Decision Support Tools to Support the Operations of Traffic Management Centers (TMC)

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Disclaimer

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the State of Florida Department of Transportation.

Metric Conversion Chart

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
TEMPERATURE (exact degrees)				
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
ILLUMINATION				
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
FORCE and PRESSURE or STRESS				
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.

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16. Abstract

The goal of this project is to develop decision support tools to support traffic management operations based on collected intelligent transportation system (ITS) data. The project developments are in accordance with the needs of traffic management centers (TMCs) in Florida, as identified in this project. The project developments include new models to estimate travel time based on point detectors. These models were compared with existing travel time estimation methods including the one used in the SunGuide software. The results indicate that all of the tested methods perform at acceptable and comparable levels at low congestion levels. However, their performances vary with the increase in congestion levels. The comparison with other estimation methods shows that the developed models perform well in all cases.

The developments of this study include a method to estimate traffic diversion based on the traffic detector and incident data. In addition, this study developed a method to determine the time lag between incident occurrence and the time it is recorded in the SunGuide database. This study also developed methods to estimate freeway secondary crashes, potential incident impacts on mobility, and a new method to allow incidents to be classified into categories based on primary incident attributes and impacts.

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Executive Summary

The SunGuide TMC software is an Intelligent Transportation Systems (ITS) software that has been deployed by the Florida Department of Transportation (FDOT) districts throughout the state of Florida. The ITS data collected by the SunGuide software can be used to support both real-time and long-term strategic decision making processes at the Traffic Management Centers (TMCs). The goal of this project is to develop decision support tools to support traffic management operations based on the collected ITS data. The specific objectives of this project are:

- Determining the needs for the development of decision support tools for TMC applications
- Develop and test decision support tools based on the identified needs
- Document all results, products, and conclusions of this project

At the beginning of the project, a requirement analysis task was conducted to review the needs of FDOT TMCs for decision support tools based on interviews with the FDOT district ITS engineers, TMC operation managers, and Central Office ITS section staff. The project developments are in accordance with the needs of the FDOT TMCs identified in the requirement analysis task.

Travel Time Estimation

One of the important tasks identified in the requirement analysis was the need to investigate methods for travel time estimation based on point detector data under different conditions such as different congestion levels, incident conditions, detector errors, and various estimation method basic parameters.

A review of previous studies indicates that although speed-based methods similar to those used in the SunGuide software can produce acceptable results at lower levels of congestion, there are questions regarding their abilities to produce accurate and reliable estimates of travel times under recurrent and non-recurrent congested conditions. This study has developed two hybrid on-line travel time estimation models and two

corresponding off-line methods to estimate freeway travel times based on point detector measurements. Hybrid Model 1 combines the Mid-Point method (which is similar to the SunGuide method) with a traffic flow-based method. Hybrid Model 2 combines the Mid-Point method with the Minimum Speed method. The switching between the travel time estimation methods within each model is accomplished based on the congestion levels and queue status. In addition, during incident conditions with fast changing queue lengths, refinements are introduced to the developed models to account for the fast queue prorogation and recovery.

The travel time estimates obtained from existing speed-based methods, traffic flow-based method, and the developed models are tested by using both simulation and real-world travel time data as ground truth data. The results indicate that all of the tested methods perform at acceptable and comparable levels at low congestion levels. However, their performances vary with the increase in congestion levels. The comparison with other estimation methods shows that the developed hybrid models perform well in all cases. Further comparisons between the on-line and off-line travel time estimation results reveal that off-line methods perform significantly better only during fast changing congested conditions such as during incidents. The difference in performance between the on-line and off-line methods increases with the increase in congestion levels.

During low congestion levels, the Minimum Speed method and flow-based methods produce slightly less accurate results compared to other methods. However, the difference is not significant. For moderately recurrent congested conditions assessed using real-world travel time measurements, the minimum speed method and Hybrid Model 2 perform the best among the tested methods. The traffic flow method and Hybrid Model 1 also perform relatively well compared to other methods. Comparing the results from the off-line methods with those from the on-line methods indicates that the off-line estimation improves the travel time estimation slightly.

For fast changing conditions during incidents; simulation results indicate that the SunGuide method underestimates the travel time during the queue forming stage, and overestimate the travel time at the end of lane blockage. Similar trends can be found for other methods at varying degrees depending on the tested method and the degree of congestion. The flow-based methods, the Minimum Speed method, and the developed hybrid models perform better than other speed-based models. However, they also overestimate the travel times at the later stages of lane blockage due to the effect of the front recovery shockwave during incident clearance. This overestimation becomes higher with the increase in the queuing severity during incidents. The refinements introduced to account for queue propagation and recovery stages are proposed to deal with these estimation problems.

Based on the results of this study, it is recommended that the Minimum Speed Method and/or the Hybrid Model 2 developed in this research are considered for implementation and testing in SunGuide. This recommendation is based on these model performances and the ease of their implementations compared to traffic flow models. The refinements to account for queue growth and dissipation dynamics should be also considered.

SunGuide includes a limited real-time testing for detector errors. Additional real-time testing for erroneous detector data is presented in this document and is recommended for use in the SunGuide software. The impacts of major influential factors, such as data preprocessing procedures, detector errors, and travel time posting strategies, on the performance of travel time estimation, are investigated in this study. The sensitivity analysis results show that these factors do not have significant impacts on the estimation accuracy and reliability during uncongested conditions, however, for incident conditions, the travel time estimation performs better with the usage of a short rolling period for data smoothing, more accurate detector data, and frequent travel time updating.

The results of the investigation presented in this document indicates that the spatial imputation method used in the SunGuide software to account for missing data appears to perform as good as other investigated methods. When estimating travel time during incident conditions, the use of the exponential moving average produces more accurate and reliable results compared to the simple moving average method used in SunGuide, since the exponential moving average method can give more weights to the latest data in the smoothing and thus can account better for the fast changing dynamic conditions during incidents. When using the simple moving average method during incident conditions, shorter rolling time periods produce better results.

The results of the study also show that intrinsic errors due to measurement noise, systematic errors (e.g., due to inadequate calibration or device inaccuracy), and data missing due to incidental and/or structural failure can affect negatively the performance of travel time conditions during congested conditions but not uncongested conditions.

The results from this study indicates that for uncongested conditions, a longer travel time updating interval does not lead to worse estimation performance. For incident scenarios, the errors increase and the reliability decreases with the increase in travel time update interval. The errors also increase with the increase in the travel time link length under incident conditions. It appears that a posted travel time range of two-three minutes generally produces good results for uncongested conditions. However, if the travel time range is further reduced to one minute, the reliability of the estimated travel time is significantly impacted. For incident scenario, slightly larger travel time range may increase the reliability of travel time estimation, but the improvement is not significant.

Diversion Rate Estimation

A number of technologies are deployed for disseminating information to travelers. One of the most important parameters for assessing the impacts and benefits of these deployments is the diversion rates under different incident and traffic conditions. The estimation of the diversion rate is important to justify the deployments from a cost and benefit point of view. In addition, the estimation will support the assessment of the guidelines and procedures of information dissemination. Estimating the percentages of travelers likely to divert to alternative routes also allows better estimation of the impacts on the alternative routes and the optimization of signal timings on these routes during incident conditions. In this research, a method was developed to estimate traffic diversion based on the traffic detector and incident data. Regression models were developed for a case study to estimate the diversion rate as a function of potential influencing factors. The developed models indicate that daylight versus night condition, the level of traffic demands, queuing delay, and queue length are significant factors affecting the diversion rate.

Time Lag between Incident Occurrence and Recording

One of the important performance measures of incident management is incident detection. Incident detection time is defined as the time from the occurrence of the incident to the time when the first incident management agency is notified of the incident occurrence. However, this time cannot be estimated based on incident management data. This is because the first time that the incident appears in the TMC incident management database is when the TMC is notified, which is the time that the TMC operators become aware of the incident. There have been no good methods to estimate the time lag between incident occurrence and TMC recording of the incident. This time lag is referred to in this study as the incident recording time lag. This measure is important because the longer it takes for an agency to record the incidents in its database, the shorter the calculated incident duration will appear based on analyzing this database, which is obviously not correct. This study has developed a method to determine the incident recording time lag based on a combination of detailed traffic detector and incident management databases.

Estimation of Secondary Incidents

This study has also developed a method to estimate freeway secondary crashes and their contributing factors. The method identifies secondary crashes as those that occur upstream of an incident within the estimated queue length and queue dissipation time of the primary incident. Both descriptive statistics and logistic regression analyses are applied to identify potential factors that contribute to these crashes. The regression model developed indicates that the factors that have significant effects on the likelihood of secondary crash occurrence include primary incident type, primary incident lane blockage duration, time of day, and the corridor on which the incident occurs.

Estimation of Incident Impacts and Severity Levels

Effective incident management requires the identification of incident severity and its potential impacts on the transportation system and its users. For on-line applications, while incidents are active, this identification allows agencies to determine the required levels of response such as dynamic message sign messaging decisions, diversion plan activations, and allocation of response resources. For off-line applications, analyzing historical data to classify incidents by severity level allows for the better planning of incident management activities.

This study presents models and methods to estimate the potential incident impacts on mobility and safety in real-time. In addition, a new method is developed to allow incidents to be classified into categories based on primary incident attributes and impacts. These attributes and impacts include the number of lanes blocked, predicted incident duration, estimated queue length, average delay, and secondary incident probability.

A model developed in this study to estimate lane blockage duration shows that several factors affect this duration including the time of day that the incident occurs, incident verification and response times, environmental factors, incident type, incident response, activated incident management processes, and incident attributes.

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1. Introduction

1.1. Background

Traffic management center (TMC) operations are critical components of advanced traffic management systems. At TMC, critical decisions are made in both real-time and off-line to optimize the performance of the transportation systems. Intelligent transportation Systems (ITS) are generating a wealth of real-time and historical data that can be used in combination with traffic analysis, simulation modeling, data fusion/data mining, and optimization to support the decisions made by TMC operators and managers

In Florida, there are currently ten traffic management centers that are managed by the Florida Department of Transportation (FDOT). The FDOT traffic management centers in Florida are responsible for incident management activities, controlling various Intelligent Transportation Systems (ITS) devices, and the exchange of traffic information with other transportation agencies. The existing FDOT TMCs are:

- FDOT District 1 TMC in Fort Myers
- FDOT District 2 TMC in Jacksonville
- FDOT District 4 TMCs in Fort Lauderdale and West Palm Beach
- FDOT District 5 TMC in Orlando
- FDOT District 6 TMC in Miami
- FDOT District 7 TMC in Tampa
- Florida Turnpike Enterprise TMCs at Turkey Lake and Pampano Beach Turnpike plazas

In addition, it is expected that by early 2011, FDOT District 3 will start operating a TMC located in Pensacola, Florida.

A large proportion of the urban limited access corridors in Florida are currently equipped with traffic detectors deployed as part of ITS. Data from these traffic detectors are currently being used and archived by the FDOT TMCs. In addition, detailed incident management data are being collected and archived as well. Data from these sources can be used to support both real-time and long-term strategic decision making processes at the TMCs throughout the state. The analysis of real-time and historical data using advanced computational techniques will provide the FDOT engineers and TMC operators with the information necessary to make better operation and maintenance decisions and to disseminate more accurate and reliable information to travelers.

1.2. Project Objectives

The goal of this project is to develop decision support tools to support traffic management operations based on the collected ITS data. The specific objectives of this project are:

- Determining the needs for the development of decision support tools for TMC applications
- Develop and test decision support tools based on the identified needs
- Document all results, products, and conclusions of this project

1.3. ITS Data

The SunGuide TMC software is a set of ITS software that allows for the control of roadway devices as well as the exchange of information across transportation agencies. The software represents a common software base that has been deployed by FDOT districts throughout the state of Florida.

The SunGuide system maintains operational data in several different places for use in report generation. Aggregated operational data are stored in Oracle database files, while the raw data are stored in comma separated (CSV format). Below is a description of the two archived SunGuide files that were used for the purpose of this study:

- Incident Archives: For each SunGuide incident record, the stored information includes incident timestamps (detection, notification, arrivals, and departures), incident ID, responding agencies, event details, chronicle of the event, and environmental information. The detection timestamp is the time when an incident is reported to the TMC and inputted in the SunGuide system. The notification timestamps are recorded per responding agency and refer to the time when such responding agencies are notified. The arrival and departure timestamps are also recorded per responding agency and refer to the time when responding agencies arrive and depart from the incident site.

- Detector Data Archives: The traffic condition data are stored in Traffic Sensor System (TSS) text flat files, with each file including data for all the detection stations for a 24-hour day. The TSS file contains one record for each lane of each detection station for every 20-second polling interval. Each TSS data record includes the following information: timestamp, detection station name, lane number, speed, occupancy, and raw count.

In addition, the Statewide Transportation Engineering Warehouse for Archived Regional Data (STEWARD) has been developed as a proof of concept prototype for the collection and use of ITS data in Florida (Courage and Lee, 2008). The current effort has concentrated on archiving point traffic detector data and travel time estimates. The STEWARD database contains summaries of traffic volumes, speeds, and occupancies collected from point traffic detectors. This database was also used in this study, as described when discussing the various developments of this project.

1.4. References

Courage, K.G. and S. Lee. Development of a Central Data Warehouse for Statewide ITS and Transportation Data in Florida: Phase II Proof of Concept. A Report Developed for the Florida Department of Transportation by the University of Florida, Tallahassee, FL, 2008.

2. Requirements Analysis

This chapter summarizes the activities and results of a task conducted at the beginning of this project to review the needs of TMCs for decision support tools based on interviews with the FDOT district ITS engineers, TMC operation managers, and Central Office ITS section staff. The interviews were conducted face-to-face in some cases and using internet-based conference calls with shared Microsoft Power Point presentations in others. The results from the interviews were analyzed to identify the areas of focus in the research. The following sections discuss theses interviews, the associated results, the analysis of the results, and recommendations of focus areas for this study.

2.1. Initial Lists of Focus Areas

Initially, the research team identified potential areas for the focus of the research in this project. This identification was based on an assessment of the TMC operation processes and the SunGuide™ software modules. The following is a list of these initial focus areas:

- Incident detection
- Situation assessment
- Accurate and reliable travel time estimation
- Detector malfunction detection and correction
- Optimization of ITS Resources
- Device maintenance
- Diversion support
- Assessment of the effectiveness of ITS devices

Within each of the above areas, initial research topics were identified. These areas and topics formed starting points of discussions in meetings later conducted with the FDOT stakeholders to identify the research needs related to the objectives of the study. Based on the results of the meetings, the initial areas and topics were revised, expanded, and prioritized as discussed later in this chapter.

2.2. Interview Results

This section presents a summary of the results of the interviews conducted as part of this project.

2.2.1. FDOT District 1

A web-based meeting was conducted with FDOT District 1 ITS staff to discuss the focus areas that are considered by FDOT District 1 as high priority areas. At the time of the interview, FDOT District 1 had just started its TMC operations. Below is a summary of the discussion with FDOT District 1:

- The areas of interest from the most important to the least important are accurate and reliable travel time, incident detection, optimization of road ranger service patrol operations, diversion plan development, and device maintenance.
- Travel time estimation is a high priority and many of the issues discussed regarding this focus area were considered to be important by FDOT District 1.
- Topics related to situation analysis are important including the following:
    - Better definition of incident severity levels is important since this could be used for better identification of response plans.
    - Incident detection including a method to automate the selection of the parameters for incident detection in the SunGuide software.
- Optimization of Road Ranger service patrol is important.
- With regard to device maintenance, device lives need to be tracked. However, FDOT District 1 did not have maintenance data at the time of the interview and must depend on data from other districts to derive this information.
- Diversion plan is an important issue to District 1. During the lane closure, the Florida Highway Patrol (FHP) may need to know when and where to divert people. This could also be used as a basis to optimize signal timing plans during diversion.

2.2.2. FDOT District 2

A web-based meeting was conducted with FDOT District 2 ITS staff. The following is a summary of the results of the discussion.

- The most important focus area for District 2 is device maintenance, followed by incident detection and situation assessment, followed by accurate and reliable travel time estimation and optimization of ITS resources.
- Travel time estimation is fairly accurate in Jacksonville. Investigating the accuracy of travel time estimation may be important to other districts that have more complex networks, but not for FDOT District 2.
- Predicting the impacts of weather on travel time is important. FDOT District 2 tracks the weather and makes decisions regarding displaying dynamic message sign (DMS) messages based on this.
- Important topics in the area of incident detection and effectiveness of ITS devices include:
    - Comparison between the detector-based incident detection algorithms and other detection sources such as phone calls, CCTV cameras, etc.
    - Improvements to incident detection algorithms.
    - The benefits of CCTV cameras.
- Device maintenance is ranked the highest focus area by District 2. This is because optimizing and analyzing device maintenance is considered to be critical especially for future funding arrangements.
- For Situation assessment:
    - Displaying queue lengths is useful and should be compared with time of day "historical" data to generate responses. FDOT District 2 has a three-phase response plan, depending on the travel time and queue length.
- Optimization of Road Ranger:
    - The optimization of Road Ranger could be helpful and should depend on time of day.
- Other potential areas of research mentioned by FDOT District 2 include:
    - Incorporation of partner agency data (for example, data from FHP, fire and rescue, etc.) into SunGuide operations.
    - Performance measurements for ITS.

2.2.3. FDOT District 4

Meetings were held with the FDOT District 4 ITS Program Manager and the TMC Operation Manager. The following is a summary of the issues identified as high priority issues based on the interview:

- Travel time estimation
    - The most important issue identified by FDOT District 4 is the reliability of travel time estimation under different conditions; travel time may be accurate on average, but how reliable are the estimates under different conditions?
    - What is the increase in estimation error as the segment length increases under different congestion levels?
    - There may be a need to use a factor to increase the estimated travel time during the peak period based on time of day, since there may be an underestimation of travel time in the peak periods.
    - At the time of the interview, there was a rounding error effect in the SunGuide software (60 mph yields much lower travel time than 59 mph). This needed to be corrected.
    - There is a need to investigate the effect of the averaging of detector data from different lanes on travel time estimation.
    - Also, there is a need to estimate the effect of the averaging of travel time based on measurements from previous time steps under different conditions.
- Incident detection and effectiveness of ITS devices
    - FDOT District 4 does not rely on traffic detectors in their incident detection and thus it does not consider improving incident detection based on detectors as a high priority.
- Effectiveness of ITS devices
    - There is an interest in knowing how people are actually using both the incident information and the travel time information under incident and no-incident conditions.

    - There is an interest in knowing the effect of different ITS components (CCTV cameras, VisioPad, service patrol, etc.) on the system performance to prioritize and justify investments in ITS.
- Situation analysis
    - There is a need to provide alerts of erroneous and missing data due to detector malfunctions and configuration problems. SunGuide configures field devices separate from the field so the detectors may not be synchronized with the SunGuide software. This may have significant effects.
    - There is a need for a better visualization of real-time and historical detector data such as queue length. There is a need to use different speed thresholds to indicate congestion for different times of the day.
    - Reliability of the transportation system in real-time could also be an interesting area of research.
    - A real-time gauge of system performance is an interesting area as well.

2.2.4. FDOT District 6

A meeting was held with FDOT District 6 ITS staff. The following is a summary of the results of the discussion:

- FDOT District 6 identified incident detection and travel time estimation as the highest priority topics.
- Travel time estimation: There is a need for research to improve the methods and parameters of travel time estimation.
- Incident detection: Some of the areas of interest related to incident detection are
    - Comparing the effectiveness of different detection algorithms and optimizing the parameters of the algorithms,
    - Testing to determine if the detection can be improved by adding more detectors, and
    - Allowing the incident detection threshold to vary by season and/or to be different in weekdays vs. weekends (In the Sunguide software, the incident detection threshold is only a function of time of day, occupancy, and speed).

- Effectiveness of ITS devices
  - There is an interest in comparing incident detection based on the different detection sources such as VisioPad, detectors, and other sources.
  - Optimization of service patrol resources is an area in which research is needed.
- Situation Analysis
  - In the current Sunguide software, when a threshold is exceeded, the map color turns to red from green. However, the map does not show the speed, occupancy, and queue length. More details and better graphics are needed to allow the operator to make better decisions.
  - A display of the expected-versus-current delay and queue length is of interest.
  - A better definition of incident severity levels may be needed.
  - The identification and correcting of detector malfunctions is important.
- Route diversion
  - FDOT District 6 is interested in route diversion, especially the diversion with signal optimization on the alternative arterials, but to a lesser extent than travel time estimation, incident detection, and situation analysis. It is suggested that this can be done using simulation as part of a separate effort.
- Maintenance of devices: Topics of interest in this area include comparison of the number of days required to maintain the different types of devices.

2.2.5. FDOT District 7

A web-based meeting was conducted with FDOT District 7 ITS Program Manager and the ITS Operations Manager in District 7. The following is a summary of the discussion:

- FDOT District 7 believes that the travel time estimation by the SunGuide software is currently accurate in the Tampa Bay area and there is no need for further investigation.
- FDOT District 7 believes that the only way to improve the incident detection and response processes is to increase the number of cameras.
- Better display of queue length on the map could be useful.
- Other areas discussed are not important to FDOT District 7.

2.2.6. Florida Turnpike Enterprise

A meeting was conducted with the Traffic Operations Engineer of the Florida Turnpike Enterprise. Below is a summary of the results of the discussion:

- The focus areas of highest priority are travel time estimation and service patrol optimization.
- Some of the issues related to travel time estimation discussed in this meeting and considered to be important are listed below.
  - The accuracy of travel time during incidents: This could be challenging since the number of blocked lanes are dynamically changing during incidents.
  - Estimation of the effect of lane closures due to construction on travel time estimation: This could increase the accuracy of travel time during these conditions.
  - The effect of weather on travel time.
  - Comparison of probe detection (Automatic Vehicle Identification (AVI)-based detection) and point detection in estimating travel time.
  - The impact of spacing of detectors and spacing of AVI on travel time estimation.
  - Investigating the provision of the upper end of the range versus provision of the range to travelers. The current implementation of the range in SunGuide is based on the mean value of travel time with the range increasing as the mean of travel time increases.
  - Determining if the difference between lanes should be considered when calculating the range.
- Service patrol optimization: This is of particular importance considering budgetary cuts.
- Following travel time estimation and service patrol optimization in importance are incident detection and situation recognition. Topics of interest in incident detection and situation recognition include:
  - Comparison of different detection techniques (CCTV, VisioPad, FHP notifications, service patrol detections, etc.). FDOT District 4 showed that certain

percentages of incidents are first detected by VisioPad. The importance of this must be quantified.

  - Revision of incident severity levels. Current levels do not consider whether the closed facility is a ramp or a mainline. These levels do not consider the expected duration of blockage and time of day. It may be possible to relate DMS messages to new, improved severity categories.

2.2.7. FDOT Central Office

An interview was conducted with the FDOT Central Office ITS staff in Tallahassee, FL. Below is a summary of the results of the interview:

- Travel time estimation and many of the topics discussed in the interview regarding travel time estimation are important focus areas of this project, including those in the following list. At this stage, short-term future prediction of travel time is not as important as accurate and reliable estimation of the instantaneous travel time. Once accurate and reliable estimation is achieved, then prediction can be investigated in a future effort, if needed. Important research topics include:
  - The effect of detector malfunctions and data errors and the threshold of detector failures beyond which not to display travel time;
  - Whether a single value or a range of travel time should be disseminated to motorists, and the method of deciding the range to display;
  - The method of setting the minimum and maximum values required as inputs to SunGuide;
  - Frequency of time message generation;
  - Estimating the speed during very low volume (for free-flow speed) and for congested traffic conditions; and
  - The effect of detector locations and frequency on travel time estimation.
- Incident detection:
  - There is no need for an in-depth comparison of different incident detection algorithms since the incremental benefits may be small and the traffic detectors may not be the main source of detection, given that many other sources exist.

    - Comparing the performance of VisioPad with detector-based incident detection algorithms is of interest.
- Situation analysis:
    - Showing queue length and other measures on the map; and
    - Better definition of the level of incident severity.
- Route diversion: This area should not be a high priority for this project, particularly considering the difficulty in conducting route diversion in real-time.

2.3. Ranking of Focus Areas

Based on the results presented in the previous section, it was possible to rank the research issues by priority. This ranking is presented in Table 2-1.

TABLE 2-1 Ranking of Focus Area based on Project Stakeholder Inputs

Area	**Rank**	**Justification**
Travel time estimation accuracy and reliability under different influencing factors	1	This area has been identified as having the highest priority by FDOT Districts 1, 4, 6, Turnpike Enterprise, and the Central Office.
Detection of detector malfunctions, configuration problems, and data errors	1	This is a basic area that is important to all decision support tools based on detector data, and is accorded high importance by the stakeholders.
Situation recognition and performance measurement and prediction	2	Better real-time indicators and visualization of network performance based on collected data and better incident severity categorization have been ranked as high priorities by all stakeholders,
Effectiveness of incident notification methods	3	Most stakeholders indicated that comparing CCTV cameras, detectors, FHP calls, VisioPad, service patrols, and other detection devices would be useful.
Optimization of service patrol operations	4	Most districts considered this as a high priority, particularly given the recent cut in the funding.
Investigation of the use of disseminated information by travelers	5	Comparing the benefits of incident and travel time information dissemination under different conditions.
Device maintenance	6	This area was ranked highest by District 2 and was of interest to some other districts. Some districts have said that they are already developing their own tools for this purpose. Others said that it will take some time to collect enough data to support the development and use of such tools.
Algorithms and parameters of incident detection based on traffic detector data	7	This area was ranked high by Districts 1, 2, and 6, and low by Districts 4 and the Central Office.
Rout diversion	8	This area was important area of research to Districts 1 and 6.

2.4. Conclusions

Based on the discussion of this chapter, the following areas of research are recommended for the "Decision Support Tools to Support the Operations of Traffic Management Centers (TMC)" project:

1. Accuracy and reliability of travel time estimation including the following issues:
    a. Effects of incident conditions on travel time estimation
    b. Investigation of the impact of the selected range of travel time on travel time reliability
    c. Investigation of the impacts of the frequency of generating travel time messages
    d. Effect of the travel time link length
    e. Effect of temporal averaging and smoothing method and interval
2. Detection of detector problems and data errors and the impacts of data filling, cleaning, and correction methods on travel time estimation
3. Situation recognition and impact analysis including:
    a. Estimation of incident impacts
    b. Estimation of incident duration based on incident attributes
    c. Estimation the potential for secondary incidents based on incident attributes
    d. Estimation of congestion level
    e. Estimation of queue length for on-line and off-line applications
    f. Better estimation of the incident detection time by identifying the time lag between the occurrence of the incident and the time it is entered in the database
    g. Estimation of diversion rates

The followings are areas of research that are recommended as future research efforts:

a) Travel time prediction for a short-term in the future based on current travel time data.
b) Performance measurements, prediction and visualization of the transportation systems
c) Tools for analysis and optimization of ITS device maintenance.

d) Methods to optimize route diversion and alternative route operations including optimizing signal timing in conjunction with route diversion.
e) Tools to maximize the use of partner agency data such as FHP data, fire rescue, county, transit, and other agencies.
f) Effectiveness of incident notification/detection methods
g) Comparison of the effectiveness of various incident detection sources.
h) Tools to optimize service patrol operations.

3. Travel Time Estimation

3.1. Introduction

Accurate and reliable estimation of freeway travel time based on point detector measurements is needed to support advanced traveler information systems (ATIS) and advanced traffic management systems (ATMS). Transportation agencies (including Florida districts) are increasingly posting travel time information on their dynamic message signs (DMS), traveler information telephone services (511), web sites, and other ATIS devices. Transportation agencies also use this information to support better traffic management.

Existing travel time estimation methods based on point traffic detectors can generally be classified into speed-based methods, traffic flow theory-based methods, and statistics-based methods. The speed-based methods (also referred to as the extrapolation methods or trajectory-based methods) construct the trajectory of speed along a roadway based on point measurements of speed by traffic detectors and use this information to estimate the travel times. Different assumptions regarding the speed trajectory lead to different speed-based methods. Examples of these methods include the Point-to-Point method, Mid-Point method, Average Speed method, Minimum Speed method, the Minnesota Algorithm (Kothuri et al. 2007), Piece-wise Linear Speed Based Model (Van Lint 2004), Piece-wise Constant Acceleration Based Model (Shen 2008), and Truncated Quadratic Speed Trajectory method (Sun et al. 2008). A brief description of these existing speed-based estimation methods can be found in Appendix A.

On the other hand, the traffic flow theory-based methods use volume and/or occupancy measurements as input variables to estimate travel time instead of using speed measurements. The cumulative curve method (also referred as traffic dynamic approach) and the shock wave analysis method are two examples of previously proposed traffic flow theory approaches. The cumulative curve methods are based on estimating the time spent on a segment by comparing the cumulative traffic entering and exiting the segment at frequent time intervals. The cumulative curve methods were first developed by Nam and Drew (1996, 1999) for normal and congested conditions. Various improvements were made to these models later (Vanajakshi 2004, Zhang 2006). Vanajakshi (2009) further proved that the two cumulative curve equations previously developed for normal and congested conditions can be unified to be one equation. The shock wave methods provide estimates of shock wave speed and thus allow estimating the queue lengths during lane closure and incident conditions. When applying shockwave methods to travel time estimation, the travel time of the vehicles within the queue depends on the queue discharge rate at the bottleneck location, while the travel time for the vehicles outside of the queue is estimated based on the measured flow and occupancy (Dhulipala 2002).

The statistics-based methods attempt to relate the freeway travel time with traffic flow parameters such as the traffic counts at upstream and downstream detector locations or the accumulated flows within the segments. The methods range from simple regression analyses (Petty et al. 1998) and cross correlation analyses, to more complicated probabilistic regression models (Petty et al. 1998; Zhang et al. 1999; Guo and Jin 2006). The probabilistic regression model proposed by Petty et al. (1998) considers the average travel time along the link as a random variable, whose probability density function is assumed to be the same as the arrivals at the upstream detector location. A regression analysis over the upstream and downstream flow measures during a given estimation window is used to determine this probability density function. Later extensions of this method include using the B-splines, exponential moving (Zhang et al. 1999), and correlation analysis (Guo and Jin 2006) to improve the estimation of the probability density function.

Currently, most traffic management centers use simple speed-based approaches for travel time estimation. For example, the TMCs in Portland, Oregon use the Mid-Point method for travel time estimation, while the TMCs in San Antonio, Texas, apply the Minimum Speed method (Kothuri et al. 2007). SunGuide used in Florida allows the users to specify the limits of the travel time link associated with each detection station. Thus, the user can select the links to correspond to the Point-to-Point, Mid-Point methods, or somewhere in between these methods, if they choose to. Although the speed-based methods may produce acceptable results at lower levels of congestion, there have been questions regarding their abilities to produce accurate and reliable estimates of travel times under recurrent and non-recurrent congested conditions (Li et al. 2006; Kury 2008; Kothuri et al. 2008). This is because many detection technologies are not able to measure speed accurately under congested traffic conditions. In addition, the speed measurements made at point locations may not reflect the speeds along the segment that they are supposed to represent. On the other hand, some but not all traffic flow theory-based methods rely on assumed average effective vehicle lengths for density calculations and/or assumed constant queue discharge rates at the bottleneck locations, which reduce the accuracy of the estimation (Dhulipala 2002). In addition, using traffic volumes and occupancies to estimate speeds may not be appropriate for uncongested conditions since the speed is not sensitive to traffic demand under these conditions (Vanajakshi 2004). Statistics-based methods such as the probabilistic regression are proven to be robust during congested conditions (Guo 2006). However, such methods usually use a data sampling interval of 1-second, which is not commonly available in practice, where traffic detector data are commonly polled at 20-second or 30-second frequency in current traffic management applications.

Since different methods perform differently under different traffic conditions, instead of using one simple method, researchers are exploring the development of hybrid approaches to estimate freeway travel time. Vanajakshi (2004, 2009) applied an extrapolation method for very low volume conditions and a traffic flow approach for the remaining situations. The cut-off threshold used to switch between the two methods is 500 veh/hr/lane, which is arbitrarily selected and seems to be a very low value. Further, using the volume as the threshold may not be appropriate as one given flow rate may correspond to two different conditions, one is uncongested conditions and another one is congested conditions. In addition, this study only investigated the travel time along a very short distance (about 1.9 miles).

Dhulipala (2002) used the shock wave method to estimate travel times under lane-closure and incident conditions, and a Mid-Point method based on flow and density instead of speed for non-incident and non-closure conditions. When using the Mid-Point method, the estimates were increased by 20% when the density at the downstream detector was greater than 60 veh/mile/lane and the density at the upstream detector was less than 60 veh/mile/lane, with the purpose of capturing the existence of a compression wave. Similarly, a factor of 40% was applied to the results of the Mid-Point method when both the densities at the upstream and downstream detectors were greater than 60 veh/mile/lane. These two factors were approximated from the relationship between speed and density measurements. In another study, Xia and Chen (2007) first estimated travel time based on traffic parameters such as flow rate and occupancy measurements, and then adjusted the segment travel time using the shock wave method for incidents with significant impacts. However, this method requires incident starting time and estimates of the initial queue length based on detector measurements.

The above literature review indicates that the hybrid travel time estimation approach has been proposed as an effective method to estimate travel time under different congestion level but has not been adequately explored and compared with existing methods. This project tasks includes developing and assessing hybrid models to estimate the freeway travel time during non-congested conditions, recurrent congestion, and incident conditions. The investigated hybrid models will include implementing combinations of speed-based methods and traffic flow theory-based methods, and switching between the implemented methods based on the congestion levels. The performances of the developed models in terms of accuracy as well as reliability are quantified and compared in this study.

3.2. Methodology

This section includes a detailed discussion of the freeway travel time estimation methodologies developed and investigated in this study. This includes data acquisition and preprocessing, traffic condition identification, and travel time estimation models.

3.2.1. Data Acquisition and Preprocessing

The traffic data used in this study is collected using point detectors (true-presence microwave detectors), which measure the values of speed, traffic count, and occupancy at small time intervals (e.g., every 20 seconds). The detector data is archived by the freeway traffic management software used at the traffic management centers of FDOT in TSS files that contain one record for each lane of each detection station for every 20-second polling interval, as explained in Chapter 1 of this report.

The requirement analysis, presented in Chapter 2, indicates that the identification and consideration of erroneous detector data is an important issue that needs to be addressed. Detector data of good quality is a prerequisite for accurate and reliable travel time estimation. However, current detector data usually include erroneous or missing measurements. In addition, there is a need for aggregating and smoothing the measurements in an optimal manner for different applications. Thus, data preprocessing procedures are required. These procedures include data filtering, temporal and spatial data aggregation, and data imputation as described below.

Data Filtering

Limited filtering is implemented to identify problems with real-time traffic detector data in SunGuide. In this study, the use of additional filtering is investigated. A rule-based test is applied first to identify erroneous detector data. The rules are set based on an examination of the types of errors commonly found in the detector data archived by the SunGuide software. The rule-based test includes the following steps (the detailed tests are presented in Appendix A):

- Identify duplicate data records such as the same records repeated more than once; two records with the same timestamp and lane identification (ID) but with different measurement (speed, volume count, and occupancy values); or data with the same lane ID and same measurements but with a polling interval less than 20 seconds.
- A univariate test of data measurements aggregated at the 20-sec aggregation level to check whether the values of individual traffic parameters exceed predefined minimum or maximum thresholds.
- A multivariate test of data measurements aggregated at the 20-sec aggregation level to check for unreasonable combinations of traffic parameter values such as a combination of zero speed, zero occupancy, and non-zero volume values.
- A temporal variability check to test for constant values of speed, volume, and occupancy for a long period of time, including all zeros.
- Multivariate tests for the average effective vehicle length and maximum density at the used aggregation level in the estimation of travel time. Aggregation at the used level is important for this test since testing at the 20-sec level may not guarantee that the test results are valid at the aggregated level.

Data Smoothing

The filtered 20-sec lane-by-lane detector data needs to be smoothed to reduce the impacts of noise in the detection data. Two smoothing methods are tested in this study: the simple moving average method used in SunGuide and the exponential moving average method. The simple moving average method is the average of previous *m* data points, where *m* is specified by the rolling period. The mathematical expression for the simple moving average method is:

$$Y_t = \frac{1}{m}\sum_{i=1}^{m} X_i \tag{3-1}$$

where X_i represents the raw ith measurement while Y_t is the smoothed traffic parameter at the t timestamp.

The second type of smoothing, the exponential moving average method, is described in Equation 3-2.

$$Y_t = \alpha X_t + (1-\alpha)Y_{t-1} \tag{3-2}$$

The symbol α in this equation refers to a smoothing factor selected by the user. Since detectors may have incidental or structural failures, the time interval between two acceptable neighboring records may not be consistent, and therefore a time-dependent smoothing factor is used instead of a constant value. The expression for α is shown in Equation 3-3 below:

$$\alpha = 1 - e^{-\Delta t/\tau} \tag{3-3}$$

where Δt is the time interval between two consecutive records. τ is a time constant, estimated based on the commonly used value of 0.4 for α (Shen 2008) for a time interval of 20 seconds between detector data measurements. Once the data is smoothed as described above, the lane data is further aggregated to the station level for use in travel time estimation.

Data Imputation

In the SunGuide software, the measured lane-based speed data is smoothed by a simple moving average method and then capped by the speed limit to avoid reporting short travel time that may encourage speeding. The lane-based data is further aggregated to the station-level and used for travel time estimation. In cases of detector failures (when a speed measurement is not reported by the detection system, the missing speed data is replaced by neighboring data (Dellenback and Heller 2006). This method first attempts to use a neighboring lane measurement and if this is not available it uses a neighboring station measurement.

In this study, additional spatial and temporal data imputation procedures are investigated to substitute for the missing or erroneous data identified in the data filtering step. The spatial imputation employs the neighboring detector information to impute the missing values while the temporal imputation uses the historical information of the same detector to replace the missing values. In this study, the spatial data imputation procedure is conducted at two levels: within the same detector station and between the stations. For the same detector station, if only part of the lanes have missing or erroneous speed measurements, the missing values are filled with the average of the speeds measured using detectors on adjacent lanes with available speed measurements. When the whole station data is missing, between stations imputation approach is used. Initially, three types of methods for between-station imputations were considered in this study: simple average, linear interpolation, and factor method.

The simple average uses the average of measurements from neighboring stations to estimate the missing values, as shown in Equation 3-4.

$$Y_{2,t} = \frac{1}{2}(Y_{1,t} + Y_{3,t}) \tag{3-4}$$

where Y can be speed, volume count, or occupancy. $Y_{2,t}$ is the estimated value for missing data at timestamp t. $Y_{1,t}$ and $Y_{3,t}$ are the measurements at neighboring stations, as shown in Figure 3-1.

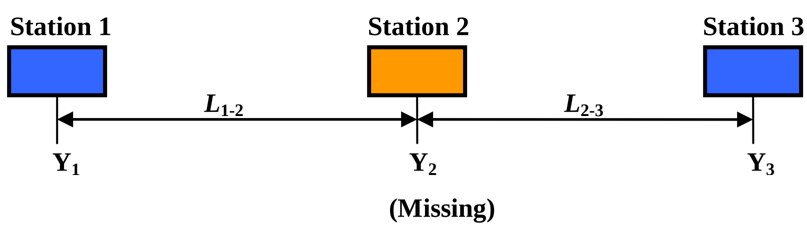


FIGURE 3-1 Sketch Diagram for Spatial Imputation

The linear interpolation method assumes linear spatial variation of traffic parameters. Thus, the missing data can be estimated as:

$$Y_{2,t} = \frac{L_{2-3}}{L_{1-2} + L_{2-3}} Y_{1,t} + \frac{L_{1-2}}{L_{1-2} + L_{2-3}} Y_{3,t} \tag{3-5}$$

where L denotes the distance between neighboring stations. For the factor method, the factor is defined as the ratio of current station traffic data to the upstream or downstream values, as described below:

$$F_{i,j,t} = \frac{1}{p}\sum_{p}\frac{Y_{i,t}}{Y_{j,t}} \tag{3-6}$$

where $F_{i,j,t}$ represents a factor between station *i* data and its neighboring station *j* at time of day *t*. The station *j* can be either the upstream station or downstream station. *p* is the total number of days available. The missing value is then estimated as:

$$Y_{2,t} = F_{2,1,t}Y_{1,t} + F_{2,3,t}Y_{3,t} \tag{3-7}$$

In this study, the exponential moving average method is applied for temporal imputation, as the future detector data are not available for on-line applications. The missing value is replaced by the forecasted value based on the exponential moving average. The corresponding expression is as follows:

$$Y_{2,t} = f_{2,t} = \alpha Y_{2,t-1} + (1-\alpha) f_{2,t-1} \tag{3-8}$$

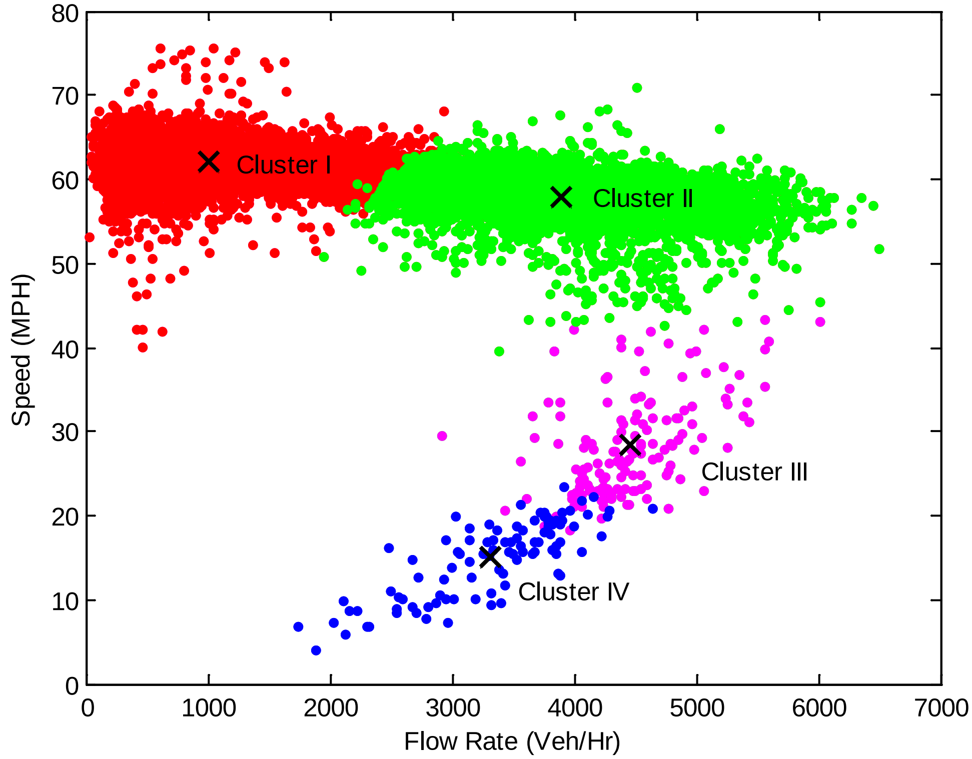
where *f* represents the forecasted values. Note that the formulation in Equation 3-8 is similar to that in Equation 3-2. However, the values in the previous time period are used to impute the missing data at the current time period. Based on previous studies (Van Lint 2005; Shen 2008), the value of the smoothing factor α is set to 0.4.

