MD-10-SP808B4M

Martin O'Malley, *Governor*
Anthony G. Brown, *Lt. Governor*

Beverley K. Swaim-Staley, *Secretary*
Neil J. Pedersen, *Administrator*

STATE HIGHWAY ADMINISTRATION

RESEARCH REPORT

DEVELOPMENT OF A TRAFFIC SIMULATOR FOR I-695, THE BALTIMORE BELTWAY, FOR TRAFFIC OPERATIONS AND INCIDENT MANAGEMENT

XIAODONG ZHANG
GANG-LEN CHANG

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING
UNIVERSITY OF MARYLAND
COLLEGE PARK, MD 20742

SP808B4M
FINAL REPORT

NOVEMBER 2010

Technical Report Documentation Page

Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MD-10-SP808B4M		

4. Title and Subtitle Development of a Simulator for I-695,the Baltimore Beltway for Traffic Operations and Incident Management	5. Report Date November 2010 6. Performing Organization Code
7. Author/s Xiaodong Zhang and Gang-Len Chang	8. Performing Organization Report No.
9. Performing Organization Name and Address University of Maryland, Department of Civil and Environmental Engineering, Maryland, College Park, MD 20742	10. Work Unit No. (TRAIS) 11. Contract or Grant No. SP808B4M
12. Sponsoring Organization Name and Address Maryland State Highway Administration Office of Policy & Research 707 North Calvert Street Baltimore, MD 21202	13. Type of Report and Period Covered Final Report 14. Sponsoring Agency Code (7120) STMD - MDOT/SHA

15. Supplementary Notes

16. Abstract
Due to rapid traffic growth in recent years, the Baltimore Beltway (I-695) is now experiencing considerable congestion even after the normal peak periods. Hence, identifying effective tools for contending with worsening congestion on I-695 has emerged as a priority task for the Maryland State Highway Administration (SHA). This study expanded the current traffic simulation laboratory developed by SHA and the University of Maryland College Park (which includes simulators for I-495, I-270, and I-95), and began the construction of the I-695 simulator for use by SHA engineers in performing Baltimore area traffic studies. The simulator system contains the following principal components: (1) an intelligent system interface for input, output, and potential applications; (2) a GIS database for key information related to all network geometric features, driver characteristics, and traffic volume distributions; (3) a microscopic simulation database to model traffic behavior and the daily evolution of traffic patterns; and (4) a knowledge-based expert system module to project the durations of detected incidents. The completed I-695 traffic simulator will be part of the Traffic Simulator System sponsored by SHA, which can be used independently by traffic engineers for the Baltimore area or integrated with other existing simulators (e.g., I-495, I-270) to analyze the regionwide traffic conditions between the Washington and Baltimore metropolises.

17. Key Words	18. Distribution Statement: No restrictions
simulator, congestion, incident management	This document is available from the Research Division upon request.

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. Of Pages	22. Price
None	None	53	

Form DOT F 1700.7 (8-72) Reproduction of form and completed page is authorized.

Table of Contents

CHAPTER 1: INTRODUCTION

1.1 Research Background

Minimizing nonrecurrent congestion in commuting transportation corridors is a major concern of highway management agencies, especially in most metropolitan areas. Recent transportation studies have estimated that nonrecurrent congestion accounts for 60 percent of all congestion in urban areas, about half of which is due to incidents such as accidents, disabled vehicles, spilled loads, and inclement weather.

Traffic congestion caused by incidents certainly degrades the safety and mobility of all travelers. Major incidents can actually affect thousands of vehicles in the entire traffic network and can also cause secondary incidents which require responses from the same agencies already engaged in managing the primary incident.

The Baltimore Beltway (I-695) is a full access-controlled freeway connecting with many other major roads radiating from the Baltimore area, including I-97 near Glen Burnie, Baltimore Washington Parkway (MD 295), I-70 near Woodlawn, I-795 near Pikesville, and I-83 in the Timonium area, and I-95 to Northeast and Southwest of Baltimore City. Due to rapid traffic growth in recent years, the Baltimore Beltway is now experiencing considerable congestion even after the normal peak periods. Hence, identifying effective tools for contending with worsening congestion on I-695 has emerged as a priority task for the Maryland State Highway Administration (SHA).

Simulation has long been viewed as one of the most cost-effective tools for analyzing various traffic operation- and control-related issues. Continuous advances in computing technologies and modeling algorithms over the past decade have made the simulation increasingly powerful for use in real-time evaluation of alternatives for traffic control, incident management, and Intelligent Transportation Systems (ITS) applications.

Recognizing the great potential of a well-designed traffic simulator, SHA has worked with the research team at the University of Maryland over the past decade to develop several such tools, including simulators for the I-95/US1, I-270/MD355, and I-495/I-95 systems. All such simulators, with their specially customized interfaces, have been used extensively by

SHA engineers, authorized consulting firms, and university researchers to study traffic-control- and incident-management-related issues.

Despite the successful development and application of these simulators, they have been applied mainly to those commuting corridors connected to the Capital Beltway. Traffic networks around the Baltimore metropolitan area have not been covered by any of such powerful traffic simulators. Thus, neither SHA's traffic incident management program, Coordinated Highways Action Response Team (CHART), nor the responsible district engineers can take advantage of such an effective tool when contending with the increasing congestion in the Baltimore metropolitan area and its pressing needs for incident management.

This study expanded the current traffic simulation laboratory developed by SHA and the University of Maryland College Park (which includes simulators for I-495, I-270, and I-95), and focused on construction of the I-695 simulator for use by SHA engineers in performing Baltimore area traffic studies.

1.2 Research Objective

The primary objective of this study was to develop a real-time traffic simulator to analyze and project traffic conditions such as queue length, speed, and travel time on the I-695 Baltimore Beltway. The proposed simulator system contains the following principal components:

- an intelligent system interface for input, output, and potential applications;
- a GIS database for key information related to all network geometric features, driver characteristics, and traffic volume distributions;
- a microscopic simulation database to model traffic behavior and the daily evolution of traffic patterns; and
- an expert system module to project the durations of detected incidents.

The completed I-695 traffic simulator will be part of the Traffic Simulator System, and it can be used independently by traffic engineers for the Baltimore region or integrated with other existing simulators (e.g., I-495, I-270) to analyze the regionwide traffic conditions between the Washington and Baltimore metropolises.

1.3 Report Organization

Based on the research objectives, the report has been organized into six chapters. A brief description of the contents of each chapter follows:

Chapter 2 provides a comprehensive review of related literature, including some key studies on estimating incident duration and assessing incident impact. The identified strengths and deficiencies offer a solid basis for this study to design an expert system module to predict incident duration.

Chapter 3 presents the framework of the Baltimore Beltway (I-695) simulator, based on the essential functions for an incident management system. This chapter also discusses the interrelationships between the input, simulation, knowledge-base, and output modules, along with their applications to incident response and management.

Chapter 4 presents the key characteristics of the CORSIM simulation program and the principle functions of the integrated traffic simulator for incident management. The traffic simulator, designed mainly for incident management, consists of information on network geometry, traffic demand, and control strategies. The chapter also includes the procedures for calibrating and validating the developed simulator so that it can generate reliable results for analysis.

Chapter 5 highlights the procedures used to develop the prediction model embedded in the I-695 simulator for incident duration estimation, including the dataset for calibrating the primary rule-based module and all supplemental functions to enhance the prediction accuracy. This chapter also presents the interrelationship between incident duration and its nature, justifying the necessity of using a different prediction method for each category of incidents. The data limitations and strengths of each employed models are also part of this chapter.

Chapter 6 first presents an example application of the system to guide potential users via a step-by-step procedure to obtain any target information and to perform necessary analyses. It then summarizes the key findings of this research and describes potential enhancements for the developed I-695 traffic simulator. This chapter also discusses lessons associated with the data collection for system calibration and potential operational issues.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter presents a review of some key studies from past decades about incident duration estimation and impact assessment. Some vital findings from the literature provide the basis for designing the incident duration model and the core structure of the entire system. The next section summarizes existing studies of incident duration estimation. Then, Section 2.3 reports related models for assessing incident impacts. The last section summarizes research findings and conclusions.

2.2 Incident Duration Estimation

Many researchers have studied incident duration estimation over the last several decades using various methodologies. Most of those studies fall into one of the following categories: (1) probabilistic distributions, (2) conditional probabilities, (3) linear regression models, (4) time sequential models, (5) decision trees, and (6) discrete choice models.

A probabilistic model is a relatively straightforward method that models the incident duration as a random variable and attempts to find a probability density function (PDF) to fit the data set. Golob et al. (1987) conducted their research using approximately 530 incidents that involved trucks; they found that their incident duration data fit well with a log normal distribution. Other studies by Giuliano (1989), Garib et al. (1997) and Sullivan (1997), analyzing data for the durations of freeway incidents, supported their findings. In 1999, Ozbay and Kachroo also found that the distribution of incident durations from their data set produced a shape very similar to a log normal distribution, although a few statistical significance tests rejected their hypothesis.

Probability models for incident duration can be extended to conditional probability models. The key idea of such models is to find the probability distribution of incident durations under certain given conditions. For example, control center operators may be interested in the probability of an incident lasting over 30 minutes, after its onset for 15 minutes. However, due to the limited data availability for parameter calibration, most existing models on this subject still focus on estimating the unconditional probabilities, such as the probability of an incident lasting over 30 minutes.

One of the most representative studies was conducted by Nam and Mannering (2000). Taking a set of two-year data from Washington State, their report indicated that incident duration (i.e., detection/reporting, response, and clearance times) was significantly affected by numerous factors, and different distributions were recommended for different incident data. They also found that their estimated coefficients with this method were unstable. Hence, they concluded that this approach is more useful for determining which variable has greater influence on incident duration rather than for predicting the incident duration.

Most studies in this category include a number of binary factors as independent variables to capture incident characteristics and use a continuous or categorical variable as a dependent variable (i.e., incident duration). One of the best-known linear regression models for incident prediction was developed by Garib et al. (1997) using 277 samples from California. They used various independent variables to represent incident characteristics (e.g., incident type, number of lanes affected by the incident, number of vehicles involved, and truck involvement) and weather conditions (e.g., rainy or dry). Their results with a long-form form are similar to those from Golob et al. (1987) and Giuliano (1988), indicating that the police response time is the most significant factor in determining the incident duration.

Khattak et al. (1995) realized that a full set of variables for predicting incident duration would be available only after the incident has been cleared. Hence, models relying on such data are less likely to be useful for managing incidents in real time. Thus, they introduced a time sequential model that divides the incident duration into ten distinct stages based on the availability of information. Each stage indicates a specified range of incident duration, which can be predicted with a separate truncated regression model. Each stage includes progressively more variables to explain the resulting incident duration. Despite its novelty, this model has not been tested or validated due to the lack of field data.

Ozbay and Kachroo (1999) used a decision tree to predict incident clearance times in the Northern Virginia region. The authors first followed a series of trial prediction methods and received poor results. Their experiments indicated that linear regression techniques generate low R-square statistics and that the duration data do not follow either a log-normal or log-logistic distribution. After determining the independent variables, they constructed their decision tree. Note that the intended output of the decision tree method is an average duration of similar incidents and the possible range of variation.

Most studies in the literature viewed the incident duration as a continuous variable. Dividing the incident duration into a set of intervals, Lin et al. (2004) developed a system that integrates a discrete choice model and a rule-based model to predict incident duration. They first adopted ordered probit models to classify sample incident data for incident duration into several time intervals. Then, they developed a rule-based supplemental model to enhance the accuracy of prediction results.

2.3 Incident Impact Assessment

Since analyzing the impact of a detected incident is an essential part of traffic management, transportation researchers have developed various models for this need. Most of such studies belong to either of the following two categories: (1) queuing diagram methods, or (2) simulation-based approaches.

One widely used approach for estimating traffic queues is based on the queuing diagram, which uses the area between the traffic's cumulative arrival and departure curves to calculate the cumulative vehicle hours of delay (see Figure 2.1). For example, Morales (1986) proposed a deterministic approach, based on the assumption that demand and capacity are constants in small time intervals; this approach estimated the cumulative delay with the linear arrival and departure curves of traffic flows.

Lindley (1987) and Schrank et al. (1990) developed similar methods that allowed comparisons across urban areas with similar indexes of congestion. Lindley obtained data from the Highway Performance Monitoring System (HPMS) developed by the Federal Highway Administration (FHWA), and then developed a computer program to assess the urban freeway congestion parameters, including congested travel times, recurring delays, nonrecurring delays, excess fuel consumption, and user costs for the areas covered in the database. Note that the above-mentioned methods are intended only for after-incident analysis and are not suitable for real-time traffic management, which requires more detailed, time-varying traffic information.

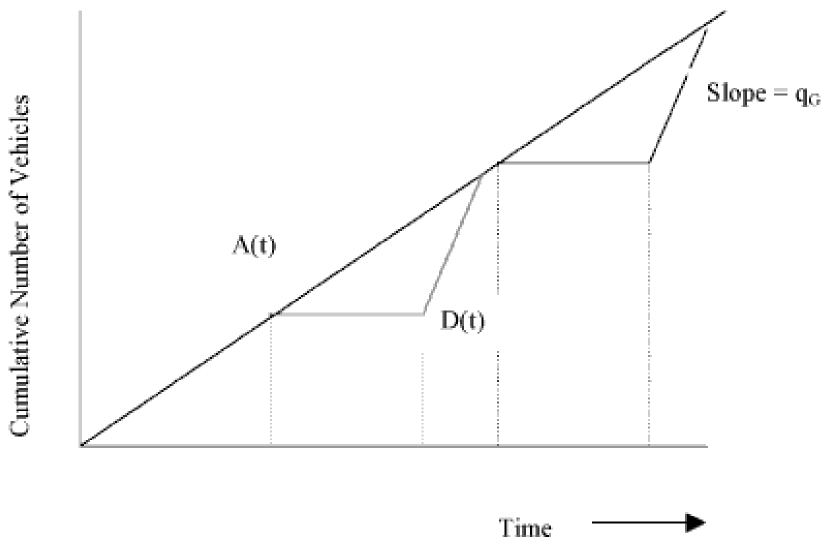


Figure 2.1: Queuing diagram for calculating traffic delay due to an incident.

Al-Deek et al. (1995), Mongeot (2000), and a study from Cambridge Systematics, Inc. (1998) developed macroscopic simulation methods to assess incident-related impacts. However, macroscopic simulations, which may perform well in estimating averages for network-wide traffic conditions, cannot reliably analyze local bottlenecks arising from incidents. Although macroscopic simulations could estimate time-varying traffic impacts, they failed to account for complex interactions between driver responses and traffic conditions; thus, they could substantially underestimate the impacts incurred by an incident, degrading their reliability for real-time operations (e.g., posting information on variable message signs (VMS) in time to guide approaching motorists).

Microscopic simulation has been recognized as an efficient tool for transportation studies in recent years. However, because this tool needs extensive data and familiarity with its complex operating procedures, existing studies have not used this method for real-time applications (Raub et al., 1998; Zou et al., 2003). Recent advances in computing technologies and graphical interfacing methods have offered the potential for using such a reliable tool for real-time traffic management. For instance, Chang et al. (2000, 2001, and 2002) constructed several simulators using CORSIM for several freeways and local arterials in the State of Maryland, including the entire I-270 corridor, I-95 from I-495 to I-695, and I-495 between I-95 and MD-97. These simulation networks have sufficiently short execution times for real-time incident management. A specially designed interface for each simulator also enables traffic engineers to avoid complex modeling and data input efforts and to conveniently employ the developed simulators to analyze traffic conditions.

2.4 Conclusion

This chapter has provided a comprehensive review of existing research efforts to estimate the duration of detected incidents and their impacts. Although a variety of modeling techniques yield acceptable results, most developed models are location-specific and not transferable. Hence, it is essential to develop a well-calibrated incident duration model that is customized for traffic conditions and driving populations on the I-695 Baltimore Beltway.

As for using microscopic simulation for real-time traffic analysis, this method has emerged as a promising tool in recent years, due to advances in computing technology and to its flexibility in representing actual geometries and driving populations, as well as a variety of other system features, such as signal control. Thus, a simulation that is properly integrated with statistical models will certainly offer an effective and efficient tool for traffic engineers to contend with nonrecurrent congestion.

CHAPTER 3: SYSTEM FRAMEWORK AND KEY COMPONENTS

3.1 Introduction

During daily incident response and management, the control center operator will immediately dispatch emergency response units (ERUs) to the incident site upon receiving an incident report and then will estimate potential traffic impacts, such as the evolution of traffic queues, vehicle delays, and speeds during the response period. Such traffic impact information will offer operators in the control center the basis for determining where and how to inform the approaching travelers and for evaluating the necessity, as well as the effectiveness, of implementing any traffic control strategies. The I-695 traffic simulator, with proper calibration, can assist traffic operators in performing these critical prediction and evaluation tasks during real-time incident management.

