North Carolina
Department of Transportation
Research Project No. 2019-30

Post-Implementation Evaluation of Integrated Corridor Management (ICM) in NC

ITRE
Institute for Transportation Research and Education

June 2021

This page is intentionally blank.

1. Report No. **FHWA/NC/2019-30**	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle **Post-Implementation Evaluation of Integrated Corridor Management (ICM) in North Carolina**		5. Report Date **June 2021**
		6. Performing Organization Code
7. Author(s) R. Thomas Chase, Shoaib Samandar, Sreekanth Gopi, Tao Li, and Chris Cunningham		8. Performing Organization Report No.
9. Performing Organization Name and Address **Institute for Transportation Research and Education** **North Carolina State University** **Centennial Campus Box 8601** **Raleigh, NC**		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. NCDOT RP 2019-30
12. Sponsoring Agency Name and Address **North Carolina Department of Transportation** **Research and Analysis Group** **104 Fayetteville Street** **Raleigh, North Carolina 27601**		13. Type of Report and Period Covered **Draft Final Report** **August 2018 – May 2021**
		14. Sponsoring Agency Code **NCDOT/NC/2019-30**

Supplementary Notes:
Conducted in cooperation with the U.S. Department of Transportation, Federal Highway Administration

16. Abstract

Integrated Corridor Management (ICM) systems offer the potential to manage both travel demand and network demand in normal and abnormal conditions. Traditionally, ICM is typically applied in an urban setting where multiple transportation modes are readily available. NCDOT has applied ICM principles, but in more rural applications where less modal and network options are likely to exist. NCDOT has deployed ICM on 22 miles of I-85 from MM 10 to 32 near Charlotte with a focus on managing incident-related congestion on the interstate and parallel US-74 arterial. This deployment includes traveler information on Dynamic Message Signs, activatable detour trailblazer signs for individual incidents, and incident-specific signal timing plans for intersections included in the detours.

Observations of traffic flow patterns are essential to accurately capture the traffic diverted due to ICM activations. In this project, Bluetooth and Wi-Fi traffic monitoring devices were placed throughout the corridor and used to match trips along the primary and detour routes to establish baseline O-D patterns which can be compared to ICM activations after implementation. This project also adapted an existing sketch-planning NCDOT analysis method used in the project prioritization process to compare estimated delays on primary and detour routes during ICM operation. The inputs for diversion rates and capacity benefits from ICM-specific signal timing can be updated as observations provide better estimates.

This project developed a live dashboard integrating data feeds from public and private sources presented in a compact set of maps and graphs. NCDOT performs after action reviews of severe incidents including those in the I-85 ICM deployment, which may use the dashboard to supplement their review. Finally, this project developed an evaluation framework which captures delay, safety, environmental, administrative, and capital impacts of ICM deployment. This analysis framework is recommended for the I-85 deployment and others with fixed strategies; however it would need to be augmented with the strategy selection algorithm to account for a dynamic system.

17. Key Words **Corridor Management, ICM, Detour, Bluetooth, TSMO**	18. Distribution Statement No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 43	22. Price

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

Disclaimer

Acknowledgments

The research team thanks the North Carolina Department of Transportation for supporting and funding this project. We are particularly grateful to the Steering and Implementation Committee members and key stakeholders for the exceptional guidance and support they provided throughout this project:

Jennifer Portanova (Chair)
Lisa Penny (Former Research Engineer)
John Kirby (Current Research Engineer)
Zachary Clark
Dominic Ciaramitaro
Matthew Carlisle
Joseph Hummer
Neil Avery
David Phipps
Shawn Troy
Chris Howard
JP Couch
Jim Fox

Executive Summary

Integrated Corridor Management (ICM) systems offer the potential to manage both travel demand and network demand in normal and abnormal conditions. Through increased awareness, decision-support, and institutional coordination, ICM systems strive to change the traditional reactive model of traffic management to a proactive approach. With ICM, system operators take action before corridor performance degrades and, in cases where degradation has already occurred, take action to promptly restore normal conditions. Traditionally, ICM is typically applied in an urban setting where multiple transportation modes are readily available. NCDOT has applied ICM principles, but in more rural applications where less modal and network options are likely to exist. These initiatives will provide potential opportunities to measure benefits and provide guidance for future implementation of ICM elsewhere in the state.

NCDOT has deployed ICM on 22 miles of I-85 from MM 10 to 32 near Charlotte with a focus on managing incident-related congestion on the interstate and parallel US-74 arterial. This deployment includes traveler information on Dynamic Message Signs, activatable detour trailblazer signs for individual incidents, and incident-specific signal timing plans for intersections included in the detours.

The goal of this research project is to support the I-85 ICM deployment with data collection and monitoring as well as develop an analysis framework for Before and After analysis. Due to impacts to NCDOT budgets and COVID-19 traffic, the I-85 ICM activation occurred later than planned and the analysis framework can be applied in a future effort to evaluate the system impacts.

Observations of traffic flow patterns are essential to accurately capture the traffic diverted due to ICM activations. In this project, Bluetooth and Wi-Fi traffic monitoring devices were placed throughout the corridor and used to match trips along the primary and detour routes to establish baseline O-D patterns which can be compared to ICM activations after implementation.

This project also adapted an existing sketch-planning NCDOT analysis method used in the project prioritization process to compare estimated delays on primary and detour routes during ICM operation. This analysis then uses incident rates and time of day traffic patterns to estimate the total delay with and without ICM operation to estimate the benefit of ICM. The inputs for diversion rates and capacity benefits from ICM-specific signal timing can be updated as observations provide better estimates.

This project developed a live dashboard integrating data feeds from public and private sources presented in a compact set of maps and graphs. NCDOT performs after action reviews of severe incidents including those in the I-85 ICM deployment, which may use the dashboard to supplement their review. Reviewing the probe data provides a view of the experienced travel time for drivers remaining on the primary route and those detouring, while GPS data may indicate when diversion may utilize other routes when following third party device recommendations.

Finally, this project developed an evaluation framework which captures delay, safety, environmental, administrative, and capital impacts of ICM deployment. For both benefits and costs, it is important to separate the incremental or specific impacts of the ICM deployment with the understanding that other projects and background traffic patterns continue to affect the corridor. This analysis framework is recommended for the I-85 deployment and others with fixed strategies; however it would need to be augmented with the strategy selection algorithm to account for a dynamic system.

This page is intentionally blank.

Table of Contents

List of Tables

List of Figures

1. Introduction

Integrated Corridor Management (ICM) systems offer the potential to manage both travel demand and network demand in normal and abnormal conditions. Through increased awareness, decision-support, and institutional coordination, ICM systems strive to change the traditional reactive model of traffic management to a proactive approach. With ICM, system operators take action before corridor performance degrades and, in cases where degradation has already occurred, take action to promptly restore normal conditions.

Traditionally, ICM is typically applied in an urban setting where multiple transportation modes are readily available. NCDOT has applied ICM principles, but in more rural applications where less modal and network options are likely to exist. These initiatives will provide potential opportunities to measure benefits and provide guidance for future implementation of ICM elsewhere in the state.

Actively managing the corridor from a transportation operator's perspective implies an awareness of all the routes and the ability to accept, adjust, and deploy advisory and control strategies which can affect the entire system. From a traveler's standpoint, ICM offers enhanced travel options including the ability to dynamically shift transportation options based on actionable information provided on traffic and road conditions.

NCDOT has deployed ICM on 22 miles of I-85 from MM 10 to 32 near Charlotte with a focus on managing incident-related congestion on the interstate and parallel US-74 arterial. This deployment includes traveler information on Dynamic Message Signs, activatable detour trailblazer signs for individual incidents, and incident-specific signal timing plans for intersections included in the detours.

The goal of this research project is to support the I-85 ICM deployment with data collection and monitoring as well as develop an analysis framework for Before and After analysis. Due to impacts to NCDOT budgets and COVID-19 traffic, the I-85 ICM activation occurred later than planned and the analysis framework can be applied in a future effort to evaluate the system impacts. The objectives of the project are:

1. Collect travel data from existing and novel sources to capture the traffic trends and incident impacts.
2. Develop a monitoring online dashboard which can be used to review data after incidents.
3. Develop a planning-level estimation tool for ICM deployments.
4. Develop an analysis framework for a Before and After study of ICM deployments.

The report is laid out in four distinct sections. First, background literature on the subject of ICM deployments, detour route selection, capacity estimation, and information dissemination are provided. Second, the research team's data collection and monitoring tools are described. Third, the analysis method is provided and case studies are run using the planning method described. Last, recommendations and lessons learned are recorded for future deployments.

2. **Literature Review**

Integrated Corridor Management (ICM) is defined as the coordination of transportation operations to improve travel management. The concept of ICM was introduced by USDOT in 2006 to mitigate the problem of congestion *(1), with many states now implementing ICM strategies to combat traffic issues during non-recurrent congestion*. This section provides an overview of ICM in four areas: implementation of ICM, selection of detour routes, capacity estimation, and techniques for dissemination of information to the traveling public.

2.1. ICM Implementation

As part of USDOT's introduction of ICM in 2016, three pioneer sites in Texas, Minnesota, and California were selected for analysis, modeling, and simulation of various response strategies, with only two going to actual implementation - US-75 in Dallas, TX and I-15 in San Diego, CA *(1)*. The objectives set for ICM in the three initial test sites were to make use of the right modelling software, ensure that the modelling tools meet the analysis needs, to validate the potential benefits, develop new strategies based on trends and collaborate among ICM's public and private sector champions. The major performance measures that were utilized to quantify the benefits of ICM were safety, mobility, reliability and emission savings. The initial results from modeling and simulation showed promising trends, with 12.6% and 11.8% improvements in travel time reliability in San Diego and Minneapolis, respectively. Based on the simulation modeling analysis, it was determined that for successful ICM implementation, three important considerations must be accounted for: 1) enhancing capabilities necessary for modelling multimodal assignments, 2) reliable data collection is necessary to accurately project what is likely to happen when traffic is diverted, and 3) modelling of possible incidents is necessary rather than just the typical day.

Petrella presented the findings from ICM traveler behavior surveys deployed in the US-75 corridor in Dallas *(2)*. The set of panel surveys included the use of "baseline" and "endline" surveys for general drivers and "pulse" surveys for traveler's use of travel information during incidents. License plate capture methodology was used to sample the drivers with 3% response rate for drivers and 22% response rate for transit users. It was observed that during incidents, use of Google Maps as a navigational aid increased rapidly with an increase in minor route usage for afternoon peak trips**.** A key finding from the baseline and endline surveys is that the drivers were more satisfied with the predictability of their trip time.

As part of the Domestic Scan program under NCHRP 20-68B, a scan team visited five locations across the U.S. to review existing and planned ICM programs to help accelerate beneficial innovation by facilitating information sharing and technology exchange among the states and other agencies *(17).* The following five locations were chosen for the review: New York/New Jersey/Pennsylvania, Dallas, Minneapolis, Phoenix, and San Diego. In developing an ICM, the scan team proposed the use of a five-step process-focused model considering factors such as coordinated operations, multi-agency data sharing, traveler information, and a decision support system. Shown in Figure 1, an ICM Capacity Maturity Model (CMM) was developed which shows evolutionary processes designed to compare a corridor agency's existing ICM maturity to a fully mature system *(3)*.

		Level 1 Site	Level 2 Centralized	Level 3 Partially Integrated	Level 4 Multi-modal Integrated	Level 5 Multi-modal optimized
Institutional Integration	Inter-Agency Cooperation	Agencies do not coordinate their operations	Someagencies share data but operate their networks independently	Agencies share data, and some cooperative responses are done	Agencies share data, and implement multi-modal incident response plans	Operations are centralized for the corridor, with personnel operating the corridor cooperatively
	Funding	Single Agency	MPO tracks funding	Coordinated funding through MPO	Cooperatively fund deployment projects	Cooperatively fund deployment and operations and maintenance projects
Technical Integration	Traveler Information	Static Information on corridor travel modes	Static trip planning with limited real-time alerts	Multi-modal trip planning and accounting based alerts	Location-based, on-journey multi-modal information	Location-based, multi-modal proactive routing
	Data Fusion	Limited or manual	Near real-time data for multiple modes	Integrated multi-modal data (one-way)	Integrated multi-modal data (two-way)	Multi-source multi-modal data integrated and fused for operations
	Performance Measures	Some ad hoc performance measure on historical data	Periodic performance measures based on historical data	High-level performance measures using real-time data	Detailed Performance measures in real-time for one or more modes	Multi-modal performance measures in real-time
Operational Integration	Decision Support System	Manual coordination of response	Pre-agreed incident response plans	Tool selection of pre-agreed plans	Model-based selection of pre-agreed plans	Model-based creation of incident response plans

Figure 1. ICM Capability Maturity Model, or CMM (16)

2.2. Selection of Detour Routes

In 2005, commuting drivers in Brisbane, Australia were surveyed to determine commuter route choice behavior in response to traveler information systems. To observe drivers' compliance to recommended detour routes, Dia and Panwai used survey responses to develop agent-based neural network models *(4)*. The results from this modeling effort clearly indicated that "prescriptive, predictive, and quantitative real-time delay information" were most effective in influencing driver behavior to change routes. Similarly, through surveys of automobile commuters in downtown Chicago, Khattak et. al. determined that, on average, 60% of the travelers are willing to adopt a detour route if they perceive over time that the information provided is timely and accurate *(5)*.

Liu et al. developed a generalized ICM diversion control model for freeway incident management capable of concurrently optimizing detour rates and arterial signal timings over multiple roadway segments between the freeway and the detour *(6)*. The major objective of this model was to maximize the utilization of available corridors while not significantly increasing the total time spent by travelers on the detour route to ensure their compliance to routing guidance. The model also accounts for more complex operational challenges such as having multiple detour routes. Models were tested on a stretch along the westbound I-94 corridor from Milwaukee to Waukesha. Data were collected using various sources such as vehicle tracking with bluetooth sensors, traffic data from Wavetronix, a database of crashes, automatic traffic recorder stations, and tube counters. The parameters used for the model calibration are maximum and minimum cycle lengths, minimal green time, intergreen time for phases, maximum percentage of traffic that can diverge from the freeway to arterial, genetic algorithm population size, maximum number of generations, crossover probability, mutation probability, length of projection stage in rolling time horizon, and length of control intervals. It was observed that it was capable of determining proper time and control points for detour operation. Also, it was found to be consistent with variable driver behavior as it outperformed other similar models.

Kopelias et. al. developed a practical algorithm for selection of the most appropriate detour route in case of freeway closure by the means of a “Route Efficiency Index”, or REI *(7)*. The REI was calibrated on the basis of opinions of experts and an analytic hierarchy process with parameters safety, cost, and environment. Each parameter is scored and REI calculated using weights for every performance measure. Last, the REI was calibrated for three conditions: a) peak hour without traffic management, b) peak hour with traffic management, and c) off-peak hour. The team concluded that the safety parameter was the primary criterion for establishing detours over cost and environment. They also developed a decision matrix to guide the users on selecting the best detour in the event of an incident.

Smith et. al. developed and introduced a new algorithm to design detour routes using an extension of the open-source tool Simulation of Urban Mobility, or SUMO, which takes into consideration real time updates from the consequence of an accident *(8)*. The study considered three locations to evaluate various parameters of the re-routing algorithm in this tool. After running extensive testing on the effects of collisions on travel time, the proposed algorithm was able to drive the overall increase in travel time down by as much as 35%.

Rather than using just incident duration and lane blocking in the decision model process, Liu et. al considered other factors such as the observed traffic conditions, time-of-day, day-of-week, and the number of lane blockages to develop the detour decision model *(9)*. The decision model was developed to replicate real world scenarios within a confidence level of 95%, which in turn allowed the research team to justify if there was truly a need for detour operation or not. The model calculates the probability value (p) using a utility function depending on the parameters listed above and only implemented when the probability is greater than or equal to 0.5.

In 2006, FHWA published Alternate Route Handbook which defined the alternate routes and how traffic agencies can implement them in different areas *(10)*. FHWA defined an alternate route as a route which provides additional capacity to service primary route traffic and classified them into the following four different categories: Metropolitan-Freeway, Metropolitan-Street, Urban/Rural-Freeway, and Urban/ Rural-Street. The handbook defines the alternate route planning process into three steps which are Alternate route selection, Alternate route plan development, and traffic management planning. The flow chart for the process was summed up in the handbook and is shown in Figure 2. Figure 3 consists of the barriers to developing alternate route plans and ranks them from largest to smallest.

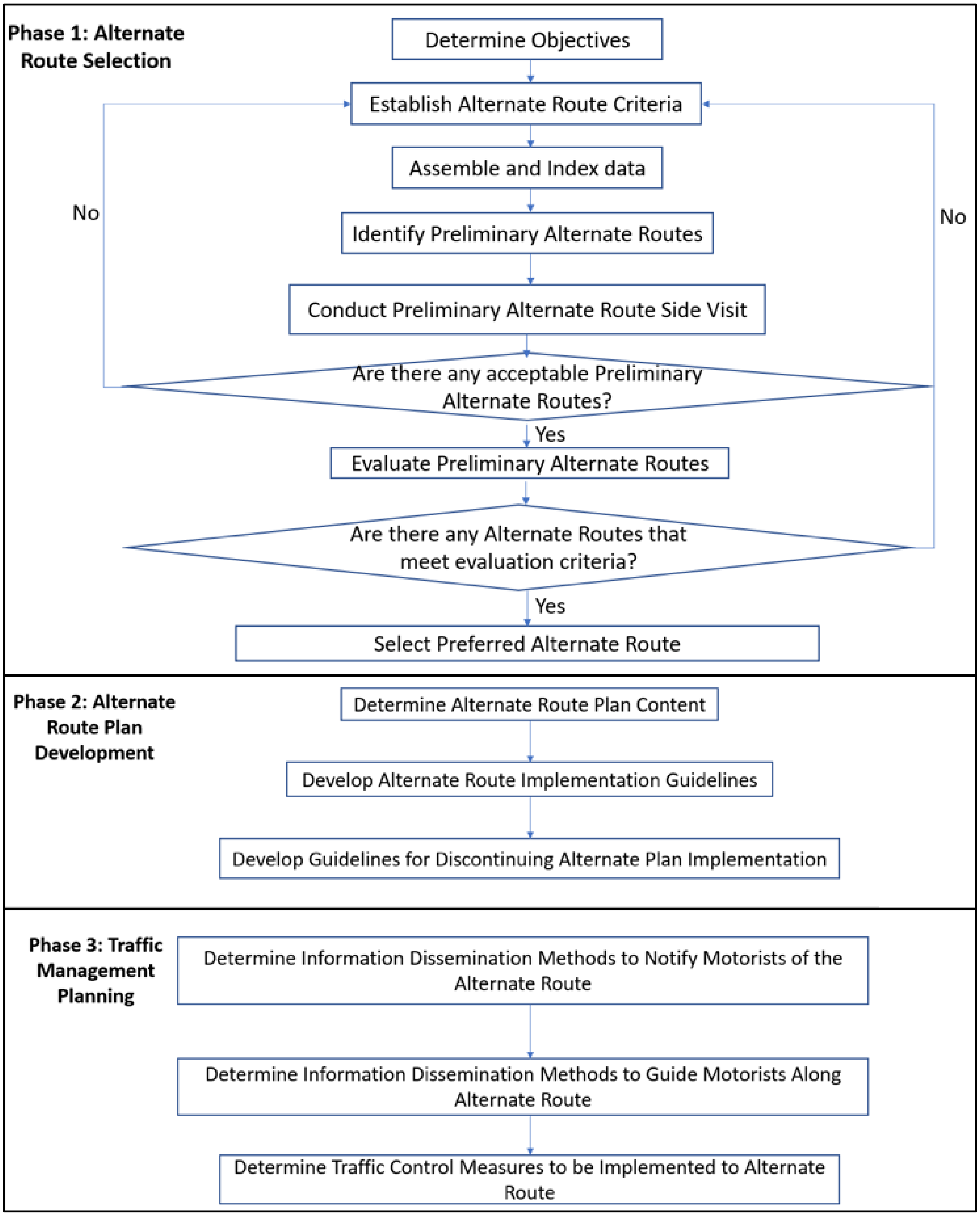

Figure 2. Flow chart of the FHWA alternate route planning process (9)

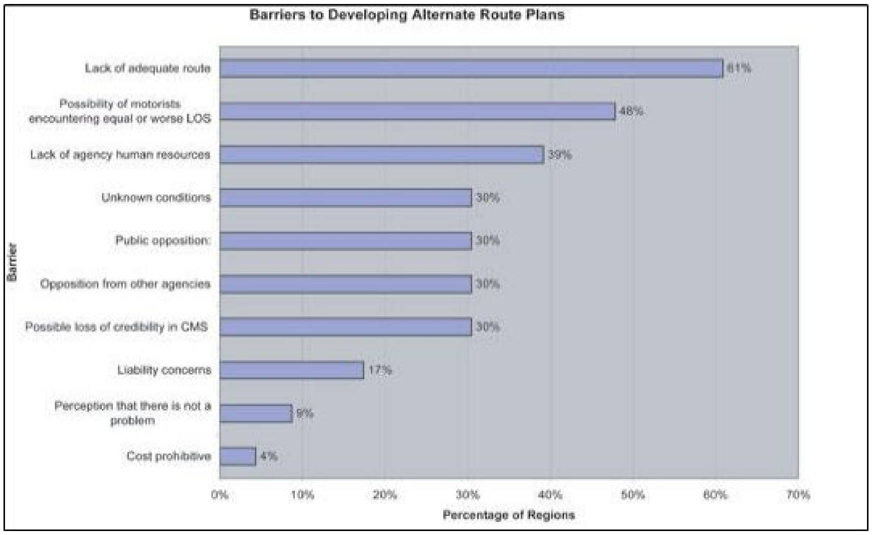

Figure 3. Barriers to developing alternate route plans (9)

2.3. Capacity Estimation of Freeways

In 2005, Chang et. al. conducted an evaluation of Maryland Department of Transportation's incident management program "Coordinated Highway Action Response Team", or CHART. This evaluation looked to assess the efficiency of CHART and the potential resulting benefits based on incident operations records *(11)*. Detection, response, and recovery were the three key aspects considered for evaluating efficiency. The incident data were collected and distributed based on roads, blockage duration, peak and off-peak hours, weekday and weekend, lane blockage, and location. In estimating capacity reduction on the freeway network for detour route planning purposes, it was observed that average lane closures per incident were 2 (including shoulder closures). Not completely unexpected, it was observed that 88% of incidents took place on weekdays; however, unexpectedly approximately 64% of incidents took place during off-peak hours. To help with non-recurrent congestion, the research team recommended studying the traffic demand patterns carefully and establishing links with incident features such as day-of-week, time-of-day, and duration.