3.2.2. Congestion Level Identification

As mentioned earlier, the hybrid approaches investigated in this study to estimate travel time uses combinations of methods and switch between these methods depending on the congestion levels. A key point for the success of this approach is to identify the roadway conditions and determine the time at which traffic congestion occurs. In addition, in the case of traffic congestion that involves queuing, the methodology requires the determination of whether a traffic queue is forming or dissipating. In addition for use in travel time analysis, the identification of congestion level is an important consideration in situation analysis and performance measurements.

Previous studies used predefined speed thresholds (for example, 35 mph or 50 mph) or predefined occupancy thresholds to identify the congestion (Chan 2003; Ban and Benouar 2007; Yeon and Ko 2007; Zhang and Levinson 2004). Kaneko et al. (1995) recommended using all three traffic parameters: speed, volume, and occupancy to identify traffic status. In this study, the k-means clustering algorithm is used to classify the traffic states at each detection station to different clusters based on historical measurements of all three traffic parameters. Note that in the clustering analysis, the measurements are normalized using the z-score method to account for the different scales in the three traffic parameters, and the Euclidean Distance is used to quantify the dissimilarity between two data points. Based on the literature review, the number of clusters is selected to be four in this study. These four clusters are associated with different congestion levels in the fundamental traffic flow theory diagram. When applying the proposed method to estimate travel times in real-time, traffic measures at each detection station are associated with one of the predetermined clusters (congestion levels) for the detection station based on its distances from each cluster centroid, as reflected by the Euclidean Distance.

Figure 3-2 presents an example of the clustering results for a detector station, DS-1507E, located on SR 826 eastbound in Miami-Dade County, Florida, based on the traffic detector data from December 1, 2008 to December 31, 2008. The four cross symbols in these figures denotes the locations of the cluster centroids. As shown in Figure 3-2, the traffic states are separated into four clusters. Cluster I corresponds to close to free-flow conditions and the average speed is almost constant at the free flow speed regardless of the demand. Traffic cluster II is still uncongested but with a reduced speed. Cluster III is a more congested region, where the speed drops but to a lesser degree than the points in cluster IV. Cluster IV corresponds to extremely congested conditions, with low speed and low constrained flows. It was decided to use four clusters instead of just two corresponding to the congested and uncongested regions to allow more flexibility in combining or separating any two of the clusters based on the results of the analysis.



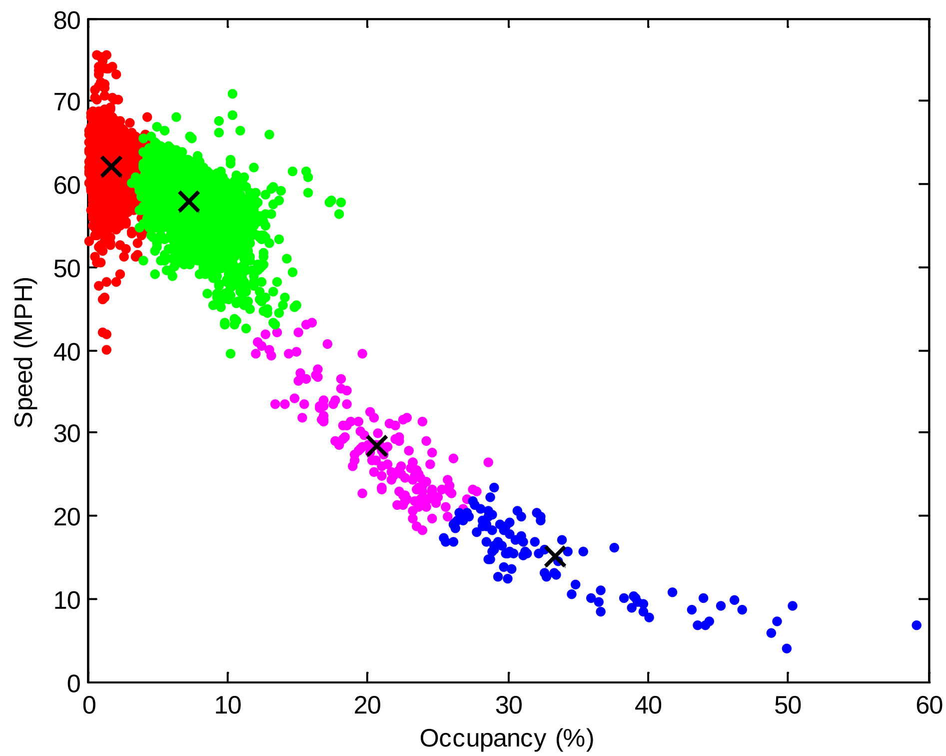


FIGURE 3-2 Clustering Results for a Detection Station on SR 826

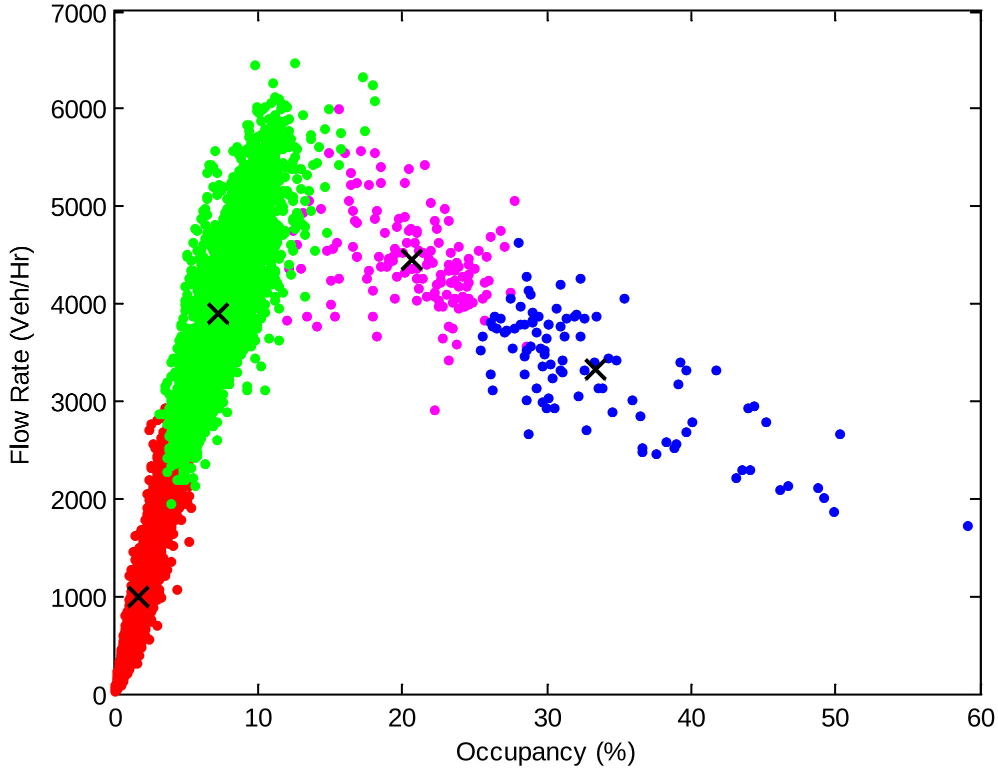


FIGURE 3-2 Clustering Results for Detection Station SR 826 (Con't)

3.2.3. Queue Length Estimation

This study requires the estimation of queue length when using the travel time estimation method that is based on traffic flow theory. In addition, as mentioned in Chapter 2 of this study, the queue length estimation is an important measure for situation recognition and performance analysis. This section discusses how the queue length is estimated in this study based on detector data.

Based on the identified traffic congestion states at the upstream and downstream detector stations (see Section 3.2.2), each roadway link can be identified as one of four states: a head of a queue, a tail of a queue, in queue, or outside a queue. For an identified head of a queue link, the traffic state at the upstream station is determined to be congested, that is, in cluster III or IV, and the traffic states at the first and second downstream stations are in cluster I or II. The consideration of the second downstream station in addition to the first is to avoid a situation where a temporary traffic state change in the first downstream station can result in a sudden change in the calculated queue length value. On the other hand, if both the two upstream stations are uncongested, that is, in the region of cluster I or II, and the downstream station is in the cluster III or IV, the link is categorized as a tail of a queue. The links between a head of a queue link and a tail of a queue link are identified as in-queue links, and the remaining links are identified as outside of queue links.

Once the head and the tail of a given queue are identified, the queue length can be estimated. In addition, as another important parameter to the methodology, the queue status (growing, dissipating, or stationary), can be determined by comparing the current locations of the head and tail of the queue with those at previous timestamps. Figure 3-3 presents one example of queue identification for the SR 826 limited access facility in the eastbound direction. As shown in this figure, the queue starts from the link located between station DS-1533E and DS-1535E at time 7:08 A.M. and extends to the first upstream link due to an incident at DS-1533E. The queue length starts to decrease at time 8:16 A.M. and completely dissipates at 8:48 A.M.

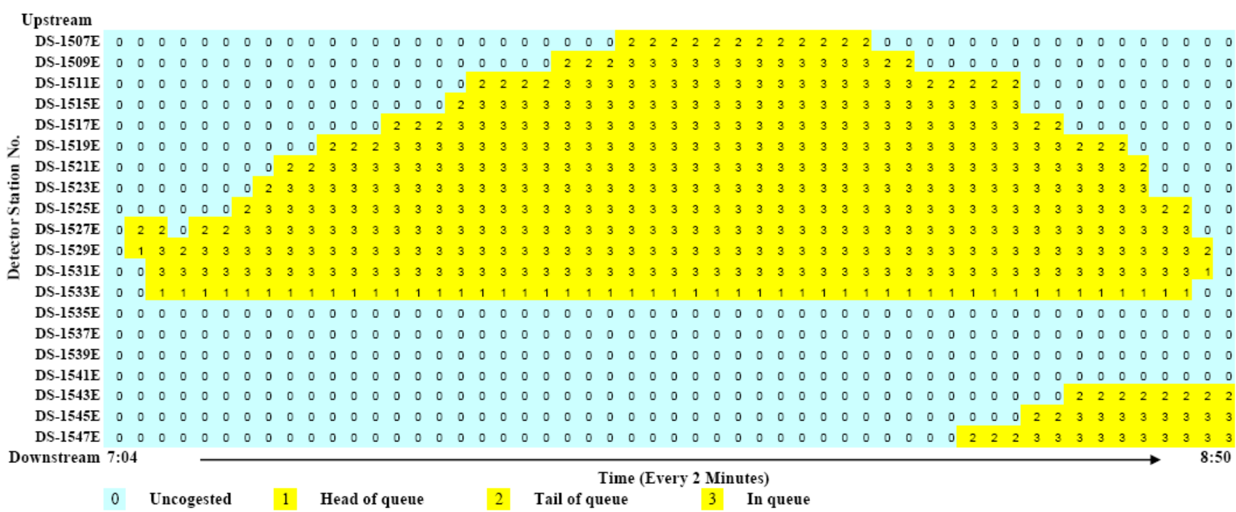


FIGURE 3-3 Example of Queue Identification Results

3.2.4. On-Line Travel Time Estimation

Travel time is estimated in this study using different methods for on-line (based on real-time data) and off-line (based on historical data) applications. As clarified later in this chapter, additional information is available in the case of off-line applications, allowing more accurate estimation of travel time. This section describes the on-line travel time estimation methods investigated in this study.

As mentioned earlier, the hybrid approaches developed in this study apply different methods to estimate travel time based on the identified congestion level and queue location. Two on-line hybrid travel time estimation models are developed. The first (referred to as On-Line Hybrid Model 1) combines a speed-based method with a traffic flow theory-based method. The second (referred to as On-Line Hybrid Model 2) combines two different speed-based methods. Below is a description of these hybrid models. The two hybrid models were compared with various speed-based methods and traffic flow methods and the results are reported later in this chapter.

On-Line Hybrid Model 1

The rationale behind Model 1 is that previous studies have reported that speed-based travel time estimation methods work well under free-flow conditions, while travel time estimation methods based on traffic flow theory work well under congested conditions. Thus, the combination of these two estimation methods has the potential of producing a better performance. Model 1 uses a speed-based method to estimate travel times for non-congested segments and a traffic flow theory-based method for congested segments.

The speed-based method selected for use is the Mid-Point method, since it is widely used in practice and was shown in this study to perform well for uncongested conditions, as described later. This method estimates the travel time along uncongested links as follows.

$$TT_{i,t} = \frac{L_i}{2S_{i,1,t}} + \frac{L_i}{2S_{i,2,t}} \tag{3-9}$$

where $TT_{i,t}$ is the estimated travel time for link i at time t. L_i denotes the length of the link that connects upstream and downstream detector station, and $S_{i,1,t}$ and $S_{i,2,t}$ are the speeds at the detection stations upstream and downstream of the link, respectively.

The travel time for a congested (fully queued) link is estimated using a traffic flow theory-based method that is based in the relationship between the three macroscopic traffic variables (speed, flow, and density), as follows:

$$TT_{i,t} = \frac{L_i k_{i,t}}{q_{i,2,t}} = \frac{L_i (k_{i,1,t} + k_{i,2,t})}{2q_{i,2,t}} \tag{3-10}$$

where $q_{i,2,t}$ is the flow rate at downstream station of the link *i* at time *t*. The k_i in this equation is the link density, which is calculated as the average of the densities at the immediate upstream and downstream stations. It should be mentioned that the density *k* in above equations is estimated from the measured occupancy and the average effective vehicle length estimated by using the measured values of speed, volume count, and occupancy when the traffic is free-flow, that is,

$$L_{eff,j} = \frac{1}{m} \sum_t \frac{q_{j,t}}{S_{j,t} \times 52.8 \times O_{i,t} \times N_j} \tag{3-11}$$

where $L_{eff,j}$ is the average effective vehicle length at detector station *j*. *N* is the total number of lanes at the detector station. *m* is the total number of detector records with a free-flow traffic condition within the same peak period.

When the link is located at the head of the queue, it may be identified as partially queued (when the queue is identified upstream of the link but not downstream of the link). Therefore, the travel time estimation for a head of queue link consists of two parts: one for the queued section and one for the unqueued section, as shown below.

$$TT_{i,t} = \frac{L_{i,1} k_{i,1,t}}{q_{i,1,t}} + \frac{L_{i,2}}{S_{i,2,t}} \tag{3-12}$$

where $L_{i,1}$ is the length of queue section within the link, while $L_{i,2}$ is the remaining uncongested section. Similar expression can be used for the travel time estimation of a tail of a queue link since such a link can be partially queued also.

While testing the above model, it was determined that the fast change in the queuing status during lane blockage incident conditions requires two refinements to the above model. The refined model is referred to as the Refined On-Line Model 1. The first refinement is to predict the queue length during the queue forming stage to account for the lag between the times the vehicles receive the information (e.g., at a DMS location) and the times they arrive at the tail of the queue. The predicted queue length is calculated based on the current location of the vehicle, current ending location of the queue and the propagation of the backward forming shock wave. This propagation speed is calculated as follows:

$$\omega_b = \frac{q_2 - q_1}{k_2 - k_1} \tag{3-13}$$

where ω_b denotes the shock wave speed. q_2 and q_1 are the flow rates within the queue and at the upstream of the queue, respectively. k_2 and k_1 are the corresponding densities. In this study, q_2 and k_2 are approximated by the flow and density at the downstream station of tail of the queue, while q_1 and k_1 are the traffic parameters at the upstream station of this link. The speed within the queued section is estimated as the average speed of all of the detector stations within the queue. This speed is calculated as a function of flow and density.

The second refinement to the model considers a front recovery shock wave few minutes before the time at which the incident is forecasted to be cleared. This refinement can be applied only when such forecasting is possible, for example, by an operator who is monitoring a real-time video display of the incident scene and communicating with the incident management team[1]. This refinement is to account for vehicles that receive travel time information at the DMS locations, with the travel time calculated under the assumption that the front of the queue due to the incident at a given location is fixed at that location, but in fact, because the traffic is in the recovery stage after the lane blockage is cleared, the queue length is decreasing with the head of the queue moving upstream due to the fast moving backward recovery shockwave. If this reduction in queue is not considered then the travel time received by the affected vehicles at the DMS location will be an overestimated travel time. The refinement applied to address this issue includes the estimation of the recovery shock wave speed as follows:

$$\omega_f = \frac{c_2 - c_1}{k_2 - k_1} \tag{3-14}$$

where ω_f represents the speed of the recovery shock wave. c_1 is the capacity during the incident while c_2 is the queue discharge rate during incident clearance. These two parameters can be estimated from the normal roadway capacity and the capacity reduction factor during the incidents. The capacity and capacity reduction can be estimated based on the Highway Capacity Manual (HCM) procedures and parameters, or estimated based on detector station data, if this is possible. Parameters k_1 and k_2 are the corresponding densities. The reduction in queue length due

[1] The utilization of an incident duration prediction model was also considered but eliminated from further consideration due to the expected variation in the durations of incidents with similar attributes.

to the recovery shockwave is then calculated based on the vehicle starting location, the time that incident starts to clear, and the speed of recovery shock wave. The average speed, determined from the capacity c_2 and the density k_2, is used for those recovered roadway segments.

It should be pointed out that at the finalizing stage of this project; it was found that similar to this study, Yi (2009) developed a travel time estimation framework by combining a speed-based method with a traffic-flow theory based method and a statistics-based method. However, Yi study (2009) is different from this study in that it requires 1-sec detector data and the knowledge of the timestamps when each vehicle enters and exits the detection zone. This study requires 20-sec detector data for speed, volume count and occupancy; which is the typical aggregation level of detector data of traffic management systems. Further, Yi (2009) only tested the algorithms for very short links with a length up to 3,300 feet which may not capture the impacts of queue propagation and did not test the algorithm during incident conditions. Finally, for on-line application, Yi study (2009) did not take the dynamics of queue into consideration.

On-Line Hybrid Model 2

Instead of combining a traffic flow method and a speed based method as is done in On-Line Hybrid Model 1, Hybrid Model 2 combines two different speed-based methods: the Mid-Point method and the Minimum Speed method. The rational is that there is a feeling among the FDOT ITS staff that the mid-point method underestimates travel time during congested conditions. Thus, using the minimum of the speeds measured at upstream and downstream detectors as is done in the minimum speed method may produce better results.

The existence of the queue and its status, identified by clustering analysis as explained above, can be used with the On-Line Hybrid Model 2 to select the appropriate method for travel time estimation as follows:

- If there is no queue identified along a path, the traffic is under non-congested conditions and the Mid-Point method is applied to estimate the travel time for these conditions.
- When the queue exists and it is growing backward, the Minimum Speed method is selected for the travel time estimation to capture the dynamic growth of the queue. Since the Minimum Speed method uses the lower value of the upstream and

downstream station speeds to represent the average link speed, it implicitly considers the queue propagation to the upstream station.

- If the queue is dissipating with a forward recovery shockwave, which occurs at the time when the recurrent congestion starts to dissipate at the bottleneck due to the reduction of upstream demands, the Minimum Speed method is also applied to account for the congestion considering that the recovery shockwaves in this case is slow and not as fast as the recovery shockwave in case of incident clearance, which is described next.
- If the queue is dissipating with a backward recovery shockwave, such as in the case of incident clearance, the travel time estimation switches back to the Mid-Point method. This is because the fast moving recovery shockwave will result in a fast reduction in queue length and it is expected that there will be an overestimation if the Minimum Speed method is used in this case.

Similar to Hybrid Model 1, a refinement is applied to Hybrid Model 2 by including in the calculation a front recovery shock wave that is used to account for the incident recovery conditions. The procedures to estimate the impact of the recovery shock wave speed on the length of the congested region is the same as that used in Model 1. However, Model 2 does not need to predict the queue length during the queue forming stage under incident conditions, as was done in the Refined Hybrid Model 1, since the Minimum Speed method seems to be able to account for the dynamic growing of queue.

3.2.5. Off-Line Travel Time Estimation

Although this study mainly focuses on the real-time (on-line) estimation of travel time; for comparison purposes and for potential use for off-line applications, corresponding hybrid off-line estimation models that utilize historical data are also developed. This is also useful since off-line estimates have been used used in the training process of real-time short-term travel time prediction methods such as Neural Network, Time Series, Regression, or Nearest Neighbor.

The difference between on-line and off-line estimation methods is that for on-line applications, future traffic conditions along the paths of the vehicle are not available and only the instantaneous travel time (based on the traffic conditions at the time of the estimation) can be used in the estimation. For off-line estimation, the traffic conditions at later time periods are known using the historical data. Thus, the actual travel time experienced by the vehicles can be estimated based on traffic conditions as the vehicle progresses in its route from one link to the next.

The method used in this study divides the whole time duration into small time periods depending on the temporal aggregation level of the detector data, as shown in Figure 3-4.

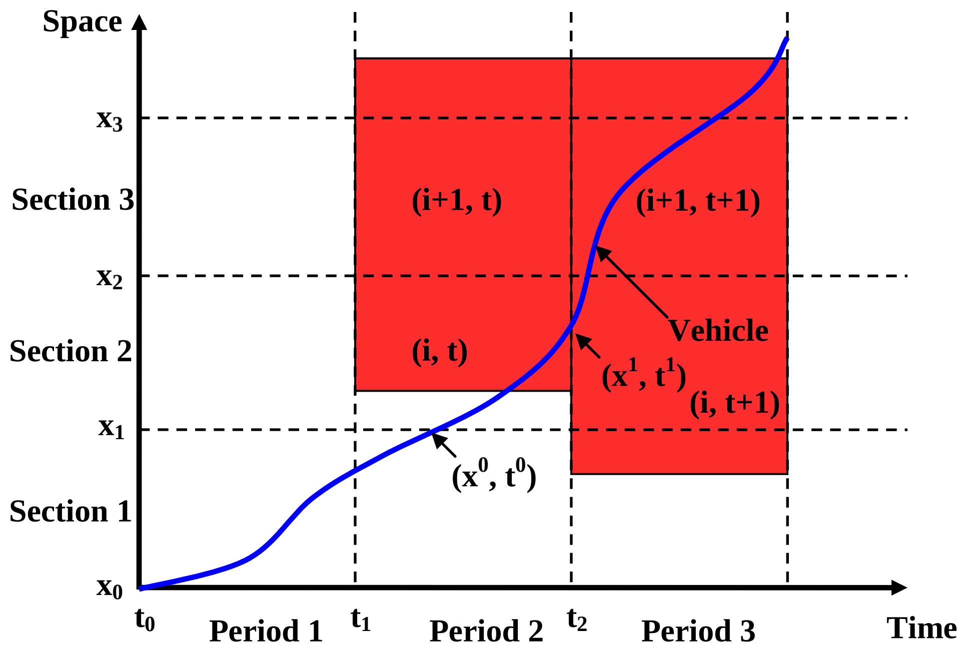


FIGURE 3-4 Schematic Diagram for Off-Line Travel Time Estimation

As shown in the figure, a vehicle enters cell *i* at location x^0 and time t^0. The remaining time in this time period is compared to the time that is required to reach the downstream station, and the minimum value of these two is used in the travel time estimation for this cell. Depending on the location of exit point (x^1, t^1), the vehicle can either enter the next link during the same period, which is cell (*i*+1, *t*); stay on the same link but experience different traffic conditions at time *t*+1, which is cell (*i*, *t*+1); or enter the downstream link at the next period of time; which is cell (*i*+1, *t*+1). The resulted route travel time of a vehicle is the time that the vehicle arrives at the destination (last detection station on the path for which the travel time is estimated) minus the time that the vehicle departs the origin (first detection station on the path for which the travel time is estimated). This concept is similar to the concept presented by Van Lint (2004).

However, instead of using the Piece-wise Linear Speed method as was done in the study of Van Lint (2004), hybrid methods developed in this study are used to calculate the travel time within each cell. In parallel to the two on-line hybrid models mentioned above, two hybrid off-line models are also developed, which are explained below.

Off-Line Hybrid Model 1

Similar to the On-Line Hybrid Model 1, the travel time within each cell for the Off-Line Hybrid Model 1 are either estimated by the Mid-Point method or Flow-based method, depending on the congestion level identified by the clustering analysis, as described above. Given the entering location and time (x^0, t^0) at each cell, the exit location and time (x^1, t^1) can be written as

$$(x^1, t^1) = \begin{cases} \left(x_d, t(x_d)\right) & t(x_d) \le t_p \\ \left(x(t_p), t_p\right) & t(x_d) > t_p \end{cases} \tag{3-15}$$

where x_d indicates the downstream detector location for each cell. The symbol t_p refers to the ending timestamp for the cell, which corresponds to the time of the next travel time update. $t(x_d)$ is the timestamp when reaching the downstream detector location and $x(t_p)$ is the location that can be reached by the vehicles at timestamp t_p. The expressions for these two parameters vary with the congestion level in the cell. Below is the detailed discussion of how to calculate $t(x_d)$ and $x(t_p)$ under different conditions.

<u>Case 1: The cell is free of congestion.</u>

In this case, the Mid-Point method is used for travel time estimation as it performs well under uncongested conditions. Since the Mid-Point method assumes that each detector speed measurement represents the speeds of half distance to the next detector on both sides, the travel time estimation in this case is divided into two parts, depending on whether the entering point of vehicles x^0 is within the first half of the cell or the second half of the cell.

If the entering point of vehicles x^0 is within the second half of the cell, that is,

$$x^0 \ge x_u + \frac{1}{2}(x_d - x_u) \tag{3-16}$$

where x_u indicates the upstream detector locations. The corresponding timestamp when reaching the downstream detector location $t(x_d)$ is expressed as:

$$t(x_d) = t^0 + \frac{x_d - x^0}{S_d} \tag{3-17}$$

Meanwhile, the location $x(t_p)$ that can be reached by the vehicles at the timestamp t_p is

$$x(t_p) = x_0 + (t_p - t^0) \times S_d \tag{3-18}$$

In the case that the entering point of vehicles is within the first half of the cell, that is,

$$x^0 < x_u + \frac{1}{2}(x_d - x_u) \tag{3-19}$$

The expression for $t(x_d)$ is

$$t(x_d) = t^0 + \frac{x_u + \frac{1}{2}(x_d - x_u) - x^0}{S_u} + \frac{\frac{1}{2}(x_d - x_u)}{S_d} \tag{3-20}$$

The location $x(t_p)$ at the timestamp t_p is written as

$$x(t_p) = \begin{cases} x^0 + S_u \times (t(x_m) - t^0) + S_d \times (t_p - t(x_m)) & t(x_m) \le t_p \\ x^0 + S_u \times (t_p - t^0) & t(x_m) > t_p \end{cases} \tag{3-21}$$

where $t(x_m)$ is the timestamp when the vehicles reach the mid-point of the cell, which is calculated as

$$t(x_m) = t^0 + \frac{x_u + \frac{1}{2}(x_d - x_u) - x^0}{S_u} \tag{3-22}$$

<u>Case 2: The cell is in-queue.</u>

When the status of the cell is in-queue, the flow-based method is applied to calculate $t(x_d)$ and $x(t_p)$, that is,

$$t(x_d) = t^0 + (x_d - x^0) \times \frac{1}{2}(k_u + k_d) / q_d \tag{3-23}$$

$$x_d(t_p) = x^0 + 2q_d / (k_u + k_d) \times (t_p - t^0) \tag{3-24}$$

where k_u and k_d are the densities at the upstream and downstream detector locations, respectively. q_d represents the flow rate at the downstream detector location of this cell.

<u>Case 3: The cell is a head of a queue.</u>

Similar to the on-line Hybrid Model 1, the head of queue cell consists of two parts, the one within the queue and an uncongested part downstream of the congestion. If the vehicles enter the cell in the uncongested part, the values of $t(x_d)$ and $x(t_p)$ are obtained from the downstream detector speed, that is,

$$t(x_d) = t^0 + \frac{x_d - x^0}{S_d} \tag{3-25}$$

$$x(t_p) = x_0 + (t_p - t^0) \times S_d \tag{3-26}$$

However, if the vehicles enter the cell within the congested part, the corresponding expressions for $t(x_d)$ and $x(t_p)$ are

$$t(x_d) = t^0 + (x_q - x^0) \times k_u / q_u + \frac{x_d - x_q}{S_d} \tag{3-27}$$

$$x(t_p) = \begin{cases} x^0 + q_u / k_u \times (t(x_q) - t^0) + S_d \times (t_p - t(x_q)) & t(x_q) \le t_p \\ x^0 + q_u / k_u \times (t_p - t^0) & t(x_q) > t_p \end{cases} \tag{3-28}$$

where x_q is the ending location of the queue within the cell. $t(x_q)$ is the timestamp when the vehicles reach the location of x_q. The vehicles may exit the cell either from the congested region or uncongested region, and thus two different expressions are formulated for $x(t_p)$ in Equation 3-28.

Case 4: The cell is a tail of a queue.

Contrary to the head of a queue case described above, the first part of a tail of a queue cell is uncongested while the second part of this cell is within the queue. The method used for the estimation of travel time for a tail of queue cell follows the same idea as a head of queue cell.

If the entering location $x^0$of a vehicles is within a congested region, the expressions for $t(x_d)$ and $x(t_p)$ are written as

$$t(x_d) = t^0 + (x_d - x^0) \times k_d / q_d \tag{3-29}$$

$$x_d(t_p) = x^0 + q_d / k_d \times (t_p - t^0) \tag{3-30}$$

Otherwise, the corresponding expressions are

$$t(x_d) = t^0 + \frac{x_q - x^0}{S_u} + (x_d - x_q) \times k_d / q_d \tag{3-31}$$

$$x(t_p) = \begin{cases} x^0 + S_u \times (t(x_q) - t^0) + q_d / k_d \times (t_p - t(x_q)) & t(x_q) \le t_p \\ x^0 + S_u \times (t_p - t^0) & t(x_q) > t_p \end{cases} \tag{3-32}$$

where x_q is the starting location of the queue within the cell. $t(x_q)$ is the timestamp when the vehicles reach the location of x_q.

As mentioned above, the resulted route travel time of a vehicle is the time that the vehicle arrives at the destination (last detection station on the path for which the travel time is estimated) minus the time that the vehicle departs the origin (first detection station on the path for which the travel time is estimated).

Off-Line Hybrid Model 2

The Off-Line Hybrid Model 2 utilizes the Mid-Point method for uncongested cells and the Minimum Speed method for the fully or partly congested cells. The combination of these two speed-based methods aims at utilizing the advantages of each individual estimation methods and thus improving the overall estimation performance.

With the Off-Line Hybrid Model 1, the exit location and exit time (x^1, t^1) can be expressed as the function of entering location and and time (x^0, t^0) as in Equation 3-33.

$$(x^1, t^1) = \begin{cases} (x_d, t(x_d)) & t(x_d) \le t_p \\ (x(t_p), t_p) & t(x_d) > t_p \end{cases} \tag{3-33}$$

For the uncongested cells, the expressions for $t(x_d)$ and $x(t_p)$ in the above equation are exactly the same as those described in Model 1 and are omitted here for brevity.

The expressions of $t(x_d)$ and $x(t_p)$ for the fully congested or partly congested cells are

$$t(x_d) = t^0 + \frac{x_d - x^0}{\min(S_u, S_d)} \tag{3-34}$$

$$x(t_p) = x_0 + (t_p - t^0) \times \min(S_{u,} S_d) \tag{3-35}$$

Note that since the traffic parameters at later time periods are known, the off-line hybrid models do not need the refinement as the on-line hybrid models. Compared to the previous travel time estimation studies, the hybrid off-line models developed in this study do not need additional information about incidents, such as the incident occurrence time and duration, since the clustering analysis described above will automatically detect the occurrence and disappearance of queue.

3.3. Model Assessment and Comparison

The accuracy and reliability of travel time estimates obtained using various existing speed-based methods including the SunGuide algorithm for travel time calculation, a simple traffic flow-based method based on flow and occupancy, the modified N-D method (a traffic flow method), and the hybrid models described above, are evaluated and compared in this study. The comparisons are made using simulation models as well as real-world travel time data. The existing methods included in the comparison of this study are briefly described in Appendix B.

Figure 3-5 shows the corridor used as a case study in the comparison. The study corridor is the eastbound section of State Road 826, located in Miami-Dade County, Florida, starting from the location of detector DS-1509E to the location of detector DS-1549E. It includes six interchanges with a total length of about 6.48 miles. As shown in Figure 3-5, there are 21 true presence microwave detector stations deployed along this section with an average spacing of about 0.3 to 0.5 miles. However, it is found that detector station DS-1513E reported erroneous data for the period of the study, and therefore this station is excluded from analysis.

FIGURE 3-5 Study Corridor and Detector Locations

Two performance measures are used to quantify the accuracy of the estimated travel times. These performance measures are the mean absolute error (MAE) and the mean absolute percentage error (MAPE). These two performance measures are defined as follows:

$$MAE = \frac{1}{N}\sum_{t}\left|TT_t - TT_{t,a}\right| \tag{3-36}$$

$$MAPE = 100 \frac{1}{N} \sum_{t} \frac{|TT_t - TT_{t,a}|}{t_{t,a}} \quad (3\text{-}37)$$

where TT_t is the estimated travel time at time t, and $TT_{t,a}$ is the corresponding real-world or simulated travel time (depending on the source of ground truth data). N is the total number of estimates.

Because FDOT districts generally post ranges of travel time values rather than fixed travel time values on their traveler information devices, it is necessary to quantify the reliability of the estimated travel times, as well. In this study, the reliability of the travel time estimates is defined as the percentage of vehicles with travel times that are within the range of the travel time posted on the traveler information devices. In addition, the percentage of vehicles with travel times that are less than the posted minimum travel time as well as the percentage of vehicles with travel time greater than the posted maximum travel time is also reported. This study calculates the travel time ranges, using the same method used by the traffic management centers in South Florida in their real-world operations (Florida Department of Transportation District 6, 2010). With this calculation, if the estimated travel time is less than five minutes, the traveler information message to travelers is “Under 5 Minutes.” If the travel time is more than 35 minutes, the message is “Over 35 Minutes.” A 3-minute range is used when the estimated travel time is between 5 minutes and 10 minutes, and a 5-minute range is used for travel times between 10 minutes and 35 minutes.

3.3.1. Assessment Based on Simulation Data

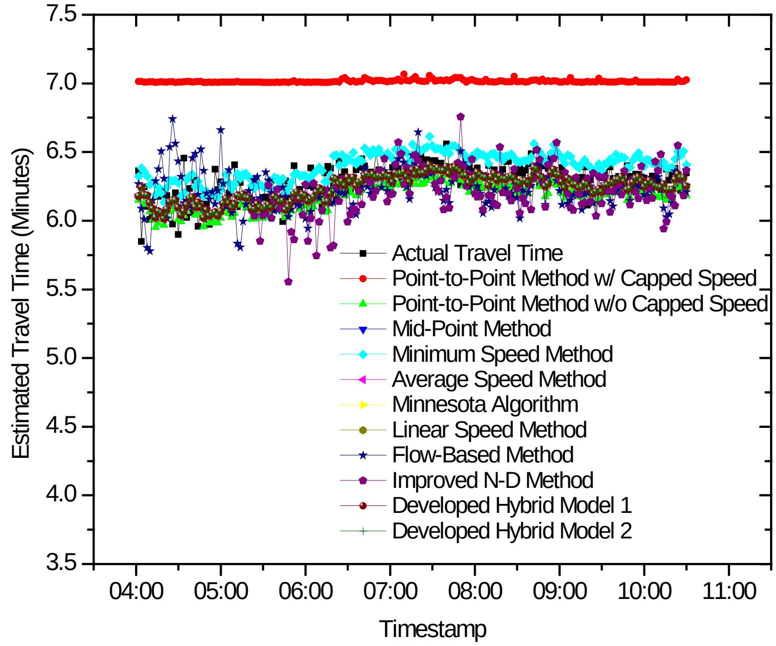
First, different travel time estimation methods were tested using a simulation model that is calibrated for incident and no-incident conditions. The utilized simulation tool is the CORSIM microscopic simulation model. As part of a separate FDOT Research project, the researchers of this study developed new procedures for the development and calibration of simulation models using data collected from ITS (Hadi et al. 2010). These procedures were used in this study. The details of these procedures are presented in the final report of the research project mentioned above and will not be repeated here.

Three scenarios were used in the comparison described below: the first scenario represents uncongested condition and the other two are with one-lane blockage incidents with different attributes. It should be noted that the comparison based on simulation presented in this section assumes that all detector measurements have 100% accuracy. This assumption is relaxed later in this document to determine the impacts of detector errors on the results. The temporal aggregation level of travel time used in the comparison is 2 minutes, which a common aggregation level used in travel time estimation. The SunGuide software is assumed to use the Point-to-Point method for travel time estimation. The measured speeds are capped by the speed limit (for SR-826, the speed limit is 55 mph) in SunGuide system before used in travel time calculation. In the comparison, the comparison with the SunGuide estimation is done with and without capping of the speed.

Simulated Uncongested Scenario

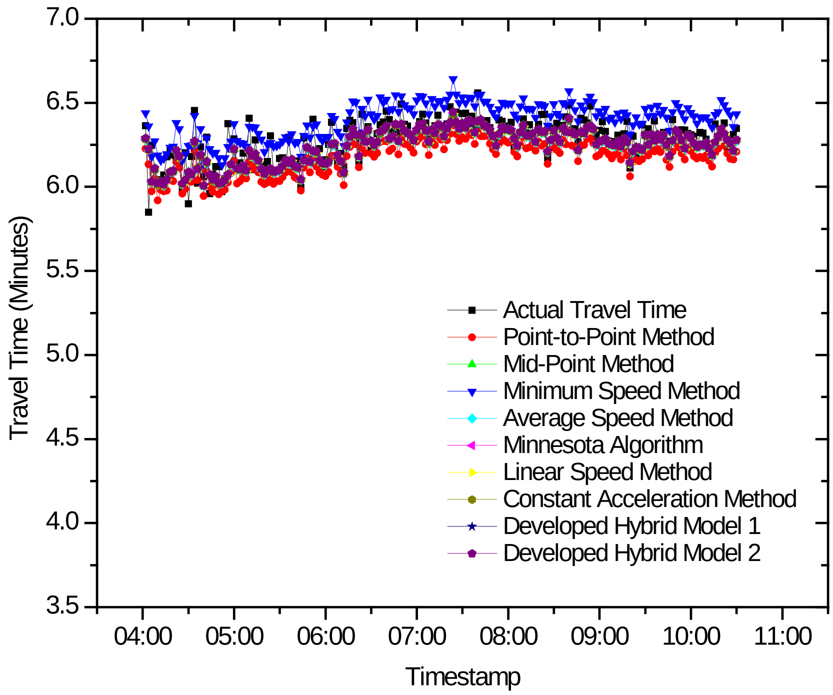
Figure 3-6 presents the travel time results for uncongested conditions and Table 3-1 shows the accuracy and reliability of various on-line travel time estimation methods for this scenario. The flow-based method in Table 3-1 is the method that uses the volume count and occupancy to estimate the travel time as described in Appendix B, and the improved N-D method refers to the method developed by Vanajakshi (2009), which was selected as an example of the latest traffic flow theory-based methods that can be found in the literature.

As show in Table 3-1, almost all of the on-line travel time methods can achieve good accuracy and reliability during uncongested conditions except the Point-to-Point method with capped speed, which overestimates the travel time due to the capped speed. The comparison among the different speed-based methods shows that the Minimum Speed method has slightly higher errors and lower reliability relative to the other speed-based methods. It also can be seen in Table 3-1 that the developed models perform well in this case. Compared to the on-line estimation methods, the off-line methods can achieve slightly better estimation performance, as shown in Table 3-2. However, this improvement is not significant.



(a) On-Line Estimation Results

FIGURE 3-6 Estimated Travel Time for Simulated Uncongested Condition



(b) Off-Line Estimation Results

FIGURE 3-6 Estimated Travel Time for Simulated Uncongested Condition (Con't)

TABLE 3-1 Accuracy and Reliability of Tested On-Line Travel Time Estimation Methods for Simulated Uncongested Condition

Method	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method w/ Capped Speed	0.74	11.77	80.59	19.41	0
Point-to-Point Method w/o Capped Speed	0.12	1.92	100	0	0
Mid-Point Method	0.08	1.31	100	0	0
Minimum Speed Method	0.14	2.18	97.58	2.42	0
Average Speed Method	0.08	1.34	100	0	0
Minnesota Method	0.08	1.32	100	0	0
Linear Speed Method	0.08	1.33	100	0	0
Flow-Based Method	0.15	2.38	99.5	0.44	0
Improved N-D Method	0.15	2.38	99.29	0.71	0
Developed Hybrid Model 1	0.08	1.31	100	0	0
Developed Hybrid Model 2	0.08	1.31	100	0	0

TABLE 3-2 Accuracy and Reliability of Tested Off-Line Travel Time Estimation Methods for Simulated Uncongested Condition

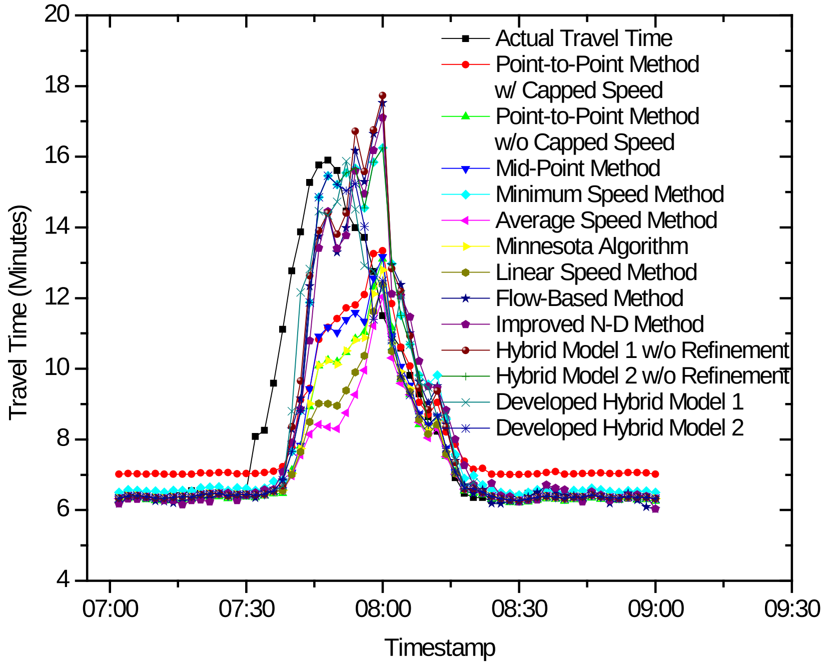
Method	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	0.11	1.76	100	0	0
Mid-Point Method	0.06	0.94	100	0	0
Minimum Speed Method	0.12	1.99	97.83	2.17	0
Average Speed Method	0.06	0.99	100	0	0
Minnesota Method	0.06	0.95	100	0	0
Linear Speed Method	0.06	0.97	100	0	0
Constant Acceleration Method	0.06	0.96	100	0	0
Developed Hybrid Model 1	0.06	0.94	100	0	0
Developed Hybrid Model 2	0.06	0.94	100	0	0

Simulated Incident Scenario 1

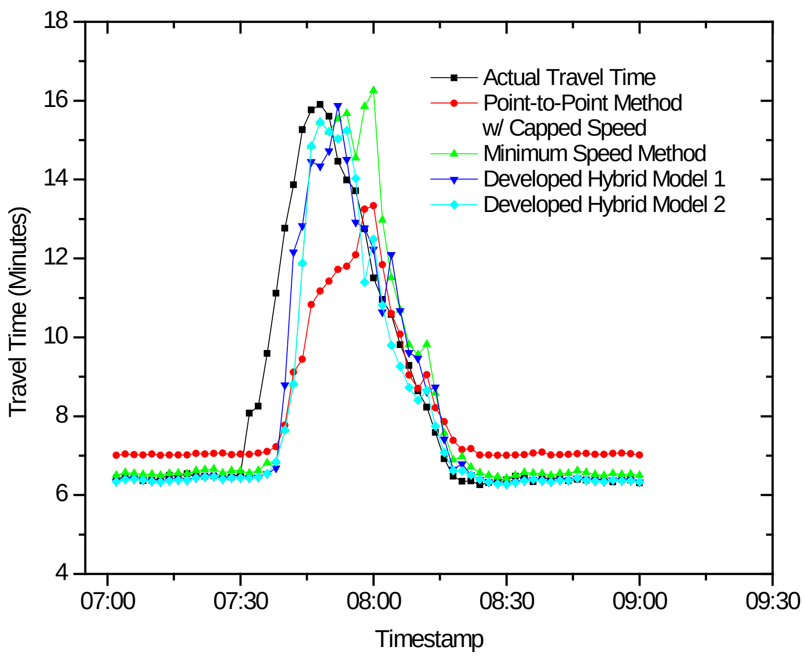
Figure 3-7(a) presents the results of the on-line travel time estimation for one of the incident scenarios used as a case study and referred to as simulated incident scenario 1 in the discussion of this report. In this simulation case, a one-lane blockage incident occurs at 7:35 A.M. and lasts for 25 minutes. For clarity, Figure 3-7(b) presents the same results presented in

Figure 3-7(a) but only for the Point-to-Point method with capped speeds (i.e., SunGuide method), the on-line Minimum Speed method, and the on-line hybrid models developed in this study. Figure 3-7(c) shows the corresponding off-line travel time estimation results. . Figure 3-7(a) shows that, unlike the uncongested case, the results obtained from different travel time estimation methods vary significantly. It appears that the Minimum Speed method can produce better results than the other speed-based methods for this incident scenario. The flow-based method and the improved N-D method can also produce relatively good results. However, these three methods (Minimum Speed, Flow-based method and the improved N-D method) overestimate the travel time at the later stage of lane blockage due to the effect of the front recovery shockwave, described earlier. Figure 3-7(a) also includes the results obtained from the hybrid models without refinements, which are slightly to moderately better than those of the flow-based method and the Minimum Speed method but also suffers from the front recovery shockwave effect. The developed refined on-line models that consider the front recovery shock wave performed better than the other methods, as shown in Figure 3-7(b). Figure 3-7(b) also shows that the SunGuide method does not perform well and significantly underestimate the travel time under this incident scenario. Please note that in the figures presented in this chapter, the developed hybrid model 1 and 2 referred to the models with the refinement mentioned above.

