Data and Modeling Support of Off-Line and Real-Time Decisions Associated with Integrated Corridor Management

FDOT Project BDV29-977-38

Final Report

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By

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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)				
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
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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A Decisions support systems (DSS) is considered an important component of ICM. A DSS provides the necessary support for real-time operations as well as planning for operations of the transportation systems. Previous national ICM efforts have utilized offline and online decision support modules based on data from multiple sources and modeling tools. The Florida Department of Transportation (FDOT) have started considering, planning, and/or initiating efforts for the development and implementation of such tools. However, there are many issues and considerations when implementing model-based DSS to support ICM deployment in Florida.

The goal of this research was to assess the applicability, feasibility, and effectiveness of data, analysis, modeling, and simulation approaches to support the decision-making process associated with offline and real-time operations of ICM. This project provides findings that support the maximization of ICM benefits by identifying approaches to the effective use of decision support tools for real-time and offline applications.</td></tr>
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EXECUTIVE SUMMARY

There has been an increasing interest in deploying Integrated Corridor Management (ICM) strategies in Florida. Some regions have started developing or have developed operational scenarios for ICM implementation involving multi-modal and multi-facility operation and management strategies to address the various issues facing the transportation system.

A Decisions support systems (DSS) is considered an important component of ICM. A DSS provides the necessary support for real-time operations as well as planning for operations of the transportation systems. Previous national ICM efforts have utilized offline and online decision support modules based on data from multiple sources and modeling tools. The Florida Department of Transportation (FDOT) have started considering, planning, and/or initiating efforts for the development and implementation of such tools. However, there are many issues and considerations when implementing model-based DSS to support ICM deployment in Florida.

The goal of this research was to assess the applicability, feasibility, and effectiveness of data, analysis, modeling, and simulation approaches to support the decision-making process associated with offline and real-time operations of ICM. This project provides findings that support the maximization of ICM benefits by identifying approaches to the effective use of decision support tools for real-time and offline applications.

The specific objectives of the project were:

- Review the models and methods that are currently available and their applicability for ICM operational scenarios in Florida.
- Identify methods to support the decisions associated with various ICM applications.
- Assess the capability needed to implement analysis and modeling to support ICM decisions considering the staff requirements, data, tools, and resources needed by the FDOT.
- Demonstrate the ability of data and modeling analytics to support operational scenario decisions.

E.1 STATE OF THE PRACTICE REVIEW

The review of the state of the practice in this project provides a review of national applications to support the offline and real-time decisions associated with ICM. In addition, it provides an overview the different types of modeling tools that are available and their applications to online and offline ICM DSSs as well as lessons learned from existing implementations of decision support tools to support the decisions associated with the use of such tools and the estimated benefits.

E.1.1 Existing ICM Decision Support Tool Applications

Model-based decision support systems (DSS) have been used for the offline and real-time decisions associated with ICM. To date, the two main experiences with real-time use of such tools are the DSS developed for the US-75 ICM project in Dallas, TX, and the DSS developed for the I-15 ICM project in San Diego, CA. The tools used in these applications provide recommendations for operating agencies to apply management and traveler information strategies during congestion conditions, particularly during non-recurrent congestion such as during freeway and arterial incidents. Another important ICM implementation is the ongoing effort for DSS development at a third site (I-210 in Southern California), which is funded by the California Department of Transportation (Caltrans). A number of ICM efforts have also been initiated by FDOT districts and are reviewed in this document.

In general, the DSS can be considered to consist of five elements: offline use of modeling, real-time data collection and fusion, user interface, real-time response plan recommendations, and real-time predictive engine. Each of these elements has its own requirements. The real-time data collection and fusion component gathers information from multiple sources using center-to-center standards, processes and fuses the data, and provides the information needed by a rule-based DSS and the modeling-based predictive engine. The rule-based expert system has been used to generate response plans during non-recurrent congestion conditions for consideration by operations personnel of the partner agencies. An important aspect of the rule-based expert system module is the required periodic post-review of the implemented and proposed plans and the modification of these plans as needed, based on the review. More advanced real-time generation of the response plans, rather than the selection from a library as is done using the expert system, has been proposed in research studies. However, this has not been implemented in ICM real-world deployments. The utilized predictive engine normally uses a mesoscopic or microscopic simulation-based modeling tool to predict the performance of the corridor in the next 30 minutes to one hour under the recommended response plans by the expert systems to allow the prioritization of the plans and more informed decision by the operator.

It has been recommended to use a modular software architecture that allows separating the elements of the ICM, including the real-time data collection and fusion, user interface, real-time response plan recommendations, and model-based real-time predictive engine, into separate components that interface with each other using industry standards.

E.1.2 Analysis, Modeling, and Simulation (AMS) Tools

The Analysis, Modeling, and Simulation (AMS) tools have been used as important components of ICM DSS for offline planning for operation analysis. Simulation tools have also been proposed and used as the main component of the performance prediction in the real-time DSS. Thus, this document provides a brief review of existing AMS tools and the associated guidance and methodology regarding their applications to ICM.

A good source of information on this topic is found in the Federal Highway Administration (FHWA) traffic analysis toolbox documents. These documents have provided guidance regarding the use of AMS tools and can be found on the FHWA website (http://ops.fhwa.dot.gov/trafficanalysistools). The Florida Department of Transportation has produced a Traffic Analysis Handbook that is used by practitioners in Florida when utilizing AMS. The AMS tools can be classified as of macroscopic, mesoscopic, and microscopic resolutions. Macroscopic models analyze the impact of the traffic as a whole, on a section-by-section basis rather than by tracking individual vehicles. Microscopic simulation analyzes the network in much more detail than macroscopic models, simulating the movement of individual vehicles based on microscopic traffic flow models such as car-following, lane-changing, and gap acceptance. Mesoscopic models have more detailed traffic representation than macroscopic models, but less detailed representation than microscopic models, allowing the modeling of larger sub-networks and possibly small to midsize regional networks. Mesoscopic simulation models generate and track individual vehicles or packets of vehicles. The movements of these vehicles or packets, however, follow the macroscopic approach of traffic flow or a low fidelity car-following approach.

The Dallas ICM deployment utilizes mesoscopic simulation while the San Diego deployment utilizes microscopic simulation. However, even simple macroscopic simulation may have a role in the offline and real-time decision support of ICM. A previous FDOT research project conducted by the research team proposed the use of a multi-resolution modeling framework (Hadi et al., 2016). This framework can be used to support the required modeling activities associated with ICM projects.

An important aspect of the ICM AMS methodology is the need to simulate transportation systems under varying operational conditions, including those associated with both recurrent and non-recurrent traffic congestion. The USDOT ICM modeling guidance states that the key ICM impacts may be lost if only "normal" travel conditions are considered. Thus, the analysis should take into account different levels of travel demands within the corridor, with and without incidents, and possibly with and without adverse weather conditions. The distributions of demands and frequency of non-recurrent events such as incidents are important to estimate the impacts by advanced strategies.

E.1.3 Online Commercial Simulation-Based DSS Tools

Open source and university-developed tools such as Dynasmart and DIRECT have been investigated and used for real-time DSS support. DIRECT was used in the Dallas implementation by the developer of the tool who was part of the development team. However, there are two commercially available modeling platforms that have been proposed for DSS implementation. PTV Optima is a model-based real-time traffic management tool developed by the PTV Group. The core of PTV Optima is a PTV VISUM model for typical days that simulates traffic flow using dynamic traffic assignment at the macroscopic or microscopic resolution levels, although it may be possible to use VISSIM mesoscopic and microscopic simulation also. PTV Optima also acts as a data hub. It collects, compares, validates, and merges real-time traffic data from various sources, Aimsun Live is also a model-based real-time traffic management and forecasting tool that can be used for the real-time assessment of advanced traveler information system and advanced traffic management system. It combines real-time traffic data with large-scale simulation to simulate the movement of traffic within a road network for the next hour. Aimsun can also model the network at the macroscopic, mesoscopic, and microscopic levels. Although PTV Optima and Aimsun Live have their own data hubs and response plan selection modules, it is possible to integrate the underlying models with separate DSS collection and fusion hubs and response plan selection modules, as is done in the San Diego and Los Angles deployments.

E.1.4 Data-Based Prediction

The evaluation conducted as part of the literature indicates that the use of predictive traffic management strategies produces better results than the utilization of responsive traffic management strategies. Predictive engines applied to existing ICM projects have utilized simulation-based prediction. Prediction of near-future traffic conditions can also be achieved using data-based models. This prediction, however, has a disadvantage in that it is impossible or difficult to predict the impact of alternative response plans on traffic conditions without modeling. Nevertheless, such prediction may still have a role in ICM DSS, either by itself or in combination with model-based prediction.

Traffic flow parameter prediction based on data is a topic that has been researched for some time. The wide deployment of traffic detectors and automatic vehicle identification devices such as Bluetooth/Wi-Fi readers and electronic toll readers provides a rich data source for such prediction. The existing traffic flow parameter prediction methods can be classified into four categories: naïve methods, traffic flow theory-based methods, statistical and regression methods, and machine learning-based methods.

E.1.5 Offline Utilization of AMS to Model ICM-Related Strategies

Even if real-time DSSs are not utilized, considerable benefits may be expected by utilizing AMS to model ICM response plan impacts. The AMS tools were used in the USDOT ICM during the life cycle of the ICM projects in refining and updating the ICM strategies and response plans and in post-deployment evaluation of these strategies. Post-deployment AMS activities were also conducted to identify the impacts of the "as-deployed" ICM system, which may differ from "as-planned" ICM. The AMS models were updated as more data became available from the ICM to allow better calibration and validation of the underlying models, including data collected using the Intelligent Transportation System (ITS) and surveys of site-specific traveler behaviors and responses.

E.1.6 Lessons Learned from ICM DSS Deployments

One of the products of the USDOT ICM program is a document that summarizes the lessons learned from the two ICM pilot deployments, with few items related to the DSS. The document points out that including modeling and forecasting in the DSS requires significant computing power and storage capabilities. It recommends that the user specifies an acceptable time window for a DSS-generated response plan to be issued after the request is generated and cautions that any generated plan that takes greater than five minutes could be too long in a dynamic network with changing conditions.

With regard to DSS development, the document recommended the use of a "focused iterative approach when defining, designing, and building the DSS." It also recommended the "fine tuning of the decision tools until acceptable output is achieved." The DSS will need to be assessed and adapted for the subject corridor. The calibration and validation of the model demand and supply can be time consuming and requires significant effort to ensure that the results from the tool are valid.

With regard to the response plan development and adjustments, the document points out that the response plans used by the DSS will need to be adjusted after the tool becomes operational and experience gained with it. It was realized that the response plan development will take time, will have many dependencies, and will require close coordination with signal timing agency plans. Response plans need to consider existing timing plan coordination, time of day timing plans, and direction of travel. Periodic meetings to troubleshoot DSS issues and review the system and data output were recommended including showing the results of assessing the performance of the generated response plans in analyses.

E.1.7 ICM DSS Assessment

An important aspect of the implementation of ICM DSS is to assess its performance for the purpose of both refining it in the specific deployment for which it has been implemented for, as well as for providing lessons learned for future implementations. Reviewing previous assessment of DSS is critical to its deployment in Florida. The USDOT has conducted a comprehensive review of the Dallas and San Diego DSS. The DSS USDOT ICM program evaluation involves assessing a number of DSS aspects including investigating the effectiveness of the data fusion engines, the quality of responses generated by the DSS, the accuracy of DSS predictions of conditions 30 minutes or more into the future, the speed of response plan generation, and how varying conditions such as different incidents characteristics impact DSS performance. Unfortunately, although the associated DSS test plans are available, the results from the evaluation have not been published. The hypothesis utilized in the ICM DSS test plans can be actually converted to objectives and associated performance measures for the DSS implementations that are useful in the FDOT effort. The hypothesis are: improve situational awareness, enhance response and control, better inform travelers, improve corridor performance, have benefits greater than cost, improve or not adversely impact air quality and safety, and provide a useful and effective tool for ICM project managers.

E.1.8 Benefit-Cost Analysis

The USDOT ICM program identified a plan for conducting the Benefit-Cost Analysis (BCA) of ICM deployment. The estimated or measured outcomes from the ICM deployments can be converted to economic benefits through travel time savings, enhanced travel time reliability, reduced motor fuel costs, lower emissions, and reductions in the number and severity of crashes. It is recommended to develop and implement methodologies for post-deployment assessment of ICM. In addition, a module for pre-deployment assessment of potential ICM DSS is recommended to be implemented in Florida ITS/TSM&O evaluation tools such as FITSEVAL for use in planning and planning for operations decisions of ICM.

E.1.9 ICM AMS Results

It is useful to review the results of utilizing the AMS methodology described in Section E.1.5 to estimate the impacts of ICM. Such results can be considered for use in a sketch-planning level of ICM deployments in Florida. Thirteen operational conditions were analyzed in the pre-deployment stage of the US-75 ICM project in Dallas, Texas, that cover the conditions of low, medium, and high demands without or with minor or major incidents. The estimated benefits of the ICM strategies were very small for the US-75 corridors. However, the overall benefit/cost ratio over a 10-year life cycle was reported to be about 20.4:1. When combining the results for all the scenarios, the aggregated performance measures showed 0.5% to 0.6% reduction in average travel time, 1.4% to 1.9% reduction in average delay, 1.2% to 2.0% reduction in total delay, 0.5% to 0.6% reduction in the planning time index, 4.3% to 6.7% reduction in travel time variance, and 0.3% to 0.7% reduction in passenger hours traveled. In the after-deployment, ten scenarios were analyzed including two hypothetical scenarios. The survey results showed an increase in the awareness of traveler information; however, the use of the traveler information did not increase. Travelers changed their routes and switched to transit only during severe incidents. Based on the post-deployment analysis results, the biggest travel time benefits occur along the peak direction during a severe incident with the deployed ICM system. Most of the scenarios showed significant reduction in person mile travelled compared to the before deployment condition. However, the US-75 ICM project did not generate the expected benefits in mobility and reliability after deployment. Two recommendations were made by the research team: updating response plans frequently as the post-deployment response plan was based on the pre-deployment conditions and adopting real-time adaptive response planes.

Twelve operational conditions were modeled in the I-15 ICM project in San Diego, California, before the actual ICM deployment. The modeled scenarios include the daily operations in a future year as a baseline, a freeway incident, and an arterial incident, combined with low, medium, and high demands. The resulted pre-deployment performance measure estimates indicated a 1.5% reduction in network-wide delays, an improvement of 0.3% in the overall planning time index, and 10.6% improvement in corridor-wide travel time variance. The most benefited roadways were the I-15 SB and arterials. However, the impacts of the ICM strategies on throughput was small. There were also some dis-benefits for managed lane users due to the opening of the lanes during the severe freeway incidents. About 93% of the ICM benefits were from the operational conditions with medium or high demands. The overall benefit/cost ratio for the I-15 ICM project is 9.7:1 based on pre-deployment analysis. Nine scenarios including one hypothetical scenario were examined in the post-deployment stage of the I-15 ICM project based on matching incidents with identified clusters of high occurrence percentage. The benefit results from the post-deployment analysis was found to be consistent with those obtained from the pre-deployment conditions.

E.2 POTENTIAL ICM APPLICATIONS

This project identifies the ICM applications for implementation consideration in Florida. These applications have been selected as part of an existing ICM plan in Florida and/or already identified based on the review of the national ICM efforts. For each application, this document provides a description of the application; applicable operation scenarios; potential approaches to the DSS implementation to support the application; review of related previous work; and required modeling, data, and capabilities for the DSS Implementation.

As indicated in Table E - 1 identifies 15 ICM applications based on a review of the ICM concepts from around the United States and Florida. The operational scenarios including those under normal conditions, incidents, and adverse weather that benefits from these applications are also identified. The 15 application are:

- Dynamic activation of ramp metering
- Dynamic modification of express lane pricings and restrictions
- Dynamic Ramp Management (Metering Activation, Deactivation, and Closure)
- Dynamic Modification of Express Lane Pricings and Restrictions
- Coordination of Ramp Metering and Signal Control
- Periodic Signal Retiming

- Traffic Adaptive Signal Control
- Special Signal Plans During Freeway and Arterial Incidents
- Alternative Route and Predicted Travel Time Information Provision to Motorists
- Provision of Optimal Emergency Vehicle Routing
- Rerouting of Express Buses
- Mode Shift During Severe Highway or Transit Incidents
- Hard Shoulder Running
- Restricting, Rerouting, and Delaying Commercial Traffic
- Special Events and Construction
- Disaster Response

This document presents a description; a review of current work; potential approaches to support the decision-making process; and modeling, data, and capability requirements associated with ICM applications. The analysis presented in this document indicates that there is a range of alternative approaches that can be used to support the offline and real-time decisions associated with different ICM applications. Although the four major existing or planned ICM deployments in Orlando, San Diego, Dallas, and Los Angles include both online and real-time models that require significant modeling resources and capabilities; it is possible to use data-based, offline model-based, and/or less detailed online models based to support ICM with less resource requirements. This may be important considering the variations in the capability maturity of different agencies.

Alternative DSS solutions can involve combinations of offline utilization of data analytics, HCM-based analysis, macroscopic simulation, mesoscopic simulation, microscopic simulation, and dynamic traffic assignment and online utilization of some of these modeling and analysis techniques. The particular approach to be utilized in a region will depend on the considered ICM applications and the data, modeling, and capability maturity of the agency considering the applications. A less involved approach, that can be referred to as a light version of the DSS (DSS-Lite), may be desirable when there are limitations on the capabilities and resources. Such DSS-Lite approaches may be as effective as or less effective than the detailed approaches utilized in the concepts developed for the four major ICM deployments mentioned above. This will be tested in future tasks of this project.

Obviously, there will be components of the DSS that will be required no matter what will be the level of the DSS support. For example, the utilization of clustering analysis based on data from multiple sources to identify traffic, incident, and weather patterns will be critical to allow the development of response plans. Offline modeling to derive response plans will also always be critical to the DSS applications.

Table E - 1: ICM Interventions Identified in Previous ICM Efforts

Intervention	Description	Inclusion in National and Florida ICM	Applicable Operational Scenarios
Dynamic Ramp Management (Metering Activation, Deactivation, and Closure)	Dynamic ramp management includes ramp metering activation, deactivation, and closure.	FDOT District 4, FDOT District 5, San Diego I-15, and Los Angles I-210 Connected Corridors	Daily operations to accommodate stochastic variations, freeway and arterial incidents, and weather events.
Dynamic Modification of Express Lane Pricings and Restrictions	Proactive changing to rates and eligibility of using EL can be applied when conditions reach a level with high probability of breakdown.	FDOT District 4, San Diego I-15	Daily operations to accommodate stochastic variations, freeway and arterial incidents, and weather events
Coordination of Ramp Metering and Signal Control	Generate special signal timing plans to prevent ramp spillback due to metering and provide information to drivers to divert from the ramps.	San Diego I-15 and Los Angles I-210	Daily operations to accommodate stochastic variations, freeway incidents, and weather events
Periodic Signal Retiming	Offline optimization of signal timing plans and their times of activation based on historical system performance measures estimated using detailed data from multiple sources	FDOT District 5	Daily operations including stochastic variations.
Traffic Adaptive Signal Control	Optimize overall signalized intersection performance by continually adapting signal timing for each movement to actual traffic conditions	I-95/I-395 ICM project in Virginia	Daily operations (stochastic variation), freeway incident and weathers events, and arterial major events. However, it is not clear how adaptive signal control perform under incident and event scenarios.
Special Signal Plans During Freeway and Arterial Incidents	Application of plans to flush diverted traffic during freeway events and plans that consider capacity drops during arterial incidents.	FDOT District 4, FDOT District 5; Dallas US-75, San Diego I-15, Los Angles I-210 Connected Corridors	Freeway incidents, weather events, and arterial events.

Intervention	Description	Inclusion in National and Florida ICM	Applicable Operational Scenarios
Alternative Route Provision to Motorists	Provision of alternative route information to motorists during freeway and arterial incidents and other events	Maryland CHART program, San Diego I-15, Los Angles I-210 Connected Corridors	Freeway and arterial events, weather events, and other special events.
Predicted Travel Information Provision to motorists	Predicted travel time from origin to destination is provided to the public such that they can plan their trips before departure and change travel mode or routes during trip	San Diego I-15 and Dallas US-75	Freeway and arterial events, weather events, and other special events.
Provision of Optimal Emergency Vehicle Routing	Provision of optimal alternative route information to emergency vehicles during severe freeway and arterial incidents and other events	Dallas US-75	Freeway and arterial incidents
Rerouting express buses	Provision of optimal alternative route information to express bus during severe freeway and arterial incidents and other events	Dallas US-75	Freeway and arterial events
Mode Shift during Severe Highway or Transit Incidents	Operational data from transit agencies, such as significant schedule delays, route deviations, parking occupancy data, where available, can be provided to travelers to encourage the usage of transit during severe highway and arterial events. Such information can also help transit users to switch to another transportation mode during severe transit delays. Passengers disembark and a bus bridge can be provided to the nearest station/bus stop/alternative transit line routing and bus priority	FDOT District 4, FDOT District 5, Dallas US-75, San Diego I-15, and Los Angles I-210 Connected Corridors	Severe freeway and arterial incidents, weather events, transit events, and other events.
Hard Shoulder Running	Allow temporary use of either left or right shoulders on freeways to provide additional roadway capacity during congestion.	FDOT District 5, Los Angles I-210 Connected Corridors; Chicago DMA testbed	
Restrict/ reroute/ delay commercial traffic	Restrict the commercial vehicle usage of roadways and divert them to alternative routes during a severe freeway or arterial incident or other event	FDOT District 5	

Intervention	Description	Inclusion in National and Florida ICM	Applicable Operational Scenarios
Special Events and Construction	disseminating event, closure, and detour information; providing parking management and information systems; implementing special signal timing plans; providing additional transit services, rerouting transit vehicles, and notifying customers of service.	FDOT District 4	
Disaster Response	This response involves modifying ramp meter rates, modifying Express Lane toll/restrictions, providing contraflow lane operation, providing information to travelers, coordinating closure information, providing signal timing adjustments, and making resources (buses) available for evacuations.	FDOT District 4	

E.3 ASSESSMENT OF AGENCY CAPABILITY

This project also addresses the capability maturity assessment of the agency ability to utilize decision support systems for ICM planning, operations, and management. The managers of the FDOT transportation system management and operations (TSM&O) programs in four FDOT districts were interviewed (Districts 1, 2, 4, and 5) as part of this effort to get information to support this effort. This task assesses the needed capabilities based on these interviews and information gather in the previous tasks. The discussion is structured around the dimensions of the Capability Maturity Modeling (CMM) (FHWA, 2018a) originally developed for TSM&O as part of the SHRP2 Reliability program (Parsons Brinckerhoff, & Delcan Corporation, 2012) based on the concept widely used for various applications in Information Technology.

E.3.1 Capability Maturity Frameworks Overview

The motivation for the use of the CMM to guide the capability discussion in this document is that it was developed to identifying an understanding the barriers to the adoption of different types and levels of DSS and for the provision of recommendations for action to improve the capabilities. The CMM framework is used to guide discussion about the needed capabilities and improvements to achieve an effective ICM decision support system. Consistent with the above mentioned framework, the discussion is organized in the same six dimensions of the framework.

1. Business processes
2. Systems and technology
3. Performance measurement
4. Culture
5. Organization and workforce
6. Collaboration

Four to five capability levels are defined in this study to rate the ICM capability levels.

E.3.2 Findings Related to the Six ICM Capability Dimensions

This section presents a review of main findings for the six ICM Capability Dimensions.

E.3.2.1 Business Processes

Decision support tools should be used to determine the ICM project feasibility, value, and significance should affect project development decisions. Return-on-investment or at least the expected improvements in outcome performance measures related to the goals and objectives identified by the project stakeholders should be conducted to support the analysis. At a minimum, a planning level analysis utilizing highway capacity manual (HCM) level analysis combined with data analysis should be used. More detailed simulation modeling is desirable.

Funding, particularly those related to operations and maintenance (O&M) is obviously a major concern for agencies. Based on the above, it seems that the ICM deployments can use FDOT work program, MPO federal funding, local agency funding, and even Central Office and federal funding. FDOT districts have also supported ICM partners with ICM O&M funding needs, particularly with local agencies that have limited resources.

E.3.2.2 System and Technologies

<u>Use of Systems Engineering and Regional Architecture</u>

As with other Intelligent Transportation Systems (ITS) projects, the ICM planning, design, and deployment should follow the system engineering process. FDOT ITS projects has a system engineering process and regional architectures that have been in place for almost 15 years. It is anticipated that this process will be used for ICM projects. The ICM deployments in Florida will also utilize center-to-center and center to field ITS standards and FDOT specifications and guidelines, as required by the United States Department of Transportation (USDOT) and FDOT.

<u>Offline Decision Support</u>

The utilization of an effective decision support system is an important foundation of the deployment of ICM. DSS determine, offline and in real-time environment, congestion conditions that require a response, recommend coordinated response(s), and evaluate these responses.

Offline modeling and data analyses are an important aspect of ICM that should be utilized in all ICM deployments to determine the effectiveness of different ICM strategies in the planning stage and to identify the response plans in the design stage. It should be recognized that modeling can be done at different levels. More complex deployments like the ones tested in San Diego and Dallas, and planned for Orlando and Los Angles use dynamic traffic assignment (DTA)-based mesoscopic and/or microscopic modeling. Even if agencies lack the resources to develop a large scale DTA-based mesoscopic or microscopic simulation models, consideration should be given to utilizing existing simulation models that were developed for other purposes in the region. Some interviews revealed that big scale DTA-based model may require a lot of resources and the

District may not have experience in it. The modeling office may provide the needed capabilities. However, the modelers need to understand the level of details and accuracy required for TSM&O applications versus planning level applications.

Freeway and urban arterial HCM-based procedures can provide important support for the selection and effectiveness of the response plans. It should be recognized that modeling can be done at different levels. More complex deployments like the ones tested in San Diego and Dallas, and planned for Orlando and Los Angles use dynamic traffic assignment (DTA)-based mesoscopic and/or microscopic modeling. Freeway and urban arterial HCM-based procedures can provide important support for the selection and effectiveness of the response plans. Another important aspect of offline analysis is data analytics that can provide considerable support of planning and design of ICM.

<u>Real-Time Decision Support</u>

In general, real-time DSS, as implemented in the two USDOT pilots and planned in District 5 in Orlando, can be considered to consist of four elements: data collection and fusion, user interface, real-time response plan recommendations, and model-based real-time predictive engine. The Florida District 5 DSS deployment will include a model-based predictive. The development in District 5 will provide lessons learned to other districts and some of the developments may be transferrable, although the specific utilized simulation model for the predictive engine may be different or even if simulation modeling is not utilized at all. Depending on funding, data, and resource availability, a different level of DSS can be implemented that may not include a model-based predictive engine.

It appears that the districts are waiting for FDOT District 5 experience with the system. An important issue is that not all ICM local partners will appreciate this approach. Thus, a proof of concept is necessary.

As with offline modeling, real-time modeling can be as simple as running HCM-based procedures in real-time. In addition, data mining/machine learning approach to real-time evaluation and even real-time generation of plans can be used either in combination with or to replace the real-time expert-rule system and the model-based predictive engine.

<u>Traveler Information Systems</u>

The traveler information will continue to be provided by the public and private agencies. The main method of disseminating the information by public agencies is expected to be through DMS, 511 App, and providing information to TV/Radios. The interviewed districts said that they would provide alternative route information during events that the system is responding to. There is currently an FDOT policy not allowing the provision of information and this needs to be changed.

The interviewed agencies have not mentioned immediate plans for the provision of transit information as part of the ICM. This is due to unavailability of good alternative mode solution in some cases and the lack of required transit vehicle technologies (like bus real-time tracking) in some cases.

In many cases, the districts are currently only considering diverting to State Roads even if there are better County road alternatives since state roads maintained by the FDOT and can be accounted for by current consultant contacts. Sometime, recommend changes to the timings of other street are given, if their operations impact state road performance. There are no resources currently available to expand them.

E.3.2.3 Performance Measurements

Existing and emerging sensor, mobile, and vehicle technologies in addition to data from multiple other sources are increasingly available and will provide a strong support for ICM. Bluetooth data has been installed on alternative routes. In few cases, Microwave detectors (MVDS) at mid-blocks were also installed and in some cases high resolution controller data were collected.

The FDOT is currently archiving the data collected by their traffic management center using the Regional Integrated Transportation Information System (*RITIS*); which is an automated data sharing, dissemination, and archiving system maintained by the University of Maryland. Additional data will be generated through the ICM. One option is to archive all additional data in RITIS. Another option is to develop ICM data marts that pull data and archive data from different sources.

Data availability, sharing and governance are important to the success of ICM. In addition to data warehousing, effective management of the data requires data governance. Data governance ensures the availability, usability, consistency, integrity, and security of the data. It will also ensure accountability for the adverse effects of poor data quality. The data governance and associated guidelines should be followed, enforced, and updated as needed.

The ICM deployment requires the definition of performance measures that are related to the regional goals and objectives and ICM project objectives. The performance measures can be in different levels of details to support strategic, programmatic, tactical and operational decisions with more detailed measures defined going from strategic to the operations levels. However, the performance measures at different levels should be aligned and mapped to the goals and objectives. In general, FDOT districts have been tracking measures for their limited access facilities. Some of these districts have started producing dashboards of these measures.

The performance measurement capability does not provide benefits to the agency unless they are used in an effective manner to support the decision processes associated with ICM. Business Intelligence (BI) applications should be used to convert the performance measures to information that support the decision process both offline and in real-time. The FDOT districts indicated that the use of performance measures based on data is important but currently its use is not institutionalized as part of the business process for use in different decision levels. This is needed for effective use of data.

E.3.2.4 Organization and Workforce

It is important to meet the staffing requirement for ICM plan development, fine-tuning, and activation. These responsibilities may be assigned to existing staff but most likely additional staffing will be needed to meet the additional workload.

The setup and utilization of DSS will require new capabilities and training not currently available at traffic management centers. An issue mentioned by the districts is that need for quality staff who have the background in data analytics, simulation and modeling and are interested in the new approach. Staff should have some exposure to modeling.

It was stated in the interviews with the districts that the district modelers need to be involved. However, they need to be informed about the difference between the needed models for TSMO versus the planning level models. At the same time, although The ICM managers do not need to be expert in modeling, they need to know enough to explain to the modelers the objectives and requirements of modeling and interact with them during the modeling process. Another mentioned concern about modeling is the need for agency to understand the strengths and limitations of modeling considering the many inputs regarding their effectiveness.

E.3.2.5 Collaboration

Coordination and collaboration is critical to the success of ICM and the associated DSS. Some locations will have the ICM operation centralized in one locations. This option appears to be the preferred option by FDOT Districts.

There has been a strong recommendation for formal memorandum of understanding (MOUs) and agreements to support the operation and maintenance activities. The interviews and review of the literature conducted in this study indicates that this can be a good option in many cases to support ICM, particular when the needed collaboration, cooperation, and sharing is expected to impact cost or agency business processes. Currently, there are not formal ICM agreements signed at FDOT districts. Some FDOT districts are of the opinion that there is definitely a need for such agreement to address issues like roles and responsibilities, operations, and funding. The signing partners will have to include at least signal maintaining agencies, transit agencies, and MPOs. MPOs can play a role in collaborative activities, long-range strategic plans, and funding. The agreement will help building working relationship has and generating trust. Initial guidelines may be rigid but that is acceptable until trust/comfort level is built. However, in other cases, the districts was of the opinions that formal agreements are not immediately needed since there are already a strong relationships between TSM&O partners. In these cases, formal agreements may not be necessary due to the high level of collaboration and trust between the partners and it was stated that the formal agreements may introduce rigidity to the collaboration process.

E.3.2.6 Culture

ICM projects need a champion that can be a part of a leading agency that implement and/or operate the ICM. Such leader and/or champion should at least understand a high level the concepts, strengths, and weaknesses of data-based and model-based DSS. All interviewed districts see the ICM to be led by FDOT as a centralized operation.

Another culture-related element that contribute to the success of ICM project is the organizational support and institutionalization of the use of data analytics and model for ICM decision making. One need to ask how is the application of DSS and modeling and data analytics use as part of DSS is valued within the partner agencies.

E.4 DEMONSTRATION OF ANALYSIS ABILITY TO SUPPORT ICM

This part of the study demonstrated the ability of data and modeling analytics to support various operational scenario decisions.

E.4.1 Utilization of Clustering Analysis to Identify Traffic Patterns

Clustering analysis can be used to identify of traffic patterns that are representative of traffic conditions in support of transportation system operations and management (TSM&O); integrated corridor management; and analysis, modeling, and simulation (AMS). Recognition of various clustering and the percent of data in each cluster will allow agencies to better plan, design, and invest in strategies, tactics, and operations. However, there has been limited information to support agencies in their selection of the most appropriate clustering technique(s), associated parameters, the optimal number of clusters, clustering result analysis, and selecting observations that are representative of each cluster.

This study investigates and compares the use of a number of existing clustering methods for traffic pattern identifications, considering the above. These methods include the K-means, K-prototypes, K-medoids, four variations of the Hierarchical method, and the combination of Principal Component Analysis for mixed data (PCAmix) with K-means. Among these methods, the K-prototypes and K-means with PCs produced the best results. The document then provides recommendations regarding conducting and utilizing the results of clustering analysis.

E.4.2 Identification of the Impacted Diversion Routes

Traffic incidents on a highway create temporal bottlenecks that disrupt traffic flow, produce traffic congestion, and cause additional delays. A portion of travelers who encounter the situation divert to alternative routes potentially causing congestion on the alternative routes. Route diversion during incidents on freeways has been proven to be a useful tactic to mitigate non-recurrent congestion. However, the capacity constraints created by the signals on the alternative routes put limits on the diversion process since in many cases the regular time-of-day signal control plans cannot handle the sudden increase in the traffic on the arterials due to diversion. Thus, there is a need for active transportation management strategies that support agencies in identifying the routes used by the diverted travelers during freeway incidents to support agency in their decisions to adjust the traffic signal timing under different incident and traffic conditions. This study investigates the use of a data analytic approach based on the long short term memory (LSTM) (a deep neural network method) to predict the alternative routes dynamically using incident attributes and the traffic state on the freeway and the travel time on both the freeway and alternative routes during the incident.

E.4.3 Use of Connected Vehicle Data to Identify Congestion Patterns on Alternatives routes

The additional diverted traffic from freeways to alternative arterial streets deteriorates the intersection movement performance causing delays, long queues, spillbacks to the upstream intersections, spillovers to adjacent lanes, and so on. At the critical intersections, the diversion most likely will affect only specific movement(s) in the direction of the diverted traffic rather than the whole intersection. Thus, transportation agencies need to identify the impacted movements and the associated congestion patterns to implement active traffic management strategies to accommodate the additional traffic

This study investigates the use of data from connected vehicle (CV) technology combined with high-resolution controller (HRC) to automatically identify traffic congestion patterns at the signalized intersections due to diversion. A micro-simulation model is developed using VISSIM to emulate the CV, HRC and loop detector data. Four different clustering techniques: K-means, K-means with Principal Component Analysis (PCA), t-distributed stochastic neighboring embedding (t-SNE), K-means with t-distributed stochastic neighboring embedding (t-SNE), and Deep Embedded Clustering (DEC) are used to identify the patterns, and their performances in identifying the congestion patterns are evaluated. Then, supervised machine learning was applied to categorize the traffic patterns in real-time operations based on the pre-determined categories identified as a result of clustering analysis. The pattern identification can be used in implementing signal timing plans to better accommodate the diverted traffic without significantly deteriorating the performance of other movements at the intersection. This method can be used as part of a decision support system (DSS) to manage the traffic proactively during the incidents on the freeway

E.4.4 Prediction of Diversion Rate based on Detector Data

As part of a project funded by the Southeastern Transportation Research, Innovation, Development and Education (*STRIDE*) Center University Transportation Center (UTC) that this project is used for, the research team developed a methodology for the prediction of diversion rate during incidents based on detector data. A brief summary of this method is presented in this document for completeness. The readers are referred to the STRIDE UTC final report for the details. The developed method utilizes a combination of cumulative volume analysis, clustering analysis, and predictive data analytics. The purpose of clustering analysis is to associate the incident day traffic pattern before the occurrence of the incident with similar normal day patterns. This allows the use of the cumulative volume analysis method to determine the volumes on the freeway with and without incidents and thus estimate the diversion. Data analytic models are developed allowing the prediction of the diversion rate based on the incident severity, number of blocked lanes, time of the incident occurrence, and incident locations.

E.4.5 Selection of Signal Timing during Arterial Incidents

As part of another project funded by the *STRIDE* UTC that this project is used as matching for, the research team developed a methodology for the selection of signal timing during arterial incidents. A brief summary of this method is presented in this document for completeness. The readers are referred to the STRIDE UTC final report for the details. As a part of this project, the history of the responses of the traffic signal engineers to non-recurrent conditions is captured and utilized this experience to train a machine learning model in order to automate the process of updating the signal timing plans during non-recurrent conditions.

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1. INTRODUCTION

1.1 BACKGROUND

There has been an increasing interest in deploying Integrated Corridor Management (ICM) strategies in Florida. Some regions have started developing or have developed operational scenarios for ICM implementation involving multi-modal and multi-facility operation and management strategies to address the various issues facing the transportation system.

A Decision support system (DSS) can be considered the "heart" of ICM system (Lee and Pack, 2012a; Lee and Pack, 2012b). A DSS provides the support necessary in real-time operation as well as in planning for operations of transportation systems. Previous national ICM efforts have utilized offline and online decision support modules based on data from multiple sources and modeling tools. ICM has been included as a major strategy in the Strategic Plan of the Transportation Systems Management and Operations (TSM&O) of the Florida Department of Transportation (FDOT) (FDOT, 2017). The Action Plan of the FDOT Statewide Arterial Management Program (STAMP) identified the following related action items: development of the Integrated Corridor Management Guide, development of DSS for ICM, and implementing a DSS for ICM (FDOT, 2018). The FDOT District 5 has initiated efforts for the development and implementation of decision support tool based on transportation system modeling and data support.

However, there are many issues and considerations when implementing modeling methods and tools as part of a DSS to support ICM deployment in Florida. Addressing these issues will ensure the sustainability, usability, and return on investment of the implementations. First, ICM implementations at various locations are different in terms of operational scenarios, corridor characteristics, existing management and control strategies, and the availability of existing simulation models in the region. Second, the effectiveness and applicability of various approaches will have to be assessed considering the above factors. This is important considering the limited experience with ICM in Florida. Third, the project activities will need to identify the levels of capability required for implementing and operating the decision support as well as provide recommendations for such implementation considering the existing capability maturity with regard to ICM DSS implementations in different districts. Furthermore, data availability may vary between different locations, particularly as related to arterial streets and transit.

1.2 GOAL AND OBJECTIVES

The goal of this research was to assess the applicability, feasibility, and effectiveness of data, analysis, modeling, and simulation approaches to support the decision-making process associated with offline and real-time operations of ICM. This project had provided findings that support the maximization of ICM benefits by identifying approaches to the effective use of decision support tools for real-time and offline applications. The specific objectives were:

- Review of the models and methods that are currently available and their applicability for ICM operational scenarios in Florida
- Identify methods to support the decisions associated with various ICM applications.
- Assess the capability needed to implement analysis and modeling to support ICM decisions considering the staff requirements, data, tools, and resources needed by the FDOT
- Demonstrate the ability of data and modeling analytics to support operational scenario decisions

2. STATE-OF-THE-PRACTICE REVIEW

The review of the state of the practice of this project provides a review of national applications to support the offline and real-time decisions associated with ICM. In addition, it provides an overview the different types of modeling tools that are available and their applications to online and offline ICM decision support systems. As well as, lessons learned from existing implementations of decision support tools to support the decisions associated with the use of such tools and the estimated benefits.

It is useful; before starting the discussion of the ICM DSS, their components, and their applications; to provide a brief review of USDOT ICM program. This program has provided the foundation for the ICM deployment efforts in the United States. This effort started in 2006 to "explore and develop ICM concepts and approaches and to advance the deployment of ICM systems throughout the Country" (USDOT, 2018). The USDOT ICM Initiative has occurred in the four phases, listed below (USDOT, 2007).

- Phase 1 - Foundational Research: Phase 1 included a review of the state of corridor management and produced feasibility studies and technical guidance documents.
- Phase 2 - Corridor Tools, Strategies and Integration – This phase developed a framework to model, simulate and analyze ICM strategies and worked with eight Pioneer Sites to further develop specific ICM concepts for the sites.
- Phase 3 - Corridor Site Development, Analysis and Demonstration: Three of the eight sites (Dallas, San Diego, and Minneapolis) conducted analysis, modeling, and simulation (AMS) of ICM strategies. Also, in this phase, two sites (Dallas and San Diego) went to demonstrate and evaluate their ICM systems in real-world deployment. The results from the real-world implementation was further used to refine the AMS calibration.
- Phase 4 - Outreach and Knowledge and Technology Transfer (KTT) - The USDOT has communicated the knowledge and materials developed in previous to transportation practitioners around the country.

The USDOT ICM program has provided guidance to assist agencies in implementing ICM and creating supporting analysis tools, approaches, and technical standards. A large number of documents have been produced particularly those developed as part of the San Diego and Dallas implementations. These documents include concept of operations development, system requirements, pre-deployment and post-deployment AMS, decision support systems, test plans, and analysis results. The documents can provide an important starting point to any ICM and associated DSS development efforts. However, the amount of information available in these documents make is difficult for the user to obtain the needed information. In addition, it is sometime very difficult to navigate to the document parts that discuss certain issues of interest. One of the focuses of this section of the document is to provide a concise summary of these documents and documents from other sources and provide recommendations based on the summary to support the FDOT ICM effort.

2.1 ICM DECISION SUPPORT TOOL APPLICATIONS

This section presents a review of existing applications of decision support tools for the offline and real-time decisions associated with ICM. To date, the main two experiences with real-time use of such tools are the DSS developed for the US-75 ICM project in Dallas, TX and the DSS developed for I-15 in San Diego, CA. The tools used in these applications provide recommendations for operating agencies to apply transportation system management and traveler information strategies during congestion. These tools are reviewed in this section. The on-going effort for DSS development at a third site (I-210 in Southern California) is also reviewed in this section. This effort is funded by the California Department of Transportation (Caltrans).

In general, the DSS can be considered to consist of five elements: offline use of modeling for planning for operations, real-time data collection and fusion, user interface, real-time response plan recommendations, and predictive engine. Each of these has its own requirements. This section provides descriptions of the real-time elements for the three applications of ICM DSS mentioned above: US-75 in Dallas, TX; I-15 in San Diego, CA; and I-210, in the Los Angles (LA), CA. The offline components are discussed later in the document.

2.1.1 Dallas US-75 ICM DSS

As mentioned earlier, the ICM of the US-75 corridor (see Figure 1) in Dallas, TX is one of the USDOT sponsored pilot ICM projects. The US-75 ICM Demonstration is led by Dallas Area Rapid Transit (DART) in collaboration with the USDOT, City of Dallas, Town of Highland Park, North Central Texas Council of Governments (NCTCOG), North Texas Tollway Authority (NTTA), City of Plano, City of Richardson, Texas Department of Transportation (TxDOT), and the City of University Park. US-75 is a north-south radial corridor with a weekday mainline traffic volumes that reaches 250,000 vehicles, with another 30,000 vehicles on the frontage roads (USDOT Intelligent Transportation Systems Joint Program Office. 2011). Dallas has implemented a DSS that uses expert knowledge combined with data collection and fusion tool and a model-based predictive tool to recommend multiagency multimodal responses to incidents on US-75. The different element of the DSS are described in the following subsections.

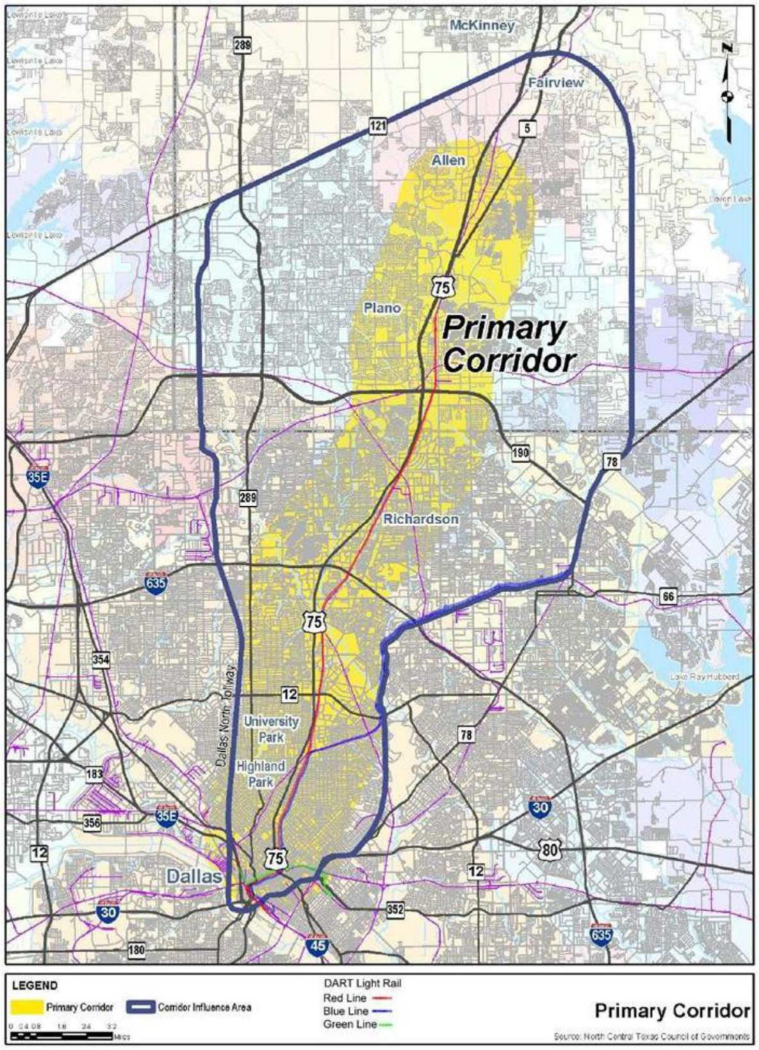


Figure 1: US-75 corridor boundaries of Dallas ICM deployment

Data Fusion and User Interface

An important component of the DSS is the real-time data collection and fusion. The Dallas region has a regional information exchange network referred to as SmartNET™, which is a commercial web-based data integration and dissemination tool provided by Kapsch. SmartNET™ is the combination of the SmartNET graphical user interface subsystem and the SmartFusion data fusion subsystems (California PATH, 2013). The SmartNET Subsystem provides the graphical user interface that supports multiagency input and information sharing including incidents, construction, special events, and current status of devices and network performance. As shown in Figure 2, the system gathers information from multiple sources including transportation management systems, emergency management systems, dispatch systems for law enforcement, and other types of systems using center-to-center standards. SmartNET is also used to disseminate and monitoring response plans. The SmartFusion Subsystem focuses on data collection, processing, fusion, and dissemination (Alexiadis and Chu, 2016a). In addition to the above functionalities, the system is critical to provide the information needed by the rule-based decision support and the modeling-based predictive engine, described in the following subsections.

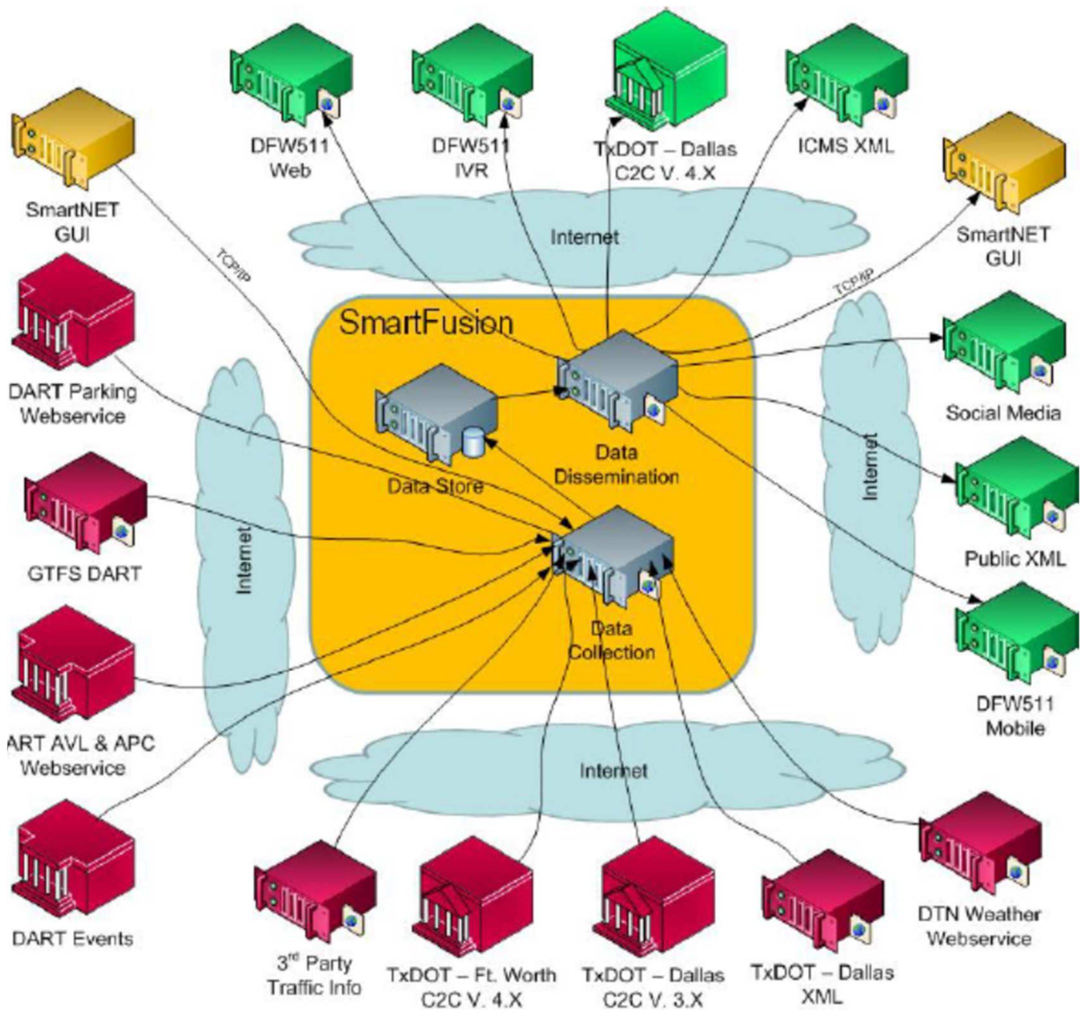


Figure 2: SmartNET™ used in Dallas, TX

Rule-Based Expert System

The US-75 ICM DSS in Dallas, TX has a rule-based expert system that generates response plans during incident conditions for consideration by operations personnel. The expert system recommend plans based of the incident attributes, the availability of alternate routes, transit capacity, parking capacity, and the performance of the response as assessed by the predictive tool. The DSS recommends diversion to the frontage roads, arterials, and/or in the case of severe incidents to light rail. The system also recommends the implementation of special signal timing plans to maximize throughput on the diversion routes (Lee and Pack, 2012b).

The expert system uses traffic and transit data collected in real-time, event data (such as incident location, estimated incident duration, affected traffic lanes), and weather conditions to assess the corridor conditions. The considered parameters in the decision may include the location of the incident, the direction of travel, length of the queue, available capacity on adjacent arterials and frontage roads, and transit passenger and associated parking capacity. When the expert system determines that an event will impact the mobility of the corridor, it makes initial diversion strategy recommendations (i.e., type of route diversion or mode diversion) and identifies predetermined response plans (e.g., special signal plan on the alternative routes) (Miller et al., 2015). The mode shift to transit is only recommended if the incident is major with significant impacts. The expert system then requests the predictive engine (the DIRECT simulation model) to predict the performance of the plans and uses this prediction in prioritizing the plans. The plans together with their predicted performance and prioritization are passed to the operators to make the final plan selection decision including not selecting any plan. It is interesting to note that the functionality of the expert rule-based system is separated from the mesoscopic-simulation based prediction subsystem. In cases when the simulation is not able to produce a timely or accurate prediction, the expert system will recommend plans based on existing conditions collected using the data fusion component without the use of simulation assessment of the impacts of the recommended plans. The system continues to monitor the network operations and revise events/locations/timing plans as needed based on performance.

An important aspect of the DSS Expert System module is the required periodic post-review of the implemented and proposed plans and modifying them as needed. Monthly or biweekly review will allow effective response plan identification.

Predictive Engine

The mesoscopic simulation-based modeling tool, DIRECT is used to provide the real-time prediction of the performance of the corridor in the next 30 minutes under the recommended response plans. When incidents occur, the Dallas DSS selects candidate operational strategies and request their analysis using the predictive engine. This analysis includes a prediction of future conditions under the possible strategies identified by the rule-based expert system. The analysis confirms the impact of an identified strategy for use in the decision making process, if the performance can be estimated in a timely manner. It should be noted that the predictive engine runs only when requested by the DSS, although it could have been set to predict the performance at regular times for no-incident conditions.

The DIRECT model requires data such as the network description, behavioral data (e.g., to allow the estimation of driver diversion due to information provision), and current roadway conditions data. Static data is retrieved from the historical data store. Real-time data such as link speeds and incident data are received from the SmartFusion subsystem, discussed earlier. Additional model parameters (such as recommended response plan and traffic signal plan the schedule) are obtained from the expert rules subsystem. All data are translated into inputs to the DIRECT model (Miller et al., 2015). The prediction manager then calls the DIRECT model to assess current and future conditions under different plans.

The performance measures produced by DIRECT for use in the decision include: travel time, number of travelers, travel delay and distance travelled (Roberts et al., 2014). The measures are segregated/aggregated by facility, direction, and mode (car, bus, rail and Park and Ride). The SYNCHRO signal optimization tool is used offline in optimizing the signal plans for the corridor to support the development of the response plans to be stored for use in real-time.

2.1.2 San Diego I-15 ICM DSS

The I-15 Corridor in San Diego, shown in Figure 3, is one of the two USDOT ICM pilot sites that went to the real-world deployment stage. Decision support tools were designed and utilized for this deployment to support operational decisions. The I-15 ICM Demonstration is a collaborative effort led by the San Diego Association of Governments (SANDAG) in collaboration with the USDOT, California Department of Transportation (Caltrans), the Metropolitan Transit System, the North County Transit District, and the cities of San Diego, Poway, and Escondido (USDOT Intelligent Transportation Systems Joint Program Office, 2011). As with the US-75 Dallas deployment, the utilization of DSS can be categorized into the following elements: Off-Line AMS Tool Applications, Data Collection and Fusion, User Interface, Rule-Based Decision Support System, and a simulation-based predictive engine. This section provides descriptions the real-time DSS elements.

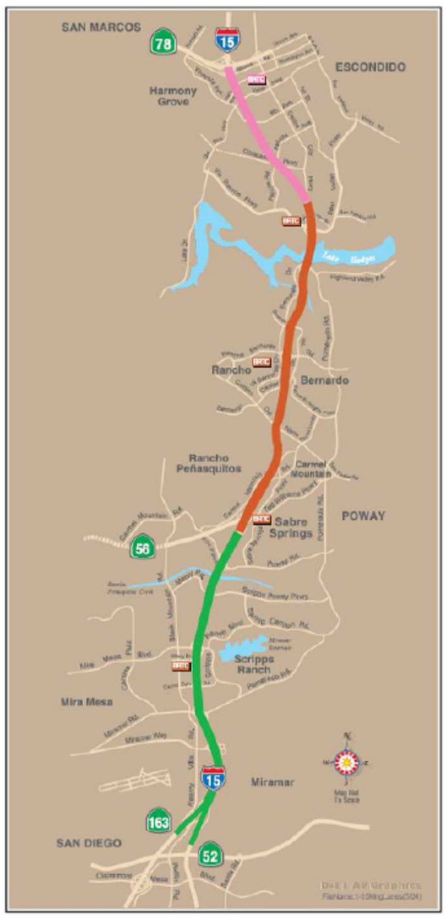


Figure 3: San Diego I-15 ICM network

Data Fusion and User Interface

The real-time data collection and fusion and user interface components of the I-15 corridor ICM is referred to as the regional Intermodal Transportation Management System (IMTMS). IMTMS allows an information exchange network between networks and agencies, provides automated real-time information sharing capability, establishes a historical data archiving system, provides en route traveler information to corridor travelers, and provides pre-trip traveler information to corridor travelers. Figure 4 shows the interfaces to various external systems and the information exchanged with these systems. The IMTMS acts as a data hub that collects data from systems operated by corridor stakeholder agencies, provide data to the decision support tool, and receives control requests from the system via a standardized regional communication network. The utilized operating platform is the Delcan's Intelligent NETworks (iNET) application (Lee and Pack, 2012a) (Delcan was later acquired by Parsons). The operating platform was used to implement all required functionalities including system access and associated control, parameter configuration, data visualization, response plan development processes, and response plan implementation processes.

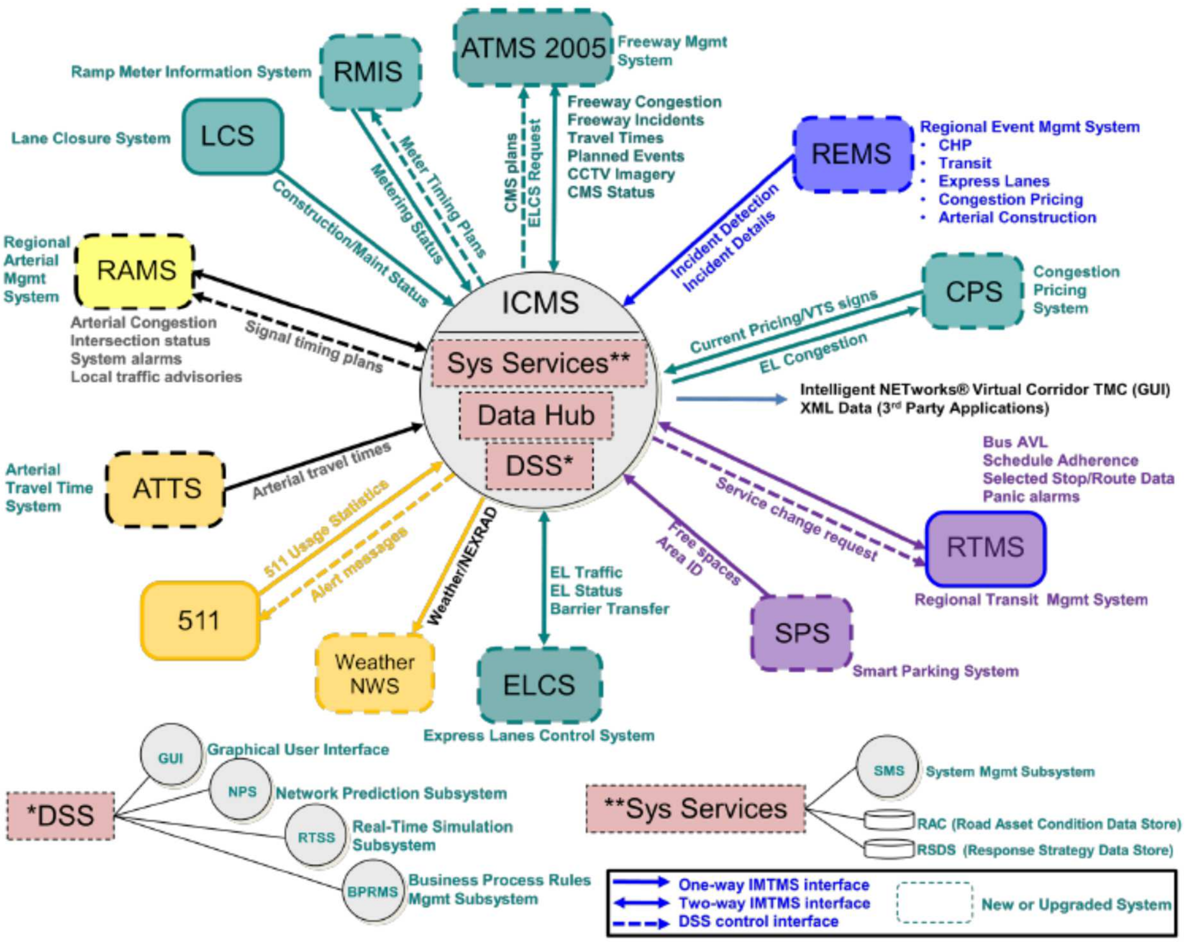


Figure 4: Context of San Diego ICM system data inputs and outputs (Source: Lee and Pack, 2012a)

Rule-Based Expert System

Information collected by the IMTMS from different sources, as described in the previous section, are used as inputs to a rule-based engine that is used to recommend response plans. The DSS provides recommendation regarding the coordination of the operation of freeway ramp meters and nearby traffic signals, modifying ramp metering rates to accommodate traffic shifting from arterial, and modifying arterial signal timing to accommodate traffic diverted from the freeway. The system also manages a lane use control system to change the number of lanes on the managed lanes (ML) and modifies the ML restrictions (such as the minimum number of passengers) based on real-time conditions, and changes in transit routes (Dion and Skabardonis, 2015). In addition, the system provides traffic and transit traveler information using dynamic message signs (DMS), a new 511 smart phone app to support trip traveler choices, and activate dynamic wayfinding signs on arterials to re-direct diverted traffic back to the freeway. The generated response plans consider the incident location, type, severity, and impact that is assessed based on the time of day and other parameters. The generated plans are sent to various management systems that make final decisions regarding implementing the plans. As the event is on-going, the DSS can continue monitoring traffic conditions and provide updates to the recommendations as necessary.

The decision making process compares the current and projected corridor operations against normal operations. Figure 5 shows an interface of the system operators to specify the thresholds for identifying congestion events on the freeway and arterials. The following are key parameters used to determine whether the observed conditions meet thresholds for congestion events (Dion and Skabardonis, 2015):

- Situations in which demand does not exceed capacity are determined based on the minimum speed differential from speed limit, the minimum percent speed differential from speed limit, the minimum increase in delay from free-flow situation, and the minimum v/c ratio differential from free-flow situation.
- Situations in which demand exceeds capacity (oversaturation) are identified based on minimum speed differential from historical data, minimum percent speed differential from historical data, minimum increase in delay from historical data, and minimum percent delay increase from historical data.

Figure 5: Snapshot of system operator interface for specifying congestion threshold (Source: Dion and Skabardonis, 2015)

Predictive Engine

Response plans that can be implemented as assessed by the system are identified by the DSS component. These plans are then evaluated using a simulation-based predictive tool that utilizes the Aimsun microscopic simulation model (see Figure 6). The model predicts the performance of the corridor in the next 60 minutes under the different plans. The results are used to select a plan for implementation. The predictive engine utilizes capacity and demand conditions across the corridor up to an hour in advance in 15 minute slices. The network prediction looks at estimating demand and the consequent travel conditions across the various modes in the corridor. This information is shared with the corridor operators. The prediction will be refreshed every 3-5 minutes (Dion and Skabardonis, 2015).

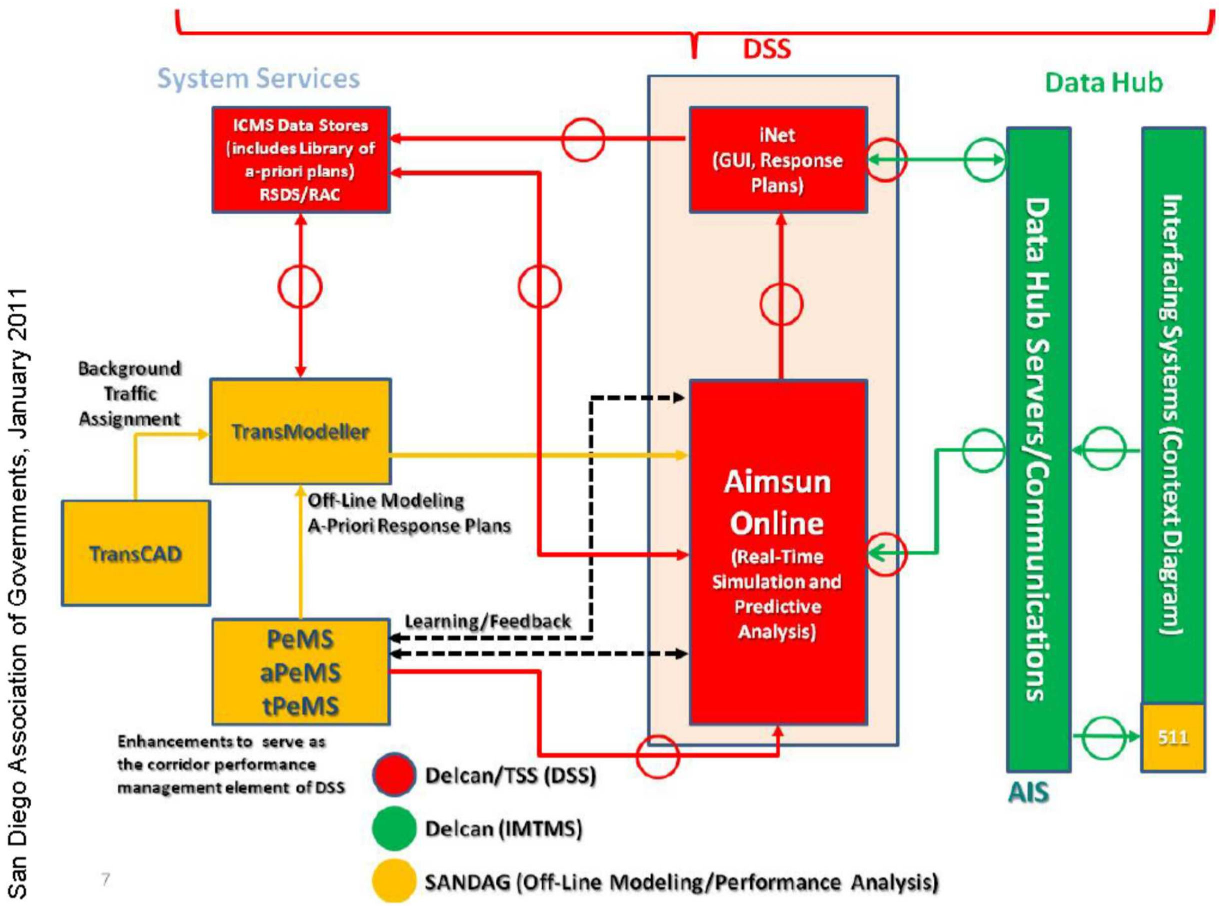


Figure 6: DSS-centric view of the ICMS (Source: Lee and Pack, 2012a)

2.1.3 I-210 Connected Corridor Pilot

The Connected Corridors is a California statewide program that focuses on transportation corridors to improve system performance (California PATH, 2015). The corridors are to include freeways, arterials, transit, parking, travel demand strategies, agency collaboration, among others. Although there are five corridors designated by Caltrans as "Connected Corridors," the I-210 corridor is of a particular interest to this study since a DSS system is been developed for the

ICM of this corridor. The I-210 Pilot is located in the San Gabriel Valley, northeast of LA, CA (Dion et al., 2015). Figure 7 is a map of the corridor.

