ABSTRACT

Title of Dissertation: A DATA-DRIVEN FRAMEWORK FOR THE PREDICTION OF NON-RECURRENT TRAFFIC CONGESTION RECOVERY TIME ON FREEWAYS

Aliakbar Kabiri, Doctor of Philosophy, 2024

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This study introduces a comprehensive approach aimed at improving the management of incident durations. It delves into enhancing traffic incident management by integrating diverse incident datasets, including Maryland State Police incident data and Coordinated Highways Action Response Team (CHART) incident data, to improve the assessment of traffic incident durations. The dissertation employs spatial and temporal thresholds to explore matching different incident datasets and identifies discrepancies between various incident reports. The dissertation also explores methodologies for estimating traffic recovery times of each incident, utilizing historical data and pre-incident conditions as baselines to establish normal traffic conditions. A novel framework is introduced to estimate non-recurrent traffic congestion recovery time, revealing that many incidents recover faster than their reported clearance times. In these cases, traffic flow returns to normal conditions quickly.

Further, the study examines predictive modeling for traffic recovery time, highlighting the Random Forest model's effectiveness among various machine learning algorithms. This model's superiority, based on precision, recall, and F1-scores, underlines its potential in accurately predicting traffic incident recovery time categorized as short-duration, medium-duration, and long-duration incidents. In particular, the random forest model results in a precision of 0.7 for short-duration incidents, 0.3 for medium-duration incidents, and 0.5 for long-duration incidents. For instance, the precision of 0.5 for long-duration incidents indicates that half of the cases predicted as long-duration incidents are indeed long-duration incidents. Key predictors such as link-level vehicle volume, clearance time, response time, and number of lanes closed are identified, providing valuable insights for traffic management strategies. This dissertation underscores the importance of data-driven approaches in traffic incident management, aiming to enhance the efficiency of transportation systems through accurate prediction and estimation of incident recovery times.

A DATA-DRIVEN FRAMEWORK FOR THE PREDICTION OF NON-RECURRENT TRAFFIC CONGESTION RECOVERY TIME ON FREEWAYS

by

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List of Abbreviations

AADT	Annual Average Daily Traffic
ACRS	Automated Crash Reporting System
CHART	Coordinated Highways Action Response Team
CV	Connected Vehicle
EDA	Exploratory Data Analysis
HCM	Highway Capacity Manual
FN	False Negative
GB	Gradient Boosting
KNN	K-nearest Neighbors
LR	Logistic Regression
ML	Machine Learning
MPD	Mean Percentage Difference
NN	Neural Network
OHE	One-Hot Encoding

RF	Random Forest
RITIS	Regional Integrated Transportation Information System
SMOTE	Synthetic Minority Over-sampling Technique
TMC	Traffic Message Channel
TN	True Negative
TP	True Positive

Chapter 1: Introduction

Traffic incident management holds paramount importance for transportation agencies. Prolonged incident duration times significantly elevate the probability of subsequent incidents and exacerbate traffic congestion (Chung et al., 2015; Mannering and Bhat, 2014), which is one of the main factors causing air pollution, waste of time and damages caused by accidents (Rasaizadi et al., 2022). Consequently, minimizing incident duration time is considered the foremost priority for mitigating the repercussions of traffic incidents. To accomplish this objective, it is essential to explore the factors that influence incident duration time and their effects, along with accurately measuring the components of the incident duration time.

1.1. Overview

Traffic congestion has two distinct types: recurrent and non-recurrent traffic congestion. Recurrent traffic congestion usually occurs due to variations in traffic demand, the operational approach applied to the freeway, and the specific design of the freeway's physical layout (Skabardonis et al., 2003) and happens during typical weekday commutes, unaffected by accidents, adverse weather conditions, or other unpredictable incidents (Dowling et al., 2004). Non-recurrent traffic congestion is an irregular disruption in the traffic network resulting from various factors such as traffic accidents, adverse weather conditions, special events, and construction zones (Isa et

al., 2018). Figure 1 shows the two types of congestion. Traffic incidents, such as accidents, breakdowns, and unexpected road closures, pose a significant challenge to transportation systems worldwide. These non-recurrent incidents disrupt traffic flow, causing congestion, delays, and, in some cases, severe safety risks.

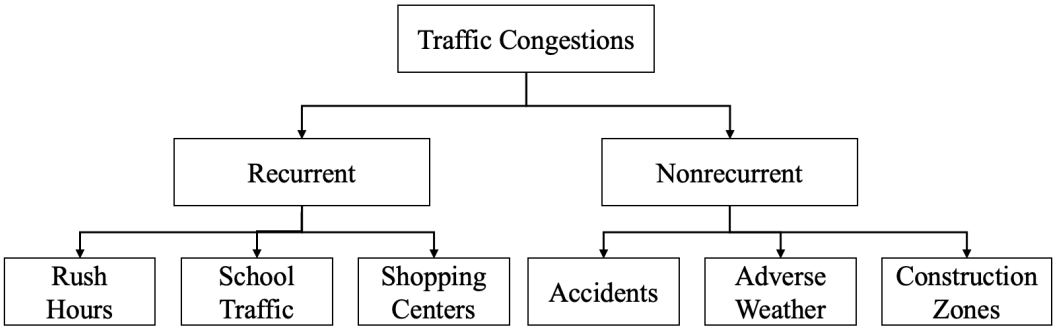

Figure 1. Types of congestions.

The duration of a non-recurrent traffic incident can be broken down into four phases, each representing different components of how long an incident takes time (Shang et al., 2022). The detection phase begins when an incident actually occurs and is first detected by either a monitoring system (e.g., traffic cameras, sensors) or reported by a bystander, a driver, or a first responder. The response phase starts when the incident is confirmed and appropriate authorities or emergency responders are dispatched. It includes the time it takes for responders to arrive, assess the situation, and begin implementing response measures. The clearance phase encompasses the time required to address the incident and its aftermath, including clearing the scene, providing

medical assistance, and ensuring the safety of those involved. Lastly, the recovery phase begins when the incident has been fully addressed and cleared, and traffic flow returns to normal. It includes the time it takes for congestion to dissipate, for traffic patterns to stabilize, and for road infrastructure to be restored to its pre-incident state.

Previous studies in traffic management and incident analysis have typically defined traffic recovery time as the period that begins after the clearance time when an incident has been fully addressed and authorities have given the green light for traffic to resume its normal flow. During this conventional recovery phase, it is assumed that traffic gradually returns to its usual conditions, with congestion gradually dissipating until things return to normal.

Figure 2 shows the conventional incident duration phases (Fu et al., 2019; Mohammed et al., 2021; Shang et al., 2022).

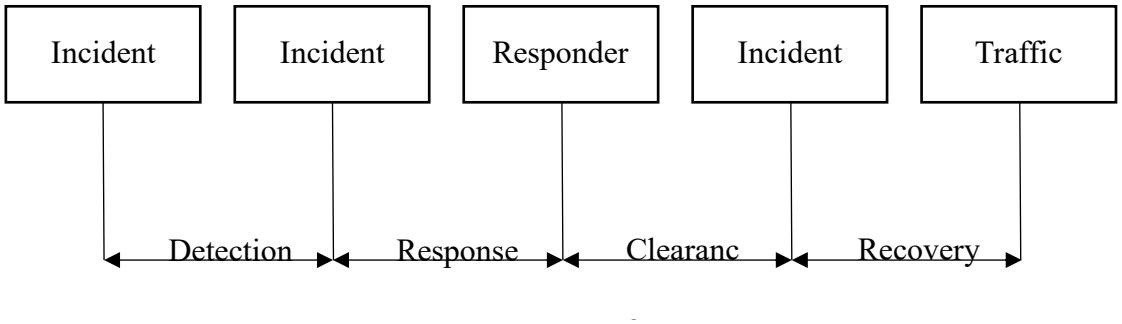

Figure 2. Conventional incident duration phases.

However, probe vehicle data reveals a more nuanced picture of traffic behavior during incident recovery. In many cases, this data indicates that traffic starts returning to its normal condition well before the official clearance time or may even be resolved before the scene is fully cleared.

Possible reasons for such observations include but are not limited to partial clearance, where sometimes responders clear part of the incident scene, allowing some lanes to reopen while other portions are still being addressed. This partial clearance can lead to the gradual recovery of traffic in sections of the affected area. Real-time traffic information and updates provided to drivers through various sources, including navigation apps and variable message signs, can also help them make informed decisions to navigate around the incident and reduce congestion.

Understanding that traffic recovery may commence before official clearance is critical for incident management and traffic control. It highlights the importance of adaptive strategies that respond to the evolving traffic dynamics during an incident. This insight also emphasizes the need for a holistic approach to incident duration analysis that considers the conventional post-clearance recovery and the dynamic nature of traffic as it naturally starts to normalize during the incident resolution process.

The motivation behind this dissertation lies in the pressing need to develop a data-driven framework that can accurately predict the duration of non-recurrent traffic incidents. The reliability of predicting incident-induced delay depends significantly on

the accuracy of recovery time prediction. If recovery time prediction is inaccurate, it undermines the reliability of delay forecasts. By leveraging statistical methods and cutting-edge machine learning algorithms, this research aims to revisit the current approaches in the literature and address this critical issue with a multifaceted approach.

1.2. Objectives

The first objective is to revisit the established incident duration time phases, with particular emphasis on cases where the recovery time commences before the official end of the clearance time. The study seeks to provide a nuanced perspective on the temporal dynamics of incident management and recovery by scrutinizing instances where traffic normalization begins during the incident resolution process.

The second objective involves the exploration of diverse sources of incident data supplied by different agencies. A method is proposed for effectively matching these disparate datasets, driven by the goal of gathering useful information from different data sources together and conducting incident duration time prediction. The analysis will focus on comparing the accuracy of predictive models using different combinations of incident-related datasets, shedding light on the advantages and challenges of integrating various data sources for incident duration assessment.

The third objective centers on developing a robust methodology for labeling the incidents with an accurate traffic recovery time. This methodology leverages probe

vehicle and CHART data, encompassing variables like speed reported at minute intervals for each road segment. The study aims to provide accurate assessments of traffic recovery by harnessing this rich dataset.

The final objective of this study is to provide a comprehensive prediction model for traffic recovery time post-disruption, utilizing an analysis that considers various influencing factors. This model aims to assess the impact of different variables, such as the scale of accidents, environmental conditions, and the effectiveness of emergency response efforts, on the duration required for traffic conditions to return to normal.

This study is important for several reasons. Traffic incidents can vary significantly in terms of their severity and impact on traffic flow. This research can help predict the recovery time of non-recurrent traffic incidents more accurately. This information is crucial for efficiently allocating responders and resources. When multiple incidents occur simultaneously, as can often happen in congested urban areas, accurate predictions of recovery times are essential for prioritizing responses and ensuring that resources are distributed effectively.

Previous incident response methods and cost analysis often focus solely on the incident location. However, traffic incidents can have ripple effects that extend to upstream zones, affecting traffic flow and causing congestion in unexpected areas. This research goes beyond the incident location and considers the broader impact of incidents on

traffic patterns. The results of this broader analysis can be utilized to lead to a more accurate assessment of the financial costs associated with incidents. Such insights are invaluable for policymakers and transportation authorities when deciding resource allocation and infrastructure improvements.

Traffic congestion is a significant problem in many urban areas, leading to wasted time and fuel, increased pollution, and decreased overall quality of life. By accurately predicting incident recovery times and analyzing their broader effects on traffic flow, this research can help transportation agencies implement more effective congestion mitigation strategies. This might involve adjusting traffic signal timings, rerouting traffic, or providing real-time information to commuters to help them make informed decisions about their routes to reach their destination in the shortest time (Allwell et al., 2012; Baykal-Gürsoy et al., 2009; Schrank et al., 2015). Ultimately, this can lead to reduced congestion and improved traffic flow, benefiting both commuters and the environment.

1.3. Research Contributions

This dissertation represents a novel and pioneering study within the field, making significant contributions in multiple dimensions. It explores the integration of multiple traffic incident datasets to find benefits and challenges associated with data-matching procedures. This effort addresses the critical need to harness the collective insights

from various data providers, such as the Maryland State Police and CHART, to inform more accurate assessments of traffic incidents.

Furthermore, this research leverages a vast and real-world probe vehicle dataset at the state level, marking a substantial advancement in the application of large-scale probe vehicle data in the context of incident analysis. This novel utilization of probe vehicle data enhances the precision of incident recovery time prediction and introduces the capability to detect non-recurrent incidents—an aspect overlooked in traffic incident data analysis.

Another distinctive facet of this study is its revisiting conventional traffic incident phases, uncovering scenarios where recovery time initiates before the official clearance time—a phenomenon largely overlooked in existing incident management literature. In response to this revelation, the dissertation introduces a pioneering methodology for estimating recovery time using probe vehicle data, a valuable contribution that fills a critical gap in the field.

Another significant contribution of this study is its novel approach to analyzing traffic recovery time. Unlike previous studies in the literature, which typically focus solely on the incident location when examining recovery time using similar travel time and speed datasets, this research broadens the scope. Specifically, it explores the upstream zones, offering a more comprehensive understanding of the dynamics influencing traffic recovery. This expanded perspective provides valuable insights into how incidents

impact traffic conditions beyond their immediate vicinity, enhancing this field's depth and breadth of knowledge.

Furthermore, the existing literature lacks investigation into defining baseline conditions in traffic flow analysis. The study delves into the complexities and challenges of establishing a normal traffic condition baseline by exploring two distinct approaches—utilizing historical data from several days and examining adjacent same-day pre-incident conditions. This research expands the understanding of traffic flow analysis and provides valuable insights for developing more robust and more accurate models for predicting and managing traffic conditions, specifically on long-duration incidents, thereby contributing to advancements in transportation planning and management strategies.

In summary, this dissertation is a pioneering and groundbreaking effort, offering a holistic and innovative approach to traffic incident analysis. It integrates diverse crash datasets, harnesses the power of real-world probe vehicle data, redefines conventional incident phases, and provides new methodologies for recovery time measurement and real-time incident detection. These contributions collectively advance the understanding of traffic incidents and underscore the potential for transformative enhancements in incident management practices.

1.4. Dissertation Structure

In the second chapter, an extensive literature review is conducted on the various components of traffic incidents, delving into incident detection, response, clearance, and recovery phases. Additionally, existing predictive approaches for traffic incident durations are explored, encompassing machine learning and statistical methods and their accuracies.

The third chapter elucidates the three primary data sources underpinning the research: the Maryland State Police Crash Data, CHART Data, and Probe Vehicle Data.

The fourth chapter explores how different traffic incident datasets can be integrated. The methodology employed for such integration is outlined, with a specific emphasis on spatial and temporal matching. This chapter explores how additional data can enhance predictive models and delves into the considerations related to sample size. The experimental design and the results of data matching efforts, accompanied by thorough analysis, are presented.

The fifth chapter focuses on the approach used to estimate traffic recovery time following an incident and the related research outcomes. It outlines the process for aligning data from probe vehicles with incident reports, a strategy for identifying upstream links within a specific road network, and the method for defining and

recognizing the normal traffic patterns through probe vehicle data. Ultimately, it suggests a structure for calculating the duration of traffic incident recovery.

In the sixth chapter, a detailed exploratory data analysis is performed on the dataset containing information about traffic incidents. This analysis aims to uncover patterns, anomalies, or any insights that could inform the development of predictive models. Following this, the chapter progresses to apply various machine learning algorithms to forecast how long it will take for traffic to return to normal conditions after an incident. The chapter evaluates the performance of these predictive models, focusing on their accuracy in forecasting traffic recovery times. Furthermore, it delves into the importance of different features—variables or attributes the models use to make predictions. This involves analyzing which aspects of the traffic incident data (e.g., location, time of day, type of incident) most significantly impact the model's predictions.

The seventh chapter presents the research conclusions with a summary of findings and methodologies while acknowledging the study's limitations. It offers insights into future research directions, suggesting how further investigations could address these limitations and advance the field of traffic incident management even further.

Chapter 2: Literature Review

2.1. Probe Vehicle Data

Road traffic data, including speed, volume, density, and travel time, provide real-time information for road operators and passengers (Rasaizadi et al., 2023). Probe vehicle data are among those that can provide such invaluable information.

Probe vehicle data refers to the information collected from vehicles equipped with sensors and communication devices to transmit real-time data about their location, speed, and other relevant parameters. This data is increasingly used in transportation engineering and crash analysis for various purposes. In transportation engineering, probe vehicle data is utilized for estimating traffic volumes at signalized intersections (Zheng and Liu, 2017), real-time traffic-state estimation, and short-term travel-time prediction on freeways (Nanthawichit et al., 2003). Additionally, it is used for accurately estimating networkwide traffic states and metrics (Nagle and Gayah, 2014), understanding near-crash events through pattern recognition (Kong et al., 2022), and identifying time-of-day breakpoints based on vehicle trajectory data (Wan et al., 2019).

Probe vehicle data has been extensively utilized in the context of traffic incident duration time analysis. Kinoshita et al. proposed a method for detecting traffic incidents from probe-car data by identifying unusual events that distinguish incidents from spontaneous congestion (Kinoshita et al., 2015). Asakura et al. studied the properties

of traffic flow dynamics during incidents. They proposed incident detection methods using floating data collected by probe vehicles equipped with onboard global positioning system (GPS) equipment (Asakura et al., 2015). Additionally, Houbraken et al. highlighted using probe vehicle data for automated incident detection, paving the way for traffic state estimation, travel time measurements, and traffic management applications (Houbraken et al., 2017).

Furthermore, Kwon et al. highlighted the use of probe vehicle data for travel-time prediction, emphasizing the transition towards autonomous systems that rely on such data (Kwon et al., 2000). Additionally, Nanthawichit et al. emphasized using probe vehicle data for real-time traffic-state estimation, travel-time prediction, and queue length estimation (Nanthawichit et al., 2003). These studies underscore the versatility of probe vehicle data in providing insights into traffic conditions and dynamics. The work of Achar et al. and Li et al. emphasized the use of probe vehicle data for estimating travel times and queue lengths at signalized intersections, showcasing the applicability of probe vehicle data in traffic management and signal control (Achar et al., 2018; Li et al., 2017). In addition, the study by Flintsch et al. highlighted the practical use of probe vehicles in pavement management applications to describe ride quality, indicating the diverse applications of probe vehicle data beyond traffic monitoring (Flintsch et al., 2012).

These studies collectively demonstrate the significance of probe vehicle data in analyzing traffic incident duration time. Researchers have developed effective incident detection methods by leveraging real-time data collected from probe vehicles and have gained insights into traffic flow dynamics during incidents. This has implications for improving incident management, enhancing traffic safety, and optimizing transportation systems.

2.2. Traffic Incident Duration Prediction

2.2.1. Traffic Incident Duration Components

Traffic accidents represent the primary causes of irregular congestion, contributing to between 25% and 60% of the overall congestion experienced on highways (Cambridge Systematics, 2005; Skabardonis et al., 2003). Therefore, they have significant implications for traffic flow, congestion, and overall transportation system performance. Cattermole-Terzic and Horberry (2020) focused on improving traffic incident management using Team Cognitive Work Analysis, with priorities including optimizing casualty outcomes, minimizing traffic flow disruption, and ensuring responder team safety. Wedagama (2019) studied the influence of mixed traffic on congestion levels and marginal road congestions, emphasizing the need for independent analysis considering vehicle dimensions, speed, and proportion within the traffic stream (Wedagama, 2019). Yang & Oguchi (2019) conducted a sensitivity analysis of market penetration rates and demand levels of connected vehicles to

develop an advisory lane-changing assistant at vehicle incident locations (Yang and Oguchi, 2019).

The most apparent and quantifiable consequence of traffic incidents is the period it takes for the incident to conclude or incident duration (Evans et al., 2020). As previously noted in the Introduction, the conventional method of dividing the time for incident duration involves segmenting it into the following phases: detection time, response time, clearance time, and recovery time (Islam et al., 2021). Many previous studies have defined incident duration as the sum of the first three components: detection, response, and clearance time (Garib et al., 1997; Nam and Mannering, 2000). For instance, a recent study investigated the factors that impact the duration of incidents (calculated as the total of the initial three phases) to gain insights into the determinants of incident duration and offer suggestions for enhancing traffic incident management strategies (Tirtha et al., 2020). In previous analyses, there has been a significant lack of attention given to recovery time (Tavassoli Hojati et al., 2014), and there is a scarcity of practical studies that can be used to estimate the duration of post-incident recovery (Jeihani et al., 2015).

2.2.2. Traffic Incident Duration Prediction Models

Researchers have categorized methods for predicting incident durations in two ways: as either one-time or sequential models (Qi and Teng, 2008). Alternatively, these prediction methods can classified into statistical models, such as regression models

(Garib et al., 1997; Zhang and Khattak, 2010), risk mixture models (R. Li et al., 2015a, 2015b), and hazard-based duration models (Chung et al., 2015; Ghosh et al., 2014; R. Li et al., 2015a; Lin et al., 2016; Nam and Mannering, 2000), and machine learning models such as artificial neural networks (Lopes et al., 2013; Wei and Lee, 2007). It is worth noting that statistical and machine learning methods can overlap, with some studies combining elements from both into a unified model (Dimitriou and Vlahogianni, 2015). Researchers also used various other methods and data mining techniques such as fuzzy logic models (Wang et al., 2012), partial least squares regression (Wang et al., 2013), Bayesian Networks approaches (Ozbay and Noyan, 2006; Park et al., 2016; Yang et al., 2012) and Kalman filtering algorithm (Ozen and Saracoglu*, 2019). Tang et al. (2020) developed a model for traffic incident clearance time prediction and influencing factor analysis using the Extreme Gradient Boosting Model, highlighting its superior performance compared to other models (Tang et al., 2020). Islam et al. (2022) evaluated the impact of Freeway Service Patrol on incident clearance times, providing valuable insights for state traffic incident management agencies (Islam et al. 2022). Laman et al. (2018) proposed a copula-based approach for joint modeling of traffic incident duration components, emphasizing the relationship between reporting, response, clearance time, and traffic recovery time (Laman et al., 2018). Cong et al. (2018) introduced a dual-learning Bayesian network model to estimate traffic incident duration based on heterogeneous factors (Cong et al., 2018).