Table 3-3a lists the accuracy and reliability of each on-line travel time estimation method for this simulated incident case between 7:00 A.M. and 9:00 A.M. As stated previously, the lane blockage incident occurs at 7:35 A.M. and lasts for 25 minutes. It can be seen from this table that in general the accuracy and reliability of the estimated travel time during the incident conditions are not as good as those for the uncongested condition. The MAPE of travel time estimated by the SunGuide method with capped speed is about 12.79% and the corresponding reliability is 76.54% with 7.72% vehicles arriving early and 15.74% vehicles arriving late. Table 3-3a also shows that the performance of the compared speed-based methods and flow-based methods are close. Compared to the other methods, both of the developed hybrid models have less errors and higher reliability even without the refinements. With the refinement, the accuracy and reliability of the hybrid models improved even further. Comparison of the results of the developed Hybrid Model 1 and Hybrid Model 2 shows that Model 2 performs slightly better than Model 1.

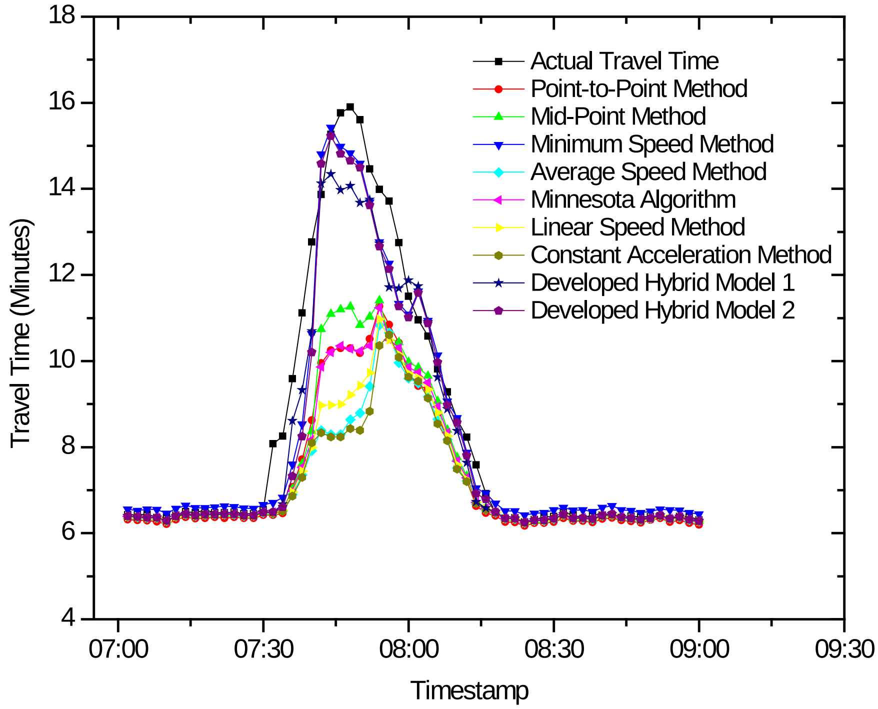


(a) On-Line Estimation Results



(b) On-Line Estimation Results

FIGURE 3-7 Estimated Travel Time for Simulated Incident Scenario 1 (continued on next page)



(c) Off-Line Estimation Results

FIGURE 3-7 Estimated Travel Time for Simulated Incident Scenario 1 (Con't)

TABLE 3-3a Accuracy and Reliability of Tested On-Line Travel Time Estimation Methods for Simulated Incident Scenario 1 between 7:00 A.M. and 9:00 A.M.

Method	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method w/ Capped Speed	1.24	12.79	76.54	7.72	15.74
Point-to-Point Method w/o Capped Speed	1.10	9.07	79.66	0.85	19.49
Mid-Point Method	0.96	7.83	80.48	2.00	17.52
Minimum Speed Method	0.86	8.23	75.53	15.55	8.92
Average Speed Method	1.26	9.88	78.24	0.58	21.19
Minnesota Method	1.06	8.50	80.18	1.64	18.18
Linear Speed Method	1.18	9.32	78.70	0.58	20.72
Flow-Based Method	0.94	8.64	80.21	8.76	11.03
Improved N-D Method	0.99	9.30	79.93	9.20	10.87
Hybrid Model 1 w/o Refinement	0.87	7.76	82.26	7.45	10.29
Hybrid Model 2 w/o Refinement	0.76	6.80	82.23	7.88	9.88
Developed Hybrid Model 1	0.58	5.55	85.98	4.93	9.09
Developed Hybrid Model 2	0.60	5.50	87.85	1.59	10.57

Table 3-3b presents the performances of the on-line travel time estimation methods only between 7:30 A.M. and 8:30 A.M., as the time period from 7:00 A.M. to 9:00 A.M. includes partly uncongested conditions, while the traffic during the period of time between 7:30 A.M. and 8:30 A.M. is completely congested. Compared to the results in the time period 7:00 A.M. to 9:00 A.M., the errors during the time period 7:30 A.M. to 8:30 A.M. are higher and the reliabilities are lower. Table 3-3b indicates that the selection of the study period for comparison has a great impact on the travel time estimation performance evaluation.

TABLE 3-3b Accuracy and Reliability of Tested On-Line Travel Time Estimation Methods for Simulated Incident Scenario 1 between 7:30 A.M. and 8:30 A.M.

Method	**MAE (Minutes)**	**MAPE (%)**	**Reliability (%)**	**% Early**	**% Late**
Point-to-Point Method w/ Capped Speed	1.87	16.08	57.9	9.08	33.03
Point-to-Point Method w/o Capped Speed	2.07	16.28	57.32	1.78	40.90
Mid-Point Method	1.86	14.78	59.05	4.19	36.76
Minimum Speed Method	1.58	14.43	55.20	26.08	18.73
Average Speed Method	2.45	18.81	54.34	1.21	44.46
Minnesota Method	2.05	16.10	58.42	3.45	38.14
Linear Speed Method	2.29	17.72	55.31	1.21	43.48
Flow-Based Method	1.74	15.21	59.33	17.52	23.15
Improved N-D Method	1.83	16.34	58.82	18.38	22.80
Hybrid Model 1 w/o Refinement	1.68	14.65	62.78	15.62	21.60
Hybrid Model 2 w/o Refinement	1.46	12.73	62.72	16.54	20.74
Developed Hybrid Model 1	1.11	10.24	70.59	10.34	19.07
Developed Hybrid Model 2	1.15	10.12	74.50	3.33	22.17

Tables 3-4a and 3-4b present the accuracy and reliability of various off-line estimation methods for simulated incident scenario 1 from 7:00 A.M. to 9:00 A.M. and from 7:30 A.M. to 8:30 A.M., respectively. As stated before, the off-line estimation can be used as a basis for training travel time prediction algorithms. Thus, examining off-line estimation results give an indication whether travel time prediction has the potential to improve the accuracy and reliability of the calculated travel time. As shown in both tables, for off-line applications, the Minimum Speed method has a relatively better performance than other speed-based methods. Again, the developed refined hybrid models have higher accuracy and reliability than the other methods.

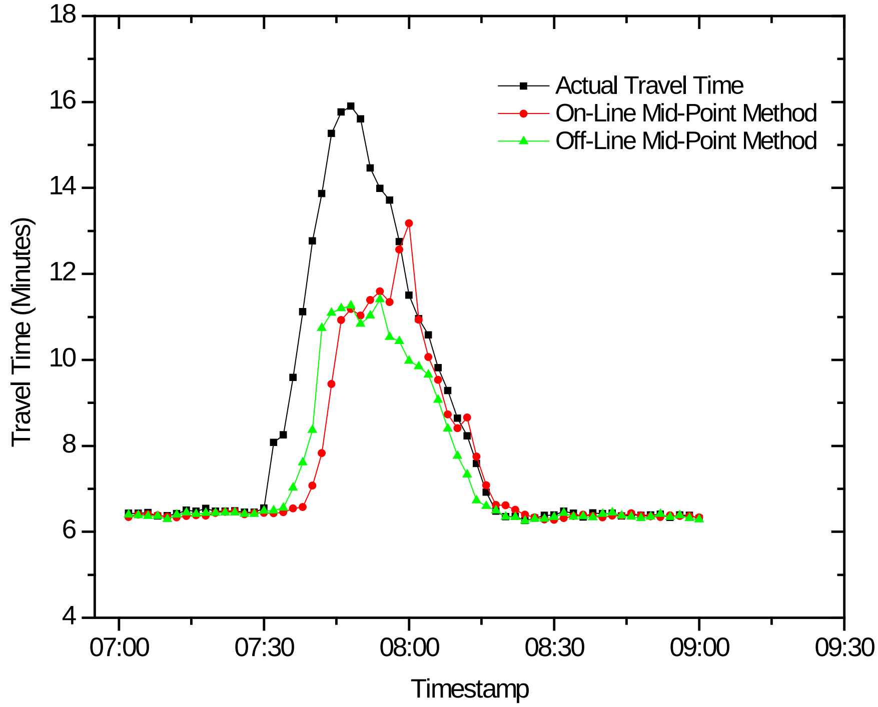
The comparison between the results in Table 3-3b and Table 3-4b shows that both the on-line methods and off-line methods have similar performance except the off-line Minimum Speed method and the developed off-line hybrid models perform better than their on-line versions. These results can be explained by considering the Mid-Point method and the Minimum Speed method as examples in Figure 3-8. Figure 3-8(b) shows the results for on-line and off-line Minimum Speed methods.

TABLE 3-4a Accuracy and Reliability of Tested Off-Line Travel Time Estimation Methods for Simulated Incident Scenario 1 between 7:00 A.M. and 9:00 A.M.

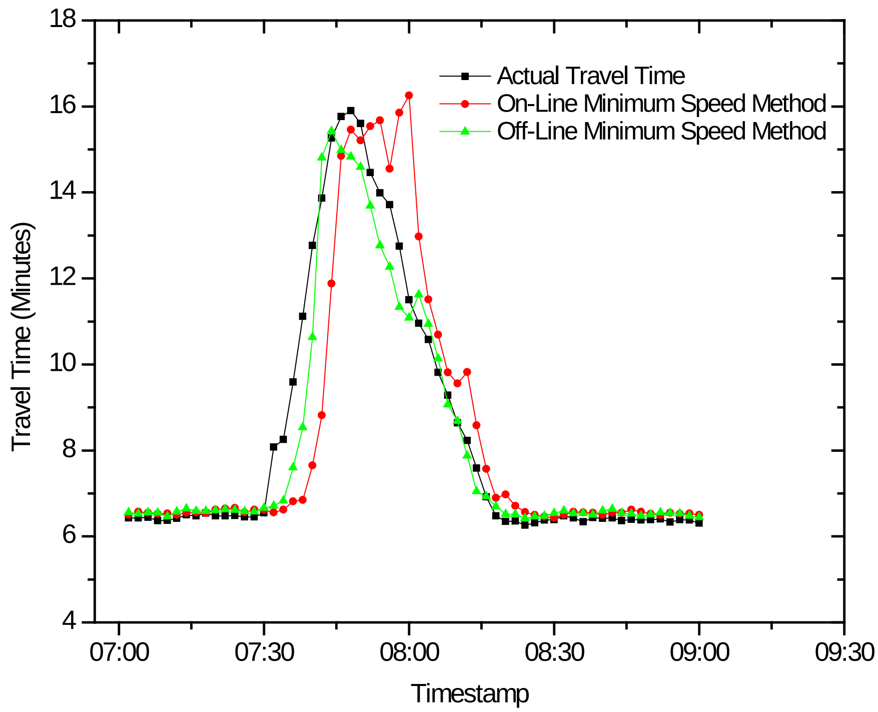
Method	**MAE (Minutes)**	**MAPE (%)**	**Reliability (%)**	**% Early**	**% Late**
Point-to-Point Method	1.09	9.28	80.65	0	19.35
Mid-Point Method	0.94	7.74	83.63	0	16.37
Minimum Speed Method	0.44	4.45	91.30	4.76	3.94
Average Speed Method	1.25	9.99	80.07	0	19.93
Minnesota Method	1.04	8.51	79.99	0	20.01
Linear Speed Method	1.17	9.41	79.39	0	20.61
Constant Acceleration Method	1.28	10.19	79.39	0	20.61
Developed Hybrid Model 1	0.42	3.84	94.17	1.18	4.65
Developed Hybrid Model 2	0.42	3.86	91.65	1.59	6.76

TABLE 3-4b Accuracy and Reliability of Tested Off-Line Travel Time Estimation Methods for Simulated Incident Scenario 1 between 7:30 A.M. and 8:30 A.M.

Method	**MAE (Minutes)**	**MAPE (%)**	**Reliability (%)**	**% Early**	**% Late**
Point-to-Point Method	2.06	16.76	59.39	0	40.61
Mid-Point Method	1.83	14.82	65.65	0	34.35
Minimum Speed Method	0.75	6.82	87.02	4.71	8.27
Average Speed Method	2.45	19.24	58.19	0	41.82
Minnesota Method	2.04	16.32	58.01	0	41.99
Linear Speed Method	2.29	18.10	56.75	0	43.25
Constant Acceleration Method	2.50	19.65	56.75	0	43.25
Developed Hybrid Model 1	0.80	7.02	87.77	2.47	9.76
Developed Hybrid Model 2	0.79	7.05	82.48	3.33	14.19



(a) Mid-Point Method

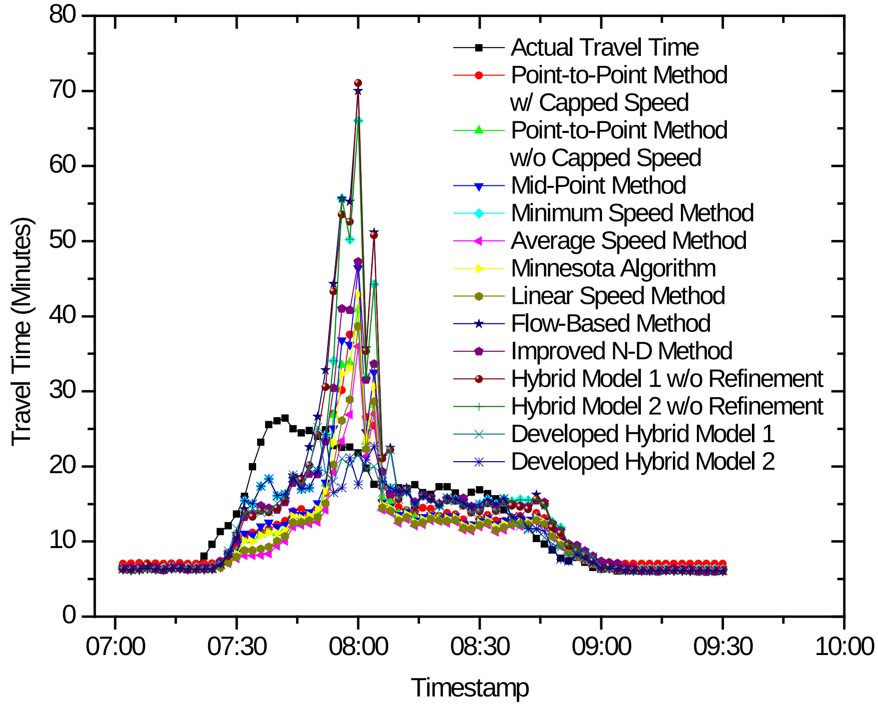


(b) Minimum Speed Method

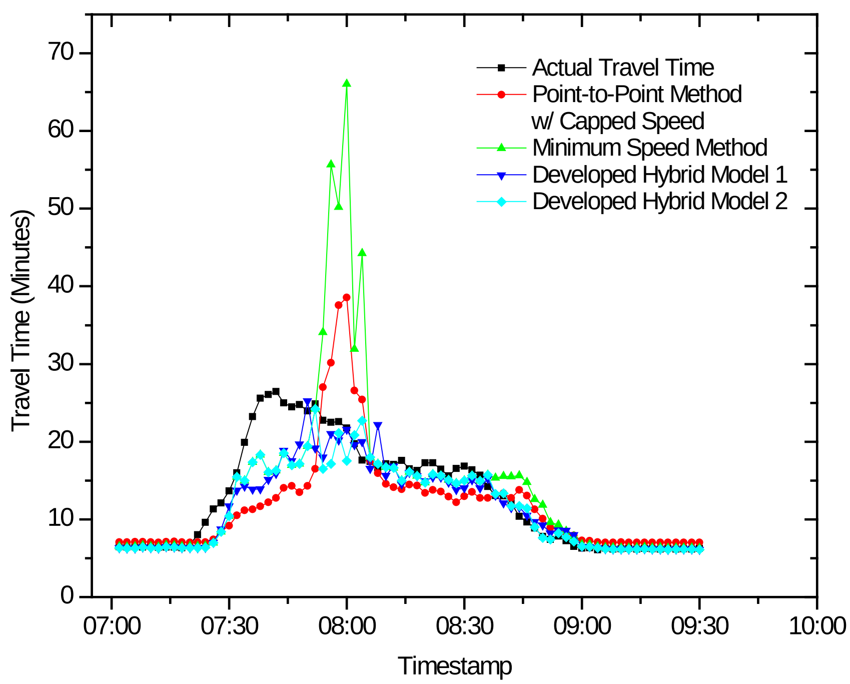
FIGURE 3-8 Comparison of On-Line and Off-Line Estimation Methods

Simulated Incident Scenario 2

Figure 3-9 presents the results for on-line travel time estimation for simulated incident scenario 2. Similar to the simulated incident scenario 1, the incident attributes correspond to a real-world incident from the FDOT District 6 SunGuide incident management database. This one-lane blockage incident occurred at 7:23 A.M. and is more severe than incident scenario 1. After 35 minutes, the incident was moved to the shoulder and the blocked lane was open. The incident was completely cleared at 8:45 A.M., 82 minutes after it started. This incident is more severe than incident 1, as it has a longer duration and the capacity drop due to the incident is higher by about 35% compared to incident 1. The arrival of fire trucks at this incident location appears to have a higher impact on capacity compared to Incident Scenario 1. Figure 3-9(a) shows the estimation results from the various on-line methods. To show the results more clearly, Figure 3-9(b) presents the same results but only for the SunGuide method, Minimum Speed method, and on-line Hybrid Models. As shown in these two figures, the travel time estimated using various on-line methods are not satisfactory in this incident scenario unless the refinement is applied to the hybrid models to account for the front shockwave recovery. The SunGuide method (i.e., Mid-Point method with capped speed) underestimate the travel time during the queue forming stage, and overestimate the travel time at the end of lane blockage. Similar trend can be found for other methods. One reason for this is that these methods estimate the travel time based on the current traffic conditions, without capturing the dynamic changes in the queue length as the vehicles progress from the departure location to the destination. As shown in Figure 3-9(b), the on-line hybrid models overcome this shortcoming with the consideration of a front recovery shock wave. Figure 3-9(c) presents the corresponding off-line travel time estimation results. It is seen from this figure that the off-line estimation methods can avoid the unrealistic estimated peaking in travel time at the later stage of lane blocking resulting when using the on-line methods without considering the front recovery shockwave.

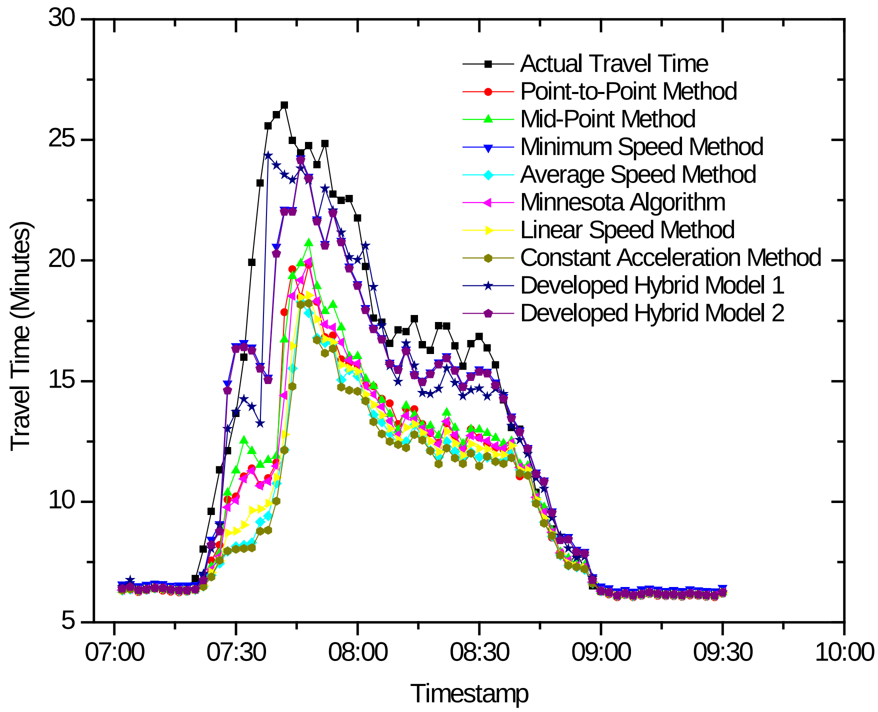


(a) On-Line Estimation Results



(b) On-Line Estimation Results

FIGURE 3-9 Estimated Travel Time for Simulated Incident Scenario 2 (continued on next page)



(c) Off-Line Estimation Results

FIGURE 3-9 Estimated Travel Time for Simulated Incident Scenario 2

Table 3-5 presents the performance of on-line and off-line travel time estimation methods for simulated incident scenario 2. As shown in Table 3-5, the travel time produced by the SunGuide method with capped speed has a MAE of 3.61 minutes, a MAPE of 22% and a reliability of 55%. About 18% of the vehicles arrive to the destination earlier than posted travel time range and 26% of vehicles arrive late. Without capping the speed, the results are a little bit better. Table 3-5 also reveals that the on-line hybrid models do not perform well without the refinements. However, with the refinements, the developed on-line hybrid models produce much better results when compared to the other methods. The comparison between these two on-line hybrid models shows that Model 2 has lower errors and higher reliability than Model 1 under this scenario. The reason for the difference in performance of the travel time estimation methods between incidents 1 and 2 is that incident 2 has more severe capacity constraint. Removing this constraint during the incident clearance stage resulted in higher and faster impact on the experienced travel time. Thus, not accounting for the recovery shockwave has a higher impact in incident 2 compared to incident 1.

Table 3-6 lists the performances of the off-line estimation methods for the simulated incident scenario 2. Compared to the results of Table 3-5, the off-line estimation methods perform much better than the on-line estimations. For example, the MAE, MAPE, and reliability are 3.71 minutes, 20%, and 61%, respectively for the on-line Mid-Point method; and 2.51 minutes, 13%, and 72%, respectively for the off-line counterpart. Again, the off-line Minimum Speed and the hybrid models produce satisfactory results under this scenario as shown in Table 3-6. The results in Table 3-6 indicate that travel time prediction could be beneficial for incident conditions, particularly more severe incidents with long incident durations.

TABLE 3-5 Accuracy and Reliability of Tested On-Line Travel Time Estimation Methods for Simulated Incident Scenario 2

Method	**MAE (Minutes)**	**MAPE (%)**	**Reliability (%)**	**% Early**	**% Late**
Point-to-Point Method w/ Capped Speed	3.61	22.27	55.36	18.37	26.27
Point-to-Point Method w/o Capped Speed	3.56	19.57	61.27	8.66	30.07
Mid-Point Method	3.71	20.31	61.11	9.61	29.28
Minimum Speed Method	3.88	22.28	59.53	21.59	18.88
Average Speed Method	3.74	20.36	59.97	6.60	33.43
Minnesota Method	3.68	20.17	60.22	9.45	30.33
Linear Speed Method	3.70	20.23	60.10	7.63	32.27
Flow-Based Method	4.49	25.04	60.46	20.32	19.22
Improved N-D Method	3.32	19.92	59.61	20.52	19.87
Hybrid Model 1 w/o Refinement	4.42	24.47	62.87	17.34	19.79
Hybrid Model 2 w/o Refinement	3.84	21.66	60.87	18.94	20.19
Developed Hybrid Model 1	1.89	11.08	67.46	10.50	22.04
Developed Hybrid Model 2	1.75	9.82	70.03	7.71	22.26

TABLE 3-6 Accuracy and Reliability of Tested Off-Line Travel Time Estimation Methods for Simulated Incident Scenario 2

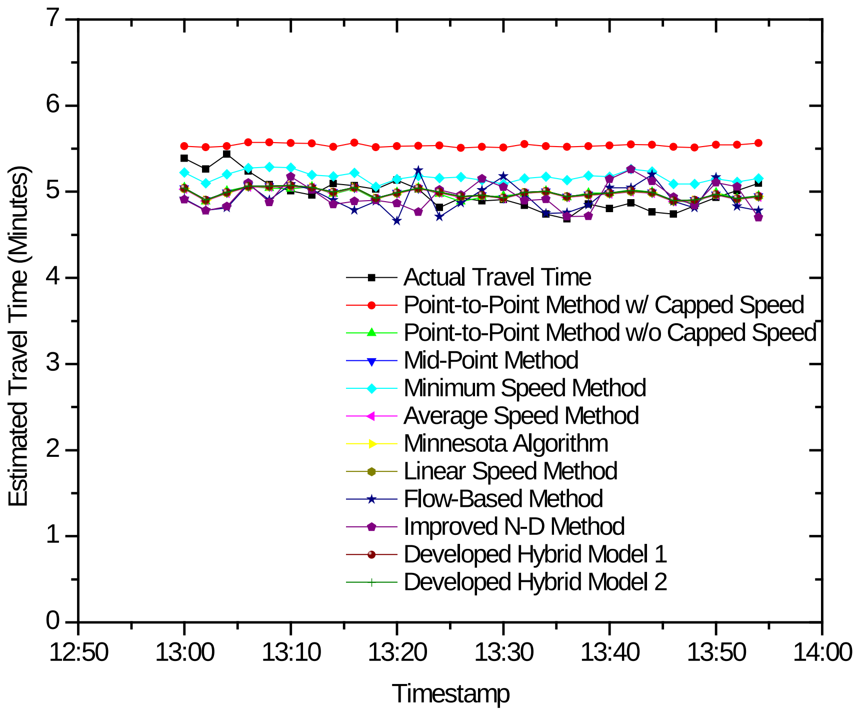
Method	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	2.73	14.75	70.60	1.67	27.72
Mid-Point Method	2.51	13.37	72.32	2.15	25.54
Minimum Speed Method	1.21	7.35	73.68	11.49	14.83
Average Speed Method	3.31	17.62	65.16	0.99	33.85
Minnesota Method	2.77	14.74	69.41	2.04	28.55
Linear Speed Method	3.10	16.47	67.22	0.99	31.79
Constant Acceleration Method	3.43	18.23	64.08	0.99	34.93
Developed Hybrid Model 1	1.03	6.28	76.69	8.90	14.41
Developed Hybrid Model 2	1.21	7.07	75.60	9.05	15.36

3.3.2. Comparison Based on Real-world Data

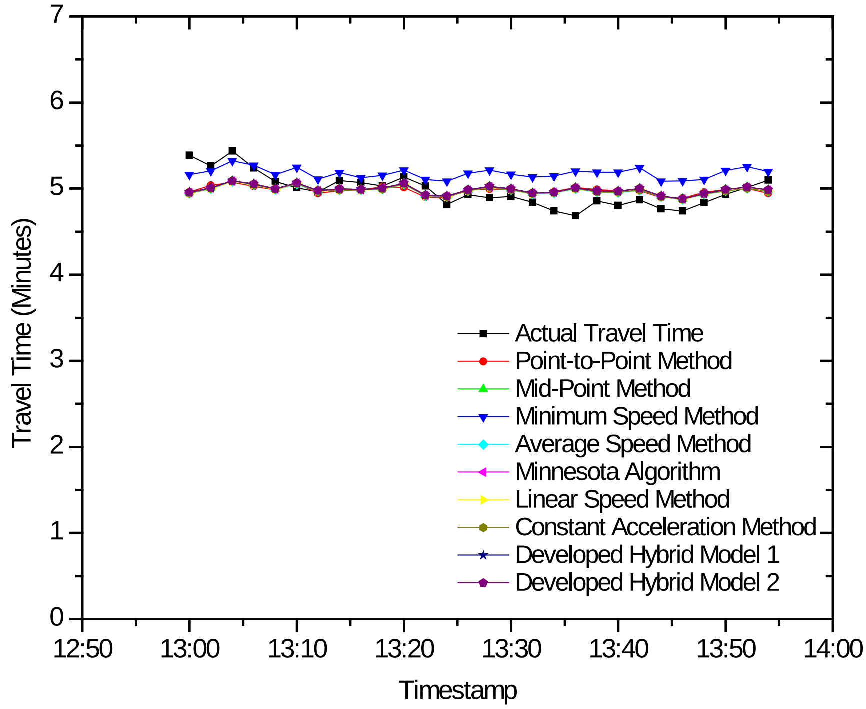
In addition to the use of simulation, further assessment of travel time estimation methods was made using real-world data. The actual travel time was collected using videos from CCTV cameras deployed along the study corridor by matching the vehicles passing the field of view of one CCTV camera location to those passing the field of view of another CCTV camera location. The results for one congested case and one uncongested case are presented in this report. Both investigated cases represent recurrent conditions (no incident conditions). For the uncongested case, the travel times between two detector stations, DS-1515E and DS-1545E (a distance of about 5.02 miles) were collected for the Midday period on December 2, 2008. For the congested case, the travel times between detector stations DS-1519E and DS-1545E (a distance of about 4.58 miles) were collected for the morning peak period on March 10, 2010.

Figure 3-10 presents the travel time estimation results for the two cases mentioned above. It should be mentioned that the congestion level in the congested case is significantly lower than the congestion level resulting from the incident scenarios explored in the simulation models and discussed in Section 3.3.1. Figures 3-10(a) and Figure 3-10(b) show the estimation results for uncongested conditions during the Midday period. It is seen from these figures that even though the travel times produced by the Point-to-Point method with capped speed overestimates the travel time due to the capped speed, the difference between the estimated travel times by the SunGuide method and the actual travel time is small. The travel time estimates obtained using the speed-based methods as well as the developed models were also very close when the traffic is not congested. Compared to the other methods, the Minimum Speed method slightly overestimated the travel time, and the results from the flow-based method and improved N-D method are more fluctuated.

For the congested case, the results shown in Figures 3-10(c) and Figure 3-10(d) indicate that except for the Minimum Speed method, all the other speed-based methods, including the Point-to-Point method with capped speed, underestimated the travel time under congested traffic conditions. This was true for both the on-line and off-line applications. The flow-based method and the improved N-D method performed better. The developed hybrid models also produced travel times that were also close to the actual travel times.

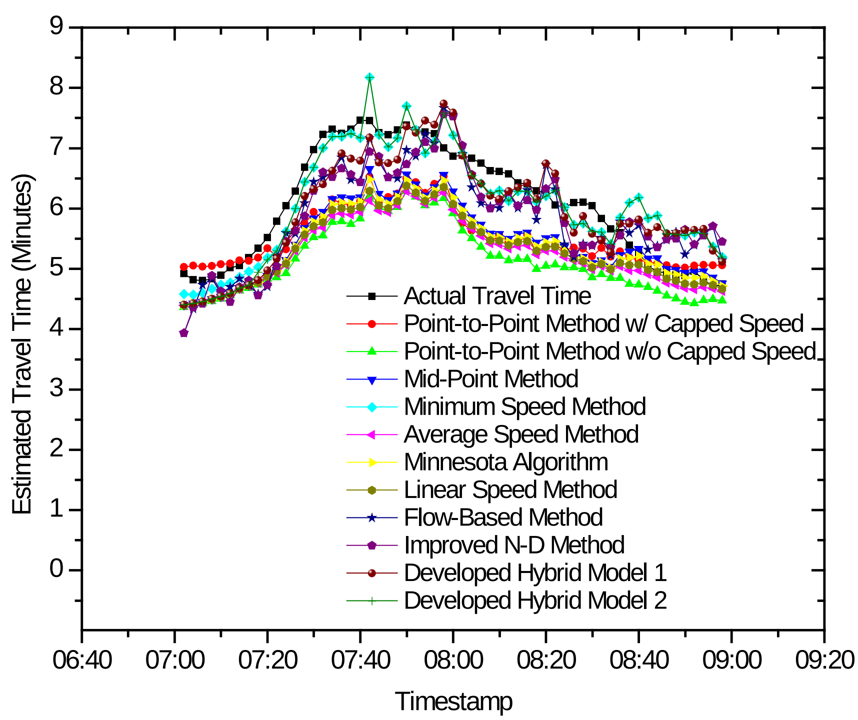


(a) On-Line Estimation Results during Midday on Dec. 2, 2008

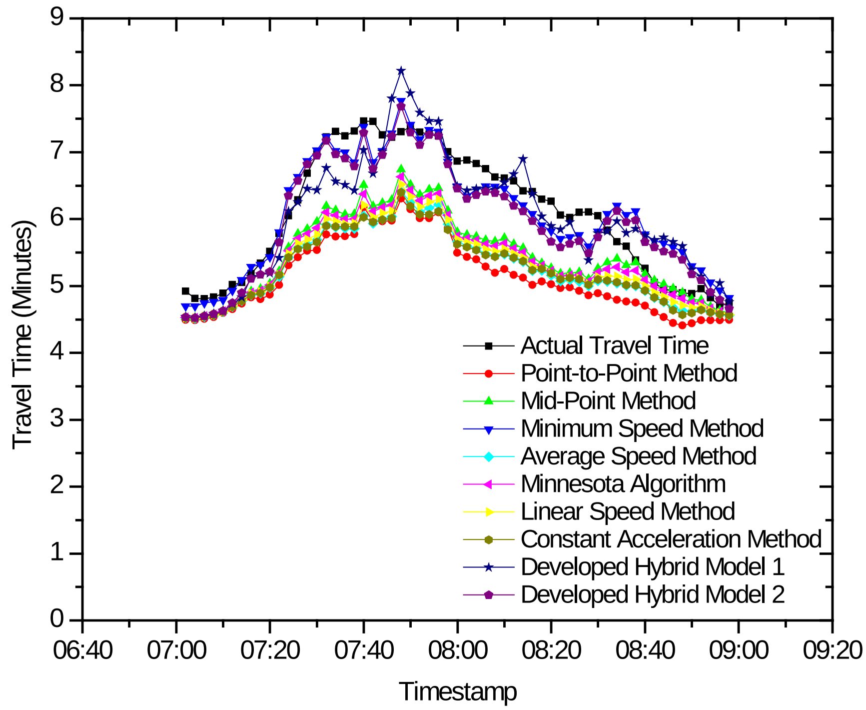


(b) Off-Line Estimation Results during Midday on Dec. 2, 2008

FIGURE 3-10 Estimated Travel Time for Real-world Cases



(c) On-Line Estimation Results during Morning Peak Period on Mar. 10, 2010



(d) Off-Line Estimation Results during Morning Peak Period on Mar. 10, 2010

FIGURE 3-10 Estimated Travel Time for Real-world Cases (Con't)

TABLE 3-7 Accuracy of Tested On-Line Travel Time Estimation Methods for Real-world Cases

Method	**Case 1 (Uncongested)**		**Case 2 (Congested)**	
	MAE (Min.)	**MAPE (%)**	**MAE (Min.)**	**MAPE (%)**
Point-to-Point Method w/ Capped Speed	0.56	11.32	0.65	9.95
Point-to-Point Method w/o Capped Speed	0.14	2.81	0.94	14.78
Mid-Point Method	0.14	2.87	0.66	10.20
Minimum Speed Method	0.23	4.71	0.37	6.31
Average Speed Method	0.14	2.83	0.81	12.66
Minnesota Method	0.14	2.86	0.70	10.86
Linear Speed Method	0.14	2.84	0.76	11.76
Flow-Based Method	0.18	3.56	0.53	8.79
Improved N-D Method	0.20	3.90	0.54	9.03
Developed Hybrid Model 1	0.14	2.87	0.46	7.75
Developed Hybrid Model 2	0.14	2.87	0.39	6.80

TABLE 3-8 Accuracy of Tested Off-Line Travel Time Estimation Methods for Real-world Cases

Method	Case 1 (Uncongested)		Case 2 (Congested)	
	MAE (Min.)	MAPE (%)	MAE (Min.)	MAPE (%)
Point-to-Point Method	0.14	2.71	0.94	14.75
Mid-Point Method	0.14	2.70	0.63	9.68
Minimum Speed Method	0.23	4.67	0.33	5.40
Average Speed Method	0.13	2.66	0.81	12.55
Minnesota Method	0.14	2.68	0.69	10.61
Linear Speed Method	0.13	2.67	0.75	11.65
Constant Acceleration Method	0.13	2.66	0.82	12.63
Developed Hybrid Model 1	0.14	2.70	0.38	6.20
Developed Hybrid Model 2	0.1	2.70	0.35	5.74

Since not all individual vehicle travel times can be collected and the actual travel time distribution is unknown using the collect real-world data, the reliability of the estimated travel time cannot be calculated based on the real-world as was done using data produced using simulation. Thus, only the accuracy performance measures are presented in Tables 3-7 and 3-8. As shown in Table 3-7, the performance of various travel time estimation methods during uncongested conditions (Case 1) are similar to those obtained from simulation. The Minimum Speed method, flow-based method, and the Improved N-D method were slightly less accurate than other methods. For congested conditions (Cases 2), the minimum speed method and Hybrid Model 2 perform the best among the tested methods. The traffic flow method and Hybrid Model 1 also perform relatively well compared to other methods. Comparing the results from the off-line methods with those from the on-line methods indicates that the off-line estimation improved the travel time estimation slightly.

3.4. Impacts of Influential Factors

In addition to the travel time estimation algorithms, factors such as the impacts of data preprocessing procedures, detector errors, and travel time posting strategies are also expected to affect the accuracy and reliability of travel time estimation. Therefore, their impacts on the on-line travel time estimation are investigated in this study. The results discussion presented in this section is using the Hybrid Model 2 as an example, since the impacts of these factors on all other methods generally show the same trend as Hybrid Model 2. The analysis results of the other estimation methods can be found in Appendix C. Note that Hybrid Model 1 and Hybrid Model 2 in these tables refer to the refined on-line hybrid models developed in this study.

3.4.1. Data Preprocessing

Data preprocessing includes data filtering, data smoothing, data aggregation, and data imputation. This study investigates and compares the impacts of different methods to perform these steps on travel time estimation, as described below.

Data Smoothing

In this section, two different smoothing methods are compared: the simple moving average (which is the method used in SunGuide) and the exponential moving average. The simulated incident scenario 1, described in Section 3.3, is used to test the impacts of data smoothing methods on travel time estimation. In this scenario, the estimated travel time is updated every 2 minutes, and the estimation performance is calculated for the time period 7:30 A.M. – 8:30 A.M. Table 3-9 presents the estimation results with these two types of smoothing methods for the on-line Hybrid Model 2. As shown in Table 3-9, for the simple moving average method, the estimation errors generally increase with the increase in the value of rolling period. As mentioned in the previous section, the rolling period is a parameter that controls the moving window size for the determination of number of data points to be used in the moving average. When a large rolling period is used, more historical information will be included in the travel time estimation, which can dilute changes in traffic conditions such as the impacts of queue length changes, thus resulting in higher estimation errors in dynamically changing situations like incident scenarios. It is also seen in this table that a smaller rolling period can achieve better reliability in travel time estimation for incident conditions.

The travel time estimation results obtained using the exponential moving average is also presented in Table 3-9. The smoothing factor in the exponential moving average method can have any value between 0 and 1. A higher value of this smoothing factor reduces the effects of older observations faster. Comparing the results with those calculated from simple moving average indicates that for Hybrid Model 2 and the investigated incident scenario, the exponential moving average method produces more accurate and reliable results than the simple moving average method, since the exponential moving average method can give more weights to the latest data in the smoothing. It should be mentioned that these results are based on simulation analysis that assumes 100% detector measurement accuracy.