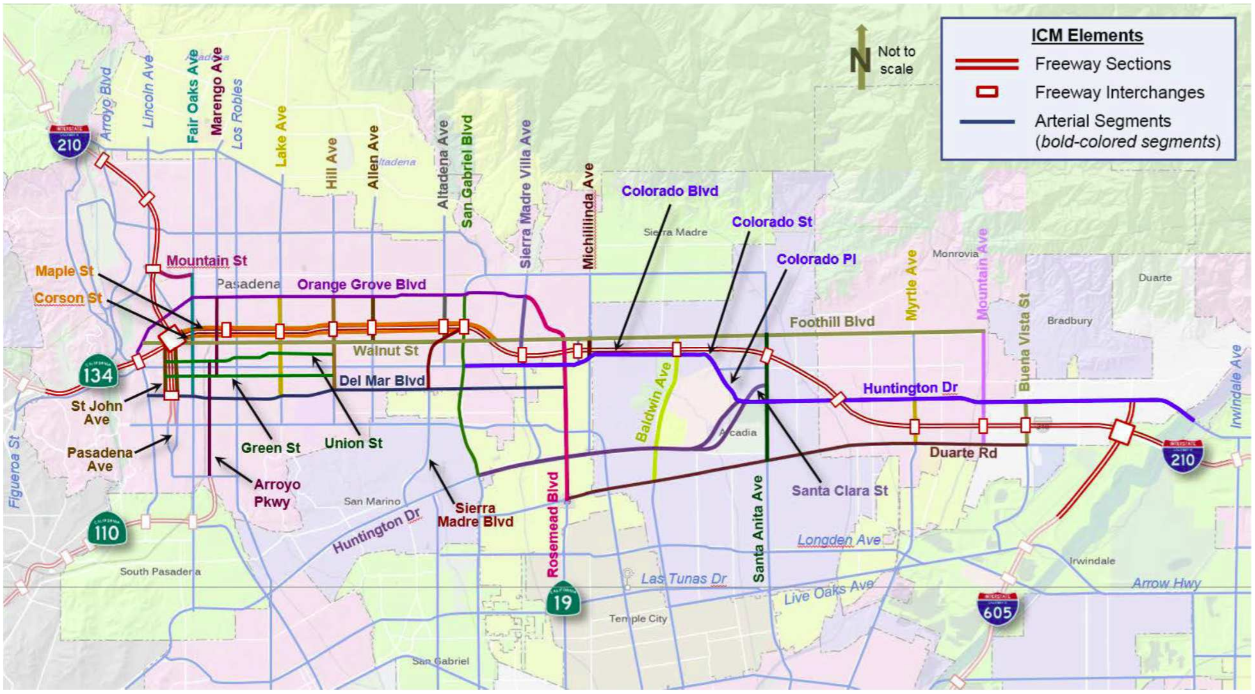


Figure 7: A Map of the I-210 Pilot Network

The I-210 Connected Corridor ICM Design documents point out that a main difference in the system software design of the I-210 ICM DSS compared to other systems utilized in transportation system operations is that it utilizes a more recent software architecture and design, which are better suited for big data volumes and real-time processing (California PATH and Caltrans. 2017). The design takes advantage of two elements: a microservices architecture and Cloud technology and design. Using these two elements allow the utilization of additional server and computational resources on demand. In general, a microservices architecture involves self-contained components, each providing a specific service or function, which are loosely coupled to provide one or more system capabilities. This architecture allows separating the elements of the ICM architecture including the data hub, DSS, operator interface, and predictive engine into separate components. The ICM DSS design documents states that using this architecture provides high levels of scalability, reliability, resilience to failure, parallelization, speed of processing, ability to adapt, and very high data throughput capabilities. Using the cloud technology supports many of the capabilities that can be achieved using the microservices architecture.

Data Fusion

The data hub allows sharing and processing of corridor data and also interfacing with other components of the system (the operator interface and the DSS). The system deals with the operational data storage. Long-term archiving of the data will be done at the statewide level using the California's PeMS. The data hub will operate at the regional level supporting multiple ICMs in the region, while the DSS will operate at the local level (individual ICM).

The data hub receives data from each of data sources, as shown in Figure 8 (California PATH and Caltrans. 2017). The received data is validated for completeness and data quality and transformed into a standardized format. All data within the ICM system is made available to other systems and components via an internal data bus. The provided data includes live real-time data, recent data (0-90 days), aggregated data, and archived data. The data hub gathers and archive information regarding traffic operations, transit operations, and the operational status of relevant control devices within the I-210 corridor. It also identifies unusual travel conditions on the I-210 freeway or nearby arterials based on data provided by various traffic, transit, and travel monitoring systems. In addition, the data hub will be responsible for "Orchestration" of the services and workflows between the three primary ICM components; the data hub, operator interface, and DSS with all communication between the three systems passes through the data hub. For example, once an incident is confirmed, the data hub ensures all needed data is captured. It then informs the DSS of the progress of the incident and requests response plans. The DSS responds with the need for a response plan, the response plans, and the results of evaluation and selection of response plans. The data hub captures, stores, and forwards the selected response plan to the operator interface with the evaluation and ranking. If the response plan is rejected by the operator, the data hub stores that result and forwards the next response plan.

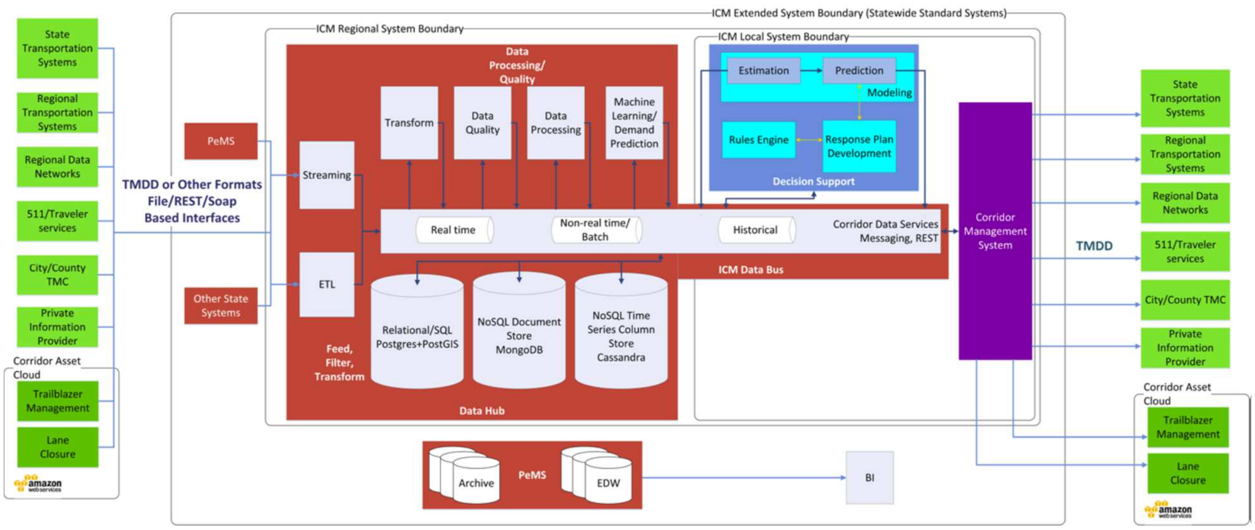


Figure 8: Data hub used in the I-210 pilot ICM project (Source: California PATH and Caltrans. 2017)

Operator Interface

The user interface is referred to as the Corridor Management subsystem in the I-210 implementation (California PATH and Caltrans. 2017). This component provides the primary user interface for system operators, a method for users to monitor the system conditions, and an interface with the DSS. This allows the operator to review, evaluate, select, and approve the response plans generated by the DSS. The system also allows interaction with external systems to support the execution and management of the response plans. The Corridor Management subsystem controls corridor and sends the approved response plans to the appropriate systems and entities. The subsystem does not directly control the associated corridor assets but only sends the response, predicted outcomes from implementing the plans, and other information associated with the plans.

Rule-Based Expert System

The roles of the rule-based expert system are to identify the response plans, request the evaluation of the plans by the predictive engine, evaluate response plans, and rank them based on user defined criteria (California PATH and Caltrans. 2017). This allows the recommendation of one or more plan to corridor operators using the Corridor Management subsystem together with the results of the evaluation produced by the predictive engine. The DSS has an interface for sending and receiving information with the data hub. It has a response plan management component that receives information from the data hub and uses a rules engine to identify and request the evaluation of the plan by the predictive engine. The response plan management also ranks response plans based on the evaluation results.

Predictive Engine

The I-210 ICM DSS project concept and design includes two different modeling components, the first utilizes simple macroscopic models is to fill gaps in estimating existing conditions and the second use simulation-based model as a predictive engine to predict the performance with and without implementing the response plan. Kalman filter is used in the processing of real-time road sensor data to provide good quality data to the models (California PATH and Caltrans. 2017).

The corridor traffic state estimation utilizes arterial and freeway macroscopic traffic models developed by the University of California of Berkeley. The freeway traffic estimation model uses a macroscopic simulation that is based on the cell transmission model (CTM). The CTM based simulation can be used both in current state estimation and predictions of future state, but is used only for estimating the current traffic state of the freeway in real-time in this implementation. The arterial traffic estimation model uses an intersection queuing model based on intersection detection, signal timing, and cycle time information. From the limited description, this appears to be similar to what is used in calculating delays in high resolution controller data processing. The results from the freeway and arterial models are merged to estimate the corridor traffic conditions.

The ICM DSS also includes a modeling component for short-term prediction of conditions under different plans utilizing the Aimsun simulation tool. The traffic prediction component utilizes information form the data collected by the data hub as well as the estimated state based on the macroscopic models mentioned above. The prediction component produces metrics assessing for the response plans identified by the DSS for use in plan recommendation and selection.

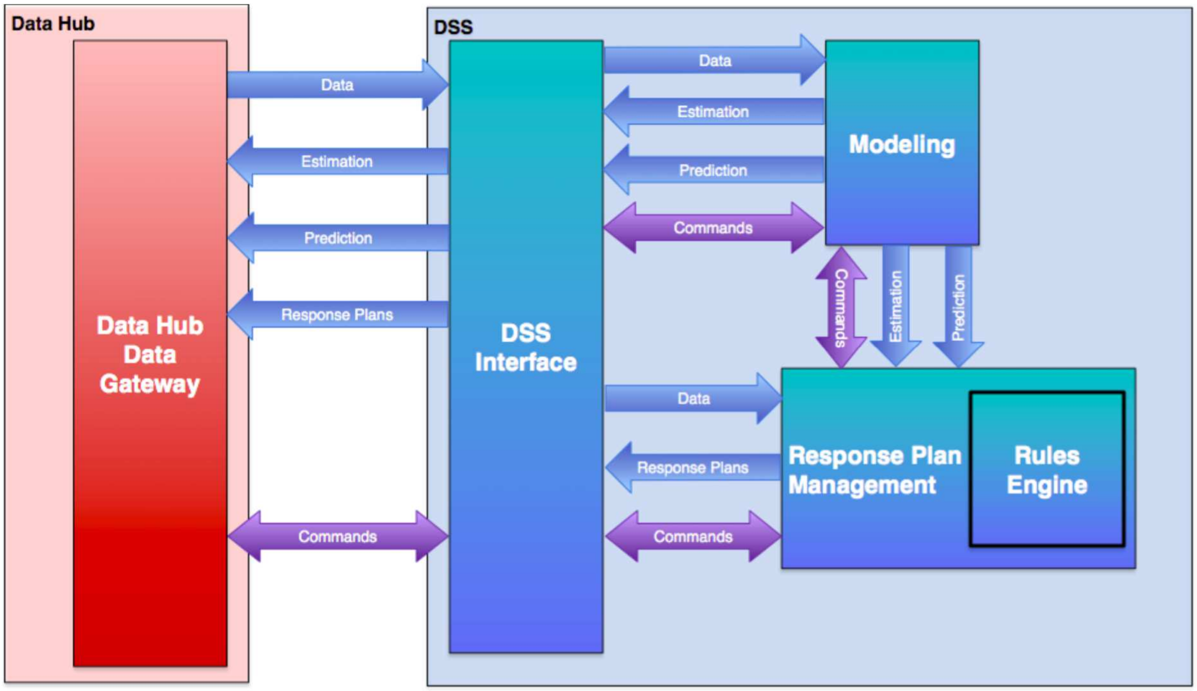


Figure 9: I-210 ICM DSS (Source: California PATH and Caltrans. 2017)

2.2 ANALYSIS, MODELING, AND SIMULATION (AMS) TOOLS

The Analysis, Modeling, and Simulation (AMS) tools have been used as important components of ICM DSS for offline planning for operation analysis. Simulation tools have also been proposed and used as the main component of the performance prediction, in the real-time DSS. Thus, it is important to give a brief review of AMS tools and the associated guidance and methodology regarding their applications to ICM.

A good source of information on this topic is the FHWA traffic analysis toolbox documents. These documents have provided guidance regarding the use of AMS tools and can be found in the FHWA website (http://ops.fhwa.dot.gov/trafficanalysistools). The Florida Department of Transportation has produced a Traffic Analysis Handbook (FDOT, 2014) that is used by practitioners in Florida when utilizing AMS. Another source of information for modeling in Florida is the final report of the "Framework for Multi-Resolution Analyses of Advanced Traffic Management Strategies - FDOT Project BDV29-977-19" research project (Hadi et al., 2016).

Different levels of tools have a role in ICM AMS. Below is a description of these levels:

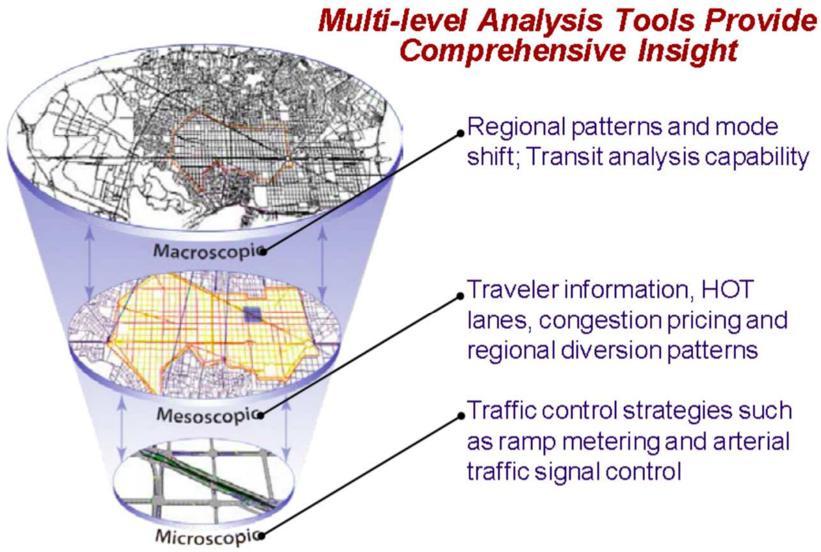
Macroscopic models analyze the impact of the traffic as a whole, on a section-by-section basis rather than by tracking individual vehicles. These models are less complicated and have considerably lower computer requirements than microscopic models. They do not, however, have the ability to analyze transportation improvements in as much detail as microscopic models, although some of these models are able to model queuing, shockwaves, and spillbacks, as stated above. The models range from simple equations such as those used as part of demand forecasting models to more advanced macroscopic models such as those that implement the highway capacity manual (HCM) freeway and urban street facility procedures.

Microscopic simulation analyzes the network at much more detailed levels than macroscopic models. In general, microscopic simulation tools simulate the movement of individual vehicles based on microscopic traffic flow models such as car-following, lane-changing, and gap acceptance. Vehicles are tracked through the network over small time intervals, as low as one tenth of a second. The modeling effort and computer requirements for microscopic models are significantly more than macroscopic models, usually limiting the network size and the number of simulation runs that can be completed. In particular, extensive effort is required for the calibration and validation efforts of large networks modeled using microscopic simulation. Examples of microscopic simulation models are VISSIM, PARAMICS, CORSIM, TransModeler, and Aimsun.

Mesoscopic models have more detailed traffic representation than macroscopic models, but less detailed representation than microscopic models, allowing the modeling of larger sub-networks and possibly small to midsize regional networks. Mesoscopic simulation models generate and track individual vehicles or packets of vehicles. The movements of these vehicles or packets, however, follow the macroscopic approach of traffic flow described above. As with advanced macroscopic models, mesoscopic models utilize the relationships between speed, density, and flow and consider queuing and spillback due to the subject link capacity and downstream link queuing capacity. Mesoscopic models provide less fidelity than microscopic simulation models. However, they provide better computational and modeling efficiency, which is important for simulation-based dynamic traffic assignment (DTA). Examples of mesoscopic simulation tools are Dynasmart-P, DynusT, Direct, DTALite, Cube Avenue, and Dynameq (the first four tools are based on the original development of Dynasmart). Both Aimsun and VISSUM/VISSIM platform now includes macroscopic, mesoscopic, and microscopic modeling options. Although significant amount of data is still required to develop, calibrate, and validate mesoscopic traffic simulation models, the required calibration and validation effort is significantly lower than microscopic simulation tools.

An important component of the modeling of advanced strategies is DTA. DTA provides a more realistic modeling of traffic flow and driver responses compared to the static models used in traditional demand forecasting models. DTA tools combine the modeling of traffic operations with advanced time-dependent, shortest path identification, and associated assignment algorithms to model route choice impacts as a result of changes in network performance. These tools model route choices at fine-grained time intervals (15-30 minutes is usually used). The traffic modeling associated with DTA can be at the macroscopic, mesoscopic, and microscopic levels. More details about DTA can be found in Hadi et al. (2012), Hadi et al. (2013a), DTA primer (Chiu et al., 2011), and FHWA DTA guidelines (FHWA, 2012a).

An ICM AMS Guide has been incorporated into the Federal Highway Administration (FHWA) Traffic Analysis Toolbox (Volume XIII) (FHWA, 2012b). This AMS Guide recognizes the complexity of this type of analysis and recommend the combined use of multiple classes of available modeling tools (utilizing a multi-resolution modeling approach), as shown in Figure 10. In such framework, the rule and extent of each tool type depends on the scope, complexity, and questions to be answered in the effort under consideration.



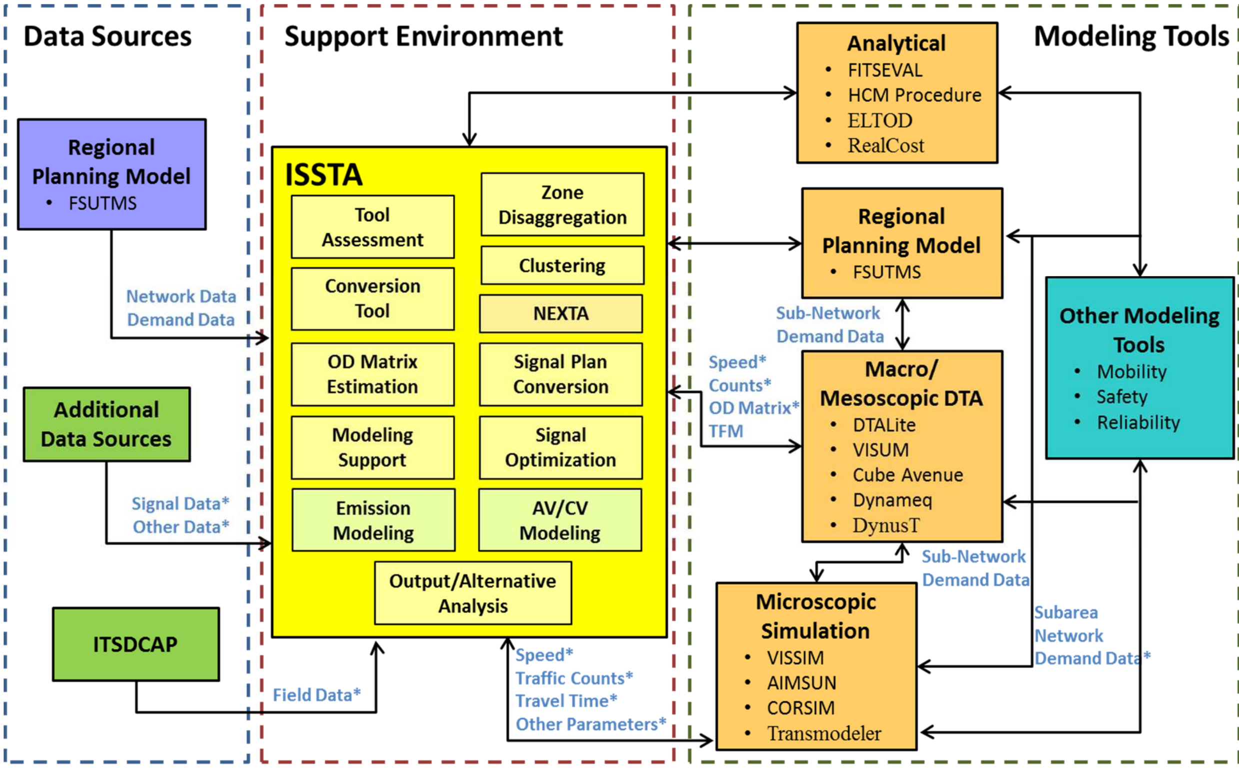
[Source: Cambridge Systematics, Inc., September 2009.]

Figure 10: The ICM AMS multi-resolution modeling methodology

The ICM AMS document stated that the use of the different models allows specific strengths of the individual models to be combined since each tool type (macroscopic, mesoscopic, and microscopic) has different advantages and limitations and is better than other tool types at some analysis capabilities. The guide further stated that "there is no one tool type at this point in time that can successfully address the analysis capabilities required by the ICM program. An integrated approach can support corridor management planning, design, and operations by combining the capabilities of existing tools."

Hadi et al. (2016) proposed a framework for multi-resolution analysis. The framework consists of three components:

- Data collection and processing that allow the utilization of data from multiple sources to support modeling tasks
- Supporting environment that assist modelers in developing, calibrating, and processing the results of the selected modeling tools
- Modeling tools of different types and resolution levels that allow the estimation of various performance measures.



*: The data files are interfaced through the csv format.

Figure 11: Multi-resolution modeling framework proposed for use in Florida (Hadi et al 2016)

An important aspect of the ICM AMS methodology is the need to simulate transportation systems under varying operational conditions including those associated with both recurrent and non-recurrent traffic congestion. The USDOT ICM Modeling Guide stated that the key ICM impacts may be lost if only “normal” travel conditions are considered. Thus, the analysis should take into account both average- and high-travel demands within the corridor, with and without incidents (Alexiadis and Sallman, 2017). The frequency of non-recurrent events such as incidents is also important to estimates of the impacts of advanced strategies.

Appendix A presents a brief description of the existing tools. Theses simulation-based tools, as stated above, vary in the level of details from macroscopic to mesoscopic to microscopic. Tools with different level of resolution are suitable for different applications. However, combining these tools in a single application can provide capabilities and functionalities that are not possible with the use of one type of models. The selection of the specific tools or combination of tools should be made based on detailed requirements to determine which tools can best satisfy the needs for the project. All of the above tools can be considered as candidates for use. However, not all the tools can meet specific project requirements. For example, only some of the above models are capable of assigning individual trips from activity-based models to the network. Thus, if other tools are used, these trips will have to be aggregated into O-D matrices, resulting in the loss of some of the resolution in the process.

The above discussion indicates that agencies will have to assess the suitability of a given tool for a certain applications based on detailed requirements. With the goal of assisting agencies in this effort, Hadi et al. (2012, 2016) presents a catalog of assessment criteria to allow the comparison and testing of various assignment methods and tools. Additional criteria may have to be added when modeling advanced strategies based on a close examination of these strategies.

Some of the reviewed tools are open source tools, while other are commercial tools. Some of the issues with the open source software versus propriety software that are supported by vendors are the level of technical support provided to the customers, adequate documentation of software enhancements, and ensuring continuity in the support of the software in future years. These are very important issues that need to be confirmed before the use of open source software in large-scale projects. If the user of the tool is a "power user" that can use the tools with a minimal need for technical support, then the use of open source tools is possible. Otherwise, the slow technical support associated with open source tools can be a problem. On the other side of the coin, some of the open source tools have been used in national initiatives and implemented several advanced modeling techniques that may not be available in commercially available tools.

2.3 ONLINE COMMERCIAL SIMULATION-BASED DSS TOOLS

Open source and university developed tools such as Dynasmart and DIRECT have been investigated and uses for real-time DSS support. DIRECT was used in the Dallas implementation by the developer of the tool who was part of the development team. However, there are two commercially available modeling platforms that have been proposed for DSS implementation.

This section describes these two commercially available platforms for real-time simulation-based DSS.

2.3.1 PTV Optima

PTV Optima is a model-based real-time traffic management tool developed by the PTV Group. The core of PTV Optima is a PTV VISUM model for typical days that simulates traffic flow using dynamic traffic assignment with input of demand matrices. VISUM is a macroscopic simulation-based DTA tool. PTV Optima acts as a data hub. It collects, compares, validates and merges real-time traffic data from various sources, including detector data, floating car data, automatic number plate recognition, and incident and construction information. These data are applied to calibrate the VISUM model to reflect the current traffic conditions. The VISUM model can be executed from Optima in real-time to forecast traffic conditions up to the next 60 minutes. The current and forecasted traffic conditions for the roadway segments with detectors, as well as those roads without detectors can be visualized through a web-based graphical user interface, referred to as the Traffic Supervisor, to identify critical locations. The impacts of different combinations of traffic management strategies (e.g., traffic signals, dynamic message signs, hard shoulder running, etc.) can be assessed first offline in PTV VISUM and then online in PTV Optima to support real-time traffic operations. Based on a discussion with the vendor, it may be possible to use VISSIM for some segments, if desired.

PTV Optima has been successfully implemented in an area of 25,000 square kilometers (9,765 square mile) in Piedmont, Italy to predict traffic behavior and support decisions. There are two main applications of PTV Optima. The first one is to disseminate incident information and suggest incident response strategies such as opening extra lanes and disseminating information through dynamic message signs, websites, mobile apps, or the radio. In the second application, a warning is automatically sent to the traffic manager when the current traffic behaviors are different from normal patterns more than a predefined threshold. An intervention strategy will also be recommended by the system, for example, closing tunnels during a severe weather event.

PTV Optima has been also used in Romania to provide nationwide real-time traffic information along about 80,000 kilometers of roadway. PTV Optima collects data from floating cars, detectors, automatic number plate recognition, and reports of crashes and constructions. These data are then compared, validated, and harmonized using dynamic weights and merged to provide overall pictures of network-wide speed, density, and congestion. Within 5 minutes, such information can be delivered to those vehicles equipped with on-board units.

2.3.2 Aimsun Live

As is the case with PTV Optima, Aimsun Live is also a model-based real-time traffic management and forecasting tool that can be used for the real-time assessment of advanced traveler information system and advanced traffic management system. It combines real-time traffic data with large-scale simulation to simulate the movement of traffic within a road network for the next hour. The network size can range from a single corridor to an entire major city.

Starting with a comparison of the previous 30-minute records with the historical patterns in the database, Aimsun Live allows the user to input O-D demand matrices and simulate the individual vehicle movements under the current roadway capacities using the combinations of dynamic user equilibrium and stochastic route choice with mesoscopic, microscopic, or hybrid modeling. Such simulation is supported by a time series analysis to produce travel time forecasts and provide incident detection capability. Aimsun Live continuously monitors the performance of forecasting by comparing the predicted values with the field measurements once the prediction horizon is passed. This improves the accuracy of the updated traffic conditions. Figure 12 shows the flow chart of the process in Aimsun Live.

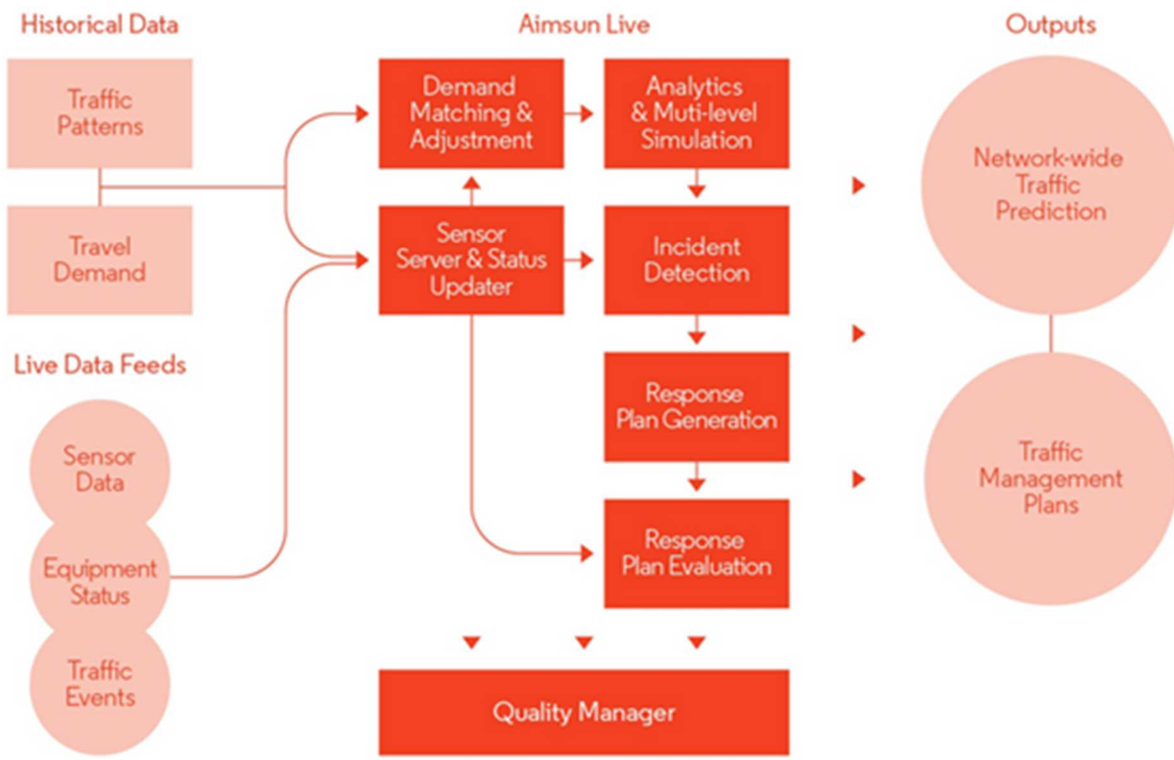


Figure 12: Flow chart of the process in Aimsun Live (Source: https://www.aimsun.com/aimsun-live-2/)

Aimsun Live also allows the assessment, comparison, and visualization of the impacts of strategies such as ramp metering, signal coordination, lane reversal, variable speed limit, traffic information system, and so on before implementing them in the field. Furthermore, the user has access to the simulated individual vehicle information, including vehicle position, route, speed, travel time, delay, pollutant emissions and other characteristics. This provides the flexibility for the users to customize the measure of effectiveness when comparing different strategies.

Aimsun Live has been used in the Grand Lyon Opticities pilot project, a three-year project sponsored by the European Commission Directorate-General for Research and Innovation, to predict the impacts of various congestion management strategies on the traffic along approximately 875 mile roads in the Grand Lyon area, and in turn to support traffic operators' decisions in real-time. Aimsun Live processes the real-time field data from different sources, including static model, public transport data, signal control plans, traffic demand data, historical traffic data, and the definition of events and response scenarios. Real-time simulation conducted by Aimsun Live is applied to compare different traffic management scenarios. Indicators are used in the caparison of strategies including global fluidity, dynamic congestion, road level hierarchy, and indicators for pedestrian data. Such indicators help traffic operators to select the best strategy for implementation in the field both under the recurrent traffic conditions and incident conditions.

This produce has also been used for the I-15 ICM project in San Diego, as described earlier to assess the impacts of incident response and congestion management strategies to support operation decisions. Another application of Aimsun Live is in the metropolitan area of Madrid that covers 360 miles sections, 1,391 intersections, and about 75,000 vehicles. The product is implemented to collect live traffic feed, deduce actual demand, forecast traffic conditions in the next 30 to 45 minutes, and recommend the best safety and congestion mitigation strategies. This process takes about 2 to 3 minutes using microsimulation and fewer than 30 seconds when using hybrid simulation. Once the suggested solution was accepted, the corresponding strategies such as dynamic message sign, speed limitation variation, and/or ramp metering would be activated manually or triggered based on detection. In addition, the predictions from Aimsun Live are compared to real-world data each day to verify the performance.

2.4 OFFLINE UTILIZATION OF AMS TO MODEL ICM-RELATED STRATEGIES

As stated earlier, AMS tools were used in Phase 2 of the USDOT ICM initiative to evaluate candidate ICM strategies. Such tools developed in the pre-deployment phase of the ICM initiative were used to determine the feasibility of ICM alternative strategies, refining these strategies. as well as the offline identification and fine-tuning of the response plans. The tools were used during the life cycle of the ICM corridor in refining and updating the ICM strategies and in post-deployment evaluation of these strategies. Post-deployment AMS activities are conducted to identify the impacts of the "as-deployed" ICM system, which may differ from "as-planned" ICM strategies. The AMS models are updated as more data become available from the ICM to allow better calibration and validating of the underlying models, including data collected using the intelligent transportation systems (ITS) and surveys of site-specific traveler behaviors and responses. This section describes the utilization of AMS to model ICM-related strategies.

2.4.1 As-Planned AMS Modeling of the US-75 Corridor in Dallas, Texas

An integrated analysis approach was used for offline analysis of the ICM pilot project along the US-75 Pioneer Corridor in Dallas, Texas during the planning stage (Papayannoulis et al., 2010). In this approach, the regional travel demand model provides important inputs to the modeling effort. The regional demand forecasting model was used as the primary source for the vehicular trip (origin-destination) tables and networks. Parameters required for modeling such as the value of time and operating cost per mile were also obtained from the regional demand model but they were reviewed, and adjusted before using as inputs to the mesoscopic simulation model. The transit origin-destination demand was obtained from the DART on-board survey.

The core of this analysis approach is the Dynamic Intermodal Routing Environment for Control and Telematics (DIRECT), a mesoscopic simulation model (Papayannoulis et al., 2010). This is the same model used as the predictive engine for the real-time DSS. Although, microscopic simulation using VISSIM was first considered, it was not selected due to the unavailability of VISSIM models for the network and the time it takes to develop such models. Each traveler is assigned to a route and a travel mode in DIRECT by minimizing the traveler's generalized cost including travel time, toll, and transit costs, and matching the traveler's mode preference regarding carpool and using transit. Four types of route-mode options are available in DIRECT: routes for drive along vehicles, routes for carpool vehicles, routes for park-and-ride, and routes for transit, depending on traveler's willingness to carpool and using transit. The selections of route and mode are conducted simultaneously with the mesoscopic simulation of network congestion in DIRECT. The resulted departure time, route and mode for each traveler is stored as a traveler file and used for normal traffic conditions.

Under adverse traffic conditions (e.g., incident, or heavy demand, or severe weather events), travelers may switch route or mode. In this analysis approach, three groups of travelers are considered depending on the accessibility to the information, that is, Group A without access to information; Group B with access to pre-trip information; and Group C with access to both pretrip and en route information (Papayannoulis et al., 2010). These travelers may divert to different routes (i.e., non-historical routes) when passing a DMS sign, or when accessing pre-trip or en route information, or when experiencing congestions. The mesoscopic simulation estimates the route shifts, mode shifts, and the impacts of corridor-specific traveler information (pre-trip and en-route) on these shifts. As part of the model input, each origin-destination pair is assigned a value to represent the percentage of travelers who are willing to use transit or carpool. These percentages were set either based on the values presented in literature or the default values in DIREC. The mode and route choice are functions of the congestion estimated by DIRECT.

The model utilizes a multi-objective shortest path algorithm coupled with an incremental all-or-nothing, rather than a dynamic user equilibrium assignment usually used to model commuters. In addition, the travel times used in the assignment are the link travel times when the travel started (instantaneous travel times) rather than the estimated link travel times at the time that the traveler is predicted to enter the link (experienced travel times), which is used in some of the well-known DTA tools. Not using experiences travel time and dynamic traffic assignment appears to be done to reduce the computational requirements of running the model.

A clustering analysis was conducted to examine the impacts of travel demand, incident, and weather events and to determine the distribution of different operating conditions (Papayannoulis et al., 2010). After eliminating the scenarios with less probability, 13 freeway operating scenarios were identified including 3 scenarios for no incident condition, 5 scenarios for the condition with minor incident, and 5 scenarios for the condition with major incident, as shown in Table 1.

Table 1: Freeway Operating Scenarios (Source: Papayannoulis et al., 2010)

	No Incident			Minor Incident					Major Incident				
Demand	Low	Med	High	Low	Med	Med	High	High	Low	Med	Med	High	High
Scenario No.	1	2	3	4	5	6	7	8	9	10	11	12	13
Incident Duration	NA	NA	NA	45 min	45 min	45 min	45 min	45 min	1 hour	1 hour	1 hour	1 hour	1 hour
No. of Lanes Blocked	NA	NA	NA	1	1	1	1	1	3	2	3	2	3
Incident Location	NA	NA	NA	Belt Line Road	Belt Line Road	Forest Lane	Belt Line Road	Forest Lane	Belt Line Road	Belt Line Road	Belt Line Road	Belt Line Road	Belt Line Road
Incident Start Time	NA	NA	NA	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.	7:00 a.m.
Probability	19.9%	34.6%	18.4%	7.8%	5.4%	5.4%	3.75%	3.75%	0.3%	0.25%	0.25%	0.05%	0.05%
No. of Runs Pre-ICM (13)	1	1	1	1	1	1	1	1	1	1	1	1	1
No. of Runs Post-ICM (44)	0[a]	3[b]	3[b]	0[a]	3	3	3	3	2	6	6	6	6
Total No. of Runs (57)	1	4[b]	4[b]	1	4	4	4	4	3	7	7	7	7

[a] Scenario 1 (No incident, low demand) and Scenario 4 (Minor Incident, low demand) will use the "Pre-ICM" run results for the "Post-ICM" cases.
[b] HOT lane and Express Toll lane operation are not considered ICM strategies. The U.S. 75 team will make these additional runs to see the benefit of these managed lane strategies for medium and high demand.

Before applying the developed model to simulate the impacts of ICM strategies, the simulation model was calibrated based on the three-step strategy recommended in the FHWA Guidelines for traffic simulation: capacity calibration, route choice calibration, and system performance calibration (Papayannoulis et al., 2010). Table 2 and Table 3 list the validation criteria used in this analysis.

Table 2: Model Validation Criteria for the US-75 Pioneer Corridor Analysis (Source: Papayannoulis et al., 2010)

Validation Criteria and Measures	Validation Acceptance Targets
• Traffic flows within 15 percent of observed volumes for links with peak-period volumes greater than 2,000 vph	• For 85 percent of cases for links with peak-period volumes greater than 2,000 vph
• Sum of all link flows	• Within five percent of sum of all link counts
• Travel times within 15 percent	• > 85 percent of cases
• Visual Audits Individual Link Speeds: Visually Acceptable Speed-Flow Relationship	• To analyst's satisfaction
• Visual Audits Bottlenecks: Visually Acceptable Queuing	• To analyst's satisfaction

Table 3: Transit Validation Criteria for the US-75 Pioneer Corridor Analysis (Source: Papayannoulis et al., 2010)

Validation Criteria and Measures	Validation Acceptance Targets
• Light-rail station passenger volumes within 20 percent of observed volumes	• For 85 percent of cases
• Light-rail park-and-ride lots: Individual lot usage	• Within 30 percent of actual
• Light-rail park-and-ride lots: Total lot usage	• Within 20 percent of actual

To address the congestion in the scenarios mentioned above, the following ICM strategies were identified and used in the analysis:

- Comparative, multimodal travel time information
- Incident signal retiming plans for arterials and frontage roads
- High-occupancy toll lane with HOV 2+ free
- HOT lane with 2+one-half price with congestion pricing
- Smart parking system for light-rail transit
- Red line capacity increase
- Light-rail station parking expansion for both private and valet parking

The project assessed performance in terms of mobility, reliability and travel time variability, safety, emissions, fuel consumption, costs, toll revenue, and transit ridership to quantify the effectiveness of the ICM strategies, as listed in Table 4.

Table 4: Summary of Performance Measures and Operational Characteristics for Analysis (Source: Alexiadis and Chu, 2016a)

Category	Performance Measure
Mobility	Travel time: average travel time Delay: vehicle-hours of delay, person-hours of delay Throughput: vehicle miles traveled, person miles traveled, vehicle hours traveled, person hours traveled
Reliability	Planning Time Index
Variability	Changes in the standard deviation of average travel time
Emissions	Kilograms of Nitrogen oxides (NO_x), particulate matter (PM), hydrocarbons (HC), volatile organic compounds (VOCs), carbon monoxide (CO), sulfur dioxide (SO_2), hazardous air pollutants (toxics), and greenhouse gases (CO_2)
Fuel Consumption	Gallons consumed for each fuel type
Cost Estimation	Infrastructure costs and incremental costs for capital costs, operating costs, and maintenance costs
Operational Characteristics	
Facility Type	Mainline, High-Occupancy Vehicle (HOV) lanes, Surface Streets
Mode Type	Drive, Transit
Direction of Travel	Northbound, Southbound
Time of Day	AM peak period, PM peak period, PM off-peak period
Scenarios	with-ICM, without ICM

2.4.2 As-Deployed AMS Modeling of the US-75 Corridor in Dallas, Texas

Among the proposed ICM strategies, the following five strategies were implemented, as part of the US-75 ICM project (Alexiadis and Chu, 2016a):

- Pre-trip and en route travel time information
- Incident signal timing plans for arterials
- Incident signal timing plans for frontage roads
- Light-rail transit information on parking availability
- Red/Orange line capacity increase

A similar integrated analysis approach was used in the planning stage to conduct a post-deployment assessment of the ICM. However, three categories of enhancement were made to the model in the post deployment evaluation. The model input data modifications included the reduction in study area to reflect the actual implementation of ICM strategies and for real-time prediction. It also included the extension of the analysis from the AM peak period to the entire day, O-D matrix and network geometry adjustments to improve the simulation accuracy, utilization of multiple signal timing to reflect real-world deployment, and the adjustment of the percentage of travelers with access to traveler information, as measured. A modifications of the DIRECT model logic was also made allowing inputting multiple signal plans; extending to a full-day model; including the ability to activate and deactivate certain response plan; better representing the travelers' choice under non-recurrent congestion; and producing performance measures at a 30-minute back horizon instead of whole analysis period. Post-processors were also used to calculate travel time reliability, emissions and fuel consumption based on model outputs.

2.4.3 As-Planned AMS Modeling of the I-15 Corridor in San Diego, California

AMS was used as part of the San Diego deployment for pre-deployment and post-deployment assessment of advanced strategies. The ICM strategies that were analyzed in AMS included pre-trip and en-route, traveler information, mode shift to transit, freeway ramp metering, signal coordination on arterials with freeway ramp metering, bus priority, and congestion pricing on managed lanes. In the pre-deployment analysis, the regional demand forecasting model that utilizes the TransCAD modeling engine was integrated with a microscopic traffic simulation model (TransModeler) that is provided by the same software vendor as TransCAD (Dhindsa et al., 2010). The network and the initial trip (origin-destination) tables were obtained from the demand model. The trip tables were manipulated before using them as inputs to the simulation of the corridor. Models were utilized to estimate the time of departure, travel mode, and travel route (including re-routing in response to information dissemination) in response to the implemented ICM strategies implemented (Alexiadis, 2008; Cambridge Systematics, Inc. 2009). The traffic performance at the intersection and ramp levels were estimated using microscopic simulation. The analysis framework is shown in Figure 13. It is interesting to note that according to the framework the trip tables and travel times are passed back and forth between the different levels in search for reaching a relative "stability" between the different levels, although absolute convergence was not guaranteed because of differences in the level of details of various modeling levels.

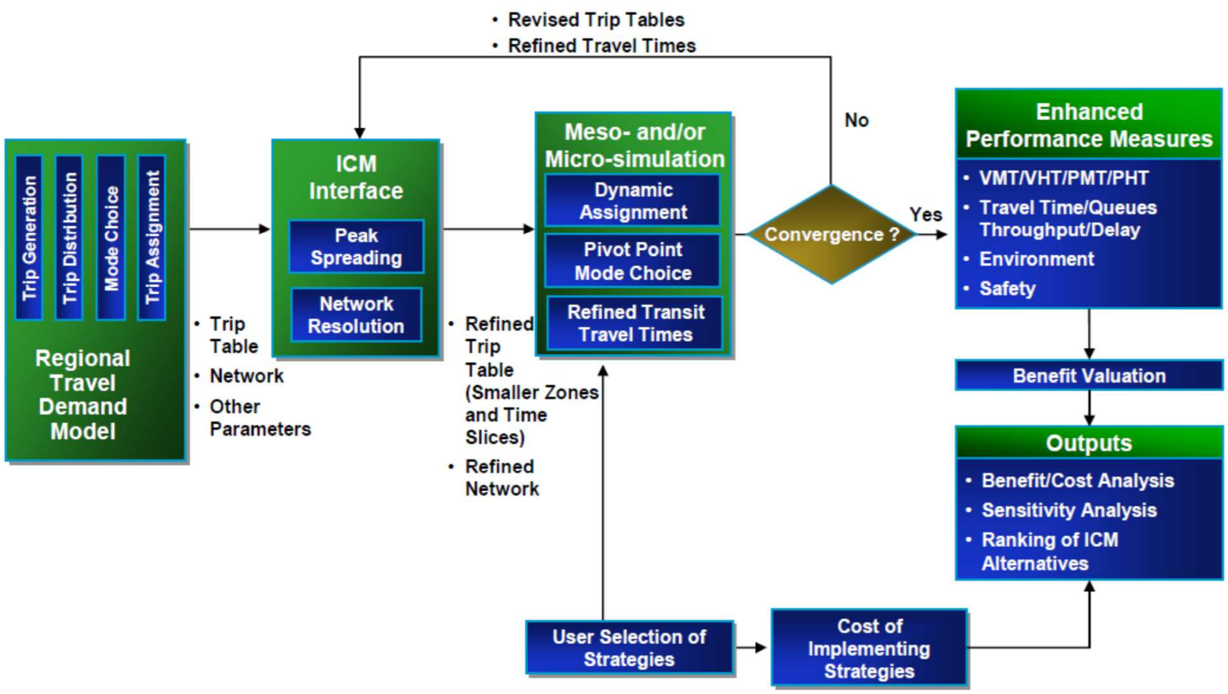


Figure 13: I-15 ICM project analysis framework as planned (Source: Alexiadis, 2008)

The mode choice of travelers at the beginning of trip was determined using the mode-choice module in the SANDAG travel demand model. During incidents or congestions, travelers were also allowed to shift mode with available en route information at the microsimulation level. The route choice was calculated by the Stochastic User Equilibrium (SUE)-based traffic assignment in Transmodeler. The SUE assumes that travelers do not have a perfect information about network path and travel time and is consistent with the concepts of discrete choice and logit-based route choice. Drivers were divided into two groups, one with information and the other group without GPS and not 511 users. The first group may change route or switch mode based on real-time in-car information. The second group may also change mode or route based on information posted on the DMS. The methodology used for the I-15 AMS analysis also considered the time-of-departure choice. It assumes that the peak spreading of demand is a function of the congestion level. A different temporal distribution was used for each origin-destination pair.

The FHWA methodology of three-stage calibration was used to calibrate capacity, route choice, and system performance. The calibration criteria applied in this study are the same as those presented when discussing the offline AMS application for the Dallas ICM.

The effectiveness of the ICM strategies were assessed against a baseline scenario. The performance was assessed based on mobility, reliability and variability of travel time, safety, emission and fuel consumption, and cost estimation. The evaluation was conducted for a total of 16 scenarios including low, medium, and high travel demand levels. Table 5 lists scenarios used in the AMS and the evaluated strategies for each scenario.

Table 5: Scenarios used in the AMS and the Corresponding ICM Strategies (Dhindsa et al., 2010)

Strategy	Baseline operations	Daily ICM operations	Freeway incident	Arterial incident	Disaster response
Pre-trip and en-route traveler information		•	•	•	•
Provision of transit signal priority		•	•	•	•
Ramp meters/traffic signal coordination		•	•	•	•
Bus Rapid Transit system		•	•		•
Congestion pricing for I-15 Express Lanes		•	•		•

2.4.4 As-Deployed AMS Modeling of the I-15 Corridor in San Diego, California

To assess the post-deployment impacts of ICM strategies, an integrated approach that combines macroscopic and microscopic simulations was used in the AMS analysis for the I-15 corridor in San Diego, California. The SANDAG Regional Coordinated Travel-Regional Activity Based Modeling Platform (CT-RAMP) travel demand model provided the 15-minute OD matrices and the parameters for mode shifts. In the post-deployment analysis, the Aimsun simulation model was used instead of TransModeler. The static and dynamic traffic assignment in Aimsun were used to determine vehicle routes. Informed drivers were assumed to have perfect knowledge of real-time travel information and dynamically rerouted themselves to current shortest time path, while other drivers may switch the routes based on congestion level and historical travel time information.

Four types of ICM strategies were evaluated at the post-deployment stage, including pre-trip and en route traveler information, ramp metering, and traffic signal timing during a congestion event. Compared to the pre-deployment analysis, a number of modifications were made to the post-deployment AMS, as listed below.

- The analysis tool was switched from Transmodeler to Aimsun because all ICM strategies had been coded in Aimsun for both AM and PM peak periods and the Aimsun model had all archived data associated with different operational conditions, even though modifications had to be made to Aimsun including modeling full peak period instead of an hour traffic, modeling real-time mode shift, parking demand and capacity, and meeting validation benchmarks.
- The model was not only calibrated for a typical day but also for an incident day to ensure that I-15 ICM is accurately presented in the model.
- The model was tested and modified to represent the real-world percentage of express lane users.
- A tool was used to extract the 60-minute online simulation results and apply to an offline simulation to examine the impacts of ICM strategies for the whole peak period.
- Traveler information availability and the percentage of travelers that changed route, mode, and destination were updated based on the behavioral data collected through a panel survey.
- Changes in geometry, transit route and service, and signals were made to the network.
- Demands were updated based on the newly collected data.
- An initial state file for the online microsimulation was created every 15 minutes based on the adjusted matrices, which provides a warm start for the next 15-minute simulation.

- The model was enhanced to calculate travel time reliability and also emissions and fuel consumptions based on the standards in California.

The traffic and incident conditions after deployment were matched to the clusters identified in the pre-deployment stage. Based on the occurrence of each cluster, a total number of 9 representative days/incidents were determined as the study scenarios for comparison of alternatives. The performance measures were calculated and used to assess the impacts of the deployed ICM strategies.

2.4.5 I-210 Pilot AMS in California

Phase 1 of the I-210 pilot ICM study focused on creating analysis methodology and procedures, examining data availability and quality, and conducting a preliminary analysis of the selected scenarios (Patire et al., 2016). In this phase, the Cell Transmission Model (CTM), a macroscopic model implemented in a tool developed by University of California in Berkeley, was selected as the modeling platform. The following four reasons were given for this: 1) the CTM-based tool can simulate the existing control and management strategies; 2) the CTM model development and calibration is simple; 3) The CTM parameters such as free-flow speed and capacity can be readily observed in the field; and 4) The model running time is very short. However, the CTM cannot model in detail certain strategies, including dynamic mobility applications, adaptive signal control, alternative intersection design, and traveler information services.

Figure 14 shows the model building process for this project (Patire et al., 2016). As shown in this figure, data from different sources were processed first to generate the data for model development, calibration and validation. The street network was created from a base map. The turning movement demands at each node and boundary flows were obtained from traffic sensors, counts from traffic studies, and other models. The signal plans were retrieved from a large-scale Synchro model for the I-210 corridor. The parameters in the triangular fundamental diagram used in CTM were either obtained from traffic sensors or from the HCM procedures. In this study, the CTM models for the freeway and arterial were first developed separately and then combined together.

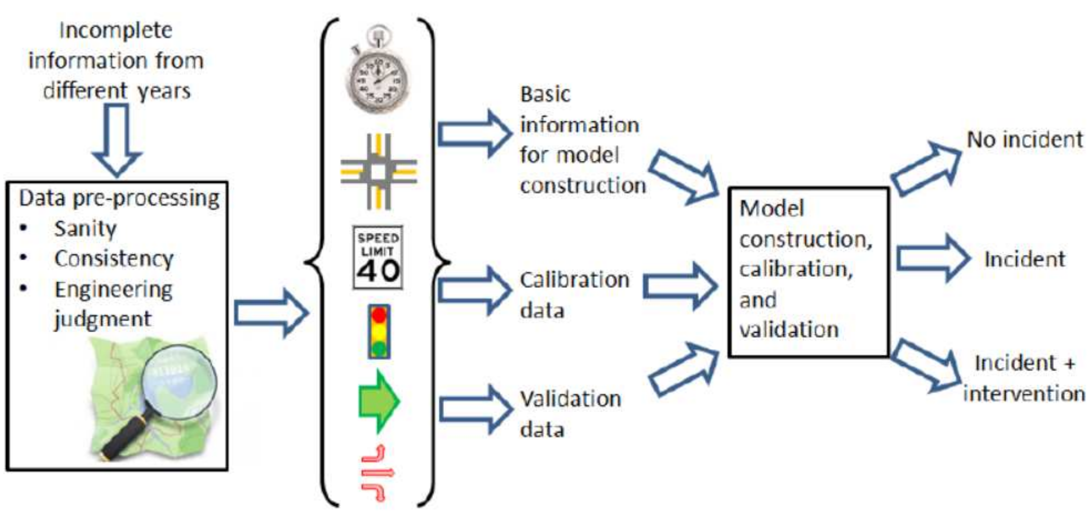


Figure 14: Model building process for the I-210 pilot corridor (Source: Patire et al., 2016)

A calibration process was conducted to calibrate the parameters in the fundamental diagram (including free-flow speed, capacity, and jam density), boundary flow, and turning split ratios at intersections and ramps to replicate the congestion pattern on a representative day. The calibration criteria and the corresponding acceptance targets are listed in Table 6.

Table 6: Calibration Criteria and the Corresponding Acceptance Targets (Patire et al., 2016)

For arterial and freeway models:

Individual link flows	Target
Flow within 100 vph for link flows < 700 vph	> 85%
Flow within 15% for link flows between 700 and 2700 vph	> 85%
Flow within 400 vph for link flows > 2700 vph	> 85%
Individual link GEH < 5	> 85%
Sum of all link flows	**Target**
Total flow within 5% of measurements	< 5%
Total GEH < 4	< 4

For freeway model:

Spatio-temporal extent of congestion	Target
Recurrent bottleneck start time	Within 30 min
Recurrent bottleneck end time	Within 30 min
Recurrent bottleneck extent	Within 0.5 miles

Figure 15 shows the classification process used in the cluster analysis for the I-210 project. This process was applied to identify the occurrence of incident days, normal days, and special days. Based on the occurrence of incident frequency and severity as well as the cluster analysis results, a one-lane blockage incident with 30-minute duration was selected for modeling. Four scenarios were studied and compared, that is, no incident, incident without intervention, incident with change in signal plan, and incident with change in signal plan and the provision of traveler information. The performance measurements assessed include travel time, delay, level of service, vehicle-hours traveled (VHT), and vehicle-miles traveled (VMT).

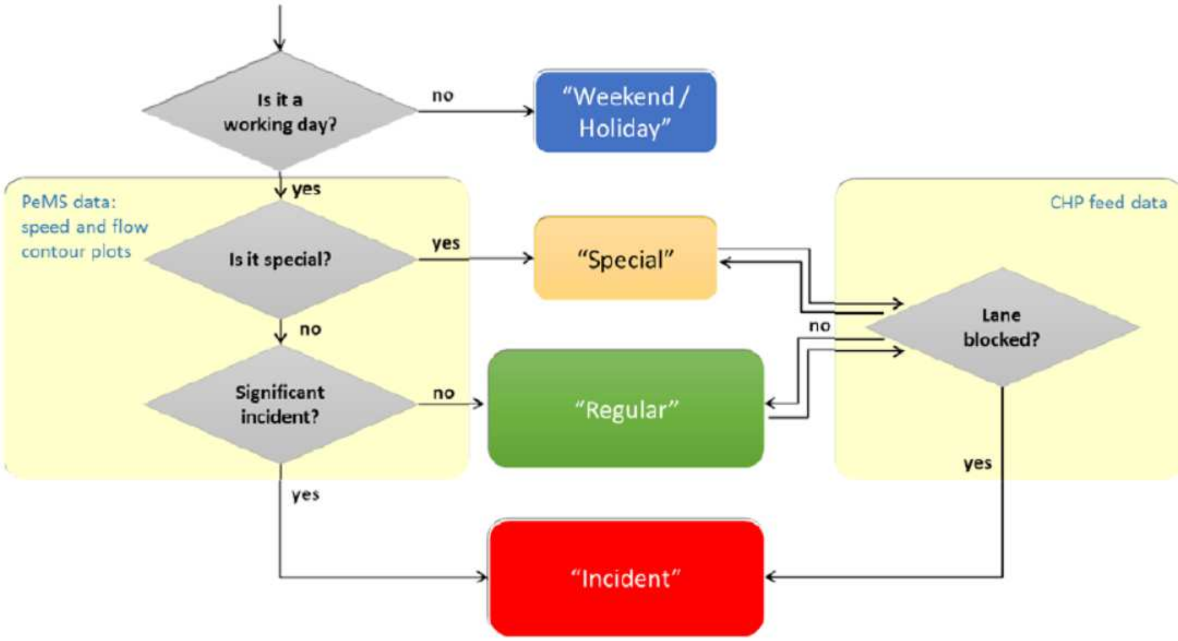


Figure 15: Classification process in the cluster analysis for the I-210 pilot corridor (Source: Patire et al., 2016)

In addition, the costs of upgrading sensors and the supporting infrastructure for congestion management were estimated. The corridor version of Cal-B/C, a PC-based spreadsheet tool developed by Caltrans' Economic Analysis Branch and System Metrics Group, was applied to assess the benefits of the improvements including reduction in delay, vehicle operating costs, and emissions.

Phase 2 of this ICM project focused on the generation and assessment of incident response plan. Three elements were initially considered in the response plan, that is, detour routes, intersection signal control requests, and ramp meter control request. Data quality was first checked using the same method utilized in Phase 1 before inputting to the simulation model. In Phase 2, instead of CTM, the Aimsun software was used to simulate the diversion behavior resulting from incident-related congestion and secondary diversion due to the response plan. The utilized calibration procedure puts more emphasis on matching conditions near and around freeways and associated alternative routes.

2.4.6 AMS Utilization in ATDM/DMA Testbeds

The FHWA conducted an effort for identifying the best approaches for the AMS in the assessment of active transportation and demand management (ATDM) strategies and dynamic mobility applications (DMA) of connected vehicles. As part of this effort, the FHWA has funded testbeds in a number of locations to pilot test such analyses as part of a project entitled "Analysis, Modeling, and Simulation (AMS) Testbed Framework for Dynamic Mobility Applications (DMA) and Active Transportation and Demand Management (ATDM) Program" (FHWA, 2013a; FHWA, 2013b; Vasudevan and Wunderlich. 2013). This effort investigated a suite of modeling tools and methods that allow the evaluation of the potential benefits of implementing ATDM and DMA strategies for planning, design, and operations purposes.

Six testbeds were selected to test the ATDM and DMA AMS concepts (Vasudevan and Wunderlich. 2013). These include the San Mateo (US 101), Pasadena, Dallas, San Diego, Phoenix, and Chicago testbeds. However, the results from the Mateo deployment was not included in the final report. The AMS effort in most of these testbeds emphasized the importance of multi-resolution AMS that involves combining macroscopic, mesoscopic, and microscopic AMS. On the supply side, it is important to model changes to network supply or capacity between days including the stochasticity of capacity and incident and weather impacts. On the demand side, it is necessary to capture the changes in demand patterns between days and also to capture traveler behaviors, as a response to implemented dynamic actions. An important concept of modeling ATDM strategies is to model days with different traffic patterns rather than an average day. This is because the benefits of ATDM strategies are mainly to accommodate the variations in recurrent and non-recurrent traffic conditions. In addition, different ATDM strategies are beneficial under different traffic condition scenarios. Data categorization and clustering algorithms based on detailed data collected using monitoring systems for a long period of time have been used for this purpose.

The AMS testbed effort also emphasized that it is essential to capture the dynamic interactions between supply and demand and how the supply changes affect the trip chain. Special considerations listed for modeling ATDM includes the need for the identification of the appropriate performance measures, supporting data, capabilities of modeling advanced strategies, traveler behavior modeling, and model execution speed for real-time operations. Clustering analysis to determine various analysis scenarios is an important component of the approach utilized in the ATDM and DMA modeling.

The testbeds attempted to answer questions such as the additional benefits of applying combination of ATDM strategies, which strategies yield the most benefits for specific operational conditions, what strategies conflict with each other, what is the benefit of increased prediction, which parameters are critical for prediction quality (e.g., length of prediction horizon, prediction accuracy, prediction speed, and geographic area covered by prediction), the cost-effectiveness of strategies, and what is the impact of latency in performance measures on performance. The research questions and methods of this effort are directly relevant to the ICM deployment effort. The following subsections discuss each testbed and the associated results.

Phoenix Testbed

The Phoenix Testbed is a multi-level multi-resolution simulation model for testing DMA and ATDM applications and strategies (Yelchuru et al., 2017a). The model framework uses a combination of the mesoscopic simulation-based DTA tool (DTALite) and VISSIM microscopic simulation and the modeling of a combination of adaptive ramp metering and adaptive signal control (RHODES), as well as route diversion. DTALite and VISSIM were closely integrated in run-time through customized interfaces. Table 7 shows the modeled scenario in the Phoenix study based on clustering analysis results.

Table 7: Model Scenarios at the Phoenix Testbed

Descriptive Label	HD-LI	HD-HI	LD-LI	HD-MI-WW
Representative Day	7/17/2014	5/21/2014	6/29/1014	11/22/2013
Operational Condition	High Traffic + High Speed + Low Incidents	High Traffic + High Speed + High Incidents	Low Traffic + High Speed + Low Incidents	High Traffic + Low Speed + Medium Incidents + Wet
Avg. Volume (veh/hr)	8383	8782	6004	7708
Avg. Speed (mph)	65	65.4	65.4	38.4
Weather Condition	Dry	Dry	Dry	Rainy (0.01 in/hour)
Incident Severity[11]	9	22	3	23

For the Phoenix Testbed, Adaptive Ramp Metering and Adaptive Signal Control (as well as their combination) works the best under the High Demand, Medium Incident Severity and Wet Weather condition scenarios. Under the Low Demand and Low Incident Severity scenarios, Adaptive Signal Control showed the least improvement in travel time. Similarly, High Demand and Low Incident Severity had the least improvement in travel time when Dynamic Route Guidance was implemented with Predictive Traveler Information.

Combining Adaptive Ramp Metering and signal control was shown to be not beneficial in many cases compared to implementing them in isolation. DTALite allows a user-defined portion of total travelers to switch their routes to avoid congestions and reach their destinations. The baseline (0% dynamic routing travelers) case was compared with the case where 20% of the travelers are dynamic routing travelers with predictive traveler information under all four operational conditions. It was concluded that Dynamic Routing was able to reduce the network-wide travel time by up to 40 percent during incidents. However, the authors admitted that this may have been an overestimation of the benefits due to not reflecting higher capacity constraints on the parallel arterials.

The researchers found that using longer prediction horizon (10 min) in ATDM strategies will bring a reduction of freeway travel time compared to 5-minute prediction. Prediction error was found to cause about 7.5% increase in travel time. The impact of information latency was found to be marginal (less than 1%).

Dallas Testbed

The US-75 Corridor in Dallas, TX which was used as a pilot in the ICM program as described earlier in this chapter was also used as one of the AMS (Yelchuru et al, 2017a). Four operational conditions were identified based on clustering analysis, as shown in Table 8. Figure 16 illustrates the overall framework of the analysis that was utilized in the Dallas Testbed. The framework was designed to virtually emulate the decision-making process in a typical traffic network management center.

Table 8: Operational Conditions in the US-75 ICM Study

Descriptive Label	*MD-LI*	*HD-LI*	*HD-MI*	*MD-HI*
Representative Day	08/31/2013	07/26/2013	10/22/2013	11/13/2013
Operational Condition	Medium-High Demand + Minor Incident	High Demand + Minor Incident	High Demand + Medium Severity Incident	Medium to High Demand + High Severity Incident
VMT	324,504	362,694	349,158	332,891
Weather Condition	Dry	Dry	Dry	Dry
Incident Severity (min.)	12.6	10.2	32.2	141.6
Travel Time (min.)	23	32	40	45

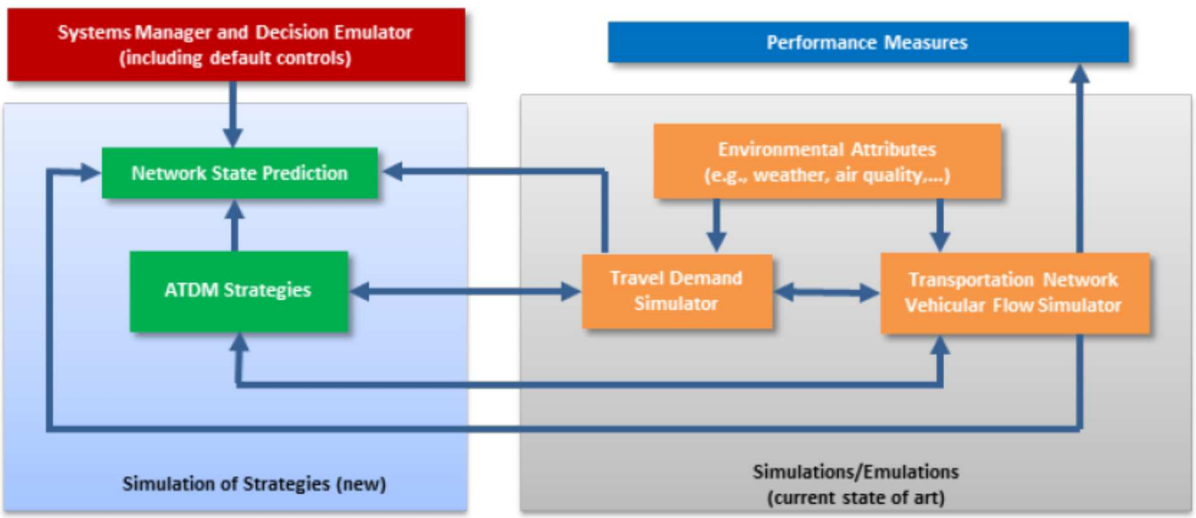


Figure 16: US-75 ICM project analysis framework

The DIRECT model used in the ICM project, discussed earlier in this document, was used. The network prediction module was assumed to be activated at intervals (e.g., every 5 to 10 minutes) to predict network conditions over a predefined horizon (30 minutes to 1 hour). A Genetic Algorithm (GA) approach was used to generate efficient ATDM response plans. The possible control actions include: a) Dynamic Routing; b) Responsive Traffic Signal Control; c) Adaptive Ramp Metering, d) Dynamic Shoulder Lane, and e) Dynamically Priced Parking strategy to influence traveler's behaviors.