The proposed simulator comprises the following four principle modules:

- *Input module*: To assist users in conveniently identifying the incident location and other incident-related information;
- *Simulation module*: To reflect the speed, density, and vehicle queue length during the period and clearance operations;
- *Knowledge-based incident duration estimation module*: To let users retrieve similar historical incident scenarios and to predict the duration of a detected incident in real-time, based on all data received via the input module;
- *Output module*: To display the time-varying traffic conditions on the I-695 Baltimore Beltway network based on the simulation results.

Figure 3.1 shows the overall framework of the entire system and the interrelationships between its principal components.

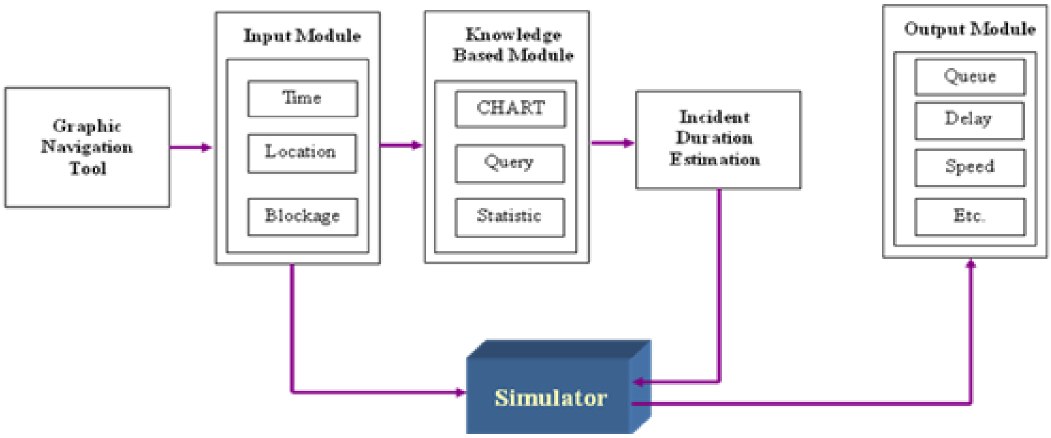


Figure 3.1: Interrelationships between principal system components.

3.2 System Development Principles

To ensure the reliability and efficacy of the proposed I-695 simulator, the research team has adopted the following design principles:

- *Ensuring the accuracy of data used in developing the simulator and its database*: To replicate real-world traffic conditions at a desirable level of fidelity, the simulator must have accurate data about network geometries, traffic volume, and all related controls. The traffic simulator was constructed with the actual highway design plans and digital maps of the target area, including Google satellite images and field surveys of key geometric as well as traffic data.

- *Minimizing human-factor-related errors*: The system has been carefully designed to minimize input errors caused by human factors. For instance, the location of an incident identified in the input module will appear continuously during the data input and system execution periods. Such a feature intends to constantly remind the user to review and correct the location information prior to the simulator execution. Figure 3.2 illustrates the function of automatic error detection at the data input stage.

- *Minimizing the required input efforts*: To facilitate the use of all available functions, the simulator was designed to replace the complex command-language syntax by direct manipulation of the object of interest. As shown in Figure 3.3, the graphic input communicates more effectively with users than a text-based design.

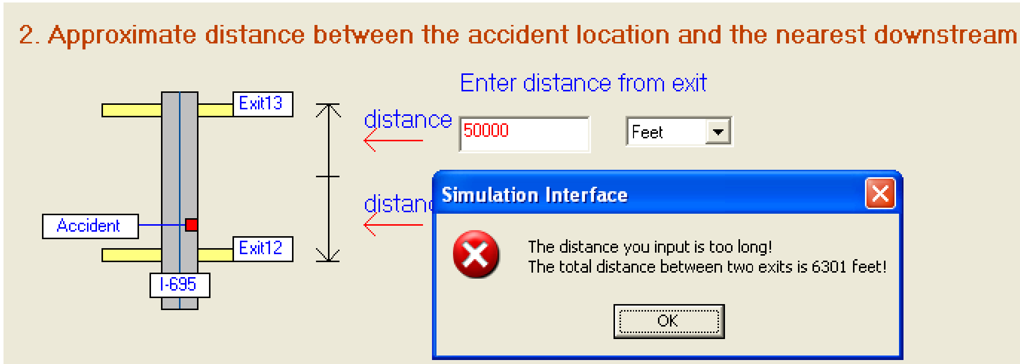
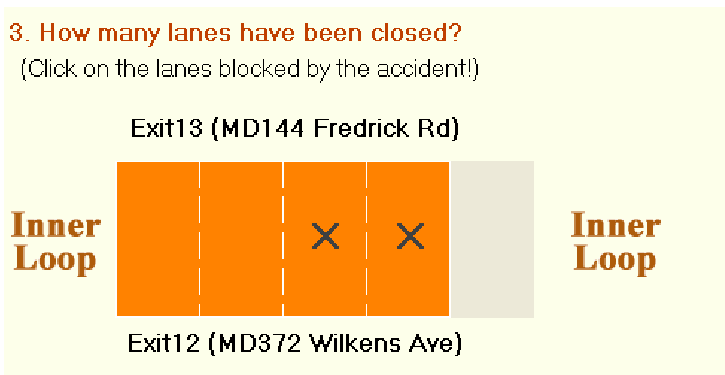


Figure 3.2: An example showing that the system can automatically detect a human-factor-related error.



Graphic input for lane blockage

Text type selection for lane blockage

Figure 3.3: A comparison between a graphic input and a text-based selection for the lane blockage information

3.3 Key Module Features

Input Module

This module employs a GIS design concept that enables users to first directly identify from the map the approximate location of the target freeway segment affected by the incident and then to input any related information through subsequent interactive questions, where the geometry data contained in the Baltimore Beltway microscopic simulator module are directly imported from the highway design plans. This type of GIS-based design can circumvent the complex input process required by most commercial simulation programs and minimize the learning time, as well as potential input errors.

The map-based interface provides two levels of features for identifying incident location: (1) an overall map of entire I-695 network so that users can quickly and conveniently navigate to the target freeway segment for incident input (see Figure 3.4), and (2) a more detailed map to let users zoom into the target highway segment to identify the precise location of a detected incident (see Figure 3.5).

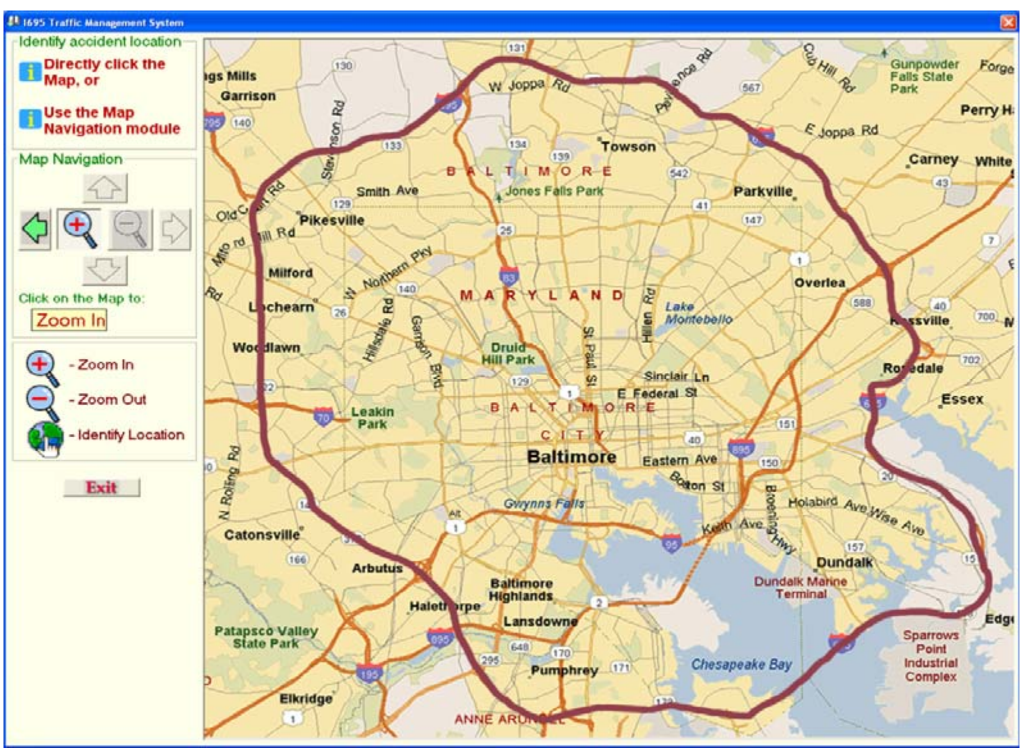


Figure 3.4: The overall map view for input module.

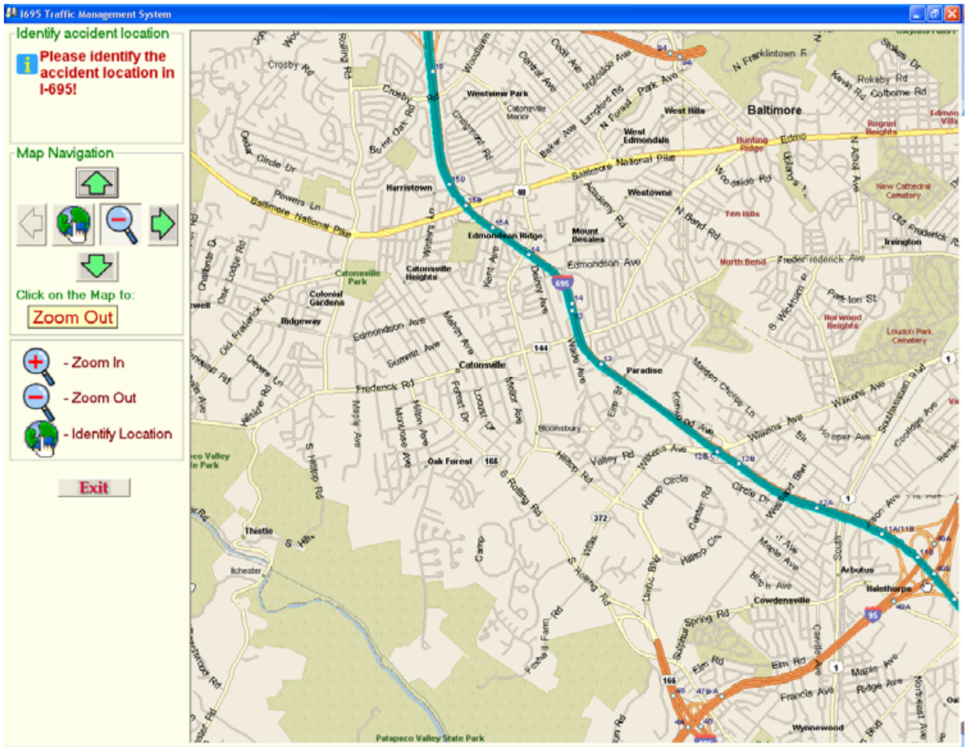


Figure 3.5: A detailed map view for identifying the incident location.

Simulation module

The simulation module, the core of the I-695 simulator, has the ability to simulate actual traffic conditions over the period of incident operations and to assess the effectiveness of various candidate incident management strategies. Since the traffic simulator is mainly for incident impact analysis, its database contains all essential information for simulation execution, including network geometric features, traffic demand distribution, and available control strategies. This module also provides various system measures of effectiveness (MOEs), based on the needs of traffic operators to evaluate performance.

Knowledge-Based Module

This module is designed to take advantage of information and operational experience accumulated from managing previous incidents and stored in a CHART database. The CHART database keeps detailed records of response times, incident durations, lane-blockage conditions, incident locations, and incident natures for each incident response across the State of Maryland.

To improve computing efficiency, the I-695 simulator includes only the data from incidents occurring on the Baltimore Beltway from Year 2003 to Year 2006, which will reduce the effort needed to retrieve relevant data from the CHART database. Such information can offer traffic control operators a reliable reference for estimating the potential duration of a detected incident.

The research team developed a set of discrete choice models for estimating incident durations and embedded them in this module to help users predict incident durations based on historical information. This module also serves to approximate the maximum possible queue length, based on the estimated incident duration. All such information will enable traffic operators to first assess the approximate impacts of a detected incident on the traffic network, and then to execute the simulator to compute the resulting delay, based on the real-time traffic volume and the implemented incident response strategies.

Output Module:

While executing the incorporated CORSIM simulator, this module will first yield the projected traffic conditions from the knowledge-based module in response to the request of traffic operators. After successful execution of the simulator, this module will display the estimated delay, average speed, travel time, and queue information. Responsible traffic agencies can then act early, as necessary, to minimize the impact of detected incident on congestion.

3.4 Conclusion

This chapter discussed the design principles and the framework of the I-695 simulator for incident management, covering the input, simulation, knowledge-based, and output modules. Overall, the system takes advantage of the strengths of simulation, knowledge bases, GIS, and integrated information, such as roadway geometry, volume, and control strategies, to predict incident duration and its effects on traffic management. With such a system, traffic operators can refer to previous incident scenarios to provide the immediate incident impact assessment, and then execute the simulator to evaluate the effectiveness of different candidate management strategies.

CHAPTER 4: INTEGRATED TRAFFIC SIMULATOR FOR THE I-695 SYSTEM

4.1 Introduction

Microscopic traffic simulations have been widely used to evaluate various traffic operations and management strategies. This chapter introduces the key characteristics of the CORSIM simulation program and the principle functions of the integrated traffic simulator of the incident management system.

4.2 Key Characteristics of CORSIM

CORSIM, a microscopic corridor simulation program developed by the FHWA, has become increasingly popular among transportation professionals. The I-695 simulator employs CORSIM, instead of other traffic simulation software, for the following reasons:

- *It can model complex geometry conditions.* CORSIM can handle various networks of different geometric features, including surface streets with different combinations of through lanes and turning pockets, multi-lane freeway segments, different types of on- and off-ramps, and freeway interchanges such as those on the I-695 Baltimore Beltway network. It can also model special geometric features, such as lane-drop and lane-addition.

- *It can simulate different traffic conditions.* CORSIM can be calibrated to accurately simulate a wide range of traffic conditions, from moderate demand to very congested conditions. It can also effectively simulate traffic flow during an incident, from queue buildup to its recovery to normal traffic conditions. The ability to simulate over congested traffic flow conditions gives CORSIM a unique advantage over traditional empirical/analytical methods. This feature is one of the major considerations influencing our selection of CORSIM simulation for system development.

- *It can simulate different traffic control, management, and operational strategies.* CORSIM can simulate different traffic control devices, such as stop or yield signs and fixed timing or actuated controls at surface street intersections. It can also simulate freeway ramp metering, and HOV (high occupancy vehicle) lane operation.

- *It can account for the interactions between different network components.* CORSIM can simulate integrated networks with surface streets, freeway mainlines, and ramps as their components. Unlike most traditional methods, which analyze the operations of each component independently, CORSIM can simulate the traffic flow of the network in an integrated fashion. This enables CORSIM to simulate congestion spillover from one network component to another, such as queue spillback from an off-ramp to the freeway or from an on-ramp to the surface street.

- *It can model time-varying traffic and control conditions.* CORSIM uses record types to organize data inputs for geometries, volumes, surveillance and detecting devices, traffic controls, engineering criteria, run controls, and output requirements. This feature allows users to design customized output modules and to display time-varying simulation results.

Using Google Maps, a complementary source, Figure 4.1 displays the resulting simulator network for the Baltimore Beltway.

4.3 Modeling the Baltimore Beltway Network

This section details the effort to model the Baltimore Beltway network. It starts by discussing the modeling of freeway network features and then describes simulation activities for signalized/unsignalized intersections on local arterials.

To imitate traffic conditions in a real-world traffic network, the CORSIM-based I-695 simulator has captured the following key network elements with its database and interface:

- *Road network (in the form of a link-node diagram)*: including mainline lanes, ramps, acceleration/deceleration lanes, and lane-drop and addition.

- *Traffic signs*: such as those for speed limits, ramps, congestion, and geometric changes, as well as VMS.