In 1987, Jeffrey Lindley set out to evaluate the fraction of capacity available when freeway incidents take place *(12, 13)*. Data such as average speed and maximum service flow were collected from the Highway Performance Monitoring Systems (HMPS) database and was programmed using FORTRAN IV to yield several parameters including capacity reduction factors by lane for several freeway scenarios. The fraction of freeway section capacity available under incidents for varying facility types is summarized in Table 1.

Table 1. Fraction of freeway capacity available during incidents on various freeway facility (11)

No of lanes in each direction	Shoulder Disablement	Shoulder Accident	One Lane blocked	Two lanes blocked	Three lanes blocked
2	0.95	0.81	0.35	0	0
3	0.99	0.83	0.49	0.17	0
4	0.99	0.85	0.58	0.25	0.13
5	0.99	0.87	0.65	0.40	0.20
6	0.99	0.89	0.71	0.50	0.25
7	0.99	0.91	0.75	0.57	0.36
8	0.99	0.93	0.78	0.63	0.41

2.4. Techniques for Dissemination of Incident Information

When informing about detour operations to travelers, different tools can be utilized such as dynamic message signs (DMS), highway advisory radio (HAR), commercial radio television, GPS in-vehicle navigation, and E511 service. As a commuter, one or more of tools can be adopted based on its purpose, informing travelers during the actual trip or for pre-trip planning. In a 2016 study by Robert Gordon found that the use of DMS and GPS in-vehicle navigation were the most efficient amongst all other methods *(14)*. Related to the dissemination method, Srinivas et. al. determined the probability of diversion along a detour route based on message content. It was observed that the maximum diversion probability was 0.89 when the message contained location of incident, expected delay, and best detour strategy. Table 2 shows more detail on probability of diversion based on other message content evaluated *(15).*

Table 2. Probability of diversion based on message content (14)

Message Strength	**Message Content**	**Probability of diversion**
1	Occurrence of accident	0.20
2	Location of the accident	0.19
3	Expected delay	0.32
4	The best detour strategy	0.37
5	Location of the accident and the best detour strategy	0.67
6	Location of the accident and the expected delay	0.75
7	Expected delay and the best detour strategy	0.80
8	Location of accident, expected delay and the best detour strategy	0.89

The FHWA developed a process of coordinating the resources of different partner agencies and private sector companies to detect, respond to, and clear traffic incidents as quickly as possible *(16)*. This program was called the Traffic Incident Management System and consisted of eight major disciplines for the core constituency: fire and rescue, emergency medical, transportation, towing and recovery, hazardous material remediation, public safety, communications, and traffic reporting. The main objectives of the system were to protect on-scene responders and the traveling public, reduce the incident delays for the travelers, avoid secondary accidents, and ensure that response resources tied up at incidents are put back into service quickly. The program noted that the necessary aspects of an effective and efficient TIMS are on-scene operations, communications and technical coordination, and program and institutional coordination.

Funded by FHWA, Jiaqi et. al. also developed the Traffic Incident Management Benefit-Cost (TIM-BC) tool, a comprehensive benefit-cost estimation software to evaluate the performance of various TIM strategies. The tool estimates the costs related to incidents on highways using factors such as number of lanes closed, amount of time taken for responders to arrive, etc. The algorithm is based on a database of five tables containing information on travel delays, heavy vehicle percentage, average wages for drivers, operators, and sectors contributing in cost as well as a set of multiple regression equations for travel delay and fuel consumption. TIM-BC takes into consideration the eight most effective strategies which are safety service patrols, driver removal laws, authority removal laws, shared quick-clearance goals, pre-established towing service agreements, dispatch allocation, TIM task forces and Strategic Highway Research Program training *(17)*.

Last, a 2002 paper by Pal and Sinha found that freeway service patrols can help significantly reduce incident clearance time, allowing freeways to return more quickly to normal operations and reduce the potential for secondary crashes *(18)*. As part of their research, a simulation model was developed for practitioners designing a new patrol program configuration or looking to improve operations of an existing program. The simulation software, named “Hoosier Helper”, has four major modules: incident generation, traffic simulation, simulation of incident response, and estimation of system performance measures. The simulation software evaluated five common service patrol policies listed below:

1. Policy A: First reached first served without crossing to the other side
2. Policy B: First reached first served with crossing to the other side
3. Policy C: Most severe first
4. Policy D: Most severe with minimum time to respond first with vehicle patrolling
5. Policy E: Most severe with minimum time to respond first with a vehicle waiting on the shoulder

The results from the simulation model revealed that the best way to operate freeway service patrols was to use policy E.

3. Monitoring and Data Collection

3.1. Facility/Route Descriptions

The ICM facility includes Interstate 85 and the US 74 arterial west of Charlotte, NC. The two facilities run parallel to each other. On the west side, the site starts at the boundary of the city of Kings Mountain, runs through the city of Gastonia, and ends at the vicinity of Charlotte Douglas International Airport. The I-85 study area begins east of Billy Graham Parkway (Exit 33) and extends west of US 74 (Exit 10), containing 15 interchanges along the interstate. NCDOT Division 12 owns and operates all signals along US 74 west of Catawba River, and the City of Charlotte DOT operates the signals to the east.

A two-lane drop exists along I-85 between Exit 26 and Exit 27. The multi-lane reduction compounded with the presence of a ramp merge in the proximity leads to excessive congestion and backups on I-85 each afternoon in the PM peak. The queue quickly backs up and extends to I-485 on a typical weekday.

This section of the I-85 experiences a sufficient number of incidents every week, making it a prime candidate for such programs. The area around Belmont on I-85 experiences an average of three crashes per week. Crashes occurring on I-85 Southbound can cause backups extending to Billy Graham Parkway, forcing traffic to get to US 74 from Billy Graham Parkway. Furthermore, the impacts of sun glare along I-85 in the McAdenville area causes congestion and incidents in the morning rush hour heading NB in the AM peak hour.

The alternative route for the corridor, US 74, runs parallel to the main route and has 88 signalized intersections throughout the study area. The use of the alternative routes depends on the triggers and the associated locations of the triggers. Twelve operational scenarios were developed to detour the traffic from I-85 to the US-74 in case of incidents along the freeway. Figure 4 shows a schematic drawing of the site.

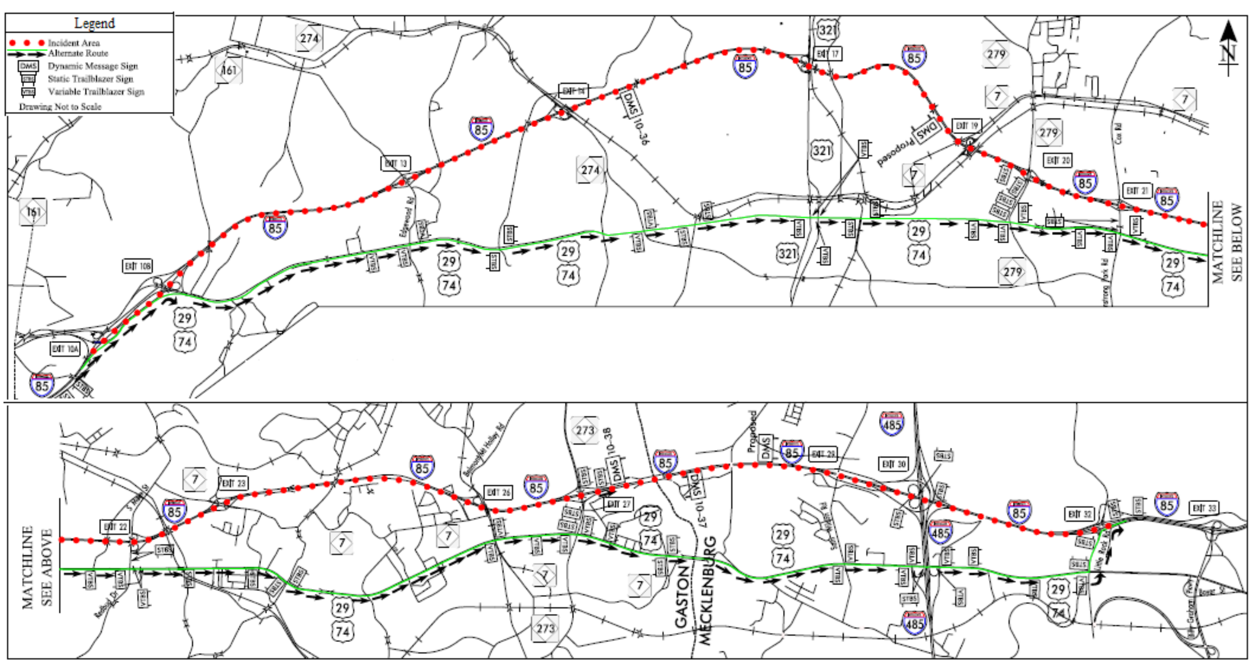

Figure 4. ICM Corridor along I-85 and US-74

The major stakeholders for the ICM initiative include Metrolina, NCDOT (Divisions 10 and 12, ITS and COST Units), city of Gastonia (police, fire-rescue, and engineering), Charlotte DOT, city of Belmont (police and fire-rescue), State Highway Patrol, IMAP, and the FHWA.

In addition to utilizing the available intelligent transportation systems (ITS) infrastructure, the ICM project involved deploying several devices that would enable implementing the new ICM strategies. The data collection efforts assess current transportation network conditions and recommend pre-approved response plans when events or incidents affect corridor operations. The response plans are location-specific and include specific scenarios based on both the location and severity of the incidents.

3.2. Data Description

3.2.1. Clearguide

The probe vehicle data provider for this project was Iteris' Clearguide. Clearguide analyzes transportation data obtained through their partners and produces (near) real-time and historical visualizations that can be used to pinpoint problem areas and assess the performance of a system using such metrics as signal performance measures, arterial performance measures, and highway performance measures.

The ICM project used Clearguide's two suites of products – contour maps and freeway/arterial travel times. Contour maps were used to investigate traffic levels at a macro level. This service proved an indispensable tool for assessing traffic levels post Covid-19 pandemic and helped the research team better understand the traffic patterns along the corridor. Furthermore, Clearguide travel time was used as a validation tool for incidents along the corridor, third-party travel time providers for comparison with Bluetooth and Google travel times, and was used in the estimation of vehicle hours of delay.

3.2.2. Bluetooth

Bluetooth units provided three of the most important datasets in this project. These sensors are capable of providing ground truth travel time, origin-destination information, and diversion rate estimation. The following paragraphs provide details of travel time estimation and the outlier detection procedure.

Each Bluetooth sensor unit records one line/record of data for each detection of a Bluetooth device in its vicinity. This record includes a timestamp of the detection, a partial media access control (MAC) address identifying the device, and the received signal strength indicator (RSSI). As a device passes the sensor unit, it is typically detected many times. All individual detections are written to a file as separate records. There are two main steps in distilling the raw Bluetooth device detections into travel time records: converting the individual Bluetooth detections into single-time records and matching those records based on their MAC address. Both steps are automated through the use of the vendor's dashboard, BlueMac Analytics.

While most of the travel times were representative of the traffic stream, some trips were deemed to be outliers induced by intermediate stops or exiting and re-entering the freeway and had to be flagged as such. A simple non-parametric statistical filter known as IQR4 was used to screen for outlier travel times by the software package employed for the generation of travel times from Bluetooth devices. This statistical filter flags as an outlier any travel time record that is three or more standard deviations away from the mean of the thirty most adjacent travel time records. To approximate the standard deviation, the IQR4 filter uses the interquartile range (the difference between the 25th and 75th percentile readings) as an estimate of 0.75 times the standard deviation. This inter-quartile range is then multiplied by four to arrive at the screening buffer value approximately equal to three standard deviations. The procedure results in valid individual driver travel times that can be used to generate driver-specific travel time distributions under different traffic and roadway conditions.

While IQR4 was found to be robust for freeway travel time outlier detection, its results were questionable for arterials. As such, a new outlier detection algorithm was introduced that would effectively flag non-representative arterial travel times. The newly developed algorithm uses information such as speed limit, number of traffic signals, cycle length, minimum green and red phase length.

Valid individual travel times obtained through this process can shape the origin-destination matrix between sensors and estimate the diversion rate for scenarios where incidents are present on the freeway. The latter is achieved by comparing sensor match rates for the day and time when the incident is present to a similar day when the incident is not present.

3.2.3. Twitter

Live incident data on the ICM corridor is gathered through the Twitter API by listening to NCDOT's Tweets. These Tweets include the incident's timestamp, roadway, mile marker, city, incident type, and number of lanes closed. A back-end script in Python automates this task of listening to NCDOT's tweets, and the script is running 24/7 with the collected data saved in the project SQL database.

3.2.4. Google Maps

Upon detection of an incident in NCDOT’s tweet, the back-end script connects with Google Maps API and requests two items: detour routing information and travel time for the detour. While NCDOT’s ICM will provide detour information to travelers, not all drivers will divert as instructed by the signs. Some may be using third-party apps such as Google Maps and rely on the detour information provided by them. The detour route and travel time information are crucial data points in determining the diversion rate.

3.2.5. TIMS

Incident data were acquired from NCDOT’s Traveler Information Management System (TIMS). This system logs incident information on the types of events that most often cause delays on the highway systems and include major accidents, construction or maintenance projects, and natural disasters. The TIMS database contains incident attributes such as road name, direction, mile marker, start and end time, severity, number of closed lanes, coordinates, and many more. The acquired incident log is filtered temporally and spatially using the reported start times and mile markers. Furthermore, incidents with extremely long durations (hundreds of days), negative duration, and those not identified as incidents in the HCM were flagged as outliers and excluded from the analysis dataset.

3.3. Dashboard

3.3.1. ICM Dashboard Description

The Integrated Corridor Management (ICM) Dashboard is a web-based data visualization tool that visually tracks, analyzes, and displays traffic incident data at a section of the I-85 corridor in North Carolina. The dashboard is aimed at providing information to engineers and researchers on the impact of individual incidents and can be used as an additional data source for after action reviews. It is a web-based platform developed using JavaScript as the primary language (Node.js interpreter) and MySQL database. The ICM

Dashboard is hosted at ITRE's DataLab on secure state-networked servers. Further details on the dashboard and its uses are documented in the user guide in Appendix A.

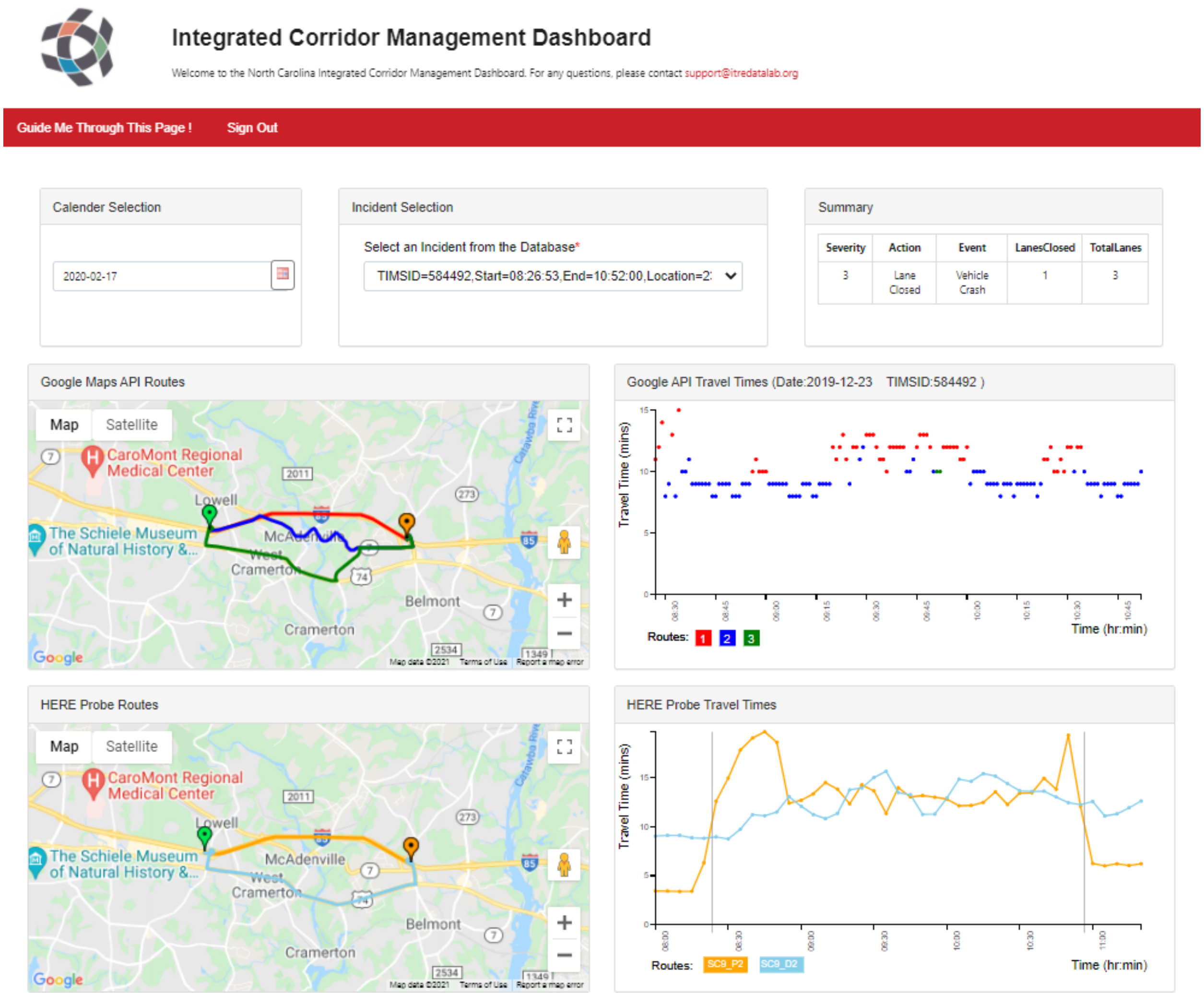

Figure 5. ICM Dashboard Example

The ICM Dashboard incorporates travel time data from two primary sources and collects NCDOT Traffic Incident Management System (TIMS) data for each incident on the facility. The first source is Google Maps API data indicating the routing and travel time directions provided at regular intervals through the incident period. The routing for Google Maps may change throughout the incident, so multiple routes are designated using color codes for the map and graph. NCDOT uses HERE probe travel times available through the ClearGuide website and these are stored through API access in the dashboard. The HERE travel times are requested for the mainline and detour routes pre-planned under the ICM deployment and are not dynamic, however for bidirectional incidents both directions of mainline and detour routes are shown on the map and graph.

