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Data Driven Approach To Characterize And Forecast The Impact Of Freeway Work Zones On Mobility Using Probe Vehicle Data

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**DATA DRIVEN APPROACH TO CHARACTERIZE AND FORECAST THE IMPACT OF
FREEWAY WORK ZONES ON MOBILITY USING PROBE VEHICLE DATA**

by

MOHSEN KAMYAB

DISSERTATION

Submitted to the Graduate School

of Wayne State University

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Approved By:

Advisor

Date

DEDICATION

To my beloved family and all my well-wishers.

ACKNOWLEDGMENT

I am grateful to many people for their support as I wrote this dissertation. I would like to extend my deepest gratitude to my committee chair Dr. Stephen Remias for his excellent guidance and insight at each step of this process. I am extremely grateful for his continuous support, encouragement and patience. Special thanks to all my committee members whom provided me with their generous guidance and support. My sincere gratitude goes to Prof. Mumtaz Usman who thought me a great deal of professional and personal lessons with a wonderful attitude. I am also grateful to Dr. Steven Lavrenz for his insight and expertise. I would like to acknowledge Prof. Shi, from computer science department, for inspiring my interest in the development of innovative technologies. Finally, thanks to the many researchers and scholars in a broad range of technical fields who have produced work that has ignited, encouraged and greatly influenced my passion for transportation research.

EXECUTIVE SUMMARY

The objective of this study is to utilize data-driven analytics to assist current practices for work zone mobility impact measurement, prediction, and decision-making procedures. Work zones, or lane-closures, are defined as areas of highway with construction, rehabilitation, or utility work activities. The presence of work zones on freeways cause traffic congestion and create hazardous conditions for commuters and construction workers. Traffic congestion resulting from work zones causes negative impacts on traffic mobility (delay), the environment (vehicle emissions), and safety where stopped or slowed vehicles are vulnerable to traffic rear-end collisions. Work zone mobility management has been a challenge for transportation engineers due to its complex nature in which numerous factors are being involved.

The Federal Highway Administration (FHWA) has emphasized the importance of improving the current practices in order to minimize the negative safety and mobility impacts associated with work zones. The FHWA recommends transportation agencies to develop systematic approaches to evaluate and improve their current mobility management strategies which highlight the importance of utilizing advanced and innovative methodologies in this area.

Intelligent Transportation Systems (ITS) strive to utilize advanced technologies to provide efficient solutions to improve current mobility management strategies. Due to the recent enhancements in data collection methodologies using smartphones and navigation telematics, a tremendous amount of mobility data is currently available for historical work zones. This data facilitates applying advanced data-driven analytics in the area of work zone traffic management. Data from thousands of work zones on Michigan interstates were gathered and mined to achieve the following objectives:

- Develop a systematic approach to measure and visualize the impact of work zones
- Predict the impact future work zones will have on interstate's mobility
- Develop a decision-making support approach to better plan future work zones

To achieve these objectives, three analytic approaches including descriptive, predictive, and prescriptive methods were used. These approaches and their applicability for work zone management is discussed in the following sections.

Descriptive approach: Work Zone Mobility Audit (WZMA)

A scalable Work Zone Mobility Audit (WZMA) framework was developed to measure mobility performance of each work zone using a visual and quantitative methodology. This framework characterizes mobility using several metrics to quantify the user delay and traffic slowdowns in a two-page summary for each individual work zone. These metrics were defined to assess mobility in a spatiotemporal manner. The temporal analysis focused on identifying times that negative mobility impact happens while the spatial analysis was focused on characterizing freeway locations which experience severe slowdowns and queueing condition. A software was developed based on this framework to automate performing the WZMA process for a larger number of work zones which can be utilized for further diagnostics of mobility.

Predictive approach: A machine learning framework to forecast work zone mobility

A machine learning framework was developed to learn from historical projects and predict the spatio-temporal impact of future work zones on mobility. This method utilized historical work zone observations along with speed distributions for each highway segment to forecast the expected impact on mobility. This study extracted speed distribution from probe vehicle data, as a substitute for hourly traffic volume, to apply Random Forest, XGBoost, and Artificial Neural Network (ANN) classification algorithms. Various traffic data sources were collected from 1,160 work zones which occurred on Michigan interstates between 2014 and 2017. The results showed that the ANN model outperformed the other models by reaching up to 85% accuracy. This study highlights how historical traffic speeds can be used as an alternative to hourly traffic volumes when identifying non-recurrent traffic congestion patterns as a result of interstate lane-closures.

Prescriptive approach: State-wide work zone mobility evaluation and management

A high-level mobility assessment was performed to provide an overview of the overall impact work zones have on mobility in a state-wide level. In addition, a statistical analysis was performed to identify significant factors affecting work zone mobility. The WZMA process was performed for more than 1,700 work zones that occurred on Michigan interstates which provided a rich data set for further assessment. A visual procedure was developed to characterize the impact based on interstates and work zone categories. In addition, a Pareto sort process was developed to identify significant projects which were account for a majority of the overall impact. The purpose of the Pareto sort was to highlight the most problematic and significant projects among all the case studies. Furthermore, a decision tree modeling approach was developed to provide decision-making rules using statistically significant factors affecting mobility performance. The decision-trees provided a tree like model of work zone projects and their possible negative impact on mobility. These decision-trees could be utilized to determine worst, best, and expected impact for different work zone strategies which could potentially enhance work zone planning policies.

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CHAPTER 1 INTRODUCTION

Problem Statement and Motivation

The presence of work zones on freeways causes traffic congestion and creates hazardous conditions for commuters and construction workers. Traffic congestion resulting from work zones causes negative impacts on traffic mobility (delay), the environment (vehicle emissions), and safety where stopped or slowed vehicles are vulnerable to traffic rear-end collisions. According to the Federal Highway Administration (FHWA), approximately 24 percent of nonrecurring freeway delays are due to work zone projects; as a result 888 million hours and 310 million gallons of fuel were lost in 2014 (1). Furthermore, work zone presence resulted in approximately 96,000 crashes on US roadways, which was an increase of 42 percent from approximately 68,000 work zone crashes in 2013 (1). These negative effects are growing while numerous short-term work zone activities such as pothole patching, crack sealing, pavement resurfacing, and long-term work-zones such as pavement reconstruction and bridge replacement are happening every day on the US interstate system. US highways are aging, and agencies are beginning to invest more resources for the maintenance and enhancement of roads, meaning more construction and repair projects will be required in the near future. In addition, the overall traffic congestion is increasing on US highways and the supply, or number of lane-miles, will not match the growth in demand.

To alleviate work zone congestion and safety issues, transportation engineers have used various traffic simulation and analytical approaches to assess and forecast the impact of work zones. Traffic simulation approaches include both micro-simulation and macro-simulation in which work zone configurations are modeled in simulation digital environment. Although traffic simulation provides the flexibility to simulate new work zone strategies, this approach requires extensive effort for model preparation, calibration, and validation. Furthermore, analytical approaches have used both parametric and non-parametric methods to identify variables that affect work zone capacity. Practitioners will also use the predicted work zone capacity to identify

the work zone impact on queue formation and delay. For instance, the Highway Capacity Manual (HCM) proposes a linear correlation between work zone attributes and capacity (2). Parametric approaches are easy to use due to their simplistic nature; however, these approaches suffer from lack of adequate accuracy. The reason these simplistic models were used in the past has been due to a lack of data availability for more in-depth analysis. In the past, work zone data collection has been either labor intensive or expensive due to extensive infrastructure installation. Therefore, limited research has been done to study the impact of lane closures on traffic mobility using historical speed data from real world work zone projects.

Work zone impact is dependent on numerous factors such as the work zone configuration, traffic condition, driver behavior, weather condition, and roadway characteristics. However, traffic simulation and analytical approaches only consider some of these factors. Therefore, the predicted impact using either of these approaches might be quite different than what actually happens on roadways. Recently, the advent of technology and viral use of smart phones have enabled third party vendors to provide detailed work zone traffic mobility data. The availability of comprehensive traffic data facilitates use of data driven analytical approaches to characterize a work zone's impact on traffic mobility. In addition, advanced forecasting algorithms can then be applied to predict future work zone impacts using historical work zone traffic data. This data driven approach enables practitioners to utilize the historical work zone data to assess different work zone scenarios and optimize traffic mobility throughout their work zone activities.

Work zone projects are causing enormous negative impact on traffic mobility and safety. This issue will continue to cost US citizens billions of dollars if this issue does not receive enough attention. In 2004, the FHWA initiated several efforts to address the impact of work zone on traffic mobility and safety (3,4,5,6). The FHWA published an update to the work zone regulations at 23 CFR 630 Subpart J which is referred to as Work Zone safety and Mobility rule (3). The rule requires all transportation agencies to initially develop overall policies to systematically consider

and manage work zone impacts; thereafter, this rule requires agencies to establish agency-level processes and procedures to implement and sustain formerly defined work zone management policies. Last but not least, the rule demands agencies develop project-level procedures to monitor and manage work zone projects individually (Figure 1).

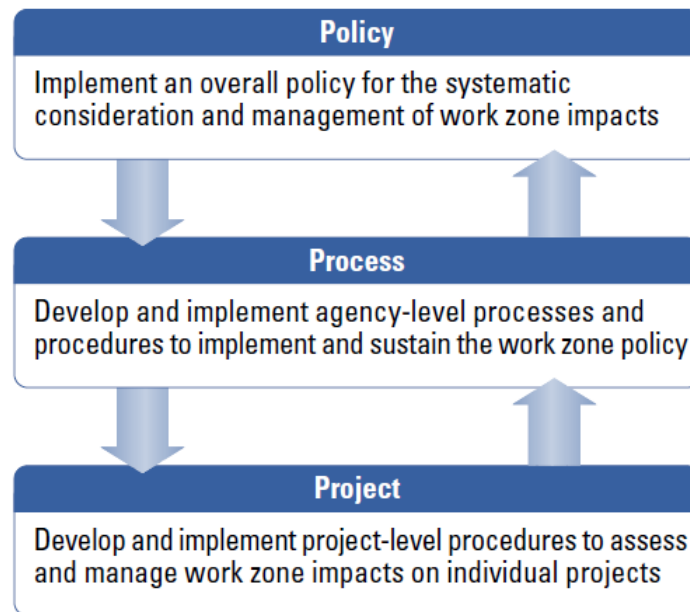


Figure 1. Implementing the rule on work zone safety and mobility (4)

Also, the rule encourages agencies to develop and implement Traffic Management Plans (TMPs) for work zone impact assessment specifically for “Significant Projects”. This rule defines significant projects as the projects that will cause a relatively high level of disruption and impact on traffic mobility and safety. The rule defines that developing a TMP for a significant work zone project contains an iterative process which attempts to revise the TMP as needed to optimize the work zone management strategy effectiveness. That is, assessing work zone impact starts in planning/design phase of the project, and practitioners initiate a preliminary work zone impact assessment along with developing a basic TMP. The developed TMP is then assessed more in detail based on the overall applicable policies and technical assessments; afterwards, the TMP is finalized and construction phase of the project starts. In the construction phase of the project, the rule requires agencies to monitor work zone impact using performance measures and revise the TMP as needed. After the project is completed, the rule requires agencies to conduct post-project evaluation using performance measures to update and revise implemented policies and procedures. This iterative process is shown in Figure 2.

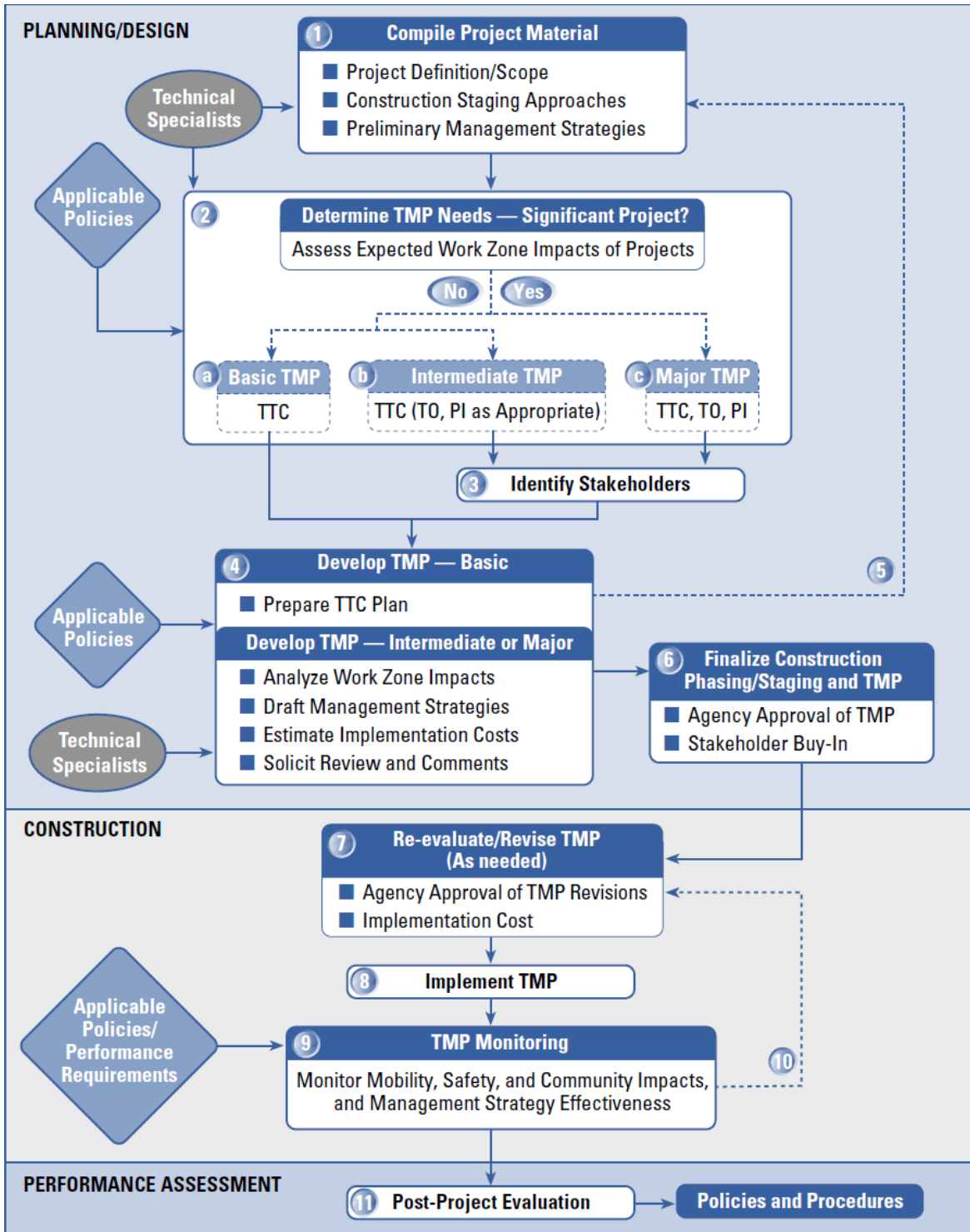


Figure 2. A process for TMP development (4)

The main rule implementation guide (4) provides guideline and sample approaches that can be applied by transportation agencies to improve safety and mobility in and around work zones. Figure 3 demonstrates policy development and implementation process of the rule for each significant project. These steps start with developing a policy and setting goals and objectives for the work zone projects. After policy development, it continues to apply the policy to program delivery stages. A crucial step in policy development process is performance assessment which provides the opportunity for agencies to refine and update their policies in future.

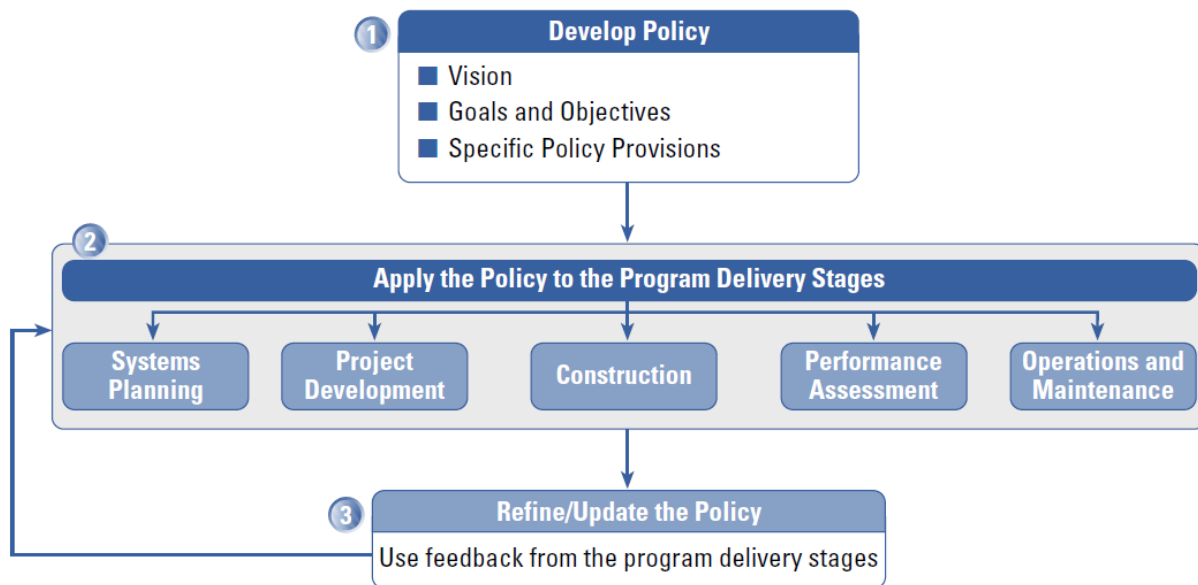


Figure 3. Policy development and implementation process (4)

Although previous studies have used different approaches to address work zone monitoring, data-driven approaches have not been studied and utilized adequately in the past due to lack of data availability. Agencies use different work zone operational strategies to conduct their work zone projects. However, there have not been adequate studies to assess and forecast the performance of each of these operational strategies. Data driven methods have been used in other practices extensively and have shown great applicability and reliability. This approach can

also be used in work zone management which facilitates this opportunity to characterize and forecast mobility impacts of different work zone strategies in the future.

Research Objectives

The overall objective of this study is to develop data-driven approaches to measure and predict mobility for freeway work zones along with an approach to provide useful information for work zone decision-makers. This includes the following specific objectives:

1. Develop a systematic approach to measure and visualize the impact of work zones
2. Predict the impact future work zones will have on interstate's mobility
3. Develop a decision-making support approach to better plan future work zones

Research Scope and Contribution

This study is devoted to the development of methodologies for performance measurement, prediction, and decision-making for interstate work zones in state of Michigan. The work zones categories included in this study were from shoulder-lane to multiple-lane closures. Both spatial and temporal impact of work zones were considered to characterize mobility using several delay and queueing metrics. The methodology was performed for partial closures in which the traffic is restricted to use fewer lanes for travel and the traffic is not crossed over the median.

Dissertation Organization

Chapter 1: Description and significance of the problem, research objectives, tasks and contributions.

Chapter 2: Review of existing literature on various approaches used in work zone mobility measurement and prediction.

Chapter 3: Description of the methodology to use probe vehicle data to monitor and measure the work zone mobility along with a description of the mobility metrics used.

Chapter 4: Description of the methodology utilized to audit mobility for work zones using probe vehicle data along with case studies showing its applicability.

Chapter 5: Description of the methodology to apply machine learning algorithms to predict spatiotemporal mobility for future work zones.

Chapter 6: Description of the methodology to characterize work zone mobility in a state-wide level. In addition, a discussion of the methodology to identify and rank significant projects which account for majority of the overall negative impact. Description of a statistical approach is discussed which can provide more actionable information for work zone mobility decision makers.

Chapter 7: Conclusion and Recommendations

CHAPTER 2 LITERATURE REVIEW

Work zone lane closures cause a restriction of highway capacity; therefore, commuters experience excessive delay specifically during peak hour periods. This review section firstly reviews parameters that impact work zone capacity. Thereafter, work zone impact assessment and prediction approaches are reviewed.

Parameters Affecting Work Zone Performance Measures

Work zone capacity has numerous parameters, and previous studies have identified the parameters which most impact work zone capacity. In 2012, Weng and Meng (7, 8) identified 16 important parameters that impact work zone capacity (Figure 4).

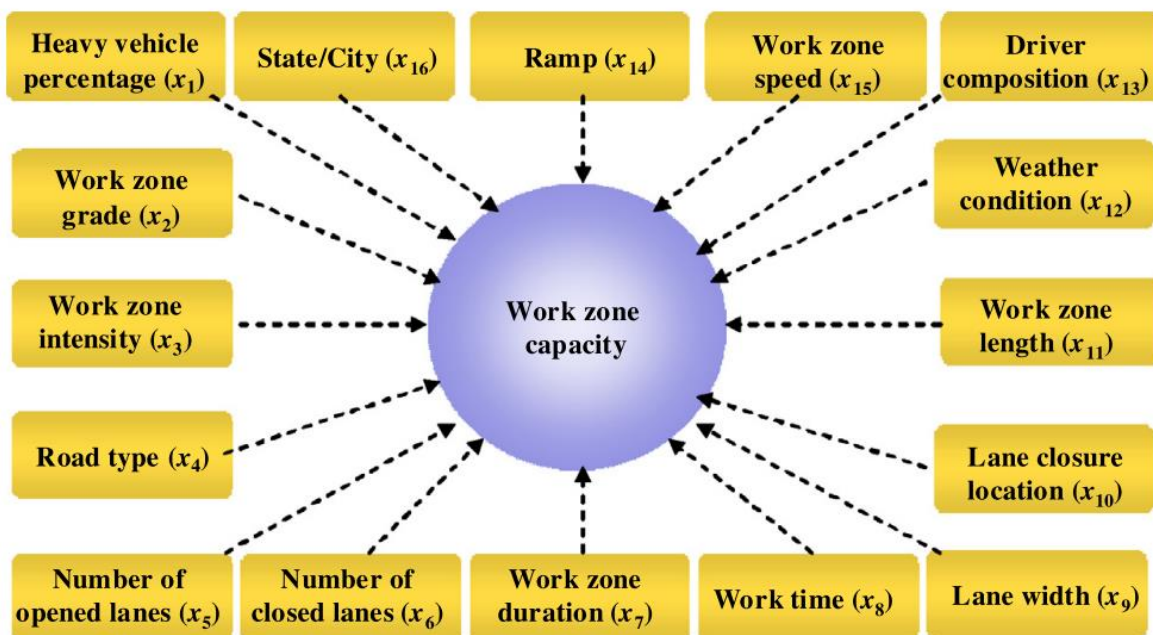


Figure 4. Sixteen factors affecting work zone capacity (7)

These parameters are generally categorized into five groups: 1) work zone configuration, 2) roadway geometry and location, 3) work activity characteristics, 4) environmental characteristics, 5).traffic characteristics (Figure 5).

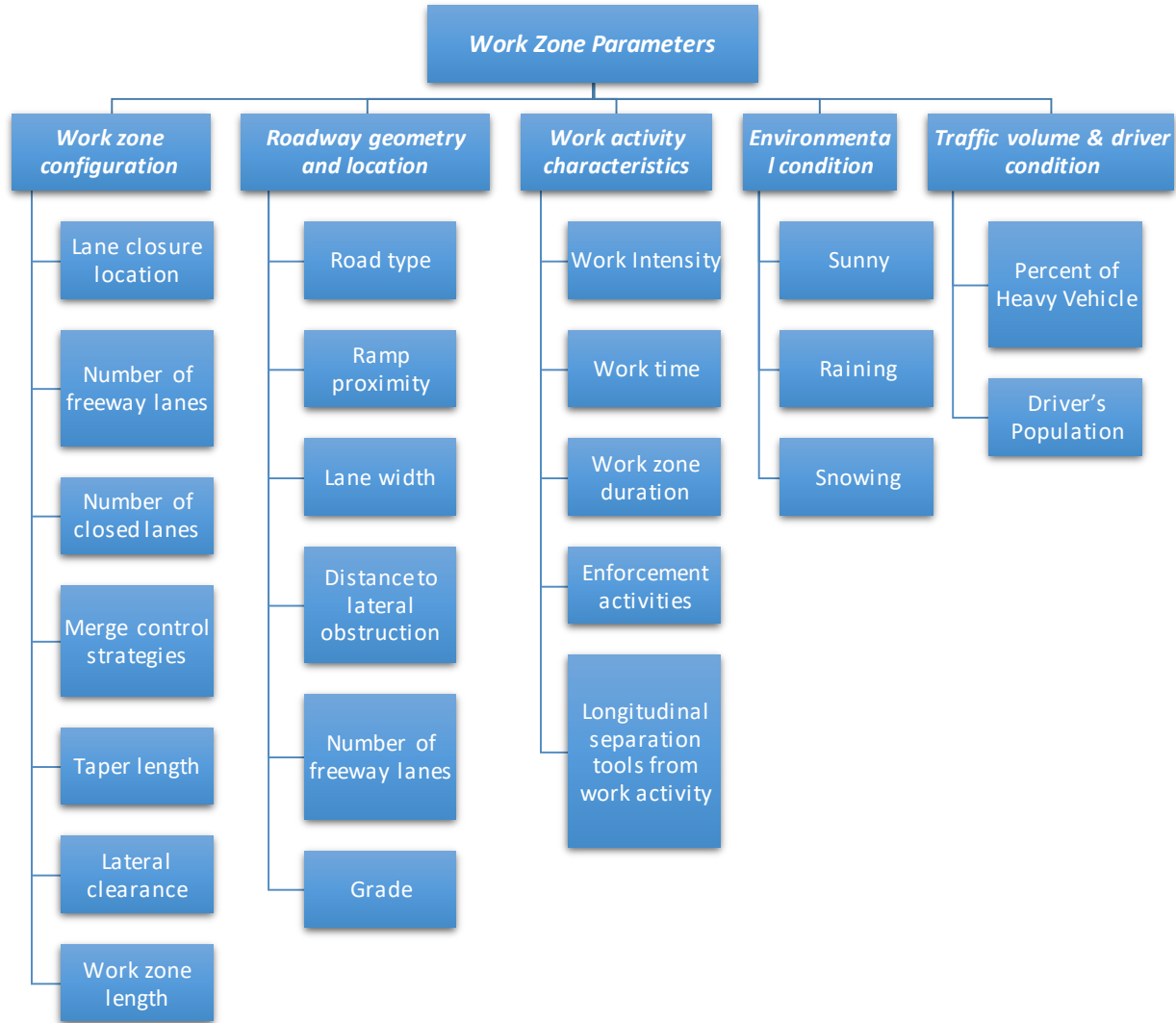


Figure 5. Parameters affecting work zone performance measures

In the following sections, each of these categories and studies which considered these parameters are reviewed separately.

Work zone configuration

Work zone configuration includes factors such as number of closed lanes, lane closure location, work zone length, lateral clearance, taper length, and merge control strategies (Figure 6). In 1980s and 1990s, studies on freeway work zones in North Carolina (9) and Texas (10,11) illustrated that work zone capacity depends on both freeway number of lanes and number of lane

closures. Moreover, there have been other studies to determine impact of work zone length on work zone capacity. In 2001, Kim et al. (12) concluded that longer work zone length results in lower capacity. However, in 2009, Heaslip et al. (13) found that work zone length could not significantly affect the capacity

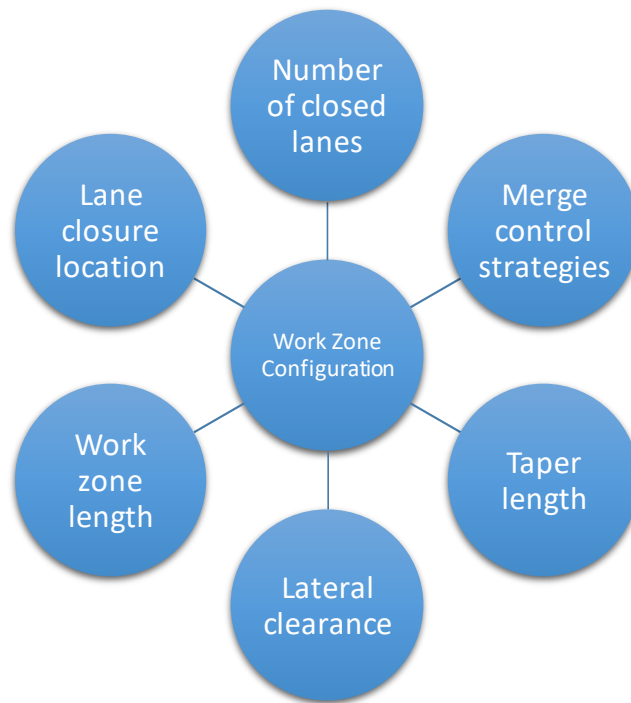


Figure 6. Work zone configuration elements

Roadway geometry and location condition

Roadway geometry and location characteristics also impact work zone capacity. These parameters include number of freeway lanes, type of road (urban or rural), ramp proximity, lane width, roadway grade, and distance to lateral obstructions (Figure 7). In 1996, a study by Dixon et al. (9) compared work zone capacity in rural and urban roads in North Carolina and concluded that the capacity on an urban road is usually 20-30% more than that on rural roadways. In addition, presence of ramps near the work zone area can affect work zone capacity. HCM 2010 states that presence of entrance ramp in work zone area can create traffic turbulence and negatively impact

the capacity (2). Also, distance to lateral obstructions could disturb driver's behavior in work zone area which results in capacity reduction. According to HCM 2010, lane width also impacts the capacity, and capacity reduction factor of up to 14% is suggested to account for the effect of lane width. In addition, roadway grade also affects work zone capacity. Kim et al. (12) concluded that roadway grade can negatively impact the capacity specifically with the presence of heavy vehicles.

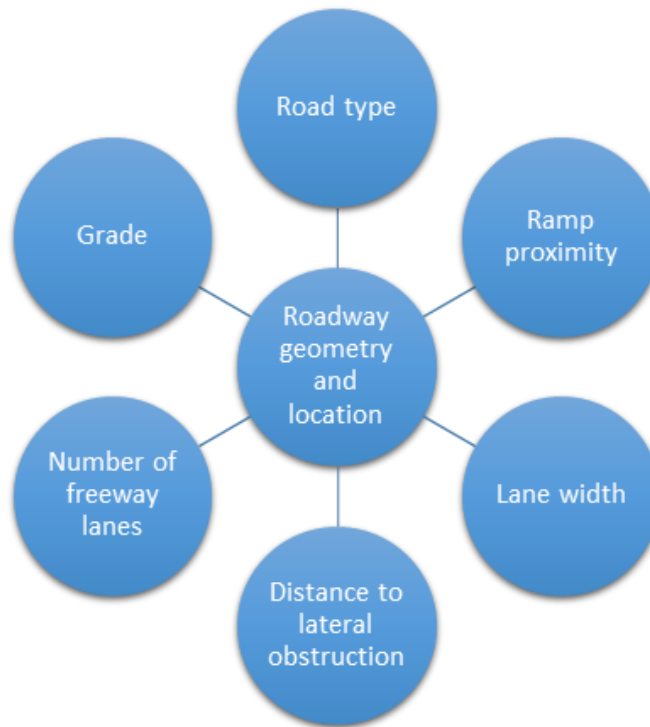


Figure 7. Roadway geometry and location elements

Work activity characteristics

Work activity characteristics include work intensity, work time, work zone duration, enforcement activities, and longitudinal separation tools from work activities (Figure 8).