TABLE 3-9 Accuracy and Reliability of Travel Time Estimation Using Different Smoothing Methods

Hybrid Model 2	Factor		MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Simple Moving Average	Rolling Period	1-minute	1.44	12.72	63.70	17.17	19.13
		2-minute	1.59	13.86	61.45	16.72	21.83
		3-minute	1.73	15.00	58.93	16.72	24.35
		4-minute	1.89	16.29	56.23	19.01	24.76
		5-minute	2.04	17.72	48.65	24.81	26.54
Exponential Moving Average	Smoothing Factor	0.2	1.49	12.51	69.21	3.33	27.46
		0.4	1.15	10.12	74.50	3.33	22.17
		0.6	1.03	9.28	73.92	4.36	21.71
		0.8	0.99	8.98	74.73	4.54	20.74
		1.0	1.09	9.60	73.23	4.48	22.29

Data Imputation

To test the effects of different data imputation methods, 50% of the detector measurements were randomly removed for the simulated incident scenario 1. As mentioned earlier in this chapter, data imputation can be conducted spatially and/or temporally, and the spatial imputation can be performed within a station or between stations. Therefore, different combinations of these imputation types were tested in this study including with or without within-station imputation for speed, with or without temporal imputation, and four different types of between-station imputations. These four types are the simple average, linear interpolation, linear interpolation for speed and occupancy but factor method for volume, and factor method for all traffic parameters, as mentioned in data preprocessing section. For the factor method, the factors are estimated based on data for all the workdays in December, 2008.

TABLE 3-10 Results of Different Data Imputation Methods

Hybrid Model 2	Temporal Imputation	Between-Station Imputation	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Developed Hybrid Model 2 w/o missing data			1.15	10.12	74.50	3.33	22.17
w/o Within-Station Imputation	w/o Temporal Imputation	Simple Average	1.23	10.72	72.20	4.77	23.03
		Linear Interpolation	1.23	10.70	72.20	4.77	23.03
		Linear Interpolation for S and O, and Factor for V	1.23	10.70	72.20	4.77	23.03
		Factor Method	1.24	10.77	71.97	4.77	23.26
	Average of Temporal and Spatial Imputations	Simple Average	1.23	10.64	72.20	4.77	23.03
		Linear Interpolation	1.22	10.61	72.20	4.77	23.03
		Linear Interpolation for S and O, and Factor for V	1.22	10.61	72.20	4.77	23.03
		Factor Method	1.23	10.64	72.20	4.77	23.03
w/ Within-Station Imputation	w/o Temporal Imputation	Simple Average	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation for S and O, and Factor for V	1.20	10.48	73.58	4.77	21.65
		Factor Method	1.20	10.48	73.58	4.77	21.65
	Average of Temporal and Spatial Imputations	Simple Average	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation for S and O, and Factor for V	1.20	10.48	73.58	4.77	21.65
		Factor Method	1.20	10.48	73.58	4.77	21.65

* S represents speed, V dictates volume count, and O is occupancy.

Table 3-10 shows the impacts of the data imputation methods on the performance of travel time estimation results. It should be mentioned that the performance calculation is based on the time period between 7:30 A.M. and 8:30 A.M. that is heavily impacted by the incident conditions. The results in this table show that the impact of randomly missing data when properly imputed is not high. As mentioned above 50% of the detector measurements were removed. Slight differences in the accuracy of the resulting travel times can be observed from Table 3-10 for different imputation methods.

3.4.2. Detector Errors

Traffic data measured by point detectors include errors of different types:

- Intrinsic error due to measurement noise,
- Systematic error (for example, due to inadequate calibration or device inaccuracy), and
- Data missing due to incidental and/or structural failure resulted from temporary power outages or detector malfunctions.

The impacts of these three types of errors on travel time estimation performance are discussed below.

Intrinsic Error

Intrinsic errors are inherent to detectors and reflect their measurement accuracies. The magnitude of the intrinsic error in measuring a given variables depends on the detector type under consideration. For example, Electronic Integrated Systems Inc. (EIS) the vendor of the RTMS detectors reported that for RTMS detectors from a side fire location; the errors are expected to be 10% in speed, 5% in volumes, 10% in long vehicle volumes, and 5% in occupancy (EIS 2010). To investigate the impacts of such errors on travel time estimation, the detector data resulting from CORSIM were modified to emulate these types of errors. Similar to the study of Byon et al. (2009), a normal distribution was used to introduce the intrinsic errors in the simulated detector data of this study. The used normal distribution has a mean of zero, and a standard deviation determined by device measurement accuracy. It is assumed that 99.7% of measurements are within 6 standard deviations of the mean detector error (zero). This assumption leads to the following equation:

$$6\sigma = 2X_{typical} \times Err \tag{3-38}$$

where σ denotes the standard deviation, X_{typical} is selected to be a common measurement value at the high end of each of the three basic variables (speed, volume, or occupancy), and *Err* is the corresponding measurement error. Measurement at the high end is selected such that the worst case standard deviation is accounted for. This investigation assumes that the speed measurement is within ±10%, volume measurement within ±5%, and occupancy measurement within ±5%. With the assumptions of 65 mph, 1700 veh/hr, and 100%, as typical speed, volume, and occupancy measuremewnts; Equation 3-38 yields the following standard deviations values: 2.2 mph for speed, 28.3 veh/hr for volume, and 1.7 for occupancy.

In this study, the intrinsic errors were introduced in two simulated scenarios: an uncongested scenario and incident scenario 1. For each scenario, 10 random cases were generated and the results are presented in Table 3-11 for Hybrid Model 2 and in Tables C-5 and C-6 (in Appendix C) for other methods. As shown in Table 3-11, the performance of Hybrid Model 2 does not change much with the intrinsic errors introduced for the uncongested scenario. However, the performance is affected by the error for the incident scenario. It should be noted that the results presented in Table 3-11 is with data filtering and imputation. The impacts of intrinsic errors are expected to be higher without proper filtering and imputation and also with higher detector error.

TABLE 3-11 Impacts of Intrinsic Errors on Travel Time Estimation Performance

Hybrid Model 2	Cases		MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Simulated Uncongested Conditions	w/o Intrinsic Errors		0.082	1.31	100	0	0
	w/ Intrinsic Errors	Average	0.083	1.33	100	0	0
		Minimum	0.081	1.30	100	0	0
		Maximum	0.085	1.36	100	0	0
Simulated Incident Conditions	w/o Intrinsic Errors		1.15	10.12	74.50	3.33	22.17
	w/ Intrinsic Errors	Average	1.58	12.87	64.59	4.24	31.17
		Minimum	1.23	10.66	61.17	2.59	22.34
		Maximum	1.75	13.97	71.17	6.49	34.75

Systematic Error

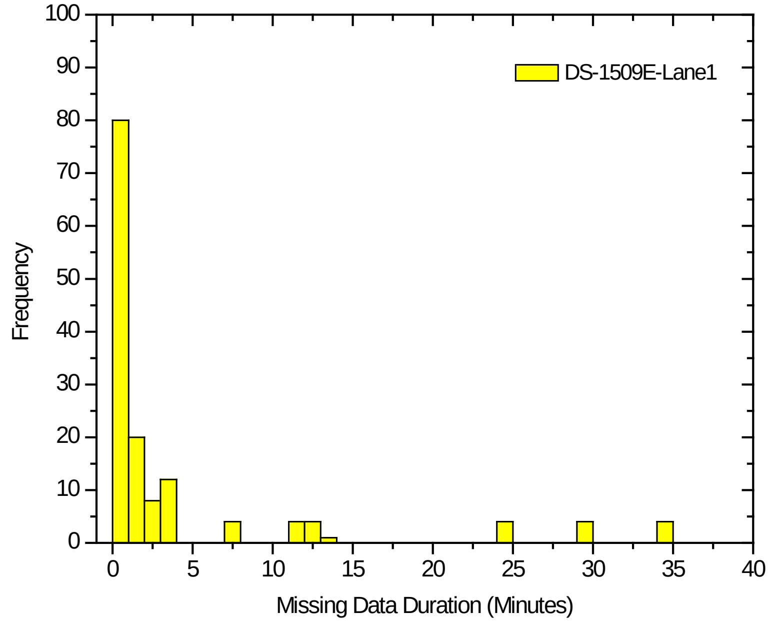
Point detectors are not always well calibrated or have underestimation or overestimation problems in measurements. These are referred to as systematic errors in the reported measurements. The accuracy of some types of point detectors decrease under low speed conditions. To test how such errors in low speed measurements affect the accuracy and reliability of travel time estimation methods, systematic errors are introduced to the perfect simulated detector data when speed is less than 20 mph, and the analysis results are presented below by using Hybrid Model 2 as an example. It is seen from Table 3-12, when the measure low speeds are artificially increased or decreased by 20%, the error of the estimated travel time increased slightly from 10.1% to about 12%. However, with an introduced systematic error of 40% in the measured speeds, the estimated error in travel time increased by 4%-5%, compared to the case without errors in measured speeds. The reliability of travel time estimates decrease significantly when the point detector systematically reports lower speeds than the actual values during the congested conditions, as shown in Table 3-12.

TABLE 3-12 Impacts of Systematic Errors in Low Speed Measurements on Travel Time Estimation Performance for Simulated Incident Conditions

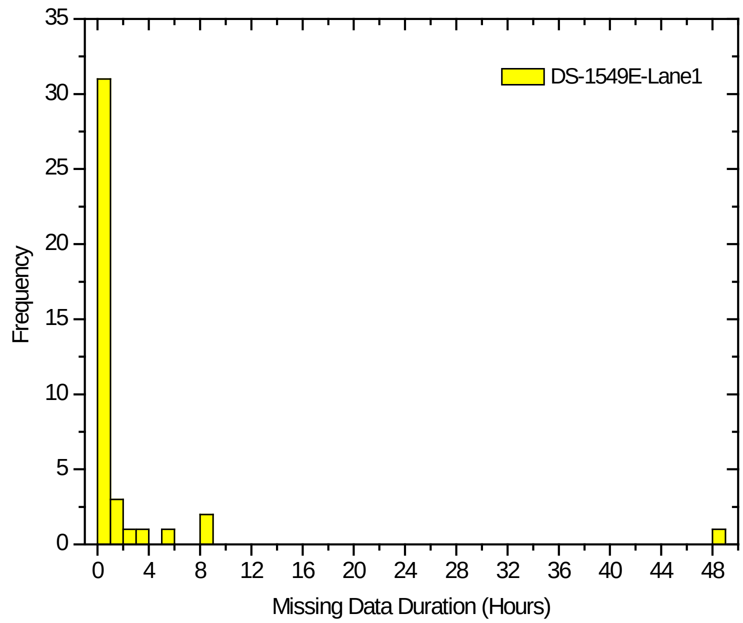
Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Hybrid Model 2	w/o Errors	1.15	10.12	74.50	3.33	22.17
	20% Increase in Low Speed	1.37	11.52	71.97	1.21	26.82
	40% Increase in Low Speed	1.66	13.57	68.18	0.98	30.84
	20% Decrease in Low Speed	1.46	12.33	61.69	16.94	21.37
	40% Decrease in Low Speed	1.88	15.19	57.15	16.83	26.02

Incidental and Structural Failure

In addition to the two types of errors mentioned above, incidental and/or structural failures may also exist in detector data (Vant Lint 2004). The incidental or occasional failure occurs randomly. Various factors may contribute to its occurrence, such as temporary communication system failure resulting from power outrages for example. Figure 3-12 presents histograms of incidental and structural failures for detectors DS-1509E-Lane-1 and DS-1549E-Lane-1, as examples, and also for all the detectors along SR826 in December, 2008. Note that the units of the x-axis in Figure 3-12(a) and Figure 3-12(c) are minutes and those for Figure 3-12(b) and Figure 3-12(d) are hours. Most of the missing data duration is less than 2 minutes.

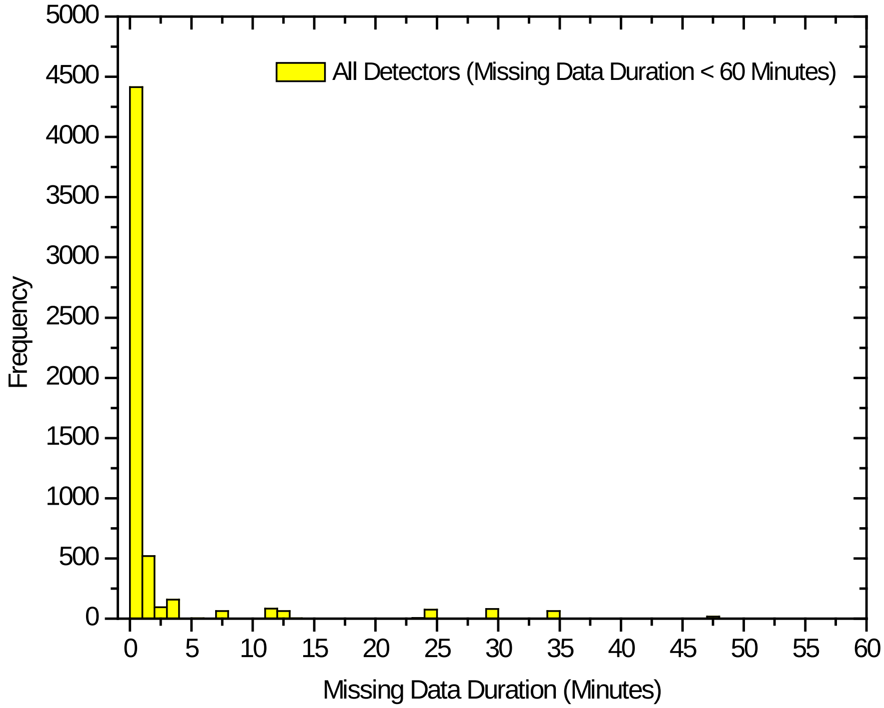


(a)

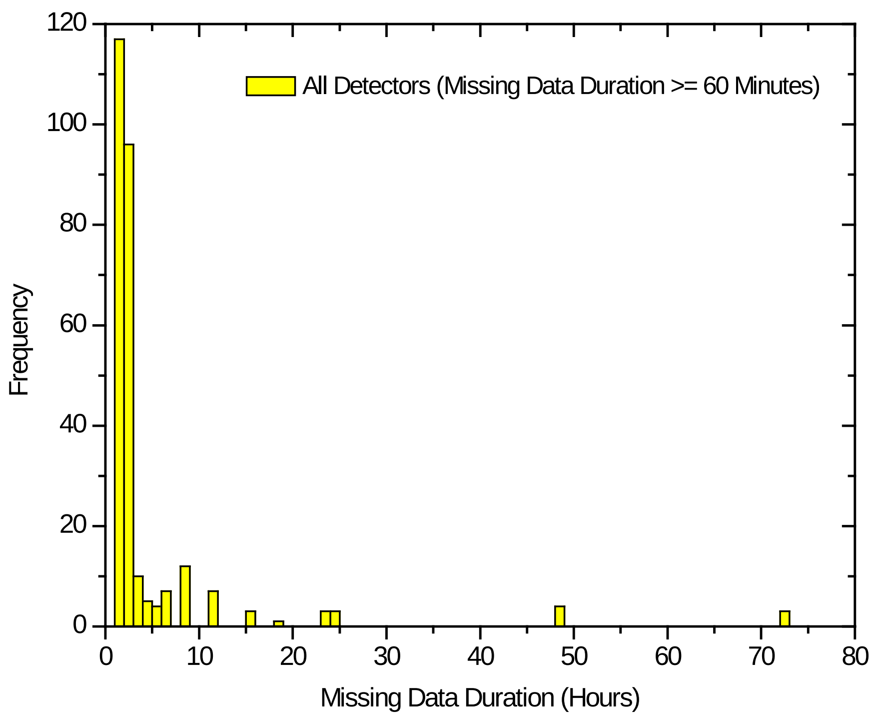


(b)

FIGURE 3-12 Examples of Incidental and Structural Failures



(c)



(d)

FIGURE 3-12 Examples of Incidental and Structural Failures (Con’t)

To quantify the impacts of incidental and structural failures, worst case scenarios were created by introducing failures to the error-free simulated detector data. These failure scenarios were created based on what happens in real-world detector data during the study period in December, 2008. Since a detector may fail more than once, the longest duration of the missing data during the failure period was used.

Table 3-13 shows the impacts of incidental and structural failures on travel time estimation performance during both uncongested and incident conditions. The results in this table show that, even with the worst case of incidental and structural failures, after imputing the missing data, these failures do not have high impacts on the estimated travel time accuracy for the uncongested conditions. However, for the incident scenario, the existence of incidental and structural failures can result in large increase in estimation errors and also reduction in reliability. This can be explained by the fact that even though the data imputation procedure is applied to replace the missing data during incident conditions, due to fast changes in traffic conditions, the filled data may not be able to completely capture such changes, resulting in a less satisfying performance.

TABLE 3-13 Impacts of Incidental and Structural Failures on Travel Time Estimation Performance

Hybrid Model 2	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Simulated Uncongested Conditions	w/o Errors	0.08	1.31	100	0	0
	w/ Incidental and Structural Errors	0.10	1.54	100	0	0
Simulated Incident Conditions	w/o Errors	1.15	10.12	74.50	3.33	22.17
	w/ Incidental and Structural Errors	1.95	17.58	62.44	15.45	22.11

3.4.3. Travel Time Posting Configurations

Travel time posting strategies, such as travel time updating frequency, travel time link length, and the range of posted travel time are also expected to affect the accuracy and reliability of travel time estimates. This section includes the results of tests conducted in this study to investigate the impacts of these influential factors.

Travel Time Updating Frequency

Sensitivity analysis is conducted in this study to understand the impacts of the travel time updating frequency on the accuracy and reliability of travel time estimates. Updating frequencies ranging from 1 to 5 minutes are included in the analysis. Table 3-14 displays the travel time estimation results for the simulated uncongested conditions and incident conditions as well. The results in this table indicate that for the uncongested conditions, a longer travel time updating interval does not lead to worse estimation performance, since the traffic is relatively stable under uncongested conditions. But for the incident scenario, it is seen that the errors increase and the reliability is reduced with the increase in travel time update interval. This indicates that a more frequent updates in travel time estimates is preferred for incident conditions due to the varying traffic conditions during incidents.

TABLE 3-14 Travel Time Estimation Performances with Different Travel Time Updating Frequencies

Hybrid Model 2	Updating Frequency	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Simulated Uncongested Conditions	1-minute	0.10	1.62	100	0	0
	2-minute	0.08	1.31	100	0	0
	3-minute	0.07	1.16	100	0	0
	4-minute	0.07	1.15	100	0	0
	5-minute	0.07	1.06	99.89	0.11	0
Simulated Incident Conditions	1-minute	1.16	10.21	74.24	2.58	23.18
	2-minute	1.15	10.12	74.50	3.33	22.17
	3-minute	1.31	11.31	70.55	4.64	24.81
	4-minute	1.35	11.85	55.38	17.69	26.93
	5-minute	1.34	11.25	69.56	6.86	23.58

Travel Time Link Length

To show the impacts of travel time link lengths, four different travel time links are defined as follows:

- DS-1523E – DS-1549E (Distance: 4.24 miles)
- DS-1521E – DS-1549E (Distance: 4.55 miles)
- DS-1517E – DS-1549E (Distance: 5.27 miles)

- DS-1509E – DS-1549E (Distance: 6.42 miles)

Table 3-15 presents the travel time estimation accuracy and reliability for these defined travel time links under the uncongested and incident 1 scenarios. The mean absolute errors are seen to increase with the increase in the link length. However, the mean absolute percentage errors do not monotonically change with such increase in distance as this performance measure is also related to the actual travel time for the studied travel time link. The reliability does not necessarily decreases as the distance increases since the reliability is also determined by the range of posted travel time. Similar conclusions can be obtained based on the results in Table 3-15 for the incident conditions. Any conclusions based on the reported results are limited to the range of the increase in length investigated in this study.

TABLE 3-15 Travel Time Estimation Performances with Different Travel Time Link Lengths

Hybrid Model 2	Origin-Destination	Distance (Miles)	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Simulated Uncongested Conditions	DS-1523E-DS-1549E	4.24	0.05	1.16	100	0	0
	DS-1521E-DS-1549E	4.55	0.05	1.15	99.69	0.08	0.23
	DS-1517E-DS-1549E	5.27	0.06	1.09	100	0	0
	DS-1509E-DS-1549E	6.42	0.08	1.31	100	0	0
Simulated Incident Conditions	DS-1523E-DS-1549E	4.24	0.88	13.69	91.40	0	8.60
	DS-1521E-DS-1549E	4.55	1.05	13.50	81.94	4.59	13.47
	DS-1517E-DS-1549E	5.27	1.05	10.90	75.52	3.38	21.10
	DS-1509E-DS-1549E	6.42	1.15	10.12	74.50	3.33	22.17

Posted Travel Time Range

As mentioned above, the FDOT District 6 divides the estimated travel time into four categories: less than 5 minutes, between 5 and 10 minutes, between 10 and 35 minutes, and greater than 35 minutes (FDOT District 6 2010). The corresponding ranges of travel time for these four categories are under 5 minutes, 3-minute range around the estimated travel time, 5-minute range around the estimated travel time, and over 35 minutes; respectively.

Sensitivity analysis is conducted to see how the reliability of travel time estimation changed by adjusting the posted travel time range. The corresponding estimation performance is listed in Table 3-16. This table shows that for uncongested conditions, the reliability of the posted travel time is close to 100% even when the posted travel time range is decreased to 2 minutes. However, if the travel time range is further reduced to one minute, the reliability of the estimated travel time is significantly impacted.

Note that the posted travel time range in Table 3-16 for incident conditions is mainly for travel time estimates that are greater than 10 minutes, due to the congestion caused by the incident. It can be seen from this table that if the upper value of travel time range is increased to higher than 3 minutes, the reliability of the estimated travel time does not improve. This indicates that this is not beneficial. Decreasing the lower rang to 1 minute reduces the reliability.

TABLE 3-16 Travel Time Estimation Reliability with Different Posted Travel Time Ranges

Hybrid Model 2	**Range of Posted Travel Time**	**Reliability (%)**	**% Early**	**% Late**
Simulated Uncongested Conditions	[TT-2, TT+2]	100	0	0
	[TT-1, TT+2]	100	0	0
	[TT-1, TT+1]	99.29	0	0.71
	[TT-0.5, TT+0.5]	70.07	0.42	29.52
Simulated Incident Conditions	[TT-2, TT+3]	74.50	3.33	22.17
	[TT-2, TT+4]	75.88	3.33	20.79
	[TT-2, TT+5]	75.88	3.33	20.79
	[TT-1, TT+4]	69.67	9.54	20.79
	[TT-1, TT+5]	69.67	9.54	20.79
	[TT-1, TT+6]	70.25	9.54	20.22

3.5. Conclusions

A review of previous studies indicates that although speed-based methods similar to those used in the SunGuide software can produce acceptable results at lower levels of congestion, there are questions regarding their abilities to produce accurate and reliable estimates of travel times under recurrent and non-recurrent congested conditions. This study has developed two hybrid on-line travel time estimation models and two corresponding off-line methods to estimate freeway travel times based on point detector measurements. Hybrid Model 1 combines the Mid-Point method (which is similar to the SunGuide method) with a traffic flow-based method. Hybrid Model 2 combines the Mid-Point method with the Minimum Speed method. The switching between the travel time estimation methods within each model is accomplished based on the congestion levels and queue status. In addition, during incident conditions with fast changing queue lengths, refinements are introduced to the developed models to account for the fast queue prorogation and recovery.

The travel time estimates obtained from existing speed-based methods, traffic flow-based method, and the developed models are tested by using both simulation and real-world travel time data as ground truth data. The performance measures for these methods are quantified in terms of accuracy as well as reliability. The results indicate that all of the tested methods perform at acceptable and comparable levels at low congestion levels. However, their performances vary with the increase in congestion levels. The comparison with other estimation methods shows that the developed hybrid models perform well in all cases. Further comparisons between the on-line and off-line travel time estimation results reveal that off-line methods perform significantly better only during fast changing congested conditions such as during incidents. The difference in performance between the on-line and off-line methods increases with the increase in congestion levels.

During low congestion levels, the Minimum Speed method and flow-based methods produce slightly less accurate results compared to other methods. However, the difference is not significant. For moderately recurrent congested conditions assessed using real-world travel time measurements, the minimum speed method and Hybrid Model 2 perform the best among the tested methods. The traffic flow method and Hybrid Model 1 also perform relatively well compared to other methods. Comparing the results from the off-line methods with those from the on-line methods indicates that the off-line estimation improves the travel time estimation slightly.

For fast changing conditions during incidents; simulation results indicate that the SunGuide method underestimates the travel time during the queue forming stage, and overestimate the travel time at the end of lane blockage. Similar trends can be found for other methods at varying degrees depending on the tested method and the degree of congestion. The flow-based methods, the Minimum Speed method, and the developed hybrid models perform better than other speed-based models. However, they also overestimate the travel times at the later stages of lane blockage due to the effect of the front recovery shockwave during incident clearance. This overestimation becomes higher with the increase in the queuing severity during incidents. The refinements introduced to account for queue propagation and recovery stages are proposed to deal with these estimation problems.

Based on the results of this study, it is recommended that the Minimum Speed Method and/or the Hybrid Model 2 developed in this research are considered for implementation and testing in SunGuide. This recommendation is based on these model performances and the ease of their implementations compared to traffic flow models. The refinements to account for queue growth and dissipation dynamics should be also considered.

SunGuide includes a limited real-time testing for detector errors. Additional real-time testing for erroneous detector data is presented in this document and is recommended for use in the SunGuide software. The impacts of major influential factors, such as data preprocessing procedures, detector errors, and travel time posting strategies, on the performance of travel time estimation, are investigated in this study. The sensitivity analysis results show that these factors do not have significant impacts on the estimation accuracy and reliability during the uncongested conditions, however, for the incident conditions, the travel time estimation requires the usage of a short rolling period for data smoothing, more accurate detector data, and frequent travel time updating to achieve better performance.

The results of the investigation presented in this document indicates that the spatial imputation method used in the SunGuide software to account for missing data appears to perform as good as other investigated methods. When estimating travel time during incident conditions, the use of the exponential moving average produces more accurate and reliable results compared to the simple moving average method, since the exponential moving average method can give more weights to the latest data in the smoothing and can account better for the fast changing dynamic conditions during incidents. When using the simple moving average method during incident conditions, shorter rolling time intervals produce better results.

The results of the study also show that intrinsic errors due to measurement noise, systematic errors (for example, due to inadequate calibration or device inaccuracy), and data missing due to incidental and/or structural failure can affect negatively the performance of travel time conditions during congested conditions but not uncongested conditions.

The results from this study indicates that for uncongested conditions, a longer travel time updating interval does not lead to worse estimation performance, since the traffic is relatively stable under uncongested conditions. For incident scenarios, the errors increase and the reliability decreases with the increase in travel time update interval. The errors also increase with the increase in the travel time link length under incident conditions. It appears that a posted travel time range of two minutes generally produces good results. However, if the travel time range is further reduced to one minute, the reliability of the estimated travel time is significantly impacted.

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4. Estimation of Traffic Diversion

4.1. Introduction

A number of technologies are used for disseminating traveler information, such as highway dynamic message signs (DMS), Highway Advisory Radio (HAR), traveler information telephone systems, and web sites. One of the most important parameters for assessing the impacts and benefits of these deployments is the diversion rates under different incident and traffic conditions. The estimation of the diversion rate is important to justify the deployments from a cost and benefit point of view. In addition, the estimation will support the assessment of the guidelines and procedures of information dissemination. Estimating the percentages of travelers likely to divert to alternative routes also allows better estimation of the impacts on the alternative routes and the optimization of signal timings on these routes during incident conditions. In this research, a method was developed to estimate traffic diversion based on the traffic detector and incident data.

4.2. Literature Review

Researchers have used Stated Preferences (SP) and Revealed Preference (RP) to estimate the the percentages of travelers diverted due to information provision. The SP methods involves conducting a survey of travelers that usually includes presenting a series of hypothetical scenarios to be evaluate. The travelers are asked to make discrete choices between travel alternatives under different conditions. On the other hand, the RP approaches use field data collection techniques to evaluate the effectiveness of ATIS technologies on drivers' route choice behavior. The advantage of the SP approach is the ability to control the choice content and the independent variables that will be entered into the demand model. The disadvantages of the approach are related to the fact that individuals are not committed to behave in accordance with their stated preference responses.

Several studies (Madanat et al. 1995, Peeta el al. 2000, Wardman et al. 2003) have conducted SP surveys to evaluate the drivers' responses to DMS and other ATIS devices. Peeta et al. (1995) conducted three different types of surveys (mail back, on-site, and web-based surveys) to estimate the driver's response to DMS. The aim of the survey questionnaire used in this study was to obtain information about drivers' response to DMS (driver's willingness to use the information posted on the DMS or not). The responses were related to driver's familiarity with alternate roadways, estimated trip time, and socio-economic characteristics. From this study, it was revealed that the content of the message disseminated had a significant impact on drivers' responses; for example, drivers were more willing to divert to alternate routes when the message posted on DMS indicated that the incident type is accident. Khattak et al. (1993) found that significantly more commuters diverted to alternate routes when the motorists where informed that the queue length was higher. Another study conducted by Madanat (1995) concluded that approximately 5% of the drivers surveyed were willing to divert when the delays expected were greater than half an hour. An SP study conducted by Huchingston et al. (2005) in Chicago showed that travelers are more willing to divert during the non-recurring conditions as opposed to daily rush hour congestion. Commuters were more willing to take alternate routes when the incident occurred in the morning peak hours dominated by home-work trips.

In general SP surveys concluded that the disseminated information can result in up to 60% to 70% of freeway traffic exiting the freeway ahead of an incident location (Barfield et al. 1989, Benson 1996, Madanat et al. 1995, Chatterjee et al. 2002). However, limited information is available about the actual diversion due to traveler information as reflected by field measurements (revealed preference). Several European field studies have found that DMS compliance rates range from 27% to 44% (Tarry and Graham 1995). Knopp et al. (2009) in another European study found that for major incidents, up to 50% of travelers take another route. Luk and Yang (2003) developed a simulation modeling framework to assess the performance of Advanced Traveler Information Systems (ATIS) under different conditions. They assumed the average diversion rate to be 15% and the highest diversion rate to be 30%. Cragg and Demetsky (1995) used the CORSIM microscopic simulation tool to analyze route diversion strategies from freeways to arterial roads. The study concluded that there was often an optimal diversion percentage beyond which the system delays increased. This diversion percentage is expected to be different for different systems depending on traffic and incident conditions on the original and alternative routes.

With the advent of ITS, enormous traffic data is being generated daily by the ITS devices deployed on the freeway systems. As such, interest has increased in using such data to better the transportation decision making processes. Huo and Levinson (2006) conducted a study to evaluate the effectiveness of DMS located on the I-35E corridor in Minnesota. A total of 45 messages displayed under different incident conditions were studied. Based on the five-minute interval traffic data from loop detectors (including both mainline and ramps), a weighed probit model was developed to estimate diversion behavior. They found that the content of the message displayed on DMS had a significant impact on diversion behavior. After DMS installation, travel time was reduced by 6.4% and the delay was reduced by 5%, with a diversion of about 8%.

The review of literature conducted in this study indicated that additional research is needed to develop methods to estimate driver diversion based on archived ITS data. The objective of this task is to develop such a method. The method should allow the estimation of the diversion rates without requiring measurements from on-ramp and off-ramp detectors since on-ramp and off-ramp detectors are not normally installed in typical ITS deployments in Florida.

4.3. Methodology

The first step in the methodology of this study to determine the average diversion rate for a given corridor is to extract the attributes of a sample of the incidents that occur on the corridor from the incident database. A set of criteria should be set for the selection of incidents, depending on the purpose of the study. The selected incidents have to be associated with measurements from traffic detector stations at locations upstream and downstream of the incident location. This association allows the determination of the diversion rate at each detector location based on detector measurements. The methodology of this study estimates diversion rates based on calculating the difference in the cumulative traffic volumes between an average typical non-incident day and the incident day based on traffic detector measurements. Therefore, the average "typical" non-incident day and incident day traffic volumes should be determined before the actual diversion rate is calculated.

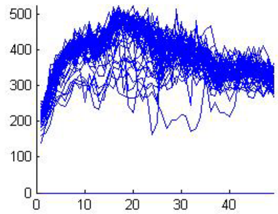
4.3.1. Demand Estimation

As mentioned above, the cumulative volumes for the no-incident and incident days are required for the methodology of this study. These volumes are obtained based on data collected by traffic detection stations. The volumes for the incident day will need to be obtained by extracting traffic detector measurements for the incident day. This will require the association of the time and location of the incident with the traffic data from detectors.

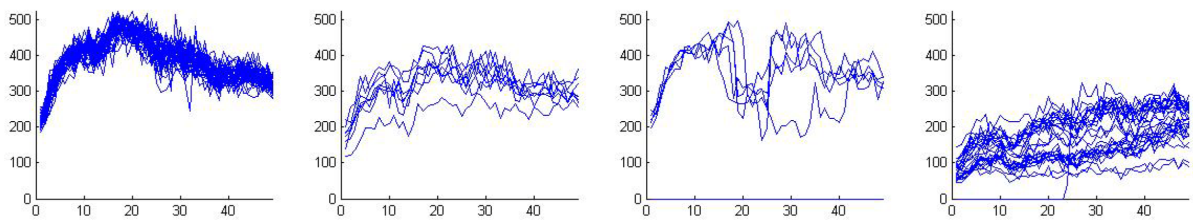
Another necessary step is the calculation of the average cumulative volume for typical non-incident days that have traffic demand patterns similar to the expected demand pattern during the incident day, if the incident does not occur on that day. The procedure described below is utilized to obtain this volume.

The identification of the typical non-incident days was accomplished using the *k*-means clustering algorithm as discussed in another FDOT research project conducted by the authors (Hadi et al. 2010). The algorithm utilizes the time-variant detector measurements at each detection station to classify the days into groups with similar traffic patterns. By examining these patterns, the analyst can clearly identify the typical day pattern that is expected to be similar to the incident day pattern, if no incident occurs.

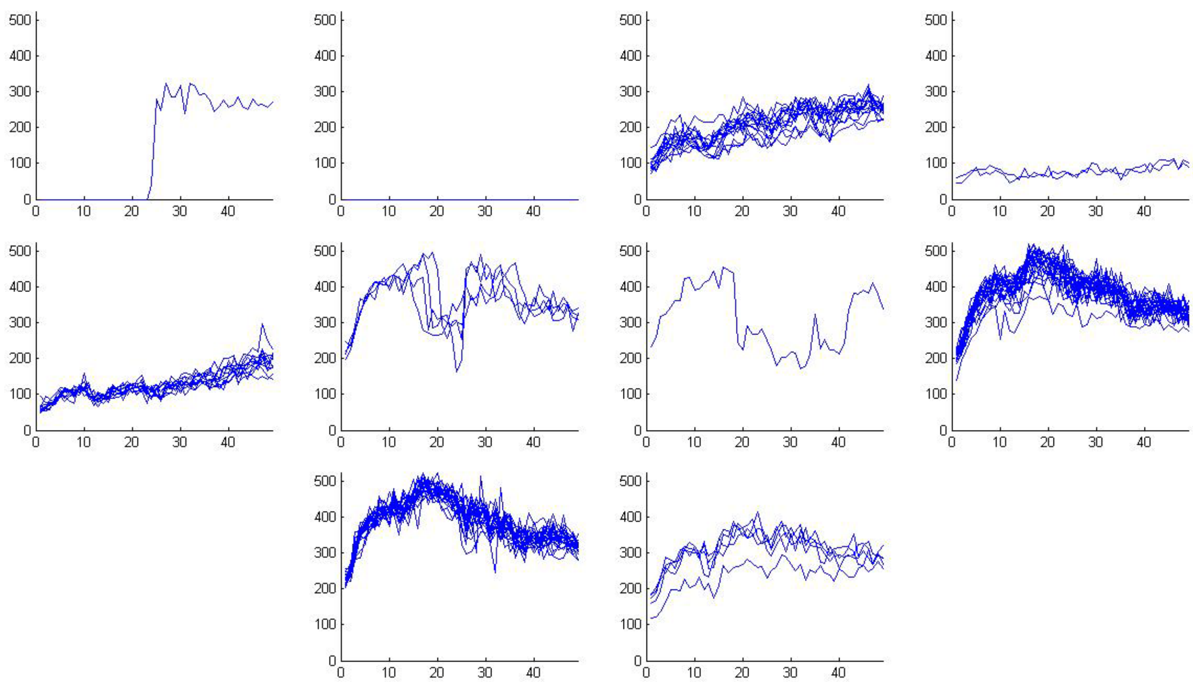
The developed module to cluster the days into different groups as mentioned above gives analysts the option of specifying the number of clusters that derive from the analysis. Figure 4-1 shows the results of applying the data selection procedure to a set of 40 days using different numbers of clusters. The initial dataset contains weekdays, weekends, and days with incidents, bad weather, special events, and/or detector malfunctions. Clearly, the greater the number of clusters used, the more homogeneous each cluster will be. However, too many clusters will not be useful since in most cases the aim of the analyst is to identify major differences in the patterns, and thus be able to simulate a limited number of patterns. Figure 4-1 shows the results of the clustering when specifying two, four, and ten as the number of patterns resulting from the clustering procedure. As can be seen from Figure 4-1(a), specifying two patterns is not sufficient, since the algorithm basically classifies the days into a weekday and a weekend pattern. Figure 4-1(b) shows the results of requesting four patterns to be produced. The procedure was able to classify the patterns in two different weekday clusters. The first cluster from the left in Figure 4-1(b) represents weekdays with higher demand compared to those days represent by the second pattern from the left in the figure. The third pattern from the left represents incident days and the fourth pattern represents weekends. Figure 4-1(c) shows the results of the analysis when ten patterns are specified. By examining the resulting patterns and the associated information, the analyst can determine which cluster to use as a cluster for typical days that are expected to have similar traffic patterns to that of the incident day, if no incident occurs It is interesting to note that the second pattern from the left in Figure 4-1(c) does not have any detector measurements. These patterns represent days in which the detection station at this location malfunctioned. More details about the clustering procedure and the associated tool developed to facilitate the implementation of the procedure can be found in the Hadi et al. (2010).



(a) Two clusters. Vertical axis is traffic volume per 5 min and horizontal axis is time in minutes.



(b) Four clusters. Vertical axis is traffic volume per 5 min and horizontal axis is time in minutes.



(c) Ten clusters. Vertical axis is traffic volume per 5 min and horizontal axis is time in minutes.

FIGURE 4-1 Clustering Results Using Different Numbers of Clusters

4.3.2. Diversion Rate Estimation

To estimate the diversion rate, the methodology requires calculating the average demands for the days that are in the cluster selected for use to represent a typical day, as explained in the previous step. These demands are assumed to represent the demands during the no incident day, if no incident occurs. After the typical days are obtained, as described above, it is possible to construct the cumulative volume curves for these days, as shown in Figure 4-2, and to estimate the diversion rates based on the traffic demands, as described below.

The accumulations of volumes used in the calculation should include the period while the queue exists, as shown in Figure 4-2. Figure 4-2(a) shows that under the no diversion conditions, the cumulative arrival and departure volumes by the end of the incident will be the same. Figure 4-2(b) shows that if diversion occurs, the cumulative arrival volume will be higher than the cumulative departure volume by the end of the incident. The difference between the two cumulative volumes represent the number of vehicles diverted.

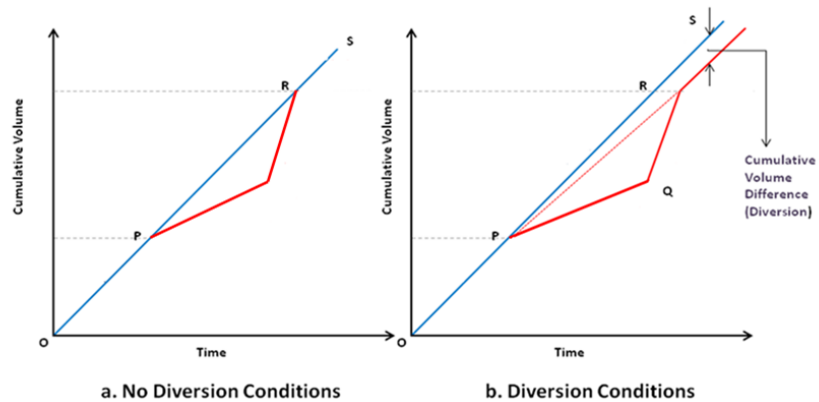


FIGURE 4-2 Cumulative Volume Curves under Diversion and no Diversion Scenarios

For each incident selected from the incident database, the cumulative traffic volumes based on detector data aggregated at five-minute intervals were calculated for each traffic detector station and for both the average typical non-incident days and incident days. Traffic diversion was then estimated as the cumulative volume difference between the average normal traffic day and the incident day over the analysis period. The calculation method is explained below.

Let V_{ijN} denotes the volume for time interval 'i' at detector station 'j' during normal traffic day conditions and $V_{ijI,}$ denote the volume for the time interval 'i' at detector station 'j' during a specific incident day conditions. Then:

$$\text{Diversion Rate (\%) due to the incident} = \frac{\sum_{i=t}^{t+\Delta t} V_{ijN} - \sum_{i=t}^{t+\Delta t} V_{ijI}}{\sum_{i=t}^{t+\Delta t} V_{ijN}} \times 100 \qquad (4\text{-}1)$$

One of the challenges of the methodology described above is to identify the analysis period for which the cumulative curve has to be calculated. As described above, the period should include the period while the queue exists. This study has evaluated several criteria for analysis time period selection and has chosen to use the time period from the detection of an incident to fifteen minutes after all travel lanes are reopened. If the lane reopen timestamp is missing, the calculation will use one hour after the incident detection as the end of the analysis time period. In this study, three immediate upstream detectors and the first downstream detector are chosen for the normal day and incident day volume calculations. However, the analysts can select other detectors based on their requirements. Statistical Analysis

Once the diversion rates for each selected incidents are calculated, they are saved to a database together with incident and traffic attributes during the incident for statistical analysis. Regression analysis allows the development of models to estimate the influence of incident and traffic attributes on diversions. In linear regression, the dependent variable *Y* is a linear combination of the parameters, which can be expressed as follows:

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + ... + e_i \qquad (4\text{-}2)$$

In Equation 4-2, *Y* is the dependent variable, X_i are the independent variables, α_i are the coefficients, and e_i is the residual (error term). It should be noted that in multiple linear regression, functions or transformations of the independent variables are permitted. In linear regression analysis, the goal is to minimize the s used as the goodness-of-fit measure for regression analysis. The R^2 is defined as one minus the ratio of the sum of squared estimated errors to the sum of squared deviations about the mean of the dependent variable. It takes a value between zero and one, and a higher value of R^2 indicates that the developed regression model is able to better explain the variation in the dependent variable. Linear regression analyses assume that the dependent variable is normally distributed. This assumption can be evaluated using the Analysis of Variance (ANOVA) table. The ANOVA analysis outputs a p-value, which is the smallest level of significance at which the null hypothesis can be rejected. In addition, there is a possibility that two identified independent variables may be closely related, thus resulting in a multi-collinearity problem. The Variance Inflation Factor (VIF) values for the independent variables are chosen to evaluate the collinearity in the regression analysis. Overall, the R^2, standard error, F-statistics, p-values, t-values, and VIF values are used to measure the quality of regression analysis.