Li (2015) discussed the time-varying variables that affect the duration of traffic incidents (Li, 2015).

In previous research, machine-learning methods have been employed to predict the duration of traffic incidents. These approaches, characterized by their flexible framework, can effectively handle complex and highly nonlinear relationships between dependent and independent variables. A study developed an artificial neural network model for forecasting clearance time, employing a sequential model for continuously updating the clearance time phase (Wei and Lee, 2007). In another study, a comparison was conducted between Support Vector Machine (SVM) and Artificial Neural Network (ANN) models for incident duration prediction. The findings indicated that ANN exhibited superior performance, particularly in predicting longer durations (Yu et al., 2016).

Furthermore, there are researchers specializing in conducting comparative analyses of various methods. In the study by Hamad, Khalil, and Alozi (Hamad et al., 2020), they evaluated the performance of different models, including regression decision tree, SVM, ensemble tree, Gaussian process regression (GPR), and ANN, for predicting the duration of traffic incidents. They used a dataset of over 110,000 short-term event records, each containing more than 50 variables, with incident durations ranging from 5 to 120 minutes. In terms of Mean Absolute Error (MAE), SVM outperformed the other models. However, SVM ranked the lowest when considering the Root Mean

Square Error (RMSE), while GPR performed the best. Additionally, in terms of training time, the regression decision tree had the shortest training time, whereas SVM and GPR required more time for training.

In another study conducted by Lin and Li (Lin and Li, 2020), they examined the duration of four different traffic conditions following accidents using crowdsourced data by calculating the congestion delay index. They used a dataset comprising 13,338 traffic accident records from Beijing in 2017 to validate and compare the performance of RF, SVM, and neural network (NN) models. Their findings indicated that the NN model generally outperformed the other two models in most cases.

The studies by Wei et al. (2007) and Lopes et al. (2012) explore the dynamic and sequential forecast of traffic incident durations using artificial neural network (ANN) models. These studies highlight the importance of a phased approach to incident duration prediction, which becomes more accurate as more information becomes available post-incident. Initially, primary data such as incident time, location, type, notification time, and weather conditions are utilized for the first estimation. As the incident progresses, secondary data, including the number of injuries or fatalities, response time, and the number of affected lanes, are incorporated to refine and update the model's predictions. This tiered approach allows for the development of real-time estimation models that can adapt to new information, significantly improving the accuracy of traffic incident duration forecasts. By updating the estimation in three or

four steps, these models provide more precise and timely information for traffic management and emergency response operations (Lopes et al., 2013; Wei and Lee, 2007).

Another key goal in the incident duration analysis is to investigate the connection between how long an incident lasts and the factors that explain it—essentially, causal analysis. Details about incidents play a crucial role in providing comprehensive traffic information (Liu and Yang, 2021).

It is worth noting that when predicting the duration of traffic incidents, prediction models are heavily influenced by geographical factors (Zhao et al., 2022). Asif et al. emphasized that insight into spatial and temporal trends can improve the performance of Intelligent Transportation Systems (ITS), further emphasizing the significance of considering spatial and temporal dimensions in traffic incident analysis (Asif et al., 2014). Additionally, Tajtehranifard et al. and Li et al. proposed dynamic models to assess traffic incidents' temporal and spatial impacts on network reliability (X. Li et al., 2015; Tajtehranifard et al., 2016).

The interdependence of incident durations and the analysis of secondary incidents have also been investigated. Khattak et al. (2009) examined the interdependence of incident durations and identified secondary incidents (Khattak et al., 2009), while Zahng et al. (2015) considered the joint analysis of queuing delays associated with secondary incidents (Zhang et al., 2015).

Furthermore, the traffic demand on the road segment prior to the incident has been employed to calculate the expected incident delay, encompassing the time required for recovery (Garib et al., 1997; Sullivan, 1997). In a study, investigators employed hazard-based duration models to statistically assess the time required for detecting/reporting, responding to, and clearing incidents. They took into account temporal, environmental, geographic, and incident-related factors. The outcomes demonstrated that numerous factors had a notable impact on incident duration, and distinct distributional assumptions for the hazard function were suitable for different incident timeframes under investigation (Nam and Mannering, 2000). One should note that in cases where many and various extracted features are utilized, some sort of data dimensions management might be necessary (Rasaizadi et al., 2024). This research seeks to leverage various data sources to maximize available information, empowering researchers to offer comprehensive insights.

2.2.3. Incident Duration Categories and Model Accuracies

Saracoglu and Ozen (2020) evaluated the effectiveness of four decision tree models (CHAID, CART, C4.5, and LMT) in estimating traffic incident durations, segmented into short (0 to 30 minutes), medium (30 to 60 minutes), and long (≥ 60 minutes) categories. Their findings, based on testing data, revealed that the CHAID model was particularly effective in predicting short-duration incidents with an accuracy of 91.4%, while its performance for medium and long-duration incidents was lower, at 37.9% and

22.2%, respectively. This study underscores the CHAID model's potential in traffic management, particularly for short-duration incident predictions, while also indicating a need for improved modeling for longer incidents.

Rahmat-Ullah et al. (2021) conducted a study to evaluate the application of two machine learning techniques, Random Forest (RF) and Artificial Neural Networks (ANN), in predicting traffic incident durations. The incidents, sourced from TranStar Houston's Transportation Management Centre, were classified into four categories based on their duration: minor (5 to 15 minutes), intermediate (15 to 30 minutes), major (30 to 60 minutes), and severe (60 to 120 minutes). The study aimed to determine which machine learning model would offer higher prediction accuracy across these incident classifications. The results indicated that the Random Forest model outperformed the Artificial Neural Network model, achieving a prediction accuracy of 71%, which is 10% higher than that of the ANN. It was observed that the accuracy of predictions varied significantly across the different incident durations, with the highest accuracy for minor incidents and the lowest for long-duration (severe) incidents. Additionally, the study reported a mean squared error (MSE) of 28.4% for ANN and 18% for RF, highlighting RF's superior performance in both accuracy and error minimization.

Chung (2010) developed a hazard-based model to predict traffic incident durations on South Korean freeways, analyzing 4869 incidents. The model's accuracy was assessed with a mean absolute percentage error (MAPE) of 47% and an average prediction error

of 18 minutes. (Chung, 2010). Lopes et al. (2013) explored using artificial neural networks (ANNs) to predict the clearance time of traffic incidents, analyzing a dataset of 10,762 incidents from Portugal collected between 2008 and 2011. Their model demonstrated accuracies of 72% for predictions within a 10-minute deviation and 92% for a 20-minute deviation (Lopes et al., 2013). Ozbay and Noyan (2006) conducted a study using Bayesian networks to estimate the clearance times of traffic incidents, analyzing a dataset of 650 incidents. Their approach achieved an accuracy rate of 81% in predicting incident durations (Ozbay and Noyan, 2006).

Lin et al. (2016) developed a predictive model for urban freeway traffic accident durations by integrating the M5P tree algorithm with a hazard-based model. This innovative approach was tested on two distinct datasets comprising traffic accident records from various highways between 2005 and 2012. The model's effectiveness was evaluated using the mean absolute percentage error (MAPE), with the results showing MAPE values of 36.20% for one dataset and 31.87% for the other (Lin et al., 2016).

In their research, Chang and Chang (2013) utilized the Classification and Regression Trees (CART) method to predict the duration of traffic incidents, analyzing a dataset of 4697 incidents provided by the Taiwan National Freeway Bureau from 2008. Before applying the CART method, they segmented the data into three categories—short, medium, and long duration—using K-means clustering. The study revealed an overall accuracy rate of 73.6% for the incident duration estimation. Notably, the accuracy for

short-duration incidents was exceptionally high at 96.7%, while the accuracy significantly dropped for medium (17.2%) and long-duration (11.4%) incidents. This stark contrast in prediction accuracy underscores the challenges in estimating longer incident durations and highlights the CART method's effectiveness for short-duration incident prediction (Chang and Chang, 2013).

Al-Ruzouq et al. (2019) conducted a study focusing on identifying traffic incident hot spots by implementing a weighted multi-attribute framework that considers the attributes of traffic incidents. Their analysis categorized traffic incidents into five distinct duration groups: less than 5 minutes, 5 to 30 minutes, 30 to 120 minutes, 120 to 360 minutes, and more than 360 minutes (Al-Ruzouq et al., 2019).

Several other reports and studies categorized incidents based on duration. Here is a summary of these studies:

- Smith and Smith (2001) categorize freeway accident clearance times as short (≤15 min), medium (>15–≤30 min), and long (>30 min) (Smith et al., 2002).
- Lin et al. (2004) define incident durations with binary classification, distinguishing between other incidents (≤60 min) and severe incidents (>60 min) (Lin et al., 2004).
- Texas Department of Transportation (2006) classifies incidents based on duration as minor (≤60 min), intermediate (>60–≤240 min), and major (>240

min) (“Texas Department of Transportation: Texas Manual on Uniform Traffic Control Devices (TMUTCD), 2006 Edition, Revision 1, Texas (2006),”).

- Manual on Uniform Traffic Control Devices (MUTCD), Chapter 6I (2009), provides a classification for incident durations as minor (≤30 min), intermediate (>30–≤120 min), and major (>120 min) (Traffic, 2009).
- Chattanooga Urban Area Highway Incident Management Plan (2010) outlines an incident delay classification with low priority (≤30 min), moderate priority (>30–≤60 min), high priority (>60–≤120 min), and catastrophic (>120 min) (*Chattanooga-Hamilton County Regional Planning Agency and Transportation Planning Division: Chattanooga urban area highway incident management plan, Tennessee (2010)*).
- Zhang et al. (2012) analyze large-scale incidents on urban freeways with a classification of other incidents (≤120 min) and large scale (>120 min) (Zhang et al., 2012).

2.2.4. Limited Traffic Recovery Time Prediction Studies

In particular, studies that explored the traffic recovery time phase are limited. Some scholars have attempted to ascertain the recovery time for traffic following an accident. Their primary approach involves comparing post-accident speeds with historical speed records (Haule et al., 2019; Jeihani et al., 2015; Tavassoli Hojati et al., 2014). They define the duration in which speed significantly drops as the actual traffic accident

duration. In 2014, Hojati and his team employed the quantum frequency algorithm (QFA) to generate a historical speed cycle curve (Tavassoli Hojati et al., 2014). In 2019, Henrick utilized velocity data gathered by the BlueTOAD device (Haule et al., 2019). However, it's important to highlight that the BlueTOAD data is collected at 15-minute intervals, which could introduce prediction inaccuracies.

Among these studies, Zeng and Songchitruksa (2010) expanded upon the difference-in-travel-time approach for estimating traffic recovery time. They did so by incorporating data related to both traffic incidents and travel times. The method they introduced utilized percentile statistics to define the typical conditions travelers expect when there are no incidents. They then applied this concept to calculate the gap in travel time, taking into account incident-related information from the database, to estimate how long it will take for traffic to recover (Zeng and Songchitruksa, 2010). This research paper focuses solely on the segment where a traffic incident has occurred and does not analyze the upstream segments. By only examining the segment where the incident occurred, the paper overlooks the potential impacts of the incident on upstream segments of the road network. Traffic congestion often ripples backward, affecting the flow of vehicles in the vicinity. Ignoring these upstream effects may lead to an incomplete understanding of traffic recovery dynamics.

In another study, a hazard-based duration modeling approach was employed to create a model for the incident duration, including incident detection and recovery time as its

components. This model considered various factors that impacted the duration of traffic incidents. The analysis demonstrated that incident duration was influenced by factors such as the severity of the incident, its type, presence of injuries, medical requirements, and infrastructure features like roadway shoulders. Additionally, factors like the time of day and traffic conditions also played a significant role in determining incident duration (Tavassoli Hojati et al., 2014).

Another study introduced a methodology for estimating post-incident traffic recovery time. It employed traffic simulation to assess how various combinations of factors, including traffic demand defined as volume to capacity ratio, incident duration, and incident severity defined as the proportion of lane closures, influenced the time it takes for traffic to recover after an incident. Simulations covered a wide range of scenarios, including different traffic intensities, incident durations, and incident severity levels. Subsequently, the study used the simulation results, including speed, traffic density, and flow data, to compare the traffic recovery time estimates with well-established analytical delay prediction formulas. Additionally, the researchers developed a regression model that effectively estimated recovery time based on three primary variables: traffic intensity, incident duration, and the extent of lane closures. In this paper, traffic recovery time refers to the time period following incident clearance, during which traffic returns to pre-incident conditions (Jeihani et al., 2015).

Another research investigated the correlation between incident clearance time and roadway clearance time by employing micro-simulation using VISSIM modeling to simulate various traffic incident scenarios. Incident clearance time was defined as the duration from the initial recording of the incident by a responsible agency to either the first confirmation that all traces of the incident were removed or the departure of the last responder from the incident scene. On the other hand, the roadway clearance time was defined as the span from the first record of the incident by a responsible agency to the first confirmation that all lanes were fully operational again. Several traffic incident scenarios were created to collect data on different incident types occurring under various traffic conditions. Variables considered in the analysis included the number of through lanes, the number of blocked lanes, and traffic volumes. Subsequently, a mathematical model was developed to illustrate the relationship between roadway clearance time and incident clearance time (Zhou and Tian, 2012).

2.2.5. Research Gaps

The existing literature lacks a comprehensive approach that integrates disparate traffic incident datasets. By amalgamating these diverse data sources, this study contributes to a more holistic and comprehensive resource for future incident analysis, filling the void in understanding the potential benefits and insights that could arise from integrating these varied datasets. The literature review also highlights the absence of utilizing probe vehicle data for real-time crash detection and recovery time estimation.

By leveraging this type of data and integrating it with incident data, this study pioneers an approach that fills this gap, offering a novel method for estimating and managing traffic recovery times more efficiently and effectively.

Furthermore, the conventional understanding in the literature predominantly emphasizes the official clearance time without considering scenarios where the recovery process initiates before this time. This study's disclosure of these overlooked scenarios contributes to a more nuanced understanding of incident management phases, challenging conventional perceptions. Moreover, it highlights the literature's concentration on the immediate incident location when examining recovery time. The gap lies in the lack of attention to conditions and factors in the zones upstream from the incident site. By exploring these upstream conditions, this study broadens the scope of analysis, shedding light on factors that may influence recovery time, thus contributing to a more comprehensive understanding of incident dynamics and response strategies.

Chapter 3: Datasets

3.1. Probe Vehicle Data

Probe vehicle data refers to information collected from vehicles equipped with GPS (Global Positioning System) or other tracking technology. These probe vehicles continuously transmit their location, speed, and other relevant data to a centralized system. This data is valuable for a wide range of applications, particularly in transportation and traffic management.

The probe vehicle data utilized in this study consists of traffic-related information for different road segments of the study area, the State of Maryland, over time provided by INRIX for 2019. Table 1 shows a sample of the probe vehicle data used in this study. Here's a description of the dataset and its columns:

1. tmc_code: This column contains unique for different road segments or locations within a road network. Each code corresponds to a specific stretch of road, allowing one to distinguish between different segments of the transportation network.
2. measurement_tstamp: This column represents the timestamp or time at which the data was recorded. It records each data point's exact local date and time in a format similar to YYYY-MM-DD HH:MM:SS. This timestamp is used to track the temporal aspect of the data, allowing one to analyze how traffic conditions change over time.

3. speed: This column contains the recorded speed for each road segment at the specified timestamp. The speed is measured in miles per hour (mph) and provides information about how fast traffic moves on that particular road segment at a specific moment.
4. travel_time_minutes: This column provides the estimated travel time, in minutes, required to traverse the road segment from the beginning to the end during the recorded time interval.

Table 1. A Sample of Probe Vehicle Data that is used in this study.

tmc_code	measurement_tstamp	speed	travel_time_minutes
110+04648	2019-08-01 00:00:00	62	0.99
110+04648	2019-08-01 00:01:00	62	0.99
110+04648	2019-08-01 00:02:00	64	0.95
110N04644	2019-08-01 06:17:00	60	1.16
110N04644	2019-08-01 06:18:00	60	1.16
110N04644	2019-08-01 06:19:00	59	1.18

3.2. Coordinated Highways Action Response Team (CHART) Data

CHART, short for Coordinated Highways Action Response Team, represents a pivotal component in transportation management and incident response.

CHART data encompasses a wealth of information, such as current traffic speeds, congestion levels, accident reports, and weather conditions. This data is not only crucial for monitoring everyday traffic but is also instrumental during emergencies and incidents. When incidents occur, CHART helps swiftly detect and respond to them. Table 2 to Table 6 detail the data attributes CHART provided.

3.3. State Police Crash Data

Maryland State Police crash data refers to a comprehensive collection of information about motor vehicle accidents and incidents investigated and recorded by the Maryland State Police through the Automated Crash Reporting System (ACRS). This data is a critical resource for analyzing traffic safety, identifying trends, and formulating strategies to reduce accidents and improve road safety within Maryland. Table 7 provides details about the data attributes provided by CHART.

Table 2. Traffic speed and crash data attributes in CHART

Traffic Speed and Flow data	
Column	Definition
speed_5	Speed 5 minutes before the start of the incident from probe vehicle data.
average_speed_5	Average speed during the last 5-minute interval before the start of the incident from probe vehicle data.
speed_10	Speed 10 minutes before the start of the incident from probe vehicle data.
average_speed_10	Average speed during the last 10-minute interval before the start of the incident from probe vehicle data.
speed_15	Speed 15 minutes before the start of the incident from probe vehicle data.
average_speed_15	Average speed during the last 15-minute interval before the start of the incident from probe vehicle data.
speed_at_crash	Speed at the moment when the incident occurred from probe vehicle data.

Table 3. Road and lane data attributes in CHART

Road and Lane Data	
Column	Definition
num_lanes	The number of lanes on the road.
total_lanes	The total number of lanes available.
open	The number of lanes that are open for traffic.
closed	The number of lanes that are closed.
unknown	The number of lanes with an unknown status.
LaneTime_Start	Time difference between the start time and the time the first update on lane status is received
func_class	Functional classification of the road

Table 4. Weather and environmental data attributes in CHART

Weather and environmental conditions	
Column	Definition
precip_rate	Precipitation rate.
precipitation_flag	Categorization of precipitation (e.g., nothing, snow, rain).
weather_flag	Weather conditions, often related to precipitation.

Table 5. temporal data attributes in CHART

Temporal Data	
Column	Definition
hour	The hour of the day when the incident occurred.
day_of_week	The day of the week when the incident occurred.
Month	The month when the incident occurred.
doy	Day of the year.

Table 6. Incident details data attributes in CHART

Incident Details	
Column	Definition
event_subtype	Severity or type of the incident.
Notif_flag	A binary flag (0 or 1) indicating whether the notified time is available or not.
Arrive_flag	A binary flag (0 or 1) indicating whether the arrival time is available or not.
category	Categorization of the incident (e.g., 'CHART Unit,' 'MDOT Response Unit,' etc.).
county	Name of the county where the incident occurred.
vehicle_id	Unique Identifier for the vehicle.
VehNumCat	Number of vehicles involved by type: car, SUV, Tractor, Bus, Car &Trailer and Van
VehInc	Number of vehicles that overturned, jackknifed, or lost their load

Table 7. Description of the data attributes in State Police Data

Road Conditions	
Column	Definition
LIGHT_DESC	Description of lighting conditions at the scene.
RD_DIV_DESC	Description of the type of road in terms of dividers.
FIX_OBJ_DESC	Description of any fixed objects at the scene.
SIGNAL_FLAG_DESC	Traffic control signal flag (0 or 1), indicating the presence of traffic control signals.
C_M_ZONE_FLAG	Construction zone flag, indicating if the incident occurred in a construction zone.
JUNCTION_DESC	Description of the type of junction where the incident occurred.
Other incident-related details	
Column	Definition
COLLISION_TYPE_DESC	Description of the type of collision (e.g., head-on, single vehicle, rear-end, right turn, etc.).
HARM_EVENT_DESC2	Description of any harmful events involved in the incident, such as u-turn, animal-related incidents, fires, etc.

Chapter 4: Incident Data Enhancement Exploration

This chapter focuses on enhancing incident data by leveraging the Maryland State Police crash data and CHART (Coordinated Highways Action Response Team) data. The primary objective is to explore the possibility of improvement in the quality and comprehensiveness of the crash dataset by integrating information from these two separate sources.

4.1. Dataset overview

Maryland State Police Crash Data: This dataset contains information on crashes reported to and handled by the Maryland State Police. It includes details such as the location of the crash, involved vehicles, contributing factors, and possibly some demographic information about the individuals involved.

CHART Data: CHART is a comprehensive traffic management and incident response system that collects real-time data from various sources, including traffic cameras, road sensors, and incident reports. This dataset is valuable for its real-time and extensive coverage of traffic-related events and conditions.

4.2. Data Matching

The first step in enhancing incident data is to find matching records between the Maryland State Police crash data and CHART data. In this study, matching incidents between the Maryland State Police crash data and the CHART data relies on using spatial and temporal information. Spatial information pertains to the geographical location associated with each incident (latitude and longitude), while temporal information involves the timing of these incidents, which is crucial for establishing a chronological order of events. By leveraging these two key factors, the related crashes are linked from the two datasets.

To match the incident data records, two thresholds are defined: A distance threshold that is a predefined limit that determines how close two incidents must be in terms of geographical proximity to be considered potential matches. For example, if the distance threshold is set to 0.4 miles, any crashes within 0.4 miles of each other will be regarded as candidates for matching. A time threshold is another predefined limit specifying how close two incidents must be to be considered potential matches. For instance, if the time threshold is set to 15 minutes, any crashes occurring within 15 minutes of each other will be regarded as candidates for matching.

The study applies the CHART dataset's spatial and temporal thresholds for each incident record. This means that the methodology is looking for incidents in the Maryland State Police incident data that occurred within the specified distance and time range of the CHART crash record. The matching process involves identifying the nearest crash record in the Maryland State Police dataset that meets the defined spatial and temporal criteria. This nearest incident record is then matched to the corresponding CHART incident record. Using spatial and temporal thresholds ensures that the matching process is precise and pairs up crashes that are highly likely to be related, possibly representing the same incident from different data sources.