Figure 8. Work activity characteristics

Work intensity is defined as the type of construction activity. Construction activities can vary from guardrail installation, which requires a short-term lane closure, to bridge repair, which demand long-term lane closures with significant amounts of activities. HCM 2010 (2) recommends modification of work zone base capacity to account for work intensity, however it does not provide any guideline to define categories and their modification factors. Previous studies have classified work intensity into different categories subjectively. For instance, a study by Karim and Adeli (14) which used three categories (low, medium, and high) and another study by Adeli and Jiang (15) which used six categories (Figure 9).

Intensity level	Qualitative description	Work type examples
1	Lightest	Median barrier installation or repair
2	Light	Pavement repair
3	Moderate	Resurfacing
4	Heavy	Stripping
5	Very heavy	Pavement marking
6	Heaviest	Bridge repair

Figure 9. Categories of work intensity in work zones (15)

Another element of work zone activities is the time of work, which categorizes work zones into nighttime or daytime periods. In 2001, a study by Al-Kaisy and Hall (16) found that commuters pay less attention during nighttime periods which results in a reduction of nighttime work zone capacity compared to daytime periods. Another aspect of work zone activities is the temporal duration of a work zone which is categorized as short-term (less than a day), intermediate (one to three days), or long-term (longer than three days). For light activities such as guardrail repair, lane closure can be as short as 0.5 hours, while major construction projects may last numerous years. Generally, short-term work zones create more turbulence in traffic flow because commuters do not expect any construction activities and are not familiar with work zone setup. Long-term work zones allow frequent commuters to become familiar with the work zone configuration and adjust their driving behavior which results in greater average capacity for long-term work zones compared to short-term work zones (7). Additionally, the speed limit is reduced within and adjacent to work zone areas to provide safe travel conditions for both the travelers and the workers. In 2003, a study by Adeli and Jiang (15) concluded that lower work zone speeds reduce work zone capacity. However, the compliance of travelers with reduced speed limit depends on driver's behavior and police enforcement. In 2011, a study by Wasson et al. evaluated spatial and temporal speed limit compliance for highway work zones with and without police enforcement (17). They found that even though police enforcement reduced traveler's space

mean speed by 5 mph, 75% of travelers exceeded speed limit in most of study segments even at the absolute peak of enforcement.

The last element of work zone activities is material and tools that work zone crew use to longitudinally separate work zone area from the moving traffic. These tools vary from traffic cones for short-term lane closures to concrete barriers for long-term work zones.

Environmental condition

Different weather conditions such as rain and snow impact work zone capacity. A study by Hainen et al. used probe vehicle data to characterize road conditions associated with inclement weather (18). They illustrated that roadway space mean speed decreased by approximately 20 mph during one of the winter storms they analyzed. HCM 2010 (2) recommends 10-20% capacity reduction to address inclement weather conditions without providing any specific guidelines.

Traffic volume & driver condition

Traffic volume consists of heavy vehicles and passenger cars. Generally, heavy vehicles travel slower than passenger cars and occupy more space. Heavy vehicles prevent passenger cars from accelerating and discharging a traffic queue since they have lower acceleration rates compared to passenger vehicles. These effects result in a reduction in work zone capacity for scenarios with high percentages of heavy vehicles (19,20). In addition, the traveling public consists of regular drivers who commute the route commonly, and visitors and tourists who are not familiar with the route. A study by Weng et al. concluded that the presence of visitors and non-regular travelers in work zone area reduces work zone capacity (7).

Current Work Zone Impact Analysis Approaches

Previous studies which predicted work zone delay can be categorized into four main approaches: 1) parametric, 2) non-parametric, 3) traffic simulation, and 4) big data analytics. The literature regarding each of these categories is provided separately.

Parametric Capacity Analysis

Parametric analysis of work zone delay generally is based on two theories: 1) deterministic queuing theory, and 2) shockwave theory. The deterministic queuing theory has been in practice for decades and widely used to predict work zone delay (8,10). This approach uses traffic volume, roadway capacity under normal and work zone conditions, and work zone duration as the main inputs to predict the work zone delay (8,21,22). This approach is suitable for work zone delay prediction in planning/design phase of work zone projects. However, it suffers from a lack of accuracy especially in fluctuating and congested traffic conditions (23). In addition, this approach has limited capability to assess work zone impact both spatially and temporally (24). Shockwave theory is another well-known approach used to predict work zone delay (25,26). This theory assumes that traffic flow is similar to fluid flow; as a result the flow-speed-density relationship is used to predict the traffic flow condition both spatially and temporally. This approach requires practitioners to identify several attributes of traffic such as jam density, roadway capacity, critical density, free-flow speed, and speed at capacity (27). However, collecting all of these features requires sufficient traffic volume and speed data which may not be available. Using these parametric approaches, researchers have conducted studies to identify work zone capacity. For instance, Krammes et al (19) recommended an updated capacity for short term freeway lane closures using data collected from 33 work zones in Texas between 1987 and 1991. A base capacity value of 1600 vehicle per hour per lane was recommended. They also proposed new adjustments for the effects of intensity of work activity, the percentage of heavy vehicles, and the presence of entrance ramps near the beginning of work zone lane closures. In addition, Dixon et al (9) proposed new work zone capacity values using an analysis of 24 work zones in North Carolina. They included speed-flow behavior analysis and evaluated work zones based on lane configuration and site location. They found that intensity of work activity and the type of study site (rural or urban) impacted work zone capacity significantly. For heavy work in a one to two-lane

work zone configuration, they recommended values of 1200 and 1500 vehicles per hour per lane for rural and urban areas, respectively. Also, Kim et al (28) used multiple regression modeling to investigate various independent factors that contribute to capacity reduction. They considered several primary factors which were the number of closed lanes, proportion of heavy vehicles, slope of the roadway, and intensity of work activity. They compared their proposed model with previously applied methods, and their model showed improvements in terms of model performance.

Non-parametric Capacity Analysis

Considering that numerous parameters affect work zone performance, a simple mathematical formula using parametric approaches is not adequate to predict both the spatial and temporal impact of work zone. Therefore, other studies have used non-parametric approaches such as Artificial Neural Network (ANN) and K-nearest neighbors methods (14,15,22,29). For instance, Adeli et al (15) applied an adaptive neuro-fuzzy logic model using seventeen factors to assess work zone capacity. They compared the new proposed model with two other previously proposed empirical models by Krammes and Lopez's (1994), and Kim et al (2001). The new model provides more accurate prediction of work zone capacity compared to the other two empirical models specifically when the data for parameters affecting work zone capacity are only partially available. In 2009, Castro-Neto et al (30) applied a supervised statistical learning technique called Online Support Vector machine, or OL-SVR, for the prediction of short-term freeway traffic flow under both typical and atypical traffic conditions. They found that OL-SVR has a better performance for non-recurring traffic conditions, such as work zones, compared to other well-known prediction models such as Gaussian maximum likelihood (GML), Holt exponential smoothing, and artificial neural net models.

Traffic Simulation

Traffic simulation has been another approach widely used to predict the impact of work zones. Simulation models are based on different traffic flow theories. Several studies have used traffic simulation to assess the impact of work zones. For instance, software packages such as CORSIM (31), VISSIM (32,33), QUEWZ (34), QuickZone (35), and Paramics (36) have been used to assess work zone impact. Once simulation models are calibrated and validated, they are capable of measuring work zone performance under different configurations. However, developing a simulation model requires extensive efforts to collect origin-destination traffic volume and speed data, high computational resources, time consuming calibration processes, and long running times (37). Since traffic volume data are not available for historical work zone case studies in Michigan, this study attempts to apply data-driven approaches using speed data as a substitute for traffic volume data.

Data Driven Analytics

Work Zone Mobility Data

In the past, collecting work zone mobility data was performed using manual labor-intensive data collection methods which typically involved personnel recording speed and queue length during preselected hours at work zone locations. Further developments in data collection technology introduced automated systems to collect mobility data (38). License plate recognition systems have been used to collect travel times of vehicles through work zones (39). Researchers at Texas A&M University developed an approach using Global Positioning System (GPS) devices to monitor work zone mobility (40). Using roof-mounted GPS devices, travel time runs were performed to collect travel time, delay, and queue length information as key mobility-based performance measures. Researchers at Purdue University used Bluetooth technology to measure the travel time of vehicles through work zones (41). With the improvement and penetration of GPS enabled cell phones and navigation devices, third-party vendors have begun providing ubiquitous

crowdsourced probe vehicle data, which provides a representative speed for roadway segments for continuous time intervals. Researchers at Purdue University used this crowdsourced data to collect mobility data and examine the impact of an unexpected bridge closure in southern Indiana (42). The Vehicle Probe Project (VPP) was initiated in 2008 by the I-95 Coalition with the goal of enabling a wide-variety of operational and planning applications that require this high-quality data source (43). Using probe vehicle data, Remias et al published a series of Interstate mobility reports to characterize the congestion trends of Indiana Interstate highways (44,45). In 2013, researchers at the University of Maryland conducted a pilot project for FHWA to examine the applications of probe data in work zone performance measurement (46). The authors found that this data is sufficient to support work zone performance measures. In 2013, the FHWA published guidance on data needs, availability, and opportunity for work zone performance measures (47). The guidance illustrates that probe vehicle data can be used to assess mobility-based performance measures such as travel time reliability, delay, and queue length.

Big data analytics are relatively new techniques to assess work zone impact since work zone mobility data was not available in the past. However, several companies such as INRIX, HERE, and TomTom have recently started to provide speed datasets collected from GPS devices on roadways. A study by Du et al. (24) applied an ANN model to forecast spatial and temporal impacts of work zones incorporating probe vehicle data for the first time. They illustrated that this approach outperformed traditional deterministic modeling approaches. In their modeling approach, they used speed data instead of traffic volume data to train their model. Therefore, agencies that suffer from a lack of accurate traffic volume data can use this approach to predict their work zone impact. In another effort, Du et. al (48) developed a hybrid machine learning model incorporating road geometry, traffic volume, and probe vehicle data to forecast work zone delay. They used Support Vector Machine (SVM) to predict work zone capacity values based on HCM suggestions. Then, they used the capacity value as an input for the ANN model to predict the

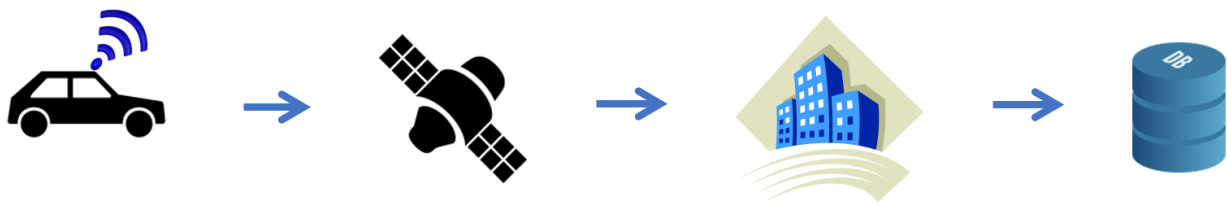
work zone spatiotemporal impact. Their results showed that their new approach outperformed previous models in terms of in terms of the least root mean square error (RMSE).

Work Zone Mobility Prediction

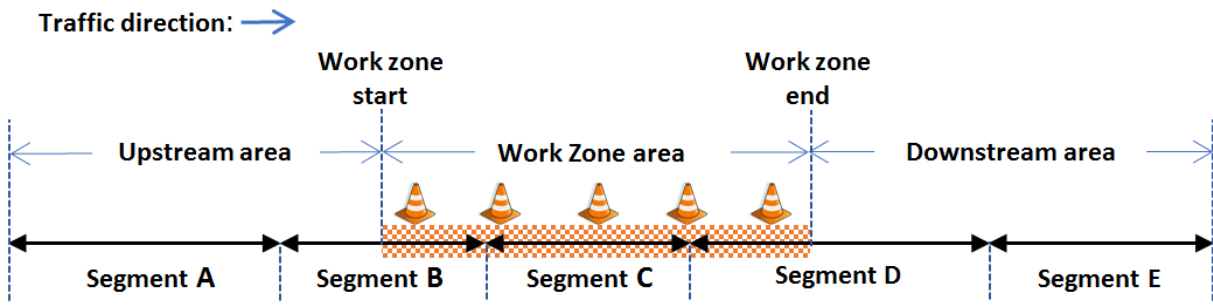
Although these data have been used extensively in recurrent traffic congestion prediction, there has been limited usage to forecast non-recurrent traffic congestion resulting from highway lane-closures. Du et al. used probe vehicle data along with an ANN model for estimating temporal and spatial freeway work zone delay (102,24). Du et al also forecasted work zone delay and cost using a hybrid machine learning model consisting of an ANN model with one hidden layer coupled with a Support Vector Machine (SVM) model. The SVM was initially used to predict and feed capacity to the ANN model for traffic speed prediction (48). In an earlier attempt, classification modeling was applied to predict speed ranges for each highway segment using historical speed data which were used to represent traffic volume (54). In the absence of traffic volume, distributions of historical traffic speeds were used to provide a mobility baseline for a Random Forest and XGboost classification algorithms. Historical observations were used to train and evaluate these models' performances when there were no traffic volumes in the data inputs. Although, these models showed a decent performance, there are various approaches that can improve the previous models including using additional parameters, applying resampling techniques, and applying different and more sophisticated modeling strategies. This study attempts to further previous studies by examining different resampling techniques to address imbalanced data set issues and applying a different mobility baseline. In addition, this study seeks to evaluate applicability of this approach with different work zone configurations in a larger scale.

CHAPTER 3 METHODOLOGY

This study will use Probe Vehicle data as a source for traffic mobility data. This data provides continuous average space mean speed of vehicles passing over a predefined segment of roadway over time. Figure 10a illustrates the process that probe vehicle data is gathered and stored in database. Figure 10b shows a work zone location relative to a hypothetical corridor which contains five Traffic Message Channel (TMC) segments. Also, Table 1 illustrates a sample of probe vehicle speed data with one-minute time interval.



a) Probe-vehicle data collection process



b) Segmentation Scheme

Figure 10. Probe vehicle data overview & work zone location.

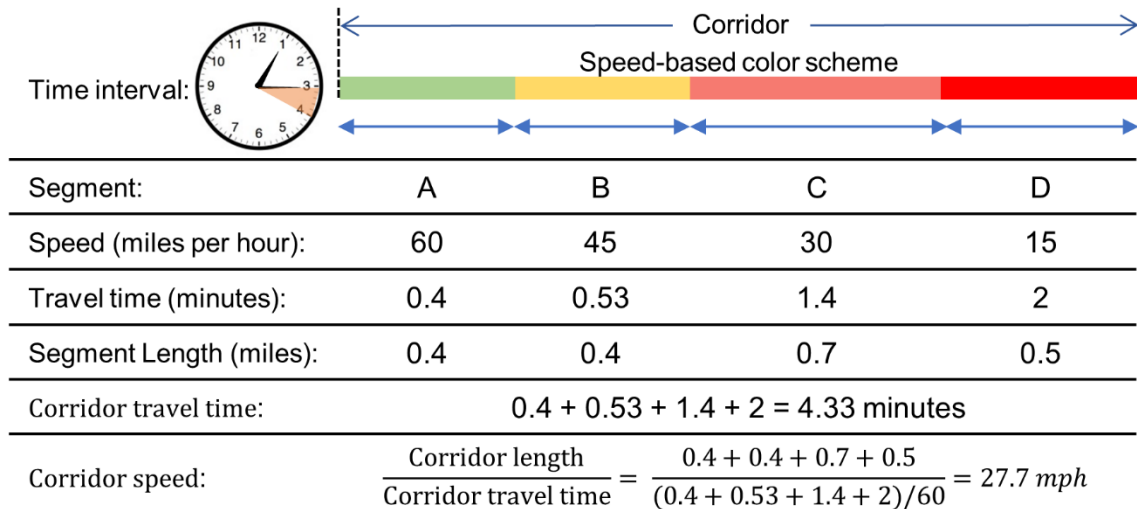
Table 1. Probe vehicle data sample.

Segment	Timestamp	Speed (mph)
A	2/1/2015 14:00	56
B	2/1/2015 14:00	50
C	2/1/2015 14:00	45
D	2/1/2015 14:00	53
E	2/1/2015 14:00	65
A	2/1/2015 14:01	59
B	2/1/2015 14:01	53
C	2/1/2015 14:01	48
D	2/1/2015 14:01	56
E	2/1/2015 14:01	68

Segment-Based & Corridor-Based Approaches

Two general approaches, segment-based and corridor-based, were applied to assess mobility for a work zone project. In the segment-based approach, mobility data were queried for each TMC segment and averaged for each five-minute interval. In the corridor-based approach, however, the average speed and travel time are calculated for the entire work zone corridor. Table 2 illustrates the average speed and travel time values for a hypothetical corridor. In this table, four TMC segments constitute a corridor, and the average of the speed and travel time values represents the conditions for a five-minute interval between 1:15 PM and 1:20 PM. In this five-minute interval, each TMC segment experiences different traffic conditions from near free flow (Segment A) to queue formation (Segment D). The aggregated corridor level speed is shown to be 27.7 mph. Corridor level metrics work well for key performance indices or summarizing high level trends. Segment level performance measures work well for locating exact problem areas and more in-depth analysis.

Table 2. Segment-based vs. corridor-based approaches.



Mobility Performance Measures

These performance measures are currently of interest to the FHWA due to the release of the MAP-21 National Performance Management Measures (NPRM). Performance measurement is an important aspect being used to transform the federal-aid highway program by providing a results-driven investment system. Expanding on the uses of these performance measure tools to incorporate work zones will provide numerous benefits to tax payers including:

- Opportunities to assess and improve the mobility of existing and future work zones
- Designing or adjusting traffic management plans to better suit individual work zones
- Identification of flexible start times to improve work zone mobility
- Reduction in costs by avoiding physical infrastructure
- Opportunities to incentivize contractors based on performance data
- Providing implementation-ready information

Numerous types of performance measures can and have been chosen by various states, which were previously discussed. For the purpose of the work zone mobility audit tool which will be shown later in this document, Mobility performance measures are categorized into delay and queueing metrics. For the delay metrics, a corridor-based approach was used to assess travel

time throughout the work zone period. These metrics are then compared with the typical corridor travel time to capture the impact of the work zone on traffic mobility. For the queueing metrics, a segment-based approach was used to assess mobility for each individual TMC segment separately. These metrics are defined in the following sections using simple and intuitive visualizations.

Delay Metrics

Probe vehicle data provides a representative speed for each TMC segment for a predefined time period, typically 1-minute. Using the speed, travel time can be calculated for each TMC segment for each of the time bins. An average of those travel times over each 5-minute bin can then be used to represent a segment's travel time. If all segments located in the work zone corridor had a representative travel time during each 5-minute bin, then these travel times were added together to calculate corridor's travel time during each 5-minute bin. It is important to mention that if there is a missing travel time for one segment throughout the corridor, the travel time values cannot be added together to represent corridor's travel time. After calculating work zone travel time, a typical travel time was required to assess the work zone impact on mobility. This typical travel time, also called mobility baseline, is defined as 50th percentile of travel times from the prior year of the work zone with the same season, day of week, hour of day, and 5-minute bin.

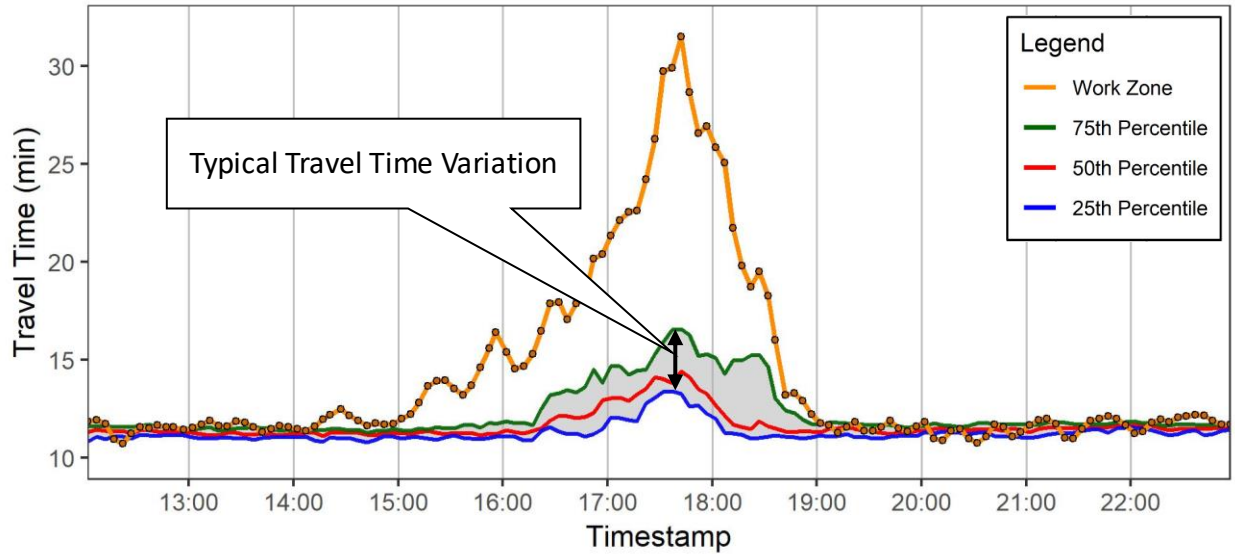


Figure 13. Work zone travel time variation

Figure 13 illustrates work zone travel time along with distribution of travel times from the prior year. The prior year travel times are pulled for the same season and day of week. For instance, for a work zone that happens this year during a summer month on a Monday afternoon, travel time values for all Mondays during the previous summer are queried first. Then, these travel times are aggregated together for each hour of day, and each 5-minute bin. Using these travel times, a distribution of travel time for each 5-minute been is captured. The gray band on the Figure 13 shows the travel time variation for this corridor on a typical Monday. The blue line shows 25th percentile of travel times, and the green line shows 75th percentile of travel times as the lower and upper edge of the gray band, respectively. The 25th and 75th percentile of travel times were used to capture majority of travel times that were experienced in the prior year. Also, this approach, naturally, disregards outlier travel times which could be the result of a crash or another work zone from the prior year.

a) Delay Definition

In this study, the 50th percentile of travel times was used as a representative typical travel time. Delay is defined when work zone travel time exceeds the typical travel time. The delay metrics such as total delay, average delay, and maximum delay are then calculated comparing work zone travel time with the defined typical travel time.

b) Total Delay & maximum user delay

Figure 14 shows work zone travel times (orange line) compared with typical travel times (red line). As shown, the gray area between red and orange line show the total delay caused by the work zone presence. It is worth to mention that if work zone travel time falls below the typical travel time, there is no delay accounted for the work zone.

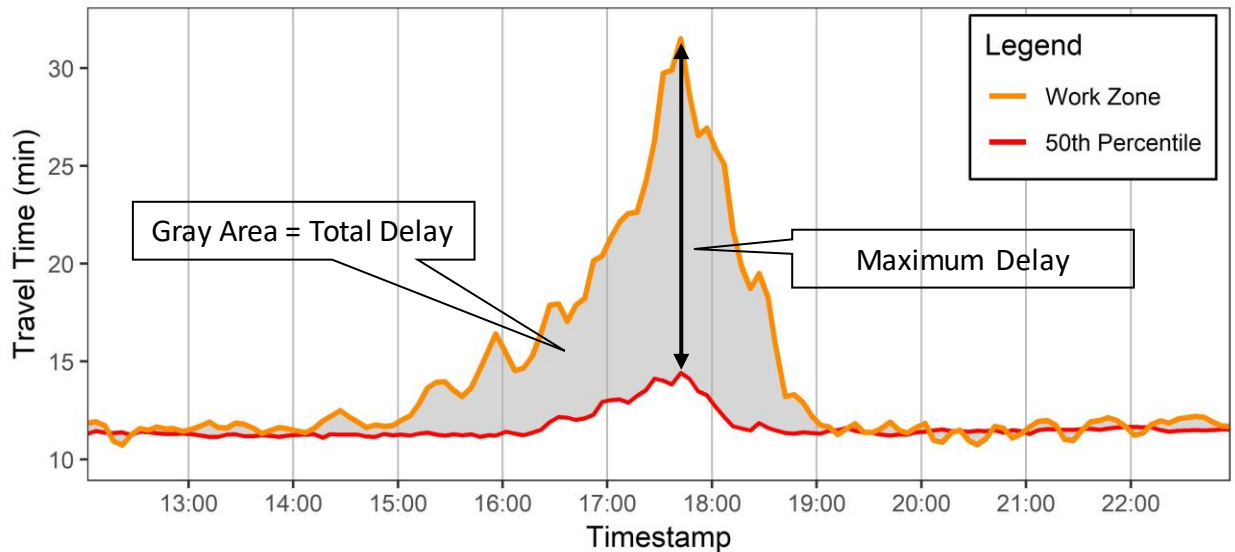


Figure 14. Work zone delay

The total delay metric adds all the delay record to provide a cumulative delay that was caused by a work zone. This Total Delay metric is different than what is typically defined as the total delay. Volume is not considered in this calculation. Instead, total delay is calculated as if one

vehicle drove the corridor every five minutes throughout the life of the work zone. If accurate hourly counts were collected by a DOT, this could easily be considered in the calculation.

Queue Metrics

Queue metrics are among the most important mobility metrics since the presence of a queue creates dangerous traffic conditions for commuters. When a queue forms on a highway, commuters who are approaching the back of queue are facing a high risk of rear-end type crashes which may lead to additional secondary traffic congestion and crashes.

Using the segment-based approach, the queueing condition is defined when at least one segment has a speed below 15 mph. The queueing metrics used in this study attempt to quantify different aspects of the queueing condition including maximum queue duration, total queue duration, maximum queue length, and number of queue events. These metrics are discussed in the following sections. All of these metrics are calculated using segment-based approach.

a) Queue Identification Using Probe Data

The severity of the traffic interruptions depends on the number of lanes and the traffic volume. When there is not enough capacity for traffic, vehicular speeds reduce and congestion propagates to upstream segments. As this congestion propagation continues, the upstream traffic segments experience lower traffic speeds. Using probe vehicle data, these speeds were available to investigate historical lane-closure projects. These traffic speeds ranged from zero miles per hour (mph), when vehicles are stopped in a queue, to greater than 70 mph when traffic was operating in free-flow conditions. Figure 11 illustrates how traffic congestion propagates to upstream segments over time and space.

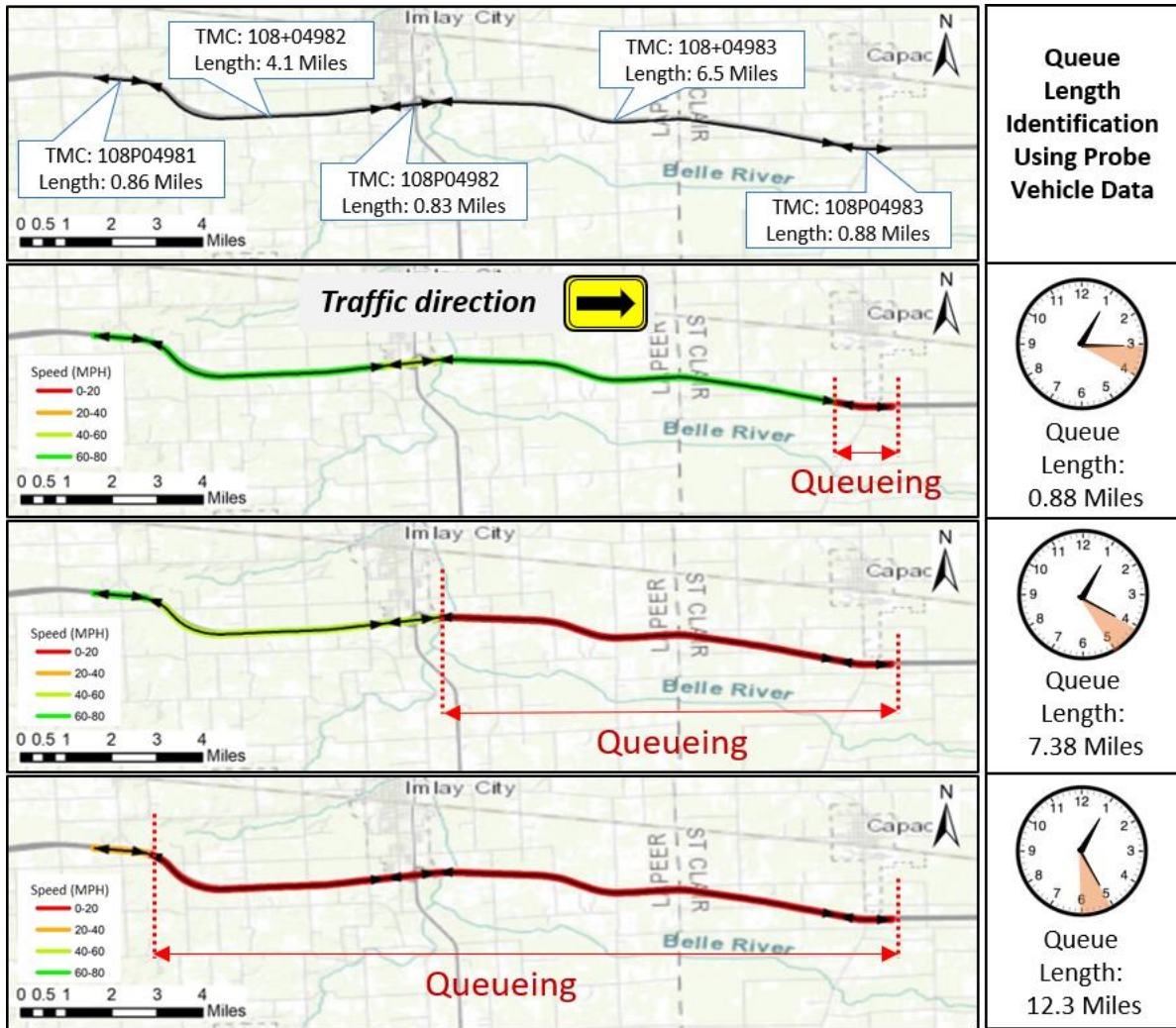


Figure 11. Congestion propagation identification using probe vehicle data.

b) Maximum Queue Length

The maximum queue length metric uses cumulative length of segments that were experiencing a queueing condition at each time interval. Then it returns the highest value as the maximum queue length for a work zone.

c) Maximum Queue Duration

The maximum queue duration metric captures the longest duration (minutes) in which the queueing condition was present on a roadway. For example, if the maximum queue duration was

40 minutes, it means that at least one segment had a speed below 15 mph for 40 consecutive minutes.

d) Total Queue Duration

Total queueing duration metric captures and adds all the time durations that queueing condition was present on the roadway throughout the duration of the work zone.

e) Number of Queueing

Number of queueing event metric counts number of distinct times that a queue occurs on a roadway. In this metric, a 10 minute threshold was used to separate major queueing events from each other. For instance, if the gap between two queueing events was 5 minutes, those two queueing events were combined into one queueing event.