The results from the Dallas Testbed showed that all of the ATDM strategies improve the overall network performance during non-recurrent congestion scenario. Integrated ATDM strategies such as Dynamic Signal Timing, Dynamic Routing, Adaptive Ramp Metering and Dynamic Shoulder Lane could have significant benefits in terms of congestion reduction. More travel time savings are generally observed by integrating multiple ATDM strategies in the generated ATDM response plans. The dynamic shoulder lane strategy was found to have significant impacts on alleviating the congestion associated with the incident. A significant travel time saving is observed in all scenarios in which this strategy is adopted as part of the generated ATDM response plans. An increases in the error of prediction from 5% to 10%, reduced the travel time saving. The network performance generally improves as the length of the prediction horizon increases. Promptly responding to the incident (zero latency) helps in alleviating the congestion, and achieving considerable saving in total network travel time. The benefit reduced with high latency.

Pasadena Testbed

The Pasadena Testbed involves the modeling of the roadway network of the City of Pasadena in Los Angeles County, CA (Yelchuru et al., 2017a). The initial network was derived from the regional travel demand model. The VISSIM microscopic simulation model was used to quantify and compare the potential benefits associated with each strategy. The testbed team also utilized PTV VISUM for DTA modeling and overall model development and management. A separate TRANSIMS simulation was developed to emulate the use of model-based real-time predictive engine decision system that recommends response plans. TRANSIMS receives information from virtual detectors in the VISSIM transportation network and predicts the operational performance and recommends the strategy with the best operational performance. Active management strategy applied in GeoDyn2 was used to represent the freeway management decision support system (ATDM strategies). The tested strategies The ATM strategies included in this analysis are: a) Adaptive Ramp Metering; b) Dynamic Signal Control; c) Hard Shoulder Running; d) Dynamic Junction Control; e) Dynamic Speed Limit plus Queue Warning; and f) Dynamic Route Guidance. The Pasadena Testbed team identified three operational conditions for the testbed based on the cluster analysis, as shown in Table 9. Figure 17 shows the framework of the analysis.

Table 9: Operational Conditions Considered at the Pasadena Testbed

Description Label	Operational Condition 1	Operational Condition 2	Operational Condition 3
Representative Day	12/18/2013	01/06/2014	11/14/2013
Operational Condition	High Demand + Low to Medium Incident	Medium to High Demand + High Incident	High Demand + Medium Incident
VMT	934,711	953,332	953,332
Incident Frequency (Incident / Day)	2.26	2.80	2.56
Weather Condition	Dry	Dry	Dry
Network Travel Time (Vehicle Seconds)	2,639,326	2,308,780	2,723,258

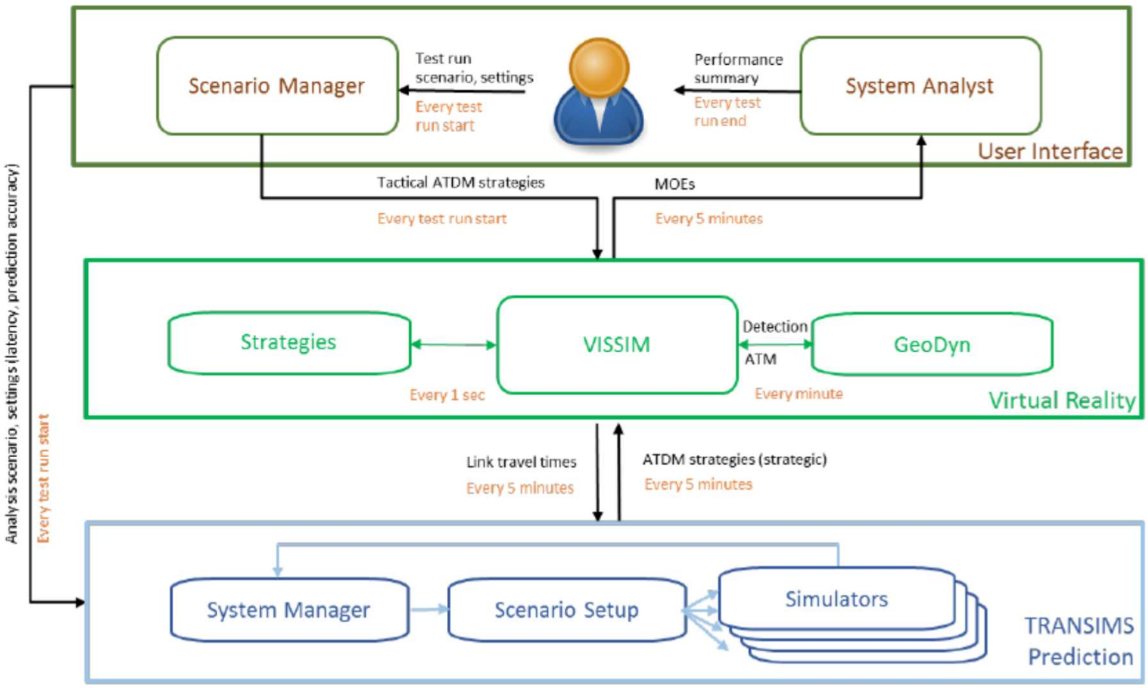


Figure 17: Analysis framework for pasadena testbed (Yelchuru et al., 2017a).

The results from the Pasadena testbed showed that the benefits of different strategies and combination of strategies depend on the tested scenario. The results also indicate that all tested strategies improved travel time when the strategies were deployed using prediction compared to time-of-day, indicating that predictive traffic managed had better network performance than responsive traffic management. The results from the Pasadena testbed also showed that a prediction horizon of 30 minutes to 60 minutes for freeway focused strategies and 15 minutes to 30 minutes for arterial focused strategies produced the best results. It was also concluded that the impact of the prediction accuracy varies depending on the ATM strategy for which the demand is estimated. In general, the prediction capability was found to allow early deployment of the ATDM strategy before the congestion is formed. The Pasadena testbed also demonstrated that the prediction latency has a significant effect on arterial strategies compared to freeway strategies

San Diego Testbed

The San Diego Testbed is for the I-15 freeway facility and associated parallel arterials, which is also used in the USDOT ICM pilot deployment (Yelchuru et al., 2017a). Four operational conditions were identified based on a cluster analysis that was performed as part of the ICM Demonstration Evaluation project, as shown in Table 10. The traffic simulation tool that was used for the San Diego Testbed is Aimsun that was also used for the ICM pilot project discussed earlier. Although Aimsun can model traffic at the macro, meso, micro, and hybrid meso-micro levels, the microscopic simulator was used for the San Diego Testbed. The modeled strategies include Dynamic Lane Use/Congestion Pricing, Dynamic Speed Limits, Ramp Metering, Dynamic Merge Control, Predictive Traveler Information, and Dynamic Routing strategies.

Table 10: Operational Conditions Considered at the San Diego Testbed

	AM1	AM2	PM3	PM4
Representative day	05/27/15	02/09/15	06/30/15	07/07/14
Operational Condition	Southbound (AM) +Medium Demand + Medium Incident	Southbound (AM) +Medium Demand + High Incident	Northbound (PM) +Medium Demand + High Incident	Northbound (PM) +Medium Demand + Medium Incident
VPH	6201	6348	9034	8870
Total Cluster Delay (min)	49.88	108.03	99.72	63.25
Number of Incidents/Period	1.9	3.7	5.5	2.1

It was found that for the San Diego Testbed, Dynamic Lane Use and Dynamic HOV/Managed Lanes are effective only in congested situations. The locations of incidents and bottlenecks impacts the effectiveness of these strategies. Dynamic Speed Limits reduce the speed change between consecutive road segments, at the expense of reducing the overall speed along the corridor. Dynamic Merge Control was found sometimes to facilitate the entrance at the expense of mainline traffic. Predictive Traveler Information with Dynamic Routing is more effective with higher demand and with more severe incidents. The analysis shows that there are no significant conflicts or significant synergies between the different strategies.

Chicago Testbed

The Chicago Testbed network includes Chicago downtown area and the surround freeways and arterial networks. The testbed was modeled in DYNASMART, a mesoscopic simulation-based intelligent transportation network planning tool (Yelchuru et al., 2017a). The model can be configured to run offline or online. The offline model (DYNASMART-P) includes dynamic network analysis and evaluation, while the online model (DYNASMART-X) adds short term and long term prediction capabilities. The evaluated strategies include traffic responsive signal control, dynamic shoulder lane (use), dynamic lane use, dynamic speed limit, predictive traveler information, dynamic route guidance, and winter weather-related real-time maintenance plan generation and assessment.

The modeled network consists of over 4800 links and 1500 nodes, with over 500 signalized intersections, nearly 250 metered and non-metered ramps. The network demand was coded for 24 hours at 5-minute intervals with over a million vehicles simulated. The Chicago Testbed simulated six operational conditions including a hypothetical operational condition. Unlike other testbeds, the Chicago consisted of weather-specific events and the selected operational conditions involve moderate to heavy rain or snow. These conditions were combined with hypothetical incident events. The details on these operational conditions are shown in Table 11.

Table 11: Operational Conditions Considered at the Chicago Testbed

Description Label	*OC1*	*OC2*	*OC3*	*OC4*	*OC5*	*HO1*
Representative Day	4/22/2009	2/18/2009	12/22/2009	12/19/2009	1/9/2009	N/A
Operational Condition	High AM High PM Demand, No Incidents	High AM, High PM Demand, No Incidents, Moderate Rain AM, Moderate Rain to Snow	Medium AM, High PM Demand, No Incidents, Moderate Snow	Low AM Medium PM Demand, No Incidents, Moderate Snow	Medium AM High PM Demand, No Incidents, Moderate to Heavy Snow	Medium AM to High PM Demand, AM Incidents, Moderate Snow
Number of Vehicles	1,191,575	1,065,901	986,978	902,225	1,076,431	986,978
Average Travel Time (Minutes)	16.26	16.53	18.63	14.09	19.71	20.34

From the Chicago Testbed results, it can be concluded that the provision of traveler information at a low to medium penetration rate of traveler information access and use yields the most benefits for system performance. High penetration rate requires coordination in vehicle routing to achieve benefits. It was also found that the tested active transportation and demand management and the weather-related strategies are synergistic, depending on the operational scenario. The benefits of individual strategies also depend on the test scenario.

The performance of the predictive strategies also vary under different operational conditions. In clear weather scenarios, the best performance was achieved with higher prediction accuracy at a shorter prediction horizon and roll period for the peak hours when travel demand is high. In the snow-affected scenarios, a longer prediction horizon is preferred. More frequent updates with shorter roll periods of the predictive strategies may lead to instabilities in system performance.

2.5 LESSONS LEARNED FROM ICM DSS DEPLOYMENTS

One of the products of the USDOT ICM program summarizes the lessons learned from the two ICM pilot deployments with few items related to the DSS (Christie et al., 2015). The document points out that including modeling and forecasting into the DSS requires significant computing power and storage capabilities. It recommends that the user specifies an acceptable time window for a DSS-generated response plan to be issued after the request is generated and cautions that any generated plan that takes greater than five minutes could be too long in a dynamic network with changing conditions.

With regard to DSS Development, the document recommended the use of a "focused iterative approach when defining, designing, and building the DSS." It also recommends the "fine tuning of the decision tools until acceptable output is achieved." The DSS will need to be assessed and adapted for the subject corridor.

With regard to the response plan development and adjustments, the document points out that the response plans used by the DSS will need to be adjusted after the tool becomes operational and experience gained with it. It was realized that the response plan development will take time, will have many dependencies, and will require close coordination with signal timing agency plans. Response plans need to consider existing timing plan coordination, time of day timing plans, and direction of travel. Periodic meetings to trouble shoot DSS issues and review the system and data output were recommended including showing the results of assessing the performance of the generated response plans in analyses. The examination should include how often the DSS recommends response plans.

2.6 DATA-BASED TRAFFIC FLOW PARAMETER PREDICTION

The evaluation conducted as part of the literature in the previous sections indicates that the use of predictive traffic management strategies produces better results than the utilization of responsive traffic management strategies. Predictive-engines applied to existing ICM projects have utilized simulation-based prediction. Prediction of near future traffic conditions can also be achieved using data-based models. This prediction, however, has a disadvantage in that it is not possible or difficult to predict the impact of alternative response plans on traffic conditions without modeling. Nevertheless, such prediction may still have a role in ICM DSS, either by itself or in combination with model-based prediction.

Traffic flow parameter prediction based on data is a topic that has been researched for some time. The wide deployment of traffic detectors and automatic vehicle identification devices such as Bluetooth/Wi-Fi readers and electronic toll readers provides a rich data source for such prediction. The existing traffic flow parameter prediction methods can be classified into four categories: naïve methods, traffic flow theory-based methods, statistical and regression methods, and machine learning-based methods. Extensive reviews of these methods can be found in the references such as Vlahogianni et al. (2014) and Van Lint and Van Hinsbergen (2012).

Example of naïve methods are instantaneous measurement method, historical average method, and the combination of the two (Rakha and Van Aerde, 1995; Guo et al., 2010). Instantaneous measurement method assumes that the traffic condition remains the same for the next prediction horizon and therefore the current instantaneous measurements of speed, or volume, or travel time are used as the predicted values. Historical average forecasts traffic conditions based on the periodic pattern of traffic. These naïve methods are widely used in the practice. They are very simple and easy to be implemented. However, their accuracy are usually low as they cannot capture the dynamic changes in traffic.

Traffic flow theory-based prediction methods forecast traffic based on traffic time functions such as the Bureau of Public Road (BPR) curve, fundamental diagram, queuing theory, and/or shock wave theory (Li et al., 2013). These methods are also simple; however, they require the provision of demands as input, which may not be available at an acceptable level of accuracy. The parameters required for use as inputs to these models such as capacity and demand are stochastic in nature. Any small deviations in these parameters will result in cumulative and large errors (Van Lint and Van Hinsbergen, 2012).

Traditional statistical and regression-based prediction methods are mostly limited to linear models. Among these models, the statistical time series methods have been widely studied. Time series analysis models the predictions as a linear function of the past observations and error functions. Examples of this type of methods include auto-regressive integrated moving average (ARIMA) (Levin and Tsao, 1980; Hamed et al., 1995) and its variations such as seasonal ARIMA with periodic terms added (Williams and Hoel, 2003), subset ARIMA with partitions of the time series (Lee and Fambro, 1999), Kohonen ARIMA with sophistical method for determining the weights and terms (Voort et al., 1996), ARIMAX that incorporates exogenous input (Williams, 1999), VARMA using vector method (Kamarianakis and Prastacos, 2003), and spatiotemporal STARMA (Kamarianakis and Prastacos, 2003). The ARIMA method relies on the assumption of the stationarity of the time series, which could be violated when there is an abrupt change in traffic. A regression model can also be developed to determine the predicted traffic parameters as a function of the values of spatial and temporal parameters. Another type of popular prediction models is the Kalman Filter (KF) and its variations such as unscented KF and Monte Carlo-particle filtering. The KF method recursively estimates the evolution of the state and combines the newly observed data to produce the estimation. The advantage of this method includes no requirement for memory as the predicted state is calculated based on only the last state and newly available information. However, the KF methods require accurate inputs and boundary conditions. The dynamic tensor completion method was proposed by Tan et al. (2014) to predict travel time by considering travel time as a multidimensional tensor and predicting the future in the same way as imputing as imputing missing data.

With the wide deployment of ITS devices, rich traffic data becomes available, which facilitates the use of machine learning methods for traffic parameter prediction. Compared to the traditional statistical-based prediction models, the machine learning-based methods do not require the assumptions of the type of the error distributions and detailed mathematical forms. These methods implicitly capture the relationship among variables by learning from data. Examples of the utilized machine learning-based prediction approaches are clustering method, nearest neighbor method, fuzzy logic method, Bayesian belief network (BBN), support vector regression (SVR), and artificial neural networks. The clustering-based method is simple however, it has a high computation cost and requires a large amount of data. Good accuracy can be achieved in general when traffic flow does not have fluctuations. The k-nearest neighbor method searches a historical database to find k closest events to the current traffic condition and uses the simple average or weighted average of these k events for prediction (Oswald et al., 2001; Rice and van Zwet, 2004; Bajwa et al., 2004; Kim et al. 2005). This method is fast. Its accuracy is better than the naïve method, but worse than other advanced methods. The fuzzy logic method first converts observations into fuzzy variables and then combines them based on predefined rules to produce the prediction of traffic conditions (Coufal and Turunen, 2004; Li et al., 2006). The comparison conducted by Huisken (2003) showed that the prediction obtained by this method is not as accurate as that produced by artificial neural network. Bayesian belief network is a directed graph model where the states of belief are related by conditional probabilities (INRIX, 2007). This method is used by the company INRIX in their prediction of travel time. The support vector regression aims at finding a function that can separate the target values from all the other training data (Smola and Scholkopf, 2004). This method can outperform the naïve methods based on the study of (Smola and Scholkopf, 2004).

Among the various machine learning-based methods, the most widely investigated category is the artificial neural network. Artificial neural networks can be considered as nonlinear regression models. Different topologies of neural networks have been used for predicting traffic parameters. Examples of these topologies are gradient-based back propagation neural network (Ishak and Alecsandru, 2004; Mark et al., 2004), divide-and-conquer strategy-based modular neural network (Ledoux, 1997; Zhang et al., 2000; Alecsandru, 2003; Zheng et al., 2006), and radial basis frequency neural networks (RBFNN) with a hidden layer of basis functions to cluster input space (Xie and Zhang, 2006). The prediction performance of these neural networks can be further improved by combining with various data preprocessing methods such as wavelet neural network (Xie and Zhang, 2006), Fourier expansion (Park et al., 1999; Rilett and Park, 2001), Kohonen self organizing feature map (SOFM) (Tan et al., 2004), and so on. In addition to back propagation-based neural network, a number of recurrent neural networks were proposed for use in the prediction of travel time parameters, including the Jordan-Elman network or simple recurrent neural network (SRNN) (Alecsandru, 2003; Ishak et al., 2003), partially recurrent network (PRNN) (Alecsandru, 2003; Ishak et al., 2003), state-space neural network (SSNN) (van Lint, 2008), finite impulse response neural network (FIRNN) (Yun et al., 1998), and time delay recurrent neural network (TDRNN) (Yun et al., 1998; Dia, 2001). Compared to the static neural network, dynamic neural networks contains memory units that can store the hidden layer output at the previous time step and feed them back as either input values or at the hidden layers. This provides a mechanism to recognize recurrent patterns. These neural network methods generally have better prediction performance; however, they act as black-boxes, are location-specific, and cannot be easily transferred to other locations.

Recently, deep learning methods have become popular due to their capability to handle a large amount of high-dimensional data. The deep learning techniques that have been explored in the literature are: (1) Deep belief networks (DBN) (Huang et al., 2014), stacked autoencoder (Lv et al., 2014), and deep learning structure with a combination of a linear model and a sequence of tanh layers (Polson and Sokolov, 2017) for traffic flow prediction; (2) The combination of deep restricted Boltzmann machines (RBM) and recurrent neural network for congestion prediction (Ma et al., 2015a); (3) The long short-term memory (LSTM) (Ma et al., 2015b) and convolutional neural network (CNN) (Ma et al., 2017) for speed prediction; and 4) The LSTM and CNN methods for network-wide travel time prediction (Hou and Edara, 2017).

Each traffic parameter prediction method has advantages and disadvantages. Instead of relying on a single method for prediction, ensemble-based methods have also been proposed in the literature to combine different prediction models with a purpose of improving prediction performance. The combinations that have been investigated in the previous studies include the Bayesian method (Van Hinsbergen and van Lint, 2008), neural network with genetic algorithm and fuzzy logic, wavelet transform combined with ARIMA or neural network (Wang et al, 2013), random forest (RF) (Guo et al., 2013), the ensemble tree-based extreme gradient boosting (XGB) method (Mousa and Ishak, 2016), wavelet neural network combined with Markov Chain and GJR-GRACH model (Yang et al., 2018), and the ensemble learning model of CNN-LSTM combined with linear regression and LSTM deep learning models (Liu et al., 2018) All the results showed that the ensemble-based prediction methods can outperform the other single methods. It should be pointed out that the accuracy of prediction not only depends on the selection of estimation methods but also on how these model parameters are set up.

2.7 ASSESSMENT OF THE DECISION SUPPORT TOOL PERFORMANCE

An important aspect of the implementation of ICM DSS is to assess its performance for the purpose of both refining it in the specific deployment for which it has been implemented for, as well as for providing lessons learned for future implementations. Reviewing previous assessment of DSS is critical to its deployment in Florida. The USDOT has conducted a comprehensive review of the Dallas and San Diego DSS. The DSS USDOT ICM program evaluation involves assessing a number of DSS aspects including investigating the effectiveness of the data fusion engines, the quality of responses generated by the DSS, the accuracy of DSS predictions of conditions 30 minutes or more into the future, the speed of response plan generation, and how varying conditions such as different incidents characteristics impact DSS performance. Unfortunately, although the associated DSS test plans are available, the results from the evaluation have not been published yet. This section summarizes information from the DSS test plans, which are useful for the purpose of this study.

It is interesting to list the hypothesis utilized in the ICM DSS test plans. These hypotheses can be actually converted to objectives and associated performance measures for the DSS implementations that are useful in the FDOT effort. The hypothesis are: improve situational awareness, enhance response and control, better inform travelers, improve corridor performance, have benefits greater than cost, improve or not adversely impact air quality and safety, and provide a useful and effective tool for ICM project managers. An overview of the DSS test and associated analysis is shown in Figure 18.

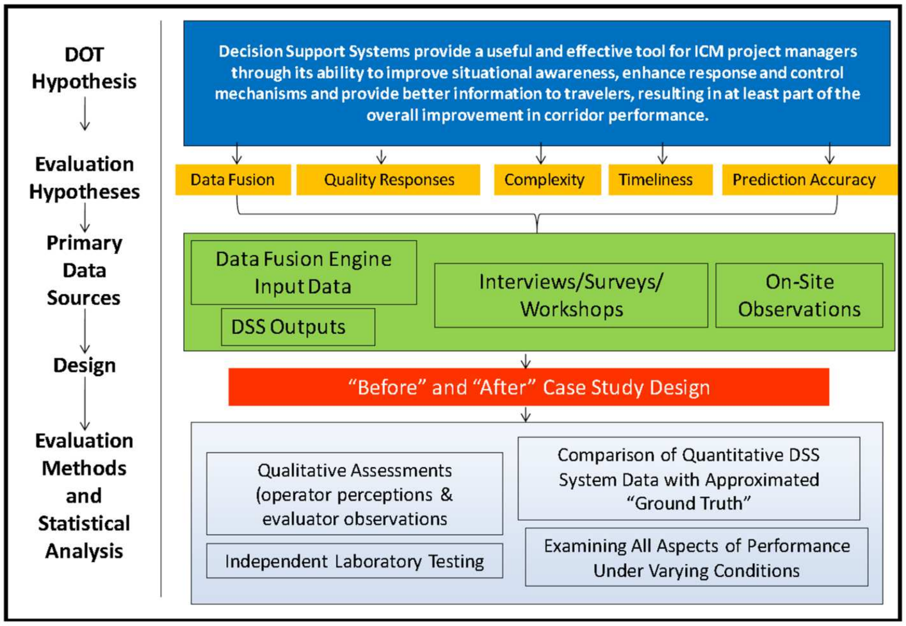


Figure 18: Overview of decision support systems analysis

The utilized measures of effectiveness listed below can also be used as basis for future assessment of FDOT DSS deployments.

- Success rate of ICMS in taking data from disparate sources and standardizing data
- Success rate of ICMS in recognizing overlaps in data, if any
- Success rate of ICMS in recognizing and fixing gaps in data or missing data streams
- Difference between predicted outcomes and actual operation conditions in terms of corridor performance (volumes, speeds, travel times, throughput), in various scenarios
- Percentage of times operator implements recommended responses
- Percentage of times operator alters recommended responses
- Average time DSS to deliver an actionable response plan
- Average time for DSS to deliver predictions of strategy outcomes
- Average number of response plans generated per event-hour3
- Responses consistent with operators' experience and perceptions
- Perceived quality of responses, including improvement relative to any comparable pre-ICM approaches
- Perceived usefulness of information provided to operators for interpretation and decision making, including improvements relative to pre-ICM approaches
- Rate the quality of incident responses prior to the deployment of the DSS
- Perceived quality of responses, including improvement relative to any comparable pre-ICM approaches
- Perceived usefulness of information provided to operators for interpretation and decision making, including improvements relative to pre-ICM approaches
- Level of operator intervention in altering recommended responses
- Perceived accuracy of DSS predictions
- Perceived usefulness of the DSS predictions

- Perceived quality of responses, including improvement relative to any comparable pre-ICM approaches
- Perceived accuracy of DSS predictions

Table 12: USDOT ICM Evaluation Hypotheses

Hypothesis	Description
The Implementation of ICM will:	
Improve Situational Awareness	Operators will realize a more comprehensive and accurate understanding of underlying operational conditions considering all networks in the corridor.
Enhance Response and Control	Operating agencies within the corridor will improve management practices and coordinate decision-making, resulting in enhanced response and control.
Better Inform Travelers	Travelers will have actionable multimodal (highway, arterial, transit, parking, etc.) information resulting in more personally efficient mode, time of trip start, and route decisions.
Improve Corridor Performance	Optimizing networks at the corridor level will result in an improvement to multimodal corridor performance, particularly in high travel demand and/or reduced capacity periods.
Have Benefits Greater than Costs	Because ICM must compete with other potential transportation projects for scarce resources, ICM should deliver benefits that exceed the costs of implementation and operation.
The implementation of ICM will have a positive or no effect on:	
Air Quality	ICM will affect air quality through changes in Vehicle Miles Traveled (VMT), person throughput, and speed of traffic, resulting in a small positive or no change in air quality measures relative to improved mobility.
Safety	ICM implementation will not adversely affect overall safety outcomes, and better incident management may reduce the occurrence of secondary crashes.
Decision Support Systems*	Decision support systems provide a useful and effective tool for ICM project managers through its ability to improve situational awareness, enhance response and control mechanisms and provide better information to travelers, resulting in at least part of the overall improvement in corridor performance.

2.8 BENEFIT-COST PLAN

The USDOT ICM program identified a plan for conducting the Benefit-Cost Analysis (BCA), as one of seven analyses that comprise the evaluation of the ICM Pilot demonstration phase (Balducci, 2012). It was recognized that ICM strategies generate outcomes that can be monetized and used in the BCA. The outcomes can be converted to economic benefits through travel time savings, enhanced travel time reliability, reduced motor fuel costs, lower emissions, and reductions in the number and severity of crashes. An overview of the BCA approach of the USDOT ICM program is summarized graphically in Figure 19.

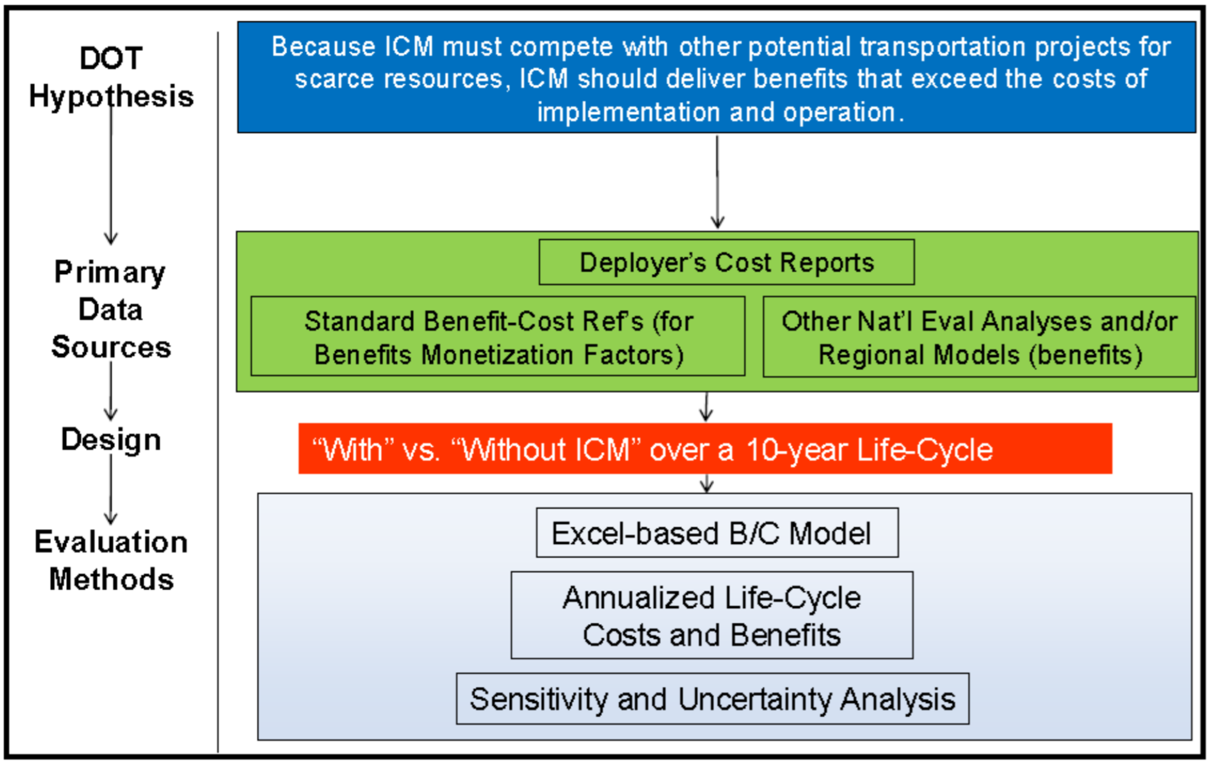


Figure 19: Overview of benefit-cost analysis (Source: Balducci, 2012)

Figure 20 presents the major benefit and cost elements, recommended for use in the BCA. The procedures and data used to support this analysis were also detailed in the documents. Potential outcomes that were listed for use in the analysis are below. However, only the results of travel time and travel time reliability are available.

- Change in travel times (Corridor Performance – Mobility)
- Change in travel time reliability (Corridor Performance – Mobility)
- Change in number and severity of crashes (Corridor Performance – Safety)
- Change in emissions levels (Air Quality)
- Change in transit ridership (Traveler Response)

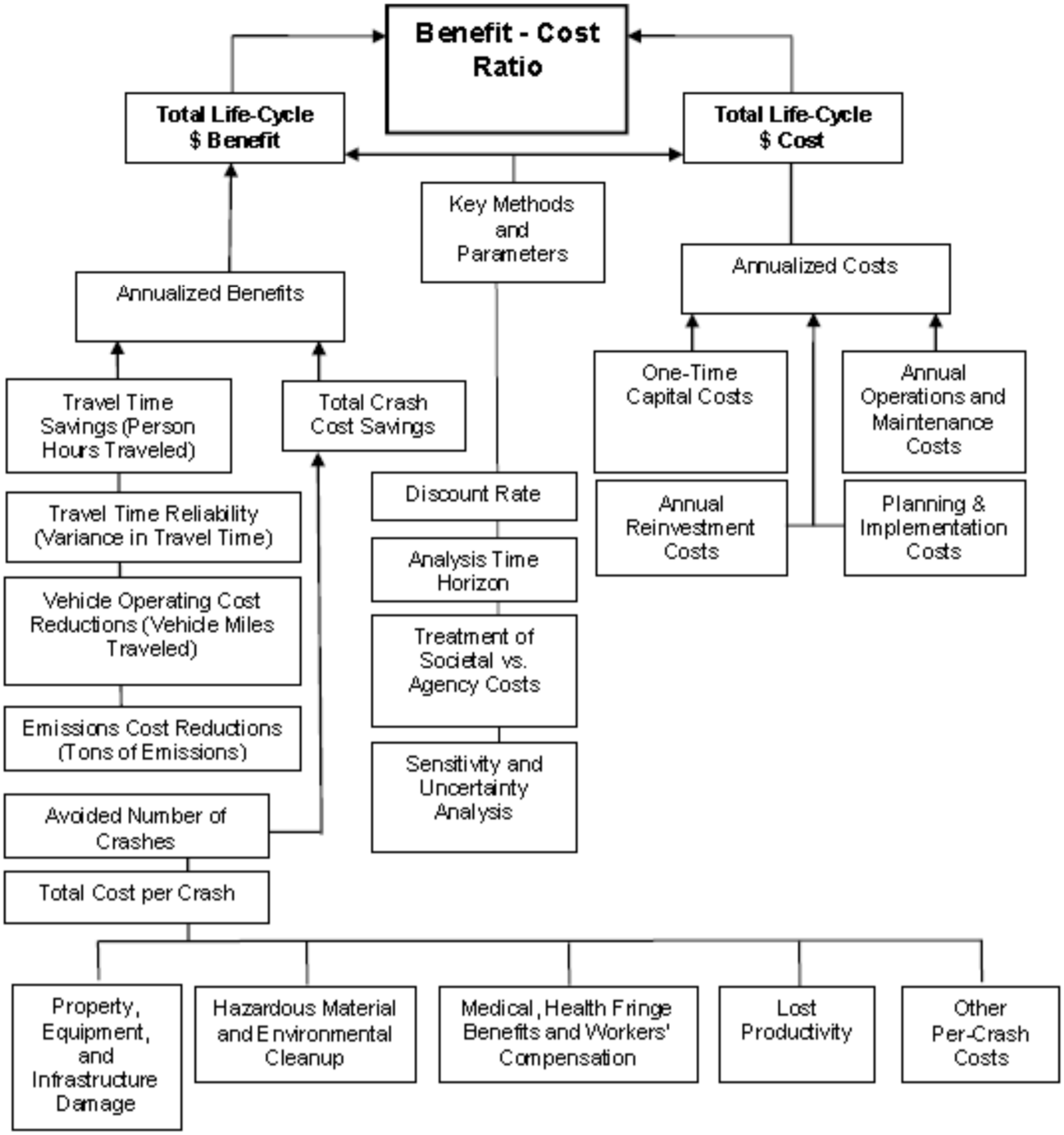


Figure 20: Framework for estimating ICM benefits and costs (Source: Balducci, 2012)

2.9 ICM AMS RESULTS

This section presents the results of utilizing the AMS methodology described earlier in this chapter to estimate the impacts of ICM. These results can be considered for use in a sketch-planning level of ICM deployments in Florida.

2.9.1 US-75 in Dallas, Texas

The US-75 ICM deployment was assessed before deployment and after deployment as discussed in the following subsections.

AMS Results before Deployment

Thirteen operational conditions were analyzed in the pre-deployment stage of the US-75 ICM project in Dallas, Texas. As shown in Table 13, these 13 scenarios cover the conditions of low, medium, and high demands without or with minor or major incident. High-priority ICM strategies were also identified for each of these operational scenarios.

Table 13: Freeway Operational Conditions and the Associated ICM Strategies Studied before Deployment for US-75 in Dallas, Texas (Source: Alexiadis et al., 2010b)

Scenario	Daily Operations – No Incident			Minor Incident			Major Incident		
Demand	**L**	**M**	**H**	**L**	**M**	**H**	**L**	**M**	**H**
Traveler Information									
Comparative, multimodal travel time information (pretrip and en-route)	●	●	●	●	●	●	●	●	●
Traffic Management									
Incident signal retiming plans for frontage roads[1]					●	●	●	●	●
Incident signal retiming plans for arterials[2]					●	●	●	●	●
Managed Lanes									
HOV lane[3]	○	○	○	○	○	○	○	○	○
Light-Rail Transit Management[4]									
Smart parking system								●	●
Red line capacity increase								●	●
Station parking expansion (private parking)								●	●
Station parking expansion (valet parking)								●	●

Notes:

1 The frontage road retiming plan was run as an individual traffic management strategy for minor incidents.

2 The traffic management strategies (frontage road timing and arterial timing) are combined and were not run as separate strategies for a major incident.

3 HOV lane 2+ currently is in operation, thus is not considered an ICM strategy, but was part of all scenarios.

4 The LRT Smart Parking System strategy was always conducted with the other three transit management strategies. Private and valet parking expansion were not implemented as a combined strategy.

L = Low; M = Medium; and H = High.

For the no incident conditions, the study assumed that the use of ATIS system and DMS will increase the awareness of roadway conditions, and therefore the following parameters were adjusted when simulating the scenarios without ICM strategies (Pre-ICM) and with ICM strategies (Post-ICM):

- Congestion diversion was activated in DIRECT.
- The awareness of pre-trip information was increased from 60% pre-ICM to 80% post-ICM and the use of pre-trip information was modified from 10% pre-ICM to 20% post-ICM.
- The awareness of en route information was increased from 50% pre-ICM to 60% post-ICM and the use of en route information was modified from 20% pre-ICM to 30% post-ICM.
- The use of DMS information was increased from 60% pre-ICM to 75% post-ICM.

The analysis results for the scenarios without incident showed that the ICM strategies are only beneficial at the high demand level. However, the changes in the average travel time, person miles traveled, person hours traveled, and total delays are very small for all the demand levels.

Similar to the scenarios without incidents, traveler information was considered for the scenarios with minor incident. The changes in modeling parameters for the pre-ICM and post-ICM scenarios are the same as those listed for the scenarios without incidents. In addition, signal retiming along both the frontage roads and arterials were included in these scenarios. The study assumed a 15% increase in the capacity of these roads because of signal retiming. The simulation results for the scenarios with minor incidents revealed that the use of ICM strategies are beneficial under all demand levels. The person hours traveled was reduced by 0.5% to 1.8% and person hours of delay was reduced by 1.4% to 4% with the ICM strategies considered.

Building upon the scenarios with minor incidents, additional ICM strategies were considered in the scenarios with major incident, which includes:

- The increase of the parallel light-rail transit service by reducing the headway from 10 minutes to 7.5 minutes
- The deployment of Smart Parking systems at park-and-ride lots that allows the utilization of park-and-ride lots increasing from 95% to 100%
- The increase of parking spaces by 250 at the President George Bush Turnpike park-and-ride lot

The results for the scenarios with major incidents showed a reduction of about 0.01% to 0.11% in person miles traveled, a reduction of 1.04% to 1.49% in person hours traveled, and about 2.8% to 3.6% reduction in total delays with the presence of the ICM strategies. An increase of 6% to 7% was also estimated for both the ridership of the parallel light-rail transit and the utilization of park-and-ride lots in the post-ICM scenarios with a three-lane blockage incident compared to the pre-ICM scenarios.

When combing the results for all the scenarios, the aggregated performance measures showed 0.5% to 0.6% reduction in average travel time, 1.4% to 1.9% reduction in average delay, 1.2% to 2.0% reduction in total delay, 0.5% to 0.6% reduction in planning index, 4.3% to 6.7% reduction in travel time variance, and 0.3% to 0.7% reduction in passenger hours traveled.

The net annual benefits of the ICM strategies were also estimated as a function of the travel time savings, travel time reliability, fuel consumption and emissions. The results showed that most of the ICM benefits are from arterials and other roadways. The benefits of the ICM strategies are very small for the US-75 corridors, and the ICM benefits can even be negative or negligible for other freeways. However, the overall benefit/cost ratio over a 10-year life cycle was reported to be about 20.4:1 for the proposed ICM deployments.

AMS Results after Deployment

In the after-deployment, ten scenarios were analyzed including two hypothetical scenarios. These scenarios were identified based on incidents that match the high-impact clusters identified in the clustering analysis and also based on feedback and input from local agencies.

Table 14 lists the representative days/incidents in these ten scenarios. Note that TEARS in the table refers to the implementation of special signal timing plans during incidents.

Table 14: Summary of Representative Days of Incidents in the 10 Scenarios Modelled after Deployment for US-75 in Dallas, Texas (Source: Alexiadis and Chu, 2016a)

Scenario	Date of Representative Day	DSS Plan Type (TEARS, DMS Message, Intended Diversion)	DSS Plan ID	Total Cluster Day Impact (Minutes)	Percent of Total Time Period
NB PM 1	9/3/14	No TEARS, Information Only	J75N262 PM	62	9.5%
NB PM 2	8/8/14	TEARS, DMS 1, frontage	J75N260 PM	122.64	20.0%
NB PM 3[a]	4/21/14	TEARS, DMS 1, frontage TEARS, DMS 2, arterial	J75N260 PM J75N261 PM	228.03	31.4%
NB PM 4	5/14/14	No TEARS, Information Only	J75N252 PM	89.46	13.3%
SB AM 1	9/10/14	TEARS, DMS 1, frontage	J75S260 AM	114.84	23.7%
SB AM 2	7/2/14	TEARS, no DMS, frontage	J75S354 AM	117.6	32.3%
SB PM 1	5/23/14	TEARS, DMS 1, frontage	J75S254 PM	126.00	28.8%
NB AM 3	5/5/14	No TEARS, Information Only	J75N162 AM	33.12	11.3%
NB 6-8 PM Hypothetical	6/17/14	TEARS, DMS 1, frontage	J75S260 PM	–	–
Severe Transit Hypothetical[a]	5/2/14	Model: TEARS, DMS 3, transit; Actual: No TEARS, Information Only	J75S250 AM, J75S352 AM, J75S352 MD, N75S301 MD	N/A	N/A

[a] More than one DSS plans implemented for the same event.

(Source: ICM Evaluation—Dallas Incident Matching - Revised, Battelle, 11/13/15, p. 3, unpublished.)

The AMS model requires the input of the proportions of travelers' access to information and their corresponding responses to the information. Three types of surveys were conducted before and after ICM deployments to examine the impacts of the ICM strategies on travelers' behaviors such as the use of pre-trip and en route traveler information, including a set of panel survey, pulse survey immediately following incidents, and a survey of transit riders. The panel survey results showed an increase in the awareness of traveler information; however, the use of the information did not increase. Similarly, the pulse survey also did not show an increase in the use of apps or smartphones during incidents after deployment. Travelers still relied more on radio and television for traveler information. Even though the panel survey shows consistency in travel behaviors (e.g., route change, mode shift, etc.) at the corridor level before and after deployment, the trip-level pulse survey results, shown in

Table 15, revealed an increase in route change and transit use in response to traveler information. It was found that such increases were due to two severe incidents. Once these two severe incidents were removed, the changes in traveler behaviors were negligible. The transit user survey showed that the main source of transit information was smartphone. At the time of survey, only one-quarter of transit riders were aware of the newly deployed 511 service and only 1% of users used the 511 service. The results of transit user survey also indicated that there is no significant change in transit riders' behavior with the deployment of ICM strategies.

Table 15: US-75 Pulse Survey Results for Real-Time Information (Source: Alexiadis and Chu, 2016a)

Travel Changes	All Pulse Surveys			Excluding Two Pulse Surveys
	AM Peak	PM Peak	Reverse Peak Trips	AM Peak
Minor route changes				
Pre-ICM	19%	28%	11%	18%
Post-ICM	26%	35%	18%	20%
Completely different route				
Pre-ICM	17%	7%	7%	3%
Post-ICM	29%	4%	9%	5%
Left earlier				
Pre-ICM	14%	5%	10%	10%
Post-ICM	11%	8%	13%	6%
Left later				
Pre-ICM	6%	1%	3%	9%
Post-ICM	7%	1%	5%	1%
Changed stops				
Pre-ICM	2%	1%	2%	*
Post-ICM	1%	*	1%	*
Used DART				
Pre-ICM	*	*	*	1%
Post-ICM	*	*	*	*

Table 15: US-75 Pulse Survey Results for Real-Time Information (Source: Alexiadis and Chu, 2016a) (Cont'd)

Travel Changes	All Pulse Surveys			Excluding Two Pulse Surveys
	AM Peak	PM Peak	Reverse Peak Trips	AM Peak
Used other transit				
Pre-ICM	<0.5%	<0.5%	<0.5%	<0.5%
Post-ICM	<0.5%	<0.5%	<0.5%	1%
Carpooled				
Pre-ICM	1%	1%	2%	1%
Post-ICM	<0.5%	<0.5%	<0.5%	<0.5%
Other				
Pre-ICM	5%	1%	<0.5%	7%
Post-ICM	4%	1%	<0.5%	2%
No changes				
Pre-ICM	47%	61%	69%	59%
Post-ICM	30%	51%	58%	66%
Sample Size (Pre-ICM)	**660**	**249**	**187**	**479**
Sample Size (Post-ICM)	**434**	**242**	**523**	**144**

(Source: Overview of the Dallas Traveler Response Panel Survey—Draft, Volpe Center, 5/18/16, p. 93.)

The ten scenarios were modeled in DIRECT and the corresponding performance measures in terms of mobility (including travel time, delay, and person throughput), reliability and variability (including planning index and average travel time standard deviation), emissions, fuel consumption, and cost estimation were calculated and compared for both the conditions with and without ICM strategies. Below is a list of the findings from the analysis results.

- The biggest travel time benefits occur along the peak direction during a severe incident with the deployed ICM system. This may be due to the design of the ICM system specifically to accommodate the route diversion in the peak direction.
- Most of the scenarios show significant reduction in person mile travelled compared to the before deployment condition.
- No mobility benefits can be found for extending the ending time of the operation of the DSS system from 6:00 pm to 8:00pm based on daily person miles traveled, but the results show benefits of the ICM deployment during a severe incident.
- The planning time index remains the same or slightly increased with the deployment of the ICM strategies which may be due to the influx of travel demand on diversion routes with the traveler information provided.
- The average travel time standard deviations also increase with the presence of the ICM system except for one of the aggregated scenarios that is associated more with incidents.
- Further enhancements are needed for the DIRECT tool to better represent signal timing and phasing.

The US-75 ICM project did not generate the expected benefits in mobility and reliability. Two recommendations were made by the research team: updating response plans frequently as the post-deployment response plan was based on the pre-deployment conditions and adopting real-time adaptive response planes.

2.9.2 I-15 in San Diego, California

The I-15 ICM deployment was assessed before deployment and after deployment as discussed in the following subsections.

AMS Results before Deployment

Twelve operational conditions were modeled in the I-15 ICM project in San Diego, California, before the actual ICM deployment. The modeled scenarios include the daily operations in a future year as a baseline, a freeway incident, and an arterial incident, combined with low, medium, and high demands. Four ICM strategies were assessed for each operation condition, including

- Pre-trip and en route traveler information
- Ramp-metering and arterial signal coordination
- BRT
- Congestion pricing for ML

For the future baseline scenarios, the study assumed that the percentage of drivers that are informed by real-time information is 5% without ICM and 30% with ICM, and the travel time information is updated every 20 minutes without ICM and every 15 minutes with ICM. The comparison of the network-wide results for the future baseline scenario without and with ICM showed that:

- Vehicle mile traveled drops by 0.2% for the scenario with low demand, 0.17% for the scenario with medium demand, and 0.5% for the scenario with high demand
- Vehicle hour traveled decreases by 0.26% for the scenario with low demand, 1.13% for the scenario with medium demand, and 1.5% for the scenario with high demand
- Delay is reduced by 0.21% for the scenario with low demand, 3.7% for the scenario with medium demand, and 3.4% for the scenario with high demand

Most of the benefits were estimated to occur along the I-15 SB and arterials.

The freeway incident scenario involves a severe incident with a 3-lane blockage during the first 30 minutes followed by a two-lane blockage in the next 15 minutes. In addition to the assumptions used for traveler information awareness and update frequency in the baseline scenario, the analysis also assumed that incident information was disseminated after 2 minutes of occurrence instead of 10 minutes, the managed lane was opened to all vehicles during the incident, and signal optimization became effective 30 minutes after the incident. The analysis results showed that the use of the ICM strategies slightly increases the vehicle mile traveled by 1.07% to 1.27%, but it significantly reduces delays (by 7.7% for medium demand and 8.4% for high demand). Opening the managed lane reduces vehicle hour traveled by 1.8% to 2.6%.

An arterial incident that occurs east of the I-15 was introduced in the simulation model. The same ICM strategies used for the freeway incident was also used in this case except not including the opening of managed lane. Compared to the scenarios without ICM strategies, the inclusion of ICM strategies results in a 4.3%, 4.1%, and 3.8% in the total network-wide delays and 1.2%, 1.8%, and 4.3% reduction in VHT for low, medium, and high demand scenarios, respectively.

All the analysis scenarios were combined based on their occurrence in a year. The resulted performance measure results indicated a 1.5% reduction in network-wide delays, an improvement of 0.3% in the overall planning time index, and 10.6% improvement in corridor-wide travel time variance. The most benefited roadways were the I-15 SB and arterials. However, the impacts of the ICM strategies on throughput was small.

Similar conclusions can also be drawn from the benefit/cost analysis, that is, the application of the ICM strategies helps reduce travel time, improve travel time reliability, and save fuels, especially along the I-15 SB and arterials. However, no significant impacts on throughput can be found. There were also some dis-benefits for managed lane users due to the opening of ML during the severe freeway incidents. About 93% of the ICM benefits were from the operational conditions with medium or high demands. The overall benefit/cost ratio for the I-15 ICM project is 9.7:1.

AMS Results after Deployment

Nine scenarios including one hypothetical scenario were examined in the post-deployment stage of the I-15 ICM project based on matching incidents with identified clusters of high occurrence percentage.

Table 16 lists the nine scenarios and the ICM strategies considered in each scenario.

Table 16: I-15 Study Scenarios and Associated ICM Strategies (Source: Alexiadis and Chu, 2016b)

Scenario	Date of Representative Day	DSS Plan Type Implemented	Total Cluster Day Impact (min)	Percent of Total Time Period	DSS Event ID	DSS Response ID
NB PM 1	6/16/15	Ramps, Signals, ATIS	41.8	16.3%	845922	30617
NB PM 2	6/09/15	Ramps, Signals	23.4	7.7%	842085	30451
NB PM 3	5/05/14	Ramps, Signals, ATIS	99.7	34.6%	853963	31039
NB PM 4	7/07/14	Ramps, Signals, ATIS	63.3	24.0%	639956	19536
NB PM 5	2/19/15	Signals, ATIS	18.7	2.9%	760369	28292
SB AM 1	5/27/15	Signals	49.9	27.9%	817649	30332
SB AM 2	2/09/15	Signals, ATIS	108.0	37.5%	754666	27929
SB AM 3	5/07/15	Ramps, Signals, ATIS	34.6	7.7%	804238	30028
Hypothetical	5/26/15	None. Express Lanes opened.	N/A	N/A	N/A	N/A

(Source: ICM Evaluation – San Diego Incident Matching, Battelle, 4/14/16, p. 5, unpublished.)

Similar to the US-75 ICM project, panel surveys, pulse surveys immediately following the occurrence of incidents, and transit rider surveys were conducted before and after the ICM deployment. The baseline and end-line panel survey results showed an increase in the awareness of traveler information; however, the use of the information were not shown to increase. The surveys also indicated the utilized information source was almost the same as before except with an increase in the use of the Google Maps from 45% to 55%. The frequency at which the survey respondents consult information was also increased. Regarding the travel behavior in the corridor, the surveys showed consistent results for the baseline and end-line conditions, that is, to start trip earlier or change routes with the knowledge of congestion from pre-trip information, and to change route with en route traveler information. Table 17 and Table 18 present the pulse survey results for pre-trip and en route information. As shown in these two tables, a small increase in the response to the pre-trip information can be observed for the after the ICM deployment conditions. The percentage of no changes in behaviors increases for the en route information response after the ICM deployment. The results of transit surveys revealed that most of transit riders use smartphone to obtain traffic and transit information. Google website and apps are also a main source for transit riders to obtain traffic information. However, a majority of transit riders would not make any changes even with real-time information based on the survey results.

The nine scenarios as mentioned above were simulated using the Aimsun software. Below is a list of the main findings of the analysis results.

- The implementation of the ICM strategies significantly reduced person hours traveled and person-hours of delay.
- No changes were obtained in the person-mile traveled as a performance measure for throughput with the presence of the ICM strategies. This may be because no excess demand exists at the beginning of the simulation. It was suggested that throughput measures may be calculated at hourly or 15-minute intervals.
- Travel time reliability was examined in terms of median travel time, buffer time, and 95th percentile travel time index. All these measures show an improvement.
- The standard deviation of travel time that quantifies the variability of travel time shows a very small decrease with the deployment of the ICM strategies.
- The annual benefits of the ICM strategies were estimated by multiplying the ICM impacts for the nine scenario results with the corresponding number of days. The benefit results from the post-deployment analysis was found to be consistent with those obtained from the pre-deployment conditions.
- The percentage of travelers along the corridor that are expected to experience improved travel time was about 50%, while the percentage of travelers with the increase in travel time was about 47% to 49% and the percentage of travelers with unchanged travel time was about 1.2% to 2%.

The comparison between the pre-deployment and post-deployment analysis results reveals that the benefits in delay savings obtained from the post-deployment analysis are nearly at the same level as those estimated from the pre-deployment analysis.

Table 17: I-15 Pulse Survey Results for Pre-Trip Information (Source: Alexiadis and Chu, 2016b)

Travel Changes	AM Peak	PM Peak	Reverse Peak Trips
Minor route changes			
Pre-ICM	7%	12%	7%
Post-ICM	10%	10%	9%
Left earlier			
Pre-ICM	4%	5%	12%
Post-ICM	5%	6%	11%
Left later			
Pre-ICM	3%	4%	<0.5%
Post-ICM	3%	3%	4%
Completely different route			
Pre-ICM	2%	3%	2%
Post-ICM	3%	2%	3%
Changed stops			
Pre-ICM	<0.5%	<0.5%	6%
Post-ICM	1%	1%	<0.5%
Changed to MTS Express/Rapid			
Pre-ICM	<0.5%	<0.5%	<0.5%
Post-ICM	<0.5%	<0.5%	<0.5%
Changed to other transit			
Pre-ICM	<0.5%	<0.5%	<0.5%
Post-ICM	<0.5%	<0.5%	<0.5%
Carpooled			
Pre-ICM	1%	1%	2%
Post-ICM	<0.5%	1%	2%
Other			
Pre-ICM	1%	<0.5%	<0.5%
Post-ICM	<0.5%	<0.5%	<0.5%
No changes			
Pre-ICM	81%	76%	73%
Post-ICM	79%	78%	73%
Sample Size (Pre-ICM)	**332**	**248**	**145**
Sample Size (Post-ICM)	**311**	**235**	**106**

Table 18: I-15 Pulse Survey Results for En Route Information (Source: Alexiadis and Chu, 2016b)

Travel Change	AM Peak	PM Peak
Minor route changes		
Pre-ICM	11%	16%
Post-ICM	10%	16%
Completely different route		
Pre-ICM	6%	5%
Post-ICM	4%	3%
Changed stops		
Pre-ICM	1%	1%
Post-ICM	<0.5%	<0.5%
Used MTS Express		
Pre-ICM	<0.5%	<0.5%
Post-ICM	<0.5%	<0.5%
Used other transit		
Pre-ICM	<0.5%	<0.5%
Post-ICM	<0.5%	<0.5%
Other		
Pre-ICM	5%	1%
Post-ICM	6%	3%
No changes		
Pre-ICM	77%	78%
Post-ICM	80%	79%
Sample Size (Pre-ICM)	**215**	**127**
Sample Size (Post-ICM)	**178**	**180**

2.10 CONCLUSIONS

Based on the review presented in this document, the following conclusions and recommendations can be given:

- In general, the ICM DSS can be considered to consist of five elements: offline use of modeling for planning for operations, real-time data collection and fusion, user interface, real-time response plan recommendations, and model-based real-time predictive engine.

- Based on literature review, it has been recommended to use a modular software architecture that allows separating the five elements of the ICM into separate components that interface with each other using industry standards.

- The real-time response plan recommendation has been done utilizing rule-based expert systems. An important aspect of the expert system module is the required periodic and frequent post-review of the implemented and proposed plans and modifying these plans as needed. There is a need for fine tuning of the decision tools until acceptable output is achieved. Monthly or biweekly review will allow effective response plan identification. However, the response plan development will take time, will have many dependencies, and will require close coordination with partner agencies.

- More advanced real-time generation of response plans (real-time adaptive response plan generation) has been proposed instead of selection from a library as is done by the expert system. However, this has not been implemented in ICM real-world deployments and should be investigated.

- The analysis, modeling, and simulation (AMS) tools have been used as important components of ICM DSS for offline planning for operation analysis. Simulation tools have also been proposed and used as the main component of the performance prediction in the real-time DSS. The AMS tools can be classified as having macroscopic, mesoscopic, or microscopic resolutions. The Dallas deployment utilizes mesoscopic simulation while the San Diego deployment utilizes microscopic simulation. However, even simple macroscopic simulation may have a role in offline and real-time decision support.

- Tools with different levels of resolution are suitable for different applications. Combining these tools in a single application can provide capabilities and functionalities that are not possible with the use of one type of model. This will be explored in future tasks of this project. A previous FDOT research project conducted by the research team proposed the use of a multi-resolution modeling framework, which can be used to support the required modeling actives associated with ICM projects.

- Agencies that are not considering using modeling tools for real-time applications should consider at least offline AMS to guide the development, selection, and implementation of response planes during the planning and planning for operations stages.

- The evaluation of the two ICM pilot projects and ATDM/DMA modeling testbeds indicate that the benefits of the implemented advanced strategies and the synergy between strategies depends on the specific conditions and scenarios under consideration. This further indicates the need for AMS to support the selection of strategies.

- An important aspect of the modeling component is the need for the identification of the appropriate performance measures, supporting data, capabilities of modeling advanced strategies, traveler behavior modeling, and model execution speed for real-time operations.

- Clear requirements should be developed to guide the selection of the modeling tools for offline and real-time applications.

- It recommends that the user specifies an acceptable time window for a DSS-generated response plan to be issued after the request is generated. It should be recognized that any generated plan that takes greater than five minutes could be too long in a dynamic network with changing conditions.

- An important aspect of the ICM AMS methodology is the need to simulate transportation systems under varying operational conditions including those associated with both recurrent and non-recurrent traffic congestion. The USDOT ICM Modeling Guidance states that the key ICM impacts may be lost if only “normal” travel conditions are considered. Thus, the analysis should take into account different demand levels within the corridor, with and without incidents and possibly with and without adverse weather. The frequency of non-recurrent events such as incidents is also important to estimate the impacts of advanced strategies. On the supply side, it is important to model changes to network supply or capacity between days including the stochasticity of capacity and the impacts of incident and weather impacts. On the demand side, it is necessary to capture the changes in demand patterns between days and also to capture traveler behaviors, as a response to implemented dynamic actions.

- Different strategies are beneficial under different traffic condition scenarios. Data categorization and clustering algorithms based on detailed data collected using monitoring systems for a long period of time have been used for the identification of analysis scenarios. Using clustering analysis to determine various analysis scenarios is an important component of the utilized approach and will be investigated in this study.

- Open source and university developed tools such as Dynasmart and DIRECT have been investigated and use for DSS support. DIRECT was used in the Dallas implementation by the developer of the tool who was part of the development team. The slow technical support associated with open source tools is an important issue when using these tools in practice. However, there are two commercially available modeling platform that have been proposed for real-time DSS implementation: PTV Optima and Aimsun Live. Although the PTV Optima and Aimsun Live have their own data hubs and response plan selection, it is possible to integrate the underlying models with separate DSS data collection and fusion hubs and response plan selection tools modules for FDOT, if so desired.

- The evaluations conducted as part of the reviewed efforts indicate that the use of predictive traffic management strategies produces better results than responsive traffic management strategies. Longer prediction horizon and more accurate prediction has been shown to produce better results. Predictive-engines as have been applied in existing ICM projects utilize simulation-based predictive engines. Prediction of near future traffic conditions can also be achieved using data-based models. This prediction, however, has a disadvantage in that it is not possible to predict the impact of alternative response plans on traffic conditions. Nevertheless, such prediction may still have a role in ICM DSS either by itself or in combination with model-based predictive engine. This will be considered in this project.

- The calibration and validation of the model demand and supply can be time consuming and requires significant effort to ensure that the results from the tool is valid. The FDOT should ensure that the utilized model achieve the required levels of accuracy not only at the link volume level but also at the link speed and turning movement count levels.

- There is a need to assess DSS deployment performance for the purpose of both refining it in the specific deployment for which it has been implemented, as well as for providing lessons learned for future implementations. An evaluation should be done to determine that the DSS achieves its goals.

- The estimated or measured outcomes from the ICM deployments can be converted to economic benefits as a result of travel time savings, enhanced travel time reliability, reduced motor fuel costs, lower emissions, and reductions in the number and severity of crashes. It is recommended to develop and implement methodologies for post-deployment assessment of ICM DSS. In addition, a module for pre-deployment assessment of potential ICM DSS is recommended to be implemented in Florida ITS/TSM&O evaluation tools such as FITSEVAL for use in planning and planning for operations decisions of ICM.

- Based on the survey results from the USDOT ICM projects, the dissemination of pre-trip and en route traveler information during the ICM projects may increase in the awareness of traveler information; however, the use of the traveler information may still be the same. Outreach activities to increase awareness and usage of the provided information should be conducted. Surveys should be conducted before and after ICM deployments to assess the degree of success in influencing driver behaviors.

- The implementation of ICM strategies produces benefits in network-wide mobility and reliability. Most of these benefits occur and during severe incidents. However, such improvement may not be significant in some cases, depending on the specific implementation of response plans.

- The demand forecasting and simulation modeling community can play an important role in supporting TSM&O agencies in their development, implementation, and maintenance of model-based DSS and they should be involved in this effort.

3. REVIEW OF ICM DSS CONCEPTS IDENTIFIED FOR FLORIDA

This section presents a review of the ICM DSS concepts currently identified for Florida, as part of scopes of service, concepts of operations (ConOps) documents and other documents. A list of the applications is then presented based on this review and the review presented in Chapter 2.

3.1 CENTRAL FLORIDA ICM DSS

The ICM deployment in Orlando, which is in the implementation stage, is the only ICM concept in Florida that includes a full plan to utilize model-based Decision Support System (DSS). Although the focus is on the I-4 corridor, the developed product is supposed to be scalable to the entire FDOT District 5. Figure 21 shows the I-4 Corridor in yellow, with the influence area shown by the dark line. The I-4 Corridor and influence area contains a primary freeway, a commuter-rail line, transit bus service, park-and-ride lots, major regional arterial streets, toll roads, bike trails, and intelligent transportation systems (ITS) infrastructure. The I-4 ICM deployment will implement and evaluate the potential benefits of corridor management strategies utilizing simulation-based DSS in real-time and offline environments.

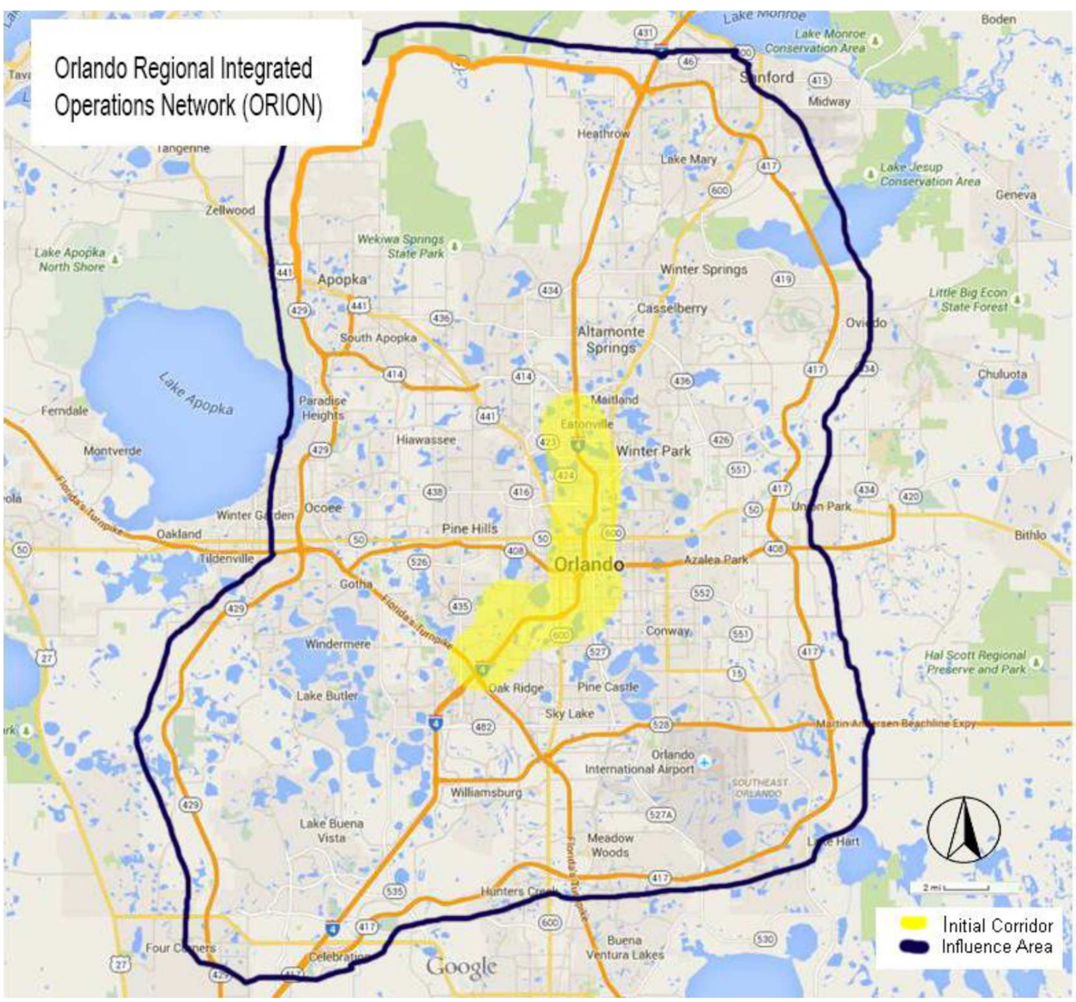


Figure 21: Orlando regional integrated management system

The planned Integrated Corridor Management System (ICMS) will collect, clean, fuse, archive, and interface data from multiple sources to support the management and operations of the corridor. The data will be pre-processed, fused, and used in support of the decision-making process. The main ICM applications specified in the concept of operations include (FDOT District 5, 2017):

- ***Traffic Incident Response on Limited-Access Facilities*** – This application determines an appropriate adjacent corridor flush strategy and other strategies to respond to an I-4 incident. As specified, the effectiveness of the response plan is to be assessed using a mesoscopic simulation model of "a reduced network." If approved by the responsible agency, the response plan is implemented through the SunGuide software. Adjustment to the plan is made as necessary during the life of the incident and it is deactivated when it is no longer necessary.

- ***Traffic Incident Response on Arterial Facilities*** **–** This application will detect incidents by monitoring turning movement counts and other signal performance measures to detect an increase in queue length and/or travel time relative to a configurable percentage of historical value. The system will then select a signal timing, from a library of existing plans, based on the detection. If approved by the responsible agency, the response plan is implemented through the SunGuide software. Adjustment to the plan is made as necessary during the life of the incident and it is deactivated when it is no longer necessary.

- ***Periodic Signal Timing Optimization*** – This application involves the offline optimization of signal timing plans and their times of activation based on 5-minute detail measures. This optimization system utilizes high-resolution controller data and data from other sources, combined with modeling and analysis techniques. As specified, the offset selection is to be based on an algorithm that utilizes the detailed data, such as the Purdue system's link pivot algorithm. Figure 22 shows an example display of the corridor optimization recommendation included in the I-4 ICM Scope of Service. The Scope of Service goes into a detailed description of how the green splits are assigned in different intervals. The time intervals are grouped based on their saturation rates (the scope defined this as the volume to capacity ratio; but more correctly it should be referred to as the volume to saturation flow ratio). The Euclidean distance between two contiguous intervals is used in the grouping. The optimal timing plan for an intersection is calculated by proportioning green time based on saturation rates of each movement. The system will select the adjacent and nearby segments and signals to include in the modification. In addition, it will calculate the optimal plans for the intersection and select from the available plans based on the Euclidean distance.