3.3.2. ICM Dashboard Example: One Lane Closure

On February 17, 2020 a vehicle crash closed one lane of I-85 SB at MM 23. The incident (TIMS ID: 584492) was reported to begin around 8:30 AM and end around 10:50 AM. It is important to note that due to the dynamic nature of the incremental collection of API data that the incident end times are not as precise and should be confirmed using the TIMS database record if exact times are needed. The Google Map in Figure 6 shows three routes were recommended on that platform, while the travel time graph in Figure 7 shows that the mainline route (red) was rapidly increasing in travel time before arterial detours were recommended. Throughout the incident, there were time periods that the mainline route was again recommended, as each dot on this graph indicates a single routing request response.

The green detour route was briefly recommended, which does use a portion of the planned detour under the ICM program. As the Google Maps routes are dynamically calculated, it was observed in many incidents with detours that had similar travel times to the mainline route that the recommendations would often switch back and forth between the mainline and detour.

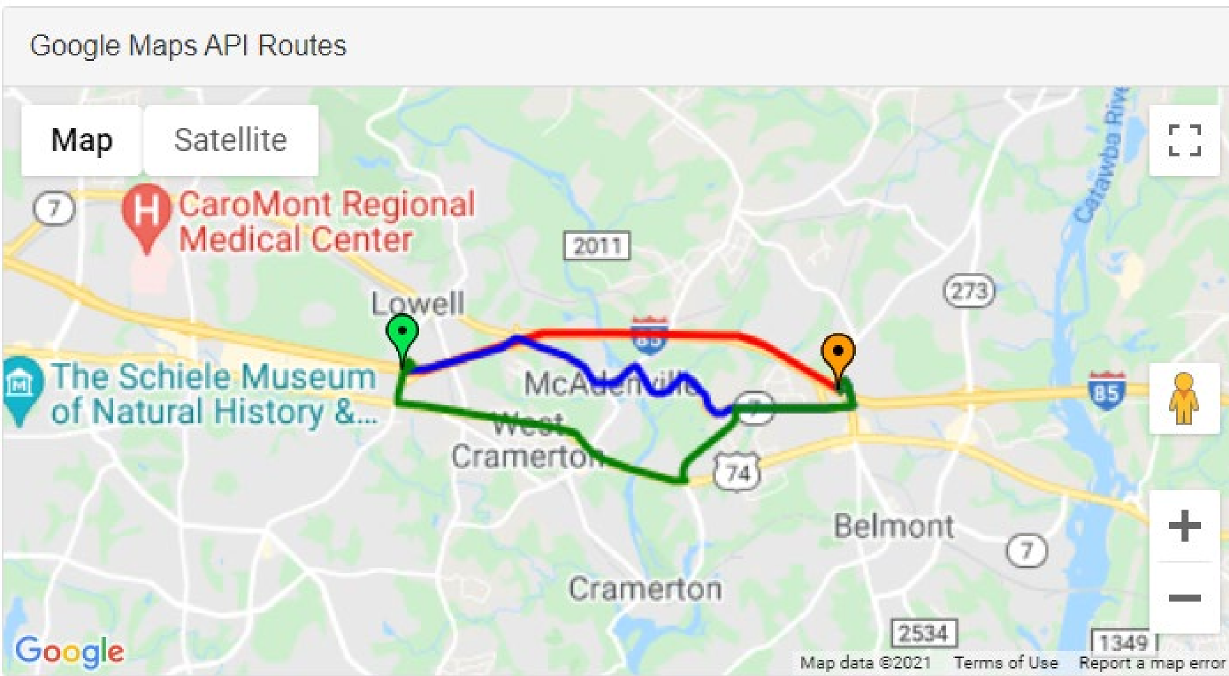

Figure 6. ICM Dashboard Example Google Map

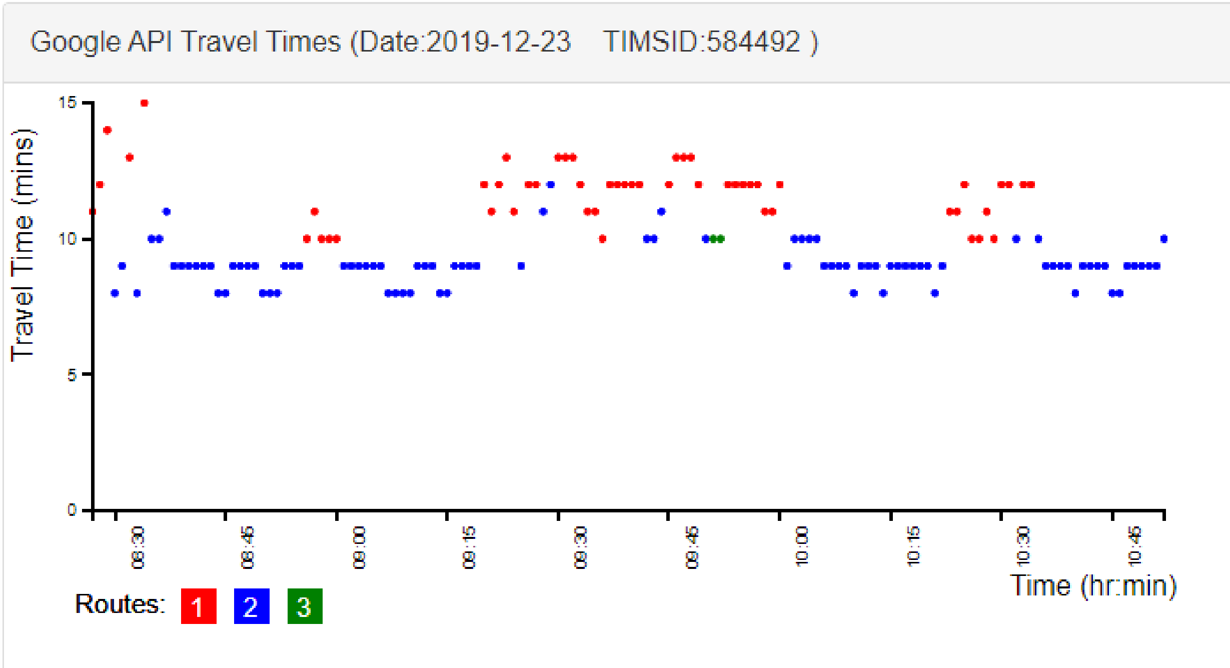

Figure 7. ICM Dashboard Example Google Travel Times

While the Google data is collected only during the reported incident period, probe data from HERE is collected throughout every day through the ClearGuide API for the planned mainline and detour route. These planned routes are defined into scenarios based on the location of the incident, with MM 23 on I-85 SB contained in Scenario 9. The mainline and detour routes are shown in Figure 8 mainly utilizing US-74 to bypass the incident. Figure 9 shows the travel times for 30 minutes in advance of and after the reported incident. In this case, the incident start and end times cleanly line up with the time periods that the mainline travel time consistently exceeds then recovers below the detour travel time. While the Google Maps travel time graph can only show one route's travel time per time period, both the mainline and detour travel times are collected and reported throughout the incident from the probe data.

While this example incident occurred prior to the deployment of the ICM system, even analysis of "before" data can be instructive in understanding the dynamics of the transportation system in the corridor. The two sources provide unique perspectives, where the Google Maps API can demonstrate the volatility in "ideal" route selection as well as potentially what travelers may get from other sources than NCDOT DMS, while the probe data can clearly show when and how much benefit travelers may receive by utilizing the detour route if and when detours are recommended.

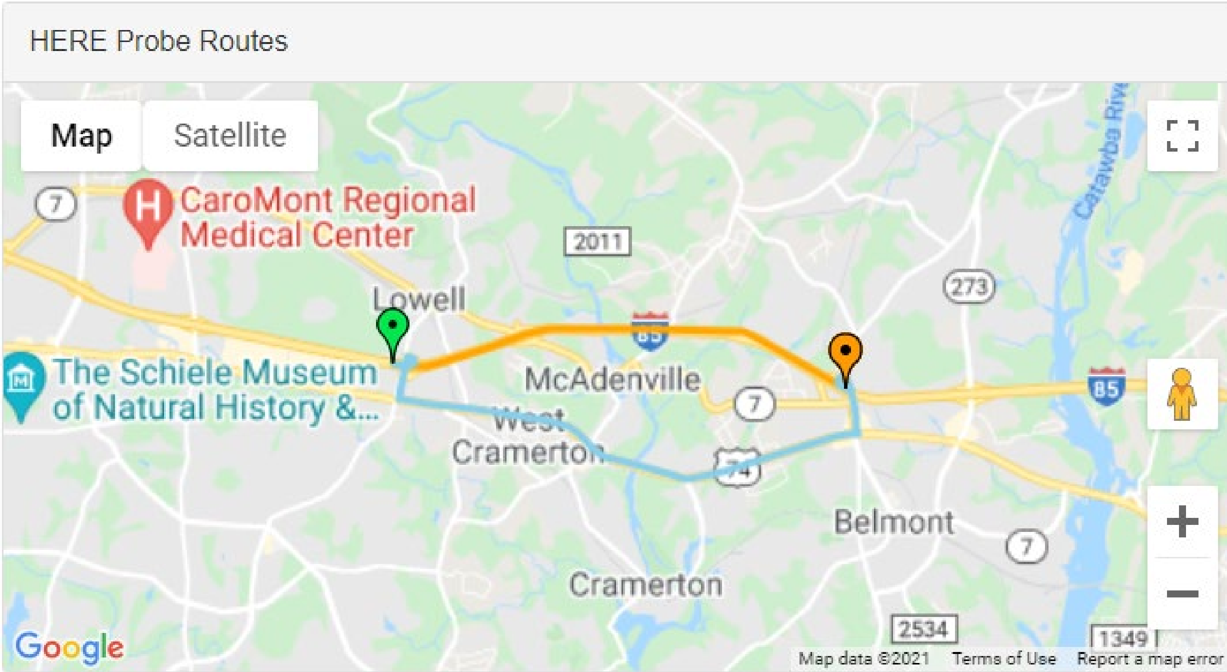

Figure 8. ICM Dashboard Example Probe Map

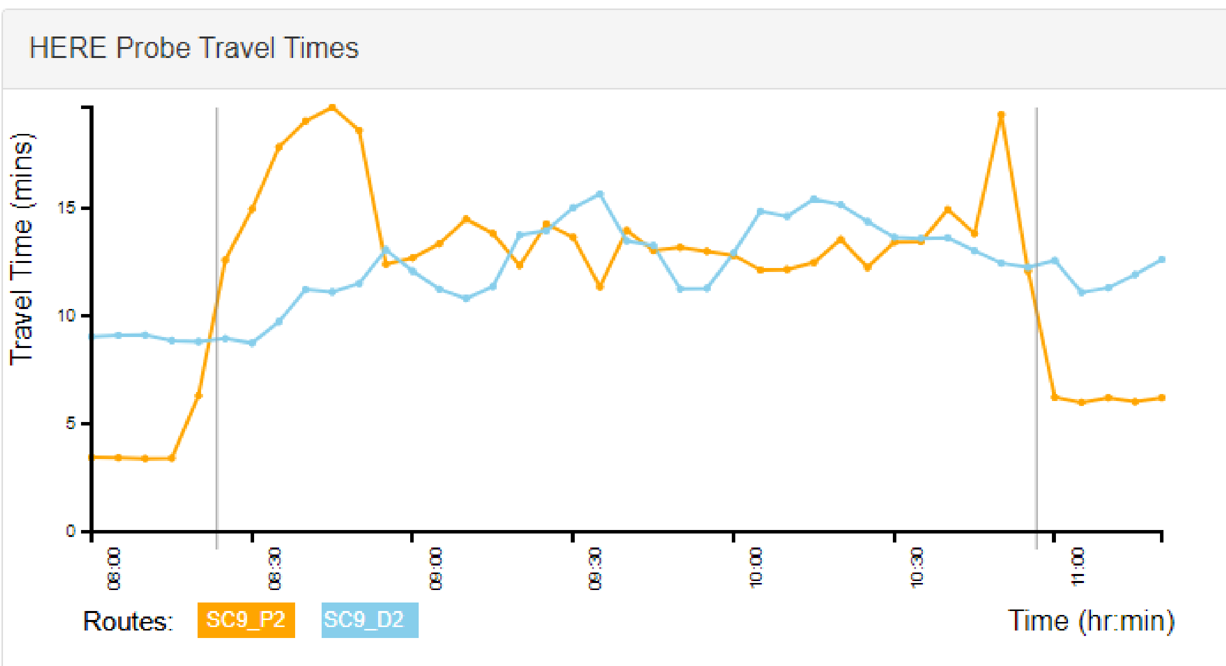

Figure 9. ICM Dashboard Example Probe Travel Times

4. I-85 Before Analysis

4.1. Data

The data sources for the before analysis include the ClearGuide data that provides the travel times for all routes and the incident data from TIMS. The primary, detour, and non-incident travel times are found for each incident and merged with other features like incident type, condition name, duration of the incident, expected impact, time-of-day, and day-of-week. Vehicle hours of delay (VHD) is calculated using the 80th percentile of the non-incident travel time as baseline and multiplying this excess delay with the vehicle volumes of each route, as shown below.

1. Estimating traffic volumes

$$V_{t,sc} = AADT_{sc} * D_{sc} * K_{t,sc} * DM_t$$

   where,

   D_{sc} = Directional Distribution
   DM_t = Daily Multiplier to convert AADT to ADT
   $K_{t,sc}$ = Hourly volume factor for the time-of-day, day-of-week, and peaking pattern
   $V_{t,sc}$ = Time-of-day estimated hourly volume on scenario

2. Estimating excess incident delay

$$EID_{t,i,sc} = maxPTT_{i,sc} - 80^{th} percentile\ of\ NTT_{sc}$$

   where,

   $PTT_{i,sc}$ = Primary Travel Time for incident i
   NTT_{sc} = Non-incident base line travel time for that scenario

3. Vehicle hours of delay (VHD)

$$VHD_i = \sum_{t=0}^{T} EID_{t,i,sc} * V_{t,sc}$$

4.2. Delay Methodology

The data was divided into training and test sets. The model was trained on the training set and the prediction accuracy of the model was tested on the test data set. Both linear and non-linear models were studied and the models with the most accurate predictions were selected.

4.2.1. Linear Model

A linear model was created using Numerical Features to predict VHD. The model was then tested for linearity assumptions which are described below.

- Linearity of Residuals: The Q-Q plot shows that the residuals are only approximately normal.

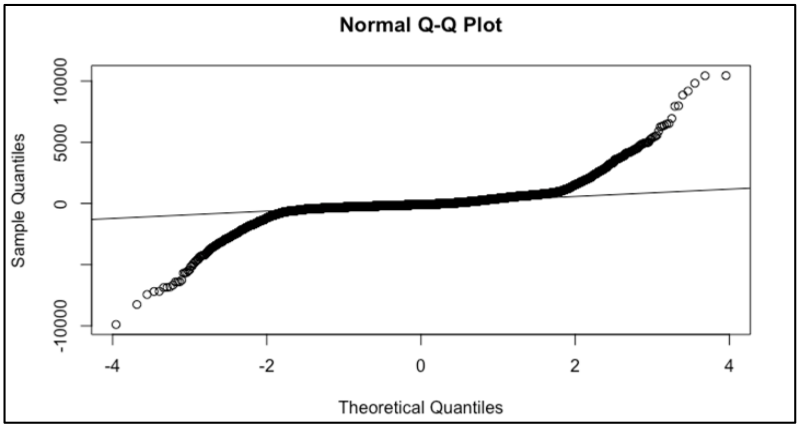

Figure 10. Linearity of residuals

- Constant variance of error terms: The funnel shape shows the presence of heteroskedasticity.

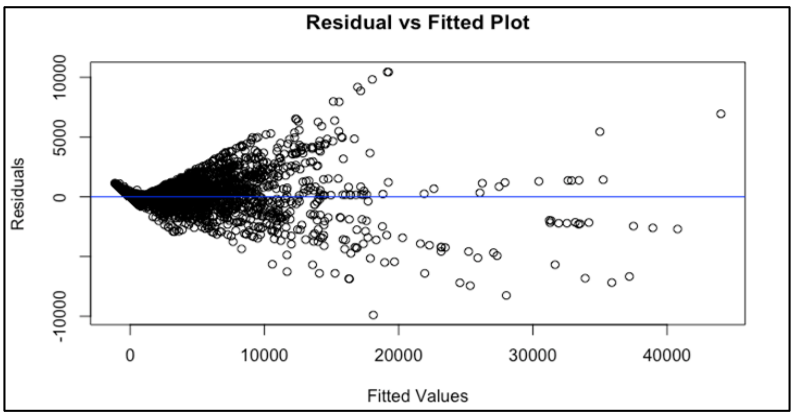

Figure 11. Constant variance of error terms

- Correlation of Residuals: A p-value was calculated and since it is less than 0.05, we rejected the null hypothesis that the consecutive errors are not correlated, meaning errors are not independent.
- Normality of residuals: A histogram was created and the residuals were found to be only approximately normal.

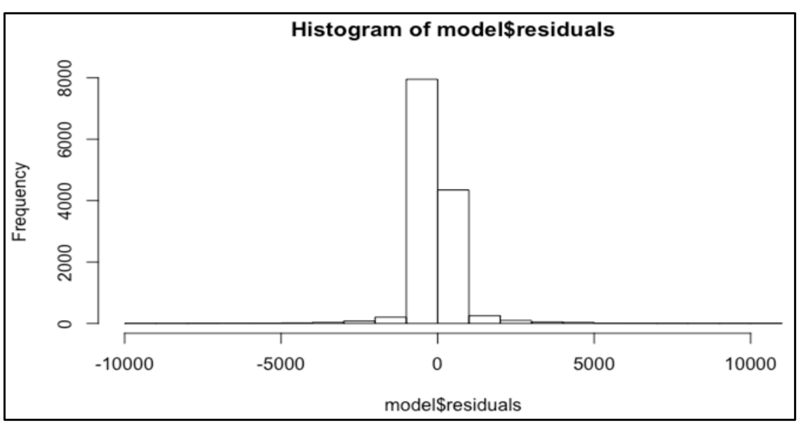

Figure 12. Normality of residuals

The results of the diagnostics indicated that the model violates the linearity assumptions. Since the numerical features are found to be highly correlated and the uncorrelated features in the dataset are categorical, non-linear models were explored.

4.2.2. Non-Linear Model

Three models, namely Multivariate Adaptive Regression Splines, Gradient Boost, and a Neural Network model, were tested for predicting VHD. The results were compared on the basis of root mean squares error (RMSE) and symmetric mean absolute percentage error (SMAPE). A description of each model is provided below for reference followed by a summary of results.

1. Multivariate Adaptive Regression Splines (MARS). MARS is an adaptive procedure for regression, and is well suited for high-dimensional problems (i.e., a large number of inputs). It can be viewed as a generalization of stepwise linear regression or a modification of the CART method to improve the latter's performance in the regression setting (Friedman et al., 2001). Due to the nature of the dataset, a degree of 3 is used for building the MARS model.
2. Gradient Boosting. Gradient boosting is a machine learning technique which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function. We use the gradient boosting decision tree algorithm “XGboost” for our analysis.
3. Neural Network Model. A neural network is a two-stage regression or classification model, typically represented by a network diagram (Friedman et al., 2001). The network consists of three hidden layers which implement a rectified linear unit (ReLU) activation function. The model uses the Adam optimizer to minimize the mean squared error for training the neural network.

4.2.3. Results and Discussion

VHD was estimated using the three models – MARS, Gradient Boosting and Neural Network. The data was divided into training and test sets. The model is trained and then tested for prediction accuracy using the test set on the basis of RMSE and SMAPE values. Table 3 shows the results of the analysis.

Table 3. RMSE and SMAPE values for 3 non-linear models

Model	RMSE	SMAPE
MARS	63555	1.09
Gradient Boosting	52809	1.06
Neural Network	51989	1.27

The RMSE obtained from the Neural Network model is the lowest on the test dataset. However, this value fluctuates every time the model is run. This indicates that the data samples are not identically distributed and there is a lot of unexplained variance. The RMSE obtained from the Gradient Boosting model is comparable to the Neural Network and the value of SMAPE is lowest among all three models. Since the Neural Network model is a “black-box” model, it makes it difficult to infer the effect of the features on the response variable. In that aspect, the Gradient Boosting model may be preferable. However, Figure 13 shows that the MSE of the test data set decreases with the increasing number of training periods of the Neural Network. Hence, with greater computational power, we may be able to reduce the MSE even further by increasing the number of epochs in the Neural Network.