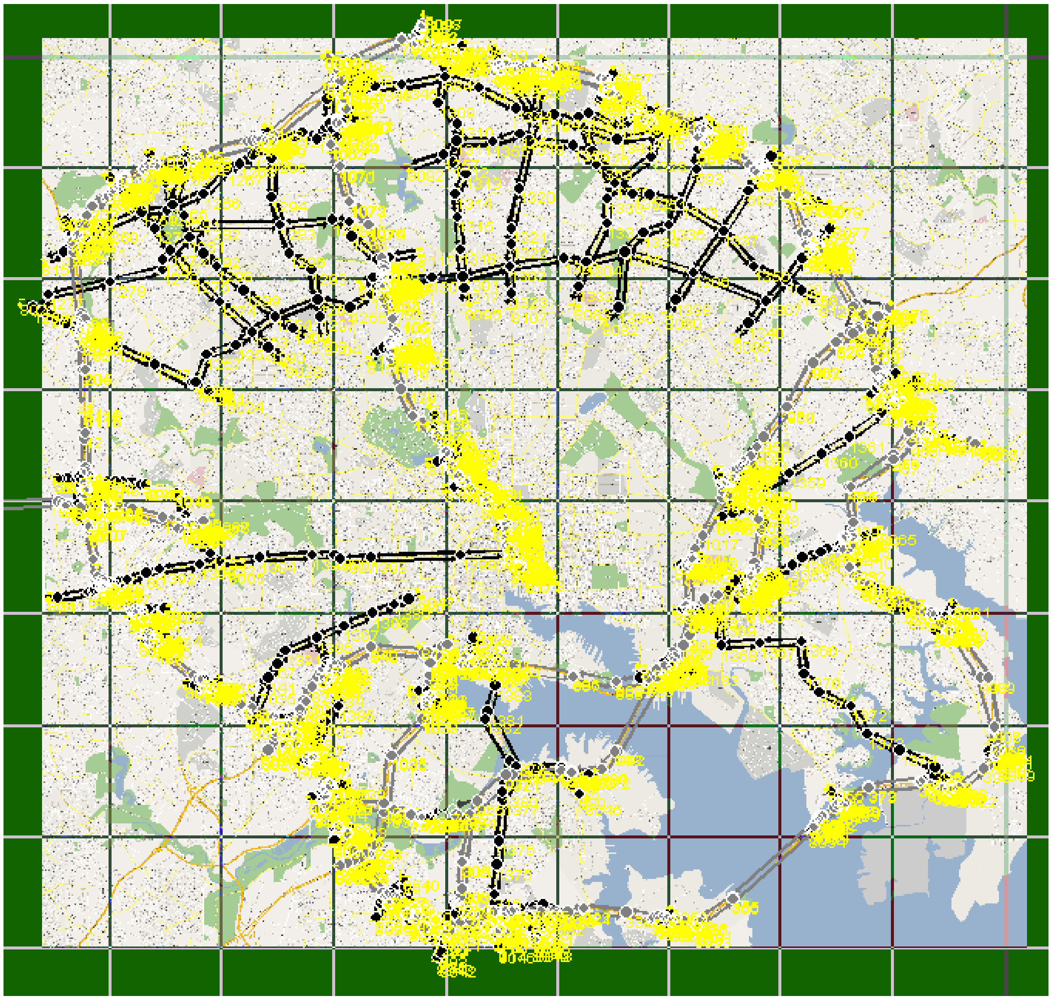


Figure 4.1: Overview of the Baltimore Beltway simulator with CORSIM.

- *Incident-related information*: including the number of lanes being blocked and incident duration.

- *Vehicle types and driving behaviors*: Such as the percentage of trucks in traffic and the distribution of driving populations. The simulation module is also capable of capturing different types of driving patterns through its car-following and lane-changing parameters.

- *Geometry information*: including both vertical and horizontal alignments (see, for example, Figure 4.2). Such information is essential for identifying potential bottlenecks.

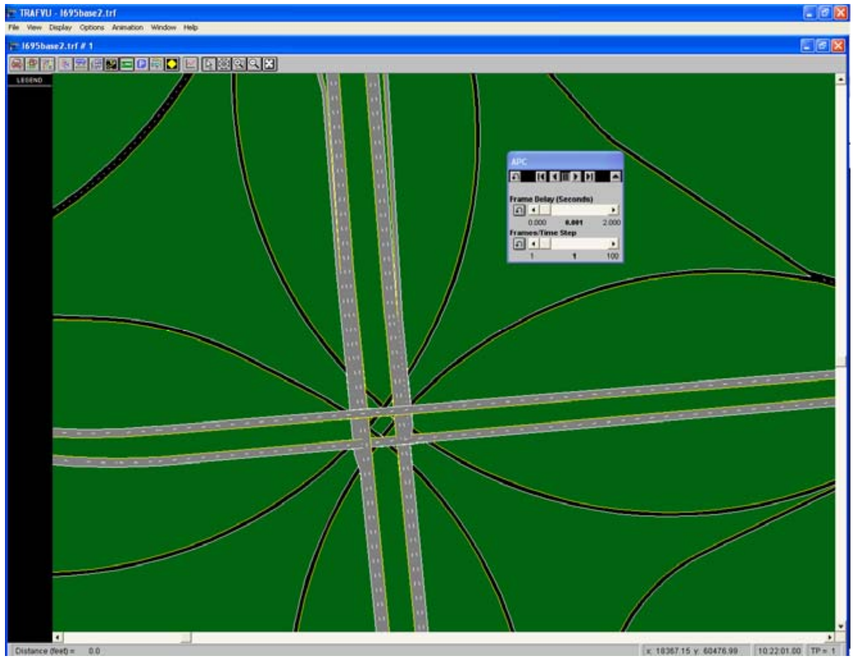


Figure 4.2: A cloverleaf interchange designed with CORSIM.

The simulator models all traffic signal controls and demand patterns at intersections on major arterials connected to the Baltimore Beltway, including lane channelization (such as left-turn only and/or right-turn only), intersection approach geometry, stop and yield signs, signal controls, traffic surveillance systems, and queue discharge distribution at intersections. More specifically, the simulator has incorporated the following key features in its network database:

- *Lane channelization*: including all different lane channelizations at the intersection, such as protected left turns, right-only turns, and bus-only lanes.
- *Intersection geometry information*: including left turn pockets, right-turn-only lanes, and other types of lane alignment (see Figure 4.3).
- *Signal controls*: including both pretimed signals and actuated signal controls. The model for actuated signal control includes signal phases, detector locations, and phase parameters, such as maximum green time and all red time, as well as signal coordination. The simulator also offers a function for users to change signal timings at target intersections to accommodate detour traffic.
- *Traffic signs*: including two-way or four-way stop signs, yield signs, and commonly used warning signs on local arterials.

Figure 4.3: An actuated controlled signal designed with CORSIM.

This research used the AM and PM peak hour traffic volumes for existing conditions, provided by SHA, as input for the simulator. These volumes represent average weekday conditions and have been derived from traffic counts on the mainline and ramps with adjustments for seasonality and count type.

Figure 4.4 shows volume information for the local arterials connected to I-695 and turning volume at those off-ramps. Figure 4.5 shows an example of information associated with an interchange between I-83 and I-695.

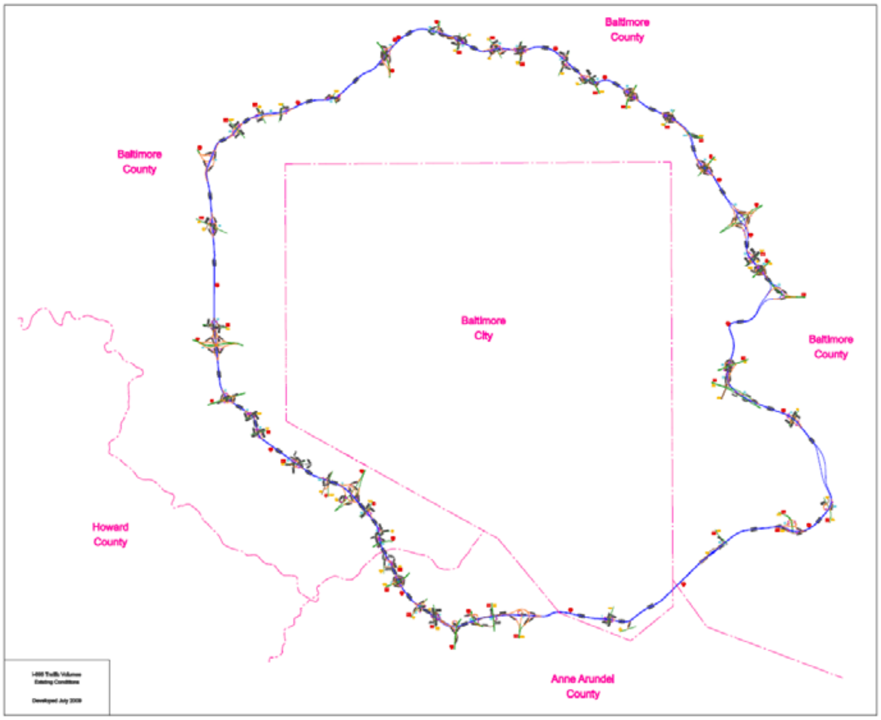


Figure 4.4: Overview of the volume information on I-695.

Figure 4.5: Graphical display of volume information on I-83 and I-695.

CHAPTER 5: A KNOWLEDGE-BASED INCIDENT DURATION MODEL

5.1 Introduction

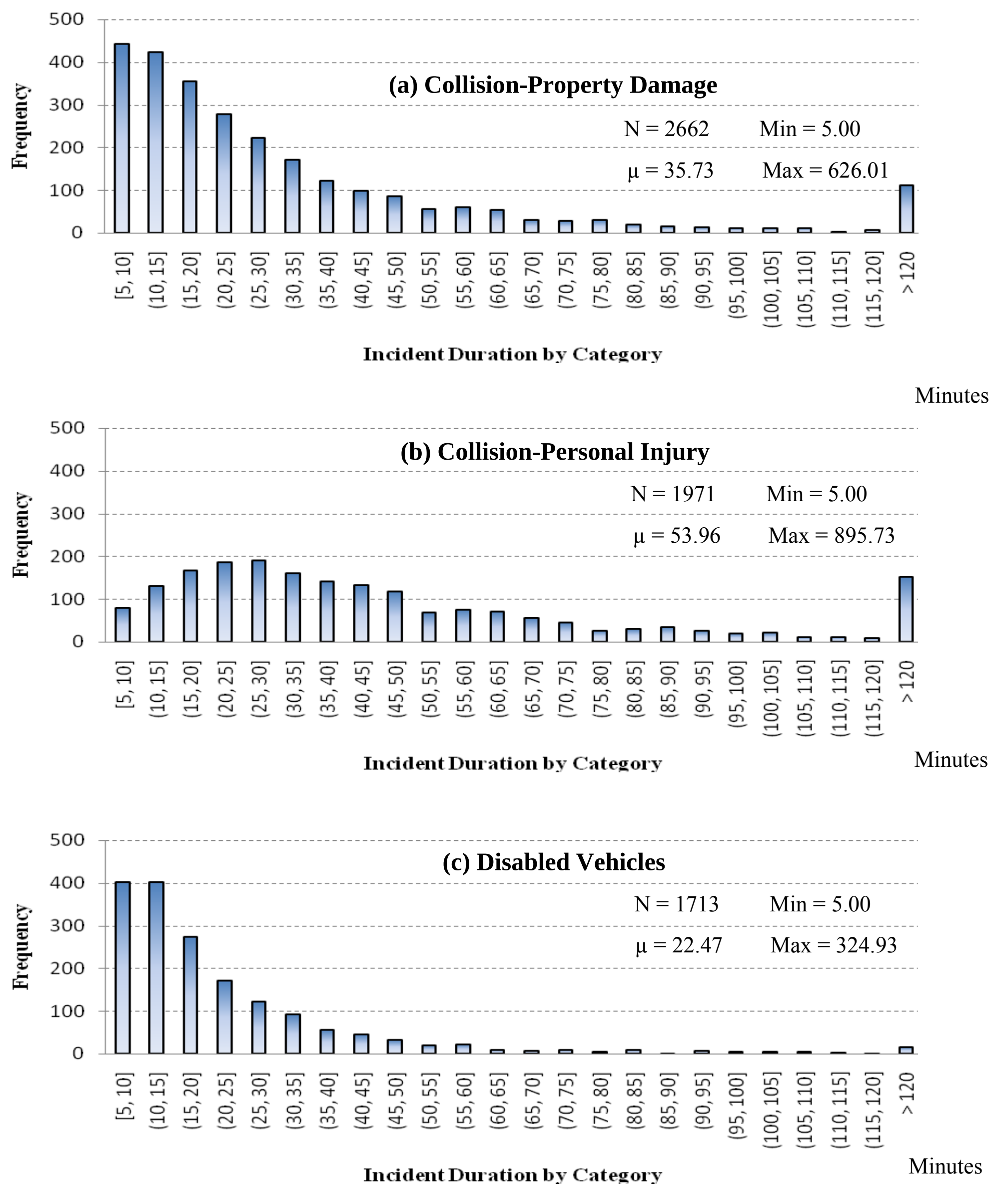
This chapter summarizes the methodology of a statewide knowledge-based (KB) system embedded in the I-695 simulator for estimating incident duration. A detailed description of the KB system's development process and its model structure can be found in a recent SHA report by Chang and Kim (2009). The KB system developed with the CHART incident database and Police Accident Reports can predict the incident duration in the format of a time interval it may fall in, such as between 15~30 minutes. Depending on the nature of a detected incident, its predicted duration interval could range from 15 minutes to 60 minutes. The next section first presents the characteristics of incident data from the existing database, and then discusses the core modeling methodology. Section 5.3 briefly illustrates the model development procedures and the resulting formulations. Section 5.4 summarizes related research findings used for use by the I-695 simulator.

5.2 Data Characteristics

For model calibration, this study employed the highway incident data from the CHART-II Database and the Accident Report database from the Maryland State Police. The CHART-II database maintained by SHA contains detailed information associated with each incident in Maryland, including incident nature, detection time, response time, number and type of vehicles involved, number of lanes/shoulders blocked, response units, pavement conditions, etc. For crashes causing injuries or fatalities, the Accident Report database records extensive information associated with fatalities and personal injuries, such as the number of fatalities/injuries, collision types, light conditions, etc.

Prior to the model development, the research team first investigated the relationship between incident nature and the resulting duration. Figure 5.1 illustrates the frequency distribution of incident duration and the statistics of four major incident types: collision-property damage, collision-personal injury, disabled vehicles and collision-fatality.

As reflected in Figure 5.1, different incident types exhibit remarkable differences in their duration distributions. For instance, incidents involving disabled vehicles and property damage are likely to have a shorter duration, while incidents causing personal injuries generally need a longer duration for traffic to recover to its normal state. Notice that the majority of fatality-involved incidents lasted longer than two hours. Each type of incident distribution disperses in a wide range without any distinctive pattern. Hence, it is unlikely to fit such incident duration data with any continuous or discrete statistical distribution.



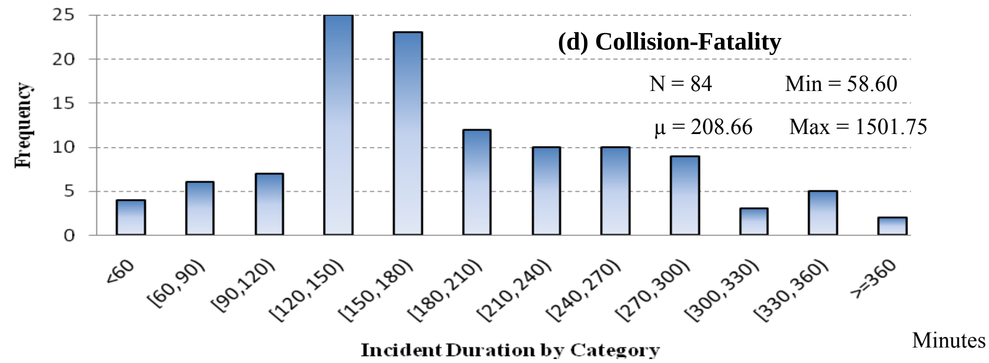


Figure 5.1: Duration Distribution by Incident Nature

Based on the literature review and the analysis of incident duration nature, all available data was divided into two categories: non-fatality and fatality involved incidents. The Rule-Based Tree Method (RBTM) serves as the primary module for non-fatality involved incidents and the multinomial logit model functions as its supplemental module. Due to the unique distribution pattern, this study selected the Naïve Bayesian Classifier (NBC) to develop the prediction model for fatality-related incidents.

5.3 RULE-BASED TREE MODEL (RBTM)

A tree model has long been used for both classification and prediction purposes due to its independence of distributional assumption and the flexibility to fit any discrete data patterns. Based on the findings from the preliminary analysis, this study redesigned a conventional tree model, named a Rule-Based Tree Model (RBTM), for non-fatality involved incidents using the following procedures.

Step 1: Set the incident nature as the first splitter.