When dealing with events on the freeway or the arterial streets, the ICM system (ICMS) will evaluate the event severity and, based on the expert rules, select the most appropriate response plans from the response plan repository; also, request that these plans are evaluated using mesoscopic predictive simulation analysis. This function will be repeated while the event is still active. A score is calculated for each response plan based on its impacts, as evaluated by the simulation. The system will determine which plan is the best response plan. If that plan meets the threshold of improvement over the Do-Nothing plan, based on the assessed system performance, a recommendation for implementation is sent based on the scores (see Figure 23).

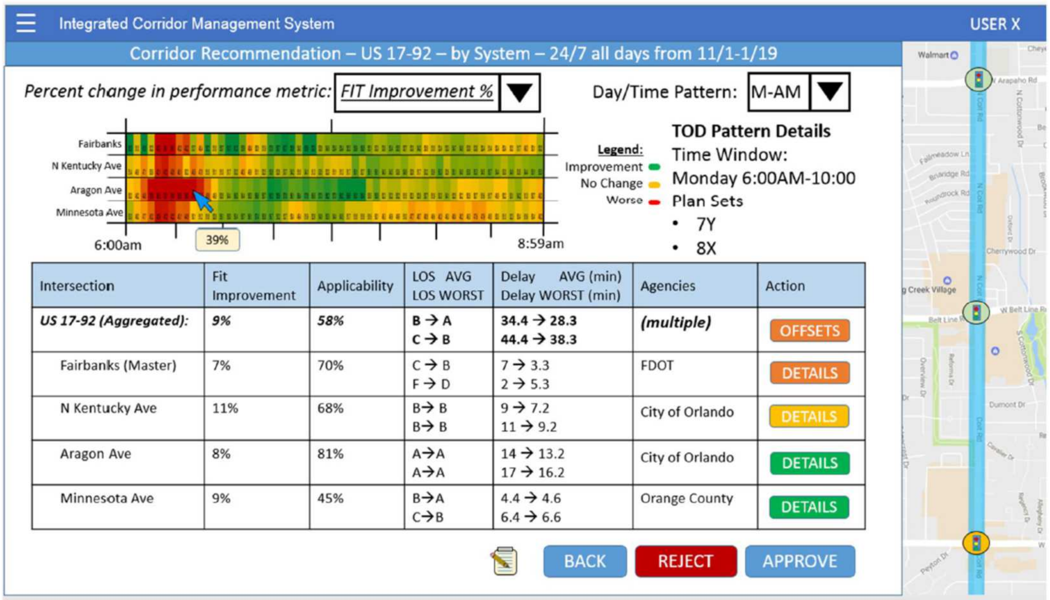


Figure 22: Example display of the corridor optimization recommendation included in the I-4 ICM scope of service

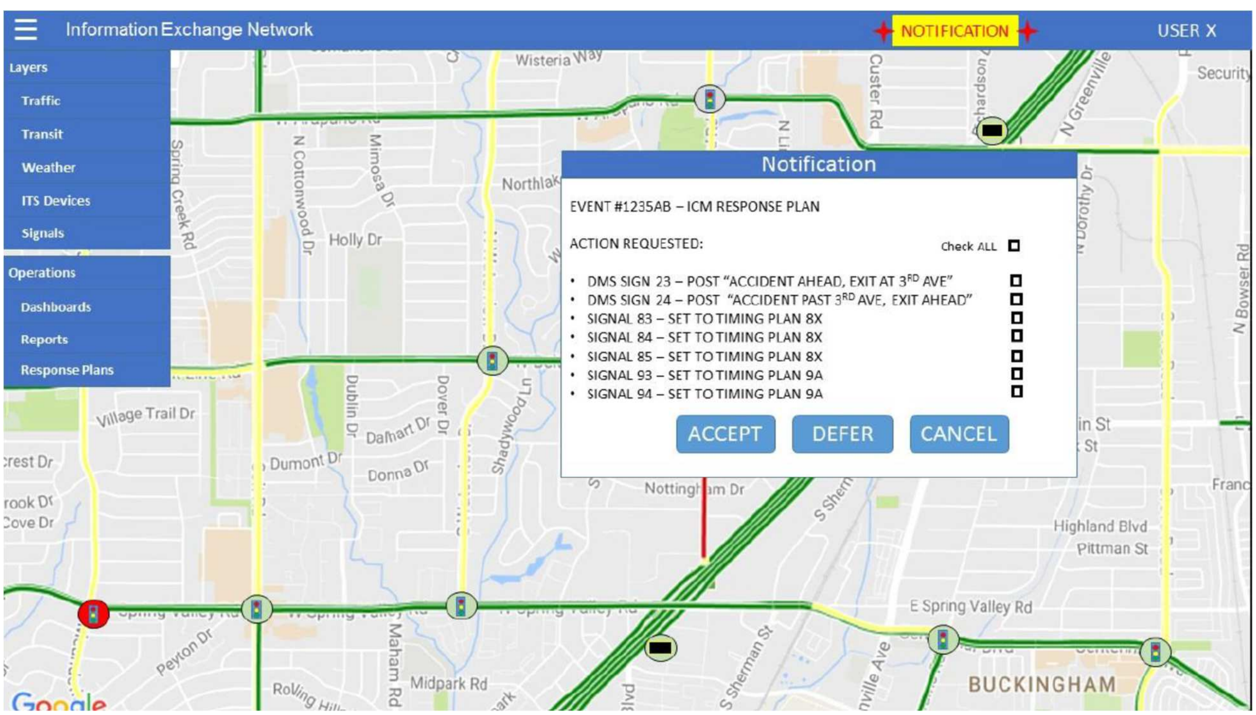


Figure 23: Example display of the ICM response plan notification included in the I-4 ICM scope of service

The ICM system (ICMS) will consist of commercial off-the-shelf (COTS) modeling software, a custom-built decision support system (DSS), a custom-built information exchange network (IEN) subsystem (that includes dashboards and other user interfaces to the system), and a data fusion environment (DFE) to host data sources for both the ICMS and other external users and applications. These four components have been used in other national ICM implementations, as discussed in Chapter 2.

The DSS and ATMS Software Operational Concept document lists the following strategies to be included in response plans, as examples (Kapsch TrafficCom Transportation, 2016):

- Coordinated timing plan for central traffic signal software;
- Metering state and rates for ramp meters;
- Hard shoulder running;
- Dynamic messaging for diverting traffic;
- Disable pricing on managed lanes;
- Responder dispatch and coordination; and
- Transit rerouting and bus bridging

The DSS and ATMS Software Operational Concept document addressed the following operational scenarios and associate strategies (Kapsch TrafficCom Transportation, 2016):

- Daily Operations: The DSS and ATMS software focuses during this "daily operations" on automated information sharing and ensuring operational efficiency at network junctions and interfaces. These strategies are "baseline" strategies that will also be applicable in other scenarios. As defined in the FDOT District 5, daily operations do not include congestion due to stochastic variations in capacity and demands (these are referred as non-recurrent congestion in the next bullet). Note that in the common terminology of the literature, non-recurrent congestion includes only those due to events.
- Non-recurring Congestion: This scenario includes congestion to reasons other than incident events. The specified strategies for this scenario include change to signal timing plan and DMS messages based on modeling.
- Major Freeway Incidents: In addition to baseline scenario strategies, the strategies under this scenario include: promoting route/ network/mode shifts via traveler information, hard shoulder running, restrict/ reroute/ delay commercial traffic, and modify arterial signal timing to accommodate traffic shifting from freeway.
- Commuter Rail Incidents - Strategies under this scenario include emergency vehicle signal preemption, transit vehicles connection protection, and emergency road closure.
- Arterial Incidents: Associated strategies include emergency road closure (including freeway off ramps), modify arterial signal timing to accommodate traffic shifting from the incident location, and reroute transit vehicles.
- Special Events: Strategies include adding transit capacity, rerouting transit vehicles, and providing transit priority.
- Planned road closure and restrictions: Strategies include modifying ramp metering rates to accommodate traffic, and implementing special traffic signal timing plans, parking management, and police assistance in directing traffic.

3.2 CENTRAL FLORIDA ICM DSS MODELING SUPPORT

As described in the previous section, FDOT District 5 identified the need for the use of traffic modeling software for the support of the DSS of the Central Florida Regional Integrated Corridor Management System (ICMS). The District specified that the same modeling software is to be used for both the Predictive Engine (PRE) as part of real-time DSS and the offline ICM planning model. The FDOT advertised two professional services contract: One to supply the software and one to build and calibrate the planning model.

FDOT District 5 advertisement of the modeling software specifies that it will consist of, but not be limited to; mesoscopic modeling and microscopic modeling and allow real-time modeling and offline modeling. The modeling environment is also specified to include what is referred to as a "deterministic model," which appears to reference a signal optimization tool that based on requests can optimize the signal timing plans. These new timing plans may be sent to the mesoscopic simulation to be evaluated. The modeling software is to be commercial off-the-shelf (COTS).

The mesoscopic traffic simulation model gets the request from other components of the DSS and builds required models to assess the performance of the response plans versus the Do Nothing alternative. Real-time information and historical data are used in building the model. Then, simulations are run in parallel and the results are used to provide information about the performance of the plans to other components of the DSS. This information is used to calculate the score for each response plan based on the estimated measures of effectiveness (MOE) and evaluating the benefits of the response scenarios versus the Do Nothing.

FDOT District 5 ICM documents also state that the ICM DSS will require a large-scale mesoscopic simulation model for use at the planning level. At this level, the model will be used to provide initial demand and supply information to the real-time models, analyze the impacts of planned and unplanned events throughout the network, estimate diversion under different conditions, design and assess the response plans prior to their implementations, fine-tune the plans after implementations, and review and deconstruct implemented strategies post deployment. The offline model will utilize inputs from the Central Florida regional demand forecasting model as well as system data. The FDOT specified that the mesoscopic model should be able to replicate different response strategies that include, but are not limited to: traffic signal timing functionality, ramp metering algorithms, transit operations, and dynamic routing. The advertisement recognized some elements of the planning model may require the development of additional capabilities using the software API facility.

The real-time predictive engine will utilize sub-areas of the planning model and will run a mesoscopic simulation of the subarea network in real-time and provide predictions of the network performance with and without response plans, 10, 20, and 30-minute forecast into the future. It is specified that the 30-minute horizon predictions are to be repeated every 5 minutes, runs 24-hours a day / 7-days a week, and is available for evaluations at any time.

It was stated that the planning model will be configured for typical day operations. Thus, the predictive engine model will need further refinement on the demands and operational parameters to be able to accurately represent any day of the year under different operation scenarios. The predictive engine will also include a "deterministic model" as part of the ICMS that will work with the simulation model to evaluate and optimize the signalized intersection corridors within the network (FDOT District 5, 2017).

3.3 BROWARD COUNTY I-95 ICM SCOPE OF SERVICE

FDOT District 4 and Broward Metropolitan Planning Organization (MPO), with an initial grant from the Federal Highway Administration (FHWA) have developed a Concept of Operations (ConOps) for an ICM for the I-95 corridor in Broward County (AECOM, 2013). Figure 24 shows the I-95 corridor location in Broward County. It was recognized that the proposed I-95 ICM system has the potential to be expanded throughout the Tri-County region (that includes Palm Beach and Miami-Dade Counties) in the future.

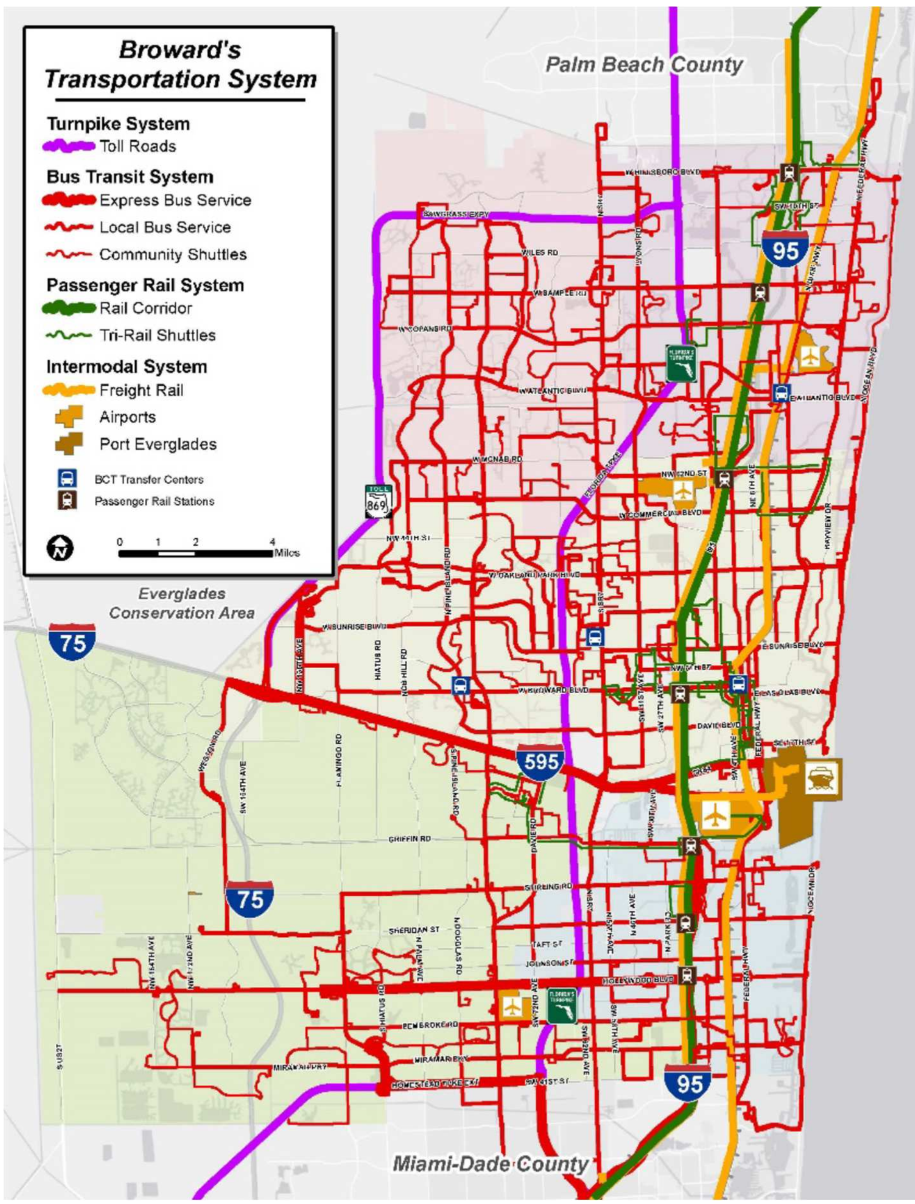


Figure 24: Location of the proposed I-95 ICM system (Source: Broward MPO and FDOT, 2016)

In its review of the existing situation, the ConOps document pointed out that the detected incidents are currently classified into three severity levels based on their attributes by the SunGuide TMC standard operating procedures. The scope and severity of an event/incident are determined based on personal injuries (nature of crash, position of occupants, fire, etc.), risk to public safety (disabled vehicle/person in moving traffic, hazardous spill, etc.), and the potential impact to traffic or the total number of travel lanes affected. The response to incidents is generated based on these severity levels. Currently, the arterial management program (AMP) staff of District 4 consider providing active arterial signal timing plan adjustments for all Level 2 and Level 3 severity events, and it is up to the judgment of the AMP Operations Manager/Timing Engineer whether or not a timing adjustment is necessary and/or beneficial to each situation. Currently the incident detection on arterial is mainly done based on operator scanning of CCTV cameras based on criteria such as low volume, long queue, large number of lane changes, and vehicle slowing observations.

The ConOps document points out that there is a desire among the project stakeholders to employ a DSS to produce and recommend "pre-developed and pre-agreed" response plans when incidents or events are experienced within the study corridor. These events or scenarios may be triggered by pre-set thresholds (such as queue lengths, volume, vehicle speed, incident levels, etc.) or manual inputs. The affected agencies should have the option to accept, reject or modify the recommended response plan. The specified high level requirements of the DSS include (Gannett Fleming, 2016):

- "The system shall provide operators with an integrated regional view of current and forecast road and traffic conditions
- The system shall identify network imbalances and potential course of action.
- The system shall compare the impact of potential course of action and make recommendations to the operator.
- The recommended actions shall include predefined incident response plans, signal timing plan changes, DMS messages, lane control strategies, and freeway control strategies including ramp metering and toll rate adjustments in express lanes.
- The recommended actions shall include multimodal strategies that include suggested transit strategies and suggested route and mode choices for travelers.
- The system shall provide an interface to operators to input control parameters for the decision support process and receive recommended actions and supporting information."

Figure 25 illustrates the high-level components of the proposed I-95 ICM System.

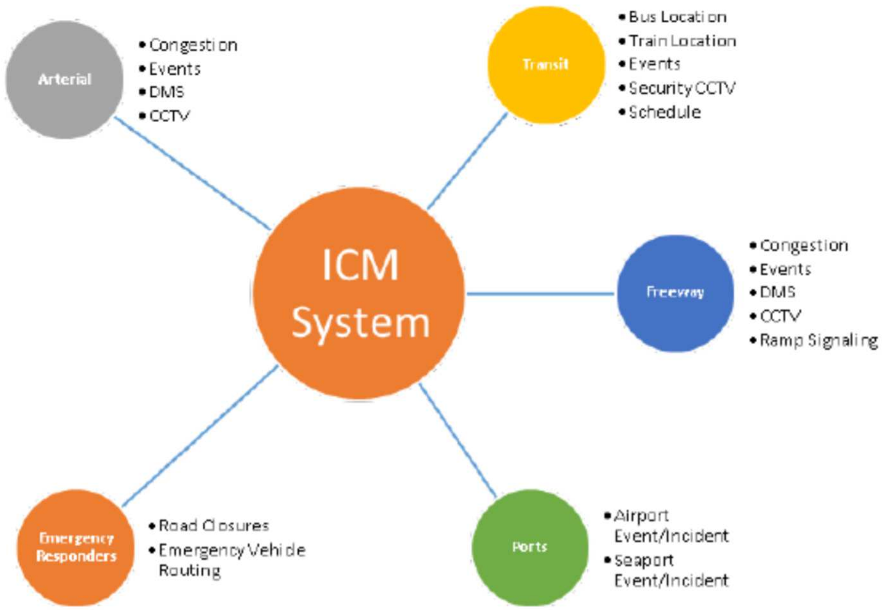


Figure 25: High-level ICM concept

The ConOps document identified six operational scenarios and associated ICM DSS-related strategies as follows (Gannett Fleming, 2016):

- Daily Operations: Strategies include modifying ramp metering rates. modifying express lane rates, modifying signal control, and providing information to travelers.
- Freeway Incidents: Strategies include suggesting alternate routes and provide travel time info, modifying ramp meter rates, implementing signal timing adjustments for diverted traffic, rerouting buses as necessary and notifying travelers, modifying Express Lanes toll rates, and providing traffic incident management (TIM).
- Arterial Incidents: Strategies in response to arterial incidents include providing information using freeway and arterial DMS, ramp closures, diversion to alternate route implement special signal timings, rerouting buses as necessary and notifying travelers, and providing traffic incident management (TIM).
- Transit Incidents: Strategies in response to transit incidents include common incident reporting system, automated information sharing, emergency roadway and off-ramp closure, emergency vehicle signal preemption, notification to transit users via app, enhance real-time trip planning, connection to alternate transit service, Transit signal priority (TSP), adjusting arterial signal timings.
- Special/Planned Events: The focus with these events is on disseminating event, closure, and detour information; providing parking management and information systems; implementing special signal timing plans; providing additional transit services, rerouting transit vehicles, and notifying customers of service.
- Disaster Response: This response involves modifying ramp meter rates, modifying Express Lane toll/restrictions, providing contraflow, provide information to travelers,

coordinating closure information, providing signal timing adjustments, and making resources (buses) available for evacuations.

3.4 JACKSONVILLE ICM STRATEGIES

FDOT District 2 has been considering the implementation of ICM strategies and associated simulation-based DSS for some time. One important consideration to the district is the time required to execute the model and provide response plan recommendations. It was stated that the ICM will benefit from existing and planned deployment of new regional traffic management center (RTMS), Bluetooth devices, upgraded traffic signal controllers, transit signal priority, traffic signal preemption, arterial DMS and CCTV cameras in Jacksonville. It appears that the focus of the ICM initially will be on the I-95/US 1 corridor in south Jacksonville. Future expansions can include the I-10/Normandy Boulevard, I-95/Main Street in north Jacksonville, and I-295/Southside Boulevard corridors. A third phase is to use the same approach for the SR 15/SR 21 (Clay County) and US 1/I-95 (St. Johns County) corridors since a majority of the ITS and traffic signal system equipment is already in place. Traffic on I-95 is to be diverted toUS-1 with TMC operators monitoring congestion, post detour messages, and change signal timing to better control traffic flow on US-1. When an incident occurs on US-1, traffic can be diverted to I-95.

3.5 SUMMARY OF ICM APPLICATIONS AND ASSOCIATED APPROACHES

Based on the review presented in Chapters 2 and 3, Table 19 presents the ICM operation scenarios and ICM applications identified in the Florida and national ICM efforts.

Table 19: ICM Interventions Identified in Previous ICM Efforts

Intervention	Description	Inclusion in National and Florida ICM	Applicable Operational Scenarios
Dynamic Ramp Management (Metering Activation, Deactivation, and Closure)	Dynamic ramp management includes ramp metering activation, deactivation, and closure.	FDOT District 4, FDOT District 5, San Diego I-15, and Los Angles I-210 Connected Corridors	Daily operations to accommodate stochastic variations, freeway and arterial incidents, and weather events.
Dynamic Modification of Express Lane Pricings and Restrictions	Proactive changing to rates and eligibility of using EL can be applied when conditions reach a level with high probability of breakdown.	FDOT District 4, San Diego I-15	Daily operations to accommodate stochastic variations, freeway and arterial incidents, and weather events
Coordination of Ramp Metering and Signal Control	Generate special signal timing plans to prevent ramp spillback due to metering and provide information to drivers to divert from the ramps.	San Diego I-15 and Los Angles I-210	Daily operations to accommodate stochastic variations, freeway incidents, and weather events
Periodic Signal Retiming	Offline optimization of signal timing plans and their times of activation based on historical system performance measures estimated using detailed data from multiple sources	FDOT District 5	Daily operations including stochastic variations.
Traffic Adaptive Signal Control	Optimize overall signalized intersection performance by continually adapting signal timing for each movement to actual traffic conditions	I-95/I-395 ICM project in Virginia	Daily operations (stochastic variation), freeway incident and weathers events, and arterial major events. However, it is not clear how adaptive signal control perform under incident and event scenarios.
Special Signal Plans During Freeway and Arterial Incidents	Application of plans to flush diverted traffic during freeway events and plans that consider capacity drops during arterial incidents.	FDOT District 4, FDOT District 5; Dallas US-75, San Diego I-15, Los Angles I-210 Connected Corridors	Freeway incidents, weather events, and arterial events.

Intervention	Description	Inclusion in National and Florida ICM	Applicable Operational Scenarios
Alternative Route Provision to Motorists	Provision of alternative route information to motorists during freeway and arterial incidents and other events	Maryland CHART program, San Diego I-15, Los Angles I-210 Connected Corridors	Freeway and arterial events, weather events, and other special events.
Predicted Travel Information Provision to motorists	Predicted travel time from origin to destination is provided to the public such that they can plan their trips before departure and change travel mode or routes during trip	San Diego I-15 and Dallas US-75	Freeway and arterial events, weather events, and other special events.
Provision of Optimal Emergency Vehicle Routing	Provision of optimal alternative route information to emergency vehicles during severe freeway and arterial incidents and other events	Dallas US-75	Freeway and arterial incidents
Rerouting express buses	Provision of optimal alternative route information to express bus during severe freeway and arterial incidents and other events	Dallas US-75	Freeway and arterial events
Mode Shift during Severe Highway or Transit Incidents	Operational data from transit agencies, such as significant schedule delays, route deviations, parking occupancy data, where available, can be provided to travelers to encourage the usage of transit during severe highway and arterial events. Such information can also help transit users to switch to another transportation mode during severe transit delays. Passengers disembark and a bus bridge can be provided to the nearest station/bus stop/alternative transit line routing and bus priority	FDOT District 4, FDOT District 5, Dallas US-75, San Diego I-15, and Los Angles I-210 Connected Corridors	Severe freeway and arterial incidents, weather events, transit events, and other events.

Intervention	Description	Inclusion in National and Florida ICM	Applicable Operational Scenarios
Hard Shoulder Running	Allow temporary use of either left or right shoulders on freeways to provide additional roadway capacity during congestion.	FDOT District 5, Los Angles I-210 Connected Corridors; Chicago DMA testbed	
Restrict/ reroute/ delay commercial traffic	Restrict the commercial vehicle usage of roadways and divert them to alternative routes during a severe freeway or arterial incident or other event	FDOT District 5	
Special Events and Construction	disseminating event, closure, and detour information; providing parking management and information systems; implementing special signal timing plans; providing additional transit services, rerouting transit vehicles, and notifying customers of service.	FDOT District 4	
Disaster Response	This response involves modifying ramp meter rates, modifying Express Lane toll/restrictions, providing contraflow lane operation, providing information to travelers, coordinating closure information, providing signal timing adjustments, and making resources (buses) available for evacuations.	FDOT District 4	

The rest of this section provide for the applications listed in Table 19; a description, applicable operation scenarios, potential approaches, review of literature, role of data and data needs, role of offline modeling, role of online modeling, and risks and constraints.

3.5.1 Dynamic Ramp Management

Description

Dynamic ramp management includes ramp metering activation, deactivation, and closure**.** Although listed as an ICM Strategy, ramp management is in reality a pure active transportation system (ATM) strategy when it deals with the congestion on the facility itself. In addition to implementing traffic adaptive metering (like SWARM and Fuzzy Logic), this strategy provides recommendations to activate ramp metering when the conditions result in a high probability of breakdown. This occurs during high demand, incidents, and bad weather when the stochastic probability of the volume to capacity ratio exceeding 1.0. This intervention is included in FDOT District 4, FDOT District 5, San Diego I-15, and Los Angles I-210 Connected Corridors. In the I-15 and I-210 ICM, this intervention also includes the deactivation of metering in case of arterial events, to support the diversion of motorists to freeways and in case of freeway incidents to support merging back to the freeway downstream of the incident. The FDOT District 4, San Diego I-15, and Los Angles I-210 Connected Corridors ICM concepts also include on-ramp closures during freeway incidents and off-ramp closures during arterial incidents.

Applicable Operational Scenario

Daily operations to accommodate stochastic variations, freeway and arterial incidents, and weather events.

Potential Approach to Support Decisions

This section discusses the potential approaches to support the decisions to activate and deactivate metering.

<u>Activation</u>

A prior FDOT research conducted by the current project team developed a method to recommend the activation of metering based on the stochastic probability distributions of demand-to-capacity ratio during non-event and event days (Hadi et al., 2017c). These distributions are obtained based on data analysis. Thresholds are set to activate metering when the demand-to-capacity ratio is determined to exceed a threshold that corresponds to the production of a certain probability of the volume-to-capacity ratio exceeding 1.0. The methodology considers weather and incident impacts on capacity and demands. The methodology is based entirely on data and does not require modeling. However, offline microscopic simulation is helpful to test the model and associated parameters before implementation.

<u>Deactivation of Metering</u>

In this strategy, the meters are deactivated when it is estimated that vehicles will diverted to the freeway due to arterial incidents or downstream of freeway incidents. This can be achieved based on data and/or modeling to determine the level of potential diversion of vehicles to each ramp under a given condition and deactivate the meters on these ramps, if the predicted maximum metering rate is predicted to produce demand-to-capacity ratio on the ramp that is greater than a given threshold or the queue length on the ramp is shown, based on simulation results, to spill back to the neighboring arterials. This methodology can be based entirely on data using a data mining technique and does not require modeling. However, offline microscopic simulation is helpful to test the model and associated parameters before implementation. If incident or ramp data are not available, then macroscopic simulation or mesoscopic-based dynamic traffic assignment (DTA) can be used to estimate the diversion routes.

Review of Previous Work

Ramp metering can be activated either based on a daytime schedule or manually or dynamically according to current or predicted traffic conditions. The simplest is the daytime operation based on a fixed schedule (e.g., every day at 4:00 pm in the northbound direction). With the manual strategy, an operator watches traffic conditions using CCTV cameras and activate or deactivate the meters in reaction to real-time traffic conditions. The dynamic metering strategy implements an automated method that utilizes current traffic measurements (or predicted traffic conditions) to prevent breakdown and congestion. Non-recurrent traffic conditions such as incidents can also trigger ramp metering activation. With more advanced and automated methods, the need for manual intervention is less.

The NCHRP Report 3-87 recommends considering the probability of breakdown as a measure to activate the ramp meters or be incorporated into the metering algorithms to calculate the metering rate (Elefteriadou et al., 2009). A 20% probability of breakdown was recommended as the threshold for the activation of ramp metering. This method is effective to decide on the activation during days with no incidents, construction, or weather events that impact capacity. However, the method does not allow the determination in real-time of which ramps. Moreover, this method is only applicable to recurrent traffic conditions and does not support the activation during non-recurrent conditions resulting from incident, weather, and construction events.

Two approaches to activate ramp metering were developed by Hadi et al. (2017c). In the first approach, a linear programming formulation of freeway and ramp system is applied in real-time to determine when to activate and deactivate ramp metering and which ramps to meter based on the stochastic capacity and the predicted demands in the next 15 minutes. The second approach uses a Look-Up Table derived offline that relates the ramps to be metered to the predicted demand/capacity ratio at the real-time activation decision stage, allowing identification of the specific ramps to be metered can be determined, as well as the time of their activation.

The I-210 Connected Corridor Pilot study conducted by Patire et al. (2016) compared four scenarios for a freeway incident, including no incident, incident without intervention, incident with coordination of ramp metering and signal control, and incident with coordination of ramp metering, signal control, and traveler information. For the scenarios with interventions, signal timing plans were changed to provide extra arterial capacity on alternative routes and ramp metering was changed to facilitate vehicles to reenter the freeways at the downstream of incident.

The San Diego I-15 ICM project defined 17 ramp metering-related response actions, which include no action, meter off, and meter rates from 1 to 15 (Dion and Skabardonis, 2015). Figure 26 shows the interface of ramp metering response options used in this ICM project. This interface allows the users to select ramp metering operations during an upstream or downstream incident in either a conservative, or moderate, or aggressive way.

Figure 26: Interface of the ramp metering response options used in the San Diego I-15 ICM project

Required Modeling, Data, and Capabilities

The following modeling, data and capabilities will be needed:

- Historical and real-time traffic flow parameters will need to be derived based on mainline and on-ramp and off-ramp sensor data for a whole year. This will allow the prediction of stochastic demands and capacities, identifying operation scenarios (based on clustering), and determining the probability of breakdown. If no ramp sensors are available, historical data from three-day tube counts on the ramps can be used. Although this is not as effective as using ramp sensor data, the method developed by Hadi et al. (2017c) can be used for activation decision based on the data,
- For ramp metering deactivation during arterial incidents, traffic counts from arterial traffic detectors will be needed. High-resolution controller data will be helpful in determining the shifts, although not necessary. Such data can be used to train a model using data mining techniques and/or to calibrate dynamic traffic assignment models.
- Travel time on arterials based on AVI and/or third party probe vehicle data is useful but not necessary, if deactivation during arterial incidents is to be implemented.
- Traffic management data is needed including ramp metering activation information and implemented metering rate and the activation and messages on dynamic message signs (DMS)

- Crash, incident and weather data is needed to determine the operation scenarios, frequencies, and associated capacity drops due to these events
- Offline microscopic simulation can be used to select the probability of breakdown threshold to use to activate metering. In the absence of such simulation, 20% probability of breakdown has been used.
- Offline microscopic modeling is useful to assess the impacts of ramp metering. The simulation should be done under different operational scenarios (multi-scenario evaluation), account for the stochasticity of the demand and capacity under each conditions, and account for the drop in capacity due to weather and incident events. The model must accurately reflect the impact of bottlenecks on the freeway mainline and on-ramps and accurately model the merging behaviors including those of trucks and their impacts on capacity and performance. The microscopic simulation model should be able to simulate ramp metering operations including the specific adaptive metering algorithm selected for the region (e.g., the Fuzzy Logic algorithm in Miami I-95 implementation and the Swarm algorithm in Broward I-95 implementation) using API extension of the program.
- For deactivating metering, a macroscopic or mesoscopic simulation-based dynamic traffic assignment (DTA) modeling is helpful. The simulation should be able to model the drop in capacity and change in performance and anticipated diversion and routes due to incidents utilizing a combination of behavioral models and DTA.
- Online microscopic, mesoscopic, or macroscopic model may be used to confirm the benefits of activation based on current data and forecasted conditions before implementation. The utilization of online modeling will increase the requirements in terms of reducing and utilizing real-time data in the model, ensuring that the model runs correctly in real-time, and meeting the latency requirement. Additionally, online modeling will require more expensive modeling tools, more complex ICM software and interfaces, and at least one analyst/modeler at the traffic management center to support ICM operations.
- Online software modules are required to implement rule-based, machine learning, and/or simulation modeling (if real-time simulation is used) to support real-time decisions.
- A data and traffic analyst is needed to analyze the collected data and utilize the method developed by Hadi et al. (2017c). Microscopic and DTA-based modelers will be needed if these tools are to be used.

3.5.2 Dynamic Modification of Express Lane Pricings and Restrictions

Description

In addition to implementing the pricing algorithms currently utilized for express lanes (EL) in the State, proactive changes to the rates and lane use restrictions can be applied when demand reaches a level with high probability of breakdown due to demand and capacity stochasticity, incident, and weather impacts. This can be accomplished using a similar procedure to that described for activating ramp metering in the previous section. The dynamic modification of EL management parameters can be done in conjunction with activation/deactivation of metering.

Applicable Operational Scenario

Daily operations (stochastic variation), freeway and severe arterial events, weather events, and special events.

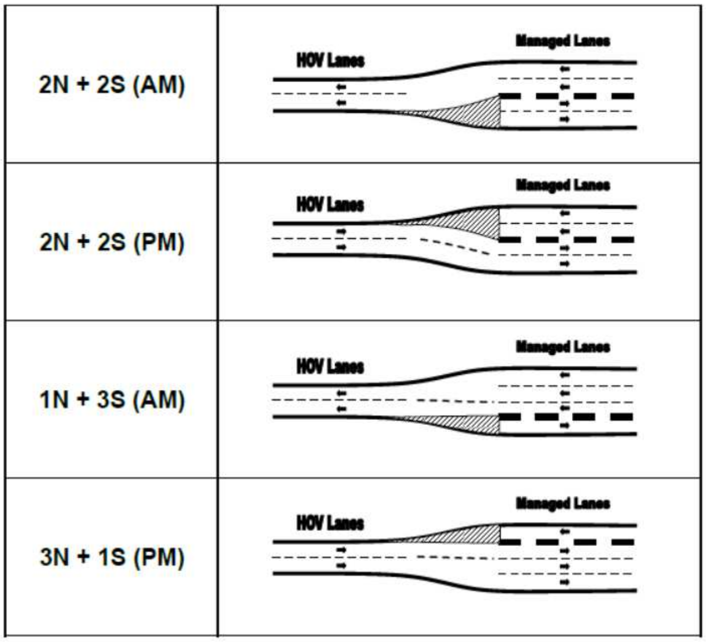
Potential Approach to Support Decisions

Three potential operations can be considered for express lane during severe incidents or special events along general-purposed lanes, including reducing or eliminating express lane pricing, reducing HOV occupancy requirements, and opening express lane to all traffics. A decision tree can be developed to determine when to apply these express lane operation modification strategies, depending on incident duration, number of lanes blocked, and traffic congestion levels on both general-purposed lanes and express lanes. The parameters of this decision tree can be decided using a data mining approach based on offline simulation modeling and/or traffic flow theory analysis approach similar to that proposed by Hadi et al. (2017c) for ramp metering activation. Offline simulation-based DTA modeling is needed. Online simulation is helpful.

Review of Previous Work

Dynamically modifying to the rates and restrictions of EL has been listed in the ConOps of FDOT District 4 and San Diego I-15 ICM.

Dynamic congestion pricing on managed lanes, increased HOV occupancy requirements, and their combinations were considered in the pre-deployment analysis plan, among the ICM strategies for the I-15 corridor in San Diego, CA (Dhindsa et al., 2010). High Occupancy Toll (HOT) lanes were opened to all traffic during major incidents to maximize throughput. This strategy was originally proposed in the I-15 Managed Lanes Operations and Traffic Incident Management Plans (HNTB Corporation and VRPA Technologies, Inc., 2007). The 20-mile 4-lane I-15 managed lanes are equipped with a movable barrier that can dynamically change number of managed lanes in response to directional traffic flow and major incidents. Figure 27 presents the configurations of managed lane for standard daily operations. Table 20 lists the twelve possible combinations of four managed lane (ML) and neighboring two reversible high occupancy vehicle lanes (RL). As shown in Table 20, four of the scenarios are for standard daily operations and the remaining eight scenarios are for incident management. A decision tree was proposed in this reference to determine the operations scenario of managed lanes when an incident occurs within the general purposed lanes, which is shown in Figure 28. It can be seen in this figure that when a general-purposed lane has a duration that is greater than 2 hours, the opening of managed lanes to all traffic depending on incident duration, lane blockage, peak direction of traffic flow, time of day and weekday or weekend. But it is noticed in this figure that when incident has a duration less than 2 hours and the number of lanes blocked is greater than 3, managed lanes are opened to all traffic regardless of traffic direction, time of day, and day of week.



Note: the letter "N" means "Northbound," the letter "S" means "Southbound," and the numbers indicate the number of lanes in that direction. For example, 2N+2S means two northbound lanes and two southbound lanes, and 3N+1S means three northbound lanes and one southbound lane. 2N+2S (AM) refers to 2N+2S configuration for the Managed Lanes with the HOV Lanes in the southbound direction during the AM commute hours, while 2N+2S (PM) refers to the same general configuration on the Managed Lanes with the HOV Lanes in the northbound direction during the PM commute hours.

Figure 27: I-15 managed lane configuration for standard daily operations (HNTB Corporation and VRPA Technologies, Inc., 2007)

Table 20: I-15 Operational Scenarios Relationship to the Utilization of Managed Lanes (ML) and Reversible HOV Lanes (RL)

ML	RL	→	ML	RL	Type
		Change To	2N+2S (PM)	2N	Standard Daily Operations
2N+2S (AM)	2S	Change To	1N+3S (AM)	2S	Incident Management
		Change To	3N+1S (PM)	2N	Incident Management
		Change To	2N+2S (AM)	2S	Standard Daily Operations
2N+2S (PM)	2N	Change To	1N+3S (AM)	2S	Incident Management
		Change To	3N+1S (PM)	2N	Incident Management
		Change To	1N+3S (AM)	2S	Standard Daily Operations
3N+1S (PM)	2N	Change To	2N+2S (PM)	2N	Incident Management
		Change To	2N+2S (AM)	2S	Incident Management
		Change To	3N+1S (PM)	2N	Standard Daily Operations
1N+3S (AM)	2S	Change To	2N+2S (PM)	2N	Incident Management
		Change To	2N+2S (AM)	2S	Incident Management

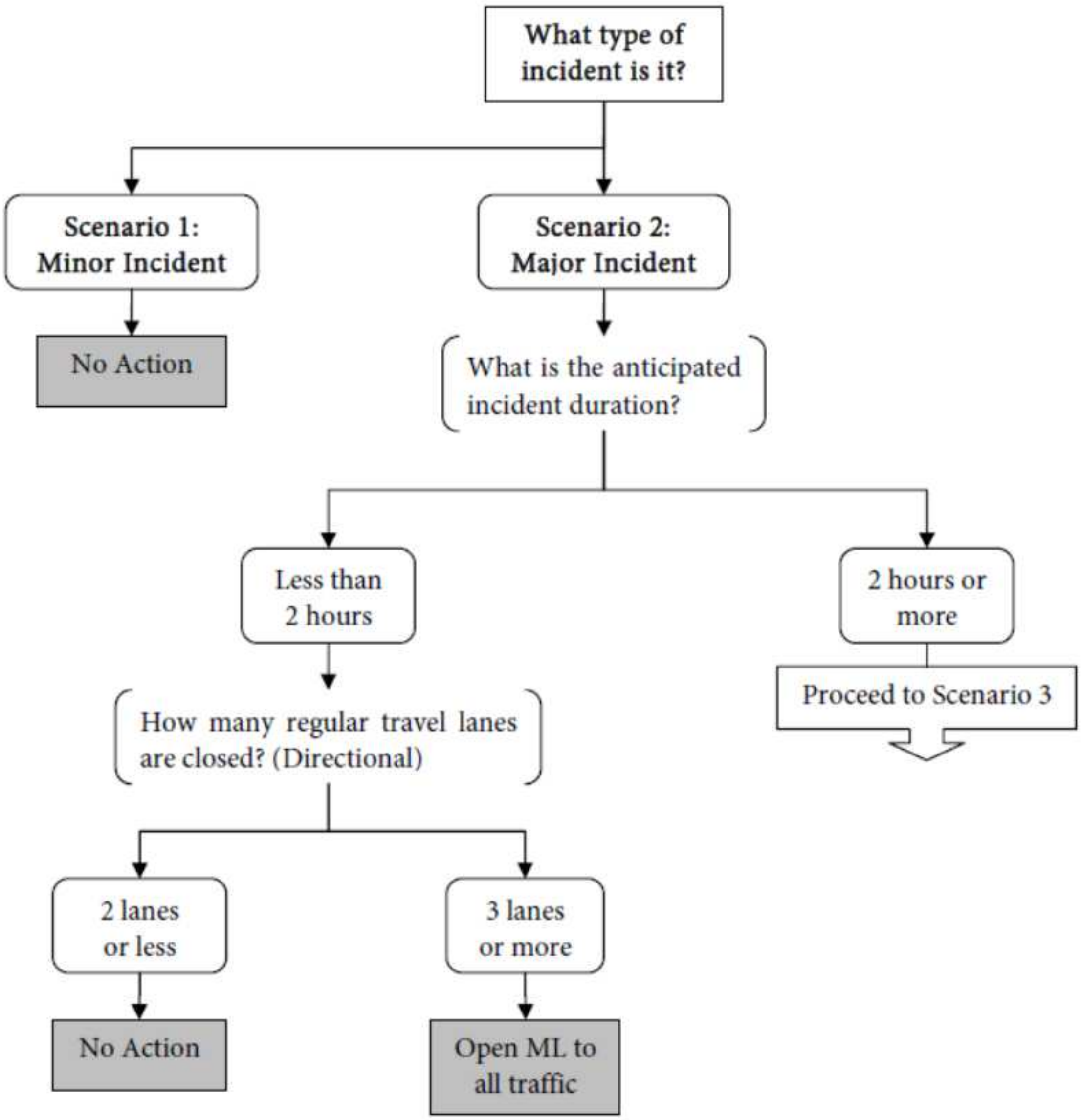


Figure 28: Decision tree for managed lane operation along I-15 in San Diego during a general-purposed lane incident (HNTB Corporation and VRPA Technologies, Inc., 2007)

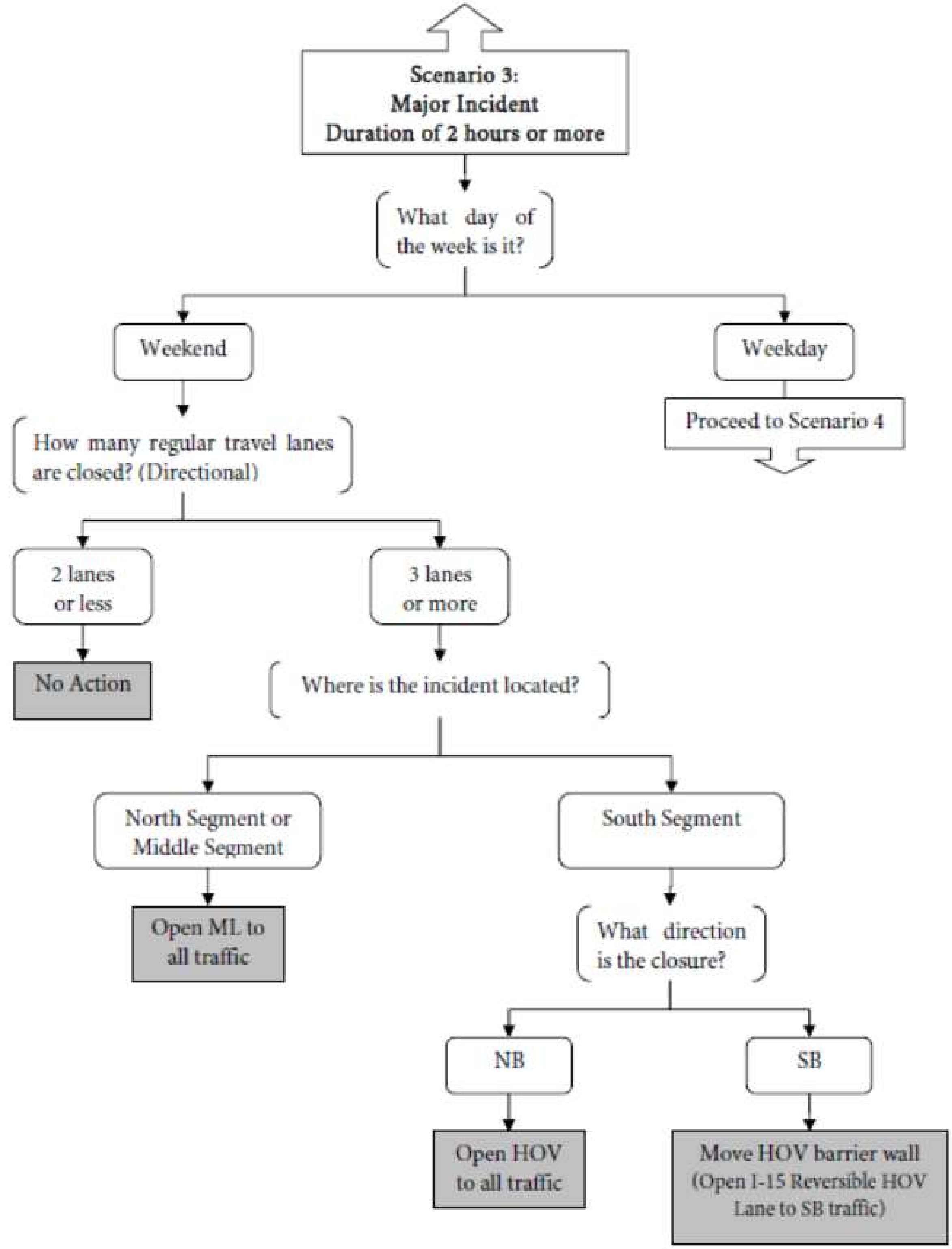


Figure 28: Decision tree for managed lane operation along I-15 in San Diego during a general-purposed lane incident (HNTB Corporation and VRPA Technologies, Inc., 2007) (Cont'd)

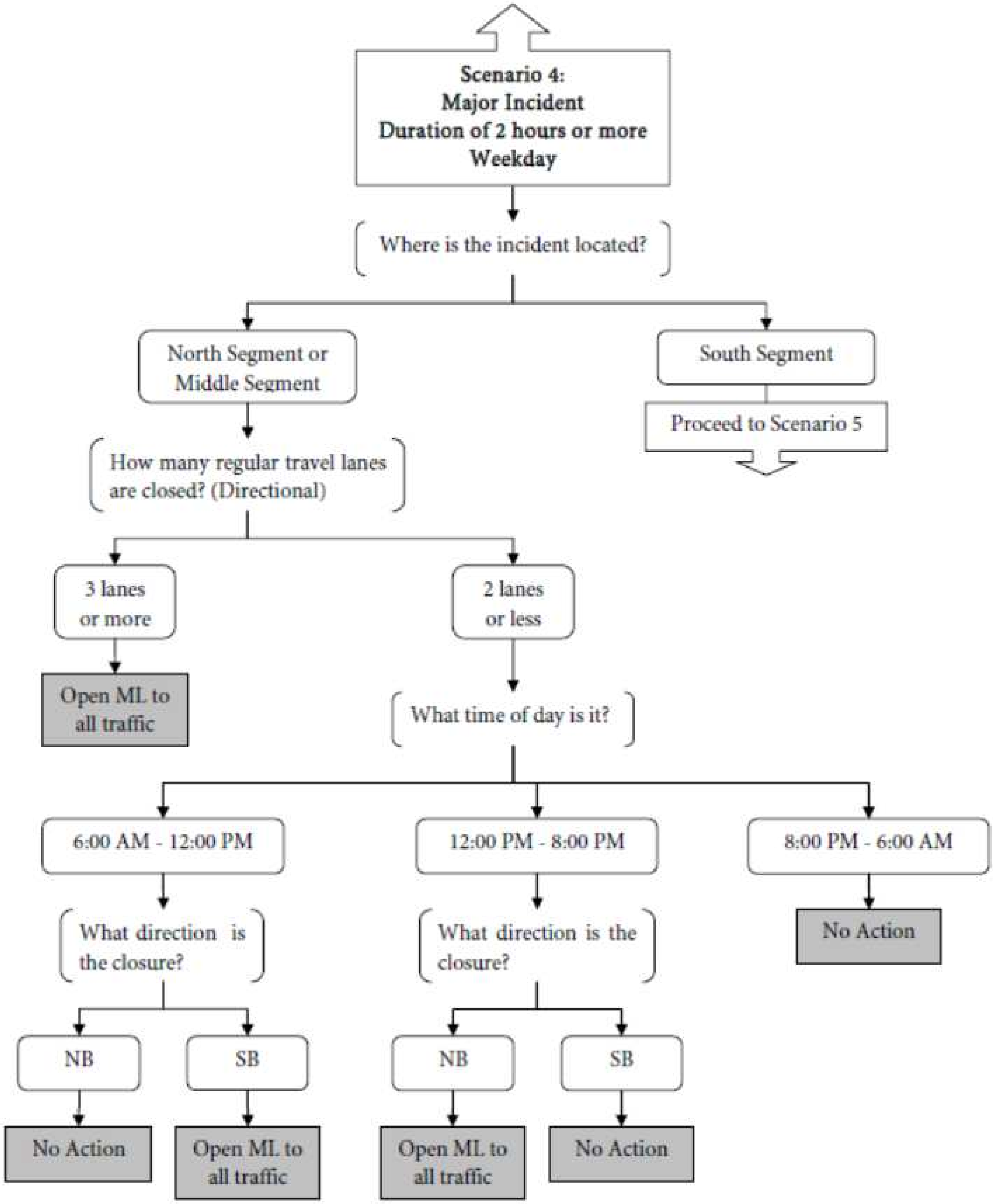


Figure 28: Decision tree for managed lane operation along I-15 in San Diego during a general-purposed lane incident (HNTB Corporation and VRPA Technologies, Inc., 2007) (Cont'd)

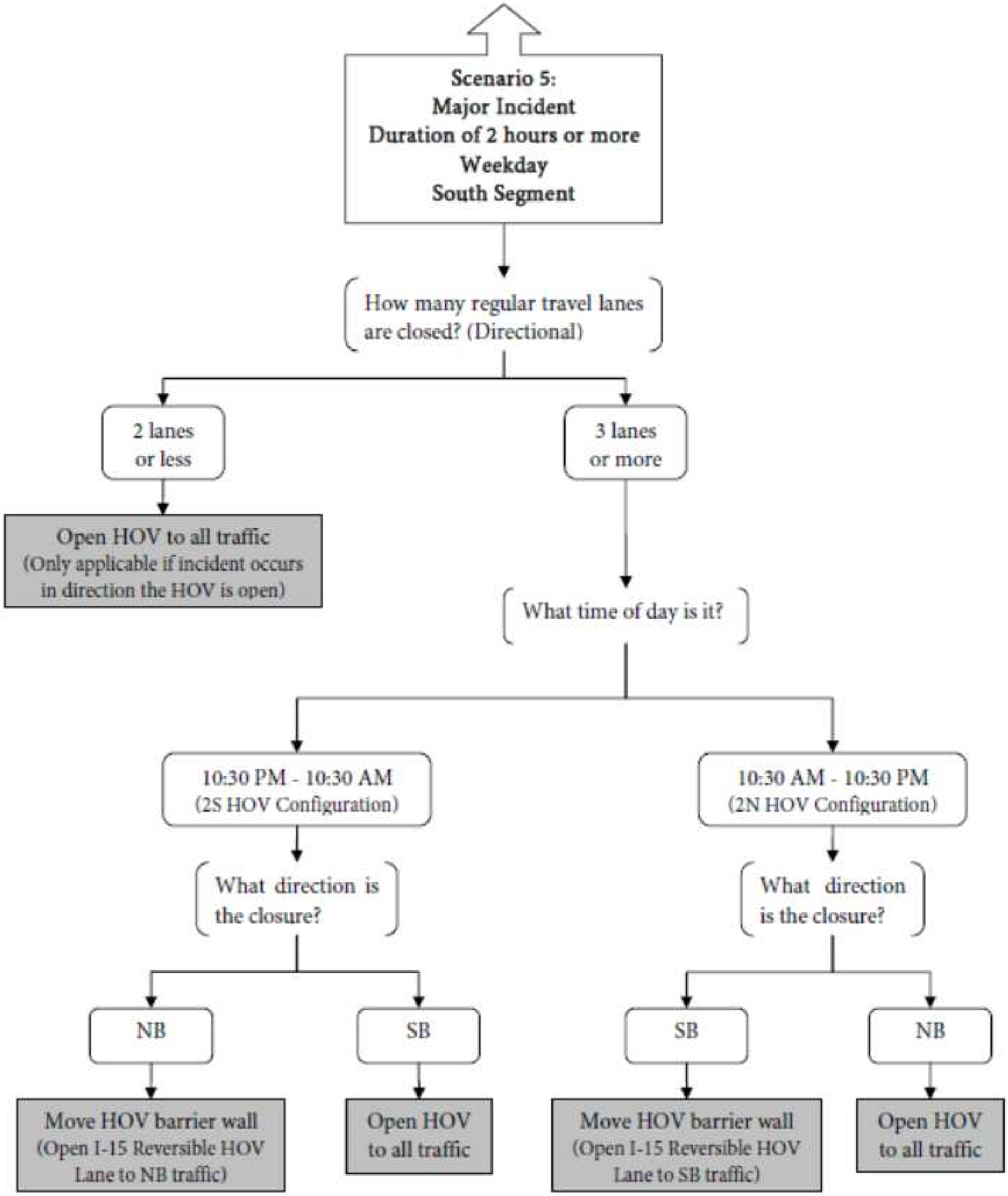


Figure 28: Decision tree for managed lane operation along I-15 in San Diego during a general-purposed lane incident (HNTB Corporation and VRPA Technologies, Inc., 2007) (Cont'd)

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with dynamically modifying express lane pricings and restrictions.

- Sensor data including traffic volume, occupancy, and speed data is required for both general-purposed lanes and managed lanes. Incident, weather, and event data is also needed. This data will be used for operation scenario generation through clustering, offline and online data analysis, and modeling support. Express lane tolling schedule and the actual charged pricing rates are also needed.
- There is a need to model the anticipated diversion between general purpose lane and express lanes utilizing a combination of behavioral models and dynamic traffic assignment (DTA) under different managed lane pricing and use constraints. A macroscopic or mesoscopic simulation-based DTA modeling is needed to model standard daily traffic operations as well as traffic conditions under incident conditions. The model should be able simulate the existing dynamic congestion pricing schedule.
- This strategy will benefit from offline use of a macroscopic and mesoscopic DTA model to model the impacts and to derive the parameters of a rule-based or data mining approach such that of decision trees to modify express lane parameters. The model should be able to account for the value of time in a region. This requires an offline modelers experienced in DTA and demand modeling.
- Macroscopic or Mesoscopic simulation-based DTA can be run in real-time to confirm the benefits of the strategies derived offline. These online DTA model needs to accurately capture the percentage usage of express lanes with the proposed or implemented express lane operation strategies based on origin-destination data estimated in real-time. The model should be able to react to triggers such as traffic, incident, and weather events to adjust the managed lane pricing and other operation parameters. Online use of modeling is not necessary but if applied correctly, it can be useful. There is an opportunity for using simpler online modeling based on the highway capacity manual procedures.
- Online software modules are required to implement rule-based, machine learning, and/or simulation modeling (if real-time simulation is used) to support real-time decisions.

3.5.3 Coordination of Ramp Metering and Signal Control

Description

This strategy involves generating and implementing special signal timing plans to prevent ramp spillback due to metering and provide information to drivers to divert from the ramps.

Applicable Operational Scenario

Daily operations (stochastic variation), freeway events, weather events, and incidents.

Potential Approach to Support Decisions

Four potential approaches can be proposed for supporting the decision to coordinate ramp metering and signal control. The first approach is to model ramp metering and signal control in an offline microscopic simulation model combined with a signal optimization algorithm. An optimization can be conducted offline to determine the optimal signal timing plans and ramp metering rates for each operational scenario. These plans can be saved in a library and selected in real-time when the associated operation condition is detected from a table look-up or using knowledge-based rules. The second approach is a variation of this approach that involves running the simulation model and optimization in real-time. Instead of relying on optimization, the third approach uses a heuristic method to determine the freeway metering rate and signal timing plan with a consideration of coordination between these two components. A fourth potential approach is to extend the fuzzy logic ramp metering algorithm to modify signal timing parameter selection. Microscopic simulation is also needed with the third and fourth approaches to adjust the parameters. Macro or meso-based DTA is not needed unless an assessment of potential diversion to alternative ramps is needed.

Review of Previous Work

This strategy has been selected as part of the San Diego I-15 and Los Angles I-210 deployments.Adjustment signal timing and phases has been proposed as one of the ramp terminal treatments in the FHWA Ramp Management and Control Handbook to manage on-ramp queue spillback to adjacent arterials and off-ramp queue spillback to freeway mainline (Jacobson et al., 2006). This Handbook recommends that at a minimum, traffic signal plans at ramp terminals should be reviewed every three to five years. It is expected that this will reduce average delay by 15% to 40%, travel time by up to 25%, fuel consumption by up to 10%, and pollutant emissions by up to 22%.

In the pre-deployment ICM analysis of I-15 in San Diego, CA, signal coordination on arterials with freeway ramp metering was selected as one of the prioritized ICM strategies (Dhindsa et al., 2010). The TransModeler microsimulation tool was used to model the coordination between ramp metering strategy and signal timing plan setup along the arterials. An assessment was made to identify the best plan that maximizes the operations on both the freeway and the arterials. Such coordination between ramp metering and signal control was also included in the post-deployment analysis, which utilized in the Aimsun microsimulation tool (Alexiadis and Chu, 2016b).

Lu et al. (2013) developed two control approaches to coordinate freeway ramp metering and arterial traffic signal and then implemented the first approach in the field at one intersection in City of San Jose, CA. The first method is a heuristic approach. It divides the freeway traffic conditions into five categories from low volume, to medium, to high. Different ramp metering and signal control operations were proposed for each category of freeway traffic conditions, as shown in Table 21.

Table 21: Heuristic Approach Proposed by Lu et al. (2013) for Coordinating Freeway Ramp Metering and Arterial Traffic Signal Control

Freeway Traffic Condition	Entrance Ramp Metering	Intersection Traffic Signal
Low traffic volume with an occupancy less than 4%	Ramp metering is all time green	Feeding movements have higher priority into the freeway
Medium to high traffic volume (Occupancy is between 4% and 8%)	Proportional ramp metering control strategy (ALINEA) that regulates the occupancy of the immediate downstream of the entrance ramp (that is, merging area) close to the critical occupancy of 8%	Balance the demand/supply ratio of all the movement subjected to entrance ramp storage limit, which implicitly uses intersection storage
High traffic volume (Occupancy is between 8% and 20%)	Ramp metering rate is proportional to mainline occupancy (ALINEA) that regulates the occupancy of the merging area close to a certain threshold (for example, 15%) to delay freeway traffic breakdown with the constraints of entrance ramp and intersection storage. Entrance ramp storage capacity is fully used.	Green time distribution to balance the demand/supply ratio of all the movements subjected to entrance ramp storage limit
Traffic over capacity (Occupancy is between 20% and 30%)	Ramp metering rate is proportional to mainline occupancy (ALINEA) that regulates the occupancy of the merging area close to a certain threshold (for example, 25%) to stabilize the freeway traffic. Entrance ramp storage capacity is fully used.	Fill up the intersection storage first, and reduce green times of the movements to the entrance ramps while using the upstream intersection storage if necessary. Then balance the demand/supply of other movements except the movements to the entrance ramp. Use extra cycle time for other movements.
Saturated traffic with an occupancy greater than 30%	Increase the ramp metering release rate but this may be limited by the vehicle acceptance of freeway mainline. An alternative approach is to use the minimum metering rate. Entrance ramp storage capacity is fully used in this case.	Fully use intersection storage while avoid gridlock and use upstream intersection storage. Green time distribution to balance the demand/supply ratio of all the movements except those leading to the freeway entrance ramp.

The second approach is a system-wide optimization. The optimization objective function can be the weighted vehicle-hour traveled (VHT) and vehicle-mile traveled (VMT) for freeway and arterial. The testing results showed that the developed method can improve turning movement throughputs, reduce total delay and improve the use of the entrance ramp. However, the performance of the freeway mainline volume remained the same due to the implementation of the proposed method only at one onramp site.

Min et al. (2016) enhanced a mixed-control algorithm by including an expression for ramp entrance flow rate as a function of upstream intersection flows into the formulation. Note that the original mixed-control algorithm only considers the difference between freeway mainline upstream and downstream flow to calculate ramp metering rate. Figure 29 shows the flowchart of the enhanced control algorithm. The symbols in this figure, p, L, G, r, represent the control objective function, ramp queuing length, green time of the upstream intersection, and ramp entrance flow rate, respectively. The control objective function p is a weighted average of ramp queueing length and the difference between downstream density and downstream critical density.

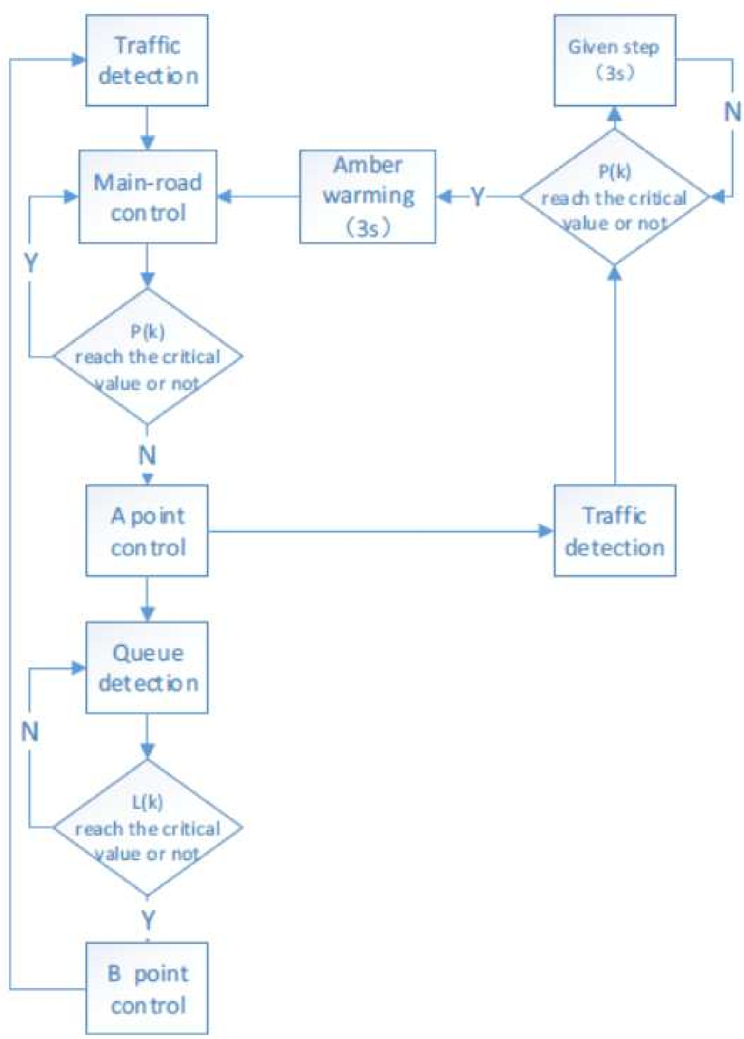


Figure 29: Flowchart of the enhanced coordinate control of entrance ramp (Min et al., 2016)

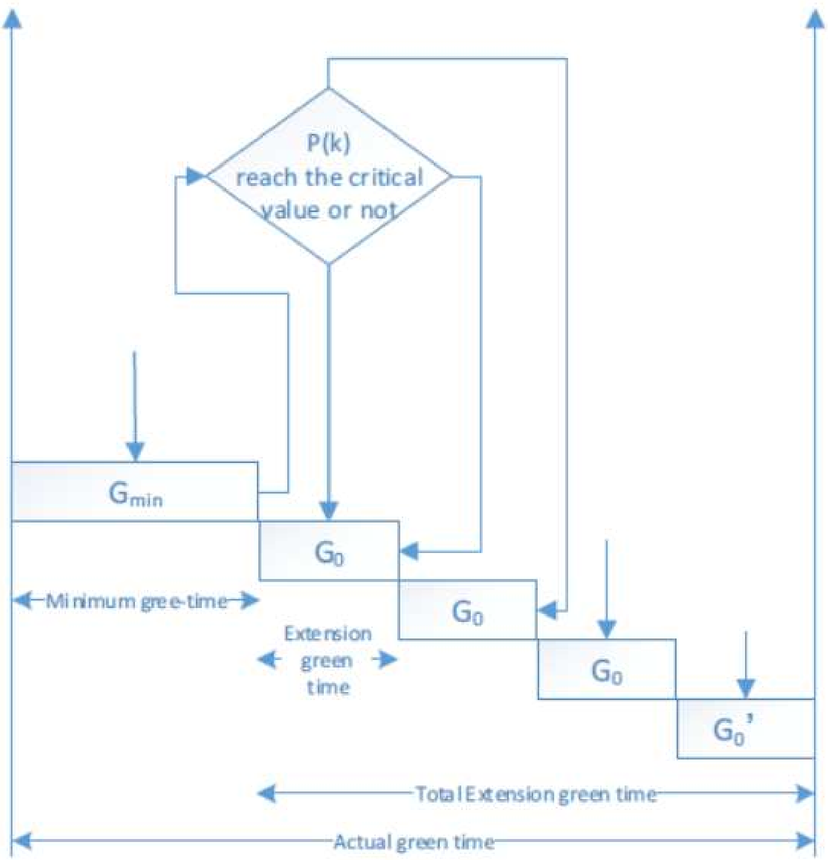


Figure 29: Flowchart of the enhanced coordinate control of entrance ramp (Min et al., 2016) (Cont'd)

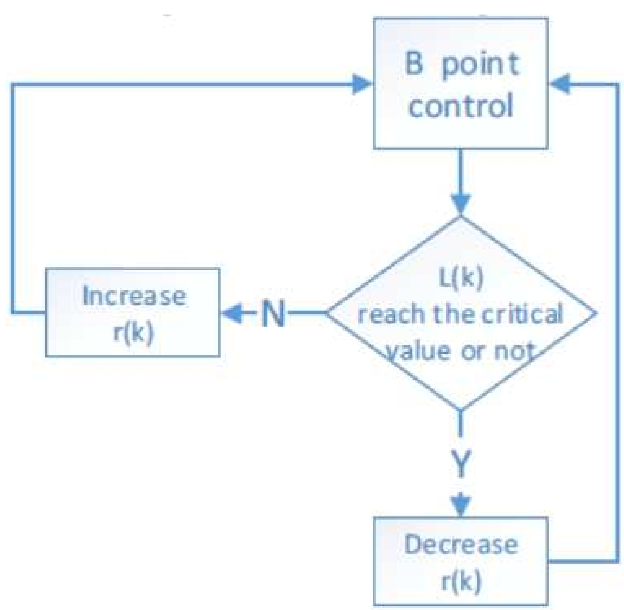


Figure 29: Flowchart of the enhanced coordinate control of entrance ramp (Min et al., 2016) (Cont'd)

On-ramp queue override has been a common approach used in practice to avoid on-ramp queue spillback to adjacent arterial streets, which increases the ramp metering rate to a maximum value when on-ramp queue is detected by the detector at the entrance of on-ramp. However, based on a study by Kan et al. (2017), the queue override approach can reduce freeway queue discharge flow by 5-10%. Instead, Kan et al. (2017) proposed a control strategy to coordinate freeway ramp metering and adjacent arterial signal. An analytical expression for the upper limit of cycle length was developed by constraining the excess accumulation of vehicles on the on-ramp to be less than the on-ramp queue storage capacity. The simulation results in Aimsun showed that the proposed algorithm can reduce system-wide delay with a moderate penalty on adjacent arterials.