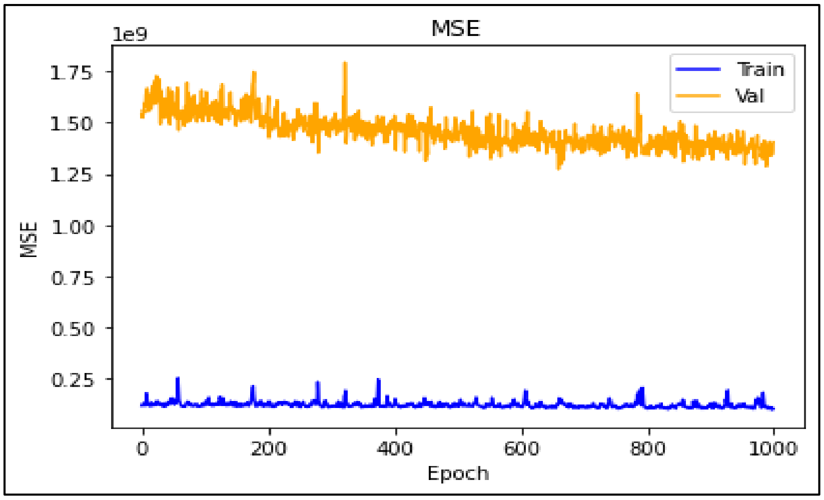

Figure 13. Decrease in mean squared error over epochs

The results from the above sections clearly indicate the lack of variables that can explain the variance in VHD. A consistent pattern observed from these models is that no matter how much we increase the flexibility (capacity) of the model, the RMSE remains high. The features that have been investigated need to be improved to explain the VHD more accurately. Future work needs to focus on deriving more efficient features that are the cause for incidents. Another approach that can be tried is bucketing the VHD into different classes and using classification algorithms to classify the categories of VHD given the features. This could help to get more accurate results of the range of possible VHD for a given scenario and can be further narrowed if additional information about the incidents if available.

4.3. Origin-Destination Methodology

4.3.1. Setup/Placement of Bluetooth Sensors

The study site employed 30 commercial Bluetooth sensors. The focus was to have at least one sensor at each endpoint of a given ICM scenario and place intermittent sensors along the detour routes to have reserved option for detection of traffic taking the detour in case they are missed by the first sensor on the facilities. The Bluetooth sensors used were seventh-generation BlueMAC units, manufactured by Digiwest LLC.

Units were installed on different NCDOT available infrastructure such as gantry poles located in the wide median on Interstate 85, signs, and other available roadside posts. Figure 14 shows the approximate location of majority of the devices deployed in this project.

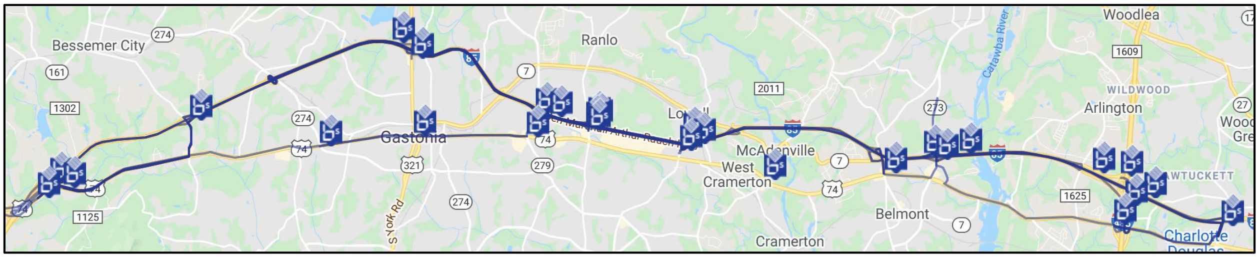

Figure 14. Location of deployed Bluetooth sensors

Figure 15 shows the basic elements of the Bluetooth sensor deployment used at the study sites. The rectangular unit is the main operating structure, housing one 12V 12Ah battery, a GSM mobile radio, the Bluetooth (both high and low energy) radio, WiFi radio and antenna proper, and a solar charging assembly. The solar charging panel is mounted on the front of this top unit and is adjusted in the field for maximum efficiency. The unit is mounted to an existing pole or other available infrastructure using metal brackets and straps as shown.

Figure 15. Example of Bluetooth sensor installation

4.3.2. Bluetooth Data Pre-Processing

Data pre-processing related to the Bluetooth tasks for this project was divided into two parts: the pre-processing of data necessary to obtain true travel times for the study sites and outlier detection to segregate valid travel times from the invalid travel times.

4.3.2.1. *Travel Time Generation*

For the duration of each study, each Bluetooth sensor unit recorded one line/record of raw data for each detection of a Bluetooth device in its vicinity. This record includes the date and time of the detection, a partial media access control (MAC) address identifying the device, and the received signal strength indication (RSSI). As a device passes by the sensor unit, it is typically detected many times. All of the individual detections are written to file as separate records, and uploaded to the server nightly.

There are three main steps in distilling the raw Bluetooth device detections into travel time records: converting the individual Bluetooth detections into single-time records, matching those records based on

MAC address, and removing the outliers. The first two steps are the same for both the primary route (freeways) and the detour routes (arterials). A Matlab script was developed to take care of these two steps.

4.3.2.2. *Outlier Detection*

4.3.2.2.1. Freeway Outlier Detection

For freeway outlier detection, the research team used a simple statistical filter to screen for "outlier" travel times, which is referred to as IQR4. Any travel time record that is three or more standard deviations away from the mean of the thirty most adjacent travel time records is flagged as an outlier travel time. As noted later, there are many possible reasons for outlying travel times, from unexpected vehicle departure from the facility and subsequent re-entry to vehicle speed significantly lower than the traffic stream. To approximate the standard deviation, the IQR4 filter uses the inter-quartile range (the difference between the 25th and 75th percentile readings) as an estimate of 0.75 times the standard deviation, which is near what such value would be on a truly normal distribution. This inter-quartile range is then multiplied by four (thus resulting in the name IQR4) to arrive at the buffer value equal to three standard deviations used in screening.

4.3.2.2.2. Arterial Outlier Detection

Although IQR4 is a robust method for detecting outliers on freeways and arterials, it does not do a good job where number of detections are low (low traffic volume) and/or a significant percentage of vehicles exit and re-enter the roadway. In situations like these, fixed thresholds should be used for the ceiling and floor values. In an arterial sitting, the value of ceiling and floor depend on these characteristics of the arterial: free flow travel time, cycle lengths, minimum green, queue clearance time at downstream intersection, free flow speed (speed limit) and distance between intersections. Following two equations show the relationship of ceiling and floor values to these characteristics.

$$C = FFTT_r + \sum_{i=0}^{n}\left(C_i - G_{i_{min}}\right) + T_{qcli+1},$$

$$F = \frac{D}{FFS + 9}$$

where,

C = ceiling value
$FFTT_r$ = free flow travel time
C_i = cycle length for intersection i
Gi_{min} = minimum green for intersection i
T_{qcli+1} = time to clear the initial queue at the downstream intersection
F = floor value
D = distance between the two intersections
FFS = free flow speed or speed limit

4.3.3. Case Studies

To test the robustness of the developed methods for outlier detection both for the main and detour routes, and estimation of detour percentage, the team selected two scenarios where both incident and non-incident days were available. Selection of routes to include incident and non-incident days were deemed crucial for testing of the outlier detection algorithms and analysis of the detour rate to ensure they work under both incident and non-incident scenarios. Two sites were selected with different ramp and signalized intersections density. The first case study is located along the west side of the ICM facility from exit 10A to exit 13, while the second case study is located in the middle of the facility and runs from exit 21 to exit 22. The analysis and results can be found in Appendix B.

Application of the developed algorithms for outlier detection to both incident and non-incident periods revealed robustness of the methodology. Both the freeway and arterial outlier travel time detection methods were able to flag travel times not representative of traffic stream. The flagged travel times were removed from analysis. The resulting travel times can be used for travel time, origin-destination, and diversion rate analysis. The latter analysis was conducted on the second study site. The findings show promising results conducting this type of analysis using Bluetooth sensors.

4.4. Sketch-Planning Method

4.4.1. Planning Tool Description

The research team developed a tool to generate incident scenarios in freeways and analyze the impact of using specific detour routes. The core delay methodology utilizes NCDOT's CALC methodology used in the Prioritization process, which provides a sketch-planning estimate of travel time and delay using the HCM methodology. This methodology is repeated for each scenario, made up of an incident condition and time of day. Four incident severities have been modelled for in this analysis: Shoulder closure, 1 lane closure, 2 lane closure, and 3 lane closure. The final outcome of the analysis is an estimate of the expected savings in vehicle-hours due to the use of ICM and detour routes. Savings are estimated for a set of scenarios defined by the time of day and severity of incident. The total expected savings is the sum of each scenario's Vehicle Hours Traveled (VHT) saved and the probability of that scenario occurring.

$$Expected\ Savings = \sum_{k=1}^{K} VHT\ Savings_k * P_k$$

4.4.1.1. *Scenario VHT*

1. First, an individual scenario is defined with a given time of day and incident condition (Shoulder, 1, 2 or 3 lanes closed).
2. Time-of-day is used to estimate the percentage of AADT in the facility. Table 4 shows the percentage of AADT in the facility throughout the day for both AM and PM peaking facilities. This distribution should be updated with facility-specific distributions if available.

Table 4. Percentage of AADT for different times-of-day

Time	AM PEAK	PM PEAK	Time	AM PEAK	PM PEAK
12:00 AM	0.007	0.008	**12:00 PM**	0.054	0.057
1:00 AM	0.005	0.005	**1:00 PM**	0.055	0.060
2:00 AM	0.004	0.005	**2:00 PM**	0.057	0.066
3:00 AM	0.005	0.005	**3:00 PM**	0.061	0.075
4:00 AM	0.008	0.008	**4:00 PM**	0.066	0.083
5:00 AM	0.022	0.017	**5:00 PM**	0.071	0.084
6:00 AM	0.060	0.040	**6:00 PM**	0.056	0.063
7:00 AM	0.092	0.062	**7:00 PM**	0.039	0.045
8:00 AM	0.082	0.059	**8:00 PM**	0.031	0.035
9:00 AM	0.061	0.053	**9:00 PM**	0.026	0.029
10:00 AM	0.052	0.052	**10:00 PM**	0.020	0.021
11:00 AM	0.052	0.055	**11:00 PM**	0.014	0.015

3. Next, the average travel time (ATT) per vehicle, in hours, is computed for both the freeway and detour facility with and without ICM using the input AADTs. ATT is calculated using the CALC methodology also used in NCDOT's Prioritization process for each roadway type. This methodology is only adjusted in that the volume on the mainline and arterial are affected by the amount of diverted traffic and adjustments to capacity based on incident severity and the effect of signal retiming on the detour route.

$$ATT = Free\ flow\ TT * CF$$

where,

ATT = average travel time
FFTT = free flow travel time, computed based on the project length and speed limit
CF = congestion factor, calculated as a function of the v/c ratio

A partial view of the lookup table for the CF function is shown in Table 5. The congestion factor is capped at a value of 5.0.

4. Next, vehicle hours traveled is calculated as

$$VHT = AADT_{time\ period} * ATT$$

where,

VHT = vehicle hours traveled
AADT = average annual daily traffic
ATT = average travel time

The VHT is calculated for each of the four conditions below.

a) Incident Mainline VHT without diversion
b) Incident Mainline VHT with volume diversion to detour
c) Incident Detour VHT with volume diversion to detour

The VHT savings for an incident scenario can then be calculated using the formula

$$VHT\ Savings = [a - (b + c)] * \frac{duration\ of\ incident}{60}$$

Table 5. Partial look-up table for congestion factor (CF)

V/C	Congestion Factor	V/C	Congestion Factor
0	1.00	1	1.50
0.01	1.00	1.01	1.52
0.02	1.00	1.02	1.53
0.03	1.00	1.03	1.55
0.04	1.00	1.04	1.56
0.05	1.00	1.05	1.58
0.06	1.00	1.06	1.60
0.07	1.00	1.07	1.61
0.08	1.00	1.08	1.63
0.09	1.00	1.09	1.65
0.1	1.00	1.1	1.67
0.11	1.00	1.11	1.68
0.12	1.00	1.12	1.70
0.13	1.00	1.13	1.72
0.14	1.00	1.14	1.74
0.15	1.00	1.15	1.76
0.16	1.00	1.16	1.78
0.17	1.00	1.17	1.80
0.18	1.00	1.18	1.82
0.19	1.00	1.19	1.84
0.2	1.00	1.2	1.86
0.21	1.00	1.21	1.89
0.22	1.01	1.22	1.91
0.23	1.01	1.23	1.93
0.24	1.01	1.24	1.95
0.25	1.01	1.25	1.98
0.26	1.01	1.26	2.00
0.27	1.01	1.27	2.02
0.28	1.01	1.28	2.05
0.29	1.01	1.29	2.07
0.3	1.01	1.3	2.10

4.4.1.2. *Scenario Probability*

The first step is to calculate the frequency of all incidents for the freeway segment. The frequency of all incidents is the product of the incident rate and the VMT for the freeway. The incident rate can be calculated as the ratio of the crash rate to the crash to incident ratio. The default value taken for the crash to incident ratio is 4.9. The crash rate for a freeway segment is calculated using the crash prediction model incorporated in the HERS team for urban freeways developed by Richard Margiotta (19). The following fifth order polynomial used to calculate the crash frequency is provided below.

$$CR = (154.0 - 1.203 \times ACR + 0.258 \times ACR^2 - 0.00000524 \times ACR^5) \times e^{0.0082 \times (12 - LW)}$$

where,

ACR = the ratio of AADT to the capacity of the freeway
LW = lane width of the freeway.

4. Incident scenarios are generated for each incident type for every hour during the day. The duration for each of these incidents is estimated using a random variable with an inverse normal distribution, the mean and standard deviation of which are listed in Table 6. The values have been referred from the HERS safety model assessment for urban freeways.

Table 6. Probabilities, average, and standard deviation for duration of each closure type

Severity	Probability of incident severity	Average	Standard deviation	Median
Shoulder closed	0.754	34	15.1	36.5
1 Lane Closure	0.196	34.6	13.8	32.6
2 Lane Closure	0.031	53.6	13.9	60.1
3 Lane Closure	0.019	69.6	21.9	67.9

5. In the next step, the probability for each incident scenario is computed by considering the incident severity type and the time-of-day of the incident. Table 6Table 4 contains the probability for each incident severity. This final scenario probability is the likelihood of any given incident both occurring at this time based on demand and being the specific severity.

4.4.1.3. *Expected Savings*

As described in the introduction, the expected savings for an incident severity type can be taken as the VHT savings that can be expected for an incident at any hour of the day. To calculate the expected savings for each incident severity type, the sum product of VHT savings × Probability for each of the incident severity throughout a day is taken.

4.4.1.4. *Assumptions and Case Study*

In order to complete the analysis, the following factors were assumed and can be updated to be facility-specific or new state-wide defaults may be created as data become available.

1. The percentage of volume diverted taken for each incident severity is listed in Table 7 for a four-lane cross-section. As no diversion conditions have yet been observed these are simple assumptions that should be updated as data become available.

Table 7. Percent of mainline volume diverted to detour for each closure type

Incident severity	Percentage of mainline traffic diverted to detour
Shoulder Closure	5
1 lane closure	10
2 lane closure	15
3 lane closure	20

2. The increase in capacity for signalized intersection in the detour route is taken as 20%. This value indicates how much additional capacity is available due to ICM-specific timing plans for the detour route but does not account for additional delay that side streets may experience.
3. The directional factor for the freeway facility is defaulted as 0.55. This value should be facility specific when available.
4. The default crash to incident rate is taken as 4.9. This indicates the average number of incidents per one reported crash. This value may be updated with a local factor when available.

The team also conducted a case study in the tool for the I-85 NB freeway in Charlotte, NC. The facility has been broken into six individual segments with six alternate routes that were proposed. The VHT savings for the each of these detours have been estimated using the planning tool. The facility information was obtained from various sources such as NCDOT AADT and Google Maps. The Detour information is detailed in Appendix C. The final estimates of the expected savings have been documented in Table 8, below. The trend across incident types is that for one lane closures, the detour route has enough capacity to provide substantial benefits to the network while two lane closures congest the freeway and detour and leave less room for benefits. One limitation is that the CALC method used for VHT calculation does not incorporate queue length, so benefits to quicker queue clearance under the two lane closure condition cannot be estimated.

Table 8. Calculated expected savings for I-85N detours

Scenario	I-85 Detours (Exits)	Expected Savings per Incident (in hrs)			
		Shoulder closed	1 Lane Closed	2 Lanes Closed	3 Lanes Closed
1	10A - 13	409	30,998	1,397	#N/A
2	13 -17	1,039	81,125	5,096	#N/A
3	17 - 21	1,156	318,252	20,953	#N/A
4	21-27	6,125	285,008	28,899	#N/A
5	27-30	33,503	3,062,752	200,789	#N/A
6	30 - 33	2,580	347,037	41,064	#N/A

4.5. Before and After Analysis Framework

The before and after analysis framework below is intended to be used once sufficient after data are available for evaluation. It is recommended that at least 100 incidents are included in the analysis for each period to account for potentially large variation between incidents however statistical tests may show significant results at smaller sample sizes if the results are more consistent. The framework is designed for an operational-level analysis rather than planning-level meaning empirical incident details, travel times and routing data are needed.

4.5.1. Incident Impact Performance Measures

Incident Severity is the maximum impact to travel lanes at the incident location, and may vary by roadway direction in cases where incidents affect both travel directions. Incidents often have varying impacts to travel lanes as responders arrive and clear the roadway, and this timeline may be considered during review of individual incidents however it is difficult to incorporate directly into an analysis of all incidents together.

Excess Incident Delay (EID) is delay incurred during incidents beyond the recurring level of congestion for a certain time of day. This accounts for the incremental impact of incidents rather than *Travel Delay* which is based only on speed limit travel time. Times of day with no recurring congestion calculate EID beyond speed limit travel time. The *Recurring Congestion Baseline* accounts for this recurring level of congestion in non-incident days at that time of day. Figure 16 shows an example of how EID can be visually interpreted.

$$Recurring\ Congestion\ Baseline\ (RCB_{tr}) = max \begin{Bmatrix} Non - Incident\ 80th\ Percentile\ Travel\ Time_{tr} \\ Speed\ Limit\ Travel\ Time_{r} \end{Bmatrix}$$

where,

t = Time of day/Day of week

r = Route C = ceiling value

$$Excess\ Incident\ Delay\ (EID_{tir}) = max \begin{Bmatrix} TT_{tir} - RCB_{tr} \\ 0 \end{Bmatrix}$$

where,

i = Unique incident identifier

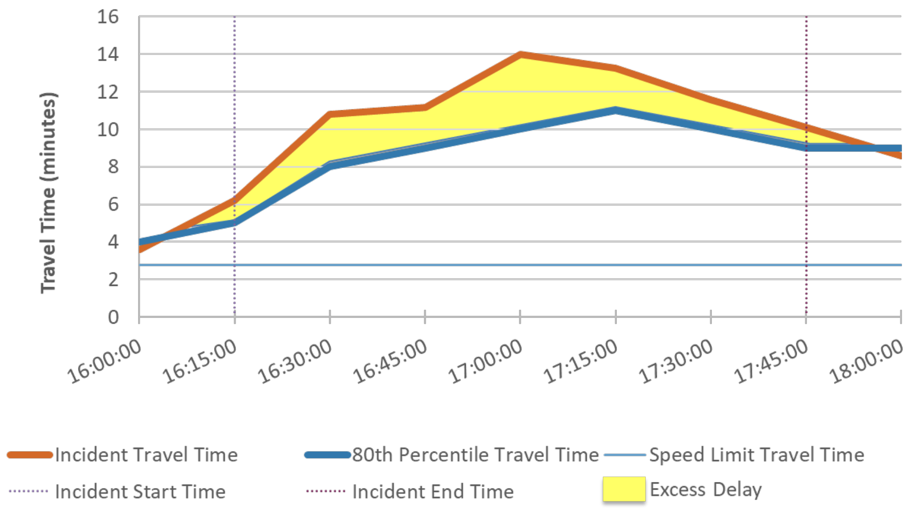

Figure 16. Illustrative example of Excess Incident Delay

As EID is calculated on per vehicle basis for each time period, volumes must be assigned to each time period. *Volume distributions* indicating the percent of daily traffic traveling at each time period of the day may be estimated or observed using sensors on the facility. The following estimation equation can be used in the absence of raw counts:

$$V_{tr} = AADT_r * D_r * K_{tr} * DM_t$$

where,

V_{tr} = Time of Day estimated Hourly Volume on Route
$AADT_r$ = the average annual daily traffic volume on route
D_r = Directional Distribution (assume 0.5 or use local value)
K_{tr} = Hourly Volume Factor for Time of Day, Day of Week and Peaking Pattern
DM_t = Daily Multiplier to convert AADT to ADT

Hourly vehicle volume distributions shown in
Figure 17 are incorporated from the 2019 TTI *Urban Mobility Report* (Source: https://mobility.tamu.edu/umr/). Daily Multipliers, found in Table 9, adjust AADT to ADT for a specific day of the week, which were obtained from NCDOT's Traffic Survey Unit.