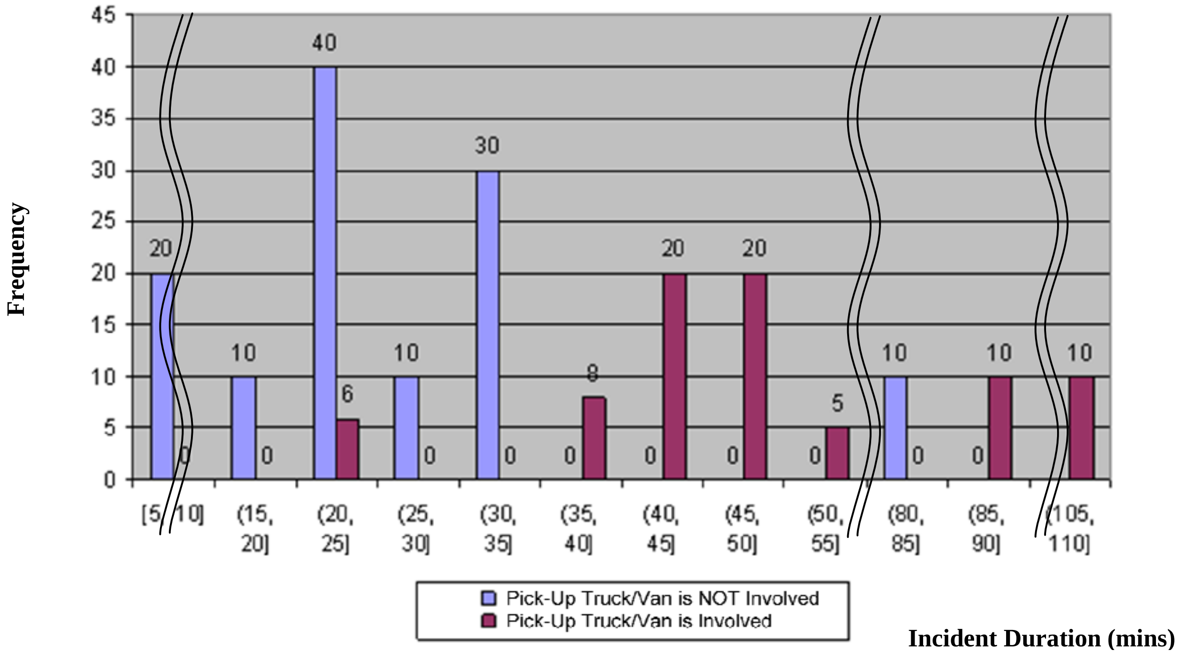
All incident data classified by its nature will fall into one of the following categories: collision-fatality (CF), collision-personal injury (CPI), collision-property damage (CPD), disabled vehicles (Disabled), or others (Others) that includes fire, road debris, constructions, and police activities. Due to the relatively small sample size, the category of *Others* was excluded from this study. Since the incident duration data classified by its nature displays different distribution patterns (see Figure 5-1), this factor was selected as the first splitter for developing RBTM.

Step 2: Determine the next splitter for each node.

This step is to generate a cross-tabulation table and to determine the next splitter for each node. A cross-tabulation table can display the number of cases in each category defined by two or more specified variables. For each independent and dependent variable (i.e., incident duration), this step shall create a cross-tabulation table along with a bar chart to show the frequency distribution of the independent variable that is potentially associated with the incident duration. Then, the independent variable that can classify the incident duration data into two distinctly different categories shall be selected as the next splitter.

Figure 5.2 provides a further illustration for this step, where those displayed cases were taken from part of the dataset used for this research. This bar chart is created with the data of collision-personal injury from Step 1. Figure 5.2 shows a frequency bar chart created for each selected independent variable, that is, whether any pick-up truck/van is involved with incidents or not. In this instance, these two categories display substantially different distributions. Incidents without any pick-up truck/van involvement are usually cleared within 30 minutes, while those involving pick-up trucks/vans are more likely to take a longer time.

To investigate if any other independent variables can best classify the available data into distinctly different categories, the same bar charts were created for every available independent variable. By comparing the resulting patterns, the most critical independent variable for each category can be selected as the next splitter.



*Note: some of the incident duration ranges are omitted since their frequencies are zero and are replaced with a symbol

Figure 5.2: Frequency distribution of incidents with and without involving a pick-up van

Step 3: Split the node based on the determined splitter in each category.

The focus of this step is to convert each splitting node into *If-then; and Else-then* logic statements, and to produce the set of rules for determining the incident duration for the target node.

For instance, consider an example category of collision-personal injury (CPI) presented in the previous steps and assume that the pick-up truck/van involvement indicator is selected as the next splitter, then the split nodes of this splitter can be presented as: *If Incident Nature is CPI & Pick-up Truck/Van is Not involved, then Incident Duration is …; If Incident Nature is CPI & Pick-up Truck/Van is involved, then Incident Duration is ….*

Step 4: Assign the estimated/predicted incident duration range for each split node.

This is to determine the best representative range for the incident duration data clustered for each node. To achieve this, one shall first search the interval that is less than or equal to 30 minutes but can cover at least 70 percent of all cases within a node. If no suchinterval exists within the node, then one can assign the shortest interval covering at least 60 percent of all cases within the node as the predicted incident duration for that node.

In Figure 5.2, most incidents that did not involve pick-up trucks/vans are distributed in the range of 5~30 minutes. Since the interval of 30 minutes covers about 92 percent (i.e., 110/120) of all incidents within the given conditions (within this node), one can accept the interval of 5~30 minutes as the most plausible incident duration at that node level.

In contrast, incidents involving pick-up trucks/vans are more widely distributed, and thus it is more difficult to determine their incident duration range under the given conditions. Hence, one first needs to find out if any 30 minute-interval can cover most incidents; it turns out that the interval of 20~50 minutes can cover approximately 68 percent of incidents at the node. Since it does not exceed 70 percent, one can proceed to find any shortest duration interval that can cover at least 60 percent of all incidents in this category. As Figure 5.2 shows, the interval of 35~50 minutes can offer about 61 percent of coverage.

Step 5: Repeat Step 2 to Step 4 for all nodes until the predetermined stopping criteria is satisfied.

The tree shall stop at that node when a node satisfies one of the following criteria:

- No independent variable is available as a splitter.

- There exists only one observation in a node.

Repeating Step 2 to Step 4 will help improve the model's performance. Considering the instance presented previously, adding another splitter can either narrow the range of predicted incident durations or increase the percentage of incidents covered by the specified duration range. This procedure can continue until no independent variable that can be used to further divide the data in its category into distinctly different distributions.

Figure 5.3 describes the structure of the Rule-Based Tree Model (RBTM). The developed RBTM starts from the first splitter, and then select the second splitter independently based on incidents falling in each category under the first splitter.

Note that the second layer of splitters can be different for each subset of incidents, depending on their characteristics and distributions. Figure 5.3 illustrates the procedures to number the second layer of splitters, named as *2nd Splitter-1* or *2nd Splitter-2*. The tree model continues to extend to the third layer of splitters and so on. In this study, the first splitter turns out to be the incident nature, and it consists of five branches to extend to the next layer.

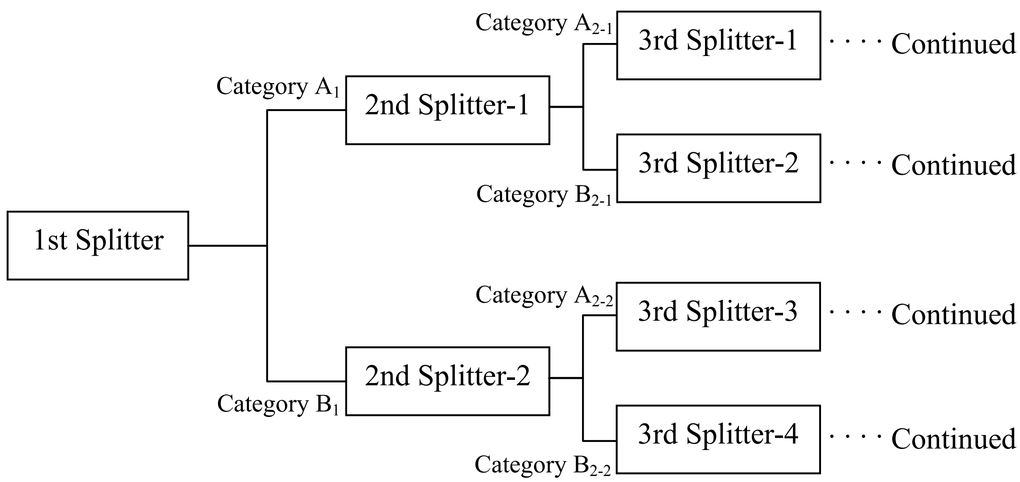


Figure 5.3: Structure of the Rule-Based Tree Model

For each group of non-fatality involved incidents, we have explored the use of supplemental models to improve the resulting accuracy. This is due to the fact that the Rule-Based Tree Model with its simple classification logic cannot fully reflect all embedded relations and perform the prediction at a sufficiently reliable level. Figure 5.4 displays the structure of the proposed hybrid model using RBTM and multinomial Logit Model (MNL) to estimate non-fatality incidents. Table 5-1 summarizes the calibrated MNL models for incidents in the category of collision-personal injury, and Table 5-2 lists the set of variables included in development of those models.

5.4 Naïve Bayesian Classifier for Fatality-Involved Incidents

Unlike other types, fatality-involved incidents have relatively few samples, and their duration data distribute over an extremely wide range. Also, most fatality-involved incidents took from two hours to several hours for traffic to recover to its normal state, which are quite different from other incident types. The unique feature of those incidents resulting in fatalities prevents the Rule-Based Tree Model from providing satisfactory classification. Thus, this study selected the Naive Bayesian Classifier as an alternative approach to develop the prediction model for fatality-involved incidents. This section briefly illustrates the background of this methodology, followed by presentation of the proposed model's structure.

Naïve Bayesian Classifier

The NBC assigns the object *I* to one of the discrete categories, $D_1, D_2, \cdots, D_m$, based on its attributes, $X_1, X_2, \cdots, X_m$. The NBC calculates the probability that I belongs to each category, conditioning on the observed attributes. I is assigned to the category with the greatest probability. This classifier is based on Bayes' theorem with the assumption that the presence of a specific attribute is unrelated to the presence of any other attributes. The probability that I belongs to each category is calculated on the observed attributes, that is, $P(I \in D_i \mid X_1, X_2, \cdots, X_n)$. By applying Bayes' Theorem, one can rewrite this relation as follows:

$$P(I \in D_i \mid X_1, X_2, \cdots, X_n) = \frac{P(I \in D_i)\, P(X_1, X_2, \cdots, X_n \mid I \in D_i)}{P(X_1, X_2, \cdots, X_n)} \qquad (5.\ 1)$$

Under the mutual conditional independence assumption, this reduces to

$$P(I \in D_i \mid X_1, X_2, \cdots, X_n) = \frac{P(I \in D_i) \prod_{j=1}^{n} P(X_j \mid I \in D_i)}{P(X_1, X_2, \cdots, X_n)} \qquad (5.\ 2)$$

for each category D_i. Since the denominator will be the same for all categories, one needs to calculate only the numerator for each category.

The attributes X correspond to observable incident characteristics, such as pavement conditions, locations of incidents, the number of vehicles involved, the number of blocked lanes and so on. When an incident occurs, the NBC would calculate the probability for the duration of the detected incident to fall into each discrete category, and select the one with the highest probability. This method can still be used to compute the probability even if the data associated with some of the attributes are not available. All model parameters (*i.e.*, the probabilities $P(I \in D_i)$ and $P(X_j \mid I \in D_i)$) can be approximated with relative frequencies from the training set, the data set generated for calibration of model parameters.

Note that if the given category and attribute values never exist together in the training set, then their frequency-based probability estimate will be zero. This is problematic since it will wipe out all information in the other probabilities when they are multiplied together. Hence, in applying this method one needs to replace all zero probabilities with a small positive number.

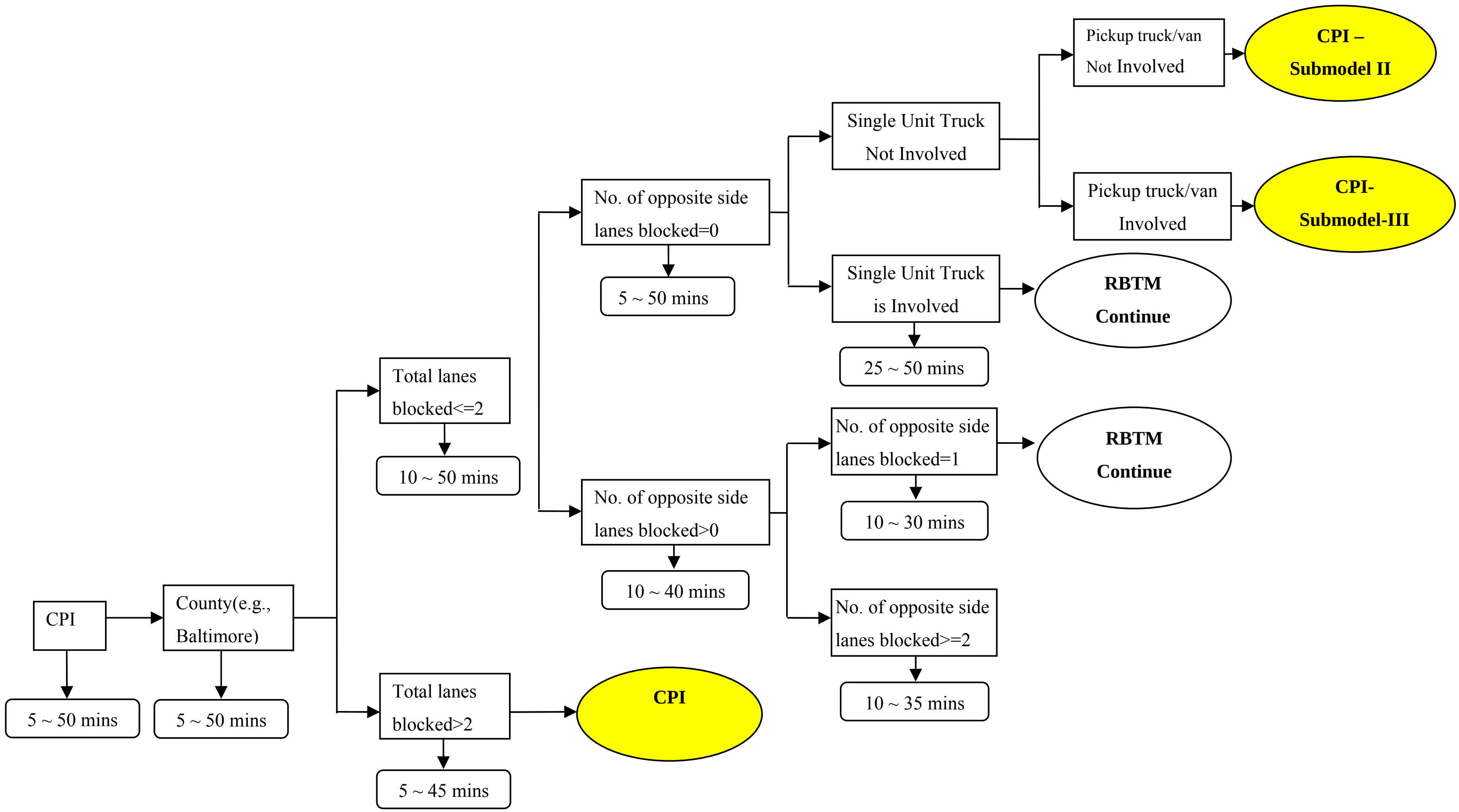


Figure 5.4: Rule Based Tree Model and Structure of the Hybrid Model for Collision-Personal Injury

Table 5.1 (a) Calibrated MNL Model I for Collision-Personal Injury

CPI-Sub-Model I

R_{5-25} = 0.910 -3.550*NoTT -2.140*Night -0.536*NoVehInv +2.434*I495 -3.053*NoSUT -0.971*NoPUV
(0.9) (-2.9) (-2.4) (-2.4) (3.2) (-3.3) (-2.3)
+1.053*Pave_Dry
(1.6)

R_{25-45} = 2.131 -1.241*NoTT -2.678*Night -0.536*NoVehInv +1.253*I495 -3.053*NoSUT
(2.9) (-2.0) (-3.2) (-2.4) (1.9) (-3.3)

R_{gt45} = 0 (Base)

The number of observations used : 98
Likelihood with zero coefficients = -106.5654
Likelihood with constants only = -105.5362
Final value of Likelihood = -76.2511

Table 5.1 (b) Calibrated MNL Model II for Collision-Personal Injury

CPI-Sub-Model II

R_{5-25} = 1.952 +1.827*I270 -0.655*NoVehInv +2.663*I495 -2.776*Pave_SI -2.050*Ex495
(2.5) (2.0) (-3.1) (2.3) (-2.7) (-2.1)

R25-50 = 1.576 +1.568*I270 -0.422*NoVehInv +2.471*I495 -3.626*Pave_SI -2.253*Ex495
(2.0) (1.8) (-2.2) (2.1) (-2.7) (-2.3)

Rgt50 = 0 (Base)

The number of observations used : 189
Likelihood with zero coefficients = -206.5391
Likelihood with constants only = -179.5752
Final value of Likelihood = -167.4129

Table 5.1 (c) Calibrated MNL Model III for Collision-Personal Injury

CPI-Sub-Model III

R_{5-25} = 1.868 -3.346*NoTT -2.773*Night -2.509*PEAKHR -3.874*Ex270
(2.8) (-3.2) (-2.1) (-2.2) (-3.6)

R_{25-45} = 3.031 -3.346*NoTT -1.603*Night -2.095* PEAKHR -2.727* Ex270 -0.865*Ex495 -1.099*Pave_Dry
(3.8) (-3.2) (-1.7) (-1.9) (-3.1) (-1.5) (-2.1)

R_{gt45} = 0 (Base)

The number of observations used : 82
Likelihood with zero coefficients = -90.0862
Likelihood with constants only = -85.9470
Final value of Likelihood = -65.3223
Note : Numbers in parentheses are *t*-statistic values.