Required Modeling, Data, and Capabilities

In addition to the data and modeling required for dynamic activation of metering, the followings additional requirements associated for coordinating ramp metering and signal control:

- Additional data requirements include archived ramp queuing detector data and the associated metering override data. This data will be used to calibrate the models and/or for data mining purposes. Arterial segment detectors and possibly AVI or third party private sector data are helpful to assess arterial performance. High resolution controller data of upstream signals can be also very helpful.
- Offline microscopic simulation models can be used to assess the interaction between ramp metering and signal control. The model should be able to react to traffic conditions in the simulation and apply updates to metering and signals based on algorithms coded using the Application Programming Interface (API) of the simulation model. Optimization algorithm is needed in combination with simulation.
- The developed models can be implemented in real-time to support the decision. An alternative approach is to utilize a table look-up, rule-based, fuzzy logic, or a data mining approach to select a response plan based on real-time data.

3.5.4 Periodic Signal Retiming

Description

Periodic signal retiming optimizes signal timing plans and their times of activation offline based on signal optimization models combined with detailed data that becomes available from different sources such as high-resolution controller data and connected vehicle data. Traditional signal optimization methods and tools use very limited amount of data and depend on default values to model network performance under different signal optimization strategies. In recent years, new data collection technologies are becoming available allowing better optimization of signal control parameters including data from automatic-vehicle based identification technologies, third party crowdsourcing data, connected vehicles, and connected automated vehicles data.

Applicable Operational Scenario

Daily operations including stochastic variations.

Potential Approach to Support Decisions

The signal retiming can be based on data, modeling, or a combination of the.   There is a great potential for the use of high resolution controller data, as formulated in the work by Purdue University (Sharma et al., 2007; Day et al., 2015; and Mackey, 2014) and connected vehicle data in signal timing optimization; either by themselves or in combination with simulation or highway capacity manual-based (HCM-based) models. The data will also enable better inputs to signal optimization and simulation tools including the estimation of demands, saturation flow rates, lost time, platoon progression, arrival on green, queue length, delay, split failure, phase termination type, and so on. The above mentioned new and emerging data collection technologies combined with more advanced signal optimization models are expected to have transformative changes in improving signal timing optimization and management processes of transportation agencies. The time to switch between signal timing plans can be also determined based on clustering analysis combined with the use of HCM-based or simulation models.   Microscopic simulation may be used to confirm the performance assessment of the plans estimated based on the optimization tool. Macro or meso-based DTA is not needed.

Review of Previous Work

The Signal Timing Manual developed by Urbanik et al. (2015) recommended a list of steps for retiming an intersection for under-saturated conditions:

- Perform a qualitative evaluation of the intersection performance to determine if it is possible to make any obvious improvements.
- Adjust the splits to accommodate demand on competing approaches.
- Adjust the offsets to reflect platoon arrival time.
- Adjust the start and end times of a time-of-day signal timing plan.
- Review the cycle length to determine the need for a new signal timing study.

For oversaturated conditions, the Signal Timing Manual (Urbanik et al., 2015) recommended to review the splits first and then cycle length, and adjust these two if possible. If improvements cannot be made with such adjustments, the oversaturation mitigation strategies listed in Table 22 can be applied. These strategies range from maximizing intersection throughput to managing queues.

Gordon (2010) conducted a comprehensive review of traffic signal retiming practices in the United States. Based on this review, it was concluded that agencies usually retime signals every 3 to 5 years. Examples of the signal retiming methodologies include 1) performing a comparative analysis of cycle lengths, offsets, phase sequence, and other timing parameters as part of the signal timing evaluation and implementation process; 2) considering different signal phase sequences to minimize interruption of traffic progression for a coordinated system; 3) using actuation and off-peak timing practice to improve flow when traffic is light; and 4) timing actuated controllers; using operational strategies to promote smooth and efficient traffic movement along arterials when traffic is light. It was also reported that agencies usually rely on signal timing software to conduct signal retiming, which include the Highway Capacity Software (HCS). Macroscopic and microscopic simulations are used to evaluate the impacts of signal retiming.

Table 22: Mitigation Strategies for Oversaturation Conditions (Source: Urbanik et al., 2015)

Operational Objective	Type of System	Mitigation Strategy	Definition
Maximize Intersection Throughput	Individual Intersection(s)	Split Reallocation	Reallocating split time from under-saturated phases to oversaturated phases.
		Cycle Length Increase	Adding split time to oversaturated phases without reducing split time for minor movements, effectively increasing the cycle length.
		Operation of Closely Spaced Intersections on One Controller	Operating two intersections using one controller, allowing close coordination.
	Arterial	Phase Sequence Modification for Left Turns[1]	Changing the phase sequence to lead or lag left turns, increasing the bandwidth for progressing platoons.
		Preemption Flushing ("Green Flush")	Progressing oversaturated movements by placing calls from downstream intersections to upstream intersections.
		Alternative Timing Plan Flushing	Using a timing plan to increase the cycle length and give the majority of the green time to the oversaturated phases.
Manage Queues	Individual Intersection(s)	Green Extension	Adding green time to a phase when a detector exceeds a defined threshold of occupancy.
		Phase Re-Service	Serving an oversaturated phase twice during the same cycle.
		Phase Truncation	Termination of a green interval (despite demand) when there is minimal to no flow over a detector.
	Arterial	Simultaneous Offsets	Setting offset to zero between intersections, so that queues move simultaneously.
		Negative Offsets	Starting the green interval earlier at downstream intersections to allow the downstream queue to dissipate before upstream vehicles arrive.
		Offsets to Prevent Queue Spillback	Choosing offsets that allow the downstream queue to clear before the upstream vehicles reach the end of the downstream queue.
		Offsets to Prevent Starvation	Choosing offsets that ensure the first released vehicle at the upstream intersection joins the discharging queue as it begins to move.
	Network	Metering (Gating)	Impeding traffic at appropriate upstream points to prevent traffic flow from reaching critical levels at downstream intersections.
Maximize Intersection Throughput and Manage Queues	All	Adaptive Control	Applying detection data and adaptive signal control algorithms to adjust signal timing.
		Combination of Mitigation Strategies	Combining mitigation strategies and/or using them in sequence throughout the oversaturated period.

[1] This strategy can also be applied at the individual intersection level, but is primarily used for arterials.

The Broward County Traffic Engineering Department (BCTED) conducted a signal retiming in year 2011. The updated signal timing plans were originally based on the results of Synchro files for four time periods of a weekday, including AM peak, Midday, PM peak, and night periods. These signal timing plans were further fine-tuned in the field (Stevanovic et al., 2015) and the adequacy of current signal timing plans was assessed based on recent Microwave Vehicle Detection System (MVDS) data. The performance in terms of delay produced by the Synchro files using current signal timing plans and using optimized signal timing plans were compared.

In the scope of service for FDOT District 5 (FDOT District 5, 2017), a clustering-based approach was proposed to periodically optimize signal timing. In this approach, 5-minute time intervals are to be aggregated into groups based on day of the week or special days such as holidays and Euclidian distance of the volume to capacity ratio for all movements between two contiguous intervals. Each group can only have one active signal timing plan at a given time. These groups are further clustered into a configurable number of groups based on their centroids. The purpose of clustering is to reuse a signal plan for multiple groups. For each group resulting from clustering analysis, the optimized signal timing is obtained by allocating green times based on saturation flow rates for each movement. A "FIT" Score of a timing plan is calculated as the Euclidean distance between the existing timing plan and optimized signal timing plan. The FITS score of a corridor or a network is based on the volume weighted average of the FITS score of individual intersections.

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with periodic signal timing optimization.

- Collecting archived arterial midblock detector data and high resolution controller data combined with AVI data (such as Bluetooth and Wi-Fi) and/or third party private sector data will allow determining issues in the existing signal timing and control, identifying operational scenarios to consider in the optimization , guiding signal fine tuning, and providing more detailed data for signal timing optimization tools. Controller data especially high-resolution controller data that includes signal timing and detection at 0.1 second resolution, in combination with data from other sources such as AVI data can be used to support Automated Traffic Signal Performance Measures (ATSPM).
- High resolution controller data will require controllers or data loggers that can report high-resolution controller data to a central software. An ATSPM software will be required to produce performance measures.
- Data mining techniques like clustering and pattern recognition can be used to associate time and space with specific plans.
- Optimization, machine learning, rule-based, or fuzzy logic algorithms have the potential to be used to optimize timing parameters based on data.
- Signal control can be optimized using existing off-the-shelve optimization tools that usually use macroscopic analysis to assess the performance of alternative solutions in the optimization. Optimization procedures have also been used that combine microscopic simulation with heuristic optimization techniques such as Genetic Algorithms.
- When conducting the optimization, multi-scenarios should be considered with different levels of demand.
- Periodic signal retiming is usually conducted offline based on archived signal control data and traffic data. There is no need for real-time modeling. However, the selection of signal timing plans can be conducted based on traffic conditions from a library of plan in real-time, as is usually referred to as traffic responsive plans.

- Utilizing emerging concepts in signal timing optimization requires staff knowledgeable in high resolution controller, data analytics, signal control optimization, and associated optimization and simulation tools.

3.5.5 Adaptive Traffic Signal Control

Description

Adaptive Traffic Signal Control (ATSC) optimizes overall signalized intersection performance by continually adapting signal timing for each movement to actual traffic conditions. ATSC is typically chosen for its capability to handle high day-to-day and within-a-day traffic variability Examples of early adaptive signal control system include Split Cycle Offset Optimization Technique (SCOOT), Sydney Coordinated Adaptive Traffic System (SCATS), Real Time Hierarchical Optimized Distributed Effective System (RHODES), Optimized Policies for Adaptive Control (OPAC) "Virtual Fixed Cycle". Examples of newer systems are the Adaptive Control Software Lite (ACS Lite), InSync, and SynchroGreen.

Applicable Operational Scenario

Daily operations (stochastic variation), freeway incident and weather events, and arterial major events. Adaptive signal control can be implemented along strategic arterials that can response to the real-time changes in demand due to diverted traffic from freeways. However, it is not clear how well can adaptive signal control operates under sharp differences in condition such as those occurring during incidents and adverse weather conditions.

Potential Approach to Support Decisions

Performance measures estimated from high-resolution controller data as well as data from other sources such as AVI data can be used to estimate adaptive signals and arterial street performance under different conditions. In addition, the effectiveness and operation of adaptive signal control may be modeled using a microsimulation environment utilizing the API facility of the simulation and compared to other ICM strategies under different recurrent, incident, and weather scenarios.

Review of Previous Work

Fehon et al. (2012) developed a report entitled "Model Systems Engineering Documents for Adaptive Signal Control Technology Systems" to guide professional in preparing for systems engineering documents that cover the evaluation, selection, and implementation of adaptive signal control system.

One of the strategies used in the I-95/I-395 ICM project in Virginia was to implement adaptive signal control along arterials that are considered as freeway alternative routes and arterial routes connecting I-95 to park-and-ride lots (Dion, 2013).

Frank and Lennon (2015) evaluated the potential ICM strategies for the operations of a freeway and a parallel arterial using the VISSIM model. One of the strategies is to deploy adaptive signal control along the parallel routes to encourage the usage of these parallel routes.

Fontaine et al. (2015) evaluated 13 ATSC corridors in Virginia, using Bluetooth and INRIX data. The results of the evaluation showed that mainline traffic operations improved if (1) the corridor was not oversaturated; (2) the platoon dispersion is not high; and (3) the corridor did not already function well. The study found that the side street delays generally increased, although there were net benefits in overall corridor travel time.

Mirchandani et al. (2017) developed an integrated meso- and micro-simulation models to evaluate traffic management strategies. In this study, a high-resolution DTA (HD-DTA) based on the DTALite tool was developed, which can run the simulation on a second by second basis. As it is difficult to implement adaptive signal control system within HD-DTA; an adaptive signal control system, RHODES, was integrated in VISSIM. This study built additional linkage between HD-DTA and VISSIM such that VISSIM can send all real-time signal phase status to HD-DTA and HD-DTA can send detector calls to RHODES. This integrated models have been used in the Phoenix Connected Vehicle Dynamic Mobility Applications (DMA) and Active Traffic and Demand Management (ATDM) strategies testbed funded by the Federal Highway Administration (FHWA) (Yelchuru et al., 2017b).

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with adaptive signal control.

- The adaptive signal control systems add significant hardware and software requirements including reliable detection, in addition to extra cost for setting the system. Adaptive signal control requires reliable detection of all intersection movements to provide data to the control algorithm.
- The required locations of the detectors vary depending on the specific adaptive signal control system. Most existing adaptive signal control system have stop line detection and advance detection.
- Microscopic simulation allows the assessment of the effectiveness of adaptive signal control. The effectiveness need to be examined under different operation scenarios including diverting vehicles from freeways to parallel arterial streets and during arterial events. Mesoscopic simulation can be used in combination with microscopic simulation to estimate the diversion between routes. The simulation can be used to compare the effectiveness of adaptive signal control with other ICM strategies.
- In most adaptive signal control, there is no need for real-time simulation. One known exception is the Adaptive Control Decision Support System (ACDSS) system developed by KLD Associates, Inc in collaboration with other team members. The system conduct real-time optimization for both over- and under-saturated traffic in near real-time using the Aimsun microscopic traffic simulation.
- The deployment can require significant effort to calibrate and fine-tune the system.
- Adaptive signal control systems require staffs that are well trained on the specific installed system.
- The selected system must adapt to unexpected surges in traffic conditions expected with ICM operations. It is not clear how well can existing adaptive signal control deal with these shifts such as maximizing green time on diversion routes to flush traffic.

3.5.6 Special Signal Plans during High Demand and Events

Description

Travel demand at signalized intersections can be significantly different from "normal" traffic conditions due to stochastic demand surges, during freeway events as vehicles divert to alternative arterial streets or during an arterial event with reduced capacity. It is necessary to adjust signal timing under these circumstances and provide more green time to the affected movements to minimize the overall delay experienced by travelers.

During arterial incidents, capacity drops requires the implementation of signal timing plans that maximize the throughput and minimize queue spillback. Such plans, if well designed, could be activated under incident conditions that are determined to benefit from such activation.

Applicable Operational Scenario

Freeway incidents, weather events, and arterial events.

Potential Approach to Support Decisions

A clustering analysis should be conducted based on traffic, incident, and weather data; first to classify incidents and events into different groups based on event duration, number of lanes blocked, and traffic parameters along the subject segment and alternative routes. Then, a special signal plan need to be derived and implemented based on each scenario. One approach is to construct a library of special signal plans by using a microscopic simulation model combined with a signal timing optimization software or algorithm for each incident/event operational scenario identified based on clustering. Mesoscopic simulation for a larger network can be applied to estimate the diversion rates and utilization of alternative routes. Based on real-time and predicted traffic conditions as well as incident status, agencies can select the best signal timing plan from the library using a look-up table or rules. A second approach is to run the optimization algorithm and the simulation online when an event occurs to determine the optimal signal control.

Review of Previous Work

Signal control strategies were recommended for three special conditions in Signal Timing Manual (Urbanik et al., 2015), which include weather events, traffic incidents, and planned events. Four weather-related signal timing strategies were proposed in this documents:

- Increase vehicular red clearance intervals by one to two seconds to reduce right-angle crash potential at signalized intersection
- Increase minimum green times to account for start-up lost time due to weather events
- Implement phase recall to mitigate the ineffectiveness of vehicle detection system because of severe weather impacts such as ice over video detection
- Weather-responsive coordination plans developed specifically for weather events

For traffic incidents, a list of factors can be considered by agencies determine when and where to deploy incident-related signal timing plans.

- Estimate incident duration, type, and severity of the incident and the number of lanes closed.
- Observe traffic conditions and note time of day and day of week
- Estimate amount of available capacity along the alternative route
- Monitor traffic along the alternative route
- Improve traffic control and equipment along the alternative route

Below are the recommendations for terminating incident-related signal timing plans.

- Removal of incident from the primary facility and full restoration of capacity
- Partial restoration of capacity along the primary facility and traffic demand can be accommodated by primary facility capacity
- Deterioration of traffic conditions on the alternative route

Special event-related signal timing plans can be determined in the same way as incident-related plans. Four common strategies are recommended for both incident-related and special event-related signal timing plans.

- Select an existing time plan with longer cycle lengths
- Implement a customized signal timing plan
- Deploy a contingency “flush” plan that includes extended phase or cycle for main movements
- Manual control of traffic signal operations

The New York State Department of Transportation (NYSDOT) is sponsoring the Lower Hudson Transit Link program (NYSDOT, 2018). This program aims to improve travel conditions across the I-287 corridor between Rockland Westchester Counties including the implementation of an ICM system. Based on the design of this system, sensors will relay information to Hudson Valley Transportation Management Center (HVTMC) that intersection is backed up. The HVTMC adjusts signal timing to alleviate congestion for higher-demand direction.

The Coordinated Highway Action Response Team (CHART) in the State of Maryland monitors incident using detectors, cameras, a cellular phone system, and weather sensors. Once an incident is detected, the associated information is sent to the operation agencies who will decide if a diversion and a change of signal timing is needed (Koonce et al., 2008). The signal system software allows pre-set signal plans to be implemented when needed. Similar practice is also carried out by the City of Portland, where the signal timing is adjusted to accommodate the influx of volume when there is a diversion resulting from incidents (Koonce et al., 2008).

For the Dallas US-75 ICM test corridor, incident signal timing plans have been developed to flush the diverted vehicles to arterials during freeway incidents (Alexiadis and Chu, 2016a). As freeway incidents occur at various locations with different attributes, a clustering analysis was first conducted to classify incidents into different groups based on number of lanes affected, incident duration, direction, time of day, weather, freeway traffic, and probable diversion calculated from the Dynamic Intermodal Routing Environment for Control and Telematics (DIRECT). Signal timing plans were developed for those identified clusters and prioritized based on their impacts on freeway and the surrounding roadway network delays. The signal timing plans were tuned based on the probable traffic volumes estimated based on DIRECT. The DIRECT model allows the coding of green/red time split and dynamic activation of a new signal timing plan. Table 23 shows the criteria-based expert rules for response plan recommendations (Alexiadis and Chu, 2016a).

Table 23: Expert Rules for Response Plan Recommendation (Source: Alexiadis and Chu, 2016a)

Strategies	No. Affected Lanes General Purpose and HOV	Main Lanes Speed (mph)	Main Lanes Queue Length Derived from Avg. Speed (mi.)	Speed FR (on Diversion Route) (mph)	Speed GV (on Diversion Route) (mph)	Prediction Δ MOP Plan versus Do Nothing	Park and Ride Utilization	Light Rapid Transit Utilization
Minor Incident: Short Diversion to FR.	≥ 1	< 30	0.5 < Q <1	> 20	N/A	< 0%, < 2%	N/A	N/A
Major Incident: Long Diversion to FR.	≥ 1	< 30	Q ≥ 1	> 20	N/A	< 0%, < 2%	N/A	N/A
Major Incident: Diversion to FR. GV.	≥ 2	< 30	Q ≥ 1	< 20	> 20	< 0%, < 2%	N/A	N/A
Major Incident: Diversion to FR. & GV., Transit	≥ 2	< 30	Q > 4	< 20	< 20	< 0%, < 2%	< 85%	< 85%
Major Incident: Diversion to FR. and GV., Stop Transit Diversion (No DMS action)	≥ 2	< 30	Q > 4	< 20	< 20	< 0%, < 2%	> 85%	> 85%

(Source: Texas A&M Transportation Institute.)

Most of the signalized intersections within the San Diego I-15 ICM network are operated utilizing actuated signal control (Alexiadis and Chu. 2016b). For the base scenario of the ICM model, each signal control operates based on a time-of-day schedule generally with eight different coordinated control plans and one free uncoordinated plan. During a congested event, some intersections along the alternative routes switch to an alternative signal plan to provide additional green time to accommodate the increased traffic. Such information will be sent to Aimsun model through the iNET system (an automatic traffic management system for field device monitoring and control, data fusion, event management, and response plan generation) to activate the alternative signal timing plan in the model.

Changing signal timing plan during freeway and arterial major incidents was also proposed in the concept of operation of the I-210 ICM project (Dion et al., 2015). In Phase 1 of the I-210 Connected Corridors Pilot study, signal timing changes were modeled in two of the four evaluation scenarios (Patire et al., 2016). In those two scenarios, signal timing plans along the arterial were modified to increase the capacity of the main approaches by increasing the cycle length and the relative green time for the main direction while the green time for the side streets were kept constant. The simulation effort to assess the plans used Cell Transmission Model in Phase 1 of this ICM project and Aimsun software for modeling in Phase 2.

The implementation of incident responsive signal control strategies is also effective in relieving congestions during incidents. The researchers of this study develop and evaluate a methodology to support the planning for operations of incident responsive signal utilizing a multi-resolution analysis approach (Massahi et al., 2019). This study demonstrated the utilization of a multi-resolution and multi-scenario modeling approach to support the evaluation and design of incident management strategies and the associated incident responsive signal control. The results from the simulation indicated that the implementation of incident responsive signal control strategies of the investigation case study was able to provide an improvement of 18.5% and 24.5% for the total delay (in veh-hrs) of the thru movement in the incident direction for 30-minute and 45-minute arterial incidents, respectively. The corresponding reductions in total delay of all movements in the segment were 7.5% and 9.5%, respectively.

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with the implementation of special signal control plans.

- Archived and real-time freeway and arterial detector data and existing signal timing plans are needed. AVI or third party private sector data are also needed on arterial streets to support incident/congestion detection. High resolution controller data is helpful in detecting congestion/incidents and setting the signal timing plans
- There is a need for the offline modeling of freeway and arterial events including incidents and special events using macroscopic or mesoscopic simulation-based DTA to assess diversion and microscopic simulation to assess signal performance.
- There is a need to classify incidents and conditions into different groups using clustering analysis in order to decide on typical incident conditions that need to be modeled and, for which response plans are derived.
- Signal timing optimization under different incident and traffic conditions is needed based on an optimization tool or algorithm
- Offline modeling and/or pattern recognition/clustering analysis based on data is needed to determine when to activate and deactivate incident/special event-related signal timing plans.
- If real-time modeling and online signal optimization are used, there is a need to run macroscopic or mesoscopic simulation-based DTA to assess diversion, microscopic simulation to assess signal performance, and optimization modules to optimize signal timing plan.
- If the selection of plans is based on a pre-determined set of plans derived offline, there is a need for a software module to recommend the activation and deactivation of incident/special event-related signal timing plans based on real-time and predicted traffic conditions.
- For offline modeling, there will be need for a modeler that have the capability to model freeway and arterial events, and capture the impacts of these events including route diversions using DTA; macroscopic, mesoscopic, and microscopic. The developed models shall have the capability to code and select the best signal timing plans for

signalized intersection that are dynamically activated and deactivated a signal timing plan based on traffic conditions. Assessing the plans using simulation will require the use of the simulation model API. Offline simulation and optimization models need to be acquired. Most agencies have access to these tools.

- Data-based analyst is needed to classify events and conditions into different groups using statistical or data mining techniques using available commercial or open source tools.
- There is a need for signal timing specialist optimize signal timing for each group of events and assess them using modeling tools
- If real-time modeling needed, staff are needed in the traffic management center to ensure that the modeling parameters are updated correctly in real-time and that the output is correct and can be used.
- If real-time modeling is to be conducted, more expensive modules and tools will need to be purchased and the simulation effort will require significantly more resources to ensure that simulation run correctly in real-time and meet the functional, performance, and interface requirements.
- Online software modules are required to implement rule-based, machine learning, and/or simulation modeling (if real-time simulation is used) to support real-time decisions.

3.5.7 Predictive Travel Time and/or Alternative Route Provision

Description

This application involves the provision of alternative route or predictive travel time information to motorists during freeway and arterial incidents and other events to encourage motorists to use alternative routes to avoid long queues and thus reduce delays. Traveler information can be disseminated using smart phone applications, on-board vehicle units, dynamic message signs, public and private sector phone apps, TV and radio stations, web sites, on-board navigation systems, and/or other media. A certain percentage of travelers will have access to alternative route information and/or predictive travel time and a portion of these travelers will switch routes based on predefined thresholdS such as travel time savings or delay reductions. This shift is expected to be different depending on whether travel time information or alternative route information is provided. The estimation of the route shift is critical to developing ICM response plans and assessing their impacts.

Alternative information is currently provided by private sector applications. However, the routing information provision as part of the ICM effort is meant to be a component of optimizing transportation management and operations and may be integrated with other applications such as signal control, ramp control, managed lane, and incident management. It should be mentioned that, as a policy, not all transportation agencies will provide alternative route information. This is in part is due to the lack of information but is also mainly due to concerns about liability.

Applicable Operational Scenario

Freeway and arterial events, weather events, and other special events.

Potential Approach to Support Decisions

Predictive travel time and alternative route information can be provided based on the results of a combination of real-time data analytics and macroscopic or mesoscopic simulation-based DTA modeling. The model will have to be carefully calibrated or trained to replicate real-world demand and recurrent and event conditions estimated based on real-world data. Data-based prediction of travel time is possible and has been investigated in many research studies in the past. However, such prediction is not effective for conditions with significant dynamic changes such as those incident lane blockages and associated traffic responsive signal control strategies. In such cases, a macroscopic or mesoscopic model can provide such information, if well calibrated. In addition, traffic rerouting recommendations are best derived based on simulation-based DTA models. Real-time modeling, if correctly implemented and calibrated, will produce better results than relying on offline models. In cases where using real-time simulation-based DTA is not used, simpler HCM-based models combined with real-word data and behavioral analysis may produce acceptable results. The effectiveness of such simpler approach that may be appropriate for agencies with less resources should be verified.

Review of Previous Work

<u>Previous Research on Predictive Travel Time Using Modeling</u>

The provision of predictive travel time has been specified as part of the San Diego I-15 and Dallas US-75. Predictive traveler information was provided by an enhanced 511 system as part of the I-15 ICM system (Alexiadis and Chu, 2016b). This system can forecast traffic conditions up to one hour in the future considering incidents and route diversion, utilizing the microscopic simulation engine, Aimsun. The modeling effort assumes a fixed percentage of drivers who would like to change route if faced with congestion. The impacts of dynamic message signs were analyzed by coding virtual sensors in the simulation before the message signs, which would trigger the activation of a macro that assigns new routes to the percentage of drivers who would divert based on the posted information. Based on panel surveys conducted post the ICM deployment, it was found that the traveler's awareness of pre-trip and en route information is about 93% and 84%, respectively. It was also found that 8.6% of travelers used pre-trip traveler information and 8.0% of them switch to an alternative route, while 12.6% of travelers used en route information and 10.6% of them switch route.

In the Chicago AMS testbed of DMA and ATDM strategies funded by the FHWA, the mesoscopic dynamic traffic assignment tool, DYNAMSART-P was used offline to emulate the real-world traffic conditions. DYNASMART-X was assumed to be applied online to integrate data from multiple sources, to estimate and predict network traffic state, to estimate and predict O-D demands, and to conduct short-term and long-term consistency check. Two active demand management (ADM) strategies were investigated by the Chicago testbed: predictive traveler information and dynamic routing. These two were implemented as a bundle. A dynamic routing strategy calculates the shortest path from the node where the vehicle is currently located to its destination. Predictive traveler information was calculated by the DYNAMSART-X model for a predefined horizon in the future (e.g., 30 minutes). Such information is fed to DYNASMART-P that was used to simulate real-world. Figure 30 shows the flowchart of ADM strategies used in the Chicago testbed. As shown in this figure, without implementation of ADM, the shortest path for each individual vehicle will be calculated based on prevailing traffic conditions. If a vehicle can receive en route information, the route of the vehicle is updated if the travel cost of the new shortest path is less than the predefined path and the cost savings are greater than predefined thresholds, for example, 1 minute or 5 minutes for the entire trip. With predicted network state, the travel time for a given link keeps updating according to the arrival time of the vehicle to this link and the shortest path for vehicle is updated dynamically. It should be mentioned that only a proportion of drivers in the simulation have access to the predictive information and they have an option to decide whether to switch route or not.

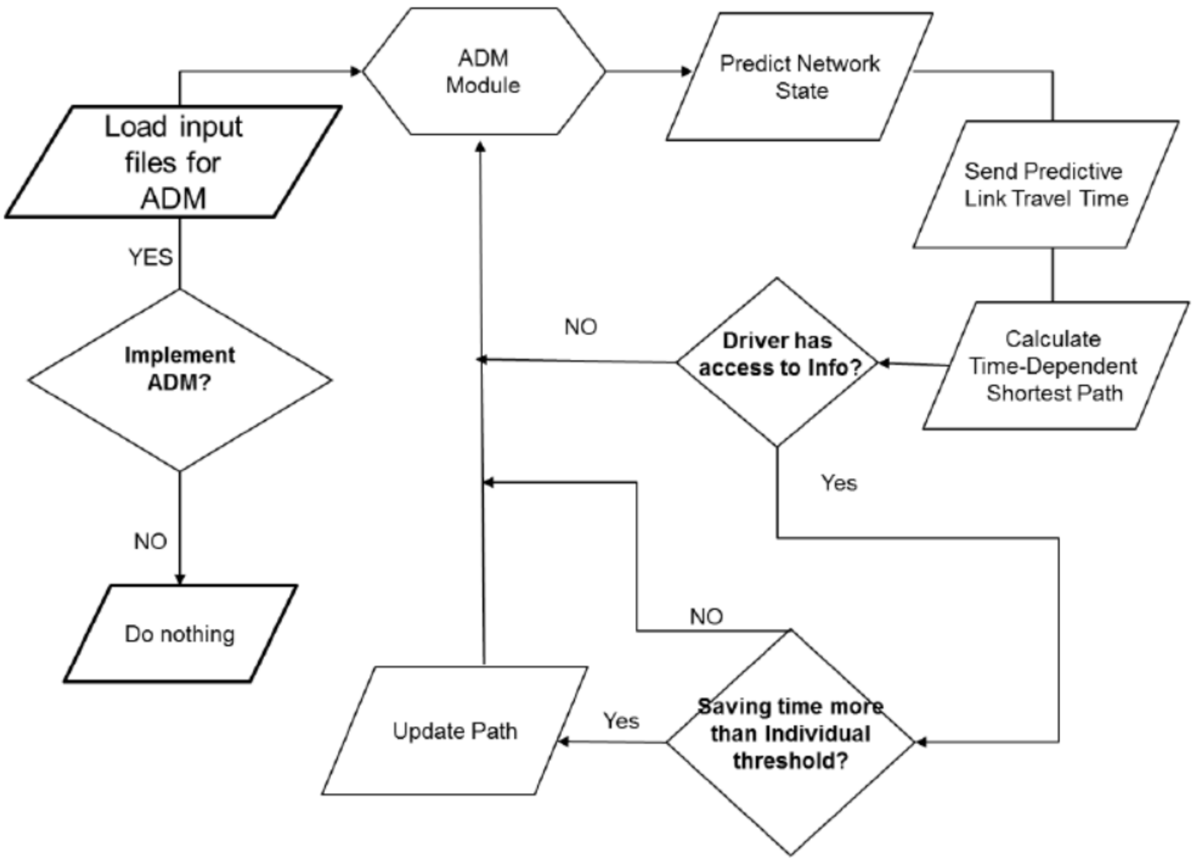


Figure 30: Flowchart of ADM strategies used by the chicago testbed (Source: Mahmassani et al., 2017)

<u>Previous Research on the Provision of Alternative Routes</u>

The provision of alternative route information has been specified as part of the Maryland CHART program; San Diego I-15 ICM; Los Angles I-210 Connected Corridors deployments.

The Coordinated Highway Action Response Team (CHART) in the State of Maryland monitors incident using detectors, cameras, a cellular phone system, and weather sensors (Koonce et al., 2008). Once an incident is detected, the information of alternative routes or expected delays are sent to users. It was estimated that this program can reduce total delays by about 30 million vehicle hours and approximately 5 million gallons of fuel consumption.

Yelchuru and Kamalanathsharma (2017) reported on the assessment of dynamic routing has been implemented in five Active Transportation and Demand Management (ATDM) simulation testbeds, including Pasadena, Dallas, Phoenix, Chicago, and San Diego. As assessed, this strategy encourages better use of roadway capacity by directing travelers to less congested facilities. Based on the testbed in Phoenix, the combined strategies of dynamic route guidance and predictive traveler information can reduce total network travel time by 45%.

As implemented in the Dallas US-75 ICM system, when an incident occurred, a set of criteria were checked as shown in Table 23 and a number of response plans were recommended (Alexiadis and Chu, 2016a). One of the ICM strategies was to suggest alternative route to travelers through dynamic message signs. In this ICM project, the route diversion was modeled utilizing the environment of Dynamic Intermodal Routing Environment for Control and Telematics (DIRECT), a mesoscopic simulation and DTA model. Each traveler was assigned to a route and a travel mode in DIRECT by minimizing the traveler's generalized cost including travel time, toll, and transit costs, and matching the traveler's mode preference regarding carpool and using transit. Under adverse traffic conditions (e.g., incident, or heavy demand, or severe weather events), travelers may switch route or mode. Three groups of travelers were considered depending on the accessibility to the information, that is, Group A without access to information; Group B with access to pretrip information; and Group C with access to both pretrip and en route information. These travelers may divert to different routes when passing a DMS, when accessing pre-trip or en route information, or when experiencing congestions. Surveys were conducted before and after ICM deployments to examine the impacts of the ICM strategies on travelers' behaviors such as the use of pre-trip and en route traveler information, including a set of panel survey, pulse survey immediately following incidents, and a survey of transit riders. The panel survey results showed an increase in the awareness of traveler information. Based on the pulse survey, 18% to 35% of travelers may have a minor route change while 4% to 9% of travelers may use completely different routes during an incident.

The San Diego I-15 ICM project provided travelers pre-trip and en route traveler information, as well as alternative route wayfinding signs to assist diverted drivers to return to the freeway downstream of an incident (Alexiadis and Chu, 2016b). Travelers' route choice was calculated by the Stochastic User Equilibrium (SUE)-based traffic assignment in Transmodeler in the pre-deployment analysis. The static and dynamic traffic assignment in Aimsun were used to determine vehicle routes during the post-deployment analysis. Panel surveys, pulse surveys immediately following the occurrence of incidents, and transit rider surveys were conducted before and after the ICM deployment. The baseline and end-line panel survey results showed an increase in the awareness of traveler information, however, the use of the provided traveler information did not change significantly. The pulse survey results revealed 9%-10% of traffic conduct minor route changes and 2%-3% complete route changes for pre-trip information. These values were 10%-16% and 3%-4%, respectively with en route information.

The Concept of Operations for the I-210 Connected Corridors ICM system in the San Gabriel Valley sub-region of Los Angeles County proposed the provision of alternative route information around incidents or severe congestion (Dion et al., 2015). This was achieved by posting information on DMSs along the freeway and using DMSs or dynamic wayfinding signs along arterial streets to indicate the route to return to the freeway. For major freeway incident, the ICM system aimed at identifying alternative routes that accommodate the diverted traffic from freeways while minimizing the impacts on local traffic. The alternative route provision was combined with the signal timing plan changes for the alternative routes and the provision of transit information. Alternative route information was also provided during a major arterial incident. Traffic was recommended to divert either to surrounding arterials or freeways depending on the location and severity of the incident and available traffic carrying capacity of surrounding arterials. The alternative route provision strategy can be combined with signal timing plan change and dynamic ramp metering.

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with information provision to motorists as part of the ICM.

- Archived and real-time freeway and arterial detector data and existing signal timing plans are needed. AVI or third party private sector data are also needed on arterial streets to support travel time estimation and incident/congestion detection. High resolution controller data is helpful in detecting congestion/incidents.
- Percentage of drivers that have access to traveler information both pretrip and en route and percentage of drivers that will follow the provided route information (estimated or measured based on surveys or sensors).
- Prediction of demand or travel time can be done based on modeling or machine learning techniques
- Modeling using macroscopic simulation or microscopic simulation based DTA can be used to predict travel time and/or determine the diversion routes and diversion under different conditions to complement findings based on survey and sensor data.
- The model results can be used to determine whether alternative route messages should be provided and the optimal diversion route under different conditions.
- The developed method/model can be used to determine the location of DMS or other traveler information system for posting alternative route information.
- Table look-up, rule-based module, or machine learning approach based on modeling results can be used in real-time based on offline analysis results.
- As proposed and/or implemented in the San Diego, Dallas, and Los Angles deployment, real-time modeling using macroscopic simulation or microscopic simulation based DTA can is used to determine the diversion routes and diversion under measured conditions. The model results are used to determine whether alternative route messages should be provided and the optimal diversion route to be used as part of the decision support tool.
- There is a need for modeler(s) that have the capability to model freeway and arterial events, and capture the impacts of these events including predicting travel times and route diversions using DTA, macroscopic, mesoscopic, and microscopic. The estimation of the diversion shall be consistent with the estimates of the willingness to divert collected using revealed preference surveys or system sensors.
- Data-based analyst and/or discrete choice modelers are need to estimate the percentage of traveler's willingness to divert. The percentage of users who have access to the information and the percentage of users who switch route or mode with the provision of each type information will have to be obtained based on surveys and/or sensors for use in the simulation. Although not desirable, if such data is not available, information based on previous studies may be used.

- Little information is available about the difference between the willingness to divert with the provision of travel time information versus that with the provision of route guidance, although some values have been assumed. Traveler surveys should attempt to get additional results.
- The question regarding system optimal versus user optimal routing needs to be addressed. The current thinking is to implement user optimal routing to ensure traveler’s compliance since utilizing system optimal routing may not be acceptable from individual traveler’s point of view.
- If real-time modeling needed, the modeler need to ensure that the modeling parameters are updated correctly in real-time and that the output is correct and can be used.
- Offline simulation and optimization models need to be acquired. Most agencies have access to these tools.
- The utilization of online modeling will increase the requirements in terms of reducing and utilizing real-time data in the model, ensuring that the model runs correctly in real-time, and meeting the latency requirement. Additionally, online modeling will require more expensive modeling tools, more complex ICM software and interfaces, and at least one analyst/modeler at the traffic management center to support ICM operations.
- Online software modules are required to implement rule-based, machine learning, and/or simulation modeling (if real-time simulation is used) to support real-time decisions.
- Some transportation agencies have policies against the provision of route guidance information to travelers.

3.5.8 Mode Shift during Severe Highway and Transit Events

Description

In this application, operational data from transit agencies is used to provide travelers with information to encourage the usage of transit during severe freeway and arterial events. Such information can also help transit users to switch to another transportation mode during severe transit delays.

Applicable Operational Scenario

Severe freeway and arterial incidents, weather events, transit events, and other events.

Potential Approach to Support Decisions

A modeling-based approach can be used to predict shifts between modes and the associated impacts. The mode shift can be modeled utilizing two potential approaches. In the first approach, a logit model can be used to estimate the mode choice of travelers based on traveler’s utility. In the second approach, mode shift during incidents between modes is modeled using a mesoscopic simulation tool. A combination of the two approaches can produce better results.

Review of Previous Work

This application has been specified for FDOT District 4, FDOT District 5, Dallas US-75, San Diego I-15, and Los Angles I-210 Connected Corridors ICM deployments.

The Dallas US-75 ICM project deployed multimodal ICM strategies, which include improving pre-trip and en route multimodal traveler information that encourages the usage of transit during major freeway incidents, parking management at park-and-ride facilities, interdependent incident response plan, mode shift/route diversion, and increasing transit capacity (Alexiadis and Chu, 2016a). The system allows the multimodal information sharing among multiagency. The DIRECT mesoscopic simulation was used to model traveler's mode and route choices by minimizing the traveler's generalized cost and matching the traveler's preference in terms of willingness to use transit or carpool. The willingness to use transit was calculated as the ratio of the number of transit users according to onboard survey to the total number of travelers estimated for each origin-destination (O-D) pair. The update of the routes and modes was conducted every 5 minutes in DIRECT. If car riders, who are assumed to be willing to use transit, receive en route incident information, they may park their cars at park-and-ride lots and switched to transit. Based on panel surveys conducted before and after ICM deployment, about three-quarters of US-75 drivers were reported never having switched to transit or carpool. The pulse survey collected immediately after incidents also showed that less than 0.5% of drivers changed to transit. The survey results for transit riders revealed that 14% of transit riders chose to drive in the last month and 22% never drove in the last month, while 58% of transit riders never switch to drive or carpool.

Transit agencies were involved in the design and implementation of ICM strategies in the San Diego I-15 ICM project (Alexiadis and Chu, 2016b). Also, transit was one of the categories that were included in a response plan. Transit-related strategies included disseminating transit information, transit signal priority, and providing extra buses if needed. Traveler surveys were conducted before and after implementing the ICM project. It was reported from the panel survey that three-quarters or more respondents never switched mode to transit or carpooling. The results from the pulse surveys conducted immediately after incidents indicated that less than 0.5% of travelers switched to transit. The survey also showed that 18% of transit riders in the last month chose to drive or carpool instead of taking transit with the implementation of ICM, while 21% of transit riders did not switch mode in the last month and 57% of transit riders never switch mode.

It was proposed in the Concept of Operations for the I-210 Connected Corridors ICM system that real-time transit operational data (e.g., bus location, schedule adherence, etc.) and real-time parking operational data (e.g., parking availability, pricing, etc.) need to be integrated into corridor monitoring system (Dion et al., 2015). In addition, a number of transit-related strategies were considered to mitigate incident impacts including:

- transit service route deviation around major incident,
- adjusting transit service,
- provision of transit and park-and-ride information,
- allowing travelers to temporary use of private parking facilities as a temporal park-and-ride,
- adjusting signal timing plans, and
- providing signal preemption to emergency vehicles at signalized intersections.

When a major transit incident occurs, the initial response strategies include adding a temporary bus service, dissemination of relevant transit information, track of travel conditions along freeways, arterials, parking occupancy, and incident reports. If the transit incident significantly affects travel conditions in the corridor, response plans such as signal timing plan change, freeway on-ramp metering rate increase, dissemination of preferred arterial routes, and additional transit service adjustment were implemented.

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with the mode shift application, in addition to those specified for alternative route provision application in Section 4.8.

- Archived and real-time transit automatic vehicle location, performance, status, passenger count and incident data.
- Offline modeling is needed to model the percentage of drivers switching mode with the provision of multimodal information and the impact of such switch on performance. The model will have to capture the stochasticity of real-time mode choice behaviors of travelers under different conditions. This information can be used to inform a real-time rule-based system, table look-up, or data mining system. Mesoscopic simulation model, possibly combined with a discrete choice behavior model needs to be developed based on surveys to capture this behavior.
- Real-time modeling utilizing mesoscopic simulation combined with discrete choice model can be conducted to estimate the percentage of transit users that will switch mode in response to information and the impact of this switch.
- The actual shift between modes during incident events is less understood and is affected by the availability of transit options and last mile availability. A well designed survey is needed to capture the probability of this shift under different conditions.
- The offline and online models shall be able to dynamically estimate the percentage of highway users and transit users under different conditions and information provision and the impacts on system performance of real-time mode shifts.
- The capabilities required for alternative route provision are also required for the mode shift application.

3.5.9 Hard Shoulder Running

Description

Hard shoulder running allows temporary use of either left or right shoulders on freeways to provide additional roadway capacity during recurrent and non-recurrent congestions. The implementation of hard shoulder running can be either fixed by time of day or triggered when there is a surge of demand due to recurrent or non-recurrent events. The existing shoulder attributes such as width, geometry, and pavement along the study corridor will have to be checked first to determine if there is enough space for shoulder utilization as a lane.

Applicable Operational Scenario

Freeway daily operations (stochastic variation), incidents, weather, construction, and other events.

Potential Approach to Support Decisions

The hard shoulder running strategy will need to be modeled in an offline microscopic simulation model or HCM facility-based model to identify the activation or deactivation threshold based on a predefined threshold of travel speed and/or travel volume. The switching can be based on a table look-up, rules, or a data mining approach such as decision tree. DTA-based modeling is only needed if diversion due to shoulder opening to traffic needs to be assessed. Real-time modeling is not necessary.

Review of Previous Work

The Concept of Operations for the I-210 Connected Corridors ICM system proposed the temporary usage of freeway shoulder or freeway off-ramp shoulder for traffic to mitigate congestions (Dion et al., 2015).

The application of dynamic shoulder lanes was assessed using the Dynasmart mesoscopic simulation model in the Chicago AMS Testbed for DMA and ATDM strategies funded by the FHWA (Mahmassani et al., 2017). In this assessment, the the shoulder lanes were assumed to open during the peak periods (5:00 am -9:00 am for the inbound direction and 3:00 pm-7:00 pm for the outbound direction) on weekdays, if the speed of general traffic is less than 35 mph. Figure 31 shows the flowchart of dynamic shoulder lanes used in the Chicago testbed.

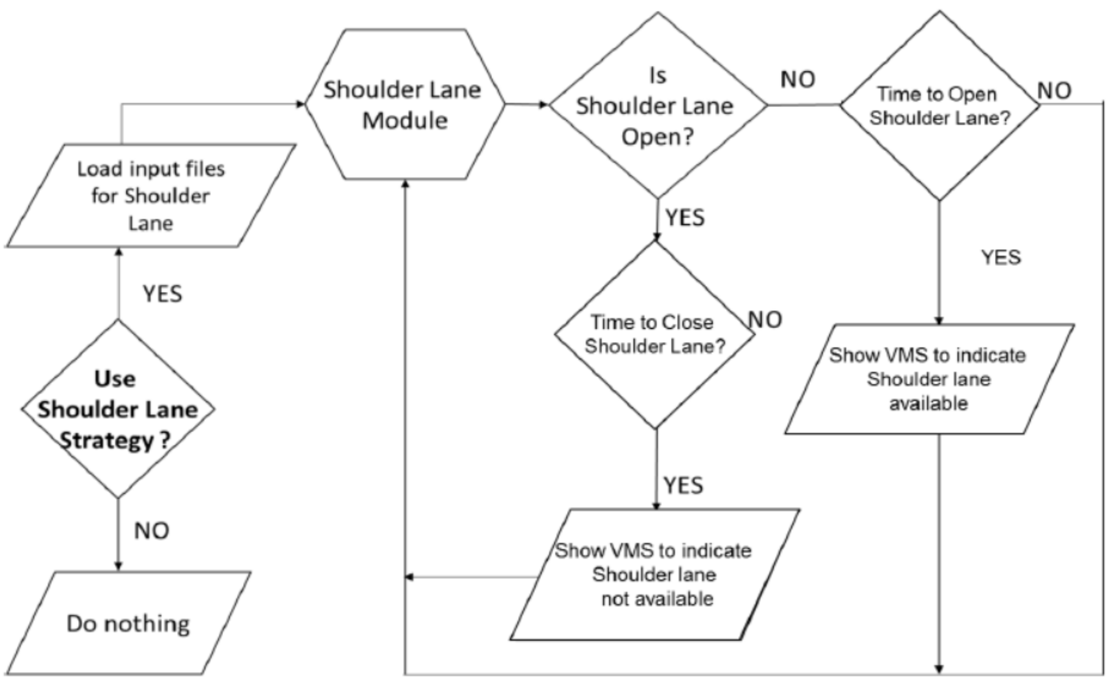


Figure 31: Flowchart of dynamic hard shoulder running used by the Chicago testbed (Source: Mahmassani et al., 2017)

Dynamic hard shoulder running was simulated in the DIRECT mesoscopic model for the Dallas testbed for DMA and ATDM strategies (Yelchuru et al., 2017a). This strategy allows the use of shoulder lanes during an incident with one or more lanes closed. In the DIRECT model, each link consists of multiple lanes. Shoulder lane was predefined and can be added to the link when activating the dynamic shoulder lane strategy. The shoulder lane can be eliminated when the dynamic shoulder lane strategy is deactivated. The saving in travel time in the tested incident operation scenario was reported to be 75,304 minutes (2.5% saving).

The dynamic shoulder lane combined with dynamic merge junction (merge) control was also tested in the Pasadena testbed using the TRANSIMS low fidelity microscopic simulation model to determine the impact of the increase the capacity on the network performance. The impact was reported to be 7.77% reduction in travel time.

To reduce congestion, the 4-lane facility of the A3-A86 section in Seine-Saint-Denis department north of Paris was changed to 5 lanes by using the hard shoulder with reduced curb width (Cohen, 2004). To compensate for possible safety problem due to hard shoulder removal, some variable message signs, emergency call boxes, and cameras were installed at the upstream of the section. The results before and after hard shoulder usage show that capacity was improved by 7%-16%. In Germany, hard shoulder running has been activated along multiple freeway when traffic volume is greater than a certain threshold (Pilz and Riegelhuth. 2007). The implementation of hard shoulder running shows that it can increase the capacity of a 2 lane motorway (A4 motorway) by 30% and a 3 lane motorway (A3 motorway) by between 22 and 27%. The ATM (Active Traffic Management) project has been implemented along a 10-mile stretch of the M42 in the west Midlands as a pilot plan by highway Agency (HA) in United Kingdom since 2006 (Chase and Avineri, 2008). One of the ATM strategies is to use hard shoulder during peak periods. Dynamic speed limit and message signs were combined with hard shoulder running to have more reliable travel times and less congestion (Chase and Avineri, 2008). A capacity increase of 7%-16% was reported for this implementation. The implementation of hard shoulder lanes can be either left or right shoulder at various location in Netherlands (Helleman, 2006). Special attention was given to the safety consequence of using shoulder lane (Middelham, 2006). Results suggest that depending on usage levels, capacity can be increased by 7% to 22% or even 50% when using hard shoulder (Helleman, 2006; Middelham, 2003). In the US, a combination of hard shoulder and HOV lane were implemented on I-66 in Virginia in 1992. The I-66 has three lanes in each direction and the hard shoulder lane was located at the rightmost (Lee et al., 2012; Ungemah and B. Kuhn, 2009). Washington State of Transportation has implemented hard shoulders on US-2 highway since 2009 (Swires, 2009).

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with dynamic hard shoulder running:

- Freeway data will be needed including detector data (volume speed, and occupancy), event and incident data (status messages, including start time, blockage pattern, and severity), weather status data. Application of clustering algorithms will be needed to identify the operation scenarios for response plan generation and for multi-scenario modeling.
- Offline modeling is needed to check the feasibility and impacts of implementing hard shoulder running. Microscopic simulation is needed to examine the operation effect of dynamic shoulder lanes. Mesoscopic or macroscopic simulation-based DTA is needed to examine the diversion behavior. The models need to allow the specification of starting

and ending time of hard shoulder running and triggers to dynamically activate metering within the modeling environment possibly using API. The model shall have the capability of coding dynamic message signs that can disseminate the information regarding the open and closure of shoulder lanes. In microscopic simulation, the DMS will indicate when drivers will start changing lanes. In DTA models, The DMS will influence diversion behaviors.

- The model shall allow the assessment of the effectiveness of hard shoulder running during recurrent congested conditions and/or incident, weather, or special to determine under which conditions hard shoulder running is most effective.
- The models need to simulate the capacity increase due to the usage of shoulder considering real-world observations in previous studies. The impacts of shoulder use on capacity and the impact of merging back to general lane have to be carefully calibrated since simulation models will not produce accurate results without such calibration.
- Online simulation of different levels can be used to model the dynamic activation of hard shoulder running based on real-world data. In the absence of such modeling; rule, table-look-up, or machine learning can be used based on offline modeling.
- The modeling of dynamic shoulder use requires a modeler who has experience in highway capacity manual procedures and microscopic simulation modeling. DTA-based simulation is only needed if the impact of diversion due to activating the shoulder use is needed. Online simulation requires additional tools, resources, and modeling capabilities.

3.5.10 Restrict, Reroute, Delay Commercial Traffic

Description

The strategy dynamically restricts commercial vehicle usage of roadways and divert them to alternative routes during severe freeway or arterial incidents or other events.

Applicable Operational Scenarios

Freeway and arterial severe incidents, weather events, and other events.

Potential Approach

The strategy to restrict/reroute/delay commercial traffic is best modeled using simulation. Offline and online macroscopic or mesoscopic simulation-based DTA modeling are best suited for supporting these strategies. Microscopic simulation or HCM-based analysis can be used to further assess the facility level operational impact, if resources are available.

Review of Previous Work

The strategy of imposing and removing truck travel restrictions based on observed traffic conditions was included in the Concept of Operations for the I-210 Connected Corridors ICM system to manage travel demand (Dion et al., 2015). The strategy of restricting/rerouting/delay commercial traffic was also included in the Concept of Operation plan of FDOT District 5 ICM project (FDOT District 5, 2017).

A menu of user services, such as real-time traffic information, dynamic routing, traffic plans by time-of-day and so on, was proposed to be provided to truck drivers and freight companies such that commercial vehicles can re-optimize their decisions by the Broward Metropolitan Planning Organization (MPO) in the Concept of Operations for the I-95 ICM project (AECOM, 2013). The strategies of converting regular lanes to truck-only and variable truck restrictions by lane, speed, network, and time of day were also considered in this document for real-time operations.

Required Modeling, Data, and Capabilities

The followings are the required modeling, data, and capabilities associated with dynamic hard shoulder running:

- In addition to freeway and alternative route detector, travel time, and event data required for other applications, data related to commercial vehicles will be needed including origin-destination data; commercial vehicle GPS data; and height, weight, and geometrics restrictions for commercial vehicles on each route. Application of clustering algorithms will be needed to identify the operation scenarios for response plan generation and for multi-scenario modeling.
- Mesoscopic or macroscopic simulation-based DTA is needed to examine the diversion behavior of commercial vehicles considering various restrictions on commercial vehicle routing during severe events. The model needs to identify the routes to be used by the commercial vehicles and assess the congestion level along these routes. The model needs to assess the impacts of various strategies on the freeway and alternative routes.
- The selected model shall allow multi-modal simulation including the demands and movement of commercial vehicles. The system shall have the capability to reroute commercial vehicles based on congestion level and shall have the capability to model the restrictive usage of lanes to commercial vehicles, including the height or weight, or geometrics restrictions. In addition, the system shall have the capability to model the response of commercial vehicles to the provision of rerouting information.
- The used models need to simulate the impacts of commercial vehicles with different horsepower to weight ratios on freeway and signalized arterial capacity.
- Online simulation-based DTA can be used to estimate truck diversion. However, offline simulation may be sufficient.
- The modeling needs modelers who has experience with demand modeling and DTA-based simulation.

3.6 SUMMARY OF ICM APPLICATION IDENTIFICATION

This chapter identified, based on a review of the ICM concepts from around the United States and Florida, 15 ICM applications. The operational scenarios including those under normal conditions, incidents, and adverse weather that benefits from these applications were also identified. The 15 application are:

- Dynamic Ramp Management (Metering Activation, Deactivation, and Closure)
- Dynamic Modification of Express Lane Pricings and Restrictions
- Coordination of Ramp Metering and Signal Control

- Periodic Signal Retiming
- Traffic Adaptive Signal Control
- Special Signal Plans During Freeway and Arterial Incidents
- Alternative Route and Predicted Travel Time Information Provision to Motorists
- Provision of Optimal Emergency Vehicle Routing
- Rerouting of Express Buses
- Mode Shift During Severe Highway or Transit Incidents
- Hard Shoulder Running
- Restricting, Rerouting, and Delaying Commercial Traffic
- Special Events and Construction
- Disaster Response

This chapter presents a description; a review of current work; potential approaches to support the decision making process; and modeling, data, and capability requirements associated with ICM applications.

The analysis presented in this document indicates that there is a range of alternative approaches that can be used to support the offline and real-time decisions associated with different ICM applications. Although the four major existing or planned ICM deployments in Orlando, San Diego, Dallas, and Los Angles include both online and real-time DTA based models that require significant modeling resources and capabilities, it is possible to use data-based, offline model-based, and/or less detailed online model based to support ICM with less resource requirements. This may be important considering the variations in the capability maturity of different agencies.

Alternative DSS solutions can involve combinations of offline utilization of data analytics, HCM-based analysis, macroscopic simulation, mesoscopic simulation, microscopic simulation, and dynamic traffic assignment and online utilization of some of these modeling and analysis techniques. The particular approach to be utilized in a region will depend on the considered ICM applications and the data, modeling, and capability maturity of the agency considering the applications. A less involved approach, that can be referred to as a light version of the DSS (DSS-Lite), may be desirable when there are limitations on the capabilities and resources. Such DSS-Lite approaches may be as effective or less effective than the detailed approaches utilized in the concepts developed for the four major ICM deployments mentioned above. This will be tested in future tasks of this project.

Obviously, there will be components of the DSS that will be required no matter what will be the level of the DSS support. For example, the utilization of clustering analysis based on data from multiple sources to identify traffic, incident, and weather patterns will be critical to allow the development of response plans. Offline modeling to derive response plans will also always be critical to the DSS applications.

4. CAPABILITY MATURITY FRAMEWORKS OVERVIEW

This project also addresses the capability maturity assessment of the agency ability to utilize decision support systems for ICM planning, operations, and management. The managers of the FDOT transportation system management and operations (TSM&O) programs in four FDOT districts were interviewed (Districts 1, 2, 4, and 5) as part of this effort to get information to support this effort. This task assesses the needed capabilities based on these interviews and information gather in the previous tasks. The discussion is structured around the dimensions of the Capability Maturity Modeling (CMM) (FHWA, 2018a) originally developed for TSM&O as part of the SHRP2 Reliability program (Parsons Brinckerhoff, & Delcan Corporation, 2012) based on the concept widely used for various applications in Information Technology.

The motivation for the use of the CMM to guide the discussion in this chapter is that it was developed to identifying an understanding the barriers to the adoption of different types and levels of DSS and for the provision of recommendations for action to improve the capabilities. In this chapter, the CMM framework is used to guide discussion about the needed capabilities and improvements to achieve an effective ICM decision support system. Consistent with the above mentioned framework, the discussion is organized in the same six dimensions (AASHTO, 2018) of the framework.

1. Business processes
2. Systems and technology
3. Performance measurement
4. Culture
5. Organization and workforce
6. Collaboration

For each of the dimensions, four levels of capability are used in the original TSM&O framework mentioned earlier and are listed below (FHWA, 2018a).

- "Level 1 - Activities and relationships largely ad hoc, informal and champion-driven, substantially outside the mainstream of other DOT activities
- Level 2 - Basic strategy applications understood; key processes support requirements identified and key technology and core capacities under development, but limited internal accountability and uneven alignment with external partners
- Level 3 - Standardized strategy applications implemented in priority contexts and managed for performance; technical and business processes developed, documented, and integrated into DOT; partnerships aligned
- Level 4 - Full, sustainable core DOT program priority, established on the basis of continuous improvement with top level management status and formal partnerships"

Four to five capability levels will be defined in this study to rate the ICM capability levels.

4.1 BUSINESS PROCESSES

TSM&O Business processes have been defined as “activities such as planning, programming, agency project development processes, and those organizational aspects that govern various technical or administrative functions such as training, human resource management, contracting and procurement, sustainable funding, information technology, agreements (partnering commitments)” (FHWA, 2018b). As related to the ICM DSS, the elements that can be related to the Business process are discussed in the following section.

4.1.1 Planning ICM Projects based on Value

Decision support tools should be used to determine the ICM project feasibility, value, and significance. Return-on-investment or at least the expected improvements in outcome performance measures related to the goals and objectives identified by the project stakeholders should be conducted to support the analysis

At a minimum, a planning level analysis utilizing highway capacity manual (HCM) level analysis should be used to demonstrate the impacts and return on investment considering the expected diversions and shifts and available capacity and congestion on the alternative mode or route. Such type of analysis can be conducted using the Highway Capacity Software (HCS), FREEVAL and STREETVAL, or Synchro among other software. There must be available capacity within the transportation network to allow managing a corridor through a multiagency or multimodal ICM approach including the use of alternative routes or modes. More advanced data analytics possibly combined with simulation modeling is desirable. Utilizing simulation is particularly attractive if a simulation model has already been developed for the corridor. Mesoscopic simulation combined with microscopic simulation and dynamic traffic assignment, if done right, is the best option since it will consider the strategic as well as the tactical and operational driver behavior, strategies, and impacts.

The benefits of ICM as estimated by the different levels of analysis can be used for pre-deployment estimates of the benefits. These benefits when converted to dollar values can be used in combination with the estimated initial and recurrent operation and management (O&M) costs can be used to estimate the return on investment. The research team in this project, as part of an on-going FDOT Research project (BDV29 TWO 977-37), is enhancing an existing ITS sketch planning tool referred to as Florida ITS Evaluation (FITSEVAL) to allow it to better calculate the return on investment of active transportation management system. The new version will have an interface to the HCM-based procedure, allowing a more detailed analysis than that of the sketch planning level. Figure 32 shows the FITSEVAL analysis framework. This tool can be extended to include the assessment of ICM and vehicle-to-infrastructure applications.

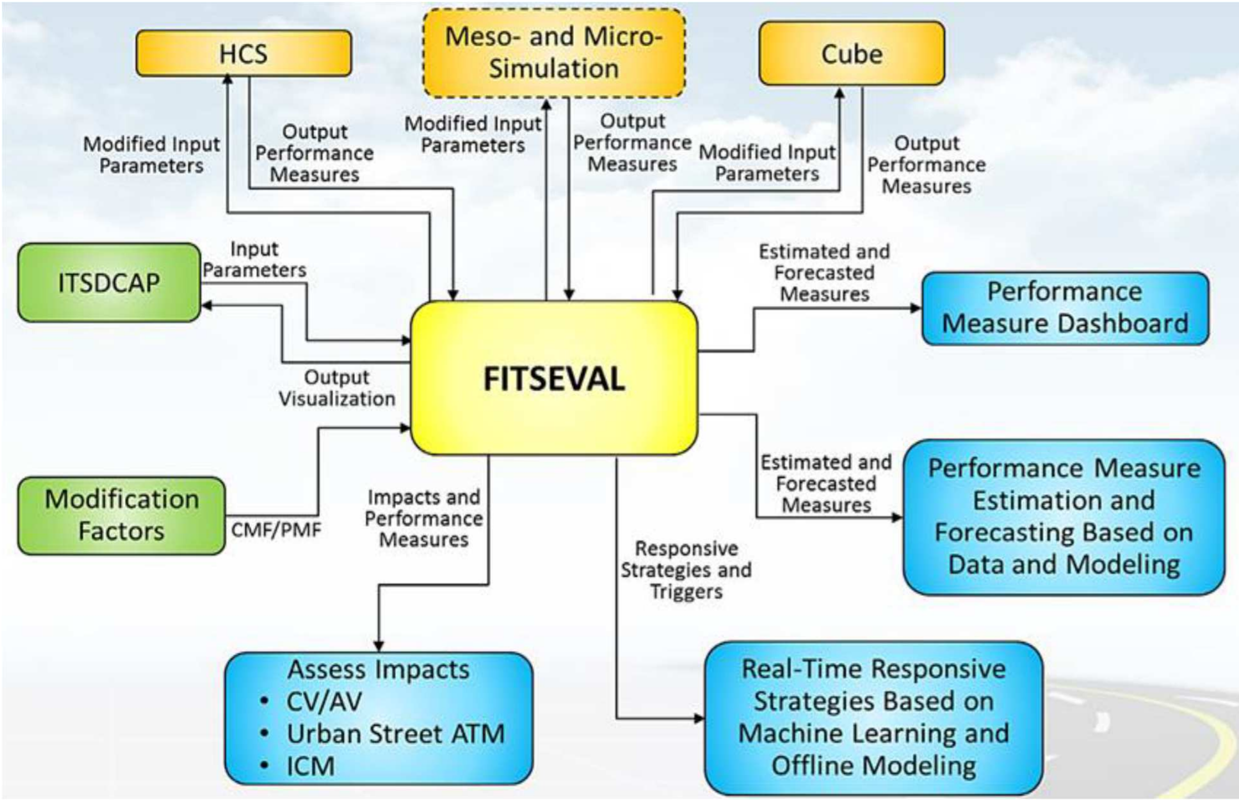


Figure 32: Planning-level analysis framework using FITSEVAL

In terms of maturity levels related to this capability, one can identify the following levels.

- Level 1 – ICM project significance and return-on-investment are not considered in most key analyses and decisions related to ICM planning
- Level 2 - Sketch planning analysis or HCM-based analysis is used to justify the project and different applications
- Level 3 – Data analysis is used to justify the project and different applications
- Level 4 – Combinations of modeling (HCM-based procedure or simulation) and data are used to justify the project and different applications

4.1.2 ICM Funding

Funding, particularly those related to operations and maintenance (O&M) is obviously a major concern for agencies. In both San Diego and Dallas, O&M funding were a concern. Our interview with local districts indicates that in particular the recurrent operation and maintenance funding is a concern to partner agencies (Spiller et al, 2014).

Some districts got funds for development a concept of operation for ICM and in the case of FDOT District 5 FHWA fund that was used to help implementing the ICM and supporting the DSS tools. The developed system in District 5 is configurable to other regions, which should reduce the required funding significantly. O&M funding was also provided by the MPOs, the central office, and local FDOT funds. The ICM is one of the focus areas of the TSMO strategic plan. FDOT allocated 25 million for implementing the plan. Generalized work program and operation funding like freeway, retiming, and operation contracts can be used to support the ICM deployment. The recent raise in sale taxes to support transportation, as was done in Broward County can be another sort of fund. It was also mentioned that the districts do not want to increase the burden on the local agencies and have tried to find budget to cover the required funding by these agencies.

Based on the above, it seems that the ICM deployments can use FDOT work program, MPO federal funding, local agency funding, and even Central Office and federal funding. FDOT districts have also supported ICM partners with ICM O&M funding needs, particularly with local agencies that have limited resources.

The following five maturity levels are recommended for the ICM funding capability.

- Level 1: No funding for ICM
- Level 2: FDOT provide ICM funding from existing operation contracts
- Level 3: Multiple agencies cooperate on specifically funding ICM deployment.
- Level 4: Multiple agencies cooperate on specifically funding deployment, operation, and maintenance of ICM.

4.2 SYSTEM AND TECHNOLOGIES

Use of the appropriate processes for design and implementation of systems will ensure that the needs of the region are appropriately addressed, that systems are implemented in an efficient manner, and that interoperability with other systems is achieved.