4.3. Data Combination

By utilizing these spatial and temporal thresholds, the study aims to establish connections between incidents in the two datasets that occurred close to each other in space and time. This matching approach allows for creating a more accurate and integrated incident dataset, which can then be used for further analysis and research into traffic accidents. Once matching records are identified, the attributes from these records in both datasets can be combined.

This includes the details recorded by the state police and incident information from CHART.

Figure 3 shows that a couple of State Police incident data (blue markers) are identified as potential candidates for being matched with a CHART crash data (the red marker). In this showcase, all the matched state police crashes are within 30-minute and 1-mile time and distance intervals, respectively. At last, the one with the lowest distance is recorded as the matched crash data record.

Using shorter thresholds in the matching process can lead to more data loss, as Figure 4 illustrates. For example, if the distance and time threshold are set to be 0.6 miles and 30 minutes, respectively, only 31.4% of the original data records will remain.

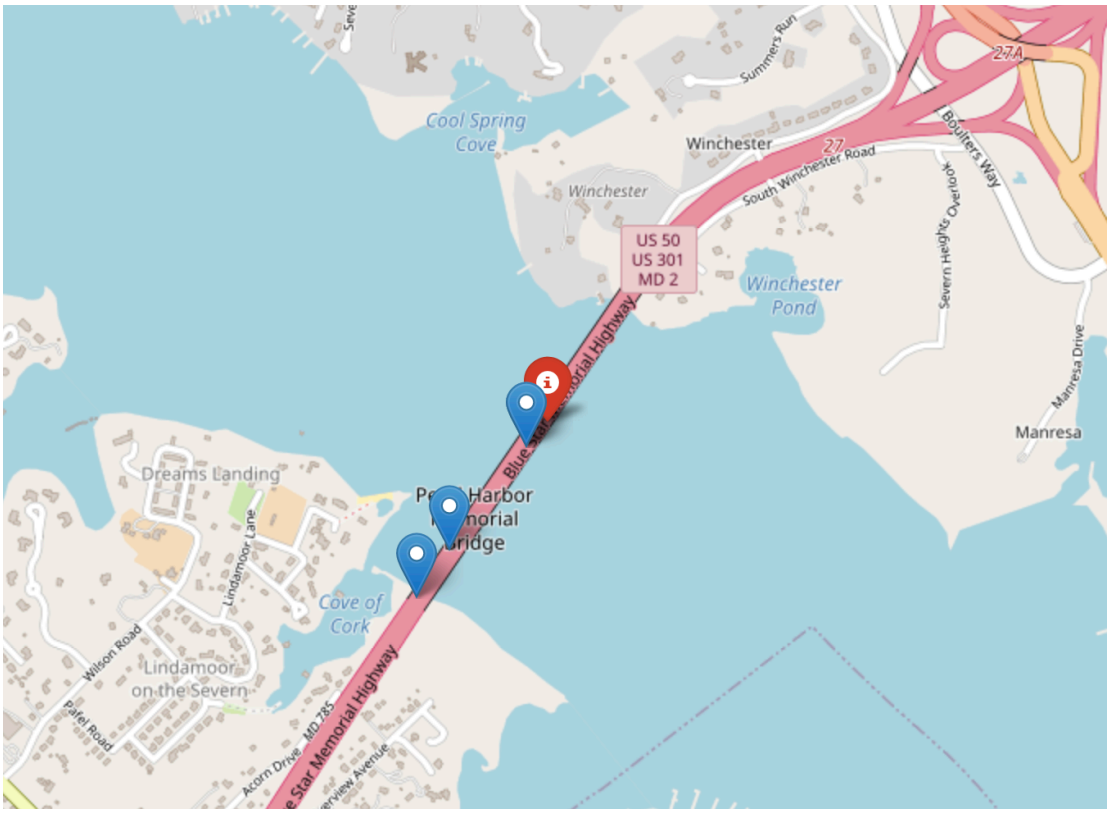

Figure 3. Potential crash candidates in the state police data (blue markers) for the CHART crash (red marker).

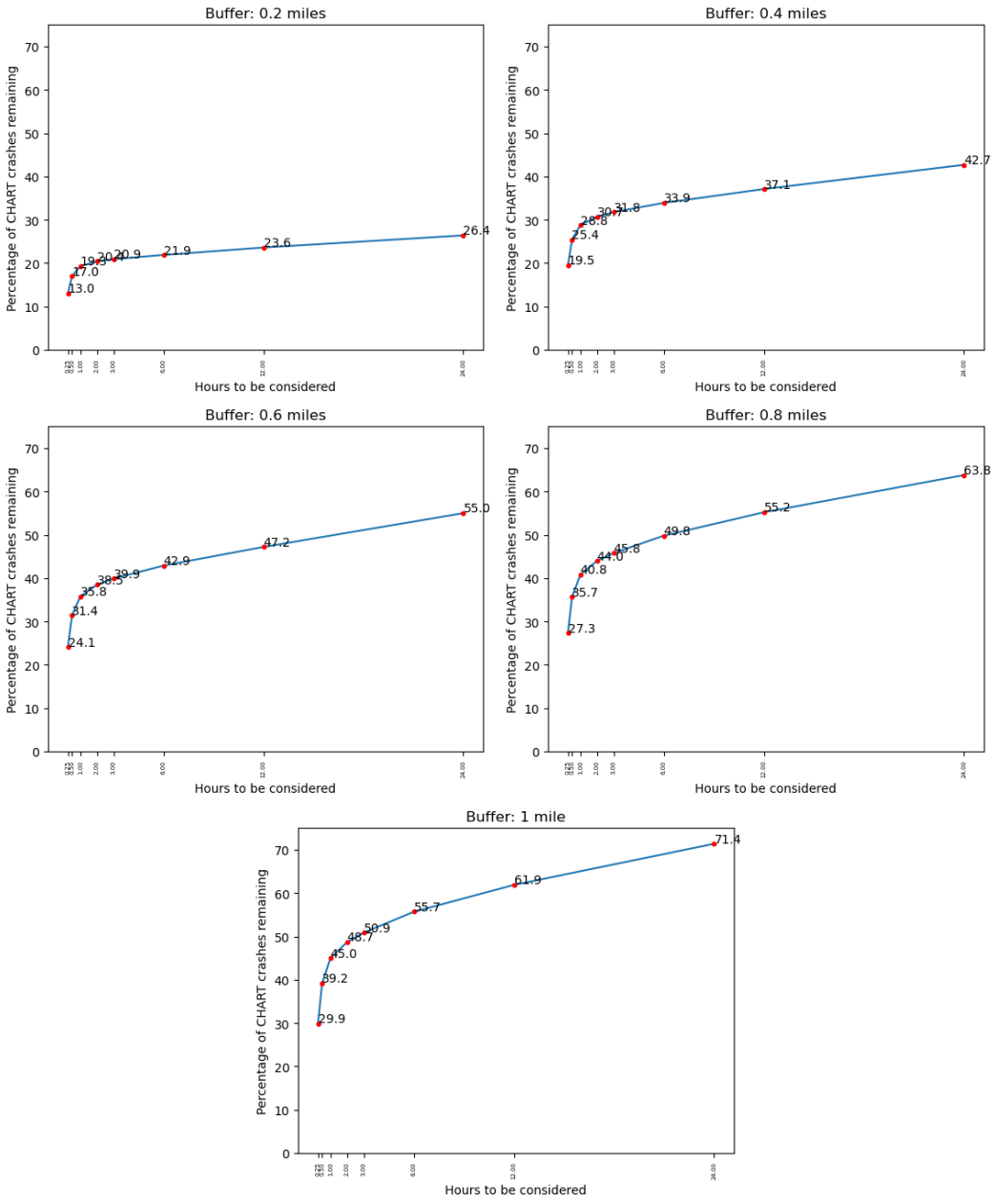

Figure 4. Percentage of CHART data records remaining in the dataset after performing data matching using different combinations of time and distance thresholds.

4.4. Parameter Selection

A data-driven approach is employed to determine the appropriate combination of thresholds for matching crash data. This involves using various machine learning methods to predict the duration of crashes reported by CHART and subsequently comparing the accuracy of these predictive models for each of the combinations.

To select the right combination of distance and time thresholds for matching incident data, it is essential to strike a balance between precision and data retention. As discussed earlier, setting shorter thresholds may result in more accurate matches but at the cost of data loss. In contrast, longer thresholds may retain more data but might lead to less precise matches. Multiple combinations of thresholds are considered to make an informed decision. Machine learning methods are employed to predict the duration of clearances of crashes reported by CHART. These methods leverage a variety of features, including but not limited to incident location, time of day, weather conditions, and road characteristics. The details of the attributes used in the study are discussed in Chapter 3.

The goal is to develop predictive models that can predict the duration of each crash clearance time as a binary variable, whether it is greater than 30 minutes or not. Several machine learning algorithms are tested and evaluated for their performance in predicting the duration of each crash clearance time. Popular models, including logistic regression, random forests, support vector machines, and gradient boosting, are utilized

for this purpose. Each model is trained on a subset of the data and tested on a holdout validation set to assess its accuracy. In particular, each dataset is divided into 80% and 20% for training and testing purposes, respectively. As the first step, since the dataset is not balanced regarding the number of data points with clearance duration category, an oversampling is done on the "less than 30-minute" category. Balancing the dataset through oversampling yields several advantageous outcomes. It mitigates the risk of model bias toward the majority class, ensuring that the machine learning algorithms learn from both categories equally. This balance, in turn, leads to enhanced model performance, more accurate predictions for all classes, and a reduction in skewed decision-making. Figure 5 shows the percentage of data points in each clearance duration category for the dataset filtered using a combination of 0.4 miles and 3 hours distance and time thresholds, respectively. Nearly 35% of the data points have an incident clearance time of fewer than 30 minutes, and the rest have an incident clearance time equal to or more than 30 minutes.

Figure 6 to Figure 9 provide the accuracy of the four aforementioned machine learning models. The heatmaps displayed on the left-hand side represent the accuracy of the models concerning the training datasets across various combinations of time and distance thresholds. These assessments are conducted using a 5-fold cross-validation approach. The findings from these analyses indicate the absence of overfitting within the models, affirming their robustness and generalizability to unseen data. On the other hand, the right-hand side heatmaps show the accuracy of the models on the testing

datasets. In general, Random Forest and Gradient Boosting offer a higher accuracy when predicting the incident clearance time, while Support Vector Machine has the lowest accuracy. Furthermore, when using the combination of 3 hours and 0.4 miles for time and distance thresholds, respectively, almost the highest accuracy is achieved in both random forest and gradient boosting models.

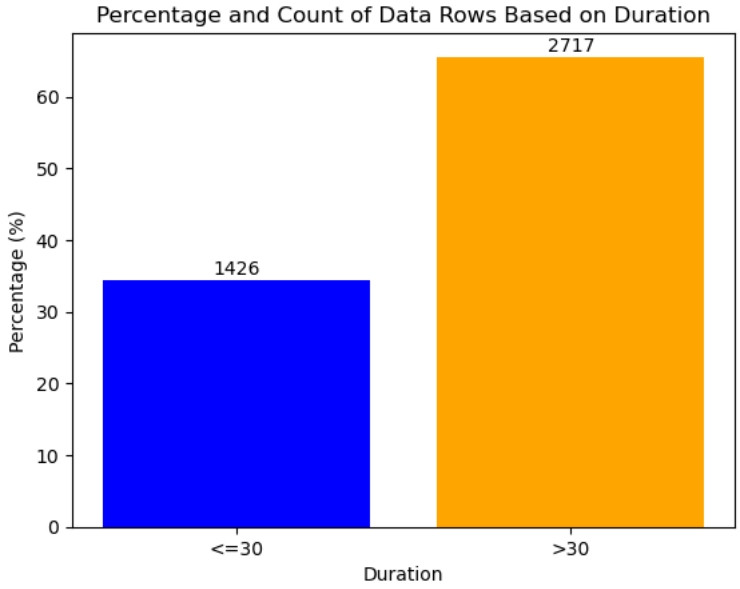

Figure 5. Percentage of data points in each clearance duration category.

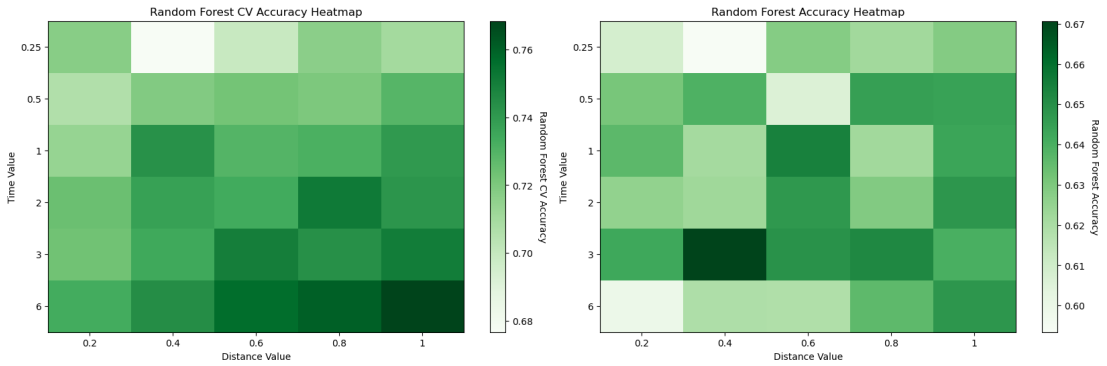

Figure 6. Accuracy of Random Forest for the training dataset (left) and testing dataset (right).

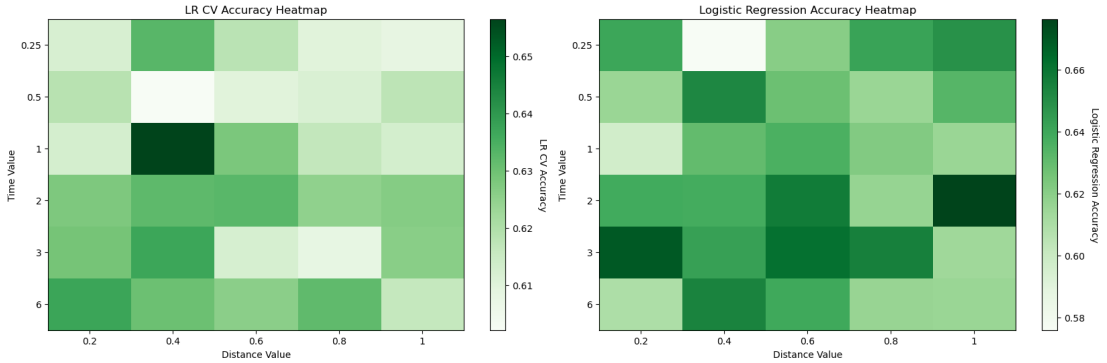

Figure 7. Accuracy of Logistic Regression for the training dataset (left) and testing dataset (right).

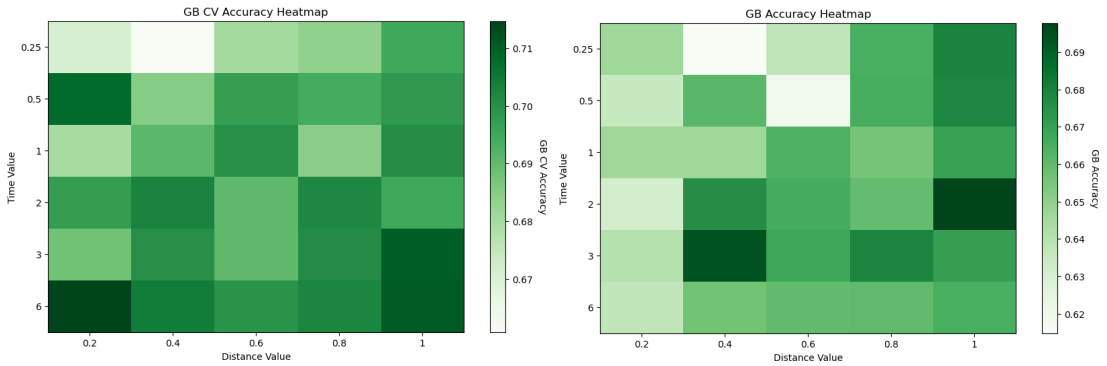

Figure 8. Accuracy of Gradient Boosting for the training dataset (left) and testing dataset (right).

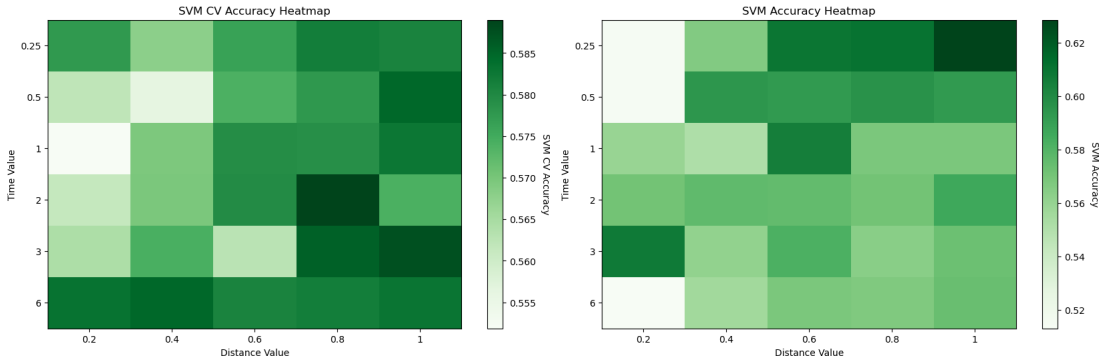

Figure 9. Accuracy of Support Vector Machine for the training dataset (left) and testing dataset (right).

When integrating both CHART and state police data for modeling purposes, a critical consideration arises due to a substantial loss of data points during the merging process. This data loss is a consequence of the matching of these two datasets. Consequently, it becomes imperative that such a merging effort must significantly enhance model accuracy to justify the sacrifice of a large portion of data points.

However, empirical evidence reveals that this data integration may not necessarily yield a proportional improvement in accuracy. To illustrate, when utilizing an equal number of data points, but this time excluding attributes sourced from State Police data, the accuracy gains are relatively modest. Specifically, the model accuracy increases by only 1%—approximately reaching 67% when employing the Random Forest algorithm and 69% with Gradient Boosting. This minimal improvement in accuracy is juxtaposed with the loss of approximately 70% of the original data points during the exclusion of State Police data attributes.

Given these findings, it became apparent that the substantial data loss incurred during the integration of State Police data may potentially impact subsequent analytical steps, such as the prediction of recovery times. Consequently, to preserve data volume and ensure the feasibility of analysis, the decision was made to proceed with only CHART data for incident recovery time prediction. This approach retains a larger dataset and minimizes the potential negative repercussions of data loss, allowing for a more comprehensive and robust exploration of traffic incident-related research questions.

Chapter 5: Incident Recovery Time Estimation

Accurate measurement and understanding of recovery time, which signifies the duration for traffic conditions to return to normal following an incident, are paramount for various aspects of transportation management and analysis. It is pivotal in informing traffic management strategies, mitigating economic repercussions, guiding urban planning decisions, enhancing public awareness, and facilitating research endeavors. This chapter is dedicated to the methodology employed for estimating traffic recovery time in the event of an accident and presents the associated research findings.

5.1. Data Preparation

It is essential to undertake several key data preparation steps to estimate incident recovery time. Initially, matching probe vehicle data with incident data is crucial; this involves aligning real-time and historical probe vehicle data collected with specific incident locations and times. This matching allows for analyzing traffic conditions immediately before, during, and after incidents. Next, identifying upstream links is vital, as it provides insights into the traffic flow and congestion patterns leading up to the incident spot, which can significantly affect recovery times. Finally, identifying a baseline for traffic flow patterns is indispensable for understanding typical traffic behavior under normal conditions and during the occurrence of incidents. This perspective aids in predicting the impact of current incidents on traffic flow and

estimating recovery times accurately. Together, these steps form a comprehensive approach to preparing data for accurately estimating incident recovery times, blending real-time observations with historical traffic patterns for a well-rounded analysis.

5.1.1. Matching Probe Vehicle Data with Incident Data

A common identifier, known as the TMC (Traffic Message Channel) zone number, is employed to decipher the speed and travel time dynamics within the incident area. Initially, the latitude and longitude coordinates of the incident location are cross-referenced with the appropriate TMC zone number. Once this matching is achieved, the subsequent step involves retrieving pertinent speed and travel time data from the probe vehicle dataset associated with the identified TMC zone. This systematic approach allows for precisely examining traffic conditions near the incident. Table 8 shows the number of TMCs in the Maryland dataset by road class.

Table 9 shows the statistical summary of Maryland TMC lengths in miles. Note that speed and travel time data are aggregated at the TMC level. On average, the TMC lengths are about 0.6 miles.

5.1.2. Upstream Link Inclusion

As the next step, to enhance the accuracy of traffic recovery time estimation, the analysis extends its focus to include the upstream area preceding the incident location.

This expanded perspective acknowledges the dynamics of incident-induced traffic queues.

Table 8. Number of TMCs in Maryland dataset by road class.

Road Class	Count
Expressway	5
Frontage	6
Interchange	1753
Interstate	1269
Parkway	50
State Route	6098
US Route	1439
Other	8054

Table 9. Statistical summary of Maryland TMC lengths in miles.

Minimum	0.002
25th Percentile	0.048
Median	0.257
Mean	0.602
75th Percentile	0.746
Maximum	13.901

When an accident occurs, a backlog of vehicles may accumulate, and as the incident is resolved, clearance typically begins at the accident site and then gradually progresses upstream. Consequently, this analysis considers all available upstream links leading back up to 5 miles from the incident location. This five-mile threshold is determined based on an examination of the speeds of upstream locations. Basically, the area of impact of the incidents is defined as the length of upstream locations that experienced some level of congestion. The process involves identifying the closest upstream location from the link where the incident occurred and ensuring that its speed on the date of the incident reaches the historical speed profile. Through this process, it is ascertained that the minimum distance and maximum distance to such an upstream location is approximately between 0 and 4.9 miles. Therefore, a five-mile threshold is adopted to encompass all potential scenarios effectively.

