the evaluation scores for three projects in the TDFMI were significantly different than those generated by the TDFM. These changes in prioritization demonstrate that the explicit consideration of a project's ability to reduce incidents is feasible with TDFMI and can materially influence which investments are selected during LRTP process.

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CHAPTER 1. INTRODUCTION

1.1 Background

The travel demand forecasting is an essential task in the Long Range Transportation Planning process (LRTP) to evaluate alternative strategies for accommodating future needs such as land use development, supply and demand, policy-related strategy, etc. The traditional Travel Demand Forecasting Model (TDFM)—an evolutionary tool based on the sequential steps of trip generation, trip distribution, mode choice, and traffic assignment—is used to evaluate these alternatives. The four step model is the primary trip-based tool for forecasting future travel demand and performance of a transportation system on a regional scale. While the investment choices are not dictated by the TDFM results alone, they provide a foundation for evaluating major infrastructure investments when preparing the LRTP (Martin and McGuckin 1998). However the existing TDFM does not have any variables or components to quantify traffic congestion properly, and thus, traffic congestion is not factored into the prioritization of capital investments in the transportation planning process.

USDOT defined the congestion as “one of the single largest threats” to the Nation’s economic prosperity and way of life (Owens et al. 2010). Work zones, crashes, breakdowns, adverse weather, sub-optimal signal timing, toll facilities, and railroad crossings caused over 3.5 billion estimated vehicle-hours of delay on U.S. freeways and principal arterials in 1999 (Chin et al. 2004). Based on 2007 data, wasted time was 4.2 billion hours and wasted fuel was 2.8 billion gallons, congestion cost about $87.2 billion combined in the top 439 urban areas in the United States (Owens et al. 2010). About 50% of all highway congestion is caused by the non-recurrent congestion, which leads the variations in travel times (Cambridge Systematics 2013a).

Table 2.1 lists the major causes of non-recurrent congestion. The Highway Capacity Manual 2010 version (HCM 2010) identified the major causes of non-recurrent congestion as: incident, weather, work zones, special events, fluctuation in demand, special events, traffic control devices, and inadequate base capacity (Transportation Research Board 2010). Other literature identified the major causes of non-recurrent congestion as: incident (including crash), work zone, and weather (Skabardonis, Varaiya, and Petty 2003).

Table 2.1 Major Causes of Non-recurrent Congestion

TRB	Skarbardonis et al.
1. Incidents	1. Crashes (both fatal and non-fatal)
2. Weather	2. Breakdowns
3. Work zones	3. Work zones
4. Fluctuation in demand	4. Weather events (rain, fog, ice, and snow)
5. Special events	5. Sub-optimal signal timing (principal arterials)
6. Traffic control devices	6. Highway-railroad crossings (principal arterials)
7. Inadequate base capacity	7. Toll facilities
	8. Commercial truck pickup and delivery (PUD) activities (urban principal arterials)

Source: * (Transportation Research Board 2010)

** (Skabardonis, Varaiya, and Petty 2003)

Traffic incidents (e.g., crash, breakdown, abandoned vehicles, etc.) account for 25% of non-recurrent congestion in urban traffic (Cambridge Systematics and Texas Transportation Institute 2005). Crashes represent a major source of non-recurrent congestion, which is estimated to be about half of all congestion in some locations (Cambridge Systematics and Maryland Bethesda 2010). Incidents cause sequential negative impacts on the road network, including but not limited to, congestion, delay, more mobile emissions, and more fuel consumption.

1.2 Research Motivations

The performance measures used by TDFM, such as vehicle miles traveled (VMT) and vehicle hours traveled (VHT), can be relatively good surrogates for measuring the system effectiveness in terms of delay, air quality, and emissions. For example, an increase in VMT will be highly correlated with an increase in greenhouse gas emissions regardless of vehicle type. However, the accuracy of these performance measures is limited in the case of TDFM because it does not consider network disruption caused by the incidents (whether planned or unplanned). As fiscal constraints require that decision makers decide which projects should be implemented, this inability to consider non-recurrent congestion may adversely affect the transportation programming process, especially in prioritizing multiple investment alternatives.

There are two main gaps in knowledge that this research addresses. First, there is no framework or methodology to incorporate network disruption from incidents into the TDFM. Second, there are very few proposed methodologies incorporating incident impacts as an additional delay in the network analysis. Previous research efforts did not explicitly consider incidents as a variable, but treated them as pre-determined additional delay time regardless of traffic conditions. They focused on either: 1) microscopic dynamic or stochastic assignment model for Advanced Traveler Information System (ATIS) strategy on simple test bed network loading (Fu and Rilett 1997; Ngassa 2006; Bian 2008; Thomas and Robert 2008), or 2) macroscopic static assignment with simplified volume delay function and incident conditions (Li, Zhou, and Rouphail 2011a; Li, Zhou, and Rouphail 2011b).

The Federal Highway Administration (FHWA) has led various management and operation (M&O) strategies to consider operational variables in the transportation planning process to improve system efficiency, reliability, and safety (Grant et al. 2010). Recently, the second Strategic Highway Research Program (SHRP 2) has conducted various research specialized in four areas (safety, renewal, reliability, and capacity) to improve the safety and reliability of the nation's highway system (Transportation Research Board of the National Academies 2013). As the part of efforts for incorporating the reliability performance measures into the transportation planning process, SHRP 2 has analyzed predefined simple scenarios for non-recurrent congestions including incident, work zone, and inclement weather to evaluate reliability performance measures (Cambridge Systematics 2013b).

The volume delay function (VDF) in traffic assignment appears to be the best place to consider incident impact properly in the four step travel demand forecasting model because it determines the relationship between supply side (free flow speed and link capacity) and demand side (loaded link volume) by an equation relating how many trips will be loaded on each link. By using a modified VDF, the TDFM incorporating incident impact (referred as TDFMI) could not only predict travel demand considering incident impact but also assess various performance measures to evaluate incident-related goals and objectives in transportation planning and prioritization of investments. From the functional form of VDF, incident impacts could be added as additional variables accommodating incidents' frequency, duration, and capacity reduction.

1.3 Problem Statement

The non-recurrent congestion is a major cause of reduced mobility, emission, and other sustainability issues, and the consequential impact of non-recurrent traffic events are already integrated with the field traffic observations that used in the calibration and validation of TDFM. However, the traditional macroscopic static TDFMs do not consider these impacts properly because they do not have the capability to analyze these impacts in the model structure. Moreover, incident impacts have not been well addressed in even emerging modeling practices such as activity-based models, dynamic traffic assignment models, and traffic simulation models regarding the travel demand forecasting techniques (Cambridge Systematics et al. 2012). The lack of data and limited analysis tools are the main reason why incident impacts are not well addressed and rely on subjective assessments in the long range planning process in many cases (Chatterjee et al. 2001; Chatterjee et al. 2003).

The factors affecting the impact of non-recurrent congestion on freeway operation are 1) incident duration, 2) reduction in capacity, and 3) demand rate (Garib, Radwan, and Al-Deek 1997). Even though conventional evaluation of various alternatives focuses mainly on transportation system effectiveness (mobility, congestion, VMT,VHT, delay, etc.) and environmental impact (air quality, emissions, and noise) as predominant performance measures, there are no variables or factors for incorporating incident in the travel demand forecasting model (Jeon 2007). The majority of goals and performance measures in sustainability are more or less related to safety issues such as crash, incident, delay, congestion, emission, etc. In order to incorporate incident impact properly into planning and decision making process, TDFM should have the capability to assess incident impacts in it because TDFM is a core component to access and evaluate various alternatives strategies for accommodating various future needs.

1.4 Research Goals and Objectives

The primary goal of this dissertation is to develop a TDFMI incorporating incident impacts. The hypothesis of this dissertation is that the TDFMI would forecast the travel demand incorporating the incident impacts that is unavailable from the traditional TDFM, which would provide additional useful information to transportation planners and decision makers to improve the decision-making process. The main objectives of this dissertation to examine the hypothesis are to:

1. Prepare incident data for base year and estimate incident data for future year to integrate incident impact (frequency, severity, and duration) into traditional TDFM.

2. Modify the functional forms of VDFs to be used in TDFMIs and calibrate them to accommodate incident impacts with additional variables.

3. Evaluate the performance of the developed base year TDFMI by comparing them with field observations and traditional TDFM.

4. Evaluate selected highway projects from 2034 Hampton Roads LRTP by using TDFMI and compare the projects prioritization results from TDFMI with those from TDFM.

1.5 Dissertation Organization

This document contains seven chapters. In chapter 1, the background, motivations and goal and objectives of this dissertation are presented. Chapter 2 presents the relevant literature reviews on the following major tasks: i) Long Range Transportation Planning process, ii) traditional Travel Demand Forecasting Modeling, iii) traffic incident modeling for frequency, duration, and reduced capacity, and iv) volume delay functions. Chapter 3 addresses a framework incorporating incident impacts into the traditional TDFM and the data preparation for the base year and future year TDFMIs. Chapter 4 presents the incident data preparation for the modification and calibration of VDFs with incident data. Chapter 5 addresses the procedure of how prepared incident data and modified VDFs are incorporated with the traditional TDFM networks. In Chapter 6, the various comparisons and evaluations of TDFM and TDFMI are presented with a prioritization of future alternative projects. Finally, in Chapter 7, conclusions and recommendations learned from this dissertation research are presented.

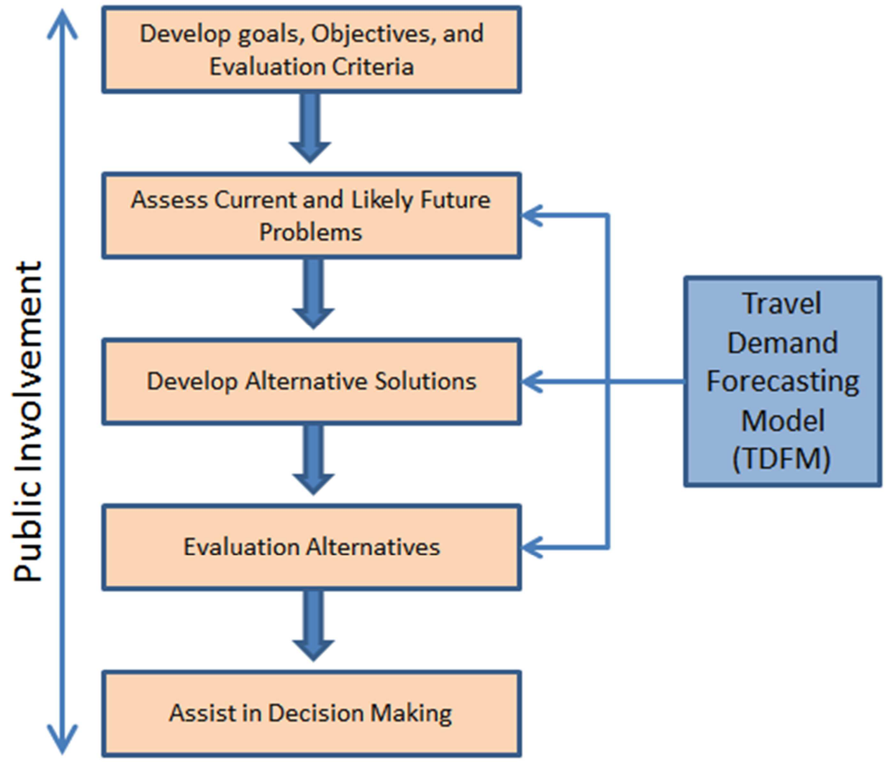
CHAPTER 2. LITERATURE REVIEW

A literature review was undertaken to understand the current best practices in Long Range Transportation Planning (LRTP), Travel Demand Forecasting Model (TDFM), network simulation combined with incident, incident analysis in various temporal and spatial horizons from real time to long range future year, and/or from corridor level to regional level.

2.1 Long Range Transportation Planning (LRTP) and Decision Making Process

By Federal law (Title 23 United States Code, Section 134 Metropolitan Planning), an urbanized area with population above 50,000 should have a Metropolitan Planning Organization (MPO), which is a regional transportation planning agency. MPOs should prepare the Metropolitan Transportation Planning and Programming Process for LRTP, which should be continuing, cooperative, and comprehensive (3Cs) with no more than a 30-year horizon (Transportation Planning Capacity Building Program 2007). The transportation planning and programming process should be prepared: 1) to promote the safe and efficient management, operation, and development of surface transportation systems, 2) to improve the mobility of people and freight within and through urbanized areas, and 3) to minimize the transportation-related fuel consumption and air pollution (Transportation Planning Capacity Building Program 2007).

Figure 2.1 shows a typical transportation planning process and the role of TDFM (Beimborn, Kennedy, and Schaefer 1996; Meyer and Miller 2001; National Highway Institute 2012).



Source: (National Highway Institute 2012)

Figure 2.1 Transportation Planning Process

Goals and objectives are established and evaluation criteria are prepared first. The problems, scope, area, and issues are defined in this step to determine the final goals and objectives. The assessments of the current (base year) problems and the expected future year problems are followed. For a reliable assessment, various data, including socio-demographic data, land use data, field traffic data, and various archived data are collected and the models are calibrated and validated. Based on the assessment results of the problems, various alternatives for the base year and the future year are developed. From the evaluation of alternatives, preferred alternatives or plans are selected. The evaluation results of selected alternatives are used to assist the final decision making process. TDFM is the major tool used to develop quantitative analyses for the assessment of problems to the evaluation of alternatives.

Many types of transportation planning analyses may be developed using the modeling approaches listed below (Virginia DOT 2007):

1. Evaluate Transportation System Performance
2. Long Range Transportation Planning for MPO areas and Statewide
3. Short Range Transportation Planning such as Transportation Improvement Program (TIP) and Six-Year Improvement Program (SYIP)
4. Support Air Quality Conformity Analysis
5. Support Alternative Analysis

Title 23 of the United States Code describes the eight Federal Planning Factors issued by Congress to emphasize planning factors from a national perspective (Caltrans 2012):

1. Support the economic vitality of the metropolitan area, especially by enabling global competitiveness, productivity, and efficiency.
2. Increase the safety of the transportation system for motorized and non-motorized users.

3. Increase the security of the transportation system for motorized and non-motorized users.
4. Increase the accessibility and mobility of people and for freight.
5. Protect and enhance the environment, promote energy conservation, improve the quality of life, and promote consistency between transportation improvements and State and local planned growth and economic development patterns.
6. Enhance the integration and connectivity of the transportation system, across and between modes, people and freight.
7. Promote efficient system management and operation.
8. Emphasize the preservation of the existing transportation system.

The Metropolitan Planning Organization considers these eight factors when developing projects and strategies during the transportation planning process. These planning factors remain unchanged in MAP-21, the Moving Ahead for Progress in the 21st Century Act (P.L. 112-141), signed into law by President Obama on July 6, 2012.

2.1.1 MPO and State Department of Transportation (DOT)

The planners and modelers in the MPOs and State DOTs have various responsibilities in carrying out the Metropolitan Transportation Planning Process and below are some examples (Virginia DOT 2007):

- Prepare and adopt a long range transportation plan

- Develop a financial plan that demonstrates how the adopted long range transportation plan can be implemented.
- For the designated non-attainment or maintenance areas for ozone or carbon monoxide under the Clean Air Act, the MPO shall demonstrate Air Quality Conformity by coordinating the development of the long range transportation plan with the process for the development of transportation control measures in the State Implementation Plan (SIP) required by the Clean Air Act.
- Review and update the financially constrained long range transportation plan to confirm its validity and consistency with current and forecasted transportation and land use conditions.
- The MPO annually certifies to the Federal Highway Administration (FHWA) and the Federal Transit Administration (FTA), with the corporation with the state DOT, that the planning and programming process is addressing major transportation issues and is being conducted in accordance with all applicable requirements.

In addition to having responsibilities associated with the planning process, the planners and modelers in the MPOs and DOTs also have certain responsibilities in carrying out the programming process for their areas as listed below:

- Developing a Transportation Improvement Program (TIP)
- Creating a financial plan that demonstrates how the TIP can be implemented

- Adhering to the Air Quality Conformity standards for the designated non-attainment or maintenance areas for ozone or carbon monoxide under the Clean Air Act.

2.2 Travel Demand Forecasting Modeling (TDFM)

Travel demand forecasting and modeling (TDFM) has been used as an important tool in transportation plans, projects, and policies under various temporal-spatial horizons in MPO areas and statewide (Cambridge Systematics et al. 2012). As noted in Chapter 2.1, TDFM develops traffic forecasts and evaluates alternative transportation scenarios and regional-wide transportation systems to assist in prioritizing transportation projects. TDFMs are usually developed using demographic, survey, and transportation network data. Demographic and survey data are used to develop the mathematical equations necessary for modeling. Highway and transit data (e.g. number of lanes, speed limit, road capacity, transit schedules and fares, etc.) are used to model the transportation network (Virginia DOT 2007).

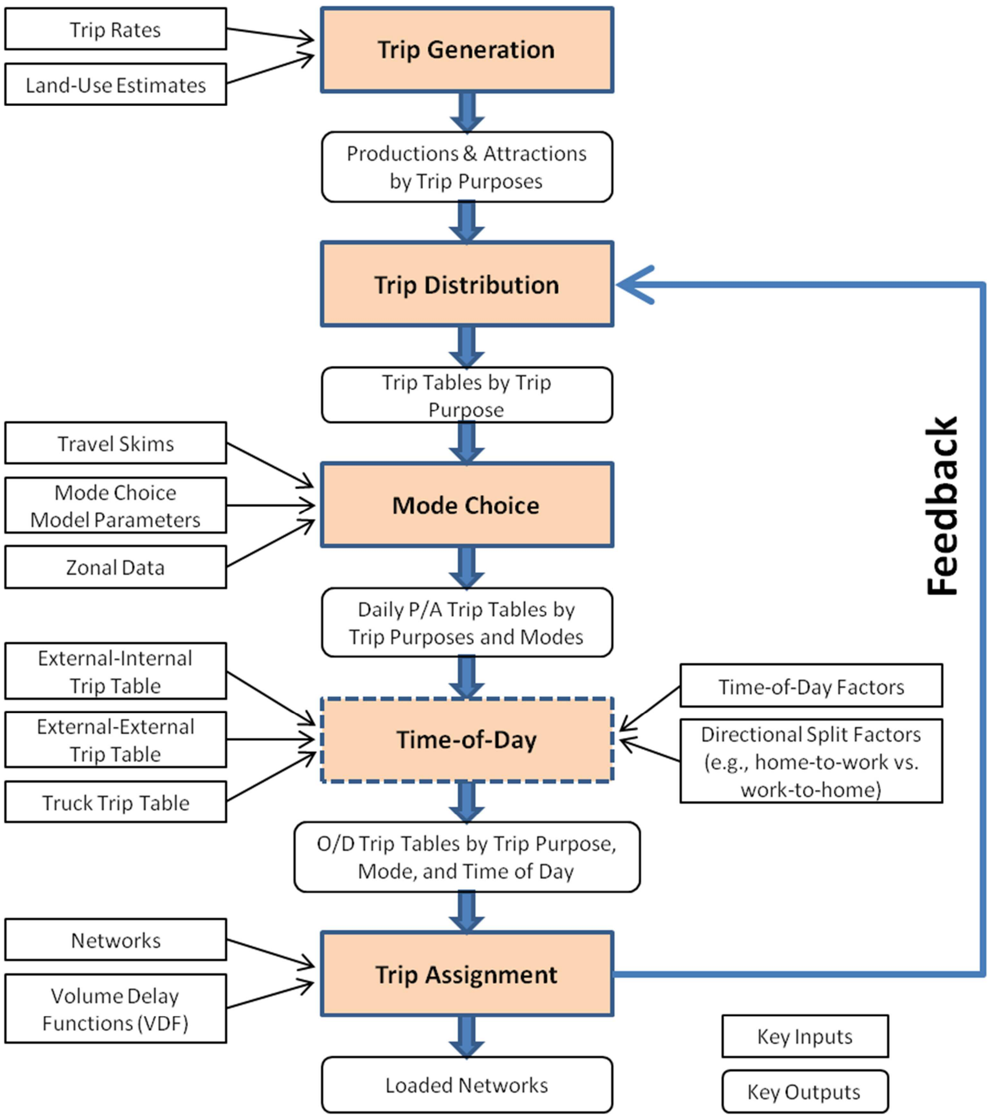
2.2.1 Four Step TDFM Model

The most common TDFM method used worldwide, including in the United States, is the traditional four step approach. This approach is an aggregate sequential process with four steps:

1. Trip Generation = How many trips will be made?
2. Trip Distribution = Where will the trips go?

3. Mode Choice = What mode of transportation will the trips use?
4. Trip Assignment = What route will the trips take?

Figure 2.2 depicts the sequential process of the traditional four step TDFM from trip generation to trip assignment. Figure 2.2 shows that each step uses the outputs from the previous step as key inputs, in addition other external input data. The Time-of-Day step is an optional step that is generally placed between the mode choice and the trip assignment step. It is widely used in the areas where traffic patterns and/or characteristics differ by time of day, such as in the morning, mid-day, afternoon and evening periods (AM, MD, PM, and NT).



Source: (National Highway Institute 2012)

Figure 2.2 Four Step Travel Demand Forecasting Modeling Process

Demographic and socio-economic data are aggregated and prepared to the Transportation Analysis Zones (TAZs) level before they are used as inputs into the four step model. TAZs are established based on geographic location and census data, and are typically derived from a combination of census blocks and/or census block groups.

Trip Generation

The Trip Generation step determines the number of person trips that begin (produced) or end (attracted) in each individual TAZ in a model region. Socio-demographic data and land use data are used in the trip generation model to determine the produced and attracted trips at TAZs. Usually the regression model or the cross-classification model is used in Trip Generation, but the cross-classification model is more accepted when modeling larger regions. In order to estimate the total number of trips generated/attracted from/to TAZs, a household travel survey data, such as the National Household Travel Survey (NHTS), is used to determine household variables (e.g. number of persons, workers, vehicles, children, income, etc.) in each TAZ. There are four trip types used in the Trip Generation model:

- (I-I) trips that begin inside and end inside of the model region
- (I-E) trips that begin inside but end outside of the model region
- (E-I) trips that begin outside but end inside of the model region
- (E-E) trips that begin outside and end outside of the model region, but travels through the model region

All trips other than E-E trips are calculated by trip generation models. E-E trips are modeled from traffic counts, Origin-Destination surveys taken from external stations, and/or relevant traffic data. Trips are usually split into trip purposes, including home-based trips and non-home-based (NHB) trips, because they have different characteristics in trip generation. Furthermore, home-based trips can be further divided into more categories, such as for work (HBW), school or college

(HBSc), shopping (HBSh), and social and recreational or other trips (HBO) (Ortuzar and Willumsen 2001).

Ortuzar and Willumsen (2001) identified major factors affecting personal trip generation as: income, car ownership, household structure, family size, value of land, residential density, and accessibility. Special facilities, such as hospitals, military bases, ports, colleges and universities, warehouses, etc., are treated as special generators because additional survey and estimation data are necessary to estimate trips from/to special facilities. To estimate freight trips in modeling region, the following data are used: number of employees, number of sales, roofed area of firm, and total area of firm are used (Ortuzar and Willumsen 2001) .

Trip Distribution

The Trip Distribution step determines the number of person trips between all pairs of TAZs. The predominant model used is the gravity model, derived from Newton's Law of Gravitation. In the functional form, the number of trips between TAZ *i* and TAZ *j* has a positive relationship to the magnitude of produced trips from TAZ *i* and attracted trips to TAZ *j* and a negative relationship to the impedance (travel time and cost) between TAZ *i* and TAZ *j* (Virginia DOT 2007). The Standard Gravity model formula is shown below:

$$Trips_{ij} = \frac{P_i * A_j * FF_{ij} * K_{ij}}{\sum_n A_j * FF_{ij} * K_{ij}} \qquad \text{Eq. (2.1)}$$

Where: *i= Origin TAZ*

j = Destination TAZ

n= Number of TAZs

P=Trip Productions

A=Trip Attractions

FF=Friction Factor

K=Optional Adjustment Factor (K factor)

The calibration of the gravity model is to fit friction factor (FF) matrices from the locally observed data per trip purposes. The FF represents the impedance between zone *i* and zone *j* in time, distance, and cost. Thus, friction factors are higher as travel time decreases. FF varies by trip types (I-I, I-E, E-I and E-E). The widely used functional form for estimating FF is the gamma function as shown below:

$$F_{ij}^{p} = a \times t_{ij}^{b} \times \exp(c \times t_{ij}) \qquad \text{Eq. (2.2)}$$

where F_{ij}^{p} *=Friction Factor*

t_{ij} *=Travel Impedance from zone i to zone j*

a,b,c = Scale Parameters

Travel impedance used to estimate the FF typically uses a generalized travel cost that is calculated by incorporating travel times, distance, and costs such as tolls, parking, etc. Travel times include in-vehicle travel time (IVTT) and out-of-vehicle travel time (OVTT) to account for the difference of the traveler’s value of time

(VOT). K-Factor is used to account for the effects of variables other than travel impendence in the gravity model (Cambridge Systematics et al. 2012).

Mode Choice

The Mode Choice step splits the person trips into mode specific trips such as Single Occupant Vehicle (SOV), High Occupancy Vehicle (HOV), Bus, Rail, etc. The expression for the probability of choosing an alternative i is (Koppelman and Bhat 2006):

$$\Pr(i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)} \qquad \text{Eq. (2.3)}$$

Where $\Pr(i)$ = probability of the decision-maker choosing alternative i

V_j = systematic component of the utility of alternative j

Multinomial logit or nested logit models are typically used in practice, based on the combination of modes in the model structure. The National Highway Institute identified factors affecting model split from five major categories (National Highway Institute 2012):

- Personal/household (HH) characteristics: vehicle availability, HH income, HH size, etc.
- Trip characteristics: trip purpose, trip chaining, departure time, origin/destination, trip length, etc.
- Land use characteristics: sidewalk, pedestrian facility, distance to transit, parking availability, etc.

- Service characteristics: facility design (HOV, bike, etc.), frequency, congestion, cost (parking, tolls, fares, out-of-pocket cost, etc.), stop spacing, etc.

Koppelman and Bhat (2006) listed the commonly used explanatory variables associated with travelers, mode, and trip itself in mode choice models. Traveler (decision-maker) related variables include traveler and/or household information, such as income, number of vehicles, number of workers, sex, age group, etc. Trip Context variables include: trip purpose, the employment density of the workplace, the population density of the residential area, Central Business District (CBD). Mode related variables include: total travel time (TVTT), in-vehicle travel time (IVTT), out-of-vehicle travel time (OVTT), wait time, number of transfers, transit headway and travel cost. Some variables are computed together to derive additional information, such as travel cost divided by household income, travel time divided by cost grouped by sex or age group, and OVTT divided by total trip distance.

Trip Assignment

The Trip Assignment step determines which transportation routes on the network will be used for mode specific trips between the origin and destination TAZs. The common traffic assignment methods are an all-or-nothing (AON) approach or an equilibrium assignment approach. AON, generally used in small urban areas and relatively uncongested networks, assigns all trips between an origin-destination pair that has the minimum travel cost. Although the AON method is useful because it is easy to understand the results and evaluate the total demand on the roadway under ideal circumstances, it is not appropriate in most cases because it generates an unrealistic flow pattern that does not consider the traveler's behavior on how they select their route from a set of all available choices.

User Equilibrium (UE) assignment, as an alternative of the AON method, utilizes the concept of capacity restraint of the roadways (National Highway Institute 2012). The UE assignment repeats the AON assignment through an iterative process using the capacity restraint methodology until Wardrop's first principle is satisfied, which is that *"the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route"* (Cambridge Systematics et al. 2012). The equilibrium assignment is a useful method because the results would be stable and satisfies certain convergence criteria, which is desirable for the comparison between alternatives with no oscillations between computational iterations (National Highway Institute 2012).

However, the UE assignment generally has an unrealistic assumption that all travelers have perfect information on all routes and always chooses the optimal route for given flow rates, which is a deterministic assignment model. As an alternative, the stochastic assignment model is based on the assumption that travelers do not have perfect information on all routes, and thus, route choice decision is not always the same even under the same flow rates due to inherent uncertainty (Tatineni, Boyce, and Mirchandani 1997). Even though stochastic assignment is a more realistic alternative over deterministic assignment in modeling assumption for loading traffic onto a network, deterministic models may be sufficient for long range transportation planning (LRTP). (Tatineni, Boyce, and Mirchandani 1997)

Both AON and UE methods allocate trips to all links on the shortest path from origin to destination at each iteration, using a fixed Origin/Destination (O/D) trip table for a fixed time period, and thus, are static assignment approaches. By contrast, a dynamic assignment approach has more than one O/D trip table for multiple time periods, so that it assigns trips to each link on the shortest path sequentially. Thus, the travel time of each link and the shortest path are updated in each simulation time period along each link.

The volume delay function (VDF) is a central part of traffic assignment models and describes how the travel time on an individual link changes based on traffic demand, which will be discussed in detail Chapter 2.4.

Model Calibration and Validation

In the four step model, the outputs of the previous step are used as the inputs of the next step. As a result, any errors from the previous step are propagated to the next step, resulting in more inaccurate data with each successive step. Thus, transportation planners must carefully calibrate and validate the each step of the model, and review the final model run results. Travel Model Validation and Reasonableness Checking Manual (Federal Highway Administration 2010) defines model calibration and model validation as below:

"Calibration is the adjustment of constants and other model parameters in estimated or asserted models in an effort to make the models replicate observed data for a base (calibration) year or otherwise produce more reasonable results.

Validation is the application of the calibrated models and comparison of the results against observed data. Ideally, the observed data are data not used for the model estimation or calibration but, practically, this is not always feasible."

Even though many modeling practitioners in MPO and local, state, and federal governments are satisfied with their current four step models and believe it is adequate for most planning purposes (Transportation Research Board 2007), typical limitations should be considered in its application. The four step model does not adequately address intersection delays, intra-zonal travel within TAZs, and time of day variations. Link capacities are over-simplified and peak hour travel is overemphasized (Beimborn, Kennedy, and Schaefer 1996)

The Transportation Research Board (2007) listed the shortcomings of the current four step modeling practice:

- *Four step model is not adequate to address many new policy concerns*
- *Four step model has inherent weakness. Since four step model is not based on travelers' behavioral nature, it is not suited to represent travelers'*

response to the policy-related scenario analyses such as toll, HOT, and congestion price.

- *Four step model has limitations to consider induced travel, interaction between land use policies, non-motorized travel*
- *Four step model has limitations to consider freight, goods movement, and commercial vehicles*

As a result, the four step model is limited in its ability to reflect small scale changes, dynamic effects, and changes in travel behavior associated with complex trade-offs of costs (Corradino, Inc. 2009). Although there have been many successful implementations of the four step modeling framework, most of the literature that addresses the limitations in the four step model propose a shift toward the activity-based model framework (Bhat and Koppelman 2003; Corradino, Inc. 2009; Transportation Research Board 2007; Cambridge Systematics et al. 2012).

2.2.2 Activity Based Model (ABM)

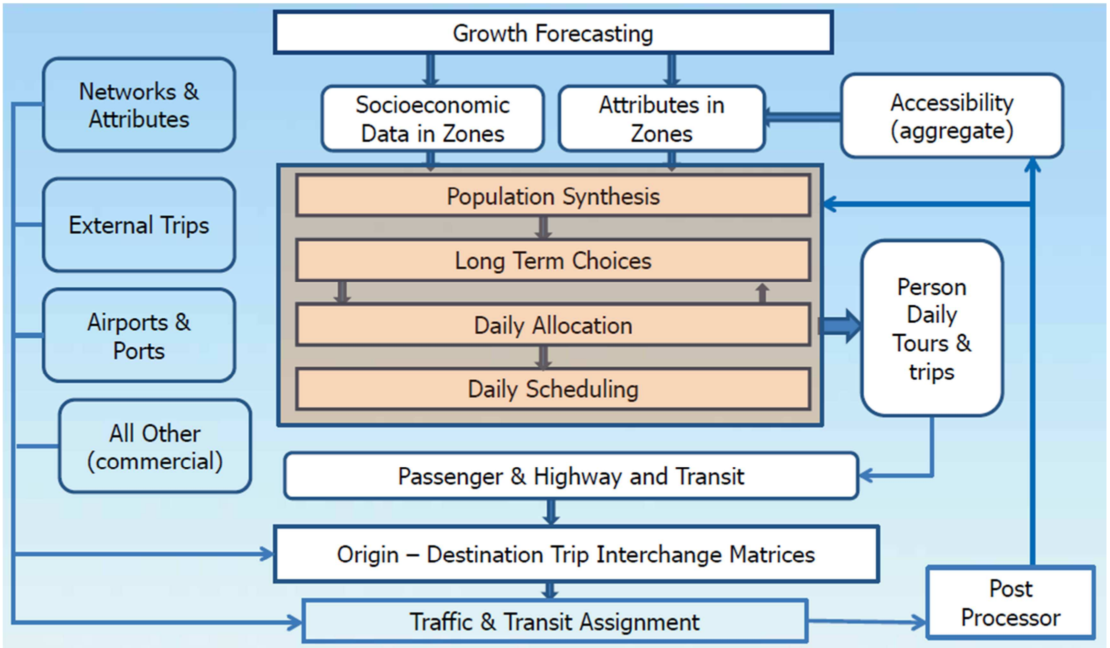
A fundamental conceptual problem of the trip-based approach, such as the four step model, is that it uses trips as the analysis unit without consideration of dependence among trips (Bhat and Koppelman 1999). Activity-Based Model (ABM) views travel as a derived demand from the need to pursue activities. It considers complex interactions between activity participation and travel behavior (Transportation Research Board 2007). Activity-based models analyze travel as “tours” that consists of multiple trips starting from and ending in important points, such as home or work

(Corradino, Inc. 2009). The major differences between the activity-based model and the four-step model are: the activity-based model has a consistent/continuous representation of time for travelers, it has a detailed representation of travelers and households, it has time-dependent routing, and it has a microsimulation of travelers and aggregated traffic (Transportation Research Board 2007).

The overall process, when an activity-based model is implemented, consists of a sequence of three steps as listed below (Cambridge Systematics et al. 2012):

1. Population synthesis
2. Long-term choice models
3. Activity-based travel models

Southern California Association of Government (SCAG), the MPO of the Los Angeles Metropolitan area, has adopted an activity-based model that incorporates the above three major steps, as shown in Figure 2.2. SCAG's ABM is currently being developed, but stage 1 was completed in 2013, which included: developing the modeling framework, completing the initial estimation of core modules, and performing an initial calibration of the 2003 base year model (G. Huang et al. 2013). The ABM is expected to be fully implemented in 2016. The completed ABM is expected to generate various performance indicators for the analyses of infrastructure investment, land use development, pricing policy, active transportation strategies, high speed rail, and travel demand management (Huang et al. 2013).



Source: (Huang et al. 2013)

Figure 2.3 Flow Chart of SCAG Activity-Based Model

2.3 Traffic Incident Models

An incident is defined as "a non-recurrent event that causes a reduction of roadway capacity or an abnormal increase in demand. Such events include traffic crashes, disabled vehicles, spilled cargo, highway maintenance and reconstruction projects, and special non-emergency events (FHWA, USDOT 2000). " As mentioned in Chapter 1.1, traffic incidents are one of the major causes of non-recurrent congestions in urban highways, which leads to variations in travel times (Cambridge Systematics 2013a). The factors affecting the impact of non-recurrent congestion on freeways are: 1) incident duration, 2) reduction in capacity, and 3) demand rate

(Garib, Radwan, and Al-Deek 1997). In this section, previous studies on various modeling analyses associated with incidents are summarized.