4.2.1 Use of Systems Engineering and Regional Architecture

As with other Intelligent Transportation Systems (ITS) projects, the ICM planning, design, and deployment should follow the system engineering process. FDOT ITS projects has a system engineering process and regional architectures that have been in place for almost 15 years. It is anticipated that this process will be used for ICM projects. The ICM deployments in Florida will also utilize center-to-center and center to field ITS standards and FDOT specifications and guidelines, as required by the USDOT and FDOT.

4.2.2 Decision Support Systems

The utilization of an effective decision support system is an important foundation of the deployment of ICM. DSS determine, offline and in real-time environment, congestion conditions that require a response, recommend coordinated response(s), and evaluate these responses. The data analytics and/or modeling required to support ICM can be categorized in four categories:

1. Describing the existing performance
2. Diagnosis of the factors that influence existing conditions
3. Predicting day-to-day performance to support organizational decisions, and real-time performance to support operational decisions

4. Recommending strategies to address issues identified in the predicted system performance

Below are the capabilities needed for offline and real-time analysis.

Of-Line Decision Support

Offline modeling and data analyses are an important aspect of ICM that should be utilized in all ICM deployments to determine the effectiveness of different ICM strategies in the planning stage and to identify the response plans in the design stage. The Analysis, Modeling, and Simulation (AMS) tools have been used as important components of ICM for pre-deployment evaluation of the impacts of various application and offline determination of response plans. In fact, these tools have been also used for post-deployment evaluation of ICM effectiveness by the USDOT ICM evaluation team due to the difficulty in measuring the impacts of ICM based on real-world data.

It should be recognized that modeling can be done at different levels. More complex deployments like the ones tested in San Diego and Dallas, and planned for Orlando and Los Angles use dynamic traffic assignment (DTA)-based mesoscopic and/or microscopic modeling. Even if agencies lack the resources to develop a large scale dynamic traffic assignment (DTA)-based mesoscopic or microscopic simulation models, consideration should be given to utilizing existing simulation models that were developed for other purposes in the region. Some interviews revealed that big scale DTA-based model may require a lot of resources and the District may not have experience in it. The modeling office may provide the needed capabilities. However, the modelers need to understand the level of details and accuracy required for TSM&O applications versus planning level applications.

Freeway and urban arterial HCM-based procedures can provide important support for the selection and effectiveness of the response plans. This approach requires less resources than big-scale DTA models and has been used to some degree by FDOT Districts 1 and 2 with the use of Synchro, which use a modeling approach at the same level of the HCM-based procedures. This approach was used to test the diversion impacts on signal operations. There is a potential to use data analytics and traveler behavior surveys combined with the HCM-level of analysis in cases when more complex modeling is not possible. FDOT District 1 developed response plans based on Synchro runs and provided it to the agencies. However, the agencies currently like to depend on the observation using cameras and fine-tuning the signal timing manually. A procedure may be needed where agencies utilize the optimized models at least initially and then they can be fine-tuned based on observations.

Another important aspect of offline analysis is data analytics that can provide considerable support of planning and design of ICM. This is further discussed in the Performance Measurement Section.

As stated earlier an important aspect of the ICM AMS methodology is the need to simulate transportation systems under varying operational conditions including those associated with both recurrent and non-recurrent traffic congestion. The USDOT ICM modeling guidance states that the key ICM impacts may be lost if only “normal” travel conditions are considered. Thus, the analysis should use multi-scenario modeling taking into account different levels of travel demands within the corridor, with and without incidents, and possibly with and without adverse weather condition. The distributions of demands and frequency of non-recurrent events such as incidents are important to estimates of the impacts of advanced strategies.

Also, specifications and guidelines need to be followed when developing the models. The request for proposal (RFP) of District 5 has some requirements. The selected consultant is producing a calibration document which will be shared when available. The FHWA and FDOT have simulation manuals and guidelines and the first version of the Transportation System Simulation (TSSM) manual will be soon available. These together with other documents produced in national efforts to simulate advanced strategies should be very help.

It is recommended that the following five maturity levels are used.

- Level 1: No utilization of model-based or data-based tools. Plans are developed based on judgment and observations
- Level 2: Limited use of HCM facility procedures or similar models to test response plans (HCS, FREEVAL, STEEVAL, Synchro)
- Level 3: Extensive use of HCM facility procedures or similar models combined with behavioral models and data analysis to estimate diversion including the use of clustering analysis to identify operational scenarios
- Level 4: Use of existing simulation microscopic models developed for the region combined with behavioral models and data analysis to estimate diversion and clustering analysis to identify operational scenarios
- Level 5: Use of DTA-based mesoscopic simulation combined with microscopic simulation and data analysis.

Real-Time Decision Support

In general, real-time DSS, as implemented in the two USDOT pilots and planned in District 5 in Orlando, can be considered to consist of four elements: data collection and fusion, user interface, real-time response plan recommendations, and model-based real-time predictive engine. Each of these elements has its own requirements. The real-time data collection and fusion component gathers information from multiple sources using center-to-center standards, processes and fuses the data, and provides the information needed by a rule-based decision support system and the modeling-based predictive engine. The rule-based expert system has been used to generate response plans during non-recurrent congestion conditions for consideration by operations personnel of the partner agencies. An important aspect of the rule-based expert system module is the required periodic post-review of the implemented and proposed plans and the modification of these plans as needed based on the review. More advanced real-time generation of the response plans rather than the selection from a library as is done using the expert system has been proposed in research studies. The utilized predictive engine normally uses a mesoscopic or microscopic simulation-based modeling tool to predict the performance of the corridor in the next 30 minutes to one hour under the recommended response plans by the expert systems to allow the prioritization of the plans and more informed decision by the operator. ICM components being developed for the District 5 implementation can be considered for possible implementation in other districts. The interview with District 5 indicates that their ICM DSS is developed with the possible use by others is a major consideration, for example, the developed interfaces to signal software can support different platforms including ATMS.NOW, Centrax, and MaxView.

One of the functionalities needed to support ICM DSS deployment is selecting the response plans in real-time and predicting their impacts. In the two pilot ICM deployments, the real-time selection of response plans from a pre-stored library of plans has been done utilizing an expert-rule system. The expert rules system select the response plans based on various variables such as the location, time of day, lane-blockage, incident severity, and so on. A real-time predictive model is then used to verify that the selected plan will provide a benefit. The utilized predictive engine uses a mesoscopic and/or microscopic simulation-based modeling tool to predict the performance of the corridor in the next 30 minutes to one hour under the recommended response plans by the expert systems to allow the prioritization of the plans and more informed decision by the operator.

A more advanced application creates response plans in real-time rather than selecting these plans from a pre-stored plans. This can be thought of in a similar manner to traffic responsive vs. traffic adaptive signal control, with the first selecting the plans from a pre-stored plan generated based on historical data and the second generating the plan in real-time. It has been reported that the San Diego system has the ability to generate a response plan for an event within the corridor.

Our interview with Florida District 5 as part of this project in addition to two interview with Arizona DOT and Tennessee DOT as part of a separate project indicates that their plans is to follow the approaches of the two USDOT pilots in their developments of ICM. FDOT District 5 has decided that modeling to calculate the performance of the plan is better than depending on judgement. The District borrowed the formula of assessing the performance of the candidate plan based on simulation results from the San Diego deployment but the threshold to switch to a new plan was left as a user input. This is because based on San Diego experience; when this threshold was set high initially, no switching was observed. The San Diego project team fine-tuned the threshold until they got at least one switching per week.

The development in District 5 will provide lessons learned to other districts and some of the developments may be transferrable, although the specific utilized simulation model for the predictive engine may be different or even if simulation modeling is not utilized at all. depending on funding, data, and resource availability, a different level of DSS can be implemented that may not include a model-based predictive engine. If no such engine is used, the developed interfaces and expert system platform developed for District 5 can be used.

FDOT District 2 is an example of a district that does not have an immediate plan to use real-time predictive modeling. The currently planned operation based on long term experience with the corridor and some modeling by their consultant using Synchro. The District does not have immediate plan for heavy use of modeling. The reason is that the options for response plan in the ICM appear to be clear and the benefits from introducing modeling is not certain. FDOT District 2 is concerned of the lag-time associated with real-time modeling compared to real-world driver behaviors as demonstrated in at least with one of the USDOT pilot. It was mentioned that most diversion behavior is a result of information provided by private sector smart phone applications like Google Map and Waze. Bluetooth and signal information utilization in real-time is preferred since the response will be based on measured conditions (green, yellow or red on the alternative routes). FDOT District 4 expressed a similar concern about the lag time and mentioned that the implementation of real-time predictive engine may be done at a later stage but not in the beginning. Partner agencies will be totally not supportive in the beginning. Offline use of the model is possible. There is a need to build confidence in the model, then at a future stage the district may use the model real-time

FDOT District 1 indicated that there is a feeling that DSS predictive modeling is useful but some human input will still be needed. The district is waiting for FDOT District 5 experience with the system. An important issue is that not all ICM local partners will appreciate this approach. Thus, a proof of concept is necessary. The good news is that the FDOT District 1 management is receptive to innovation and the MPOs have started to be interested in TSM&O. Another issue is that quality staff who have the background and are interested in new approaches are difficult to find. Staff should have some exposure to modeling.

As with offline modeling, real-time modeling can be as simple as running HCM-based procedures in real-time. In addition, data mining/machine learning approach to real-time evaluation and even real-time generation of plans can be used either in combination with or to replace the real-time expert-rule system and the model-based predictive engine. In any event, there should be weekly or monthly examination of the generated plans to determine the needed fine-tuning to the plans and associated parameters.

The following five maturity levels are recommended for use for real-time DSS.

- Level 1: Manual coordination of plans in real-time with no pre-agreed plans
- Level 2: Pre-agreed response plans determined offline without utilization of model. Plans selected in real-time manually or using expert rules
-
- Level 3: Pre-agreed response plans determined offline using models or data analytics. Plans selected in real-time manually or using expert rules.
- Level 4: Pre-agreed response plans determined offline using models or data analytics. Plans selected in real-time manually or using expert rules and evaluated using model-based or data-based predictive engine.
- Level 5: Real-time model-based or machine learning generation of plans

4.2.3 Traveler Information Systems

Traveler information systems are important to the success of an ICM DSS. There are a number of platforms currently available for delivering traveler information. Some of the existing platforms are provided by the public sector. However, the private sector companies are increasing becoming a main if not the main disseminators of traveler information, particularly through smart phone applications. The public sector delivers information using dynamic message signs (DMS), highway advisory radio (HAR), 511 phone, public agency web sites, public agency smartphone applications, and public agency social media. The private sector disseminates information through, broadcast TV/radio, in-vehicle infotainment systems (built-in and aftermarket), and private sector smartphones applications like Google Map, WAZE, Apple Map, and Inrix.

It should be mentioned that the requirements for state traveler information programs, specified in Federal Regulation 23 CFR 511, is that the provided information “shall include traffic and travel condition information for, as a minimum, all the Interstate highways operated by the state.” Traffic and travel conditions are defined as those impacting traveler experiences, including road or lane closures, roadway weather or other environmental conditions, and travel times in metropolitan areas that experience recurring congestion (ConSysTec and Cambridge Systematics 2013). FDOT normally provides travel time information (when available) for normal conditions and incident lane blockage and other event information during nob-recurrent events.

The interviewed districts said that they would provide alternative route information during events that the system is responding to. There is currently an FDOT policy not allowing the provision of information and this needs to be changed.

The main method of disseminating the information by public agencies is expected to be through DMS, according to the interviews. It may be possible to provide the information through the 511 smartphone app. FDOT districts have installed mainline DMS and in some cases arterial DMS at interchanges. Additional DMS on the arterials have been installed or considered. An SOG has been developed for diversion to Military Trail in Palm Beach County. Trailblazers will be installed at these locations to support diversion. FDOT District 2 mentioned that in addition to delivering DMS and 511 app, they work closely with TV/radio stations that provide updates at six minute intervals in the peak hour including disseminating route diversion information to US1.

At the off-ramps, there are dynamic detour signs that point people to go left or right to divert depending on the congestion on the alternate routes (US-1 vs. SR 115). The FDOT attempted to contact WAZE to determine if the routing information can be disseminated using the WAZE Smart Phone Application but this was not successful.

FDOT District 4 mentioned that the district is currently only considering diverting to State Roads even if there are better County road alternatives since state roads maintained by the FDOT and can be accounted for by current consultant contacts. Sometime, recommend changes to the timings of other street are given, if their operations impact state road performance. There are no resources currently available to expand them.

In FDOT District 5, the diversion to US 17/92 highway will be a major ICM strategy since this is a state road that is managed by FDOT. The alternative routes in the region are clear. There is no grid system, so there are not many options. A main consideration is not to send people to neighborhoods. The alternative routes were coded in a GIS layer and the information was sent to local agencies to confirm. Some of the considered factors included the congestion levels in the corridor, available capacity on alternate routes and light rail, ITS infrastructure availability, and signal controller spare capacity for new timing plans. The capacity from the demand models were considered but not the existing demands when setting the routes. A disutility was used for the roads that have stop signs. It was determined that after selecting the plans, the signals should not be activated until 25 minutes after the incident occurs to prevent continuous transition between plans.

An example of FDOT District 2 plan activation is if there is an incident on I-95 northbound before Jacksonville downtown, the traffic can be diverted to I-295 and US-1 before they get to the incident location. If I-295 is a good alternative, the traffic will be diverted to it first. Based on the experience of the staff, they have implemented one of three levels of plans – mild, moderate, severe based on factors such as time of day and percentage capacity reduction. They continuously observe the traffic based on Bluetooth data and determine if the traffic is getting any worst. FDOT has also access to the central software (ATMS.Now) through SunGuide and have predetermined plans for set criteria. The setting and activation of criteria is based on the system manager knowledge of the system and observations for each time of the year for 12 years. A capacity drop of certain percentage in the peak period for example will result in the activation of the incident plans at certain severity level. They use rule-based on plans they developed. Part of the plans was done based on their consultant offline modeling of the alternative routes. These plans were revised based on experience.

The interviewed agencies have not mentioned immediate plans for the provision of transit information as part of the ICM. This is due to unavailability of good alternative mode solution in some cases and the lack of required transit vehicle technologies (like bus real-time tracking) in some cases.

At least in one of the interviews, the low market penetration of traveler information systems like 511 was mentioned as a concern. Figure 33 shows the percentage of travelers accessing different traveler information platforms in Iowa, which is categorized by traveler information type, as reported in a 2015 report produced for the Iowa DOT (Sharma et al. 2015). From this figure, it can be seen that at least 20% of travelers use smartphone applications to obtain congestion or travel time information, compared to about 2% who use the 511 phone system, and 4% who use the 511 web site and app. This indicates that the use of private sector applications is at least 10 times greater than the 511 phone system, and 5 times greater than the 511 web system. The trend of using private sector applications is expected to increase in the coming years, with the continuing increase in smartphone ownership, the increase in the cellular connectivity of vehicles, and the introduction of vehicle-mobile phone integration technologies such as Carplay and Android Auto. Thus, the impact of these applications on the alternative routes should be considered.

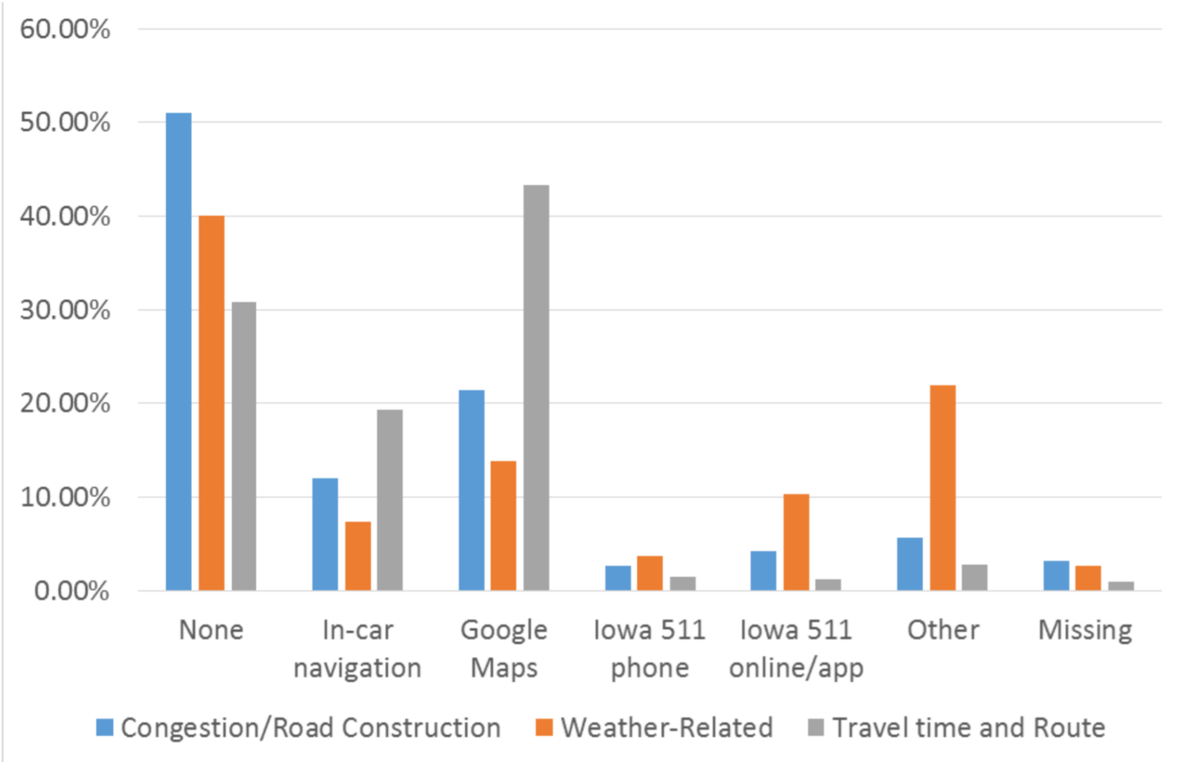


Figure 33: Traffic information services used by Iowa survey respondents (Source: Sharma et al., 2015)

The following four maturity levels are recommended for use for travel time information with route diversion.

- Level 1: Provision of travel time and lane blockage information for limited access facilities
- Level 2: Provision of travel time and lane blockage information for limited access facilities and routing information to alternative <u>state road routes</u>
- Level 3: Provision of travel time and lane blockage information for limited access facilities and routing information to alternative state road <u>and other</u> routes
- Level 4: Provision of travel time and lane blockage information for limited access facilities and routing information to alternative routes and optimize signal timing for diverted traffic
- Level 5: Same as Level 3 with the addition of transit information.

4.3 PERFORMANCE MEASUREMENTS

As defined by the Planned Special Events Capability Maturity Framework (FHWA, 2018c) "the performance measurement is essential as the means of determining program effectiveness, determining how changes are affecting performance, and guiding decision-making. In addition, operations performance measures demonstrate the extent of transportation problems and can be used to make the case for operations within an agency and for decision-makers and the traveling public, as well as to demonstrate to them what is being accomplished with public funds on the transportation system."

4.3.1 Data Collection

Existing and emerging sensor, mobile, and vehicle technologies in addition to data from multiple other sources are increasingly available and will provide a strong support for ICM. Traffic data will be available from point sensors, vehicle re-matching technologies such as Bluetooth and Wi-Fi readers, transit vehicles, and third party vendors. Data from vehicle re-matching technologies and also from third party private sector data providers are increasingly being used particularly for arterial street travel time estimation and to a lesser degree for origin-destination estimation to support planning, modeling, management, and operations. However, the estimation of traffic volume and density requires point sensors. The data from the above sources can be combined with data from other sources (such as crash, weather, incident, signal timing control, perception and preference surveys, socio-economic, and work zone data) to allow the assessment of the performance of the transportation systems and the impacts of various factors on the performance. However, it is important to ensure that the used data has acceptable data quality. Even with proven technologies such as point traffic detectors, it is important to ensure that the detectors are well installed, calibrated, and maintained to provide the required data. This is also important when using, new, sometime unproven, data collection technologies and products, and data from private sector data providers.

Bluetooth data is used by the districts to estimate arterial travel time. One of the first and largest deployment was in District 2. The collected data is used heavily by the TMC to identify the congestion level and determine if the activation should be done at what level.

Bluetooth data has been installed on all alternative routes in District 5 ICM deployments. Microwave detectors (MVDS) at mid-blocks were also installed at a limited number of locations. A main focus is on the use of high Arterial Traffic Signal Performance Measure (ATSPM) based on high resolution controller data rather than midblock detectors since these detectors are maintenance burden.

The following four maturity levels are recommended for use for data collection.

- Level 1: Traffic data is only collected for urban freeways in real-time operations and archived for possible use for offline analysis.
- Level 2: Traffic data are also collected from vehicle re-matching technologies or third party vendors for urban streets and archived for use
- Level 3: Same as Level 2 but with the collection of additional data including midblock detection on arterial links and/or high resolution controller data
- Level 4: Same as Level 3 with the addition of the collection of multi-modal data including transit, freight, pedestrian, and bicycle data; as needed according to the concept of operations of ICM.

4.3.2 Data Warehousing and Governance

The FDOT is currently archiving the data collected by their traffic management center using the Regional Integrated Transportation Information System (*RITIS*); which is an automated data sharing, dissemination, and archiving system maintained by the University of Maryland. Additional data will be generated through the ICM. One option is to archive all additional data in RITIS. Another option is to develop ICM data marts that pull data and archive data from different sources.

Data availability, sharing and governance are important to the success of ICM. In addition to data warehousing, effective management of the data requires data governance. Data governance ensures the availability, usability, consistency, integrity, and security of the data. It will also ensure accountability for the adverse effects of poor data quality. The data governance and associated guidelines should be followed, enforced, and updated as needed.

The following four maturity levels are recommended for use for data warehousing and governance.

- Level 1: Traffic data for limited access facilities of the corridor is archived
- Level 2: Traffic data for limited access facilities, parallel arterials and modes, and other data that allows determining the factors contributing to performance of the corridor are archived in an integrated data warehouse.
- Level 3: Same as Level 2 but with some elements of the data governance applied to at least one agency
- Level 4: Same as Level 3 but with data governance is institutionalized and applied for all data gathered and utilized to support ICM.

4.3.3 Estimation of Performance Measures

The ICM deployment requires the definition of performance measures that are related to the regional goals and objectives and ICM project objectives. The performance measures can be in different levels of details to support strategic, programmatic, tactical and operational decisions with more detailed measures defined going from strategic to the operations levels. However, the performance measures at different levels should be aligned and mapped to the goals and objectives.

When defining evaluation performance measures, the evaluators should keep the "SMART" criteria in mind. SMART requires the objectives to be:

- **Specific.** Target a specific area for improvement.
- **Measurable.** Quantify or at least suggest an indicator of progress.
- **Assignable.** Specify who will do it.
- **Realistic.** State which results can realistically be achieved, given available resources.
- **Time Related.** Specify when the results can be achieved.

These criteria have since been expanded to "SMARTER" by adding the following elements:

1. **Evaluated.** Allow assessment of the extent to which the goal and objectives have been achieved.
2. **Reviewed.** Allow reflection and adjustment of the approach or deployment to better reach the project goal and objectives.

Transportation agencies have used both outcome (also referred to as quality of service) and output (also referred to as efficiency or activity-based) performance measures. Output measures, sometimes referred to as activity-based measures, relate to the physical quantities of items, levels of effort, scale of activities, and the efficiency in converting resources into products. Examples of outcome measures include:

- **System Coverage.** These measures capture the coverage of technology such as dynamic message signs, cameras, and detectors.
- **Incident Management.** These measures capture incident management performance such as the reduction in detection, response, and clearance times.
- **Installed Subsystem Performance.** These measures capture the performance of a deployed subsystem or product such as failure rates and times between failures.
- **Behavior Measures.** Examples of these measures include the use of traveler information systems, diversion rates of travelers receiving the information, and compliance with variable speed limits.

Outcome measures relate to how well the project is meeting its goal and stated objectives, such as those related to mobility, reliability, safety, environmental, and the user satisfaction impacts of the transportation system improvements.

In general, FDOT districts have been tracking measures for their limited access facilities. Some of these districts have started producing dashboards of these measures (see Figure 34 for an example dashboard produced by a tool developed for FDOT by the research team of this study). Some districts have hired analysts to produce measures and the review the performance every week.

In recent years, they have also started to track the performance of some of their state road arterials. The following four maturity levels are recommended for performance measurement tracking.

- Level 1: Output measures are reported for urban freeways only but no measurement of outcome performance is reported.
- Level 2: Output and outcome performance measures are reported for urban freeways and some state arterials of the ICM. Awareness of performance tracking by partner agencies is limited, and documentation/reporting is inconsistent.
- Level 3: Output performance measures at the operation level are reported for all components of the corridor (freeway, arterial, transit, etc.) at specific intervals in a consistent manner.
- Level 4: Same as Level 3 but performance measures are also provided to executive managers to support strategic decisions and mid-level managers to support tactical decisions.

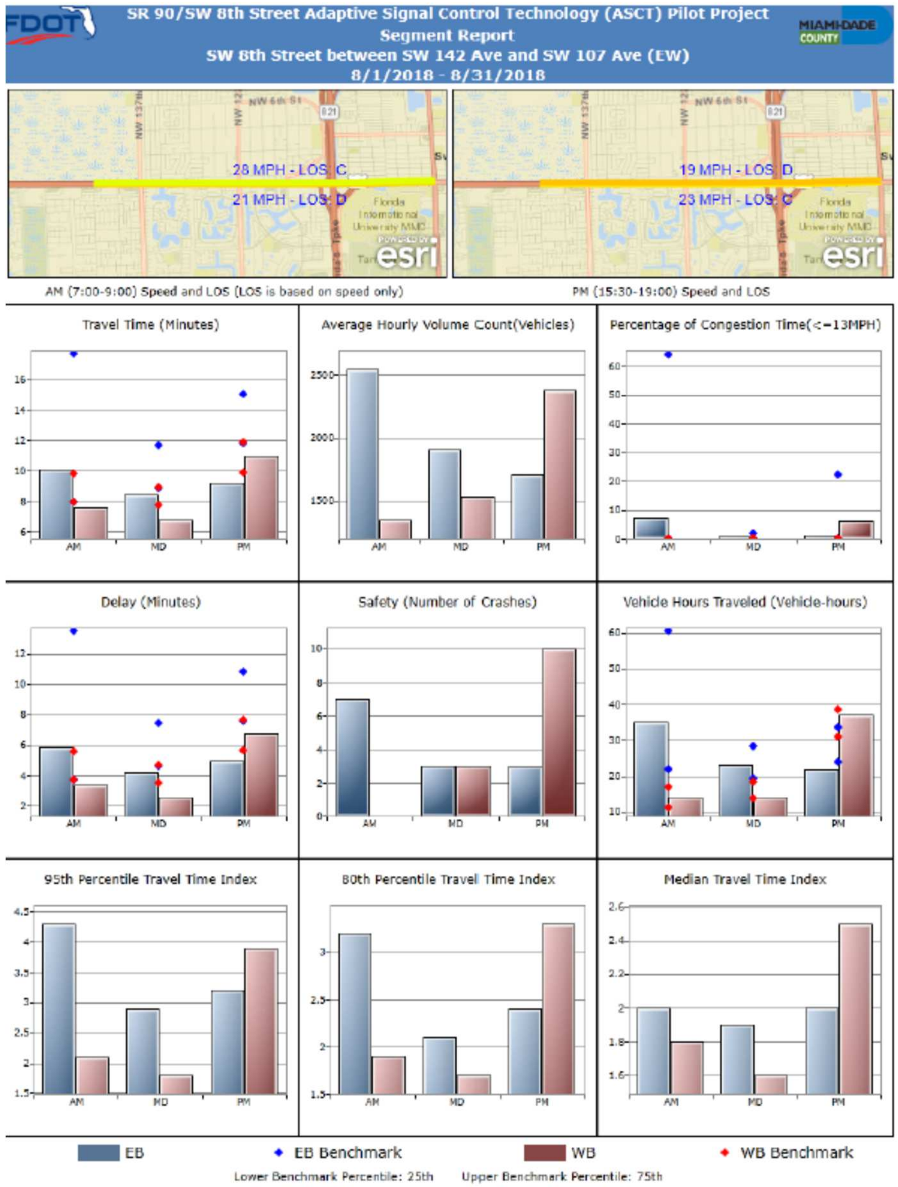


Figure 34: Example dashboard produced for the FDOT

4.3.4 Utilization of Performance Measures

The performance measurement capability discussed in Section 5.3 does not provide benefits to the agency unless they are used in an effective manner to support the decision processes associated with ICM. Business Intelligence (BI) applications should be used to convert the performance measures to information that support the decision process both offline and in real-time. Such information will involve:

- Describing the existing performance to the decision makers
- Diagnosis of the factors that influence existing conditions
- Predicting day-to-day performance to support organizational decisions, and real-time performance to support operational decisions

- Recommending strategies and actions needed to mitigate the identified issues

The Data Warehouse Institute defines BI as "the processes, technologies and tools needed to turn data into information and information into knowledge and knowledge into plans that drive profitable business action. BI encompasses data warehousing, business analytics and knowledge management." (IBM, 2018). Yeo and Koronios (2010) defined BI as a set of integrated tools, technologies and programmed products used to collect, integrate, analyze, and transform data into information. This information is then used to enable effective business decision making.

The FDOT districts indicated that the use of performance measures based on data is important but currently its use is not institutionalize as part of the business process for use in different decision levels. This is needed for effective use of data. The following four maturity levels are recommended for use for data warehousing and governance.

- Level 1: ICM performance measures, when collected, are only used to document efforts and justify costs.
- Level 2: ICM performance measures are assessed using reports and/or dashboards to determine whether plans should be revised. However, the use of measures is not institutionalized as part of the business process for use in different decision levels.
- Level 3: ICM measures are also systematically evaluated at the strategic and tactical levels to improve policies and procedures. The measures are incorporated into the strategic planning decisions for the region or agency by upper management and institutionalize as part of the business process for use in different decision levels.
- Level 4: In addition to Level 3, data mining/machine learning techniques are used to support agency decisions based on performance measures.

4.4 ORGANIZATION AND WORKFORCE

Efficient execution of processes supporting effective programs requires appropriate combination of coordinated organizational functions and technical qualified staff with clear management authority and accountability.

4.4.1 ICM Staffing

It is important to meet the staffing requirement for ICM plan development, fine-tuning, and activation. These responsibilities may be assigned to existing staff but most likely additional staffing will be needed to meet the additional workload. In Dallas, it was reported that existing operations staff members were given additional duties but a one full-time staff was hired to serve as the ICM coordinator for the US-75 corridor. FDOT District 2 has one dedicated staff and is adding a second to cover ICM expansion to four counties (Duval, Clay, St Jones, and Alachua). The staffing planned by FDOT District 5 at their traffic management is presented below. Notice that there is an additional staffing for corridor management.

- Executive Team (Weekly Oversight)
- TMC Manager
- Freeway Manager
- Freeway Operator (1 per 5.0 Real-Time Crashes)

- Arterial Manager
- Corridor Manager - 1 per county in urban area and 1 per other county in rural areas
- Public Involvement Consultant (1)
- Analysis for Performance Measurement (1)

Notice the additional staff that is added for the specific period of corridor management in the case of District 5.

The following four maturity levels are recommended for use for ICM staffing:

- Level 1: ICM activities are not specifically assigned to any specific staff; rather, they are performed by whomever might be available at the centers of the partner agency in reaction to events.
- Level 2: One or more individuals within the centers of the leading agency have ICM responsibilities as part of their job function. However, these responsibilities are not documented or completely understood by all parties. Individuals from different agencies do not routinely meet to discuss or coordinate ICM activities.
- Level 3: ICM responsibilities are formally assigned to specific individuals within each ICM partner agencies.
- Level 4: Same as Level 3 but the assignments are well documented, personnel clearly understand their responsibilities, and they routinely meet to proactively plan and prepare for ICM events.

4.4.2 Staff Capabilities and Training

The setup and utilization of DSS will require new capabilities and training not currently available at traffic management centers. An issue mentioned by the districts is that need for quality staff who have the background in data analytics, simulation and modeling and are interested in the new approach. Staff should have some exposure to modeling. It was stated in the interviews with the districts that the district modelers need to be involved. However, they need to be informed about the difference between the needed models for TSMO versus the planning level models. At the same time, although The ICM managers do not need to be expert in modeling, they need to know enough to explain to the modelers the objectives and requirements of modeling and interact with them during the modeling process. Another mentioned concern about modeling is the need for agency to understand the strengths and limitations of modeling considering the many inputs regarding their effectiveness.

The following four maturity levels are recommended for use for ICM staffing:

- Level 1: Desired knowledge and skills for ICM DSS are not formally defined or are limited to those identified for regular TMC activities
- Level 2: Knowledge and skills specifically needed to develop, implement, and evaluate ICM DSS and associated plans are identified and staff hiring is based on this identification.
- Level 3: Same as Level 2 with on-the-job training and operational exercises on as needed basis

- Level 4: Same as Level 3 but with required knowledge and skills needed across the partner agencies are regularly reviewed and updated as ICM DSS evolve. Formal operations training and exercising are institutionalized across all partner agencies with a focus on cross-training and succession planning.

4.5 COLLABORATION

Coordination and collaboration is critical to the success of ICM and the associated DSS. Some locations will have the ICM operation centralized in one locations. This option appears to be the preferred option by FDOT Districts. In some cases, multiple agencies may be co-located at the same location, although remotely connected and coordinated operations through center-to-center automated interfaces and operator-to-operator speaking to each other can be effective. FDOT District 2 said that colocation has been very useful in their case. Sometime you need operators from the two agencies to work closely together to provide the required knowledge to inform the decision.

An important aspect of the implementation and utilization of DSS are for agencies to share the data required for the ICM and to work together to deliver seamless ICM operations on the freeway, arterial streets, and transit facilities that are part of the ICM. Sharing data, video, and information could be manual but will be more effective if it includes an automated center-to-center data sharing.

There has been a strong recommendation for formal memorandum of understanding (MOUs) and agreements to support the operation and maintenance activities. The interviews and review of the literature conducted in this study indicates that this can be a good option in many cases to support ICM, particular when the needed collaboration, cooperation, and sharing is expected to impact cost or agency business processes. Currently, there are not formal ICM agreements signed at FDOT districts. Some FDOT districts are of the opinion that there is definitely a need for such agreement to address issues like roles and responsibilities, operations, and funding. The signing partners will have to include at least signal maintaining agencies, transit agencies, and MPOs. MPOs can play a role in collaborative activities, long-range strategic plans, and funding. The agreement will help building working relationship has and generating trust. Initial guidelines may be rigid but that is acceptable until trust/comfort level is built. However, in other cases, the districts was of the opinions that formal agreements are not immediately needed since there are already a strong relationships between TSM&O partners. In these cases, formal agreements may not be necessary due to the high level of collaboration and trust between the partners and it was stated that the formal agreements may introduce rigidity to the collaboration process. This point of view was also expressed in other interviews conducted with agencies outside Florida that were interviewed by the research team as part of a separate project.

Some agencies are utilizing existing agreements. For example, FDOT District 1 stated that they have a generalized operations funding agreements, but none that specifically cover ICM that can be used to support ICM. In Dallas, TX, an existing ITS cooperative agreement for the region was in place was used by the ICM partners but an O&M document was developed cooperatively by the partners (Spiller et al., 2014). In San Diego, a project charter and individual MOUs were developed initially to provide high-level guidance on the needed cooperation. Later, an ICMS operational framework document was developed by the partner agencies (Spiller et al., 2014).

There may be challenges in setting the agreements. For example, FDOT District 1 stated that a main challenge is overcoming the approval process between Manatee County and the other local agencies that are operated out of the TMC. Manatee has agreements with Sarasota County, Bradenton, and City of Sarasota for regional operations of the signals. Currently, to implement a multi-jurisdictional timing adjustment requires agreement from all agencies.

Obviously, there will be a need for Standard Operation Guidelines (SOGs) and Standard Operation Procedures (SOPs) for ICM. Such guidelines and procedures will address how the cooperative response plans are implemented. It appears that FDOT districts that are implementing are ICM have developed or are developing SOG. For example, FDOT District 5 and FDOT District 1 are developing such guidance.

Some of the challenges to collaborative ICM effort are the required resources, changing roles of operating agencies that may not be acceptable to some agencies, and the requirements for partner agencies to meet performance targets. FDOT District 5 mentioned that it is important to identify the needs of local agencies. Recognizing that what is important for them is signal timing optimization and include that in the ICM will bring these agencies to the table. This additional cost is worth it to ensure collaboration. There is a need to build comfortable and trust, work on common goals and objectives, and explain and demonstrate the benefits to partner agencies.

One of the challenges to be resolved as part of the SOGs and SOPs is the operations during the afterhours of one or more management center in the region. FDOT District 1 stated that this will be determined as part of the ICM SOG task but will likely be provided by the District. In District 5, the ICM is currently operating from 6:00 AM to 7:00 PM. When the ICM DSS software is ready it will be 24 hours a day. District 5 has convinced many agencies to provide control of the signal to the District in case of severe incidents and this is increasing. For those agencies that will not give control, they will have to provide someone to contact during incidents in the after hour.

There are different levels for collaboration. At the basic level, it will involves data and video sharing. At more advanced levels, this can include collaborative or centralized operation of the ICM, as listed in the maturity levels below.

The following maturity levels are recommended.

- Level 1: Agencies do not coordinate their operations
- Level 2: Agencies share data for use in deciding on management strategies (e.g., special signal plans during incidents) but each agency independently select and apply the plans.
- Level 3: Agencies share data and plans are selected for multi facility corridor but applied by individual agencies
- Level 4: Centralized operation and management of the corridor

4.6 CULTURE

Culture is the combination of values, assumptions, knowledge, and expectations of the agency in the context of its institutional and operating context, and as expressed in its accepted mission and related activities (AASHTO, 2018). NCHRP Project 20-68A (Spiller et al., 2014) report pointed to the facts that most of the ICM projects reviewed in the project have had a champion from one of the agencies to “help get the project started, funded, and driven to completion.” The champion can be a part of a leading agency that implement and/or operate the ICM. Such leader and/or champion should at least understand a high level the concepts, strengths, and weaknesses of data-based and model-based DSS. All interviewed districts see the ICM to be led by FDOT as a centralized operation. Another culture-related element that contribute to the success of ICM project is the organizational support and institutionalization of the use of data analytics and model for ICM decision making. One need to ask how is the application of DSS and modeling and data analytics use as part of DSS is valued within the partner agencies.

The following five maturity levels are recommended.

- Level 1: Perceived value of DSS is not valued by a champion/lead agency and partner agencies
- Level 2: Perceived value of DSS is valued and supported but the modeling and data analytics is not institutionalized as part of the offline or real-time DSS
- Level 3: The use of model and/or data analytics is valued by the champion/lead agency but not by the partner agencies and some processes are implemented to improve staff-related capabilities
- Level 4: The use of model and/or data analytics is valued by all agencies and has been institutionalized and fully integrated for offline analysis
- Level 5: The use of model and/or data analytics is valued and has been institutionalized and fully integrated for both offline and real-time analysis

4.7 SUMMARY

This section presents a review of main findings from the discussion presented in the document for the six ICM Capability Dimensions.

4.7.1 Business Processes

Decision support tools should be used to determine the ICM project feasibility, value, and significance should affect project development decisions. Return-on-investment or at least the expected improvements in outcome performance measures related to the goals and objectives identified by the project stakeholders should be conducted to support the analysis. At a minimum, a planning level analysis utilizing highway capacity manual (HCM) level analysis combined with data analysis should be used. More detailed simulation modeling is desirable.

Funding, particularly those related to operations and maintenance (O&M) is obviously a major concern for agencies. Based on the above, it seems that the ICM deployments can use FDOT work program, MPO federal funding, local agency funding, and even Central Office and federal funding. FDOT districts have also supported ICM partners with ICM O&M funding needs, particularly with local agencies that have limited resources.

4.7.2 System and Technologies

Use of Systems Engineering and Regional Architecture

As with other Intelligent Transportation Systems (ITS) projects, the ICM planning, design, and deployment should follow the system engineering process. FDOT ITS projects has a system engineering process and regional architectures that have been in place for almost 15 years. It is anticipated that this process will be used for ICM projects. The ICM deployments in Florida will also utilize center-to-center and center to field ITS standards and FDOT specifications and guidelines, as required by the United States Department of Transportation (USDOT) and FDOT.

Off-Line Decision Support

The utilization of an effective decision support system is an important foundation of the deployment of ICM. DSS determine, offline and in real-time environment, congestion conditions that require a response, recommend coordinated response(s), and evaluate these responses.

Offline modeling and data analyses are an important aspect of ICM that should be utilized in all ICM deployments to determine the effectiveness of different ICM strategies in the planning stage and to identify the response plans in the design stage. It should be recognized that modeling can be done at different levels. More complex deployments like the ones tested in San Diego and Dallas, and planned for Orlando and Los Angles use dynamic traffic assignment (DTA)-based mesoscopic and/or microscopic modeling. Even if agencies lack the resources to develop a large scale dynamic traffic assignment (DTA)-based mesoscopic or microscopic simulation models, consideration should be given to utilizing existing simulation models that were developed for other purposes in the region. Some interviews revealed that big scale DTA-based model may require a lot of resources and the District may not have experience in it. The modeling office may provide the needed capabilities. However, the modelers need to understand the level of details and accuracy required for TSM&O applications versus planning level applications.

Freeway and urban arterial HCM-based procedures can provide important support for the selection and effectiveness of the response plans. It should be recognized that modeling can be done at different levels. More complex deployments like the ones tested in San Diego and Dallas, and planned for Orlando and Los Angles use dynamic traffic assignment (DTA)-based mesoscopic and/or microscopic modeling. Freeway and urban arterial HCM-based procedures can provide important support for the selection and effectiveness of the response plans. Another important aspect of offline analysis is data analytics that can provide considerable support of planning and design of ICM.

Real-Time Decision Support

In general, real-time DSS, as implemented in the two USDOT pilots and planned in District 5 in Orlando, can be considered to consist of four elements: data collection and fusion, user interface, real-time response plan recommendations, and model-based real-time predictive engine. The Florida District 5 DSS deployment will include a model-based predictive. The development in District 5 will provide lessons learned to other districts and some of the developments may be transferrable, although the specific utilized simulation model for the predictive engine may be different or even if simulation modeling is not utilized at all. Depending on funding, data, and resource availability, a different level of DSS can be implemented that may not include a model-based predictive engine.

It appears that the districts are waiting for FDOT District 5 experience with the system. An important issue is that not all ICM local partners will appreciate this approach. Thus, a proof of concept is necessary.

As with offline modeling, real-time modeling can be as simple as running HCM-based procedures in real-time. In addition, data mining/machine learning approach to real-time evaluation and even real-time generation of plans can be used either in combination with or to replace the real-time expert-rule system and the model-based predictive engine.

Traveler Information Systems

The traveler information will continue to be provided by the public and private agencies. The main method of disseminating the information by public agencies is expected to be through DMS, 511 App, and providing information to TV/Radios. The interviewed districts said that they would provide alternative route information during events that the system is responding to. There is currently an FDOT policy not allowing the provision of information and this needs to be changed.

The interviewed agencies have not mentioned immediate plans for the provision of transit information as part of the ICM. This is due to unavailability of good alternative mode solution in some cases and the lack of required transit vehicle technologies (like bus real-time tracking) in some cases.

In many cases, the districts are currently only considering diverting to State Roads even if there are better County road alternatives since state roads maintained by the FDOT and can be accounted for by current consultant contacts. Sometime, recommend changes to the timings of other street are given, if their operations impact state road performance. There are no resources currently available to expand them.

4.7.3 Performance Measurements

Existing and emerging sensor, mobile, and vehicle technologies in addition to data from multiple other sources are increasingly available and will provide a strong support for ICM. Bluetooth data has been installed on alternative routes. In few cases, Microwave detectors (MVDS) at mid-blocks were also installed and in some cases high resolution controller data were collected.

The FDOT is currently archiving the data collected by their traffic management center using the Regional Integrated Transportation Information System (*RITIS*); which is an automated data sharing, dissemination, and archiving system maintained by the University of Maryland. Additional data will be generated through the ICM. One option is to archive all additional data in RITIS. Another option is to develop ICM data marts that pull data and archive data from different sources.

Data availability, sharing and governance are important to the success of ICM. In addition to data warehousing, effective management of the data requires data governance. Data governance ensures the availability, usability, consistency, integrity, and security of the data. It will also ensure accountability for the adverse effects of poor data quality. The data governance and associated guidelines should be followed, enforced, and updated as needed.

The ICM deployment requires the definition of performance measures that are related to the regional goals and objectives and ICM project objectives. The performance measures can be in different levels of details to support strategic, programmatic, tactical and operational decisions with more detailed measures defined going from strategic to the operations levels. However, the performance measures at different levels should be aligned and mapped to the goals and objectives. In general, FDOT districts have been tracking measures for their limited access facilities. Some of these districts have started producing dashboards of these measures.

The performance measurement capability does not provide benefits to the agency unless they are used in an effective manner to support the decision processes associated with ICM. Business Intelligence (BI) applications should be used to convert the performance measures to information that support the decision process both offline and in real-time. The FDOT districts indicated that the use of performance measures based on data is important but currently its use is not institutionalized as part of the business process for use in different decision levels. This is needed for effective use of data.

4.7.4 Organization and Workforce

It is important to meet the staffing requirement for ICM plan development, fine-tuning, and activation. These responsibilities may be assigned to existing staff but most likely additional staffing will be needed to meet the additional workload.

The setup and utilization of DSS will require new capabilities and training not currently available at traffic management centers. An issue mentioned by the districts is that need for quality staff who have the background in data analytics, simulation and modeling and are interested in the new approach. Staff should have some exposure to modeling.

It was stated in the interviews with the districts that the district modelers need to be involved. However, they need to be informed about the difference between the needed models for TSMO versus the planning level models. At the same time, although The ICM managers do not need to be expert in modeling, they need to know enough to explain to the modelers the objectives and requirements of modeling and interact with them during the modeling process. Another mentioned concern about modeling is the need for agency to understand the strengths and limitations of modeling considering the many inputs regarding their effectiveness.

4.7.5 Collaboration

Coordination and collaboration is critical to the success of ICM and the associated DSS. Some locations will have the ICM operation centralized in one locations. This option appears to be the preferred option by FDOT Districts.

There has been a strong recommendation for formal memorandum of understanding (MOUs) and agreements to support the operation and maintenance activities. The interviews and review of the literature conducted in this study indicates that this can be a good option in many cases to support ICM, particular when the needed collaboration, cooperation, and sharing is expected to impact cost or agency business processes. Currently, there are not formal ICM agreements signed at FDOT districts. Some FDOT districts are of the opinion that there is definitely a need for such agreement to address issues like roles and responsibilities, operations, and funding. The signing partners will have to include at least signal maintaining agencies, transit agencies, and MPOs. MPOs can play a role in collaborative activities, long-range strategic plans, and funding. The agreement will help building working relationship has and generating trust. Initial guidelines may be rigid but that is acceptable until trust/comfort level is built. However, in other cases, the districts was of the opinions that formal agreements are not immediately needed since there are already a strong relationships between TSM&O partners. In these cases, formal agreements may not be necessary due to the high level of collaboration and trust between the partners and it was stated that the formal agreements may introduce rigidity to the collaboration process.

4.7.6 Culture

ICM projects need a champion that can be a part of a leading agency that implement and/or operate the ICM. Such leader and/or champion should at least understand a high level the concepts, strengths, and weaknesses of data-based and model-based DSS. All interviewed districts see the ICM to be led by FDOT as a centralized operation.

Another culture-related element that contribute to the success of ICM project is the organizational support and institutionalization of the use of data analytics and model for ICM decision making. One need to ask how is the application of DSS and modeling and data analytics use as part of DSS is valued within the partner agencies.

5. DEMONSTRATION OF ANALYSIS ABILITY TO SUPPORT ICM

5.1 BACKGROUND

This chapter reports on the results from a project task initiated to demonstrate the ability of data and modeling analytics to support various operational scenario decisions.

The following abilities were demonstrated as part of this project:

- Utilization of clustering analysis to identify traffic patterns
- Identification of the impacted diversion routes
- Use of connected vehicle data to identify congestion patterns on alternatives routes to allow the selection of special signal plans

Additional abilities were demonstrated as part of a project funded by the Southeastern Transportation Research, Innovation, Development and Education (STRIDE) Center University Transportation Center (UTC), which used this project as a match. These abilities are listed below.

- Prediction of diversion rate based on detector data
- Selection of signal timing during arterial incidents

A brief summary of the development in the UTC project is presented in the section for completeness. The readers are referred to the STRIDE UTC final report for the details. The abilities tested in this project are discussed in details in the following sections.

5.2 ESTIMATION OF DIVERSION BASED ON MAIN STREET DETECTOR DATA

Estimation of the diversion rates of traffic during incident conditions is an important parameter to support the performance management of transportation systems. As part of a project funded by the STRIDE UTC, the research team of this project developed a methodology for the prediction of diversion rates based on mainline detector data combined with incident data. The primary challenge to the method developed in this study is that traffic detectors are not installed on freeway off-ramps in most current deployments. Thus, the change in volumes on these ramps cannot be detected to estimate the diverted volumes. Thus, the developed method estimates diversion solely based on mainline detector data.

The developed method utilizes a combination of cumulative volume analysis, clustering analysis, and predictive data analytics. The purpose of clustering analysis is to associate the incident day traffic pattern before the occurrence of the incident with similar normal day patterns. This allows the use of the cumulative volume analysis method to determine the volumes on the freeway with and without incidents and thus to estimate the diversion. It was found that the diversion rate can range from about 4% to 22%, depending on the severity (mainly reflecting duration), lane blockage (up to three out of five lanes), and the time of incident occurrence. This is significantly lower than what was found by the researchers of this study based on an online revealed preference survey that suggests a diversion rate close to 40% with regularly occurring incidents for the same area of the case study used in this paper. This points to the need to reviewing the results from online diversion rate surveys with caution.

Data analytic models were developed allowing the prediction of the diversion rate based on the incident severity, number of blocked lanes, time of the incident occurrence, and incident locations. Three different models were developed utilizing linear regression (LR), Support Vector Machine (SVM), and a neutral network using the Multilayer Perceptron (MLP) model. The set of variables considered for possible inclusion in the models are the number of blocked lanes, incident severity (mainly related to the expected incident duration), incident location, and time slice of incident occurrence. Table 24 shows the relationship derived using regression. The adjusted coefficient of determination for multiple regression (Adjusted R squared) of the developed model is 0.6025. The Mean Absolute Error (MAE) of the predicted diversion (Y) compared to the actual Y is 3.20%. All four variables considered for inclusion are significant at the 5% level, as shown in Table 24.

Table 24: Regression Analysis Results

Regression Model		
Variables	Coefficient	Pr(>|t|)
Lane Blockage	1.7089****	0.000392
Incident Severity	2.2655***	0.006277
Incident Location	0.4242**	0.033404
Log_e (Time slice of Incident Occurrence)	-2.6621**	0.010086
	Multiple R-squared:	0.614
	Adjusted R-squared:	0.6025
	p-value:	2.2e-16
	Mean Absolute Error	3.20%
Significant codes: 0= '****' 0.001= '***' 0.01= '**' 0.05= '*'		

The study found evidence that the diversion is constrained by the capacity of the signals at of the off-ramps, indicating the need for special signal control plans during incidents to increase the capacity of the off-ramps and adjacent signals leading to the main parallel routes. Capacity analysis of the off-ramp signals indicates that the two off-ramps that provide exits to the main connectors to the alternative routes have a limited amount of access capacity available for vehicles to exit the freeway to alternative routes.

Among the developed models, the MLP model appears to produce the best results. Figure 35 shows how well these three models predicted the diversion rates based on the freeway incident characteristics. It is clear from these figures that the SVM and MLP have better prediction capability than the LR. An interesting observation is that the estimates based on the MLP model followed the pattern of the measured diversion rate better than those based on the SVM model. On the other hand, the SVM model produced better fit at higher diversion rates.

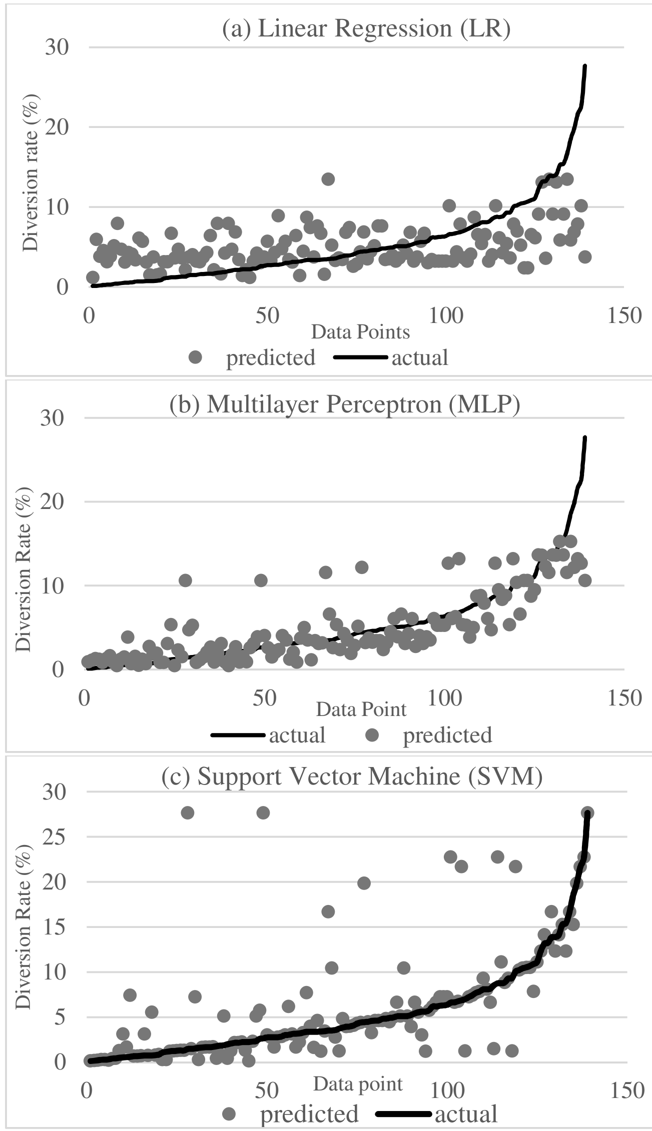


Figure 35: Plot of actual and predicted diversion rates using (a) Linear regression (LR) model, (b) Multilayer Perceptron (MLP) model, (c) Support Vector Machine (SVM) model

5.3 IDENTIFICATION OF SPECIAL SIGNAL PLANS FOR ARTERIAL INCIDENTS

The activation of special traffic signal plans during non-recurrent events is an important component of arterial active management (AAM) and can provide significant benefits in terms of performance metrics of the transportation systems. Most signal control systems in use today are still pre-timed operating either as fixed-time or traffic-actuated. With these systems, transportation agencies operate the signal control systems based on time of day (TOD). The TOD plans are prepared using historical traffic flow data collected for different times of the day and fine-tuned based on field observations. Such control cannot deal with non-recurrent congestion due to incidents and other lane blockage events and surges in demands due to special events.

Events such as surges in demands or lane blockages can create queue spillbacks even during the off-peak periods resulting in delays and spillbacks upstream intersection(s). To address this issue, some transportation agencies have started implementing processes to change the signal timing in real-time based on traffic signal engineer/expert operator's observations of incident and traffic conditions at the intersections upstream and downstream of the congested locations. Decisions to change the signal timing are governed by many factors such as the queue length, conditions of the main and side streets, potential of spilling back to upstream intersections, the importance of upstream cross streets, the potential of the queue backing up to a freeway ramp.

As a part of a STRIDE UTC project conducted by the researchers of this study, the history of the responses of the traffic signal engineers to non-recurrent conditions is captured and utilized this experience to train a machine learning model in order to automate the process of updating the signal timing plans during non-recurrent conditions. A combination of Recursive Partitioning and Regression Decision Tree and fuzzy rule-based system is utilized to develop the model in order to deal with the vagueness and uncertainty of human decisions. Comparing the decisions made based on the resulting fuzzy rules from applying the methodology to previously recorded expert decisions for a project case study indicates accurate recommendations for shifts in the green. The decision tree and fuzzy rule-based system approaches have the advantage in that they can be augmented with additional rules. Thus, new rules could be developed based on manual expert rules inputs, Automated Traffic Signal Performance Measures (ATSPMs) data, simulation results, and/or optimization results to augment the rules derived based on decision tree training of past decisions by the experts.

The developed methodology learns from the decisions made by signal engineers/expert operators to change signal timings by extending greens during incidents and produce fuzzy rules that can be used to automate the process. Figure 36 shows the decision tree generated based on the traffic signal engineer/expert operator's data feed.in this study. The decision tree algorithm first divided the dataset depending on the queue length, then the subset that has queue lengths lower than 6,057 ft. was further divided into subgroups based on the demand increment ratio and capacity reduction ratio. When the queue length is larger of 6.057 ft, the subset was divided in terms of upstream intersection cross street importance as well as incident start period, demand increment ratio, and capacity reduction ratio in the next levels.

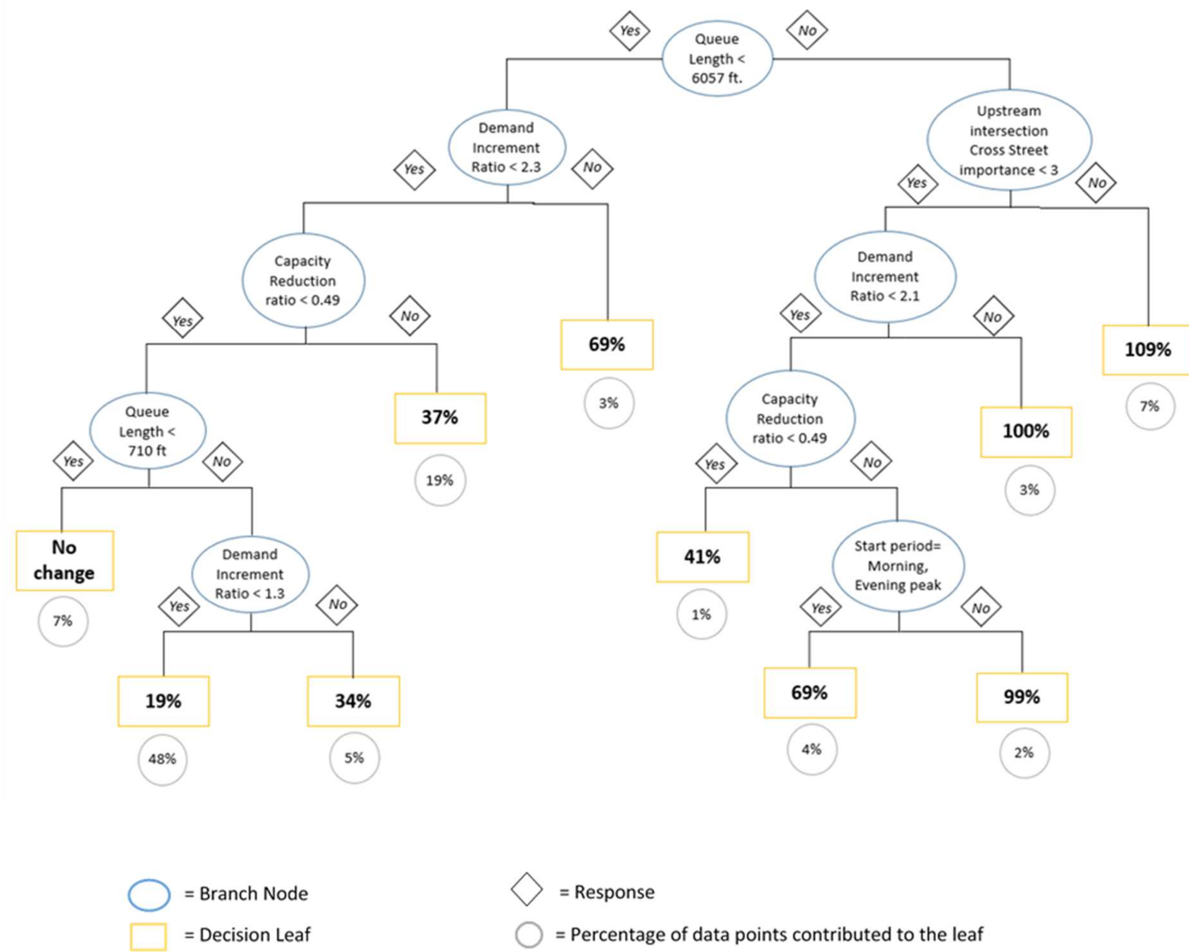


Figure 36: Decision tree generated based on the traffic signal engineer/expert operator's decisions

Comparing the decisions made based on the resulting fuzzy rules from applying the methodology to previously recorded expert decisions for the project case study indicates accurate recommendations for shifts in the green time (about 77% accuracy or 5.38% mean absolute error). The comparison was done for 10 percent of the data points randomly selected as the test sample that was not included in training the model. The simulation results indicate that changing the green times based on the output of the fuzzy rules developed based on the decision tree can decrease the delays due to lane blockages or demand surge.

5.4 UTILIZATION OF CLUSTERING ANALYSIS TO IDENTIFY TRAFFIC PATTERNS

5.4.1 Background

For long time, decisions associated with transportation systems planning and operations have been based on a limited amount of data collected for few days. This data was used to obtain information that is supposed to represent the transportation system conditions for the whole year. Thus, the assessment of management and operation strategies; signal control optimization; and the use of analysis, modeling, and simulation (AMS) has been limited in most cases to one scenario of transportation system conditions. With the advancements of transportation system management and operations programs and the associated intelligent transportation system technology deployments, quantitative and detailed traffic and event data have become available from multiple sources that allow better identification of system performance and assessment of improvement alternatives under different congestion, incident, and weather scenarios utilizing data analytics and advanced AMS tools. This is particularly important in the assessments of alternative strategies since the main benefit of these strategies is their ability to adapt to different system conditions. The Federal Highway Administration (FHWA) realizing this need has updated their guidance for utilizing AMS to include clustering analysis to identify operation scenarios as an important component of AMS. Decision support systems developed to support transportation system operation decisions also require the identification of traffic patterns, for which response plans are developed for potential real-time activations.

Clustering analysis can be used to identify of traffic patterns that are representative of traffic conditions in support of transportation system operations and management (TSM&O); integrated corridor management; and analysis, modeling, and simulation (AMS). However, there has been limited information to support agencies in their selection of the most appropriate clustering technique(s), associated parameters, the optimal number of clusters, clustering result analysis, and selecting observations that are representative of each cluster. A large proportion of the conducting clustering analysis to support the applications mentioned above have utilized the K-means clustering method. This method is also widely used in other disciplines and is very efficient in analyzing large datasets. However, its application is limited to datasets with the only quantitative variable as it utilizes the Euclidian distance as the dissimilarity matrix (Huang, 1998). Some of the contributing factors to traffic patterns are categorical variables or are usually converted to categorical variables before use. Thus, the use of the K-means method with these variables considered is not appropriate. There is a clear need to review existing clustering methods and provide recommendations regarding their applicability and performance as related to various applications.

The goal of this research is to support transportation agencies in their selection of a clustering technique and associated parameters for identifying operational scenarios. This paper investigates and demonstrates the use of a number of existing clustering methods for traffic pattern identifications. These methods include the K-means, K-prototypes, K-medoids, four variations of the Hierarchical method, and the combination of Principal Component Analysis (PCA) for mixed data (PCAmix) with K-means. In providing this investigation, this paper aim is to motivate agencies and researchers in transportation engineering to explore and understand various available clustering methods and apply the methods that are the most suitable and perform best for their applications.

5.4.2 Review of Clustering Applications in Transportation Engineering

Clustering analysis is an unsupervised learning technique and refers to a grouping or segmenting technique applied to a collection of objects to subgroup them in a way where the objects within a cluster are closely related compare to objects in different clusters (Hastie et al, 2017). Clustering methods usually utilize a dissimilarity measure to cluster the objects. Although clustering analyses have been used for a long time in other disciplines, the use of the approach in the transportation engineering field has been limited. However, there has been an increasing interest in this use in recent years due to the increasing availability of detailed data and the identified needs for scenario identification for AMS and decision support system applications, as mentioned earlier.

Xia and Chen (2007a) used K-means clustering to identify the traffic flow phases based on traffic density and speed data aggregated in 15 minutes. The authors also used a nested clustering technique, where each cluster at a level is further sub-clustered to classify the operating conditions of the freeway into several tiers (Xia and Chen, 2007b). Park (2002) found that several clustering methods such as the K-means and Fuzzy clustering were effective in traffic volume forecasting. Chen et al. (2017) used the K-means clustering along with Davies-Bouldin Index and Silhouette Coefficient to capture the distinct groups in the vehicle temporal and spatial travel behaviors using license plate recognition data. Fuzzy C-means clustering, a probability-based clustering was found successful in recognizing congestion patterns on urban roads based on GPS trajectory (Zhang et al., 2017). Spectral clustering, a method that allows clustering using fewer dimensions, was used to analyze the traffic state variation based on the quantitative speed data (Yang et al., 2017). Other studies that used clustering include Oh et al. (2005) and Alvarez and Hadi (2012).

The most extensive example of the utilization of clustering analysis in transportation engineering is its use in the AMS testbed effort funded by the FHWA (FHWA, 2013a, 2013b; Vasudevan and Wunderlich, 2013). This effort involved six testbeds to pilot test the use of AMS for the evaluation of advanced strategies. These are the San Mateo (US 101), Pasadena, Dallas, San Diego, Phoenix, and Chicago testbeds. The effort emphasized the importance of multi-scenario assessments that involve modeling days with different traffic patterns rather than an average day. The testbeds used clustering analysis to identify the traffic patterns based on measurements such as volume, speed/travel time, and event data (e.g., incident and weather).

In the Dallas AMS Testbed (Yelchuru et al., 2016a); four operational conditions were identified for each period using the K-means clustering based on vehicle miles traveled (VMT), travel time, incident severity, and precipitation. It is interesting to note that the study converted the quantitative variables to categorical variables before using them in clustering. For example, the VMT was categorized into three levels and the precipitation was categorized into wet and dry.

The San Diego Testbed (Yelchuru et al., 2016c) used incident duration, demand, travel time, and incident impact on delay in the clustering. After applying the K-means clustering, four operation scenarios were selected for each peak period.

The Pasadena Testbed (Yelchuru et al., 2016b) also utilized the K-means clustering based on VMT, travel time, the total number of incidents, total duration of incidents, and precipitation to identify three operation scenarios for the AMS during the weekday peak periods. The Phoenix Testbed (Yelchuru et al., 2016f) used the hourly traffic count, hourly travel speed, hourly precipitation, hourly incident frequency, hourly traffic counts, and travel speed in clustering. The Hierarchical clustering method was applied first to find the minimum number of clusters. The K-means clustering was then used for determining four traffic patterns in each period. Although Hierarchical clustering itself is applicable for finding the traffic patterns, the analysis team did not explain the rationale of using the K-means after utilizing the Hierarchical clustering. Since all four patterns selected using clustering represent dry days, a fifth pattern representing a rainy day was selected for the analysis using an additional K-means clustering.

The Chicago Testbed (Yelchuru et al., 2016d) utilized a two-step joint K-means clustering procedure. In the first step, weather patterns were identified based on the precipitation type (Rain, Snow, and Clear) and intensity using the K-means algorithm. In the second step, the K-means algorithm based on traffic data was used to identify sub-patterns under each weather condition. This was done because weather impacts were a main focus of the testbed.