Level of Travel Time Reliability

The FHWA recommends agencies keep their transportation network reliable for users. The FHWA uses four time periods to quantify reliability metrics. These time periods are morning (06:00-10:00), mid-day (10:00-16:00), evening (16:00-20:00), and weekend (06:00-20:00). To measure travel time reliability, the Level of Travel Time Reliability (LOTTR) metric was used for each of the defined time periods. This metric is defined as follow:

$$\text{Work Zone LOTTR} = \frac{\text{80th Percentile Travel Time}}{\text{50th Percentile Travel Time}}$$

The FHWA recommends agencies use 1.5 as a threshold for the LOTTR metric. High variation in LOTTR not only causes user dissatisfaction but it can also create hazardous traffic conditions since commuters are facing an unexpected traffic condition.

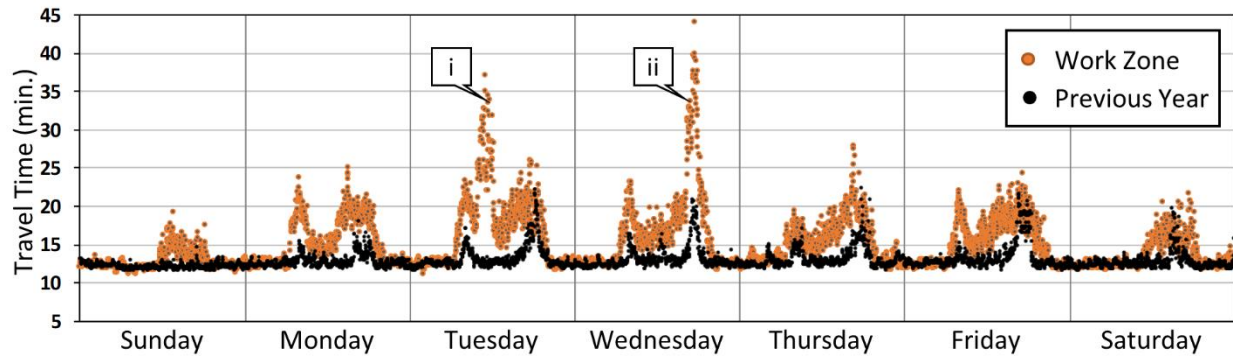
CHAPTER 4 WORK ZONE MOBILITY AUDIT

According to the FHWA (4), agencies are required to implement a procedure to mitigate safety and mobility issues caused by the presence of a work zone. Therefore, a Work Zone Mobility Audit (WZMA) framework was created to systematically assess work zone mobility. The WZMA is made up of four sections. The first section provides an overview, including a map of the work zone, location, dates of construction, AADT, and the type of work. The second section then provides visualizations that characterize the mobility of the work zone both spatially and temporally. A comments section is provided for contractors, engineers, and managers to note concerns or specific activities or anomalies that occurred during this work zone. The final section attempts to quantify the work zone impact on traffic mobility compared with the mobility baseline. A summary of mobility performance measures can assist agencies to assign a score for each of their work zone projects, compare it to similar cases, identify the projects that caused significant negative impact, and improve their future work zone management strategies.

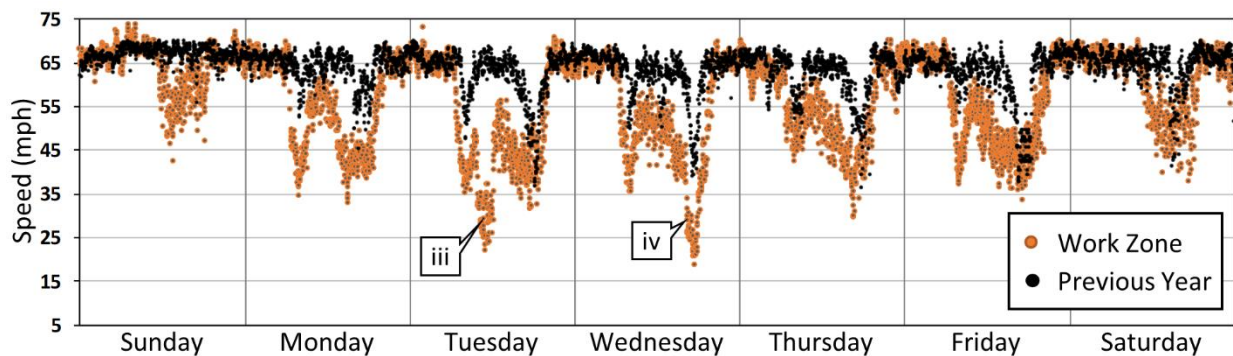
Temporal Monitoring

In temporal monitoring, the focus was to monitor work zone mobility over time. Identifying certain days of a week or hours of a day when a work zone had a significant impact on traffic would help practitioners evaluate Traffic Management Plans (TMPs) used for work zone operation. Therefore, practitioners can revise the TMP and implement a new strategy to mitigate a work zone's negative impacts. For example, Figure 12 shows representative speed and travel time measures for a week when a single-lane closure work zone was present on Interstate 75 in Oakland County, Michigan. Typical speed and travel time values are also shown on these graphs to provide an intuitive comparison for decision makers. Figure 2a shows travel times during a week in the middle of the work zone. Figure 12a callout 'i' shows a typically non-congested period during the mid-day where travel times exceeded 35 minutes through the work zone. Figure 12a callout 'ii' shows travel times in the PM peak period over double the travel time in the previous

year. These peaks can also be visualized as low speeds along the corridor in Figure 12b callout 'iii' and callout 'iv', respectively.



a) One week travel time



b) One week speed

Figure 12. Speed & travel time measures for a long-term work zone

Scatter plots are suitable to show general mobility trends; however, they do not provide an indication of system reliability. The FHWA recommends that agencies keep their transportation network reliable by reducing the variation in traffic mobility measures such as speed or travel time. Therefore, cumulative distribution functions (CDF) are used to monitor traffic mobility variation caused by work zone presence. The CDF plots illustrate the distribution of travel time while the work zone is present relative to the previous year. Three CDFs are shown in Figure 13 for the

AM, Mid-day, and PM periods. The AM period (Figure 13a) shows a median travel time during the work zone time period of approximately 16 minutes (Figure 13a callout 'i'), which is 3 minutes higher than the previous year. It is important to note that the slope of the CDF represents the reliability of the work zone. The typical conditions for the AM peak and Mid-day (Figure 13b callout 'ii') are relatively reliable, while the PM peak (Figure 13a callout 'iii') shows less reliable travel times.

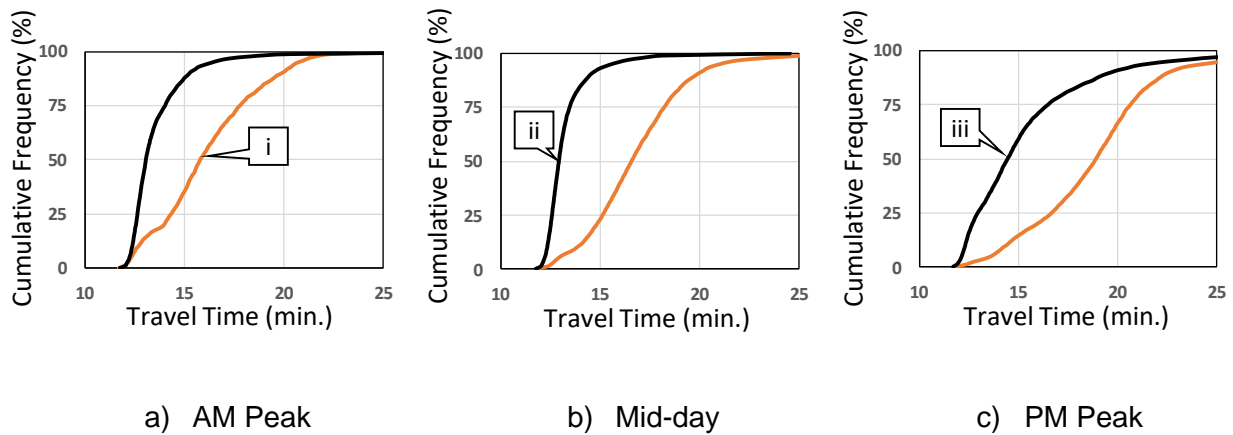


Figure 13. Work zone travel time CDF diagrams

Another important factor when considering work zone planning is determining the appropriate hours of a day to close traffic lanes. Probe vehicle data provides an opportunity for practitioners to aggregate this data based on different hours of a day. As a result, it identifies the least problematic time periods to conduct work zone activities. Figure 14 uses a radar plot to summarize the queue and congestion mobility measures for an I-94 work zone based on each hour of day. These graphs aggregate data over the work zone into a 24-hour graphic. Hour of day is found on the outer edge (Figure 14a callout 'i') and the aggregated performance metric for that hour is shown by the bands on the circle (Figure 14a callout 'ii'). These graphs show that the work zone corridor typically was experiencing minor congestion between 1600 and 1700 and negligible queueing. However, the work zone's presence caused congestion starting from 0700 to 1900

(Figure 14a callout 'iii') and queuing between 1500 and 1800, with the most severe queuing occurring at 1700 (Figure 14b callout 'iv'). These graphics are extremely helpful for agencies to determine if workers should be pulled off of a roadway at certain times.

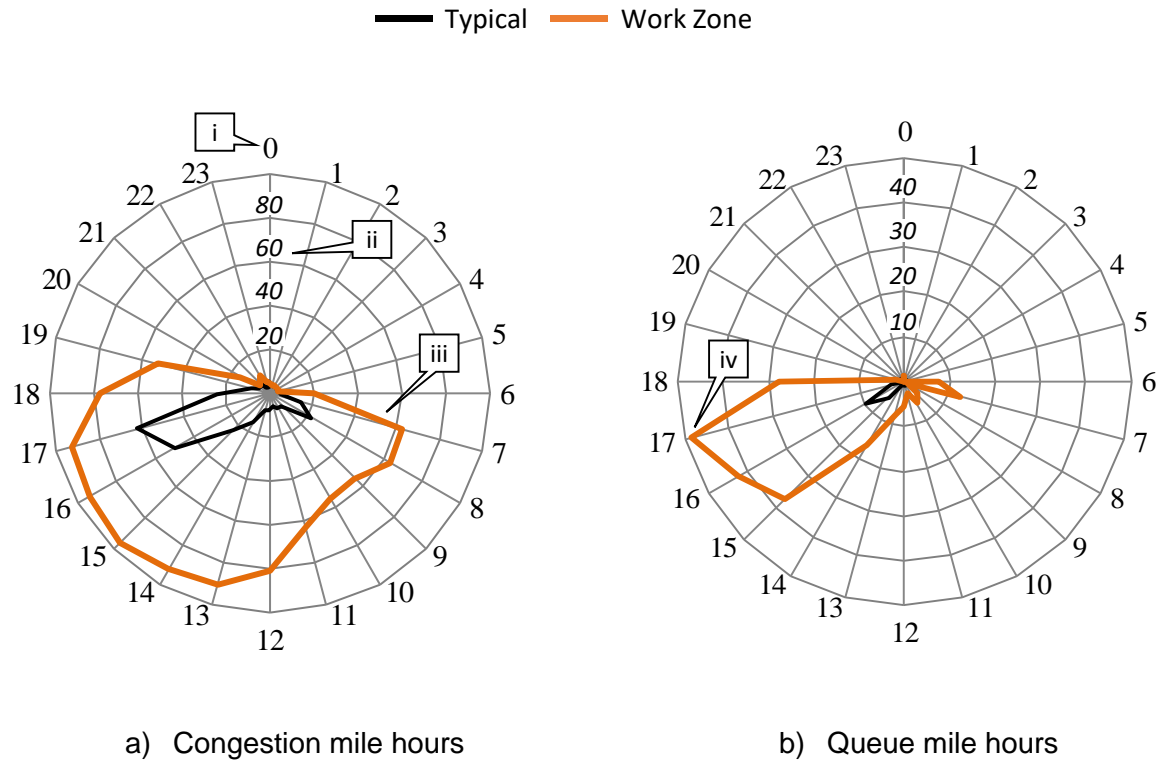


Figure 14. Radar chart: temporal mobility evaluation

Spatial Monitoring

Probe vehicle data provides the opportunity for practitioners to identify segments that experienced the most severe impact as a result of the work zone. Mobility measures for each TMC segment can be aggregated over a period of time and then visualized using a stacked area chart or “volcano” diagram. Figure 15 visualizes increased congestion (Figure 15a) and queuing (Figure 15b) for TMC segments in the upstream of work zone corridor for two months, while the work zone was taking place. This figure shows that the segments within the first five miles upstream of the work zone experience a significant negative impact.

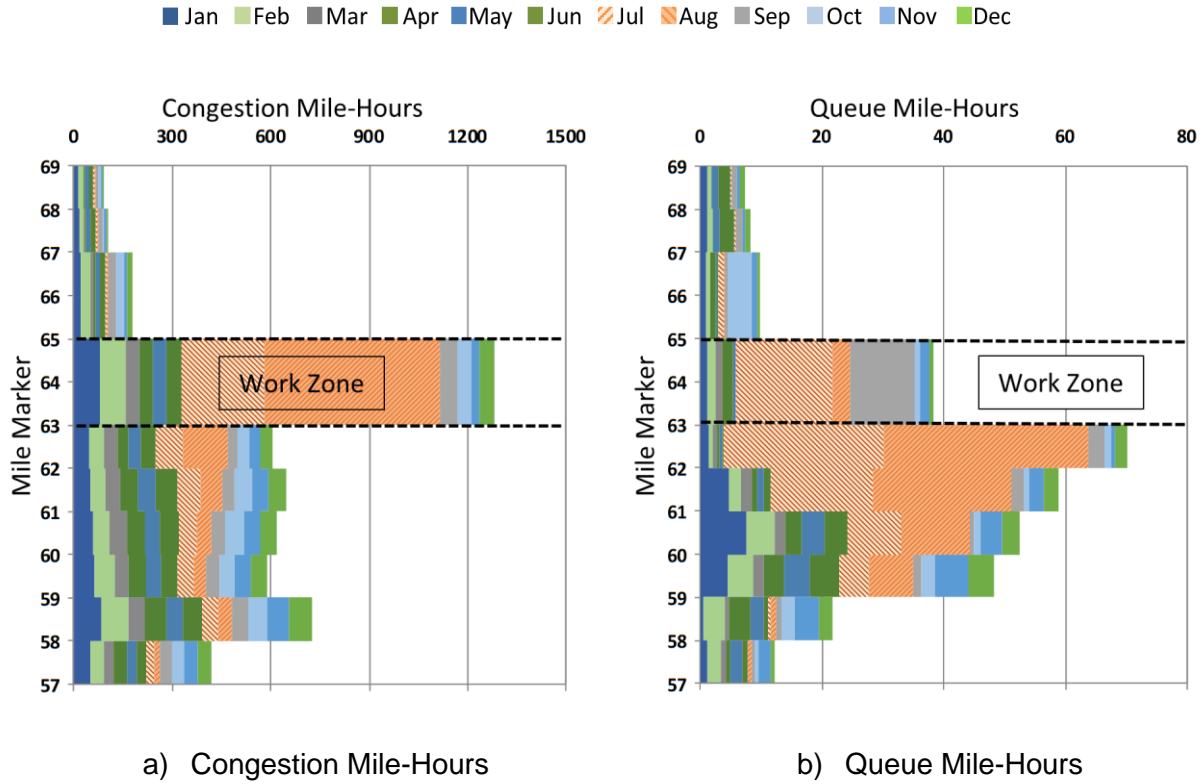


Figure 15. Volcano plot: segment-based mobility performance

Another way to visualize traffic mobility is to create a matrix of traffic speeds over time and space. Figure 16 shows a traffic speed heat-map in which the x-axis shows time and y-axis represents highway segments. This figure illustrates traffic speeds for each segment for a single-lane closure on northbound I-75 in Oakland County. This lane-closure was in place on a Tuesday in September of 2014. Traffic speeds are shown with a spectrum of colors from green to red to represent low speed and high-speed records, respectively. The yellow and red areas on the figure show traffic congestion while green areas show that traffic was operating at higher speeds.

During morning and off-peak hours, highway segments were serving traffic with high speed since there was sufficient capacity for approaching traffic volumes. However, traffic congestion happened during PM peak hour due to overwhelming traffic volumes for the remaining two lanes. As highway segments reached their capacity, traffic congestion propagated in the

upstream segments and traffic jam stretched up to about 9 miles. From the temporal perspective, this traffic congestion and severe slowdowns were experienced for five hours from 3 PM to 8 PM.

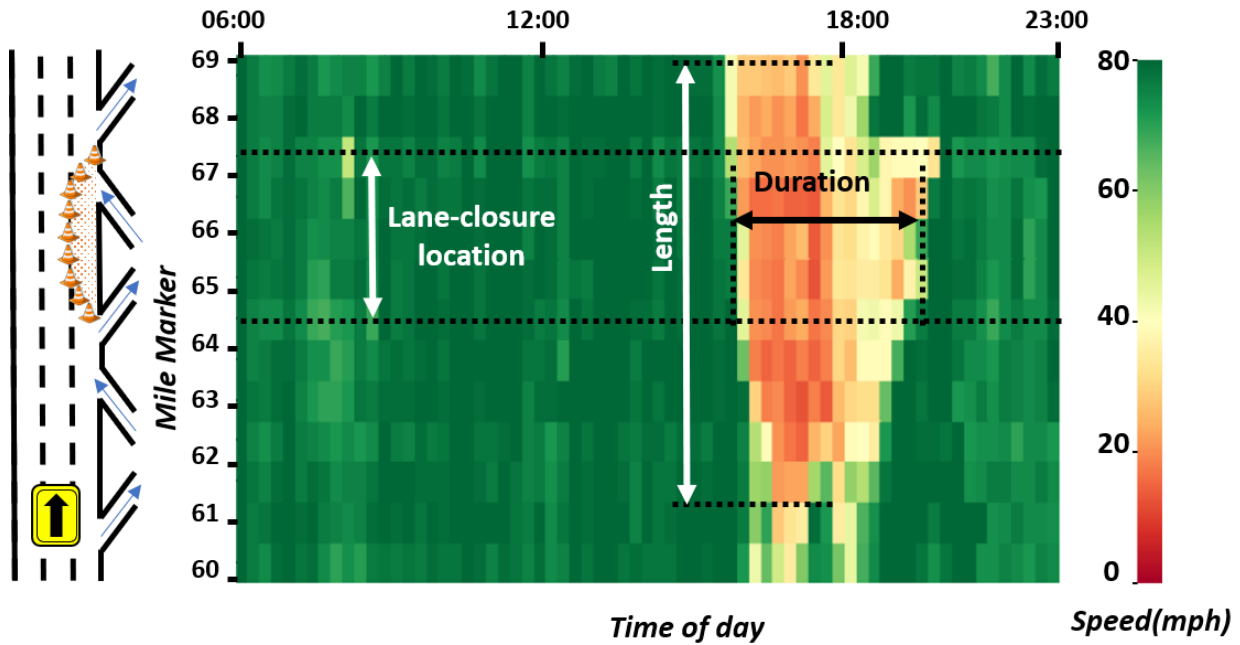


Figure 16. Speed heat-map for a double lane-closure event.

Case Studies

This section provides a series of WZMA sample case studies which were chosen based on different work zone traffic mobility scenarios. Each of these case studies shows the applicability of the WZMA in terms of identifying various traffic mobility impacts and highlights the impact in terms of duration, severity and frequency. These case studies are as follow:

- Work zone with recurrent and severe traffic congestion
- Weekend work zone with severe traffic congestion
- Work zone with moderate impact on traffic congestion
- Work zone with no impact on traffic congestion

A brief summary of these work zone impacts is provided prior to the WZMA of these case studies.

Case 1: Work zone with recurrent and severe traffic congestion

This case study provides an overview of a single lane closure on I-196 interstate highway which was conducted in August of 2016 between mile marker 68 and 70. Work zone activities lasted for 21 days including 5 weekend days and 16 weekdays. This corridor exhibited minor traffic congestion on typical weekdays and moderate traffic congestion on typical weekends based on travel time scatter plot. However, the presence of work zone caused severe traffic congestion during weekdays and moderate traffic congestion on weekends.

Throughout this project, severe traffic congestion happened in both morning and evening peak hours on weekdays while there was minor traffic impact on weekends. This lane closure increased travel time the most during the AM and PM peak periods at 8:00 AM and 5:00 PM by almost eleven minutes on average. Also, commuters experienced severe delay up to 44 and 53 minutes for AM and PM peaks respectively. In terms of travel time reliability, this work zone created an unreliable traffic condition throughout weekdays. Commuters experienced the worst unreliable traffic condition in AM peak with LOTTR of 1.6 which indicates 60% of increase in travel time compared to typical traffic condition.

In addition, this lane closure resulted in 84 queueing events with maximum queue length of 4.7 miles. The longest queueing event lasted about 5 hours on this corridor. Throughout the lifetime of this project, there were 77 hours that the corridor's traffic experienced queueing condition.

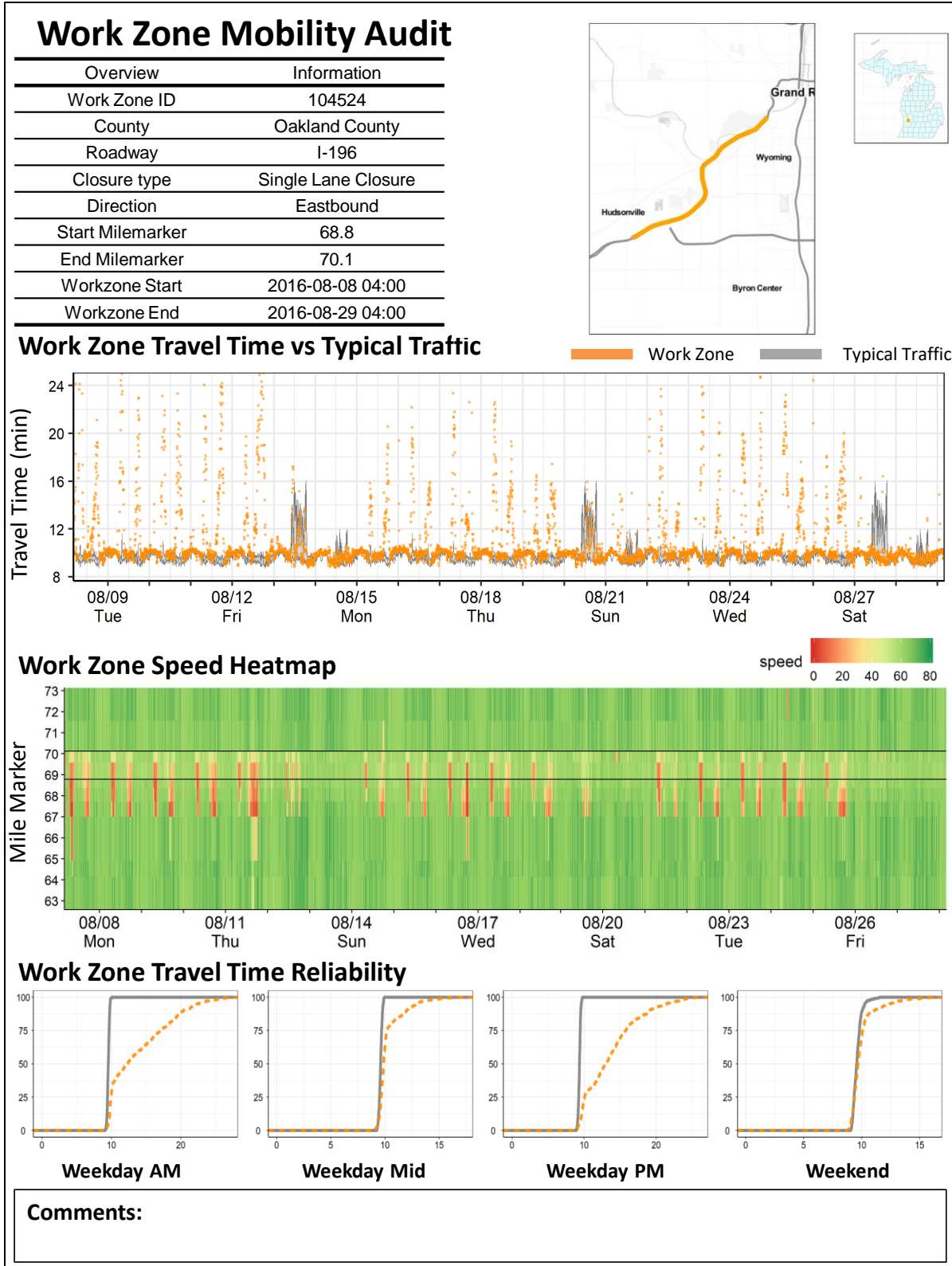


Figure 17. Case 1: Work zone with recurrent and severe traffic congestion, page 1.

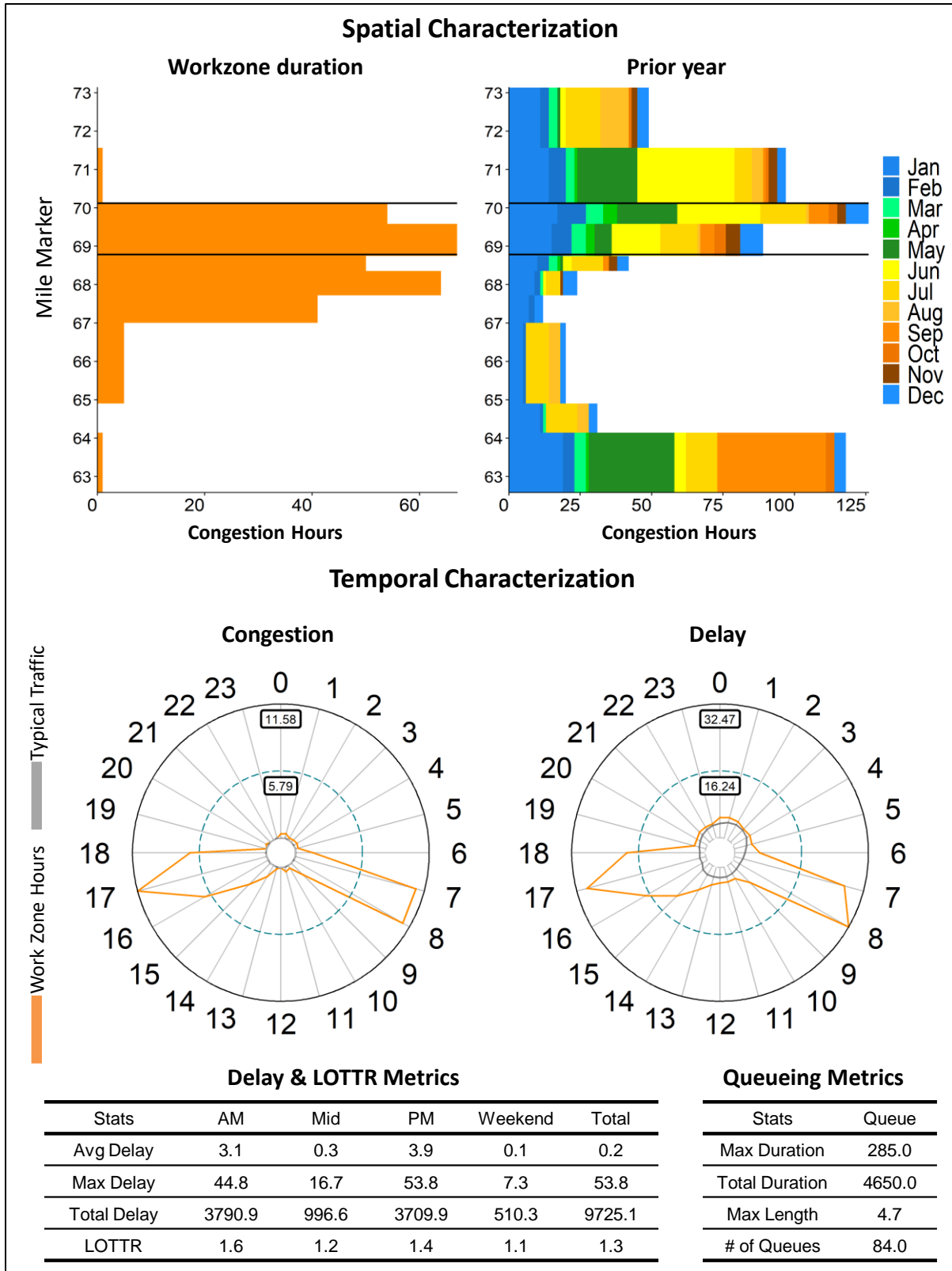


Figure 18. Case 1: Work zone with recurrent and severe traffic congestion, page 2.

Case 2: Weekend Work zone with severe traffic congestion

This case study shows a work zone project which was performed on eastbound of I-94 interstate highway from mile marker 195 to mile marker 201. In this project two traffic lanes were closed over a weekend on August of 2016. This corridor expects no traffic congestion on typical weekends based on travel time scatter plot, however presence of work zone caused severe traffic congestion and queueing.

Throughout this project, severe traffic congestion was experienced by commuters from 11 AM to 5 PM. This lane closure caused an average delay of 7 minutes and maximum delay of 29 minutes. In terms of travel time reliability, this work zone created an unreliable traffic condition throughout the weekend with LOTTR of 1.4 which indicates 40% of variation in travel time compared to typical traffic condition.

The most problematic hours during this weekend were from 11 AM to 5 PM with 100% congested condition. In addition, this lane closure resulted in 8 queueing events with maximum queue length of 5 miles. The longest queueing event lasted about 10 hours on this corridor. Throughout the lifetime of this project, there were 20 hours that the corridor's traffic experienced queueing condition.