2.3.1 Incident Frequency Model

Lord and Mannering (2010) provided a comprehensive review of crash frequency models, by type, describing the strengths and weaknesses of various prediction models and analyzed the data that they generate. The functional forms they reviewed are listed below:

- Poisson regression model
- Negative Binomial (Poisson-gamma) Regression Model
- Poisson-Lognormal Model
- Zero-inflated Poisson and Negative Binomial
- Conway-Maxwell-Poisson Model
- Gamma Model
- Generalized estimating equation Model
- Generalized additive Model
- Random-Effect Model
- Negative Multinomial Models
- Random-Parameter Models
- Bivariate/Multivariate Model
- Finite Mixture/Markov Switching Models
- Duration Models

- Hierarchical/Multilevel Models
- Neural, Bayesian Neural Network, Support Vector Machine Models

Along the models' functional forms, they raised major issues regarding data and methodology as listed below, and summarized associated problems for each issue:

- Over-dispersion and under-dispersion
- Time-varying explanatory variables
- Temporal and spatial correlation
- Low sample means and small sample size
- Crash type correlation
- Injury severity and crash type correlation
- Underreporting
- Omitted variables bias
- Endogenous variables
- functional form
- fixed parameters

Crash Analysis at the Network Level

Lamptey et al. (2010) proposed a framework for incorporating crash analysis in network level transportation planning. They developed a crash prediction model using the Safety Performance Function (SPF) at the network level for two-lanes and multi-lanes for urban and rural areas. Kiattikomol et al. (2008) developed a negative binomial regression model using segment length and Annual Average Daily Traffic

(AADT) to predict crashes on segments and intersections of urban freeways. The models were split into subgroups by segment types, number of lanes, and type of severity. These crash prediction models were developed using roadway geometry and traffic data (Tarko et al. 2008; Abdel-Aty et al. 2011).

Hampton Roads Planning District Commission (HRPDC[1]) conducted a crash analysis of interstate segments and intersections in the region as part of their congestion management system (CMS) (Ravanbakht, Belfield, and Nichols 2005). A crash severity analysis was conducted to identify the top high-crash locations in the region. Safety-related countermeasures and solutions for the top-10 high-crash locations were developed and recommended to be applied in the region's transportation improvement program (TIP) (Ravanbakht, Belfield, and Nichols 2005).

Spatial analysis of crash data

Aguero-Valverde and Jovanis (2006) developed Full Bayes Hierarchical models with county-level crash frequency and common categories of independent variables including: socioeconomic, roadway geometry, and environmental characteristics. These models were compared with traditional Negative Binomial estimates. The results showed that spatial correlation, time trends, and space-time interactions are significant at the county-level Full Bayes Hierarchical models. Huang, Abdel-Aty, and Darwiche (2010) proposed a Bayesian spatial model to account for the variation of county-level crash risk in Florida. They used four types of data (crash data, road

[1] Now its name has been changed to Hampton Roads Transportation Planning Organization (HRTPO)

and traffic characteristics, demographic and socioeconomic data, and spatial features of each county) for county-level analysis to develop linear regression models by taking the natural logarithm to the variables. Wang and Kockelman (2007) considers the spatial and temporal correlations across crash observations in China using a seemingly unrelated regression (SUR) model.

TAZ Level Crash Analysis

There are community (TAZ) level collision prediction models to evaluate the roadway safety of regional transportation plans by forecasting crash frequency (Lovegrove, Lim, and Sayed 2010; Lovegrove and Sayed 2006; de Guevara, Washington, and Oh 2004; Hadayeghi, Shalaby, and Persaud 2003). Macroscopic safety analysis using zonal level data and TDFM has been accomplished with a zonal safety planning model. Aggregated TAZ level crash prediction or collision prediction models were developed based on social-demographic data that are used in trip generation (Siddiqui, Abdel-Aty, and Huang 2011; Siddiqui 2009; Naderan and Shahi 2010) and network structure (Lovegrove and Litman 2008; G. R. Lovegrove and Sayed 2006). An et al. used TDFM and traffic analysis zone (TAZ) level data to predict planning-level crashes for estimating safety benefits from two add-capacity projects (An, Casper, and Wu 2011). Hadayeghi, Shalaby, and Persaud (2007) developed a TAZ level crash prediction model that can be commonly used in urban transportation planning. They developed 23 multiple linear regression models by selecting combinations of independent variables in model development, including land use, network, traffic, demographic, and socioeconomic data.

Planning Level Crash Analysis

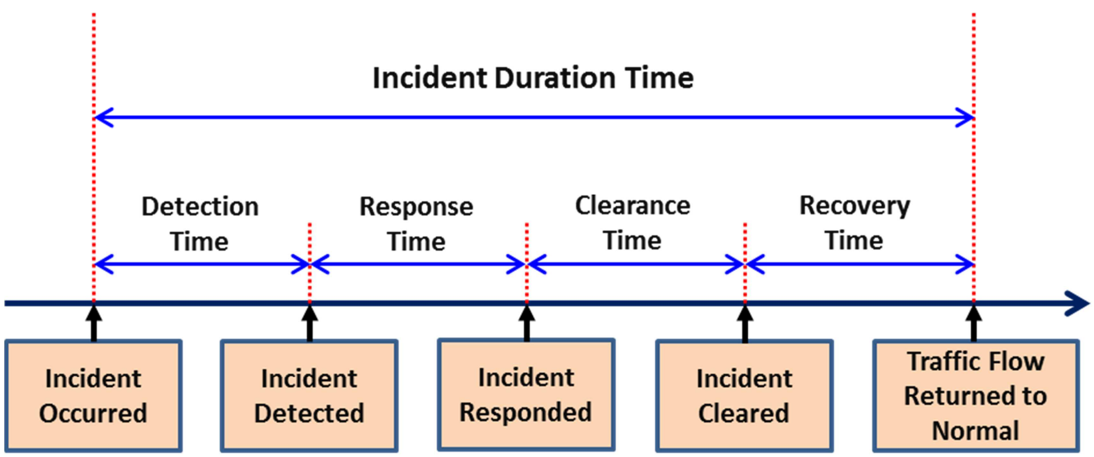
There has been some research effort to incorporate crash (part of incidents) into the planning process. Hamidi, Fontaine, and Demetsky (2010) developed a safety performance function (SPF)-based methodology to identify high-crash sections of primary roadway in Virginia, by using crash data and roadway geometry data. Miller, Garber, and Josephine (2010) and Miller, Garber, and Kamatu (2011) developed a resource guide for enhancing the incorporation of safety into the regional planning process. The guide proposed eight steps for integrating safety into the regional transportation planning process with Virginia examples.

Real Time Crash Prediction Model

Drawing from the relationship between traffic flow conditions and the likelihood of crashes, Golob, Recker, and Alvarez (2004) proposed a tool for the real-time safety assessment of any traffic flow pattern on an urban freeway. They conducted a clustering analysis with macroscopic traffic flow data (eight traffic regimes with speed and volume) and crash data (type, location, severity, etc.) on three-lane freeways. Pre-crash data with 30-second intervals for 27.5 minutes were used to prepare four traffic flow variables of speed and volume. As a safety performance monitoring tool, from comparing traffic flow data before and after crash, they accessed the benefits of Advanced Traffic Management System (ATMS) operations or other Intelligent Transportation System (ITS) applications, forecasted the safety implications of proposed projects by evaluating the level of safety implied by traffic simulation outputs, prioritized higher risk locations from simulation results, and identified where/when crash would occur on freeways.

2.3.2 Incident duration Model

As shown in Figure 2.4, the incident duration time consists of four phases: detection time, response time, clearance time, and recovery time (Transportation Research Board 2000; Smith and Smith 2000). The HCM 2010 does not provide any guidance regarding the estimation of incident duration but some researchers (L08) under SHRP 2 have been examining non-recurrent congestion, including incident duration and frequency, to revise HCM 2010 Chapter 35 'Active Transportation & Demand Management' and Chapter 36 'Travel Time Reliability' (Transportation Research Board of the National Academies 2013).

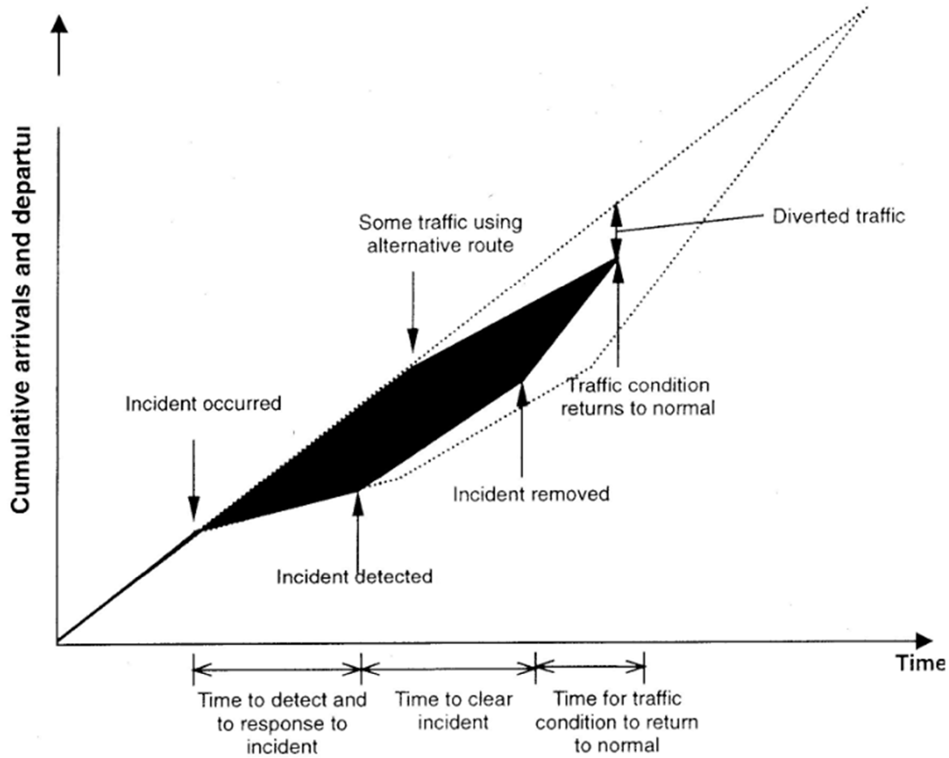


Source: (Smith and Smith 2001)

Figure 2.4 Typical 4 Phases of Freeway Incident over Time

1) Detection time: the time period between the incident occurrence and the incident detection or reporting by stakeholders, including traffic operators, police officers, or the freeway response team.
2) Response time: the time period between the incident detection and the arrival of the emergency treatment team at the scene.
3) Clearance time period: the time between the arrival of the treatment team at the scene and the incident being cleared, including treating victims, closing lanes, and removing vehicles and debris.
4) Recovery time: the time period between incident clearance and the resumption of normal traffic flow without any upstream congestion caused by the incident.

Incident duration could be analyzed on the time-spatial diagram. Abdel-Rahim and Khanal (2001) showed a diagram representing incident-based delay with and without an incident management system on the time-spatial dimension as shown in Figure 2.5. The horizontal axis shows time periods from incident occurrence to traffic conditions returning to normal, similar to the phases in Figure 2.4.



Adopted from (Abdel-Rahim and Khanal 2001)

Figure 2.5 Incident-Based Delay With and Without an Incident Management System

The vertical axis represents the distance of cumulative arrivals and departures. The area with dashed lines represents the total delay from the incident (vehicle-time) when an incident management system is not available. The black colored area represents the total delay from the incident when an incident management system is used. Thus, the total delay from the incident and incident duration is reduced when an incident management system is used.

Various statistical models and techniques have been applied and analyzed for modeling incident duration as below:

- Probabilistic model (lognormal distribution) (Golob, Recker, and Lernard 1987),
- Conditional probability model (Log-logistic hazard-based duration model) (Jones, Janssen, and Mannering 1991; Nam and Mannering 2000)
- Analysis of variance model with truck involvement (Giuliano 1989)
- Linear regression (Garib, Radwan, and Al-Deek 1997),
- Time sequential model (truncated linear regression) (Khattak, Schofer, and Wang 1994),
- Classification tree model (Smith and Smith 2000),
- Decision trees regression (Wei Wu, Pushkin, and Kaan 1998; Abdel-Aty, Keller, and Brady 2005; He et al. 2011),
- Hybrid-tree based quantile regression model (He et al. 2011)
- Ordered Probit model (Duncan, Khattak, and Counclil 1998; Li et al. 2010)
- Traffic incident duration prediction model based on support vector regression (Wei-wei Wu, Chen, and Zheng 2011)
- Influence factor analysis for incident duration by using analysis of variance (ANOVA) to apply Cusp Catastrophe Model (CCM) (Cong, Wang, and Fang 2011)
- Bayesian Decision Tree Method (Yang, Zhang, and Sun 2008)

Garib, Radwan, and Al-Deek (1997) estimated the duration of incident delays using a regression model. Variables used in the model development have been grouped into four categories: incident characteristics, traffic characteristics, weather condition, and geometric characteristics, as shown in Table 2.2.

Table 2.2 Variables used in the Incident Duration Model

Category	Variable Used in the Model
Incident Characteristics	Incident duration Number of vehicles involved in the incident Number of lanes affected by the incident Incident type (in-lane accident, in-lane breakdown, shoulder accident, shoulder breakdown, truck involvement)
Traffic Characteristics	Average traffic flow upstream of the incident before its occurrence Capacity reduction caused by the incident
Weather Condition	Rainy or dry
Geometric Characteristics	Occurrence within bottleneck Number of segments upstream of the incident

Source: (Garib, Radwan, and Al-Deek 1997)

Gomez (2005) claimed that incident duration has a Weibull distribution. Incident time, incident location, vehicle type, number of vehicles involved in the crash, and severity of the crash are the main factors that influence the incident duration. He developed the incident duration model based on Fuzzy logic theory. The following variables were used in the model development:

- vehicle size
- breakdown time, location, duration

- vehicle number
- crash time
- crash severity, duration

Ramani et al. (2009) used various variables, including: time, crash type, severity, disposal type, etc., in developing their incident duration model. All incident duration data were split into 7 categories at an increment of 20 minutes. The reliability of the model is quite satisfactory. The correct estimation ratio of the model is 69.11%. Hallenbeck, Ishimaru, and Nee (2003) claimed that models tend to overestimate the duration times when load spill is used as a dummy variable. It was simply because several incidents with load spill data had excessively long clearance times and a variety of load spill types were not incorporated into the models.

Studies have shown that modeling incident duration is very difficult (Wang, Chen, and Bell 2002). First, there is not enough data. Some variables cannot be obtained, either because of limited facilities available, or because they were not realized. Secondly, some variables are linguistic variables, such as weather conditions, date, vehicle type, etc. Thirdly, some variables are very subjective and difficult to mathematically quantify. For example, severity of incident is normally described as "not serious", "serious", or "very serious".

The primary drawback of linear regression models is the bulkiness of the predictive equation due to the categorical nature of independent variables resulting in a lot of dummy variables. Another disadvantage of using linear models is in assuming a ‘simplifying’ linear relationship between the dependent variable and the predictor variables (Gomez 2005). Golob, Recker, and Lernard (1987) claimed that none of the forecasting models produced results that were accurate enough to warrant implementation in an operational incident management system. The shortcomings of accident data greatly contributed to the poor reliability of forecasting models. Golob et al. (1987) concluded that the classification tree model stands out as a better choice to be used in an incident management system.

Golob et al. (1987) recently proposed an incident duration prediction model with a hybrid tree-based quantile regression using unbiased recurrent partitioning (URP) on both incident and traffic data. It showed that the URP trees and the hybrid tree-based quantile regression model has a higher prediction accuracy than the other models, including classification, regression tree (CART), and the K-nearest neighbor approach (He et al. 2011).

2.3.3 Capacity Reduction Model from Incidents

Regarding incident duration, a case study from Washington state shows useful information as described below (Hallenbeck, Ishimaru, and Nee 2003):

- Lane blocking incidents are responsible for between 2 and 20 percent of total daily delay in urban freeway corridors.
- Non-recurrent delay generally ranges between 30 to 50 percent of all peak period, peak direction delay, but it is between 30 and 70 percent of total daily delay.

- Lane blocking incidents generally account for between 10 and 35 percent of all non-recurrent delay.
- In peak periods, on any facility, a lane blocking incident of even a short duration tends to result in substantial delay.

Capacity reductions due to traffic accidents or vehicular breakdowns are generally short-lived, ranging from less than 1 hour (for a minor fender-bender involving only passenger vehicles) to as long as 12 hours (for a major accident involving fully loaded tractor-trailer rigs) before they are cleared. The effect of an incident on capacity depends on the proportion of the traveled roadway that is blocked by the stopped vehicles, as well as on the number of lanes on the roadway at that point (Transportation Research Board 2010).

Table 2.3 and Table 2.4 show the proportion of available freeway capacity under incident conditions. The estimated reduced capacity from the two tables were based on extensive survey data (Chin et al. 2004; Transportation Research Board 2010). The freeway capacity is reduced even when a disabled vehicle is located in the shoulder lane. The magnitude of reduced capacity varies by the number of freeway lanes going in that direction. It was found that shoulder disablement seems to have little or no effect when the total number of lanes is more than two. Other research has found that the loss of capacity is usually greater than the proportion of original capacity that was physically blocked (Lindley 1987).

Table 2.3 Reduced Capacity Due to Freeway Crashes

Effect of Crash	Number of Freeway Lanes				
	1	2	3	4	5+
Shoulder	0.450	0.75	0.84	0.89	0.93
1 Lane Blocked	0.000	0.32	053	0.56	0.75
2 Lane Blocked	N/A	0.00	0.22	0.34	0.50
3 Lane Blocked	N/A	N/A	0.00	0.15	0.20
4 Lane Blocked	N/A	N/A	N/A	0.00	0.10

Adopted from (Chin et al. 2004)

Table 2.4 Proportion of Freeway Segment Capacity Available under Incident Conditions

Number of Freeway Lanes by Direction	Shoulder Disabled	Shoulder Accident	One Lane Blocked	Two Lanes Blocked	Three Lanes Blocked
2	0.95	0.81	0.35	0.00	N/A
3	0.99	0.83	0.49	0.17	0.00
4	0.99	0.85	0.58	0.25	0.13
5	0.99	0.87	0.65	0.40	0.20
6	0.99	0.89	0.71	0.50	0.26
7	0.99	0.91	0.75	0.57	0.36
8	0.99	0.93	0.78	0.63	0.41

Adopted from (Transportation Research Board 2010)

In the case of a blocked lane, the loss of capacity is likely to be greater than simply the proportion of original capacity that is physically blocked. For example, when two lanes are blocked in a four-lane freeway, the freeway capacity may be effectively reduced to 25% of its original capacity. The reduction may range from an extra 5% capacity loss for a single-car accident and one emergency vehicle to an extra 25% capacity loss for a multivehicle accident with several emergency vehicles. The added loss of capacity arises because drivers slow to look at the incident while they are abreast of it and are slow to react to the possibility of speeding up to move through the incident area.

While some research literatures have shown mean capacity reductions per various cases, other research literatures have developed forecasting models. However, the forecasting models have not met industry expectations (Smith, Qin, and Venkatanarayana 2003; Transportation Research Board 2000; Chin et al. 2004; Knoop, Googendoorn, and van Zuylen 2008; FHWA, USDOT 2000; Transportation Research Board 2010). Most literatures have suggested that incident capacity reduction is a random variable rather than a deterministic value, due to the variations in incident characteristics (e.g., duration, extent, time of day, and traffic demand). Modeling incident capacity reduction as a random variable could provide a more realistic estimation of incident characteristics.

Lindley (1987) developed a methodology to quantify urban freeway congestion using the highway performance monitoring system (HPMS) database. He determined the reduction in section capacity due to an incident as a function of the total number of lanes and the number of blocked lanes.

Roess, Prassas, and McShane (2004) presented an example to illustrate the effect of capacity reduction on the volume to capacity ratio *(v/c).* They considered three different values for *v/c* ratios and then they simulated the losses in capacity due to an incident by changing these three values by different percentages. They concluded that decreasing capacity by 10% or more may change freeway operation from a functional system to an oversaturated system; this also depends on the demand level at the capacity reduction time.

The rubbernecking factor is also responsible for a reduction in capacity in the direction of travel opposite to that in which the accident occurred. No quantitative studies of this effect have been published, but experience suggests that it depends on the magnitude of the incident (including the number of emergency vehicles present). The reduction may range from 5% for a single-car accident and one emergency vehicle to 25% for a multivehicle accident with several emergency vehicles.

Due to the limitation of available data, it was assumed that the capacity losses on principal arterials were the same as for crashes on freeways. Since most arterials do not have a shoulder, it was assumed that any crash would produce a lane closure, independent of the type of crash and the number and type of vehicles involved. It was also assumed that the number of lanes closed was the same as for freeways. However a severe crash on a principal arterial would likely close lanes in both directions of traffic. To account for this, the total number of lanes in both directions was considered when assigning the number of lanes closed.

Incident delay on a freeway depends largely on the capacity at the incident location, which is determined by the drivers' behavior at the accident location (Knoop, Googendoorn, and Van Zuylen 2008). Knoop et al. (2008) used video traffic flow data captured by a helicopter around two accidents to investigate delay that was caused by an incident. Counts show that the (outflow) capacity of the remaining lanes is about 50% lower than the (free-flow) capacity of the same number of lanes. This means that road capacity in the opposite direction is reduced by half due to the rubbernecking effect. The capacity of the road in the direction of the accident is reduced by more than a half because not all lanes are in use (Knoop, Googendoorn, and Van Zuylen 2008).

2.3.4 Incident Analysis with Network Simulation

There are various models to estimate incident impacts with network simulation. Przybyla et al. (2011) evaluated the impact of incident information of a network based on stochastic capacity due to probabilistic crashes on simple corridor networks. Fu and Rilett (1997) estimated real-time incident delay in dynamic and stochastic networks and Li, Lan, and Gu (2006) proposed a stochastic incident delay model to estimate incident delay and its uncertainty on freeway networks. Some researchers proposed methodologies to estimate travel time using dynamic traffic assignment (DTA) under incident conditions (Ngassa 2006; Kamga, Mouskos, and Paaswell 2011) and to quantify the benefits of ATIS strategies under various stochastic capacity conditions assuming incident situations (Fu and Rilett 1997; Ngassa 2006; Bian 2008; Thomas and Robert 2008; Li, Zhou, and Rouphail 2011a; Li, Zhou, and Rouphail 2011b).

Previous research conducted incident impact analysis using network simulation tools and/or travel demand forecasting models. Some researchers proposed frameworks of ATIS strategies for driver groups who have different level of traffic information associated with incidents (Cambridge Systematics 2013b; Li, Lan, and Gu 2006; Przybyla et al. 2011; Li, Zhou, and Rouphail 2011b). They focused on static deterministic user equilibrium under stochastic capacity and/or dynamic traveler behavior modeling within the classical user equilibrium analysis. They set a simple incident case on a toy network to examine incident impact on the network with no specific incident situation including crash type, frequency, duration, capacity reduction, etc. Moreover, they did not examine any detailed relationships between incident and traffic simulation for models of large MPOs.

Mahmassani et al. (2009) developed dynamic traffic assignment (DTA) models that consider weather impact, including rainfall and snow, for traffic estimation and prediction. They investigated user responses over various inclement weather scenarios such as traffic advisory information and control actions. Samba and Park (2011) proposed a probabilistic model to determine the reduction of traffic demand from both inclement rain and snowfall conditions, which was investigated based on weather type, severity, duration, and time of day. Lam, Shao, and Sumalee (2008) developed a model to consider the impacts of adverse weather conditions such as different rainfall intensities on a road network with uncertainties. Chin et al. (2004) proposed a three-step process to estimate delay from vehicle crashes as described below:

1. Assign vehicle crash on the highway using the Monte Carlo simulation

2. Estimate capacity reduction based on look-up tables that consist of crash type, number/ type of vehicles involved, crash location, time of day, and duration.
3. Estimate delay based on capacity reduction, vehicle demand, time of day, day of week, and duration of capacity reduction

2.4 Volume Delay Function (VDF)

There has been much advanced research on functional forms, comparisons of their performance, and analytical applications regarding volume delay functions for the TDFM (Akcelik 1991; Skabardonis and Dowling 1997; Dowling, Singh, and Cheng 1998; Kurth, Hout, and Ives 1998; Singh 1999; Akcelik 2003; Cetin et al. 2011; Cetin et al. 2012).

Cetin et al. (2011) extensively reviewed various volume delay functions for their functional forms and listed different terms of volume delay functions from the basic relationship between traffic flow and travel speed as shown in Table 2.5.

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Table 2.5 Terms of Volume Delay Function by Researchers

Term	Author, Year
volume-delay function	Branston, 1976
link-capacity function	Branston, 1976
link performance function	Sheffi, 1985
congestion function	Spiess, 1990
travel time-flow function	Akcelik, 1991
link-cost function	Skabardonis and Dowling, 1997
speed-flow function	Ortúzar and Willumsen, 2001
cost-flow function	Ortúzar and Willumsen, 2001

Source: (Cetin et al. 2011)

VDF Functional Forms

Klieman et al. (2011) developed VDFs for both HOV and general purpose lanes on the freeway and arterials for several area types using field data from Maricopa Association of Governments (MAG). They estimated parameters of several functional forms, including the Bureau of Public Roads (BPR), Spiess conical delay, and Akcelik functions. From their analysis, the BPR function showed better goodness-of-fit to the data than the other functions. User equilibrium traffic assignments using BRP VDFs produced more accurate speeds and smaller errors than existing VDFs.

Lee and Munn (2009) estimated Akcelik VDFs per facility types for travel demand models in Virginia after investigating speed-flow relationships. Cetin et al. (2012) used a Genetic Algorithm (GA) to estimate the optimal parameters of various

VDFs, including BPR, Conical, and Akeclik functions in their model calibration. The following list summarizes their research:

- Evaluated speed-flow relationships per facility types including freeways, arterials, collectors
- Estimated free flow speed and capacity from field data
- Tested and calibrated VDFs of BPR, Conical, and Akcelik per facility types.
- Conducted goodness of fit test using R^2, %RMSE, and Chi-Square test
- Concluded that BPR performed well across facility types but suggested Akcelik for its more rigorous theoretical foundations

Cetin et al. (2011) categorized existing VDFs into five groups based on functional forms and characteristics, as shown in Table 2.6, which consists of linear function, curvilinear function, logarithmic/ hyperbolic function, queuing based function, and signal based function.

Table 2.6 (a) Summary of Volume Delay Functional Form

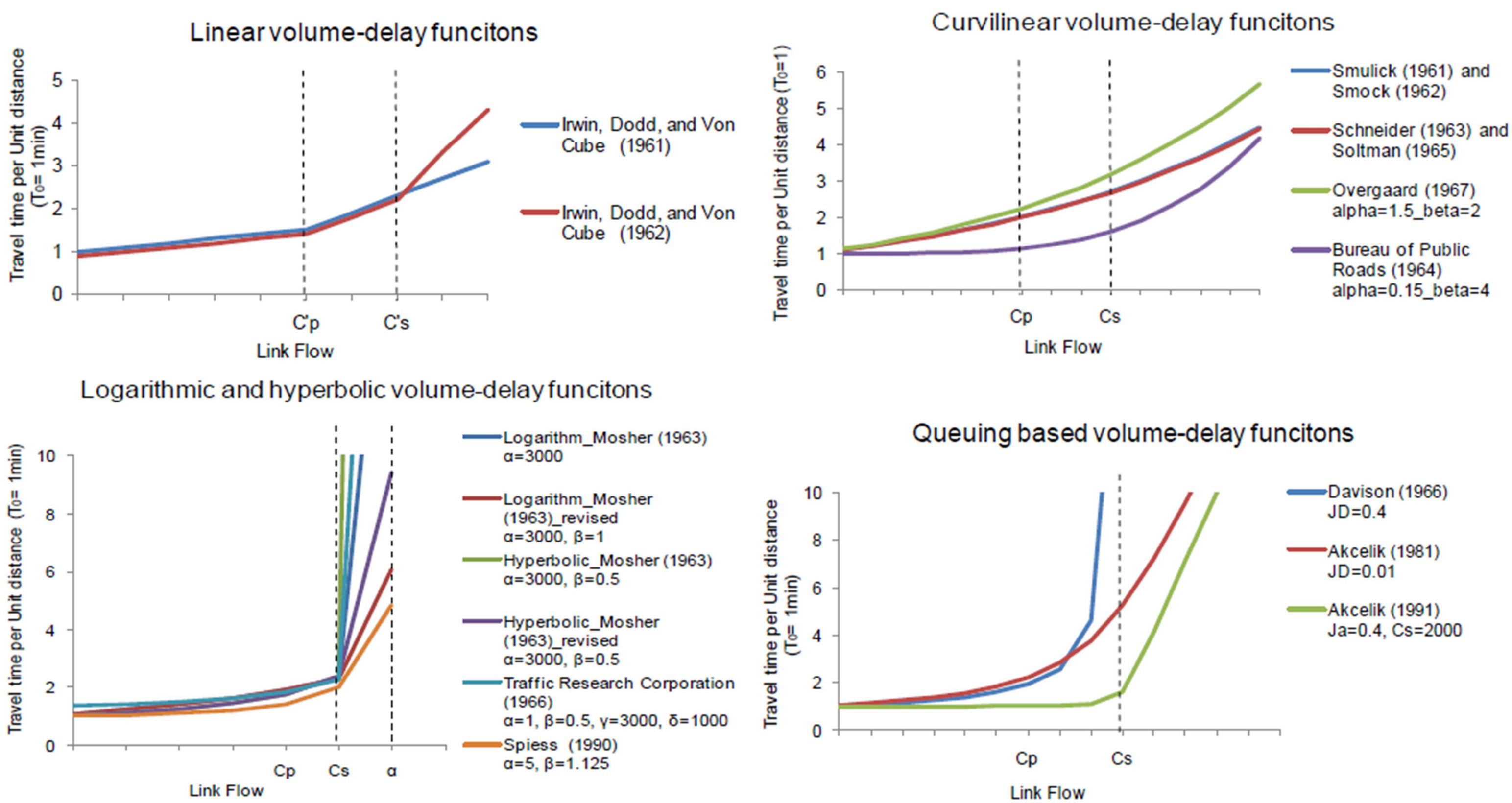
Authors	Equation and parameters	Comments	Author (Year)
Linear Functions	$T=T_0+\alpha C'p+\alpha(V'-C'p)$ for $V'<C'p$ $T=T_0+\alpha C'p+\beta(V'-C'p)$ for $V'\geq C'p$		Irwin, Dodd, and Von Cube (1961)
	$T=T_0+\alpha C'p+\alpha(V'-C'p)$ for $V'<C'p$ $T=T_0+\alpha C'p+\beta(V'-C'p)$ for $C'p\leq V'\leq C's$ $T=T_0+\alpha C'p+\beta(V'-C'p)+\gamma(V'-C's)$ for $V'>C's$		Irwin, Dodd, and Von Cube (1962)
Curvilinear Functions	$T=T_0*\exp(V/Cs)$	Exponential function	Smulick (1961) and Smock (1962)
	$T=T_0*2^{(V/Cp)}$	where V/Cp<=2, polynomial function	Schneider (1963) and Soltman (1965)
	$T=T_0*(1+\alpha(Q/C_p)^{\beta})$	Alpha=0.15, Beta=4	Bureau of Public Roads (1964)
	$T=T_0*\alpha^{(V/Cp)\wedge\beta}$	1.0<Alpha<1.7	Overgaard (1967)
	$T=T_0*(1+\alpha(Q/C_s)^{\beta})$	Alpha=2.62, Beta=5	Steenbrink (1974)
Logarithmic and hyperbolic functions	$T=T_0+\ln(\alpha)-\ln(\alpha-V)$	for $V\leq\alpha$	Mosher (1963)
	$T=T_0+\beta\ln(\alpha)-\beta\ln(\alpha-V)$ for $V\leq Cs$ $T=T_0+\beta\ln(\alpha)-\beta\ln(\alpha-Cs)+V\beta/(\alpha-Cs)$ for $V>Cs$	where $\alpha>Cs$	Mosher (1963)
	$T=\beta-\alpha(T_0-\beta)/(V-\alpha)$ for $V\leq\alpha$		Mosher (1963)
	$T=\beta-\alpha(T_0-\beta)/(V-\alpha)$ for $V\leq Cs$ $T=\beta-\alpha(T_0-\beta)/(Cs-\alpha)+V\alpha(T_0-\beta)/(Cs-\alpha)^2$ for $V>Cs$	where $\alpha>Cs$, $T_0>\beta$	Mosher (1963)
	$T=\alpha+\beta(Q'-\gamma)+\sqrt{[\beta^2(Q'-\gamma)^2+\delta]}$		Traffic Research Corporation (1966)
	$T=T_0*(2+(\alpha^2*(1-V/C)^2+\beta^2)^{1/2}-\alpha*(1-V/C)-\beta)$	where $\beta=(2\alpha-1)/(2\alpha-2)$, $\alpha>1$	Spiess (1990)

Source: (Cetin et al. 2011)

Table 2. 6(b) Summary of Volume Delay Functional Form (Continued)

Authors	Equation and parameters	Comments	Author (Year)
Queuing-based Functions	$t = t_0[1 + J_D x/(1 - x)]$		Davison (1966)
	$t = t_0\{1 + 0.25 r_f\,[z + (z^2 + 8 J_D x/r_f)^{0.5}]\,\}$		Akcelik (1981)
	$t = t_0\{1 + 0.25 r_f\,[z + (z^2 + 8 J_A x/(Q t_0 r_f))^{0.5}]\,\}$	J_A: Freeway=0.1, Uninterrupted arterial=0.2, Interrupted arterial=0.4, Secondary interupted=0.8, Secondary high friction=1.6	Akcelik (1991)
Signal-based Functions	T=T0 for V/Cs≤0.6 T=T0+α(V/Cs-0.6) for V/Cs>0.6		Campbell, Keefer, and Adams (1959)
	T=min[T0, 1/β(1- γV)]+nα/(1-V/λS)		Wardrop (1968)
	T=T0/(1- γV)+αβ/(α-V)/L	where α>Cs, γ<1/Cs	Wardrop (1968)
	$T=(T0+0.5NC(1-g/C)^2PF)(1+0.05(V/C)^{10})$		Skabardonis and Dowling (1997)
	$T=T0+0.9(C(1-g/C)^2/2(1-g/C{*}V/C)+(V/C)^2/2q(1-V/C))$	where 0<=V/C<1, q=arrival rate (veh/sec)	Xie, Cheu, and Lee (2001)

Source: (Cetin et al. 2011)



Where: C_p: practical capacity a link, C'_p: practical capacity per lane of a link,
C_S: state-state capacity a link, C'_S: state-state capacity per lane of a link
α: delay parameter to be estimated

Source: (Cetin et al. 2012)

Figure 2.6 Relationship between Flow and Travel Time per VDF Group

FFS Estimation

Dowling, Kittelson, and Zegeer (1997) investigated various techniques to estimate speed and service volume for planning applications. They examined speed-flow relationships of various methods including BPR type methods, HCM methods, and other methods using traffic operation tools used in different areas for uninterrupted and interrupted flow facilities. They also showed how travel speeds are changed over different levels of volume/capacity ratio in various VDFs. The BPR type function, as shown Equation (2.4), is still widely used in most TDM applications.

$$T_a = T_0 \left(1 + \alpha \left[\frac{v}{C}\right]^{\beta}\right) \quad \text{Eq. (2.4)}$$

where: T_a: Congested link travel time

T_0: Link travel time at free flow speed

α and β: Parameters

v: Link volume

c: Link capacity

However, a BPR type VDF cannot explicitly consider delays due to oversaturation conditions at intersections. Unlike the BPR function, the Akcelik function considers oversaturation conditions and delays at both the node and link simultaneously (Akcelik 1991; Dowling and Skabardonis 2008). Akcelik function has advantages as below:

- Akcelik VDFs consider intersection approach delays, which are based on simple gap-acceptance theory, similar to those used in the SIDRA intersection modeling software
- Akcelik VDFs have special procedures for modeling over-capacity conditions on the motorway

Akcelik (2003) states that the HCM speed-flow models for both basic freeway segments and multilane highways indicate some features that do not appear to be consistent with expected traffic flow characteristics related to in-stream vehicle interaction and queuing considerations. The HCM speed-flow models suggest that, when traffic flow increases, the rate of delay increase is much higher than the rate of speed reduction. Further, the traffic delay is larger at higher roadway facilities.

Singh (1999) claimed that the Akcelik function has been applied successfully in their applications and analytical comparisons with other functional forms from many studies. Dowling et al. (1998) claimed that the Akcelik curve is as accurate as the updated BPR curve and has the advantage of correctly predicting the linear impact of congestion on speeds. The Akçelik curve results in significantly improved traffic assignment run times and provides more accurate speed estimates than the standard or modified BPR curves (Dowling, Singh, and Cheng 1998). In the Akcelik function, link parameters (i.e., capacity, free speed, etc.) are allocated globally based on defined link type. The Akcelik function has variables to assess intersection approach delays as well. Intersection approach capacities are based on simple gap-acceptance theory and have special procedures for modeling over-capacity conditions on the motorway (Akcelik 1991).