The process of identifying upstream TMCs operates as follows: for each incident, the corresponding TMC is initially determined. Subsequently, within the entire study area, the method seeks out the TMC that shares the same road direction and road functional class and has an end latitude and longitude identical to the start latitude and longitude of the crash's TMC. This identified TMC is considered the immediate adjacent upstream TMC.

This procedure then iterates on the newly found upstream TMC, searching for a second adjacent upstream TMC that meets the same criteria. This iterative process continues

until either the search exhausts all TMCs meeting these criteria within the study area or the cumulative length of upstream TMCs extends beyond the 5-mile threshold. This methodology ensures a systematic identification of relevant upstream TMCs for comprehensive analysis while adhering to the specified spatial limit. Figure 10 shows the flowchart of the upstream link inclusion methodology.

Figure 11 serves as an example illustrating an incident reported by CHART on January 5, 2019, at 4:59 p.m. The figure highlights the immediate impact of the incident, where, within just a few minutes, the three closest links upstream of the crash location experience a notable decrease in reported speeds by probe vehicle data. This rapid decrease in speed clearly demonstrates the immediate influence of the incident on traffic conditions in the vicinity.

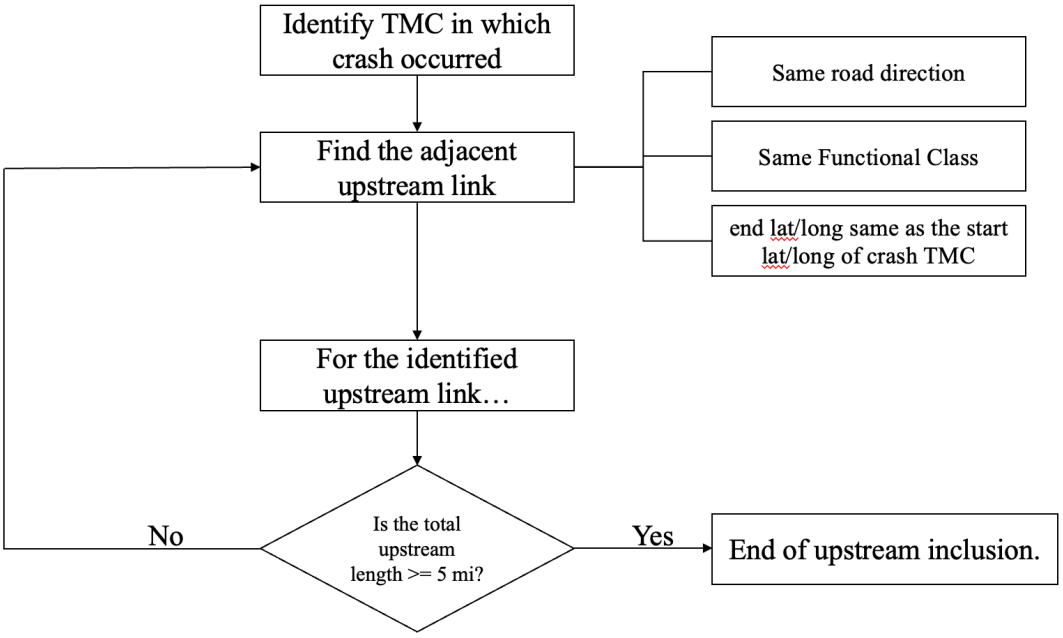

Figure 10. Flowchart of the upstream link inclusion methodology.

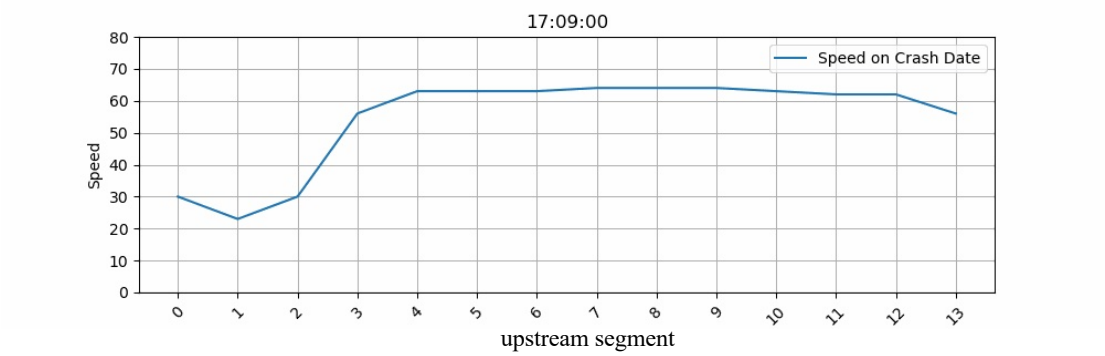

Figure 11. Recorded speed data on the crash date at 5:09 pm.

5.1.3. Baseline Traffic Speed Pattern Determination

This study employs two distinct approaches to explore traffic speed patterns to establish a baseline for normal conditions. The first approach leverages historical data to define normal traffic conditions. By utilizing statistical percentiles derived from historical speed data, specifically computing the 50th percentile of these data, this study identifies what constitutes a 'normal' traffic speed pattern for a specific area impacted by the incident. This percentile is chosen as it represents the median speed, reflecting a balanced condition that drivers experience under typical circumstances.

The second approach diverges by focusing on the traffic conditions immediately preceding the occurrence of an incident. This approach assumes that the state of traffic speed pattern right before an incident offers a pertinent baseline for assessing the impact of the incident on traffic, thereby providing a more immediate context for comparison.

This comparative analysis aims to evaluate how each approach influences the estimation of traffic recovery time, shedding light on their respective advantages and disadvantages. The historical data method benefits from a broader dataset, offering stability that may not be affected by anomalies. However, it might not account for day-to-day variations accurately. Conversely, the pre-incident condition method offers real-time relevance, capturing the immediate traffic state, which can be highly informative for specific incidents but may be more susceptible to short-term fluctuations and less

representative of general traffic patterns. This study discusses the implications of each approach on traffic management strategies and the estimation of recovery times following incidents.

5.1.3.1. Baseline Determination Using Historical Data

To determine when traffic returns to its normal condition, a foundational step involves defining what constitutes this "normal" state. This study establishes this definition using statistical percentiles derived from historical speed data. Specifically, the 50th percentile of historical speed data is computed and chosen to represent the normal condition for a specific TMC.

The derivation of historical data involves a time interval selection. The study employs a month-based approach to manage data size and computational complexity. The historical data utilized corresponds to the same month in which the incident occurred.

An additional refinement is applied since travel patterns often differ between weekdays and weekends. If the incident happened on a weekday, the historical data exclusively includes weekdays from the corresponding month, excluding the incident day. Conversely, if the incident occurred on a weekend, all weekends from the corresponding month are included, except for the incident day. This approach accounts for variations in travel behavior based on the day of the week and ensures that the historical data aligns with the specific circumstances of the incident.

As an illustrative example, Figure 12 and Figure 13 present the historical speed patterns for the same crash discussed in the previous section, both before the incident occurrence time and during its clearance phase, respectively. Before the incident occurs, the speed data closely aligns with the established historical pattern, indicating a consistent traffic speed. However, during the clearance period of the incident, a noticeable deviation becomes evident between the historical speed data and the data corresponding to the incident date. This divergence highlights the impact of the incident on traffic conditions, leading to an observable offset between the two datasets.

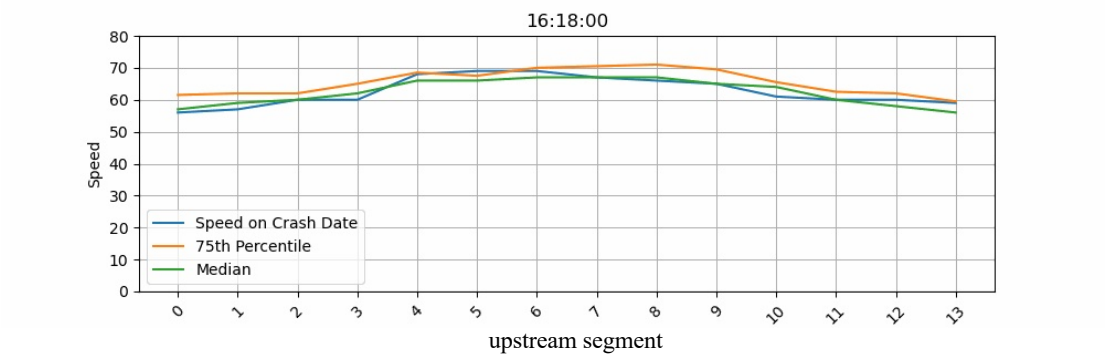

Figure 12. Speed profile on the incident date a few minutes before the onset of the incident compared to historical data.

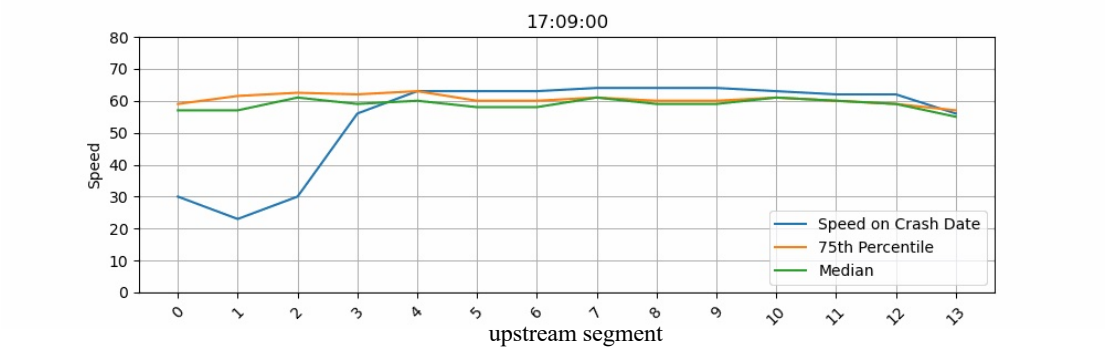

Figure 13. Speed profile on the crash date a few minutes after the onset of the incident compared to historical data.

5.1.3.2. Baseline Determination Using Pre-incident Conditions

The baseline determination using the pre-incident conditions method focuses on understanding the immediate traffic conditions just before an incident occurs. This approach offers a snapshot of traffic speed patterns, enabling analysts to gauge the deviation in traffic patterns caused by the incident. By examining a thirty-minute interval for all the upstream TMCs within a 5-mile length before the incident, this method aims to establish a baseline that reflects the most relevant and immediate traffic conditions. This baseline serves as a comparison point to assess the extent of traffic disruption and the subsequent recovery time.

Figure 14 and Figure 15 illustrate the speed patterns at the site of an accident and in the areas leading up to it moments after the incident occurred and again about 90 minutes later. It is evident from these figures that there exists a discernible divergence between the conditions before the incident and the immediate aftermath. However, with the

passage of time, the speed profile gradually returns to normal free-flow speed conditions, indicating the diminishing impact of the incident.

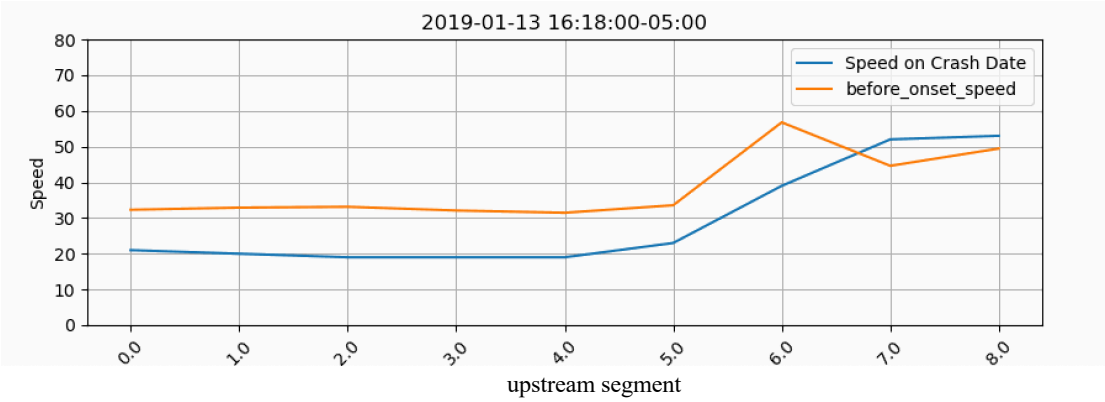

Figure 14. Speed profile a few minutes after the onset of the incident compared to pre-incident conditions.

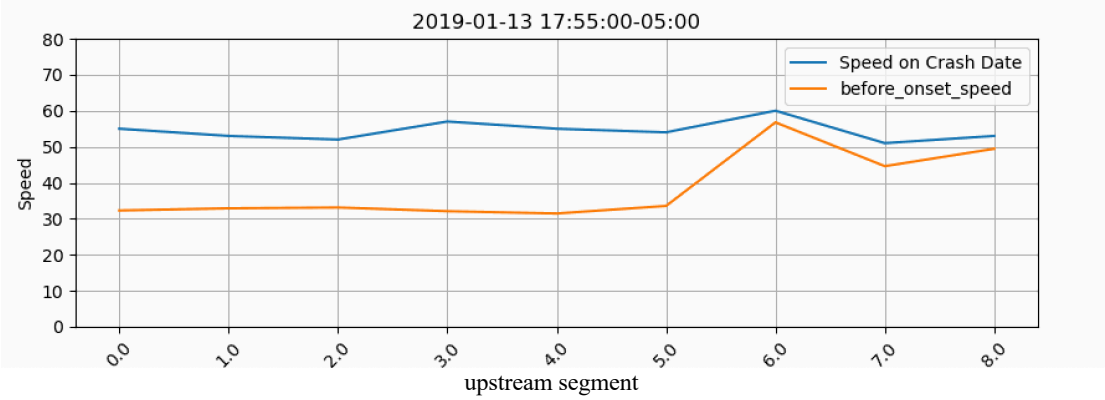

Figure 15. Speed profile 90 minutes after the onset of the incident compared to pre-incident conditions.

5.1.3.3. Comparison of the two baseline determination methods

The advantages and disadvantages of the two methods mentioned above are discussed in this section.

The baseline determination using historical data has the following advantages and disadvantages:

Advantages:

- **Stability and Consistency:** Historical data provides a stable and consistent baseline, as it is derived from a broad dataset that smoothens out daily fluctuations and short-term anomalies, offering a reliable measure of normal traffic conditions.
- **Data Integrity and Analysis Continuity:** This method ensures that datasets remain robust and comprehensive, even in the face of missing values. By selecting historical days that mirror the conditions of the day with missing data, analysts can fill gaps without compromising the dataset's overall quality. This continuity is crucial for performing consistent trend analysis, modeling traffic behaviors, and making informed decisions based on reliable data.

Disadvantages:

- **May Not Reflect Current Conditions:** Relying solely on historical data might not accurately capture the current state of traffic or immediate changes in traffic patterns, such as new road constructions or changes in traffic regulations.

- **Data Collection and Quality:** The effectiveness of this method is contingent on the availability and quality of historical data. Inaccuracies, gaps, or biases in the data can lead to misleading baselines.
- **Ignoring Day-to-Day Variability**: While historical data smoothens out anomalies, it may also overlook relevant day-to-day variability, such as the difference between weekday and weekend traffic patterns, which could be significant for incident impact analysis.

On the other hand, the baseline determination using pre-incident conditions has the following advantages and disadvantages:

Advantages:

- **Relevance:** This method provides a highly relevant baseline by capturing the traffic conditions immediately before the incident, ensuring the baseline is closely aligned with the current traffic state.
- **Sensitivity to Daily Variations:** By focusing on the pre-incident conditions, this approach is sensitive to daily variations in traffic patterns, such as rush hours, making it more accurate for incidents occurring during these periods.
- **Immediate Context:** It offers an immediate context for the incident's impact, allowing for a direct comparison of traffic conditions before and after an incident, which can help in understanding the immediate effects of the incident on traffic speed.

Disadvantages:

- **Short-term Fluctuations:** The method may be more susceptible to short-term fluctuations in traffic that aren't representative of general traffic patterns, potentially leading to a less stable baseline.
- **Inaccuracy in Incident Detection Time:** The effectiveness of utilizing pre-incident conditions as a baseline is significantly compromised by the potential inaccuracies in pinpointing the exact time an incident begins. This is due to limitations in the measurement and detection technologies available. Determining the true pre-incident traffic conditions becomes challenging without precisely identifying the incident's onset, leading to a baseline that may not accurately reflect the situation immediately before the incident.
- **Lack of Historical Perspective:** Unlike methods that use historical data, this approach does not account for long-term trends or seasonal variations in traffic, which can be important for understanding broader traffic patterns.
- **Potential for Anomalies:** The pre-incident period might already be influenced by unrelated incidents or events that could skew the baseline, making it difficult to isolate the impact of the target incident.
- **Data Availability:** This method relies on the availability of real-time data, which may not always be accessible or accurate, potentially limiting its applicability in certain situations.

5.2. Incident Recovery Time Estimation Framework

This section introduces a comprehensive framework for estimating traffic incident recovery time.

5.2.1. The Proposed Framework Methodology

The methodology begins by defining a specific time frame for each traffic incident in the dataset. To ensure a thorough analysis, this time frame extends from one hour before the incident's reported start time, as recorded by CHART, and encompasses a period of five hours following the incident's clearance time. This strategic time interval serves multiple purposes:

Detection Time Variability: By incorporating the hour preceding the reported start time, the framework accommodates potential delays in incident detection by CHART. This inclusion accounts for situations where the incident may not be immediately detected, ensuring a more accurate analysis of the incident's impact.

Comprehensive Observation: The five-hour window after the incident's clearance time allows for a comprehensive examination of post-incident conditions. It enables the study to capture the extended effects of the incident on traffic flow and assess how long it takes for traffic to return to its normal state.

Once the designated time frame is defined, the subsequent task involves calculating the Mean Percentage Difference (MPD) for each 1-minute interval. In this calculation, the

speeds of the upstream TMCs, which include the TMC where the incident occurred, are considered. Specifically, the speeds recorded on the day the incident happened within each 1-minute interval are compared to the 50th percentile of speed values obtained from historical data or the speed values obtained from pre-incident conditions depending on the speed profile baseline determination method. This MPD computation is a crucial step in evaluating the accuracy of recovery time predictions, as it quantifies the percentage difference between speed values of the incident location when the traffic is normal and the speed values when the incident happened.

The MPD calculation using each of the baseline determination methods is discussed below:

The MPD calculated using the historical data is as follows:

$$MPD_j = \frac{\sum_i^n \left(\max\left(\frac{S_{i,j} - H_{i,j}}{H_{i,j}}, 0\right)\right)}{n} \times 100 \qquad (1)$$

Where:

MPD_j: the MPD calculated for time interval j.

n: the number of TMCs derived as the upstream TMCs for the incident, including the TMC where the incident happened;

$S_{i,j}$: speed value on the day the incident took place in the i^{th} TMC at time j;

$H_{i,j}$: the 50th percentile of historical speed value in the i^{th} TMC at time j;

The MPD calculated using the data of the pre-incident conditions is as follows:

$$MPD_j = \frac{\sum_i^n \left(\max\left(\frac{S_{i,j} - P_{i,j}}{P_i, j}, 0\right)\right)}{n} \times 100 \qquad (2)$$

Where:

MPD_j: the MPD calculated for time interval j.

n: the number of TMCs derived as the upstream TMCs for the incident, including the TMC where the incident happened;

$S_{i,j}$: speed value on the day the incident took place in the i^{th} TMC at time j;

$P_{i,j}$: the pre-incident condition speed in the i^{th} TMC at time j;

With the MPD values computed for each one-minute interval, the end of the recovery time is determined based on a specific criterion. The end of the recovery time is defined as the start time of a 30-minute interval following the onset of the incident, as reported by CHART, where the MPD remains below 10% during the interval. This criterion ensures that the recovery time is considered complete when traffic conditions in the upstream TMCs have stabilized, specifically with MPD values consistently below the 10% threshold. The 10% threshold is chosen because, in situations where there is no incident, fluctuations observed in the speed profile on different days show that the MPD is almost always under 10%. Therefore, the normal condition is set to have an MPD of less than this threshold.

5.2.2. The Proposed Framework Results

This framework is exemplified through a practical illustration. Consider an incident that occurred on January 15, 2019, at 7:22 a.m. and was officially cleared according to CHART's report at 9:22 a.m. Figure 16 visually represents the speed dynamics at both the incident location and the identified upstream TMCs. Notably, approximately 8 minutes following CHART's reported incident initiation time, a noticeable decline in speed within the first TMC is evident. This decrease in speed becomes progressively more pronounced as time passes before gradually returning to its normal pattern, as observed in historical data.

Figure 17 displays the variation of MPD at the case study location over time. In Figure 17.A, the actual MPD fluctuations are visible, highlighting specific moments of variation. Figure 17.B shows the MPD variation using a 5-minute moving average to mitigate the influence of abrupt, localized changes, which smooths out short-term fluctuations and reveals more significant trends.