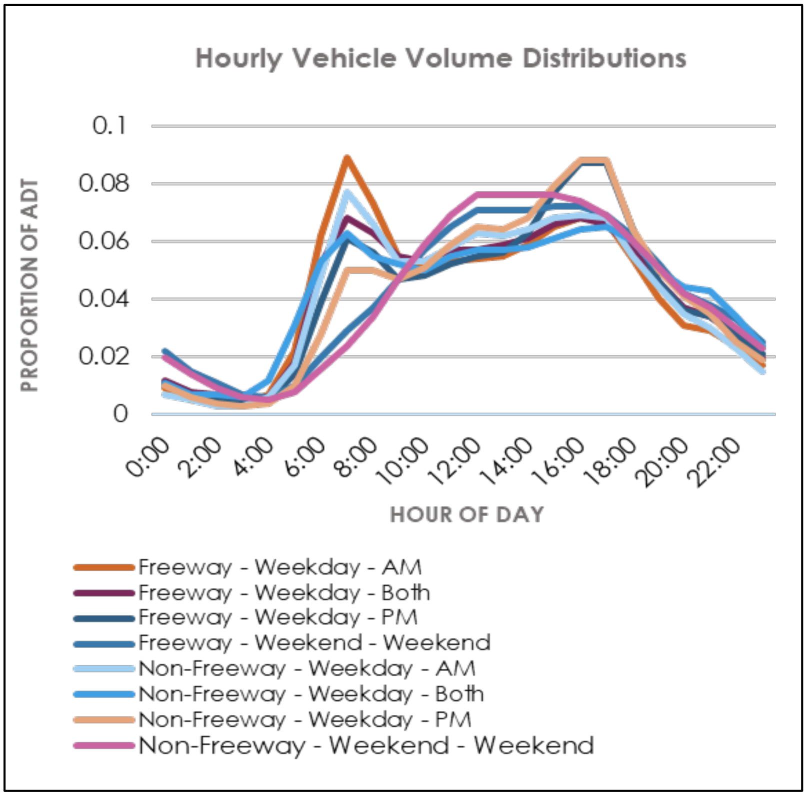

Figure 17. Hourly Vehicle Volume Distributions by Functional Classification, Day of Week, and Peaking Pattern

Table 9. Daily Multipliers to Adjust AADT to ADT

Day of Week	Daily Multiplier
Monday – Thursday	1.05
Friday	1.1
Saturday	0.9
Sunday	0.8

The equation below can be used to calculate *Incident Vehicle Hours of Delay* for a given incident. Incidents are tracked beyond the recorded start and end time to account for potential delays in incident identification at the TMC or queue discharge.

$$Incident\ VHD_{ir} = \sum_{t=0}^{T} EID_{tir} * V_{tr}$$

where: *t* varies from incident start of incident (t=0) to the end of the incident at t=T, with T being the total impact duration plus 30 minutes Before and after.

Diversion Percentage is the average percent of mainline traffic that diverted onto the detour route during the incident. The goal of the ICM deployment is to manage traffic flows such that the diverted traffic reduces the mainline congestion while still benefiting from the detour route travel times. This may be estimated through the matching method described in 4.3 or other methods of O-D analysis.

4.5.2. Benefit-Cost Analysis

The Benefit-Cost Analysis (BCA) includes the following benefits and costs which can be aggregated to net benefits or a Benefit-Cost Ratio. The analysis should also note any unmeasured or unrecorded benefits or costs which can be used to contextualize the findings. Often many institutional benefits are unable to be measured, especially for pilot deployments of new operational strategies.

4.5.2.1. *Benefits*

Travel Time and Delay Savings is calculated from the total reduction in vehicle-hours of excess delay. This excess delay is an estimate of only the incident-specific delay and accounts for recurring congestion expected on that day of week and time of day. In the case of incidents occurring in the after period, the excess incident delay must be calculated for both the mainline route and detour route, weighted by the diversion rate. Analysis should use a vehicle class weighted value of time (VOT) to estimate the user cost of delay with an average vehicle occupancy assumption.

Secondary Incidents are defined as incidents that occur in the vicinity of an active incident. These may be due to unexpected queues on the freeway or drivers distracted by the incident and/or responders. Based on a review of incident duration and frequency changes, an average reduction of secondary incidents in total is estimated. Additionally, NCDOT has estimated that incident management may reduce the severity of the remaining secondary incidents with an average of 9% reduction in fatal and severe injury crashes. For all incidents, the additional delay savings can be monetized as user cost, and the crashes will be monetized according to EPDO crash costs NCDOT uses based on severity.

Fuel Savings may be estimated utilizing the NCDOT methodology developed in NCDOT Research Project 2013-09. It utilizes the average price of gasoline and diesel over the analysis period, and estimates fuel consumption tied to the delay savings of the project.

Emission Savings may be estimated utilizing NCDOT's emission methodology used in CMAQ evaluation for speed improvement project types in urban counties. The CMAQ methodology estimates savings in NOx, VOC and CO based on speed improvements and idle time reduction.

4.5.2.2. *Costs*

Construction and Deployment Costs include the construction of DMS and dynamic trailblazer signs as well as infrastructure upgrades that can be solely attributed to the deployment. If planned infrastructure upgrades occurred in tandem with the deployment, a justifiable percentage of these costs may be attributed to the ICM project.

Administrative and Operation Costs should include TMC staffing and salary costs of NCDOT staff needed to operate the ICM program. Similarly, these costs should be apportioned at a justifiable percentage of the total based on the portion of effort attributable solely to the ICM program. These costs should also reflect a long-term recurring cost rather than an initial higher effort that may be needed for a first pilot deployment such that the costs can be used to estimate future project costs.

5. Recommendations and Conclusions

Origin-Destination Data Collection

Observations of traffic flow patterns are essential to accurately capture the traffic diverted due to ICM activations. In this project, Bluetooth and Wi-Fi traffic monitoring devices were placed throughout the corridor and used to match trips along the primary and detour routes. Field tests should be performed to test the actual performance of the Bluetooth sensor. Particularly, tests should be done to study whether the performance (e.g., detection range, detection rate) can be affected by terrain, traffic density, and distance of the Bluetooth devices to the roadway. Improper placement can result in matching trips from the incorrect roadway and lead to errors in estimating the amount of diverted traffic.

The settings and configurations of all the Bluetooth sensors should be the consistent. These settings include the data format, device check-in frequency and the data upload frequency. Additionally, the system collecting and storing the device data should be configured to provide notifications and alerts in the event of offline or atypical device status. The system used in this study stores all timestamps internally in UTC, which is automatically converted on the server dashboard but must be manually converted if the raw data is utilized.

Finally, there are additional data source options emerging for origin-destination data that utilize probe or Location Based Service data for traffic monitoring. The research team reviewed two data providers as potential resources for this project and found that the data quality was sufficient for long-term detours but both providers had a minimum match rate per 15-minute reporting period. This meant that for short, dynamic operations found in an ICM environment, periods with detours may report “0 trips” when there were actual observations that did not meet the minimum match rate. For a longer-term detour due to construction however, enough time periods may be aggregated to ensure that the total sampled detouring trips exceeds the minimum match rate. Further review of these sources is recommended once the technology has matured further as this method avoids the need for field devices and can be collected for historic periods.

Planning for Integrated Corridor Management

Planning methods exist for estimating the benefits of ICM deployments through the FHWA-developed TOPS-BC tool. This tool is built on a synthesis of operational benefits observed in Transportation System Management and Operations (TSMO) strategies. This tool is currently on version 4.0 and is targeted as a strategy screening tool and provides “order of magnitude” Benefit Cost Analysis estimates. FHWA recommends utilizing local or derived data in place of the default parameters to improve these estimates. One major limitation to utilizing TOPS-BC for the NCDOT ICM deployment was the scope and area type of the deployment compared to those found in the literature. NCDOT focused on a more rural/suburban corridor with limited modal options while previous ICM deployments studied were in urban areas often with multiple transit options in addition to detouring.

This project also adapted an existing NCDOT analysis method used in the project prioritization process to compare estimated delays on primary and detour routes during ICM operation. This method, CALC, requires HCM inputs for the critical segment on the primary and detour route as well as estimated diversion and increases in detour capacity when signal retiming is part of the ICM activation. This analysis then uses incident rates and time of day traffic patterns to estimate the total delay with and without ICM operation to estimate the benefit of ICM. The inputs for diversion rates and capacity benefits from ICM-specific signal timing can be updated as observations provide better estimates to improve this method. The method does have limitations when long (in distance or time) detours are modeled and the critical segment is no longer able to represent the expected delays.

There are additional options for estimating the benefits of ICM through network modeling or microsimulation of specific routes, though these methods are relatively high effort compared to the sketch-planning methods. Regional network models can be utilized with scenarios for lane closure types at locations along the ICM primary route to understand where traffic may naturally divert. Planned diversion under ICM will not always match this natural diversion due to the additional driver information and capacity improvements made on detouring routes but the network model outputs can be used to help select preferred detour routes. Once specific routes are established, microscopic modeling of the primary and detour routes can better estimate the traffic impacts of individual ICM activations and can also be used to develop signal timing plans for each activation. When modeled separately, the amount of diverted traffic is an input to the microsimulation and this should be updated when diversion rates are established through observation.

Monitoring Integrated Corridor Management Deployments

Once data sources are established, continuous monitoring of the ICM deployment is recommended for both evaluation purposes as well as to improve strategic decision-making. This project developed a live dashboard integrating data feeds from public and private sources presented in a compact set of maps and graphs. This dashboard framework can be adapted for additional deployments using detour route data including incident locations from TIMS as well as primary and detour routes in ClearGuide. These data sources can only be collected in real time and then recorded, so the dashboard cannot look back past the point at which it was originally created.

NCDOT performs after action reviews of severe incidents including those in the I-85 ICM deployment, which may use the dashboard to supplement their review. An example of an incident review of dashboard data is provided in this report, though every incident may have unique features within the data. The probe data view may be utilized to identify latency in identifying or closing out the incident, while the Google Maps data is only shown during the period that the incident is active in TIMS.

Review of ICM activations may also identify specific conditions under which the system is more or less beneficial, as it is possible that low-severity events may not need diversion when the detour route remains a longer travel time. Reviewing the probe data provides a view of the experienced travel time for drivers remaining on the primary route and those detouring. Likewise, it is possible that the planned detour routes are not consistently the fastest for diverted traffic, which can be seen in the Google Maps view. It is important to consider that these more dynamic recommended routes may not have sufficient capacity to handle the additional diverted traffic from the new traveler information compared to the drivers who are utilizing GPS-recommended detours.

Finally, review of the activations along specific detour routes can be used to update signal timing strategies associated with each activation type. This process should be supplemented by the modeling used to develop the original timings, as the dashboard will show only the travel time along the detour route and not the increased delays to the minor streets that will be incurred by increasing green times to the detouring movements.

Evaluation of Integrated Corridor Management

The evaluation of the benefits and costs of an individual ICM deployment utilizes the combination of knowledge gained from each of the previous efforts. Data options selected for analysis may change as more cost effective or remote sources become available. This project developed an evaluation framework which captures delay, safety, environmental, administrative, and capital impacts of ICM deployment. For both benefits and costs, it is important to separate the incremental or specific impacts of the ICM deployment with the understanding that other projects and background traffic patterns continue to affect the corridor.

Measuring the delay benefits of operational strategies is especially difficult compared to a traditional delay analysis that focuses on total before and after delay. ICM activations occur at random periods and with random impacts on the primary route due to the nature of incidents and therefore it is possible that worse incidents may occur by chance in the after period and yield a larger “total delay”. Instead, the recommended framework establishes an excess delay measure by which each incident can be individually evaluated compared to the recurring congestion level at that time of day and day of week. This excess delay can then be compared before and after the deployment by incident location and severity.

Diversion is a key input to the planning and operation of ICM deployments. Incidents may naturally incur diversion through driver information provided by in-vehicle GPS, but planned detour routes during ICM are also displayed on the primary route. As most passive data sources currently utilized only collect travel times, diversion estimates are key to understanding the total impact to the transportation network. The sensor-based method introduced in this report compares device matches for primary and detour routes with and without incidents to identify diversion, and this can be extended to the emerging data sources once they are capable of reporting rates at an appropriate resolution.

Finally, the analysis presented is focused on ICM deployments with a fixed set of strategies. Research and pilot deployments are underway utilizing a dynamic ICM system capable of determining a strategy for each specific incident or traffic condition. This analysis framework is recommended for the I-85 deployment and others with fixed strategies; however it would need to be augmented with the strategy selection algorithm to account for a dynamic system.

6. References

1. USDOT, "FHWA Integrated Corridor Management (ICM) Program: Major Achievements, Key Findings, and Outlook." November 2019. [Online].
2. Petrella, M. and L. Conwell (2017). "Integrated Corridor Management Initiative: Traveler Response Panel Survey Dallas," Intelligent Transportation Systems Joint Program Office.
3. NCHRP 20-68A, "Advances in Strategies for Implementing Integrated Corridor Management (ICM) – Scan Team Report," AASHTO, 2014.
4. Dia, H. and S. Panwai (2007). "Modelling drivers' compliance and route choice behaviour in response to travel information," *An International Journal of Nonlinear Dynamics and Chaos in Engineering Systems,* vol. 49, no. 4, pp. 493-509.
5. Khattak, A.J.; Schofer, J.L.; and F.S. Koppelman (1995). "Effect of traffic information on commuters' propensity to change route and departure time," *Journal of Advanced Transportation,* vol. 29, no. 2, pp. 193-212.
6. Liu, Y.; Li, P.; Wehner, K.; and Y. Jie (2013). "A Generalized Integrated Corridor Division Control Model for Freeway Incident Management," *Computer-Aided Civil and Infrastructure Engineering,* pp. 604-620.
7. Kopelias, P.; Kepaptsoglou, K.; Sarandtidis, V.; and A. Theofilatos (2018). "Route Efficiency Index as an operational tool for detour decision making in an urban motorway," *Advances in Transportation Studies: An International Journal,* pp. 63-76.
8. Smith, D.; Djahel, S.; and J. Murphy (2014). "A SUMO Based Evaluation of Road Incidents' Impact on Traffic Congestion Level in Smart Cities," in *3rd IEEE International Workshop on Global Trends in Smart Cities*, Edmonton, Canada.
9. Y. Liu, W. Kim and G.-L. Chang (2013). "Decision Model for Justifying the Benefits of Detour Operation under Non-Recurrent Congestion," *Journal of Transportation Engineering,* vol. 139, no. 1, pp. 40-49.
10. Dunn Engineering Associates (2006). "Alternate Route Handbook," Federal Highway Administration, Washington, DC.
11. Chang, G.; Shrestha, D.; and J.Y. Point-Du-Jour (2000). "Performance of CHART: An Incident Management Program".
12. J. A. Lindley (1987). "A Methodology for Quantifying Urban Freeway Congestion," *Transportation Research Record 1132,* pp. 1-7.
13. FHWA (1987). "Quantification of Urban Freeway Congestion and Analysis of Remedial Measures_Final Report," Turner-Fairbank Highway Research Center, McLean, VA. FHWA/RD-87/052.
14. R. Gordon (2016) "Intelligent Transportation Systems: Functional Design for Effective Traffic Management", Springer International Publishing.
15. Srinivas, P.; Ramos, J.; and R. Pasupathy (2000). "Content of Variable Message Signs and On-Line Driver Behavior," in *Transportation Research Record 1725*.
16. FHWA, "TIM Technologies and Techniques." November 2019. [Online].
17. Jiaqi, M.; Lochrane, T.; and P. Jodoin (2016). "Traffic Incident Management Programs and Benefit-Cost Analysis," *Institute of Transportation Engineers Journal.*
18. Pal, R. and K. Sinha (2002). "Simulation Model for Evaluating and Improving Effectiveness of Freeway Service Patrol Programs," *Journal of Transportation Engineering,* vol. 128, no. 4, pp. 355-365.

19. Highway Safety Manual, 1st ed. American Association of State Highway and Transportation Officials, Washington, D.C., 2010.
20. Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1, No. 10). New York: Springer series in statistics.

Appendix A

ICM Dashboard User Guide

User Guide for the NCDOT Integrated Corridor Management Online Dashboard

Institute for Transportation Research and Education
North Carolina State University

Thomas Chase
Shoaib Samandar
Chris Cunningham

May 18, 2021

ITRE
Institute for Transportation Research and Education
at North Carolina State University

TABLE OF CONTENTS

1. INTRODUCTION

This document provides guidance on the use of the ICM dashboard. Integrated Corridor Management (ICM) dashboard is a web-based data visualization tool that visually tracks, analyzes, and displays traffic incident data at a section of the I-85 corridor in North Carolina. It is a web-based platform developed using JavaScript as the primary language (Node.js interpreter) and MySQL database. The ICM dashboard is developed as part of NCDOT research project No. 2019-30 "*Post-Implementation Evaluation of Integrated Corridor Management (ICM) in North Carolina*". All data used in the dashboard are documented in a NCDOT Project (No. 2019-30) final report. The ICM Dashboard is hosted at ITRE's DataLab on secure state-networked servers.

The ICM Dashboard provides real-time information on corridor performance to assist ICM system operators manage both travel demand and network demand in normal and abnormal conditions. Although intentionally developed with NCDOT's first ICM deployment in mind, the tool can be made available for uses with any ICM corridor. This dashboard can be useful for transportation operators to visually identify all the routes and the ability to accept, adjust, and deploy advisory and control strategies which can affect the entire ICM system. In addition, ICM system operators can use this tool to take action before corridor performance degrades and, in cases where degradation has already occurred, take fast action to promptly restore normal conditions.

1.1 Disclaimer

The ICM Dashboard is <u>not a commercial software product</u> and it relies exclusively on the findings of the NCDOT project No. 2019-30 "*Post-Implementation Evaluation of Integrated Corridor Management (ICM) in North Carolina*". This ICM tool will directly assist NCDOT to measure benefits and provide guidance for future implementation of ICM elsewhere in the state. The contents of this document reflect the views of the authors and are not necessarily the views of the Institute for Transportation Research and Education or North Carolina State University. The authors are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the North Carolina Department of Transportation or the Federal Highway Administration at the time of publication. This user guide does not constitute a standard, specification, or regulation.

2. ICM Dashboard Navigation

To use the tool, the user needs to login to the ICM portal at (http://icm.itredatalab.org/) using credential provided by the team or NCDOT ICM team This will navigate to the ICM Dashboard shown in Figure 1.

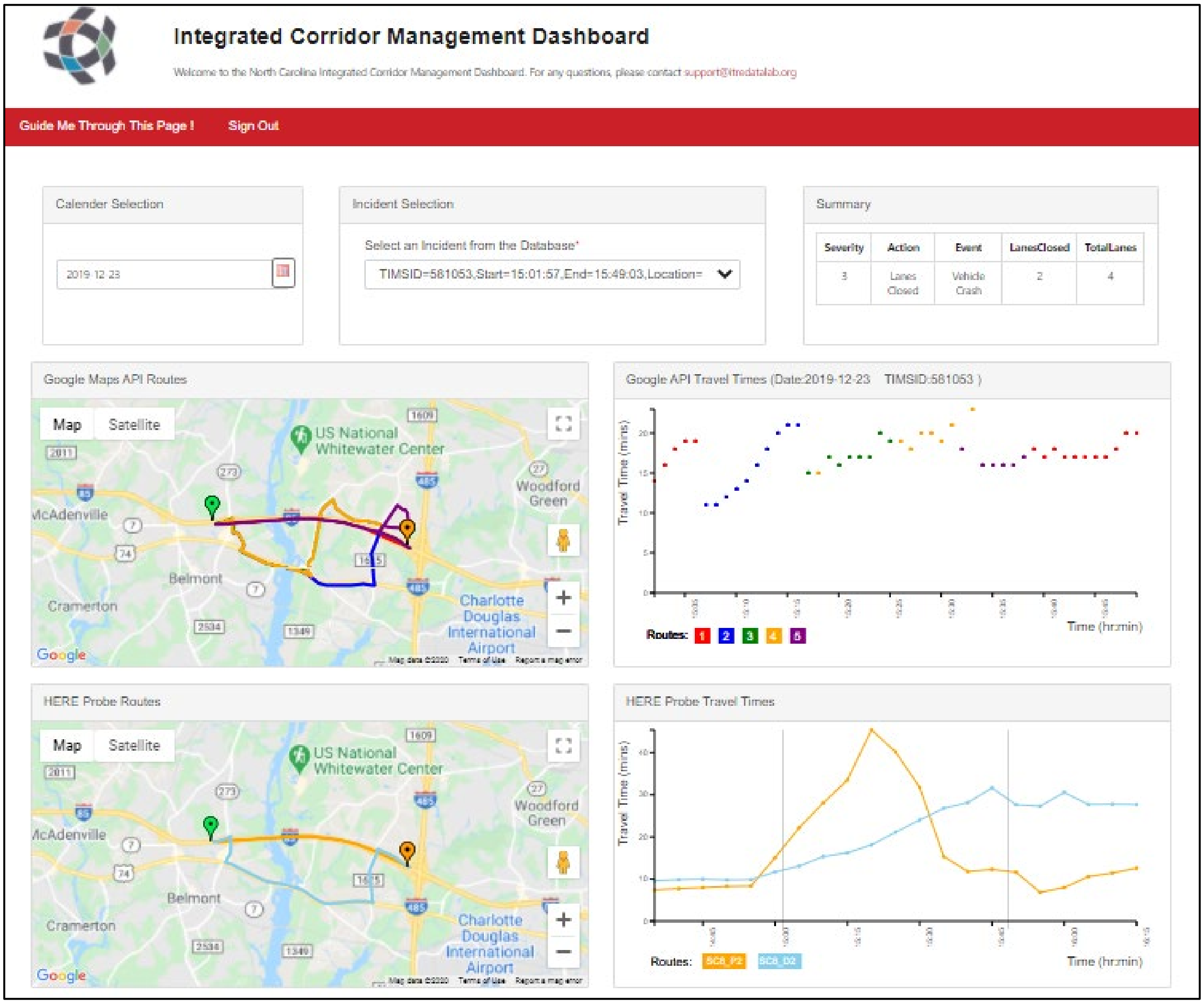

Figure 1 – ICM Dashboard

2.1 *Banner Links*

Two options are provided at the top of the website in the red banner. The "Guide Me Through This Page!" tab helps explain what each section of the webpage does. The content will vary based on the path the user is located. The "Sign Out" tab will log the user out of the ICM dashboard.