When evaluating data for demands less than the approach capacity, many equations perform equally as well. The fitted BPR, fitted exponential, and the fitted Akcelik equations all performed equally as well. The fitted Akcelik equation performed slightly better because it adds signal delay to the segment free-flow travel time, rather than treating delay as a multiplicative factor of the segment length, as is done in the BPR and exponential equations (Dowling et al., 2008).

When evaluating the speed-flow equations against theoretical delays for hourly demands greater than hourly capacities, only the Akcelik equation produced the expected delays due to oversaturated conditions at the downstream signal on a street segment. The other equations significantly underestimated delay within the 1.00 to 2.00 v/c range. At significantly higher v/c's the BPR curve eventually catches up to and surpasses the delay estimates produced by queuing theory and the Akcelik equation.

The ideal speed-flow curve would not cross the theoretical solid line for queue delay. As can be seen, both the standard and fitted BPR curves cross the theoretical queuing delay line. Both of these curves underestimate the delay due to queuing when demand exceeds the real world capacity of an intersection at the end of the link. The fitted Akcelik curve is consistent with the queue delay line, because the Akcelik curve is derived from classical queuing theory.

Kalaee (2010) found that that for v/c < 1, the calibrated BPR functions has the best overall performance among tested models for studied locations, but standard BPR functions overestimate travel times for v/c ratios close to 1. The conical function highly overestimates travel times for v/c < 1. The conical function assumes that the travel time at capacity is two times larger than the free-flow travel time, which is not always true. When v/c > 1, the Akçelik and the HCM 2000 models were found to be the most consistent models with queuing theory. The Akçelik and HCM 2000 models underestimate travel times for v/c < 0.9 and overestimate travel times for v/c close to 1. Akcelik has two components - segment (link) delay and intersection (node) delay. Total delay is the sum of both link delay and node delay.

$$t = t^l + t^n \quad \text{Eq. (2.5)}$$

$$t^l = t_f^l + 0.25T\left[(X-1) + \sqrt{(X-1)^2 + \frac{8J_AX}{cT}}\right] \quad \text{Eq. (2.6)}$$

$$t^n = 0.5C\,\frac{(1-g/C)^2}{1-Xg/C} \quad \text{Eq. (2.7)}$$

Where, t = Total delay

t^l =Segment delay,

t^n = Intersection delay,

t_f^l= Free-flow travel time per unit distance,

X = Degree of saturation (volume-to-capacity ratio),

T = Duration of analysis period (h),

c = Capacity (vph),

J_A= Delay parameter (unitless),

g = Green time,

C = Cycle length

The delay parameter J_A corresponds to the quality of service provided by the road section and is independent of the traffic flow but sensitive to the value of travel time at capacity (Dowling et al. 2004; Akcelik 1991). To obtain a rough estimate of the delay parameter, Akcelik provided the following formula:

$$J_A = \frac{2c}{T}(t_c - t_0)^2 \qquad \text{Eq. (2.8)}$$

Where, t_c: Travel time at capacity

t_0: Travel time at free flow

When evaluating data for demands less than the approach capacity, many equations, including the fitted BPR, the fitted exponential, and the fitted Akcelik functions, all performed equally well. However, the BPR type curves underestimate the delay due to queuing when demand exceeds the real world capacity of an intersection at the end of the link.

The fitted Akcelik curve is consistent with the queue delay line because the Akcelik curve is derived from the classical queuing theory. When v/c > 1, the Akcelik and the HCM 2000 models were found to be the most consistent with queuing theory (Dowling and Skabardonis 2008). In addition, the Akcelik equation assumes no initial queue at the start of the flow period. The HCM 2000 suggests the modified speed-flow equation that calculates the extra delay caused by the leftover queue from the prior period and adds to the Akcelik equation (Dowling et al. 2004; Transportation Research Board 2000).

Recently, a couple of researchers used surrogate measures to consider over saturated traffic conditions in parameter calibration (Lee and Munn 2009; Klieman et al. 2011; Huntsinger and Rouphail 2011). V/C was derived by dividing the given density by the density at the maximum flow (capacity), so that the oversaturated traffic condition at V/C>1.0 was available to be used in curve fitting with data (Lee and Munn 2009; Klieman et al. 2011). The measured queue at the bottleneck was added to the capacity at the bottleneck to adjust demand, which was used to calculate the Demand over Capacity (D/C) ratio as a surrogate measure of V/C in VDF calibration (Huntsinger and Rouphail 2011).

Intersection delay at intersection

Although recent research efforts considered the delay at a node, including signalized intersections (Mazloumi, Moridpour, and Mohsenian 2010; Paschai, Yu, and Mirzaei 2010), they used BPR type functions for link delay estimation and their application is limited to undersaturated traffic conditions. The functional form of VDF should be continuous, monotonically increasing, and differentiable to guarantee convexity, convergence, and unique solution, and must be defined for oversaturated regions as well (Sheffi 1984).

The Davidson function is not defined for flows over the practical capacity, and the travel time goes to infinity as the link flow approaches the practical capacity.

Akcelik proposed modified forms of Davidson's function to obtain finite values of travel time for flows near and above capacity (Akcelik 1991). As identified by Akcelik, his function does relate to intersection delay modeling and indeed forms the basis of the SIDRA intersection modeling software. For interrupted facilities, replace the free-flow travel time t_f with t_0.

$t_0 = t_n + d_m$ *, which is the travel time in seconds at zero flow*

d_m *i*s the minimum delay per unit distance (sec/km) at zero flow conditions

$d_m = 0$ for uninterrupted facilities.

$d_m = 0.5r(1-u)$, *at a signalized intersection with zero flow (or flow ratio y=0)*

$$= 0.5C\frac{(1-u)^2}{1-y} = 0.5C\frac{(1-u)^2}{1-xu}$$

$$= 0.5C\frac{(1-g/C)^2}{1-Xg/C}$$

Where $r =$ effective red time

u = green time ratio (g/C)

g=green time and

C=cycle length

From the comprehensive comparison of different VDFs, Cetin et al. (2011) proposed the below recommendations for choosing the correct VDFs;

- If link counts are used, use the BPR function and Genetic Algorithm (GA) to optimize the VDF parameter values.
- BPR parameters range $0<\alpha<2.0$ and $1.0<\beta<10.0$.
- If speed-volume data is used, the Akcelik equation provides more realistic travel times than the conical and BPR functions, especially when v/c exceeds 1.0.

2.5 Chapter Summary

This chapter provided an overview of the long range transportation planning (LRTP) process and travel demand forecasting modeling (TDFM). The various incident models for forecasting frequency, duration, reduced capacity and VDFs were reviewed. Research literature has indicated that the incident duration modeling is difficult due to the lack of data availability at some facilities, and linguistic and/or subjective variables such as weather conditions and incident severity. A recent research showed that the URP trees and hybrid tree-based quantile regression model has a higher prediction accuracy than previous models. There is literature to suggest that incident capacity reduction is a random variable rather than a deterministic value due to the variations in incident characteristics.

For incident impact analysis using network simulation tools and/or travel demand forecasting models, researchers used a simple incident case on a toy network to examine the incident impact on the network without taking into account specific incident situations, like crash type, frequency, duration, capacity reduction, etc.

Regarding the VDFs, there are many advanced analytical applications regarding volume delay functions for the TDFM. Even though BPR type functions are still widely used in TDFM applications, it cannot explicitly consider delays due to oversaturation conditions and intersections. Unlike the BPR function, the Akcelik function considers oversaturation conditions and delays at both the node and link simultaneously. The Akcelik curve is as accurate as the updated BPR curve and has the advantage of correctly predicting the linear impact of congestion on speeds. The fitted Akcelik curve is consistent with the queue delay line because the Akcelik curve is derived from classical queuing theory.

CHAPTER 3. METHODOLOGY AND DATA PREPARATION

3.1 A Framework Incorporating Incident Impact in the TDFM

Figure 3.1 shows the proposed framework of the TDFMI. There are three major differences when TDFMI is compared to the traditional TDFM. As shown in the green shaded steps in Figure 3.1, the major differences between TDFM and TDFMI are: the use of incident-related data as additional network information and the Traffic Assignment step in the four step modeling process. Prior to running the traditional four step model, incident data and incident-related traffic data are prepared. For the 2009 base year model, historical incident data are analyzed and prepared for individual weekdays as key inputs of TDFMI.

For the 2034 future year model, annual incidents are forecasted and assigned on future networks. In order to forecast future incidents, loaded link volumes from future TDFM, the safety performance function (SPF), and incident forecasting models are used. Both base year and future year incident data are incorporated into the existing base year and the future year TDFM networks with additional node and link attributes later. Networks incorporating incident data, referred as TDFMI networks, have three incident related attributes: incident frequency, reduced capacity, and incident duration.

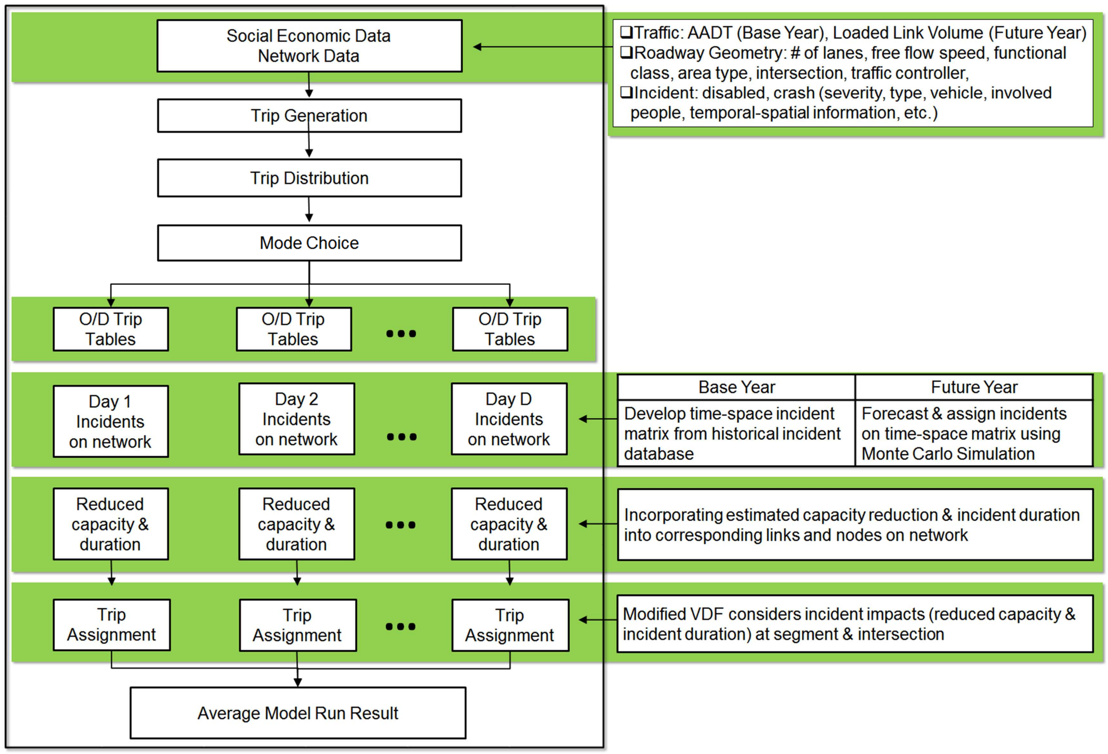


Figure 3.1 Framework of TDFMI for Incorporating Incident Impact into Travel Demand Forecasting Modeling Process

As opposed to the traditional TDFM structure that has a feedback loop between trip distribution through trip assignment, the TDFMI, on this dissertation research, assumes that all input/outputs from three steps (i.e., trip generation, trip distribution, and mode choice) prior to traffic assignment are not changed and remain the same for the whole modeling process. The main reason why this assumption is more reasonable in the TDFMI is that travelers rarely have the perfect information on incidents that occur randomly in the model area. If the feedback loop between trip distribution and trip assignment in the TDFM was applied to the TDFMI, there would be a significant influence in the highway skims that determine the amount of trips between origin and destination in the trip distribution step. This overestimated impact would be propagated and exaggerated in the sequential steps - mode choice and trip assignment. This is obviously a different situation with the typical case for the scenario analysis, such as a long term road closure for road work.

TDFMI addresses short term route choices made in response to unforeseen incidents. Accordingly, it would not be appropriate to use such network conditions—which change daily—to modify the trip generation, distribution, or mode choice steps. Thus, there is not a feedback loop from the results of this traffic assignment piece to these earlier steps. If one had reason to believe, however, that somehow knowledge of incidents should inform travelers' long term residential, employment, and mode choices, then the computational complexity increases. (Note that the required model execution time would be more than doubled since one would have to re-execute the steps of trip distribution, mode choice, and traffic assignment until convergence was achieved.)

For the base year model, since incident records vary for each of the 249 individual weekdays in 2009, 249 TDFMI networks, one for each weekday are prepared for the 249 runs of traffic assignments. Weekends and holidays are excluded from this study as the TDFM and the TDFMI have focused on weekday traffic. For the future year model, multiple TDFMI networks are also prepared to consider daily variation of incident impact on the network. Existing O/D trip tables, after the mode choice step, are used with TDFMI networks in the traffic assignment step. In the traffic assignment step, VDF is modified to accommodate incident impacts (incident frequency, reduced capacity, and incident duration) within its functional form.

For the base year model, traffic assignment is repeated 249 times with different TDFMI networks to simulate the incident impact of each of the 249 individual weekdays in 2009. Then, the results of 249 individual runs of TDFMI are averaged to make an annual average result. Final TDFMI results are compared with results from the TDFM that ran just once in the model evaluation.

3.2 TDFM Data Preparation

3.2.1 Existing TDFM

To apply the proposed TDFMI to a large size real model, this dissertation study uses the Hampton Roads TDFM. Hampton Roads is the largest MPO area in Virginia, USA. Many local jurisdictions in Northern Virginia area do not have their own MPO for TDFM but are part of the MPO of Washington D.C. Hampton Roads TDFM was recently developed with various modeling resources, including: 2009-2010 NHTS, 2009 VEC, ESRI Business Analyst, GIS resources (RNS and NavTeq), INRIX, TMS traffic database, and external-to-external origin-destination survey. Hampton Roads TDFM consists of four time-of-day models covering am peak, midday, pm peak, and night time. The TDFM network, as shown in Figure 3.2, consists of 1,094 TAZs, 21,160 nodes, 39,372 links, and 6,723 intersections or junctions. It covers freeways, major arterials, minor arterials and major collectors in the modeling area. The network also includes minor collectors and local streets to provide appropriate connectivity in the network.

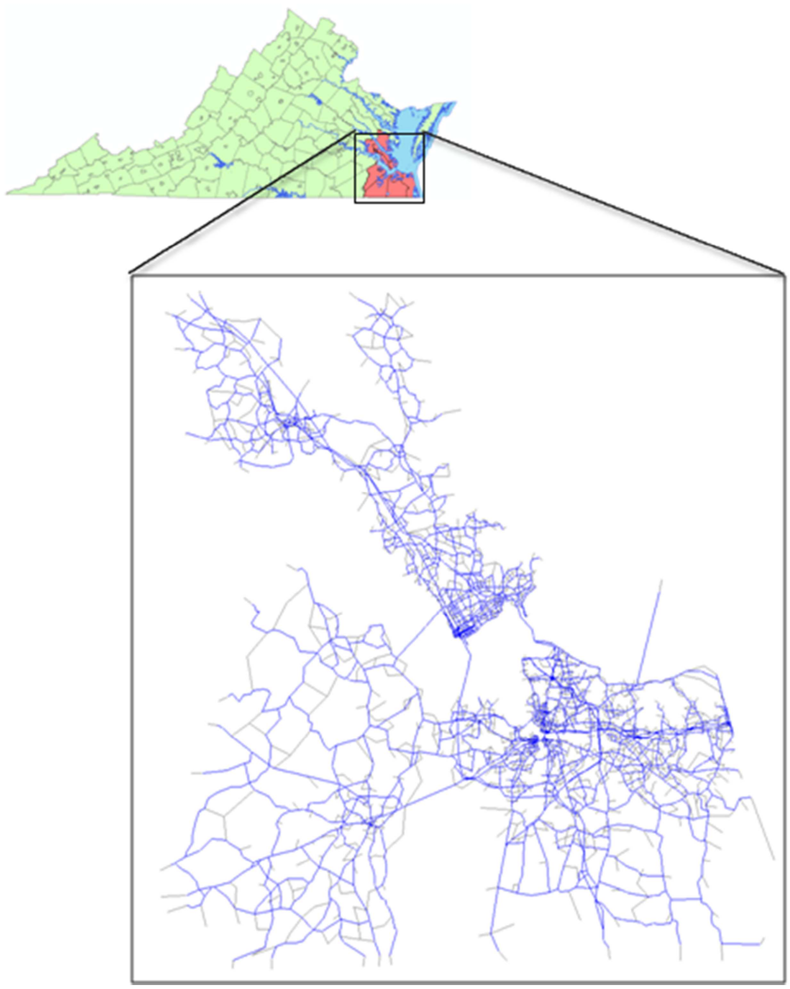


Figure 3.2 Hampton Roads TDFM Network (2009 Base Year)

The Hampton Roads TDFM model area comprises 13 jurisdictions – Gloucester County, Isle of Wight County, James City County, York County, City of Chesapeake, City of Hampton, City of Newport News, City of Norfolk, City of

Poquoson, City of Portsmouth, City of Suffolk, City of Williamsburg and City of Virginia Beach.

Table 3.1 shows land use data information relating to households, population, the number of vehicles, retail employment, and non-retail employment for the model area.

Table 3.1 Base Year (2009) Land Use Data

Data	Number
Total Households	606,902
Total Population	1,627,273
Total Autos	1,263,199
Total Retail Employment	187,111
Total Non-Retail Employment	853,826

The area type of a zone was determined by the density of the population and employment of each zone. Both density thresholds were split into seven categories based on visual observations (AECOM 2013). Based on the combination of two densities in the entire modeling region, area types are categorized as Central Business District (CBD), Urban, Dense Suburban, Suburban and Rural (AECOM 2013). Hampton Roads area has TAZ 1 through TAZ 1,503 but consists of 1,464 internal TAZs and 30 external TAZs. HR TDFM has totally 12 facility types based on their function and/or design characteristics associated with area type and the development density of each link (AECOM 2013). The combination of area type and facility type determines the free flow speed and capacity, which was developed as a cross-classification table.

Figure 3.3 shows the major bridges, tunnels, toll roads, and HOV lanes in Hampton Roads.

Figure 3.3 Bridges, Tunnels, Tolls, and HOV Lanes in Model Area

The Hampton Roads area has the following High Occupancy Vehicle (HOV) Lane corridors during peak hours (6-8 AM and 4-6 PM):

- I-264 between Virginia Beach and Norfolk
- I-64 between Norfolk and Chesapeake (reversible divided HOV for some segments)
- I-64 between Hampton and Newport News

As shown in Figure 3.3, the Hampton Roads area has the following bridges and tunnels, which form the bottlenecks of major roadways:

- Hampton Roads Bridge Tunnel (HRBT) on I-64
- Monitor Merrimac Memorial Bridge-Tunnel (MMMBT) on I-664
- James River Bridge on Route 17
- Downtown Tunnel on I-264
- Midtown Tunnel on Route 58
- Chesapeake Bay Bridge Tunnel on Route 13 (Toll)
- George P. Coleman Bridge on Route 17 (Toll)
- Berkley Bridge on I-264
- High Rise Bridge on I-64
- Gilmerton Bridge on Route 13/460
- Jordan Bridge on Route 337 (Toll)
- Chesapeake Expressway (Toll)

Since Hampton Roads has limited roadway connections, with bridges and tunnels between regions, vehicle traffic is interrupted when bridges and tunnels are closed, which has a significant negative impact to the region. Incidents at bridges and tunnels will be analyzed in Chapter 3.3.

There are four toll facilities in the Hampton Roads area. Three toll facilities are located on bridges and one is located on Route 168 near the state boundary with North Carolina. In the TDFMI, two fixed toll locations (George P. Coleman Bridge and Chesapeake Expressway) were modeled and two locations were excluded; the Chesapeake Bay Bridge Tunnel was coded as an external TAZ, which trip was given as fixed input, and the Jordan Bridge was closed for construction in 2009. Transit routes are operated by Hampton Roads Transit (HRT) and Williamsburg Area Transit Authority (WATA).

As a reference model, the existing TDFM was run and all results were saved for comparisons with those of TDFMI. Using incident and crash data from 2009, incident duration was calculated first, and reduced capacity was determined using a cross-classification table developed from research literature (Chin et al. 2004; Transportation Research Board 2010).

Free flow speed and link capacity were determined using a cross-classification table based on facility type and area type, which was developed from the old Hampton Roads TDFM. Free flow speed was updated using observed speed data by INRIX.

3.2.2 Existing Volume Delay Functions (VDFs)

Conical VDF developed by Spiess was used in the Hampton Roads TDFM due to its geometrical interpretation and its ability to deliver optimal calibration results from VDFs at the preliminary analysis level under a limited time schedule (AECOM 2013). The hyperbolic conical sections is defined below (AECOM 2013). Functional form and used parameters are shown in Equation (3.1.) and Table 3.2.

$$T = T_0 * \left\{2 + [\alpha^2 * (1 - V/C)^2 + \beta^2]^{1/2} - \alpha * (1 - V/C) - \beta\right\} \quad \text{Eq. (3.1)}$$

where, T = average link travel time

T_0 = link travel time at free-flow status

V = volume (or demand)

C = capacity

B $= (2\alpha - 1)(2\alpha - 2), \alpha > 1$

Table 3.2 Parameters of Conical VDF Used in the Model

Facilities	Alpha	Beta
Freeways	9.0	1.06
Minor Freeways/Principal Arterials	7.0	1.08
Major/Minor Arterials, Major Collectors	4.5	1.14
Minor Collectors/Locals	2.0	1.50

Source: (AECOM 2013)

Cetin et al. (2012) conducted VDFs calibrations for MPO models in Virginia. They examined BPR, Conical, and Akcelik VDFs and recommended BPR functions under general conditions and Ackelik Functions for congested conditions.

Since the Hampton Roads area has a very high portion of heavy truck traffic from/to port facilities and numerous freight warehouses, truck traffic of Class 6 or higher, based on the FHWA vehicle classification definition, was modeled using a truck model (AECOM 2013). The truck trip generation and distribution models were developed separately. Truck zones were identified to estimated truck trips as special generators (AECOM 2013).

3.2.3 Base Year TDFM Mode Run Statistics

Table 3.3 shows the performance measures (%RMSE and volume over count ratio) of the TDFM base year model runs statistics, using 3,287 links that have traffic observations. Performance measures were categorized within three subgroups: loaded link volume group, facility type, and area type. Virginia Travel Demand Modeling Policies and Procedure Manual (VTM PPM) defined the validation criteria and their target values (Virginia DOT 2011). In the case of a large MPO model such as the Hampton Roads TDFM, validation standards are shown below:

- R^2 for the Model Region > 0.90
- Percent RMSE for Model Region < 40%
- Percent RMSE by Facility Type:
  - Freeways < 20%

- Principal Arterials < 35%
- Minor Arterials < 50%
- Collectors < 90%

Overall, the performance measures of the model show that %RMSE is very close to the threshold and volume-to-count ratio is very close to 1.0. However, when it comes to %RMSE per facility type, not all TDFM results exceeded the threshold of %RMSE. Freeways %RMSE exceeded the threshold 20% and appeared to be under-assigned from the volume-to-count ratio. Meanwhile, arterials and collectors were less than the thresholds of 35% and 50%, respectively. However, arterials and collectors appeared to be over-assigned when compared to field counts.

Table 3.3 2009 Base Year TDFM Model Run Statistics

	Subgroup	Count	Sites	% RMSE	Volume	Volume/Count
Loaded Link Volume	1 - 5,000	3,585,574	1,599	72.13	4,196,262	1.17
	5,000 - 10,000	5,315,469	752	40.13	5,632,658	1.06
	10,000 - 20,000	9,044,430	637	29.12	9,247,413	1.02
	20,000 - 30,000	4,205,604	174	25.17	3,939,216	0.94
	30,000 - 40,000	1,870,669	55	20.43	1,847,092	0.99
	40,000 - 50,000	1,982,331	45	18.52	1,785,410	0.90
	50,000 - 60,000	1,048,384	19	24.50	957,715	0.91
	60,000 - 70,000	195,459	3	30.26	158,896	0.81
	70,000 - 80,000	223,816	3	21.05	178,167	0.80
Facility Type	Interstate Freeway	5,347,521	150	23.24	5,177,018	0.97
	Minor Freeway	1,303,229	72	27.20	1,306,282	1.00
	Principal Art	6,335,433	394	30.47	6,751,022	1.07
	Major Art	1,586,969	180	38.54	1,502,746	0.95
	Minor Art	9,790,532	1,248	38.94	9,996,655	1.02
	Major Collector	408,273	228	71.60	425,635	1.04
	Minor Collector	2,600,421	972	63.86	2,692,414	1.04
	Local	29,782	36	43.38	29,803	1.00
	H.S. Ramp	27,812	1	27.32	20,213	0.73
	L.S. Ramp	41,764	6	57.32	41,042	0.98
Area Type	CBD	128,030	10	68.11	62,859	0.49
	OBD	5,342,234	525	38.90	5,323,046	1.00
	Urban	6,174,351	703	35.79	6,231,953	1.01
	Sub Urban	7,328,412	778	41.64	7,236,930	0.98
	Rural	8,498,709	1,271	43.35	9,088,041	1.07
All		27,471,736	3,287	40.98	27,942,829	1.02

3.3 Incident Data Preparation for Base year

As reviewed in Chapter 2, this dissertation considered three major incident factors in developing the TDFMI: incident frequency, incident duration, and the reduced capacity resulting from the incident. From the 2009 incident dataset for the base year, three key incident data (frequency, duration, and reduced capacity) were prepared first. Incident data were matched with corresponding links and nodes of the TDFM network by using geographic location information on GIS software. During the GIS matching process, each individual incident record was identified as either segment or intersection incident based on the intersection boundary. After matching incident data with the TDFM network, data on the three key incident factors were merged with the TDFMI network as additional link attributes. Figure 3.4 shows the flow of how incident data was prepared for the base year.

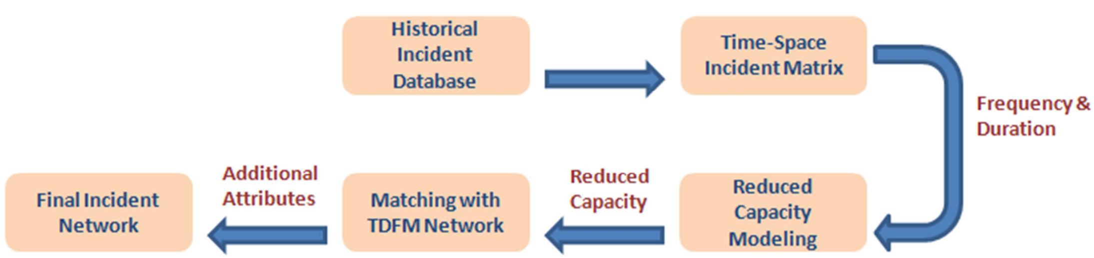


Figure 3.4 Flow of Incident Data Preparation for Base Year

3.3.1 Incident Frequency

This study utilized incident data from the Virginia DOT's traffic database, referred to as VaTraffic, which categorizes incidents into five types: incident, event, planned event, short term weather, and long term weather (Virginia DOT 2011). Short term weather events are defined as localized weather events in a small area, such as fog, high winds, and standing water. Long term weather incidents include large, widespread weather events, such as hurricanes, flooding, or snow/ice storms (Virginia DOT 2011). Within the "incident" category, incidents are further divided into three sub-categories: traffic, disaster, and security. For the traffic incident category, VaTraffic has collected data on vehicle crashes (recorded as accidents), disabled vehicles, bridge/tunnel stoppage, and other traffic incidents (Virginia DOT 2011). The key information on each incident include: time, location, duration, facility type, crash severity, number of total lanes, number of affected lanes, etc. VaTraffic incident data are entered by staff members from the one of five Regional Transportation Operations Centers and tunnel facilities in the Hampton Roads area. Incident data is entered close to real-time, with minimal time delay, as it is entered by the Virginia State Police, Safety Service Patrol, or observed on cameras, etc. (Rose Lawhorne 2013).

VaTraffic database had, in total, 20,046 incident records with various incident related information within the Hampton Roads modeling boundary in 2009. Table 3.4 shows the cross-classification of incident frequency between major categories, including time of day, roadway types, and incident types. Table 3.5 and Table 3.6 show the proportion of incident frequency by category and the component ratio within each category.

When it comes to the category ‘Time of Day (TOD)’, about 15% and 23% of incidents occurred during the AM peak (6 AM to 9 AM) and PM peak periods (3 PM to 6 PM), respectively, while 41% and 21% of incidents occurred during the Midday (9 AM to 3 PM) and Nighttime (6 PM to 6 AM of next day) periods, respectively. About 38% of incidents occurred during the peak periods (a duration of six hours), while 62% of incidents occurred during the non-peak periods (a duration of 18 hours). It was found that the PM peak period had the highest incident rate per hour, which is equivalent to 8% of daily incidents. On the contrary, the Nighttime period had the lowest incident rate per hour, which is about 2% of daily incidents.

From the incidents by roadway facility types, as shown in Table 3.5, about 24% of incidents occurred at interstate freeways. Over three quarters of disabled vehicle incidents and congestion/delay incidents occurred at special facilities, such as bridges and tunnels, which contributed to 71.5% of all incidents that occurred at special facilities. As shown in Figure 3.3, there are many bridges and tunnels on interstate freeways and major arterials. Bridges and tunnels are known as major traffic bottlenecks in Hampton Roads. When examining incidents at special facilities by incident types, as shown in Table 3.5, it was found that a very high proportion of incidents occurred at special facilities, such as bridges and tunnels. It was found that 78% of incidents at special facilities were categorized as bridge/tunnel stoppage (43.5%) and congestion/delay (34.4%), as shown in Table 3.6.

Consequently, bridge/tunnel stoppage and congestion/delay at a bridge/tunnel contributed to more than 55% of total incidents in the Hampton Roads area. Selected bridges are frequently closed at the request of vessel traffic passing through under the bridges. Temporary bridge closures are typically arranged in advance with bridge operation agencies.

Since the majority of incidents were found at interstate freeways and bridges/tunnels, less than 5% of incidents were found at the primary and secondary roadways, as shown in Table 3.5 and Table 3.6. The reason why such a small proportion of incidents were found at the primary and secondary roadways is that VaTraffic has been more focused on the safety and mobility of interstate freeways and special facilities in Hampton Roads.

VaTraffic incident records categorize incident types as: crashes (17.9%), congestion/delay (32%), bridge/tunnel stoppage (31.1%), disabled vehicles (14.3%), and other (4.7%), as shown Table 3.6. Other incidents encompasses all other types of incidents, including vehicle fire, security, brush fire, chemical, other disaster, etc. (Virginia DOT 2012).

When incidents were broken down by time-of-day and incident type, as shown as Table 3.6, it was found that different types of incidents occurred at different times during the day. Congestion/delay incidents were the most common during both AM and PM peak periods, while bridge/tunnel stoppage incidents occurred most frequently during MD and NT non-peak periods. Indeed, congestion/delay incidents comprised of 48% and 46% of total incidents in the AM and PM peak periods, while incidents at bridges/tunnels accounted for 44% and 32% of total incidents during MD and NT periods, respectively.

When incidents are analyzed by incident type and roadway type, as shown in Table 3.5, it was found that about 78% and 18% of crashes occurred at interstates and special facilities, such as bridges/tunnels, respectively. Interestingly, most of the non-crash incidents occurred at special facilities (bridges and tunnels).

Table 3.4 Incident Frequency per Subcategory

Counts		Roadway Type					Incident Type					Row Sum
		Interstate	Primary	Secondary	Special	Others	Crash	Disabled Vehicles	Bridge/ Tunnel	Congestion / Delay	Others	
Time of day	AM	534	225	-	2,246	1	487	408	579	1,433	99	3,006
	MD	1,274	301	7	6,638	9	976	914	3,641	2,331	367	8,229
	PM	1,531	183	8	2,912	13	955	692	705	2,115	180	4,647
	NT	1,421	187	10	2,539	7	1,173	846	1,310	537	298	4,164
Roadway Type	Interstate						2,793	689	2	888	388	4,760
	Primary						114	8	3	591	180	896
	Secondary						18	-	-	-	7	25
	Special						644	2,162	6,230	4,936	363	14,335
	Others						22	1	-	1	6	30
Column Sum		4,760	896	25	14,335	30	3,591	2,860	6,235	6,416	944	20,046

Note: Special Roadway Type represents Tunnels and Bridges

Table 3.5 Proportion of Incident Frequency per Subcategory by Column Sum

		Roadway Type					Incident Type					Row Average
		Interstate	Primary	Secondary	Special	Others	Crash	Disabled Vehicles	Bridge/ Tunnel	Congestion / Delay	Others	
Time of day	AM	11.2	25.1	-	15.7	3.3	13.6	14.3	9.3	22.3	10.5	15.0
	MD	26.8	33.6	28.0	46.3	30.0	27.2	32.0	58.4	36.3	38.9	41.1
	PM	32.2	20.4	32.0	20.3	43.3	26.6	24.2	11.3	33.0	19.1	23.2
	NT	29.9	20.9	40.0	17.7	23.3	32.7	29.6	21.0	8.4	31.6	20.8
Roadway Type	Interstate						77.8	24.1	0.0	13.8	41.1	23.7
	Primary						3.2	0.3	0.0	9.2	19.1	4.5
	Secondary						0.5	-	-	-	0.7	0.1
	Special						17.9	75.6	99.9	76.9	38.5	71.5
	Others						0.6	0.0	-	0.0	0.6	0.1
Column Sum		100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Note: Special Roadway Type represents Tunnels and Bridges

Table 3.6 Proportion of Incident Counts per Subcategory by Row Sum

		Roadway Type					Incident Type					Row Sum
		Interstate	Primary	Secondary	Special	Others	Crash	Disabled Vehicles	Bridge/ Tunnel	Congestion / Delay	Others	
Time of day	AM	17.8	7.5	-	74.7	0.0	16.2	13.6	19.3	47.7	3.3	100.0
	MD	15.5	3.7	0.1	80.7	0.1	11.9	11.1	44.2	28.3	4.5	100.0
	PM	32.9	3.9	0.2	62.7	0.3	20.6	14.9	15.2	45.5	3.9	100.0
	NT	34.1	4.5	0.2	61.0	0.2	28.2	20.3	31.5	12.9	7.2	100.0
Roadway Type	Interstate						58.7	14.5	0.0	18.7	8.2	100.0
	Primary						12.7	0.9	0.3	66.0	20.1	100.0
	Secondary						72.0	-	-	-	28.0	100.0
	Special						4.5	15.1	43.5	34.4	2.5	100.0
	Others						73.3	3.3	-	3.3	20.0	100.0
Column Average		23.7	4.5	0.1	71.5	0.1	17.9	14.3	31.1	32.0	4.7	100.0

Note: Special Roadway Type represents Tunnels and Bridges

Even though VaTraffic provides very useful incident information, it has incomplete crash records in the Hampton Roads area because VDOT has primarily focused its resources on reporting incidents on interstate freeways and special facilities, such as bridges/tunnels. Thus, crash data compiled by the Virginia Department of Motor Vehicles (DMV) was used to account for the missing incident data on primary and secondary roadways, and complete the crash data analysis. Virginia DMV's crash database includes all crash records reported by police officers, which includes crashes involving death, injury, or total property damages exceeding $1,000.

The DMV's crash database contains 121,143 crash records that originated from all over the state in 2009. Hampton Roads had 20,176 crashes within its jurisdiction boundary. However, the DMV's crash database also lacks information that is required in this research: 1) how long traffic was blocked (or affected) due to the crash and 2) accurate location where each crash occurred. Not all crash records have locatable data. Only 11,686 crash records (57.9%) included latitude and longitude coordinates and even then, 9.1% of those records (1,068 crashes) listed incorrect location information.