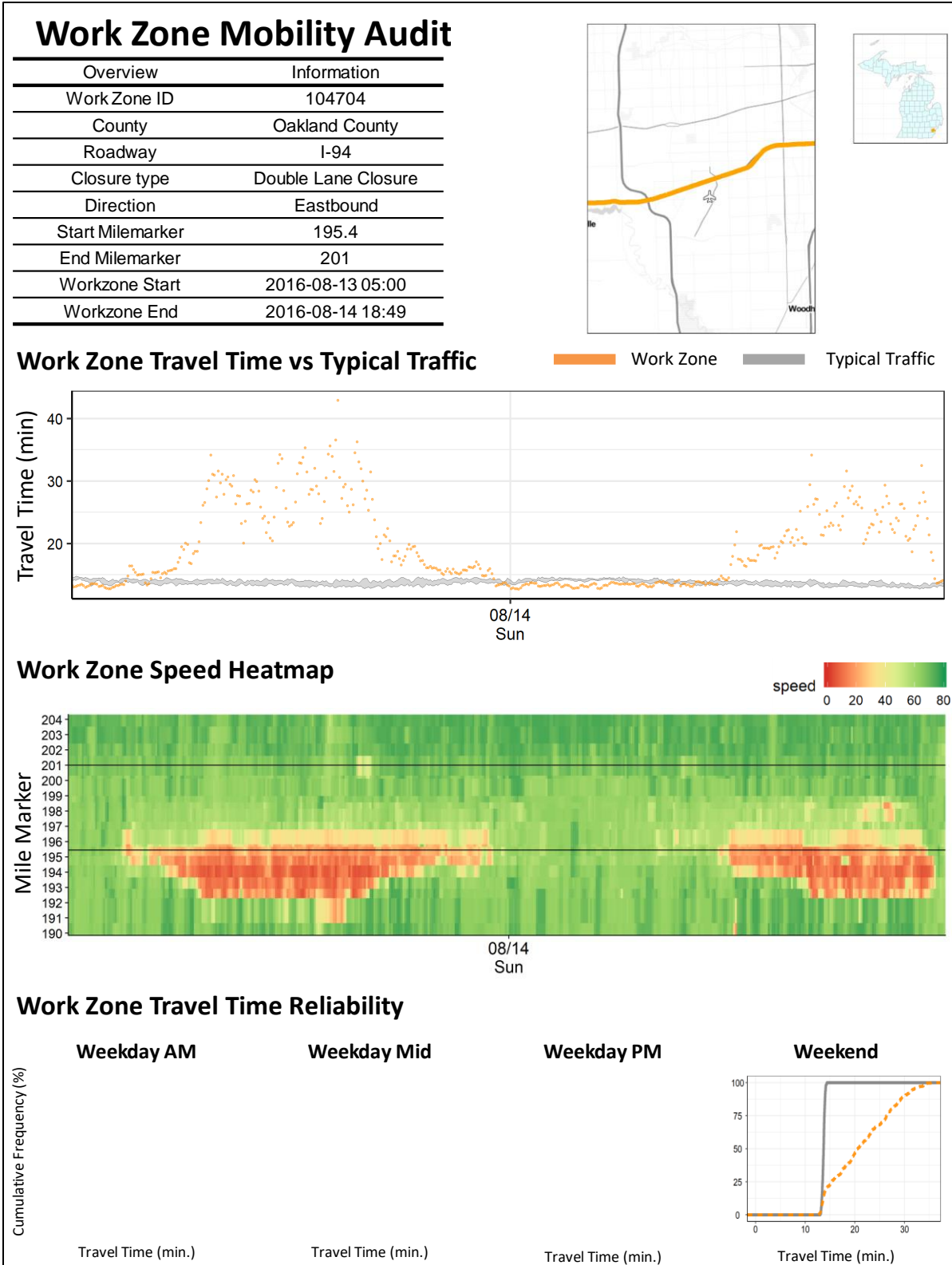


Figure 19. Case 2: weekend work zone with severe traffic congestion, page 1.

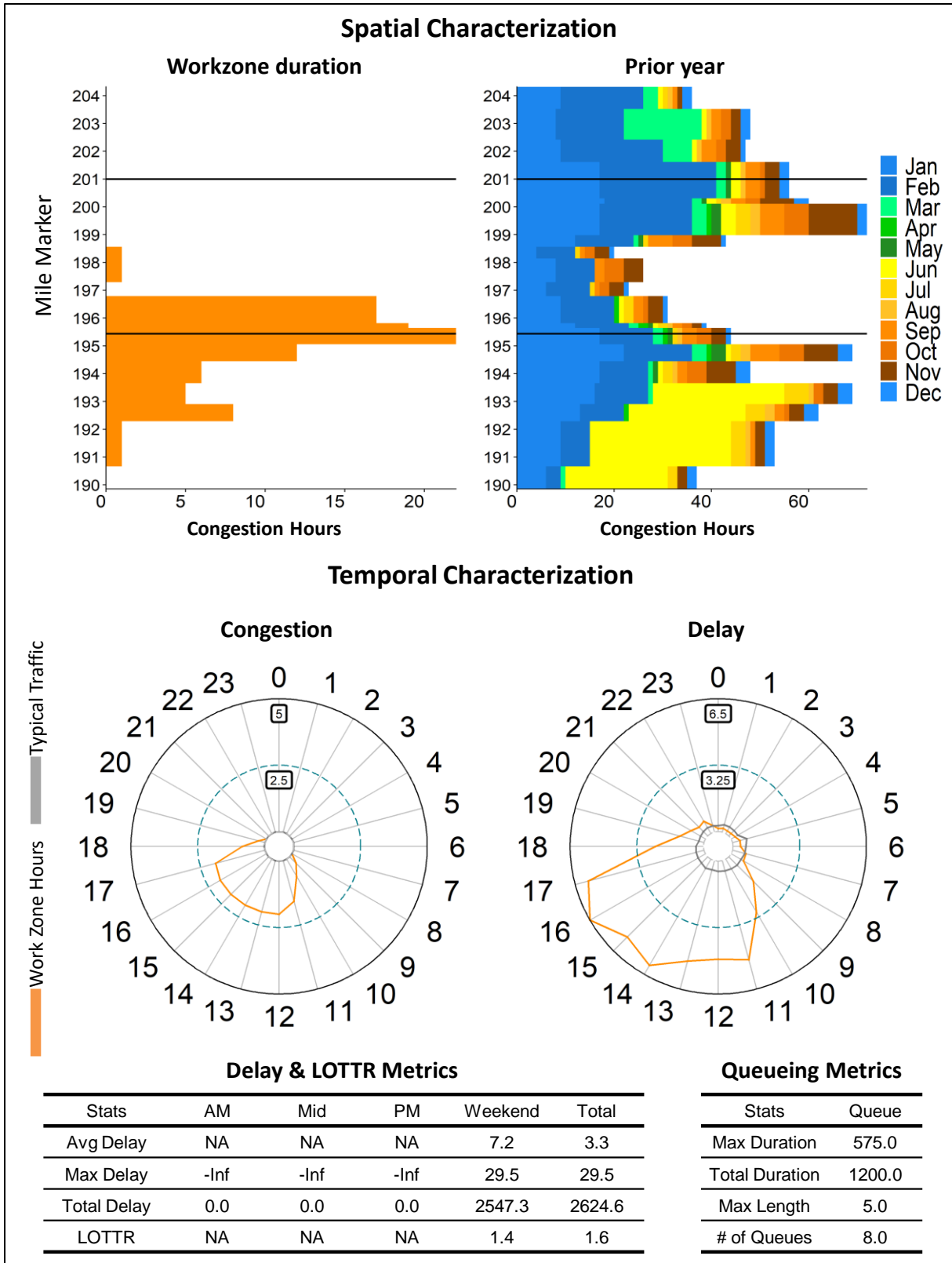


Figure 20. Case 2: weekend work zone with severe traffic congestion, page 2.

Case 3: Work zone with moderate impact on traffic congestion

This case study shows a work zone project which was performed on northbound of I-75 interstate highway from mile marker 73 to mile marker 76. In this project single traffic lanes were closed for more than two weeks during summer of 2016. This corridor expects moderate traffic congestion on typical weekends during peak hours based on travel time scatter plot, and minor traffic congestions on weekend. Presence of work zone on this corridor caused moderate increase in traffic congestion.

Throughout this project, moderate increase in traffic congestion was experienced by commuters from during PM peak hours starting from 3 PM to 5 PM. This lane closure caused an average delay of 2.6 minutes and maximum delay of 20 minutes during PM peak hour. In terms of travel time reliability, this work zone created an unreliable traffic condition throughout the PM peak hours with LOTTR of 1.5 which indicates 50% of variation in travel time compared to typical traffic condition.

The most problematic hours during this work zone were from 4 PM to 5 PM which were congested 80% of the time. In addition, this lane closure resulted in 39 queueing events with maximum queue length of 6.8 miles. The longest queueing event lasted about 3 hours on this corridor. Throughout the lifetime of this project, there were 38 hours that the corridor's traffic experienced queueing condition.

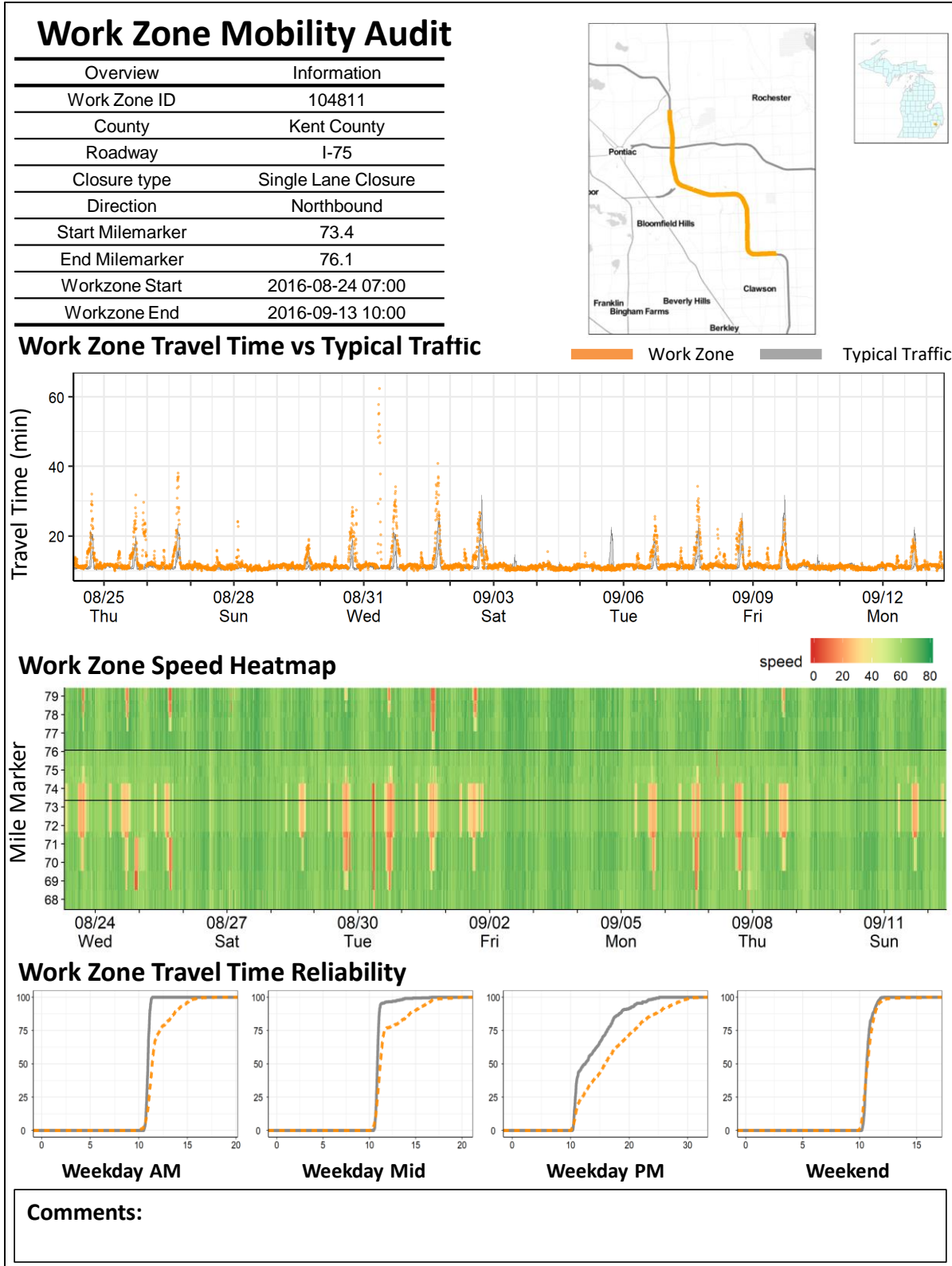


Figure 21. Case 3: long-term work zone with moderate impact on traffic congestion, page 1.

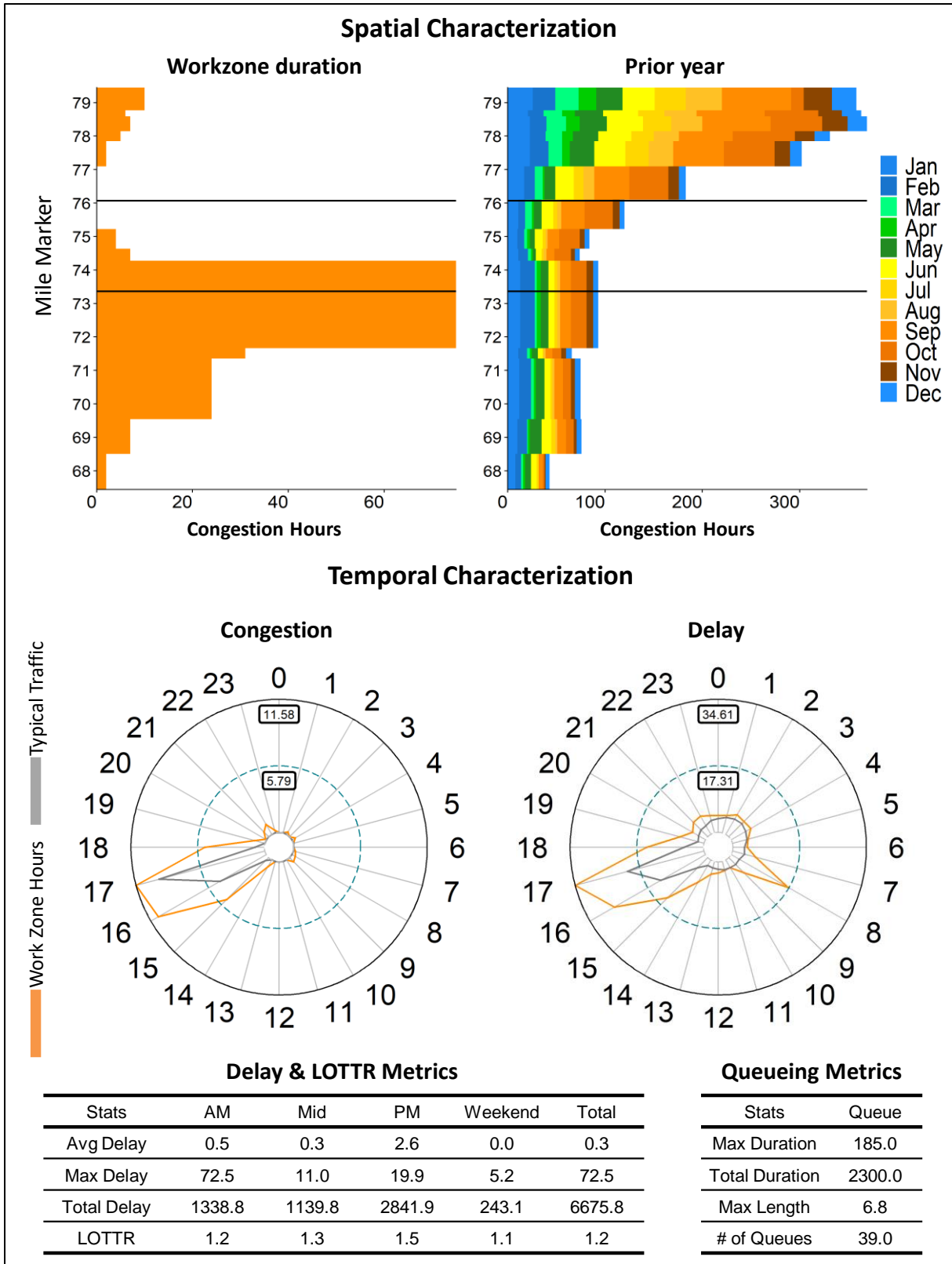


Figure 22. Case 3: long-term work zone with moderate impact on traffic congestion, page 2.

Case 4: Work zone with no impact on traffic congestion

This case study shows a work zone project which was performed on eastbound of I-60 interstate highway from mile marker 130 to mile marker 141. In this project single traffic lanes were closed for 10 days during summer of 2016. This corridor expected no traffic congestion on typical weekdays and weekends. The presence of a work zone on this corridor did not cause any increase in traffic congestion.

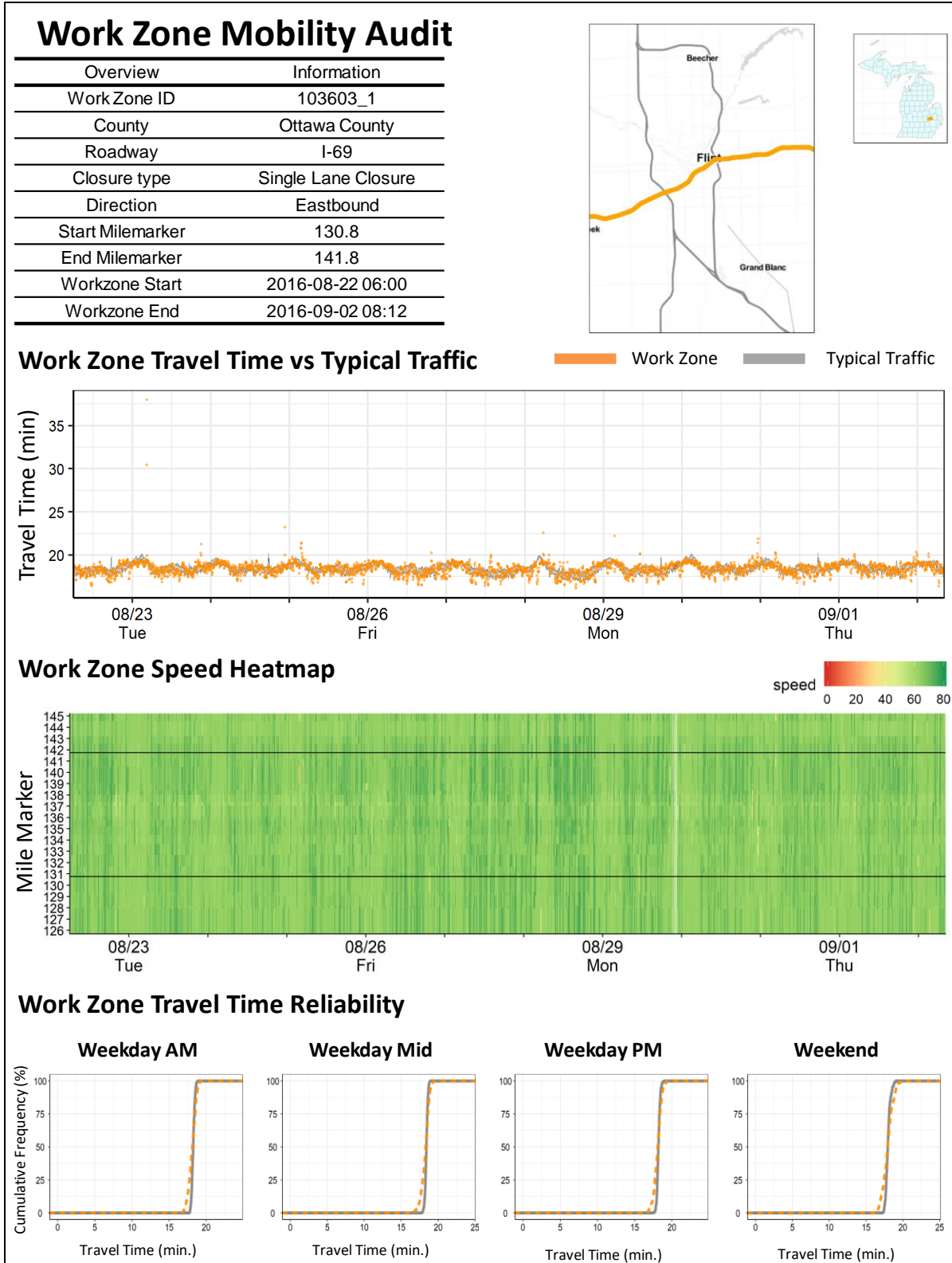


Figure 23. Case 4: work zone with no impact on traffic congestion, page 1.

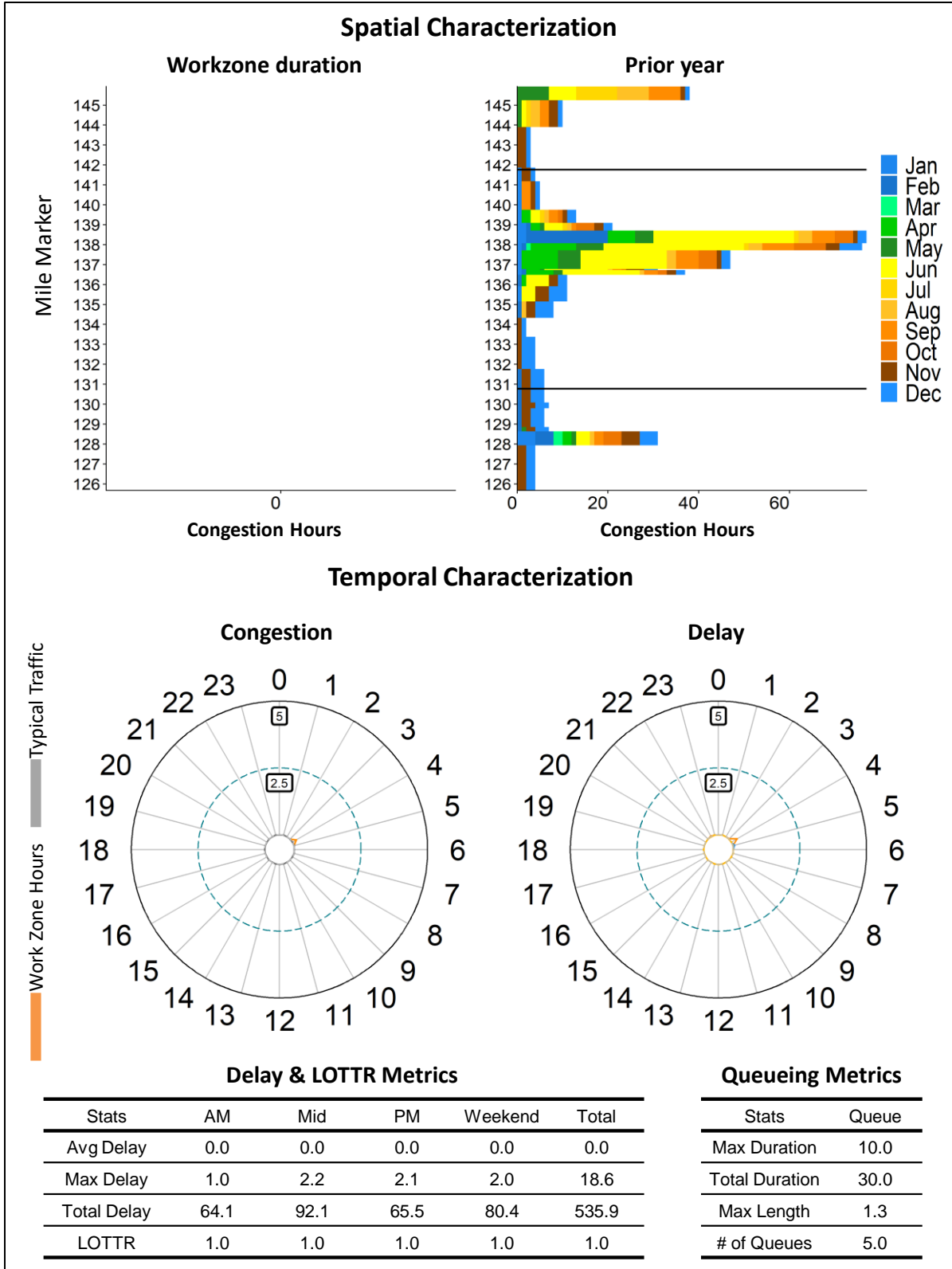


Figure 24. Case 4: work zone with no impact on traffic congestion, page 2.

The WZMA can be used for both short-term work zones and long-term work zone projects. The Manual on Uniform Traffic Control Devices (MUTCD) defines the following categories of work zone duration: 1) long-term: more than 3 days, 2) intermediate-term: between one and three days, and 3) short-term: less than one day (52). For each of these categories, practitioners can adjust the WZMA time granularity to monitor the traffic mobility. For instance, practitioners can adjust the temporal granularity to five minutes interval for a short-term work zone. Furthermore, larger granularity such as daily or monthly aggregations can be used to characterize the traffic mobility measures for a long-term work zone project.

CHAPTER 5 WORK ZONE TRAFFIC FORECASTING USING MACHINE LEARNING

Introduction

Traffic congestion prediction is a vital part of intelligent transportation systems (ITS) which provide traffic mobility information for both road users and transportation agencies. It helps traffic operation centers (TOCs) and state departments of transportation (DOTs) to proactively design their traffic management plans to minimize the mobility and safety concerns related to lane-closures. In the era of big data, machine learning (ML) algorithms are capable of learning dynamic patterns from previous real-world examples and predicting future scenarios. These algorithms explore historical observations to capture underlying patterns. Although these algorithms have been widely used to predict recurring traffic congestion, there have been limited research efforts to examine their applicability to forecast non-recurrent traffic congestion. Currently, traffic mobility data from these non-recurrent traffic scenarios is available which provides this opportunity to further examine ML applications in this area. This paper seeks to apply supervised modeling techniques to forecast the spatio-temporal impact of lane-closures on traffic mobility using historical speed data as a substitute for hourly traffic volume.

Methodology

This study adopted a supervised machine learning approach to estimate traffic speeds for highway segments when lane-closures occur. The severity of the traffic interruptions depends on the number of lanes and the traffic volume. When there is not enough capacity for traffic, vehicular speeds reduce and congestion propagates to upstream segments. As this congestion propagation continues, the upstream traffic segments experience lower traffic speeds. Using probe vehicle data, these speeds were available to investigate historical lane-closure projects. These traffic speeds ranged from zero miles per hour (mph), when vehicles are stopped in a queue, to greater than 70 mph when traffic was operating in free-flow conditions. Figure 25 shows a traffic speed

heat-map in which the x-axis shows time and y-axis represents highway segments. This figure, illustrates traffic speeds for each segment for a single-lane closure on northbound I-75 in Oakland County. This lane-closure was in place on a Tuesday in September of 2014. Traffic speeds are shown with a spectrum of colors from green to red to represent low speed and high-speed records, respectively. The yellow and red areas on the figure show traffic congestion while green areas show that traffic was operating at higher speeds.

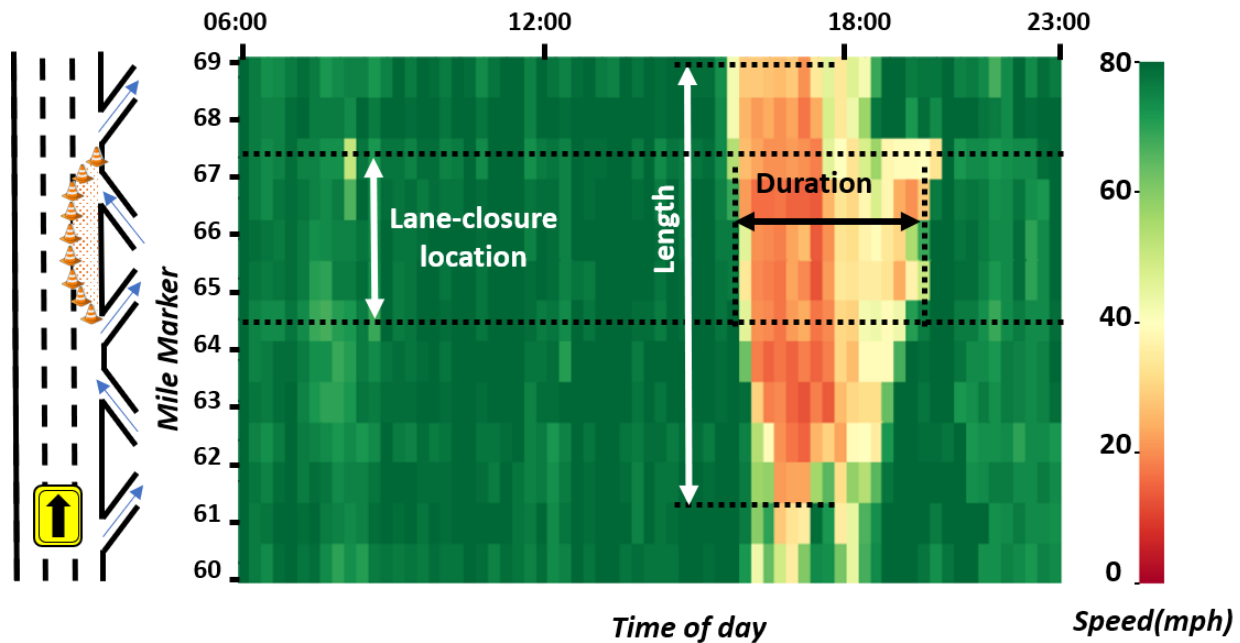


Figure 25. Speed heat-map for a double lane-closure event.

During morning and off-peak hours, highway segments were serving traffic with high speed since there was sufficient capacity for approaching traffic volumes. However, traffic congestion happened during PM peak hour due to overwhelming traffic volumes for the remaining two lanes. As highway segments reached their capacity, traffic congestion propagated in the upstream segments and traffic jam stretched up to about 9 miles. From the temporal perspective, this traffic congestion and severe slowdowns were experienced for five hours from 3 PM to 8 PM.