There are two categories of variables that need to be retrieved for use in the regression analysis. One category include incident and traffic condition attributes that are directly measured by the ITS system and can be extracted from the SunGuide incident and traffic databases. The second category includes estimates of queues and delays that were calculated using the deterministic queuing equation in this study. Two models were developed in this study based on the incident attributes. The first includes the two categories of attributes mentioned above and the second does not include the estimates of queuing and delay attributes to determine if the performance of the model improved with the inclusion of the queuing and delay attributes

.

As stated above, the queuing attributes were calculated using the deterministic queuing theory equations. The calculated attributes include the time duration in queue, maximum queue length, maximum individual delay, and total delay. The used equations can be found in standard traffic flow theory text book but are listed below for convenience.

$$t_Q = t_R(\mu - \mu_R) / (\mu - \lambda) \tag{4-3}$$

$$Q_M = t_R(\lambda - \mu_R) \tag{4-4}$$

$$d_M = 60 t_R(\lambda - \mu_R) / \lambda \tag{4-5}$$

$$TD = t_R t_Q(\lambda - \mu_R) / 2 \tag{4-6}$$

where,

t_Q = time duration in queue, in hours;

Q_M = maximum queue length in vehicles;

d_M = maximum individual delay in minutes;

TD = total delay in vehicle-hours;

t_R = incident lane blockage duration;

μ = capacity in vph;

μ_R = reduced capacity under incident condition in vph; and

λ = arrival rate in vph.

To be able to solve Equations 4-3 through 4-6; the arrival rate, incident lane blockage duration, freeway capacity, and the reduced freeway capacity under incident conditions must be known. The approach to estimate the arrival rate has been discussed previously in this chapter. The Highway Capacity Manual (HCM) procedures are used to calculate the freeway capacity for the incident site with no incident. The remaining capacity during lane blockage incidents was calculated using capacity reduction factors presented HCM procedure. Table 4-1 shows the available capacity under incident conditions for different lane blockage conditions according to the HCM.

TABLE 4-1 Proportion of Freeway Segment Capacity Available under Incident Conditions

Number of Freeway Lanes by Direction	One Lane Blocked	Two Lanes Blocked	Three Lanes Blocked
3	0.49	0.17	0
4	0.58	0.25	0.13
5	0.65	0.4	0.2

4.4. Process Automation

The manual application of the method described above for calculating diversion rates is time-consuming. Therefore, the proposed methodology was implemented as part of a computer program to automate the process. This computer program contains three modules: the first is to select potential incidents to include in the analysis based on the criteria identified by the user. The selection criteria can consider attributes such as the analysis corridor(s), direction of the freeway, day of year, time of day, incident type, and lane blockage condition. The second module implements the pattern identification algorithm used to determine the typical no-incident day traffic volumes. The third module performs the actual traffic diversion rate calculation based on the extracted information.

Figure 4-3 shows the incident selection interface. For each selected incident, relevant attributes from the SunGuide database are displayed for the analysts to identify potential “good” candidates to include in the analysis. These attributes, as shown in Figure 4-4, include the timestamps for the activities of different responding agencies, number of lanes blocked, and other associated attributes. In addition, the visualization of volume drops during incident also serves as a check of the impacts of each selected incident to allow the analyst to determine if it should be included in the analysis. As an example produced using the developed tool, Figure 4-5 shows the volumes extracted for an analysis period for three upstream and three downstream detectors. When the analyst decides to proceed with calculating the diversion rate for a given incident, the next step is to identify the regular day traffic demands. Figure 4-6 shows the traffic pattern selection interface. At this step, the user will have a chance to adjust the definition of the analysis period for each incident. The default definition of the analysis time period is from the start of the incident to fifteen minutes after all travel lanes are reopened or one hour after incident start when the lane reopen timestamp is missing. It is recommended that general users should stick to the default analysis time period definition. The user is also able to adjust the number of patterns, which is needed as described in Section 4.3.1. Figure 4-7 shows seven generated traffic patterns. In this case, patterns 3 and 4 are selected to represent average typical day conditions. The demands of all days in these two clusters are averaged and used as a typical no-incident regular day traffic demands. Finally, the developed tool uses Equation 4-1 to calculate the diversion rate and result is shown as in Figure 4-8.

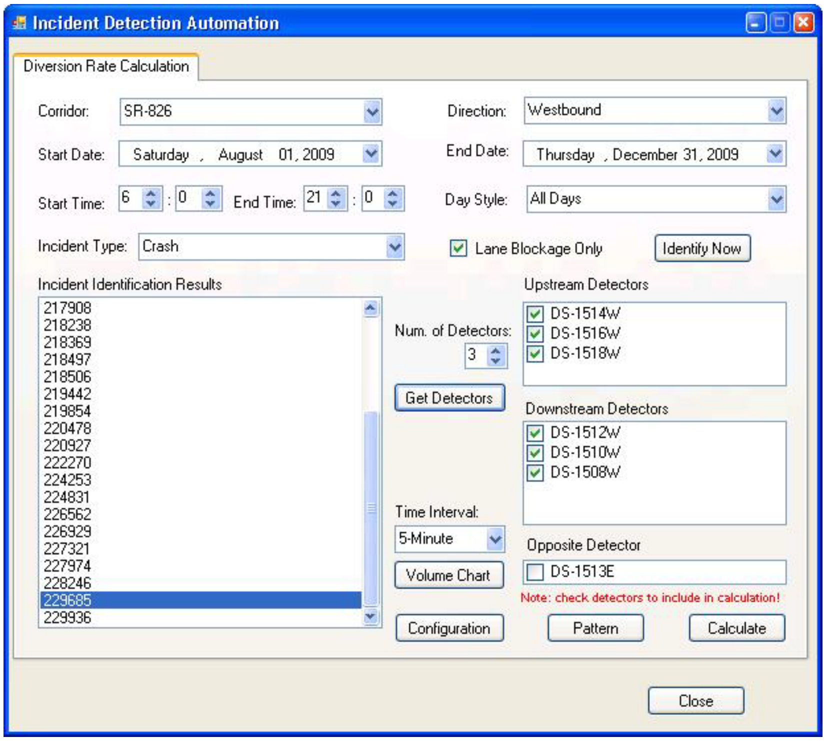


FIGURE 4-3 Diversion Rate Calculation User Interface

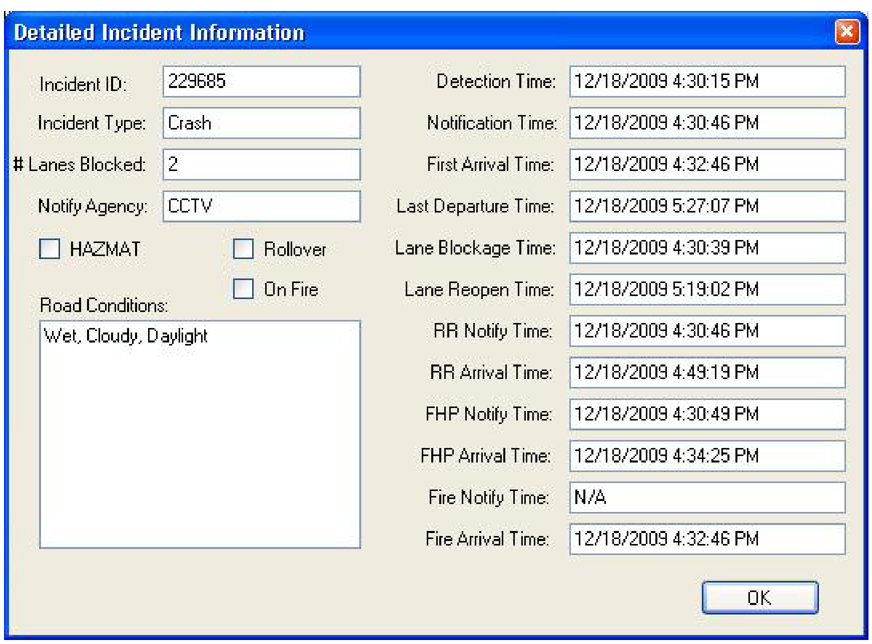


FIGURE 4-4 Attributes for a Selected Incident

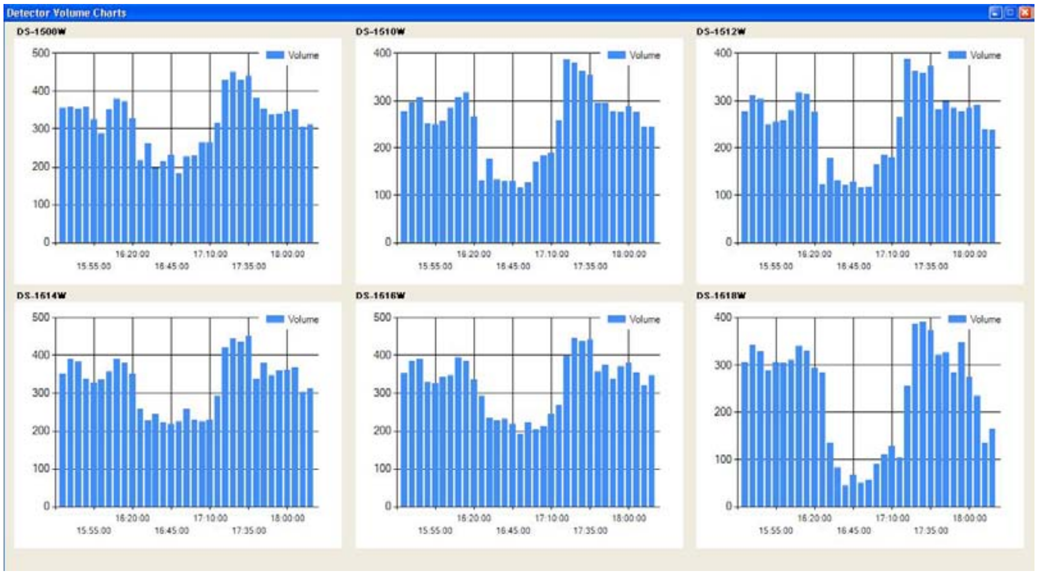


FIGURE 4-5 Volume Charts for Adjacent Detectors

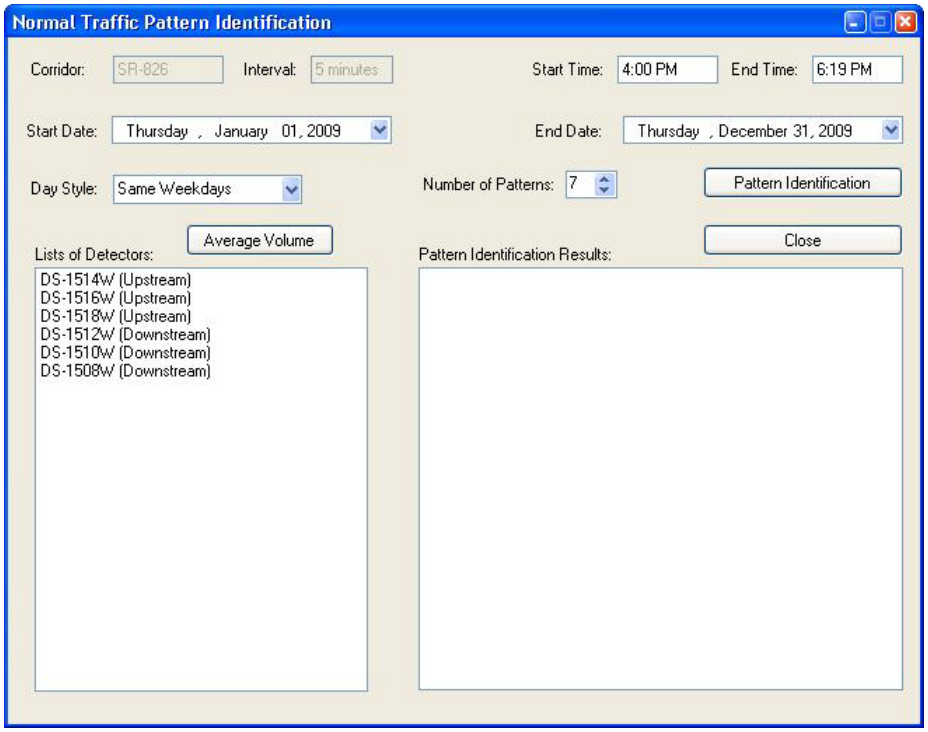


FIGURE 4-6 Pattern Selection

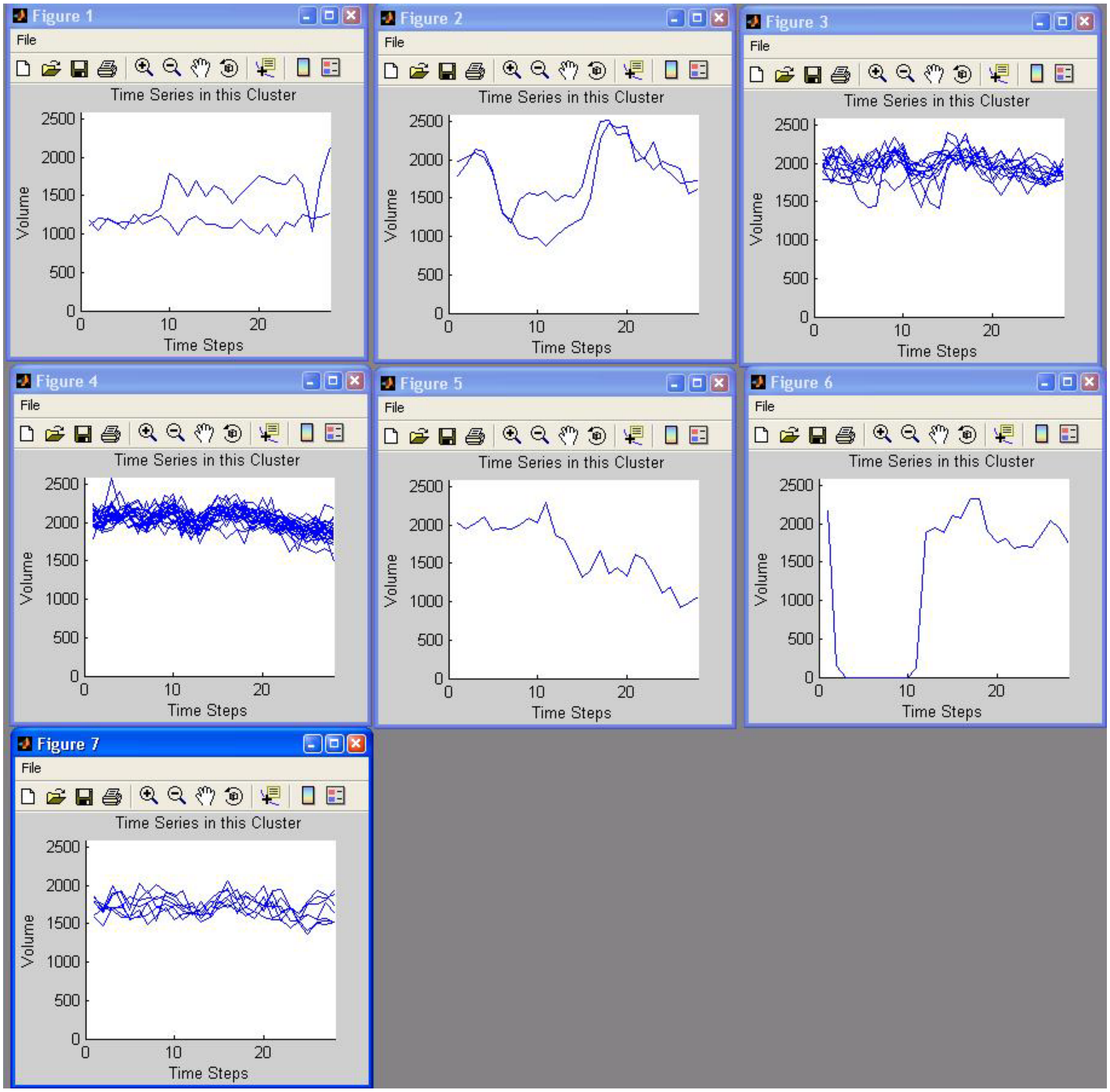


FIGURE 4-7 Patterns for Normal Day Traffic Volume Identification

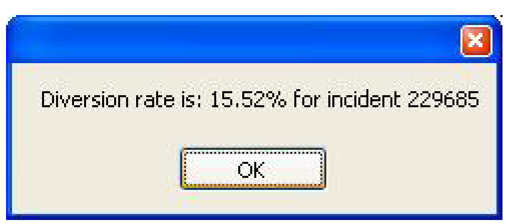


FIGURE 4-8 Diversion Rate Calculation Results

4.5. Case Study

The corridor chosen for this study is a East-West section of state road 826 (SR-826) in Miami-Dade County, Florida, which includes six interchanges and begins west of the NW 67th Avenue interchange and ends east of the NW 12th Avenue interchange with a total length of 6.5 miles. The study area is shown in Figure 4-9. The SR-826 East-West section was also used in case studies in other chapters of this document. The case study segment includes a total of five DMS signs, 50 true presence microwave detectors, and seven CCTV cameras. This corridor is heavily congested in both directions during the morning and the evening peak hours. However, the morning peak is predominant in the eastbound (EB) direction during the hours from 6 A.M. to 8 A.M. for workdays and the evening peaking occurs in the westbound (WB) direction from 3 P.M. to 5 P.M. during workdays. There is a parallel frontage road to this freeway segment in both directions that serves as an alternate route during incident conditions. Another two major diversion routes are through the use of NW 57th Avenue and NW 27th Avenue interchanges, which some motorists use to access Florida's Turnpike and Miami Gardens Drive north of the corridor in case of incident.

Traffic data to estimate the diversion rates were obtained from the STEWARD database. All incidents that occurred from January to December 2009 within the study area were reviewed and incidents that resulted in at least one-lane blockage that lasted for a time period greater than 30 minutes were identified and used in the analysis. Any other criteria can be set by the analysts depending on the analysis requirements.

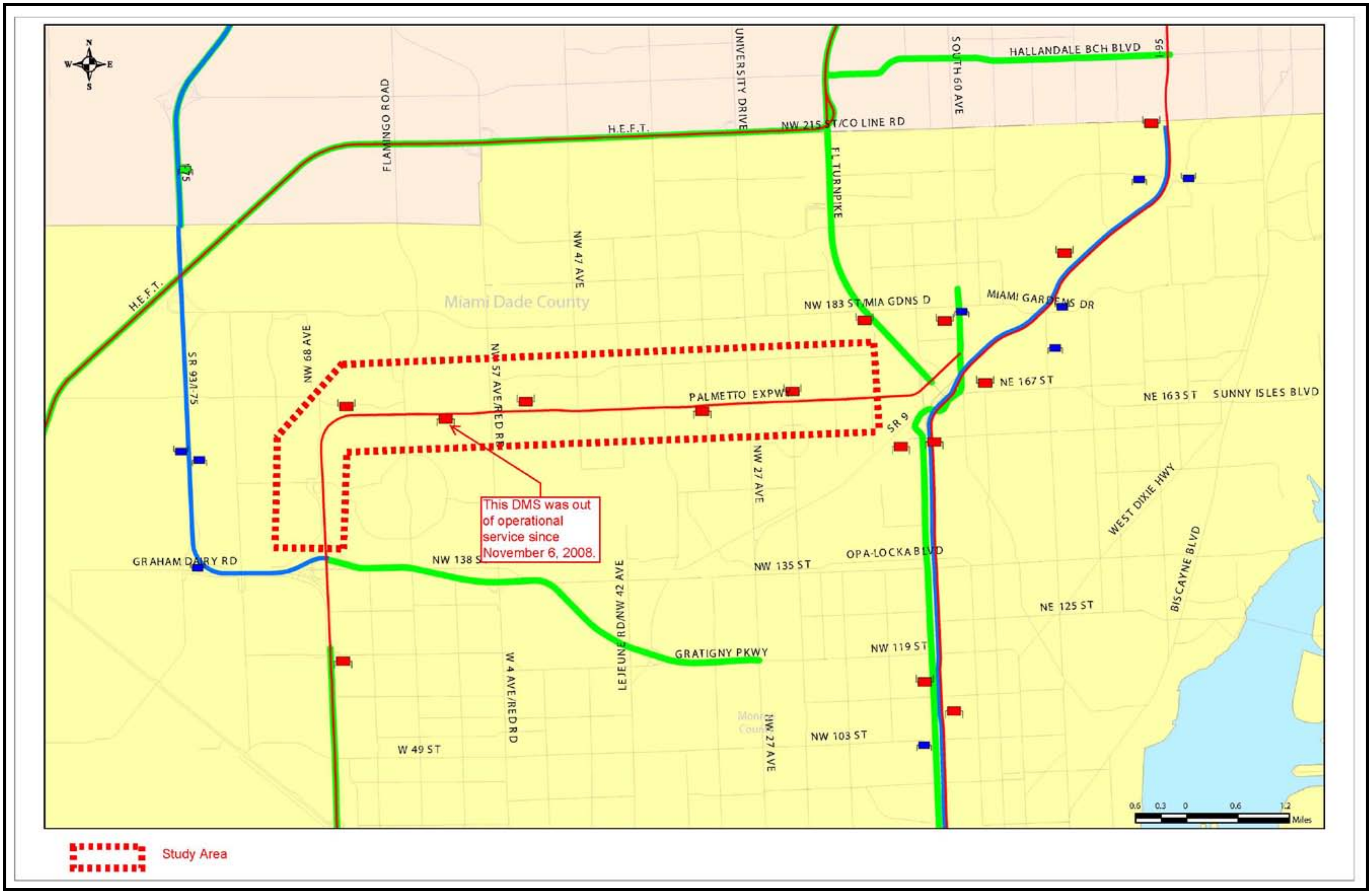


FIGURE 4-9 Study Area for Traffic Diversion Rate Calculation

In this study, the immediate three upstream detectors and the first downstream detector were selected to determine the diversion rate. The volumes of these four detectors were used to calculate the diversion rate. Figure 4-10 shows the calculated diversion rate distribution for the analyzed time period. It shows that for the selected incidents, diversion rates range from about 0% to 58.5%,. About half of the examined incidents had a diversion rate of 10% or less and about two-third of the incidents had a diverson rate less than 20%. The average diversion rate was 12.97% and the 85 percentile value was 25.01%.

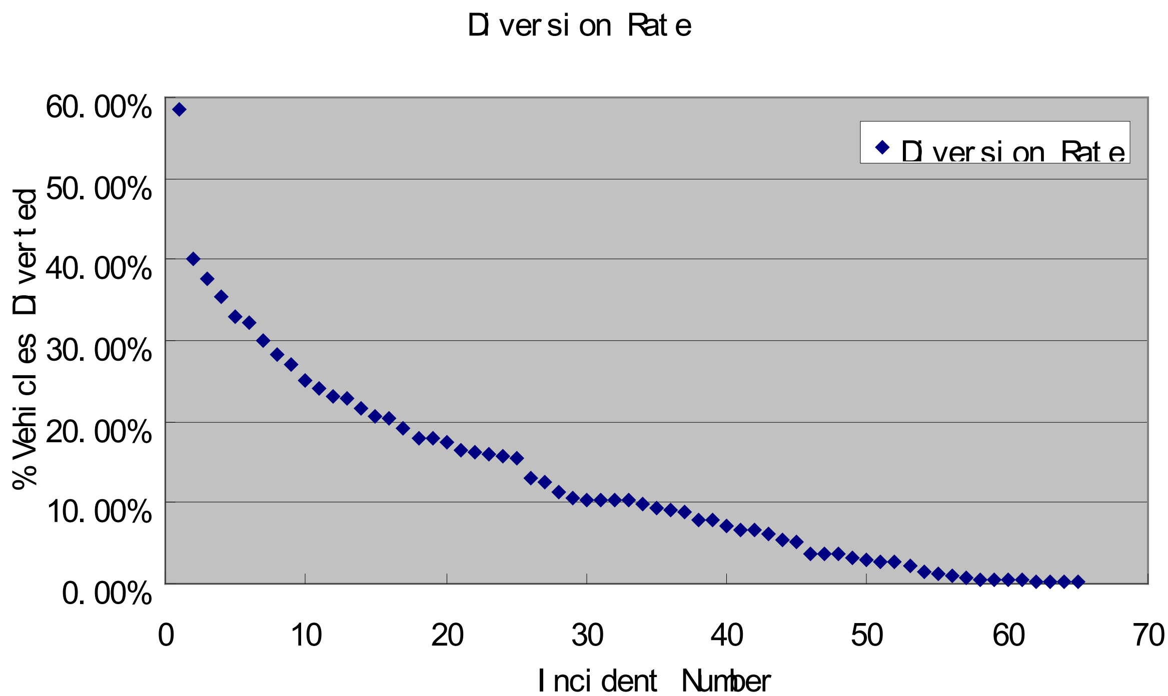


FIGURE 4-10 Diversion Rate Distributions for the Analysis Period

4.6. Statistical Analysis Results

Diversion rates calculated as described in the previous sections are stored in a database table and their associated incident attributes are used for the model development. Two linear regression models were developed in order to identify the impacts of the influencing factors: one with derived factors such as the estimated arrival rate, maximum individual delay, and the queue length, and another model with only factors that are directly retrieved from the SunGuide database. The developed model with derived factors is listed below as Equation 4-7:

$$LM = -0.138 + 0.045 \times IfDaylight + 0.025 \times LN(ArrivalRate)\_ + 0.002 \times MaxDelay + 0.043 \times QueueLen \quad (4\text{-}8)$$

Where,

IfDaylight = if an incident occurs under daylight condition;

ArrivalRate = the estimated arrival rate based on historical data during incident time period, the unit is vph;

MaxDelay = the maximum individual delay calculated from queuing theory, the unit is minute; and

QueueLen = the length of queued vehicles calculated from queueing theory, the unit is mile.

All identified variables are significant at the 0.05 confidence level. The values of t-statistics are all greater than 2.0. The R^2 for the calibrated model is 0.548 with a standard error of 0.09. The F value for this model is 11.415.

The developed model shows that daylight versus night condition, level of traffic demand, individual delay in the queue, and queue length are significant factors affecting the diversion rate. The model shows that the diversion rate is much higher during the daytime than during the nighttime. Also, during peak hours with higher demands, people are more willing to divert. Severe incidents with long queues and long delays also cause more people to divert.

The regression model with factors directly retrieved from the SunGuide database is shown below as Equation 4-8:

$$LM = -0.092 + 0.101 \times IfDaylight - 0.066 \times Weather + 0.002 \times BlockagePercent + 0.031 \times LN(Duration) \quad (4\text{-}8)$$

Where,

IfDaylight = if an incident occurs under daylight condition;

Weather = if the pavement is dry (0) or wet (1);

BlockagePercent = how many percent of the travel lanes are blocked; and

Duration = the incident duration.

All identified variables are significant at the 0.05 confidence level. The values of t-statistics are all greater than 2.0. The model can only achieve R^2 value of 0.345. The F statistics is 7.110.

The second model confirmed that drivers are more willing to divert during daytime and the weather condition is good. The longer the incident duration and the higher the percent of travel lanes are blocked, the more travelers will divert. The lower R^2 of the second model compared to the first model illustrates that the use of queuing theory to estimate the queue and delay due to the incident and use these attributes as independent variables in regression model allows the derivation of a better regression model.

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5. Estimation of Time Lag Between Incident Occurrence and Recording

5.1. Introduction

One of the most critical functions of traffic management centers (TMCs) is the support of incident management operations. In recent years, traffic management agencies (including FDOT TMCs) have started maintaining detailed and accurate archives of their incident management operations. The availability of this data has allowed the identification of critical parameters of incident management operations and the factors influencing these parameters. This can and has been used to assess incident impacts and the effectiveness of incident management programs, in addition to the development of decision support tools to support the planning, design, and operations of incident management programs.

Figure 5-1 shows the incident timeline as defined by the FDOT. An assessment can be made of the incident management operations based on the time consumed to accomplish each of the incident management processes shown in Figure 5-1. One of these processes is incident detection. The incident detection time is defined as the time from the occurrence of the incident to the time when the first incident management agency is notified of the incident occurrence. However, this time cannot be estimated based on incident management data. This is because the first time that the incident appears in the TMC incident management database is when the TMC is notified, which is the time that the TMC operators become aware of the incident at a minimum, a few minutes after the incident actually occurs. Incidents are detected or reported to the TMC through different sources including service patrols, CCTV cameras, enforcement agencies (in the case of Florida state roads, the Florida Highway Patrol), incident detection alarms based on detector data generated by the SunGuide software, and/or other sources. There have been no good estimates of the time lag between incident occurrence and TMC recording of the incident. This time lag is referred to in this study as the incident recording time lag. This measure is important because the longer it takes for an agency to record the incidents in its database, the shorter the calculated incident duration will appear based on analyzing this database, which is obviously not correct. The resulting calculated time is biased against the agencies that record the incident occurrence in their databases earlier. In addition, the incident recording time lag reflects the incident detection time by the TMC, which is an important performance measure of incident management operations that should be estimated and kept track of.

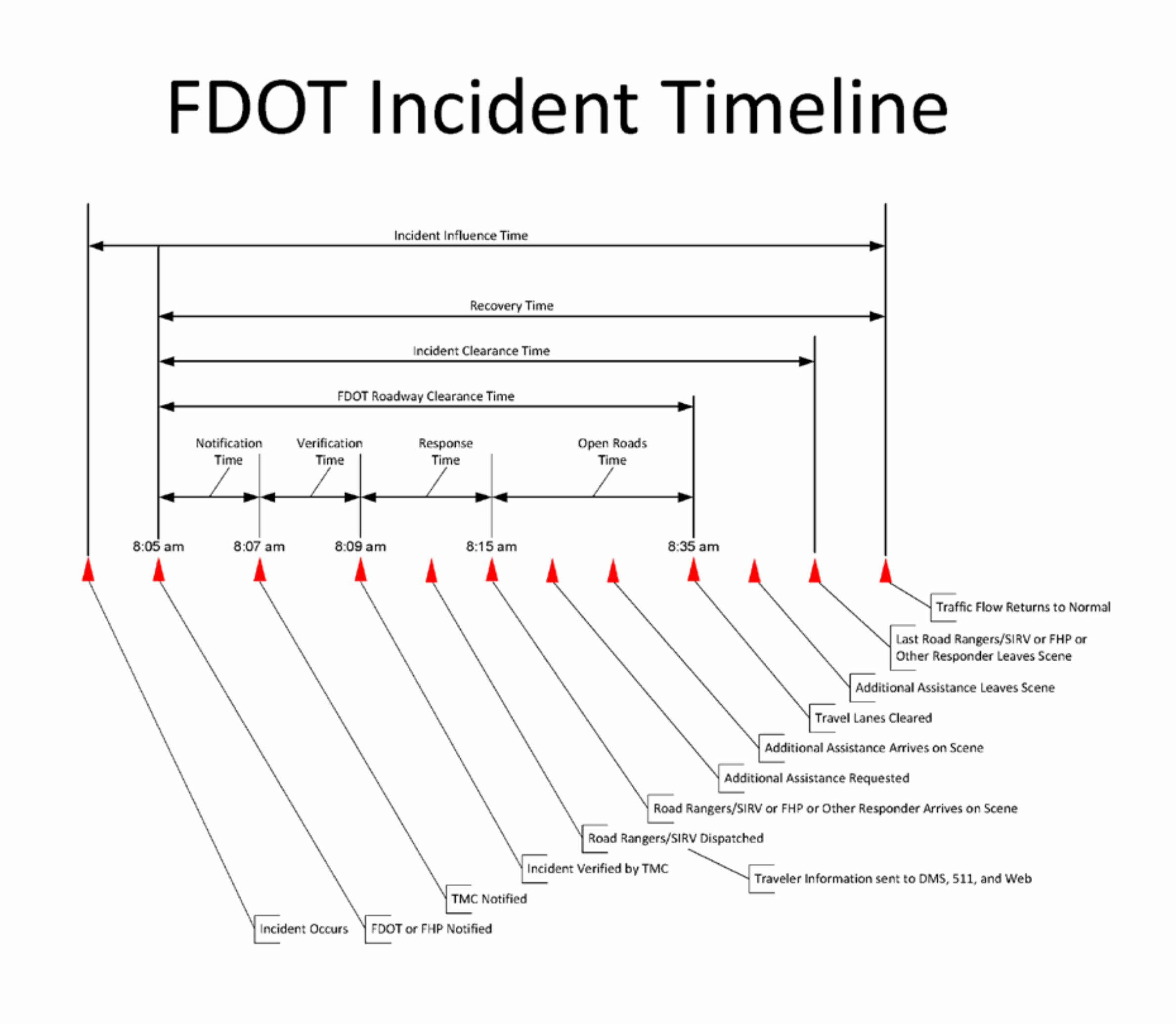


FIGURE 5-1 The Incident Time Line as Defined by the Florida Department of Transportation

Archived traffic detector measurements provide an additional source of data that can be used in estimating the incident recording time lag and the associated influencing factors. This study attempts to develop a method to determine the incident recording time lag based on a combination of detailed traffic detector and incident management databases. The methodology will allow better assessment of the time needed to detect incidents by TMC, the factors that influence this time, and ways to shorten this time. Furthermore, it will provide for a better estimation of incident duration for use in the calculation of incident impacts.

5.2. Literature Review

Most existing studies on the estimation of incident durations have calculated the incident duration as the time from the TMC notification to the time the incident is cleared, with no consideration to the incident recording time lag (Wang 1991, Ozbay and Kachroo 1999). Similarly, this time lag has generally not been considered, or roughly estimated, in studies conducted to estimate the benefits of incident management strategies (Levinson and Parthasarathi 2001, Khattak and Rouphail 2005, Guin et al. 2007, Hadi et al. 2008).

Stamatiadis et al. (1998) evaluated a service patrol program in Massachusetts. The study estimated that the incident detection/response time on average is 10 minutes with the program and 25 minutes without the program. The time with the program was estimated based on the average route length and the average travel speed through the congested area of the service patrol. The detection and response time with no service patrol program was estimated based on the state police patrol route, the average travel speed through the congestion area, and the estimated percentage of incidents that are detected based on motorist calls.

Nam and Mannering (2000) applied hazard-based duration models to estimate the time it takes to detect and report, respond to, and clear incidents based on various influencing factors. The average incident detection/reporting time was estimated to be 12.2 minutes in 1994-1995 with 56% of the incidents having detection/reporting time of less than 5 minutes. The incident detection/reporting duration was measured from the time that an incident occurs until the time it has been reported to the incident response team. The study, however, did not discuss how it was able to identify the time at which the incidents occur.

Martin et al. (2001) presented a comprehensive review of previous studies that tested automated incident detection algorithms based on inductive loop detectors. The conclusion was that for most algorithms, the detection time ranges from 30 seconds to more than five minutes, with typical times being about two minutes. However, the study pointed out that these algorithms produce a large number of false alarms, and do not perform well with incidents that have low impacts on traffic, and cannot detect shoulder incidents. Hall et al. (1993) evaluated the McMaster algorithm in Toronto and reported that operators can detect incidents on an average of two minutes before the automated algorithm. Stephanedes et al. (1993) reported that in many cases, the TMC operators were able to detect incidents based on watching closed circuit television (CCTV) videos before an automated algorithm was able to do so.

Mussa and Upchurch (2001) used simulations to determine the effects of varying the number of people with cellular phones who are willing to report incidents on the detection time. The study concluded that detection based on motorist calls is better than using automated traffic detection algorithms based on traffic data. If 1% of drivers called to report an incident, the study estimated that 80% of the incidents would be detected within five minutes. If the percentages increased to 10%, all incidents would be reported within 1.5 minutes.

The studies above suggested that incident detection based on CCTV cameras, motorist calls, and/or traffic detectors can be achieved in a relatively short period of time, or possibly less than five minutes. However, real-world data have not been adequately used to determine the incident detection/notification times for different scenarios. For this reason, in most cases, analysts have used the notification time (the first time that the operator becomes aware of the incident) rather than the occurrence time to represent the start of incidents. In other cases, analysts have added arbitrary lengths of time to account for the difference between the detection and notification time due to the lack of this information (Hadi et al., 2008).

5.3. Methodology

As stated earlier in this document, the objective of this study is to develop a methodology to determine the TMC recording time lag statistics under different conditions. With the developed methodology, data from traffic detectors upstream of the incident locations are analyzed for a time period starting at least 30 minutes before the timestamp at which the incident first appears in the incident management database (the TMC notification time). The impact of incidents on the first detection station upstream of the incident location is identified by analyzing the drop in speed and volume and increase in the occupancy based on the 20-second detector measurements stored in the traffic detector database. This time is actually not the time at which the incident occurs, but the time that the queuing shockwave from the incident location reaches the first upstream detection station. Thus, a correction factor needs to be applied to account for the time that it takes the shockwave to reach the detector, as described later in this section.

In a number of FDOT districts, the longitude and latitude of each incident are measured by the global position systems (GPS) equipment in the service patrol vehicles and uploaded automatically to the SunGuide incident management database. The location of each detection station together with the monitored corridor name and direction of travel are stored in the

SunGuide TSS database. The longitude and latitude of incidents and detectors are used in this study to identify the detectors affected by the incidents, the incident location, and the distance between the incident and upstream detectors. This distance is needed to calculate the time required for the queuing shockwave to arrive at upstream locations. The longitude and latitude of detectors and incidents are then imported to a Geographical Information System (GIS) application that allows the identification of the required information mentioned above.

In the discussion below, the timestamp t_1 is defined as the time at which the speed drops due to the arrival of the queuing shockwave at the first detection station upstream of the incident location. The actual time t_0 at which the incident occurs can then be calculated as t_1 minus the time it took the shockwave to travel from the incident location to the first upstream detection station. The timestamp t_2, is the timestamp that the incident is reported to TMC and recorded in the SunGuide incident database. Although this is referred to as the detection time in SunGuide, it is the time that the TMC is actually notified of the incident. The difference between t_2 and t_0 is the TMC recording time lag.

. Estimating t_0 as discussed above requires the calculation of the time taken for the shockwave to arrive at the first upstream detection station. To perform this calculation, the estimation of the shockwave speed is needed. The shockwave speed was calculated based on the flows and densities of these detectors using the following equations (May 1990):

$$U_{12} = \frac{q_i - q_j}{k_i - k_j} \tag{5-1}$$

$$k_i = \frac{5280 \times O_i}{L_v + L_d} \tag{5-2}$$

where

U_{12}	=	the shockwave speed in mph,
q_i and q_j	=	the flow rates in veh/hr of the two detection stations immediately upstream of the incident location (these stations are referred to as the first and second upstream detectors in this report),
k_i and k_j	=	the density of the two upstream detection stations in veh/mile/lane,

O_i = the occupancy of detector i,

L_v = the average length of the vehicle in ft, and

L_d = the length of the detector in ft.

The TMC recording time lags were identified for a sample of incidents selected for use in the analysis. The time lags together with the attributes of the incidents were used as inputs to regression analysis in order to identify the influencing factors that impacts the time lags. Before conducting the regression analysis, the incidents were categorized by the detection agencies and the regression was performed for each category separately. This was done since the detections of incidents by different sources are expected to be influenced by different factors. In this study, incidents were classified into three categories by three different detection agencies. These agencies are Florida Highway Patrol (FHP), Closed Circuit Television (CCTV) cameras, and the service patrol vehicles (called Road Rangers in Florida).

5.4. Applications and Results

The methodology described in the previous section to obtain the TMC recording time lag was tested for lane blockage incidents on two corridors in Florida. The two corridors are managed by two different FDOT districts. It was found that most lane blockage incidents are detected by TMC operators watching traffic speed maps and CCTV cameras, service patrol vehicles, and notifications from Florida Highway Patrol (FHP), the enforcement agency on the corridors. It should be noted that most motorist calls reporting incidents are routed to the FHP. Thus, these calls contribute to the detection of incidents, but the detections of these incidents are recorded in the database as FHP notification events.

For the first corridor, incident and traffic detector data were obtained for the period from January 2008 to May 2009. A total of 73 lane blockage incidents were used in the analysis of this corridor. For the second corridor, a total of 85 lane blockage incidents were used in the analysis. This section first presents a detailed description of the application of the TMC recording time lag methodology to an incident on one of the two investigated corridors. Then, it presents an illustration of how the methodology was applied to obtain information regarding the detection time of lane blockage incidents.

An accident with two blocked left lanes on December 23, 2008, was first recorded in the SunGuide software at 18:03:31, which is referred to as the notification time in the software. According to the methodology described in the previous section, speed data for the first and second upstream detection stations were analyzed starting at least 30 minutes before the first timestamp provided in the incident database. Based on the longitudes and latitudes of incident and detector locations, the first upstream detector is located a 0.3-mile distance upstream of the incident and the second upstream detector is positioned at a 0.45-mile distance. Figure 5-2 shows a plot of speed data for the first upstream detector, measured every 20 seconds between 17:30 and 19:00.

Figure 5-2 presents the lane speed information at the first upstream detector of the incident location. The lane selection is determined by the incident condition. Figure 5-3 shows lane speed data for the second upstream detector, which is located 792 feet upstream of the first detector. As can be seen from Figure 5-2, the timestamp of speed reduction due to the incident was identified to be 17:50:30. The speed, traffic flow rate, and occupancy at this timestamp were 10 mph, 1260 veh/hr, and 38%, respectively. The previous 20 second timestamp measurements of speed, traffic flow, and occupancy were 52 mph, 1620 veh/hr, and 9%, respectively. This indicates the sharp increase in congestion on this detector due to the arrival of the queuing shockwave from the downstream incident location.

The shockwave speed was calculated using Equations 1 and 2. In this case, based on the data of the first upstream detector, k_1, k_2, q_1, and q_2 values were estimated to be 19 veh/mi/ln, 80.3 veh/mi/ln, 1620 veh/hr, and 1260 veh/hr, respectively. The estimated queuing shockwave speed based on this calculation is 5.87 mph. The calculated queuing shockwave speed combined with the distance between the incident and the first upstream detection station were used to estimate the time required for the queuing shockwave to reach the upstream detector. This time was estimated to be 183 seconds. The time between the first timestamp of the incident in the incident database (t_2) and the time of the drop in speed at the upstream detector (t_1) was calculated to be 13 minutes, based on the data presented earlier in this section. Thus, the total TMC recording time lag (t_2-t_0) is estimated to be 16 minutes. It should be mentioned here that this lag time is significantly higher than the average time calculated for the lane blockage incidents in the region. It is presented here to illustrate the fact that some incidents may take long times to be input to the database. The agency can investigate these incidents to determine why they took longer times to detect.

Other important timestamps from the incident database are superimposed over the first and second upstream detector data in Figures 5-2 and 5-3, respectively. Additional important information can be obtained from combining incident and traffic detector data. It can be shown that the speed during queuing conditions upstream of the incident fluctuated between 0 and 10 mph with an average of about 5 mph until the blocked lanes were opened. For this incident, the TMC operator recorded the lane re-opening time to be 18:31:25 in the SunGuide software. Figure 5-2 indicates that the speed at the upstream detection station started to increase around that time. This comparison between the increase in the speed and the time for lane reopening as entered by the operator can be used to further check the accuracy of the operator inputs for blocked lane reopening timestamps.