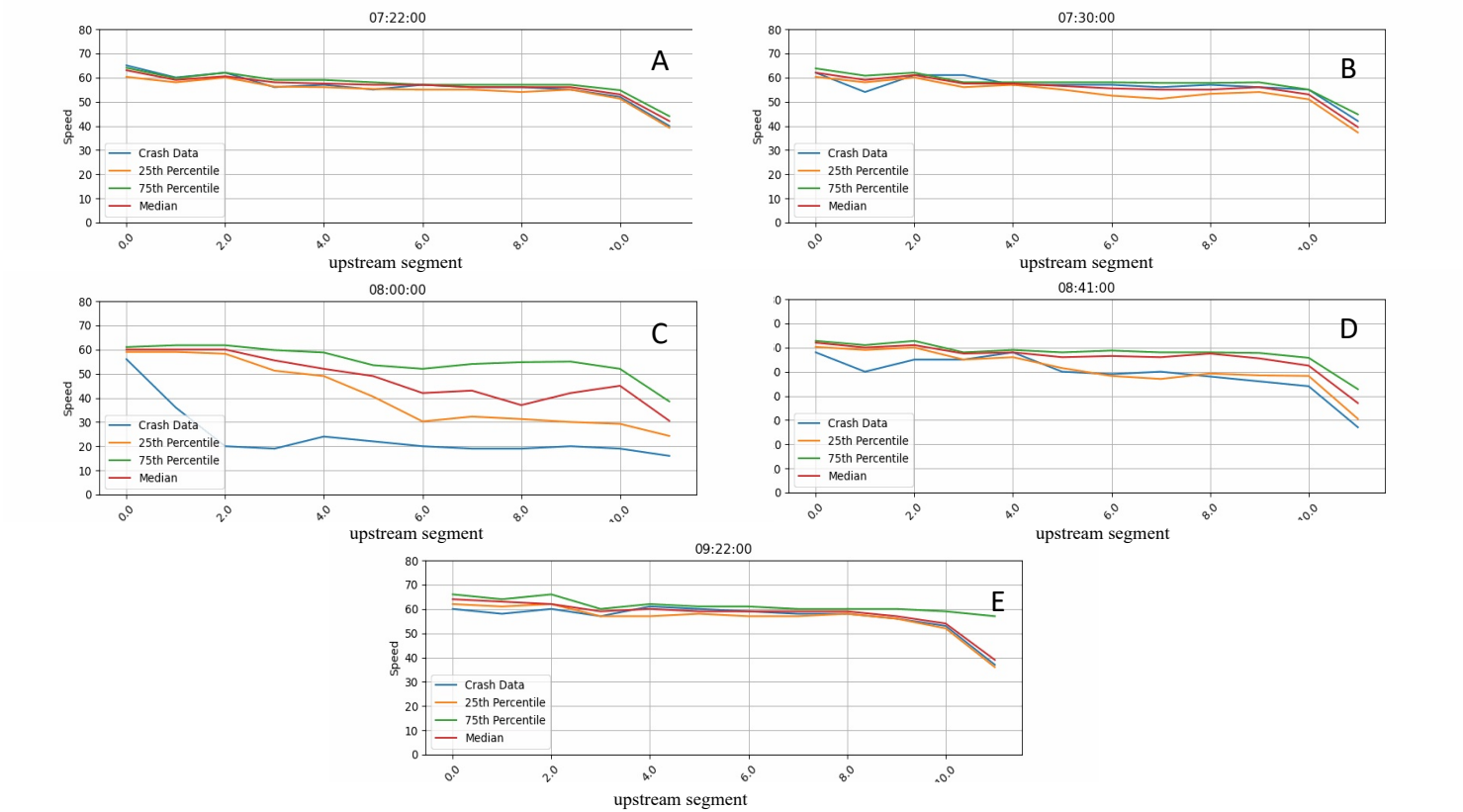

Figure 16. Speed variation of case study throughout the time. A) when the incident occurred; B) When a discrepancy started; C) in the middle of the clearance phase; D) when the algorithm identifies the end of recovery time. E) CHART clearance time.

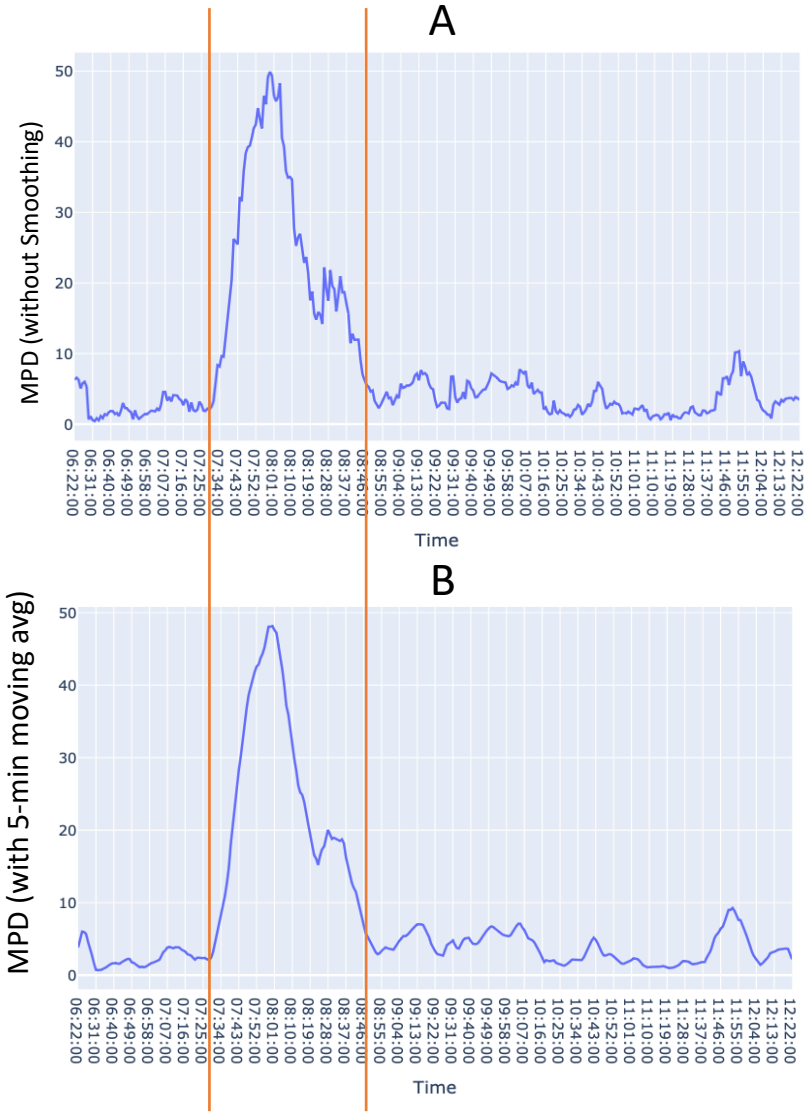

Figure 17. Variation of MPD throughout the time. A) without smoothing; B) with smoothing using a 5-minute moving average.

In the specific case study highlighted, the incident start time reported by CHART was recorded at 07:22 a.m. However, the proposed algorithm identified the recovery time as 08:41 am, which notably precedes the clearance time reported by CHART at 09:22 am. This case study underscores a unique aspect of our research. It challenges conventional notions of traffic incident phases by revealing situations where the recovery time commences before the official clearance time—a phenomenon often overlooked in existing incident management literature.

The methodology put forth was rigorously applied to a comprehensive set of 3448 traffic incidents from each season within the year 2019, specifically targeting the months of January, April, July, and October. This temporal spread ensured a robust dataset reflective of seasonal variations in traffic conditions. The initial phase involved identifying the upstream incident locations, a process delineated in the 'Upstream Link Inclusion section.' Subsequently, all pertinent TMC links were fed into the RITIS (Regional Integrated Transportation Information System) tool. Utilizing the Data Archive feature of RITIS, speed data were meticulously extracted for further analysis.

It is worth noting that the number of incident records used in predictive modeling can play a crucial role in determining the accuracy and reliability of the predictions. In this study, four months of data from 2019 were utilized due to constraints in resources and the need for efficient model running times. However, expanding the dataset to include more months or years of data could enhance the model's accuracy and reliability by

providing a more comprehensive view of traffic incident patterns, leading to more precise and dependable predictions and also providing an insight into traffic management systems and whether the policies made in the previous year actually worked in the following years.

The analytical tasks were carried out in Python, where the proposed method was implemented to find the incident recovery times. This computation utilized both baseline determination methods previously detailed, with the recovery times serving as the dependent variable, or labels, for the predictive models discussed in Chapter 6 of the dissertation. The outcomes of these calculations, which are instrumental in understanding traffic patterns post-incident, are visually represented in Figure 18 and Figure 19. These figures exhibit the distributions of traffic recovery times found through each baseline determination method, offering a comparative insight into the efficacy and characteristics of the different approaches employed in the study.

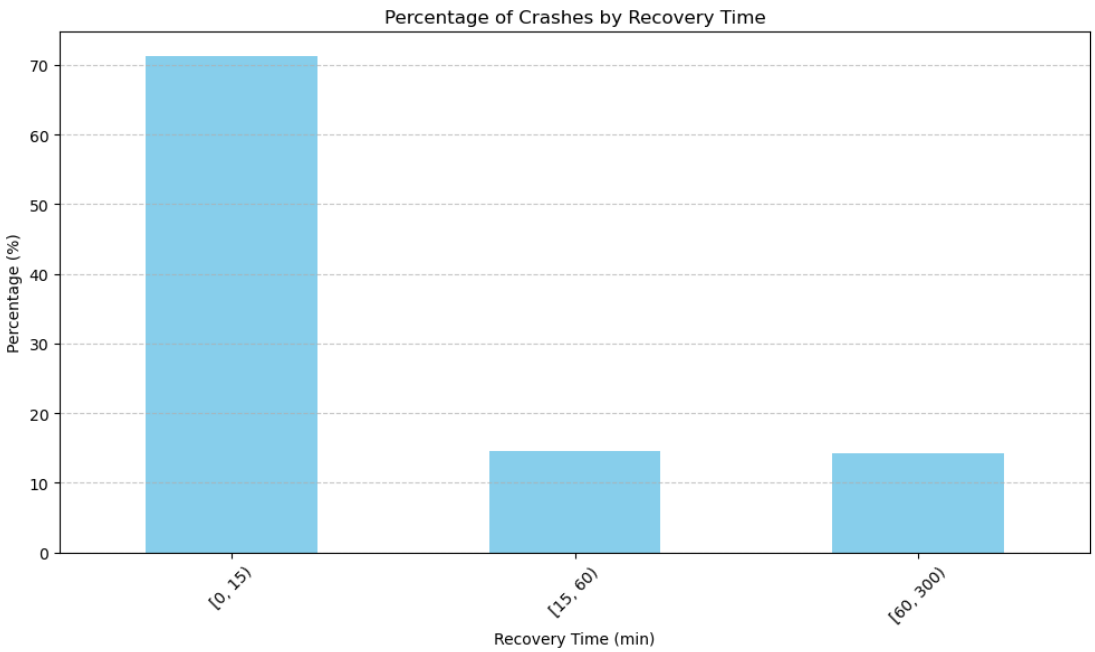

Figure 18. Percentage of crashes in each recovery time bin using baseline determination by historical data.

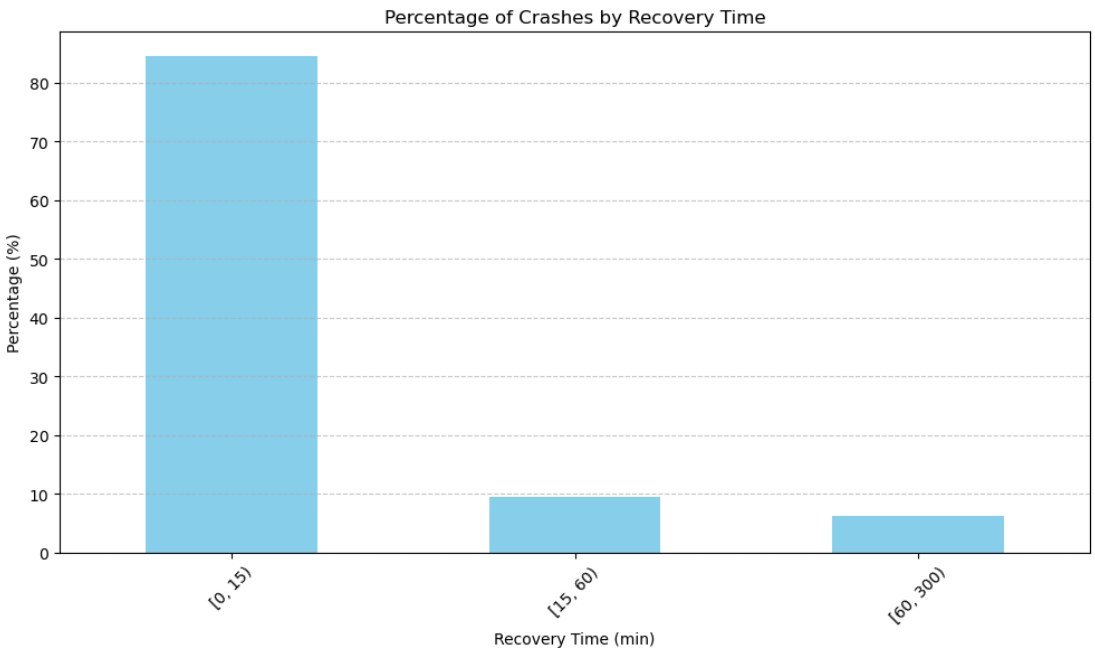

Figure 19. Percentage of crashes in each recovery time bin using baseline determination by pre-incident conditions data.

Figure 20 and Figure 21 depict the distribution of incidents based on the difference between recovery time and clearance time, categorized into different time intervals using both baseline determination methods.

The figures show that a significant number of incidents have a recovery time between 15 and 60 minutes shorter than the clearance time. This suggests that, in these cases, traffic conditions took less time to return to the baseline state compared to clearance time. In other words, the traffic conditions returned to normal well before the clearance time reported by CHART.

Furthermore, nearly a quarter of crashes have a recovery time between 15 minutes shorter to 15 minutes longer than the clearance time, indicating that for a considerable number of incidents, the recovery time is fairly close to the clearance time.

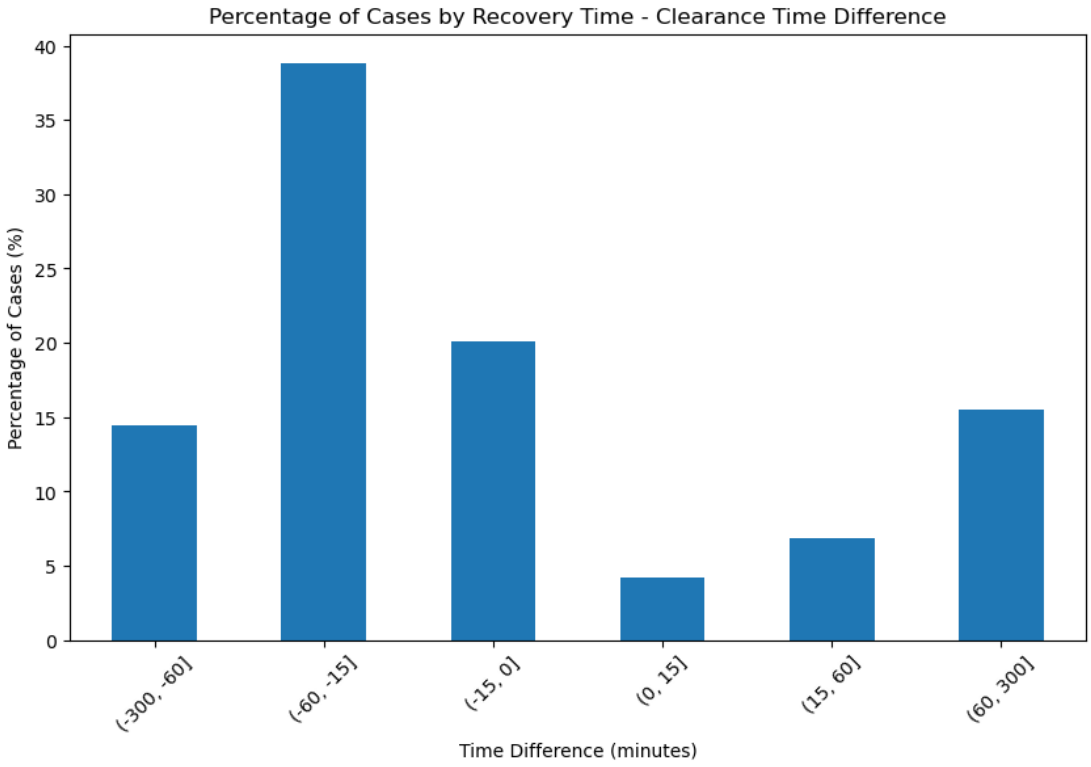

Figure 20. Percentage of incidents in each difference in recovery and clearance time bin using baseline determination by historical data.

There is a portion of incidents with recovery times that are significantly shorter (less than -60 minutes) or longer (more than 60 minutes) than the clearance time. These cases might represent incidents with particularly quick recoveries or unusually long-lasting impacts.

When utilizing the pre-incident condition baseline for determining the recovery time of traffic incidents, the data suggests a trend where incidents tend to be resolved more quickly, leading to a higher proportion of incidents that recover sooner than the clearance time.

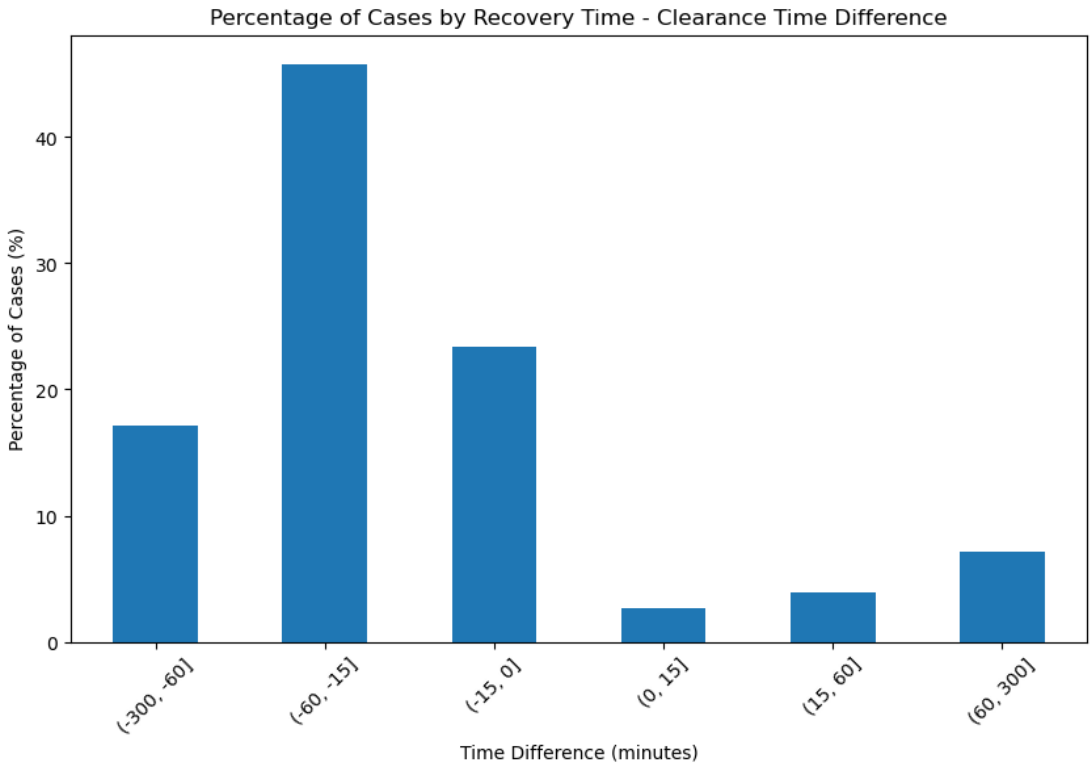

Figure 21. Percentage of incidents in each difference in recovery and clearance time bin using baseline determination by pre-incident conditions data.

This implies that the pre-incident condition baseline may offer a more conservative estimate of normal traffic speed conditions, which in turn makes the return to this baseline appear faster once the incident has been cleared. Possible reasons behind such

observations are as follows. If the pre-incident traffic conditions are particularly slow (due to rush hour or other factors), then the threshold for returning to 'normal' speeds post-incident is lower. This might result in a quicker perceived recovery as traffic does not have to improve as much to reach the pre-established baseline. Also, the pre-incident condition baseline reflects the conditions immediately before the incident, which might account for any transient changes in traffic patterns not captured in historical data, such as a special event causing unusual traffic speed patterns.

Chapter 6: Incident Recovery Time Prediction

This chapter focuses on predicting the duration needed to recover from traffic incidents utilizing probe vehicle data and assigning each incident a recovery time label, building upon the methodology introduced in Chapter 5. The exploration covers multiple predictive models, each evaluated for its efficacy in predicting recovery time. The analysis includes assessing the models' accuracy and other crucial performance metrics. The objective is to identify the most effective model for predicting recovery times to enhance traffic incident management strategies.

6.1. Exploratory Data Analysis

This section embarks on exploratory data analysis (EDA) to lay the groundwork for modeling. This is crucial for understanding the underlying structure and characteristics of the dataset collected through probe vehicle data and augmented by information provided by CHART related to each incident. The EDA process thoroughly examines the dataset, identifying potential patterns, anomalies, or correlations among the variables that could influence the accuracy of incident recovery time predictions. The numerical and categorical variables used for modeling are statistically described in Table 10 and Table 11, respectively. Figure 22 also shows the distribution of categorical independent variables.

Table 10. Descriptive statistics of numerical independent variables used for modeling.

	mean	min	25%	50%	75%	max
Clearance Time (min)	44.42	0.2	14.2	29.4	53.2	1449.8
Response Time (min)	5.36	0	0.3	2.2	7.9	275.3
AADT	47450	948	29673	43602	67092.75	163336
Precipitation Rate (mm/hr)	0.33	0	0	0	0	50.54
# total lanes	12.57	2	11	13	14	26
# lanes open	8.97	0	6	8	12	25
# lanes closed	0.84	0	0	0	1	11
# lanes unknown	2.76	0	0	0	6	18
# Car	1.41	0	1	1	2	21
# SUV	0.19	0	0	0	0	14
# Tractor	0.01	0	0	0	0	1
# Bus	0.01	0	0	0	0	2
# Car&Trailor	0.00	0	0	0	0	1
# van	0.00	0	0	0	0	1
# involved	1.58	0	1	2	2	21
# overturned	0.03	0	0	0	0	2
# Jack Knifed	0.01	0	0	0	0	14
# Lost_Load	0.00	0	0	0	0	1

Table 11. Descriptive statistics of categorical independent variables used for modeling.