Table 5.2 Descriptions for variables included in the CPI-Sub-Models

Description for Variables Included in the CPI-Sub-Models	
I495	1 if an incident occurred on Road I-495; 0 otherwise
Night	Binary variable for incident time (Night=1, otherwise=0)
NoTT	Number of tractor-trailers involved
NoPUV	Number of pickup/vans involved
NoVehInv	Number of vehicles involved
NoSUT	Number of Single-Unit Truck involved
Pave_Dry	1 if pavement condition is Dry; 0 otherwise
I270	1 if an incident occurred on Road I-270; 0 otherwise
Ex495	Binary variable to indicate the specific locations on I-495 (exit numbers. 27, 28, 33, 34, 36, 38, and 39)
Pave_SI	1 if Pavement Condition is Snow/Ice; 0 otherwise
Ex270	Binary variable to indicate the specific locations on I-270 (exit numbers. 1, 4, 9, 13, 15, 18, and 22)
PEAKHR	PEAKHR : 1 if an incident occurred in peak hours; 0 otherwise

To explore which attributes can best improve the NBC model, the research team first developed a simple Naïve Bayes Classifier (NBC) model for each attribute. By comparing the estimating results, one can select attributes with best results as the initial set.

For each of those selected attributes, the research team added another attribute to create a two-attribute set. Then, those two-attribute sets were ranked based on the estimation results, and this process was repeated until acquiring the best set of attributes. The following list of factors belongs to the best set of attributes selected for the model development:

- Counties (if use the entire statewide data set in the KB system)
- Pavement Conditions: Unknown, Dry, Wet or Snow/Ice
- Number of Tractor-Trailers

- Number of Pick-Up Trucks/Vans
- PM Peak Hour Indicator: 1 if occurred in 4 PM ~ 6:30 PM; 0 otherwise
- Night Indicator: 1 if occurred in 8 PM ~ 6 AM; 0 otherwise
- Number of Shoulder Blockage
- Number of drivers/occupants injured
- Number of drivers/occupants killed
- Lighting conditions: Daylight, Dawn/Dusk, Dark-Lights on or Dark-No lights
- Collision Type-Head On indicator
- Collision Type-Head On Left Turn indicator
- Road-795: 1 if an incident occurred on I-795; 0, otherwise

5.5 Conclusion

This chapter has illustrated the set of models developed for predicting the duration of a detected incident. These models, calibrated with the data from CHART and Police Accident reports, have been programmed into the I-695 simulator to work with the embedded historical dataset to produce the estimated incident duration. Potential users of the I-695 traffic simulator can execute the simulation to project the incident impacts, based on either the incident duration estimated by the embedded models or the average duration from those incidents incurred at the nearby locations with similar characteristics. One can conveniently update this incident duration database and update the parameters of those prediction models as better incident data become available.

CHAPTER 6: SYSTEM OPERATIONS FOR REAL-TIME INCIDENT MANAGEMENT

6.1 Introduction

This chapter presents the application of the I-695 Baltimore Beltway simulator for real-time incident management, based on the overall structure described in Chapter 3 and the incident duration and impact models discussed in Chapter 5. The next section first illustrates the key functions of all essential system components and then discusses their interrelationships in real-time operations. Section 6.3 details how to use the developed system via its user interface to predict traffic queue evolution and how to generate the available output MOEs of interest from each operational step. Section 6.4 will summarizes some conclusions from this study and offer suggestions for future system enhancement.

6.2 Key System Functions

Figure 6.1 illustrates the real-time operational structure of the I-695 Baltimore Beltway system for incident management. Its online operations rely on interactions between the following components: (1) a surveillance system to receive traffic conditions and incident-related data; (2) a user interface to transfer all detected or estimated information into the computing module; (3) embedded models to predict incident duration and impacts; and (4) the simulation engine to project the evolution of traffic congestion and impacts under the selected control strategies. The system output includes an initial approximation of traffic congestion and queue and a detailed projection of traffic pattern evolution during the incident response and clearance period. The responsible agency can also use the system's embedded functions and MOEs to select the most cost-effective traffic management strategies for minimizing the impacts of the incident on the entire network.

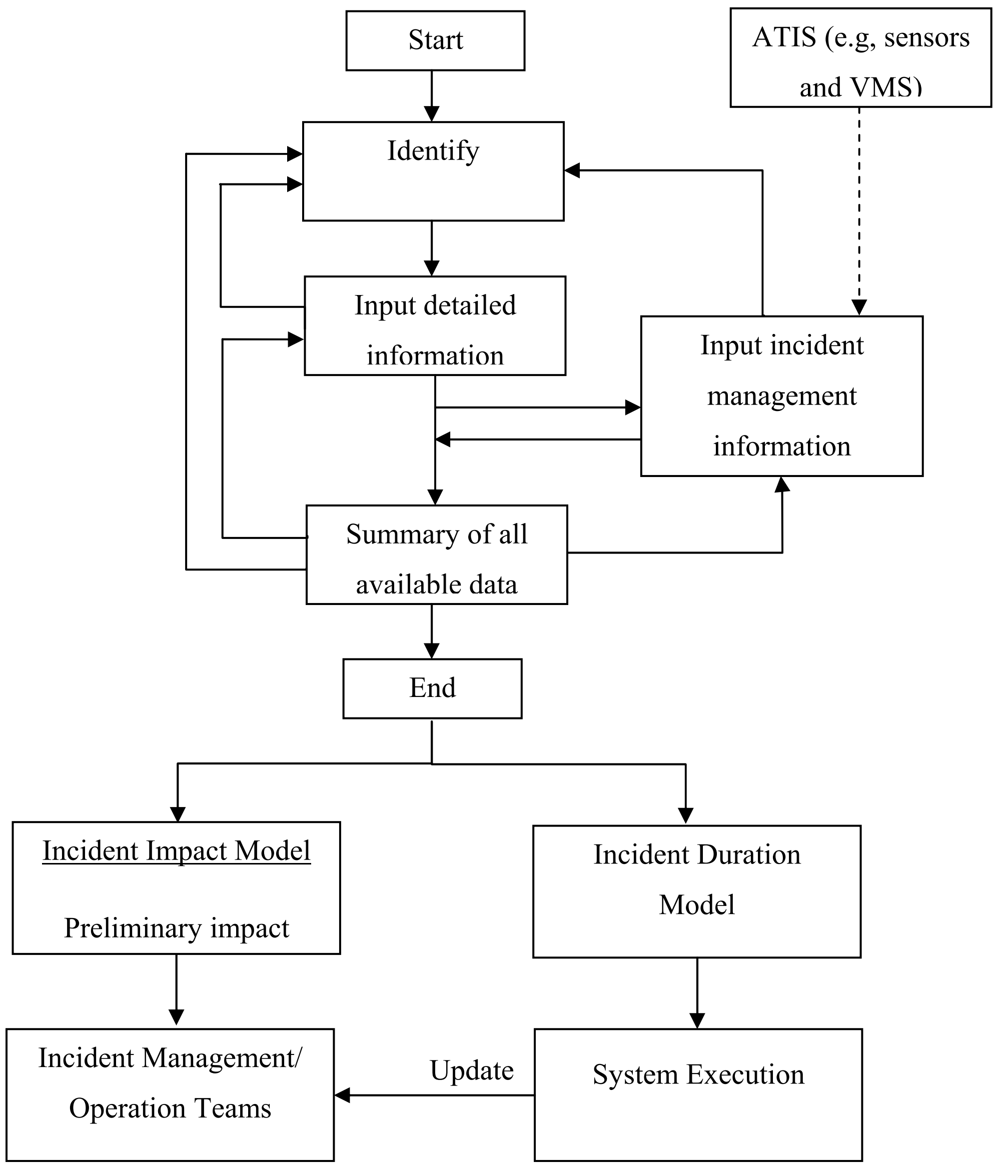


Figure 6.1: Real-time operational structure of the I-695 simulator

Selection of background information

To supplement the inadequate real-time coverage of traffic conditions, the proposed system contains six sets of historical traffic data for analysis. Users can directly select from the list (see Figure 6.2) to integrate with any available sensor data. Figure 6.3 shows the map-based display of the coverage of the entire system.

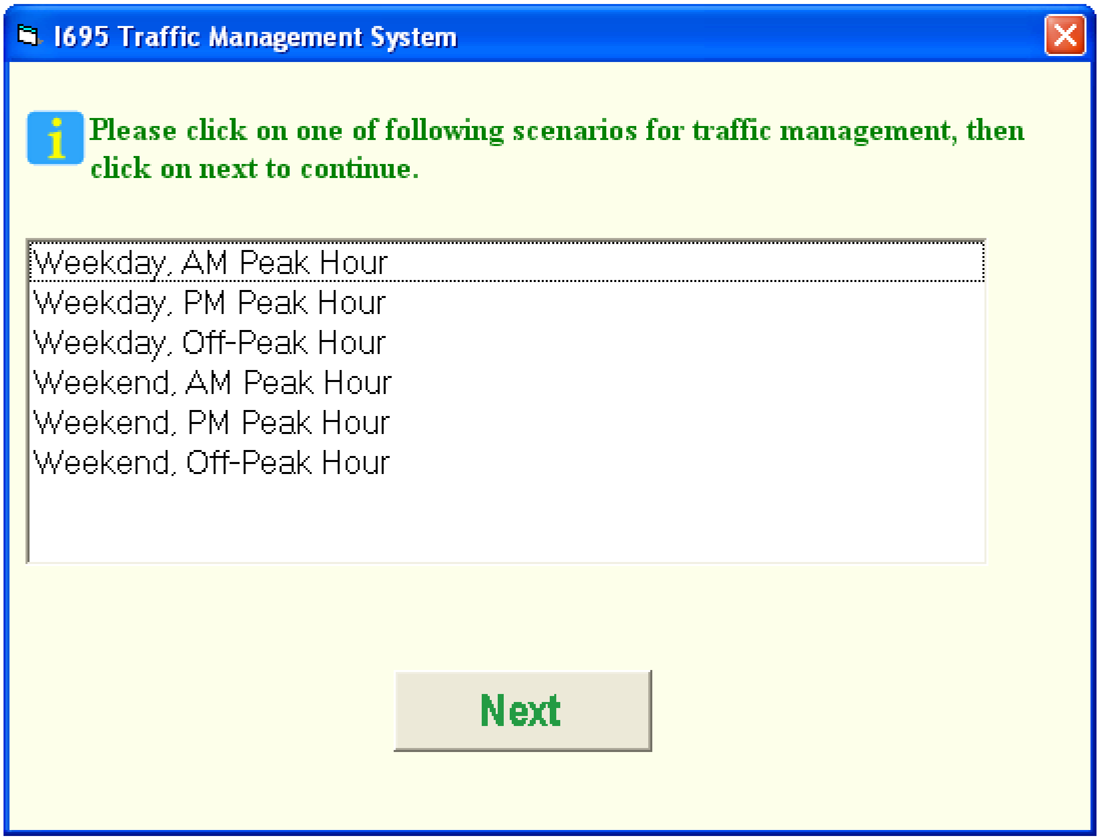


Figure 6.2: Selection of background traffic conditions from the system database.

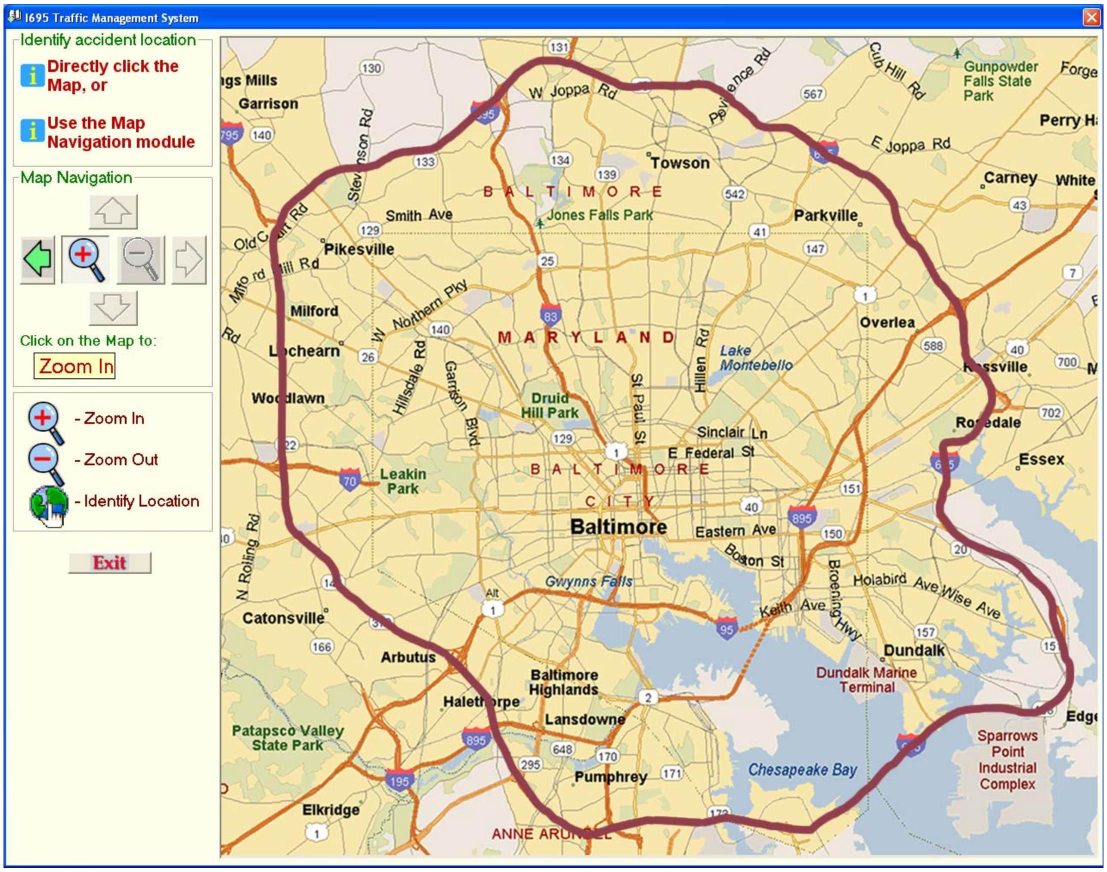


Figure 6.3: The map-based display of the entire system's coverage.

On-line input of real-time incident information

After integrating the background information and real-time detected traffic data, the system needs to obtain the following the incident characteristic data to execute its prediction functions:

- The reported incident location from the map-based interface (see Figure 6.4);
- The direction of traffic impacted directly by the incident: inner or outer loop (see Figure 6.5);
- The distance (in feet) from the incident location to the nearest upstream or downstream ramp (see Figure 6.6);
- The number of lanes blocked by the reported incident (see Figure 6.7); and

- The incident onset time, the estimated clearance duration, and the required simulation time to cover the entire impact area.

Note that the I-695 simulator actually offers users two complementary ways to estimate the incident duration. As shown in Figure 6.8, the control center can estimate the duration of the detected incident with the embedded incident duration model, or it can approximate the required clearance duration based on all similar cases in the database, such as having the same location, having the same number of blocked lanes, and occurring at the same time of day. Figure 6.9 illustrates the final predicted incident duration, using the system's embedded modules. Such information can serve as the basis for the responsible agencies to take immediate traffic response actions and can also be used as the input for projecting the evolution of traffic conditions over time during the clearance operations.

Figure 6.10 summarizes all identified and estimated information associated with the detected incident that should be shared with all parties involved in incident response and traffic management. Based on the projection results, the control center operators may need to update the information in real time and to revise the control strategies based on the projected system effectiveness.