Typical Traffic Mobility Baseline

Probe-vehicle data provide an opportunity to observe historical trends in traffic and use those trends to understand future congestion risk on a segment of roadway. Historical speed data from the same day of week, hour of day, and 15-minute bin for each segment was queried from the year prior to the lane-closures. Several percentile values were used to represent speed distributions (traffic behavior) for each segment. In statistics, a percentile measure is used to identify a value in a group of observations below which a given percentage of observations can be found. For instance, if 85th percentile of historical speeds for a highway segment is 65 mph, it means that 85 percent of traffic speeds observed for this segment are below 65 mph. Conversely, this also means that only 15 percent of the times speeds were above 65 mph. The 5th, 15th, 25th, 50th, 75th, 85th, and 95th percentiles were calculated to quantify historical traffic.

The objective of this study was to use these historical percentiles as a method to predict potential future congestion. Figure 26 illustrates several historic percentile heat-maps compared to an actual observation of traffic speeds during the same lane closure discussed in Figure 25. Figure 26a shows the 85th percentile speeds for each segment during all Tuesdays in the prior year. It shows that this corridor services traffic with speed of above 60 mph in 15 percent of times while having minor slowdowns in the PM period (callout i). Figure 26b shows that in 50 percent of times, this corridor operates with high speed except during PM period. It shows that in half of all Tuesdays in the prior year, this corridor experienced a traffic slowdown from MM 64 to 69 around 6 PM (callout ii). Figure 26c also shows that in quarter of all Tuesdays, traffic congestion was experienced in the PM period (callout iii) while traffic was operating with high speed during the rest of day. Figure 26d illustrates that in rare situations (5 percent of times), these highway segments suffered from severe traffic jam throughout the corridor during PM peak (callout iv) while highlighting that no traffic congestion happened during AM or off-peak periods. Figure 26e shows traffic speed for this corridor while right traffic lane was closed. As shown, similar

traffic congestion pattern with more severity (callout v) was shaped on this corridor during PM peak period. As we could expect from previous observations, no traffic congestion or slowdown was observed during rest of this Tuesday.

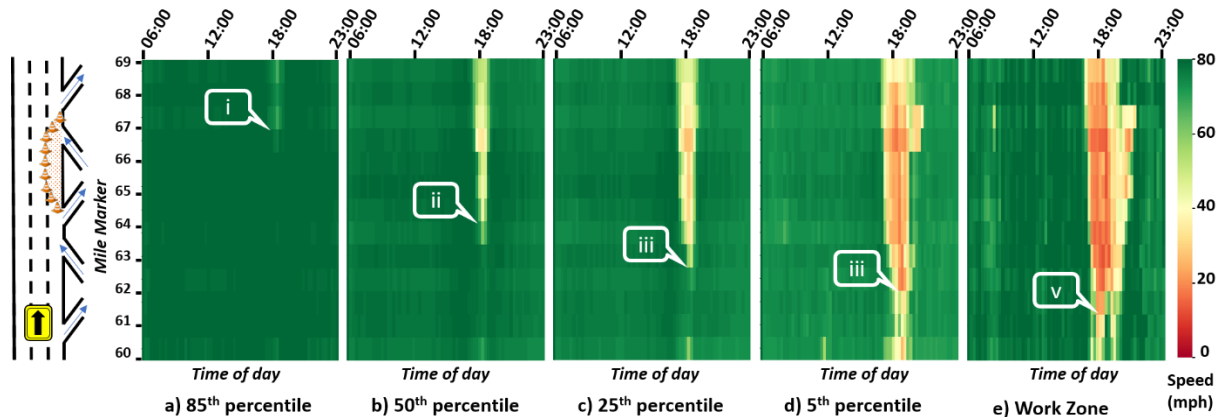


Figure 26. Speed Heat-maps for historical and lane-closure scenarios.

This figure illustrates the applicability of Greenshield's theory (55) in which traffic speed and traffic volume are related. This was, indeed, the motivation behind this study to examine the applicability of using historical traffic speeds when hourly traffic volumes are not available. Modern technology provided this opportunity to gather historical samples for these non-recurrent traffic periods. Machine learning algorithms were used in this study to learn from these historical observations and predict future scenarios. This study used a supervised learning approach to predict speed ranges for each highway segment over time. Classification algorithms used in this study were Random Forest, XGboost, and Artificial Neural Network (ANN). The following section provides a brief explanation of these algorithms and their applicability for classification tasks.

Model Selection

Artificial Neural Network:

An Artificial Neural Network (ANN) is a computational model based on the structure and functions of biological neural networks (56). The first computational model for ANN created by

Warren McCulloch and Walter Pitts (57) based on mathematics and algorithms. Neural network models contain at least one hidden layer between input (training data) and output layer (predictions) to transform the inputs into something that the output layer can use. In hidden layers, neurons take in a set of weighted inputs and produce an output through an activation function to minimize the prediction error. ANN models use large number of neurons to identify hidden patterns in previous occurrences. These models are capable of predicting complex scenarios (56) even though being computationally expensive.

Random Forest:

The first algorithm for random decision forests was created by Tin Kam Ho (58). Random forests or random decision forests are an ensemble learning method which were designed to construct multiple decision trees from previous observations, and predict future scenarios (58, 59). Single decision trees are prone to over-fitting while Random Forest models use votes from several decision trees to reduce variance in prediction (60). This comes at the expense of a small increase in the bias and some loss of interpretability, but generally boosts the performance in the final model. In almost all cases, random forests are more accurate than decision trees but are more computationally expensive (58).

XGBoost:

Extreme Gradient Boosting (XGBoost) is a decision-tree-based ensemble algorithm that uses a gradient boosting framework technique for regression and classification problems. This algorithm was proposed by Tianqi Chen (61) back in 2016, and have been used by data scientist in various competition due to its fast running speed and high performance. The most important factor behind the success of XGBoost is its scalability in all scenarios which is due to several important systems and algorithmic optimizations. These innovations include: a novel tree learning algorithm for handling sparse data; a theoretically justified weighted quantile sketch procedure to

handle instance weights in approximate tree learning; and parallel and distributed computing feature which makes learning process faster.

Data Collection

Data was collected from 1,160 highway lane closure projects on Michigan interstates from 2014 to 2017. These work zones contained both single and double lane closures with one to fifteen day durations. Lane closures of less than one day were not considered because there was not enough information to verify the exact times lanes were opened or closed. The physical lengths of the work zones ranged from 100 foot bridge repairs to seven mile pavement reconstruction. The information provided by the Michigan Lane Closure and Restrictions (LCAR) database did not include work zone configurations, such as barrel placement, taper lengths, and signage. This information would clearly be valuable for future model development.

The probe vehicle data for each work zone was collected between five miles upstream of the starting point of the work zone and three miles downstream of the ending point of the work zone. Average Annual Daily Traffic (AADT) values were collected for each work zone from the Highway Performance Monitoring System (HPMS) database (62). These AADT values were spatially joined with the highway segments to approximate approaching traffic volumes. The Michigan Traffic Crash Facts (MTCF) website (63) was also used to query all traffic crashes that occurred during the lane closure periods. The MDOT lane mile inventory was used to collect geometric features of the roadway including number of lanes and functional road class.

Historic traffic speeds were obtained using probe vehicle data, which was provided by a third-party vendor. The speeds were aggregated into 15-minute periods, for each unique day of week and hour of day. For instance, if the lane-closure was taking place on a Monday from 1:15 PM to 1:30 PM, traffic speeds were queried for all Mondays in the previous year during the same time period (1:15 PM to 1:30 PM). Using this approach traffic speed distributions were able to be

created for each segment. This aggregation strategy also removed some of the noise in the speed data set to provide more stable historic traffic speeds.

A panel data set was constructed for each of the lane closures occurring on different interstate highways in the state of Michigan. Panel data sets are defined as multidimensional data with a time component (64). The final data assembled has numerous variables that differ over time including traffic characteristics such as traffic volume, geometry, and traffic incidents, as well as lane closure information. The final data set is comprised of over one million records.

Data Preprocessing

The mobility data, which was aggregated into 15-minute bins, were paired with geometric information, temporal features, AADT, and spatial features. The speed records which were originally continuous speeds between 0 and 80 mph were converted into five categories: Class 1 (0-20 mph), Class 2 (20-40 mph), Class 3 (40-60 mph), Class 4 (60-80 mph), and Class 5 (60-80 mph). Categorical features were converted to binary features using one-hot encoding techniques. The final data set consisted of 83 features for each 15-minute speed.

Traffic data are typically considered noisy. Sources that contribute to this noise are traffic incidents, inclement weather, lane-closures, and unexpected driving behaviors. It was necessary to clean problematic data records that could potentially confuse our algorithms. Traffic incidents were cross-checked for each case study to determine the number of crashes that occurred, throughout the study corridor, at the same day as lane-closure. Case studies that experienced a traffic incident were removed from the data set.

Resampling Techniques

After constructing the final data set for a multi-class classification task, the number of records for each class label showed that the data set was highly imbalanced. There were far more high speed records than low speed records since interstate highways typically operate at higher

speeds. Figure 27 illustrates the frequency of speed classes for both single-lane and double-lane case studies.

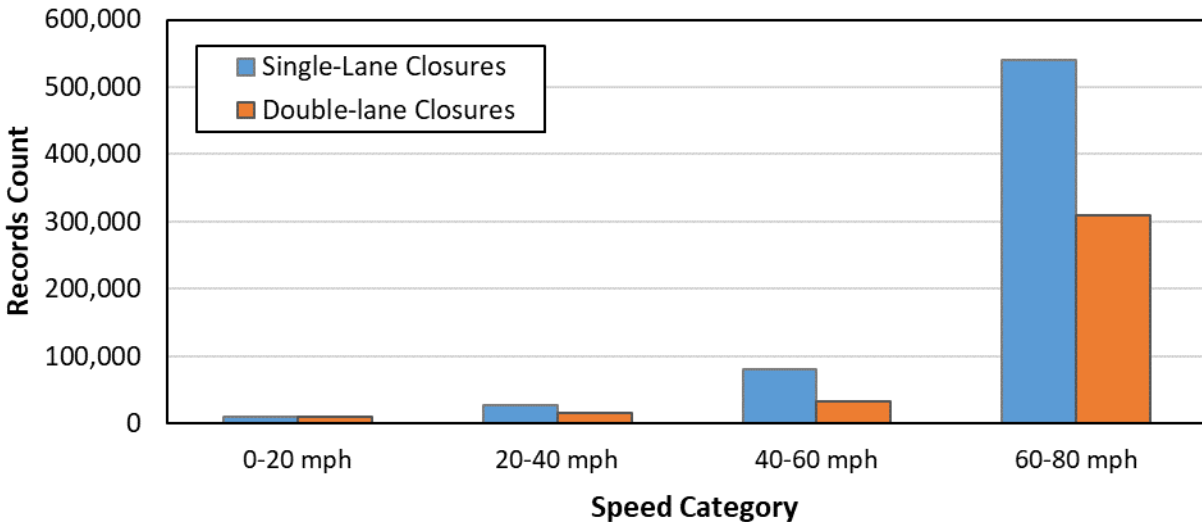


Figure 27. Record count distribution for single and double-lane closures.

To address this imbalanced data issue, several resampling techniques were applied using the `imbalanced-learn` (65) library in Python. The techniques used were the Random Under-Sampling (66), Over-Sampling (67), and SMOTE resampling algorithms (68). The Random Under-Sampling approach under-sampled the majority classes by randomly picking samples from the majority class (high-speed records). Over-sampling approach generates new samples in the classes which are under-presented (low-speed records) with replacement. The Synthetic Minority Over-sampling Technique (SMOTE) was also used to over-sample the minority classes and under-sample the majority classes. The augmented data sets were used along with the original data set to train the classifiers.

Model Development

Traffic data sets generated from the resampling methods and the original data set were used as an input for classification algorithms. 5-fold cross-validation was used to avoid over-fitting and selection bias. This cross-validation approach generated complementary subsets of data in

which a certain portion of data was used to train the algorithms and the remaining subset was used to evaluate the model's generalization. Multiple rounds of cross-validation were performed to assess variability in the model's predictive performance. An average of these results were used to represent the overall performance of the classification models. Hyper parameter tuning was performed using Grid Search and Randomized Cross Validation methods to further evaluate the models confidence and reliability (69). Grid search has been a widely used method for optimizing hyper-parameters while the Randomized method is a more recent method which requires less computational resources. Grid search requires more computational resources to create exhaustive combination of grid parameters to find optimized hyper parameters. However, the Randomized method randomly creates combinations of hyper parameters based on the distribution of these parameters.

Model Evaluation

Several measures were used to evaluate model's performance. Measures used to evaluate prediction for each class were precision, recall, and f1-score. Precision is the number of correct positive results divided by the number of positive results predicted by the classifier. Recall is the number of correct positive results divided by the number of all samples that should have been identified as positive. F1-score is the Harmonic Mean between precision and recall and tries to find the balance between precision and recall. In imbalanced data set cases, these metrics can be used to evaluate performance for each class, but they represent a misleading performance measure to evaluate overall performance. For example, when a training set consists of an unbalanced portion for each class label, the result can be biased towards the more frequent class. Consequently, by applying these metrics to test an imbalanced data set, the classifier may be prone to estimate higher accuracy which is not realistic.

Therefore, overall performance of these models were evaluated using Micro and Macro average of these metrics. Micro and macro averages represent two ways of interpreting prediction performance in multi-class settings. A macro average computes each of these metrics independently for each class and then takes the average (hence treating all classes equally). Whereas, a micro-average aggregates the contributions of all classes to compute the average metric (70). Overall model evaluation was performed using a balanced accuracy (Macro average of recalls) score to evaluate the generalization of the models (71). Mathematical formulas to calculate each of these measures are provided in the next section. In the following, we will use TP_i , FP_i , FN_i to respectively indicate true positives, false positives, and false negatives in the confusion matrix associated with the i^{th} class.

$$Precision = \frac{TP_i}{TP_i + FP_i}$$

$$Recall = \frac{TP_i}{TP_i + FN_i}$$

$$F1 - Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} = 2 \frac{Precision \times Recall}{Precision + Recall}$$

$$Micro Precision = P_{\{micro\}} = \frac{\sum_{i=1}^{|G|} TP_i}{\sum_{i=1}^{|G|} TP_i + FP_i}$$

$$Micro Recall = R_{\{micro\}} = \frac{\sum_{i=1}^{|G|} TP_i}{\sum_{i=1}^{|G|} TP_i + FN_i}$$

$$Micro F1 - Score = F1_{micro} = 2 \frac{P_{micro} \times R_{micro}}{P_{micro} + R_{micro}}$$

$$\text{Macro Precision} = P_{macro} = \frac{1}{|G|} \sum_{i=1}^{|G|} \frac{TP_i}{TP_i + FP_i} = \frac{\sum_{i=1}^{|G|} P_i}{|G|}$$

$$\text{Macro Recall} = R_{macro} = \frac{1}{|G|} \sum_{i=1}^{|G|} \frac{TP_i}{TP_i + FN_i} = \frac{\sum_{i=1}^{|G|} R_i}{|G|}$$

$$\text{Macro F1 - Score} = F1_{macro} = 2 \frac{P_{macro} \times R_{macro}}{P_{macro} + R_{macro}}$$

A true positive is an outcome where the model correctly predicts the target class. A false positive is an outcome where the model incorrectly predicts the target class. And a false negative is an outcome where the model incorrectly predicts other than the target one. G represents number of classes. Precision and recall are shown as P and R , respectively.

Example & Analysis

To illustrate applicability of this approach, traffic speed heat-map was used to show predicted values compared to actual observations for the same work zone illustrated in methodology section. Figure 28 provides a visual comparison of the predicted traffic speeds and actual observations. Figure 28a shows actual traffic speeds for each segment during the lane-closure. Figure 28b shows predicted speeds using ANN model. As shown, ANN model was able to capture the overall pattern of traffic congestion on this corridor.

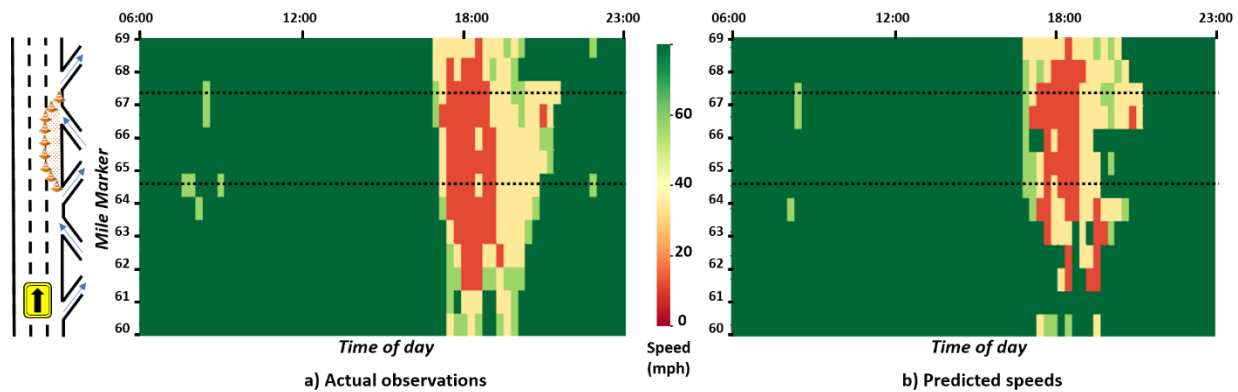


Figure 28. Speed heat-maps from predicted and actual observations.

Model Performance

Table 3 provides classification report generated for each of the applied models. Precision, recall, and F1-score metrics are reported based on each class. Also, Micro and Macro average of this metrics are shown to provide overall performance comparison between these models. As discussed earlier, balanced accuracy score were chosen to compare these model's performances. Among these models, ANN outperformed Random Forest and XGBoost models by reaching up to 85\% balanced accuracy. ANN used in this study consisted of three hidden layers with 30, 40, and 50 nodes. Hyper-parameters were tuned using Grid search cross validation method. Data set used for training was an augmented data set created by SMOTE resampling technique. This resampling technique generated a better synthetic data set compared to both original and other augmented data sets created by Random Under-sampling and Over-sampling methods. From each class perspective, the ANN model was able to predict queuing condition (0-20 mph) with 88\% accuracy compared to XGBoost and Random Forest models with 84\% and 76\% accuracies, respectively.

Table 3. Model performance results

<i>Model</i>	<i>Speed range (mph)</i>	<i>Evaluation Metrics</i>			<i>Balanced Accuracy</i>
		<i>Precision</i>	<i>Recall</i>	<i>F1-score</i>	
<i>Random Forest</i>	<i>0-20</i>	<i>0.8</i>	<i>0.76</i>	<i>0.78</i>	<i>0.74</i>
	<i>20-40</i>	<i>0.67</i>	<i>0.67</i>	<i>0.67</i>	
	<i>40-60</i>	<i>0.66</i>	<i>0.61</i>	<i>0.63</i>	
	<i>60-80</i>	<i>0.94</i>	<i>0.95</i>	<i>0.94</i>	
	<i>Macro average</i>	<i>0.76</i>	<i>0.74</i>	<i>0.75</i>	
	<i>Micro average</i>	<i>0.87</i>	<i>0.87</i>	<i>0.87</i>	
<i>XGBoost</i>	<i>0-20</i>	<i>0.78</i>	<i>0.84</i>	<i>0.81</i>	<i>0.79</i>
	<i>20-40</i>	<i>0.69</i>	<i>0.74</i>	<i>0.71</i>	
	<i>40-60</i>	<i>0.67</i>	<i>0.65</i>	<i>0.66</i>	
	<i>60-80</i>	<i>0.94</i>	<i>0.94</i>	<i>0.94</i>	

	<i>Macro average</i>	<i>0.77</i>	<i>0.79</i>	<i>0.78</i>	
	<i>Micro average</i>	<i>0.88</i>	<i>0.88</i>	<i>0.88</i>	
<i>ANN</i>	<i>0-20</i>	<i>0.85</i>	<i>0.88</i>	<i>0.87</i>	<i>0.85</i>
	<i>20-40</i>	<i>0.79</i>	<i>0.80</i>	<i>0.80</i>	
	<i>40-60</i>	<i>0.77</i>	<i>0.73</i>	<i>0.75</i>	
	<i>60-80</i>	<i>0.95</i>	<i>0.96</i>	<i>0.96</i>	
	<i>Macro average</i>	<i>0.85</i>	<i>0.85</i>	<i>0.85</i>	
	<i>Micro average</i>	<i>0.92</i>	<i>0.92</i>	<i>0.92</i>	

A clean and unambiguous way to present the prediction results of a classifier is to use a confusion matrix. Figure 29 shows the confusion matrix for the ANN model. This figure shows predicted traffic speeds are clustered around the left to right diagonal which represents the conditions where predicted records are deviating less from actual observations. Due to recurrent fluctuation in traffic speed, it was expected to have low performance when traffic speeds were transitioning from high-speed to congestion stage. However, congested scenarios (queuing condition) were identified more consistently.

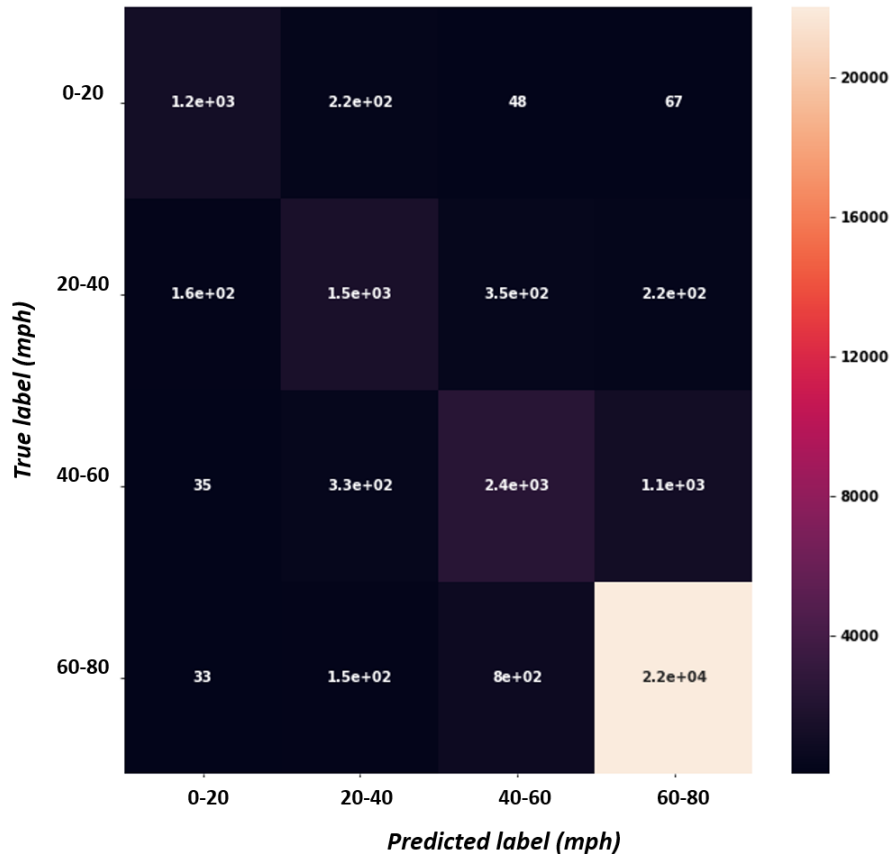


Figure 29. Confusion matrix-ANN model.

Discussion and conclusions

In this study, several supervised machine learning algorithms were applied to classify the speed range for each highway segment over time when lane-closures were present on interstate highways in state of Michigan. These models used work zone configuration, roadway geometry, AADT, and historical traffic speeds as inputs. 1,165 historical lane-closures which happened from 2014 to 2017 were used to train and evaluate the classification models. The balanced accuracy score was used for overall model performance evaluation. The results suggested that ANN outperformed the other models in terms of balanced accuracy score. The key advantage of this modeling approach was to use historical traffic speed distribution in the absence of hourly traffic

volume counts to achieve a promising accuracy in predicting the spatio-temporal impact of lane-closures on traffic mobility.

CHAPTER 6 STATE-WIDE WORK ZONE MOBILITY ASSESSMENT

Introduction

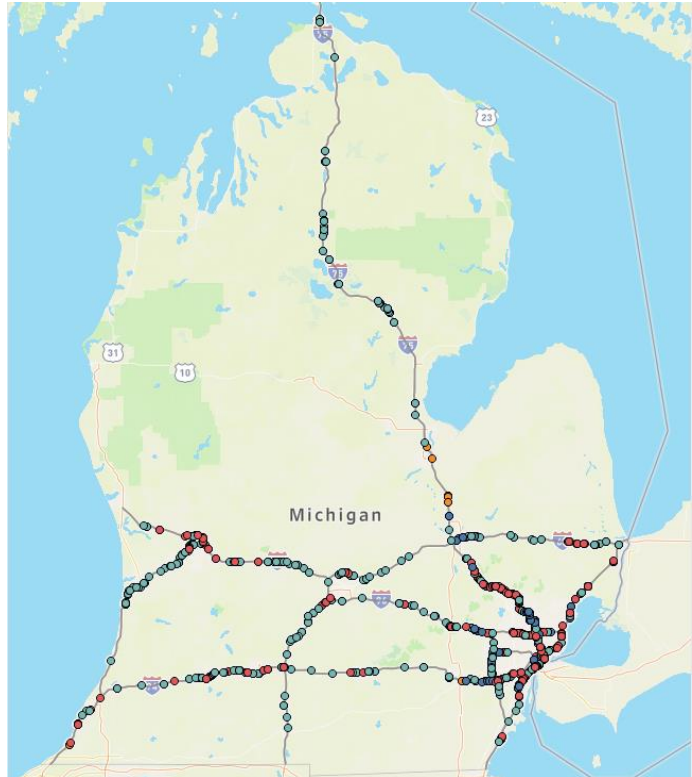
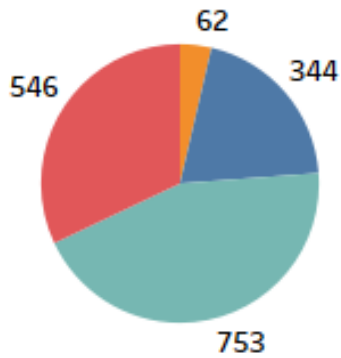
The state of Michigan has had more than 24,000 work zone projects in the past 10 years. This means that every year there are more than 2,000 work zones that need to be managed by traffic operation centers and transportation planning decision makers. FHWA requires transportation agencies to have an overall policy for the systematic consideration and management of these work zones. Mining historical work zone mobility data facilitates a quantitative approach to assess mobility performance of these lane-closures in a state-wide level. This approach utilizes mobility metrics, used in the WZMA to quantify and rank highway lane-closures based on their impact. This chapter applies Business Intelligence to provide actionable information for decision makers in the area of work zone mobility and safety management (73, 74).

Methodology

In order to derive more useful information regarding lane-closures impact on highways mobility, more than 1700 lane-closures were assessed using the WZMA process. These case studies included work zone projects in which shoulder to multiple lanes were closed throughout the project time. Also, these lane-closures lasted between one to 15 days on Michigan interstate highways from 2014 to 2018. After running the WZMA process on these cases, their information were gathered in a final data set to facilitate a large-scale assessment and a comparison between their impacts on traffic mobility. Figure 30 illustrates a quantitative summary of these case studies based on their work zone category (shoulder to multiple lane-closure) along with a visual representation of their location on Michigan interstates.

1,705 work zone case studies from 2014-2018

Count of work zones for each category:



Count of work zones for each highway based on categories:

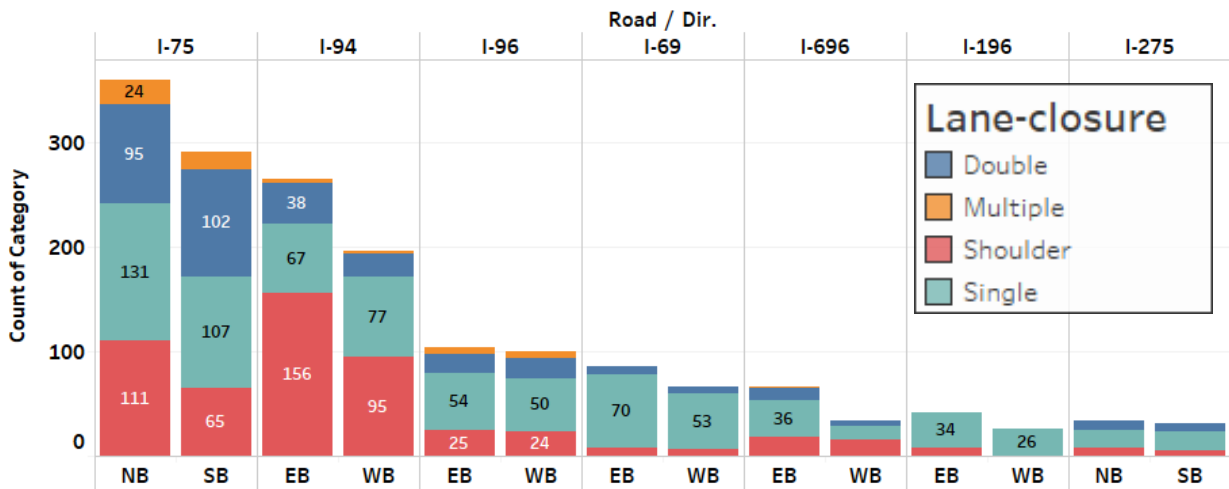


Figure 30. Summary statistics of work zone case studies

As shown in Figure 30, shoulder and single lane closures were the most commonly applied work zone categories with 753 and 546 cases among these 1705 cases. In addition, Highways I-

75 and I-94 experienced the majority of these lane closures while highways I-275 and I-196 had the least number of cases.

Another important factor regarding these cases were their duration which varied between one and 15 days. Figure 31 provides a visual representation of the duration in which each highway was experiencing these lane-closures. As shown in Figure 31, the average duration for these categories were as follow:

- Shoulder-lane closures: 4-5 days,
- Single-lane closures: 3-4 days,
- Double-lane closures: 2-3 days,
- Multiple-lane closures: 3-4 days.