Variable	categories
Day Part	Midday, Evening, PM Peak, AM Peak
Day Type	Weekday, Weekend
Season	Spring, Summer, Fall, Winter
Event Type	Property Damage, Injury Accident, Serious Accident
Road Class	Interstate, US Route, State Route
Road Condition	Dry, Wet, Ice/Snow, Chemicals, Unspecified
Responder	Agencies, CHART Unit, MDOT, Resources, Facilities, Special Needs
County	Baltimore County, Baltimore City, Montgomery, Prince Georges, Fredrick, Anne Arundel, Harford, Howard, Washington, Cecil, Other

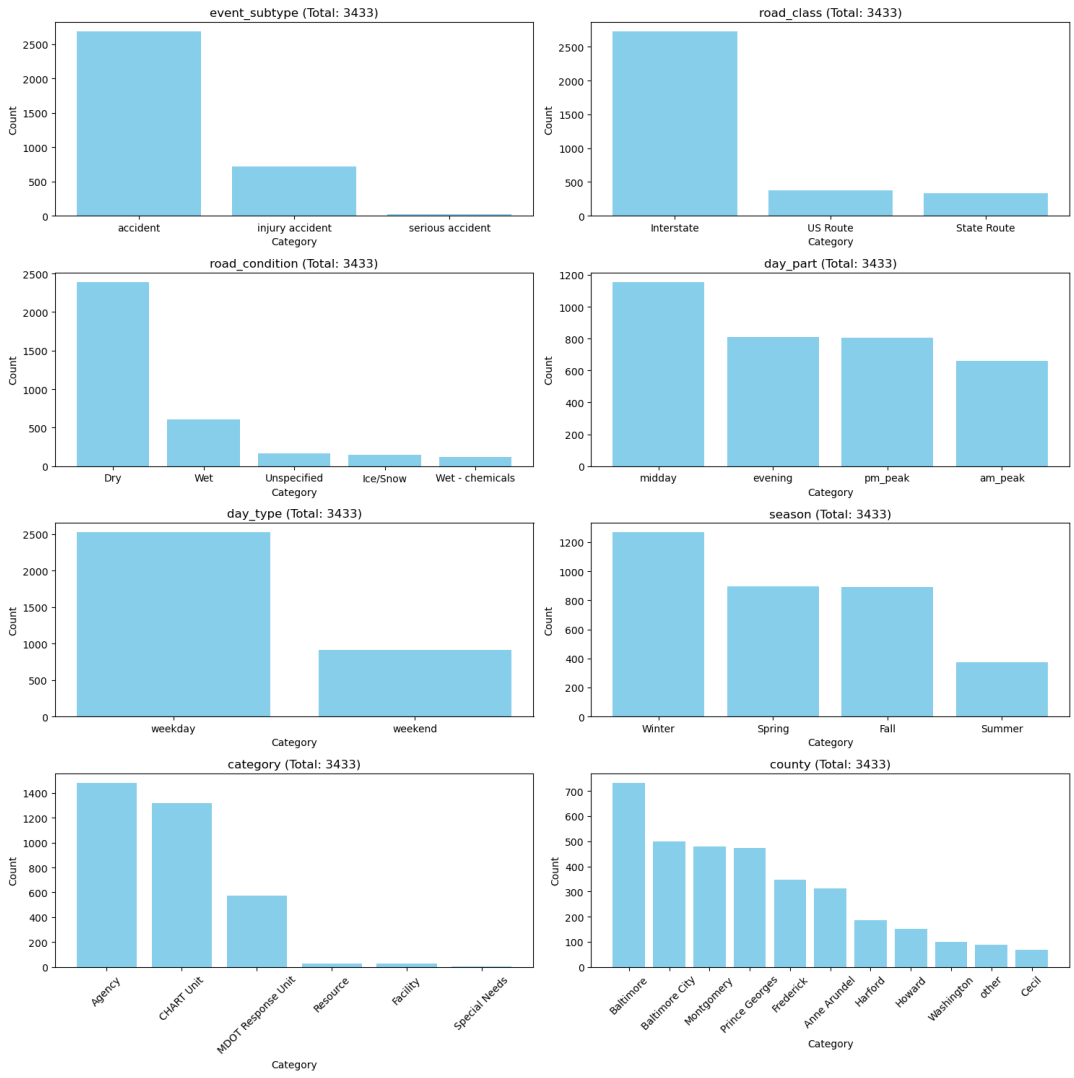

Figure 22. Distribution of values for categorical independent variables used for modeling.

Figure 23 shows the distribution of recovery time by road conditions. The most prolonged recovery times are associated with ice and snow conditions, which exhibit

the highest average recovery time and wide distribution, underscoring the substantial challenges in incident management and recovery during severe weather.

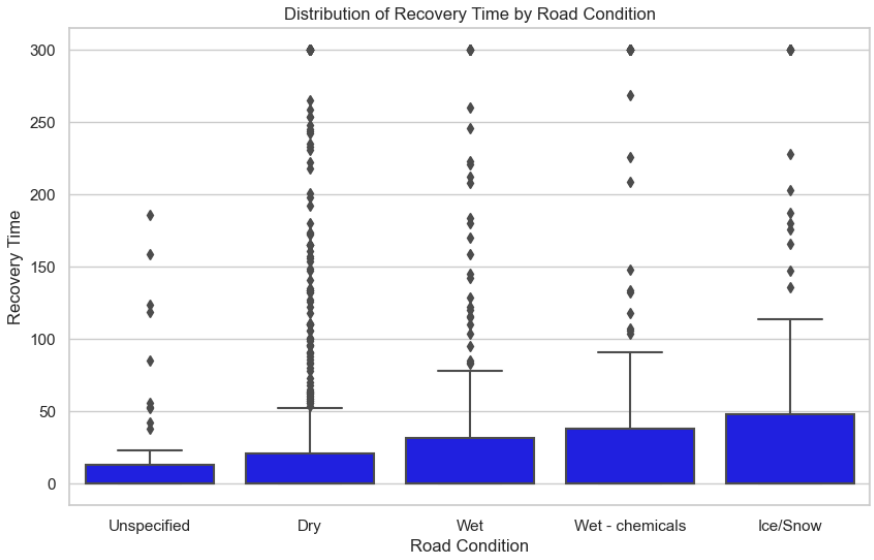

Figure 23. Distribution of recovery time by road conditions.

Among these decision variables, variables such as "Day Part," "Day Type," and "Season" are uncontrollable factors as they relate to natural time cycles and environmental changes. "Event Type," "Road Condition," and "County" also largely depend on circumstances that are not directly controllable; however, road conditions can be managed to an extent through maintenance and responses to weather conditions. On the other hand, "Response Time" and “Clearance Time” represent a decision that can be controlled and optimized by traffic management authorities to ensure the most effective response to incidents. Variables reflecting the number of lanes, such as "total lanes," "lanes open," "lanes closed," and "lanes unknown," can be managed by traffic

controllers through dynamic lane management systems in response to real-time traffic conditions or accidents. "AADT" (Annual Average Daily Traffic) is not directly controllable but can inform planning and traffic flow management decisions. Lastly, the types and numbers of vehicles involved in incidents are not controllable by traffic management but are instead influenced by broader transportation trends and individual choices. Overall, while some aspects of traffic flow and incident response can be managed to improve safety and efficiency, others are dependent on external factors or long-term strategies outside of immediate control.

Based on a thorough review of the existing literature and a detailed analysis of the dataset's balance, incidents with recovery times of less than 15 minutes are classified as short-duration incidents. This category captures the incidents that have minimal impact on traffic patterns. Incidents with recovery times ranging from 15 to 60 minutes are categorized as medium-duration incidents, reflecting a moderate impact on traffic that requires a more substantial response to resolve. Lastly, incidents extending beyond 60 minutes are classified as long-duration incidents, indicating a significant impact on traffic with potentially complex recovery efforts. This categorization scheme allows for a structured approach to modeling and analysis, acknowledging the varying degrees of traffic disruption caused by incidents and enabling targeted strategies for incident management and recovery. Figure 24 shows the distribution of incident recovery times.

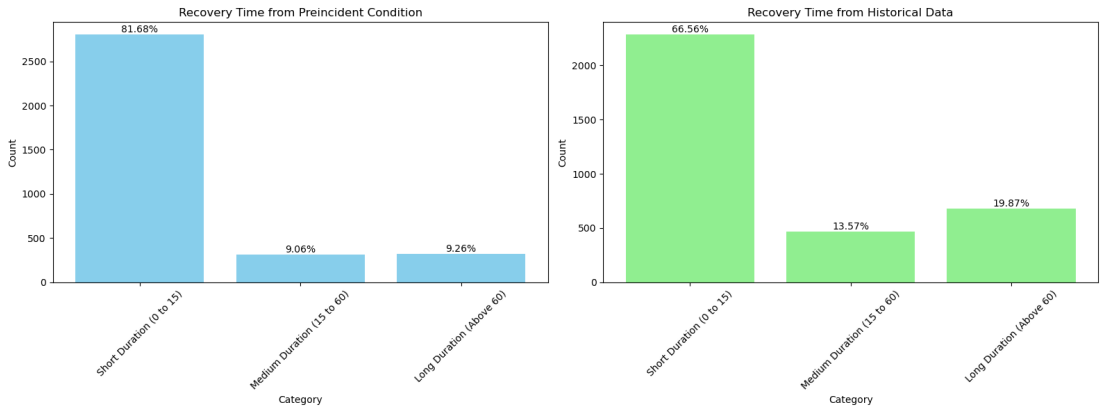

Figure 24. Recovery time distribution using both historical baseline and pre-incident condition baseline.

Figure 25 and Figure 26 show the location of all the incidents and incidents with a long-duration recovery time in Maryland. Incidents are spread all over the state.

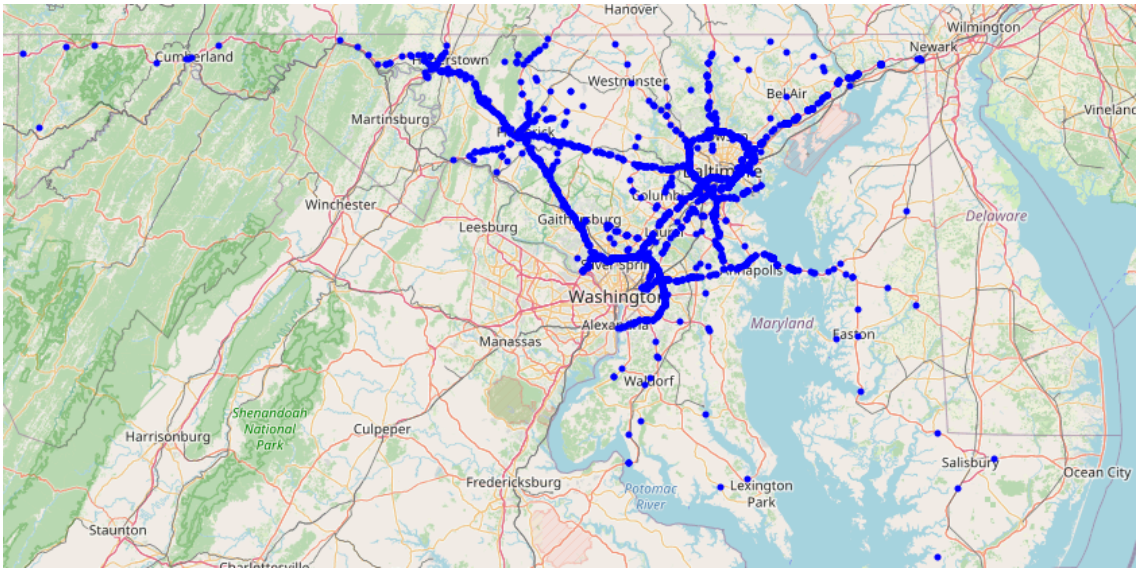

Figure 25. Location of incidents.

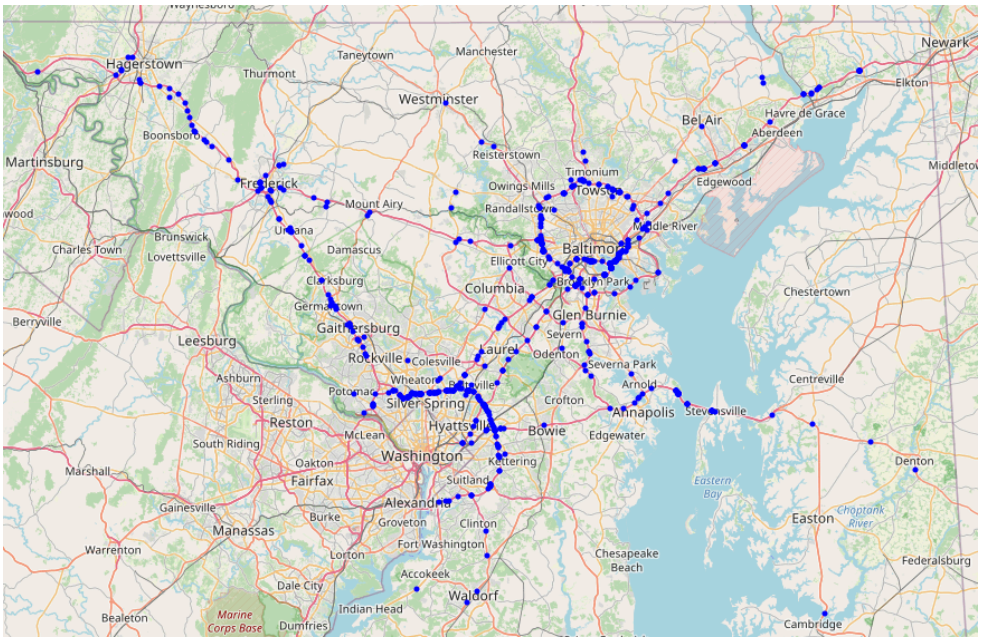

Figure 26. Location of incidents having recovery time of longer than 60 minutes using historical data baseline.

Figure 27 shows the median and 75th percentile of recovery time by hour. The peaks suggest that during certain hours, particularly early morning and early evening, the recovery times can be pretty lengthy, indicating that incidents occurring during these times may take longer to resolve.

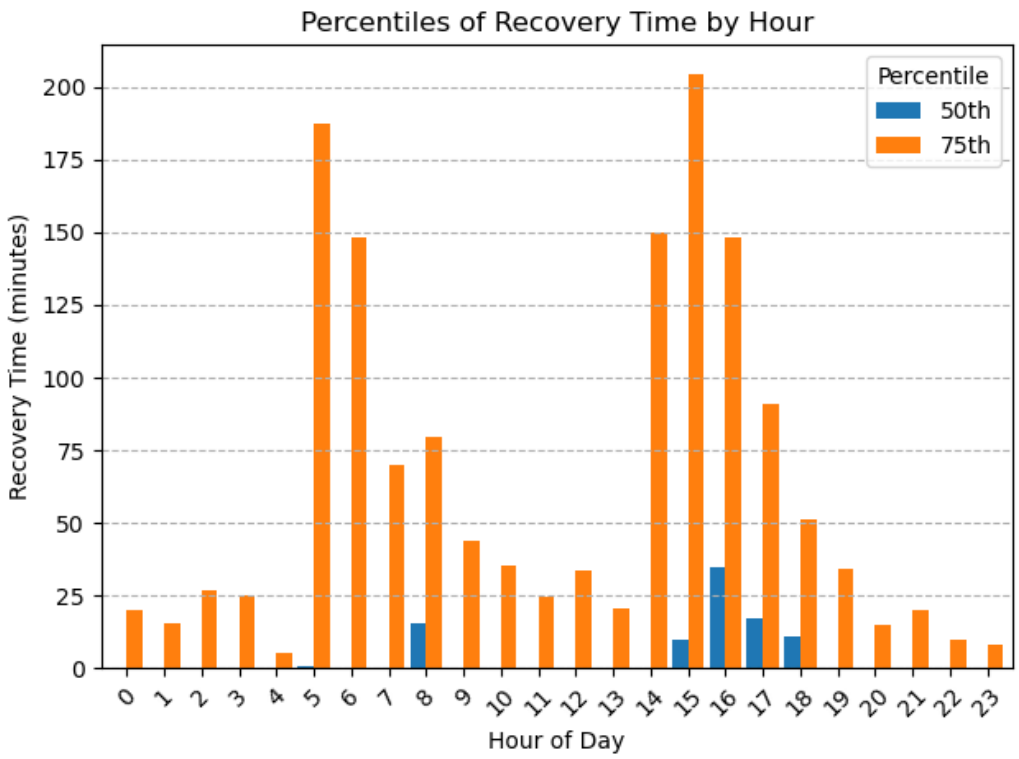

Figure 27. Distribution of recovery time of incidents by hour.

Figure 28 represents the median and 75th percentile of clearance time by hour. Clearance time refers to the time taken from the incident occurrence until the site is cleared. Similar to the recovery time, the clearance time has peaks at certain hours, notably in the late night or early morning, suggesting that incidents during these times are particularly time-consuming to clear.

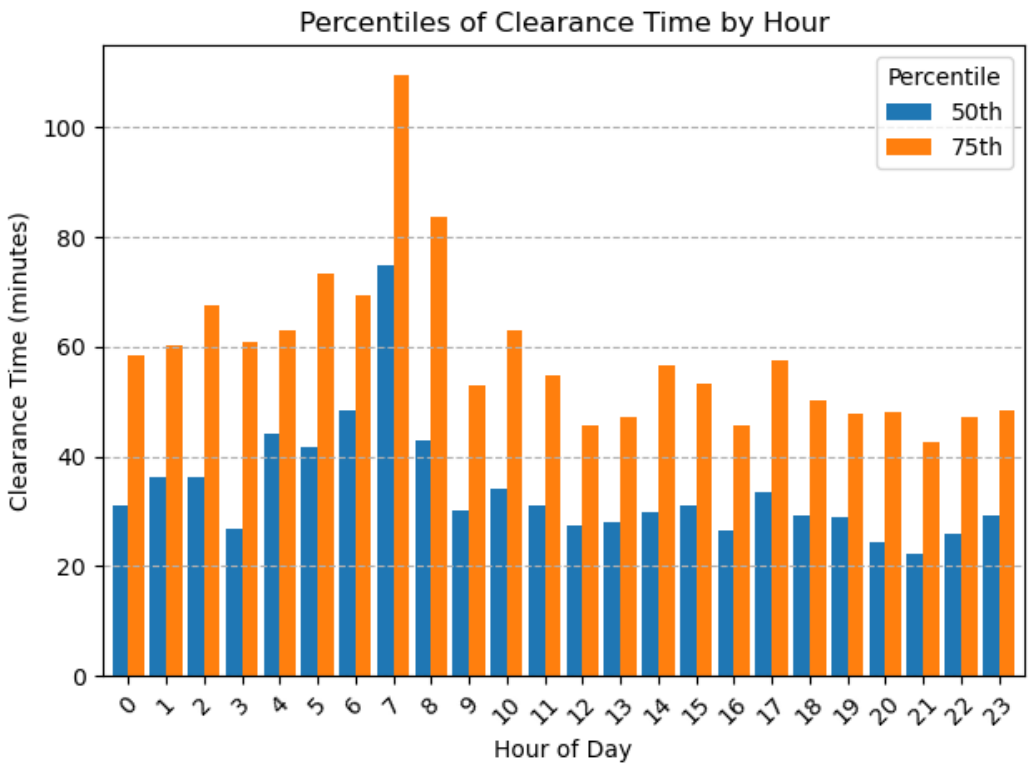

Figure 28. Distribution of clearance time by hour.

Figure 29 depicts the median and 75th percentile of response time by hour, showing the time it takes for responders to arrive at the incident scene. The response time is relatively consistent throughout the day, with a notable peak in the morning hours. This peak could indicate higher traffic volumes or other operational challenges faced by responders during this time.

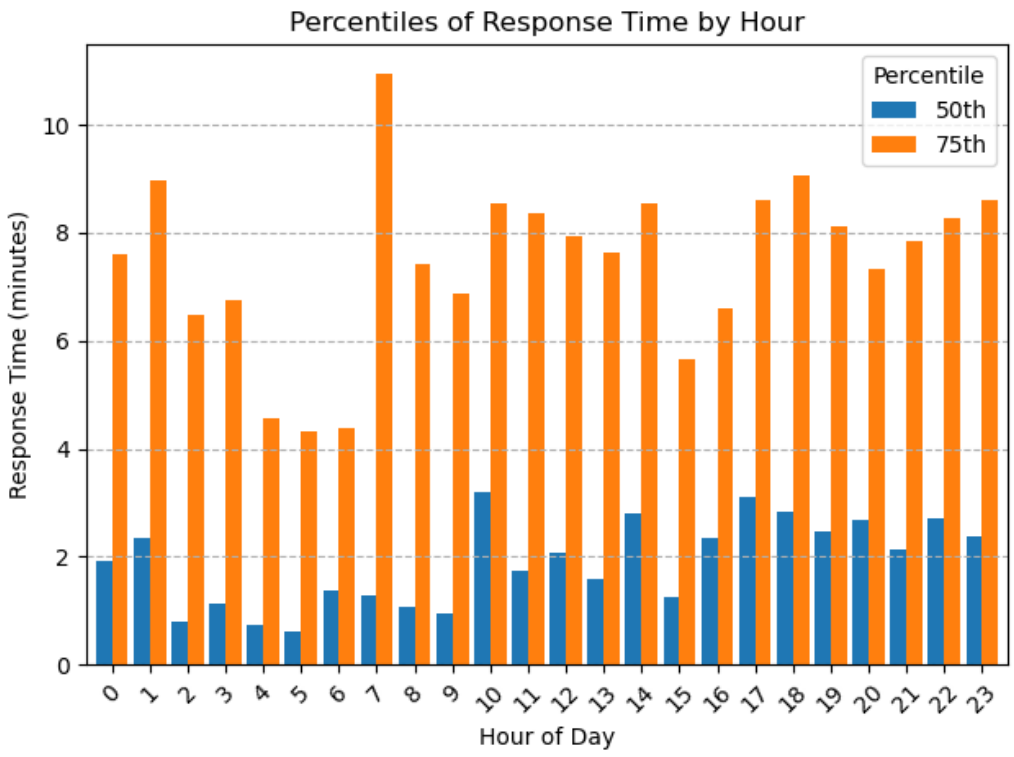

Figure 29. Distribution of response time by hour.