Figure 3.5 plots the location of each individual crash record by latitude and longitude information using data from the DMV's crash database. As shown, many crashes were located in the North Carolina area or even in the sea. Most of the incorrect locations appear to have been systematically shifted from actual locations. Thus, for crash records with invalid locations, new locations were generated using roadway route information (route prefix, route number, route suffix, and mile point) available from each crash record in the DMV database.

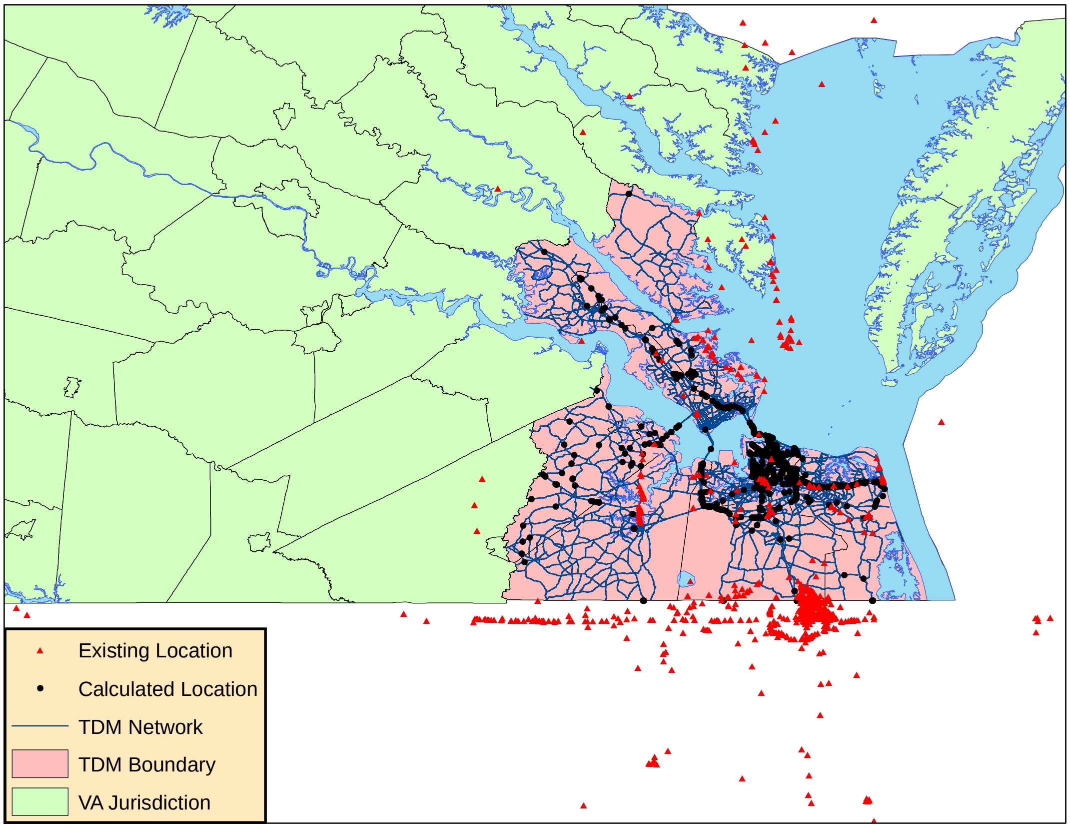


Figure 3.5 Location of Crash Data Before and After Adjustment

This study generated new Route IDs based on routable information for two purposes: 1) to double check if the given latitude and longitude coordinates on the DMV's crash records were correct and 2) to generate new Route IDs for the crash records with invalid location information. Each new Route ID consists of 14 digits of three components: a route prefix (4 digits), a route number (5 digits), and a route suffix (5 digits). The final latitude and longitude coordinates of each crash record were determined by a mile point indicating the distance from the starting point of

Route IDs. Table 3.7 shows examples of new Route IDs and new latitude and longitude coordinates based on routable information (route prefix, route number, route suffix, and mile point).

Table 3.7 Example of New Route ID and X-Y Coordinates

Prefix	Route No.	Suffix	New Route ID	Mile Point	New Latitude	New Longitude
134	8669		13408669	0	-76.003991	36.550387
SR	165		SR00165	0	-76.344216	36.740913
C1SR	168		C1SR00168	12.65	-76.245788	36.749314
IS	264	W	IS00264W	16.58	-76.137144	36.834076
C7US	17		C7US00017	5.23	-76.344888	36.756823
IS	64	E242B	IS00064E242B	0.21	-76.646113	37.25666
IS	64	W	IS00064W	234.5	-76.731263	37.352841
US	58		US00058	496.74	-76.197433	36.85524
US	17		US00017	0	-76.37627	36.550595

After the successful processing of routable data, 93.4% of all crash data have new latitude and longitude. 6.6% of crash records were omitted from this study as no routable information was available in the DMV's crash database. Figure 3.5 shows the final location of each crash record after correcting the ones with invalid location information.

After correcting location information on crash records with invalid data using route information, comparisons were made between the original location coordinates with the corrected location coordinates to examine if the new location coordinates were reliable. After excluding outliers located outside of the Hampton Roads jurisdiction, a total of 10,450 corresponding locations were compared in a XY plot as shown Figure 3.6.

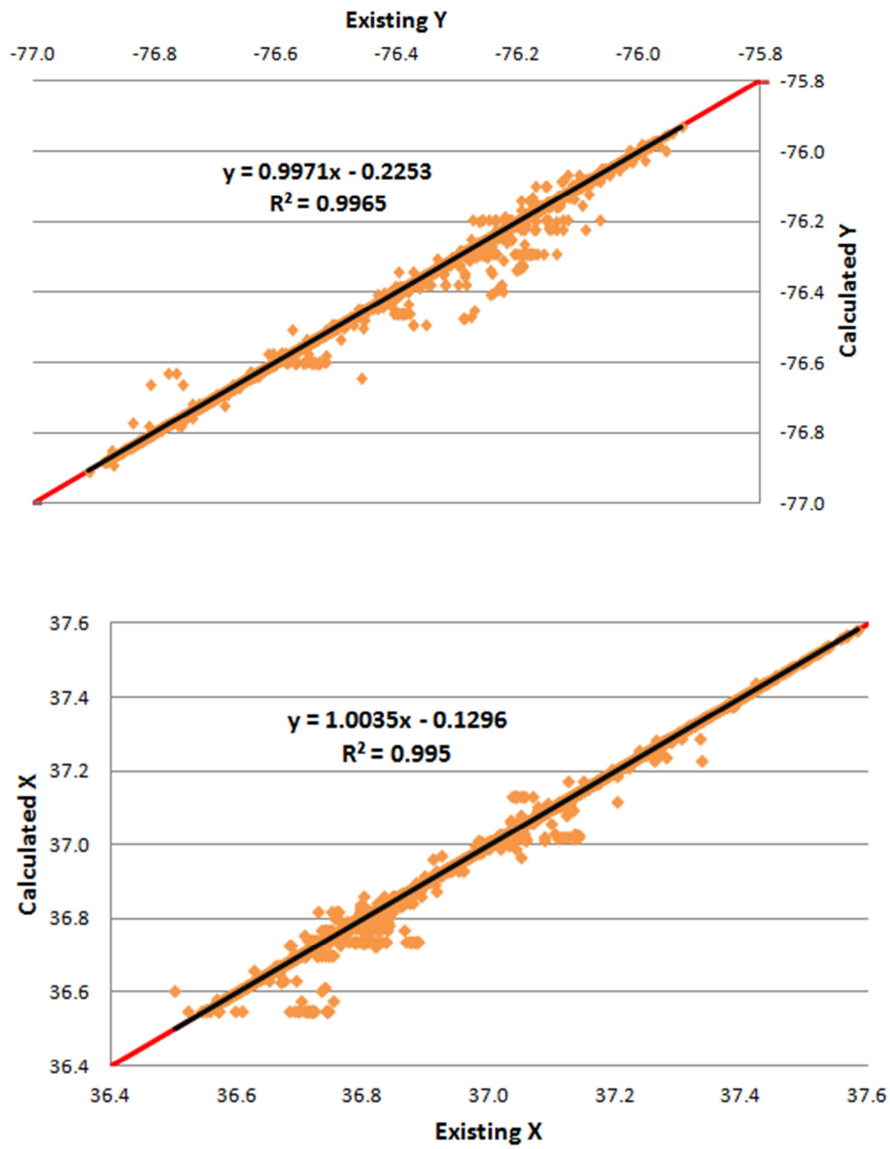


Figure 3.6 Comparisons between Observed and Estimated Coordinates of Longitude (Top) and Latitude (Bottom)

Both latitude and longitude coordinates matched very well. Linear regression models for both cases have $R^2 > 0.995$. Consequently, about 96% of all crash data have new reliable location information, which was used in matching process with TDFM network.

Regarding the crash database, VDOT is currently undergoing a migration process to put all GIS and traffic related resources into a single new database called the Roadway Network System (RNS). The RNS has maintained all crash records that were provided by Virginia DMV throughout the state.

Even though VaTraffic accumulated incident data close to real time from various sources on incidents that occurred on the interstate freeway, and primary and secondary roadways in Virginia, its data heavily relied upon input from personnel.

Table 3.8 shows crash records from VDOT's VaTraffic and DMV's crash database. VaTraffic has only 2% of DMV's crash records on non-freeways, while it has about 73% of DMV's crash records on freeways. It appears that not all crashes on the freeways have been reported to VaTraffic. Even worse, most of the crashes on non-freeways were not reported to VaTraffic. Thus, all crash data used in this dissertation research came from the DMV database, as it has complete crash records, while non-crash incidents all came from VaTraffic to avoid potential duplication.

Table 3.8 2009 Hampton Roads Crash Data from VaTraffic and DMV

Source	Freeway	Non-freeway	Total
Crash in VaTraffic (1)	3,329	262	3,591
Crash in DMV(2)	4,584	15,259	19,843
Percentage (1)/(2)	72.6	1.7	18.1

This study focused on crashes, disabled vehicles, and bridge/tunnel stoppages. Congestion delays were excluded because congestion/delay is a traffic phenomenon during over-saturated traffic conditions, which is not directly related to incidents. Incident type, severity level, and priority level are the key variables used in incident analysis (Virginia DOT 2011)**.**

After excluding crashes and the congestion/delay data from VaTraffic, 6,945 and 3,094 incidents were finally prepared for freeways and non-freeways, respectively. Table 3.9 shows the final cross-classification table of incident data associated with incident type (crash and non-crash incident) and roadway type (freeway, segment of non-freeway, and intersection of non-freeway). Table 3.10 and Table 3.11 also show the percentages of final incident frequency by incident type and roadway type, respectively.

Table 3.9 Final Incident Counts Used in the TDFMI Network

	Freeway	Non-freeway		Row Sum
		Segment	Intersection	
Crashes	4,584	6,727	8,532	19,843
Non-Crash Incidents	6,945	2417	677	10,039
Column Sum	11,529	9,144	9,209	29,882

Table 3.10 Proportion of Final Incident Counts per Roadway Type

	Freeway	Non-freeway		Row Average
		Segment	Intersection	
Crashes	39.8	73.6	92.6	66.4
Non-Crash Incidents	60.2	26.4	7.4	33.6
Column Sum	100.0	100.0	100.0	100.0

Table 3.11 Proportion of Final Incident Counts per Incident Type

	Freeway	Non-freeway		Row Sum
		Segment	Intersection	
Crashes	23.1	33.9	43.0	100.0
Non-Crash Incidents	69.2	24.1	6.7	100.0
Column Average	38.6	30.6	30.8	100.0

More specifically, 66.4% of all incidents are crashes and 33.6% of all incidents are non-crash incidents, as shown in Table 3.10. Freeways have 38.6% of all incidents on the TDFMI network and non-freeways have about 61.4% (30.6% for the segments and 30.8% for the intersections) of all incidents, as shown in Table 3.11. When roadway types are combined with incident types, 40% of all crashes and the 60% of non-crash incidents occurred on the freeways. Regarding non-freeway incidents, 73.6% of segment incidents and 92.6% of intersection incidents are crashes.

Figure 3.7 shows the average daily incident frequency throughout the TDFMI network. Most of the interstate freeways have more than one incident per day and some segments of interstate freeways have higher incident frequencies - up to 10 incidents per day.

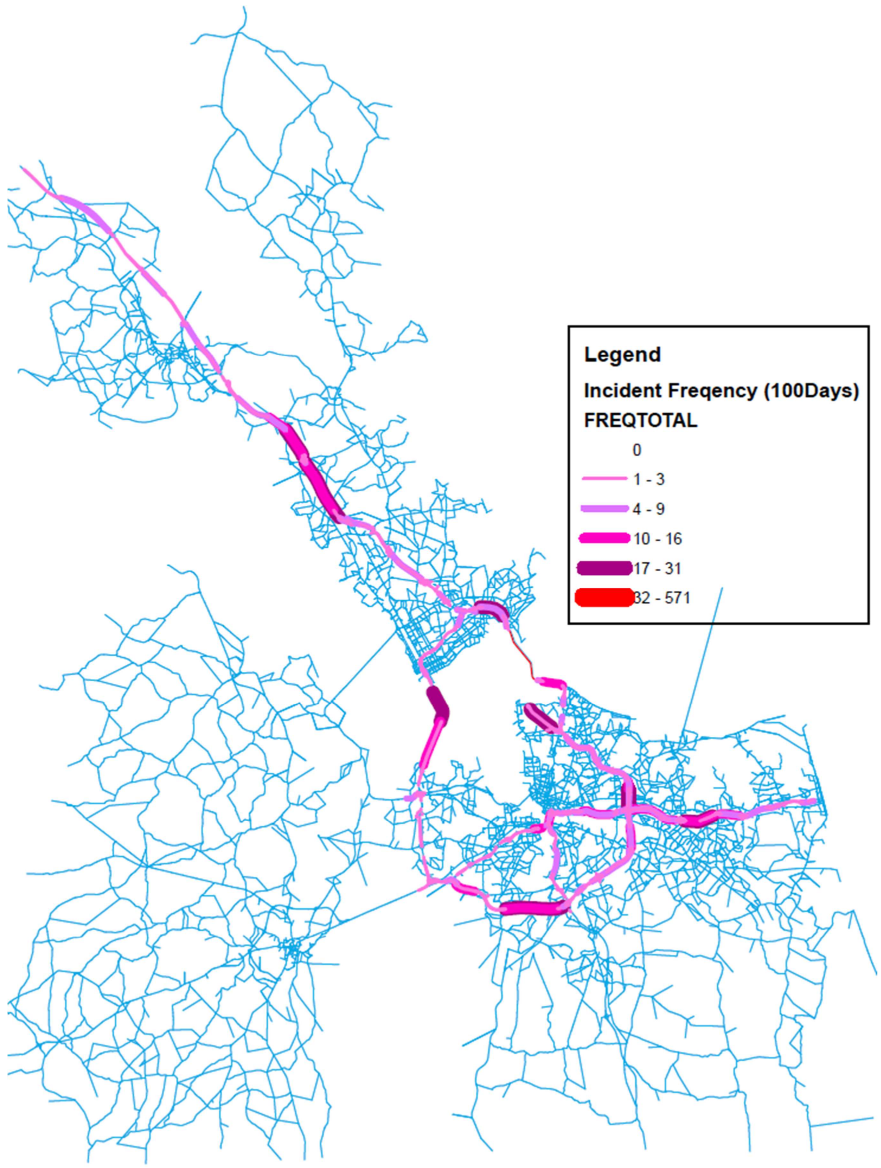


Figure 3.7 Average Daily Incident Frequency on the TDFMI Network

In particular, some segments located at the entrance of key bridges/tunnels, including the Hampton Roads Bridge Tunnel (HRBT) and the Monitor Merrimac Memorial Bridge Tunnel (MMMBT), have very high incident frequencies ranging 10 to 30 incidents per day.

3.3.2 Incident Duration

In VaTraffic, the incident duration is measured since an event is verified and logged in, until all responders have cleared (Virginia DOT 2011). Table 3.12 shows cross-classification tables listing average incident duration by time-of-day, roadway type, and incident type.

The average incident duration varies by time-of-day, roadway type and incident type. AM had the highest incident duration at 64 minutes, while NT had the lowest incident duration at 34 minutes. The average incident duration at interstates and special facilities, such as the bridges/tunnels, were 48 minutes and 40 minutes, respectively, while the average incident duration at primary roadways was 147 minutes. The secondary and other roadway types had too small of a frequency (less than 30) for values to be meaningful.

When it comes to incident duration by incident type, crashes had an average duration of 47 minutes, while the average incident duration at bridges/tunnels was only 6 minutes. Congestion/delay had the highest incident duration time at 99 minutes. When the three categories were combined, it was found that the average duration time at primary roadways was greater than the averages for all four time periods, while duration times at special facilities such as the bridges/tunnels were less than the averages for all four time periods. Regarding the duration on interstate freeways, both AM and PM peak periods had higher duration times than the overall average duration time while both non-peak periods (MD and NT) had lower duration times than the average duration time.

From the incident types, the average durations of the congestion/delays were much greater than the average durations for four time periods. On the contrary, the averages of durations at bridges/tunnels were much smaller than the average durations for all time periods. Regarding the duration of the crash, both AM and PM peak periods had higher durations than the average had while both non-peak periods (MD and NT) had lower duration time than the average had.

Table 3.12Average Duration Time (minute) of Incidents per Subcategory

		Roadway Type					Incident Type					Row Average
		Interstate	Primary	Secondary	Special	Others	Crash	Disabled Vehicles	Bridge/ Tunnel	Congestion/ Delay	Others	
Time of day	AM	44	144	-	61	120	47	17	6	108	45	64
	MD	53	153	296	38	49	48	16	4	114	73	45
	PM	46	126	66	49	55	41	17	6	82	48	51
	NT	47	162	125	17	57	52	17	9	75	46	34
Roadway Type	Interstate						49	24	13	63	48	48
	Primary						100	25	51	160	140	147
	Secondary						88	-	-	-	323	154
	Special						28	15	6	98	19	40
	Others						54	2	-	14	79	56
Column Average		48	147	154	40	56	47	17	6	99	57	47

Table 3.13 shows the cross classification of the incident frequency as shown in Chapter 3.3.1 among duration and three sub-categories: time of day, roadway type, and incident types. The incident duration data were split into five categories from 0 to over 120 minutes with 30-minute intervals.

Table 3.13 Frequency of Incident Duration per Subcategory

		Incident Duration (min)					Row Sum
		< 30	30-60	60-90	90-120	> 120	
Time of Day	AM	1,420	430	280	230	646	3,006
	MD	5,957	802	390	177	903	8,229
	PM	2,469	798	461	317	602	4,647
	NT	2,898	600	338	89	239	4,164
Roadway Type	Interstate	2,068	1,373	767	294	258	4,760
	Primary	121	128	83	60	504	896
	Secondary	6	4	4	2	9	25
	Special	10,538	1,117	611	453	1,616	14,335
	Others	11	8	4	4	3	30
Incident Type	Crash	1,498	1,092	650	201	150	3,591
	Disabled Vehicles	2,539	229	68	15	9	2,860
	Bridge/Tunnel	6,114	71	29	8	13	6,235
	Congestion/ Delay	2,027	1,083	654	553	2,099	6,416
	Others	566	155	68	36	119	944
Column Sum		12,744	2,630	1,469	813	2,390	20,046

Table 3.14 and Table 3.15 show the incident duration category combined with time-of-day, roadway type, and incident types. 56.3% of all incidents on the primary roadways and 36.0% of all incidents on the secondary roadways had an incident duration of greater than 120 minutes. 32.7% of all congestion/delay incidents had an incident duration of greater than 120 minutes.

Table 3.14 shows that 63.6% of all incidents had a duration of less than 30 minutes, 76.7% of all incidents had a duration of less than 60 minutes, and 11.9% of all incidents had a duration of over 120 minutes. When incident duration is analyzed for incidents across all time periods, all roadway types, and all incident types, the majority of incidents had a duration of less than 30 minutes, except for incidents on primary and secondary roadways.

Table 3.14 Proportion of the Incident Duration per Subcategory by Row Sum

		Incident Duration (min)					Row Sum
		< 30	30-60	60-90	90-120	> 120	
Time of Day	AM	**47.2**	14.3	9.3	7.7	21.5	100.0
	MD	**72.4**	9.7	4.7	2.2	11.0	100.0
	PM	**53.1**	17.2	9.9	6.8	13.0	100.0
	NT	**69.6**	14.4	8.1	2.1	5.7	100.0
Roadway Type	Interstate	**43.4**	28.8	16.1	6.2	5.4	100.0
	Primary	13.5	14.3	9.3	6.7	**56.3**	100.0
	Secondary	24.0	16.0	16.0	8.0	**36.0**	100.0
	Special	**73.5**	7.8	4.3	3.2	11.3	100.0
	Others	**36.7**	26.7	13.3	13.3	10.0	100.0
Incident Type	Crash	**41.7**	30.4	18.1	5.6	4.2	100.0
	Disabled Vehicles	**88.8**	8.0	2.4	0.5	0.3	100.0
	Bridge/Tunnel	**98.1**	1.1	0.5	0.1	0.2	100.0
	Congestion/ Delay	**31.6**	16.9	10.2	8.6	**32.7**	100.0
	Others	**60.0**	16.4	7.2	3.8	12.6	100.0
Column Average		**63.6**	13.1	7.3	4.1	11.9	100.0

Table 3.15 shows that the proportion of the incident duration time for each of the three sub categories. Reviewing incident duration by time-of-day showed that 46.7% of all incidents that had a duration of less than 30 minutes occurred during the MD period only. 60.8% of all incidents that had a duration of between 30 and 60 minutes occurred during MD and PM periods. Reviewing incident duration by roadway types showed that the majority of the incidents occurred at the interstate

freeways or special facilities, such as bridges/tunnels, for all incident duration categories. Specifically, the 82.7% of all incidents that had the duration of less than 30 minutes occurred at special facilities.

Table 3.15 Proportion of the Incident Duration per Subcategory by Row Sum

		Incident Duration (min)					Row Average
		< 30	30-60	60-90	90-120	> 120	
Time of Day	AM	11.1	16.3	19.1	28.3	27.0	15.0
	MD	**46.7**	**30.5**	26.5	21.8	37.8	41.1
	PM	19.4	**30.3**	31.4	39.0	25.2	23.2
	NT	22.7	22.8	23.0	10.9	10.0	20.8
Roadway Type	Interstate	16.2	**52.2**	**52.2**	**36.2**	10.8	23.7
	Primary	0.9	4.9	5.7	7.4	21.1	4.5
	Secondary	0.0	0.2	0.3	0.2	0.4	0.1
	Special	**82.7**	**42.5**	**41.6**	**55.7**	**67.6**	71.5
	Others	0.1	0.3	0.3	0.5	0.1	0.1
Incident Type	Crash	11.8	**41.5**	**44.2**	24.7	6.3	17.9
	Disabled Vehicles	19.9	8.7	4.6	1.8	0.4	14.3
	Bridge/Tunnel	**48.0**	2.7	2.0	1.0	0.5	31.1
	Congestion/ Delay	15.9	**41.2**	**44.5**	**68.0**	**87.8**	32.0
	Others	4.4	5.9	4.6	4.4	5.0	4.7
Column Sum		100.0	100.0	100.0	100.0	100.0	100.0

Over 90% of all incidents with a duration of less than 120 minutes, occurred at both the interstate freeways and special facilities. Reviewing incident duration by incident types showed that the majority of incidents (48%) at bridges/tunnels had a duration of less than 30 minutes. The majority of all incidents with a duration of greater than 30 minutes were caused by crashes and congestion/delays.

Duration of Crash Data

As mentioned earlier, the crash records in the DMV's database do not have incident duration information. Since all incident records in VaTraffic have duration information, the crash records in VaTraffic were utilized to generate an incident duration estimation model for DMV's crash records. From the comparison between the DMV's crash database and the VaTraffic incident database, 42 common variables were selected for incident model development.

Various independent variables in different categories associated with crash duration were available, and they interact with each other and are highly correlated. The independent variables used in the model development consists of 42 variables from the three major categories: crash information, roadway geometric information, and environmental information, as shown Table 3.16.

If a single global model, such as a linear or non-linear model, is developed by using the 42 variables, it may be difficult to interpret the model results even if the developed model generates good results, because 42 variables may arguably interact with each other in complicated, non-linear ways. As a result, many independent variables should be modeled for the various features (Shalizi 2006).

As an alternative approach to linear and non-linear regression, a Classification and Regression Tree (CART) model may be used, which can handle data that have non-linear relationships and the interactions between the variables. A CART does not need to specify any functional forms because it is a nonparametric model, and does not need to select variables in advance of developing the model (Roman Timofeev 2004). A CART model has a recursive binary decision tree method in hierarchical clustering manner for the regression. A recursive partitioning at the each branching node is repeated, based on the values of explanatory variables, until stopping criteria are met (e.g., the minimum number of sample size, and the maximum reduction of variance) (S. Sumathi and Surekha Paneerselvam 2010). The global model of the regression tree consists of two parts - the partition and the regression (Shalizi 2006). Hierarchical partitioned clusters show key information that divides the group into child groups, which is very useful to understand the underlying nature of the data (MathWorks 2013).

Table 3.16 Independent Variables used in Regression Tree Models for Duration

Category	Independent Variables
Crash Information	• Accident Severity (CAT) • Collision type (CAT) • Crash Hour (CAT) • Damage Amount • Day of Week (CAT) • Fatal Count • Pedestrian Fatal Count • First Harmful Event (CAT) • Injury Count • Non Pedestrian Fatal Count • Non Pedestrian Injury Count • Pedestrian Fatal Count • Pedestrian Injury Count • Reported Vehicle Count
Roadway geometric Information	• DMV Surface Type (CAT) • Facility Type (CAT) • First Harmful Event Location (CAT) • Intersection Type (CAT) • Jurisdiction (CAT) • Lane Count • Related to Roadway • Roadway Relation Type (CAT) • Roadway Alignment Type (CAT) • Roadway Defect Type (CAT) • Roadway Surface Condition Type (CAT) • Roadway Surface Type (CAT) • Roadway Type (CAT) • School Zone Type (CAT) • Shoulder Width (CAT) • Speed Limit (CAT) • Surface Width (CAT) • Traffic Control Status Type (CAT) • Traffic Control Type (CAT) • Traffic Controller Working (CAT) • Work Zone Location Type (CAT) • Work Zone Related (CAT) • Work Zone Type (CAT) • Work Zone Workers Present (CAT) • Work Zone (CAT)
Environmental information	• Light Condition (CAT) • Lighting (CAT) • Weather Condition (CAT)

Note: CAT represents category data

The CART models using the crash data in VaTraffic were developed to estimate the incident duration for four time-of-day periods (AM peak, Midday, PM peak, and Night time). Both categorical and continuous variables were used simultaneously in model development. In CART models, after the entire tree building structures are developed, a pruning algorithm is applied to the entire tree structure to make the optimal tree structure by minimizing the errors between predicted values and real observed values. The pruning algorithm maximizes the tree size and removes all branches and leaves that do not generalize to avoid overfitting of the data (S. Sumathi and Surekha Paneerselvam 2010). To predict the optimal size of the tree, a *v*-fold cross validation method was applied, which is known to be accurate, especially for analyses with small sample sizes because it does not need to separate learning (training) sample and testing (validating) sample data (S. Sumathi and Surekha Paneerselvam 2010).

Prior to predicting the incident durations, classification tree models are developed first to check how well the independent variables explain the duration. The criteria to find the optimal regression tree structure were to minimize the error of predictions compared to the learning and testing data. Table 3.17 shows the model summary of optimized tree structures for four TODs. Mean Square Error (MSE), Percentage Root Mean Square Error (%RMSE), and R^2 from learning data and testing data show that the four models did not generate good estimation results. Further, optimized models showed poor prediction results (R^2 values from testing data were much worse than those from learning data). Table 3.17 shows selected important variables that have high contribution from classification tree analyses.

Table 3.17 Summary of Developed Classification Tree Models

	AM	MD	PM	NT
Mean Square Error	2024.047	1077.076	1796.729	1408.848
% RMSE	44.989	32.819	42.388	37.535
R^2 Learn Data	0.116	0.412	0.324	0.215
R^2 Test Data	0.040	0.063	0.154	0.107
Important Variables	Reported Vehicles Fatal Count Pedestrian Fatal Count Collision Type Day of Week Work zone Damage Amount # of Lanes Traffic Control type Related to Roadway	Shoulder Width Day of Week Collision Type First Harmful Event Location Speed Limit Roadway Defect Type Fatal Count	Day of Week Crash Hour Pedestrian Injury Pedestrian Fatal Count Fatal Count Reported Vehicles Roadway Surface Type Jurisdiction Collision Type Shoulder Width Roadway Defect Type Surface Condition	Fatal Count Reported Vehicles Pedestrian Injury Pedestrian Fatal Count Day of Week Facility Type Shoulder Width

The trade-off between tree impurity and complexity of the tree exists for determining the optimal tree size. When the size of the tree increases, misclassification error decreases. At the maximum tree structure, misclassification error is zero. However, complex decision trees often poorly performed on independent data (Roman Timofeev 2004). Even though the larger tree structure makes variance (relative error) increase, it could generate better goodness-of-fit (R^2) results with a smaller bias.

By using selected important variables from the classification tree analysis, as shown in Table 3.17, the full structure of regression tree models were developed to predict the duration of four time-of-day periods. Figure 3.8 shows the comparison results between the observed duration from VaTraffic and the estimated duration from the developed models for four time-of-day periods. Overall, the estimated durations appeared to fit well with the observed durations, but the values were lower for all time periods. The majority of the data had durations of less than 100 minutes. The estimated durations of less than 100 minutes were matched well with observed durations for all time-of-day categories. Even if some of the estimated durations of greater than 100 minutes were overestimated or underestimated compared to the observed durations, it’s impact is expected to be insignificant from the overall analysis, because this study uses incident duration as a categorical variable from 0 to greater than or equal to 120 minutes for base year models, and from 0 to greater than or equal to 90 minutes for future year models with 30-minute intervals.

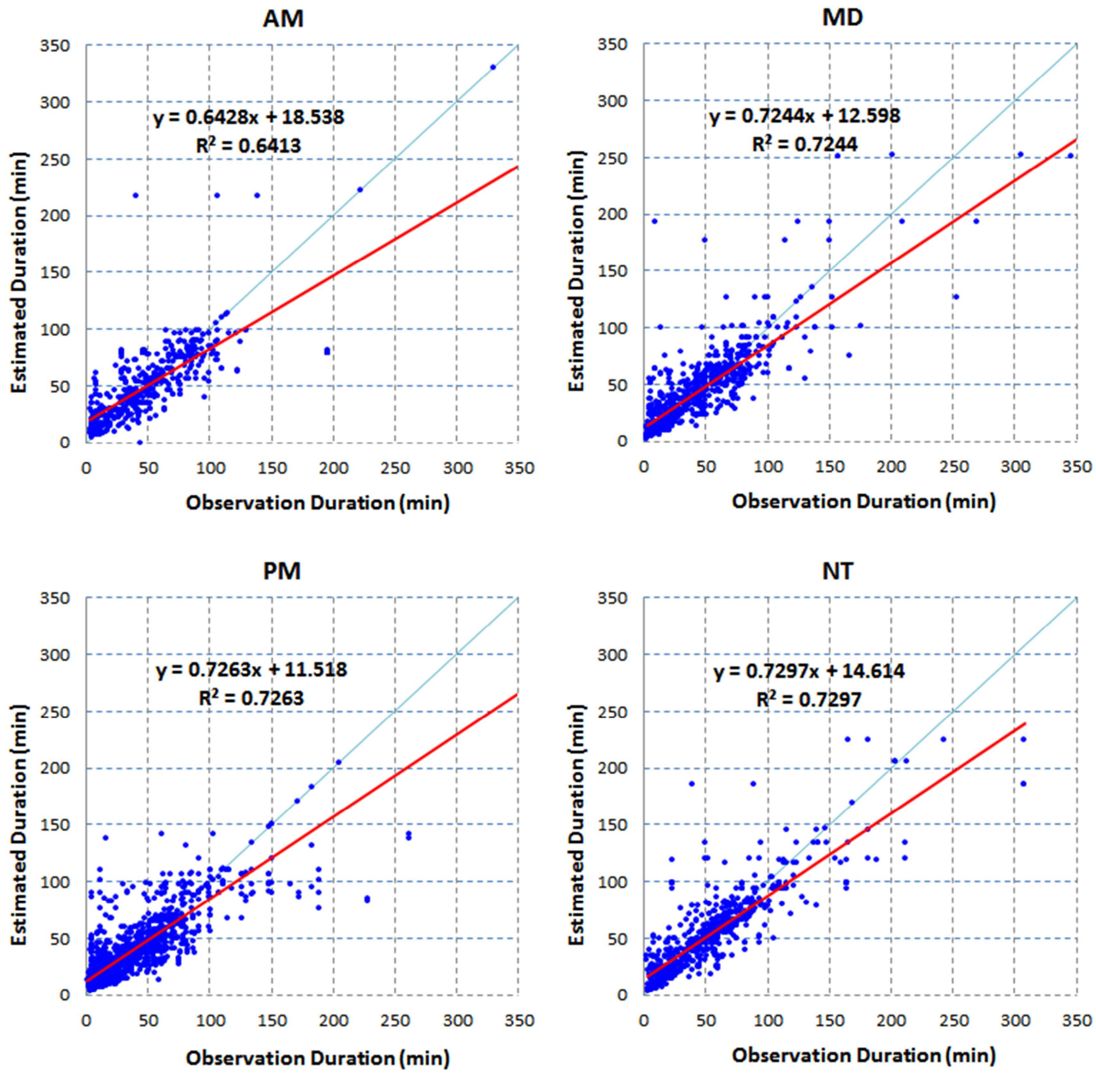


Figure 3.8 Comparison of Duration between Observation and Estimation for Four Time Periods

The developed duration models were then applied to DMV's 2009 year crash data (i.e., base year) to estimate the duration for four time periods. Figure 3.9shows the average daily incident duration throughout the network. Most of the interstate freeways had an average incident duration of longer than 10 minutes per day. In particular, some segments of interstate freeways located in the upstream of key bridges/tunnels, including the Hampton Roads Bridge Tunnel (HRBT) and the Monitor Merrimac Memorial Bridge Tunnel (MMMBT), have much higher incident durations, ranging 10 to 60 minutes per day.