The main steps involved in the ICM Dashboard are shown in Figure 2. The user selects an incident date from the calendar, and then different incidents corresponding to the selected date are populated in the dropdown list. The user can further select an incident from dropdown lists to generate the TIMS incident summary, Google API routes & travel times, and Probe Data routes & travel times. The detailed input and output steps are described in the following sections.

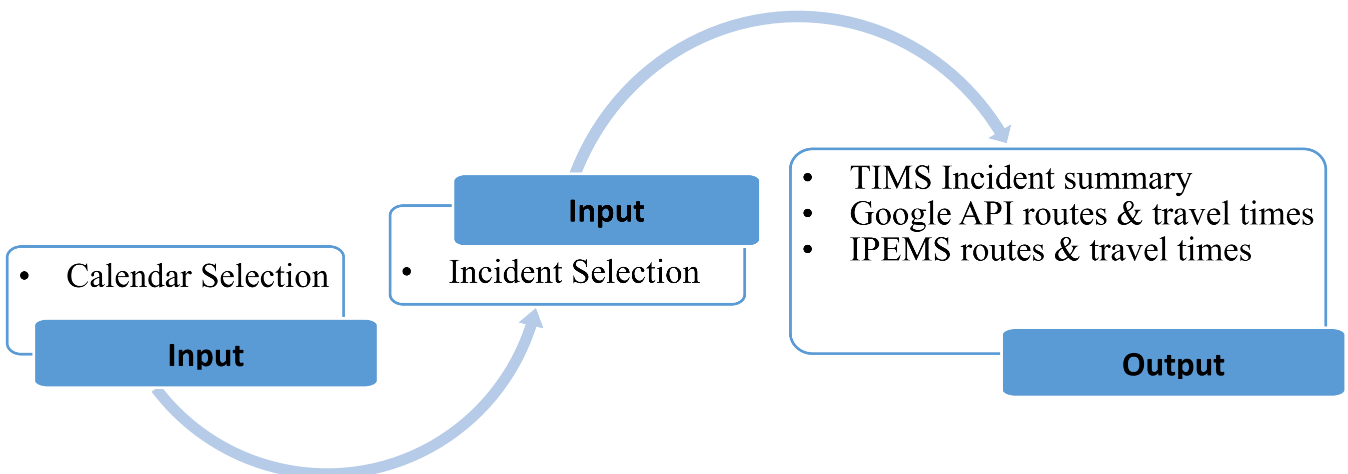

Figure 2 – ICM Dashboard – Navigating to Particular Incident Events

Note: Users must follow the analysis steps in the sequential order as shown above. The following sections provide details of each step.

2.2 Input

This section focuses on the step-by-step input process of the ICM dashboard. It starts with incident date selection from the calendar, followed by selecting a unique incident on the selected date from dropdown lists. Each of these components is described below.

2.2.1 Calendar Selection

As shown in Figure 3, all traffic incident dates are formatted as ***bold and black*** color in the calendar while dates with no incidents are transparen. Users can select one incident date at a time by clicking on a day in the calendar. Upon successful selection of date, the selected date background is filled with red color. A warning message “alert: No incident reported on this date” will appear if the user selects a non-incident date in the calendar.

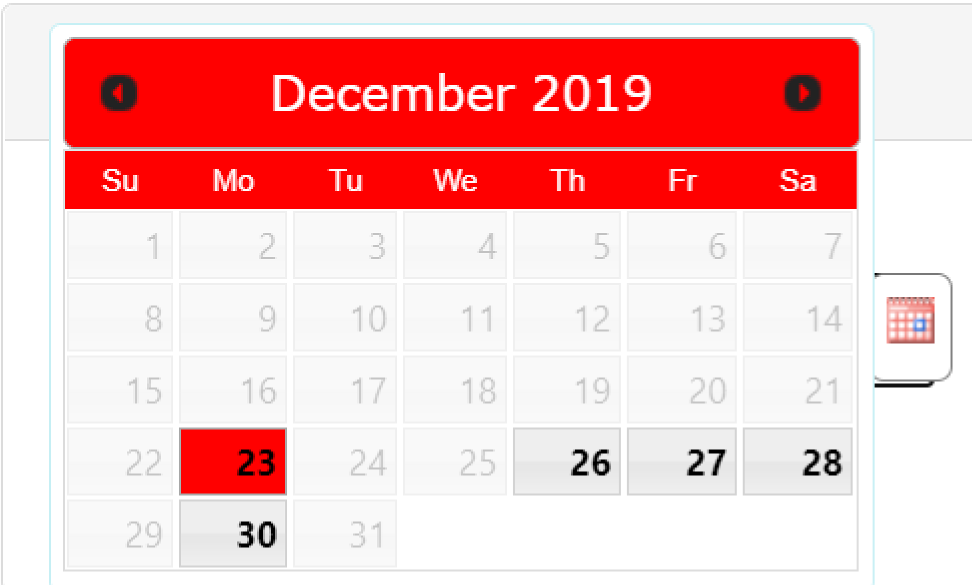

Figure 3 Calendar selection – ICM Dashboard

2.2.2 Incident Selection

For the user-selected incident date in the calendar selection step, the dropdown list is populated with a unique incident ID (TIMSID), start time, end time, location, and direction of the incident (Figure 4). Users can select an incident date at a time to visualize it.

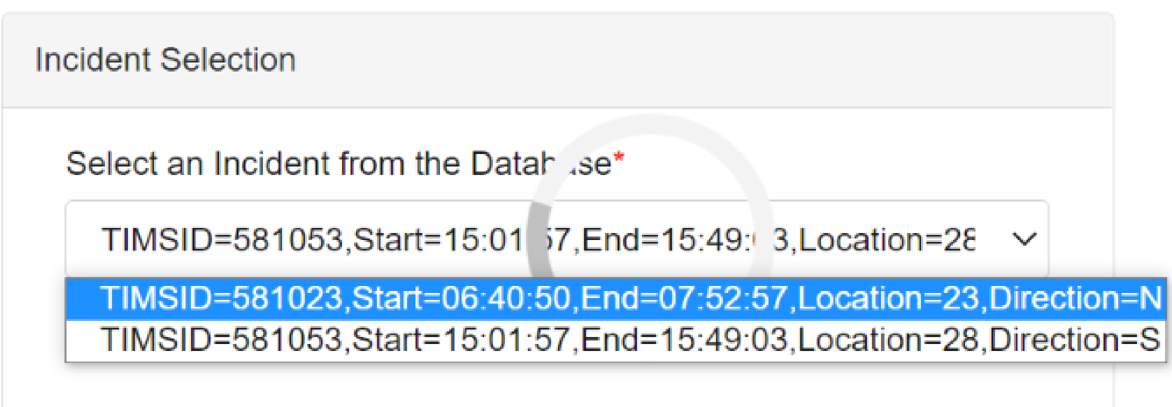

Figure 4 Incident Selection

2.3 Output

This section focuses on the output generated in the ICM dashboard for the selected. The output provides a TIMS incident summary, Google API routes along with the associated travel times, and Probe Data routes with associated travel times. Each output components are discussed below.

2.3.1 Incident Summary

For each selected incident a summary table provides key information such as severity, action, event, number of lanes closed, and total number of lanes available (Figure 5).

Summary

Severity	Action	Event	LanesClosed	TotalLanes
3	Lanes Closed	Vehicle Crash	2	4

Figure 5 – Incident Summary Table for a Sample Selected Incident

2.3.2 Google Maps API Routes and Travel Times

The generated Google map displays all detour routes for the selected as shown in Figure 6. If multiple detour routes are recommended by Google Maps, each route is marked with a different color. The start and end locations of each detour route are displayed using green and orange color markers, respectively. The chart displays the travel time taken by each detour route between the start time and end time of the selected incident. Each route is marked with a different color.

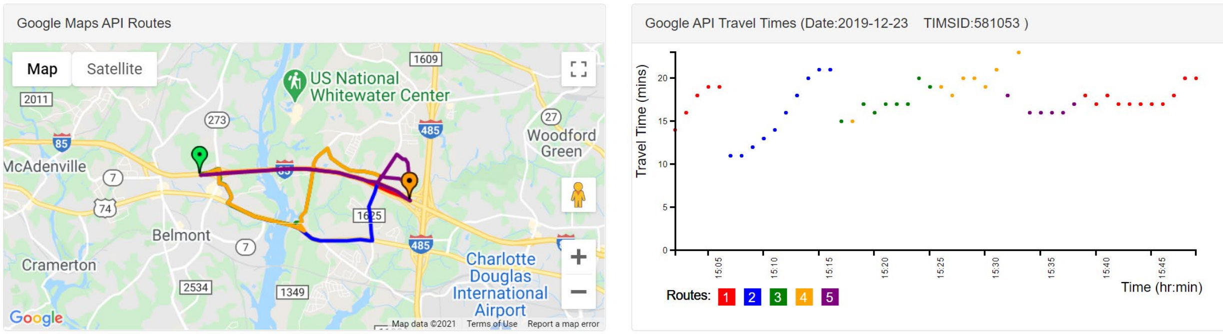

Figure 6 – Google Maps API Routes and Travel Times

2.3.3 Probe Data Routes and Travel Times

NCDOT's current Probe Data provider is HERE, which provides routing and travel time data through the ClearGuide platform. This data is also collected and stored in the ICM dashboard for visualizing the specific planned detour routes. The map displays the primary and the detour routes for the selected incident (refer to Figure 7 for illustration of an example). Each route is marked with a different color. The start and end locations of each detour route are displayed using green and orange color markers, respectively.

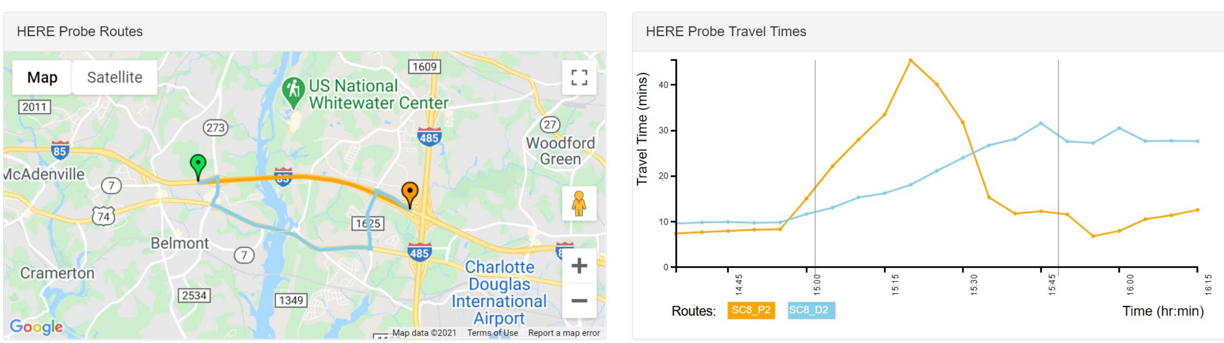

Figure 7 – IPEMS Routes and Travel Times

The chart displays the reported travel time for the primary and the detour routes during the selected incident. Each route is marked with a different color fo easy distinction. The left and right vertical lines (marked with grey color) refers to incident start time and end time, respectively.

3. Acknowledgements

The authors would like to thank the NCDOT and project steering committee and team members for NCDOT Project 2019-30 for their continuous support and insights to this effort.

Appendix B

Bluetooth Case Studies

To test the robustness of the developed methods for outlier detection both for the main and detour routes, and estimation of detour percentage, the team selected two scenarios where both incident and non-incident days were available. Selection of routes to include incident and non-incident days were deemed crucial for testing of the outlier detection algorithms and analysis of the detour rate to ensure they work under both incident and non-incident scenarios. Several sites were selected with different ramp and signalized intersections density.

Travel Time Case Studies

Case Study #1

The first case study site is located on the westside of the facility and is related to the one of developed scenarios for ICM. Following figure shows the geographical location of the scenario, Bluetooth sensor locations, and the planned detour routes. The red-dotted route represents the primary route on which an incident can happen. There are multiple speed limits along the detour route and three signalized intersections. The primary route starts from exit 10A on the westside and ends at exit 13 on the eastside. The detour route for this scenario is mainly along the US 74 and gets back on the interstate at exit 13 (Edgewood rd).

Figure 1: Location of first case study along with Bluetooth sensors

Two days representing an incident day (July 18, 2020) and a non-incident day (July 19, 2020) were selected for application of the developed algorithms. The travel times for July 19th, 2020 are shown in **Figure 2**. **Figure 2a** shows the travel times on the primary route (freeway) and **Figure 2b** shows the travel times on the alternative route. Visual observations of the **Figure 2a** show normal operation on the freeway where travel times are clustered around the free flow travel time with occasional high/low travel times that are clearly not representative of the conditions of the traffic stream. These travel times, colored orange, are outlier trips detected by the IQR4 algorithm. Observations of the figure reveals that the algorithm is able to effectively remove the outliers during a non-incident period. Similarly, **Figure 2b** shows the travel time on the alternative route (US 74) for the same day. The travel times on the alternative route, however, is scattered and does not portray any meaningful cluster. This is expected due to the presence of multiple signalized intersections along the route, different speed limits, and friction from businesses along the corridor. Observations of the figure reveals that the fixed threshold algorithm is able to detect obvious outliers and flag them as such. The top and bottom lines in **Figure 2b** represent the ceiling and floor values. Any travel times above the ceiling and below the floor lines are flagged as outliers and excluded from the analysis.

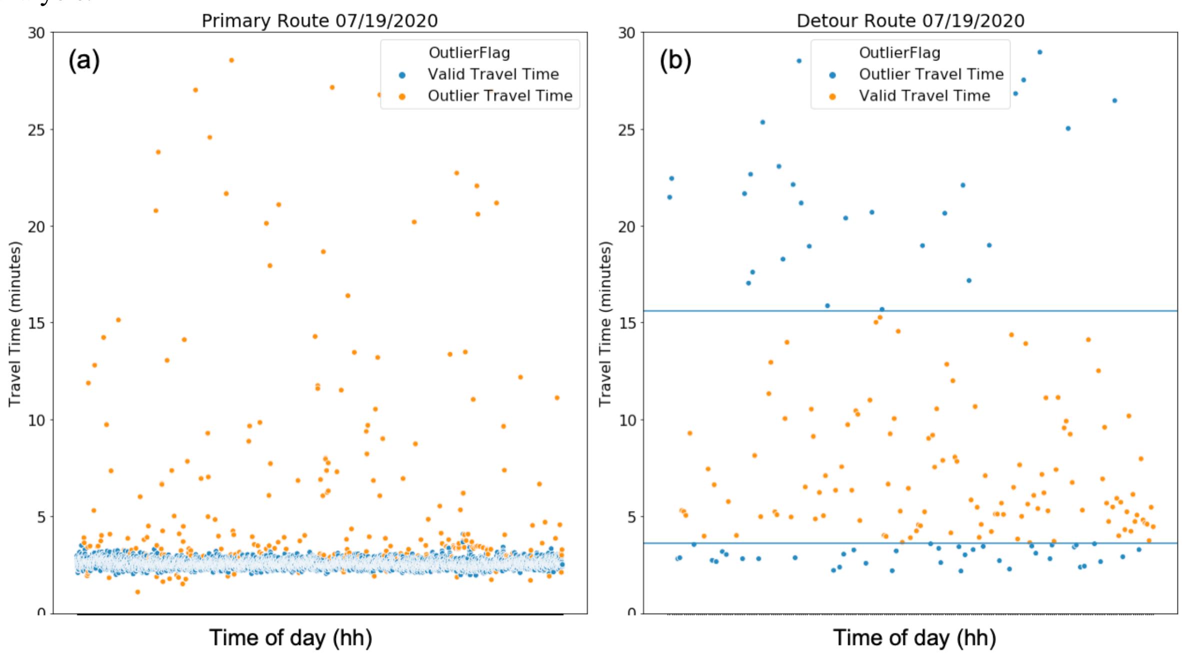

Figure 2: Individual travel time observations for the primary and alternative route for a non-incident day

Travel time observations for July 18, 2020 is shown by **Figure 3**. The abrupt increase in travel time during the early morning hours of the day is caused by an accident occurring on the freeway and closing the shoulder and one of the lanes. **Figure 3a** shows that the algorithms is able to navigate the abrupt increase in travel time around the accident time and correctly flag those travel times as valid observations. This is a testament to the robustness of the IQR4 outlier detection algorithm for scenarios where incidents are present on the primary route.

Figure 3b shows slight increase in travel times and number of observations on the alternative route. The incident has caused a relatively small surge of both the travel times and volume on the alternative route as drivers take the detour to prevent the longer travel times. Furthermore, observations of the figure reveal accurate identification of outliers on the detour route via the fixed threshold outlier detection algorithm.

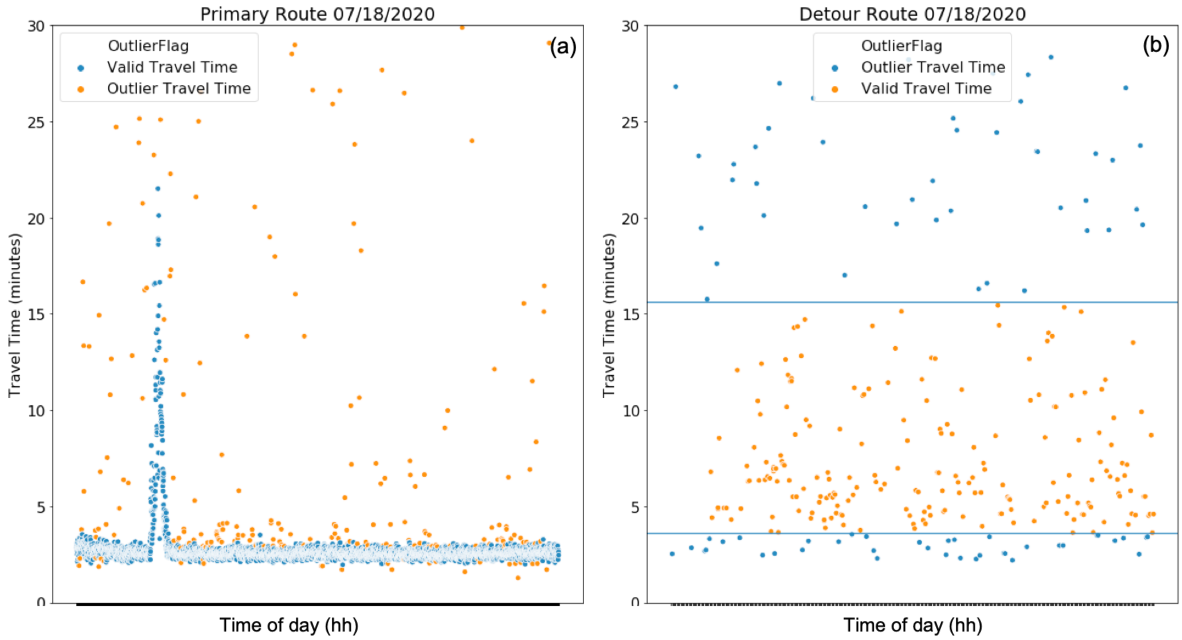

Figure 3: Individual travel time observations for the primary and detour route for an incident day

Case Study #2

The second detour route is about 2.1 miles long with a speed limit of 45 mph. There are 10 signalized intersections along the route. The first signalized intersection along the alternative route is located at the off ramp of I-85 (i.e., the start of the detour), and the last intersection is located at the on ramp to I-85 (i.e., the end of the detour). Using the fixed threshold filter introduced earlier, the lower and upper bounds for the travel time were calculated to be 2.3 and 16.38 minutes, respectively. The following figures show the thresholds for the travel times of the matched records from April 12th, 2020 and April 13th, 2020. Note that a road closure with detour happened on the nearby main route on April 13th (more discussion on the incident will be given in the following paragraphs).