6.2. Modeling Traffic Incident Recovery Time

6.2.1. Data Preprocessing Steps

In the data preprocessing phase, critical steps are undertaken to prepare the dataset for modeling. Initially, missing values in the dataset are addressed by filling them with the median values of their respective columns. This approach is often preferred over using mean values as medians are less sensitive to outliers, thus providing a more robust measure of central tendency for imputing missing data.

Following the treatment of missing values, categorical columns in the dataset are converted into a numerical format using the One-Hot Encoding (OHE) method. OHE is a process that transforms categorical variables into a form that could be provided to Machine Learning (ML) algorithms to do a better job in prediction. For each unique category in a categorical column, one-hot encoding creates a new binary column (0s and 1s), indicating the presence or absence of the category. This method effectively removes the ordinal relationship between categories, treating each category equally important without implying any order or precedence among them.

After preprocessing, the dataset is split into training and testing sets using a 25-75 split, meaning 25% of the data is reserved for testing the model's performance, while the remaining 75% is used for training the model. This split is conducted with stratification to ensure that both the training and testing sets have the same proportion of categories as the original dataset. Stratification is a technique used to maintain the same distribution of classes in both subsets as in the entire dataset, particularly useful in scenarios where the dataset is imbalanced. Doing so helps achieve a more reliable and generalizable model performance, ensuring that no subset is biased towards a particular class. This careful division and stratification of the dataset are essential steps to validate the model's effectiveness in a way that is representative of real-world conditions.

6.2.2. ML Models

Several machine learning algorithms are utilized to model traffic incident recovery time, and the models' performance is compared to each other. The following models are used as the primary models, and each is briefly described:

- Decision Tree

A decision tree model is a versatile and intuitive machine-learning algorithm that uses a tree-like structure to make decisions. At its core, the model consists of decision nodes and leaves. Each decision node represents a question or test on an attribute, with branches leading to the next node based on the outcome of the test. These nodes are arranged hierarchically, starting from a root node at the top and branching out to cover various outcomes. The leaves of the tree represent the final decisions or classifications. The decision tree makes predictions based on the input features by following the path from the root to a leaf. This approach enables classification, where the goal is to predict discrete labels.

- Random Forest

Random Forest (RF) for classification is an ensemble learning technique that constructs multiple decision trees during training and outputs the majority vote or the most common class among the trees for the final classification. This method incorporates randomness at two levels: by bootstrapping the data to create different training subsets for each tree, and by randomly selecting a subset of features for splitting at each node

within a tree. Such randomness not only adds diversity to the model, enhancing its generalization capabilities, but also helps mitigate the risk of overfitting, a common issue with single decision trees. Random Forest is highly versatile and can handle datasets with high dimensionality and a mix of categorical and numerical features without the need for scaling.

- Gradient Boosting

Gradient Boosting (GB) is a powerful ensemble learning technique used for both regression and classification problems. It builds on the idea of boosting, where weak learners are sequentially added to correct the errors made by previous models. In Gradient Boosting, decision trees are typically used as the base learners. The method involves the iterative addition of decision trees, where each new tree is trained to predict the residuals or errors of the sum of the previously built trees. The objective is to minimize a loss function, with the gradient of the loss being used to determine the direction in which the next tree should aim to reduce errors. Unlike Random Forest, which builds trees independently, Gradient Boosting builds one tree at a time, with each new tree correcting errors left by its predecessors.

- Logistic Regression

Logistic Regression is a fundamental statistical and ML technique used for binary and multiclass classification problems. It operates by estimating probabilities using a logistic function, which is an S-shaped curve that can take any real-valued number and

map it between 0 and 1, but not exactly at those limits. In the context of classification, this model predicts the probability that a given input belongs to a particular category. The logistic function, also known as the sigmoid function in the case of binary classification, models the relationship between the dependent binary variable and one or more independent variables. The output is interpreted as the probability of the dependent variable being in a particular class, and a threshold value, typically 0.5, is used to decide the class assignment.

- Neural Network

Neural Networks for classification represent a class of powerful ML models inspired by the structure and function of the human brain. These models consist of layers of interconnected nodes or neurons, where each connection represents a weight that is adjusted during the training process to minimize the prediction error. In a typical feedforward neural network used for classification, the architecture includes an input layer, one or more hidden layers, and an output layer. The input layer receives the feature data, the hidden layers perform transformations using activation functions to introduce non-linearity, and the output layer produces the classification predictions. For multiclass problems, the output layer typically consists of multiple neurons, one for each class, with an activation function representing the probability distribution across the classes.

- K-nearest Neighbors

K-Nearest Neighbors (KNN) is a simple, intuitive, and versatile algorithm used for classification and regression tasks in machine learning. The KNN algorithm assigns a class to a sample based on the majority class among its k nearest neighbors for classification. The algorithm calculates the distance (e.g., Euclidean, Manhattan) between the sample point in question and all other points in the dataset, identifies the k closest points, and then aggregates their classes to determine the sample class. One key feature of KNN is its non-parametric nature, meaning it makes no underlying assumptions about the data distribution, allowing it to perform well in scenarios where the data distribution is unknown.

Moreover, other ensemble ML algorithms, such as voting and stacking, are used in this dissertation, and they are discussed below. Voting and stacking are ensemble methods in machine learning that combine multiple models to improve prediction performance by leveraging their collective strengths. These techniques are particularly effective because they aggregate the predictions from multiple models to reduce variance and bias or improve predictions.

- **Voting**

The voting method involves multiple models, each casting a "vote" for a particular class, and the final output class is determined based on these votes. There are two types of voting:

Hard Voting: In hard voting, each model in the ensemble votes for one class, and the final prediction is the class that receives the majority of the votes. This method does not account for the confidence of the votes; it only considers the most frequently predicted class.

Soft voting, on the other hand, takes into account the probability estimates for all classes from each model, if available. The probabilities for each class are averaged, and the class with the highest average probability is predicted as the final output. Soft voting often yields better performance than hard voting because it considers the confidence level of each model's predictions. Figure 30 shows the flowchart of soft voting algorithm.

- **Stacking**

Stacking (short for stacked generalization) is another ensemble technique that builds a model on top of multiple other models to improve predictions. Figure 31 shows the flowchart of the stacking algorithm. Unlike voting, which aggregates predictions at the end, stacking uses a two-level approach:

First Level: Multiple base models (also known as level-0 models) are trained independently on the same training dataset.

Second Level: Another model (also known as the meta-model or level-1 model) is trained on the outputs of the base models as features. This meta-model learns how to best combine the predictions from the base models to make a final prediction.

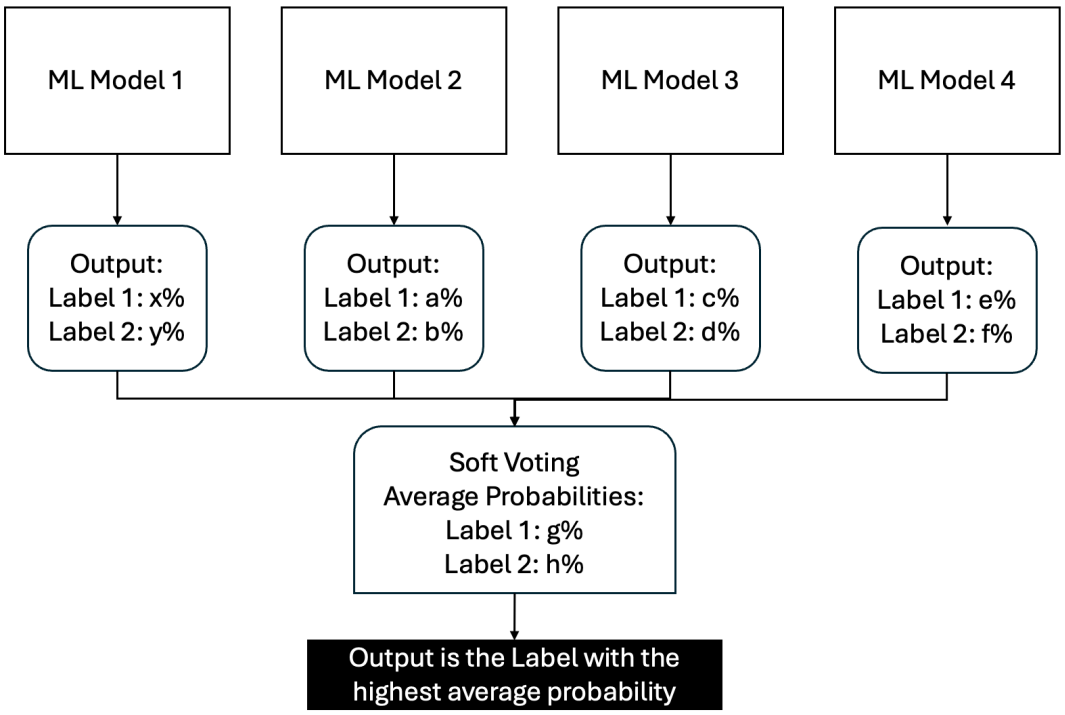

Figure 30. Flowchart of soft voting machine learning algorithm.

The key idea behind stacking is to learn from the mistakes of base models by considering how their outputs vary across different instances and using that information to make better predictions. It can be more complex and computationally expensive than voting because it involves multiple layers of modeling, but it has the potential to improve prediction accuracy by effectively combining different models. Both voting and stacking are powerful ensemble methods that can create more robust, accurate models by combining the strengths of diverse models.

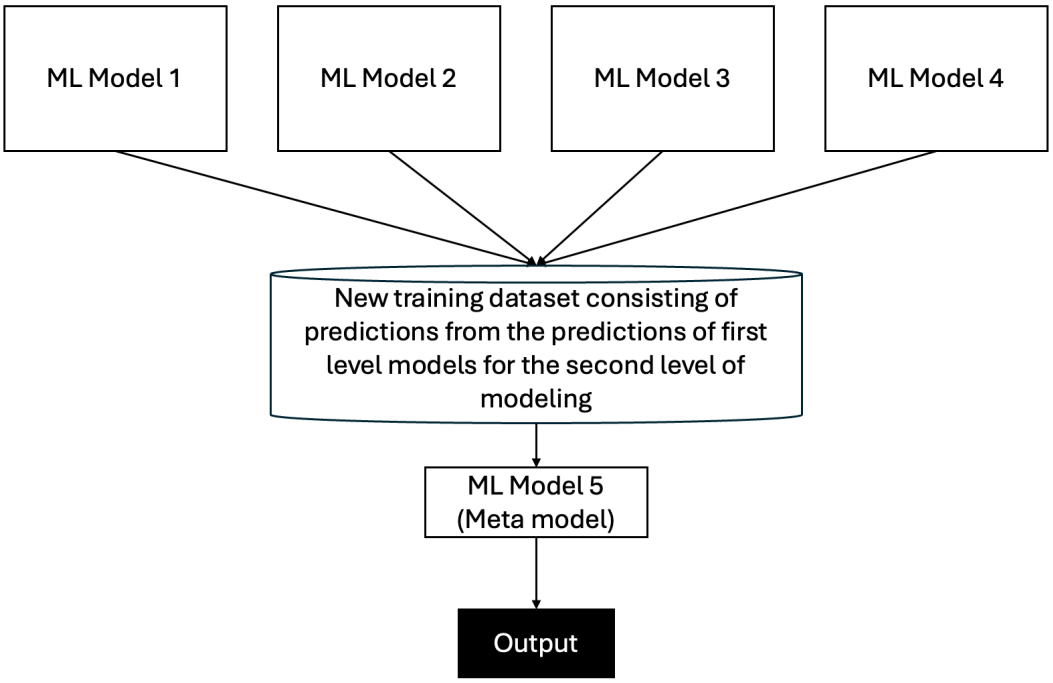

Figure 31. Flowchart of stacking machine learning algorithm.

6.3. Modeling Results and Discussions

Two labeling strategies are employed to predict incident recovery time: one based on a pre-incident condition baseline and the other using a historical condition baseline. Incidents are categorized into three duration types for classification: short-duration (0 to 15 minutes), medium-duration (15 to 60 minutes), and long-duration (60 minutes or longer). As discussed earlier, machine learning methods such as Random Forest, Gradient Boosting, Logistic Regression, Neural Networks, K-Nearest Neighbors, Voting, and Stacking are utilized to tackle this classification problem. The performance

of these models is evaluated using key metrics: precision, recall, and the F1-score, as defined below.

Precision

Precision, also known as positive predictive value, measures the accuracy of positive predictions. It is defined as the ratio of true positive predictions to the total predicted positives, including both true and false positives. In other words, precision indicates how many of the instances predicted as positive are actually positive. The formula for precision is:

$$Precision = \frac{TP}{TP + FP} \qquad (3)$$

where TP is the number of true positives, and FP is the number of false positives.

Recall

Recall, also known as sensitivity or true positive rate, measures the ability of the model to identify all relevant instances. It is defined as the ratio of true positive predictions to the total actual positives, including both true and false negatives. Recall indicates how many of the actual positives were correctly identified. The formula for the recall is:

$$Recall = \frac{TP}{TP + FN} \qquad (4)$$

where TP is the number of true positives, and FN is the number of false negatives.

F1-Score

The F1-score is the harmonic mean of precision and recall, offering a balance between them. It is particularly useful when the distribution of class labels is imbalanced. The F1-score is defined as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (5)$$

The F1-score reaches its best value at 1 (perfect precision and recall) and worst at 0.

In predicting incident recovery time, these metrics provide insight into each model's performance, particularly in correctly identifying the duration categories under varying conditions. Precision focuses on the model's accuracy for each duration category, recall assesses the model's ability to identify all incidents within a category, and the F1-score offers a balance, reflecting the model's overall efficiency in classifying incidents into the correct duration categories.

Table 12 to

Table 17 provide the performance measures of logistic regression, decision tree, random forest, gradient boosting, neural network, and k-nearest neighbors models, respectively.

Table 12. Logistic regression model performance.

	model	**Logistic Regression**				
	Historical Data Baseline			Pre-incident Condition Data Baseline		
Group	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score
Short-duration	0.69	0.95	0.8	0.82	1	0.9
Medium-duration	0	0	0	0	0	0
Long-duration	0.33	0.12	0.18	1	0.01	0.02
	Overall Accuracy	0.66		Overall Accuracy	0.82	

Table 13. Decision tree model performance.

	model	**Decision Tree**				
	Historical Data Baseline			Pre-incident Condition Data Baseline		
Group	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score
Short-duration	0.7	0.66	0.68	0.84	0.8	0.82
Medium-duration	0.15	0.18	0.16	0.13	0.18	0.15
Long-duration	0.31	0.33	0.32	0.1	0.17	0.1
	Overall Accuracy	0.53		Overall Accuracy	0.68	

Table 14. Random forest model performance.

	model	**Random Forest**				
	Historical Data Baseline			Pre-incident Condition Data Baseline		
Group	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score
Short-duration	0.7	0.96	0.81	0.82	1	0.9
Medium-duration	0.3	0.03	0.05	0	0	0
Long-duration	0.5	0.17	0.25	0.4	0.03	0.05
	Overall Accuracy	0.68		Overall Accuracy	0.82	

Table 15. Gradient boosting model performance.

	model	**Gradient Boosting**				
	Historical Data Baseline			Pre-incident Condition Data Baseline		
Group	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score
Short-duration	0.69	0.95	0.8	0.82	0.99	0.9
Medium-duration	0	0	0	0	0	0
Long-duration	0.44	0.16	0.16	0.57	0.05	0.09
	Overall Accuracy	0.67		Overall Accuracy	0.81	

Table 16. Neural network model performance.

	model	**Neural Network**				
	Historical Data Baseline			Pre-incident Condition Data Baseline		
Group	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score
Short-duration	0.71	0.8	0.75	0.84	0.88	0.86
Medium-duration	0.18	0.1	0.13	0.1	0.08	0.09
Long-duration	0.35	0.31	0.33	0.16	0.11	0.13
	Overall Accuracy	0.61		Overall Accuracy	0.84	

Table 17. K-nearest neighbors model performance.

	model	**K-nearest Neighbors**				
	Historical Data Baseline			Pre-incident Condition Data Baseline		
Group	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score
Short-duration	0.71	0.89	0.79	0.92	0.97	0.89
Medium-duration	0.11	0.04	0.05	0.2	0.04	0.06
Long-duration	0.38	0.21	0.27	0.18	0.04	0.06
	Overall Accuracy	0.64		Overall Accuracy	0.8	

Based on the calculated performance measures for the models discussed earlier, utilizing a historical data baseline for predicting incident recovery time results in more accurate predictions than using a pre-incident conditions baseline. The models' accuracy vary, with decision trees showing an accuracy of 0.53 and Random Forest models exhibiting a superior accuracy of 0.68. This finding aligns with previous literature, indicating that machine learning models tend to be more accurate in predicting short-duration incidents while demonstrating lower accuracies for longer incidents.

In particular, the Random Forest model offers the highest overall accuracy of 0.68. Its precision scores further underscore its performance across different incident durations: 0.7 for short-duration incidents, 0.3 for medium-duration incidents, and 0.5 for long-duration incidents. Although the precision for medium and long-duration incidents is not as high as for short-duration incidents, these results are still of significant value to traffic management control agencies.

For instance, the precision of 0.5 for long-duration incidents indicates that half of the cases predicted as long-duration incidents are indeed long-duration incidents. This level of precision is noteworthy because it allows for targeted interventions and strategies to minimize recovery time and mitigate traffic flow disruptions. Proper actions can be initiated with a reasonable degree of confidence, focusing resources and responses effectively to manage and resolve long-duration incidents. Thus, despite

room for improvement, especially in predicting medium and long-duration incidents, the current model predictions provide a practical tool for enhancing traffic management and control operations. Furthermore, comparing the achieved performance to the models discussed in the Literature Review Chapter, the model provides a higher accuracy for longer-duration incidents.

The observed variation in model accuracy for predicting recovery times based on incident duration can be attributed to several factors inherent to the nature of traffic incidents and the complexities involved in their resolution. Medium-duration incidents often encompass a wide range of scenarios and complexities, making them harder to predict accurately. Unlike short-duration incidents, which are typically straightforward (e.g., minor accidents or brief road blockages), medium-duration incidents may involve more intricate factors such as partial lane closures, multiple vehicles, or incidents that escalate over time. These factors introduce variability and uncertainty, complicating the prediction of recovery times. Additionally, medium-duration incidents may fall into a transitional category where the recovery dynamics are neither as predictable as short incidents nor as well-documented as long ones. This transitional nature can result in the model being less sensitive to the specific nuances that influence medium-duration recovery times, thus reducing its accuracy.

To determine whether different thresholds for traffic recovery times (short, medium, and long durations) affect the model's accuracy, the following thresholds were also

considered: 0-30 minutes/30-60 minutes/above 60 minutes, 0-15 minutes/15-45 minutes/above 45 minutes, and 0-30 minutes/30-90 minutes/above 90 minutes. None of these thresholds performed better than the 0-15 minutes/15-60 minutes/above 60 minutes threshold. Given that this threshold provides higher accuracy, is supported by literature, and balances the observations between the 15-60 and above 60 categories, it was chosen for the predictive model. The precisions and accuracies are presented in Table 18.

In addition to the primary machine learning models discussed, soft voting and stacking models were also constructed to explore different ensemble techniques and their effectiveness in predicting incident recovery times.

Table 18. The precision and accuracy of the Random Forest model given different categories of the output variable.

Group	Precision	Overall Accuracy
0-15 minutes	0.7	0.68
15-60 minutes	0.3	
+60 minutes	0.5	
0-30 minutes	0.70	0.73
30-60 minutes	0	
+60 minutes	0.39	
0-15 minutes	0.70	0.67
15-45 minutes	0.17	
+45 minutes	0.47	

0-30 minutes	0.74	0.73
30-90 minutes	0.20	
+90 minutes	0.44	

The models used for constructing the soft voting ensemble include Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, Neural Network, and K-Nearest Neighbors. Five different configurations were evaluated for stacking, each using one of these models as the meta-model and the remaining four as base models. The precision and overall accuracy of each configuration were then calculated.

The performance of these models yielded interesting insights. Specifically, the stacking approach did not demonstrate a performance improvement compared to individual models, such as the Random Forest. This outcome suggests that the complexity added by layering models in the stacking process did not translate into better predictive accuracy for this specific problem. On the other hand, the soft voting ensemble method, which aggregates predictions based on the probability estimates from different models, provided results similar to those achieved by the Random Forest model alone. The performance of stacking and soft voting models are presented in Table 19 and Table 20, respectively.

Given these observations, it is evident that, for this case, the Random Forest model stands out as a particularly effective tool for predicting incident recovery times. Its

performance not only rivals more complex ensemble approaches like stacking and soft voting but also offers a more straightforward and computationally efficient solution. Therefore, the Random Forest model emerges as a highly suitable option when considering the balance between computational cost and accuracy, especially in scenarios involving larger datasets. It achieves a high level of accuracy without the additional computational overhead associated with some ensemble methods. This makes it an optimal choice for traffic management control agencies seeking to implement predictive analytics for incident recovery time, emphasizing operational efficiency and resource optimization.

Table 19. Soft voting model performance.

	model	**Soft Voting**	
	Historical Data Baseline		
Group	Precision	Recall	F-1 Score
Short-duration	0.7	0.94	0.8
Medium-duration	0.25	0.04	0.08
Long-duration	0.45	0.17	0.25
	Overall Accuracy	0.67	

Variability in traffic congestion recovery times significantly impacts the accuracy and reliability of predictive models by introducing greater uncertainty. This variability often stems from complex interactions between factors like traffic volume, incident severity, and weather conditions, necessitating sophisticated and computationally intensive modeling techniques. Extensive and representative datasets are essential to

capture the full range of recovery times, as limited data can lead to biased models that fail to generalize to new incidents. High variability also increases the risk of overfitting, where models perform well on training data but poorly on new data. Therefore, regular updates with new data are crucial to maintain model accuracy and adapt to changing traffic patterns.

Furthermore, Figure 32 shows the importance of the features in the random forest model. The importance of the features in machine learning refers to a technique or measure that helps identify the significance of individual features (input variables) in contributing to the predictive power of a model. It essentially quantifies how much each feature contributes to the model's predictions.