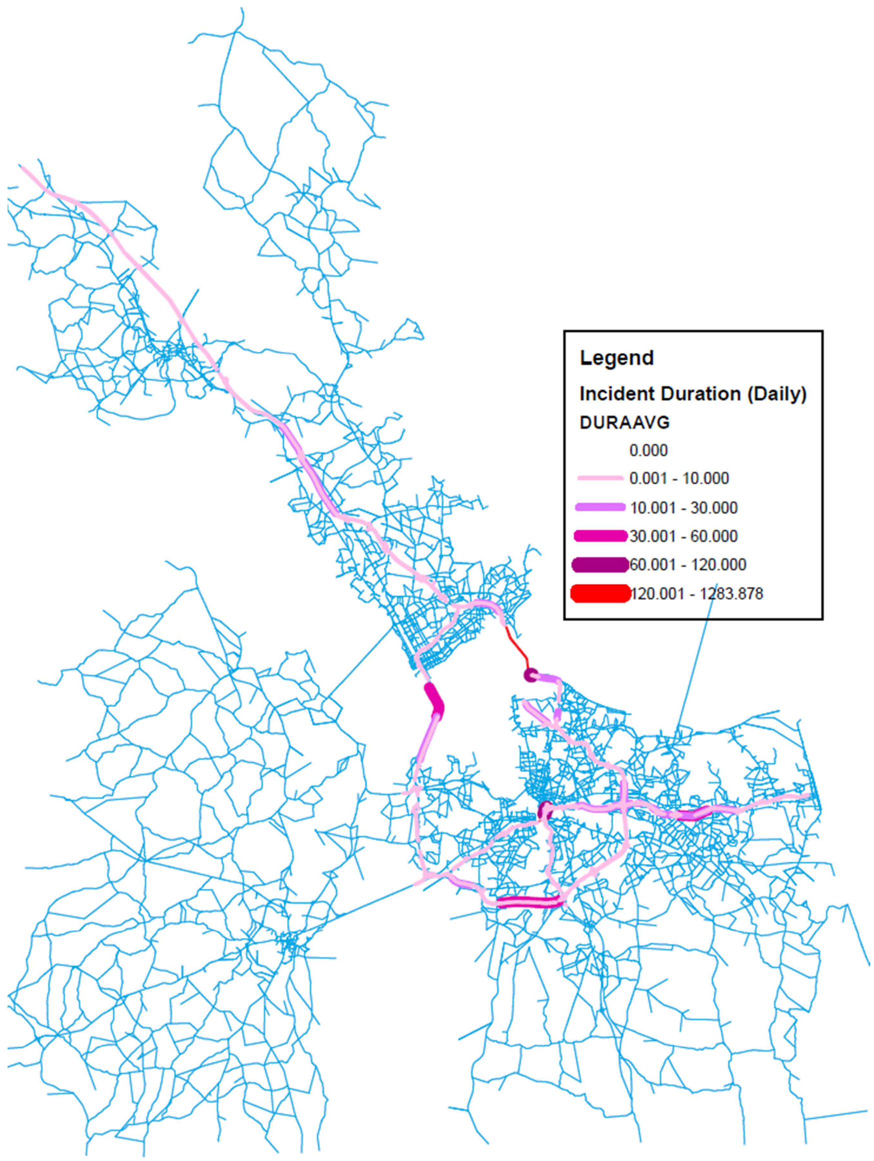


Figure 3.9 Average Daily Incident Duration on the TDFMI Network

3.3.3 Reduced Capacity from Incident

There is research literature associated with reduced capacity due to incidents. A couple of publications show how much capacity would be reduced from incidents on freeways, based on the total number of lanes on the freeway and the number of blocked lanes, including the shoulder lane, from the incidents (Chin et al. 2004; TRB 2010).

Table 3.18 shows a cross-classification table for freeways to determine the proportion of reduced link capacity based on the number of lanes that involved incidents. For example, an incident occurred at a three lane freeway, and one lane is affected (blocked) from the incident, the capacity of the freeway would be decreased to 53% (0.53).

Table 3.18 Reduced Link Capacity for Freeways

		Total Number of Lanes				
		1	2	3	4	5
Affected Number of Lanes	Shoulder	0.45	0.75	0.84	0.89	0.93
	1	0	0.32	0.53	0.56	0.75
	2	N/A	0	0.22	0.34	0.5
	3	N/A	N/A	0	0.15	0.2
	4	N/A	N/A	N/A	0	0.1
	5	N/A	N/A	N/A	N/A	0

Source: (Chin et al. 2004; Transportation Research Board 2010)

Since there is no available data for non-freeway roadways, it is assumed that the magnitude of capacity reduction of non-freeways is the same as freeways. The cross-classification table of capacity reduction for non-freeways may be updated if data becomes available in the future.

Currently, the available crash data in VDOT have no information regarding capacity reduction due to incidents. Fortunately, the total number of lanes and the number of affected lanes from the incidents are available in the VaTraffic database (Virginia DOT 2012). Thus, the cross-classification table shown in Table 3.18 was utilized to determine the reduced capacity of individual crash records by using the total number of lanes and the number of affected lanes from the incidents in VaTraffic.

3.3.4 Combination of Incident Frequency and Duration

The incident frequency and duration data were processed by a daily basis to see how the daily frequencies and average durations vary over time. Figure 3.10 Figure 3.10 shows the distribution of incident frequencies and durations for 249 weekdays in 2009. The frequency and duration show very similar fluctuations over time, which looks more obvious in the scatter plot of the two variables, as shown in Figure 3.11. A linear regression model in Figure 3.11 shows that incident frequency and duration have a positive linear relationship each other. Based on the developed model, for every incident that occurs, the total incident duration is increased by 0.775 hours (about 47 minutes) on average.

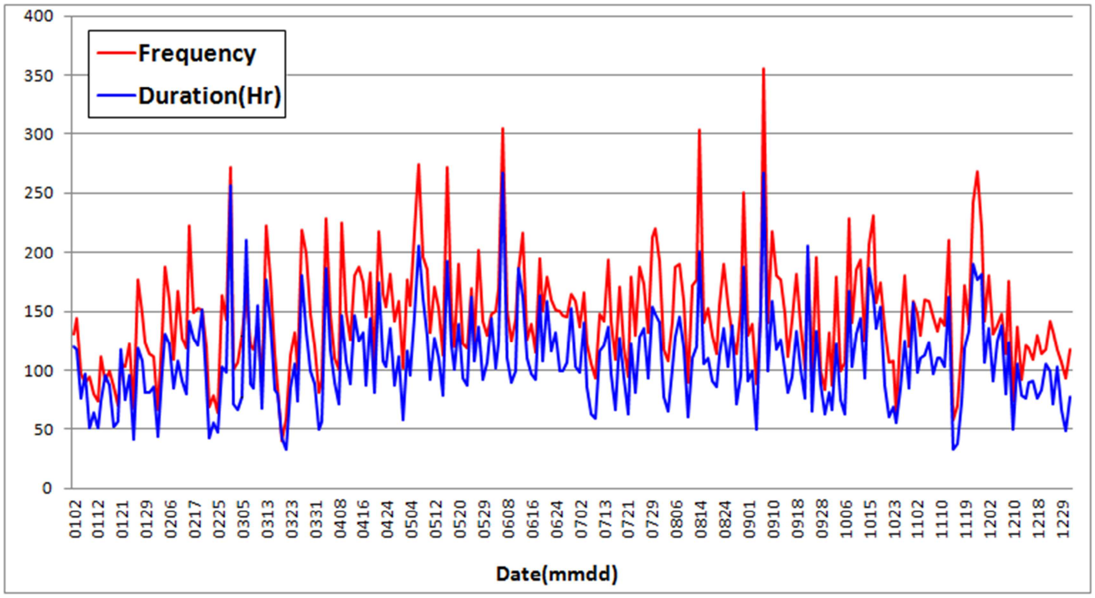


Figure 3.10 Distributions of Frequency and Duration over Time

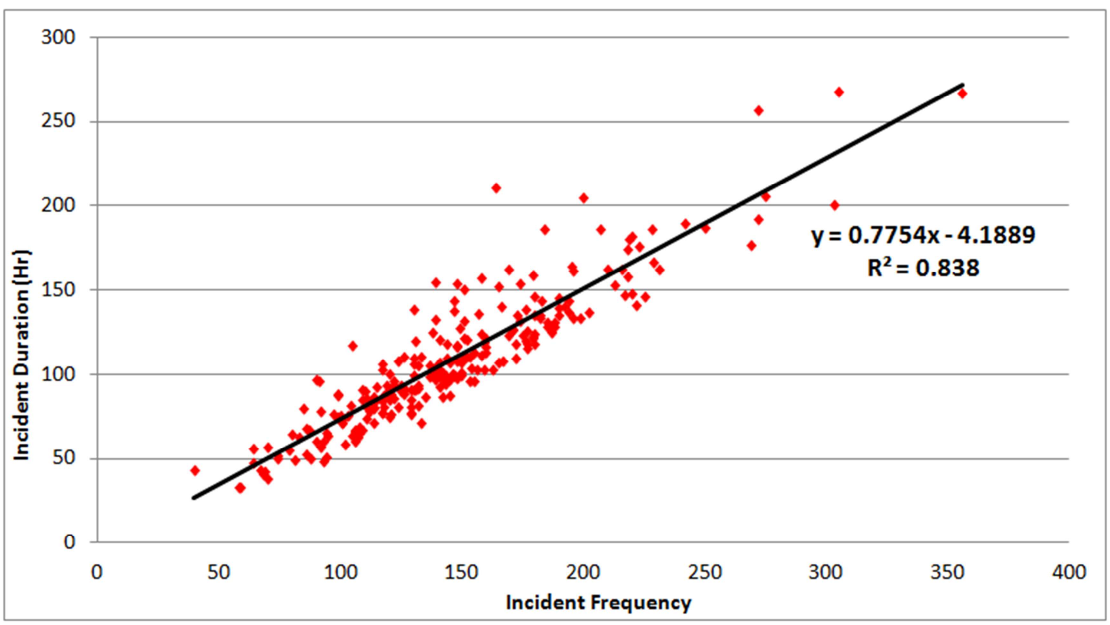


Figure 3.11 Scatter Plot of Incident Frequency and Duration

3.4 Incident Data Prediction for Future Year

The first step in predicting incidents for a future year is to forecast traffic for the future year because the loaded link volume is a key input for the prediction of incidents. Thus, the 2034 future year TDFM needs to be run to generate the loaded link volumes on the TDFM network. Figure 3.12 shows the process to prepare final incident data for the future year TDFMI.

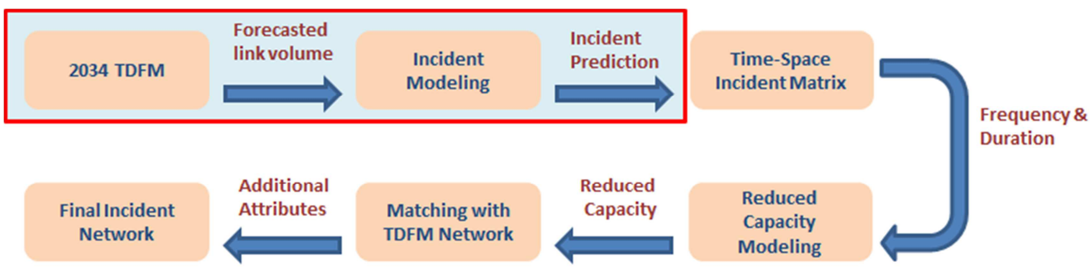


Figure 3.12 Flow of Data Preparation for Future Year

3.4.1 Incident Frequency

This study considers the three major types for incidents: crashes, bridge/tunnel closures, and the other incidents, such as disabled vehicles, vehicle fires, chemical, and bush fires. A future annual crash frequency was forecasted by using Virginia Safety Performance Functions (SPFs). To forecast the future annual frequency of stoppage at key bridges/tunnels and disabled vehicles, four linear regression models for four TODs were developed based on historical data in Hampton Roads from 2008 to 2012.

Figure 3.13 shows historical trends of non-crash incidents for each time-of-day with fitted linear regression models. The four equations showed that AM and PM have negative slopes while MD and NT have positive slopes over time. Thus, the non-crash incidents for the 2034 future year are forecasted by applying the linear regression models. As a result, the number of non-crash incidents for four TODs in 2034 is forecasted to increase by 5.0% from the 2009 incidents. The non-crash incidents for the future year could be forecasted with a revised model from the extensive data analysis later.

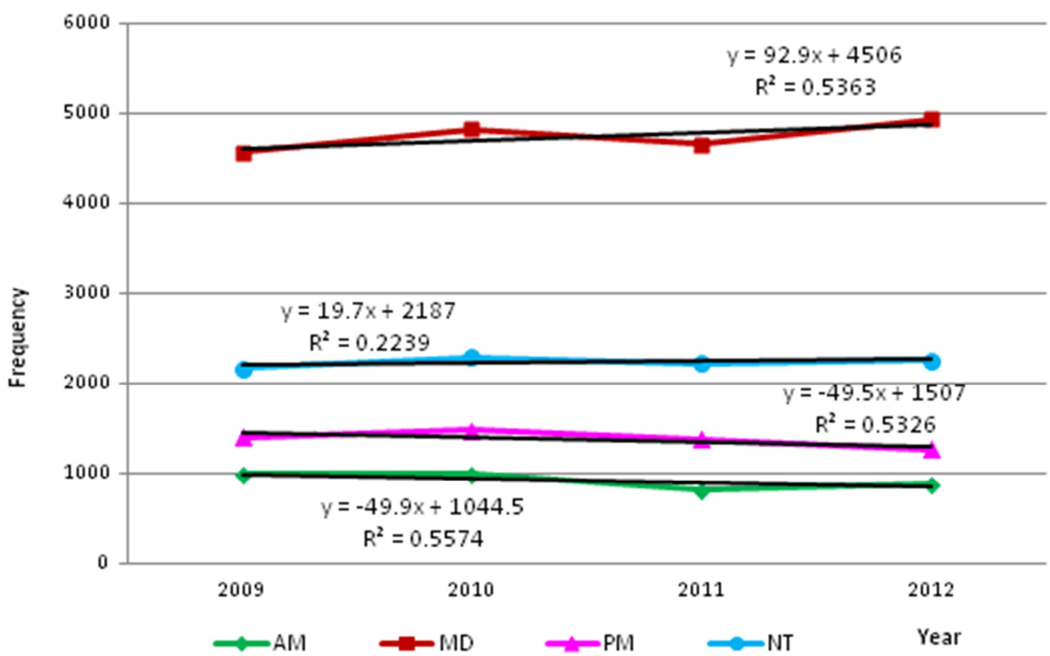


Figure 3.13 Historical Trends of Non-Crash Incidents per Time of Day

SPF is a mathematical equation estimating and/or predicting the number of crashes based on traffic and roadway information using different types of site characteristics (Carter and Srinivasan 2011). SPF has been adopted in the Highway

Safety Manual (HCS), a comprehensive highway safety analysis guide book by the American Association of State Highway and Transportation Officials (AASHTO) (Transportation Research Board 2010). SPFs shown at Equation (3.2) and Equation (3.3) are used to predict the number of crashes for a future year; the Average Annual Weekday Traffic (AWDT) is prepared from the corresponding future year.

TDFM.Link crashes = $e^{a} \times AWDT^{b} \times L$ Eq. (3.2)

where, crashes: predicted crash frequency per year

$AWDT$: annual average weekday traffic (vehicles/day)

L: segment length (miles)

a and b: regression parameters.

Intersection crashes = $e^{a} \times MajAWDT^{\beta_1} \times MinAWDT^{\beta_2}$ Eq. (3.3)

Where, crashes= predicted crash frequency per intersection per year

MajAWDT=AWDT on the major road (vehicles/day)

MinAWDT= AWDT on the minor road (vehicles/day)

β_1=coefficient of mayor AWDT

β_2=coefficient of minor AWDT

Table 3.19 shows the frequency and proportion of Virginia's 2009 crash data by severity. Fatal crashes make up less than 1% of all crashes, while property damage only accounts for 62.3%. This proportion is used to split the forecasted crashes by using forecasted AWDT and SPFs.

Table 3.19 2009 Virginia Crash Severity

	Number	Percentage
Fatal Crash	689	0.6
Injury Crashes	43,149	37.1
Property Damage Only	72,548	62.3
Total	116,386	100

The Virginia Department of Transportation (VDOT) has tried to develop SPFs with Virginia's historical crash data from 2004 to 2008 to adopt *Safety Analyst,* a highway safety management tool. As the part of the effort, SPFs for multilane highways and directional freeway segments were developed and expected to replace the default SPFs of *Safety Analyst* (Kweon and Lim 2013). SPFs developed by Kweon and Lim (Kweon and Lim 2013) were applied to forecast the 2034 future year segment crashes in the Hampton Roads area. In estimating segment crashes, different SPF model parameters for 2 lane freeways, over 3 lane freeways, and non-freeways were used. Non-freeway SPFs for the Hampton Roads district were applied. For intersection SPFs, the Virginia statewide model developed by Garber et al. was used (Garber and Rivera 2010).

For the Hampton Roads TDFM network, since there is no available information associated with traffic controllers at the intersections, each intersection was classified as signal controlled or stop sign controlled, based on the facility type information of the two crossing roadways. For example, if two arterials are crossing at an intersection, this intersection is assumed to have a signal controller. If a collector or local road is crossed with the same level or higher level facility type, it is assumed to have stop sign at the intersection. Table 3.20 shows the parameters used in SPFs.

Table 3.20 Safety Performance Functions for segment and intersections

		Alpha	Beta 1	Beta2
Segment *	2-lane freeway	-12.85	1.45	-
	3+lane freeway	-18.05	1.98	-
	Non-freeway	-7.88	0.94	-
Intersection**	Signal controlled	-7.6234	0.6742	0.3453
	Stop sign controlled	-6.9589	0.4558	0.347

Source: *(Kweon and Lim 2013) and ** (Garber and Rivera 2010)

In order to obtain incident frequency from SPFs, the number of incidents was estimated first by using the 2034 TDFM loaded link volumes and SPFs. When the number of incident frequency was estimated, Negative Binomial Distribution was applied to consider the random effect of crashes. Then, the estimated frequency was later split into subcategories for severity, which is based on Virginia’s crash data.

After the annual incident frequency was forecasted, the incidents were assigned on the network using the Monte Carlo simulation based on the relationship between the incident frequency and the functional classification of roadways and the time-of-day for each segment and intersection.

3.4.2 Incident Duration

The cross-classification table for incident duration by incident severity was compiled using the field data by Virginia DOT and New York State DOT, as shown in Table 3.21 (Virginia DOT 2012; New York State DOT 2013). The percentage of crash per severity (row sum) was calculated from the observed data in Virginia DOT's database and the percentage of crash per duration category was calculated from the observed data in New York State DOT. Based on the row sum and column sum data, the percentage of duration per crash severity and duration category were determined.

Table 3.21 Percentage of Crash Duration by Severity

	Fatal	Injury	Property	Column Sum
under 30min	0.0	8.2	13.7	21.9
30-60min	0.0	14.5	24.3	38.8
60-90min	0.0	7.8	13.1	20.9
over 90min	0.6	6.7	11.2	18.5
Row Sum	0.6	37.1	62.3	100.0

Source: (New York State DOT 2013; Virginia DOT 2012)

3.4.3 Reduced Capacity from Incident

For the reduced capacity from the incident, the future year TDFMI used the same cross-classification table used by the base year TDFMI, which is shown in Table 3.18.

3.5 Chapter Summary

This chapter identified a framework of incorporating incident impact into the TDFM process. Prior to preparing incident data, the existing Hampton Roads TDFM was briefly explored, which included the land use data summary, network dimension, key facilities, operational characteristics, VDFs, and model run statistics. Based on the proposed framework, three key incident data (frequency, reduced capacity, duration) were prepared. For the base year incident data, the incident frequency and duration were derived from incident records, while the reduced capacity was estimated by consulting research literature, as no data was available. For the future year incident data, the crash frequency was forecasted by the loaded volume from the future year TDFM and estimated SPFs. The number of non-crash incidents was forecasted by linear regression models per TOD based on historical data. Then a forecasted frequency was split into subgroups for severity and assigned on the TDFMI network using the Monte Carlo Simulation technique. For incident duration, the cross-classification table from research literature was used, which consists of incident duration and incident severity. The reduced capacity for the future year used the same look-up table as the base year case. Table 3.22 shows assumptions applied in this chapter and the expected impacts of those assumptions on the analysis results.

Table 3.22 Assumptions and Impacts on Results

Assumption	Impacts on Result
1. Feedback Loop is in trip assignment	1. Network simulation results may be different (better or worse) Computation time would increase
2. Capacity reduction in arterial is the same as freeway	2. Capacity reduction on arterials may be different ➔ Incident impact may be different (better or worse)
3. Incident impacts that are not included in TDFM network are minimal	3. Incident impacts may be underestimated (same or worse)
4. Non-crash incident frequency of future year follow the historical trend	4. Non-crash incidents for future year may be decreased ➔ Incident impact may be decreased (better or worse)
5. Crash frequency of future year can be forecasted using existing SPFs	5. SPFs may be updated in the future (better or worse)
6. Cross table of incident durations are determined by the filed data of VDOT and NYSDOT	6. Duration may affect the incident impact on network (better or worse)

CHAPTER 4. VOLUME DELAY FUNCTION WITH INCIDENT DATA

The impact of an incident on a roadway can be measured by two factors: the reduced capacity on the roadway and the incident duration. As reviewed in Chapter 2.3.3, reduced capacity can be calculated, regardless incident type, by examining how many lanes (including shoulder) were blocked from the incidents and how many lanes are still available to traffic. In this chapter, in order to incorporate the incident impact into TDFM, modified BPR and Akcelik VDFs were developed and calibrated with selected field traffic data that are associated with the crashes.

4.1 Incident Data Preparation

This study utilized field traffic data and incident data that VDOT has collected. To collect field traffic data associated with incidents (crashes), this study applied temporal/spatial information to both crash data and traffic count data archived in VDOT's Traffic Monitoring System (TMS). Consequently, once traffic and crash data have the same time and location, daily traffic data of the matched link was extracted from the TMS. The traffic data in the TMS are 15-min interval counts classified by FHWA and 21 speed bins with 5 mph range intervals from 0 to greater than 100 mph. Since a crash is a relatively rare event, all matching cases from 2007 to 2010 were searched. Figure 4.1 shows one example of field traffic data that was associated with an incident. The vertical red bars in the left and middle graphs represent the time the crash occurred, which was around 6:00 pm.

This crash occurred on the 5-lane freeway, I-264 westbound in the Norfolk area outside of the I-64/I-664 circle, on April 24, 2009. The graphs of volume (left) and speed data (middle) by the time-of-day indicate that, prior to the crash, the total traffic volume throughout the five lanes was about 2,300 vehicles per 15-minutes and the average travel speed was about 59 mph. When the crash occurred, speed was dropped drastically to around 10 mph and traffic volume was dropped to less than 1,000 vehicles per 15 minutes. It took about 105 minutes before travel speed was restored back up to 60 mph, the travel speed prior to the crash. When the speed volume graph (right) shows only seven records with traffic volumes of less than 2,500 vehicles/15-min and traffic speeds of less than 40 mph, these samples obviously represent incident traffic conditions.

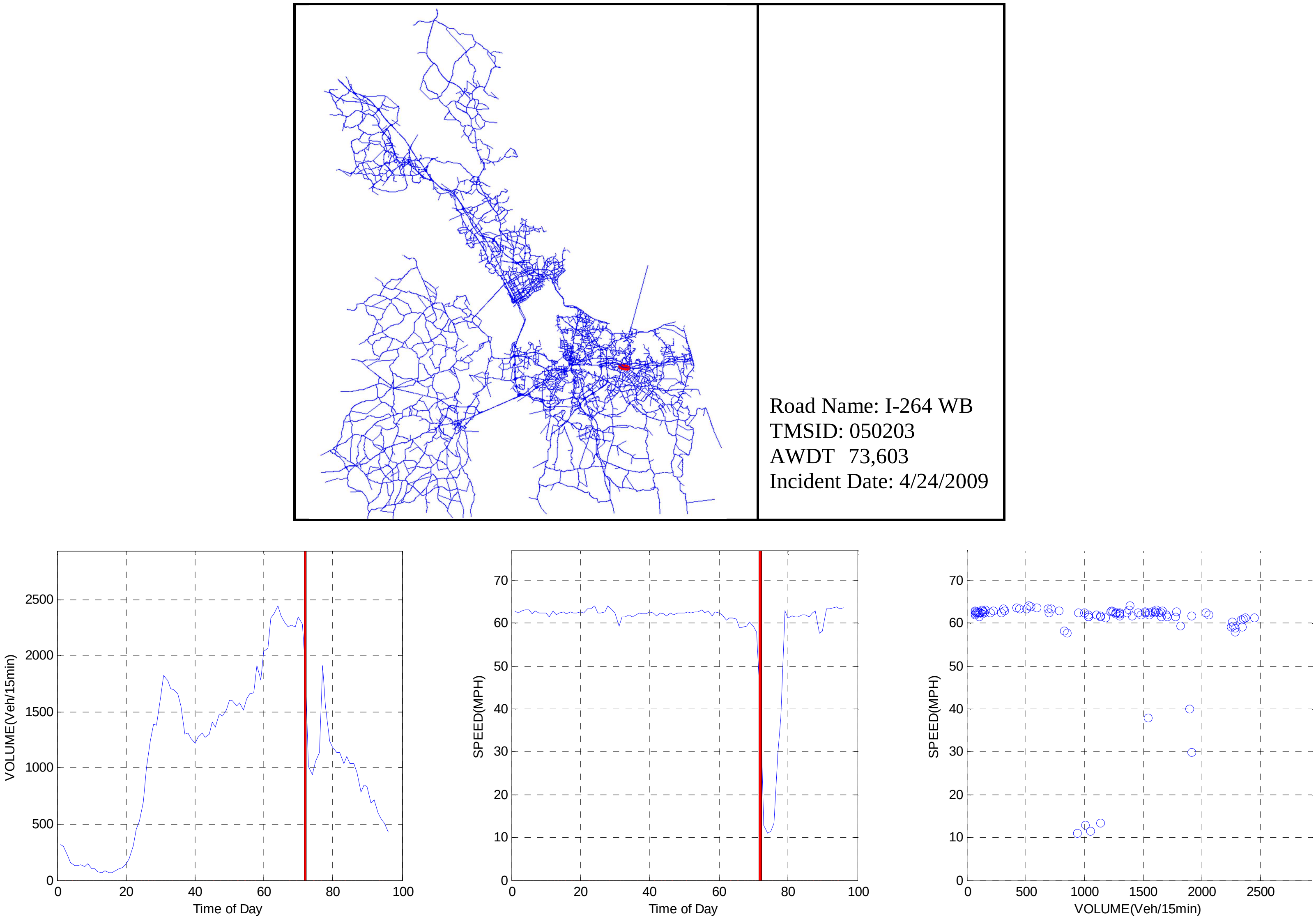


Figure 4.1 Example of Incident Involved Traffic Data

After data mining five-years of traffic crash data from 2007 to 2010 in the Hampton Roads area, 45 TMS traffic count locations with valid field traffic data for the date when crashes occurred were found. At the 45 locations, 182-day traffic data were collected, which means some locations have more than two crashes during four years. Table 4.1 shows the summary how many data points were extracted from the archived TMS database.

Even though the existing TDFM has total of 11 facility types, VDF was grouped, as below, into five classes with similar facility types, because of the lack of data for calibrating VDF functions with facility types (AECOM 2013).

- Class 1: Centroid Connectors
- Class 2: Freeways, Ramps
- Class 3: Minor Freeways/Principal Arterials
- Class 4: Major/Minor Arterials, Major Collectors
- Class 5: Minor Collectors/Locals

Since the VDFs of TDFM have five classes, this study followed the same rule to group collected traffic data that matched crashes before VDF calibration. After grouping field traffic data by facility type, minor freeways/ principal arterials have the largest field traffic data that matched with the crash data while the major/minor arterials and major collectors have the least field traffic data that matched with the crash data.

Table 4.1 Summary of Sample Data used in VDF Calibration

Facility Type	# of Sample Sites	# of Sample Dates	# of Samples
Interstate Freeway	9	25	2,864
Minor Freeway, Principal Arterial	27	129	13,901
Major/Minor Arterial, Major Collector	5	10	1,002
Minor Collector, Local Roads	4	18	1,576
Total	45	182	19,343

4.2 VDF Modification

In order to consider the incident impacts properly, VDF needs three major inputs: incident duration, reduction in capacity, and demand rate. While original VDFs have a variable for demand rate (as link volume), the modified VDF has two additional variables including reduced capacity from the incident and its duration. Thus, the final travel time is determined by the sum of travel times during non-incident and incident conditions, as shown in Equation (4.1). Previous research adopted the same concept to consider incident impacts on simplified network simulation (Przybyla et al. 2011)

$$\boldsymbol{\bar{T} = \rho(C_R) + (1 - \rho)(C_F)} \qquad \text{Eq. (4.1)}$$

Where, $\bar{T}$ = Total travel time

ρ = Proportion of Incident duration out of simulation time

C_R = Reduced link capacity

C_F = Full link capacity

For example, an incident occurred at an interstate freeway segment during the AM peak period and a roadway was cleared (or opened) to traffic 90 minutes later. Link capacity during the incident period was reduced to 40% of the full capacity. If the simulation time of am peak period is 3 hours, a proportion of incident duration would be 0.5. The rest of the simulation time (90 minutes) will represent the normal traffic condition without the incident at full link capacity (1.0).

4.2.1 BPR VDFs

Although the Akcelik VDF appears to be the best candidate for considering incident impact, the BPR VDF is also considered as another alternative because the BPR VDF has a simple functional form, and is still widely used in practice. Equation (4.2) shows the equation of a modified BPR VDF, similar to the equation presented in research (M. Li, Zhou, and Rouphail 2011b; M. Li, Zhou, and Rouphail 2011a). The original functional form was used to represent the relationship between traffic volume and travel time under non-incident traffic conditions with full link capacity (c_F). On the contrary, the modified functional form was used for the volume-time relationships under the incident condition, by replacing a variable for reduced capacity (c_R).

$$T_a = \rho\left\{T_0\left(1 + \alpha 1\left[\frac{v}{c_R}\right]^{\beta 1}\right)\right\} + (1-\rho)\left\{T_0\left(1 + \alpha 2\left[\frac{v}{c_F}\right]^{\beta 2}\right)\right\} \qquad \text{Eq. (4.2)}$$

Where, T_a = Congested link travel time

$T_0 =$ Link travel time at free flow speed

$\alpha 1\ and\ \beta 1 =$ Parameters for incident condition

$\alpha 2\ and\ \beta 2 =$ Parameters for non − incident condition

Incident duration will be represented as the proportion of incident duration out of the simulation time. For example, if an incident occurred at 12:30 PM during the Midday non-peak period (six hours from 9:00 AM to 3:00 PM) for 90 minutes, the duration parameter for the incident component will be $\rho = 90/360 = 0.25$. As a result, the duration parameter for the non-incident condition will be $(1-\rho) = (1-0.25) = 0.75$.

4.2.2 Akcelik VDFs

The one major advantage of the Akcelik VDF over the BPR VDF is that the Akcelik VDF can consider node delay and queue. In order to consider the incident impacts at links and nodes, this study modified original Akcelik VDFs. Equation (4.3) and Equation (4.4) show the functional forms of modified Akcelik VDFs that have link delay and node delay from incidents, respectively.

$$t^l = t_f^l + \rho^l \left[0.25T \left\{ \left(\mathrm{v}/c_R^l - 1 \right) + \sqrt{\left(\mathrm{v}/c_R^l - 1 \right)^2 + \frac{8J_A v}{{c_R^l}^2 T}} \right\} \right]$$

$$+(1-\rho^l) \left[0.25T \left\{ \left(v/c_F^l - 1 \right) + \sqrt{\left(v/c_F^l - 1 \right)^2 + \frac{8J_B v}{{c_F^l}^2 T}} \right\} \right] \qquad \text{Eq. (4.3)}$$

$$t^n = \rho^n \left[\frac{0.5C(1-g/C)^2}{1-(v/c_R^n)(g/C)} \right] + (1-\rho^n) \left[\frac{0.5C(1-g/C)^2}{1-(v/c_F^n)(g/C)} \right] \qquad \text{Eq. (4.4)}$$

Where, t^l = link delay

t^n = node delay

t_f^l = free-flow travel time per unit distance

T = duration of analysis period (h)

v = link volume

c_F^l = full capacity of link (vph)

c_R^l = reduced capacity of link (vph)

J_A = delay parameter for incident condition (unitless)

J_B = delay parameter for normal condition (unitless)

g = green time

C = cycle length

ρ^n = proportion of incident duration out of simulation period at node

ρ^l = proportion of incident duration of simulation period at link

Just like modified BPR VDFs, the modified Akcelik VDF introduced additional components for incident traffic conditions and variables for capacity and duration. For incident traffic conditions, four variables were introduced: reduced capacity variables for link (c_R^l) and for intersection (c_R^n), and the proportion of incident duration out of simulation period for link (ρ^l) and node (ρ^n). For non-incident traffic conditions, four variables were also introduced: full capacity variables for link (c_F^l) and for intersection (c_F^n), and the proportion of incident duration out of simulation period for link ($1-\rho^l$) and node ($1-\rho^n$).

4.3 BPR and Akcelik VDFs Calibration

Model calibration is the process of finding the best values for a model's input parameters, until the model's predictions are matched to field observations within some acceptable criteria (Federal Highway Administration 2010). Calibration usually minimizes objective functions, such as %RMSE, which indicate errors between observations and predictions. During the calibration process, R^2 and %RMSE are examined. The visual examination is also used to see how estimated values fit the data in sensitive areas.

For the modified VDF calibration, the major key inputs - free flow speed and link capacity - should be determined first. This study utilized the cross-classification tables developed by AECOM for TDFM as shown in Table 4.2 and Table 4.3, which were based on area type and facility type.

Table 4.2 Free Flow Speed per Facility Type and Area Type

		Area Type				
		CBD	Urban	Dense Suburban	Sub-urban	Rural
Facility Type	Interstate/Principal Freeway	55	57	60	60	64
	Minor Freeway	48	51	55	57	62
	Principal Arterial/Highway	32	39	41	47	52
	Major Arterial/Highway	29	32	36	43	45
	Minor Arterial/Highway	28	34	38	42	45
	Major Collector	27	30	34	41	44
	Minor Collector	23	30	32	38	40
	Local	20	23	26	32	33
	High Speed Ramp	40	40	40	45	45
	Low Speed Ramp	25	30	30	35	35
	Centroid Connector	17	22	27	31	35
	External Station Connector	20	25	35	45	55

Source: (AECOM 2013)

Table 4.3 Link Capacity (Vehicle/Hour) Cross-classification table

		Area Type				
		CBD	Urban	Dense Suburban	Sub-urban	Rural
Facility Type	Interstate/Principal Freeway	1,850	1,900	1,900	1,900	2,000
	Minor Freeway	1,200	1,250	1,300	1,400	1,500
	Principal Arterial/Highway	900	950	1,000	1,100	1,150
	Major Arterial/Highway	850	900	950	1,000	1,050
	Minor Arterial/Highway	800	850	900	950	1,000
	Major Collector	700	750	800	850	900
	Minor Collector	550	600	650	700	800
	Local	400	425	450	475	500
	High Speed Ramp	1,500	1,550	1,600	1,650	1,700
	Low Speed Ramp	800	900	900	1,000	1,000
	Centroid Connector	9,999	9,999	9,999	9,999	9,999
	External Station Connector	9,999	9,999	9,999	9,999	9,999

Source: (AECOM 2013)

The parameters for incident components of modified BPR and Akcelik VDFs on the TDFMI need to be calibrated with the observed incident data because the flow-speed relationships under incident conditions would not be the same as normal traffic conditions. The calibration was made by four different functional classes: 1) freeways, 2) major arterials, 3) minor arterials, and 4) collectors/local roads. Since the fifth class was for Centroid connectors, it was excluded in the VDF calibration.

van Arder's traffic Stream Model

From the successful implementations of surrogate measures for V/C to consider oversaturated traffic conditions in previous research efforts (Lee and Munn 2009; Klieman et al. 2011; Huntsinger and Rouphail 2011), this study used the density rate, the ratio of a given density divided by the density at maximum flow (capacity), to calculate V/C for both undersaturated and oversaturated traffic conditions in the VDF calibration. Density ratio K^r can be calculated by Equation (4.5)

$$K^r = \frac{k_x}{k_c} \quad \text{Eq. (4.5)}$$

Where,

K^r = density ratio

k_x= density at given level x

k_c= density at capacity

The density at capacity (k_c) indicating optimum density can be determined from field traffic data. Thus, the traffic conditions can be identified from Equation (4.5) if it is an under-saturated traffic condition (K^r <1) or an over-saturated traffic condition ($K^r \geq$ 1). In order to estimate the density rate (K^r) based on density at capacity k_c, van Arder's traffic stream model (Hesham Rakha and Brent Crowther 2002) was utilized to determine boundary conditions of the field data, including free flow speed, maximum flow (capacity), density at capacity, and jam density. van Arder's traffic stream model has the relationships between parameters and boundary conditions, as shown in Equation (4.6) to Equation (4.10) (Hesham Rakha and Brent Crowther 2002).

$$h = c_1 + c_3 u + \frac{c_2}{u_f - u} \quad \text{Eq. (4.6)}$$

$$m = \frac{2u_c - u_f}{(u_f - u_c)^2} \quad \text{Eq. (4.7)}$$

$$c_2 = \frac{1}{k_j\left(m + \frac{1}{u_f}\right)} \quad \text{Eq. (4.8)}$$

$$c_1 = mc_2 \quad \text{Eq. (4.9)}$$

$$c_3 = \frac{-c_1 + \frac{u_c}{q_c} - \frac{c_2}{u_f - u_c}}{u_c} \quad \text{Eq. (4.10)}$$

Where, c_1 = fixed distance headway constant (mile)

c_2 = first variable distance headway constant (mi^2/h)

c_3 = Second variable distance headway constant (h)

u_f = free speed (mph)

u_c = speed at capacity (mph)

q_c = flow at capacity (veh/h)

k_j = jam density (veh/mi)

m = constant used to solve for three headway constant (h/mi)

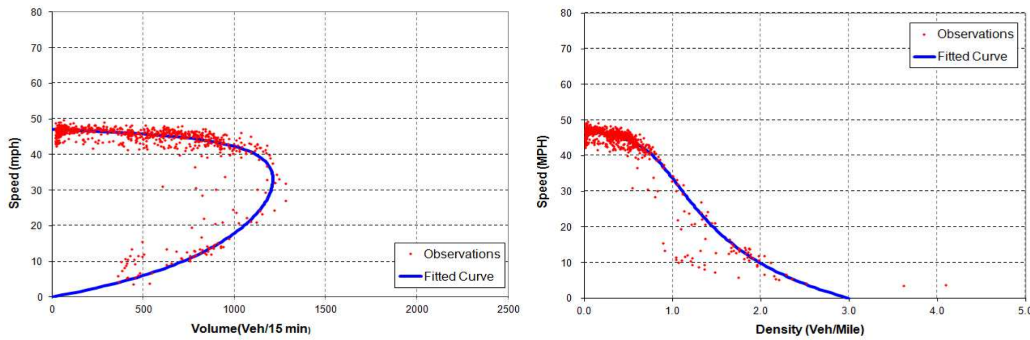
An optimization of parameter values was performed by minimizing errors between field data and predicted data from the model.