The San Mateo Testbed (Yelchuru et al., 2016e) used K-means clustering analysis based on travel time, VMT, weather, and incident frequency (categorized by three duration categories). Five clusters representing five operational conditions were recommended.

5.4.3 Review of Clustering Methods

As indicated above, the K-means clustering was used in most reviewed applications in transportation engineering. There are several other clustering methods available; the methods can be classified under four major approaches: the centroid based methods, hierarchical clustering, distribution-based clustering, and density-based clustering as shown in Figure 1 (Sarkar et al., 2018). Figure 37 also shows examples of clustering methods for the four major approaches. This section presents a brief review of methods that are relevant to the study since they are important to be reviewed to determine their performance when conducting clustering.

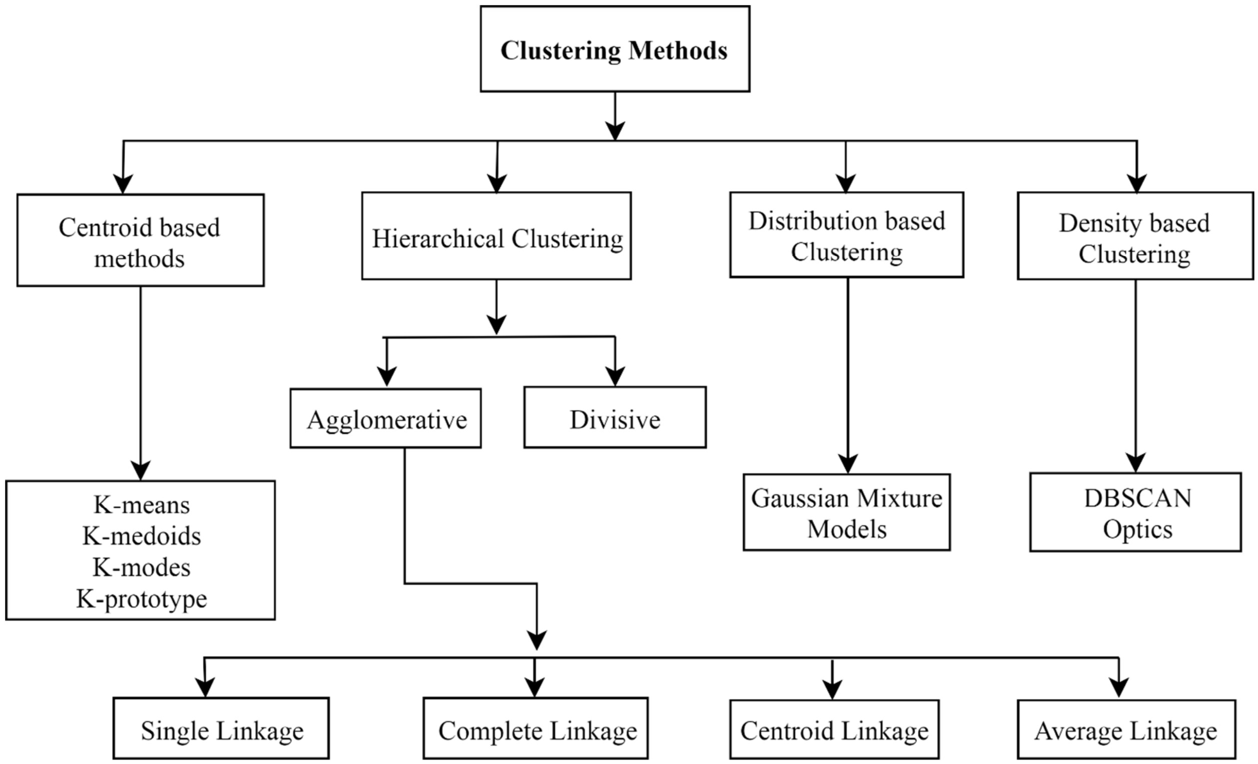


Figure 37: Different types of clustering methods

K-means

The K-means algorithm is a widely used method that is applicable for clustering data based on quantitative variables (Jain and Dubes, 1988). The method is based on an iterative algorithm in which the process is initiated by providing a fixed set of centroids (Hartigan and Wong, 1979). Each data point to be clustered is then assigned to its closest centroid using a squared Euclidian distance measure (Hartigan, 1975). To assign a point to a cluster, the goal is to minimize the sum of average pair-wise distance within-cluster dissimilarity. The centroids are then updated by computing the average of all the points assigned to each cluster. These steps are iterated until the assignment of the data points to each centroid does not change significantly. This method is efficient to analyze large datasets however, its application is limited to clustering based on the quantitative variable as it utilizes the Euclidian distance as the dissimilarity matrix (Huang, 1998).

K-prototypes

To perform clustering analysis on datasets that contain both categorical and quantitative data, a method referred to as the “K-prototypes” was proposed (Huang, 1998). The K-prototypes algorithm works in a similar fashion to the K-means algorithm but applies a combined dissimilarity measure. For quantitative variables, it uses Euclidean distance while for categorical variables, it uses a simple matching dissimilarity (Huang, 1998).

K-medoids

The K-medoids clustering algorithm is very similar to the K-means algorithm, except that it uses dissimilarity measures to allow clustering based on both quantitative and categorical variables (Hastie et al., 2017; Gower, 1971; Podani, 1999; Kaufman and Rousseeuw, 2009). In addition, it has been reported that the squared Euclidean distance measure used in the K-means lacks robustness against outliers that produce very large distances (Hastie et al., 2017). K-medoids overcomes this issue at the expense of computational efficiency, by placing the outlier into separate clusters.

Hierarchical Clustering

Hierarchical clustering does not require the specification of the number of clusters initially as required by the K-means and K-medoids. However, it requires the user to specify a dissimilarity measure between groups of observations known as "linkage" (Hastie et al., 2017). In this method, the clusters at each level of the hierarchy are created by merging clusters at the next lower level. At the lowest level, each cluster contains a single observation while at the highest level there is only one cluster containing all observations. Commonly used linkages are Single, Complete, Average, and Centroid. Respectively, these four linkages consider the dissimilarity between two groups as the smallest dissimilarity between two points in the groups, largest dissimilarity between two points in opposite groups, average dissimilarity over all pairs in opposite groups, and the dissimilarity between the centroids of the groups. The Euclidean distance is generally used as the dissimilarity measure for quantitative variables, while other dissimilarity measures such as Gower metric is used for other variables.

Principal Component Analysis (PCA) Combined with Clustering

PCA is a statistical approach for dimension reduction and compression while retaining most of the variation in the data set (Dunteman, 1989). The purpose of PCA is to convert the observations to an orthogonal system of Euclidean space and thus reduce the dimensionality by retaining only those characteristics of the data set that contributes most of its variance. PCA is effective in reducing the noise in the data set, in addition to reducing the computational cost by reducing the dimensions. In particular, PCA was found effective in capturing the cluster structure in the data set when used along with clustering methods instead of clustering methods by themselves (Meng et al., 2015). Ding and He (2004) found that K-means clustering on high dimension data was affected by the noise in the data set and applying K-means clustering in the PCA subspace improved the results significantly. However, the applicability of PCA is limited to quantitative variables. PCAmix is an extended PCA approach for mixed data set combining quantitative and categorical variables (Hill and Smith, 1976; Chavent et al. 2017) and will be investigated in this study for use in combination with clustering. Clustering with the reduced dimensions from PCA was found very effective in the recognition of the patterns in the data set and widely used approach in other fields (Marinai et al., 2006; Alzate and Suykens, 2010; Yeung and Ruzzo, 2001). Because of the mix of quantitative and categorical variables, the PCAmix approach instead of the basic PCA approach was used in the analysis.

5.4.4 Utilized Data

To investigate the performance of different clustering methods in identifying traffic patterns, data was retrieved for a corridor of about 16-miles of the I-95 freeway in Fort Lauderdale, Florida. This facility is one of the busiest and strategically important routes in the South (Office of Highway Policy Information, 2017). The analysis horizon is the time period from January 1st, 2017 to December 31st, 2017 excluding holidays and weekends. Traffic data including volume, speed, and occupancy was collected from five microwave detectors placed on average at a half-mile interval along the corridor. The data was retrieved from the regional data warehouse, which is a part of the Regional Integrated Transportation Information System (RITIS) (University of Maryland CATT Lab, 2018) in 15-minute intervals for the morning (AM) peak period (7:00 AM – 9:30 AM) in the Southbound Direction of I-95.

Incident data for the analysis horizon was retrieved from the incident management database managed by the Florida Department of Transportation (FDOT) District 4. incident data from several sources such as data sharing with the police, automatic detection based on microwave sensors and verification based on closed-circuit television cameras, and service patrol reports. The collected incident data is very detailed and includes several useful attributes, including the start and end times, lane blockage duration, total incident clearance time, number of blocked lanes, severity, time stamps of emergency vehicle arrivals, number of vehicles involved in the incident, and so on. Weather data was collected from the National Centers for Environmental Information– National Oceanic and Atmospheric Administration website (NOAA, 2018). The data was collected for the Pompano Beach Airpark weather station, which is within a 10-mile radius of the study corridor. The weather station measures the precipitation using an 8-inch gauge that is of standardized design used throughout the world for official rainfall measurements. The data set includes the hourly precipitation (in inches) for each 15 min observations. All three types of data (traffic, incident, and weather) were converted to 15-minute resolution and assembled for clustering analysis.

5.4.5 Analysis Methodology

This section presents the methodology utilized in this study. The method consists of data retrieval, data preparation, application of the clustering algorithms, performance assessment of the clustering algorithms, and operational scenarios selection. Figure 38 shows the different steps of the methodology, which are explained in detail in the subsequent sections. The statistical package "R-Studio" was used for data assembly, as well as clustering and PCAmix analysis.

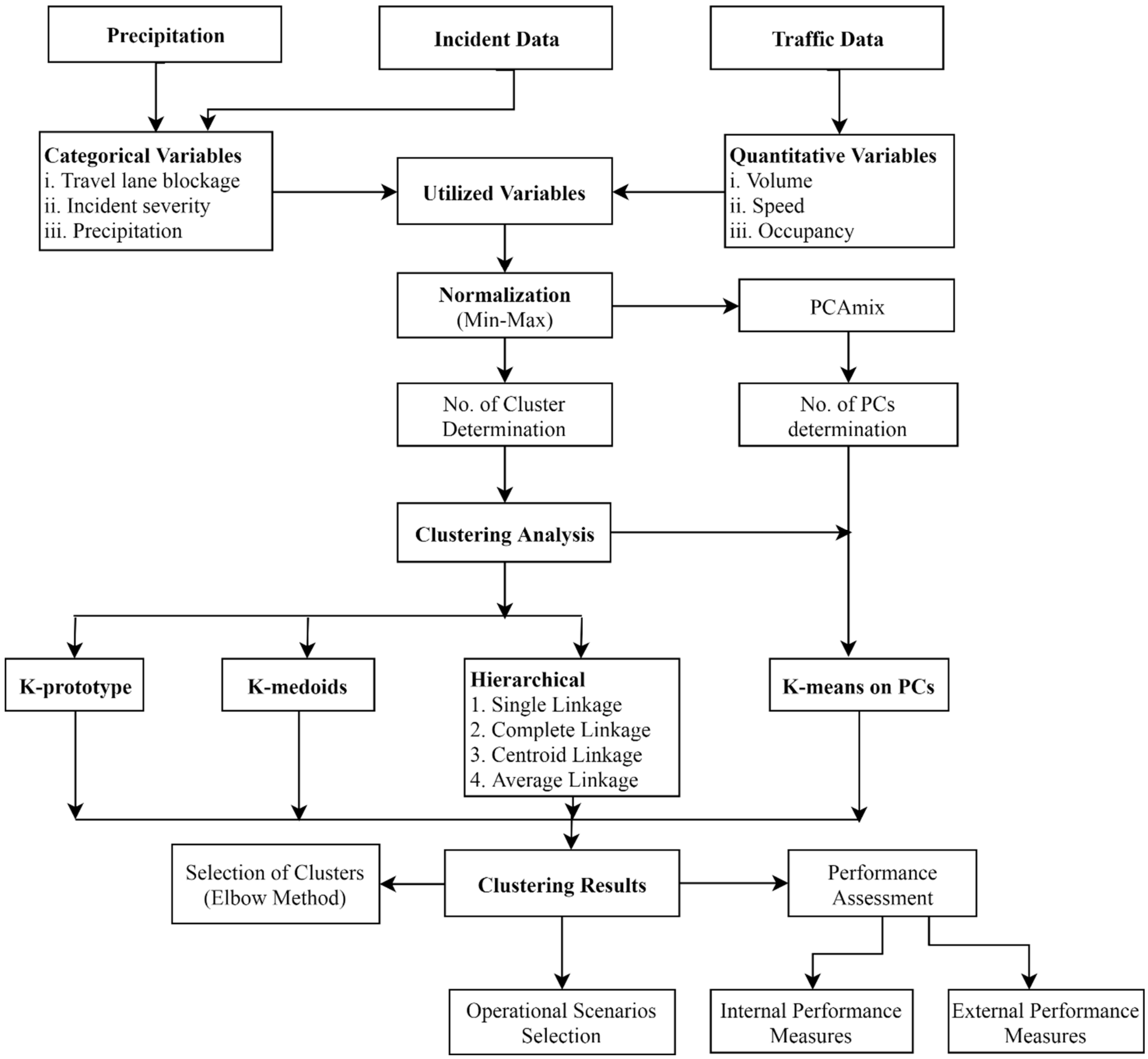


Figure 38: Flow chart of the analysis methodology

Utilized Variables

Six variables: volume, speed, occupancy, travel lane blockage due to incidents, incident severity, and precipitation estimated based on the retrieved data were selected for potential utilization in the clustering since these variables are considered to cover various influencing factors on congestion. Similar variables were considered in the FHWA AMS testbeds discussed earlier. There was no construction work on the corridor in the study period. The clustering was initially done using measures calculated based on the average of detector data for all locations of the corridor. However, it was found that better results can be obtained if the detector measurements at each of the five detection locations are used individually in the clustering. Prior to analysis, the precipitation data was categorized in the same manner utilized in the Chicago AMS testbed into four groups as follows: 0 (0 inch/hr), 1 (0-0.1 inch/hr), 2 (0.1-0.3 inch/hr), and 3 (≥0.3 inch/hr). In the analysis, volume, speed, and occupancy were used as quantitative variables, while travel lane blockage, incident severity, and precipitation were used as categorical variables. Thus, the most widely used clustering technique (K-means) cannot be used directly due to the mix of these two types of variables (Jain and Dubes, 1988). Instead, this study examines and compares the results from a number of clustering approaches.

Initial clustering without normalization in this study indicated the need for normalization of the variables to a common scale since without it, the clustering was dominated by the variables that have higher magnitudes such as volume. Several methods of normalization have been proposed in the literature including the Min-Max, Z-score, Decimal Scaling, among others. In the study, the variables were normalized using Min-Max normalization shown in Equation (1) as the method performs well to bring all the data within a common scale (Steinley, 2006).

$$X' = \frac{X - MinX}{MaxX - MinX} \tag{1}$$

Where, X'=normalized value

X= attribute value

MinX= lowest value of the attribute

MaxX= highest value of the attribute

Determining the Number of Clusters

One of the challenges with clustering is to determine an adequate number of clusters to be able to identify all frequent patterns. Widely used clustering methods such as the K-means and K-medoids require the specification of the number of clusters. Some of the clustering methods such as Hierarchal clustering can automatically recommend the number of clusters. There are several empirical methods available to identify the required number of clusters based on the results of clustering analysis, such as the Elbow Method, Average Silhouette Method, and Gap Statistics Method, among others. In this study, the process of identifying the number of clusters starts with specifying a maximum of 20 clusters, and the optimal number of clusters was selected based on the Elbow Method, which is explained briefly next.

The Elbow method is an empirical method that provides an objective approach to determine the optimal number of clusters. The method requires minimal prior knowledge about the dataset and the attributes of the dataset. The Elbow method determines the number of clusters based on the total within-cluster sum of square (WSS) for each investigated number of clusters (Ketchen and Shook, 1996). A graph is drawn between the total WSS, and the number of clusters and the location of the bend in the plot is considered as an indicator of the appropriate number of cluster. In this study, the number of clusters using this method was determined, and the results were examined to determine if this method is adequate or additional clusters are needed to identify all patterns of interest, as will be discussed when presenting the results of clustering in this paper.

Conducting Clustering Analysis

A number of methods for clustering were examined, and their results were compared to determine how well they can cluster the traffic conditions into different patterns. The examined methods include the K-prototypes, K-medoids, and Hierarchical clustering with different linkage types (single, complete, centroid, and average linkage) using the optimal number of clusters identified based on the Elbow method.

The PCAmix approach, combined with K-means clustering was also investigated. PCA is a technique to reduce the data dimensionality by geometrically projecting onto lower dimensions called the principal components (PCs), which are defined as a linear combination of the data's original variables (Lever et al., 2017). The first PC is identified by minimizing the total distance between the data and their projection onto the PC while retaining the maximum variance of the projected points. Similarly, all other PCs are formed based on the same condition in addition to no correlation among the different PCs. PCs try to retain the maximum variation within the dataset with a small number of PCs are capable of explaining the entire dataset. Six variables: volume, speed, occupancy, travel lane blockage due to incidents, incident severity, and precipitation from five detectors are used in the study. Thus, each PC is a linear combination of the six variables from all five detectors used in the analysis. The optimal number of the PCs was determined based on the plot of the cumulative proportion of variance in the data explained by the utilized number of PCs. Finally, the K-means method is applied for clustering. This is possible since the resulting PCs from the PCAmix are quantitative variables, allowing the use of the Euclidean distance as a dissimilarity measure in the K-means clustering. The subset of PCs to be used in the clustering was determined by plotting the cumulative proportion of explained variance in the dataset against the number of PCs for the project case study, as shown in Figure 39. The data were projected into a total of twenty-five PCs through the application of the PCAmix algorithm while reporting the proportion of the explained variance by each PC. Based on this figure, a subset of ten PCs was selected for use in the analysis since it can explain a large proportion of the variation of the data and able to retain the distinctive features of the data set as well. Although more PCs can be considered in the analysis, the increase in the number of PCs can eliminate the advantages of the use of PCA (Ding and He, 2004). Besides, a smaller number of PCs in the analysis reduces the computational cost and removes the noise in the data.

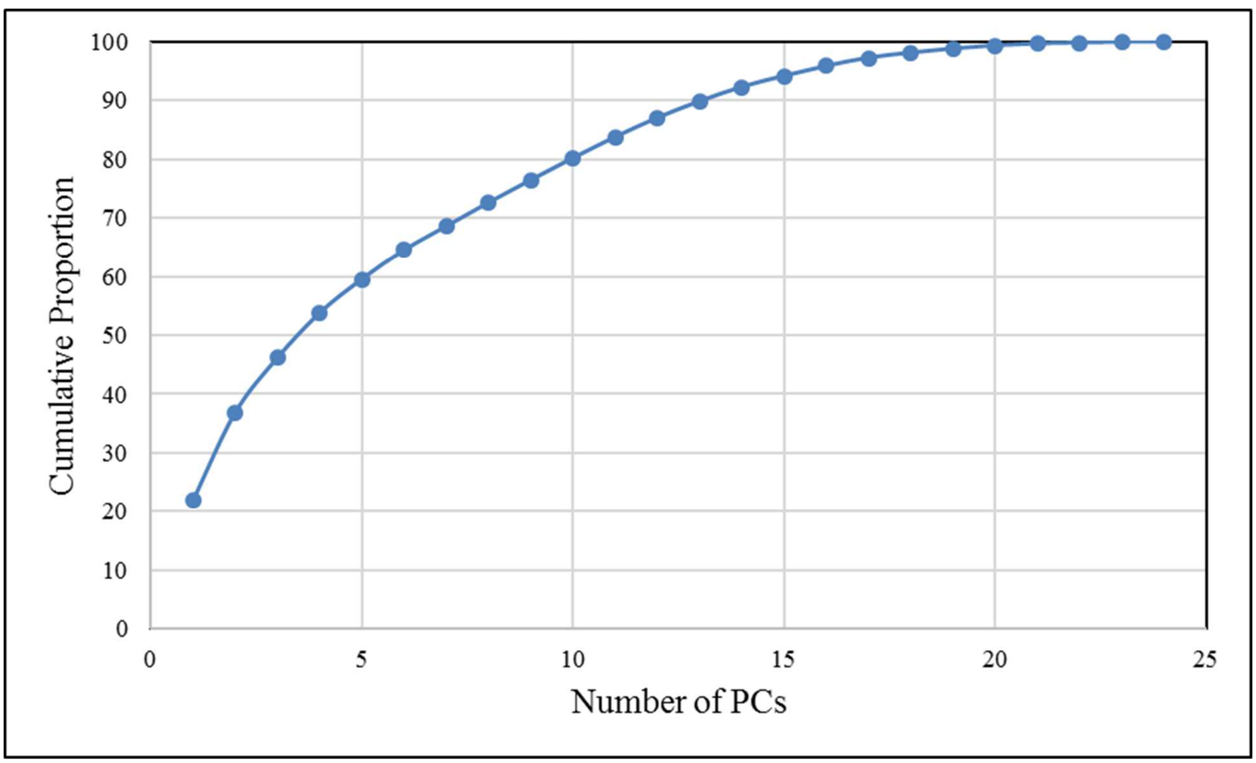


Figure 39: Proportion of variance of data explained by principal components (PCs).

Assessment of Clustering Method Performance

The performance of the investigated clustering methods was assessed utilizing external and internal performance measures. External measures evaluate the purity of the clusters (Wu et al., 2009) while internal measures evaluate the compactness of a clustering structure by determining how close the attributes of each data point are without considering additional information about the data (Tan et al., 2005). As clustering is an unsupervised technique, there is no ground truth data associated with this technique to compare to. Thus, assessment based on quantitative external performance measures based on ground truth data was not possible. However, all data within clusters were visualized to evaluate the distribution of the data among all the clusters.

Unlike the external performance measure described above, Silhouette Coefficient and Connectivity were two internal performance measures chosen in the study for their capability to assess the performance of the clustering algorithms. These measures do not need ground truth data and allow easy interpretation of the results (Rousseeuw, 1987). A higher Silhouette Coefficient depicts a dense and well-separated cluster. A lower connectivity coefficient depicts a higher degree of connectedness of the clusters (Brock et al., 2008).

5.4.6 Clustering Results

Number of Cluster Selection

The number of clusters was selected by applying the Elbow method, as mentioned earlier. For this purpose, the total within-cluster sum of square (WSS) was plotted against the number of clusters after the initial runs of the K-prototypes clustering, as shown in Figure 40. The figure indicates that seven clusters are the optimal number of clusters based on the location of the kink in the elbow of the plots. The optimal number of clusters depends on the attributes of the dataset, and it can vary between locations. If sufficient data is used, then the number of clusters can be fixed for the analyzed location. This is the case for the case study since the data used in the study is for an entire year; therefore, it automatically considered the variation of traffic for season, weather, incident, and so on. It should be mentioned here that this study is concerned with the developing of the methodology rather than finding the optimal number of clusters. Seven clusters were found to produce a good relative WSS for the other method. To allow fair comparison, the same number of cluster was used for all methods.

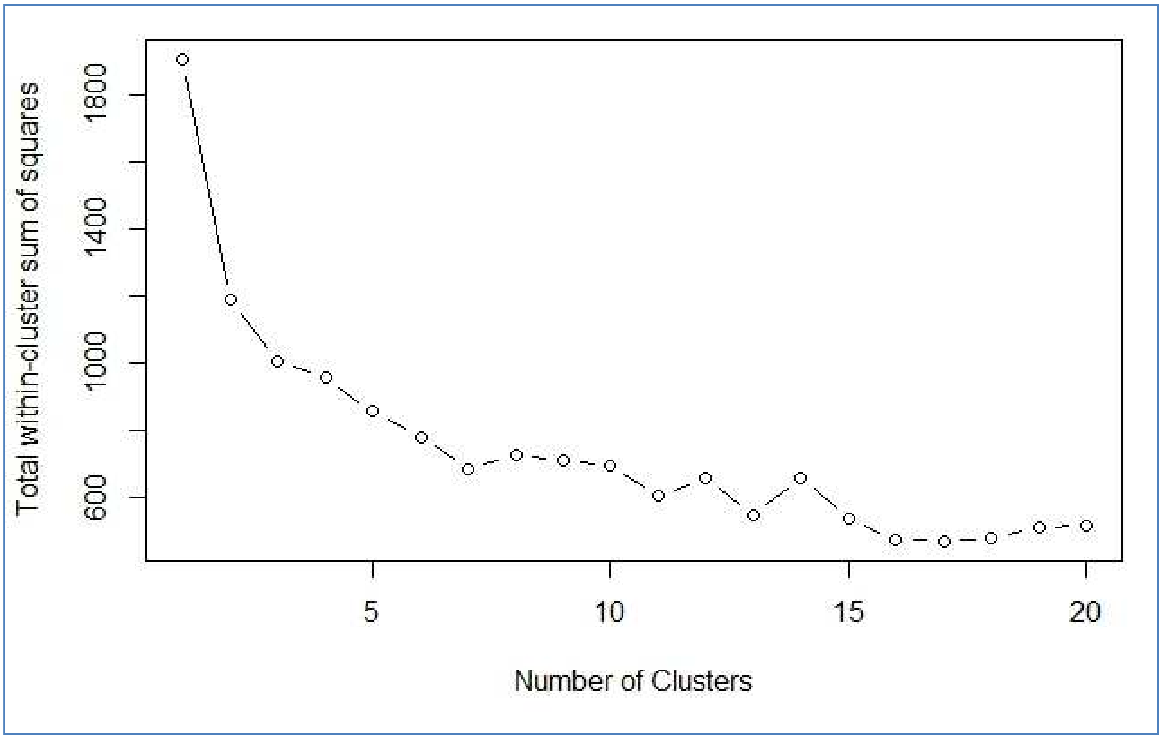


Figure 40: The relationship between the number of clusters and the total within-cluster sum of squares.

Evaluation of the Clustering methods based on Internal Measures

As stated earlier, the two utilized internal measures to assess the methods' performance were the average Silhouette Coefficient and Connectivity. The comparison of the Silhouette Coefficient of the investigated methods in Figure 41 indicates the superiority of the K-means with PCs over other clustering methods used in the study since this method produced the higher value of this coefficient. The K-medoids performance was the worst among the four tested algorithms. The assessment based on the Connectivity Measure, as depicted in Figure 42, shows a similar result with the best performance achieved with the use of K-means with PCs, as this produced the lowest value of the Connectivity Measure.

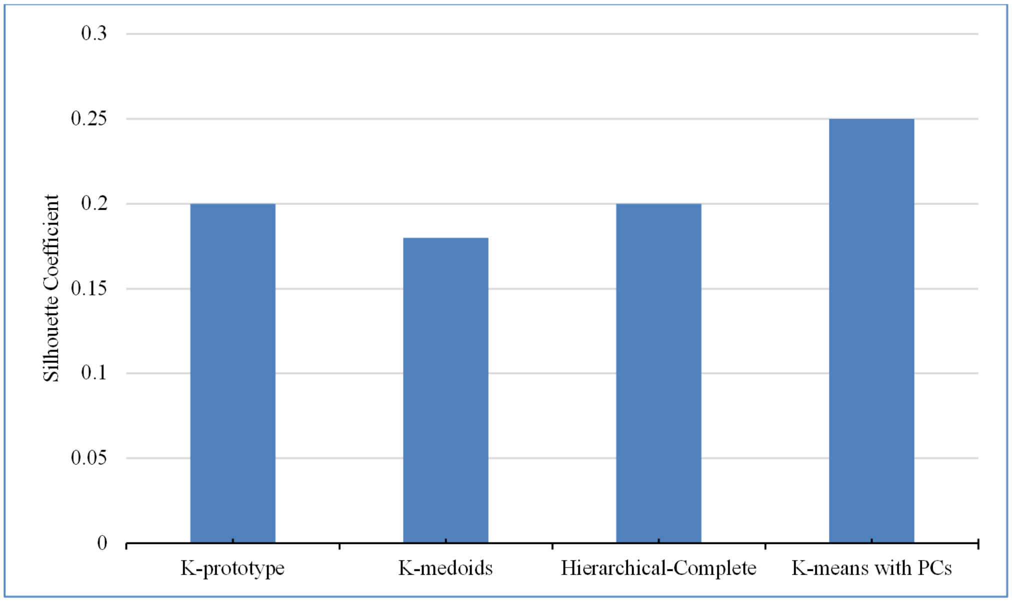


Figure 41: Silhouette coefficient for different clustering methods for the seven clusters

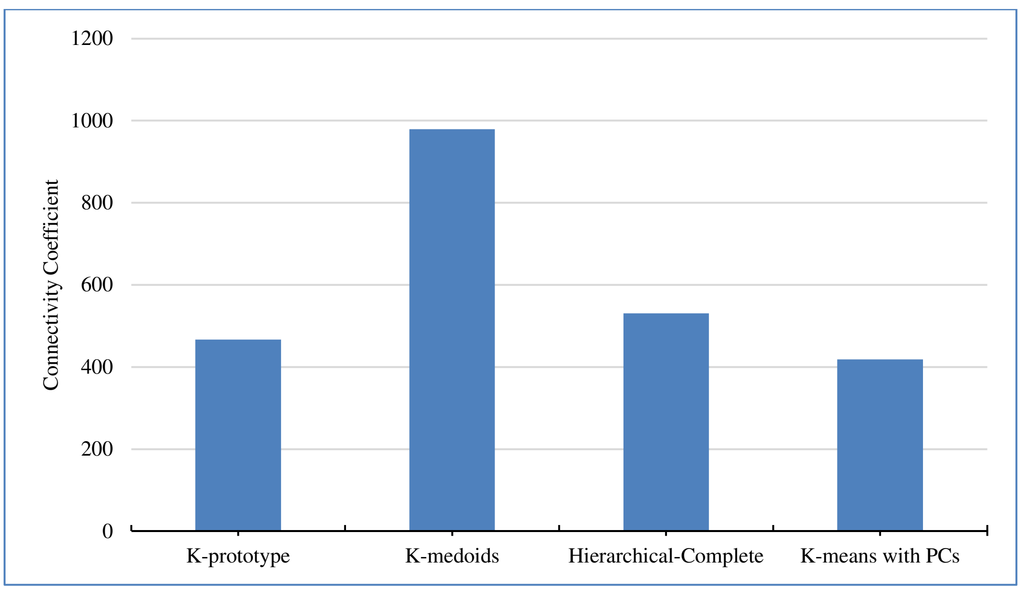


Figure 42: Connectivity coefficient for different clustering methods for the seven clusters

Evaluation of Clustering Methods based on External Measures

External measure assessment of the clustering methods evaluates the purity of each cluster. The distribution of the average volume, speed, and occupancy on all detectors (as indicated by the 10th, 50th, and 90th percentiles of these variables); incident severity variation; and precipitation variation within each cluster were examined to be sure that the method is able to separate the traffic into distinctive patterns based on the clustering variables. Such separation will allow the analysis and modeling of these patterns.

Examining the results from the K-medoids indicated that the algorithm was not able to discern between the incident and non-incident observations as well as precipitation and non-precipitation observations. As an example, Figure 43 shows that the algorithm places incident and non-incident observations into the same clusters (Cluster 1, 3, 4, 5, 6, and 7; as shown in Figure 43). This is possible because the Gower dissimilarity metric used with the K-medoids was dominated by the quantitative variables (volume, speed, and occupancy) at the expense of the categorical variables (incident and precipitation attributes).

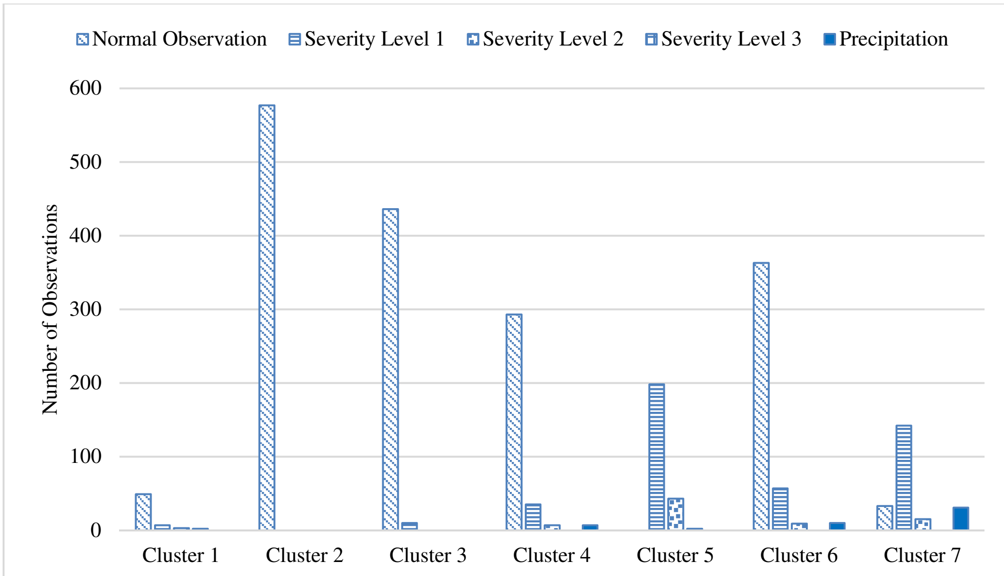


Figure 43: Observations with different levels of severity and precipitation in the clusters identified by the K-medoids method

When using the Hierarchical clustering, it was found that the "Complete" linkage produced the best results among the four investigated linkages. The remaining three linkages grouped almost all of the observations into a single cluster irrespective of the differences in the attributes associated with different period patterns. Although the Complete linkage performed a little bit better than the other three linkage types, it still had the problem of assigning a big proportion of patterns to one cluster. The Complete linkage grouped 81% of observation in one cluster while distributing the remaining 19% of the observations between the other six clusters, as shown in Figure 44. Based on the above, it can be concluded that the Hierarchical method was not able to produce good results.

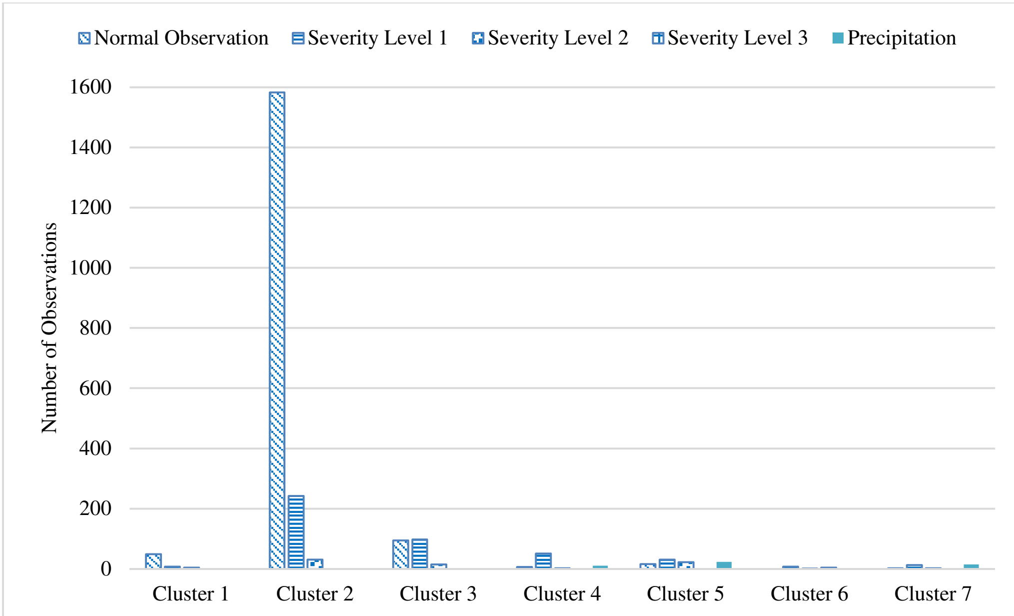


Figure 44: Observations in each cluster when using hierarchical clustering with the complete linkage

Unlike the K-medoids and Hierarchical clustering, both the K-prototypes and K-means with PCs produced distinct clusters that separate different congestion levels and the causes of congestion (incidents, "recurrent conditions", and rainy conditions). The observations in each clusters produced by both methods are shown in Figure 45 and Figure 46 respectively. The K-prototype produced three clusters with recurrent condition observations (Clusters 1, 5, and 6), three clusters (Clusters 2, 3, and 4) with incidents that have different levels of severity/lane blockages, and one cluster (Cluster 7) with combined incident and rain events. In contrast, the K-means with PCs produced two clusters (Clusters 3 and 5) with recurrent conditions, two clusters (Clusters 2 and 4) with incidents that have different levels of severity/lane blockages, and one cluster (Cluster 7) with incident and rain conditions. The K-means with PCs produced two more clusters which represent very unusual conditions. Cluster 6 contains only four Severity Level 3 incidents with all lanes blockage. The other cluster (Cluster 1) includes observations during special conditions such as days during hurricane preparation and Black Friday. Both the K-prototypes and K-means with PCs produced good clustering of the traffic patterns for the investigated case study. With both methods, the observations were clustered in three distinctive groups: normal (recurrent condition) clusters, incident clusters, and precipitation (rainy conditions) that may include incident clusters. It is important for the analyst to examine the clustering results in more detail to determine what each cluster actually represents. Further comparison of the clusters produced by the two methods is presented below.

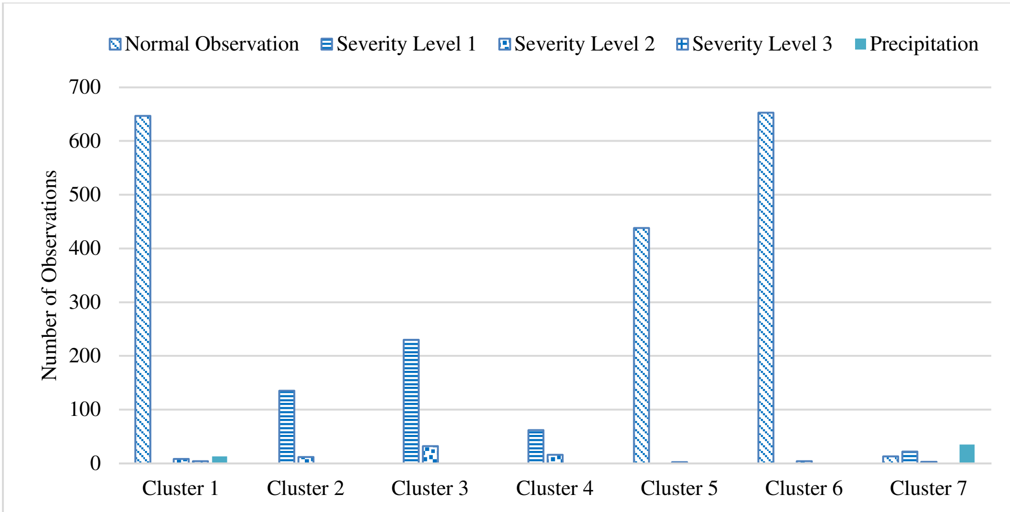


Figure 45: Observations with different level of severity and precipitation in the clusters identified by the K-prototype method

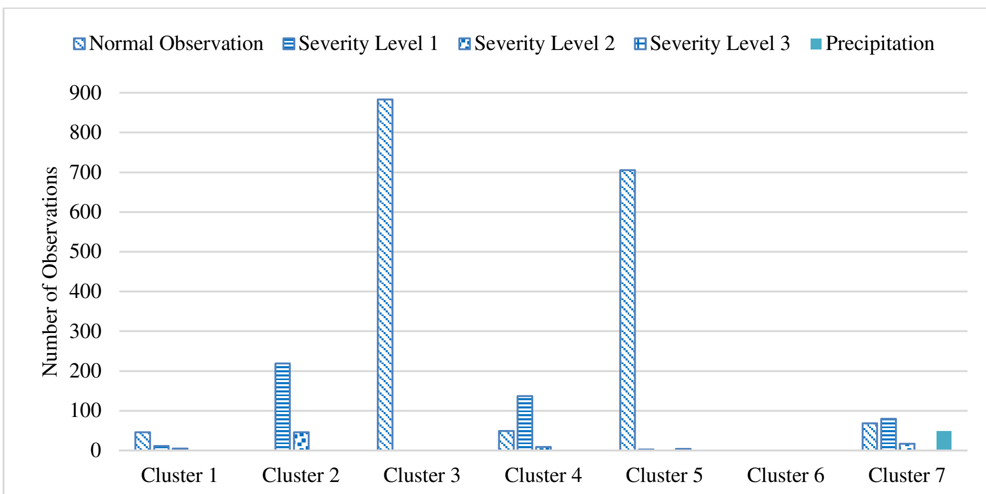


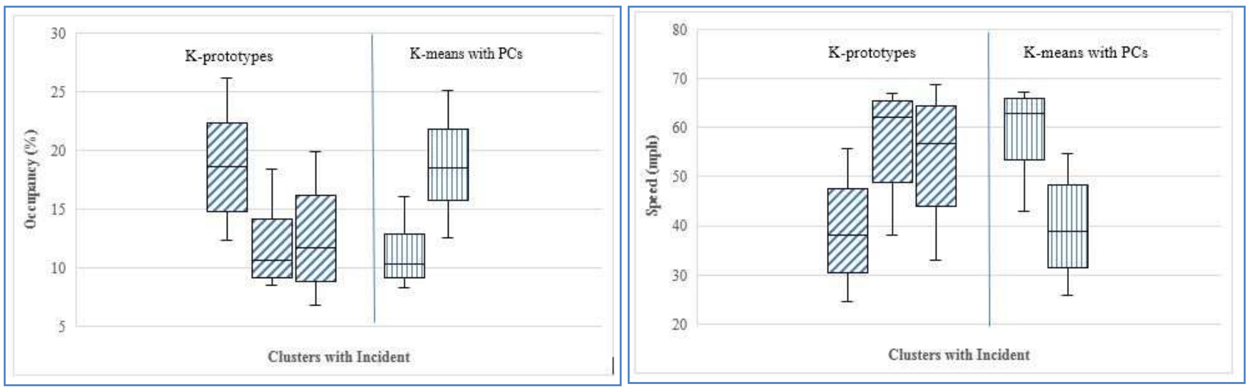
Figure 46: Observations with different levels of severity and precipitation in the clusters identified by the K-means with PCs method

Rainy Day Cluster

Rainy day cluster is one of the distinctive clusters produced by both the K-prototypes and K-means with PCs methods that include observations with increased congestion due to precipitation in some cases combined with incidents. Although not automatically separated into two clusters, the analyst may want to separate the precipitation observations into two groups for the analysis: precipitation observations with no incidents and precipitation observations with incidents; depending on the purpose of the study.

Incident Clusters

Observations with incidents were clustered in three clusters in the case of the K-prototypes method and two clusters in the case of the K-means with PCs method. To determine if it is justifiable to have three clusters vs. two clusters, the impacts of these incidents on traffic, the locations of incidents, and the time of occurrence of incidents within each cluster were examined. The box plots in Figure 47 show the 10th, 50th, and 90th percentile values of the speed and occupancy for each incident cluster identified by each of the two methods. Incident statistics of each cluster reveals that one cluster produced by each method has high incident impacts with more incidents occurring in the middle segment of the facility, which is the most congested segment, and between 7:30 am and 9:00 am, which is the peak congestion interval. The other identified clusters by the two methods have lower incident impacts and have less observations in the peak intervals. It appears that in terms of speed and occupancy, two of the three K-prototypes incident clusters are very similar. Therefore, it seems that the two clusters identified by the K-means with PCs are sufficient to represent incident impacts.

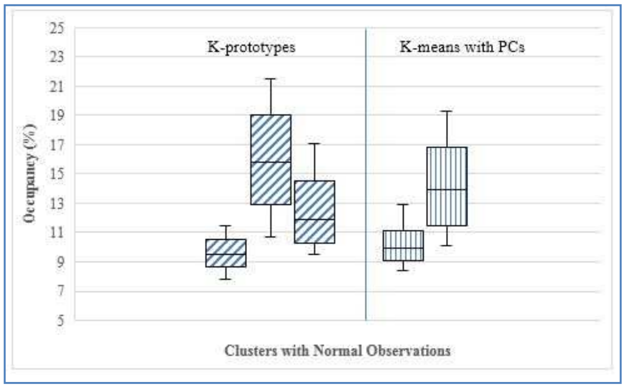


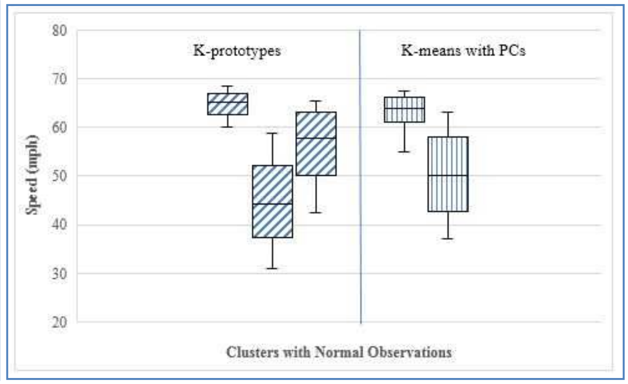
(a) Occupancy (b) Speed

Figure 47: Variation of occupancy and speed within the clusters identified by the clustering methods for incident days

Normal Clusters

The K-prototypes produced three distinctive clusters representing normal observations. These observations were grouped into only two clusters by the K-means with PC. The box plots in Figure 48 show the 10th, 50th, and 90th percentile values of the speed and occupancy for each of the normal cluster identified by the two methods. The K-prototypes seems to focus more on the quantitative traffic flow parameter variations and this is the reason that it splits the normal observations into more clusters based on these parameters. As shown in this figure, the three clusters identified by the K-prototypes divide the normal days into three levels – with a median occupancy of 9.5%, 11.5%, and 15.5%, respectively and a median speed of 44 mph, 57 mph, and 65 mph. The medians of the two clusters K-means with PC were 10% and 14% for occupancy and 50 mph and 64 mph. It appears that the two clusters are sufficient to cover the normal day conditions. However, if further clustering is needed for normal observations, a second level of clustering can be conducted on the normal observations only based on the quantitative traffic flow parameters (volume, speed, and occupancy).





(a) Occupancy (b) Speed

Figure 48: Variation of occupancy and speed within the clusters identified by the clustering methods for normal days

Selection of Operational Scenarios

Based on examining the results, five operational scenarios were identified for the inclusion in the modeling as of follows:

1. Normal traffic pattern with high volume, high speed, and low occupancy.
2. Normal traffic pattern with high volume, low speed, and high occupancy
3. Minor incident traffic pattern with high volume, moderate to high speed, and low to medium occupancy.
4. Major incident traffic pattern with low volume, low speed, and high occupancy.
5. Precipitation traffic pattern with high volume, low speed, and high occupancy.

5.4.7 Conclusion and Recommendation

This study has investigated and demonstrated the use of a number of existing clustering methods for traffic pattern identifications, considering the above-mentioned issues. These methods include the K-prototypes, K-medoids, four variations of the Hierarchical method, and the combination of Principal Component Analysis for mixed data (PCAmix) with K-means. The K-means method by itself was determined to be not suitable for use in clustering based on categorical variables and thus was dropped from the further comparison.

It was found that the K-medoids was not able to discern between normal observations and incident and rain observations, apparently because the dissimilarity metric used with the K-medoids is dominated by the quantitative variables (volume, speed, and occupancy) on the expense of the categorical variables (incident and precipitation attributes). Hierarchical clustering has the problem of putting most of the data points into a single cluster. The internal measure comparison based on the Silhouette Coefficient and Connectivity further confirm the inferior performance of the K-medoids and Hierarchical clustering.

The K-prototypes and K-means with PCs produced the best results when utilizing both internal and external measures in the comparison. However, the K-prototypes clustering was not able to distinguish special patterns like the days during hurricane preparation, Black Friday, and full lane closures. On the other hand, it splits the incidents observations and normal observations into three patterns each instead of two each when using the K-means with PCs.

In all cases, the analyst should examine the clustering results to determine if further clustering and/or merging of clusters is needed. Such decisions will have to be based on the purpose of the study. The selection of an observation from each cluster for use in AMS will also have to be carefully done. If there is a large variation in one or more pattern attributes, more than one representative observations may need to be selected from each cluster. In some cases, when there is a large variation in the attributes within each cluster, two-level clustering for finer traffic pattern identification is recommended.

5.5 IDENTIFICATION OF THE UTILIZED DIVERSION ROUTES

5.5.1 Background

Route diversion during incidents has been proven to be a useful tactic to mitigate non-recurrent congestion. Studies revealed that the diversion percentages are between 5% to 25% depending on the incident and traffic status (Foo and Abdulhai, 2006; Deeter, 2012; Haghani et al., 2013; Hadi et al., 2013b; Tariq et al., 2019). However, the anticipated congestion on the alternative routes discourages drivers from diverting, resulting in lower diversion percentages (Khattak et al., 1992). A recent study that estimated diversion based on detector data infers that the capacity of the signals constrains the diversion at the off-ramps and adjacent signals during the congested periods; indicating the need for special signal control plans during incidents to increase the capacity of the off-ramps and adjacent signals leading to the primary parallel routes (Tariq et al., 2019). This is important since the typical time-of-day (TOD) signal control cannot handle the sudden increase in the traffic on the arterials due to diversion.

The diversion of traffic during incidents on freeways triggers the need for the development and activations of alternate route plans to accommodate traffic on these routes. The Alternate Route Handbook (Dunn Engineering Assoc., 2006) provides comprehensive guidelines on how to plan and execute detour operations involving various stakeholder agencies (Dunn Engineering Associates, 2006). The Manual on Uniform Traffic Control Devices (MUTCD) (FHWA, 2009) states that major and intermediate incidents lasting more than thirty minutes usually require traffic diversion or detouring of road users, due to partial or full roadway closures (FHWA, 2009). Although these guidelines provide the agencies basic information for setting detour operations including the selection of alternative routes, these guidelines are static and do not consider the many dynamic variables that influence the decision to divert and the selection between alternative routes in real-time operations. Such variables can include the location of incidents, traffic status, alternative route conditions, time-of-day, and so on.

The primary focus of this study is to develop a methodology to operate both freeways and arterials coordinately for mitigating incident-induced congestion on the corridor by leveraging real-time data. This method can be used as part of a decision support system (DSS) to manage the traffic proactively during the incidents on the freeway. In this regard, this paper is concerned with developing a method for the prediction of the critical alternative routes utilized by motorists during incidents in the freeway, designing signal timing plans to better accommodate diversion, and estimating the benefits of activating the special signal timing plans on the critical routes to mitigate the deterioration in the performance of the movements due to diversion. The methodology developed in the paper can be easily implemented by the transportation agencies as it is based on data that are generally available to the agencies.

5.5.2 Review of Literature

Lane blockage incidents on freeways reduce capacity (HCM, 2016) resulting in significant delays to motorists. Alternative routes provide additional capacity to the impacted freeways, allowing vehicles to circumvent the congested locations. A study by Lin and Kou (2003) validated the importance of alternative route operations in response to a major freeway incident in terms of travel time benefits. Under most incident scenarios, if proper diversion plans can be implemented in time, motorists can circumvent the congested segments and best use the available corridor capacity (Kim et al., 2017).

Coordinated Freeway and Arterial Management

The Coordinated Freeway and Arterial (CFA) Operation Handbook (Urbanik et al., M2006) provides guidelines for efficiently manage traffic operations on the freeway and arterial streets. Empirical studies in four different cities (Glasgow, Seattle, Anaheim, and San Antonio) showed that CFA operations can play a decisive role in reducing traffic congestion. For example, in Anaheim, CA, the implementation of alternative corridor operation plans (signal timing plans, ramp metering plans, DMS messages, and route diversion plans) during nonrecurring congestion was found to reduce travel times by up to 30% (Urbanik et al., 2006).

The CFA operation concept was further extended to a broader area under the umbrella term of Integrated Corridor Management (ICM), a promising tool in the congestion management toolbox that optimizes the use of existing infrastructure assets by leveraging unused capacity along the urban corridors. The ICM initiative of the Federal Highway Administration (FHWA) was established to harnesses the potential of the intelligent transportation systems (ITS) to efficiently and proactively manage the congestion hence improve the mobility of the goods and people at the corridor level. The advancement of the ITS technologies, expansions of the transportation system management and operations (TSMO) programs, and the availability of supporting data make ICM both practical and feasible. Eight pioneer sites were selected to establish the ICM concepts and to assess the benefits of ICM. The assessment of ICM later resulted in two FHWA funded implementations, the first on US-75 in Dallas, Texas and the second on I-15 in San Diego, California. The FHWA ICM initiative determined using simulation that significant improvements in travel times are expected, particularly under conditions of high demands and severe traffic incidents (Alexiadis and Armstrong, 2012). It was also observed that travelers that are directly affected by the incident experience the most significant benefits of ICM (Alexiadis and Chu, 2016b). There is currently strong interest in ICM implementations around the United States with a number of ICM being planned or in the deployment stage.

Many of the previous studies utilize simulation models, sometimes combined with dynamic traffic assignment, to design and assess the coordination between arterial and freeway operations during incidents to facilitate diversion (Taylor and Narupiti, 1996; Plaisant et al., 1998; Tian et al., 2002; Zhou, 2008; Alexiadis and Chu, 2016b). However, many transportation agencies are not comfortable and/or do not have the resources to run simulation models in real-time operations. Therefore, this study focuses on data analytics and the strength of the machine learning techniques to predict the critical alternative routes and to support the updates to signal timing plans on the diversion routes during incidents. As part of the study, the travel times on potential diversion routes are predicted using data collected for the period after the occurrence of the incident on the freeway.

Related Artificial Neural Network Applications

In past research on predicting travel time on highway facilities, artificial neural network (ANN) models have been introduced for the prediction of both link and corridor travel times (Park and Rilett, 1999; Park et al., 1999; Van Lint et al., 2003). However, basic ANN models are inhibited by their inability to deal with time-series data. Several efforts have been made to deal with the time-dependent relationship among the data. A hybrid model, consisting of the Multilayer Perceptron (MLP) neural network in combination with the Time-delayed Neural Networks (TDNN), was found promising to predict travel times (Zou et al., 2008). The evaluation of this hybrid model based on field data indicated that it is capable of generating a reliable prediction of travel times under various traffic conditions, and offers the potential for being implemented on a long freeway (Zou et al., 2008).

Compared to this hybrid method described above, the Recurrent Neural Network (RNN), which is a deep learning method, was found successful and has been widely used to analyze time-series data. The long short term memory (LSTM), a variety of RNN, has been successfully applied in many real-world problems involving sequence data such as music generation and speech recognition (Hochreiter and Schmidhuber, 1997; Eck and Schmidhuber, 2002; Graves, 2012; Graves et al., 2003). Prediction of the travel time of traffic using LSTM was shown to produce promising results (Duan et al., 2016). The LSTM method also has been successfully applied in traffic performance prediction (Ma et al., 2015b) because it can model the long-term dependencies in time series and extract features from traffic data with recurrent feedback. In addition, LSTM is much faster to train compared to the standard RNNs and MLPs, and also slightly more accurate in frame-wise phoneme classification (Graves and Schmidhuber, 2005).

Traffic Signal Control during Incidents

Coordination between the freeway and arterial during the incident requires the activation of signal timing plans on the alternative route arterials in harmony with the sudden change in traffic volumes on the arterials due to diversion. Time-of-day (TOD) signal control plans do not respond effectively to real-time traffic conditions. Thus, these plans can lead to high congestion and longer recovery times during freeway incidents that cause diversion. Adaptive traffic control systems (ATCS) have been developed and implemented to react to the inherent traffic variations occurring from cycle to cycle, and therefore, they operate more efficiently than TOD-based systems. It has been reported that ATCS can reduce the delay during the incident conditions *(30).* However, the ATCS performance under such conditions and when the signal intersection approaches have long queues still need to be evaluated.

Taylor and Narupiti (1996) used microscopic traffic simulation to examine the effectiveness of traffic diversion combined with signal timing modification for various incident conditions. The study confirmed that the optimized signal timing on the diverted routes reduced the delay of traffic. The results of the study demonstrated that the effectiveness of the combined diversion and signal timing optimization increases with the increase in the severity of the incident (Taylor and Narupiti, 1996). Zhou (2008) used microscopic traffic simulation to evaluate the effects of incident management along with signal timing modifications for the diversion routes. The analysis results implied that the percentage of the diverted traffic volume has a significant impact on the total delay of the entire network. A 10% diversion rate from the impacted freeway to the adjacent arterials was found to yield minimal network-wide delays (Zhou, 2008). The coordinated control strategies were able to reduce the travel time by about 8-25% for different scenarios during the incidents compared to non-coordinated strategies (Jacob and Abdulhai, 2010).

5.5.3 Methodology

The analysis methodology in this study consists of five parts: i) Data Retrieval and Preparation, ii) Model Training and Validation, iii) Prediction of Critical Alternative Routes, iv) Development of Special Signal Plan, and v) Evaluation of the Plan. The details of the analysis process is shown in Figure 49. The analysis started with aggregating the data followed by the development of travel time prediction models. The change in travel time due to diversion (Δ-Travel Time) was then estimated based on the difference between the predicted travel time obtained from the models for the incident and normal periods. The critical routes impacted by the diversion were identified next as those routes with a significant increase in the Δ-Travel Time values. Then, special signal plans were developed using optimization, and the resulting plans were evaluated using simulation modeling. The details of each step are discussed in the subsequent sections.

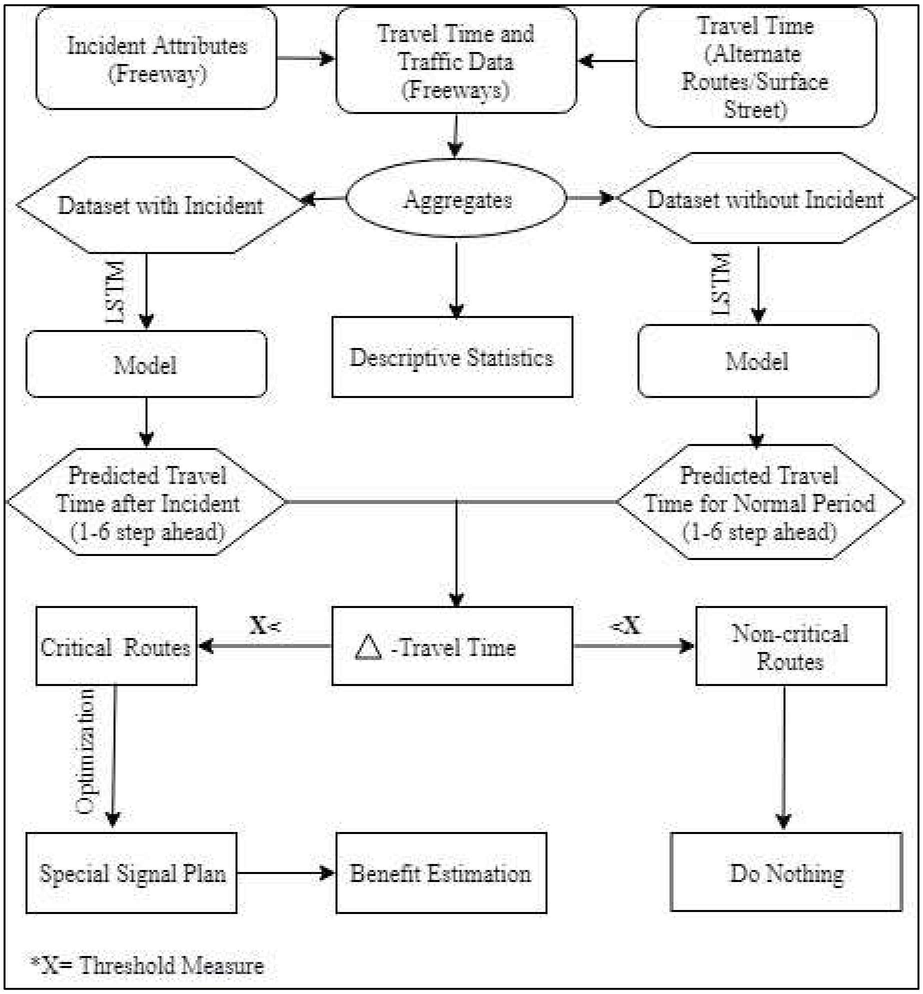


Figure 49: Flow chart of the analysis methodology

Data Retrieval

The case study in this research is a segment of the Interstate-95 (I-95) facility in Broward County, FL and surrounding major arterials (Figure 50). I-95 in this area is considered as a potential site for ICM implementation by the Florida Department of Transportation (FDOT) and partner agencies. The collected data includes incident and traffic detector data for I-95 and travel times for I-95 and four alternative routes. The analysis horizon was the time period from January 1st, 2017 to December 31st, 2018, excluding holidays and weekends. The traffic detector data for I-95, including speed and volume measurements, was retrieved from the regional data warehouse, which is a part of Regional Integrated Transportation Information System (RITIS) in 15 minute intervals for four periods: the AM Peak (7:00 am – 9:00 am), Midday (9:00 am - 4:00 pm), PM Peak (4:00 pm-7:00 pm), and Evening (7:00 pm-10:00 pm) periods in the southbound direction of I-95.

Incident data for the analysis horizon was retrieved from the incident management database maintained by the Florida Department of Transportation (FDOT) District IV. The data includes detailed attributes of the incidents used in the analysis including incident start time, incident duration, total incident clearance time, number of blocked lanes, severity, and location.

The travel time data for both the freeway and alternative routes was retrieved from the HERE (a private-sector travel time data provider) for the analysis horizon. One minute resolution data were obtained for the southbound direction of I-95, the westbound direction of the arterial connectors to the alternative routes, and the parallel southbound arterials.

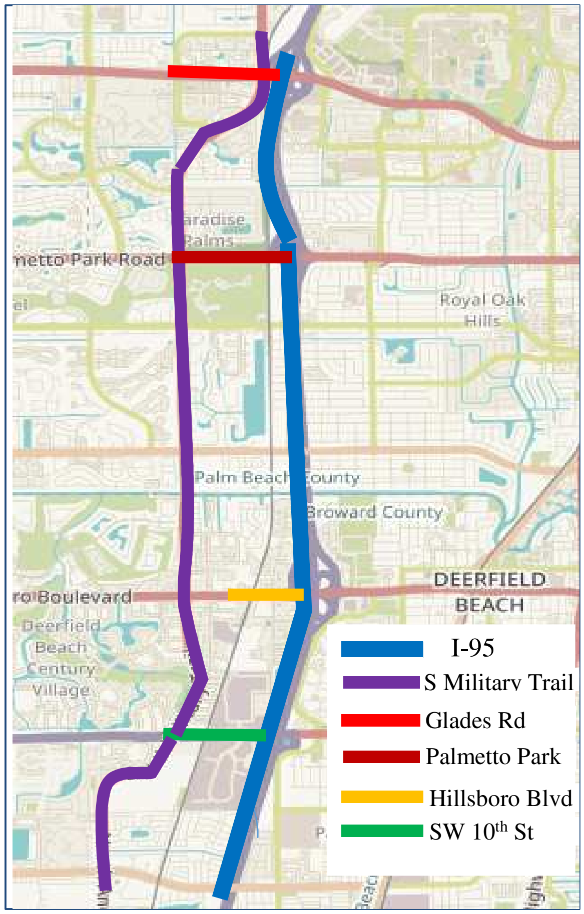


Figure 50: Study area network

Data Preparation

To prepare the data for the analysis; all data were filtered and cleaned by removing weekends, holidays, and missing data from the dataset. The travel time for each minute was aggregated to 15-minute intervals starting from the beginning of the incident. For example, if the incident begins at 08:10 am, the next 15 minute data will be from 08:10 am to 08:25 am and aggregated accordingly. Then, this data was associated with traffic attributes and incident attributes for these intervals. The processing was done using the Python programming language, which eventually produced a dataset with all essential attributes. The combined dataset was further formatted to the specific format necessary to feed the LSTM method. The incident attributes, I-95 traffic detector, and travel time data for the I-95 segment and alternative routes for each 15-minute interval from the beginning of the incident were used as the input to the model. The model provides predicted travel time for each 15-minute intervals on the alternative routes up to 90 minutes after the incident as the output in the output layer of the LSTM model.

Model Training and Validation

As stated earlier, The LSTM method was used in the development of the model in this study since this method has been shown to provide superior results over traditional RNNs in a variety of applications (Graves et al., 2009). LSTM is a recurrent network architecture along with an appropriate gradient-based learning algorithm (Hochreiter and Schmidhuber, 1997). The gradient-based algorithm eliminates the exploding or vanishing gradient by enforcing constant error flow through the internal hidden layer. The model operates with a specially designed form of the neuron that contains gate units. The gates determine whether the input is significant (in terms of the task given) to be remembered, whether the neuron should continue to remember the value, and whether a value should be in the output. The forget gate maintains a subset of information in each sequence based on their contribution to the next sequence. In addition, the modern LSTM architecture contains peephole connections from its internal cells to the gates in the same cell to learn the precise timing of the outputs (Gers et al., 2003). LSTM architecture is especially suitable for situations where there are long-time intervals of unknown sizes between important events (Kacprzyk and Pedrycz, 2015).

One of the crucial parts of the analysis is the training and validation of the model to predict the travel time on the alternative routes. The dataset described in the previous section is a time-series data with incident attributes, traffic detector measurements, and travel time measurements. The input variables used in the model are the timesteps, time-of-day, incident severity, number of lane blockage, the location of the incident (distance from a reference point), average speed and average volume per lane on the freeway, and the travel times of both the freeway and arterials. The model provides predicted travel times for all alternative arterial segments for the prediction time horizon, which is divided into six steps (Step 1 to 6 represent the 15-minute interval from 15 to 90 minutes after the incident).

The Python programming language with Keras library and Tensorflow library in the backend were used to train and validate the LSTM model. The dataset was randomly divided into two parts: training set and test set with the training set consisting of eighty percent of the data points and the test set consisting of twenty percent of data points. The model was trained for predicting the travel times for the intervals between 15 and 90 minutes after the occurrence of the incident, where every 15 minutes' data points were used to predict the next 15 minutes' travel times. The developed LSTM model consists of three hidden layers besides the input and output layers. The One-Hot Encoding was used to convert the categorical variables (i.e., timesteps, time-of-day, incident severity, number of lane blockage) into the dummy variable for use in the model. All the data were normalized using max-min normalization. The trained model was further validated using the test dataset and two different performance measures were estimated using the test dataset as reported in the result section.

Prediction of Critical Alternative Routes

The percentage changes in travel time on the potential alternative routes in the prediction horizon after the occurrence of each incident with respect to the predicted travel time without the incident during the same period is termed as the Δ-Travel Time. The Δ-Travel Time acts as a threshold measure to identify the critical routes impacted by the incidents and the mobility impacts on these routes. In real-world applications, the threshold value of Δ-Travel Time can be set by the local agencies based on the needs and resources.