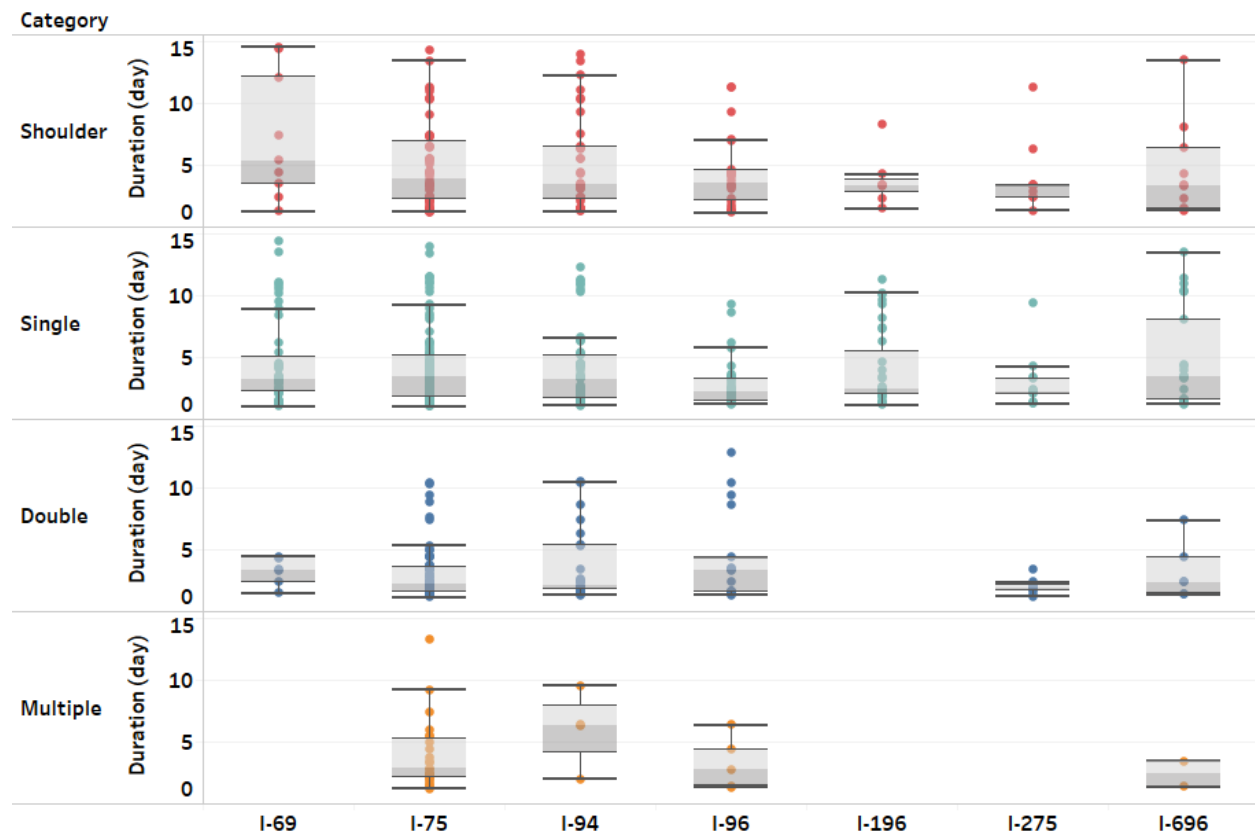


Figure 31. Work zones duration summary

Figure 31 also reveals that there were no double-lane closures on highway I-196, and no multiple-lane closures on highways I-69, I-196, and I-275.

Mobility Metrics Summary

Mobility metrics utilized in the WZMA were defined to quantify mobility impact from two major perspectives. Two metrics were defined to quantify user delay which was caused by lane-closures. These metrics were the longest user delay and the total delay caused by a work zone. In addition, four metrics were defined to quantify severe traffic slowdowns on highways. The metrics used to quantify the queueing condition were aimed to measure frequency and duration of a queueing condition both from temporal and spatial perspectives. From temporal perspective, the longest time that a queueing condition was present was measured along with total duration in which at least one highway segment exhibited a queueing condition (severe slowdown). Also, the frequency of queueing conditions was measured to quantify how many times traffic slowdowns happened due to work zone presence. From the spatial perspective, the longest length of queue was measured to represent severity of traffic slowdown in the upstream segments of highway. Table 4 summarizes the applied performance measures and their objectives.

Table 4. Mobility metrics summary & objectives

	Metric	What does it Measure?
User Delay	Total Delay	Cumulative travel time delay experienced by users throughout the lane-closure duration
	Longest User Delay	Longest travel time delay experienced by users
Presence of Queueing Condition	Longest Queue Length (mile)	Longest length of queue caused by lane-closure
	Longest Queue Duration (min)	Longest time that at least one segment of highway was performing in queueing condition.

	Total Queue Duration(hours)	Cumulative times that at least one segment of highway was performing in queueing condition.
	Number of Queues	Number of times that queueing condition formed on the highway.

Interstate Mobility Ranking

Managing traffic mobility for seven highway interstates while having different type of lane-closures with varying duration has been a challenge for traffic operation centers and transportation planning organizations. This section provides a visual representation of the impact the case studies had on highway mobility from user delay and queueing condition perspectives. Knowing how previous lane-closures impacted traffic mobility provides this facility to rank and identify highways which experienced more negative mobility impacts. The following sections rank and summarize interstate highways mobility based on the impact they experienced while having lane-closures present.

Ranking Based on Delay Metrics

A quantitate summary of the total travel time delay, which was caused by these highway lane-closures, is provided in Figure 32. This figure shows cumulative delay caused by lane-closures on x-axis while showing percentage of the total impact for each work zone category.

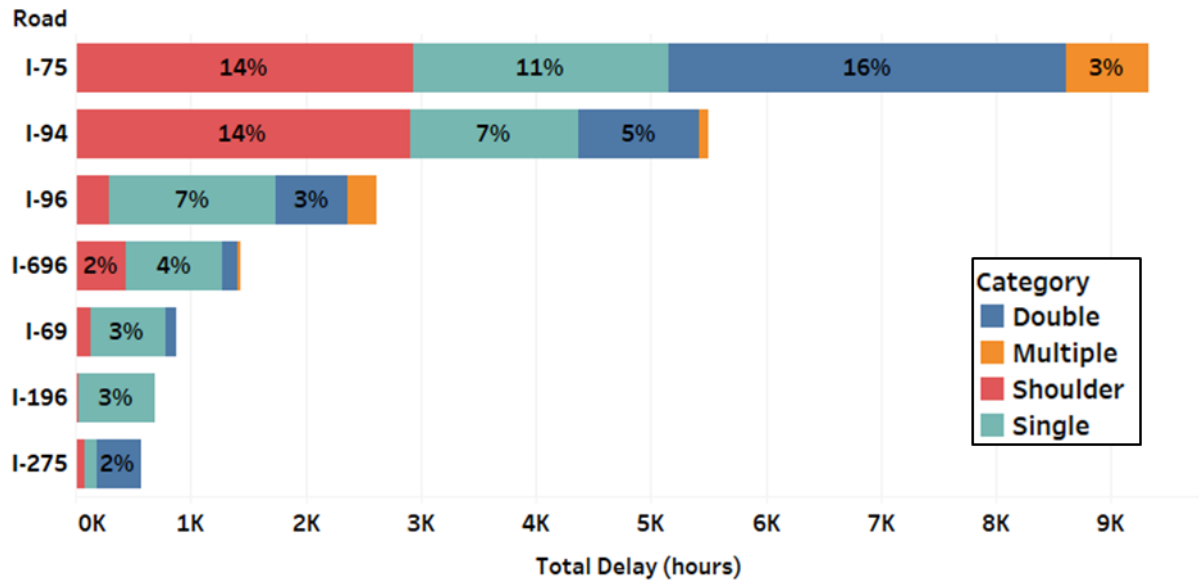


Figure 32. Quantitative summary for total work zone delay

As shown, Highways I-75 and I-94 caused the majority of travel time delay for commuters with 44% and 26% of the total delay, respectively. Identifying highways which caused the most travel time delay for commuters highlights the importance of further considerations while planning future work zones.

Another metric for assessing mobility performance was the longest delay that commuters experienced while a lane-closure was in place. This metric represents the additional time (in minutes) that commuters had to spend compared to their typical travel time. Figure 33 provides median of these longest user delay (x-axis) for each highway (y-axis) based on work zone category. Numbers on each bar show additional time commuters expected to travel (travel delay) while having different work zone category in place.

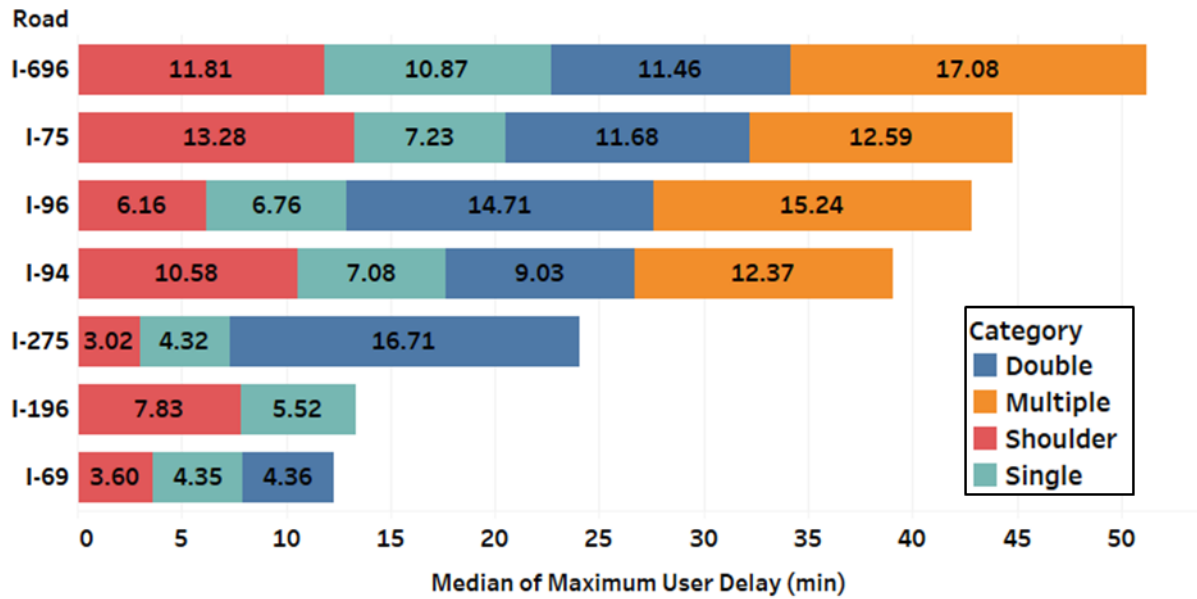


Figure 33. Quantitative summary for longest user delay

As shown, highway I-696 experienced longest user delay while lane-closures on highway I-69 caused minor delay for commuters. Multiple lane-closure projects on I-696 and I-96 and double-lane closures on I-275 were the top categories that caused the highest travel delay for users.

Ranking Based on Queue Metrics

Characterizing traffic slowdowns and queues for these lane-closures were performed using four queueing performance metrics. Figure 34 provides a summary of total queue duration experienced by each highway for each lane-closure category. This figure shows cumulative hours of queueing condition on the x-axis while showing percentage of the overall impact caused by each category on the bars.

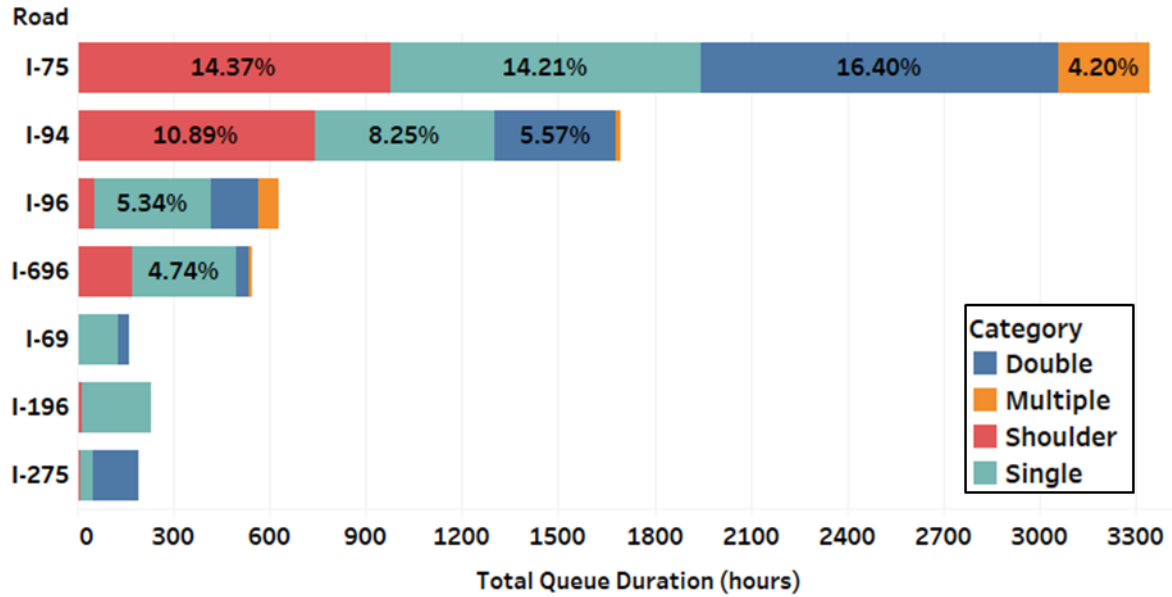


Figure 34. Quantitative summary for total queue duration

As shown, Highway I-75 experienced majority of queueing condition with having almost 3,300 hours while highway I-94 had the second rank with 1,700 hours. Also, double-lane closures on I-75 created 16.4% of the overall queueing condition.

Another queueing metric used was the number of queue formations, which represent how many times queueing conditions were formed while having lane-closures in place. Figure 35 illustrates the total number of queues that happened on each highway for each category of lane-closures.

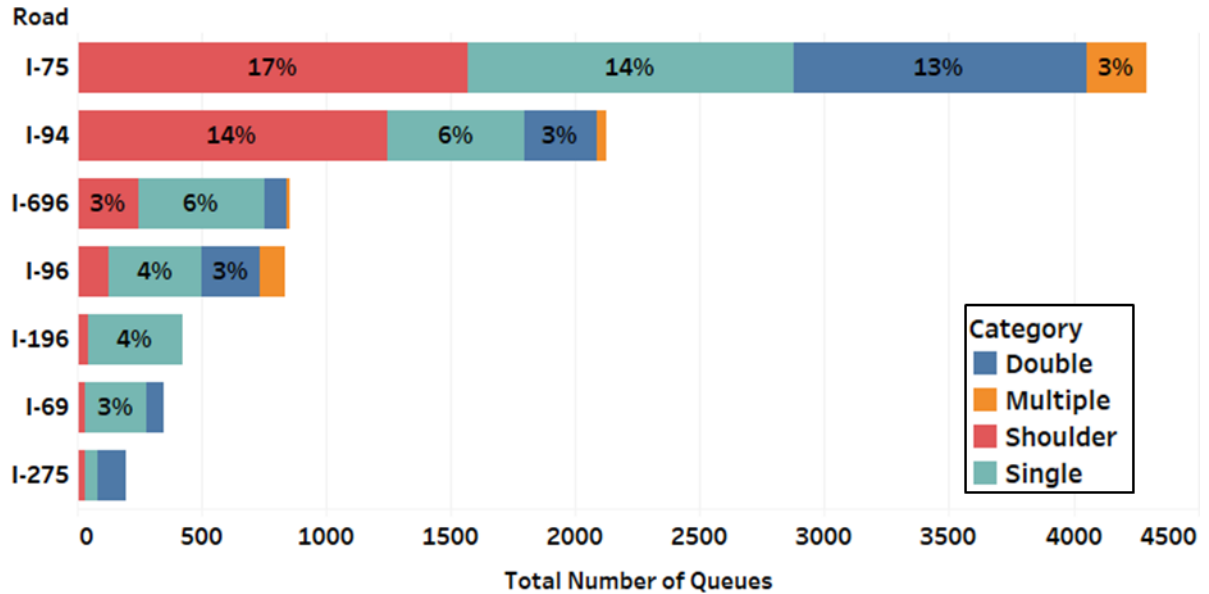


Figure 35. Quantitative summary for total number of queues

This figure shows that highway I-75 experienced the most (almost 4,400) queueing events while I-94 experienced about 2,200 queueing events.

Another queueing metric used was the longest queue length (miles) which was caused by these lane-closures. A median of this metric was calculated for each highway based on work zone category to highlight the severity of queue propagation while lane-closures reduce highway capacity. Figure 36 illustrates this metric (x-axis) for all highways (y-axis) while representing the median of longest queue lengths for each work zone category.

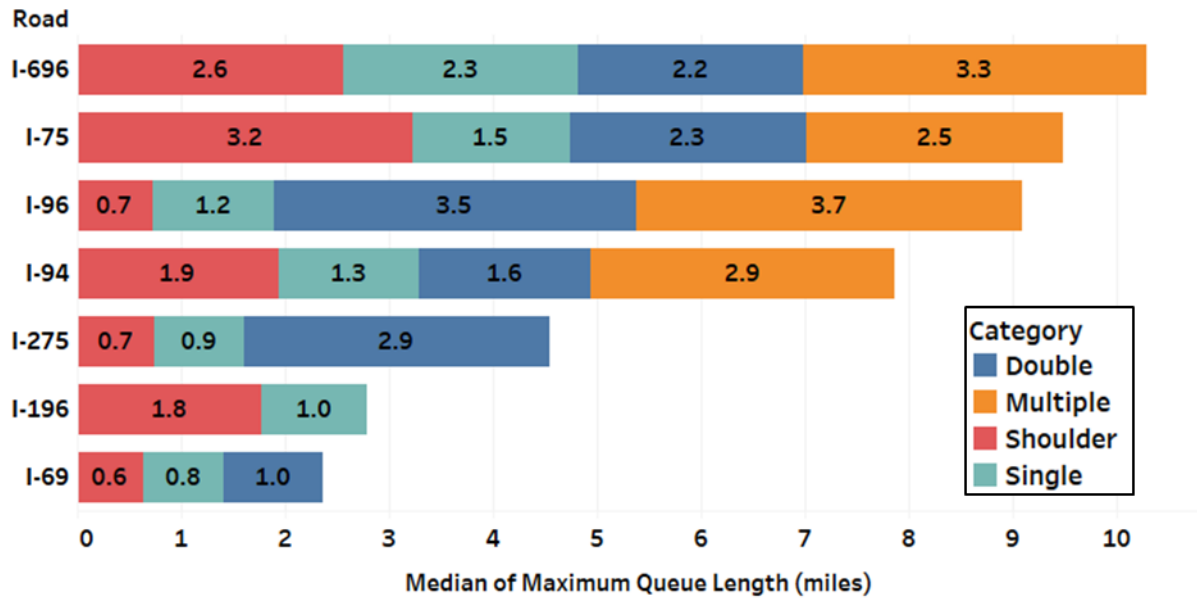


Figure 36. Quantitative summary for maximum queue length (miles)

As shown, highway I-696 ranked the first among other interstates experiencing longest queue lengths considering all work zone categories. However, commuters on I-96 experienced longest queues while multiple-lane and double-lane closures were in place with 3.7 and 3.5 miles of queueing, respectively.

Another queueing metric utilized was the duration of time in which a segment is performing under queueing condition consecutively. Figure 37 summarizes maximum queue durations for the case studies by having a median of these records on the x-axis while showing the values for each category on the bars.

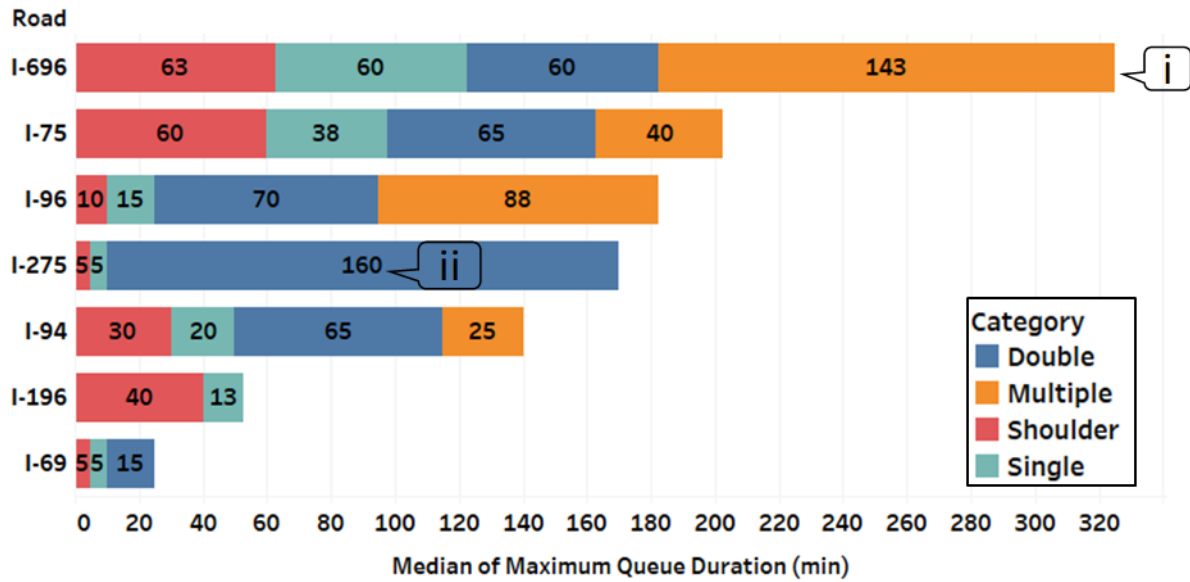


Figure 37. Quantitative summary for maximum queue duration (minutes)

As shown, I-696 experienced longest queue lengths (callout i) while considering all categories together, however, from a categorical perspective, double-lane closures on I-275 (callout ii) had the longest queue duration with 160 minutes of consecutive queueing condition. This metric highlights the concept of queue formation and resiliency while assessing mobility in large-scale. For instance, Figure 37 shows that it takes about 140 minutes for queueing condition to start and resolve in case of having multiple-lane closures on interstate 696.

Identifying Significant projects

According to the FHWA (4), agencies are required to implement a procedure to mitigate safety and mobility issues caused by the presence their significant work zone projects. FHWA defines significant projects as projects that disrupt traffic mobility significantly and create hazardous condition for users. However, FHWA does not provide a detailed definition of significant projects and allows agencies to define and identify their own significant projects. Mobility metrics introduced in the WZMA can assist agencies to rank their historical projects based on the negative impact they had on traffic. This section attempts to introduce an approach in which high impact projects are identified using delay and queueing metrics.

Pareto principle, also known as 80/20 rule, is a well-known principle used in business and project management area (75, 76). In the case of assessing many events, this principle states that roughly 80% of the impact comes from 20% of the cases. Figure 38 illustrates a Pareto chart constructed using the total queue duration metric to rank high impact projects in a descending order.

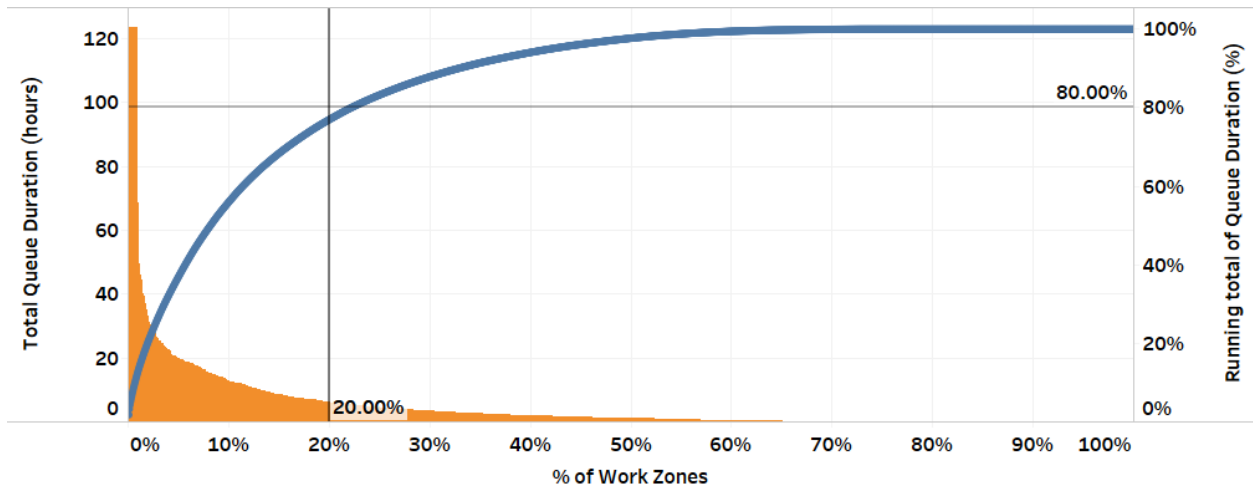


Figure 38. Ranking work zones using Pareto sort

In this figure, the x-axis represents percentage of work zone projects with their impact illustrated on y-axis by orange bars. The blue line on this graph is the running total of the impacts,

and the right vertical axis shows the cumulative percentage of total impact. According to this principle, it is feasible to identify 20% of the lane-closures which account for roughly 80% of the overall mobility impact these work zone projects had on Interstate highways in state of Michigan. Figure 39 utilized the queue duration metric to rank “significant” projects which account for the majority (80%) of the total queueing condition. In this figure, work zone projects that are ordered on the left side of the 20% vertical line (callout i) cause almost 80% of the overall impact. Figure 39c shows a Pareto sort with its top twenty percent of work zones being selected as significant projects. Figure 39a shows location of these high impact, or so called significant, lane-closures on map. Figure 39b ranks these problematic work zones based on a median of the impact (total queue duration) experienced by each highway. As shown, work zone projects on northbound of I-275 were performing in queueing condition for 18 hours (callout ii) which was highest among other highways.

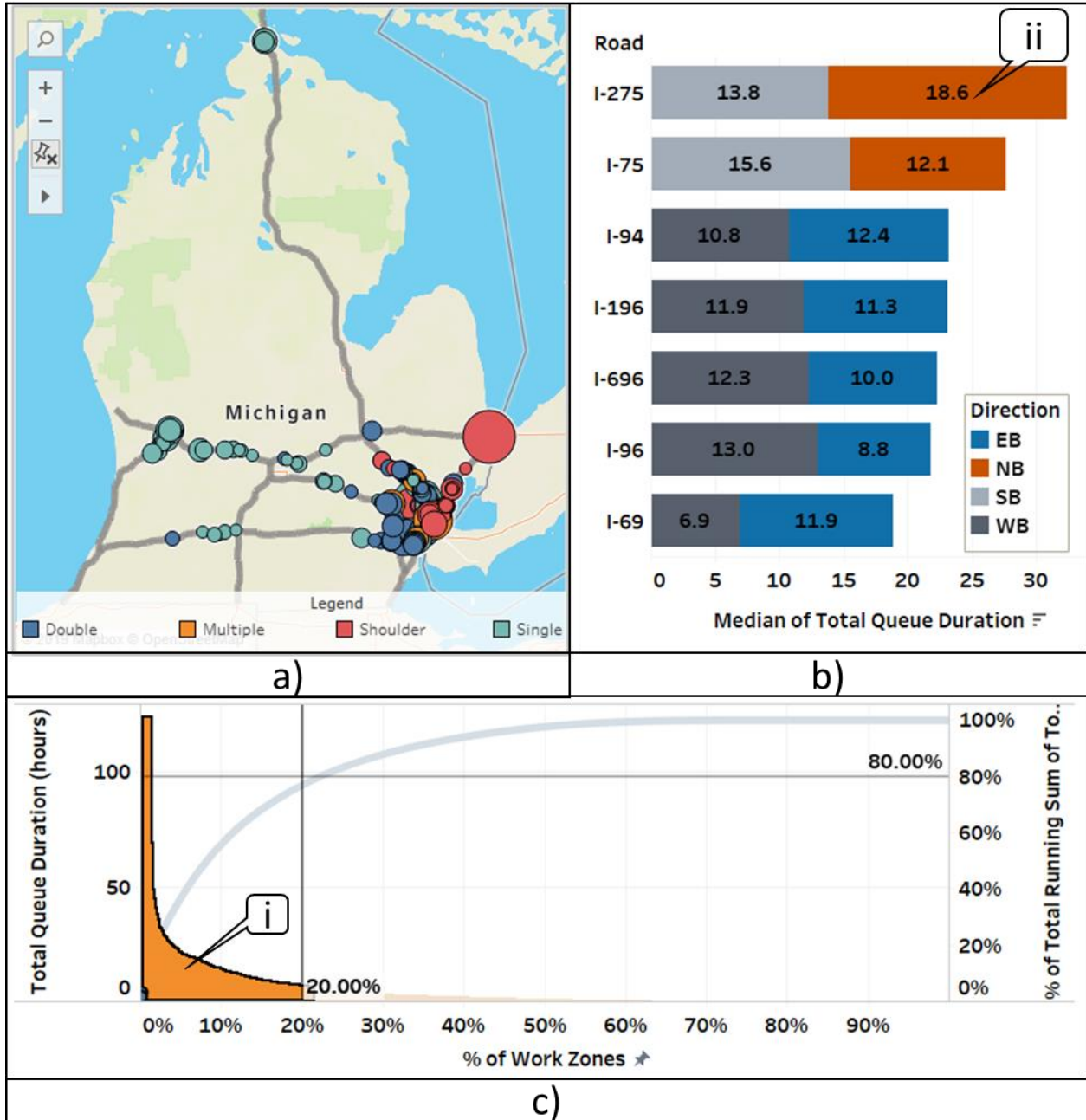


Figure 39. Ranking significant projects using queue duration metric

The graphical representation of these work zones shows clusters where work zones had severe impacts on mobility. Using the WZMA, more information can be evaluated from each of the work zones. Areas where work zones had high impacts can be archived and utilized by agencies in the future to adjust work zone management strategies.

Distribution of Work Zone impact using box-whisker chart

Another way of considering significant projects was to use the longest queue length metric. In this approach, a box-whisker plot is utilized to visualize a distribution of this metric for each highway. Box-whisker plots divide the records into sections that each contain approximately 25% of the data in that set. Transportation agencies could focus on the cases that fall into the top quartile which could also be considered as significant projects. Figure 40 illustrates the longest queue lengths shaped on each highway based on their category. In this figure, callout i shows the top quartile of work zones which created the longest queue length. Callout ii also illustrates a point which is in the top 5 percent of work zones happened on westbound of I-696.