Table 4.4 shows the boundary conditions of four facility types from the optimized van Aerde's traffic stream model.

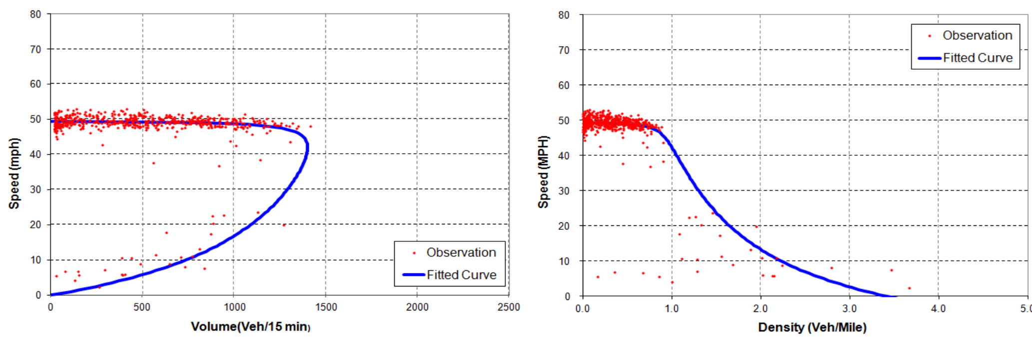
Table 4.4 Boundary Conditions of Estimated Traffic Stream Model

	Minor Collector	Major Collector Minor Arterial	Principal Arterial Minor Freeway	Interstate Freeway
Jam Density (k_j) (VPM)	108	115	168	178
Density at Capacity (k_c) (VPM)	33	36	36	38
Free Flow Speed (u_f) (MPH)	46	50	59	69
Speed at Capacity(u_0) (MPH)	35	40	53	58
Capacity (q_m) (VPH)	1,210	1,380	2,085	2,130

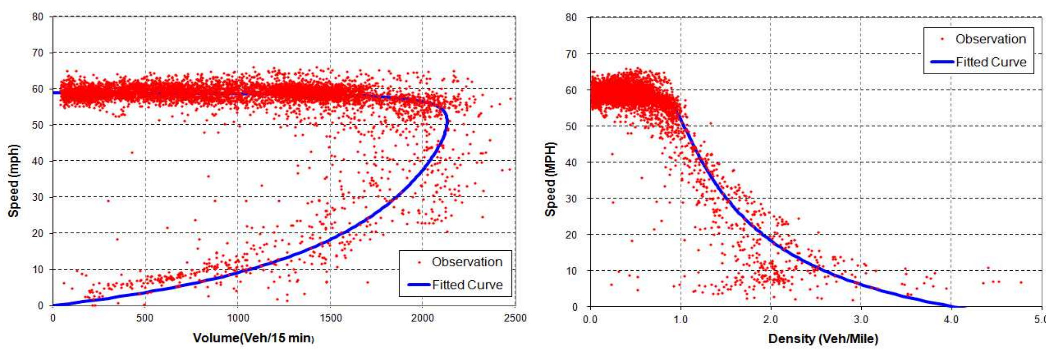
By using developed traffic stream models, the density at capacity (k_c) was determined and density measures were calculated per facility type. The relationships between speed (u) and density rate (K^r) were plotted with the developed traffic stream models as shown in Figure 4.2. Basic relationships between speed, volume, and density and their fitted curves show that all four facility types fit well with field data.



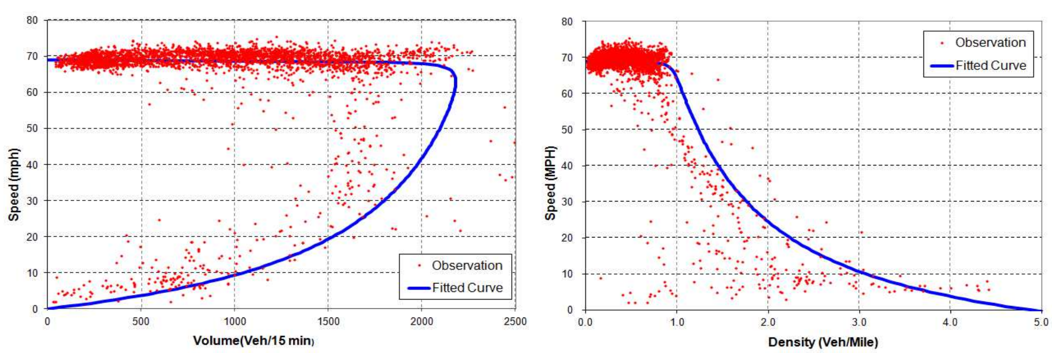
a) Minor Collectors



b) Major Arterials/Major Collectors



c) Minor Freeways/Principal Arterials



d) Interstate Freeways

Figure 4.2 Fitted van Arder Traffic Stream Models with Observations

Figure 4.3 shows the fitted curves on field crash data for four facility types of BPR and Akcelik VDFs. Table 4.5 shows the estimated parameters of BPR and Akcelik VDFs for four facility types. From the functional forms of BPR VDFs, parameter α accounts for the ratio of travel time at free flow speed over the travel time at the capacity and parameter β accounts for the level of travel time increase from the travel time at free-flow (Kalaee 2010).

From a visual examination, fitted curves fit well with field data and BPR VDFs show better shapes than Akcelik VDFs. As previous researchers have shown, BPR VDFs fit well for all V/C ranges while Akcelik VDFs do not. Akcelik VDFs show that speeds are steadily decreased as the V/C ratio increases up to V/C<0.8. As V/C is closer to 1.0, speeds are drastically dropped to lower than 10 mph at $V/C \cong 1.2$ for all facility types.

Table 4.5 Calibrated Parameters of BPR and Akcelik VDFs

	BPR		Akcelik
	Alpha	Beta	J
Interstate Freeways	0.39	3.41	0.00059
Principal Arterials Minor Freeways	0.34	2.91	0.00012
Major Collectors Minor Arterials	0.27	4.71	0.00006
Minor Collectors	0.20	5.01	0.00003

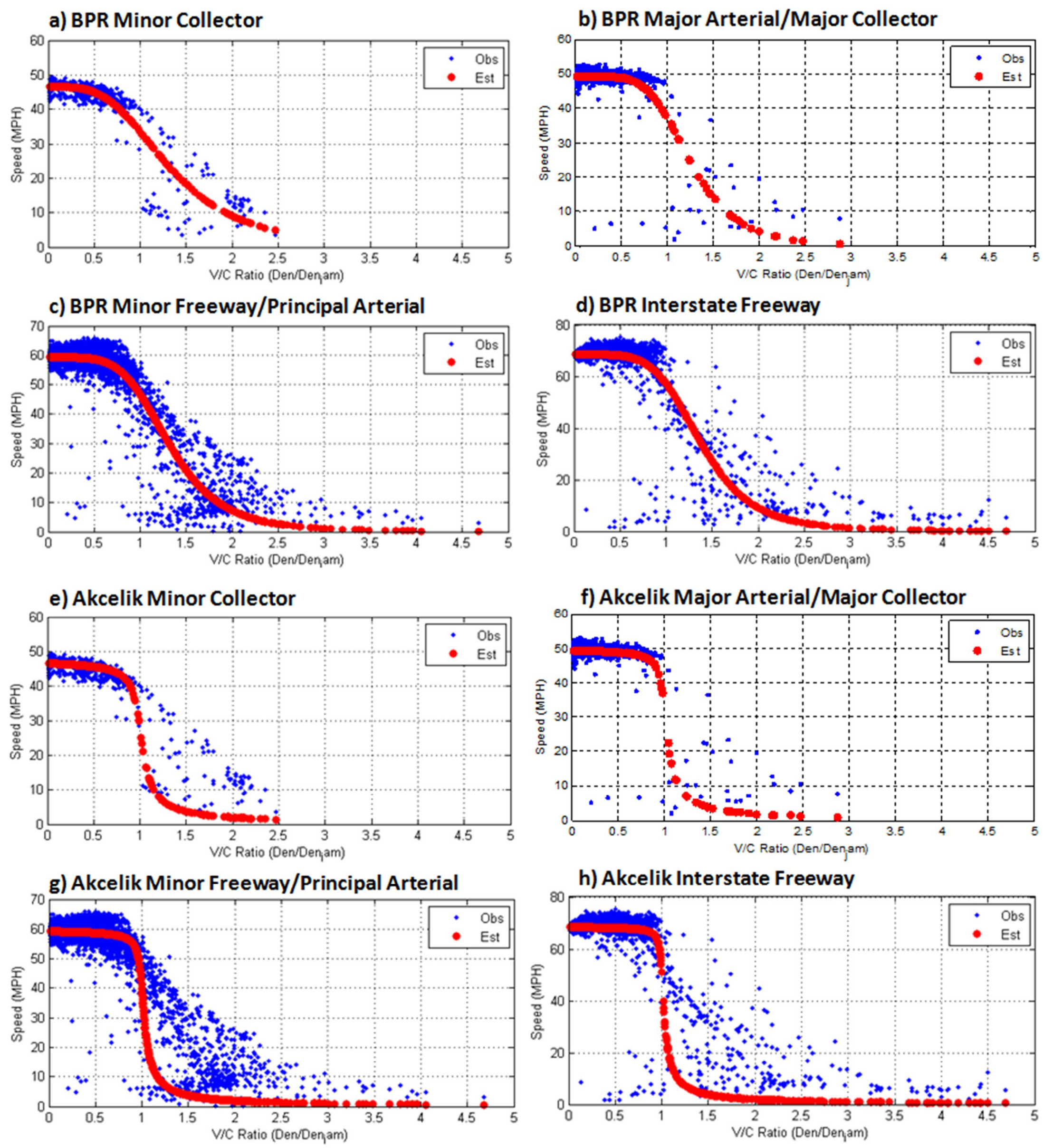


Figure 4.3 Fitted Curves on Field Crash Data for BPR and Akcelik VDFs

Table 4.6 shows the statistics of calibrated BPR and Akcelik VDFs per facility type. Both $\boldsymbol{R^2}$ and %RMSE statistics were used to evaluate the goodness of fit of calibrated VDFs. Akcelik VDFs have higher $\mathbf{R^2}$ than BPR VDFs for all facility types. However BPR VDFs showed a lower %RMSE than Akcelik VDFs, except for the major collectors/ minor arterials. The minor collectors showed the highest $\mathbf{R^2}$ and the lowest %RMSE across all categories for both VDFs.

Table 4.6 VDF Calibration Statistics

	Performance Measure	BPR	Akcelik
Interstate Freeways	R^2	0.799	0.806
	%RMSE	6.250	6.980
Principal Arterials/ Minor Freeways	R^2	0.866	0.869
	%RMSE	4.080	4.600
Major Collectors/ Minor Arterials	R^2	0.687	0.717
	%RMSE	4.340	4.250
Minor Collectors	R^2	0.872	0.894
	%RMSE	3.400	3.590

Figure 4.4 shows the calibrated curves of the BPR and Akcelik VDFs. The Akcelik VDFs showed very little speed reduction at V/C < 1.0, while the BPR VDFs have a gradual decline of the travel speed from the all facility types. The V/C range of 0.5-0.75 still had no significant changes in the Akcelik VDFs but the BPR VDFs had larger speed reductions compared to the Akcelik VDFs at the same range. When V/C approaches 1.0 and exceeds 1.0, the speed drastically dropped at all Akcelik VDFs facility types. On the contrary, BPR VDFs did not show significant drops as Akcelik VDFs did in the slope of the curves for the all of the facility types, which means BPR VDFs overestimate travel times as the V/C ratio approaches 1.0 and exceeds 1.0.

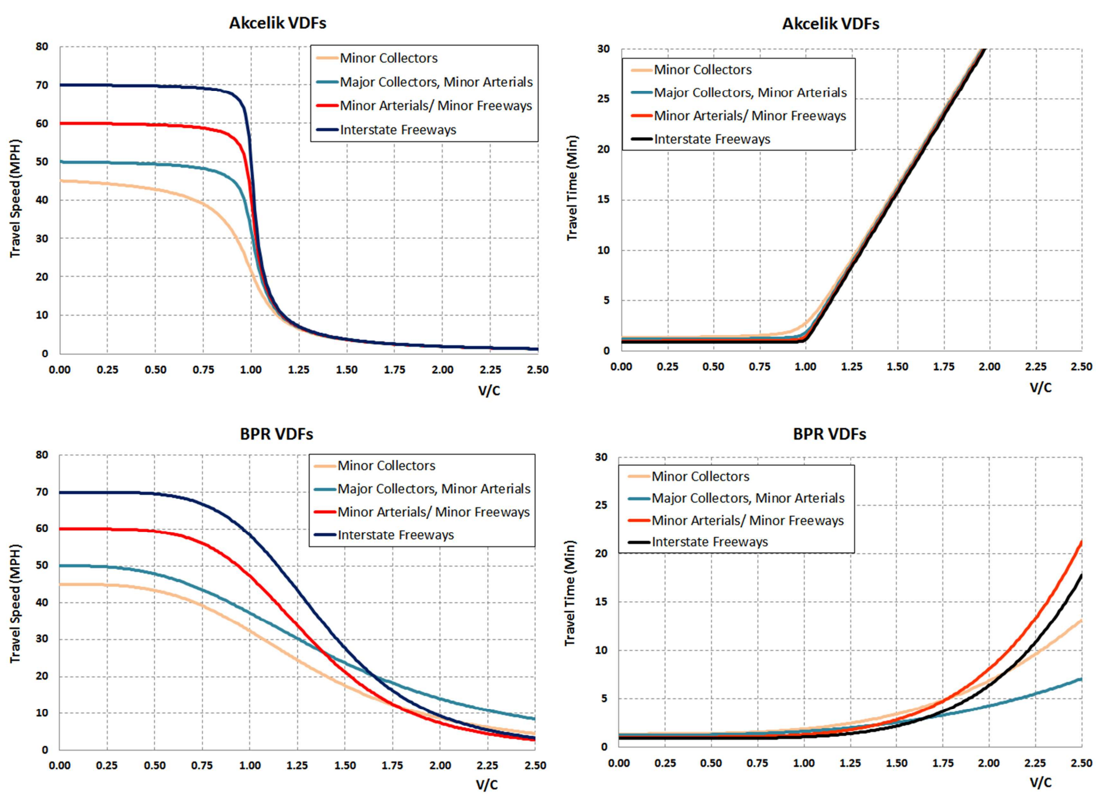


Figure 4.4 Calibrated BPF and Akcelik VDF Curves per Facility Types

4.4 Model Validation and Reasonableness Check

By applying both calibrated modified-BPR and modified-Akcelik VDFs to the traffic assignment step, the three model run results (TDFM, TDFMI with BPR VDFs, TDFMI with Akcelik VDFs) were compared and evaluated to examine if new VDFs for the TDFMI improved the existing TDFM in terms of accuracy and the level of effort of calibration. The model run results of the TDFMI are expected to be inferior to those of the existing TDFM because the TDFMI has not been extensively calibrated and validated before.

Since the major differences of TDFMI from TDFM are the network (with or without incident information on links and nodes) and the functional form of VDF (with or without incident variables), the main effort for the validation of TDFMI was placed on the traffic assignment step. In reasonableness checking of the traffic assignment step, the free flow speed and the link capacity on both networks and VDFs are usually examined (Federal Highway Administration 2010).

4.5 Chapter Summary

This chapter explored the field traffic data and crash data from the VDOT's database. The crash data and the traffic data were matched first by using the common temporal and spatial information. The crash involved data were then prepared to calibrate the modified VDFs for the incident impact. The prepared crash and traffic data were split into the facility types such as freeways, arterials, and collectors, and local roads to calibrate VDFs. The BPR and Akcelik VDFs were modified to incorporate the incident impact into the functional form in this study. The functional form of the modified VDFs had two components for the normal traffic condition and the incident condition, which had additional variables representing the reduced capacity and the incident duration from the incidents. After parameters were calibrated, R^2 and %RMSE statistics were examined to evaluate the goodness of fit of the calibrated VDFs by the facility types. Akelik VDFs have higher R^2 than BPR VDFs for all facility types. However BPR VDFs showed lower %RMSE than Akcelik VDFs except the major collectors/ minor arterials. The minor collectors showed the highest R^2 and the lowest %RMSE throughout the all categories for both VDFs.

CHAPTER 5. INCORPORATING INCIDENT IMPACTS INTO TDFMI NETWORKS

Once incident-related inputs, including incident frequency, duration, and reduced capacity resulting from incident, are prepared, as described in Chapter 3, the TDFMI network should have incident information with additional link attributes, by matching individual incident records with their corresponding nodes and links on the TDFMI network. This chapter describes how the prepared incident data are matched with segments and intersections of the TDFMI network.

5.1 Matching Base Year Incident Data with TDFMI Network

All incident data with location information needs to be matched with the TDFMI network, in order to accommodate properly in network simulation (traffic assignment step). Figure 5.1 shows various geographic information data used in the incident matching process. Since most of the incidents and crashes have location information, all incidents were matched with their corresponding segments on the actual roadways. However the TDFM network does not cover all roadways; it does not have lower classified roadways, such as local roads or frontage roads. It is assumed that the impact of incidents on roadways that were excluded from the TDFM network is small enough to ignore. Indeed, most of the incidents that occurred on local roads may not have had any impact on higher classified roadways, like interstate freeways and/or arterials, but may have had an impact on collectors. Figure 5.1 shows an example of matched incidents in the TDFM network and unmatched incidents on local roads that are excluded from the TDFM network. The matched incident data were split into incidents on freeways and non-freeways again. The incident data that matched in the TDFM network were used in the development of the TDFMI network, while the incident data did not match in the TDFM network were excluded in this study.

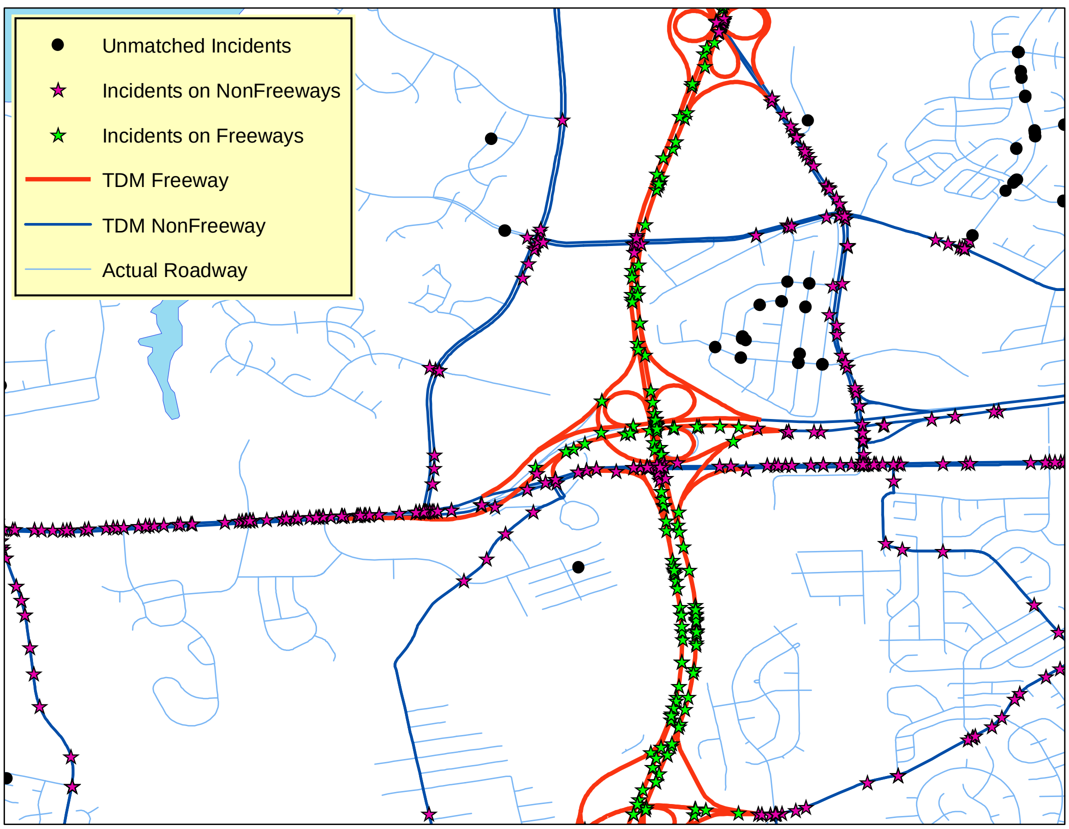


Figure 5.1 Matching Incidents with TDFM Network

Using the matched incident data, a further matching process was conducted to identify intersection incidents. The definition of an intersection crash is a crash that occurs within a 250 ft. boundary from the middle of an intersection. Thus, incidents located within a 250 ft. boundary from the virtual center point of an intersection were categorized as intersection incidents.

Figure 5.2 shows the TDFM network with matched incidents, freeway junctions, non-freeway intersections, and 250 ft. intersection crash boundaries. Every incident located inside of a 250 ft. boundary of any intersection or junction was identified as an intersection incident, and the rest of the incidents were identified as segment incidents.

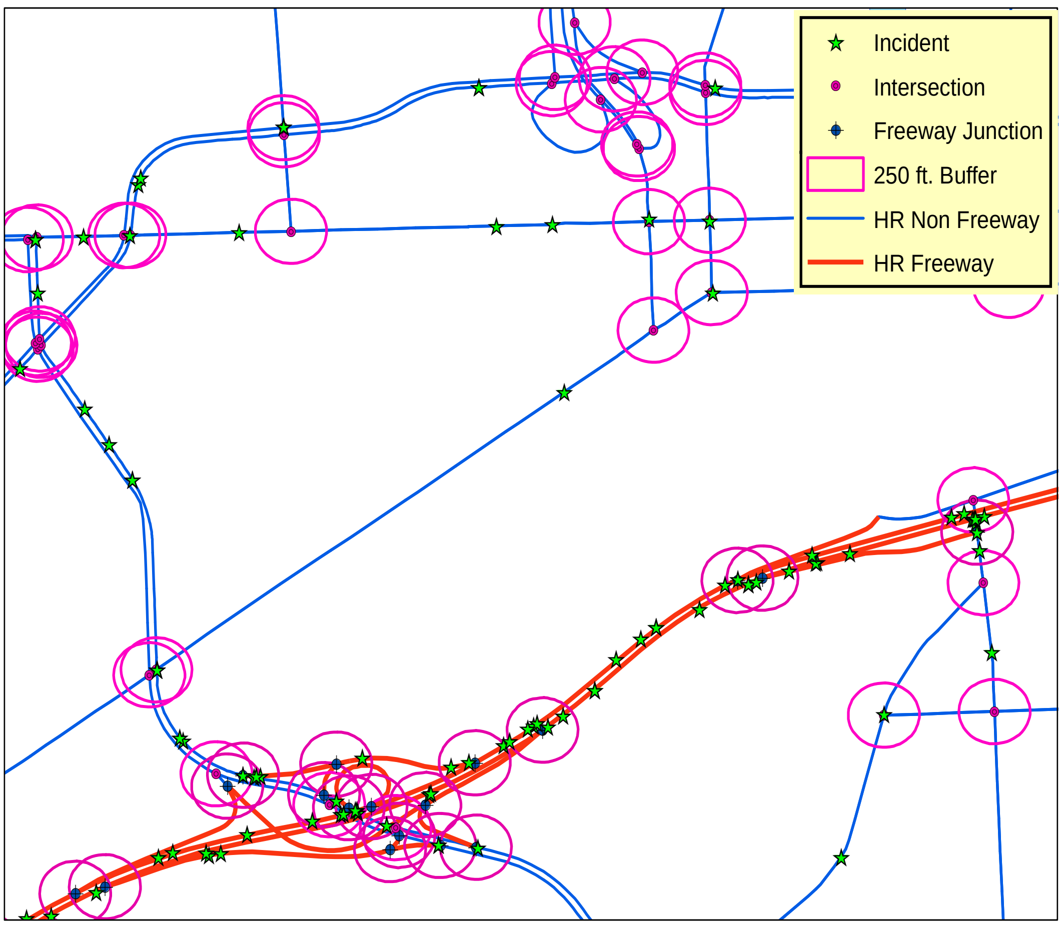


Figure 5.2 Example of Identifying Segment and Intersection Incidents

After the matching process using the 250 ft. intersection boundaries was complete, all individual incidents were categorized as either a segment incident or an intersection incident.

In the case of an intersection incident, all inbound approaches connected to the intersection were assumed to be affected by the incident. However, the proportion of reduced capacity might be different for each approach because it should be determined based on the number of lanes on each approach link. Since no adequate information was available to determine the reduced capacity difference between the incident link and its adjacent links, this study assumed that all approaches from intersection incidents have the same reduced capacity impact resulting from the incident. Thus, for intersection incidents, all approaches connected to the intersection are assumed to have the same incident duration.

After all incident data passed through the two map matching processes on the TDFM network layer and the TDFM intersection layer, the matched incident data were connected to its corresponding segment (link) or intersection (node) on the TDFMI network. This map matching process was conducted four times for different time periods, AM peak, Midday, PM peak, and Night time. Since TDFMI networks have corresponding incident information linked to a primary key based on incident IDs, additional link attributes for the frequency in numbers, duration in minutes, and reduced link capacity in proportion were added to TDFMI networks.

After the matching incidents process in the TDFM network was complete, a total of 45,470 final incidents were selected as shown in Table 5.1. It is worthy to note that each individual intersection incident was counted multiple times based on the number of the approaches associated to it. Thus, the final number of non-freeway incidents after the matching process is greater than before the matching process.

Table 5.1 Incidents After Matching with TDFM Network

	Freeway	Non-Freeway	Total
Crash	4,584	30,584	35,168
Non-Crash Incident	6,945	3,357	10,302
Sum	11,529	33,941	45,470

Once the matching of individual incident records on the TDFMI network was completed, the reduced capacity and the incident duration of the matched incident records were stored to additional link attributes on the TDFM network. Finally, the spatiotemporal incident matrices for the duration and the reduced capacity were developed.

Table 5.2, Table 5.3, and Table 5.4 show conceptual examples of spatiotemporal incident frequency, reduced capacity, and incident duration, respectively. The three tables had 39,372 rows representing the individual links of the TDFMI network and 249 columns representing individual weekdays of the 2009 base year (weekends and holidays were excluded). The three tables show different incident information associated to a common incident record on the same link of the network. For example, a link from node 10001 to node 10003 had one incident in Day1 and Day 248, respectively. Each incident had a reduced capacity of 0.55 and

0.91, respectively. And those durations were 38 minutes and 25 minutes, respectively. In summary, the link from node 10001 to node 10003 had one incident in Day 1 that caused a reduced capacity to 0.55 of normal condition for 38 minutes. After the base year TDFMIs are run 249 times, the incident information of individual links will be used in the traffic assignment step via corresponding variables in the modified VDFs (BPR and Akcelik).

Table 5.2 Example of Time-Space Incident Frequency Matrix (counts)

From	To	Day1	Day2	Day3	…	Day 248	Day 249
10001	10002				…		1
10001	10003	1			…	1	
10001	10004		2		…		
10002	10001				…		
10002	10005				…		
10002	10006	2			…		
10003	10004				…		
10003	10009			3	…		2
:	:				…		

Table 5.3 Example of Time-Space Incident Reduced Capacity Matrix (ratio)

From	To	Day1	Day2	Day3	…	Day 248	Day 249
10001	10002				…		0.25
10001	10003	0.55			…	0.91	
10001	10004		0.82		…		
10002	10001				…		
10002	10005				…		
10002	10006	0.37			…		
10003	10004				…		
10003	10009			0.35	…		0.72
:	:				…		

Table 5.4 Example of Time-Space Incident Duration Matrix (min)

From	To	Day1	Day2	Day3	…	Day 248	Day 249
10001	10002				…		85
10001	10003	38			…	25	
10001	10004		112		…		
10002	10001				…		
10002	10005				…		
10002	10006	90			…		
10003	10004				…		
10003	10009			230	…		380
:	:				…		

5.2 Matching Future Year Incident Data with TDFMI Network

Since future year incident data do not exist, incident frequency, duration, reduced capacity should be predicted to be used in the future year TDFMI. Chapter 3.4 described how to prepare the incident data for the future year TDFMI. The future year TDFM, developed by (AECOM 2013), was used to generate key input data such as AWDT from loaded link volumes for future year incident prediction. For the future year crash prediction, SPFs and forecasted AWDT were utilized, as described in Chapter 3.4.1. Once the annual incident frequency was forecasted, the incidents were assigned on the future year TDFMI network using a Monte Carlo simulation based on the relationships between the incident frequency of base year and the functional classification of the TDFM network and four time-of-day periods.

The cross-classification table for incident duration, described in Chapter 3.4.2, was used for the future year TDFMI. Table 3.21 shows the probability of incident duration based on the combination of four different incident duration periods and three levels of incident severity. Similar to incident duration, the cross-classification table for the reduced capacity ratio of the base year was also used for the future year TDFMI. Table 3.18 shows the reduced link capacity to determine how much capacity would be reduced from an incident, based on the total number of lanes and the number of blocked lanes from the incident (Chin et al. 2004; TRB 2010).

5.3 Exceptional Cases in Matching Process

When two or more incidents occurred at the same location (link or node) during the same TOD period (e.g., MD off-peak period), data for those incidents were combined and converted into a single event because the TDFMI network and the modified VDFs have a single link attribute and a single variable that accommodates incident impact for each simulation period. For example, two incidents occurred at a freeway segment at different time stamps but within the same time-of-day period (e.g., the six-hour MD period from 9 AM to 3 PM). The reduced capacity and the duration of two incidents are as follows:

- Link capacity was reduced to 0.5 by incident 1 for 30 minutes
- Link capacity was reduced to 0.3 by incident 2 for 60 minutes

Table 5.3 shows a diagram to represent two exclusive incidents and the combined incident by calculating weighted reduced capacity and combining the incident duration.

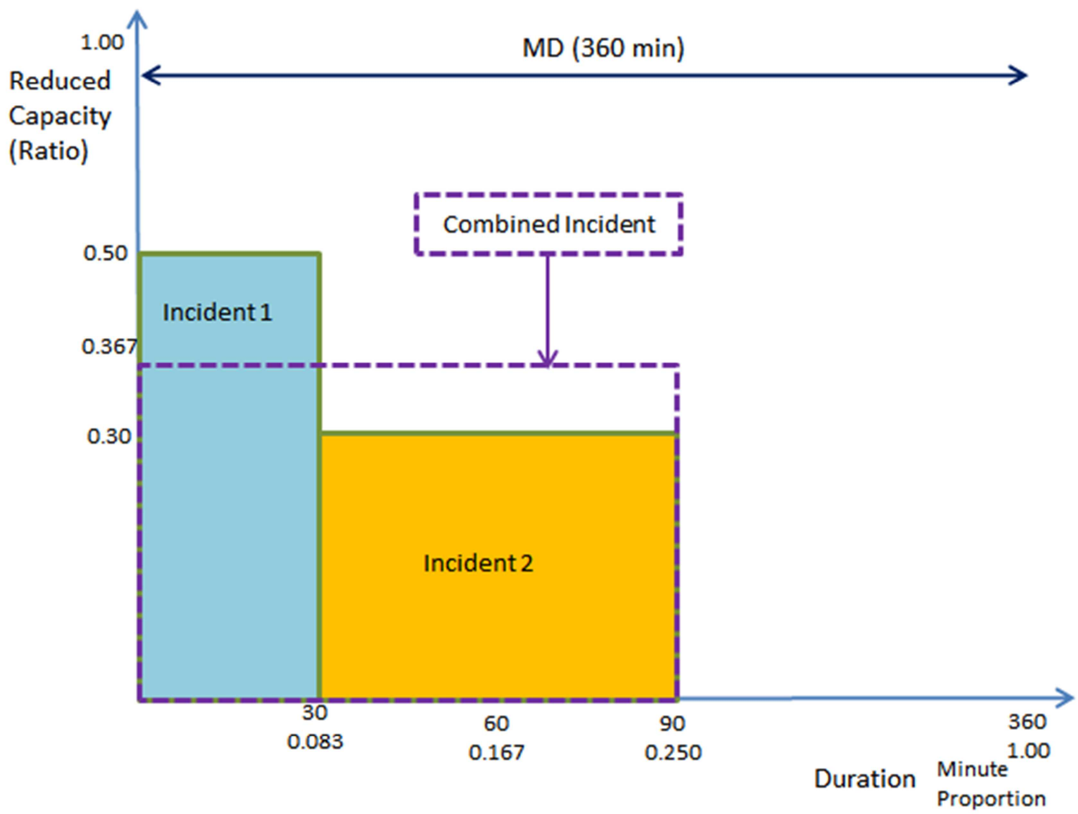


Figure 5.3 Example of Combined Incidents Impacts from Multiple Incidents

A combined incident duration can be determined by simply summing up the two incident durations. However, the combined reduced capacity needs to be calculated by using the duration and reduced capacity of each incident. An area of each incident, calculated by using the incident duration ratio and the reduced capacity ratio, represents the incident impact out of the total time-space dimension of the simulation. Thus, incident 1 has an impact of 0.042 out of the total time-space dimension (1.0) that represents a no incident (full capacity) traffic condition for 6 hours.

- $\text{Incident 1 impact} = \text{reduced capacity} \times \text{duration} = 0.50 \times 0.083 = 0.042$
- $\text{Incident 2 impact} = 0.30 \times 0.167 = 0.050$
- $\text{Combined incident impact} = (0.042 + 0.050)$

  $= \text{combined reduced capcity} \times \text{combined duration}$

  $= \text{combined reduced capcity} \times 0.250$
- $\text{Combined reduced capacity} = (0.042 + 0.050)\ /0.250 = 0.367$

Thus, the combined reduced capacity was calculated as 0.367 when its impact was 0.092 and duration was 90 minutes (0.25) from the total simulation period of 360 minutes. Table 5.5 shows the results after multiple incidents were converted into a single event.

Table 5.5 Example Calculation for Multiple Incident Impacts

	Incident 1	Incident 2	Combined
Reduced Capacity	0.50	0.30	0.367
Duration (min)	30	60	90
Proportion of Duration	0.083	0.167	0.250
Simulation Period (min)	360	360	360

As described in Chapter 4, the modified VDF has two additional variables for reduced capacity and incident duration per link. An incident at the intersection was treated as an intersection delay in the VDF. If a link does not have an incident, two variables (reduced capacity and incident duration) are zero, which makes the modified VDF the same as the original VDF. If a link has an incident, the value of the incident duration and the reduced link capacity of the corresponding link from the incident matrices are applied in the VDF. Incident duration is represented as a proportion of the incident duration out of the total simulation period, and is given a value between zero and one. There may be a situation when the duration of incidents is longer than the simulation period, or the incident duration extends into the next simulation period, regardless if a single incident or multiple incidents occurred. Since traffic simulation is run and summarized separately by individual TOD periods, incident impact should be considered separately for each TOD period.