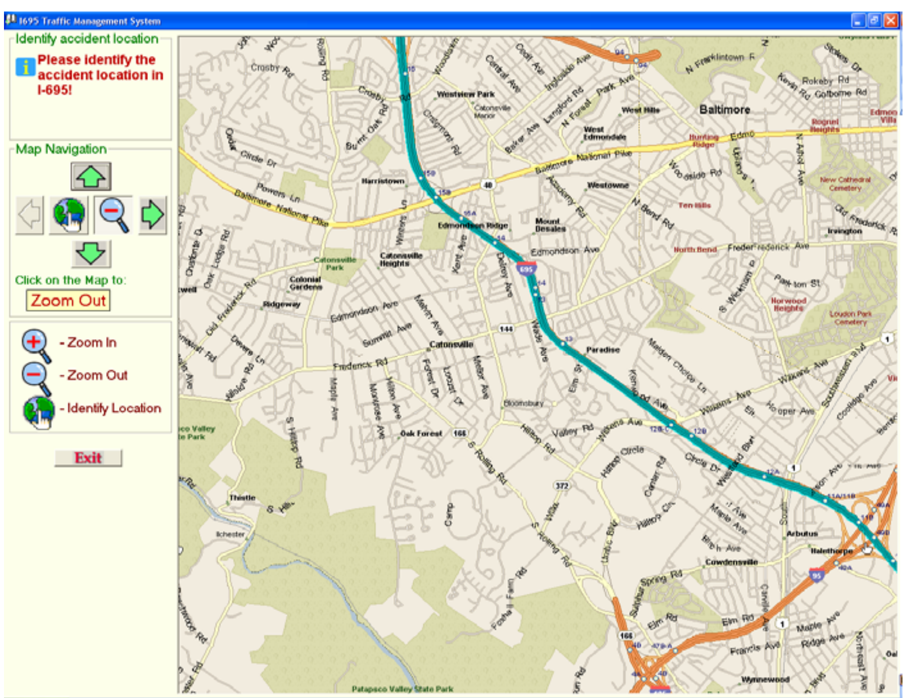


Figure 6.4: A detailed map view for the incident location.

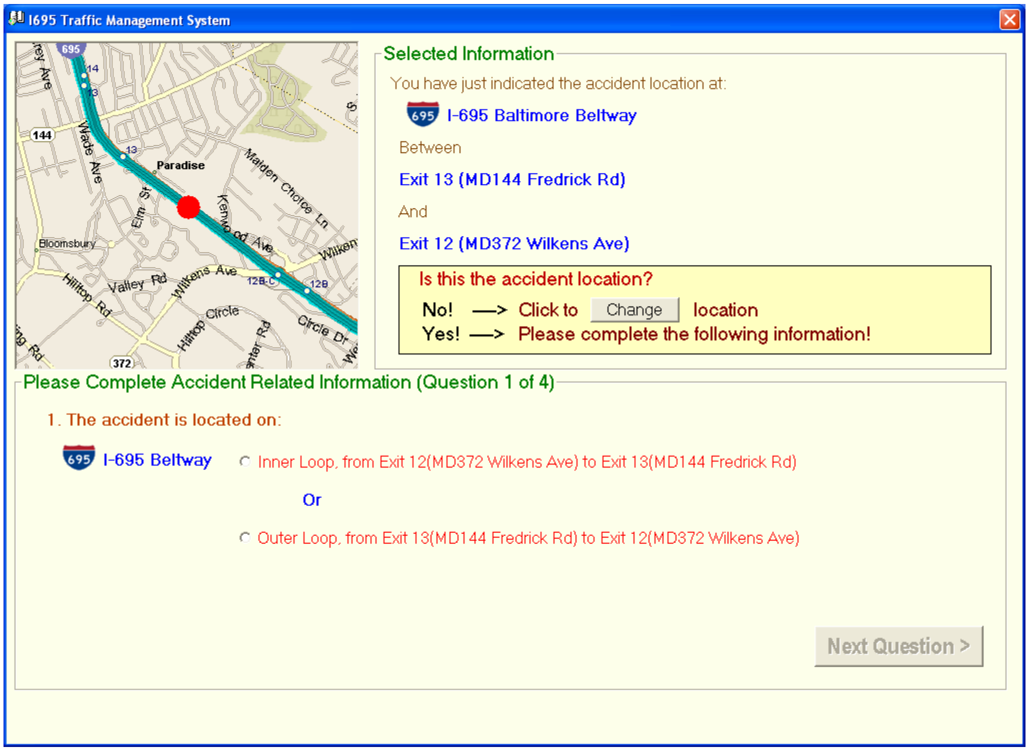


Figure 6.5: Selection of the direction directly affected by the incident.

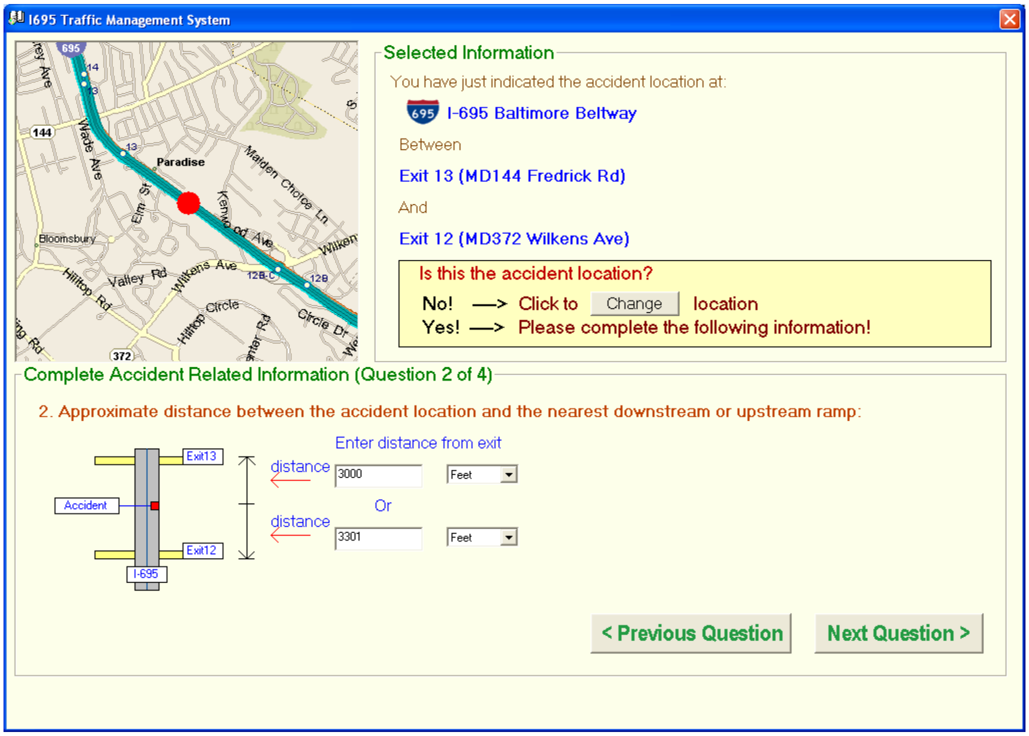


Figure 6.6: Identification of the precise incident location.

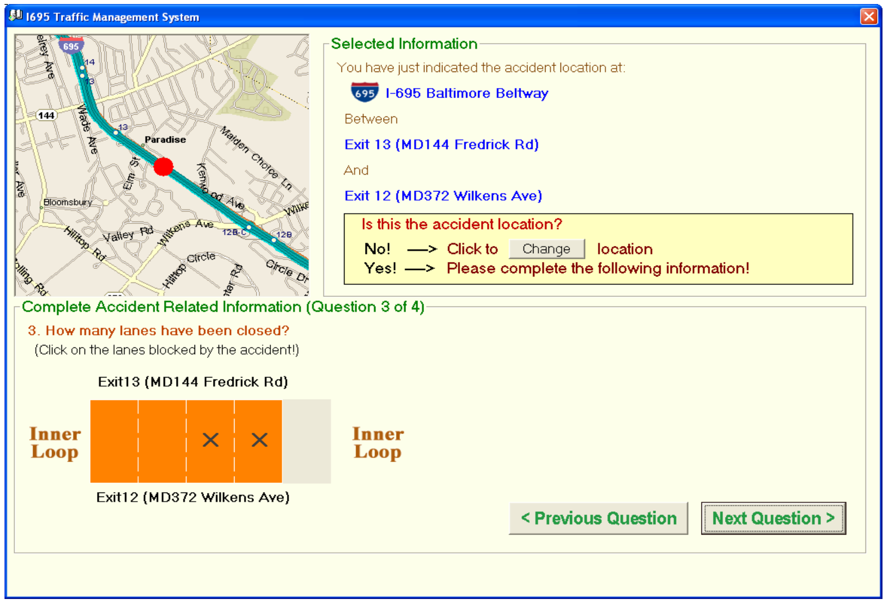


Figure 6.7: Identification of the blocked lanes.

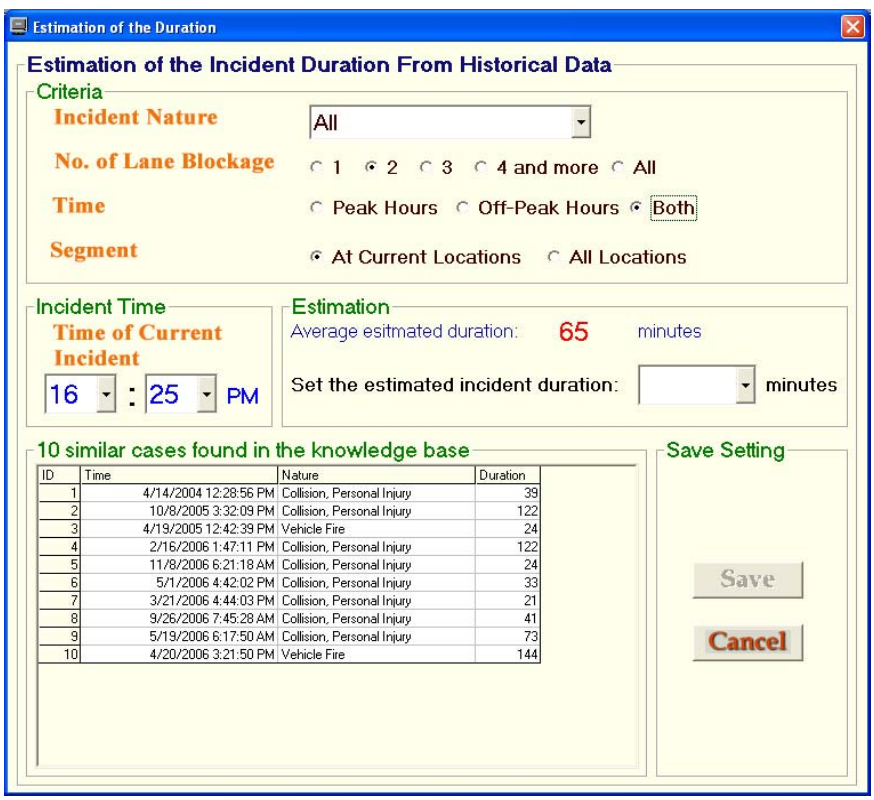


Figure 6.8: Using the interface to estimate the incident duration.

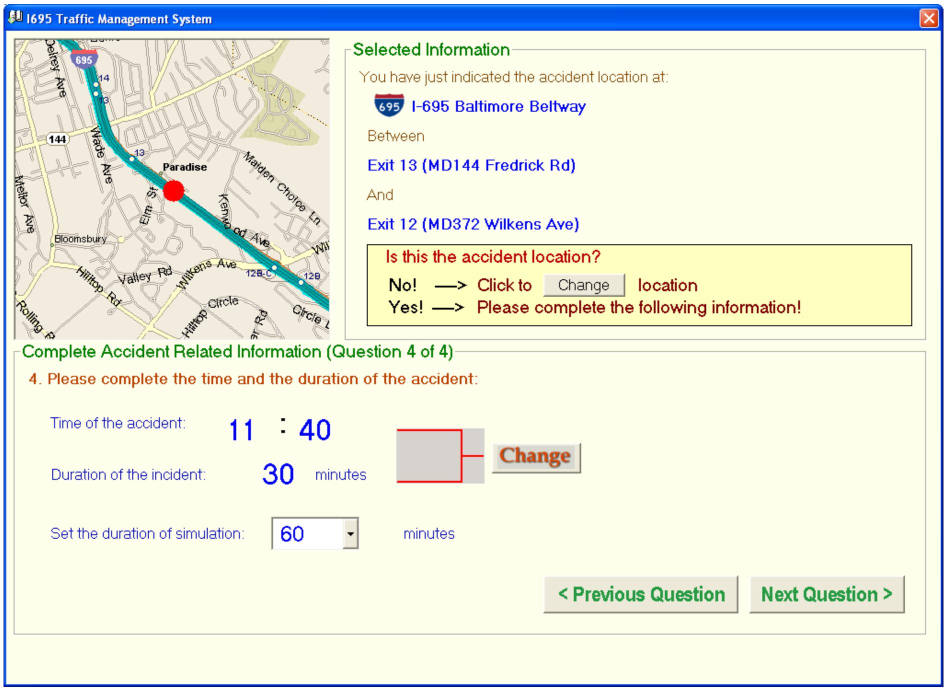


Figure 6.9: Estimated incident duration for assessing the incident's impacts.

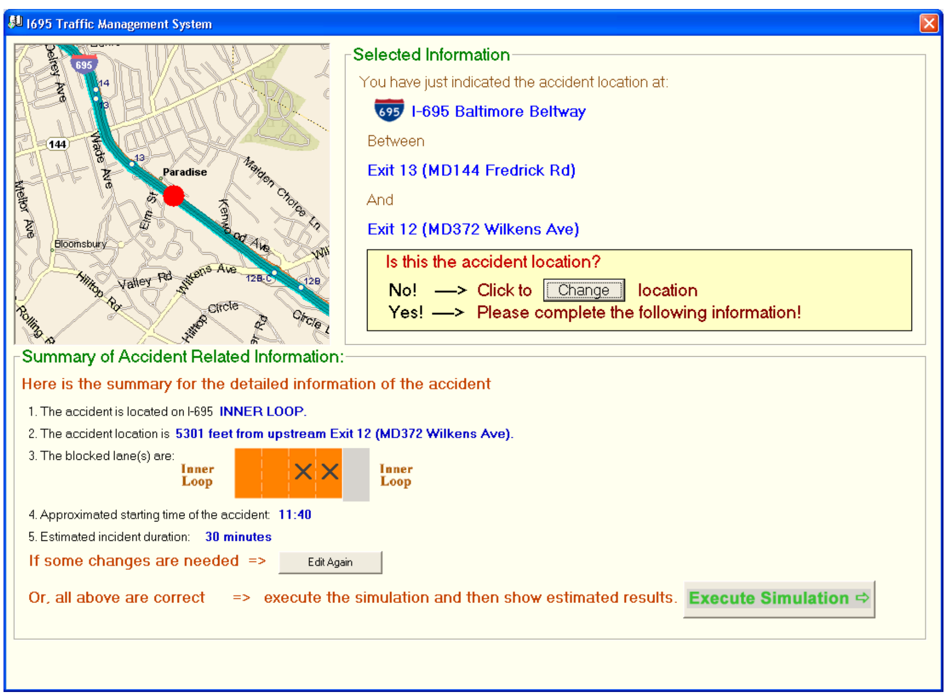


Figure 6.10: Summary of data associated with the detected incident.

The I-695 Baltimore Beltway simulator, using its embedded mathematical models, can produce an initial estimate of the incident duration (see Figure 6.8), the resulting queue, and the total delay. The simulator also allows users to track the spatial evolution of congestion patterns during the incident clearance period. Figures 6.11 and 6.12 show the available MOE output produced by the system, which includes the average speed, delay, queue length, and travel time by location over time. One can select the output MOE based on the preferred display format and submit that information to associated traveler information systems to inform drivers of the approaching traffic conditions and to advise them to take necessary actions.

Figure 6.13 illustrates a special output function that enables users to track queue evolution at the target segment (e.g., Exits 44 and 1) and to assess the need for detour operations. Figure 6.14 highlights a snapshot of the travel time versus the departure time during the incident clearance period for a target highway segment, which can serve as the basis for commuters to make informed departure and route choices.