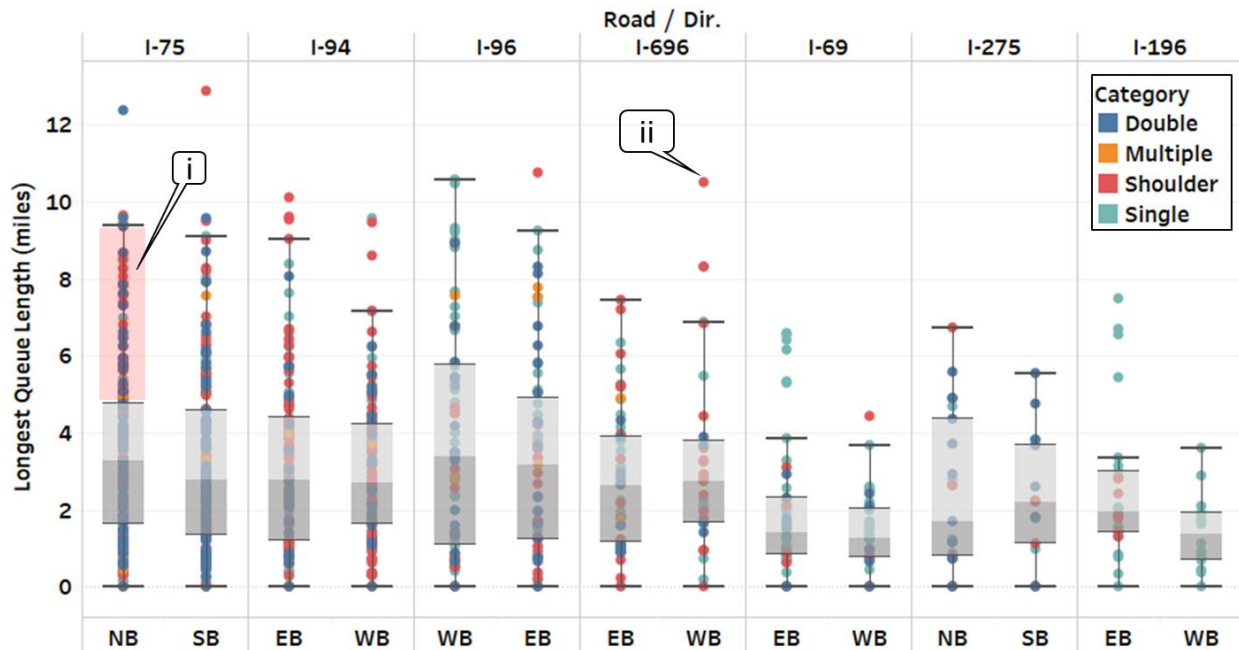


Figure 40. Distribution of the longest queue length for each highway

State-wide Work Zone Mobility Dashboard

Another data analytic approach which could be used to manage and monitor work zones in a large-scale were using Business Intelligence (BI) approaches (798081). The BI approaches have merged as an important area of study for practitioners and researchers to reflect the

importance and applicability of data-driven analytics in addressing common management issues. This approach analyzes and represents actionable information which helps work zone executives make informed decisions. A dynamic dashboard was constructed for the work zone case studies in which work zone impacts are assessed using approaches discussed earlier in this chapter. Figure 41 illustrates this dashboard utilizing the total delay metric. In this dashboard, users could choose their preferable mobility metric to analyze state-wide or freeway level mobility performance. In addition, users could target specific category of work zones to compare the magnitude of impact while having certain work zone category being implemented.

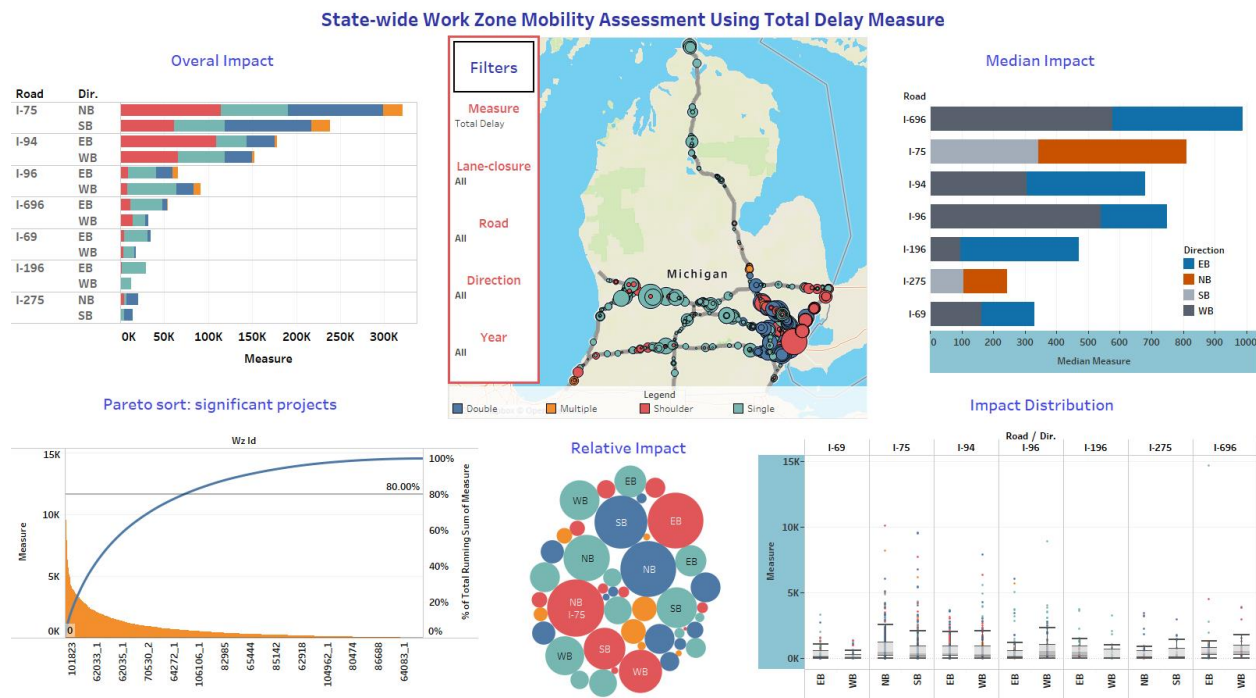


Figure 41. A dynamic BI dashboard for state-wide work zone management

This dashboard is consisted of several sections which provide certain information regarding work zones impact. These sections and their objectives are:

1. Overall impact:

- This section ranks freeways which experienced the highest impact based on the mobility metric used.
2. Work zone mapping
 - This section presents location of work zones on Michigan interstates to highlight problematic freeway locations.
 3. Median impact
 - This section utilizes median of records for the mobility metric to provide an approximate expected impact for each freeway.
 4. Pareto sort
 - This chart is utilized to rank significant projects based on the mobility impact. The shape of Pareto chart illustrates the overall number of significant projects which needs to be prioritized.
 5. Relative impact
 - This section also compares relative impact for each freeway compared to other freeways based on the chosen mobility metric.
 6. Impact distribution
 - The distribution of impact for each highway highlight the variation of impact for each highway based on the chosen mobility metric. This approach assist decision makers to be aware of impact magnitude and plan accordingly.

Statistical Analysis

Statistical analysis was performed on the data set to provide more inferences regarding significant factors affecting mobility. In this approach, a decision tree model was applied to develop a classification system for decision makers to predict and classify their future projects based on a set of decision rules. This approach, also called as rule induction, provides a clear reasoning process by using decision trees which include only the factors that are important to

make decisions in future work zone planning. CHAID, or Chi-squared Automatic Interaction Detection, was used as classification method in which chi-squared statistics were used to identify optimal splits for the decision trees (77,78). In this approach, cross tabulation was examined between the dependent and independent variables to test for their significance using chi-square independent test. Table 5 summarizes the dependent and independent variables used for this analysis.

Table 5. Variables used for statistical analysis

Mobility Metrics (dependent variables)	Work Zone Characteristics (independent variables)
<ul style="list-style-type: none"> • Total Work zone delay (normalized: hour per day) • Total Queue duration (normalized: percent of time performing in queue condition per day) • Number of queue (normalized: per day) 	<ul style="list-style-type: none"> • Work zone category (shoulder to multiple lane closure) • Roadway () • AADT • CAADT • Closure side (Left-closure or right-closure) • Duration (intermediate or long-term) • Day of week (work zone starts) • Day of week (work zone ends) • Month of year

At each step, categories of data that were significantly different were separated using tree branches while categories that show no difference were grouped together. This category merging process stopped when all the remaining categories were different at significance level of 0.005.

The first metric used to construct the decision tree was the total delay that lane-closures caused for commuters. This metric was normalized based on the duration of lane-closures to provide a comparison base. Figure 42 illustrates the constructed decision tree using the normalized delay metric. As shown, work zone categories had the highest significance to split work zones based on the delay they caused. For shoulder-lane closures, work zones were split based on interstates. Interstates 75 and 696 were categorized with mean of 2.3 delay hours per

day while other freeways experienced mean of 1.7 delay hours. For single-lane closures, freeways were categorized into three groups based on the previous impact these closures had on mobility. Also, double-lane and multiple-lane closures were not significantly different and were grouped together. For these groups, the side of closure were the most significant factor compared to other independent variables. As shown, closures on the left side of freeways caused more impact on mobility with having 9.7 delay hours per day compared to right side closures with 5.7 delay hours.

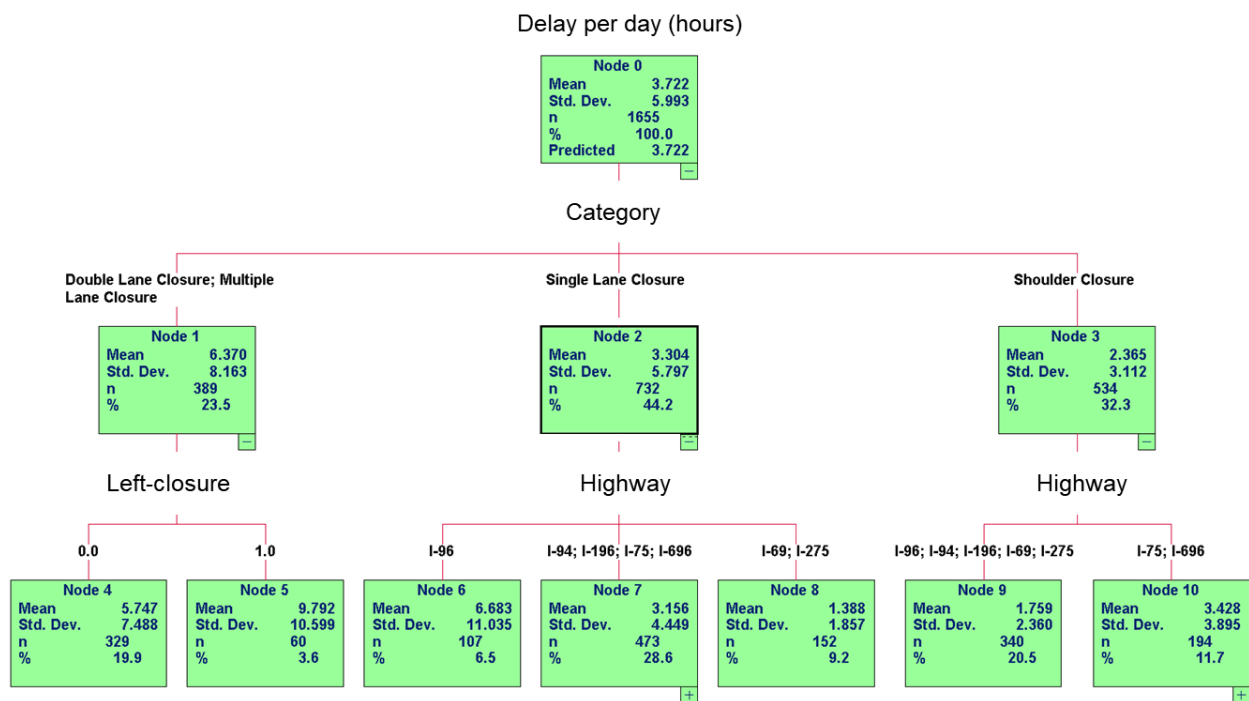


Figure 42. Decision tree based on delay metric

Using number of queue metric, the most significant factor was freeways to split the observations into three groups. As shown in Figure 43, interstates 696, 75, and 196 experienced more queueing formation (two queues per day) while second split (I-275 and I-96) and third splits (I-69 and I-94) experienced 1.5 and 0.8 queues per day, respectively. In addition, work zone category was the next significant factor to split lane-closures on I-96 and I-275 freeways.

Furthermore, the AADT volume were the significant factor to split work zones on interstates I-196, I-75, and I-696. As shown, lane-closures on sections of these freeways with more than 10,866 AADT experienced the highest frequency of queue formation with 2.4 crashes per day.

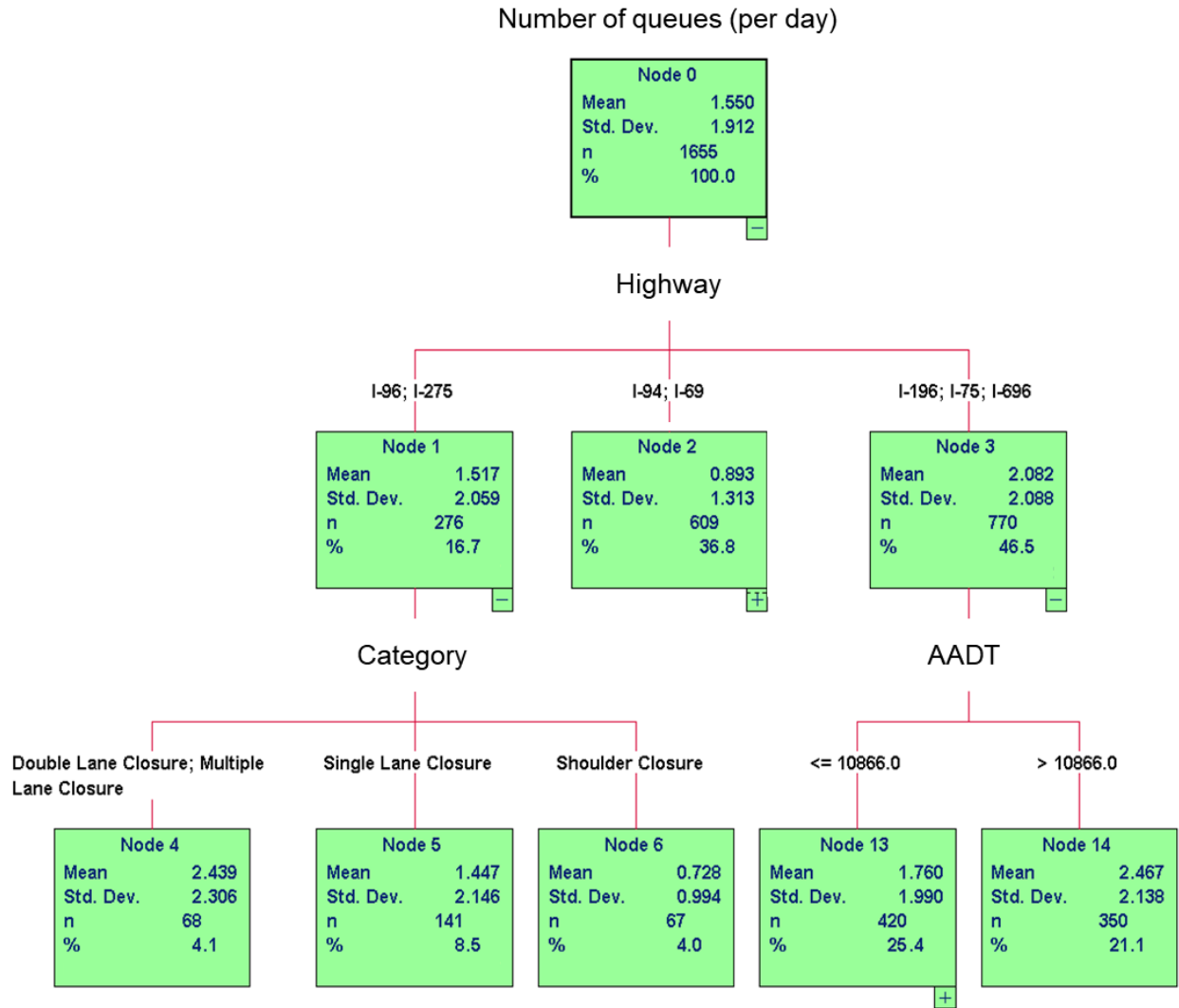


Figure 43. Decision tree based on number of queues

Another important variable for work zone traffic management decision makers is the queue spill back in the upstream segments. This longest queue metric was utilized to split work zone observations which were significantly different. Figure 44 represents expected queue length for each freeway based on the number of heavy vehicles traveling on these freeways. As shown,

interstate 69 experiences the shortest queue length of 0.9 miles while interstates 196 and 275 experienced 1.6 miles of queue length. In addition, lane-closures on I-94 had queue lengths from 1.2 miles to 3.1 miles depending on the CAADT volume. Interstates 696, 75, and 96 experienced queue lengths from 2.3 miles to 3.1 miles also depending on heavy vehicle traffic volume.

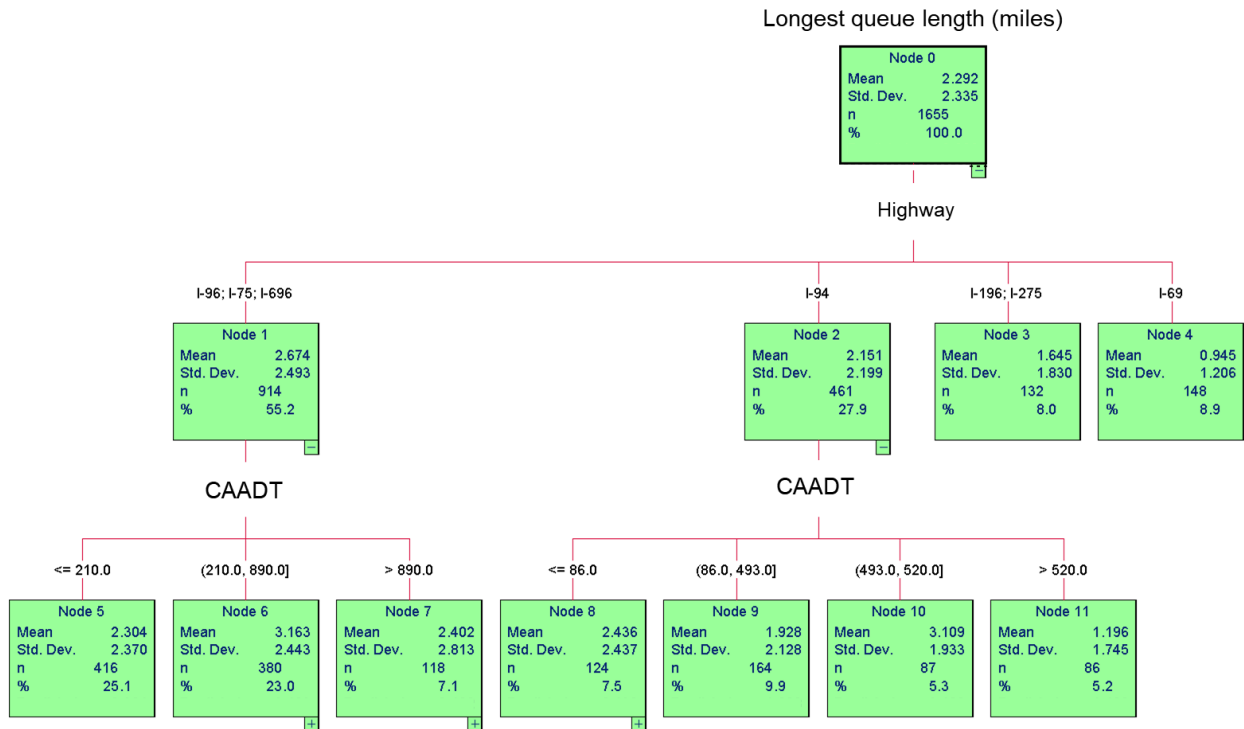


Figure 44. Decision tree based on longest queue length

A detailed statistic of CHAID analysis for these three metrics are provided in appendix B.

CHAPTER 7 CONCLUSION AND RECOMMENDATIONS

The objectives of this study were to:

- Develop a systematic approach to measure and visualize the impact of work zones
- Predict the impact future work zones will have on interstate's mobility
- Develop a high-level decision-making process to better plan future work zones

These objectives were achieved by developing three methodologies using probe vehicle data. According to the FHWA's call for developing systematic approaches to improve current work zone mobility management strategies, three analytic approaches were developed including a performance measurement framework (WZMA), a machine learning framework for prediction purposes, and a high-level assessment to enhance work zone decision-making processes. Following sections discuss each of these approaches in further detail.

Descriptive Analytics: Mobility Performance Measurement Using the WZMA

The results of this study and reviewed literature showed that incorporating probe vehicle data can improve work zone management strategies. Using probe vehicle data, agencies can implement the work zone mobility audit procedure to characterize work zone mobility impacts. This study attempted to apply a segment-based analysis to characterize work zone mobility performance both spatially and temporally. This mobility characterization assists agencies to identify problematic highway lane-closures by visually assessing the impact that work zones had on traffic mobility. In addition, summary statistics of traffic mobility provided by the WZMA were used in a state-wide assessment of mobility.

Predictive Analytics: Machine Learning Application

In addition, accurately predicting work zone impact assists practitioners to optimize their TMPs to mitigate negative mobility and safety impacts resulted from work zone presence. This study showed a proof of concept in which machine learning classification algorithms can be used

to predict work zone impact with a considerable accuracy. Three classification modeling techniques, (XGBoost, Random Forest, and Neural Network) were used to predict speed for each highway segment over time. Performance of these models showed that these models are capable of learning traffic patterns from historical occurrences and predict future scenarios.

Prescriptive Analytic: State-wide Work Zone Traffic Management

A data set of historical lane-closure information was gathered from more than 1,700 case studies. This dataset included work zones with shoulder-lane closures to multiple-lane closures. Also, these lane-closures lasted between one to 15 days on highways. All the mobility metrics defined in the WZMA were calculated for these projects to further provide a state-wide impact assessment. The final data set was mined using various approaches to rank interstate highways based on their mobility performance, including delay and queueing metrics. In addition, an approach was utilized to identify significant projects which account for the majority of the impact. Using Pareto principle, 20% of lane-closures which caused approximately 80% of the overall impact were identified and ranked. Box-whisker plots were another approach used to highlight distribution of the impact for each highway. Using this approach, lane-closures were divided into four quantiles based on their impact. Cases that fall into the top quantile could also be considered as significant projects. In addition, CHAID statistical analysis was utilized to optimally split the previous work zones into significant categories. This approach provided more actionable information for work zone traffic management decision makers to categorize and compare different work zone strategies on each Michigan freeway. Practitioners can use the decision trees to approximate the expected mobility impact while planning future work zones.

Figure 45 illustrates the work zone policy development and implementation process proposed by the FHWA along with the three approaches performed in this study to address its requirements.

Policy Development and Implementation Process proposed by FHWA

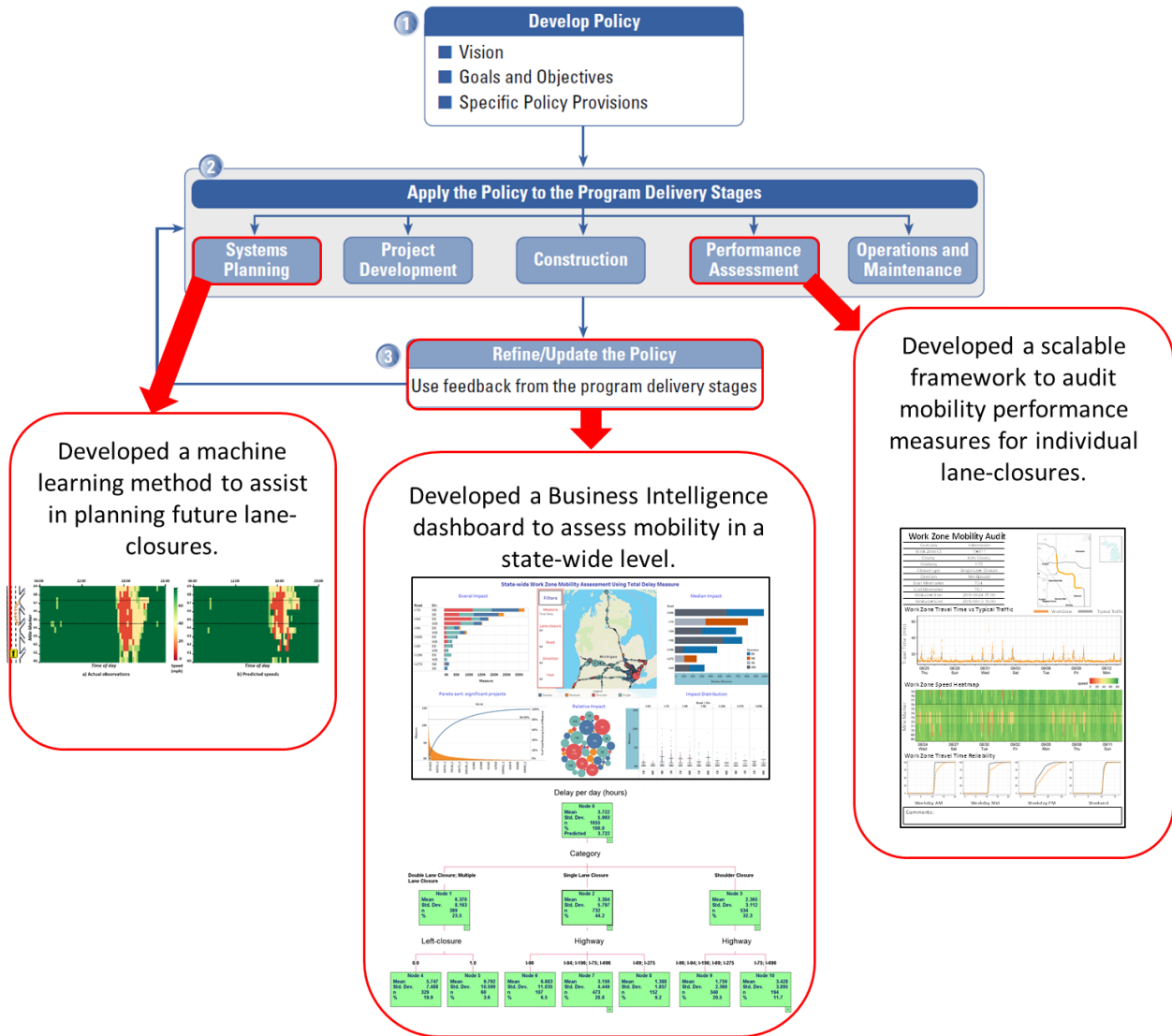


Figure 45. Summary of approaches to address FHWA requirements

Intelligent Mobility Platform

This study attempted to address the federal rule on work zone safety and mobility (3) requirements by proposing three analytic approaches. The Work Zone Mobility Audit (WZMA) framework was applied to assess mobility for each individual work zone using various delay and queuing metrics. Machine Learning techniques were also applied to predict mobility for future work zones which assists decision makers in their planning. Business Intelligence was also

applied to develop an interactive dashboard in which work zone performance measures were summarized and visualized for more actionable information. This platform was called “Intelligent Work Zone Mobility” which utilizes these approaches to provide a web-based service for transportation agencies. This platform is expected to assist transportation agencies assess and manage their work zones both for an individual and state-wide level.

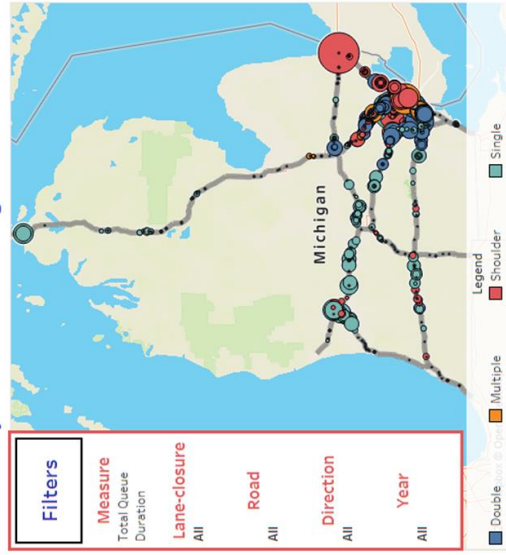
Discussion and recommendation for future research

Further research in the following areas is recommended:

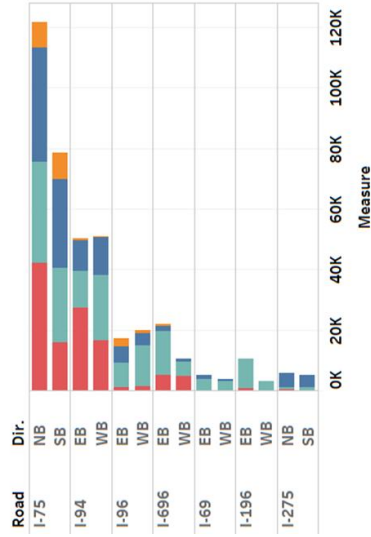
- This method is applicable for large-scale implementation to assist planning future lane-closure projects. The WZMA process was developed to use probe vehicle data for mobility assessment. Agencies have access to the National Performance Measurement Research Data Set (NPMRDS) which is another source for probe vehicle data. Future research can incorporate data from NPMRDS to run the WZMA process for all work zones on US interstates.
- Develop an algorithm to perform the WZMA process more efficiently could save computation resources specifically in large scale implementation
- As more data becomes available in future, prediction performance of machine learning algorithms is suspected to increase. Performance of these prediction models is dependent on the case studies used for training and sufficient information to describe work zone characteristics. If available, including hourly traffic volume and weather information would help to establish more accurate predictions.
- Future research work could also incorporate image processing algorithms to use work zone heatmaps for training and predicting mobility for future work zones (72).

- Agencies need to develop systematic approaches for recording lane closure activities. This will have tangible returns in future modeling practices and will facilitate more accurate mobility performance measurement.
- The choice of speed bins used by classification algorithm for prediction could be explored in the future by applying clustering algorithms to find optimal ranges. An optimal split is expected to improve the prediction accuracy.
- Further statistical and econometric analysis is recommended to diagnose the causality between mobility metrics and work zone characteristics.
- Examine game theory applications to optimize work zone planning and management strategies (82).