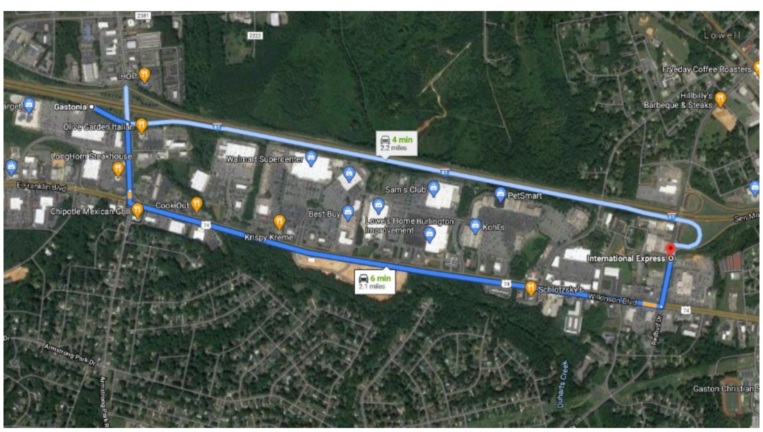

Figure 4: Location of second case study

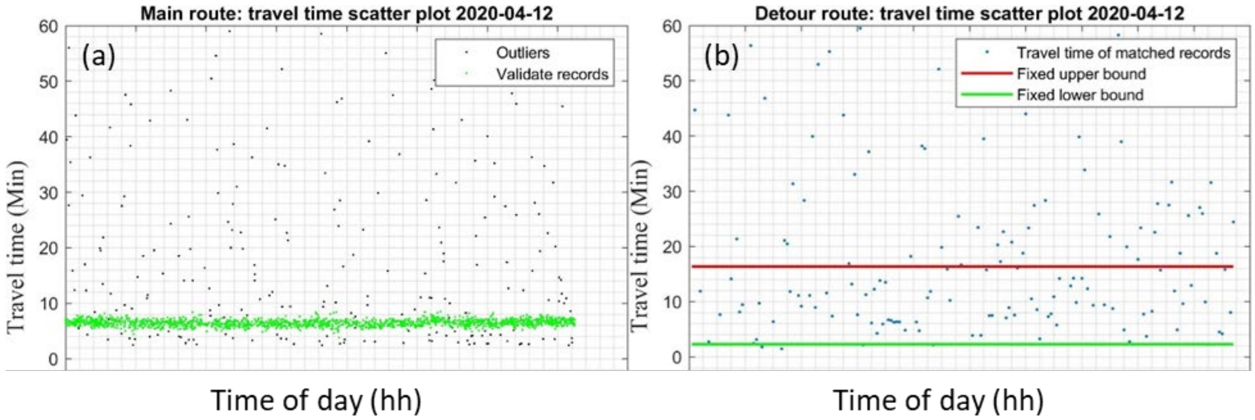

Figure 5: Scatter plot of travel times for the second case study route for April 12th (a) main route travel times (b) detour route travel times

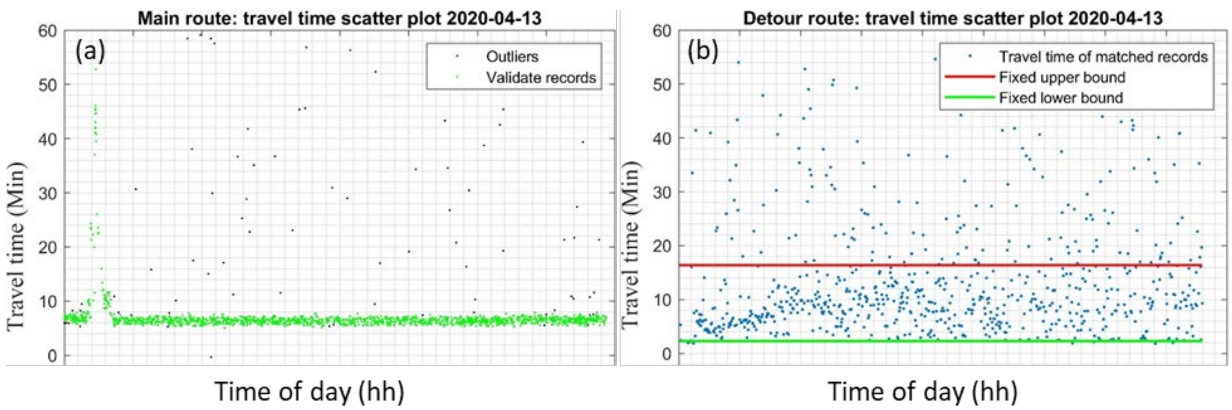

Figure 6: Scatter plot of travel times for the second case study route for April 13th (a) main route travel times (b) detour route travel times

Visual observations of **Figure 5** and **Figure 6** indicate that both of the developed algorithms are capable of detecting outlier travel time observations on the main and detour routes during incident and non-incident periods. Comparison of **Figure 5a** and **Figure 6a** shows that the latter experienced significant jump in travel times on the early hours of April 13th due to road closure. The green dots represent valid travel times in **Figure 6a** and close observation of this figure shows adaptiveness of the outlier detection algorithms. The outlier detection algorithm picks up incident impacted travel times immediately and flags them as valid travel times. Similarly, **Figure 5b** and **Figure 6b** show application of the fixed threshold outlier detection algorithm. The latter route experiences significant number of travel times, some of which are caused by the road closure on the main route. The algorithms show reasonable performance both during non-incident and incident period on the detour routes as well. As such, it can be claimed that the fixed threshold filter is reasonably filtering the outliers. The fixed threshold filter also offers a more reasonable fixed lower and upper bounds than those used by the BlueMac (between 0 and 60 minutes). Therefore, it is a promising way to filter out outliers on detour routes.

Diversion Rate Estimation
The team selected several events that caused congestion on I-85 and estimated the trips on US 74 that were detoured from I-85 with the goal of identifying the diversion rate caused by the presence of incident on the primary route.

Case Study #3
Nov 17th, 2020 was selected to evaluate the diversion rate since there was an accident that happened on this day. The accident started at around 11 am and got cleared at around 2 PM. This accident caused congestions to the westbound traffic on I-85. **Figure 7** shows the main route in red and a suggested detour route in blue.

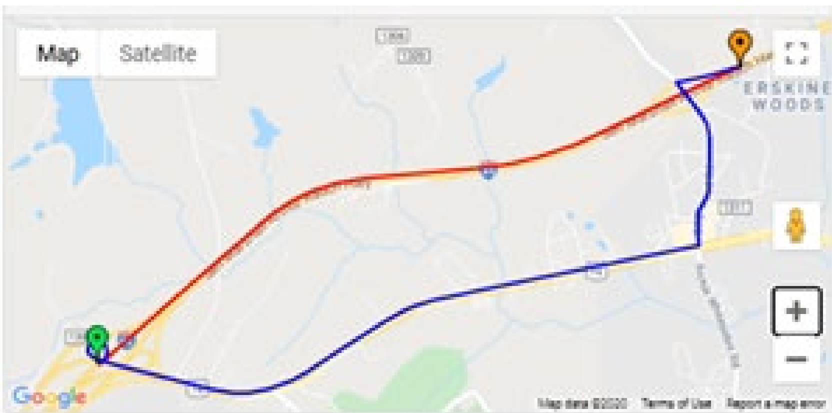

Figure 7: Primary and detour routes for an event that caused congestion on the main route on Nov 17th

The team was interested to estimate the detour trips caused by this accident on the detour route as shown by **Figure 7**. Due to the lack of operational Bluetooth sensors in the area during the incident period, the team was not able to estimate the diversion rate for the main and detour routes shown in **Figure 7**. Instead, the team estimated the detour trips between the two nearest available sensors (circled in red) shown in **Figure 8**.

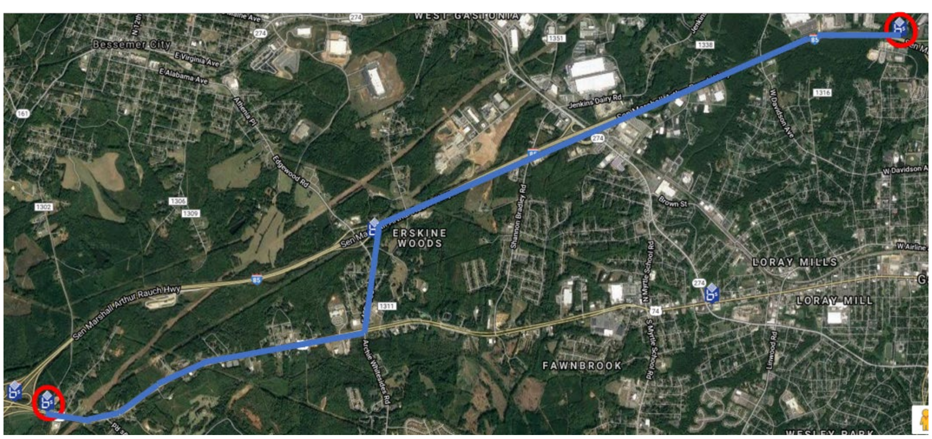

Figure 8: Sensor selected to estimate the detour trips

Figure 9 shows the number of trips on the detour route aggregated at 15-minutes intervals for the incident day along with two non-incident days. Comparison of parts (a) and (c) of the figure to part (b) show that there are significant number of trips during the time when the accident occurred (highlighted by the rectangle). The average number of trips on the detour route for each time epoch is around 2 trips for the non-incident days, while that number is around 16 trips for the incident period – showing an eight fold increase in the number vehicles taking the detour route. The estimated travel times on the detour route is also close to what Google Maps provided, which suggests that the trips are on the detour route for the purpose of averting the incident location (i.e., not for other purposes such as refueling and visit places along the route).

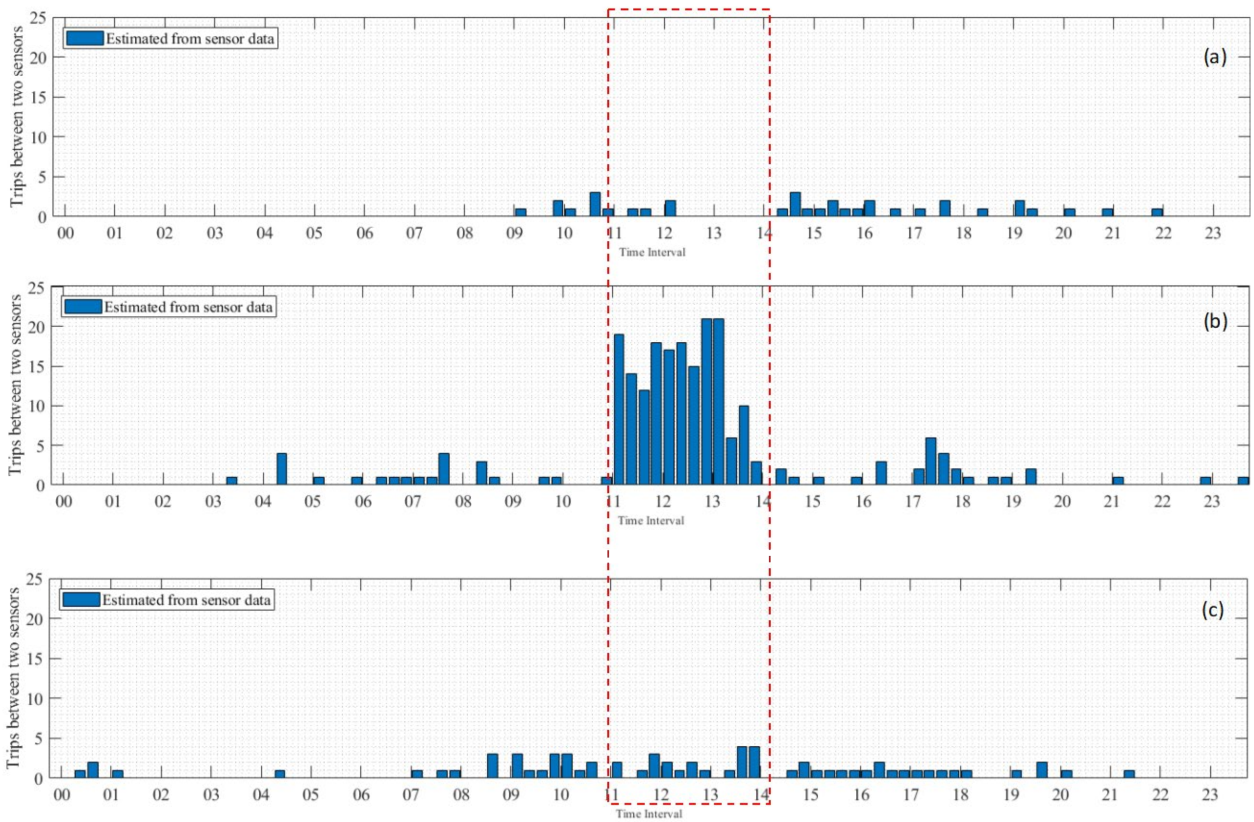

Figure 9: Number of trips detected between sensors (a) the day before the incident (11/16/2020), (b) incident day (11/17/2020), and (c) the day after the incident (11/18/2020)

Case Study #4

Figure 11 presents another case where a road obstruction (road closed with detour) happened on the main route. The incident was present from 5-10 AM on April 13th, 2020.

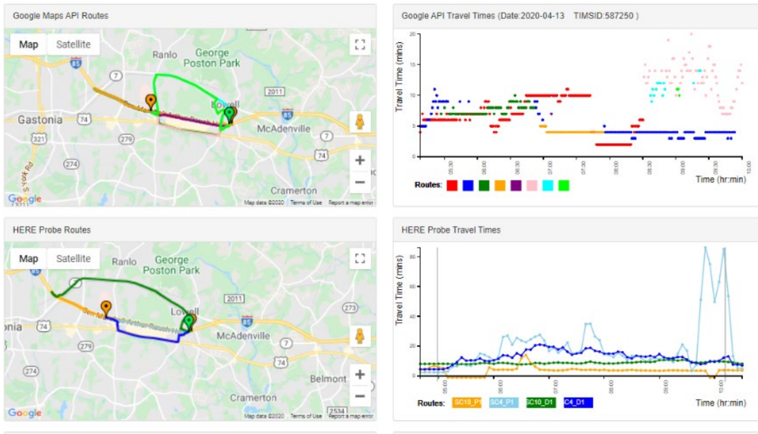

Figure 10: Road closure with detour on April 13th, 2020

Unfortunately, the information about the posted detour route for the road closure was unavailable to the research team. Based on the available sensors, we created one main route and two detour routes, which are shown in **Figure 12**.

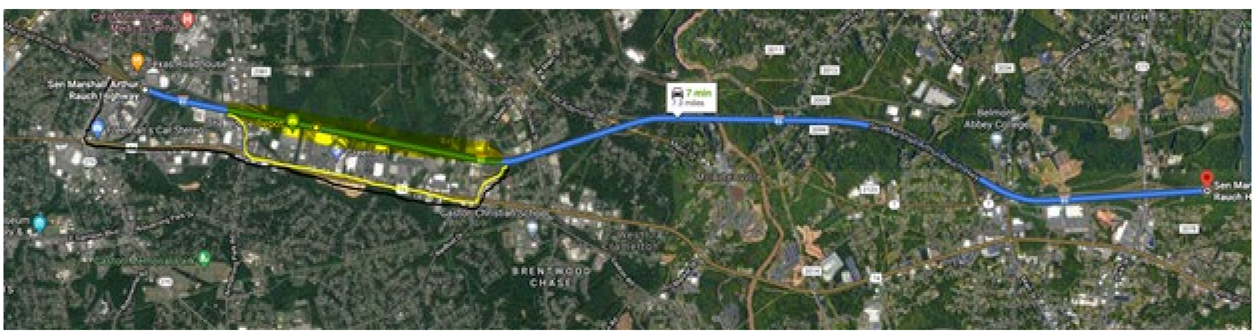
Figure 11: Main route and 2 detour routes for the road closure on April 13th, 2020. The main route is marked in blue. The first detour is marked in yellow and the 2nd detour is marked in black. The section of route closure is highlighted

Figure 13 and **Figure 14** show the number of matched records and their average speed on the main and two detour routes every 15 minutes for the day before the incident, the incident day, and the day after the incident. Part (a) and (b) of the figures are the statistics for the main route and part (c) and (d) are the statistics for the detour routes.

The impact of the road closure on the main route is apparent. For example, trips are detected on the main route on April 12th and April 14th while there are almost no trips detected during the route closure on April 13th. The trips detected from 5 to 10 AM on April 14th are higher than those on April 12th because the former includes Monday morning rush hour and the latter is a Sunday morning. For the same reason, if the road closure did not happen on April 13th, then the trips detected from 5 to 10 AM on this date is expected to be higher than those on April 12th.

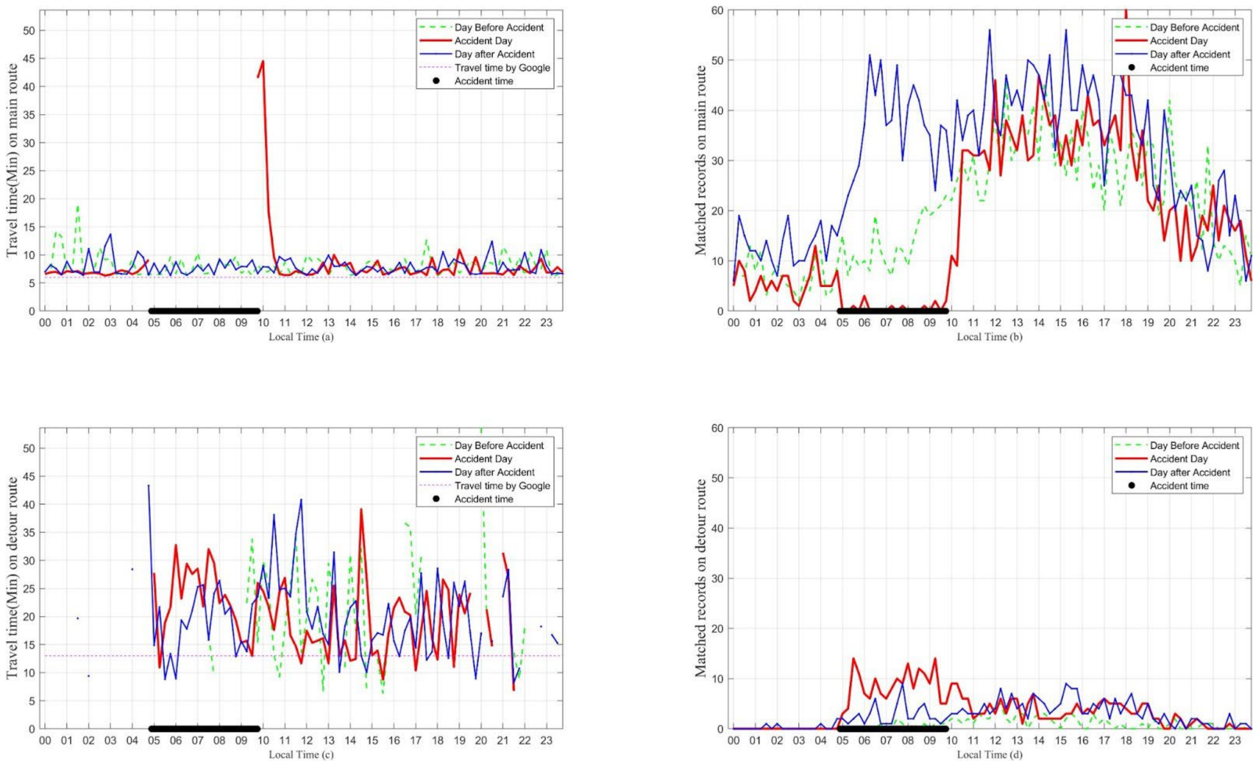

Figure 12: Number of matched records and their travel times for the main and the 1st detour route

The impact of the road closure on the two detour routes is also apparent. For example, we can observe that the number of detected trips from 5 to 10 AM on April 13th is significantly higher than these of the other two days. This surge in the number of trips on the detour route could only be caused by the diversion of the mainline traffic. In contrast, the numbers of detected trips before 5 AM and after 10 AM on April 13th are similar to these on April 12th and 14th.