Since each of the four TODs has its own simulation time period, the proportion of incident duration should be recalculated based on the actual incident duration at each TOD period. By using the starting time of each incident and the duration of each incident, the actual duration can be calculated and the proportion of the incident duration for each TOD period can be determined.

Figure 5.4 shows an example how a single incident can be split into two subsets for different TOD periods. An incident occurred at the MD period and its impact lasted for 4 hours (240 minutes). As a result, incident impact on the roadway was cleared during the PM period. This incident had negative impact (reduced link capacity to 0.367 for 240 minutes) for 180 minutes during the MD period and 60 minutes during the PM period. The proportions of incident duration for both MD and

PM periods are 0.50 (180/360) and 0.33 (60/180), respectively. Both subsets of the incident would have the same reduced capacity of 0.367. In summary, a single incident impacted two different time periods. The reduced capacity was 0.367 for both the MD and PM periods and their incident durations were 180 minutes and 60 minutes, respectively.

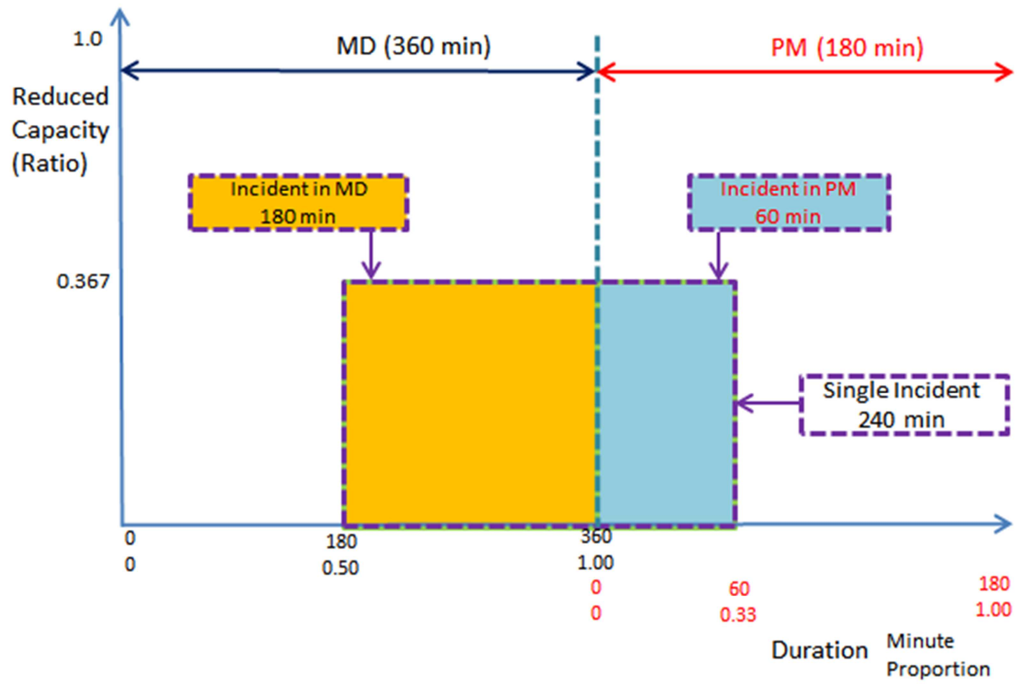


Figure 5.4 Example of Single Incident Impacts during Two Simulation Periods

5.4 Chapter Summary

This chapter described how the incident data, prepared in Chapter 3, was matched with the segments and the intersections of TDFMI networks. For the base year case, the matched links and nodes on TDFMI networks were identified by using the geometric location information from each individual incident record. When an incident occurred inside of the 250 ft. intersection boundary, determined based on the virtual center point of an intersection, the incident was assumed to be an intersection incident. Then, the matched incident data was connected to the corresponding segment (link) or intersection (node) information on the TDFMI networks. This map matching process was conducted four times for four TODs. Consequently, the incident frequency, the duration, and the reduced capacity for 249 weekdays, calculated based on information from both field data and research literature, were prepared to run 249 TDFMIs.

For the future year case, the loaded link volumes from the future year TDFM and the SPFs were used to forecast the annual incident frequency. Then, the forecasted incidents were assigned on the future year TDFMI networks using a Monte Carlo simulation technique based on the relationships between the incident frequency of the base year and the functional classification of the TDFM network and four TODs. The incident duration and the reduced capacity were prepared from field data and research literature, just like the base year case. Throughout the sensitivity test, the TDFMI runs were repeated 100 times with different inputs using the Monte Carlo Simulation technique to generate the annual average weekday travel demand, which was compared to those of the future TDFM in Chapter 6.

Table 5.6 shows assumptions applied in this chapter and the expected impact of those assumptions on the analysis results.

Table 5.6 Assumptions and Impacts on Results

Assumption	Impacts on Result
1. Intersection incident has the same impact on all approaches	1. Impact may be different to individual approaches (better or worse)
2. Impact of multiple incidents is the sum of individual incidents	2. Impact of multiple incidents may be higher than the sum of individual incidents (same or worse)

CHAPTER 6. EVALUATION OF TDFMIs

To evaluate TDFMIs, three major tasks were performed for both the 2009 base year and the 2034 future year scenarios as described below:

- Task 1: Prepared incident data (e.g., frequency, reduced capacity, and duration), as described in Chapter 3.
- Task 2: Modified & calibrated VDFs (BPR type & Akcelik type) to consider the impact of incidents, as described in Chapter 4.
- Task 3: Matched the incident impact with the corresponding links and nodes on TDFMI networks, as described in Chapter 5.

In this Chapter, the comparison between TDFM and TDFMI and the evaluation were made for both the 2009 base year and the 2034 future year. In the base year models, various performance measures and validation statistics, including VMT, VHT, volume over count ratio, %RMSE, and R^2, were used. In the case of future year models, the same performance measures as base year models were used. The validation statistics were excluded during the comparison and evaluation process, as those were unavailable for the future year models. Most of the performance measures were compared by subgroup criteria such as the facility type, area type, jurisdiction, loaded link volume group, etc.

6.1 Comparison of Base Year TDFM and TDFMI

It has been acknowledged that the four step travel demand model has very complicated and time consuming tasks to develop, especially for a big MPO area, such as Hampton Roads. Since the goals of this study are to: develop a framework and propose a methodology on how to incorporate incident impact into the traditional TDFM, and compare and evaluate incident impacts on the TDFMI, a limited effort for the calibration and reasonableness checking of the entire TDFMI framework was performed in this study. As described briefly in Chapter 2.2, TDFMs typically have large amount of inputs, outputs, parameters, factors, models, and functions to be calibrated and validated from various observed, measured, surveyed, and estimated data, such as socio-demographic data (base year and future year), traffic data, and network simulation results. VDOT Transportation Planning & Mobility Division (TMPD) has spent over a million dollars for TDFM modeling activities in the Hampton Roads area since 2010, including a revision of the TDFM with the new 2009 base year, surveys, and VDF development, etc..

Prior to the model comparison with TDFM, the brief reasonableness checks of TDFMI were made when calibrating VDFs for incidents in Chapter 4. Many valid field traffic data was used in TDFMI reasonableness checking, in the same way as traditional TDFM. Since the major differences between TDFM and TDFMI are the network attributes and the functional form of the VDF indicating incident information (duration and reduced capacity ratio), network analysis was focused on the traffic assignment step. All inputs/outputs from the previous three steps (i.e., trip generation, trip distribution, and mode choice) were assumed to be the same, which is reasonable for a short-term analysis on a daily basis focused on route choice behavior.

Table 6.1 shows the performance measures (%RMSE and volume/count ratio) of three models - the TDFM, the TDFMI with BPR VDFs, and the TDFMI with Akcelik VDFs - using 3,287 links that have traffic observations (AWDT). The performance measures were categorized by three subgroups: loaded link volume, facility type, and area type.

Even though extensive model calibration, validation, and reasonableness checking was not performed on the TDFMIs, unlike the TDFM, %RMSE and volume/count ratio for the TDMFI with BPR VDFs showed improvements in most of the subgroups and the whole model, as shown by the shaded cells in Table 6.2. The results of the TDFMI with Akcelik VDFs showed improvements in fewer subgroups compared to the TDFMI with BPR VDFs.

When two performance measures (%RMSE and volume/count ratio) were examined, significant improvements were found at some subgroups. The bold numbers in Table 6.2 indicate the areas where the %RMSE and volume/count showed improvement in the two TDFMIs over TDFM. In particular, performance measures improved in all three categories for the TDFMI with BPR VDFs, even though %RMSE showed improvement in some subgroups but did in the volume/count ratio.

Table 6.1 2009 Model Run Statistics of TDFM and TDFMI

	Subgroup	Volume	Sites	% Root Mean Square Error			Volume/Count Ratio		
				TDFM	TDFMI		TDFM	TDFMI	
					BPR	Akcelik		BPR	Akcelik
Loaded Link Volume	1 - 5,000	3,585,574	1,599	72.13	**70.72**	76.09	1.17	1.20	1.17
	5,000 - 10,000	5,315,469	752	40.13	**36.22**	**38.34**	1.06	**1.01**	**1.03**
	10,000 - 20,000	9,044,430	637	29.12	**28.08**	30.42	1.02	0.95	0.97
	20,000 - 30,000	4,205,604	174	25.17	27.70	28.16	0.94	0.90	0.89
	30,000 - 40,000	1,870,669	55	20.43	21.47	23.00	0.99	0.97	**0.99**
	40,000 - 50,000	1,982,331	45	18.52	**15.40**	26.71	0.90	**0.93**	**0.95**
	50,000 - 60,000	1,048,384	19	24.50	**20.76**	**23.73**	0.91	**0.94**	**0.97**
	60,000 - 70,000	195,459	3	30.26	**23.02**	**21.38**	0.81	**0.91**	**0.91**
	70,000 - 80,000	223,816	3	21.05	**18.17**	**19.85**	0.80	**0.82**	**0.80**
Facility Type	Interstate Freeway	5,347,521	150	23.24	**20.23**	27.71	0.97	**1.00**	**0.99**
	Minor Freeway	1,303,229	72	27.20	**26.16**	27.50	1.00	0.96	0.98
	Principal Art	6,335,433	394	30.47	**30.10**	30.71	1.07	**1.00**	**1.01**
	Major Art	1,586,969	180	38.54	**38.14**	41.05	0.95	0.88	0.91
	Minor Art	9,790,532	1,248	38.94	**38.60**	39.37	1.02	0.95	0.97
	Major Collector	408,273	228	71.60	**69.07**	75.61	1.04	1.07	**1.00**
	Minor Collector	2,600,421	972	63.86	65.44	69.25	1.04	1.12	1.11
	Local	29,782	36	43.38	44.45	49.12	1.00	1.05	1.02
	H.S. Ramp	27,812	1	27.32	**20.50**	33.31	0.73	**0.80**	0.67
	L.S. Ramp	41,764	6	57.32	60.71	**52.31**	0.98	**0.99**	**1.00**
Area Type	CBD	128,030	10	68.11	68.34	68.35	0.49	0.47	0.48
	OBD	5,342,234	525	38.90	**36.98**	42.77	1.00	0.96	0.97
	Urban	6,174,351	703	35.79	36.06	36.74	1.01	0.98	**1.00**
	Sub Urban	7,328,412	778	41.64	**40.19**	45.16	0.98	0.95	0.96
	Rural	8,498,709	1,271	43.35	**40.20**	46.12	1.07	**1.05**	**1.04**
All		27,471,736	3,287	40.97	**39.38**	43.88	1.02	**0.99**	**0.99**

In the case of the TDFMI with BPR VDFs, the shaded cells represent the subgroups of three categories that have shown improvement in both %RMSE and volume/counts compared with the TDFM results.

The higher loaded link volume groups (5,000 to 10,000 vehicles per day and greater than 40,000 vehicles per day categories) in the TDFMI showed significant improvement in %RMSE from 15.40% to 36.22% compared to the TDFM. In the facility type category, the interstate freeways and the principal arterials also showed improvements for both performance measures under the TDFMI models. When it comes to area type, the rural area showed improvements for both performance measures.

As a result, the TDFMI showed overall improvement for both the %RMSE and the volume/count ratio. Table 6.2 is a network-wide summary comparing the TDFM with the TDFMI with BPR VDFs. The TDFMI with BPR VDFs showed a higher network-wide VMT, but a lower VHT than the TDFM, which seems reasonable because some travelers would choose longer distance detour routes to avoid congestion (to reduce travel time) that they are aware of.

Table 6.2 Network-wide Summary of TDFM and TDFMI (BPR)

	TDFM	TDFMI(BPR)	TDFMI-TDFM	Percentage
Volume	236,837,428	236,796,651	-40,777	-0.02
VMT	41,111,073	42,086,016	974,943	2.37
VHT	1,146,780	1,104,196	-42,584	-3.71

Volume and Speed Comparison between TDFM and TDFMI

In order to calculate an annual average of weekday travel demand forecasting with incidents, the TDFMIs were run 249 times, once for each weekday in 2009, excluding weekends and holidays. Half-day holidays, such as the day before Thanksgiving Day and Christmas Eve, were excluded in the analysis because they were treated like regular holidays. Even though the TDFMI shows the variation of traffic conditions affected by the impact of incidents on each individual weekday, an average of TDFMI simulations showed similar results to the TDFM at the individual links level.

Figure 6.1 shows an example of the distribution of the loaded link volumes and travel speeds across 249 TDFMI runs. The average link volume and travel speed from the 249 TDFMI runs and the link volume and travel speed from a single TDFM run are shown on the same distribution graphs. The graph of the loaded link volume of Tyre Neck Rd. has a similar shape to a normal distribution, as shown in Figure 6.1 (top). The mean TDFMI link volume (1,572 vehicles per day) was very close to the TDFM link volume (1,570 vehicles per day). The TDFMI distribution of travel speeds showed a very small variation compared to link volume distribution. The TDFM travel speed and the mean TDFMI travel speed were found to be the same at 35.9 mph. No incidents were found at this link segment and intersection (both upstream and downstream sides) in the 2009 base year.

Figure 6.1 (bottom) shows another example on interstate freeway I-564 westbound which had two incidents in 2009. The mean TDFMI loaded link volume was very similar to the TDFM loaded link volume, at about 53,000 and 53,300 vehicles per day, respectively. The mean TDFMI travel speed was very similar to the TDFM travel speed, at 54.0 mph and 54.5 mph, respectively.

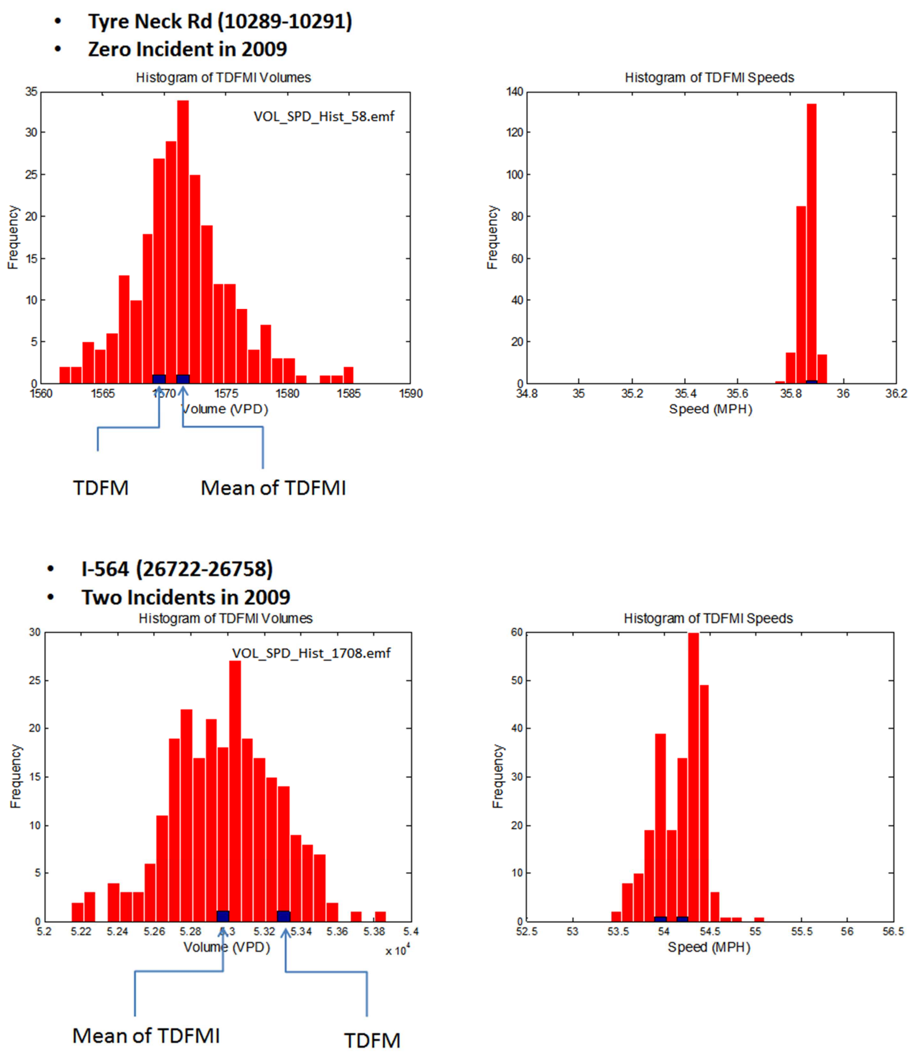


Figure 6.1 Examples of Volume and Speed Comparison of TDFM and TDFMI

It would be premature to conclude that the reason why the I-564 loaded link volume and travel speed graphs generated from 249 TDFMI runs were not close to a normal distribution because of two incidents. However, it could be expected that the variation of traffic conditions on interstates are much higher than in minor collectors. The detail analyses based on the 2009 incident observations in Chapter 3.3 show the distinctive difference of incident frequency by TOD, roadway types, and incident types. When more incidents occurred in one facility type (e.g., interstate freeways), a higher variation of traffic conditions would likely be found.

Sensitivity Test of TDFMI

Even though there are many strengths of the TDFMI over the TDFM, one of the major weaknesses of the TDFMI is its computational burden. The average model run time of 249 TDFMI base year models was 41 minutes using an Intel i7 3.20 GHz Octa Cores CPU with 60 GB of RAM on the Windows 7 64 Bit Operating System. Thus, the model run time and the storage space requirements would increase when running future year TDFMI analyses with multiple scenarios, as is required for the project list prioritization process. If the 10 projects plus a 'Do-Nothing' case needs to be evaluated with 250 simulations per scenario, 2,750 TDFMI runs are required to compare with the TDFM. The computational time may vary based on the hardware and software platform used for the TDFM and TDFMI.

To mitigate the computational load, this research examined how many simulations should be run to obtain reliable TDFMI results. To find the optimum (minimum) number of simulations, a sensitivity test was performed on 249 TDFMI runs based on the 2009 base year data. The results of the sensitivity analysis were applied to determine the number of simulations required for the 2034 future year

TDFMI scenarios. Thus, the number of dates for the incident data and the number of TDFMI networks per four TODs were determined after the number of simulations was determined.

In order to examine how many TDFMI model runs should be made to generate the same results (or results within an acceptable range of difference) as those from all 249 runs, the average model runs for five cases were compared as described below. The days for multiple runs of the sensitivity analysis were randomly selected from the 249 days.

1. One run TDMFI (G1)
2. The average of 10 TDFMI runs (G10)
3. The average of 50 TDFMI runs (G50)
4. The average of 100 TDFMI runs (G100)
5. The average of 249 TDFMI runs (G249)

Figure 6.2 shows the loaded link volume difference between the G1, G10, G50, G100, and G249. The loaded link volume difference between G1 and G249 is as high as 20% for the links of lower loaded volume groups (less than 10,000 vehicles per day) and is as low as less than 3% for the links of higher loaded volume groups (greater than 60,000 vehicles per day).

The differences between G10 and G25 are much smaller than the differences between G1 and G249, especially in the lower link volume range. G50 shows a very small link volume difference from G249. The maximum difference between G50 and

G249 at the lower link volume group is less than 3%. The volume difference between G100 and G249 becomes even smaller across all links. There is even less than a 1% difference at the lower link volume group of less than 3,000 vehicles per day.

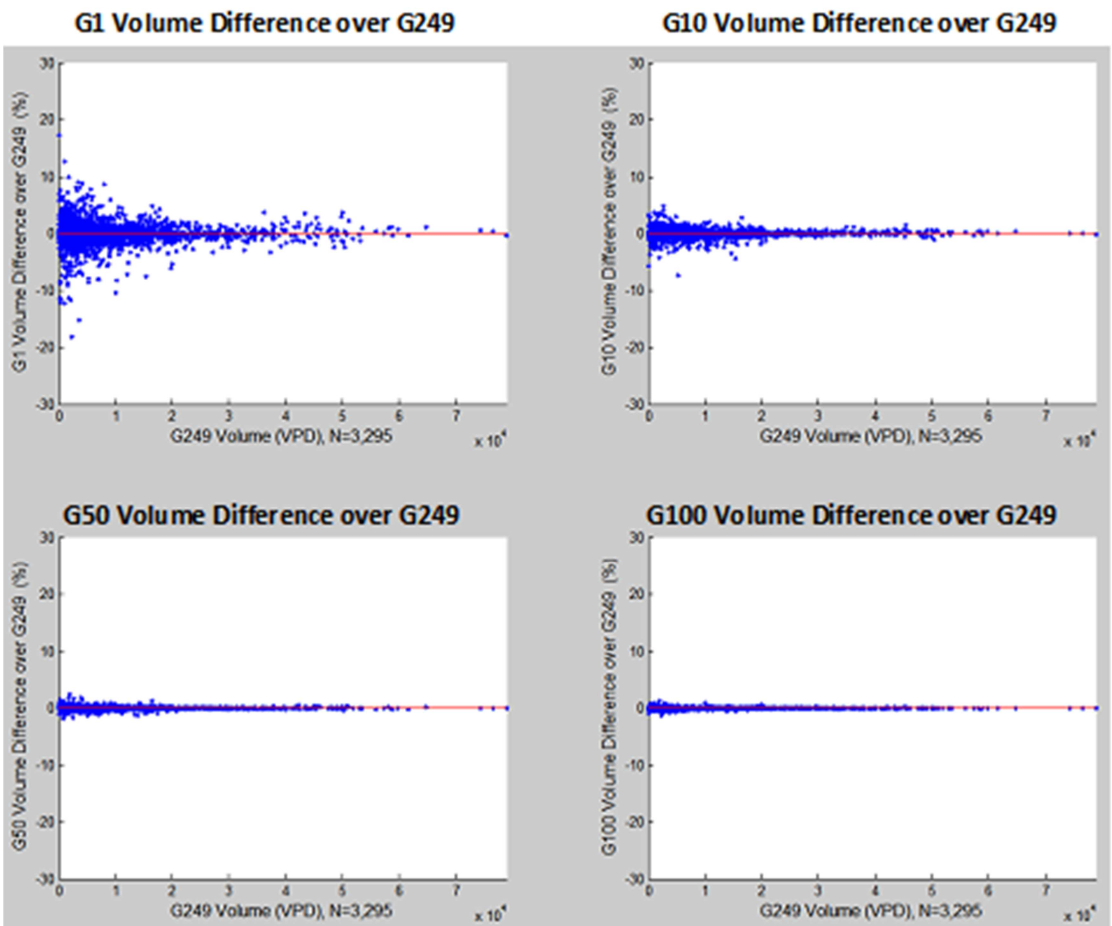


Figure 6.2 Difference of Loaded Link Volumes over G249

The histograms of differences between the G1, G10, G50, and G100 over G249, as shown in Figure 6.3, show that the G100 generated the same results as the G249 with less than a 1% error range. Even though 249 TDFMIs were used to generate the average of weekday model runs for the 2009 base year, this study assumed that 100 replications of Hampton Roads TDFMIs would be good enough and a conservative enough number of simulations for the evaluation and prioritization of 2034 future year TDFMIs.

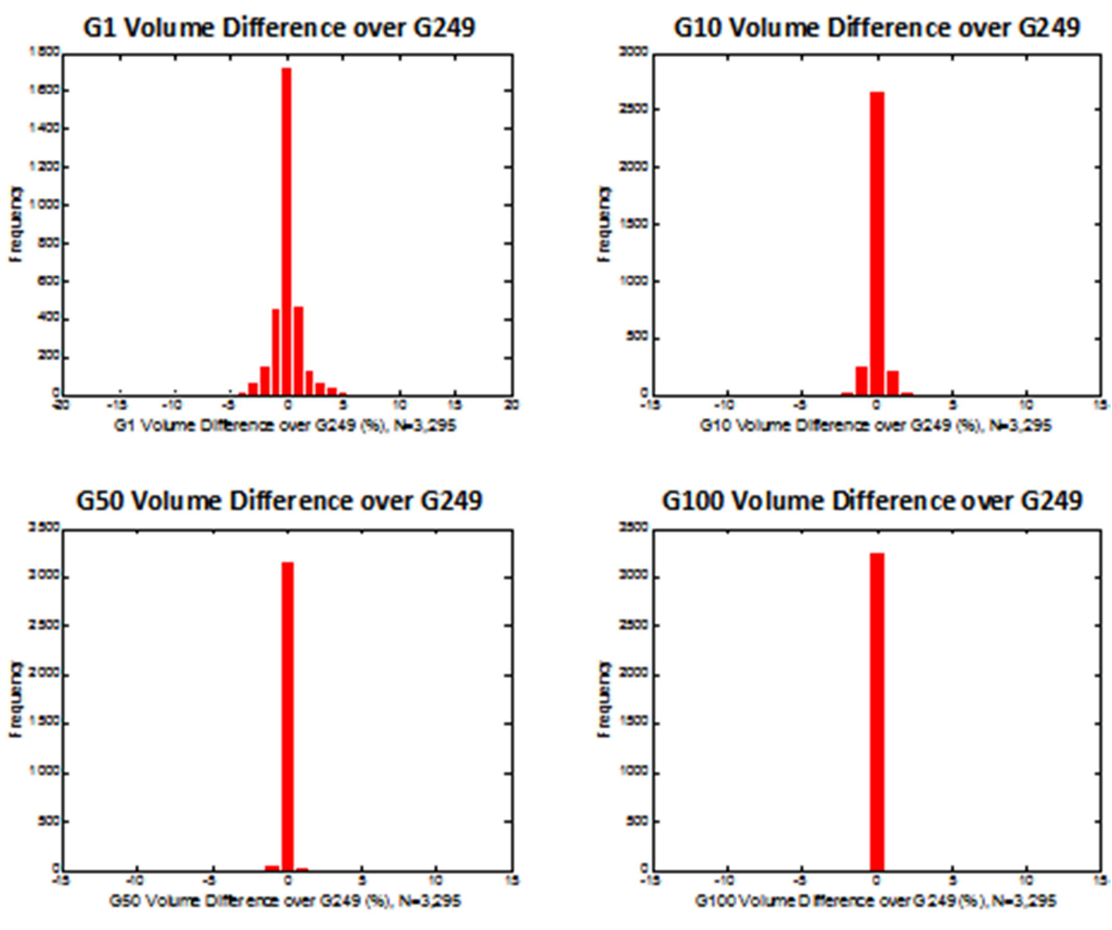


Figure 6.3 Histogram of Volume Difference over G249

However, the minimum number of replications for the TDFMIs may be mainly determined by the network characteristics, including network size, the level of detail, the level of congestion, and the variation of incidents on the network, etc. Further research is required to determine the optimal number of replications of the TDFMIs based on the levels of TDFM network and incidents.

6.2 Comparison of Future Year TDFM and TDFMI

6.2.1 Prioritization of 2034 TDFM

Hampton Roads MPO (referred as HRTPO) has published numerous technical reports regarding their project priorities for the 2034 LRTP (Kimley-Horn and Associates, Inc. 2010; Hampton Roads Transportation Planning Organization 2010). HRTPO made a list of regionally funded construction projects based on the prioritization categories: bridge/tunnel projects, highway projects, intermodal projects, transit, bicycle, pedestrian, and rail mode. Kimley-Horn and Associates, Inc. (2010) showed the project prioritization process and the evaluation results with the scores used in the 2034 LRPT.

Table 6.3 shows the 158 project candidates proposed by local jurisdictions by project type in the 2034 LRTP. In the highway investment category, 113 projects worth about $9.5 billion were proposed by local jurisdictions. Even though only 19 Tunnel and Bridge investment projects were proposed, their estimated costs were over $26 billion. Consequently, the total amount of estimated project funds for 158 proposed projects were approximately $38 billion.

Table 6.3 Project Candidates used in 2034 LRTP Prioritization

Project Type	# of Projects	Estimated Cost (YOE)
Highway	113	9,439,468,048
Interchange	18	1,184,118,458
Tunnel/Bridge	19	26,086,886,200
Multimodal	5	217,418,000
Intermodal	3	688,563,008
Total	158	37,616,453,714

YOE: Year-Of-Expenditure
Source: HRTPO, 2013

The list of projects is composed of three groups: 1) committed funded investments, 2) proposed regionally funded investments and ongoing funded studies, and 3) unfunded projects for future consideration (HRTPO, 2013). As of March 2011, approximately $6.64 B worth of funded projects were included in the 2034 LRTP, which was sourced by local, regional, state, federal, and private funds (HRTPO, 2013).

HRTPO staff conducted a thorough analysis to prioritize all 158 proposed projects. In other words, they revised the 2034 TDFM network for 158 projects and ran the TDFM model 159 times for individual different scenarios, including the 'Do-Nothing' case. From the prioritization process of all projects, HRTPO identified three major evaluation criteria - project utility, economic vitality, and project viability - to evaluate and score each project. HRTPO weighted four criteria used in their prioritization evaluation as described below:

- Evaluation of congestion level base on V/C ratio and ADT
- Cost effectiveness based on construction cost and VMT

- Travel time reduction
- Increase of travel time reliability

During the prioritization process, all projects were evaluated by three main categories that have 100 points each and consisted of sub-categories with both quantitative and qualitative criteria. Table 6.4 shows the criteria of the three major categories and their subcategories with their associated points. The shaded criteria in the Project Utility and Economic Vitality categories show the quantitative criteria contributing 85 out of a total 300 points, which are closely related to the area’s mobility. Thus, the below six criteria, equivalent to 85 points, were evaluated and scored based on the TDFMI model run results in prioritization.

- % Reduction between Existing and Future V/C Ratios: 10 points
- Existing V/C Ratio: 10 points
- Impact to Nearby Roadway (Future ADT - Existing ADT): 10 points
- Total Cost ($) / VMT: 15 points
- Total Reduction in Regional Travel Time (VHT): 30 Points
- Increase Travel Time Reliability: 10 points

Table 6.4 Criteria and Scores for Prioritization

Category	Criteria	Score
Project Utility (100)	**Congestion level:**	
	(a) % reduction in existing and future V/C ratios [(Existing V/C-Future V/C)/Existing V/C]	10
	(b) Existing V/C ratio	10
	(c) Impact to Nearby Roadways (Future ADT-Existing ADT)	10
	System Continuity and Connectivity (Regional:25, Multi-Jurisdictional:16.75, or Local:8.25)	25
	Cost Effectiveness (Estimated cost/2034 daily VMT)	15
	Land Use Compatibility	10
	Safety and Security	15
	Modal Enhancements	5
Economic Vitality (100)	**Total Reduction in Regional Travel Time (Very high:30, high:20, medium:10, low:5, very low:0)**	30
	Labor Market Access	
	(a) Increase Travel Time Reliability (high:10, medium high:8, medium:6, medium low:4, low:2)	10
	(b) Increased Access for High Density Employment Areas (very high:10, high:7, medium:3, low:0)	10
	Address the Needs of Basic Sector Industries?	30
	Defense Access?	
	Will the project significantly reduce travel time for trips to major tourism areas?	
	Will the project significantly reduce travel time for trips to ports?	
	Increased Opportunity	20
Project Viability (100)	**Funding**	
	Percentage of Funding Committed	50
	Process/Project Readiness	
	Prior Commitment (is project in LRTP)	10
	Percentage of Project Design Complete	10
	Are Environmental Documents Complete	15
	Are Environmental Decisions Obtained	5
	Is ROW Obtained and Utilities Coordinated	5
	Are additional environmental permits obtained	5
Grand Total		300

Source: HRTPO, 2013

Since this dissertation research focused solely on highway projects, the top 10 highway projects (e.g., new roadway construction, existing roadway widening) were selected to compare the prioritization results generated from the 2034 future TDFMI models with the 2034 Hampton Roads LRTP Prioritization list. Initially, the top 10 ranked highway projects were selected, but one project was excluded for further analysis because the geometric information was not sufficient to be incorporated into the TDFMI network. Thus nine separate TDFMIs corresponding to nine highway projects were developed. The nine TDFMI networks were revised from the TDFMI network for the 'Do-Nothing' case, while the modified VDFs remained the same.

Figure 6.4 shows the locations of the nine highway projects and their spatial boundaries. Table 6.4 shows the geometric boundary and other information, including length and number of lanes, for the nine projects. Project ID 65 and project ID 152 are new roadway construction projects; the seven remaining projects widen existing roadways. Project ID 5 and project ID 16 are multi-jurisdiction widening projects on I-64 and the new US-460, while the other seven projects are within a single jurisdiction.

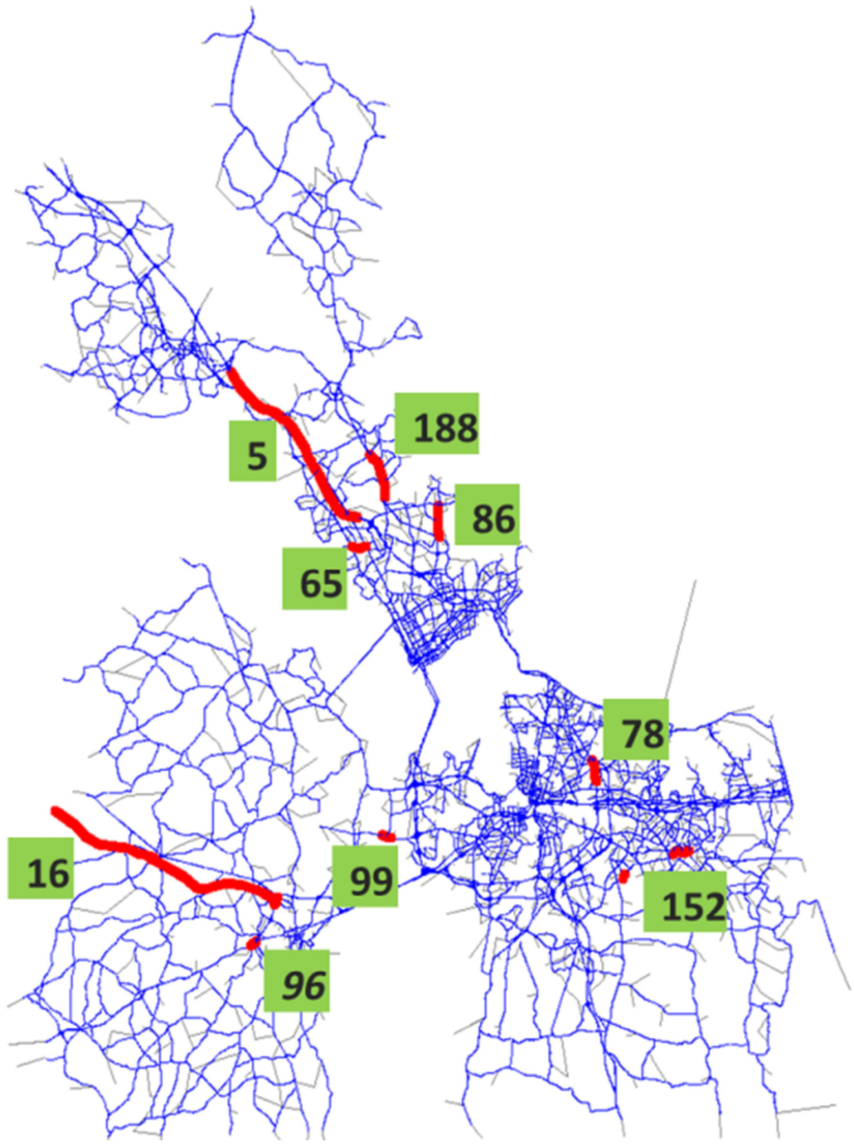


Figure 6.4 Locations Top Nine Projects in Prioritization List from 2034 CLRP

Table 6.5 Location and Brief Information of Top Nine Prioritization List from 2034 CLRP

ID	Project Name	From	To	Length (miles)	Existing Lanes	Proposed Lanes
5	I-64 Peninsula Widening	Route 199 (Exit 242)	Jefferson Ave (Exit 255)	12.83	4	8
16	US 460 Relocation	Suffolk Bypass at US 58	Southampon/IW corp limit	14.87	0	4
65	Middle Ground Blvd	Jefferson Ave	Warwick Blvd (Rte 60)	1.00	0	4
78	Military Hwy	Lowery Rd	Robin Hood Rd	1.33	4	6
86	Wythe Creek Road	Alphus St	Hampton CL	0.96	2	4
96	Holland Road (Rte 58)	Route 58 Bypass Ramp	Manning Bridge Rd	2.23	4	6
99	Nansemond Pkwy (Rte 337)	Helen St	Chesapeake CL	0.37	2	4
152	Lynnhaven Pkwy	Centerville Tnpk	Indian River Rd	2.05	4	6
188	G.W. Memorial Highway (Rte 17)	Hampton Highway	Dare Road	2.78	4	6

Table 6.6 shows the 2034 TDFM prioritization scores for the three categories and the total scores with ranking. Project ID 188, a widening project on the George Washington Memorial Highway (Route 17), ranked 1st place with the highest score of 202 in the highway project prioritization process. Even though Project 188 did not have the highest score in any of the three categories, as indicated by the shaded cells in Table 6.6, it ranked as one of top three highest scores (in bold) in all three categories and ranked 1st place with the highest overall total score. Project ID 5, a project to widen the I-64 Peninsula from 4 lanes to 8 lanes, had the highest scores at two categories (Project Utility and Economic Vitality) but had the lowest score in the third category (Project Viability). As a result, project ID 5 was ranked 5th in the overall total score.