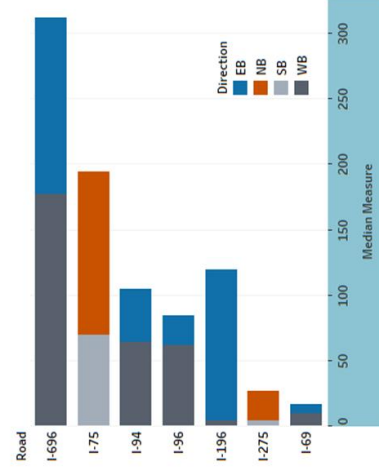
State-wide Work Zone Mobility Assessment Using Total Queue Duration Measure



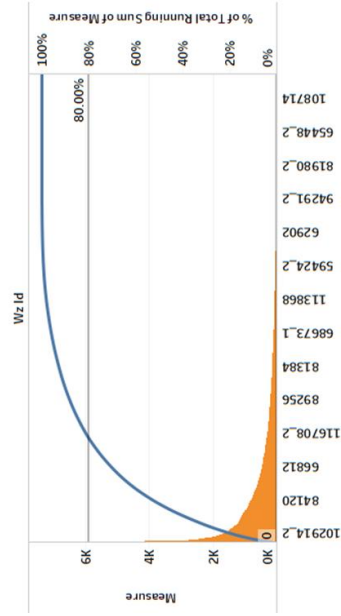
Overall Impact



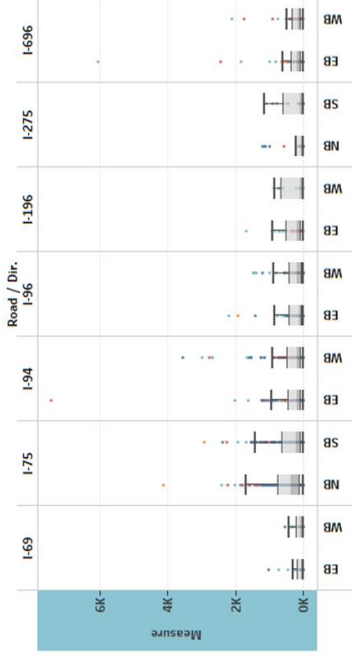
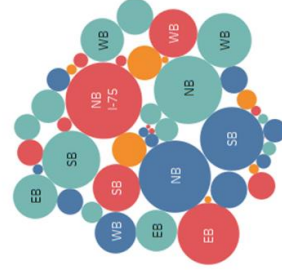
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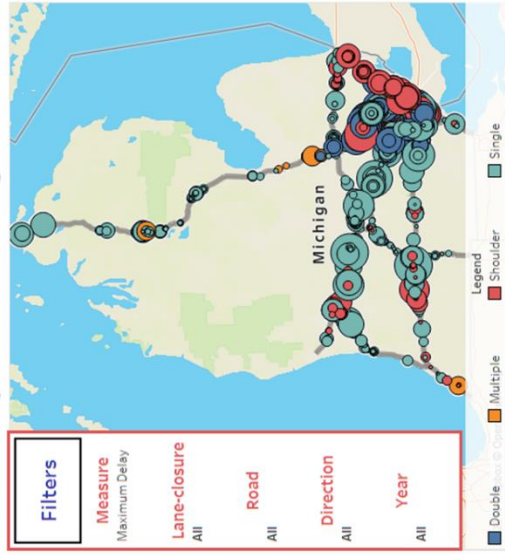
Pareto sort: significant projects



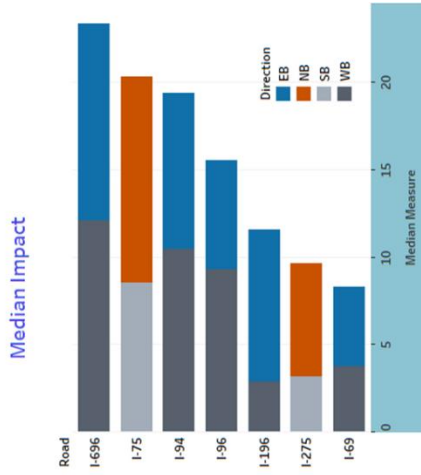
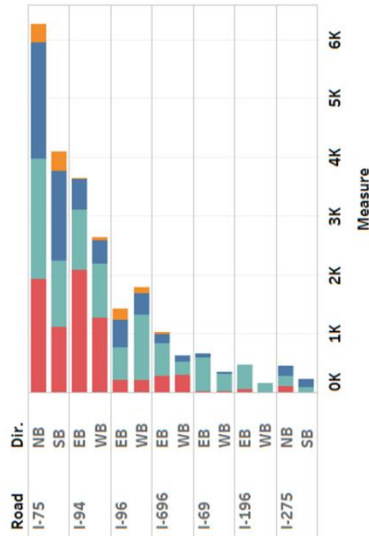
Relative Impact



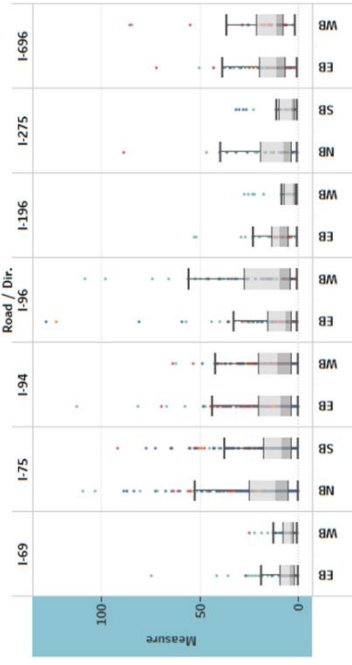
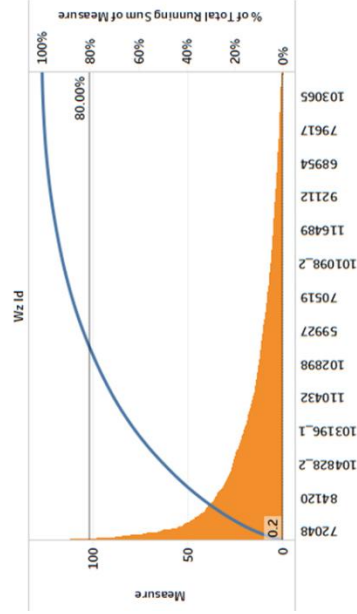
State-wide Work Zone Mobility Assessment Using Maximum Delay Measure



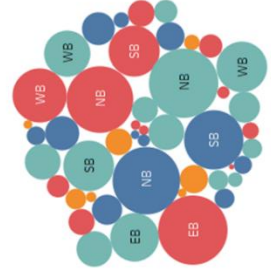
Overall Impact



Pareto sort: significant projects



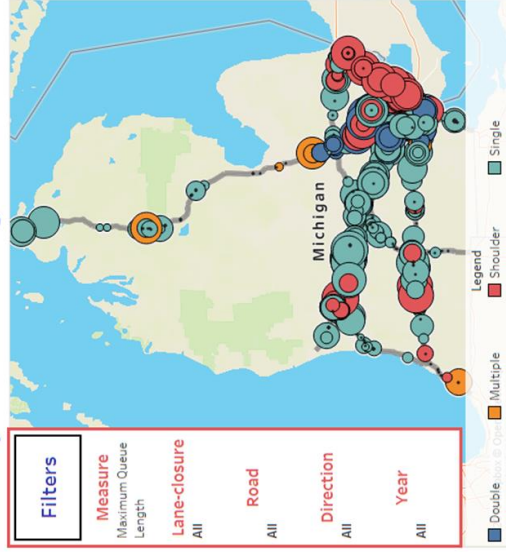
Relative Impact



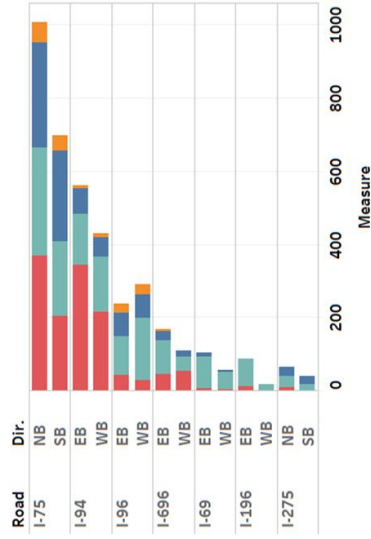
State-wide Work Zone Mobility Assessment Using Maximum Queue Length Measure

Filters

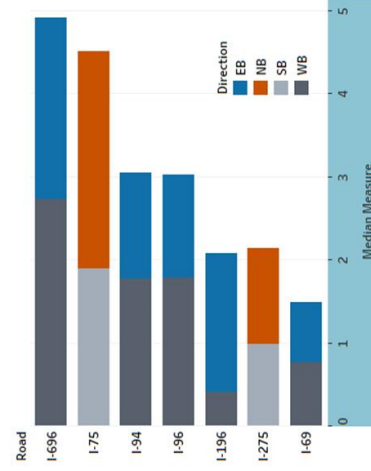
- Measure**: Maximum Queue Length
- Lane-closure**: All
- Road**: All
- Direction**: All
- Year**: All



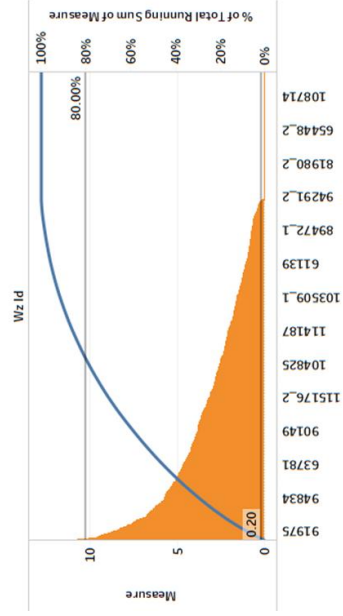
Overall Impact



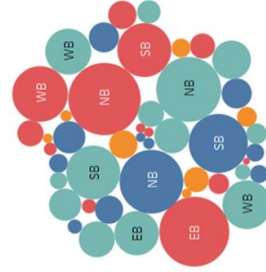
Median Impact



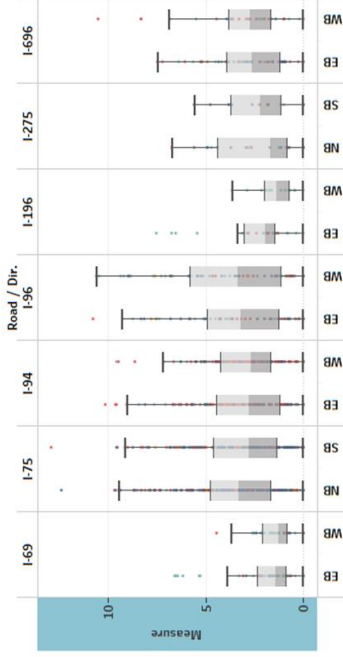
Pareto sort: significant projects



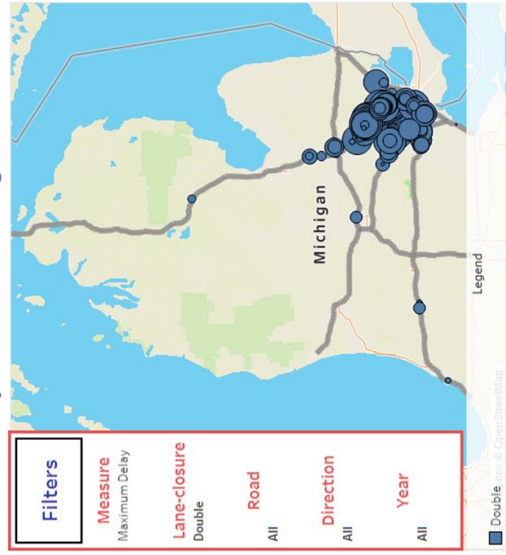
Relative Impact



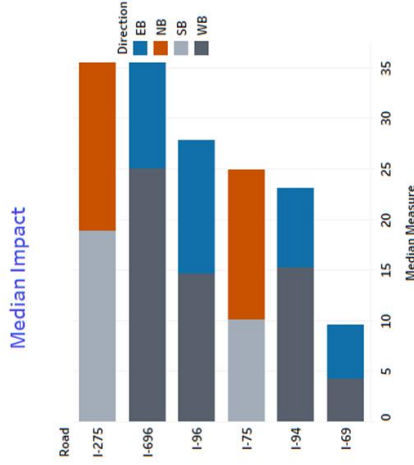
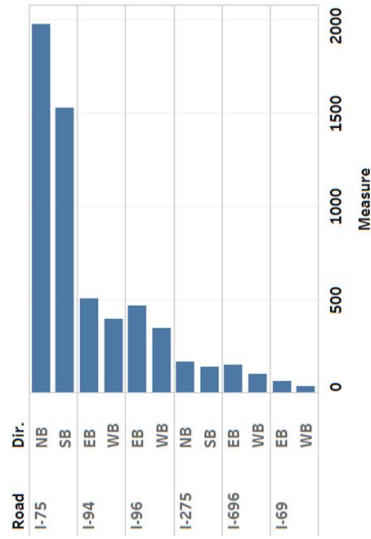
Impact Distribution



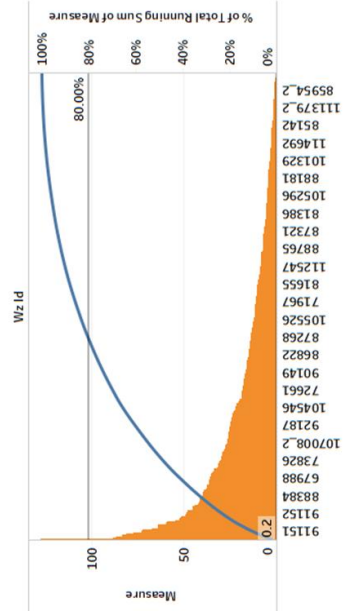
State-wide Work Zone Mobility Assessment Using Maximum Delay Measure



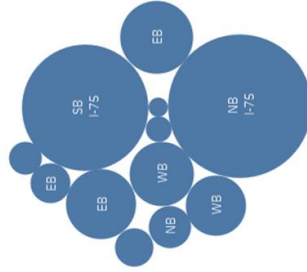
Overall Impact



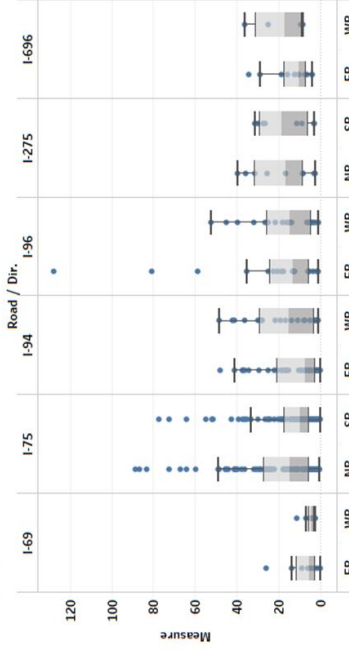
Pareto sort: significant projects



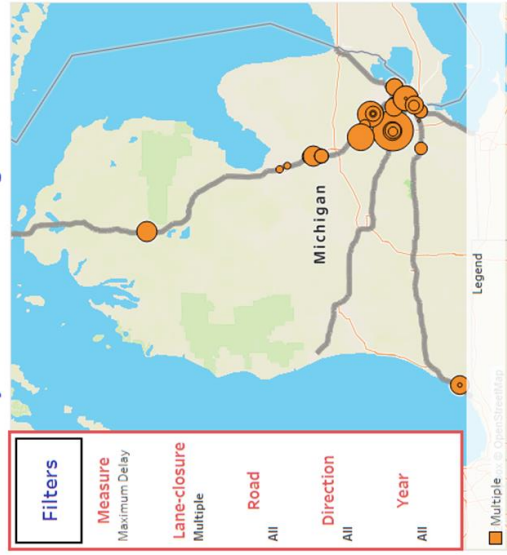
Relative Impact



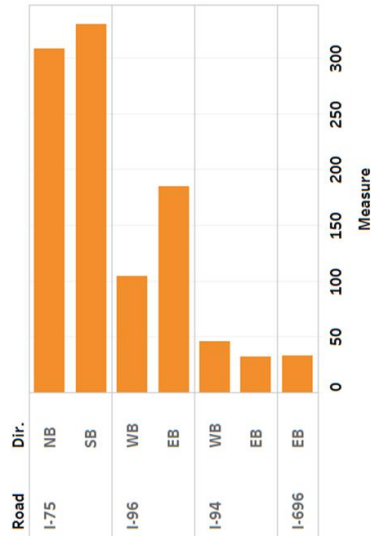
Impact Distribution



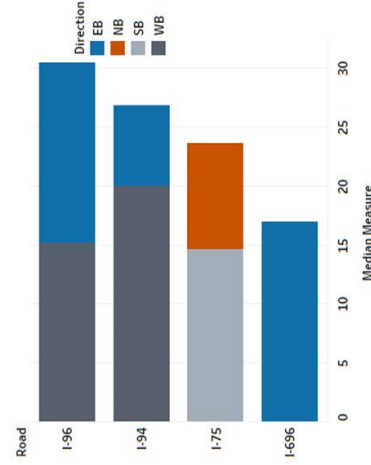
State-wide Work Zone Mobility Assessment Using Maximum Delay Measure



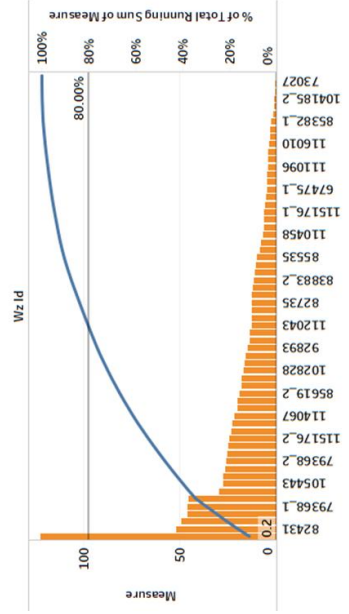
Overall Impact



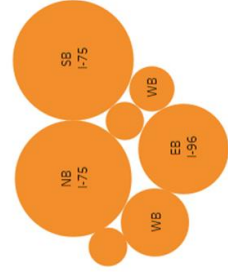
Median Impact



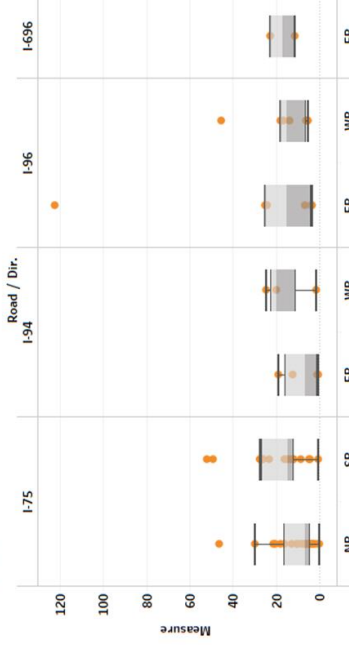
Pareto sort: significant projects



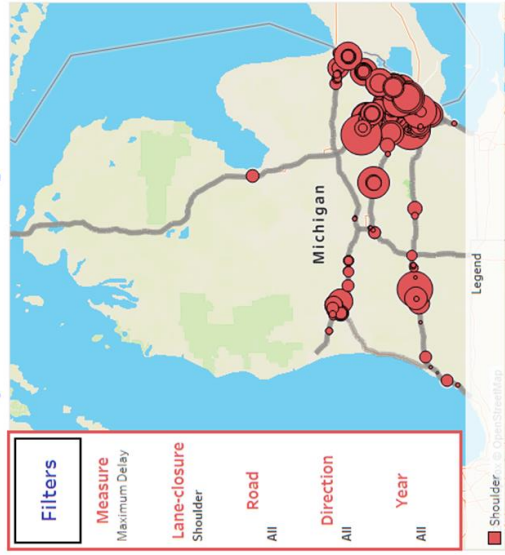
Relative Impact



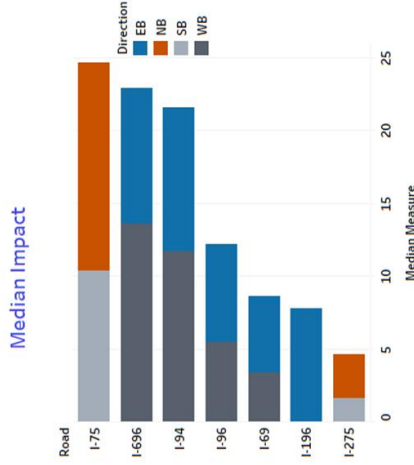
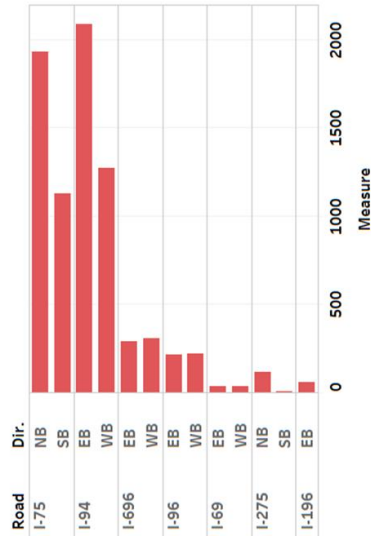
Impact Distribution



State-wide Work Zone Mobility Assessment Using Maximum Delay Measure

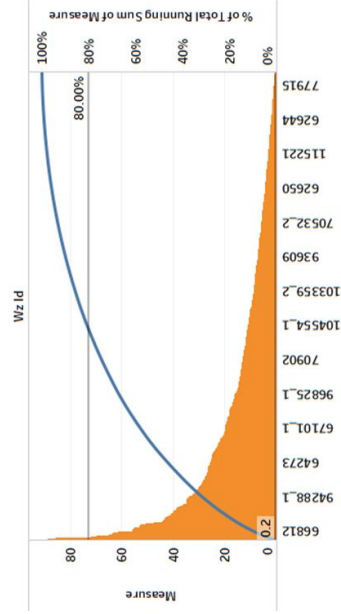


Overall Impact

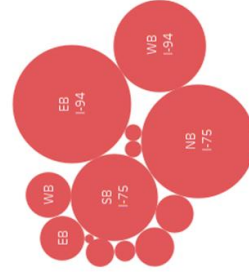


Median Impact

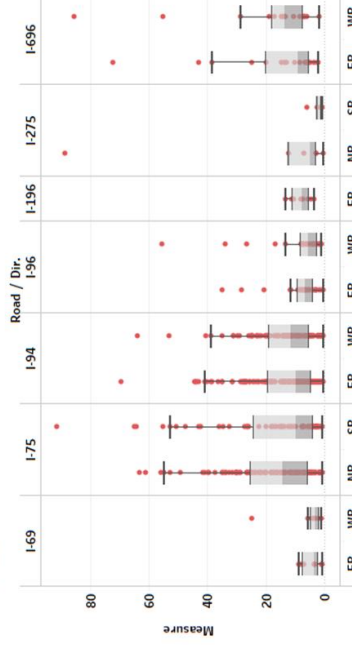
Pareto sort: significant projects



Relative Impact



Impact Distribution



APPENDIX B: Statistical analysis results

Table 6. CHAID summary statistics using longest queue length

Node	Mean	Std. Deviation	Number of records	Parent Node	Primary Independent Variable					
					Variable	Sig.a	F	df1	df2	Split Values
0	2.29	2.34	1655							
1	2.67	2.49	914	0	Highway	0.000	30.01	3	1651	I-96; I-75; I-696
2	2.15	2.20	461	0	Highway	0.000	30.01	3	1651	I-94
3	1.64	1.83	132	0	Highway	0.000	30.01	3	1651	I-196; I-275
4	0.94	1.21	148	0	Highway	0.000	30.01	3	1651	I-69
5	2.30	2.37	416	1	CAADT	0.000	12.92	2	911	<= 210.0
6	3.16	2.44	380	1	CAADT	0.000	12.92	2	911	(210.0, 890.0]
7	2.40	2.81	118	1	CAADT	0.000	12.92	2	911	> 890.0
8	2.44	2.44	124	2	CAADT	0.000	13.13	3	457	<= 86.0
9	1.93	2.13	164	2	CAADT	0.000	13.13	3	457	(86.0, 493.0]
10	3.11	1.93	87	2	CAADT	0.000	13.13	3	457	(493.0, 520.0]
11	1.20	1.75	86	2	CAADT	0.000	13.13	3	457	> 520.0
12	2.81	2.34	108	6	Day (start)	0.001	13.58	2	377	Friday; Sunday; Wednesday
13	2.04	2.04	64	6	Day (start)	0.001	13.58	2	377	Saturday; Thursday
14	3.69	2.47	208	6	Day (start)	0.001	13.58	2	377	Monday; Tuesday
15	3.17	3.11	68	7	Day (start)	0.028	13.10	1	116	Friday; Saturday; Thursday; Sunday; Tuesday
16	1.36	1.94	50	7	Day (start)	0.028	13.10	1	116	Monday; Wednesday
17	3.18	2.29	60	8	Day (end)	0.048	11.93	1	122	Sunday; Monday; Saturday
18	1.73	2.37	64	8	Day (end)	0.048	11.93	1	122	Friday; Wednesday; Thursday; Tuesday

Table 7. CHAID summary statistics using number of queue metric

					Primary Independent Variable					
Node	Mean	Std. Deviation	Number of records	Parent Node	Variable	Significance	F	df1	df2	Split Values
0	1.55	1.9120686	1655							
1	1.517	2.0594255	276	0	Highway	0.0000	71.36	2	1652	I-96; I-275
2	0.893	1.313379	609	0	Highway	0.0000	71.36	2	1652	I-94; I-69
3	2.082	2.0875107	770	0	Highway	0.0000	71.36	2	1652	I-196; I-75; I-696
4	2.439	2.3064123	68	1	Category	0.0000	12.83	2	273	Double Lane Closure; Multiple Lane Closure
5	1.447	2.145751	141	1	Category	0.0000	12.83	2	273	Single Lane Closure
6	0.728	0.9935911	67	1	Category	0.0000	12.83	2	273	Shoulder Closure
7	0.214	0.4394352	66	2	CAADT	0.0000	24.87	5	603	<= 75.0
8	1.392	1.574021	89	2	CAADT	0.0000	24.87	5	603	(75.0, 86.0]
9	0.713	1.1137315	207	2	CAADT	0.0000	24.87	5	603	(86.0, 493.0]
10	1.908	1.5508056	87	2	CAADT	0.0000	24.87	5	603	(493.0, 520.0]
11	0.891	1.3354713	76	2	CAADT	0.0000	24.87	5	603	(520.0, 6500.0]
12	0.293	0.7178189	84	2	CAADT	0.0000	24.87	5	603	> 6500.0
13	1.76	1.9904397	420	3	AADT	0.0000	22.5	1	768	<= 10866.0
14	2.467	2.1382487	350	3	AADT	0.0000	22.5	1	768	> 10866.0
15	2.244	1.9827585	122	13	Category	0.0100	10.4	1	418	Double Lane Closure
16	1.562	1.9626465	298	13	Category	0.0100	10.4	1	418	Lane Closure; Shoulder Closure

Table 8. CHAID summary statistics using delay metric

					Primary Independent Variable					
Node	Mean	Std. Deviation	Number of records	Parent Node	Variable	Significance	F	df1	df2	Split Values
0	3.722	5.9934635	1655							
1	6.37	8.162536	389	0	category	0	57.06	2	1652	Double Lane Closure; Multiple Lane Closure
2	3.304	5.7967599	732	0	category	0	57.06	2	1652	Single Lane Closure
3	2.365	3.1116174	534	0	category	0	57.06	2	1652	Shoulder Closure
4	5.747	7.4883212	329	1	left_closure	0	12.85	1	387	0
5	9.792	10.599175	60	1	left_closure	0	12.85	1	387	1
6	6.683	11.035458	107	2	roadway_x	0	28.65	2	729	I-96
7	3.156	4.4493446	473	2	roadway_x	0	28.65	2	729	I-94; I-196; I-75; I-696
8	1.388	1.8569557	152	2	roadway_x	0	28.65	2	729	I-69; I-275
9	1.759	2.3602655	340	3	roadway_x	0	37.96	1	532	I-96; I-94; I-196; I-69; I-275
10	3.428	3.8952235	194	3	roadway_x	0	37.96	1	532	I-75; I-696
11	2.461	3.4500018	282	7	AADT	0	17.61	1	471	<= 10866.0
12	4.181	5.4592507	191	7	AADT	0	17.61	1	471	> 10866.0

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ABSTRACT**DATA DRIVEN APPROACH TO CHARACTERIZE AND FORECAST THE IMPACT OF
FREEWAY WORK ZONES ON MOBILITY USING PROBE VEHICLE DATA**

by

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The presence of work zones on freeways causes traffic congestion and creates hazardous conditions for commuters and construction workers. Traffic congestion resulting from work zones causes negative impacts on traffic mobility (delay), the environment (vehicle emissions), and safety when stopped or slowed vehicles become vulnerable to rear-end collisions. Addressing these concerns, a data-driven approach was utilized to develop methodologies to measure, predict, and characterize the impact work zones have on Michigan interstates. This study used probe vehicle data, collected from GPS devices in vehicles, as the primary source for mobility data. This data was used to fulfill three objectives: develop a systematic approach to characterize work zone mobility, predict the impact of future work zones, and develop a business intelligence support system to plan future work zones.

Using probe vehicle data, a performance measurement framework was developed to characterize the spatiotemporal impact of work zones using various data visualization techniques. This framework also included summary statistics of mobility performance for each individual work zone. The result was a Work Zone Mobility Audit (WZMA) template which summarizes metrics

into a two-page summary which can be utilized for further monitoring and diagnostics of the mobility impact.

A machine learning framework was developed to learn from historical projects and predict the spatiotemporal impact of future work zones on mobility. This approach utilized Random Forest, XGBoost, and Artificial Neural Network classification algorithms to determine the traffic speed range for highway segments while having freeway lane-closures. This framework used a distribution of speed for each freeway segment, as a substitute for hourly traffic volume, and were able to predict speed ranges for future scenarios with up to 85% accuracy. The ANN model reached up to 88% accuracy predicting queueing condition (speed less than 20 mph), which could be utilized to enhance queue warning systems and improve the overall safety and mobility.

Mobility data for more than 1,700 historical work zone projects in state of Michigan were assessed to provide a comprehensive overview of the overall impact and significant factors affecting the mobility. A Business Intelligence (BI) approach was utilized to analyze these work zones and present actionable information which helps work zone mobility executives make informed decisions while planning their future work zones. The Pareto principle was also utilized to identify significant projects which accounted for a majority of the overall impact. Chi-square Automatic Interaction Detector, CHAID, algorithm was also applied to discover the relationship between variables affecting the mobility. This statistical method built several decision-trees which could be utilized to determine best, worst, and expected consequence of different work zone strategies.

AUTOBIOGRAPHICAL STATEMENT

Mohsen Kamyab joined Wayne State University (WSU) in 2015 to pursue his PhD degree in transportation engineering. He received his B.S degree in civil engineering at Bahonar University of Kerman, Iran. He continued his education to receive his M.Sc. degree in Civil Engineering focusing on transportation engineering at Yazd University, Iran. During his education at WSU, he worked as a Graduate Teaching Assistant and Graduate Research Assistant. His research interests are Intelligent Transportation Systems (ITS) and data-driven analytics.