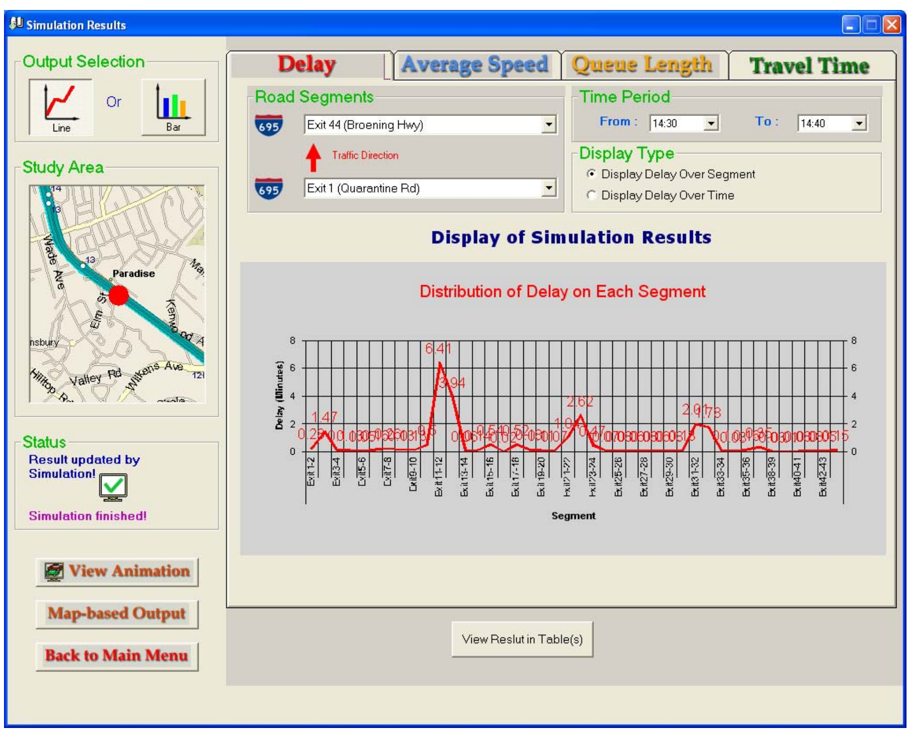


Figure 6.11: A graphical view of the delay distribution.

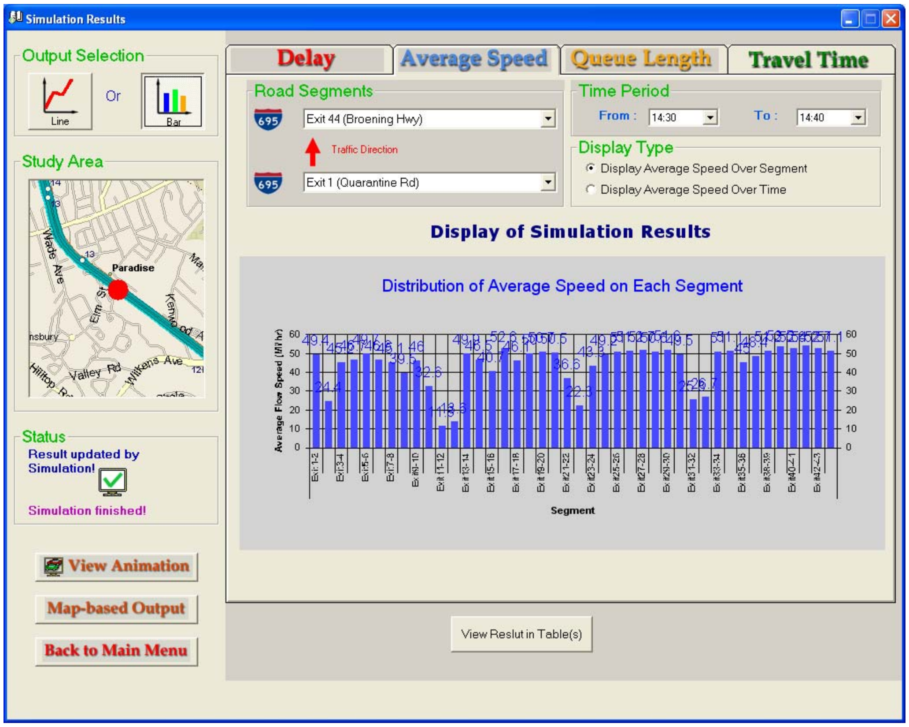


Figure 6.12: A graphical view of the speed distribution.

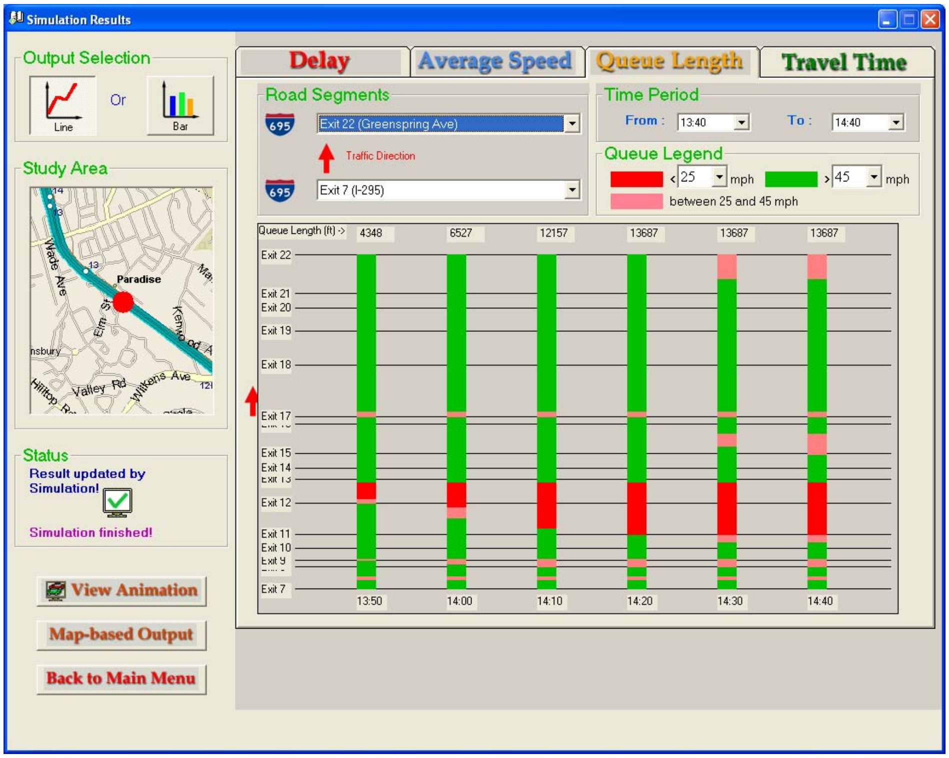


Figure 6.13: A graphical view of the system queue evolution.

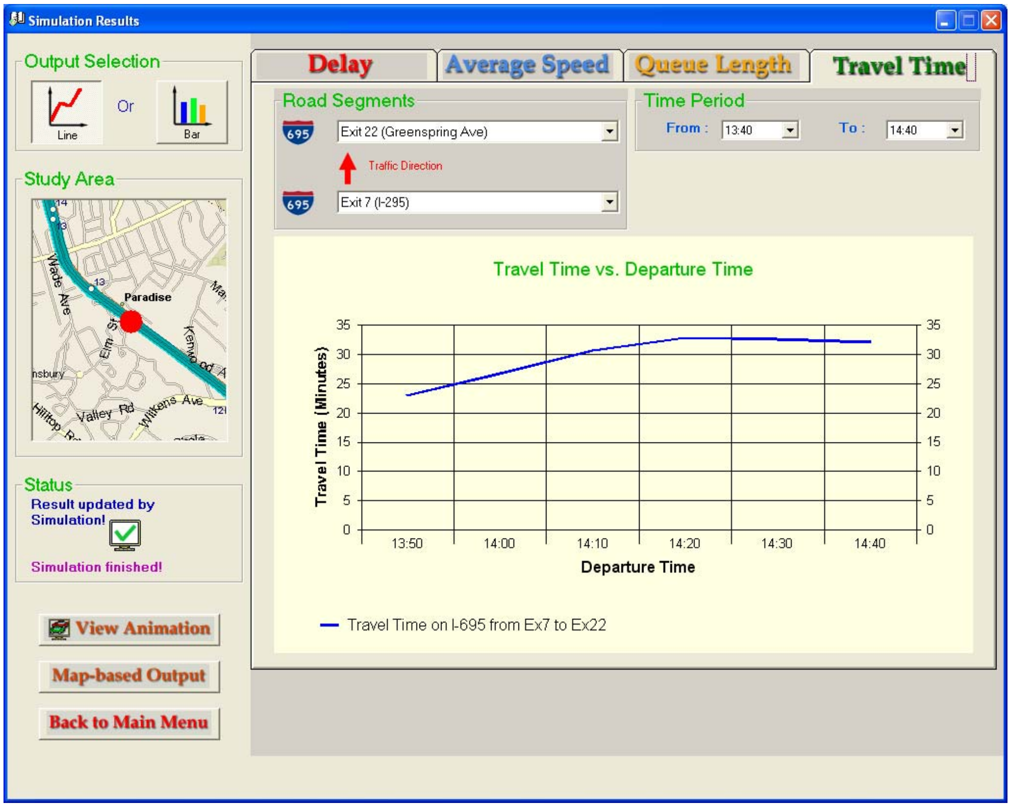


Figure 6.14: A graphical view of the travel times versus departure times.

For effective interactions with other control modules operated by the incident response/management center, this system can also produce electronic output files for various planning, evaluation, and control applications. Figures 6.15 and 6.16 show some examples of such output. To facilitate the paramount view of the entire network's traffic condition, this system can display the evolution of a selected MOE during the incident response and management period. Figures 6.17 to 6.19 illustrate the network view of the congestion pattern evolving during the selected time period of interest. Users can use such information to monitor traffic impacts and also to inform drivers of the approaching traffic conditions via available Advanced Traveler Information System (ATIS) devices such as VMSs.

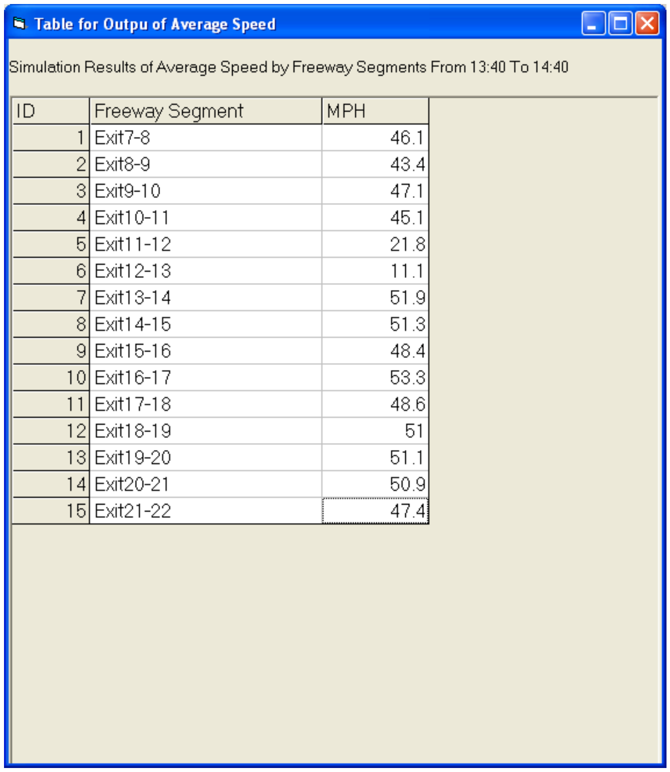


Table for Outpu of Average Speed

Simulation Results of Average Speed by Freeway Segments From 13:40 To 14:40

ID	Freeway Segment	MPH
1	Exit7-8	46.1
2	Exit8-9	43.4
3	Exit9-10	47.1
4	Exit10-11	45.1
5	Exit11-12	21.8
6	Exit12-13	11.1
7	Exit13-14	51.9
8	Exit14-15	51.3
9	Exit15-16	48.4
10	Exit16-17	53.3
11	Exit17-18	48.6
12	Exit18-19	51
13	Exit19-20	51.1
14	Exit20-21	50.9
15	Exit21-22	47.4

Figure 6.15: A graphical view of the system speed distribution.

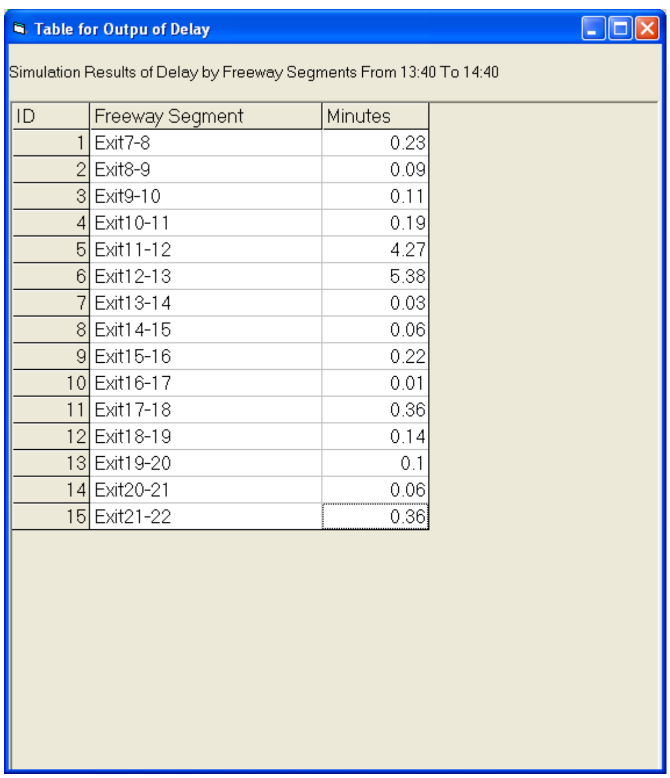


Table for Outpu of Delay

Simulation Results of Delay by Freeway Segments From 13:40 To 14:40

ID	Freeway Segment	Minutes
1	Exit7-8	0.23
2	Exit8-9	0.09
3	Exit9-10	0.11
4	Exit10-11	0.19
5	Exit11-12	4.27
6	Exit12-13	5.38
7	Exit13-14	0.03
8	Exit14-15	0.06
9	Exit15-16	0.22
10	Exit16-17	0.01
11	Exit17-18	0.36
12	Exit18-19	0.14
13	Exit19-20	0.1
14	Exit20-21	0.06
15	Exit21-22	0.36

Figure 6.16: A graphical view of the system delay distribution.

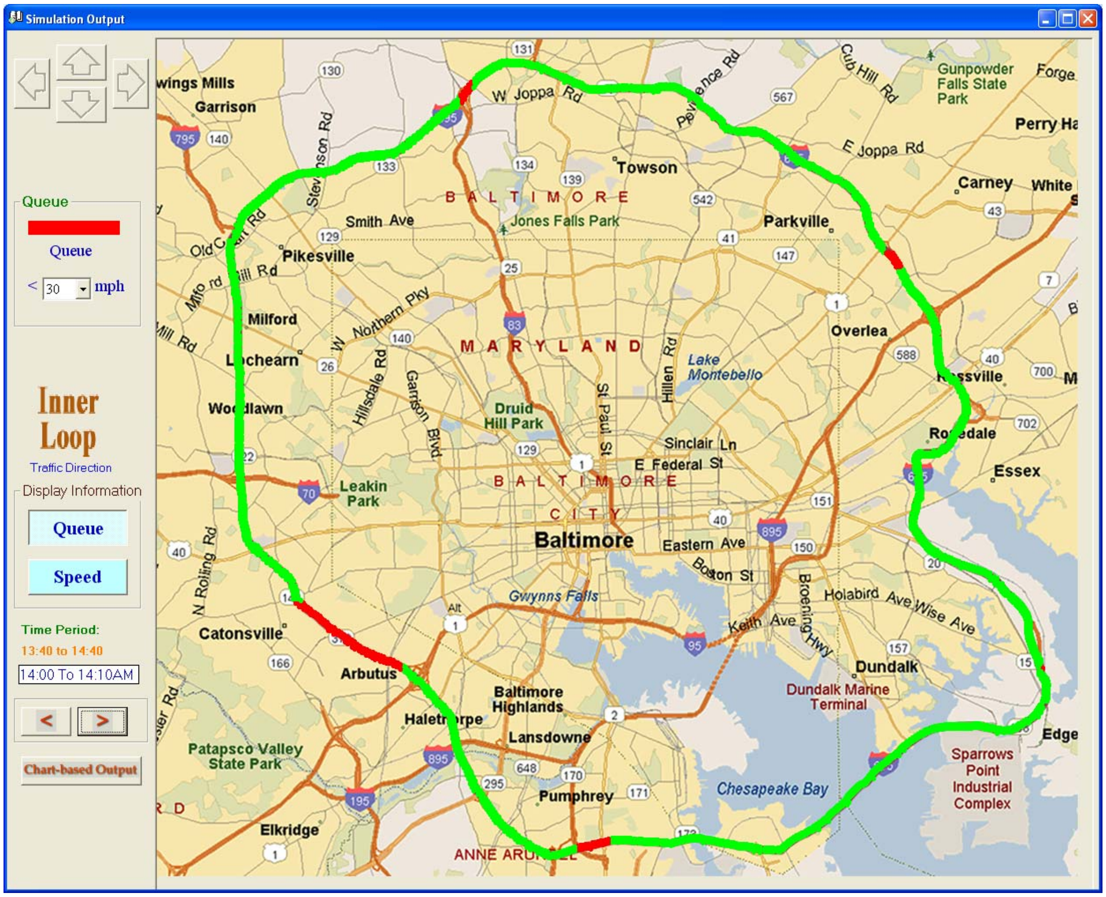


Figure 6.17: A snapshot screen of map-based output of the delay (14:00 to 14:10).