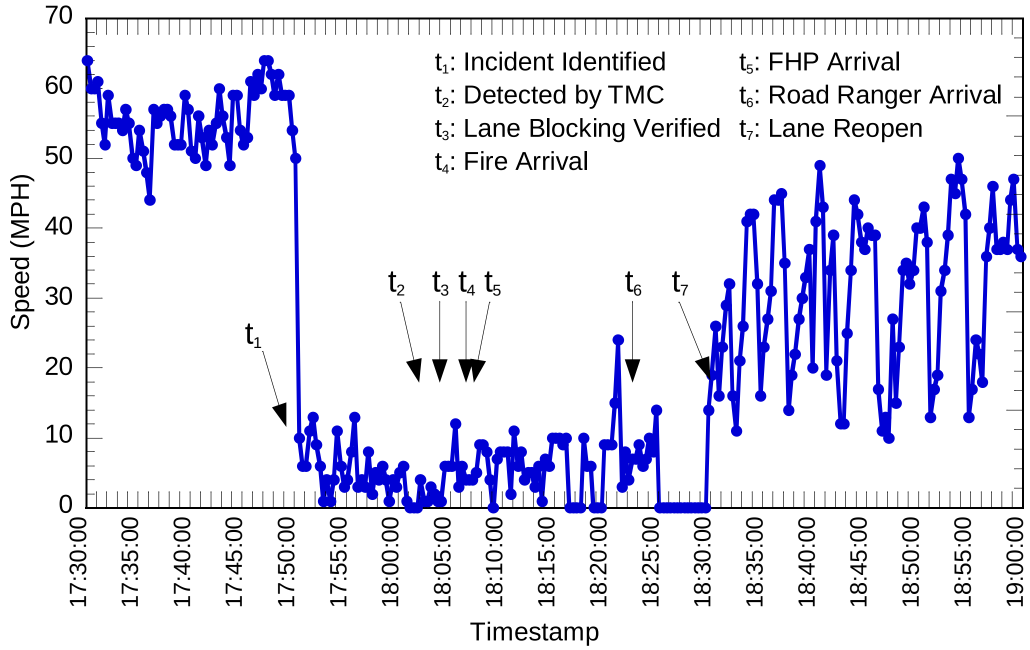


FIGURE 5-2 Speed Data for the First Upstream Detector

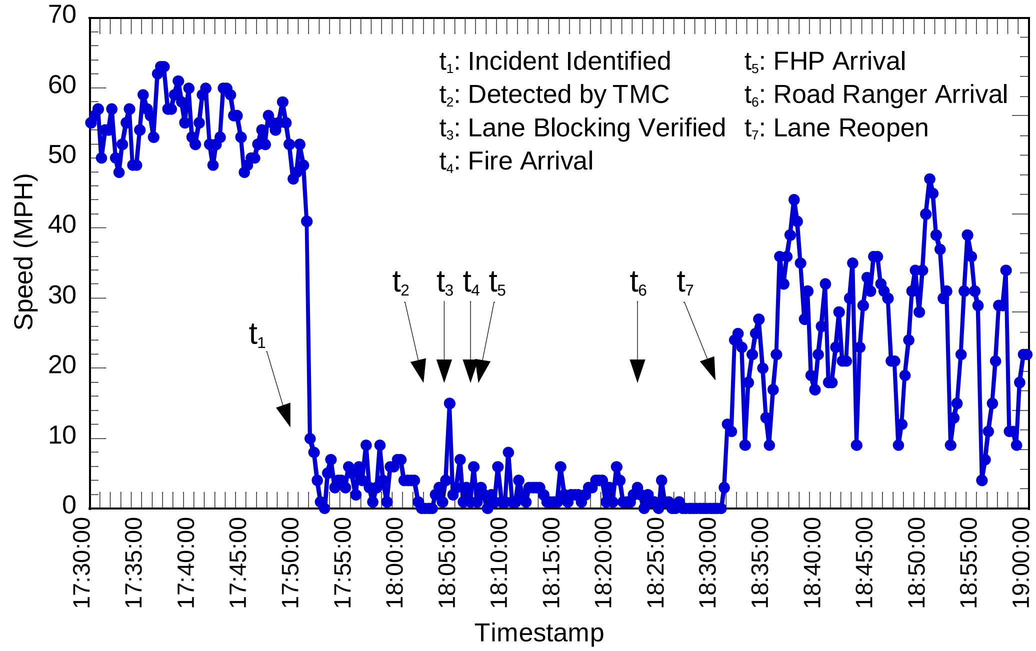


FIGURE 5-3 Speed Data for the Second Upstream Detector

Figures 5-2 and 5-3 also show the timestamps for the arrivals of the service patrol, fire truck, and FHP. As stated above, it was observed that this incident has higher detection time than other incidents on the corridor. In addition, the service patrol arrived at the incident site unusually late when compared with their arrivals to other incident sites. This type of information can be used by TMCs to explore the reasons for inefficiencies in the operations of TMC operators, service patrols, and communications with other incident response agencies.

Figure 5-4 shows the speed data for the detector located in the opposite direction of travel from the direction of the incident discussed above. Figure 5-4 covers the same period as that of Figure 5-2. This figure presents how combining incident and traffic data as proposed in this study allows the quantification of the drops in speeds for the traffic traveling in the opposite direction. This quantification has been very difficult to achieve in the past. Speed variations in Figure 5-4 indicate that a severe lane blockage incident not only affects the traffic conditions in its direction, but also has significant impacts on the speeds of the vehicles in the opposite direction, with a drop in speeds from 10 to 20 mph. It can also be noted from Figure 5-4 that the speed of the vehicles in the opposite direction started to decrease at almost the same time of the arrival of the fire truck from the other direction identified, as based on Figure 5-2 data. This indicates that the motorists traveling in the opposite direction may have started getting distracted and slowing down due to the fire truck's presence. It should be noted that this segment of the corridor has a relatively low median barrier, allowing motorists to see the opposing direction of travel. However, at other locations of the corridor with higher medians, it was observed that the effect on the opposing traffic is lower or non-existing.

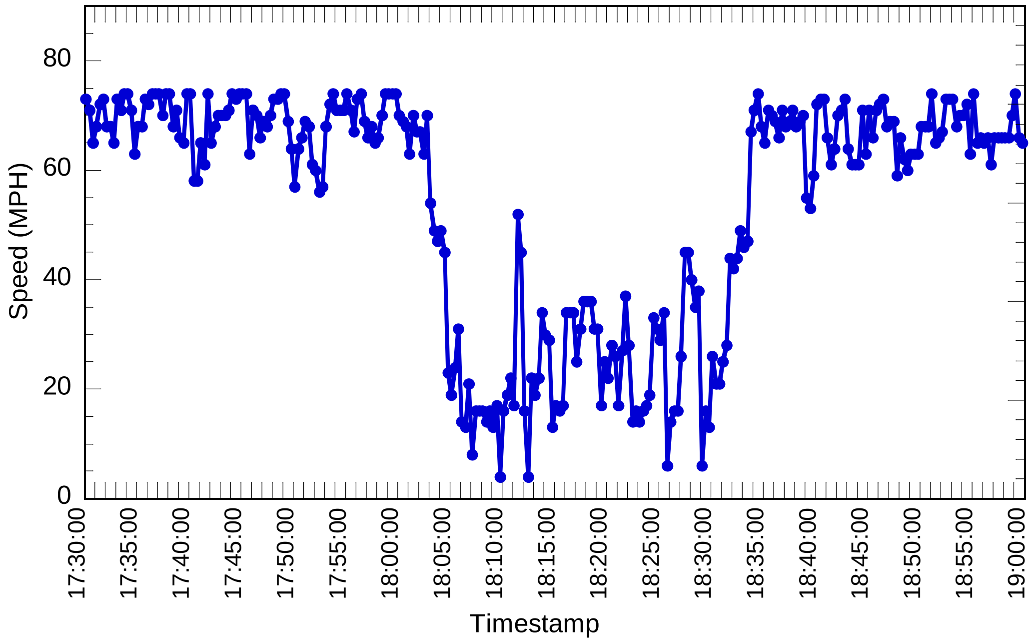


FIGURE 5-4 Speed Data for the Detector in the Opposite Direction

5.5. Process Automation

The time lag calculation method previously described requires matching incidents with traffic detector data, which is a time-consuming task if performed manually. Thus, the proposed methodology was implemented as part of a computer program to automate the process. This computer program consists of two parts, a user interface and an automatic speed falling identification algorithm. The speed falling identification algorithm can also be extended for use with volume and/or occupancy data, as needed. Figure 5-5 shows the user interface of the computer program. This interface allows the user to specify incident selection criteria, such as the corridor, incident location, direction, incident date, incident time, incident type, and lane blockage condition. Based on the selected criteria, qualified incidents will be extracted from the incident database. For each selected incident, the upstream and downstream detectors will also be automatically identified. The user will then have the option to double-click the selected incident to display attributes such as incident date, time, detection agency/source, number of lanes blocked, roadway condition, and responding agency arrival and departure times. Figure 5-6 shows the interface for displaying these incident attributes.

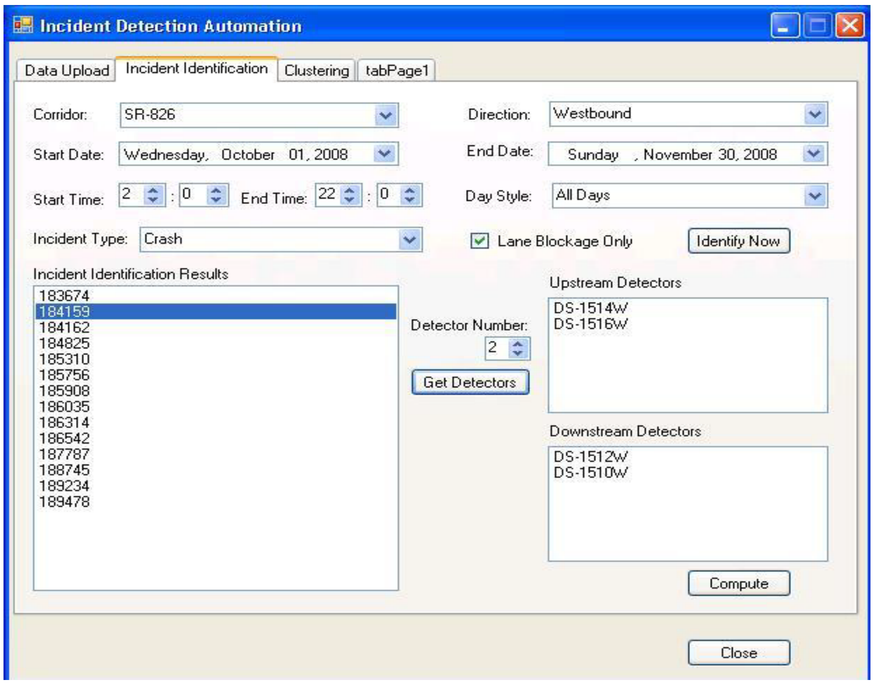


FIGURE 5-5 Main User Interface for Incident Detection Program.

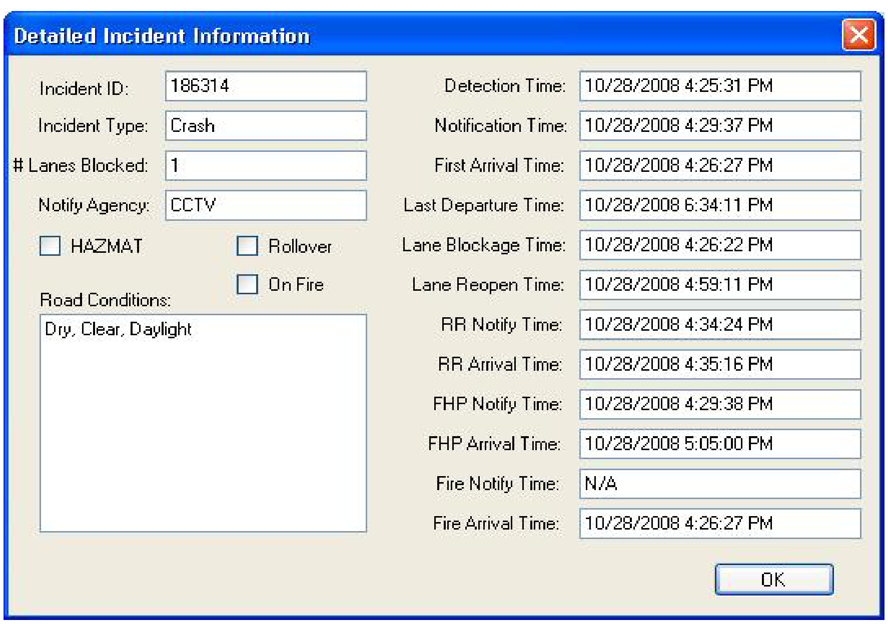
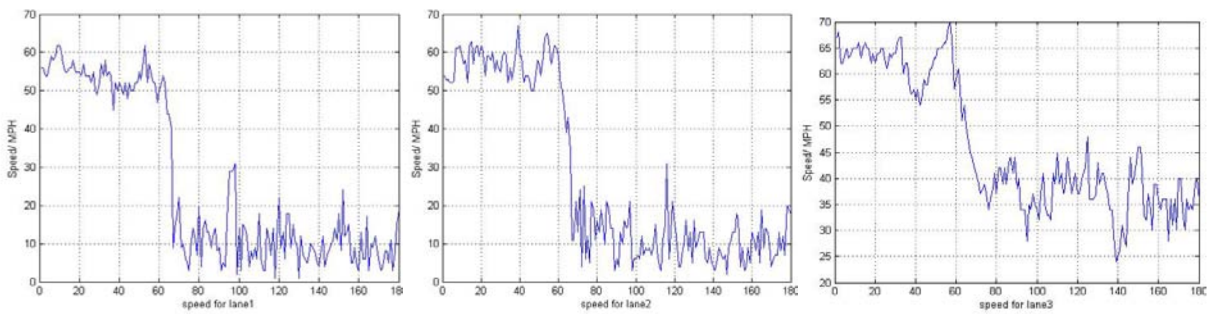
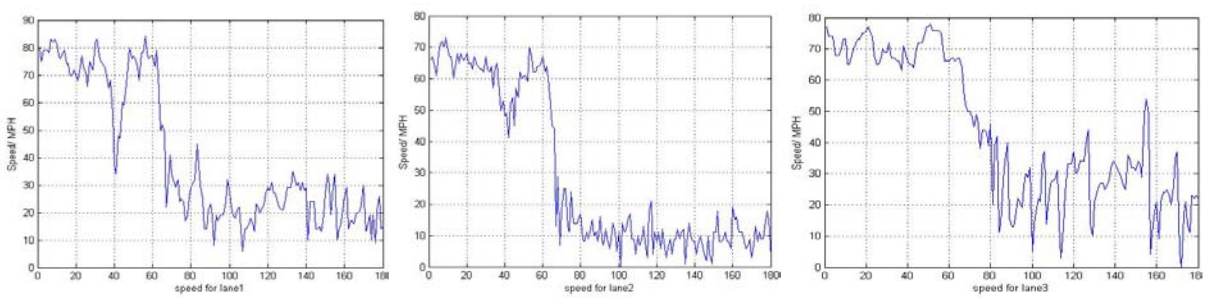


FIGURE 5-6 Interface for Displaying Attributes of Selected Incidents.

After the incidents are selected for the analysis, the next step is to apply an automatic speed falling identification algorithm to determine speed falling points for the upstream detectors. As explained before, the algorithm can also be applied to traffic volume or occupancy data, if needed. The user can request the display of incident data around the incident time for each lane of the two immediate upstream detection stations, as shown in Figure 5-7. The user can then select the lane that has the earliest and clearest change in performance measures for use in the analysis. Figure 5-8 shows the results of the calculation of the time lag for one incident.



(a) First Upstream Detector



(b) Second Upstream Detector

FIGURE 5-7 Automatic Display of Data from Upstream Detectors

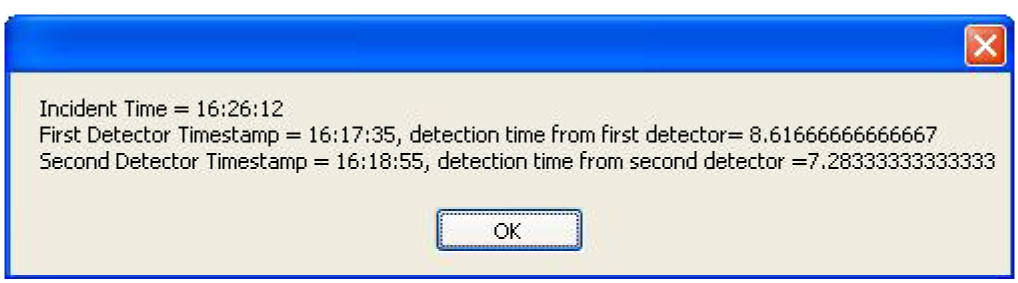


FIGURE 5-8 Final Calculation Results

5.6. Statistical Analysis

Regression analysis results show that for FHP detected incidents, the time lag is lower during daylight conditions and when the lane blockage incident is more severe (more lane blockage). The results probably reflect the higher potential for receiving calls from multiple travelers during daylight conditions and with severe lane-blockage incidents. For CCTV detected incidents, the time lag is higher during the peak periods and during rainy weather conditions, and lower for daylight (compared to night) conditions, full lane blockages, and when a higher number of vehicles are involved in the incident. These results indicate the higher possibility for traffic operators to identify incidents from CCTV cameras during dry and clear weather, daylight conditions, full blockage, and high number of involved vehicles. During the peak periods, the time lag is greater, probably due to the increased workloads of the operators.

The R^2 values of the developed regression models for FHP-detected incidents and CCTV-detected incidents were 0.882 and 0.412, respectively. Although all independent variables were significant at the 5% level, it was not possible to develop an acceptable regression model for incidents detected by the service patrols. It was expected that for these incidents, the main influencing factor on incident detection time, and thus on the time lag, is the change in the schedule of service patrol during night conditions (lower number of vehicles at night). To verify this difference, a statistical test was conducted to determine if the incident detection durations during night conditions were significantly higher than those during daylight conditions. In this case, a one-sided t-test was used to determine if the mean time lag is higher during night conditions for service patrol-detected incidents. It was found that the difference was significant and that the null hypothesis could be rejected at the 95% level.

Table 5-1 shows the statistical summary of incident detection times for one of the corridors. This summary serves as an illustration of the capability of the developed algorithms and gives a general idea of the magnitude of incident detection time lags. The table shows that the average detection time lag for all 85 cases on this corridor was 3.94 minutes with a standard deviation of 2.91 minutes. The maximum incident detection time lag was 13.1 minutes and was for an incident detected using CCTV cameras during daylight conditions.

TABLE 5-1 Statistics of Incident Detection Time for One of the Investigated Corridors

Category	Sample Size	Mean (min)	Standard Deviation (min)	Median (min)	Min Incident Detection Time (min)	Max Incident Detection Time (min)
RR (Daylight)	14	3.06	1.13	3.3	1	4.5
RR (Dark)	6	4.04	0.61	3.92	3.5	4.7
FHP (Daylight)	11	3.49	1.85	3.3	0.5	6.8
FHP (Dark)	5	3.5	0.48	3.3	3.1	4
CCTV (Daylight)	38	4.8	3.27	3.4	0.5	13.1
CCTV (Dark)	11	4.75	2.12	3.5	2.5	8.7
All Cases	85	3.94	2.91	3.5	0.5	13.1

5.7. Conclusions

This study has demonstrated that combining incident management and traffic detector databases allows the identification of information that cannot be identified based on these two data sources alone. A methodology has been developed in this study to estimate the TMC incident recording time lag, the incident impacts on the speed of the traffic approaching the incident location, and the incident impacts on the traffic in the opposite direction based on these two data sources. Combining incident management timestamps with traffic detector data can also produce valuable information to support various TMC operations.

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6. Estimation of Secondary Incidents Potential

6.1. Introduction

Secondary crashes are generally considered to be crashes resulting from primary incidents. They usually occur either at the end of or within the queues that are formed due to primary incidents. Secondary crashes have been increasingly recognized as a significant source of freeway incidents that can be influenced by traffic management strategies; it is therefore important to understand their nature and contributing factors. In general, faster clearance of freeway incidents can reduce incident durations, queue lengths, and associated freeway congestion levels, thus reducing the potential for secondary crashes. Previous studies evaluating the benefits of incident management programs have frequently assumed that these programs can reduce the likelihood of secondary crashes (Guin et al. 2007, Hadi and Zhan 2006, Latoski et al. 1999). To determine the extent of the crash-prevention benefits, however, the likelihood of secondary incident occurrence and the factors affecting this likelihood must first be determined. Understanding the contributing factors of secondary crashes is also critical to identifying potential improvements for incident management strategies.

Research on secondary crashes has been limited. This is mainly due to the poor quality of incident data and the lack of related traffic data necessary to secondary crash identification and analysis. In addition, there is no uniform definition of a secondary crash in terms of its spatial and temporal relationship to the primary incident. Therefore, it has been difficult to associate an initial incident with secondary crashes and to confirm that the first incident was indeed a contributor to these subsequent crashes (Moore et al. 2004).

In past studies, researchers have generally linked secondary crashes to primary incidents according to some pre-defined spatial and temporal criteria. The rationale was that a secondary crash should take place within a maximum distance upstream in the same direction of travel, and within a certain time range of a primary incident. Raub (1997) and Karlaftis et al. (1998) defined a secondary crash as any crash that occurs no more than one mile upstream of, and less than 15 minutes after, an initial incident. Moore et al. (2004) defined these two spatial and temporal criteria as two hours and two miles upstream of the initial incident, respectively. Hirunyanitiwattana and Mattingly (2006) suggested that the criteria be within 60 minutes and two miles upstream of the primary incident. In our previous study (Zhan et al. 2008), a secondary crash is defined as within two miles upstream and 15 minutes after the clearance of the primary incident. As can be seen from the above discussion, most previous studies have used fixed spatial and temporal threshold values for secondary crash identification. However, there is no agreement among them on a single definition of the spatial and temporal boundary criteria.

One major reason why past studies have used fixed spatial and temporal criteria is that, in most existing traffic management databases, real-time traffic information for incident sites is usually missing. This makes it difficult to estimate traffic delays, traffic queue lengths, and related queue dissipation times for potential primary incidents. Traffic delay is a function of incident and roadway attributes including incident duration, traffic volume, and roadway capacity with and without incident (Hurdle and Son 2001). Therefore, using simple fixed thresholds for secondary crash identification may significantly overestimate or underestimate the number of secondary crashes and skew analysis results. This research aims to partially resolve this issue by identifying secondary crashes through the combined use of traffic condition information and primary incident characteristics. In this research, for each potential primary incident, the related hourly traffic volume and incident duration information is retrieved. Freeway remaining capacity is then estimated using primary incident lane closure/reopen information. After that, maximum traffic queue length resulting from the primary incident is estimated using a traffic queuing analysis model. The associated maximum queue dissipation time is then computed accordingly. Any crash occurring within the boundary of the estimated maximum queue length and dissipation time is linked to the particular primary incident as a possible secondary crash.

This study presents an analysis of secondary crashes using both the traffic incident and traffic counts measured using ITS detectors or the FDOT statistics office detectors (FTI 2009). A new method for identifying secondary crashes is first discussed herein. This method uses a cumulative arrival and departure queuing model to estimate the maximum queue length and queue dissipation time from a primary lane-blockage incident. Descriptive statistical analyses are then conducted to study the factors contributing to secondary crashes. In addition, secondary crash analysis based on the logistic regression model is conducted to estimate the relationships of secondary crash likelihood and the contributing factors. Finally, conclusions are drawn based on the analysis results.

6.2. Data Sources

Incident records for I-95, I-75, and I-595 stored in FDOT District 4 database from January 2005 to January 2007 were used in this study. During the two-year period, FDOT District 4 managed 95,844 road assists, which corresponds to 131 assists per day. Among these incidents, 7,903 were crashes. During the same time period, 4,435 incidents caused one or more lane blockages. In this study, lane blockage incidents serve as a basis for identifying potential primary incidents. One major assumption behind this is that incidents with only shoulder blockages usually have minor impacts on traffic. This is especially true when there are more than three open travel lanes. In such cases, primary incidents with only shoulder blockages are less likely to cause secondary crashes.

6.3. Secondary Crash Identification

Shockwave and cumulative arrival and departure curve (queuing) models have been widely used in various traffic operations analyses, and have been essential to understanding the nature of freeway congestion (Hurdle and Son 2001). Both models are deterministic and attempt to estimate traffic delays and queue lengths resulting from freeway congestion. This study attempts to use the cumulative arrival and departure curve technique to estimate the maximum queue length incurred by lane-blockage incidents. This curve is deemed as the baseline for determining the maximum distance for possible secondary crashes. In addition, the associated queue dissipation time after a primary incident is estimated to determine the temporal criteria for secondary crash identification.

Figure 6-1 illustrates the dynamic change in the number of vehicles stranded in a queue as a result of a freeway incident. When an incident with lane blockage (except for full lane blockage, in which case the congested departure rate will be zero) occurs, freeway capacity drops significantly. The arrival traffic rate can exceed the remaining capacity of the freeway, resulting in a traffic queue for which the number of vehicles will continue to accumulate. As time passes, however, the blocked freeway travel lanes will open gradually. This is either because of freeway incident management efforts or self-assist actions by stranded travelers. In any case, as blocked lanes are opened, freeway remaining capacity will increase dramatically. When an incident is completely cleared, the freeway will be restored to its full capacity. After a recovery period, traffic flow will return to normal conditions.

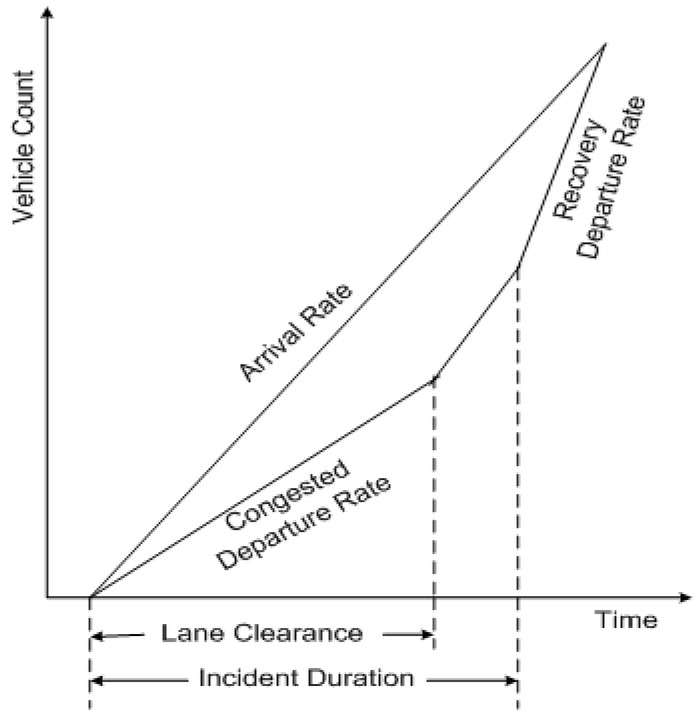

FIGURE 6-1 Cumulative Arrival and Departure Diagram for Incidents with Lane Blockages

From an initial analysis of incidents, it is determined that the majority of incidents with lane blockages are incidents with only one lane blocked, especially during the daytime period (6:00 A.M. - 7:00 P.M.). Although the data show that during the night (7:00 P.M. - 6:00 A.M.) lane clearance times are usually much higher, they are less likely to cause longer traffic queues because traffic volumes are much lower than during the day. The data also reveal that the I-95 corridor had far more lane blockage incidents during the study period than did the I-595 and I-75 segments. Historical traffic volume data show that the AADT is about 265,000 for the I-95, 168,500 for the I-595, and 110,000 for the I-75 segments in Fort Lauderdale, Florida.

Below is an example of how the calculations of maximum queue length and queue dissipation time are conducted. The calculations are for the incidents that had taken place during the weekday daytime period on the I-95 corridor with one-lane blockage.

The I-95 corridor segment in Fort Lauderdale has four travel lanes for both the southbound and northbound directions. Historical traffic data were retrieved from the Florida Traffic Information (FTI) Database (2006), which is in the Microsoft Access database format and is annually distributed by the FDOT Central Office on a CD-ROM. The traffic data show that during the weekday morning peak (AM) period (6:00 A.M. - 9:00 A.M.), the southbound average hourly traffic volume is about 7,430 vehicles per hour, which represents heavy congestion, particularly when considering the peaking of traffic during these hours. Statistical analysis of the SMART database shows that during the A.M. peak period, the average lane blockage time for incidents with one-lane blockage on I-95 is 27.98 minutes. Exhibit 22-6 of the 2000 Highway Capacity Manual (HCM) suggested that the remaining freeway capacity could be reduced to only about 58% of the full capacity with one-lane blockage, which was assumed in this study to be 2,200 vehicles per hour per lane for the given design conditions. It was also assumed that during a major freeway incident, some travelers would divert to alternative routes. In this study, the diversion rate was assumed to be 5%. With these assumptions, the maximum total number of queued vehicles incurred during an incident on I-95 SB with one lane blocked can be calculated as follows:

$$\begin{aligned}
\text{Arrival Rate} &= \text{Original Arrival Rate} \times (1 - \text{Diversion Rate}) \\
&= 7430 \times (1 - 0.05) \\
&= 7059 \text{ vehicles/hour} \\
\text{Departure Rate} &= \text{Remaining Capacity of Freeway} \\
&= \text{Full Capacity of One Lane} \times \text{Number of Lanes} \times \text{HCM Factor} \\
&= 2200 \times 4 \times 0.58 \\
&= 5104 \text{ vehicles/hour} \\
\text{Maximum Queue Length} &= (\text{Arrival Rate} - \text{Departure Rate}) \times \text{Duration} \\
&= (7059 - 2200 \times 4 \times 0.58) \times \frac{29.69}{60} \\
&= 968 \text{ vehicles}
\end{aligned}$$

To simplify the calculation of queue length in terms of distance, suppose that all of the queued vehicles are passenger cars and that the bumper-to-bumper length (space headway) occupied by one vehicle in the queue is 25 ft. The maximum possible queue length in miles can be estimated as follows:

$$\text{Maximum Queue Length} = 25 \times \frac{968}{4} \div 5280 = 1.14 \text{ miles}$$

After the blocked lane is cleared, with only shoulder disablement, the freeway can be restored to almost full capacity. Thus, the approximate recovery time for queue dissipation can be estimated as such:

$$\text{Recovery Time} = \frac{968}{(2200 \times 4 - 7059)} \times 60 = 33.34 \text{ minutes}$$

Table 6-1 shows the estimated maximum queue lengths and recovery times for the weekday AM, Midday (9:00 A.M. - 4:00 P.M.), and P.M. (4:00 P.M. - 7:00 P.M.) periods for both directions of I-95 in the case of incidents with one-lane blockage. In the case of incidents with multiple-lane blockages, statistical results show that the lane blockage times are generally much higher. However, the frequency of occurrence of multiple-lane blockages is much lower than that of incidents with only one lane blocked. In addition, when incidents with multiple lane blockages occur, some of the blocked lanes can usually be reopened much sooner than the reopening of all blocked travel lanes. In calculations for queue length and dissipation time for incidents with multiple-lane blockages, lane blockage durations are divided into periods of four-, three-, two-, and one-lane blockage. This is made possible because detailed timestamp information is available from the incident management database. The percentages of remaining capacities under different blockage situations are retrieved from the HCM. The methods for estimating maximum queue lengths and queue dissipation time remain the same as that mentioned above.

To quickly identify secondary crashes, a program was written for this study in the C# programming language to link possible secondary crashes with primary incidents. This was done according to the spatial and temporal criteria calculated above. The program identified 255 secondary crashes resulting from 221 primary incidents with lane blockages. Figure 6-2 graphically displays the three corridors managed by FDOT D4 and the spatial distribution of the identified primary incidents that have associated secondary crashes. The figure shows that primary incidents with linked secondary crashes were concentrated on the I-95 and I-595 corridors.

TABLE 6-1 Estimated Maximum Queue Lengths and Recovery Times for Incidents on I-95 with One-Lane Blockage

Direction	Period	Average Lane Blockage (min)	Average Incident Duration (min)	Average Hourly Volume (vph)	Maximum Queue Length (mile)	Recovery Time (min)	Queue Dissipation Time After Incident Clearance (min)
SB	AM	29.69	68.64	7430	1.14	33.34	0.00
	Midday	28.48	58.16	7410	1.09	31.31	1.63
	PM	28.05	56.52	7869	1.31	50.23	21.76
NB	AM	30.92	71.74	7831	1.42	53.07	12.25
	Midday	36.63	64.76	7203	1.26	32.54	4.41
	PM	33.59	66.28	7747	1.49	52.60	19.91

FIGURE 6-2 FDOT D4 Managed Corridors and Distribution of Secondary Crashes

6.4. Statistical Analyses

6.4.1. Descriptive statistics

Some relevant descriptive statistics of secondary crashes for the three corridors are listed in Table 6-2. The table shows that the percentages of secondary crashes for both directions of I-95 are significantly higher than those of I-595 and I-75. In Table 6-2 and the following tables, the primary incident percentage is calculated as the percentage of all lane closure incidents that were identified as primary incidents in this study. The secondary crash percentage is defined as the percentage of all incidents that were identified as secondary incidents (including lane blockage and non-lane blockage incidents). Table 6-2 shows that the primary and secondary crash percentages are the highest on I-95, followed by I-595 and I-75. In addition, as mentioned previously, historical traffic volume data also show that the I-95 segment has the highest AADT, followed by I-595 and I-75.

TABLE 6-2 Secondary Crash Distributions by Freeway Corridors

Freeway	Lane Blockage Incidents	Primary Incidents	Primary Incident Percentage	Crashes	Secondary Crashes	Secondary Crash Percentage
I-95 N	1,737	103	5.93%	2,857	123	4.31%
I-95 S	1,676	82	4.89%	2,787	92	3.30%
I-595 E	340	15	4.41%	650	18	2.77%
I-595 W	338	13	3.85%	640	14	2.19%
I-75 N	175	4	2.29%	500	4	0.80%
I-75 S	169	4	2.37%	469	4	0.85%
Overall	4,435	221	4.98%	7,903	255	3.23%

Table 6-3 presents the distributions of primary incidents and secondary incidents by month. The table shows that the months of January, June, and July have the highest primary incident percentages, whereas the months of January, June, July, and October experienced the highest percentages of secondary incidents. Because January, June, and July coincide with the vacation/holiday months in the study area, this suggests the potential impact of vacation and holiday traffic on primary incident and secondary crash percentages.

TABLE 6-3 Secondary Crash Distributions by Month

Month	Lane Blockage Incidents	Primary Incidents	Primary Incident Percentage	Crashes	Secondary Crashes	Secondary Crash Percentage
January	256	17	6.64%	512	24	4.69%
February	252	12	4.76%	504	13	2.58%
March	328	13	3.96%	650	14	2.15%
April	304	18	5.92%	591	21	3.55%
May	357	15	4.20%	637	16	2.51%
June	345	23	6.67%	637	25	3.92%
July	394	27	6.85%	705	36	5.11%
August	401	17	4.24%	717	17	2.37%
September	414	17	4.11%	743	17	2.29%
October	551	27	4.90%	812	31	3.82%
November	386	16	4.15%	675	21	3.11%
December	447	19	4.25%	720	20	2.78%

Figure 6-3 shows that Mondays, Thursdays, and Fridays have higher percentages of lane blockage incidents that act as primary incidents, as well as secondary incidents. The weekends have the lowest secondary incident percentages. This is not surprising as weekends generally have fewer lane blockage incidents and lower traffic volumes.

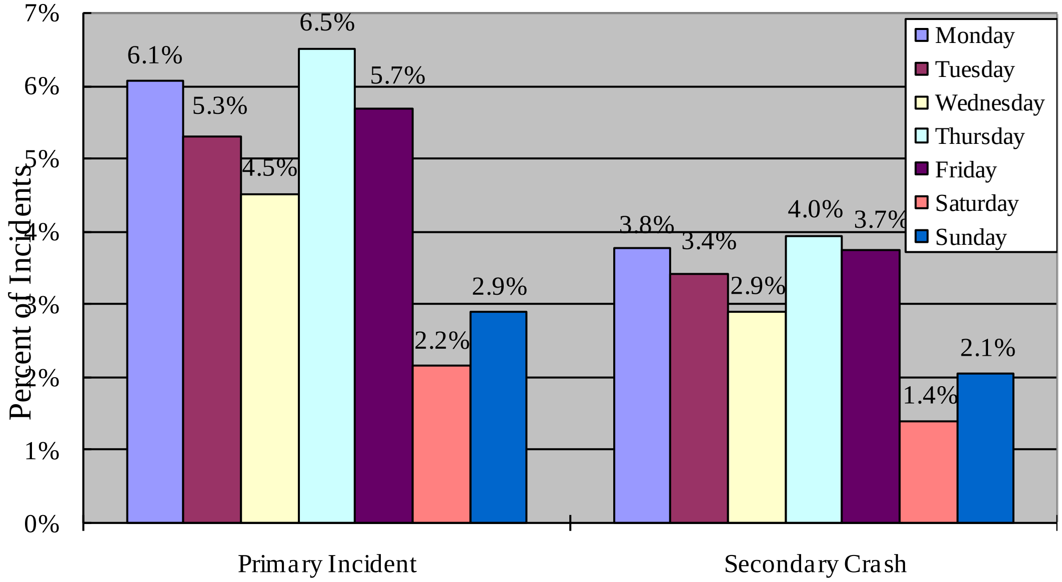

FIGURE 6-3 Secondary Crash Distributions by Day of Week

Figure 6-4 shows the distributions of primary incidents and secondary crashes by six time periods: A.M. peak, Midday, P.M. peak, and Late Night (7:00 P.M. - 6:00 A.M.) periods for weekdays, and Daytime (6:00 A.M. -7:00 P.M.) and Nighttime (7:00 A.M. - 6:00 P.M.) periods for weekends. Figure 6-4 indicates that the A.M. peak period has the highest primary incident and secondary crash percentages. On the other hand, the P.M. peak period has much lower primary incident and secondary crash percentages than the A.M. peak and Midday periods.

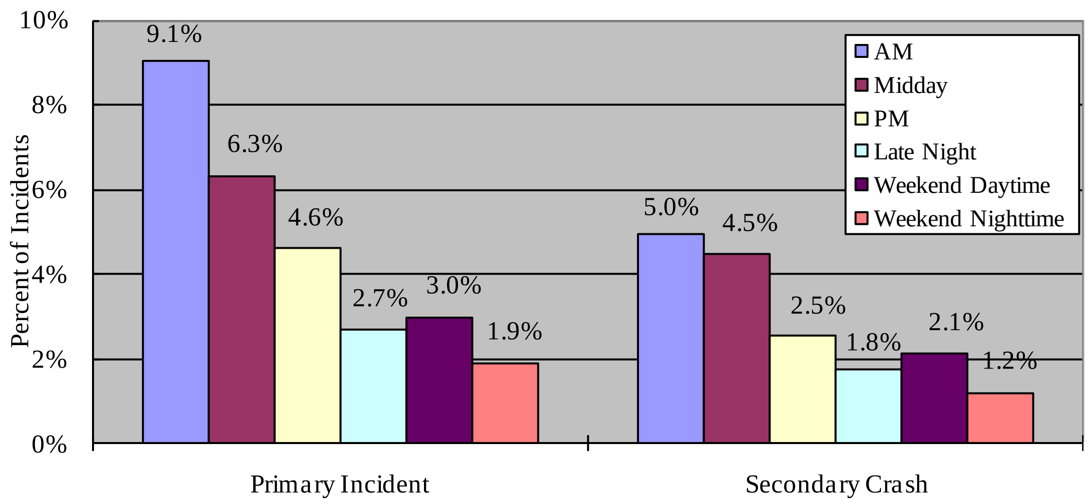

FIGURE 6-4 Secondary Crash Distributions by Time of Day

Table 6-4 shows primary incident and secondary crash distributions by number of lanes blocked and primary incident types. The table suggests that incidents with two or more lanes blocked have a higher potential to cause secondary crashes than those with only one-lane blockage. Table 6-4 also shows that about 95% of incidents with lane blockages are of the "Crash" or "Disabled Vehicle" incident types.

TABLE 6-4 Secondary Crash Distributions by Lane Blockages and Incident Types

Blockage/ Type	Lane Blockage Incidents	Primary Incidents	Primary Incident Percentage
1 Lane	2,475	108	4.36%
2 Lanes	1,118	55	4.92%
3+ Lanes	842	58	6.89%
Crash	3,459	183	5.29%
Disabled Vehicle	717	27	3.77%
Debris	105	2	1.90%
Other Types	139	9	6.47%

Previous studies have shown that the primary incident percentages ranged from 7% to 13% (Moore et al. 2004) and that the secondary crash percentages ranged from 15% to 35% (Karlaftis et al. 1998). Some previous studies on secondary crashes tend to define these crashes "relatively broadly" (Moore et al. 2004) because they do not consider the dynamic nature of traffic conditions during incidents. This could potentially result in an overestimation of the percentages of secondary crashes. This study shows that, for the three freeway corridor segments investigated, the average percentage of primary incidents was only about 5% and the average percentage of secondary crashes was 3.23%.

6.4.2. Logistic Regression Analysis

Regression analysis methods, especially linear regression models, have increasingly been used in transportation research. One objective of secondary crash model analyses is to estimate the likelihood of a secondary crash, given the characteristics of the primary incident. Because there are only two possibilities (0 or 1) for secondary crash occurrence, linear regression analysis, which assumes that the independent variable follows a continuous normal distribution, is inappropriate here. In this study, a logistic regression model is applied to analyze the relationships between the primary incident characteristics and the possibility of secondary crash occurrence. A similar approach was utilized in a study by Karlaftis et al. (1998) for analyzing the likelihood of secondary crashes and in a study by Madanat et al. (1994) on predicting the gap-acceptable probability at a stop-controlled intersection. The general form of incident occurrence probability in a logistic model is as follows:

$$P(y_i = 1 \mid x_i) = p_i = \frac{e^{\alpha+\beta x_i}}{1+e^{\alpha+\beta x_i}}$$

The odds of an event occurring (odds ratio) is defined as follows (Wang and Guo):

$$\frac{p_i}{1-p_i} = e^{\alpha+\beta x_i}$$

where,

p_i is the probability that an instance i will occur,

α is the constant,

β is the vector of coefficients for independent variables, and

x_i is the vector of independent variables.

6.4.3. Potential Independent Variables

To predict the likelihood of secondary crashes, this study examines a set of primary incident and traffic characteristics. These have the potential for possible inclusion as independent variables in the developed logistic regression model. The following variables were considered:

- Incident duration factors: Logically, the probability of secondary crash occurrence may be anticipated to increase with a rise in primary incident durations. Two incident duration factors were extracted and considered in this study, the total duration of a potential primary incident (detection plus response plus clearance durations) and the related lane blockage duration.