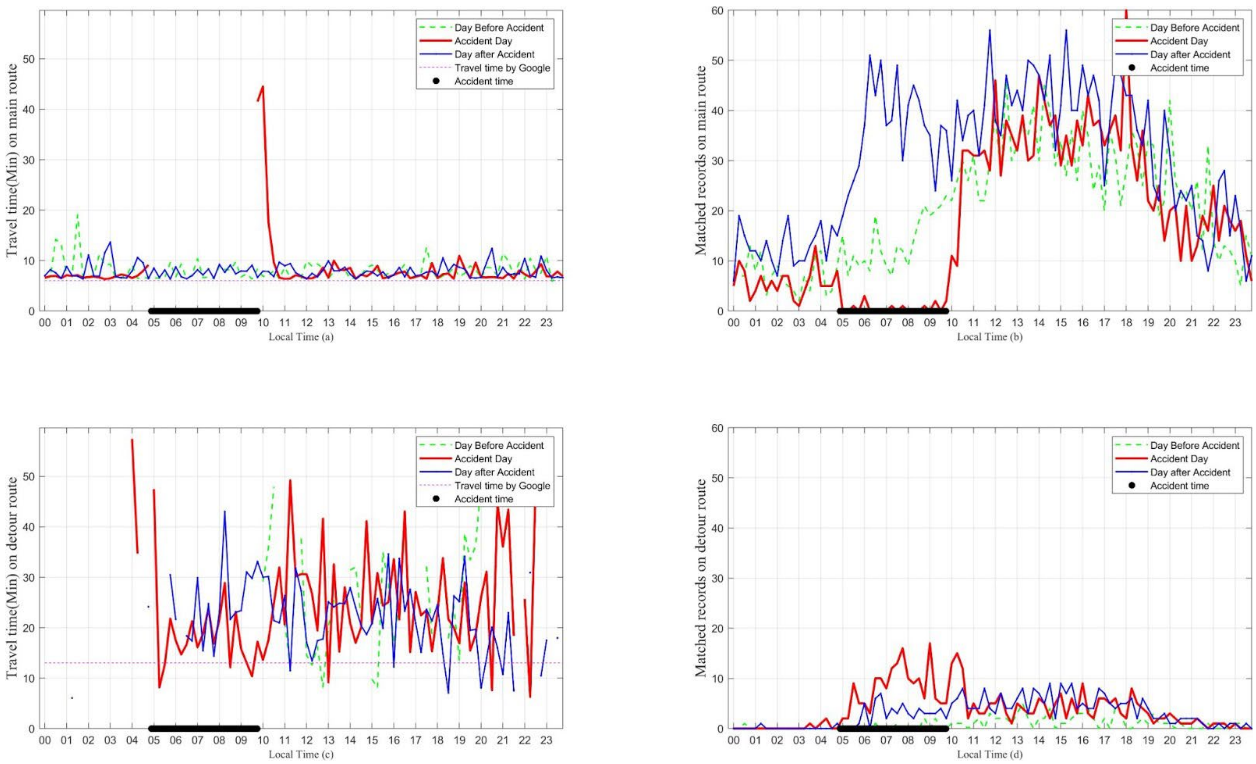

Figure 13: Number of matched records and their travel times for the main and the 2nd detour route

Summary

This appendix investigated (a) robustness of the developed algorithms for outlier travel time detection on the main and detour routes and (b) feasibility of using Bluetooth sensors as a mean to estimate the freeway diversion rate on the ICM facilities. Application of the developed algorithms to multiple scenarios with different length, signal density, speed limit, incident, and non-incident periods revealed robustness of the methodology for generation of travel times. Similarly, the diversion rate analysis showed that using Bluetooth sensors is a viable medium to obtain such estimates. In summary, Bluetooth sensors provide promising datasets which enable ICM project stakeholders to conduct travel time, diversion rate, and origin-destination analyses.

Appendix C

APPENDIX 3: Introduction to User Interface of Planning tool

This appendix describes the interface of the planning tool used to calculate the total expected vehicle hours traveled (VHT) savings for detours during incidents in freeways.

The Excel tool contains the following 2 sheets:

1. Input sheet
2. Result sheet

Input Sheet: Figure 1 shows the input sheet in the planning tool. The user can enter the number of detours for a freeway segment using the input macro available. Once the user has entered the numbers of detours, the tool will populate the “Facility” column with the mainline and detour segments. In the next step, the user has to enter the necessary inputs such as the Number of lanes, Facility type, Median type, Area type, Terrain type, Facility length, speed limit, Intersection type, AADT, Peaking type and the Functional class for the corresponding facilities. The lane width and crash to incident ratio will have 12 and 4.9 respectively as the default value which the user can change.

Facility	Number of lanes	Facility Type	Median Type	Area Type	Terrain Type	Facility Length	Speed Limit	Intersection type	AADT	Peaking type	Functional class	Calculated Daily Capacity	Lane Width	Crash to Incident Ratio
Mainline1	3	interstate	divided	rural	rolling	2.69	65		80000	AM	Interstate	112700	12	4.9
Detour1	2	arterial	divided	rural	rolling	3.18	55		8300	AM	Other Principal Art	31700	12	4.9

Input

Figure 1 Input Sheet in Planning tool

Result sheet: Once the input information has been entered, the result sheet will calculate the total VHT savings and the total expected savings for each detour. The figure A3-3 contains the tables containing the total expected savings and total VHT savings. The value next to the incident severity in the total VHT savings table shows the total VHT savings for each incident severity type in the freeway segment. The value next to the incident severity in the total expected savings table shows the expected savings for each incident severity type accounting for the probability of the incident severity type and time of day of incident. The VHT savings are higher when more lanes are closed in the freeway causing more traffic to be diverted to move to the detour. However, the expected savings won't follow a similar trend as the probability of an incident happening where 2 lanes are closed is lower than that of a shoulder being closed. Hence, the expected savings table will give the user an idea of savings that can be expected by using a detour route during an incident in a freeway segment. In the result sheet, the user can change the percentage of volume diverted detours for each incident severity type and the percentage increase in capacity for signalized intersections. Figures 2 and 3 show the result sheet in the planning tool.

Location	Start Time	End Time	Severity	Duration	Mainline v/c ratio	Mainline Travel Time (mins)	Main Route VHT	Lanes Open	Incident Mainline Capacity	Incident Mainline v/c ratio	Incident Mainline Travel Time (mins)	Incident Mainline VHT	Detour v/c ratio	Detour travel time (mins)	Detour VHT	Diversion Mainroute v/c ratio	Diversion Mainline Travel Time (mins)	Diversion Main route VHT	VHT Savings	Probability of scenario	Expected Savings
Mainline1	12:00 AM	12:39 AM	Shoulder Closec	39.35	0.05	2.48	0	3	4093.2	0.08	2.48	24	0.323	3.469	2.88	0.14	2.48	23	-16.81	0.006	-0.09
Mainline1	1:00 AM	1:33 AM	Shoulder Closec	33.22	0.03	2.48	0	3	4093.2	0.05	2.48	16	0.323	3.469	1.85	0.09	2.48	15	-9.13	0.004	-0.03
Mainline1	2:00 AM	2:39 AM	Shoulder Closec	39.71	0.03	2.48	0	3	4093.2	0.04	2.48	14	0.323	3.469	1.62	0.08	2.48	13	-9.55	0.003	-0.03
Mainline1	3:00 AM	3:43 AM	Shoulder Closec	43.97	0.04	2.48	0	3	4093.2	0.05	2.48	16	0.323	3.469	1.95	0.09	2.48	16	-12.72	0.004	-0.05
Mainline1	4:00 AM	4:17 AM	Shoulder Closec	17.11	0.06	2.48	0	3	4093.2	0.09	2.48	28	0.323	3.469	3.29	0.16	2.48	26	-8.36	0.006	-0.05
Mainline1	5:00 AM	5:19 AM	Shoulder Closec	19.18	0.16	2.48	1	3	4093.2	0.24	2.48	73	0.323	3.469	8.62	0.41	2.48	69	-24.54	0.017	-0.41
Mainline1	6:00 AM	6:33 AM	Shoulder Closec	33.35	0.43	2.48	3	3	4093.2	0.65	2.49	200	0.323	3.469	23.51	1.12	3.38	257	-154.32	0.045	-6.99
Mainline1	7:00 AM	7:03 AM	Shoulder Closec	3.75	0.66	2.50	5	3	4093.2	0.99	2.82	345	0.323	3.469	35.92	1.71	29.11	3387	-213.48	0.069	-14.78
Mainline1	8:00 AM	8:29 AM	Shoulder Closec	29.90	0.60	2.49	4	3	4093.2	0.89	2.62	289	0.323	3.469	32.25	1.53	13.72	1433	-728.10	0.062	-45.27
Mainline1	9:00 AM	9:42 AM	Shoulder Closec	42.20	0.44	2.48	3	3	4093.2	0.65	2.50	202	0.323	3.469	23.80	1.13	3.47	268	-202.66	0.046	-9.30
Mainline1	10:00 AM	10:28 AM	Shoulder Closec	28.91	0.37	2.48	3	3	4093.2	0.56	2.49	171	0.323	3.469	20.21	0.96	2.75	180	-95.16	0.039	-3.71
Mainline1	11:00 AM	11:27 AM	Shoulder Closec	27.81	0.38	2.48	3	3	4093.2	0.56	2.49	172	0.323	3.469	20.33	0.96	2.76	182	-92.45	0.039	-3.62
Mainline1	12:00 PM	12:55 PM	Shoulder Closec	55.94	0.39	2.48	3	3	4093.2	0.58	2.49	179	0.323	3.469	21.05	1.00	2.85	194	-198.29	0.041	-8.05
Mainline1	1:00 PM	1:38 PM	Shoulder Closec	38.61	0.40	2.48	3	3	4093.2	0.59	2.49	183	0.323	3.469	21.55	1.02	2.93	204	-143.55	0.042	-5.96
Mainline1	2:00 PM	2:23 PM	Shoulder Closec	23.75	0.41	2.48	3	3	4093.2	0.61	2.49	188	0.323	3.469	22.16	1.05	3.04	218	-94.03	0.043	-4.02
Mainline1	3:00 PM	3:24 PM	Shoulder Closec	24.13	0.44	2.48	3	3	4093.2	0.65	2.50	202	0.323	3.469	23.78	1.13	3.47	267	-115.58	0.046	-5.30
Mainline1	4:00 PM	4:32 PM	Shoulder Closec	32.08	0.48	2.48	3	3	4093.2	0.71	2.51	221	0.323	3.469	25.84	1.23	4.39	368	-208.58	0.050	-10.39
Mainline1	5:00 PM	5:58 PM	Shoulder Closec	58.43	0.51	2.48	4	3	4093.2	0.76	2.52	238	0.323	3.469	27.67	1.31	5.78	518	-527.73	0.053	-28.15
Mainline1	6:00 PM	6:43 PM	Shoulder Closec	43.39	0.40	2.48	3	3	4093.2	0.60	2.49	185	0.323	3.469	21.86	1.04	2.98	211	-166.35	0.042	-7.01
Mainline1	7:00 PM	7:50 PM	Shoulder Closec	50.26	0.29	2.48	2	3	4093.2	0.42	2.48	131	0.323	3.469	15.45	0.73	2.51	126	-116.56	0.030	-3.47
Mainline1	8:00 PM	8:42 PM	Shoulder Closec	42.28	0.22	2.48	2	3	4093.2	0.33	2.48	103	0.323	3.469	12.13	0.58	2.49	98	-76.24	0.023	-1.78
Mainline1	9:00 PM	9:32 PM	Shoulder Closec	32.73	0.19	2.48	1	3	4093.2	0.28	2.48	87	0.323	3.469	10.29	0.49	2.48	83	-50.03	0.020	-0.99
Mainline1	10:00 PM	10:26 PM	Shoulder Closec	26.65	0.14	2.48	1	3	4093.2	0.21	2.48	66	0.323	3.469	7.79	0.37	2.48	63	-30.82	0.015	-0.46
Mainline1	11:00 PM	11:33 PM	Shoulder Closec	33.85	0.10	2.48	1	3	4093.2	0.15	2.48	45	0.323	3.469	5.35	0.25	2.48	43	-26.86	0.010	-0.28
Mainline1	12:00 AM	12:37 AM	1	37.83	0.05	2.48	0	2	2030.4	0.16	2.48	24	0.428	3.470	3.81	0.28	2.48	23	-16.75	0.001	-0.02
Mainline1	1:00 AM	1:14 AM	1	14.32	0.03	2.48	0	2	2030.4	0.10	2.48	16	0.428	3.470	2.46	0.18	2.48	15	-4.08	0.001	0.00
Mainline1	2:00 AM	2:40 AM	1	40.06	0.03	2.48	0	2	2030.4	0.10	2.48	16	0.428	3.470	2.46	0.18	2.48	15	-11.42	0.001	-0.01
Mainline1	3:00 AM	3:36 AM	1	36.02	0.04	2.48	0	2	2030.4	0.11	2.48	16	0.428	3.470	2.58	0.19	2.48	16	-10.80	0.001	-0.01
Mainline1	4:00 AM	4:41 AM	1	41.89	0.06	2.48	0	2	2030.4	0.18	2.48	28	0.428	3.470	4.36	0.31	2.48	26	-21.21	0.002	-0.03
Mainline1	5:00 AM	5:42 AM	1	42.28	0.06	2.48	0	2	2030.4	0.18	2.48	28	0.428	3.470	4.36	0.31	2.48	26	-21.41	0.002	-0.04
Mainline1	6:00 AM	6:44 AM	1	44.42	0.43	2.48	3	2	2030.4	1.30	5.57	446	0.428	3.470	31.16	2.25	246.98	18803	-13942.61	0.012	-164.25
Mainline1	7:00 AM	7:41 AM	1	41.62	0.66	2.50	5	2	2030.4	1.99	94.18	11533	0.428	3.470	47.61	3.44	7267.44	845436	-586532.04	0.018	-10558.08
Mainline1	8:00 AM	8:23 AM	1	23.83	0.66	2.50	5	2	2030.4	1.99	94.18	11533	0.428	3.470	47.61	3.44	7267.44	845436	-335740.19	0.018	-6043.61
Mainline1	9:00 AM	9:53 AM	1	53.00	0.44	2.48	3	2	2030.4	1.32	5.89	478	0.428	3.470	31.55	2.28	272.18	20978	-18555.91	0.012	-221.30
Mainline1	10:00 AM	10:40 AM	1	40.61	0.37	2.48	3	2	2030.4	1.12	3.40	235	0.428	3.470	26.79	1.93	75.44	4937	-3358.04	0.010	-34.01
Mainline1	11:00 AM	11:35 AM	1	35.86	0.37	2.48	3	2	2030.4	1.12	3.40	235	0.428	3.470	26.79	1.93	75.44	4937	-2965.40	0.010	-30.03
Mainline1	12:00 PM	12:53 PM	1	53.01	0.39	2.48	3	2	2030.4	1.17	3.76	270	0.428	3.470	27.90	2.01	103.43	7050	-6251.10	0.011	-65.93
Mainline1	1:00 PM	1:20 PM	1	20.75	0.39	2.48	3	2	2030.4	1.17	3.76	270	0.428	3.470	27.90	2.01	103.43	7050	-2446.92	0.011	-25.81
Mainline1	2:00 PM	2:38 PM	1	38.23	0.41	2.48	3	2	2030.4	1.23	4.41	333	0.428	3.470	29.38	2.12	155.04	11128	-7108.06	0.011	-78.94
Mainline1	3:00 PM	3:31 PM	1	31.49	0.44	2.48	3	2	2030.4	1.32	5.86	475	0.428	3.470	31.52	2.28	270.39	20822	-10942.09	0.012	-130.39
Mainline1	4:00 PM	4:27 PM	1	27.94	0.44	2.48	3	2	2030.4	1.32	5.86	475	0.428	3.470	31.52	2.28	270.39	20822	-9709.62	0.012	-115.70
Mainline1	5:00 PM	5:22 PM	1	22.68	0.51	2.48	4	2	2030.4	1.53	13.84	1305	0.428	3.470	36.67	2.65	902.14	80801	-30565.72	0.014	-420.77
Mainline1	6:00 PM	6:49 PM	1	49.04	0.40	2.48	3	2	2030.4	1.21	4.20	313	0.428	3.470	28.97	2.09	138.66	9828	-8054.44	0.011	-88.21
Mainline1	7:00 PM	7:25 PM	1	25.00	0.40	2.48	3	2	2030.4	1.21	4.20	313	0.428	3.470	28.97	2.09	138.66	9828	-4105.24	0.011	-44.96
Mainline1	8:00 PM	8:30 PM	1	30.30	0.22	2.48	2	2	2030.4	0.67	2.50	103	0.428	3.470	16.07	1.16	3.71	146	-90.87	0.006	-0.49
Mainline1	9:00 PM	9:38 PM	1	38.62	0.19	2.48	1	2	2030.4	0.57	2.49	87	0.428	3.470	13.64	0.98	2.81	94	-68.22	0.005	-0.35
Mainline1	10:00 PM	10:06 PM	1	6.65	0.19	2.48	1	2	2030.4	0.57	2.49	87	0.428	3.470	13.64	0.98	2.81	94	-11.76	0.005	-0.06
Mainline1	11:00 PM	11:26 PM	1	26.69	0.10	2.48	1	2	2030.4	0.30	2.48	45	0.428	3.470	7.08	0.51	2.48	43	-21.96	0.003	-0.06
Mainline1	12:00 AM	12:54 AM	2	54.94	0.05	2.48	0	1	2030.4	0.16	2.48	24	0.534	3.473	4.75	0.28	2.48	23	-25.18	0.000	-0.01
Mainline1	1:00 AM	1:40 AM	2	40.58	0.05	2.48	0	1	2030.4	0.16	2.48	24	0.534	3.473	4.75	0.28	2.48	23	-18.60	0.000	0.00
Mainline1	2:00 AM	2:24 AM	2	24.81	0.03	2.48	0	1	2030.4	0.09	2.48	14	0.534	3.473	2.68	0.16	2.48	13	-6.40	0.000	0.00
Mainline1	3:00 AM	3:40 AM	2	40.12	0.04	2.48	0	1	2030.4	0.11	2.48	16	0.534	3.473	3.22	0.19	2.48	16	-12.45	0.000	0.00
Mainline1	4:00 AM	4:55 AM	2	55.59	0.04	2.48	0	1	2030.4	0.11	2.48	16	0.534	3.473	3.22	0.19	2.48	16	-17.25	0.000	0.00
Mainline1	5:00 AM	5:53 AM	2	53.72	0.16	2.48	1	1	2030.4	0.48	2.48	73	0.534	3.473	14.24	0.82	2.56	72	-75.74	0.001	-0.05
Mainline1	6:00 AM	6:59 AM	2	59.27	0.43	2.48	3	1	2030.4	1.30	5.57	446	0.534	3.473	38.84	2.25	246.98	18803	-18609.84	0.002	-34.66
Mainline1	7:00 AM	7:49 AM	2	49.54	0.43	2.48	3	1	2030.4	1.30	5.57	446	0.534	3.473	38.84	2.25	246.98	18803	-15555.98	0.002	-28.99

Figure 2 Result sheet in Planning tool

Severity	Probability of incident severity		Average	Standard deviation	Median
shoulder closed	0.754	0.754	34	15.1	36.5
1	0.196	0.95	34.6	13.8	32.6
2	0.031	0.981	53.6	13.9	60.1
3	0.019	1	69.6	21.9	67.9

Probability of scenario

	VHT	
Base Hourly	Main Route + Detour	volume from ncdot maps
Incident Hourly	Main Route	100 % of volume
Diversion Hourly	Main Route + Detour	95% of the volume + 5 % to detour

Increase in capacity for signalized intersections = 20

Volume Diversions	
Shoulder Closed	0.95
1	0.9
2	0.85
3	0.8

directional factor = 0.55

Total expected savings	
Shoulder closed	(160.19)
1 lane closed	(18,026.08)
2 lane closed	(1,493.07)
3 lane closed	#N/A

Total VHT savings	
Shoulder closed	(3,321.91)
1 lane closed	(1,040,546.06)
2 lane closed	(637,012.53)
3 lane closed	#N/A

20% increase in capacity for signalized intersections
5% - 15% volume diverting to detours

Figure 3 Result sheet in Planning tool