Table 6.6 2034 TDFM Prioritization Scores and Ranking

Rank	Project ID	Project Utility	Economic Vitality	Project Viability	Grand Total
1	188	**82**	**40**	**80**	202
2	152	62	30	**99**	191
3	16	**71**	**53**	63	187
4	96	75	34	71	180
5	5	**85**	**75**	18	178
6	65	55	38	**79**	172
7	86	63	26	78	167
8	99	62	19	78	159
9	78	69	26	62	157

6.2.2 Prioritization of 2034 TDFMI

To prepare the 2034 TDFMI models, 2034 TDFMs for 10 scenarios, including the 'Do-Nothing' case, were run first to generate loaded link volumes on TDFM networks, as described in Chapter 4. The key incident data (frequency, reduced capacity, and duration) for the 2034 future year TDFMI were prepared, as described in Chapter 3.4, and matched with TDFMI networks, as described in Chapter 5.2. Since incident severity is a key factor in determining incident duration and reduced capacity, it was used along with incident type and the number of blocked lanes (based on incident observations) to determine the frequency, duration, and reduced capacity. When the incident data were forecasted, the Monte Carlo Simulation technique was applied to assign the forecasted incident information on the 2034 TDFM network. As described in Chapter 6.1, 100 replications were repeated to calculate an average of TDFMI runs. The 2034 future year TDFMI model runs were repeated 100 times per scenario, and then the average TDFMI results were calculated.

Using the average TDFMI results, 10 TDFMI scenarios were summarized to calculate the scores by applying the same criteria that were used in the TDFM prioritization process, as shown in Table 6.3. Figure 6.5 shows the prioritization rankings of nine projects from the 2034 TDFM and the 2034 TDFMI based on the scores of the three subgroup criteria and total. Since the impact of incidents on the TDFMI caused changes in the V/C ratio, ADT, VMT, VHT, and travel time reliability, the final project priorities and total scores were changed. Project 188, the top ranked project in the TDFM, remained as the top rank project in the TDFMI, even though there were some changes to V/C and VHT values. Project 65, the new construction of Middle Ground Blvd, was ranked 6^{th} in the TDFM but ranked 9^{th} in the TDFMI, as it received lower or equal scores to the TDFM in all six criteria. In contrast, project 86, widening Wythe Creek Rd., was ranked 4^{th} in the TDFMI from 7^{th} in the TDFM, as it had the highest scores in reduction of VHT.

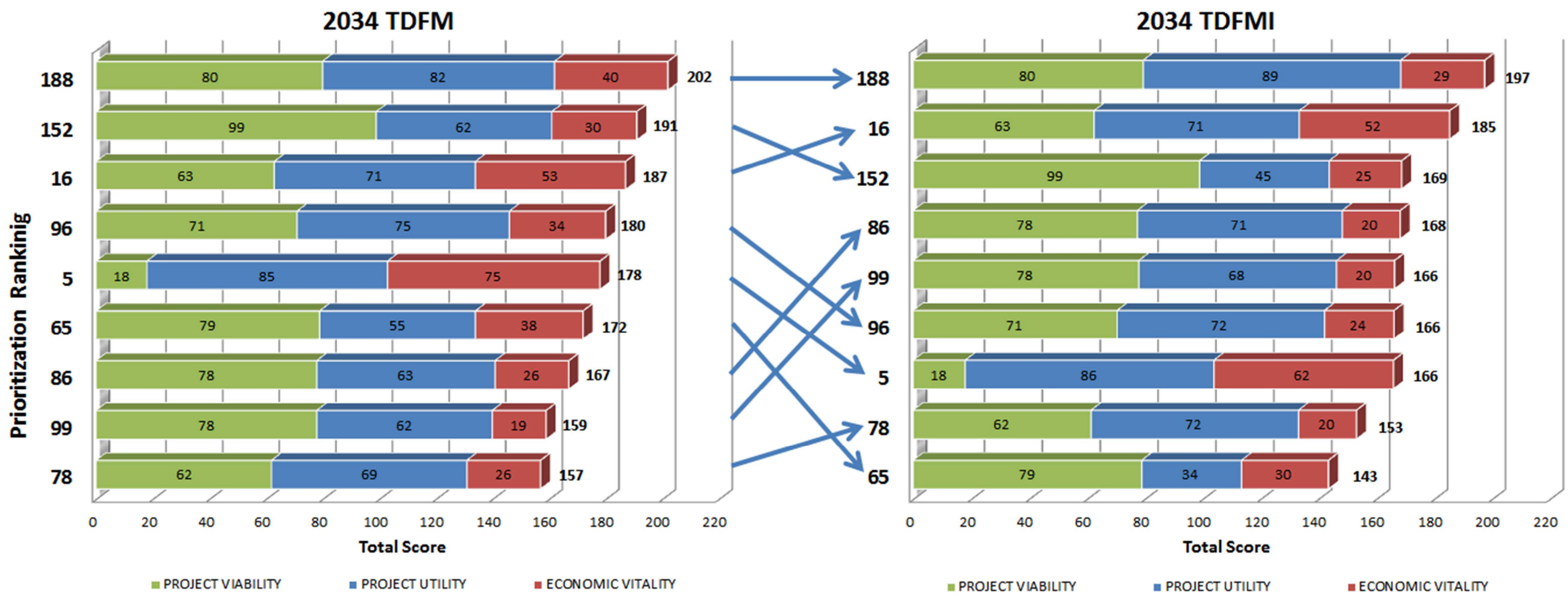


Figure 6.5 Priority Rankings and Their Scores of TDFM and TDFMI

Figure 6.6 represents the comparison results of TDFM with TDFMI under three evaluation categories. The graph of each project shows the differences between TDFM and TDFMI in the three categories. Most of the projects have significant score differences in the Economic Vitality category. No changes were found in the Project Viability category, as there were no quantitative criteria to evaluate.

When it comes to the Project Utility category, project ID 65 and project ID 152 had the biggest score reductions. They received very low scores in 'Congestion Level', which consists of three sub-criteria: current V/C level, V/C reduction in the future, and the impact to nearby roadways. TDFMI showed a lower V/C ratio and lower V/C improvements from those projects compared to TDFM. When it comes to the Economic Vitality category, project IDs 5, 96, and 188 had significant score reductions of greater than 10 points, for criteria closely related to the total reduction of regional travel time and its reliability. When the Project Utility and Economic Vitality categories were evaluated together in the Grand Total, project IDs 5, 65, 96, and 152 had significant score reductions by over 10 points. In particular, the Grand Total score of project IDs 65 and 152 were reduced by 28.5 and 22.2 points, respectively. Those significant score reductions forced their rankings to be reduced from 6th and 2nd to 9th and 3rd, respectively.

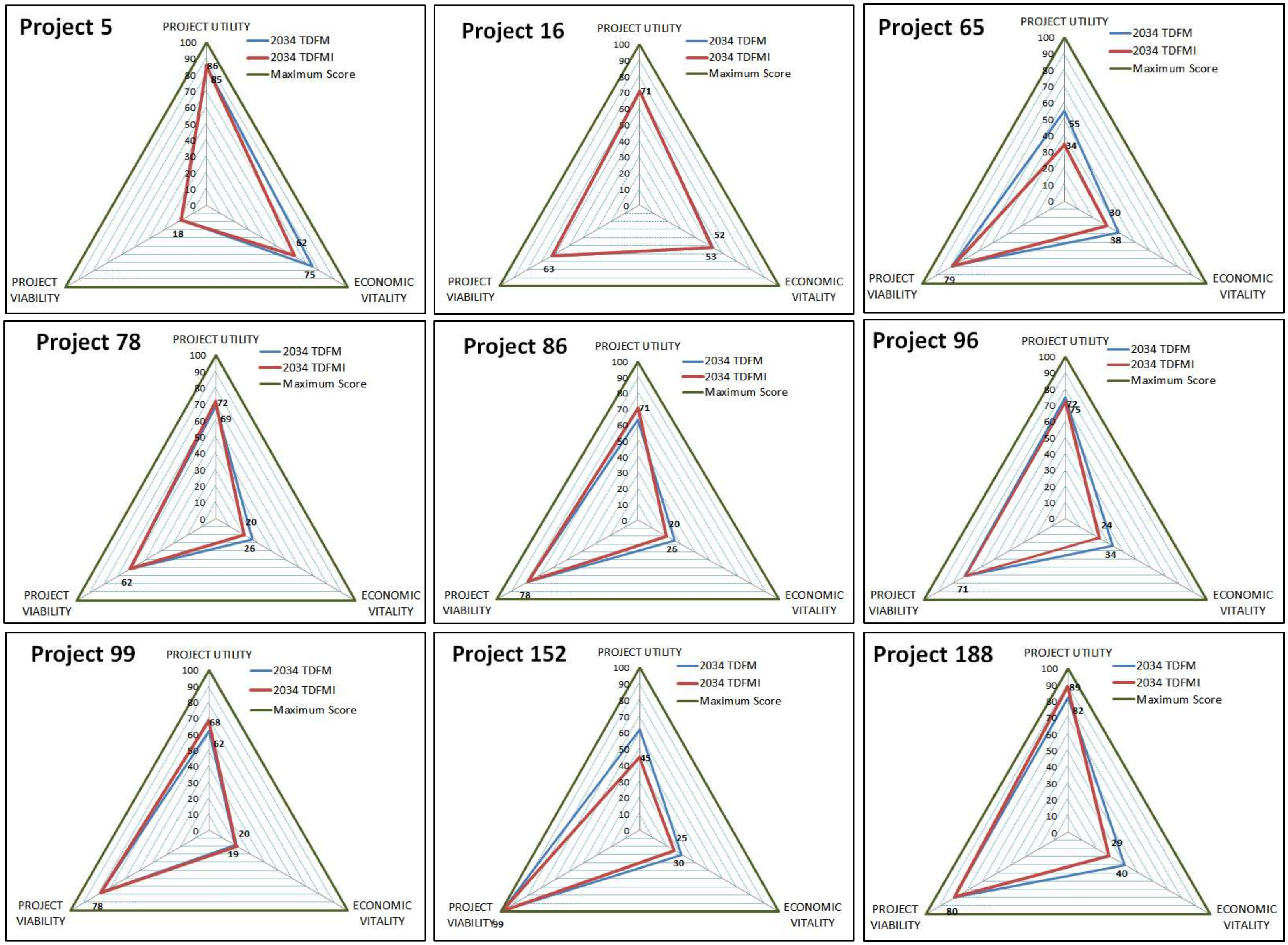


Figure 6.6 Evaluation Scores of Three Categories for Nine Projects

As opposed to the evaluation of three categories per project in Figure 6.6, Figure 6.7 shows the evaluation scores of TDFM and TDFMI for nine projects with six sub-criteria.

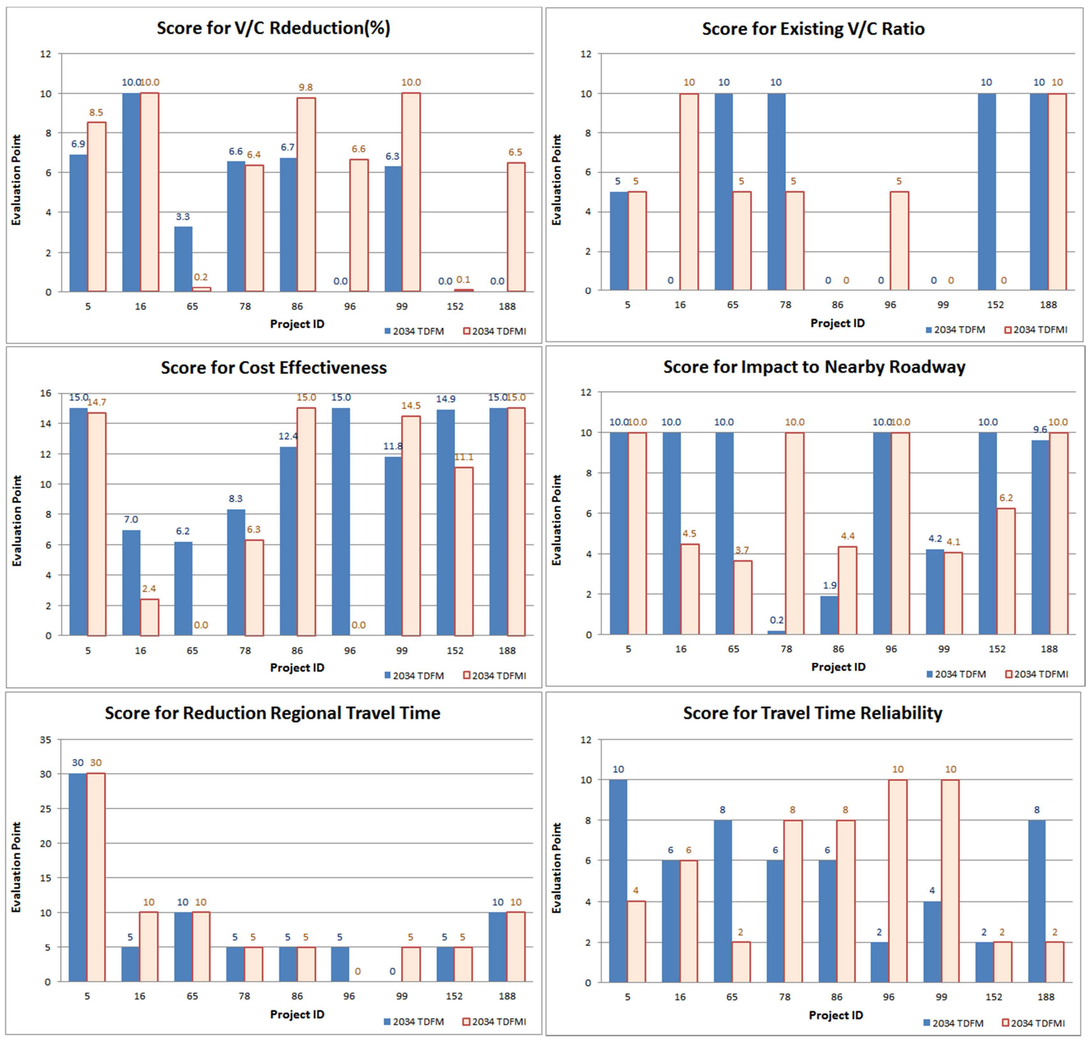


Figure 6.7 Evaluation Scores of Nine Projects for Six Sub-Criteria

Six graphs in Figure 6.7 show which projects have significant differences between the TDFM and the TDFMI by individual sub-criteria. From the visual inspection of score differences for the nine projects based on criteria, all criteria appeared to have significantly different scores throughout the projects except for ‘Cost Effectiveness’ and ‘Reduction of Regional Travel Time’.

Figure 6.8 shows the cumulative project costs of TDFM and TDFMI based on their prioritization rankings. Since the rankings of projects were changed from using TDFM vs. TDFMI, the curves of cumulative project costs by prioritization ranking may show different results. If a limited number of highway investment projects should be selected based on investment budget constraints, TDFM and TDFMI results could generate a different list of feasible investment projects to planners and decision makers.

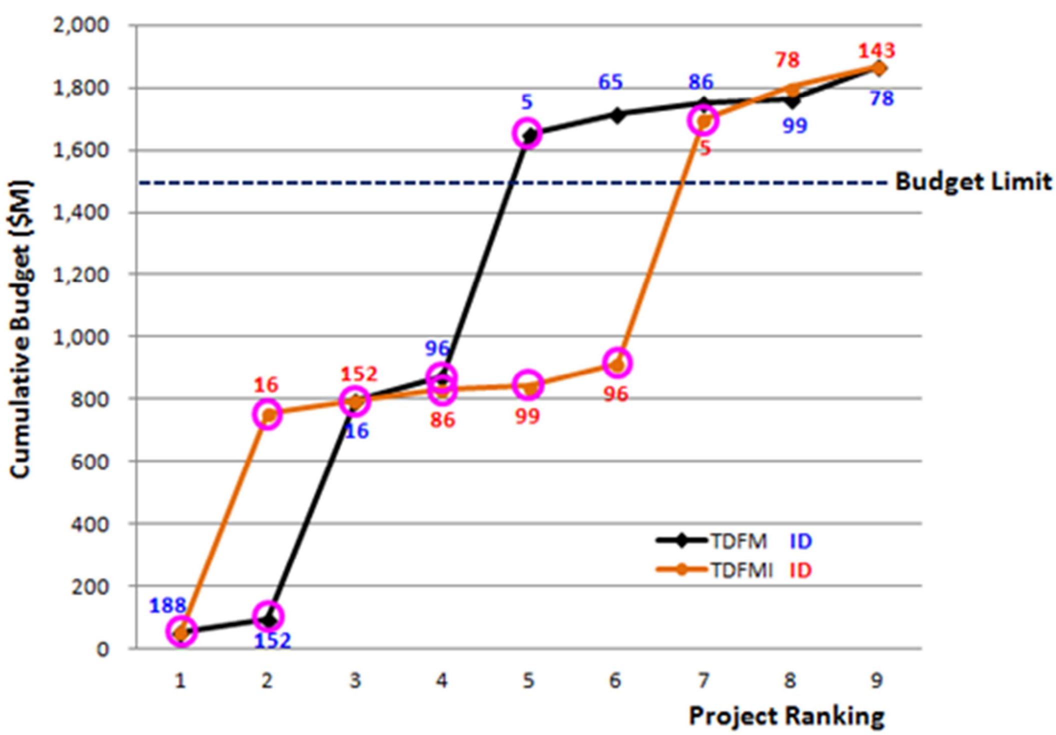


Figure 6.8 Cumulative Project Cost per Prioritization Ranking

For example, investment funding for highway projects in the 2034 LRTP is limited to $ 1.5 billion, as shown in Figure 6.8. TDFM would recommend five projects (IDs 188, 152, 16, 96, and 5), while TDFMI would recommend seven projects (IDs 188, 16, 152, 86, 99, 96, and 5) that would meet budget conditions. TDFMI added two more projects (IDs 86 and 99) as investment projects that TDFMI did not. Thus, it is worthy for HRTPO planners and decision makers to examine if they should include those two projects in their 2034 LRTP. It is noted that project ID 5 would not be selected by both 2034 the TDFM and the TDFMI, based on the budget allocated.

In addition to a visual inspection, a paired t-Test was performed using both evaluation scores from TDFMs and TDFMIs to examine if the score differences between the TDFM and the TDFMI were statistically significant over the six criteria for the nine projects. Table 6.7 shows the paired t-Test results using the evaluation scores of the six criteria for the nine projects. From the paired t-Test results for nine projects, it turns out that three TDFMI scenarios, project IDs 65, 86, and 99, generated significantly different evaluation scores between the TDFM and the TDFMI, which means that the mean difference of evaluation scores were significantly greater than zero.

On the contrary, a second paired t-Test was conducted to examine if any individual criteria generated statistically significant differences between the TDFM and the TDFMI over nine projects. Table 6.8 shows the paired t-Test results using evaluation scores of the nine projects for the six criteria. From t-values and p-values, it turns out that no one of the six sub-criteria generated significantly different evaluation scores between the TDFM and the TDFMI.

These results show that the TDFMI could generate different quantitative analysis results that would change the prioritization results. Thus, the application of TDFMI to nine candidate major investments of future scenarios shows that while the top ranked project is unaffected, three projects experienced a rank change by one position and three projects experienced a rank change by three positions. This change in prioritization demonstrates that explicit consideration of a project's ability to reduce incidents is feasible with TDFMI and can materially influence which investments are selected.

Table 6.7 Paired t-Test Results for Nine Projects

	5		16		65		78		86		96		99		152		188	
	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI
Mean	12.8	12.0	6.3	7.1	7.9	3.5	6.0	6.8	5.3	7.0	5.3	5.3	4.4	7.3	7.0	4.1	8.8	8.9
Variance	82.4	92.1	13.9	11.1	7.5	13.9	11.4	3.7	18.7	26.5	36.7	20.4	19.4	27.0	31.7	18.3	24.0	18.8
Pearson Correlation	0.962		-0.386		0.745		-0.784		0.975		-0.356		0.872		0.715		0.639	
t Stat	0.728		-0.34		4.349		-0.373		-3.068		0.017		-2.757		1.812		-0.092	
P(T<=t) two-tail	0.499		0.748		0.007		0.725		0.028		0.987		0.040		0.130		0.930	
t Critical two-tail	2.571		2.571		2.571		2.571		2.571		2.571		2.571		2.571		2.571	

Note: Observations = 6
df = 5
H_0 = The average difference between TDFM and TDFMI was 0

Table 6.8 Paired t-Test Results for Six Criteria

Criteria	1		2		3		4		5		6	
	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI	TDFM	TDFMI
Mean	4.4	6.5	5.0	4.4	7.3	7.0	11.7	8.8	8.3	8.9	5.8	5.8
Variance	13.8	14.9	25.0	15.3	16.4	8.7	13.4	43.9	75.0	73.6	7.4	11.4
Pearson Correlation	0.637		0.160		0.075		0.569		0.939		-0.439	
t Stat	-1.886		0.286		0.213		1.632		-0.555		0.000	
P(T<=t) two-tail	0.096		0.782		0.836		0.141		0.594		1.000	
t Critical two-tail	2.306		2.306		2.306		2.306		2.306		2.306	

Note: Observations = 9
df = 8
H_0 = The average difference between TDFM and TDFMI was 0

Table 6.9 shows the project rankings, evaluation scores, and project cost of TDFM and TDFMI. Since project IDs 65, 86, and 99 showed significantly different project scores and rankings between the TDFM and the TDFMI from the paired t-Test, those three projects should be examined with special care in the project selection process under a limited investment budget. Based on the example shown in Figure 6.8, project IDs 86 and 99 should be included when the investment project budget is $1.5 billion.

Table 6.9 2034 Prioritization Ranking, Scores, and Project Cost

Rank	TDFM				TDFMI			
	Project	Score	Project Cost	Cumulative Cost	Project	Score	Project Cost	Cumulative Cost
1	188	202	56.7	56.7	188	197	56.7	56.7
2	152	191	41.1	97.8	16	185	700.0	756.7
3	16	187	700.0	797.8	152	169	41.1	797.8
4	96	180	75.0	872.8	86	168	34.2	832.0
5	5	178	779.4	1,652.2	99	166	8.9	840.9
6	65	172	65.3	1,717.5	96	166	75.0	915.9
7	86	167	34.2	1,751.7	5	166	779.4	1,695.3
8	99	159	8.9	1,760.6	78	153	105.3	1,800.6
9	78	157	105.3	1,865.9	65	143	65.3	1,865.9

Unit: Million dollars
Source: HRTPO, 2011

6.3 Chapter Summary

In this chapter, the comparison between and the evaluation of the TDFM and the TDFMI were made for both the 2009 base year and the 2034 future year. For the base year models, various performance measures and validation statistics were compared by subgroup criteria. Even though extensive model calibration, validation, and reasonableness checking was not performed on the TDFMI, unlike the TDFM, %RMSE and volume/count ratio of TDMFI with BPR VDFs showed improvements in most subgroups and the model as a whole.

TDFMI results with BPR VDFs showed better improvements for most of the subgroups, compared to TDFMI results with Akcelik VDFs. For the future year models, the top nine highway projects were selected from the prioritization list in the 2034 LRTP. One TDFM for annual average daily traffic and 249 TDFMIs for 249 weekdays were prepared for the evaluation of ten scenarios, including the 'Do-Nothing' case. The average of 249 TDFMIs runs were prepared to compare with the TDFM results.

By applying the same evaluation criteria identified by HRTPO, TDFMI results were evaluated by three major criteria: project utility, economic vitality, and project viability. From the three criteria, six quantitative sub-criteria, contributing 85 points out of a total 300 points, were evaluated and scored. The comparison results between TDFM and TDFMI showed that the priority ranking of eight out of nine projects, with the exception of the top ranked project, were changed as the impact of incidents on the TDFMI influenced traffic simulation results. The paired t-Tests for the six sub-criteria showed that no one of six sub-criteria showed significantly different evaluation scores between the TDFMs and the TDFMIs.

On the contrary, the paired t-Tests for the nine projects showed that the evaluation scores for three projects in the TDFMI were significantly different than those generated by the TDFM. These results showed that the TDFMI could generate different quantitative analysis results that would change the prioritization results. This change in prioritization demonstrated that explicit consideration of a project's ability to reduce incidents is feasible with the TDFMI and can materially influence which investments are selected. Table 6.10 shows the assumptions applied in this chapter and the expected impacts of those assumptions on the analysis results.

Table 6.10 Assumptions and Impacts on Results

Assumption	Impacts on Result
1. Average of 100 replications is good enough to generate reliable future TDFMI results	1. Average of 250 replications may generate different results (same or worse)

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

7.1 Conclusions

In this section, the conclusions from conducting this dissertation research are presented below:

The integration of a travel demand forecasting model (TDFM) with models for incident frequency, duration, and reduced capacity is technically feasible.

- The approach used herein takes advantage of the large number of incident records available in areas that actively manage their roadways. It is technically feasible to integrate a travel demand forecasting model with incident data.
- Incident data (frequency, duration, and reduced capacity ratio) were prepared from historical incident records for the base year. For the future year, various models and techniques were successfully applied to forecast future incident frequency, duration, and reduced capacity
- Forecasted incident data for the future year could be allocated on the TDFMI network by using the Monte Carlo Simulation technique based on the characteristics of incidents (type, severity, TOD, duration, etc.) and roadway geometry (functional classification).

The volume delay functions (VDFs) with additional terms for incident impact should be modification and calibrated by using incident involved field data.

- The functional forms of BPR and Akcelik VDFs were modified to accommodate the impact of incidents, with additional variables for capacity reduction and incident duration.
- Field traffic data and crash data in VDOT's database were explored to find crash-involved traffic data by using common temporal and spatial information. The prepared crash-involved traffic data were split into subgroups by facility types (freeways, arterials, and collectors, and local roads) to calibrate VDFs separately.
- The modified BPR and Akcelik VDFs generated better nominal base year performance than the VDFs in TDFM.
- From the TDFMI using BPR VDFs, the higher link volume groups (5,000-10,000 vehicles/day and +40,000 vehicles/day) showed significant improvements in %RMSE from 10% to 24%, compared to the TDFM. From the facility type category, TDMFI results for interstate freeways and principal arterials also showed improvements on both performance measures. When it comes to the area type, TDMFI results for rural areaa showed improvements on both performance measures.

The Travel Demand Forecasting Model with Incidents (TDFMI) needs to be examined along with the TDFM by planners for selecting investment projects from a prioritization list under limited budget conditions.

- The TDFMI considerably affected the prioritization of investments by explicitly considering each investment's impact on incidents.
- With the exception of the region's top-ranked project, the ranking of the next eight projects were affected by the use of TDFMI; for instance, the 7th and 8th ranked projects under the TDFM became the 4th and 5th ranked projects under the TDFMI.

- Three projects (IDs 65, 86, and 99) showed significantly different project scores and rankings between the TDFM and the TDFMI from the paired t-Test evaluation. Those three projects should be examined with special care in the project selection process, especially with a limited investment budget. Thus the approach allows planners to evaluate the regional impacts of various strategies.

When compared to the TDFM, the TDFMI has more flexibility in its application for travel demand forecasting modeling, including a network analysis for 'what if' scenarios and a prioritization of investment projects.

- The TDFMI can be simplified to the TDFM when all incident variables, such as duration and reduced capacity, shown in Equation 3, are set to zero.

- Due to the additional incident impact variables, various project-level network analyses are possible by simply changing the link capacity and the duration of incidents.
- For regions that question the quality of their incident data, TDFMI model runs can be performed with and without the modification are zeros.

7.2 Research Contributions

This dissertation research made several contributions to best practices in the Transportation field, including developing a framework for the TDFMI and applying it, and introducing state-of-the-art modifications to VDFs to include incident data. Key contributions are as follows:

1. This dissertation research has developed a methodology for preparing and integrating incident impacts into the traditional TDFM.
    - This dissertation research has explored incident data and their impacts (the number of blocked lanes, duration, etc.) on the network and shown how incident data should be prepared to be integrated into traditional TDFM networks.

2. This dissertation research has modified the VDFs and calibrated the model parameters using incident involved traffic data to account for incident components.

- The BPR and Akcelik VDFs were modified with additional variables for considering the impact of incidents (duration and reduced capacity) at link segments and intersections.
- The parameters of modified VDFs were calibrated using crash-involved traffic data and the application results showed better performance measures compared to the TDFM results.

3. This dissertation research has developed a TDFMI that integrates a traditional TDFM with incident data.
   - The base year comparison results showed that the TDFMI has provided better nominal performance than the traditional TDFM, by using additional variables reflecting incident duration and the corresponding capacity reduction in the VDFs.
   - This dissertation research has shown that the TDFMI affects the prioritization of future investments by explicitly considering each investment's impact on incidents. Thus the TDFMI could allow planners to evaluate the regional impacts of various strategies.

4. This dissertation has shown that the TDFMI has a flexible opportunity in its application for planners and modelers to evaluate various incident impacts at the regional level.
   - The traditional TDFM would be a part of the TDFMI when all incident variables (duration and reduced capacity) in the TDFMI are set to zero.

- The TDFMI provides practical applications to planners and modelers at the state and/or MPO level for their various scenarios analyses (e.g., daily dynamics) to evaluate incident impact at the regional level (incident duration, number of incidents for corridor, lane blocks, etc.)

7.3 Recommendations for Future Research

TDFMI using Dynamic Traffic Assignment (DTA)

A limitation of the accuracy of both TDFMI and TDFM is that they rely on static traffic assignments, suitable for planning rather than more detailed approaches common to DTA. For future research, a TDFMI with mesoscopic or microscopic simulation models for transportation planning and decision making could generate more realistic and detailed incident impacts on the network by better considering queuing and spillback effects. Certainly, a TDFMI that is integrated with DTA could have generated more detailed incident impacts by considering queuing and spillback effects. The benefits of such detail would need to be compared with the cost of data preparation and processing, but represents an area for further exploration for some prioritizations that might occur at a sub-regional level.

TDFMI with Other Non-Recurrent Congestion Sources

This dissertation research has focused on incident impacts for incorporating with the TDFM. As mentioned earlier, incidents account for part of non-recurrent congestion in urban traffic. Other non-recurrent congestion factors, such as work zone, inclement weather, and special events may have a significant negative impact on urban traffic networks and needs to be addressed in urban traffic analysis. Like incident data, the above mentioned non-recurrent congestion factors would not have any technical or practical obstacles in preventing its incorporation into the traditional TDFM. Since the TDFMI shows potential applications to combine various operational variables in the transportation planning process, various safety and reliability research under SHRP 2 could be expanded using the TDFMI when key inputs of non-recurrent congestion factors are prepared.

Improvement of Incident Forecasting Models for Future Year TDFMI

Future year forecasting models for incident frequency, incident duration, and reduced capacity assumed that current trends based on historical observations will not be changed in the future. However, various new emerging technologies are expected to have notable impacts of reducing traffic incidents in future transportation systems. Many Intelligent Transportation System (ITS) applications have focused on the improvement of vehicles' mechanical performance, known as Advanced Driver Assistance Systems (ADAS) (Wikipedia 2013a), for safety optimization, which includes a vehicle collision warning or avoidance system, speed adaptation, Connected Vehicle (CV), etc. Recently, Google has been working on a driverless car project (self-driving car project) and has tested autonomous cars on public roads in the states of Nevada, Florida, and California in the U.S. Thus, incident models may need to account for the impact of new technologies in future incident forecasting (Wikipedia 2013b).

7.4 Recommendations for the HRTPO and VDOT

Recommendations for HRTPO

The evaluation results of the prioritization analysis with TDFM and TDFMI indicate that HRTPO may need to revisit highway projects ID 65, 86, and 99 and reevaluate if their TDFM analysis results and prioritization scores per criteria are reliable. When comparing the analysis results of TDFM with those of TDFMI, v/c ratio, cost effectiveness (cost/VMT), and travel time reliability were major contributor of the statistical difference. Thus, HRTPO could conduct a pilot study to evaluate the level of congestion, VMT, and travel time of the corridors that related to the three projects

This dissertation research examined the highway prioritization of investments with TDFMI and compared the ranking with the results of TDFM. TDFMI could be applied to other prioritization categories, such as bridge/tunnel projects, intermodal projects, transit and rail mode projects, and to compare the prioritization ranking of TDFMI with those of TDFM.

HRTPO could utilize the TDFMI in various applications, including traffic impact analysis and/or short-term network analyses. For example, if two out of three lanes need to be blocked during midday due to roadwork on the interstate freeway I-64, TDFMI could run and show the incident impact by setting the link capacity of that link and the proportion of road work time out of simulation time. By comparing the loaded network results of TDFM and TDFMI, the traffic impact of road work on interstate freeways could be assessed.

In order to analyze the incident impacts by using TDFMI in various application levels, VDOT and HRTPO could work together especially for the TDFMI model development and incident data collection. HRTPO could identify problems in the future from travel demand forecasting modeling (short term or long term) and develop alternatives to maximize the improvement from the TDFMI analysis. Based on identified problems and alternatives, HRTPO could make a list of projects and they want to analyze and data they need to collect for the analyses of specific corridors or intersections.

Recommendations for the VDOT

In order to develop TDFMIs for small and large MPO models as well as the statewide model, incident data and traffic data in VDOT's database need to be explored based on spatial and temporal boundaries. All incident data that occurred in the weekdays of the base year within modeling boundaries should be collected. Large MPO areas that use the TOD step in the TDFM structure should have separate incident dataset for each of the four TODs. For the calibration of modified BPR and Akcelik VDFs, crash-involved traffic data also need to be collected by using common temporal and spatial information from both crash and traffic data.

With the exception of the Richmond and Hampton Roads models, the networks of all MPO models should be extensively revised by using the latest GIS roadway information. Current networks of all model areas are sparsely coded and the links of lower functional classifications, such as collectors and local roads, are not included. Furthermore, all links on networks are coded as ‘stick’, which simply connects nodes with a straight line, ignoring the true shape of roadways. Thus, a true display of roadways, including collectors and local roads, is crucial when matching incidents to TDFMI networks. Indeed, at least a base year model update may be necessary because model run results would change if the network is extensively revised. If the network changes significantly, model calibration, validation, and reasonableness checking need to be conducted.

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