- Time factors: Time factors are good indicators of traffic conditions, driver alertness, and familiarity with the route. The three time factors extracted were the month of year, day of week, and time of day (AM, Midday, PM, Late Night, Weekend Day, and Weekend Night).
- Environmental condition factors: Environmental conditions at the incident site could have an impact on the likelihood of secondary crashes. For example, heavy rain may affect freeway visibility conditions and, thus, may increase the possibility of secondary crash occurrences. Five condition factors were considered: “Pavement,” “Precipitation,” “Wind,” “Visibility,” and “Illumination.” Collectively, the use of these factors reflects whether wet/dry pavement, rain, strong wind, poor visibility, and/or dark conditions are associated with secondary incidents.
- Incident type factors: The four factors extracted for this category were “Incident Type” (Crash/Abandoned Vehicle/Disabled Vehicle/Debris, etc.), “Rollover,” “Fire,” and “Hazmat” (for hazard materials).
- Location and traffic condition factors: Two factors were considered in this category, “Corridor” (analyzed corridor per direction: I-95 NB, I-95 SB, I-595 EB, I-595 WB, I-75 NB, and I-75 SB) and the volume/capacity ratio (v/c ratio) of the corridor segment on which the secondary incident occurs. To calculate the v/c ratios, the 2006 hourly traffic volume data from the FDOT for the freeway corridor segments were matched to the specific time of day at which a primary incident occurred. The freeway number of lanes information is extracted from the SMART database (*8*). The freeway capacities were estimated based on the number of lanes by assuming a lane capacity of 2,200 vphpl.
- Lane closure factor: As discussed above, incidents with two-lane blockages are more likely to have associated secondary crashes. Therefore, the number of blocked lanes is included in the regression analysis.
- Injury condition factor: Injury and fatality conditions may have a significant impact on primary incident site conditions and time. Accordingly, an injury condition factor was investigated for inclusion in the model in this study.

- Vehicle type factors: Three factors were extracted for this category “Vehicle Count” (number of vehicles involved), “Commercial” (if a commercial vehicle is involved in the incident), and “Vehicle Type” (Car/Van, Tractor, Truck, Motorcycle, Emergency Vehicle, etc.).

Note that some of the above factors are correlated with each other. Thus, only some of the correlated factors are expected to be selected by the regression model. The significance of these factors is determined as part of the model development and testing process, as described below.

6.4.4. Model for Secondary Crash Likelihood

The binary logistic regression function of the Statistical Package for Social Science (SPSS) was used to develop the model. All of the factors listed in the previous section were included in the initial model. The model is then tested to determine the significant variables. A forward conditional criterion was used to add one best fit variable at a time during the regression process. All of the identified variables are significant at the 0.05 level. During the regression process, the log-transformation was applied to the incident and lane blockage duration factors for better results (i.e., data normalization). A correlation test shows that there is not a strong relationship between the independent factors. The regression results are listed in Table 6-5, which indicates the following:

- Longer freeway travel lane blockage durations increase the likelihood of secondary crashes. Longer lane blockages will increase freeway congestion and, as traffic queue length increases, the possibility of secondary crashes increases.
- Whether an incident occurs on the northbound I-95 corridor (“I95NB”) is also identified as an important factor for predicting secondary crash likelihood. When all other factors are fixed and an incident with lane blockage occurs on I-95 northbound, the probability of secondary crashes increases. The I-95 corridor in Fort Lauderdale has four travel lanes for both directions, while the other two corridors (I-75 and I-595) only have three travel lanes. Therefore, a possible reason for an increased likelihood of secondary crashes on I-95 is the higher AADT. In addition, more travel lanes on I-95 could increase the

variations in travel speeds between the opened and closed lanes, causing drivers to change lanes more often and create traffic turbulence.

- When all other factors are fixed, compared to other time periods the likelihood of secondary crashes is higher for the weekday morning and afternoon peaks (AM, PM), as well as Midday periods. This result is consistent with what is shown in Figure 4. The coefficient of the A.M. factor is higher than that of the Midday and P.M. factors. This suggests that the possibility of secondary crashes is the highest during the weekday morning peak periods.
- When all other factors are fixed, secondary crashes are more likely to occur when the primary incident type is “Accident.”

TABLE 6-5 Logistic Regression Model Results for Secondary Crash Likelihood

Variable Name		**Coefficient**	**Exp(B)**	**Significant Level**
Constant		-7.652	0.000	<0.001
LN(Lane Blockage Duration)		2.113	8.270	<0.001
Incident Occurred on NB I-95		0.395	1.484	0.031
PM (16:00-19:00)		1.028	2.794	0.001
Midday (9:00-16:00)		1.160	3.191	<0.001
AM (6:00-9:00)		1.446	4.247	<0.001
Incident is Accident		0.565	1.759	0.048
Model Statistical Results				
Sample Size (*N*)	4,435	Model Chi-Square		491.489
Model -2Log-likelihood	970.802	Analogous R^2		0.336

Table 6-5 shows that, with the exception of the constant factor, the coefficients of the identified variables are all positive. This means that all identified variables contribute to increasing the likelihood of secondary crashes. The Marginal Effect/Odd ratio (Exp(B)) column of Table 6-5 shows the odds ratios, which are the predicted changes in odds of the dependent variable for a unit increase in the corresponding independent variable. The lane blockage duration variable has the highest odds ratio. This indicates that incident duration has the highest influence on secondary crash occurrence. The traffic management strategies that clear roadway blockages as quickly as possible will therefore have a significant impact on reducing the chance of secondary crashes.

Table 6-5 also shows the overall statistical results for the developed logistic regression model. The analogous R^2 value, which is similar to the commonly used Coefficient of Determination R^2 in multiple linear regression analysis, is taken as a measure for goodness-of-fit. The analogous R^2 is defined as 1- $\frac{LL_M}{LL_0}$, where LL_0 is the log-likelihood of the initial model ($LL_0 = LL_M$ + Model Chi-Square) and where LL_M is the log-likelihood of the final model. The analogous R^2 value is 0.336 for the model. The Chi-Square (Hosmer-Lemeshow) goodness-of-fit test shows that the Chi-Square goodness-of-fit is not significant (0.707). This suggests that the model has an adequate fit.

According to the constant and variable values identified in Table 6-5, the logistic regression model for secondary crash likelihood can be expressed as follows:

$$\left(\frac{SecondaryCrash}{NoSecondaryCrash}\right) = \text{EXP}(-7.652 + 2.113 \times \text{LN(LaneBlockage)} + 0.395 \times \text{I95NB} + 1.028 \times \text{PM} + 1.160 \times \text{Midday} + 1.446 \times \text{AM} + 0.565 \times \text{Accident})$$

In any case, at most one of the three time of day binary factors, i.e., “AM,” “PM,” and “Midday,” can be true. The model can be used to compute the ratio of likelihood that a potential primary incident will occur. If the value is greater than one, it means that the probability of a secondary crash occurrence is higher than that of no secondary crash occurrence.

The following example can be used to illustrate the idea of the developed logistic regression model. Suppose a lane blockage duration incident occurred during a weekday afternoon peak period, and that this incident was an accident. The incident also occurred on northbound I-95 and had a lane blockage duration of 15 minutes. From the model, one can derive an odds ratio $\left(\frac{SecondaryCrash}{NoSecondaryCrash}\right)$ of slightly greater than one, and thus determine that a secondary crash is more likely to occur.

6.5. Conclusions

This chapter has described an effort to better determine freeway secondary crashes for the purpose of identifying their contributing factors. A method based on a cumulative arrival and departure rate (queuing) technique was first developed. It was then used to estimate the maximum queue lengths and associated queue dissipation time for incidents with lane blockages. Based on the results, secondary crashes were identified as those that occurred upstream within a maximum possible queue length and queue dissipation time of the primary incident. Both descriptive statistics and logistic regression analyses were then applied to identify potential factors that contributed to these crashes. The regression model developed identified the following four factors as having significant effects on the likelihood of secondary crash occurrence: primary incident type, primary incident lane blockage duration, time of day, and whether the incident occurred on northbound I-95. The model showed that accidents occurring in the daytime period and with long lane blockage durations can significantly increase the possibility of secondary crashes. Therefore, traffic management strategies that clear roadway blockages as quickly as possible will have a significant impact on reducing the chance of secondary crashes.

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7. Estimation of Incident Impacts and Severity Levels

7.1. Introduction

Effective incident management requires the identification of incident severity and its potential impacts on the transportation system and its users. For on-line applications, while incidents are active, this identification allows agencies to determine the required levels of response such as dynamic message sign messaging decisions, diversion plan activations, and allocation of response resources. For off-line applications, analyzing historical data to classify incidents by severity level allows for the better planning of incident management activities.

Many measures can be used to assess the severity of incidents based on their impacts on the transportation system and its users. These can include combinations of incident attributes such as incident duration, injury level, and lane-blockage level, as well as estimated incident impacts; such as the impacts on mobility, safety, energy consumption, the environment, and traveler satisfaction. Due to the difficulty in assessing the impacts of incidents, particularly for on-line applications, transportation agencies have used simplified criteria to classify incidents based on incident attributes, as explained below.

The Florida Department of Transportation (FDOT) incident management (IM) program classifies traffic incidents into three severity levels based on incident duration and lane blockage information (SMART SunGuide 2009). Level 1 incidents are incidents with minor or no-lane blockage and an estimated impact to traffic of less than 30 minutes. Level 2 incidents are intermediate traffic incidents with impacts to traffic estimated to be between 30 minutes to 2 hours. Level 3 incidents are major traffic incidents, which last for more than 2 hours or involve closing all mainline lanes or exit lanes. The above definition is also used by the FDOT SunGuide traffic management center (TMC) software and traveler information systems to classify incident severity levels. However, this definition requires the knowledge of the incident duration, which is not known until an incident is cleared. The current implementation uses a default of 30 minutes as the incident duration, and then reclassifies a lane blockage. If 30 minutes elapse and the incident is not cleared, it is reevaluated again after two hours.

To determine the appropriate messages on dynamic message signs, the Texas Department of Transportation (TxDOT) TransGuide system classified incidents based on injury severity

(TxDOT 2009). Incidents were classified as minor if the resulting injury was minor while all other injury cases were classified as major incidents. The given rational was that incidents involving minor injuries normally require less than 15 minutes to clear.

As part of the incident response plan of the Georgia Department of Transportation (GDOT), GDOT classifies incidents into four severity levels based on lane closure and injury severity (GDOT 2009). Level 1 incidents are those with no injuries and no lane closures. Level 2 incidents include minor injuries with one lane closure. Level 3 incidents involve serious injuries with two or more lane closures. Level 4 incidents are major incidents such as HAZMAT spills and fatal injury incidents with all lane closures. The corridor traffic operation plan for US Highway 45 Reconstruction developed by Wisconsin DOT includes a more detailed classification scheme based on vehicle damage, injury level, response agencies, incident duration, and whether the incident includes debris or spill (FHWA 2000).

The Alternative Route Handbook reported the results of a survey of agencies throughout the United States and Canada to determine various aspects of their alternate route plans (Dunn 2006). A total of 26 survey responses were received. One of the survey items provided by the response agencies was the criteria for activating alternate route plans. The survey indicates that agencies mainly use lane closure as the criteria and, in some cases, combine this with a minimum threshold for the anticipated lane closure. One surveyed agency (ARTIMIS in Ohio/Kentucky) has different criteria for the peak and non-peak hours, considering that the impact of lane closure is more severe in the peak period.

The above discussion indicates that transportation agencies have mainly used simple incident attributes such as incident duration and lane blockage to classify incidents by severity. Kachroo et al (1997) proposed the use of a severity index to classify incidents. This index is calculated based on average incident delay (minutes per vehicle), incident duration, and incident type.

This chapter discusses models developed to estimate incident impacts in real-time and proposes an approach to assign an impact severity index to each incident based on the estimated incident impacts. To classify incidents by severity, the impact severity index is calculated using a K-NN classifier algorithm that accounts for all primary incident attributes and impacts on traffic operations, which has not been done in the past. The incident attributes and impacts considered are lane blockage, incident duration, average incident delay, queue length, and the potential for secondary incidents. The severity index estimation utilizes models developed in this study to predict incident duration and the potential for secondary incidents. The incident duration model developed in this study is the M5P method. This method has a number of advantages that will be discussed later in this chapter. In addition, this study separates the incident duration into incident response time and incident clearance time and has also provided separate predictions for the two components. This is significant since the factors that affect these two duration components are different.

7.2. Estimation of Incident Attributes and Impacts

A number of measures are considered important to quantify incident impacts. Such measures include the percentage of lane blockage, incident duration, average incident delay, queue length, and the potential for secondary incidents. The estimation of these parameters requires the use of models developed for this purpose, as described below.

7.2.1. Incident Duration

Incident duration is used by many agencies either alone or in combination with other parameters to determine incident severity. In addition, it is an important factor in the estimation of incident mobility and safety impacts, as described later in this chapter. When analyzing historical data, the incident durations are available from the incident data archives. However, for real-time applications, a model is needed to predict incident durations based on parameters that are available in real-time. A model was developed in this study to predict incident delay based on FDOT District 4 historical data.

Previous Studies

A number of studies have developed models to estimate incident duration. Yazici et al. (2010) provided a comprehensive summary of literatures on incident duration studies. Overall, the review identified 19 prior studies that dealt with incident duration statistics and prediction models. All of these studies were conducted prior to 1999 and applied probabilistic distribution, linear regression, conditional probability, time sequential, decision tree, and rule-based models to incident duration estimation. Initial exploration was done to determine if one or more of these models could be used to estimate incident durations for the purposes of this study. It was found that three of these models were viable to investigate. The other models could not be used either because the parameters were not available or because they were tightly linked to local conditions. The three models were those developed by Garib et al. (1997) and Wang (1991) using regression analysis, and by Smith and Smith (2001) using the classification tree method. It was found that these three models were not able to produce acceptable estimations for incident duration in the FDOT District 4 region. It is expected that one of the significant reasons for this unacceptable performance is the difference in incident and incident management attributes, and their recordings in different regions.

An advantage of regression models is that confidence intervals and other statistics measures can be added to the forecasted output (Smith and Smith 2001). However, if producing estimates with wide confidence intervals, the developed models may lack operational values. Ozbay and Kachroo (1999) used the decision tree as an alternative to predict incident durations for cases of wide confidence intervals resulting from regression. An advantage of decision tree models is that they are easy to understand and make no assumptions on the probabilistic distributions of the incident data. A disadvantage of the decision tree method is that the variables need to be categorical. Because incident duration and clearance time are continuous variables, these variables must be categorized into multiple discrete intervals. If the intervals are not divided correctly, this categorization may result in unfavorable results.

In this study, a new model for predicting incident duration was derived based on FDOT District 4 incident data. Unlike previous studies, the model estimates incident response and lane clearance durations separately, and then adds these two duration values to obtain the total lane blockage duration. The rationale is that these two durations are influenced by different factors. The lane clearance duration is the time between first responder arrival and the reopening of all travel lanes. The response time is defined for the purposes of this study as the time from the occurrence of the incident to the arrival of the first responder.

Lane Clearance Estimation

Incidents with lane closures for a one-year period from April 2006 to March 2007 were used for the prediction model development for a total of 2,535 lane-blockage incidents. A set of factors were selected for possible inclusion as independent variables in the prediction model. These factors include: time of day that the incident occurs (AM, PM, Midday, Night, Weekend), incident verification and response times, environmental factors (pavement wetness, visibility, illumination conditions, rain conditions), incident type (accident, fire, rollover, and so on), activated incident management processes (number and activities of responded service patrol, whether a severe incident response vehicle was dispatched, DMS usage), and incident attributes (total number of lanes, number of blocked lanes, injury conditions, and truck, tractor, or bus involvement). The dependent variable is the lane clearance duration (in minutes).

In this study, the decision tree method was first tried for the estimation of lane clearance duration. Since the duration is a continuous variable, it had to be converted to a categorical variable, by categorizing the durations to intervals within specific ranges, before the decision tree method could be applied. The interval had to be narrow enough to produce acceptable results while not so narrow as to have a small number of instances. Different interval combinations (10-, 15-, 30-minute) were evaluated, but the results were all poor. Considering the limitations of using the decision tree for lane clearance duration estimation, this study employs a different type of tree called the M5P tree for the estimation of lane clearance duration. The M5P tree algorithm originates from the M5 tree, which was developed by Quinlan (1992) for predicting continuous variables. One major advantage of the M5 tree over the traditional decision tree or CART tree methods is that trees built by the M5 algorithm can have multivariate linear models as their leaves instead of single values. Wang and Witten (1997) modified the original M5 tree algorithm to handle enumerated attributes and missing values and called it the M5P algorithm. This study applied the M5P tree algorithm to predict lane clearance duration due to its ability to deal with numerical variables, categorical variables, and missing values, and its ability to generate linear regression models at the tree leaves. To our best knowledge, no previous study has developed a prediction model for lane clearance time or applied the M5P tree algorithm to the study of incident duration prediction.

A ten-fold cross validation method was used for the M5P model development and evaluation. In the ten-fold cross validation, the dataset was split into ten equal-sized subsets. One subset, in turn, was used for model validation, and the other nine subsets were used for model development. Individual error estimations were averaged to achieve an overall error estimate. The minimum number of instances (records) per leaf node in the M5P tree was chosen to be 100.

The developed M5P model is shown in Figure 7-1. Figure 7-1 shows that the number of lanes closed and day versus night operations are the most important factors at the upper level categorization of incidents by duration. LM1 to LM5 in Figure 7-1 are linear regression models developed for each of the resulting categories from the upper level categorization. One of the assumptions of the linear regression method is that the error is normally distributed, a condition which may not be met, particularly for wide ranges of variable values. With a tree classification method, the data sets are classified into more closely related subsets and regression models which better meet the normality assumption produced after the classification. In addition, this study applied the Box-Cox transformation to identify the best transformation for the dependent variable (Johnson and Wichern 2002). This is a commonly used method to transform non-normal data to allow regression model analyses that require the normal distribution assumption. The maximum likelihood estimates (MLE) and residual plots were used as criteria for the evaluation of transformation optimality.

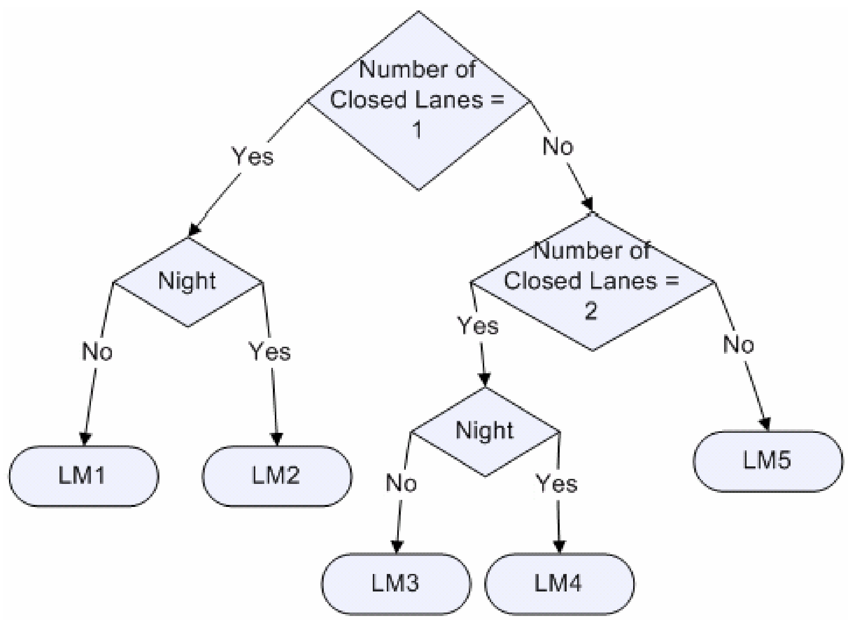

FIGURE 7-1 M5P Tree Model Developed for Lane Clearance Duration Prediction

The tree leaves of the developed regression model are given below and variable explanations are given in Table 7-1 (see Figure 7-1 for the illustration of the subsets of the data, for which the LM1 to LM5 models were developed):

LM1:

$$\tau(Y,\lambda) = 2.912 + 1.117 \times \text{NumRRAssists} - 0.091 \times \text{TMCResponse} + 0.091 \times \text{TMCVerification} + 0.892 \times \text{Injury} - 0.999 \times \text{ShoulderAvailable}$$

$$+ 2.093 \times \text{hasFullBlockage} + 0.542 \times \text{Weekend} + 0.908 \times \text{Tractor}$$
$$+ 1.602 \times \text{Truck} - 0.496 \times \text{DisabledVehicle} - 0.372 \times \text{CCTV}$$
$$+ 0.023 \times \text{DMSCount} \tag{7-1}$$

LM2:

$$\tau(Y,\lambda) = 5.219 + 1.997 \times \text{NumRRAssists} - 0.154 \times \text{TMCResponse}$$
$$+ 0.887 \times \sqrt{TMCVerification} + 4.875 \times \text{SIRV} + 12.104 \times \text{BUS}$$
$$+ 3.613 \times \text{Tractor} \tag{7-2}$$

LM3:

$$\tau(Y,\lambda) = 7.142 - 4.971 \times \text{ShoulderAvailable} + 1.694 \times \text{NumRRAssists}$$
$$- 0.155 \times \text{TMCResponse} + 2.752 \times \text{Weekend} + 0.080 \times \text{DMSCount}$$
$$+ 7.017 \times \text{BUS} + 7.025 \times \text{Emergency} + 1.825 \times \text{Illumination}$$
$$+ 2.080 \times \text{Rollover} + 0.393 \times \text{VehicleCount} + 2.826 \times \text{HasFullBlockage}$$
$$+ 1.629 \times \text{Tractor} \tag{7-3}$$

LM4:

$$\tau(Y,\lambda) = -330.463 + 2328.506 \times \text{TotalActivities} + 2058.012 \times \text{Injury}$$
$$- 1649.351 \times \text{NumRRDispatches} + 4103.359 \times \text{SIRV}$$
$$+ 1743.637 \times \text{I595E} + 851.413 \times \text{Weekend} - 68.838 \times \text{TMCResponse}$$
$$+ 60.161 \times \text{TMCVerification} \tag{7-4}$$

LM5:

$$\tau(Y,\lambda) = 5.677 + 1.146 \times \text{NumRRAssists} - 2.257 \times \text{ShoulderAvailable} - 3.250 \times \text{Midday}$$
$$+ 1.729 \times \text{Rollover} - 3.408 \times \text{PM} - 2.028 \times \text{AM} + 1.441 \times \text{Tractor}$$
$$+ 4.455 \times \text{Truck} - 0.066 \times \text{TMCResponse} + 0.683 \times \text{TotalLanes}$$
$$+ 0.677 \times \text{TotalActivities} + 1.951 \times \text{Fire} + 2.684 \times \text{HAZMAT} \tag{7-5}$$

TABLE 7-1 Variable Explanations for Lane Clearance Duration Prediction Sub-models

Name	Type	Explanation
NumRRAssists	N	Number of onsite assists by Road Ranger operators
TotalActivities	N	Total number of onsite activities by responders
NumRRDispatches	N	Number of Road Ranger vehicles dispatched
DMSCount	N	Number of Dynamic Message Signs activated
TMCResponse	N	TMC response time (in minutes)
TMCVerification	N	TMC verification time (in minutes)
DisabledVehicle	C	If the incident type is “disabled vehicle”
ShoulderAvailable	C	If shoulder is available for lane blockage incidents
HasFullBlockage	C	If ramp(s) or all travel lanes were blocked
CCTV	C	If CCTV cameras were used
SIRV	C	If a SIRV was dispatched to the incident site
Weekend	C	If an incident occurred during a weekend
Midday	C	If an incident occurred during the midday period
AM	C	If an incident occurred during the A.M. peak
PM	C	If an incident occurred during the P.M. peak
Injury	C	If personal injuries or fatalities occurred
VehicleCount	N	Number of vehicles involved
Fire	C	If any incident vehicle was on fire
Rollover	C	If any incident vehicle rollover occurred
Illumination	C	If it is daylight (0) or dark (1)
I595E	C	If an incident occurred on I-595 Eastbound
Tractor	C	If tractor/trailer was involved in the incident
Truck	C	If any dump truck was involved in the incident
Bus	C	If any bus was involved in the incident
Emergency	C	If any emergency vehicle was involved
TotalLanes	N	Total number of lanes at the incident site
HAZMAT	C	If hazard materials was involved

Note: “N” indicates numerical variable and C indicates categorical variable.

In the developed regression sub-models listed above, all the independent variables are significant at the 0.05 confidence level. The Variance Inflation Factor (VIF) values are all less than 3.0, which indicate no significant collinearity relationships. Overall, the LM1 to LM5 sub-models show that the significant factors in predicting lane clearance duration are the number of responded service patrol vehicles, injury presence, number and type of vehicles involved (tractor, truck, etc.), time of day (AM, PM, Midday, Night, Weekend), TMC verification and response time, incident type (Fire, Rollover, etc.), number of lanes blocked, presence of CCTV cameras, and the presence of SIRV. As expected, when truck, tractor, bus, or emergency vehicles were involved in an incident, the lane clearance duration would be longer than those with only cars involved. If a shoulder was available at the incident site, the lane clearance time would be generally shorter because incident vehicles could be moved to the shoulder and travel lanes could be cleared faster. When all other factors were fixed, weekends usually had longer lane clearance times, while lane clearance times during workday daytime (AM, Midday, and PM) were shorter than workday nighttime or weekends. The "TMCResponse" variable showed a negative sign in all equations, indicating shorter time with slower response of the service patrol vehicles. While this may at first seem contrary to expectations, it can be explained as follows. The response time of service vehicle is expected to be a function of the severity of the incident. As such, the more severe the incident, the faster the response it will receive. In cases of less severe incidents, the service patrol places a low priority on the incident and responds to more severe incidents first.

Table 7-2 lists a number of parameter values that are important for model acceptance. Table 7-2 shows that four of the five sub-models can achieve adjusted R^2 values equal or higher than 0.45. LM2, which is the sub-model for incidents with one lane blocked during the nighttime period, has the lowest adjusted R^2 value (0.36). This shows that, during the nighttime period, lane clearance time is more unpredictable than the other periods, which may be due to the shortage of resources. The F statistics and the generally small S_e, indicate that the models are adequate predictors.

TABLE 7-2 Statistical Results for Lane Clearance Duration Prediction Sub-models

Sub-Model Name	**Box-Cox Transformation Parameter (λ)**	**Number of Variables (V)**	**Sample Size (N)**	**Coefficient of Determination (R^2)**	**Adjusted R^2**	**Standard Error Term (S_e)**	**F Statistics**
LM1	0.25	12	1,145	0.47	0.46	1.86	38.26
LM2	0.10	6	350	0.37	0.36	1.49	16.84
LM3	0.50	12	392	0.51	0.49	3.65	18.03
LM4	2.00	8	198	0.64	0.62	1989.7	31.16
LM5	0.45	13	450	0.47	0.45	3.41	21.03

Incident Response Time

The previous section describes the estimation of lane clearance duration. The total lane blockage duration can be estimated by adding to this time the response time defined earlier in this chapter. The FDOT District 4 database was used to estimate this time by implementing a cross-classification approach. The results are shown in Table 7-3. This time was found to be shorter than the lane clearance time, and its variation was found to be relatively small. In addition, the factors that are expected to affect the response time are less than those that affect the lane clearance duration. Thus, a cross-classification approach of the type presented in Table 7-3 was used for the purpose of estimating the response time. The factors used in the cross-classification are night vs. day, weekdays vs. weekends, and the injury levels of the incidents. In addition to response time, Table 7-3 also shows the additional shoulder blockage duration after the blocked lanes are cleared.

TABLE 7-3 Agency Response and Additional Shoulder Blockage Durations

# of Lanes Blocked	# of Incidents in Category	Major Injury / Fatality	Time of Day	Response Duration (minutes)	Additional Shoulder Blockage (minutes)
1-lane	125	No	Weekend Day	8.18	24.63
1-lane	92	No	Weekend Night	7.81	25.59
1-lane	642	No	Weekday Day	6.52	26.85
1-lane	158	No	Weekday Night	7.75	25.05
1-lane	96	Yes	Day	6.53	38.73
1-lane	15	Yes	Night	8.11	22.31
2-lane	48	No	Weekend Day	6.09	24.24
2-lane	57	No	Weekend Night	5.69	17.43
2-lane	188	No	Weekday Day	7.29	31.75
2-lane	74	No	Weekday Night	7.82	17.97
2-lane	61	Yes	Day	5.09	48.10
2-lane	22	Yes	Night	8.75	19.79
3-lane	18	No	Weekend Day	6.16	35.01
3-lane	32	No	Weekend Night	6.01	23.04
3-lane	75	No	Weekday Day	6.07	35.27
3-lane	42	No	Weekday Night	5.98	19.40
3-lane	33	Yes	Day	3.90	39.52
3-lane	19	Yes	Night	8.46	10.81
4-lane	20	No	Day	7.70	26.42
4-lane	20	Yes	Day	5.42	38.59
4-lane	29	Yes/No	Night	6.77	19.28

7.2.2.Incident Delay and Queue Length

Simulation, shockwave, or queuing analysis could be used to estimate incident delays and queue length for the purposes of this study. In the results presented in this chapter, the queuing analysis approach was selected. The parameters required for the analysis include incident duration, traffic demands, and capacity with and without incidents. The traffic demands during incident conditions can be estimated based on the average historical traffic detector data at the incident location during the estimated duration of the incident. In this study, the historical traffic data was obtained from STEWARD, the Florida ITS data warehouse. The capacities during incident and non-incident conditions were estimated based on estimates presented in the Highway Capacity Manual (2000).

7.2.3.Secondary Incidents

Another important impact of incidents is the potential for secondary crashes. In this study, a logistic regression model was developed to assess the potential for secondary incidents in real-time (see Chapter 6). The model was developed based on the same FDOT District 4 incident database. The identified logistic regression model for secondary crash likelihood in Chapter 6 presented below for convenience.

$$\begin{aligned}\frac{SecondaryCrash}{NoSecondaryCrash} = \mathrm{EXP}(&-6.100 + 0.462 \times \mathrm{LN}(\mathrm{LaneBlockage}) \\ &+ 0.170 \times \mathrm{QueueLength} + 0.236 \times \mathrm{I95NB} \\ &+ 0.702 \times \mathrm{PM} + 0.959 \times \mathrm{Midday} \\ &+ 1.397 \times \mathrm{AM} + 0.451 \times \mathrm{Accident}) \qquad (7\text{-}6)\end{aligned}$$

Where,

LaneBlockage	= total length of lane blockage in minutes,
QueueLength	= maximum queue length in miles caused by the incident,
I95NB	= 1 if the incident occurred on I-95 northbound and 0 otherwise,
PM	= 1 if the incident occurred during the workday afternoon peak period,
Midday	= 1 if the incident occurred during the workday midday period,
AM	= 1 if the incident occurred during the workday morning peak period, and
Accident	= 1 if the incident type is “Accident.”

7.3. Incident Impact Severity Levels

In this study, a model is developed to obtain a combined severity index based on instances of real-world incidents with different estimated impacts and attributes. The impacts and attributes of the selected incidents were presented to ITS engineers, and the engineers were asked to assign a severity level for each incident case. The results of this assignment were then used as inputs to a k-nearest neighbor (k-NN) classification method to determine the relationships between the incident attributes and the impact severity levels, as identified by the ITS engineers.

The k-NN classification method is an instance-based learning algorithm based on the assumption that similar instances belong to similar classes. For an unknown instance, the distances (e.g., Euclidean distance) between the unknown instance and others are calculated and used to determine the k-nearest neighbors. The unknown instance is then assigned to the most common class among its k-nearest neighbors. The k-NN classifier was selected because it allows the identifications of incident severity to change as new information is added to the incident instance database. Thus, if an incident is assigned a certain severity level during the real-time execution of the developed method and the operator does not like the assignment, then he or she can overwrite the assignment results. This overwrite will be used to update the base incident severity database, which will in turn be used in the future assignment of the severity of incidents by the k-NN classifier.

In this study, the k-NN classifier was applied using the Weka software package (Witten and Frank 2005). The ten-fold cross-validation method is used to evaluate the classification performance.

7.4. Application of the Methodology

Thirty real-world incidents were selected from the FDOT District 4 incident database and used for model evaluation and comparison. These incidents were not used in the model development process. The selected incidents vary significantly in their attributes such as duration, lane-blockage percentage, location, time of day, traffic conditions, and other attributes. This variation in the attributes will allow a better assessment of the developed method and models.

Figure 7-2 indicates that, with the model developed in this study, the error in estimating the incident duration is high for some of the incidents. However, Figure 7-2 also indicates that the model fits the data relatively well and shows the correct trend in incident duration. In addition, the mean square error and average absolute difference when using the model developed in this study to estimate the lane clearance duration were 23.5 minutes and 18.3 minutes, respectively. This was significantly better than the results achieved using the models developed in previous studies.

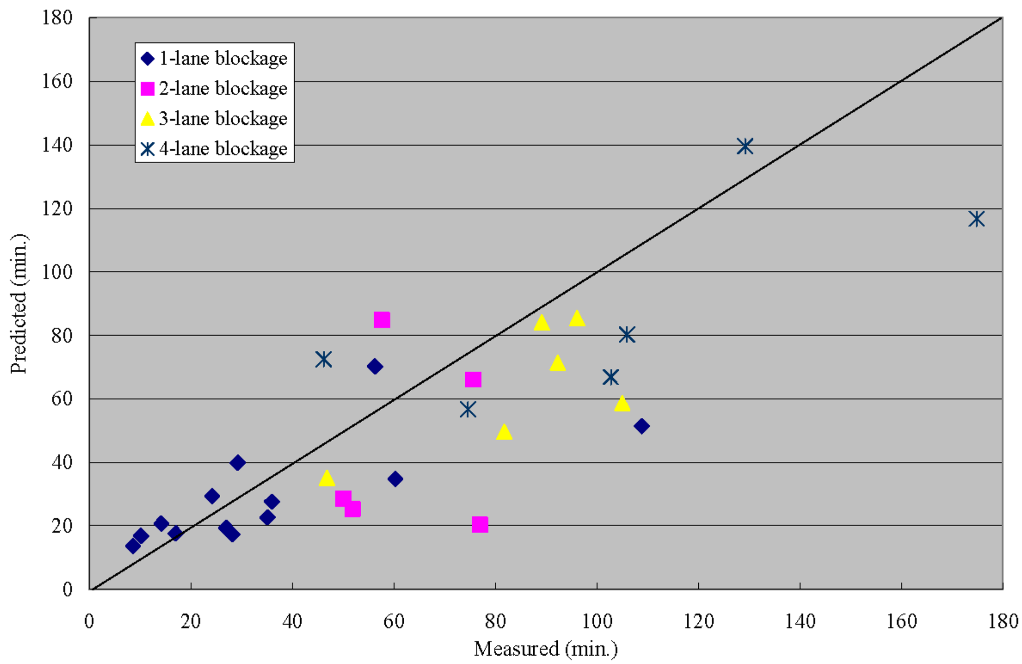

FIGURE 7-2 Measured Lane Blockage Duration Values versus Estimated Values Using the Developed Model

Table 7-4 shows the estimated probability of secondary incidents for the 30 incidents used to apply the methodology of this study. The results indicate that the probability of secondary incidents ranged between 1.2% and 33.6%, with the highest probability occurring for accidents with long queues during the A.M. peak on a congested corridor.

TABLE 7-4 Estimation of Secondary Incident Probabilities

Incident ID	Contributing Factors					Secondary Crash Probability
	Lane Blockage (min.)	Queue Length (mile)	On I-95 NB	Time of Day	Accident	
295921	3.60	0.473	Yes	AM	No	2.20%
282469	5.20	0.090	Yes	Midday	Yes	2.47%
189640	9.15	0.245	Yes	PM	No	1.63%
286095	12.00	0.604	Yes	PM	Yes	3.05%
321081	19.2	0	Yes	Night	Yes	1.72%
169906	21.98	0	Yes	Weeken	No	1.17%
170461	23.15	0.655	Yes	PM	Yes	4.12%
185138	24.23	0.927	No	Midday	No	2.90%
309983	30.92	0	Yes	Night	No	1.37%
180463	30.07	0.630	No	AM	Yes	7.09%
194627	61.15	0	Yes	Night	No	1.86%
172400	51.28	0	Yes	Night	Yes	2.68%
180713	107.9	1.532	Yes	Midday	Yes	11.60%
201530	45.02	1.987	Yes	PM	Yes	6.82%
293060	49.60	2.022	Yes	AM	Yes	13.37%
283171	58.05	0.493	No	Night	Yes	2.44%
174594	71.97	1.429	Yes	Midday	Yes	9.66%
199301	87.43	0.088	Yes	Night	Yes	3.45%
281659	41.82	3.931	Yes	PM	Yes	8.97%
175762	76.73	4.164	Yes	AM	Yes	21.37%
170019	87.3	1.628	Yes	Night	Yes	4.43%
308403	84.17	3.991	Yes	Midday	Yes	15.09%
303038	104.78	2.152	No	Night	Yes	4.17%
173832	116.38	3.134	Yes	Weeken	Yes	6.40%
192290	41.97	6.140	Yes	PM	Yes	12.56%
280226	74.37	3.990	Yes	Midday	Yes	14.37%
170840	101.08	5.249	Yes	Midday	Yes	19.32%
281282	97.93	6.624	No	AM	Yes	26.74%
191883	130.82	4.486	Yes	Night	Yes	8.33%
208447	169.82	7.040	No	AM	Yes	33.56%

The measured attributes of the thirty incidents selected were presented to three ITS engineers. The engineers were asked to assign a severity level for each incident case. The results were used as input to the k-NN classifier described previously. Table 7-6 compares the results of applying the k-NN classifier approach to the 30 incidents with the scores assigned by the ITS engineers to these incidents. The cross-validation results show that the k-NN algorithm was able to correctly classify 90% of the instances. Table 7-5 indicates that the model was able to assign the same scores assigned by the ITS engineers in 28 of the 30 cases. For the remaining two cases, the model assigned a severity of 1 instead of 2.

TABLE 7-5 Incident Impacts and Index for the 30 Incidents of the Case Study

Time	**No. of Lanes Blocked**	**Predicted Incident Duration**	**Queue Length (miles)**	**Average Delay/Veh (minutes)**	**Secondary Incident Probability**	**Engineer Assigned Severity**	**Model Predicted Severity**
AM	1	23.73	0.473	2.922	2.20%	2	2
Midday	1	26.92	0.090	0.800	2.47%	1	1
PM	1	30.8	0.245	1.958	1.63%	2	1
PM	1	50.06	0.604	3.736	3.05%	2	2
Night	1	55.67	0	0	1.72%	1	1
Weeken	1	50.06	0	0	1.17%	1	1
PM	1	49.78	0.655	4.364	4.12%	2	2
Midday	1	49.93	0.927	6.202	2.90%	2	2
Night	1	54	0	0	1.37%	1	1
AM	1	62.85	0.630	4.087	7.09%	2	2
Weeken	1	61	0	0	1.86%	1	1
Night	1	96.66	0	0	2.68%	1	1
Midday	1	83.81	1.532	9.709	11.60%	3	3
PM	2	62.32	1.987	12.558	6.82%	3	3
AM	2	73.05	2.022	12.500	13.37%	3	3
Weeken	2	104.17	0.493	8.950	2.44%	3	2
Midday	2	54.03	1.429	9.274	9.66%	2	2
Night	2	85.37	0.088	1.910	3.45%	2	1
PM	3	49.22	3.931	24.300	8.97%	3	3
AM	3	93.23	4.164	25.741	21.37%	4	4
Weeken	3	88.95	1.628	23.384	4.43%	3	3
Midday	3	95.55	3.991	27.202	15.09%	4	4
Night	3	80.23	2.152	23.195	4.17%	3	3
Weeken	3	102.13	3.134	26.997	6.40%	4	4
PM	4	111.43	6.140	40.912	12.56%	4	4
Midday	4	91.02	3.990	27.953	14.37%	4	4
Midday	4	123.96	5.249	46.469	19.32%	4	4
AM	4	112.14	6.624	40.945	26.74%	4	4
Weeken	4	131.47	4.486	56.020	8.33%	4	4
AM	4	120.91	7.040	45.692	33.56%	4	4

Note: “Weekend N” in this table indicates weekend night.

7.5. Conclusions

This chapter presented models and methods to estimate the potential incident impacts on mobility and safety in real-time. Communicating these potential impacts to TMC operators will facilitate better decisions regarding incident management strategies.

A major contribution of this work is the development of a new method based on the k-NN classifier algorithm that allows incidents to be classified into categories based on primary incident attributes and impacts. These attributes and impacts include number of lanes blocked, predicted incident duration, estimated queue length, average delay, and secondary incident probability. The developed approach utilizes inputs from Intelligent Transportation Systems (ITS) engineers and/or Traffic Management Center (TMC) operation managers to calibrate a model that automatically identifies the incident severity class. The evaluation of the method indicates that the model was able to assign the correct severity of incidents, as perceived by ITS engineers in 28 of the 30 cases studies. For the remaining two cases, the model was assigned a severity of 1 instead of 2. It is expected that as more classified incidents are added to the training set, the rate of correct classification will increase markedly. This method can be considered for use as part of TMC operations.

The model developed in this study to estimate lane blockage duration showed that several factors affect this duration, including the time of day that the incident occurs, incident verification and response times, environmental factors, incident type, incident response, activated incident management processes, and incident attributes. The model performance in terms of mean square error and absolute average error difference is better than what could be achieved with the use of three models that were borrowed from the literature. The use of even larger datasets could be investigated to see if additional data could improve the performance of the developed model.

The model developed to estimate secondary incident potential indicated that the factors that can impact the secondary incident probability include queue length, whether the incident is an accident, the period of the day at which the incident occurs, and the specific corridor on which the incident occurs. The model predicts for incidents with varying attributes that the probability of secondary incidents can range between 1.2% and 33.6%, with the highest probability estimated for accidents with very long queues that occur in the A.M. peak on a congested corridor in the region of the study.

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Appendix A Data Filtering Procedures

TABLE A-1 Rule-based Tests used in Data Filtering Steps

Aggregation Level	**Tests**	
20-second detector data	Eliminate duplicate data	• Eliminate exactly same records • Identify data with same timestamp and lane ID but different speed, volume count, and occupancy • Identify data with the same lane id, speed, volume count, and occupancy but with time interval less than 20 second
	Univariate test	• S < 0 or S > Speed limit + 30 mph • V < 0 or V > 17 for 20-second data • O < 0 or O > 100
	Multivariate test	• S = 0, V > 0, and O > 0 (except that S = 0, V = 1 and O >= 60) • S > 0, V = 0, and O > 0 • S > 0, V > 52.8×S/(180×Leff), and O = 0 • S = 0, V = 0, and 3 < O < 100 • S = 0, V > 0, and O = 0 • S > 0, V = 0, and O = 0
	Temporary variability test	• Check the maximum consecutive periods of constant speed, volume count, and occupancy including all zeros • Maximum of 30 periods (i.e., 10 minutes) for 6:00 A.M. – 10:00 P.M. • Maximum of 45 periods (i.e., 20 minutes) for 10:00 P.M. – 12:00 A.M. • Maximum of 90 periods (i.e., 30 minutes) for 12:00 A.M. – 6:00 P.M.
Temporal aggregated detector data	Average effective vehicle length	• $L_{eff} = 52.8 \times O \times S/V$ • $L_{eff} < 10$ *ft or* $L_{eff} > 60$ *ft*
	Maximum density	• $k = V/S$ • $k > 250$ *vphpl*

Appendix B Existing Travel Time Estimation Methods

This appendix provides a brief description of existing travel time estimation methods used in comparison.