Simulation Modeling

The study area network consisting of the arterial and freeway segments were coded in the VISSIM microscopic simulation tool for two purposes: i) developing a relationship between Δ-Travel Time and volume for use in real-time estimation of volume when diverted volume measurements are not available in real-time operations, and ii) evaluating the impacts of the activation of special signal plans in response to the increase in travel times on arterials during freeway incidents. Developing the relationship between the Δ-Travel Time and volume is needed since the output from the LSTM model is the change in travel times of arterial segments but not the changes in volumes. This is important since currently arterial travel times can be obtained from third-party vendors and in some cases from automatic vehicle identification readers but most agencies still do not install detectors to measure volumes on their arterials. Simulation modeling is used to determine the change in volume that produces the predicted change in travel time. The simulated network includes the freeway segment for I-95 from Glades Road to West Atlantic Blvd., the Military Trail arterial identified as the major parallel alternative route for the freeway, and three arterial connectors between I-95 and Military Trail in Southeast Florida. The connectors are segments of West Palmetto Park Rd, West Hillsboro Blvd, and SW 10th St whose lengths vary between 0.5 and 0.6 mile. The three connector segments are frequently used by travelers to divert from I-95 during incidents in the southbound direction. Examination of smartphone navigation apps (Google Map, WAZE, and Apple Map) indicates that these apps also divert traffic to these routes during incidents.

The existing actuated signal control plans obtained from the signal control agencies were coded in the simulation model. The coded network was calibrated to simulate the field conditions. Using the developed simulation model, the change in the volume of the alternative arterials as a function of the change in travel time was derived using the regression model and was portrayed in a graph. The relationship provided the volumes of traffic associated with the increases in travel times for use in developing the special signal timing plans as discussed in the subsequent section.

Development of Special Signal Plan

Special signal timing plans for different diversion scenarios were developed using the Highway Capacity Software (HCS) software. The HCS emulates the Highway Capacity Manual (HCM 2016) procedure. The current version of the HCS (HCS7) incorporates the TRANSYT-7F optimization engine, which is based on hill-climbing and Genetic Algorithm (GA) (Andrade et al., 2017) in the HCS-Streets module. Andrade et al. (2017) used HCS for multi-objective optimization of signal timing. Hale et al. (2015) used the HCS platform to compare several heuristic optimization methods for signal timing optimization. Yang (2010) used the HCS GA optimization and a separated external GA optimization for signal timing optimization and found similar results.

The GA optimization algorithm available in the HCS software was used to optimize the signal timing. All intersections were coded in the HCS-Streets module to find the new signal plan. The volumes generated from the simulation, as described in the previous section were used as inputs to the HCS-Streets. The overall delay was used as the objective function in the optimization. Only the splits for each movement was optimized in the study and the cycle length was kept at a fixed value to maintain progression between intersections. The GA optimization parameters were set as recommended by the software. Based on the newly estimated splits of the signal plan, the benefits of changing the signal plan was estimated and shown in the result section.

Estimation of Benefits

The benefits of the signal timing optimization in response to incidents on the freeway were estimated using the delay as the performance measure. Delay for the alternative arterials was estimated for both the incident and non-incident (normal or base condition) scenarios using the microscopic simulation tool. The following three scenarios were simulated in the study to estimate the benefits.

- Scenario 1: Base condition with no incident, and the optimized signal plan for the base condition.
- Scenario 2: Incident on the freeway, diversion of the traffic to the arterial, and the optimized signal plan for the base condition.
- Scenario 3: Incident on the freeway, diversion of the traffic to the arterial, and the new optimized signal plan for the incident condition.

5.5.4 Results and Discussion

Incident Statistics

The summary statistics of the incident attributes used in the analysis are shown in Table 25. The utilized data includes a total of 700 incidents with lane blockages that occurred during the analysis horizon in the southbound direction of I-95 from Glades Rd to Oakland Blvd. The majority of the incidents (65%) blocked one lane and around 24% blocked two lanes of I-95. 47% of the lane blockage durations were 15 minutes or less but there was still a significant percentage of incidents (13%), which blocked at least a lane for more than sixty minutes.

Table 25: Incident Summary Statistics

Time Period	Total	Number of Lane Blockage			Lane Blockage Duration (Minutes)			
		One	Two	Three or More	Fifteen or Less	Thirty or Less	Forty-five or less	Sixty or More
AM Peak	108	73	23	12	62	22	12	11
Midday	320	207	82	31	146	99	42	31
PM Peak	167	118	36	13	90	52	22	7
Evening	105	56	31	18	31	20	11	42
Total Incidents	**700**	**454**	**172**	**74**	**329**	**193**	**87**	**91**

Evaluation of the Travel Time Prediction Model

Two performance metrics were used to evaluate the performance of the trained LSTM models: Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). These measures were estimated using the test dataset for the case study described earlier. The performance matrices for each timestep for the two LSTM models (the incident period model and the normal period model) for each investigated diversion segment are shown in Table 26 and Table 27, respectively. It is observed from the tables that the accuracy of the prediction is good across the timesteps. However, the model for the normal period has lower errors compared to the model for the incident period because of the availability of a higher number of normal period data points to train the model and lower variability in the travel time. The MAD of travel time for the four routes ranges from 12 to 20 seconds during the incident and from 6 to 14 seconds during the normal period. Overall, the full model during the incident period is able to predict the travel time with accuracy between 82 and 90% while during the normal period the accuracy range is between 88 and 92%. Considering the high stochasticity of the travel time, and other traffic data, the prediction accuracy of the models are acceptable.

Table 26: Model Performance Statistics for the Incident Period Prediction

Error Measure	Alternative Segments	Timesteps						Full Model
		1st Step	2nd Step	3rd Step	4th Step	5th Step	6th Step	
MAD (Sec)	Glades Rd	12.8	14.1	13.5	13.5	14.3	15.0	20.8
	W Palmetto Park Rd	18.3	16.9	17.1	17.8	16.8	20.2	13.5
	W Hillsboro Blvd	15.9	15.1	15.9	15.7	15.9	13.7	19.8
	SW 10th St	13.9	16.2	14.6	13.9	16.0	17.0	15.0
MAPE (%)	Glades Rd	21.1	26.3	22.0	20.3	26.2	26.6	13.2
	W Palmetto Park Rd	14.6	12.9	13.9	12.6	13.7	16.6	17.8
	W Hillsboro Rd	19.3	20.9	19.7	19.4	20.6	19.3	15.7
	SW 10th St	13.4	15.5	13.7	12.4	17.1	16.4	15.4

Table 27: Model Performance Statistics for the Normal Period Prediction

Error measure	Alternative Segments	Time Steps						Full Model
		1st Step	2nd Step	3rd Step	4th Step	5th Step	6th Step	
MAD (Sec)	Glades Rd	14.2	10.6	10.5	12.1	10.9	11.1	12.4
	W Palmetto Park Rd	9.1	6.5	6.1	6.3	6.1	6.0	6.9
	W Hillsboro Blvd	14.9	11.8	12.1	11.7	11.5	11.5	13.4
	SW 10th St	9.6	7.6	7.6	9.4	8.1	8.3	9.5
MAPE (%)	Glades Rd	9.7	7.8	7.3	7.6	7.5	7.5	8.6
	W Palmetto Park Rd	14.3	10.3	9.9	9.8	9.7	9.5	10.8
	W Hillsboro Rd	13.5	11.1	11.1	10.5	10.3	10.4	12.5
	SW 10th St	12.2	10.7	10.7	11.3	10.9	10.9	12.1

Δ-Travel Time

The Δ-Travel Time for all time steps for all the incident was estimated based on the results from running the two models for each incident. The cumulative distribution of Δ-Travel Time for all routes for the first three time steps are shown in Figure 51 to Figure 53. Due to the incidents, the travel times on the alternative routes increased up to 150% after 15 minutes (Figure 51), 250% after 30 minutes (Figure 52), and 200% after 45 minutes (Figure 53) of the incidents. One can see that 50% to 80% of the predicted travel times using the LSTM model with incident conditions have travel times within 25% of the values predicted by the LSTM model for no-incident conditions. The variations in travel times during these incidents with 25% of the "normal" travel time may reflect the normal day-to-day variations in travel time and thus no diversion can be assumed for these incidents.

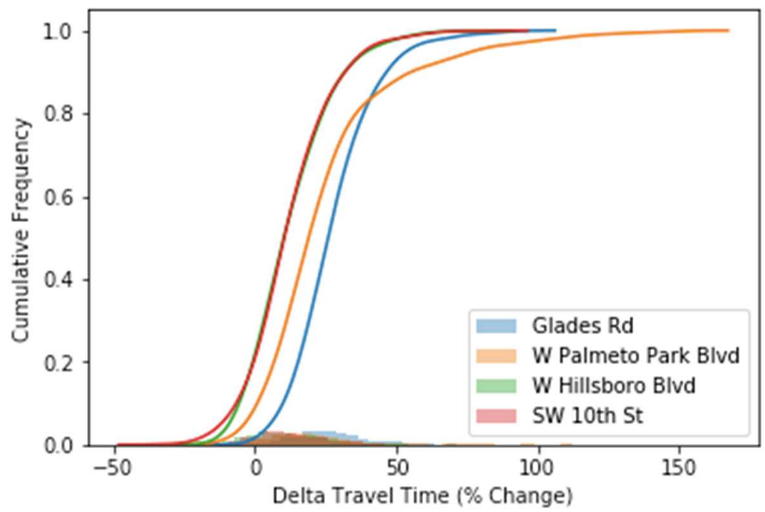


Figure 51: Δ-travel time after 15 minutes of the incident using the developed LSTM models

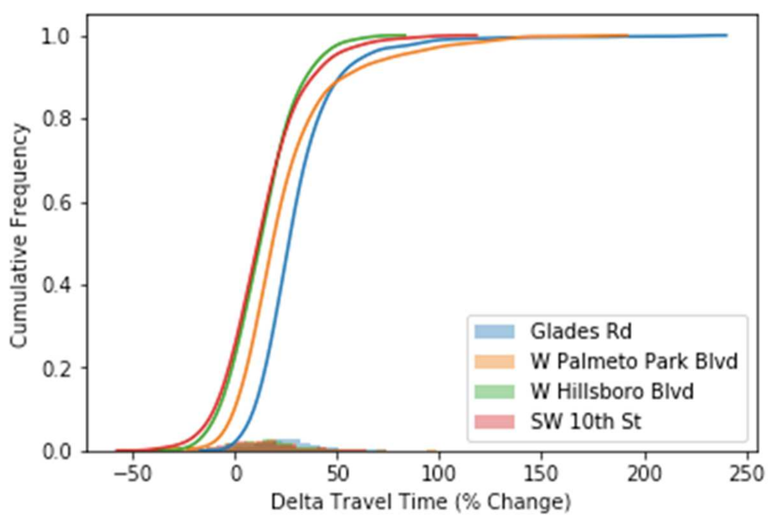


Figure 52: Δ-travel time after 30 minutes of the incident using the developed LSTM models

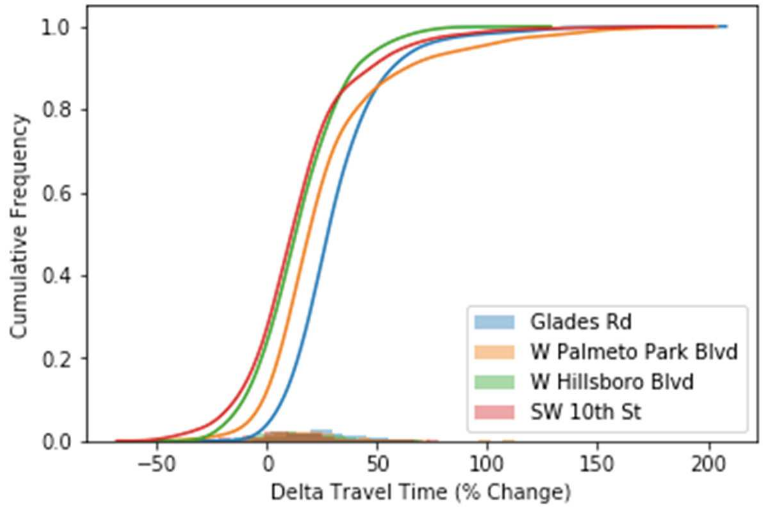


Figure 53: Δ-travel time after 45 minutes of the incident using the developed LSTM models

Traffic Count vs. Δ-Travel Time

The relationships between the increase in traffic volume and Δ-Travel Time for three arterials (W Palmetto Park Rd, W Hillsboro Blvd, and SW 10th St) in the study area is shown in Figure 54. As described earlier, the relationship was established using the VISSIM simulation model assuming all diverted vehicles from I-95 take the left turn to South Military Trail at the intersection of this road with the connectors to I-95. The 15 minutes' volumes and travel times were used to build the relationship. A linear regression model was developed for each route and portrayed in Figure 54. The coefficients of determinations (R^2) of the models range from 0.68 and 0.78 indicating a good fit. Figure 54 shows that W Hillsboro Blvd can accommodate more traffic compared to the other two routes, although the travel time increases sharply with the increase in the volume. SW 10th St is currently running close to capacity as a small increase in traffic increases the travel time rapidly. For example, an increase of 60 vehicles in 15 minutes result in doubling the travel time compared to the normal period on SW 10th St. The other route, W Palmetto Park Rd, can accommodate the higher number of vehicles than SW 10th St for the same percentage of travel time increase.

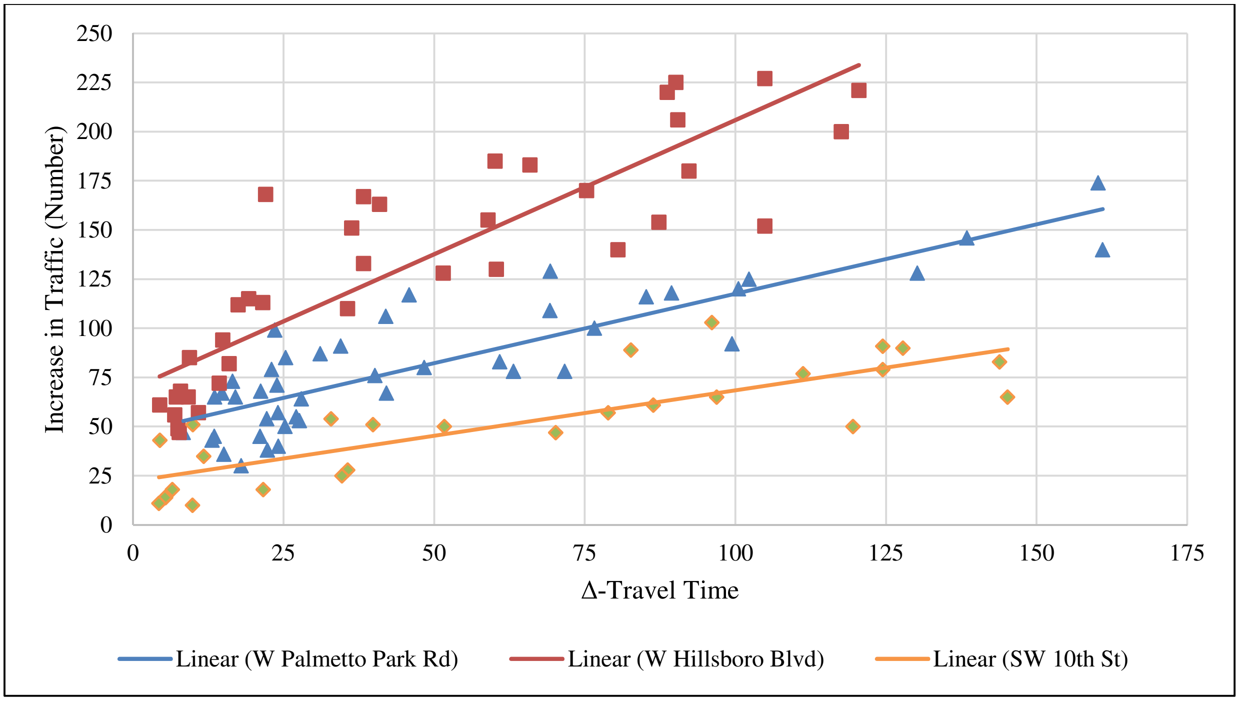


Figure 54: Relationship between the increase in traffic and travel time based on simulation results

Evaluation of Special Signal Plan

This section presents the results of the evaluation using simulation of the activation of special signal timing plans generated to accommodate diversion during freeway incidents. The optimum cycle splits were generated using the GA based signal optimization model in the HCS-Streets software for two cases: base condition with zero diversion and incident condition with a diversion to ensure comparison compatibility since the existing signal timing plan may not be optimum according to the HCS-Streets procedure. The average delays per vehicle for the whole intersection and the critical left turn movements were estimated for the three scenarios mentioned earlier and are presented in Table 28. Three cases of Δ-Travel Time increase (50%, 75%, and 100%) were used in the development and evaluation of the special signal plans. However, the agency can develop signal plans for any percentages of Δ-Travel Time based on the needs in real-time using the model output. The table shows that the optimized plans without changing the cycle time can reduce the average delay during the incident in all cases. During the incident, the diverted vehicles at the critical left turn experience 2 to 8 times more delay than usual and concurrently, increase the whole intersection delay. For W Palmetto Park Rd and W Hillsboro Park Blvd, the left turn delay decreased almost five times compared to the incident conditions without changing the signal timing.

Table 28: Average Delay during the Incident and Normal Conditions with the Special Signal Plan

Alternative Routes	Δ-Travel Time (%)	Average Delay(sec/veh)					
		Normal Condition with Optimized Plan		Incident Conditions with Optimized Timing for Normal Conditions		Incident Conditions with Optimized Timing for Incident Conditions	
		Critical Intersection	Critical Left Turn	Critical Intersection	Critical Left Turn	Critical Intersection	Critical Left Turn
W Palmetto Park Rd	50	102.5	72.7	104.7	308.1	106.2	124.4
	75			127.3	435.5	123.2	96.9
	100			138.1	542.7	125.1	96.4
W Hillsboro Blvd	50	48.4	62.4	101.5	128.5	73.1	76.5
	75			145.1	447.2	102.1	85.6
	100			157.6	529.1	133.1	111.7
SW 10th St	50	54.6	148.7	78.1	502.5	52.5	112.6
	75			81.6	540.6	54.5	86.8
	100			81.9	568.8	54.7	117.5

5.5.5 Conclusions

This paper has demonstrated methods to proactively identify in real-time the alternative routes utilized by traffic diverted due to incidents and concurrently developed a method that requires only limited amount of data to optimize special signal plans to facilitate the diversion hence mitigate the congestion during the incident on the freeway. The methodology includes the development and evaluation of methods for travel time prediction, estimation of volume increase based on travel time increase on the diversion route, and the development of special signal plans to accommodate the diverted traffic.

The LSTM models to predict the travel time impacts of the diversion showed their capability in predicting travel time on the alternative routes with or without incidents with acceptable accuracy. The models are dynamic and able to capture the variation of traffic and incident to determine the impacts on the alternative routes in real-time. As an alternative to the real-world volume data, the VISSIM simulation model was used as a tool to derive the relationship between the travel time increase and volume at each investigated intersection. This relationship provides the agency with an option to estimate the volume based on the travel time increase, given that currently most locations on the arterial streets are not equipped with sensors to detect volumes. The special signal plans developed using the GA based optimization in the HCS-Streets software was shown in this study to improve the intersection performance by reducing the average delay of the impacted movements due to diversion.

The developed method provides the agency with an easily implementable operation strategy to coordinately operate both freeway and arterials during incidents and facilitate the diversion. The methodology mainly requires travel time data that are becoming already available to the agency through third-party vendors or automatic vehicle identification readers like Bluetooth readers.

The selection of the potential alternative arterials and impacted movements on the arterials require expert knowledge and/or real-time observation of navigation apps after the incidents.

5.6 IDENTIFICATION OF CONGESTION PATTERNS DUE TO DIVERSION

5.6.1 Background

The additional diverted traffic from freeways to alternative arterial streets deteriorates the intersection movement performance causing delays, long queues, spillbacks to the upstream intersections, spillovers to adjacent lanes, and so on. At the critical intersections, the diversion most likely will affect only specific movement(s) in the direction of the diverted traffic rather than the whole intersection. Thus, transportation agencies need to identify the impacted movements and the associated congestion patterns to implement active traffic management strategies to accommodate the additional traffic. It is important to identify the correct congestion pattern due to diversion such that the correct action can be implemented. A wrong response during the incident can worsen the congestion on the directly impacted freeway and its surrounding highway network (Ahmed and Hawas, 2015; Wirtz et al., 2005).

The identification of the diversion patterns and the subsequent development and activation of special signal timing plans require archived and real-time data in high resolution. The existing data collection technologies such as Bluetooth readers, Wi-Fi, INRIX, and HERE act as a good source. However, these data provide segment-wise travel time rather than movement. Moreover, the resolution of the data is coarse and allows the assessment of traffic at aggregate (macroscopic) level rather than at a more detailed microscopic level. In contrast, connected vehicle (CV) data and high-resolution controller (HRC) data are gaining a great promise for allowing the more accurate assessment. In addition to its other benefits, CV can act as a mobile sensor for collecting various traffic data in high-resolution. High-resolution controller data also allows the estimation of multiple detailed performance measures of the traffic signal. This study investigates the use of data from CV technology combined with HRC to automatically identify traffic congestion patterns at the signalized intersections due to diversion. A micro-simulation model is developed using VISSIM to emulate the CV and HRC data. The items in the dataset were labeled utilizing clustering analysis. Then, supervised machine learning was applied to categorize the traffic patterns in real-time operations based on the pre-determined categories identified as a result of clustering analysis. The pattern identification can be used then in implementing signal timing plans to better accommodate the diverted traffic without significantly deteriorating the performance of other movements at the intersection. This method can be used as part of a decision support system (DSS) to manage the traffic proactively during the incidents on the freeway.

5.6.2 Review of Literature

This section reviews studies on congestion pattern identification, utilization of connected vehicle data, utilization of high-resolution controller data, and the application of special signal timing plans during incidents.

Congestion Patterns Identification

Previous studies identified the congestion patterns based on macroscopic traffic attributes such as flow, travel time, speed, and so on. Zhang et al. (2016) developed a method to identify the traffic flow pattern as well as anomaly detection in the flow. A dictionary-based compression theory was employed to find the congestion pattern at the detector, intersection, and sub-region levels. Lane based stop bar detectors were used to collect the volume data for every 15 minutes that eventually aggregated hourly to estimate the congestion patterns. Zhu et al. (2016) analyzed traffic flow data using Fuzzy C-Means clustering to identify the pattern and based on the findings divided the intersection flow as high peak, evening peak, and flat peak. Lopez et al. (2017) used every 10 minutes link speed data for measuring the urban congestion patterns. Ko and Guensler (2005) characterized the congestion based on speed distributions. Carli et al. (2015) used the bus as a probe vehicle to estimate the congestion time and location.

Floating-car data (FCD) is another widely used traffic data collection method for assessing the performance of traffic operation. FCD data was used for various purposes such as travel time estimation (Rahmani and Koutsopoulos, 2013; Rahmani et al., 2015) mobility data set preparation (Kong, et al., 2018), traffic state detection (Kerner, et al., 2005), congestion patterns identification (Xu et al., 2013). Xu et al. (2013) aggregated the FCD data (location, time, the duration for recurrent and significant congestions) in a cluster style to get the traffic pattern at different levels of detail of the spatiotemporal dimension. The ST-DBSCAN clustering method was used to aggregate the similar congestion events by the spatial and temporal dimensions.

Recently, vehicle trajectories data have become more accessible for identifying the traffic congestions in the network at a more detailed level including both arterials and freeways. Jianming et al. (2012) developed a method that uses vehicle trajectory data as an image that used self-correlation to extract the propagation speed of the congestion wave. This extraction was used to construct a congestion template to identify the current congestion as well as intensity using a matching algorithm. Ma et al. (2015a) used taxi trajectory data to identify the congestion patterns in a large-scale transportation network analysis. A deep Restricted Boltzmann Machine and Recurrent Neural Network architecture were utilized to model and predict the traffic congestion evolution based on Global Positioning System (GPS) data from the taxis. Several other studies used taxi trajectory data to evaluate the congestion pattern utilizing machine learning techniques (Liu et al., 2015; Thianniwet et al., 2009).

Other studies proposed the use of the image processing method for identifying congestion patterns (Krishnakumari et al., 2017; Petrovska and Stevanovic, 2015). Krishnakumari et al. (2017) proposed an image processing method using speed data contour to identify the congestion patterns. Using the expert knowledge, all the patterns found in the data set were manually classified into five classes prior to the training of classification models for use in real-time operations. The model produced an accuracy of 70% for the identification of the congestion patterns.

The above studies considered the flow pattern at the intersection and approach levels; however, they did not discern between the left turn and through movement congestion pattern, which is critical to the purpose of this study. Besides, the measures used in the previous studies were based on aggregated data. More detailed measures based on high-resolution data will allow better assessment of congestion patterns.

Utilization of Connected Vehicle Data

Connected vehicle (CV) data will allow the estimation of various performance measures. For example, CV data can be used for travel time estimation, incident detection, and possibly traffic volume estimation, which are currently estimated using other more traditional measurement methods (Iqbal et al., 2018). In addition, CV data can be used for a more detailed assessment of the performance. CVs can work as a mobile sensor by continuously reporting their status to roadside equipment (RSE) through vehicle-to-infrastructure (V2I) communication or to the cloud. CV data holds a great potential to reduce or even eliminate the needs for fixed-location detectors when the market penetration rates of these technologies increase to a certain level in future years. In the meantime, they can be used in combinations with other detection technologies for offline and real-time performance assessment.

Zheng and Liu (2017) developed an approach to estimate traffic volume using GPS-basd trajectory data from CV or navigation devices. The arrivals of vehicles at the signalized intersection was modeled as a Poisson distribution. The estimation problem was formulated as a maximum likelihood problem given multiple observed trajectories from CVs approaching the intersection. An expectation-maximization (EM) procedure was derived to solve the estimation problem. The model was validated using the field data and found that the proposed approach can work with data collected from as low as 10% market penetration.

Bekiaris-Liberis et al. (2016) proposed a traffic state estimation method by estimating the percentage of CVs in a specific section of a network to determine the total number of vehicles. The model assumed that the density and flow of the connected vehicle are available based on the CV communications.

The estimation of queue length in real-time operations is important for pattern identification and thus for allocating green times during congested conditions. Tiaprasert et al. (2015) proposed a mathematical model for real-time queue estimation using CV data. The model works without the need for signal timing and traffic volume as basic inputs. The model was validated for both pre-timed and actuated controls using VISSIM microscopic simulation modeling and this validation showed that the model can accurately estimate the queue lengths.

Christofa et al. (2013) developed two queue spillback detection methods based on CV or probe vehicle data. One method uses only CV data and is based on the assumption that non-equipped vehicles in the queue that arrive after the last CV-equipped vehicle can be modeled by using a geometric distribution. The second spillback detection method combines CV data with information about the upstream signal settings and is based on the kinematic wave theory of traffic.

Goodall et al. (2013) proposed an algorithm to determine the locations of individual conventional vehicles based on the behaviors of nearby CV by comparing a CV's acceleration with its expected acceleration as predicted by a car-following model. The study concluded that the algorithm can predict the locations of 30% of the vehicles with about 30 ft accuracy in the same lane, with only 10% of CV market penetrations. The algorithm was developed using the VISSIM simulation data and validated using the NGSIM data.

Cao et al. (2019) developed a method to estimate the probability of left-turn queue spillback. The developed method was validated using the VISSIM microscopic simulation. The study assessed updating of the signal timings based on the probability of queue spillback derived using the method. The results of the assessment showed a reduction in the average delay by 20%.

Connected vehicle technology can be beneficial for traffic operations at intersections. The information provided by cars equipped with this technology can be used to design a more efficient signal control strategy. Yang et al. (2016) developed a bi-level optimization model for controlling traffic in an isolated intersection. The developed method considered conventional, connected, and automated vehicles in different percentages and compared the results to an actuated signal control algorithm to evaluate its performance. The simulation results showed a decrease in the total number of stops and delay when using the connected vehicle algorithm for the tested scenarios.

Utilization of High-Resolution Controller

HRC data obtained from the controllers is an event-based data with a temporal fidelity of 0.1 seconds (Sturdevant et al., 2012). The data is recorded through a data logger that captures all detection and phase events at a given intersection. The data can be used to calculate a number of performance metrics such as those related to capacity utilization, movement mobility performance, progression quality, and pedestrian operations. This section discusses existing applications that utilized HRC data for performance measurements.

Smaglik et al. (2007) developed an integrated general-purpose data collection module within a National Electrical Manufacturers Association (NEMA) actuated traffic signal controller for the collection of cycle-by-cycle data. They used the data for producing quantitative graphs to assess arterial progression, phase capacity utilization, movement delay, and served volumes. Liu and Ma (2008) successfully built a system called SMART-SIGNAL (Systematic Monitoring of Arterial Road Traffic and Signals). The system can simultaneously collect and archive event-based traffic signal data at multiple intersections and automatically generates real-time performance measures including queue length, travel time, and the number of stops. The system collects two types of data: the signal events and detector events. These events are stored in a log file every day. The authors proposed a mathematical time-dependent queue length estimation model under both under-saturated and over-saturated conditions. The model provided a reasonable estimation of the intersection queue lengths and arterial travel times.

Day et al. (2011) developed a methodology for analyzing the approaching traffic flow using high-resolution signal event data. Primarily, the upstream beginning of green time is projected forward in time to a downstream detector; which would be the upstream detector of the next intersection. By subtracting the upstream beginning of green time (plus a baseline travel time) from the detector arrival times, they developed a platoon profile by aggregating the data across successive cycles. Day and Bullock (2011) used HRC data to investigate the performance of various algorithms in the offset optimization problem. The HRC raw data were aggregated to obtain cyclic flow profiles, leading to estimates of delay and the number of vehicles arriving on green. Two alternative objective functions were used and assessed: minimizing delay and maximizing the number of vehicles arriving on green. Alternative optimization methods were also investigated including a combination method, hill climbing, and a genetic algorithm. The improvements in performance were similar when using different objective functions and optimization methods. It was concluded that the HRC data can provide a superior method to coordinate the traffic based on the arrivals on green (Day et al., 2011).

The quality of progression is an important performance measure of signal and can be assessed using HRC data by building the Purdue Coordination Diagram (PCD) (Day et al., 2010; Day et al., 2012). Visualizing the data in PCD allows the identification of the quality of progression and also helps the agency to infer the reasons behind poor progression (Day et al., 2011).

Liu and Hu (2013) developed a method using high-resolution controller data to assist ICM operations. They used the high-resolution controller data to optimize the signal control by maximizing the flow during diversion of the traffic from freeway. A microscopic simulation model was used to evaluate the performance of the method. The results demonstrated the method effectiveness for reducing the network congestion and improves the network performance in terms of average delay per vehicle, the average number of stops, and average speed.

Zheng et al. (2013) developed an automated data collection unit (DCU) to collect high-resolution event-based data from signal controller cabinets. Using the high-resolution data, algorithms were developed for the fine-tuning of offset and green splits. A practical procedure was also developed for fine-tuning signal offsets by constructing the time-space diagram (TS-Diagram) to visualize the progression quality.

Dakic et al. (2017) developed a new high-resolution performance measure referred to as the Average Arrivals on Green Ratio (AAOGR). This measure considers the variability of the cycle length and green time, on a cycle-by-cycle basis and provides information on the ratio of vehicles that pass through the intersection per second of green time. Moreover, a discharge rate-based model was also proposed for computing the approach delay, which takes into consideration the possible queue build-up during red and provides a better estimation of the approach delay per vehicle.

5.6.3 Methodology

As stated earlier, this research has developed a method for the identification of the congestion patterns due to diversion based on HRC data and connected vehicle data to subsequently use the information in the selection of signal timing plans based on the identified patterns. The analysis started with collecting, aggregating, and preparing the data. The items in the dataset were labeled utilizing clustering analysis. Then, supervised machine learning was applied to categorize the traffic patterns in real-time operations based on the pre-determined categories identified as a result of clustering analysis.

Data Preparation

Three types of emulated data from the simulation: CV data, HRC data, and midblock loop detector data were collected from the subjected intersection for analysis. Initially, the data for each lane was collected and aggregated for each movement groups for each cycle. To get the data, the intersection was simulated in the VISSIM platform because real-world CV data and HRC were not available for the study network. Therefore, both CV and HRC data were emulated using the simulation.

Case Generation

For developing the machine learning-based congestion pattern identification model, a sufficient amount of data is necessary that represents all probable diversion scenarios. In this regard, the simulation model was run multiple times for various diversion scenarios representing various levels of utilization of the thru movement and left-turn movement of the impacts approach. The study by Tariq et al. (2019) summarized in Section 1.2 estimated that the maximum amount of diversion is 27% of the mainline volume. Therefore, the simulation was run for each percentage of diversion up to 27% by varying the proportion of diverted traffic in the left and through movement. Moreover, the simulation model was also run for different seed numbers.

Utilized Measures

The following attributes collected from CV, HRC, and mid-block loop detectors were used in the analysis.

- *Average Travel Time:* Travel time data were collected by averaging the travel times of CVs in each cycle.
- *CV Position in Queue from Stop Line:* The furthest stopping position of the CVs in the queue in each cycle was collected. If no CV was determined to be stopped in the queue, this value was considered as zero.
- *Served Volume/Capacity (v/c):* Total volume of vehicle served during the green time in each cycle divided by the capacity. The capacity was estimated for normal conditions using the saturation headway after calibrating the simulation model.
- *Green Occupancy Ratio (GOR):* The ratio of the detector occupancy during the green phase to the total green time (Smaglik et al., 2007).
- *Red Occupancy Ratio (ROR):* Ratio of the detector occupancy during the first five seconds after the end of yellow in the split (Day et al., 2018).
- *Mid-Block Volume:* Number of vehicles passing the midblock in each cycle.

Congestion Identification for Base Scenario

The Market Penetration (MP) of CV varies with time. An analysis in south-east Florida done by Iqbal et al. (2018) found that if NHTSA mandated CV on all new vehicles, as was expected at the time of the study, the market penetration will end up to be 15-20% and 50% by the end of the 5th and 10th year after the mandate. At the present time, NHTSA mandate is uncertain. The above discussion indicates that it is necessary to identify the accuracy of the identification of the congestion patterns at low market penetrations of CV.

Since the congestion pattern will need to be identified based on CV market penetrations less than 100%, it is important first to identify how accurate is this identification compared to a ground truth identification of the patterns using 100% CV data. Clustering is the best available unsupervised machine learning tool for identifying the patterns in the data. Several linear and non-linear clustering methods were employed with different CV market penetration levels including the 100% level (the ground truth), and the performance was evaluated. Below is a description of the clustering techniques that were tested for use in this study.

K-means

The K-means algorithm is a widely used method that is applicable for clustering data based on quantitative variables (Jain and Dubes, 1988). The method is based on an iterative algorithm in which the process is initiated by providing a fixed set of centroids (Hartigan and Wong, 1979). Each data point to be clustered is then assigned to its closest centroid using a squared Euclidian distance measure (Hartigan, 1975). To assign a point to a cluster, the goal is to minimize the sum of average pair-wise distance within-cluster dissimilarity. The centroids are then updated by computing the average of all the points assigned to each cluster. These steps are iterated until the assignment of the data points to each centroid does not change significantly. This method is efficient to analyze large datasets; however, its application is limited to clustering based on the quantitative variable as it utilizes the Euclidian distance as the dissimilarity matrix (Huang, 1998).

Principal Component Analysis (PCA) Combined with Clustering

PCA is a statistical approach for dimension reduction and compression while retaining most of the variation in the data set (Dunteman, 1989). The purpose of PCA is to convert the observations to an orthogonal system of Euclidean space and thus reduce the dimensionality by retaining only those characteristics of the data set that contributes most of its variance. PCA is effective in reducing the noise in the data set, in addition to reducing the computational cost by reducing the dimensions. In particular, PCA was found effective in capturing the cluster structure in the data set when used along with clustering methods instead of clustering methods by themselves (Meng et al., 2015). Ding and He (2004) found that K-means clustering on high dimension data was affected by the noise in the data set, and applying K-means clustering in the PCA subspace improved the results significantly. Clustering with the reduced dimensions from PCA was found to be very effective in pattern recognition and is widely used approach in other fields (Marinai et al., 2006; Alzate and Suykens, 2010; Yeung and Ruzzo, 2001).

t-Distributed Stochastic Neighbor Embedding (t-SNE)

Unlike the traditional dimensionality reduction techniques such as PCA (Hotelling, 1933) and classical multidimensional scaling (MDS; Torgersen, 1952). t-distributed stochastic neighbor embedding (t-SNE) is a non-linear dimension reduction technique that focuses on keeping the low-dimensional representations of dissimilar data points far apart. t-SNE is a variation of the stochastic neighbor embedding (SNE) technique, which uses Student-t distribution rather than a Gaussian to compute the similarity between two points in the low-dimensional space (Maaten and Hinton, 2008). The model used equality of conditional probabilities representing similarities between the data points with high dimensions and low dimensions based on the Euclidean distances in the dimension reduction. The Kullback-Leibler divergence method was used as a natural measure of the faithfulness between the conditional probabilities. SNE minimizes the sum of Kullback-Leibler divergences over all data points using a gradient descent method. SNE is hampered by crowding problem that makes cost function very difficult to optimize. t-SNE employs a heavy-tailed Student t-distribution in the low-dimensional space to alleviate both the crowding problem and the optimization problems of SNE (Maaten and Hinton, 2008). The method was successfully applied to various high-dimensional data to find the pattern and cluster in the dataset. t-SNE has been shown to successfully identify small cellular subpopulations, as low as those comprising 0.25% of the population (Amir et al., 2013). The method was effectively applied to reduce the dimensions of computational fluid mechanics data (Wu et al., 2017). t-SNE was applied in some other applications such as pattern recognition in neuroimaging (Mwangi et al., 2014), identification of tumor subpopulations from mass spectrometry imaging (Abdelmoula et al., 2016). t-SNE in combination with K-means was used to estimate day-to-day dynamic OD using high-granular traffic counts, and speed data collected over the years (Ma and Qian, 2018).

Deep Embedded Clustering (DEC)

Deep clustering, which learns feature representations for clustering tasks using deep neural networks, has attracted increasing attention for various clustering applications. Deep embedded clustering (DEC) is one of the state-of-the-art deep clustering methods. The method simultaneously learns feature representations and cluster assignments using deep neural networks. It is a parameterized non-linear mapping from the data space X to a lower-dimensional feature space Z, where a clustering objective is optimized. Unlike previous work, which operates on the data space or a shallow linear embedded space, a stochastic gradient descent (SGD) via backpropagation is used on a clustering objective to learn the mapping, which is parameterized by a deep neural network. It is a method that simultaneously solves for cluster assignment and the underlying feature representation (Xie et al., 2016). DEC was applied successfully in various filed such as the prediction of severity of age-related macular degeneration (AMD) from input optical coherence tomography (OCT) images (Mahapatra, 2019), pattern detection from seating pressure distribution during wheelchair motion (Noguchi et al., 2019), data-driven ECG exploration (Asadi and Regan, 2019). For signal exploration from ECG, DEC produced better results than clustering using the K-means and PCA with K-means methods. Using continuous wavelet transforms in combination with DEC improves the analysis (Wachowiak et al., 2019).

Evaluation of clustering methods

The performance of the investigated clustering methods was assessed utilizing external and internal performance measures. External measures evaluate the purity of the clusters (Wu et al., 2009) while internal measures evaluate the compactness of a clustering structure by determining how close the attributes of each data point are without considering additional information about the data (Tan et al., 2005). As clustering is an unsupervised technique, there is no ground truth data associated with this technique to compare to. Thus, assessment based on quantitative external performance measures based on ground truth data was not possible. However, all data within clusters were visualized to evaluate the distribution of the data among all the clusters.

Unlike the external performance measure described above, Silhouette Coefficient and Connectivity were two internal performance measures chosen in the study for their capability to assess the performance of the clustering algorithms. These measures do not need ground truth data and allow a straightforward interpretation of the results (Rousseeuw, 1987). A higher Silhouette Coefficient depicts a dense and well-separated cluster. A lower connectivity coefficient describes a higher degree of connectedness of the clusters (Brock et al., 2008).

Congestion Identification for Different Market Penetration of CV

Based on the identified congestion patterns using clustering as discussed above, a classification model was trained and validated for use to predict the congestion patterns in real-time operations. Multilayer perceptron (MLP), a feed-forward deep neural network, was applied to build the model due to its ability to classify the data with greater accuracy (Lim et al., 2007) as well as its ability to represent a non-linear mapping between an input vector and an output vector (Hecht-Nielsen, 1990). MLP consists of an input layer to receive the signal, an output layer that provides the model prediction, and hidden layers between the input and output layers (Haykin, 2009). More than one hidden layers are used in the model. The intermediate hidden layers enable the perceptron's ability to solve nonlinear problems by processing information received from the input nodes and pass the results of the processing to the output layer (Baum, 1988; Basheer and Maha, 2000). The Python programming language with ‘Keras’ library was used to train and validate the MLP model. Three hidden layers were used in the model. The data were normalized using a min-max scaler before applying the model.

5.6.4 Results and Discussion

Determination of Number of Clusters

The optimum number of clusters was determined by visualizing the entire high dimensions dataset in low dimensions using t-SNE which was further verified using the Elbow method (Ketchen and Shook, 1996). Initially, the data were reduced to two dimensions using t-SNE and visualized (

Figure 55). The figure depicts eight different patterns, color-coded in different colors. Although the interpretation of the cluster is not feasible from the figure, the method was found successful in demonstrating the number of clusters present in the dataset. Later, in the Elbow method, the sum of square error (SSE) was plotted against the number of clusters using the K-means clustering as shown in Figure 56. Based on the location of the kink in the elbow, the figure also recommends eight clusters as the optimum number of clusters. Therefore, eight clusters were considered as the optimum number and used across the methods to evaluate the performance of the methods in identifying congestions.

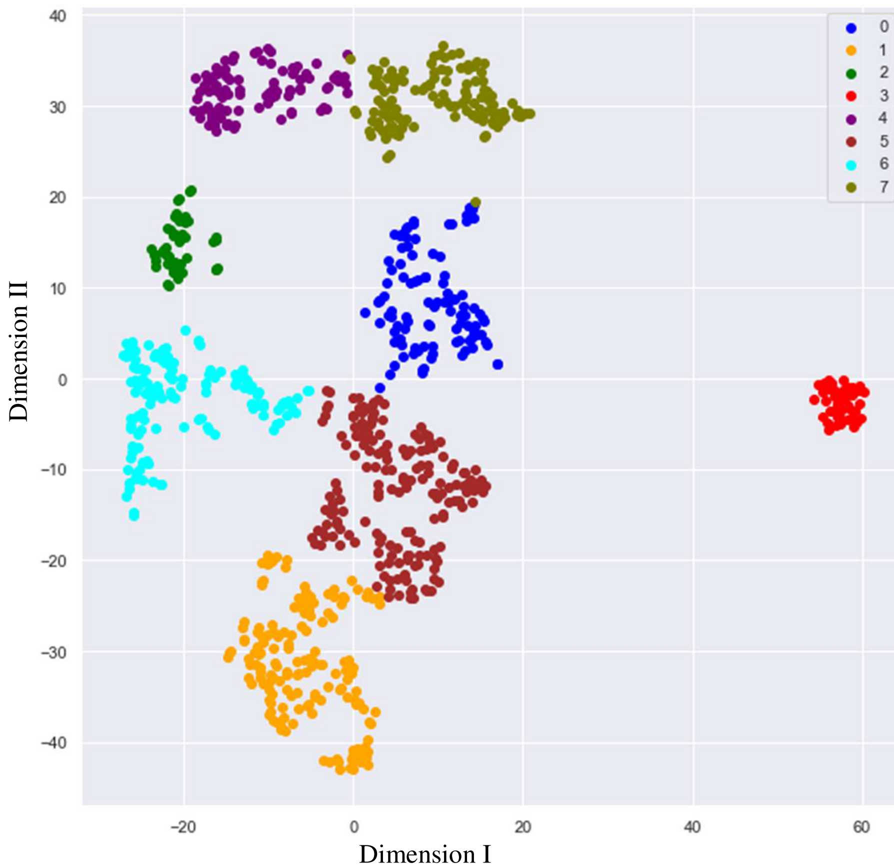


Figure 55: Visualization of the data in low dimension using t-SNE

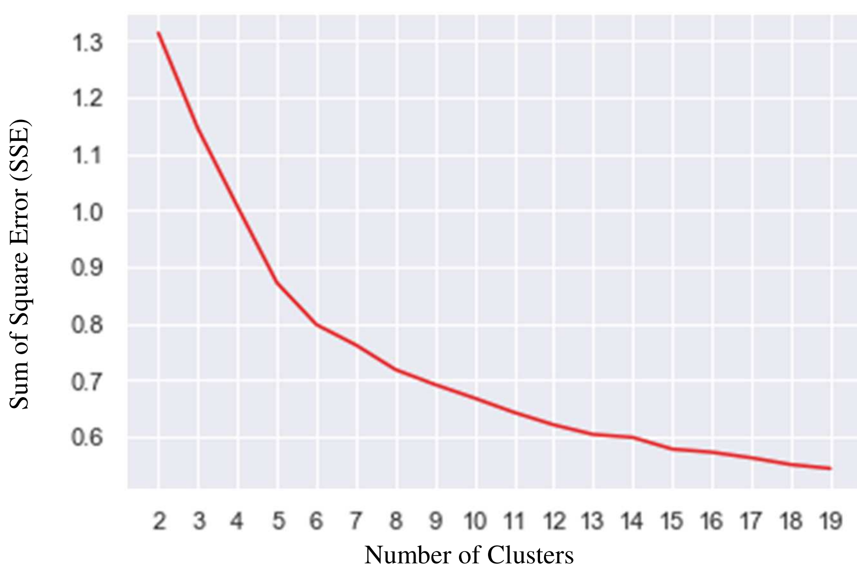


Figure 56: Sum of square error for different number of clusters

Performance Evaluation of Clustering Methods

As stated earlier, four different clustering techniques (two linear and two non-linear) were applied and their performance was evaluated. The values of the Silhouette Coefficient and the Davies–Bouldin index (DBI) from applying the methods are shown in Figure 57 and Figure 58, respectively. Based on the measures (the Silhouette Coefficient and the DBI), the DEC method came out as the best method among the four. DEC produced dense, appropriate, and well-separated clusters compared to the other methods. The performance of the K-means with PCA was the worst among the methods because of the non-linear relationship among the attributes of the data. However, the K-means method clustered the data better than the K-means with t-SNE. This possibly happened because the t-SNE approach doesn't preserve the distances or density like its linear counterpart (the PCA) during the dimension reduction.

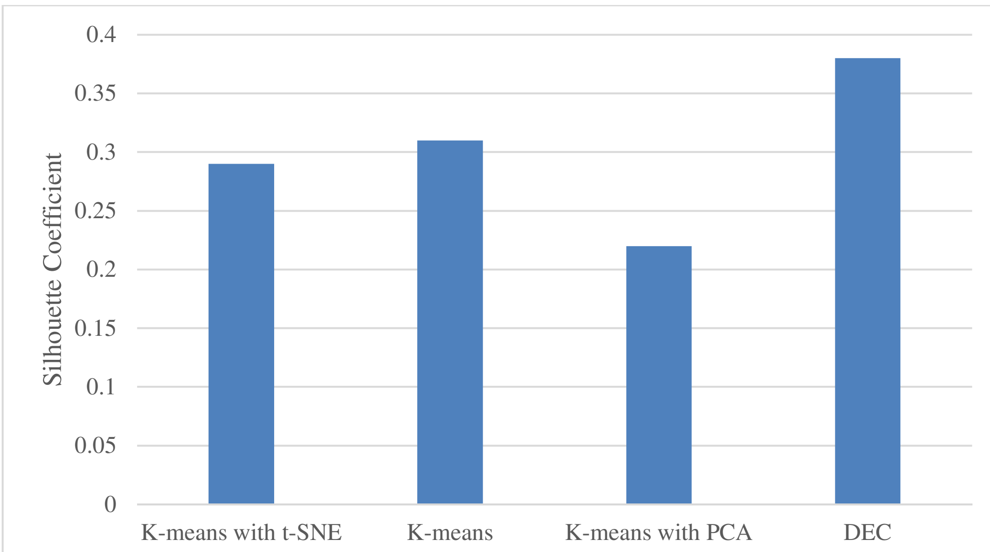


Figure 57: Silhouette coefficient for different clustering methods

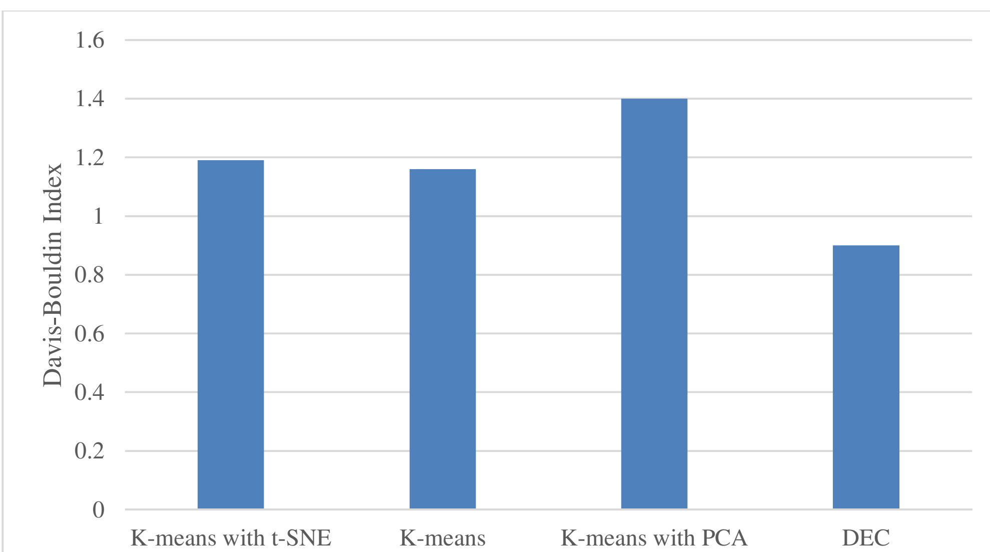


Figure 58: Davies-Bouldin Index (DBI) for different clustering methods

Congestion Patterns Identification

The eight clusters determined using the DEC method for 100% CV market penetration were evaluated to identify the congestion patterns and associated characteristics of the congestions. The characteristics of the clusters are shown in Table 29. The average queue length, average travel time and green occupancy ratio (GOR) for both thru and left-turn movements in each cluster are shown in the table. Among the clusters, Clusters 2 and 3 represent normal conditions in the intersection although the average queue lengths and travel times are higher in Cluster 3 than Cluster 2. Cluster 0 represents an extreme congested condition for both movements as indicated by the high travel time and queue length, however, the low GOR of the left-turn movement represents starvation of vehicles of that movement. This happened because the oversaturated thru movement vehicles blocked the entrance to the left turn bay and thus prevented the left-turning vehicles from entering the left-turn bay. Therefore, Cluster 0 represents the extreme congestion of the thru movement. Clusters 5 and 6 represent the opposite of Cluster 0, where the left-turn movement is highly congested. The oversaturated left-turn vehicles filled the left-turn bay and spilled over to the adjacent thru movement lanes, thus restricting the thru vehicle's movements. Clusters 1 and 7 represent slightly and moderately affected left turn movement, respectively. In these cases, the left turn vehicles did not affect the thru movement. Cluster 4 represents moderately impacted left turn that affects the thru movement. From Table 6, it is also observed that the queue length of the left turn up to 500 ft does not affect the thru movement. However, the increase in the left turn queues beyond that number affects both movements severely. In this situation, providing more green to the left turn movement will be able to reduce the overall delay in the intersection.

Table 29: Characteristic of the Clusters and Associated Patterns of Congestion

Clusters	Thru Movement			Left Turn Movement			Remarks
	Avg. Queue Length (ft)	Avg. Travel Time (Sec)	GOR	Avg. Queue Length (ft)	Avg. Travel Time (Sec)	GOR	
Cluster 0	2432.1	207.6	0.88	2425.6	300.3	0.5	Extremely affected Thru Movement
Cluster 1	216.6	66.3	0.65	424.1	197.6	0.89	Slightly affected Left Movement
Cluster 2	201.1	68.7	0.57	168.2	77.7	0.62	Normal Condition
Cluster 3	235.3	70.8	0.67	202.7	79.3	0.61	Moderately Normal Condition
Cluster 4	402.4	94.6	0.68	1954.9	716.1	0.96	Moderately Highly affected left turn movement
Cluster 5	2147.7	185.2	0.73	2310.9	753.4	0.98	Highly affected left turn movement
Cluster 6	905.2	127.2	0.51	2417.5	1090.2	0.98	Extremely affected left turn movement
Cluster 7	210.4	64.9	0.57	507.8	217.1	0.89	Moderately affected Left turn

Evaluation of the Impact of CV Market Penetration (MP)

The impact of CV MP in determining the accurate clusters vis-à-vis congestion patterns with respect to base condition (100% CV MP) was evaluated and the results are presented in Figure 59. The figure demonstrates high accuracy in the identification of congestions with as low as 10% CV market penetration. The accuracy with 10% CV is around 90% and increased to around 98% when the CV MP is 90%. The accuracy is about 95% when the CV percentage increased to 20% and remained almost the same, up to 40% MP. To check whether the methodology is applicable in the case of no CV vehicle present in the traffic stream, the clustering analysis was done considering all the vehicles as conventional vehicles and the agency does not have travel time and queue length information from the connected vehicles. Based on the accuracy measure, it is observed that without CV, the method can identify congestion with 70% accuracy. The accuracy for this case may improve if the movement travel time data based on other means such as probe vehicles, Bluetooth technology, or detector base technology, are used in the analysis. Since the 10% MP of CV provides an accuracy of around 90% and the probability of getting this MP in the traffic stream in the near future is high, the 10% CV MP scenario was considered when developing the machine learning-based classification model. The different features of the model and results are discussed in the following section.

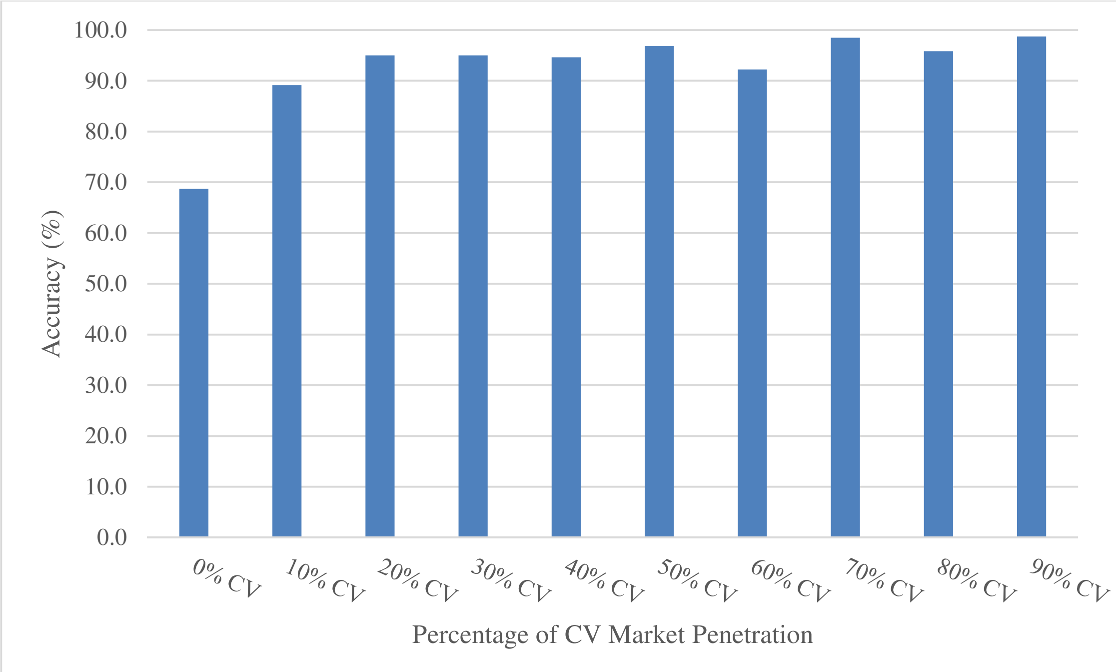


Figure 59: Accuracy in predicting congestion patterns in different MP of CV

Model Development and Evaluation

Considering the 10% CV MP scenario, a deep learning classification model using MLP was developed to predict the congestion patterns in real-time. Initially, the dataset was divided into training and test. 25% of the data records were randomly selected for the test and validation of the model, while the remaining data was used to train the model. Three hidden layers consisting of 32, 24, and 16 neurons, respectively, were used in addition to the input and output layers. The input layer consists of 48 neurons while the output layer consists of 8 neurons since the congestion was classified into eight different classes. The model was trained by putting the data in batchwise. Table 30 shows the performance of the model, in terms of the loss and accuracy measures for both the training and test cases. Loss is a measure of the sum of the error made during classification. The accuracy measure indicates how accurate can the model classify the congestions. Based on the results, the loss of both the test and training data cases are very low which means that the model behaves very well. The accuracy of the model for both cases is above 98%, meaning that the model has significantly capable of predicting the congestions in very low market penetration of CV.

Table 30: Loss and Accuracy of the MLP Model

	Loss	**Accuracy**
Training Data	0.0889	0.986
Test Data	0.0951	0.984

5.6.5 Conclusions

This study has demonstrated a methodology to identify the congestions at the intersection microscopically using a very low market penetration of CV combined with HRC data. Two linear clustering methods: the K-means and K-means with PCA and two non-linear clustering methods: the K-means with t-SNE and DEC were investigated for identifying the congestions patterns at the intersections. A deep learning-based classification model using MLP was then developed to identify the impacted movement(s) vis-à-vis congestion patterns.

The DEC clustering method was found to be the best among the four clustering approaches in separating the different congestion types into different clusters. Clustering based on the HRC data combined with as low as 10% market penetration of CV data produced a very good performance compared to ground truth clustering (clustering with 100% market penetration of CV).

The developed method allows transportation agencies to identify the congestion patterns at the critical intersection used by the motorist when diverting due to incidents on the freeway. The agency can use the recognition of these patterns to activate operational plan in real-time operations.

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APPENDIX A: EXISTING MACROSCOPIC, MESOSCOPIC, AND MICROSCOPIC SIMULATION TOOLS

The traffic modeling associated with DTA can be at the macroscopic, mesoscopic, or microscopic resolution level. This section presents an overview of some of the available tools.

HCM-Based ATDM Evaluation Approach

The Highway Capacity Manual (HCM) has freeway and urban street facility procedures that are available in commercially available tools. These tools have been further enhanced to model travel time reliability. The tools also include simple procedures to evaluate ATDM strategies based on the outputs from the operational analysis methodologies of the HCM (Dowling et al., 2013). The methodology assess the impacts on the mean travel time, travel time reliability, and facility demand. The conventional HCM data is supplemented with local historic data on incidents, work zones, and weather; allowing the generation of a set of scenarios representative of the range of conditions that may be present on the facility over the course of a year. The effects of weather, work zones and incidents on capacity and speed are computed for each scenario and the adjustments are applied using standard HCM operational analysis methodologies to determine the impacts on the facility performance measures. As with other HCM procedures, the analysis remains facility based (freeways or arterials separated from each other in the analysis) and thus system level impacts are not reflected. Also, the analysis is done at the 15 minute analysis level, as with other HCM analysis procedures, and thus highly dynamic responses below the 15 minute threshold of the HCM must be modeled, approximately.

VISUM

*V*ISUM is a tool that allows modeling transportation systems and includes a DTA model that has been added to this software for the advanced modeling of the interaction between traffic path performance and route selection. The DTA model assigns dynamic Origin-Destination (O-D) matrices onto the network based on Dynamic User Equilibrium (DUE). The model converges to the equilibrium state in which no travelers can have less experienced travel time by unilaterally changing their paths (PTV Vision, 2013a). To represent a spillback in VISUM, it is assumed that each link is characterized by two time-varying bottlenecks: one located at the beginning, and another located at the end of the link, called “entry capacity” and “exit capacity", respectively. VISUM applies Traffic Flow Fuzzy (TFlowFuzzy) model to allow Origin-Destination Matrix Estimation (ODME) using observed count data and simulated volumes. The matrix estimation data is done using an iterative method to adjust the initial O-D matrix cells to achieve better matching of observed and simulated volumes (PTV Vision, 2013a).

DYNASMART

Dynamic Network Assignment-Simulation Model for Advanced Telematics (DYNASMART) is one of the first DTA tools developed to implement a simulation-DTA modeling of transportation networks by Mahmassani et al. (2009). DYNASMART provides a mesoscopic level of traffic representation, which combines a microscopic level of representation of individual travelers with a macroscopic description of traffic flow. The movements of vehicles are governed by a modified version of the Greenshields' macroscopic speed-density relationship, but vehicular movements are tracked at the level of individual vehicles or groups of vehicles. Delay is computed using node transfer logic based on the time that takes for vehicles to transfer considering link capacity and downstream link queue spillback. The model requires that the O-D demands or individual vehicle trajectories are provided. This tool is not currently commercially available. However, it continues to be used in researching advanced applications of DTA. In addition, open source tools that are based on Dynasmart including DTALite and DynusT, which are described below) have been used in real world applications.

DynusT

DYNamic Urban Systems for Transportation (DynusT) was developed at the University of Arizona based on DYNASMART. DynusT is an open source program that was developed by Chiu (2012).

The default assignment in DynusT is based on a gap-based assignment which replaces the Method of Successive Average (MSA) assignment in a recent version of DynusT although the MSA assignment can still be requested. The gap-based assignment produces much better convergence and computational efficiency compared to MSA (Chiu and Bustillos, 2009). DynusT is an open-source tool that can be downloaded and used. It is not commercially sold, although the developers can sign agreement to provide technical support. It has been used in a number of projects in recent years.

Dynameq

Dynameq is a DTA software developed by INRO Consultants, Inc. Dynameq is a DUE-based model that iterates between finding time-dependent path flows and determining the corresponding path travel times. Vehicles are assigned to paths using the MSA, which assigns a decreasing fraction of vehicles to the shortest path in subsequent iterations. The fraction is equal to one divided by the current iteration number, so that in the first iteration, all vehicles are assigned to the shortest path. Half of all vehicles are assigned to the shortest path in the second iteration, and so on. The developers have also tested more efficient and better converging methods of assignment (Mahut et al., 2007). Dynameq is different from other mesoscopic model in that it can model individual lane flow with the lane-changing decisions are made upon entering each new link. Modeling individual lanes has the advantage of explicitly modeling scenarios when certain types of vehicles are restricted from specific lanes such as high occupancy vehicle lanes. To improve computational efficiency and allow for regional-level modeling, Dynameq's behavioral rules are simplified relative to microscopic simulators. These simplifications include not allowing vehicles to reconsider their lane choice while traveling on the link. Also, the model is updated each time an event occurs, rather than at pre-defined time intervals. Thus, Dynameq may be considered as higher fidelity mesoscopic model. More information about Dynameq and its application can be found in Mahut et al. (2004) and Florian et al. (2008).

DTALite

DTALite is an open-source DTA package that has been developed by Zhou and Taylor (2012) and has been supported by FHWA through a number of research projects. DTALite is a mesoscopic simulation-based DTA package that works in conjunction with the Network EXplorer for Traffic Analysis (NeXTA) graphical user interface. The DTALite tool aims to integrate modeling and visualization capabilities. The traffic assignment and simulation modules in DTALite iterate to either capture day-to-day user response or find steady-state equilibrium conditions. Speed, volume and density measures at the network, specific links, and vehicle trajectories can be visualized using the NeXTA user interface (Zhou and Taylor, 2012).

DTALite is a link-based simulation with capacity constraints and it has been used recently in several pilot and research project sponsored by FHWA program (FHWA, 2013a). More information about NeXTA/DTALite can be found at https://code.google.com/p/NeXTA (DTALite, 2012).

TransModeler

TransModeler is a microscopic simulation-based traffic assignment tool offered by Caliper (Caliper Corporation, 2011). One of the interesting features of TransModeler is that it allows the network modeling based on the microscopic, mesoscopic, and/or macroscopic simulation level in the same run.

TransModeler applies different algorithms that are suitable for microscopic simulation-based DTA. TransModeler can handle large-scale networks based on the microscopic simulation-based DTA. Micro-level simulation provides a more accurate representation of traffic and management operations compared to mesoscopic modeling. As these models become more efficient, this increases their attractiveness. However, calibration microscopic simulation still requests significantly more time than mesoscopic models, especially when combined with DTA. More information about TransModeler can be found at http://www.caliper.com/TransModeler/Simulation.htm (Caliper Corporation, 2011).

Cube Avenue

Cube Avenue is a dynamic traffic assignment extension of Cube Voyager (Citilabs, 2013). It models traffic at more details than the Cube Voyager's Highway program which utilizes macroscopic models, and at less detail than microscopic models. With Cube Avenue, routes and flow rates change during the modeling period based on congestion. One of the strength of Cube Avenue for regions that use the Cube modeling environment is to apply the same data format and scripting language as Highway Cube Voyager. Using this scripting language also provides more flexibility in modeling approaches. The assignment in Cube Avenue is based on user equilibrium utilizing the MSA method.

TRANSIMS

Transportation ANalysis and SIMulation System (TRANSIMS) is an open-source software developed at the Los Alamos National Laboratory to conduct transportation system analysis. It consists of four steps, one of which estimates demand by an activity-based model, which is not available in other assignment tools. TRANSIMS has been implemented for large networks such as Dallas and Portland. However, it requires an extensive amount of input data compared to other DTA models. More information about TRANSIMS can be found in Lee (2014). TRANSIM can be considered as a low-resolution microscopic simulation model.

VISSIM

Verkehr In Stadten Simulation Model, which means "Traffic in Towns Simulation Model" (VISSIM) was developed by PTV Group in Germany (PTV Vision, 2013b). Most existing simulation models operate using link-node configurations. VISSIM is a detailed microscopic simulation tool that models vehicles at the 0.1-second resolution level. VISSIM differs from these models and it utilizes a link-connector structure. This involves coding movement individually at each intersection, allowing for increased precision and flexibility in modeling traffic flow. Although this process has been simplified in more recent versions of the software, it is more complex than coding link-node models. VISSIM can display microscopic simulation results in 3D animations, including a feature that allows viewing from a selected driver's perspective. VISSIM has also a power programing extension that allows modelers to program advanced managements and pricing strategies that correspond to real-world advanced strategies. VISSIM 8 allows the user to specify the demands based on turning movement volumes, partial routes, or utilizing DTA to determine paths between origins and destinations. In addition, the tool has a managed lane model to estimate the diversion between managed lanes and general purpose lanes. (PTV Vision, 2015).

Aimsun

Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (Aimsun) was developed by TSS-Transportation Simulation Systems in Spain. It is an integrated traffic modeling software that fuses travel demand modeling, static and dynamic traffic assignment mesoscopic and microscopic simulation into one environment. It can be used to model various applications, such as toll and road pricing, work zone management, evaluation of travel demand management strategies and so on. Hybrid simulation that combines mesoscopic and microscopic simulations can also be conducted using the Aimsun software, which allows the modeling of a large area while zooming in areas with more details. Stochastic and discrete route choice model and dynamic user equilibrium are available in Aimsun at both the mesoscopic and microscopic levels. Three types of shortest paths can be selected in dynamic traffic assignment of Aimsun, that is, user predefined path, calculated shortest path tree based on initial default or user defined costs, and calculated shortest path tree based on statistical data collected in the simulation. Aimsun also provides the functions of Application Program Interface (API) for modeling ITS applications, the Aimsun Microscopic Simulator Software Development Kit (microSDK) for overriding default behavioral models, and the Aimsun Platform Software Development Kit (platformSDK) for developing interfaces. More information about Aimsun can be found in http://www.aimsun.com/wp/?page_id=21.