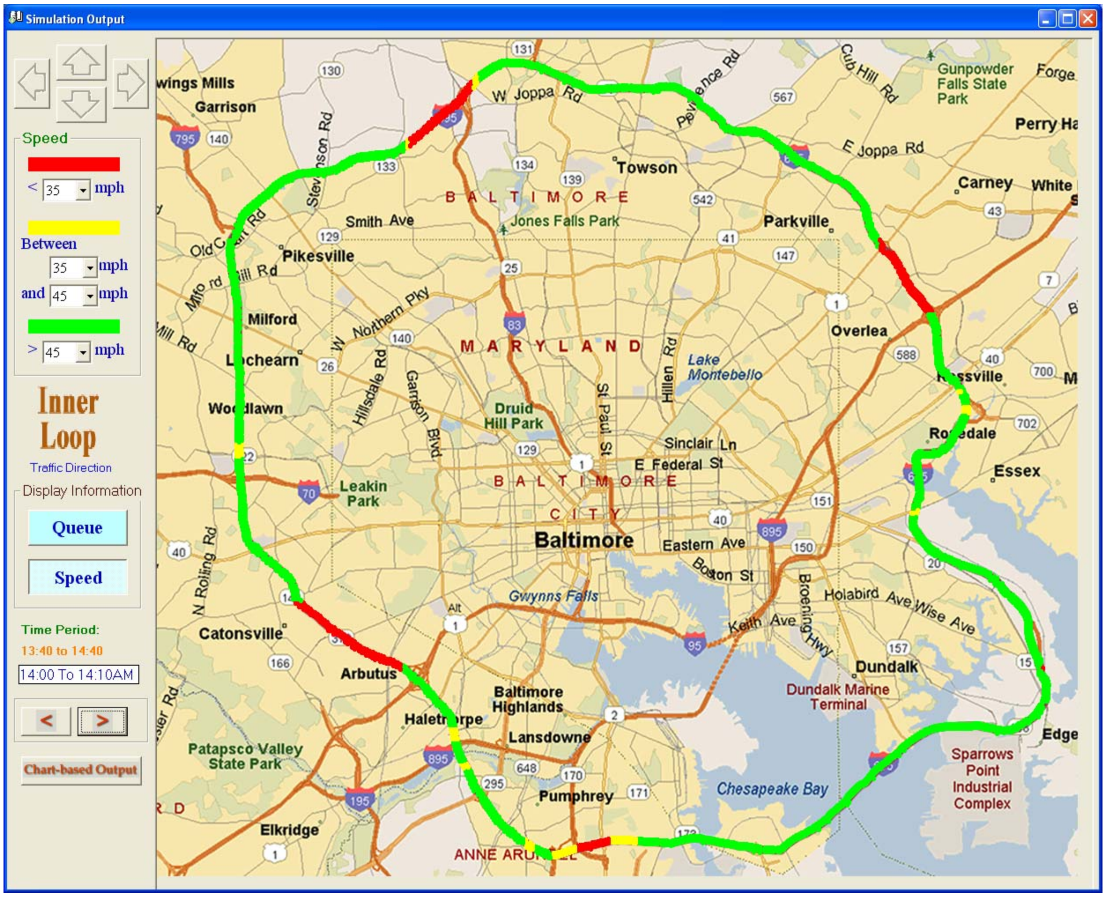


Figure 6.18: A snapshot screen of map-based output of the average speed (14:00 to 14:10).

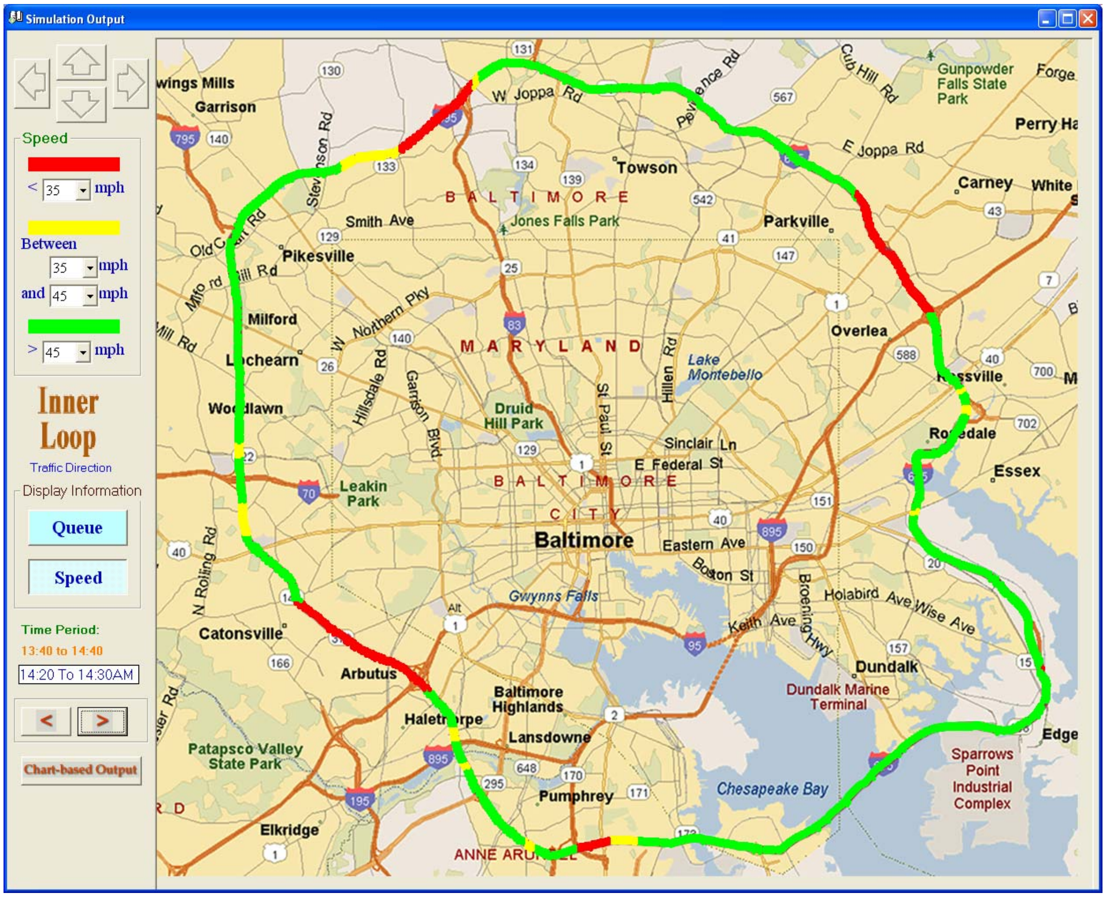


Figure 6.19: A snapshot screen of map-based output of the average speed (14:20 to 14:30).

6.3 Research Findings and Conclusions

Transportation professionals have long recognized that, despite immense investments in traffic monitoring and detection hardware over the past two decades in most metropolitan areas, the ever-increasing congestion still plagues their roadway networks. The advent of ITS seems to promise some mitigation of both recurrent and nonrecurrent congestion, but much remains to be done to take full advantage of recent advances in technology. One critical area receiving increasing attention is how to best use the information from advanced ITS modules to contend with nonrecurrent congestion caused by incidents such as crashes and unexpected events.

This study, in response to the above concern, has focused on designing an integrated real-time traffic management system to monitor and manage incidents. Using the example incident data set from CHART, the report has illustrated both the system's real-time operational process and the simulator's development procedures, including a concise review of related systems in the literature, a description of its operational relations, and the calibration of all key system components. Our illustration of an example application with the I-695 Baltimore Beltway system also constitutes part of this report. Although the entire study is exploratory in nature, many valuable research lessons, summarized below, deserve attention in the future development and implementation of similar systems:

- Any deployed traffic monitoring/detection system should be capable of receiving and integrating with a variety of information sources, such as GPS, cell-phone locations, and blue-tooth data, to justify the cost of its deployment.

- Any information associated with the response to and operations for a detected incident should be documented in sufficient detail and at a required level of accuracy. It should at least include the traffic conditions before and during the incident, time durations associated with detection, response, and clearance, and the nature of the detected incident, as well as its impacts.

- The incident data, due to its complex nature and different levels of impact, should be classified in sufficient detail, including driver assists, shoulder-lane incidents, multilane blockage, and the severity level (e.g., injury or fatality).

- The collection of field data with advanced surveillance systems is essential for the development and calibration of a reliable incident impact model. The traffic impact information should include the initial impact, any congestion pattern variations during partial incident clearance, and the resulting impact, as well as the recovery duration with and without implementing any control/detour plan.

- The assessment of how the incident will affect delays and queues should consider both the primary route experiencing the incident and the neighboring roadway network within the incident impact boundaries.

- The prediction models, including both their statistical and simulation modules, should be capable of constantly updating their parameters based on the available real-time traffic information.

- A user-friendly interface is critical to the effective integration of different traffic control and management systems and thus deserves attention in the design and operation of a traffic network control center that operates various system components developed with advanced technology.

- All incident response and operations data should be well documented to serve as the basis for evaluating the response efficiency and management effectiveness. Information about the social benefits (including reduction of delay, fuel consumption, and emissions) gained by effectively managing incidents are essential for justifying any further investment.

In view of the increasing congestion experienced in both urban traffic networks and commuting corridors, many states and counties have continued to devote tremendous resources to researching new generations of ATIS and/or ITS systems in recent years. While technological adventure for traffic needs generally yields positive contributions to our comprehension of the complex traffic dynamics, driven by technology alone without an in-depth understanding of the fundamental problem nature may produce some advanced systems with no justifiable cost/benefit in practice. Over the past two decades, many research products (e.g., dynamic traffic assignment models) and hardware technologies (e.g., automated highway control) for ITS development have suffered from this mistake. Hence, in developing the effective traffic incident monitoring and management system presented in this study, the responsible traffic agencies should take the following actions in a rigorous manner:

- Collect sufficient incident data — including the nature, impacts, and resulting severity — at the level of detail needed for classification and for the design of management strategies.

- Analyze archived traffic incident data in-depth to determine the required equipment, the most efficient response, and effective traffic management strategies to minimize the resulting incident impacts under various traffic conditions.

- Identify data needs for both real-time and off-line analyses, including congestion monitoring, impact assessment, prediction model calibration, and control strategy development.

- Design the functional requirements for the target ATIS and/or advanced traffic surveillance systems, based on the data needs identified in the previous steps.

- Develop a control center (as shown in Figure 6.1) that can seamlessly integrate various essential system functions, including acquiring information, developing models, updating parameters online, calibrating models, monitoring traffic impacts, and revising management strategies.

- Design an effective interface to facilitate application of the system, to minimize human-factor-related operating errors, and to prevent delays in integrating information from either online or offline sources.

- Document and inventory all data associated with the operation of the entire incident response and management system, including monitoring, detection, response, clearance, recovery, and incident impacts.

- Recognize inevitable malfunctions of key system components in real-time operations, and design supplemental modules to ensure that the system can function at an acceptable level of reliability.

It is also critical for an advanced traffic control center to be able to monitor the compliance patterns of drivers in response to the reported incident and implemented management strategies, such as detour operations. Responsible traffic operators can then dynamically adjust the VMS messages and control strategies based on the projected traffic distribution patterns. These types of desirable monitoring functions are not available in the existing ITS traffic surveillance systems. However, the traffic simulator developed from this study, if supported with reliable real-time traffic information, can provide some of those essential functions.

REFERENCES

1. Ben-Akiva, M. and Lerman, S.R. (1985). "Discrete choice analysis: Theory and application to travel demand." MIT Press, Cambridge, Massachusetts.

2. Bauer, K. M., and Harwood, D.W. (1998), "Statistical models of accidents on interchange ramps and speed-change lanes", FHWA-RD-97-106; MRI Rept 3195-02, 3A5A; Final Technical Report.

3. Chang, G-L, and Point-du-Jour, J. Y. (2003), "Performance evaluation of CHART – the real time incident management system in Year 2001," Final report.

4. Chang,G-L, and Kim, W. (2009), "An integrated knowledge-based system for real-time estimation of incident durations and nonrecurrent congestion delay for freeway networks," Final report, MD-09-SP708B4C, Maryland State Highway Administration.

5. Choe, T., Skabardonis, A., and Varaiya, P. P. (2002), "Freeway performance measurement system (PeMS): an operational analysis tool", National Research Council.

6. Garib, A., Radwan, A. E., and Al-Deek, H. (1997), "Estimating Magnitude and Duration of Incident Delays," Journal of Transportation Engineering, Vol. 123, No. 6, pp. 459-466.

7. Giuliano, G. (1989), "Incident Characteristics, Frequency, and Duration on a High Volume Urban Freeway," Transportation Research, Vol. 23A, No. 5, pp. 387-396.

8. Golob, T. F., Recker, W., and Leonard, J. D. (1987). "An Analysis of the Severity and Incident Duration of Truck-Involved Freeway Accidents," Accident Analysis and Prevention, Vol. 19, No. 4, August, 375-395.

9. Greene, W. H. (2000), Econometric Analysis, Fourth Edition, Printice Hall International Inc.

10. Jones, B., Janssen, L., and Mannering, F. (1991), "Analysis of the Frequency and Duration of Freeway Accidents in Seattle," Accident Analysis & Prevention, Vol. 23, No. 4, pp 239-255.

11. Khattak, A. J., Schofer, J. L., and Wang, M. H. (1995), "A Simple Time Sequential Procedure for Predicting Freeway Incident Duration," IVHS Journal, Vol. 2, No. 2, pp 113-138. 106.

12. Konstantinos, G., Zografos, N., Konstantinos, A., and Vasilakis, G. (2002), "A real-time decision support system for roadway network incident response logistics", Transportation Research Part C 10, pp 1-18.

13. Lin, P-W., Zou, N., and Chang, G-L. (2004). "Integration of a Discrete Choice Model and a Rule-Based System for Estimation of Incident Duration: a Case Study in Maryland." Proceedings of the 83rd TRB Annual Meeting, Washington, D.C.

14. Lindley, J. (1987). Urban Freeway Congestion: Quantification of the Problem and Effectiveness of Potential Solutions. ITE Journal, pp 27-32.

15. Logi, F., and Ritchie, S. (1997), "A knowledge-based system for integrated freeway and arterial incident management and control: implementation and validation results", Transportation Systems 1997, Vol 1, 1997, pp 291-296.

16. Logi, F., and Ritchie, S. (2001), "Development and evaluation of a knowledge-based system for traffic congestion management and control", Transportation Research Part C, No. 9, pp 433-459.

17. Nam, D., and Mannering, F. (2000), "An Exploratory Hazard-Based Analysis of Highway Incident Duration," Transportation Research, Vol. 34A, No. 2 pp 85-102.

18. Ozbay, K., and Kachroo, P. (1999), Incident Management in Intelligent Transportation Systems, Boston, MA: Artech House.

19. Sadek, A. W., Smith, B. L., and Demetsky, M. (2001), "A prototype casebased reasoning system for real-time freeway traffic routing", Transportation Research Part C 9, pp 353-380.

20. Smith, B. L., and Smith, K. W. (2001), "An investigation into incident duration forecasting", ITS America Meeting (11th: 2001: Miami Beach, FL), ITS connecting the America: ITS 2001: conference proceedings.

21. Sullivan, E. C. (1997). "New Model for Predicting Incidents and Incident Delay." A*SCE* Journal of Transportation Engineering, Vol. 123, July/August, 267-275.

22. Taber, J. T., Grenney, W. J., and Senti, T. E. (1995), "A knowledge-base and simulation algorithm hybrid model for traffic congestion at intersections", Developments in artificial intelligence for civil and structural engineering, Civil- Comp Press, 1995, pp 145-149

23. Zou, N., Lin, P-W, and Chang, G-L (2003) "Development of An Integrated Network Simulator for a Real-Time Traffic Management: I-95/US-1 Traffic Simulator," Proceedings of the 83rd Transportation Research Board Annual Meeting, Washington D.C.