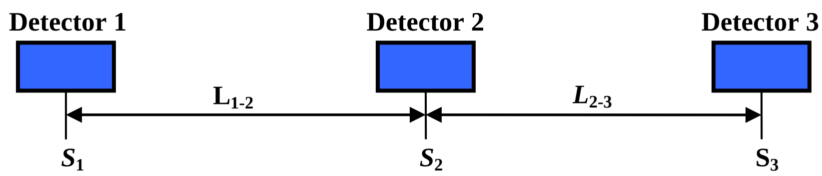

FIGURE B-1 Schematic Diagram of Detector Configuration

Point-to-Point Method

The travel time link is divided into several segments. The summation of roadway segment travel time yields the total travel time along the link. For each segment, the speed detected at the upstream detector is used to represent the average speed of the whole segment such that the travel time $TT_{1\text{-}2}$ along the segment $L_{1\text{-}2}$ is

$$TT_{1-2} = \frac{L_{1-2}}{S_1} \tag{B-1}$$

Mid-Point Method

Similar to the Point-to-Point method, the Mid-Point algorithm also estimates the travel time along a travel time link by summing up the segment travel time. However, the difference is that the speed measured by each detector in the Mid-Point method assumes that each detector speed measurement represents the speeds of half distances to the next detector on both sides. Thus, the segment travel time is calculated as follows:

$$TT_{1-2} = \frac{L_{1-2}/2}{S_1} + \frac{L_{1-2}/2}{S_2} \tag{B-2}$$

Average Speed Method

In the Average Speed algorithm, the speed along the roadway segment is approximated by the average speed of detectors at both the starting and ending points of segment. The corresponding expression for travel time estimation is listed as follows:

$$TT_{1-2} = \frac{L_{1-2}}{(S_1 + S_2)/2} \tag{B-3}$$

Minimum Speed Method

For Minimum Speed method, the lower value of detector speeds at either end of the roadway segment is used in travel time estimation, that is,

$$TT_{1-2} = \frac{L_{1-2}}{\min(S_1, S_2)} \tag{B-4}$$

Minnesota Algorithm

A modified Mid-Point travel time estimation algorithm is developed by the Minnesota Department of Transportation (Mn/DOT) and applied to the twin cities. Each roadway segment is divided into 3 regions. For the central region, the speed of the detector within that region is used, and for each side region, the average speed of two adjacent detectors is applied as follows:

$$TT_{1-2} = \frac{L_{1-2}/3}{S_1} + \frac{L_{1-2}/3}{(S_1 + S_2)/2} + \frac{L_{1-2}/3}{S_2} \tag{B-5}$$

Linear Speed Method

The Linear Speed method assumes that the speed is a linear function of space instead of being constant in certain portion of roadway segments, i.e.,

$$S(x) = S_1 + \frac{x - x_1}{x_2 - x_1}(S_1 - S_2) \tag{B-6}$$

where x_1 and x_2 are the upstream and downstream detector locations of segment. The resulted travel time can be estimated as:

$$TT_{1-2} = \int_{x_1}^{x_2} \frac{1}{S} dx = \int_{x_1}^{x_2} \frac{1}{S_1 + \frac{S_2 - S_1}{x_2 - x_1}(x - x_1)} dx = \begin{cases} \dfrac{x_2 - x_1}{(S_2 - S_1)/\ln \frac{S_2}{S_1}} & S_1 \neq S_2 \\ \dfrac{x_2 - x_1}{S_1} & S_1 = S_2 \end{cases} \tag{B-7}$$

The corresponding off-line travel time estimation method, Piece-wise Linear Speed Based Model (PLSB), was developed by Van Lint (2004). Note that for the off-line estimation, the traffic conditions at later time periods are known, allowing more accurate estimation of travel time since the travel time estimation can be done based on traffic conditions as the vehicle progresses in its route from one link to the next. However, for on-line applications, future traffic conditions are not available.

Constant Acceleration Method

The constant acceleration method assumes that the speed is a linear function of time (i.e., constant acceleration or deceleration rate) rather than a linear function of the distance, as the assumption in the Linear Speed method. The expression for the speed is as follows:

$$S(t) = S_1 + a(t - t_1) \tag{B-8}$$

where a is the acceleration or deceleration rate, calculated as:

$$a = \frac{S_2 - S_1}{t_2 - t_1} \tag{B-9}$$

Based on the principles of kinetics, it can be proved that this method is essentially the Average Speed method when using for instantaneous travel time estimation. The proof is presented below:

$$x_2 - x_1 = S_1(t_2 - t_1) + \frac{1}{2}a(t_2 - t_1)^2 = \frac{1}{2}(S_1 + S_2)(t_2 - t_1) \tag{B-10}$$

$$TT_{1-2} = t_2 - t_1 = \frac{(x_2 - x_1)}{(S_1 + S_2)/2} \tag{B-11}$$

Shen (2008) developed the Piece-wise Constant Acceleration Based Model (PCAB) for off-line travel time estimation as an improvement to the Piece-wise Linear Speed Based Model (PLSB) developed by Van Lint (2004).

Flow-Based Method

The Flow-Based Method mentioned in this study specifically refers to the travel time estimation using the data of flow and occupancy based on the fundamental relationship among the speed, flow and occupancy, which is expressed as:

$$TT_{1-2} = \frac{L_{1-2}}{q_2 / k_{1-2}} \tag{B-12}$$

where q_2 is the flow rate at the downstream detector station. $k_{1\text{-}2}$ is the average density for this link, which is calculated from the occupancies at the upstream and downstream stations, as shown below:

$$k_{1-2} = \frac{1}{2}(k_1 + k_2) = \frac{1}{2}(\frac{52.8O_1}{L_{eff,1}} + \frac{52.8O_2}{L_{eff,2}}) \tag{B-13}$$

where O denotes the occupancy while L_{eff} represents the average effective vehicle length.

Improved N-D Method

The improved N-D method refers to the method developed by Vanajakshi (2009). Nam and Drew (1996, 1999) used a traffic dynamic approach to estimate travel time based on cumulative curves. This approach includes two expressions: one for normal conditions and one for congested conditions. However, Vanajakshi (2009) proved that these two expressions can be generalized as one expression, as shown below:

$$TT_{i,t} = \frac{L_i}{2}\left(\frac{k_{i,t-1} + k_{i,t}}{q_{i,2,t}}\right) \tag{B-14}$$

where $q_{i,2,t}$ is the flow rate at downstream station of the link i at time t. $k_{i,t-1}$ and $k_{i,t}$ are the link densities at time t-1 and t, respectively. These two densities are calculated as the average of densities at the upstream and downstream detector stations. To improve the estimation accuracy, the improved N-D method uses a generalized traffic dynamic expression for travel time estimation when the link volume is greater than 500 vphpl and the Mid-Point method for the remaining link volumes.

Appendix C Sensitivity Analysis Results for Travel Time Estimation

This appendix presents detailed analysis results for the impacts of major influential factors on the accuracy and reliability of travel time estimates.

C.1 Impacts of Data Smoothing Methods

TABLE C-1 Accuracy and Reliability of Travel Time Estimation Using Simple Moving Average

Method	Rolling Period	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	1-minute	1.87	14.91	58.42	3.50	38.08
	2-minute	1.96	15.51	58.53	2.53	38.94
	3-minute	2.05	16.23	59.56	2.01	38.43
	4-minute	2.11	16.63	59.10	2.47	38.43
	5-minute	2.17	17.09	58.24	3.91	37.85
Mid-Point Method	1-minute	1.69	13.70	62.03	4.19	33.77
	2-minute	1.79	14.37	60.89	4.19	34.92
	3-minute	1.87	15.05	60.25	3.68	36.07
	4-minute	1.95	15.62	61.34	2.99	35.67
	5-minute	2.04	16.31	57.50	6.43	36.07
Hybrid Model 1	1-minute	1.49	13.54	66.57	14.36	19.07
	2-minute	1.81	15.78	56.86	18.15	24.99
	3-minute	1.78	15.66	57.21	17.81	24.99
	4-minute	1.81	16.03	54.22	20.79	24.99
	5-minute	1.91	17.08	52.79	22.23	24.99
Hybrid Model 2	1-minute	1.44	12.72	63.70	17.17	19.13
	2-minute	1.59	13.86	61.45	16.72	21.83
	3-minute	1.73	15.00	58.93	16.72	24.35
	4-minute	1.89	16.29	56.23	19.01	24.76
	5-minute	2.04	17.72	48.65	24.81	26.54

TABLE C-2 Accuracy and Reliability of Travel Time Estimation Using Exponential Moving Average

Method	Smoothing Factor	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	0.2	2.22	17.30	57.38	1.09	41.53
	0.4	2.07	16.28	57.32	1.78	40.90
	0.6	2.03	16.06	58.47	2.24	39.29
	0.8	2.04	16.09	58.24	2.24	39.52
	1.0	2.04	16.17	55.66	3.45	40.90
Mid-Point Method	0.2	2.02	15.93	58.53	3.67	37.79
	0.4	1.86	14.78	59.05	4.19	36.76
	0.6	1.82	14.49	59.97	3.10	36.93
	0.8	1.82	14.53	58.53	3.91	37.57
	1.0	1.84	14.66	59.10	3.85	37.05
Hybrid Model 1	0.2	1.50	13.51	61.63	12.52	25.85
	0.4	1.11	10.24	70.59	10.34	19.07
	0.6	1.13	10.72	66.63	14.70	18.67
	0.8	1.11	10.52	66.97	14.88	18.15
	1.0	1.44	12.77	61.00	19.30	19.70
Hybrid Model 2	0.2	1.49	12.51	69.21	3.33	27.46
	0.4	1.15	10.12	74.50	3.33	22.17
	0.6	1.03	9.28	73.92	4.36	21.71
	0.8	0.99	8.98	74.73	4.54	20.74
	1.0	1.09	9.60	73.23	4.48	22.29

C.2 Impacts of Data Imputation Methods

TABLE C-3 Results of Different Data Imputation Methods without Within-Station Imputation

Method	Temporal Imputation	Between-Station Imputation	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Temporal Imputation	Simple Average	2.09	16.38	57.09	2.93	39.98
		Linear Interpolation	2.09	16.35	57.09	2.93	39.98
		Factor Method	2.09	16.38	57.15	3.10	39.75
	Average of Temporal and Spatial Imputations	Simple Average	2.08	16.28	57.09	2.93	39.98
		Linear Interpolation	2.08	16.25	57.09	2.93	39.98
		Factor Method	2.08	16.30	57.09	2.93	39.98
Mid-Point Method	w/o Temporal Imputation	Simple Average	1.87	14.86	59.97	3.50	36.53
		Linear Interpolation	1.87	14.85	59.97	3.50	36.53
		Factor Method	1.88	14.95	59.74	3.50	36.76
	Average of Temporal and Spatial Imputations	Simple Average	1.86	14.79	59.97	3.50	36.53
		Linear Interpolation	1.86	14.77	59.97	3.50	36.53
		Factor Method	1.87	14.81	59.97	3.50	36.53
Hybrid Model 1	w/o Temporal Imputation	Simple Average	1.09	10.23	68.70	10.91	20.39
		Linear Interpolation	1.08	10.16	68.70	10.91	20.39
		Linear Interpolation for S and O, and Factor for V	1.10	10.35	68.75	10.68	20.56
		Factor Method	1.15	10.79	66.28	12.92	20.79
	Average of Temporal and Spatial Imputations	Simple Average	1.08	10.15	68.70	10.91	20.39
		Linear Interpolation	1.08	10.09	68.70	10.91	20.39
		Linear Interpolation for S and O, and Factor for V	1.09	10.20	68.70	10.91	20.39
		Factor Method	1.11	10.46	68.70	10.91	20.39
Hybrid Model 2	w/o Temporal Imputation	Simple Average	1.23	10.72	72.20	4.77	23.03
		Linear Interpolation	1.23	10.70	72.20	4.77	23.03
		Linear Interpolation for S and O, and Factor for V	1.23	10.70	72.20	4.77	23.03
		Factor Method	1.24	10.77	71.97	4.77	23.26
	Average of Temporal and Spatial Imputations	Simple Average	1.23	10.64	72.20	4.77	23.03
		Linear Interpolation	1.22	10.61	72.20	4.77	23.03
		Linear Interpolation for S and O, and Factor for V	1.22	10.61	72.20	4.77	23.03
		Factor Method	1.23	10.64	72.20	4.77	23.03

* S represents speed, V dictates volume count, and O is occupancy.

TABLE C-4 Results of Different Data Imputation Methods with Within-station Imputation

Method	Temporal Imputation	Between-Station Imputation	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Temporal Imputation	Simple Average	2.06	16.14	57.09	2.93	39.98
		Linear Interpolation	2.06	16.14	57.09	2.93	39.98
		Factor Method	2.06	16.14	57.09	2.93	39.98
	Average of Temporal and Spatial Imputations	Simple Average	2.06	16.14	57.09	2.93	39.98
		Linear Interpolation	2.06	16.14	57.09	2.93	39.98
		Factor Method	2.06	16.14	57.09	2.93	39.98
Mid-Point Method	w/o Temporal Imputation	Simple Average	1.84	14.66	59.97	3.50	36.53
		Linear Interpolation	1.84	14.66	59.97	3.50	36.53
		Factor Method	1.84	14.66	59.97	3.50	36.53
	Average of Temporal and Spatial Imputations	Simple Average	1.84	14.66	59.97	3.50	36.53
		Linear Interpolation	1.84	14.66	59.97	3.50	36.53
		Factor Method	1.84	14.66	59.97	3.50	36.53
Hybrid Model 1	w/o Temporal Imputation	Simple Average	1.13	10.49	68.52	10.91	20.56
		Linear Interpolation	1.12	10.41	68.70	10.91	20.39
		Linear Interpolation for S and O, and Factor for V	1.14	10.61	68.52	10.91	20.56
		Factor Method	1.14	10.72	68.52	10.68	20.79
	Average of Temporal and Spatial Imputations	Simple Average	1.14	10.53	68.52	10.91	20.56
		Linear Interpolation	1.13	10.48	68.52	10.91	20.56
		Linear Interpolation for S and O, and Factor for V	1.14	10.59	68.52	10.91	20.56
		Factor Method	1.17	10.84	67.15	10.91	21.94
Hybrid Model 2	w/o Temporal Imputation	Simple Average	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation for S and O, and Factor for V	1.20	10.48	73.58	4.77	21.65
		Factor Method	1.20	10.48	73.58	4.77	21.65
	Average of Temporal and Spatial Imputations	Simple Average	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation	1.20	10.48	73.58	4.77	21.65
		Linear Interpolation for S and O, and Factor for V	1.20	10.48	73.58	4.77	21.65
		Factor Method	1.20	10.48	73.58	4.77	21.65

* S represents speed, V dictates volume count, and O is occupancy.

C.3 Impacts of Intrinsic Errors

TABLE C-5 Impacts of Intrinsic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions

Method	Cases		MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors		0.121	1.92	100	0	0
	w/ Intrinsic Errors	Average	0.123	1.95	100	0	0
		Minimum	0.121	1.92	100	0	0
		Maximum	0.125	1.98	100	0	0
Mid-Point Method	w/o Errors		0.082	1.31	100	0	0
	w/ Intrinsic Errors	Average	0.083	1.33	100	0	0
		Minimum	0.081	1.30	100	0	0
		Maximum	0.085	1.36	100	0	0
Hybrid Model 1	w/o Errors		0.082	1.31	100	0	0
	w/ Intrinsic Errors	Average	0.083	1.33	100	0	0
		Minimum	0.081	1.3	100	0	0
		Maximum	0.085	1.36	100	0	0
Hybrid Model 2	w/o Errors		0.082	1.31	100	0	0
	w/ Intrinsic Errors	Average	0.083	1.33	100	0	0
		Minimum	0.081	1.30	100	0	0
		Maximum	0.085	1.36	100	0	0

TABLE C-6 Impacts of Intrinsic Errors on Travel Time Estimation Performance for Simulated Incident Case 1 between 7:30 A.M. and 8:30 A.M.

Method	Cases		MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors		2.07	16.28	57.32	1.78	40.90
	w/ Intrinsic Errors	Average	2.03	16.02	57.84	2.0	40.16
		Minimum	1.96	15.43	54.16	1.72	38.43
		Maximum	2.13	16.73	59.62	3.04	44.06
Mid-Point Method	w/o Errors		1.86	14.78	59.05	4.19	36.76
	w/ Intrinsic Errors	Average	1.83	14.59	60.24	3.95	35.81
		Minimum	1.76	14.08	58.24	3.10	34.18
		Maximum	1.91	15.15	62.26	4.77	37.79
Hybrid Model 1	w/o Errors		1.11	10.24	70.59	10.34	19.07
	w/ Intrinsic Errors	Average	1.62	13.59	63.18	10.24	26.59
		Minimum	1.27	11.00	59.51	3.91	21.94
		Maximum	2.00	16.03	69.33	14.36	30.90
Hybrid Model 2	w/o Errors		1.15	10.12	74.50	3.33	22.17
	w/ Intrinsic Errors	Average	1.58	12.87	64.59	4.24	31.17
		Minimum	1.23	10.66	61.17	2.59	22.34
		Maximum	1.75	13.97	71.17	6.49	34.75

C.4 Impacts of Systematic Errors

TABLE C-7a Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions without Data Filtering

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors	0.12	1.92	100	0	0
	Case 1	0.17	2.67	100	0	0
	Case 2	0.22	3.51	100	0	0
	Case 3	0.26	4.07	100	0	0
	Case 4	0.23	3.65	100	0	0
	Case 5	0.32	5.09	100	0	0
	Case 6	0.40	6.29	100	0	0
	Case 7	0.09	1.43	100	0	0
	Case 8	0.08	1.29	100	0	0
	Case 9	0.10	1.58	99.73	0.27	0
	Case 10	0.08	1.26	100	0	0
	Case 11	0.11	1.75	99.53	0.47	0
	Case 12	0.24	3.85	87.54	12.46	0
Mid-Point Method	w/o Errors	0.08	1.31	100	0	0
	Case 1	0.12	1.91	100	0	0
	Case 2	0.15	2.30	100	0	0
	Case 3	0.21	3.24	100	0	0
	Case 4	0.18	2.88	100	0	0
	Case 5	0.28	4.51	100	0	0
	Case 6	0.37	5.85	100	0	0
	Case 7	0.08	1.33	100	0	0
	Case 8	0.10	1.60	99.82	0.18	0
	Case 9	0.16	2.54	93.85	6.15	0
	Case 10	0.10	1.52	99.91	0.09	0
	Case 11	0.19	3.07	91.19	8.81	0
	Case 12	0.35	5.57	83.58	16.42	0
Hybrid Model 1	w/o Errors	0.08	1.31	100	0	0
	Case 1	0.12	1.91	100	0	0
	Case 2	0.15	2.30	100	0	0
	Case 3	0.21	3.24	100	0	0
	Case 4	0.18	2.88	100	0	0
	Case 5	0.28	4.51	100	0	0
	Case 6	0.37	5.85	100	0	0
	Case 7	0.08	1.27	100	0	0
	Case 8	0.09	1.45	99.95	0.05	0

TABLE C-7a Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions without Data Filtering (Con't)

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Hybrid Model 1	Case 9	0.15	2.47	94.89	5.11	0
	Case 10	0.10	1.52	99.89	0.11	0
	Case 11	0.19	3.04	91.19	8.81	0
	Case 12	0.33	5.30	83.58	16.42	0
Hybrid Model 2	w/o Errors	0.08	1.31	100	0	0
	Case 1	0.12	1.91	100	0	0
	Case 2	0.15	2.30	100	0	0
	Case 3	0.21	3.24	100	0	0
	Case 4	0.18	2.88	100	0	0
	Case 5	0.28	4.51	100	0	0
	Case 6	0.37	5.85	100	0	0
	Case 7	0.21	3.40	86.59	13.41	0
	Case 8	0.27	4.30	86.37	13.63	0
	Case 9	0.38	5.96	87.06	12.95	0
	Case 10	0.10	1.67	99.34	0.66	0
	Case 11	0.32	5.13	90.77	9.23	0
	Case 12	0.71	11.29	83.58	16.42	0

* Note that the definition for each case is explained in Table 3-12.

TABLE C-7b Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions with Data Filtering

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors	0.12	1.92	100	0	0
	Case 1	0.16	2.47	100	0	0
	Case 2	0.17	2.63	100	0	0
	Case 3	0.21	3.27	100	0	0
	Case 4	0.16	2.53	100	0	0
	Case 5	0.21	3.28	100	0	0
	Case 6	0.34	5.35	100	0	0
	Case 7	0.09	1.43	100	0	0
	Case 8	0.08	1.29	100	0	0
	Case 9	0.10	1.58	99.73	0.27	0
	Case 10	0.08	1.26	100	0	0
	Case 11	0.11	1.76	99.43	0.57	0
	Case 12	0.24	3.85	87.54	12.46	0
Mid-Point Method	w/o Errors	0.08	1.31	100	0	0
	Case 1	0.11	1.72	100	0	0

TABLE C-7b Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions with Data Filtering (Con't)

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Mid-Point Method	Case 2	0.11	1.77	100	0	0
	Case 3	0.17	2.69	100	0	0
	Case 4	0.11	1.80	100	0	0
	Case 5	0.17	2.69	100	0	0
	Case 6	0.33	5.15	100	0	0
	Case 7	0.08	1.33	100	0	0
	Case 8	0.10	1.60	99.65	0.36	0
	Case 9	0.16	2.55	94.00	6.01	0
	Case 10	0.10	1.53	99.94	0.06	0
	Case 11	0.19	3.08	91.19	8.81	0
	Case 12	0.35	5.57	83.58	16.42	0
Hybrid Model 1	w/o Errors	0.08	1.31	100	0	0
	Case 1	0.11	1.72	100	0	0
	Case 2	0.11	1.77	100	0	0
	Case 3	0.17	2.69	100	0	0
	Case 4	0.11	1.80	100	0	0
	Case 5	0.17	2.69	100	0	0
	Case 6	0.33	5.15	100	0	0
	Case 7	0.08	1.27	100	0	0
	Case 8	0.08	1.32	100	0	0
	Case 9	0.13	2.11	98.66	1.34	0
	Case 10	0.10	1.53	99.89	0.11	0
	Case 11	0.19	3.04	91.19	8.81	0
	Case 12	0.31	4.91	83.58	16.42	0
Hybrid Model 2	w/o Errors	0.08	1.31	100	0	0
	Case 1	0.11	1.72	100	0	0
	Case 2	0.11	1.77	100	0	0
	Case 3	0.17	2.68	100	0	0
	Case 4	0.11	1.80	100	0	0
	Case 5	0.17	2.69	100	0	0
	Case 6	0.33	5.15	100	0	0
	Case 7	0.21	3.40	86.59	13.41	0
	Case 8	0.27	4.30	86.37	13.63	0
	Case 9	0.38	5.95	87.06	12.95	0
	Case 10	0.10	1.67	99.34	0.66	0
	Case 11	0.32	5.13	90.77	9.23	0
	Case 12	0.71	11.29	83.58	16.42	0

TABLE C-8a Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Incident Conditions without Data Filtering

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors	2.07	16.28	57.32	1.78	40.90
	Case 1	2.09	16.47	57.50	1.61	40.90
	Case 2	2.15	16.97	57.50	1.61	40.90
	Case 3	2.25	17.98	57.27	1.61	41.13
	Case 4	2.52	19.66	55.20	0.23	44.57
	Case 5	2.76	21.81	53.99	0	46.01
	Case 6	2.92	23.40	52.67	0	47.33
	Case 7	2.04	16.09	58.07	3.10	38.83
	Case 8	2.02	15.92	60.14	3.50	36.36
	Case 9	1.93	15.70	56.40	8.73	34.87
	Case 10	1.84	14.71	58.36	6.78	34.87
	Case 11	1.83	15.20	61.69	9.88	28.43
	Case 12	2.30	20.40	46.76	35.38	17.86
Mid-Point Method	w/o Errors	1.86	14.78	59.05	4.19	36.76
	Case 1	1.89	14.98	59.51	3.10	37.39
	Case 2	1.91	15.11	59.10	2.64	38.25
	Case 3	2.04	16.28	59.45	1.61	38.94
	Case 4	2.49	19.35	53.65	0.00	46.35
	Case 5	2.81	22.15	52.56	0.00	47.44
	Case 6	3.01	24.03	51.23	0.00	48.77
	Case 7	1.83	14.67	60.77	4.25	34.98
	Case 8	1.82	14.61	60.20	5.05	34.75
	Case 9	1.80	15.31	60.60	9.82	29.58
	Case 10	1.63	13.55	67.20	6.55	26.25
	Case 11	1.82	16.10	54.80	22.46	22.75
	Case 12	3.46	29.78	33.95	48.48	17.58
Hybrid Model 1	w/o Errors	1.11	10.24	70.59	10.34	19.07
	Case 1	1.08	9.90	73.75	6.72	19.53
	Case 2	1.09	9.95	73.75	6.72	19.53
	Case 3	1.20	10.53	76.62	2.41	20.96
	Case 4	1.15	10.19	76.68	2.13	21.19
	Case 5	1.21	10.73	76.79	1.78	21.42
	Case 6	1.36	12.09	76.28	0.92	22.80
	Case 7	1.45	12.62	69.84	13.50	16.66
	Case 8	1.46	13.01	59.51	23.84	16.66
	Case 9	1.01	10.03	69.73	15.57	14.70
	Case 10	1.20	11.23	66.17	18.09	15.74

TABLE C-8a Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Incident Conditions without Data Filtering (Con't)

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Hybrid Model 1	Case 11	1.46	13.01	59.16	24.35	16.48
	Case 12	1.84	16.97	54.68	30.67	14.65
Hybrid Model 2	w/o Errors	1.15	10.12	74.50	3.33	22.17
	Case 1	1.16	10.17	74.38	2.99	22.63
	Case 2	1.16	10.21	74.84	2.53	22.63
	Case 3	1.25	11.05	74.38	1.49	24.12
	Case 4	1.99	15.88	60.02	0.23	39.75
	Case 5	2.37	19.00	54.62	0.23	45.15
	Case 6	2.54	20.62	53.88	0.23	45.89
	Case 7	1.50	13.11	64.39	15.11	20.51
	Case 8	1.25	10.95	71.22	7.64	21.14
	Case 9	1.10	10.47	75.07	8.73	16.20
	Case 10	1.58	13.26	61.86	15.91	22.23
	Case 11	1.69	14.70	52.38	22.92	24.70
	Case 12	5.62	42.88	41.53	39.06	19.41

TABLE C-8b Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions with Data Filtering

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors	2.07	16.28	57.32	1.78	40.90
	Case 1	2.08	16.33	57.38	1.72	40.90
	Case 2	2.08	16.35	57.38	1.72	40.90
	Case 3	2.18	17.18	57.27	1.61	41.13
	Case 4	2.08	16.47	58.36	2.13	39.52
	Case 5	2.30	18.21	58.64	0.23	41.13
	Case 6	2.79	22.03	52.84	0.00	47.16
	Case 7	2.04	16.08	58.76	3.10	38.14
	Case 8	2.01	15.91	60.14	3.50	36.36
	Case 9	2.03	15.97	60.94	2.87	36.19
	Case 10	1.99	15.65	57.90	4.37	37.74
	Case 11	1.97	15.71	57.84	6.38	35.78
	Case 12	2.11	17.76	56.98	13.79	29.24
Mid-Point Method	w/o Errors	1.86	14.78	59.05	4.19	36.76
	Case 1	1.87	14.79	58.99	3.62	37.39
	Case 2	1.87	14.80	58.99	3.62	37.39

TABLE C-8b Impacts of Systematic Errors on Travel Time Estimation Performance for Simulated Uncongested Conditions with Data Filtering (Con't)

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Mid-Point Method	Case 3	2.00	15.83	59.33	1.72	38.94
	Case 4	1.89	15.20	60.37	2.70	36.93
	Case 5	2.18	17.33	58.07	0.23	41.70
	Case 6	2.90	22.95	52.67	0.00	47.33
	Case 7	1.84	14.68	60.83	4.42	34.75
	Case 8	1.82	14.62	60.20	5.05	34.75
	Case 9	1.84	14.84	59.74	5.51	34.75
	Case 10	1.81	14.59	61.34	5.05	33.60
	Case 11	1.89	15.81	61.34	8.39	30.27
	Case 12	2.77	22.59	48.02	21.42	30.56
Hybrid Model 1	w/o Errors	1.11	10.24	70.59	10.34	19.07
	Case 1	1.14	10.47	71.11	9.36	19.53
	Case 2	1.14	10.49	71.11	9.36	19.53
	Case 3	1.09	9.80	75.65	4.02	20.33
	Case 4	1.66	13.64	69.39	3.04	27.57
	Case 5	1.73	14.22	66.69	2.70	30.61
	Case 6	1.64	13.84	67.09	2.64	30.27
	Case 7	1.44	12.57	69.84	13.50	16.66
	Case 8	1.46	12.93	60.77	22.57	16.66
	Case 9	1.05	10.35	66.97	19.30	13.73
	Case 10	1.61	13.69	66.40	8.90	24.70
	Case 11	1.52	12.94	68.87	5.74	25.39
	Case 12	1.46	13.05	64.62	13.79	21.60
Hybrid Model 2	w/o Errors	1.15	10.12	74.50	3.33	22.17
	Case 1	1.15	10.09	74.38	2.99	22.63
	Case 2	1.15	10.09	74.38	2.99	22.63
	Case 3	1.22	10.71	74.84	1.61	23.55
	Case 4	1.28	11.17	70.76	5.28	23.95
	Case 5	1.53	13.05	67.43	2.35	30.21
	Case 6	2.50	20.13	53.88	0.23	45.89
	Case 7	1.50	13.13	64.45	15.28	20.28
	Case 8	1.25	10.93	71.22	7.64	21.14
	Case 9	1.08	9.78	75.53	4.65	19.82
	Case 10	1.22	10.78	70.42	9.02	20.56
	Case 11	1.50	13.05	64.96	12.23	22.80
	Case 12	3.46	25.72	55.43	15.16	29.41

TABLE C-9 Impacts of Systematic Errors in Low Speed Measurements on Travel Time Estimation Performance for Simulated Incident Conditions

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	w/o Errors	2.07	16.28	57.32	1.78	40.90
	20% Increase in Low Speed	2.24	17.46	55.08	0.34	44.57
	40% Increase in Low Speed	2.42	18.86	54.62	0.11	45.26
	20% Decrease in Low Speed	1.92	15.38	57.73	6.09	36.19
	40% Decrease in Low Speed	1.76	14.50	63.47	7.58	28.95
Mid-Point Method	w/o Errors	1.86	14.78	59.05	4.19	36.76
	20% Increase in Low Speed	2.08	16.31	60.65	1.21	38.14
	40% Increase in Low Speed	2.28	17.76	54.22	0.98	44.80
	20% Decrease in Low Speed	1.68	13.75	62.67	7.06	30.27
	40% Decrease in Low Speed	1.59	13.56	66.28	9.82	23.89
Hybrid Model 1	w/o Errors	1.11	10.24	70.59	10.34	19.07
	20% Increase in Low Speed	1.18	10.68	67.89	11.83	20.28
	40% Increase in Low Speed	1.23	10.87	68.06	10.68	21.25
	20% Decrease in Low Speed	1.12	10.31	68.35	12.58	19.07
	40% Decrease in Low Speed	1.25	11.24	67.78	10.97	21.25
	5% Increase in Volume	1.10	9.91	72.95	7.98	19.07
	10% Increase in Volume	1.17	10.91	64.33	16.54	19.13
	5% Decrease in Volume	1.17	11.10	67.55	14.30	18.15
	10% Decrease in Volume	1.08	10.06	71.74	9.59	18.67
Hybrid Model 2	w/o Errors	1.15	10.12	74.50	3.33	22.17
	20% Increase in Low Speed	1.37	11.52	71.97	1.21	26.82
	40% Increase in Low Speed	1.66	13.57	68.18	0.98	30.84
	20% Decrease in Low Speed	1.46	12.33	61.69	16.94	21.37
	40% Decrease in Low Speed	1.88	15.19	57.15	16.83	26.02
	5% Increase in Volume	1.15	10.15	74.50	3.33	22.17
	10% Increase in Volume	1.16	10.18	74.55	3.50	21.94
	5% Decrease in Volume	1.15	10.12	74.50	3.33	22.17
	10% Decrease in Volume	1.15	10.12	74.50	3.33	22.17

C.5 Impacts of Incidental and Structural Failures

TABLE C-10 Impacts of Incidental and Structural Failures on Travel Time Estimation Performance for Simulated Uncongested Conditions

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point to Point Method	w/o Errors	0.12	1.92	100	0	0
	w/ Incidental and Structural Errors	0.14	2.18	100	0	0
Mid-Point Method	w/o Errors	0.08	1.31	100	0	0
	w/ Incidental and Structural Errors	0.10	1.53	100	0	0
Hybrid Model 1	w/o Errors	0.08	1.31	100	0	0
	w/ Incidental and Structural Errors	0.10	1.53	100	0	0
Hybrid Model 2	w/o Errors	0.08	1.31	100	0	0
	w/ Incidental and Structural Errors	0.10	1.54	100	0	0

TABLE C-11 Impacts of Incidental and Structural Failures on Travel Time Estimation Performance for Simulated Incident Conditions

Method	Cases	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point to Point Method	w/o Errors	2.07	16.28	57.32	1.78	40.90
	w/ Incidental and Structural Errors	2.04	16.21	55.66	6.61	37.74
Mid-Point Method	w/o Errors	1.86	14.78	59.05	4.19	36.76
	w/ Incidental and Structural Errors	2.06	17.00	58.07	10.57	31.36
Hybrid Model 1	w/o Errors	1.11	10.24	70.59	10.34	19.07
	w/ Incidental and Structural Errors	1.80	16.36	58.13	25.16	16.72
Hybrid Model 2	w/o Errors	1.15	10.12	74.50	3.33	22.17
	w/ Incidental and Structural Errors	1.95	17.58	62.44	15.45	22.11

C.6 Impacts of Travel Time Updating Frequency

TABLE C-12 Travel Time Estimation Performances with Different Travel Time Updating Frequencies for Simulated Uncongested Conditions

Method	Updating Frequency	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	1-minute	0.14	2.20	100	0	0
	2-minute	0.12	1.92	100	0	0
	3-minute	0.12	1.91	100	0	0
	4-minute	0.12	1.90	100	0	0
	5-minute	0.12	1.86	100	0	0
Mid-Point Method	1-minute	0.10	1.62	100	0	0
	2-minute	0.08	1.31	100	0	0
	3-minute	0.07	1.16	100	0	0
	4-minute	0.07	1.15	100	0	0
	5-minute	0.06	1.03	100	0	0
Hybrid Model 1	1-minute	0.10	1.62	100	0	0
	2-minute	0.08	1.31	100	0	0
	3-minute	0.07	1.16	100	0	0
	4-minute	0.07	1.15	100	0	0
	5-minute	0.07	1.03	100	0	0
Hybrid Model 2	1-minute	0.10	1.62	100	0	0
	2-minute	0.08	1.31	100	0	0
	3-minute	0.07	1.16	100	0	0
	4-minute	0.07	1.15	100	0	0
	5-minute	0.07	1.06	99.89	0.11	0

TABLE C-13 Travel Time Estimation Performances with Different Travel Time Updating Frequencies for Simulated Incident Scenario 1

Method	Updating Frequency	MAE (Minutes)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	1-minute	1.99	15.63	59.27	0.80	39.93
	2-minute	2.07	16.28	57.32	1.78	40.90
	3-minute	2.04	16.05	55.83	3.83	40.35
	4-minute	2.29	18.19	48.17	8.67	43.17
	5-minute	2.25	17.58	52.85	6.75	40.41
Mid-Point Method	1-minute	1.79	14.23	60.99	1.89	37.12
	2-minute	1.86	14.78	59.05	4.19	36.76
	3-minute	1.86	14.82	57.62	6.15	36.23
	4-minute	2.08	16.81	47.70	14.37	37.93
	5-minute	2.12	16.77	54.37	7.92	37.71
Hybrid Model 1	1-minute	1.10	9.85	73.38	9.07	17.56
	2-minute	1.11	10.24	70.59	10.34	19.07
	3-minute	1.15	10.54	69.04	12.46	18.49
	4-minute	1.54	13.77	46.77	25.31	27.92
	5-minute	1.27	11.29	66.33	8.80	24.87
Hybrid Model 2	1-minute	1.16	10.21	74.24	2.58	23.18
	2-minute	1.15	10.12	74.50	3.33	22.17
	3-minute	1.31	11.31	70.55	4.64	24.81
	4-minute	1.35	11.85	55.38	17.69	26.93
	5-minute	1.34	11.25	69.56	6.86	23.58

C.7 Impacts of Travel Time Link Length

TABLE C-14 Travel Time Estimation Performances with Different Travel Time Link Lengths for Simulated Uncongested Conditions

Method	Origin-Destination	Distance (Miles)	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	DS-1523E-DS-1549E	4.24	0.05	1.17	100	0	0
	DS-1521E-DS-1549E	4.55	0.05	1.11	99.64	0.08	0.28
	DS-1517E-DS-1549E	5.27	0.07	1.27	100	0	0
	DS-1509E-DS-1549E	6.42	0.12	1.92	100	0	0
Mid-Point Method	DS-1523E-DS-1549E	4.24	0.05	1.16	100	0	0
	DS-1521E-DS-1549E	4.55	0.05	1.15	99.69	0.08	0.23
	DS-1517E-DS-1549E	5.27	0.06	1.09	100	0	0
	DS-1509E-DS-1549E	6.42	0.08	1.31	100	0	0
Hybrid Model 1	DS-1523E-DS-1549E	4.24	0.05	1.16	100	0	0
	DS-1521E-DS-1549E	4.55	0.05	1.15	99.69	0.08	0.23
	DS-1517E-DS-1549E	5.27	0.06	1.09	100	0	0
	DS-1509E-DS-1549E	6.42	0.08	1.31	100	0	0
Hybrid Model 2	DS-1523E-DS-1549E	4.24	0.05	1.16	100	0	0
	DS-1521E-DS-1549E	4.55	0.05	1.15	99.69	0.08	0.23
	DS-1517E-DS-1549E	5.27	0.06	1.09	100	0	0
	DS-1509E-DS-1549E	6.42	0.08	1.31	100	0	0

TABLE C-15 Travel Time Estimation Performances with Different Travel Time Link Lengths for Simulated Incident Scenario 1

Method	Origin-Destination	Distance (Miles)	MAE (Min.)	MAPE (%)	Reliability (%)	% Early	% Late
Point-to-Point Method	DS-1523E-DS-1549E	4.24	0.92	14.00	86.78	0	13.22
	DS-1521E-DS-1549E	4.55	1.07	13.27	77.93	4.59	17.48
	DS-1517E-DS-1549E	5.27	1.86	16.59	57.41	2.49	40.10
	DS-1509E-DS-1549E	6.42	2.07	16.28	57.32	1.78	40.90
Mid-Point Method	DS-1523E-DS-1549E	4.24	1.13	17.15	73.36	0	26.64
	DS-1521E-DS-1549E	4.55	1.44	17.28	75.94	0.09	23.97
	DS-1517E-DS-1549E	5.27	1.74	15.85	58.30	1.38	40.32
	DS-1509E-DS-1549E	6.42	1.86	14.78	59.05	4.19	36.76
Hybrid Model 1	DS-1523E-DS-1549E	4.24	0.63	10.10	91.98	0.35	7.67
	DS-1521E-DS-1549E	4.55	0.85	11.09	87.02	0.13	12.85
	DS-1517E-DS-1549E	5.27	0.97	9.97	75.48	6.10	18.43
	DS-1509E-DS-1549E	6.42	1.11	10.24	70.59	10.34	19.07
Hybrid Model 2	DS-1523E-DS-1549E	4.24	0.88	13.69	91.40	0	8.60
	DS-1521E-DS-1549E	4.55	1.05	13.50	81.94	4.59	13.47
	DS-1517E-DS-1549E	5.27	1.05	10.90	75.52	3.38	21.10
	DS-1509E-DS-1549E	6.42	1.15	10.12	74.50	3.33	22.17

C.8 Impacts of Travel Time Posting Range

TABLE C-16 Travel Time Estimation Reliability with Different Posted Travel Time Ranges for Simulated Uncongested Conditions

Method	Range of Posted Travel Time	Reliability (%)	% Early	% Late
Point-to-Point Method	[TT-2, TT+2]	100	0	0
	[TT-1, TT+2]	100	0	0
	[TT-1, TT+1]	99.29	0	0.71
	[TT-0.5, TT+0.5]	70.07	0.42	29.52
Mid-Point Method	[TT-2, TT+2]	100	0	0
	[TT-1, TT+2]	100	0	0
	[TT-1, TT+1]	99.29	0	0.71
	[TT-0.5, TT+0.5]	70.07	0.42	29.52
Hybrid Model 1	[TT-2, TT+2]	100	0	0
	[TT-1, TT+2]	100	0	0
	[TT-1, TT+1]	99.29	0	0.71
	[TT-0.5, TT+0.5]	70.07	0.42	29.52
Hybrid Model 2	[TT-2, TT+2]	100	0	0
	[TT-1, TT+2]	100	0	0
	[TT-1, TT+1]	99.29	0	0.71
	[TT-0.5, TT+0.5]	70.07	0.42	29.52

TABLE C-17 Travel Time Estimation Reliability with Different Posted Travel Time Ranges for Simulated Incident Conditions

Method	Range of Posted Travel Time	Reliability (%)	% Early	% Late
Point-to-Point Method	[TT-2, TT+3]	57.32	1.78	40.90
	[TT-2, TT+4]	58.93	1.78	39.29
	[TT-2, TT+5]	59.97	1.78	38.25
	[TT-1, TT+4]	56.58	4.14	39.29
	[TT-1, TT+5]	57.61	4.14	38.25
	[TT-1, TT+6]	58.42	4.14	37.45
Mid-Point Method	[TT-2, TT+3]	59.05	4.19	36.76
	[TT-2, TT+4]	64.85	4.19	30.96
	[TT-2, TT+5]	68.18	4.19	27.63
	[TT-1, TT+4]	62.44	6.61	30.96
	[TT-1, TT+5]	65.77	6.61	27.63
	[TT-1, TT+6]	67.57	6.61	25.85
Hybrid Model 1	[TT-2, TT+3]	70.59	10.34	19.07
	[TT-2, TT+4]	73.12	10.34	16.54
	[TT-2, TT+5]	75.13	10.34	14.53
	[TT-1, TT+4]	65.02	18.44	16.54
	[TT-1, TT+5]	67.03	18.44	14.53
	[TT-1, TT+6]	68.12	18.44	13.44
Hybrid Model 2	[TT-2, TT+3]	74.50	3.33	22.17
	[TT-2, TT+4]	75.88	3.33	20.79
	[TT-2, TT+5]	75.88	3.33	20.79
	[TT-1, TT+4]	69.67	9.54	20.79
	[TT-1, TT+5]	69.67	9.54	20.79
	[TT-1, TT+6]	70.25	9.54	20.22