The analysis of feature importance plots from the Random Forest model reveals insightful trends regarding the factors most influential in predicting incident recovery times. The variables with the highest importance scores include Average Annual Daily Traffic (AADT), clearance time, response time, open lanes, total lanes, number of cars involved, and precipitation rate. Interestingly, the time of day, specifically midday, also emerged as a significant predictor, holding high importance compared to other variables.

This finding is intuitive and aligns well with existing literature on traffic incidents and their management. AADT represents the volume of traffic, which naturally affects the likelihood and recovery time of incidents due to congestion levels. Clearance time and

response time are direct indicators of how efficiently incidents are managed, with quicker response and clearance times often leading to shorter overall recovery times.

Table 20. Stacking model performance.

Base models	Meta Model	Group	Precision	Accuracy
LR, RF, GB, KNN	NN	Short-duration	0.69	0.65
		Medium-duration	0.17	
		Long-duration	0.40	
RF, GB, KNN, NN	LR	Short-duration	0.70	0.67
		Medium-duration	0.10	
		Long-duration	0.51	
LR, RF, KNN, NN	GB	Short-duration	0.68	0.67
		Medium-duration	0.17	
		Long-duration	0.39	
LR, RF, GB, NN	KNN	Short-duration	0.67	0.57
		Medium-duration	0.15	
		Long-duration	0.29	
GB, NN, KNN, LR	RF	Short-duration	0.69	0.66
		Medium-duration	0.21	
		Long-duration	0.36	

The status of open lanes and total lanes provides insight into the capacity of the road to handle traffic during incidents, influencing recovery time based on how traffic flow is restricted. The number of cars involved directly measures an incident's severity, with more vehicles typically indicating more complex recovery operations. Precipitation rate impacts road conditions and visibility, potentially exacerbating incident severity and recovery efforts.

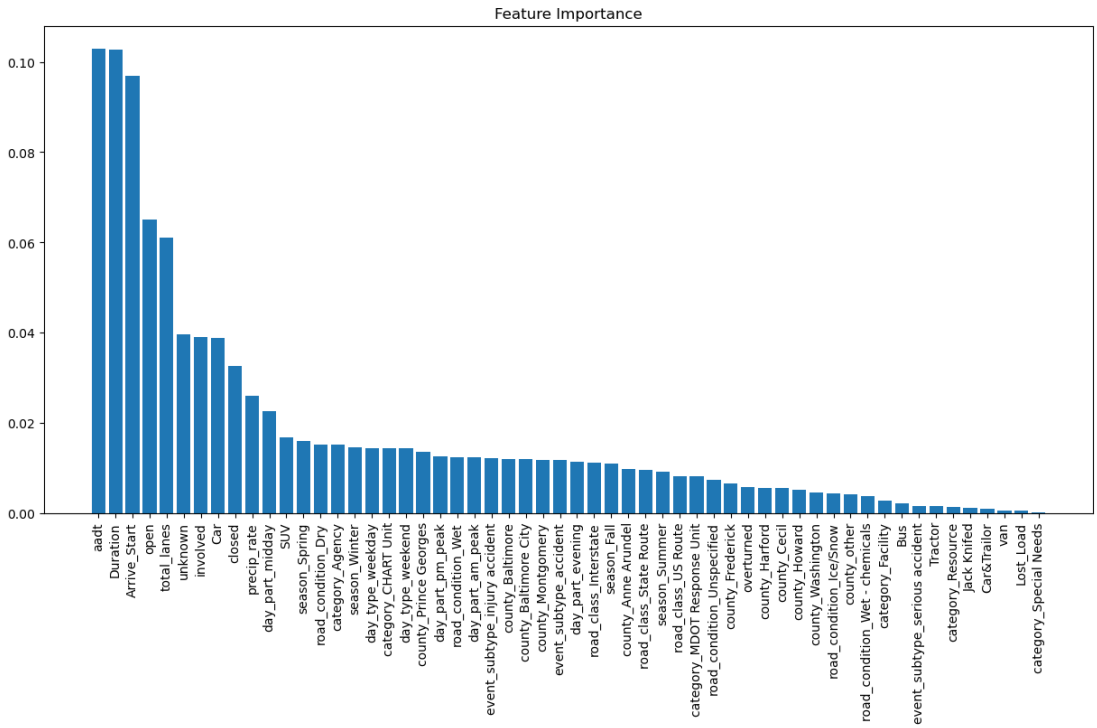

Figure 32. Feature importance of the model.

Overall, the highlighted features provide valuable insights for traffic management control agencies. By focusing on these key predictors, agencies can more effectively tailor their strategies and resources to minimize incident recovery times and enhance traffic pattern conditions, especially during peak or critical periods such as midday. A modified random forest model was built using the most important features to compare with the model with all the features. The modified model provided lower accuracy as expected, but overall, it still had a good level of precision compared to the model with all the embedded features. The performance of the modified random forest model is summarized in Table 21.

Table 21. Modified Random Forest model performance.

	model	**Modified Random Forest**	
	Historical Data Baseline		
Group	Precision	Recall	F-1 Score
Short-duration	0.7	0.95	0.81
Medium-duration	0.14	0.01	0.02
Long-duration	0.43	0.18	0.25
	Overall Accuracy	0.68	

It is important to note that exploring oversampling and undersampling techniques could provide insights into handling imbalances in the dataset. Oversampling methods such as SMOTE (Synthetic Minority Over-sampling Technique) are typically used to address skewed distributions where one class (e.g., longer duration incidents) is underrepresented compared to others (Blagus and Lusa, 2013). However, in the context

of predicting traffic congestion recovery times for non-recurrent incidents, oversampling might not be suitable. The nature of these incidents is inherently unpredictable, and generating synthetic records through SMOTE may not accurately represent real-world scenarios. Synthetic examples may not capture the diverse and dynamic nature of incident durations and their recovery times, potentially leading to biased or unrealistic model predictions. Therefore, while oversampling techniques like SMOTE are valuable in certain contexts for balancing datasets, their applicability in modeling non-recurrent traffic incidents should be carefully considered and evaluated based on the specific characteristics and variability of the data.

While, as explained, oversampling is not an appropriate approach, undersampling is taken into account, and the model results are shown in Table 22. Random Forest with undersampling model performance.In evaluating the predictive models for non-recurrent traffic congestion recovery time on freeways, both a baseline model and an undersampled model were analyzed. The undersampling technique significantly improved recall for medium and long-duration incidents while slightly decreasing precision due to increased false positives from the majority class. Consequently, the undersampled model exhibited a higher F1 score, indicating improved overall performance in identifying these critical incidents. However, this enhancement in performance came at the cost of reduced overall accuracy, as the model struggled more with accurately classifying short-duration incidents. The choice between the baseline and undersampled models depends on the specific objectives: prioritizing balanced

performance and higher recall versus maintaining higher overall accuracy despite the potential class imbalance in the dataset.

Table 22. Random Forest with undersampling model performance.

	model	**RF with undersampling**	
	Historical Data Baseline		
Group	Precision	Recall	F-1 Score
Short-duration	0.82	0.55	0.66
Medium-duration	0.14	0.35	0.20
Long-duration	0.27	0.40	0.32
	Overall Accuracy	0.50	

Chapter 7: Summary, Conclusion, and Future Work

7.1. Dissertation Summary

Traffic incident management is of utmost importance for transportation agencies due to the significant impact of prolonged incident duration times and on the likelihood of subsequent incidents and traffic congestion. Minimizing incident duration time is a top priority for mitigating these repercussions. To achieve this goal, it is crucial to investigate the factors influencing incident duration and their consequences and to develop accurate prediction and estimation models for the various components of incident duration. This research underscored the critical need for effective strategies to improve traffic incident management and enhance overall transportation system efficiency.

This dissertation presented a comprehensive study aimed at enhancing the assessment and management of traffic incident durations by integrating traffic incident data from multiple sources, notably the Maryland State Police crash data and Coordinated Highways Action Response Team (CHART) data. The dissertation began by detailing the methodology for matching incident records between these two datasets, utilizing spatial and temporal information to link related incidents, thereby creating a more comprehensive incident dataset. This enhanced dataset aimed to improve the quality and comprehensiveness of traffic incident data. The matching process employed

predefined distance and time thresholds to ensure precision in pairing incidents likely to represent the same incidents. The study explored the use of machine learning methods to predict reported incident clearance times, evaluating the effectiveness of various combinations of spatial and temporal thresholds to optimize data matching for accuracy in prediction models. The analysis highlighted the balance between precision and data retention, with machine learning models, including logistic regression, random forests, support vector machines, and gradient boosting, being assessed for their predictive performance. The findings underscored the importance of selecting appropriate threshold combinations to achieve a balance between precise data matching and the retention of sufficient data for analysis. Despite efforts to integrate data from both CHART and the Maryland State Police, the study concluded that the significant data loss incurred did not proportionally enhance model accuracy. As a result, the decision was made to proceed with CHART data alone for incident recovery time prediction, prioritizing the preservation of data volume and the feasibility of comprehensive analysis over the marginal accuracy gains offered by integrating state police data.

The study introduced the methodology for measuring the traffic recovery time of each incident on the network and presented the associated research findings. It outlined the steps necessary for preparing data for recovery time measurement, including integrating probe vehicle data with incident data, identifying upstream links to understand traffic flow toward the incident location, and establishing a baseline to

identify normal traffic conditions. Two approaches were used to establish a baseline for normal traffic conditions: one based on historical speed conditions and the other based on the conditions immediately before an incident. The advantages and disadvantages of each approach were discussed, with the historical data approach providing stability but potentially missing current conditions, while the pre-incident conditions method offered real-time relevance but was influenced by short-term fluctuations and having the possibility of missing the correct detection time of incidents. The dissertation compared these methods to understand their impact on the measurement of incident recovery time and discussed their implications for traffic management strategies.

This study then introduced a comprehensive framework for measuring traffic incident recovery time by examining the time interval from an hour before the reported incident start time to five hours after. The framework identified the end of recovery time based on a specific criterion by calculating the Mean Percentage Difference (MPD) between observed speeds and baseline speeds (using either historical or pre-incident conditions as the baseline). The end of the recovery time was defined as the start time of a 30-minute interval following the onset of the incident, as reported by CHART, where the MPD remained below 10% during the interval. The study evaluated the distributions of traffic recovery times, providing insights into the efficiency of traffic management and the accuracy of recovery time estimates by applying this framework to a large dataset of traffic incidents. This analysis revealed that a significant number of incidents

recover faster than their reported clearance times, suggesting that traffic conditions often return to normal before roadways are officially cleared.

Furthermore, This research utilized the labeled incidents to model the traffic recovery time associated with each incident. Exploratory data analysis (EDA) is performed to understand the dataset's structure and identify patterns or anomalies that might influence prediction accuracy. The chapter categorized the traffic recovery time into short (less than 15 minutes), medium (15 to 60 minutes), and long (more than 60 minutes) durations to refine the modeling and analysis. The distribution of incidents across Maryland and variations in recovery and clearance times throughout the day highlighted the complexity of predicting incident recovery times.

The data preprocessing phase addressed missing values and converted categorical variables into numerical formats to prepare the dataset for machine learning models. A variety of models were explored, including Decision Trees, Random Forest, Gradient Boosting, Logistic Regression, Neural Networks, and K-Nearest Neighbors, alongside other ensemble methods like voting and stacking. The Random Forest model, in particular, stands out for its accuracy and precision in predicting incident durations, making it an effective tool for traffic management strategies.

The model performance analysis utilized precision, recall, and F1-scores to assess each model's capability in accurately classifying incidents into the designated duration categories. This evaluation underscored the Random Forest model's superiority,

especially in predicting short-duration incidents, although it also shows promise for medium and long-duration incidents. Despite exploring sophisticated ensemble methods such as soft voting and stacking, the Random Forest model remained preferred for its balance of accuracy and computational efficiency.

The study also delved into the importance of the features utilized for modeling, revealing that factors such as Average Annual Daily Traffic (AADT), response time, lane status, the number of cars involved, and precipitation rate are pivotal in predicting recovery times.

7.2. Conclusions

The integration of multiple incident datasets presented a range of challenges for researchers. Different agencies employed various methods for collecting incident data, such as cameras versus police reports, resulting in discrepancies that complicate the data integration process. The diverse road direction reporting strategies used by different agencies, such as East/West versus Clockwise/Counterclockwise, exacerbated this, necessitating extensive data-cleaning efforts to harmonize the datasets.

Moreover, the lack of elevation data posed a significant issue, leading to the omission of incidents that occur on multiple road levels, such as those happening on bridges, versus those occurring underneath them. These challenges underscored the complexities of creating a cohesive and comprehensive incident dataset from multiple

sources, highlighting the need for standardized data collection and reporting methods across agencies to facilitate more efficient and accurate data integration.

The findings of this study revealed that the conventional method of calculating incident duration time may not always be accurate. In many cases, the impact of an incident on the network was resolved well before the official clearance time. This resulted in an overlap between the clearance and recovery time phases of each incident occurring on the network.

Furthermore, using probe vehicle data presented a promising avenue for enhancing the labeling of traffic incidents with precise recovery time estimates, thereby enriching the modeling processes. By harnessing the real-time insights provided by probe vehicle data, researchers and practitioners can augment their understanding of traffic incidents and their impact on the overall transportation network.

Although modeling the duration of non-recurrent incidents due to their unpredictable nature is sophisticated, machine learning models, when combined with domain knowledge, were able to predict their recovery time effectively. This study demonstrated that a random forest model, in particular, could provide a high level of accuracy when dealing with long-duration incidents, which have a higher chance of exacerbating traffic conditions. The study also highlighted the importance of the features utilized for modeling, revealing that factors such as Average Annual Daily Traffic (AADT), response time, lane status, the number of cars involved, and

precipitation rate were pivotal in predicting recovery times. By incorporating these features, the model captured the complexities of traffic incidents and provided more reliable predictions.

Furthermore, the predictive model developed in this thesis holds significant potential for application within the context of connected vehicles (CVs). As transportation systems evolve towards greater technology and data integration, CVs represent a transformative shift in how traffic is managed and optimized. These vehicles, equipped with advanced communication technologies, can share real-time information about their status, speed, and surrounding environment with other vehicles and traffic management systems. The predictive model for traffic congestion recovery times can leverage this rich, real-time data from CVs to enhance its accuracy and responsiveness. With access to instantaneous information about traffic incidents, road conditions, and vehicle behavior, the model can make more precise predictions about congestion recovery times. This enables dynamic traffic management strategies, such as adaptive signal control, real-time route guidance, and proactive incident response, all of which are critical for reducing congestion and improving traffic flow. Moreover, the integration of the predictive model with CV technology can facilitate more efficient resource allocation, such as directing emergency responders and maintenance crews to incident sites more quickly. This synergy between the model and connected vehicles can lead to a more resilient and adaptive transportation system, capable of mitigating the impacts of non-recurrent traffic congestion more effectively.

In conclusion, this research offers transformative applications in transportation planning and real-time operations. By leveraging advanced data analytics and machine learning, the framework accurately predicts how quickly traffic conditions return to normal after incidents like accidents or road closures. In transportation planning, the framework informs strategic infrastructure investments and resource allocations based on predicted congestion recovery times. This proactive approach optimizes traffic flow, reduces delays, and aligns future developments with projected traffic demands. In real-time operations, the framework supports dynamic traffic management and emergency response. It enables agencies to adjust traffic signals, optimize routes, and allocate resources effectively, minimizing disruptions and enhancing public safety.

7.3. Limitations and Future Work

One limitation of this research is the potential inaccuracies in the detection time of incidents, as they are often manually submitted by police or responders. This manual process introduces the possibility of human error or delays in reporting, which can result in discrepancies between the reported incident start time and the actual occurrence of the incident. Consequently, the pre-incident conditions derived from this reported start time may cause some inaccuracy when reflecting the true traffic conditions leading up to the incident. As a result, these inaccuracies may influence the estimation of recovery times based on pre-incident conditions. Addressing this

limitation could involve exploring alternative methods for detecting incident start times or implementing quality control measures to improve the accuracy of reported data.

The study evaluates various machine learning models based on historical data to predict incident durations. However, the performance of these models may vary when applied to different geographical regions or under varying traffic conditions. However, this study acknowledges variations in incident recovery and clearance times throughout the day and across Maryland. Ensuring the generalizability of the models beyond the study context may require additional validation and calibration efforts using diverse datasets from different regions or transportation networks. This expansion would enable a comprehensive analysis of how geographic and regional differences impact the performance and accuracy of traffic incident prediction models.

Another notable limitation of this study is its focus on upstream links with the same road class when estimating traffic recovery times. While this approach provides valuable insights into traffic flow dynamics leading toward the incident location, it may overlook the impact of queue propagation onto adjacent road segments with different road classes, such as ramps or secondary roads. Addressing this limitation would involve expanding the scope of analysis to encompass a broader range of road segments upstream of the incident location, including those with different road classes and interconnected traffic flow patterns. By considering the influence of queue propagation on adjacent road networks, the study could provide a more comprehensive

understanding of traffic dynamics and enhance the precision of recovery time estimates.

For future directions, researchers can delve deeper into refining the incident matching process by incorporating additional factors beyond spatial and temporal information. One avenue to explore is the integration of more granular attributes such as road direction and road class. These factors can offer a more precise matching of related incidents. By incorporating road direction, researchers can account for the specific orientation of incidents in relation to each other, avoiding mismatches of incidents occurring on the opposite side of the same road. By incorporating road class into the matching process, researchers can ensure that incidents occurring on different road segments, even if they share geographical coordinates, are correctly identified and paired with the corresponding incidents in the dataset. For instance, a traffic incident occurring on a bridge over a highway may have different clearance times and response dynamics than an incident directly on the highway itself. Data collectors must also ensure the precise collection of data attributes and adopt a consistent approach to naming attributes, such as directions. Presently, discrepancies may arise where one dataset labels a link clockwise and counterclockwise while another labels it eastbound and westbound.

Enhancing the granularity of road segments by transitioning from TMCs to XDSegments when utilizing probe vehicle data provided by INRIX, having a

maximum of 1 mile in length, can be a potential future direction as it offers several advantages for traffic data analysis and incident management. XDSegments provide a more detailed road segmentation system that considers factors such as the significance of intersections and the length of road segments, resulting in a more accurate road network representation. By utilizing XDSegments, incident data can be matched with a finer level of detail on the road network map, allowing for a more precise analysis of incident locations and their impacts on traffic flow.

Considering the impact of partial lane openings on traffic congestion recovery, a promising future direction involves enhancing predictive models to dynamically account for the number of lanes opened throughout the recovery process. Current models often assume static conditions post-incident, but integrating real-time data on lane reopening sequences and their effects on traffic flow could significantly improve accuracy. This approach would enable models to simulate better the evolving congestion dynamics caused by partial lane openings.

Another area of exploration that could enhance the accuracy of recovery time prediction models is the incorporation of information about vehicle trajectories and driver decisions in response to incidents, as well as the demand in the location. Currently, the study primarily focuses on factors such as historical speed conditions and pre-incident traffic flow to estimate recovery times. However, understanding how vehicles dynamically respond to incidents and adapt their routes based on real-time

demand can provide valuable insights for refining predictive models. By analyzing vehicle trajectories and driver decisions when encountering incidents, researchers can gain a deeper understanding of traffic behavior and identify patterns that influence recovery times. This includes examining factors such as route diversions in response to incident-induced disruptions. Additionally, considering the demand in the location, such as nearby attractions or events, can help anticipate fluctuations in traffic conditions and better adapt predictive models to changing conditions.

In addition to the variables currently included in our model, future research could explore the impact of time-related variables such as holidays. By incorporating holidays into the model, we can assess whether the accuracies of the predictions improve. This additional data may capture significant variations in behavior or trends associated with specific times of the year, potentially leading to more robust and accurate models.

Another aspect worth exploring is the impact of downstream locations of incidents on traffic congestion recovery time. Downstream locations refer to areas on the road that are beyond the incident site in the direction of traffic flow. Analyzing these locations can provide valuable insights into how traffic congestion dissipates and recovers after an incident has been cleared. Incorporating data from downstream locations might reveal patterns in how quickly traffic returns to normal flow post-incident. For example, traffic management systems and driver behavior can vary significantly

downstream, affecting the overall recovery time. Understanding these downstream effects can improve the accuracy of recovery time predictions by considering how traffic flow stabilizes after passing the incident site.

In this study, incidents were categorized and prediction models were built to forecast traffic congestion recovery times. In future work, regression techniques could also be explored and compared with the current categorization-based models. Regression methods, such as linear regression, multiple regression, or advanced machine learning regressors, can provide a continuous output for recovery times, potentially offering a more nuanced and precise prediction. Comparing the results from regression models with the existing categorical models could reveal differences in accuracy, efficiency, and practical applicability. This comparative analysis would help determine the most effective approach for predicting traffic congestion recovery times, enhancing the overall robustness and reliability of the predictive framework.

Moreover, the Highway Capacity Manual (HCM) provides essential methodologies for analyzing traffic flow and predicting congestion, especially in non-recurrent scenarios caused by accidents, weather events, or roadworks. It includes detailed calculations for road capacity and adjustments that account for reductions in capacity under different conditions, such as adverse weather or lane closures. These adjustments, often specified as percentage reductions in capacity, are crucial for accurately modeling traffic dynamics during non-recurrent events. Integrating traffic flow theory enhances this

predictive framework. Traffic flow theories, as included in the HCM, provide insights into how vehicles interact and move through a roadway system. They help in understanding the impacts of reduced capacity on traffic speed, density, and flow rates during congestion. For example, during a rainstorm that reduces capacity by 30%, traffic flow theory can predict how this reduction affects vehicle movement and queue formation. To predict congestion recovery time, the framework combines these capacity adjustments with performance metrics such as delay and queue length. Delay quantifies additional travel time caused by congestion, while queue length measures the number of vehicles waiting. By incorporating traffic flow theory and these metrics into a predictive model, researchers can simulate how quickly congestion will clear as conditions return to normal. This approach not only enhances understanding of traffic dynamics but also aids in developing effective strategies to manage and mitigate the impact of non-recurrent congestion events on roadway performance and driver experience.

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