Quantifying Air Quality Benefits of TxDOT's Traffic Incident Management (TIM) Programs

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1 INTRODUCTION

Even though the death rate attributable to traffic crashes, measured in terms of vehicle mileage, has decreased drastically over the past decades (NSC, 2024; USDOT, 2023a), crashes are still an epidemic in the United States (U.S.). On average, 40,000 roadway users lost their lives and more than 2.4 million were injured each year between 2019 and 2023 (NHTSA, 2024; IIHS, 2023; USDOT, 2023b). According to recent statistics published by the National Highway Traffic Safety Administration (NHTSA), the total economic costs of traffic crashes amounted to $340 billion in 2019, equivalent to 1.6 percent of the U.S. Gross Domestic Product (Blincoe et al., 2023). These costs included added medical expenses, lost wages, increased congestion, induced legal fees, property damage, and emergency services.

The direct public health risks as a result of fatalities and injuries, crashes pose a significant environmental risk due to worsening air quality from non-recurring congestion. Traffic incidents are responsible for almost 25 percent of total congestion on the U.S. roadway network (FHWA, 2024a; Jha and Albert, 2021). Congested traffic conditions are expected to increase fuel consumption which can exacerbate emission levels of greenhouse gases (GHG) and harmful pollutants. This is primarily due to the stop-and-go nature of vehicle operations along with the increased idling time and inefficient driving patterns (Barth and Boriboonosomsin, 2008). The Urban Mobility Report published by researchers at the Texas A&M Transportation Institute (TTI) indicated that congestion in 2020 added 1.7 billion gallons in fuel consumption which resulted in 18 million tons of GHG emissions (Schrank et al., 2021).

The exposure to traffic-related air pollution has been linked to an array of negative health effects including premature death, cancer, and chronic cardiovascular and respiratory diseases (NIEHS, 2024). Therefore, state and local transportation agencies are encouraged to understand the relationship between crashes and emissions to develop effective strategies to mitigate crash rates and ambient air pollution. For instance, there are opportunities to incorporate monitoring and communication technologies, also known as intelligent transportation systems (ITS), in programs to assist in managing traffic during temporary events that disrupt flow.

Crashes are known to impede regular traffic flow which negatively impacts travel reliability and the overall performance of transportation systems (FHWA, 2024b). Typically, congestion on a roadway link due to a crash propagates and affects adjacent links (Zheng et al., 2019), hence increasing the probability of the occurrence of a secondary crash (FHWA, 2024b). The duration of a non-recurring congested traffic condition depends on several factors such as the type of crash, vehicle types involved in the crash, occurrence time, density and connectivity of roadway networks, and crash clearance time (Zheng et al., 2019; Chand et al., 2022). Several strategies have been recognized and utilized to reduce the external impacts of crashes through the prompt deployment of emergency responders to clear incident sites (Wang et al., 2024). One of the prominent initiatives is traffic incident management (TIM).

This program is an integral part of transportation agencies. The aim is to constantly enhance the safety of roadway users and emergency responders, travel time reliability, and efficiency of clearing the incident location (FHWA, 2024b). TIM consists of a set of systematic and collaborative processes that promptly detect incidents and effectively respond to and clear these events. Consequently, normal traffic flow conditions are expected to be restored safely and on time, in return reducing pollutant emissions (FHWA, 2024b). At a regional level, states such as Texas provide training sessions to all responders in the TIM discipline covering essential topics to achieve the three objectives of the TIM National Unified Goal (NUG): safety of responders at incident locations, safe and prompt clearance of incidents, and effective communication between responders (TxDOT, 2024).

The Federal Highway Administration (FHWA) promotes the adoption of four TIM performance measures including roadway clearance time, incident clearance time, occurrence of a secondary crash, and instances when responders are struck by a vehicle (FHWA, 2024c). This requires agencies to collect reliable incident-related data to identify opportunities for improving TIM programs. Moreover, the FHWA designed a comprehensive and simple tool to estimate the benefits and costs of various TIM strategies, hence providing decision-makers with a technique to analyze and compare the potential of TIM programs before their implementation (FHWA, 2022). Users can monetize travel delays and fuel consumption by vehicle type using tables and regression equations. The information in the databases was acquired from publicly available sources and simulations. Few researchers assessed the environmental benefits of TIM programs in the U.S. (Guin et al., 2007; Kim et al., 2011; Boarnet et al., 2013) and internationally (Kaysi et al., 2003).Crashes significantly influence congestion on roadway links under different operation scenarios which is also correlated to increased vehicle emissions. Therefore, finding appropriate methodologies to evaluate the operational and environmental impact of traffic crashes is of utmost importance to help guide decision-makers in setting incident management goals to improve safety and reduce emissions. This topic is of increasing interest to researchers and several studies have been published (Guin et al., 2007; Boarnet et al., 2013, Chung et al., 2013; Son and Han, 2016; Joo et al., 2017; Goes et al., 2019; de Barros Baltar et al., 2021; Liao et al., 2023; Wang et al., 2024).

Some studies applied queuing theory and shockwave analysis (de Barros Baltar et al., 2021; Guin et al., 2007), while other studies used spatio-temporal extent (Liao et al., 2023; Chung et al., 2013) or macroscopic and microscopic simulation (Wang et al., 2024; Son and Han, 2016) to determine crash-related operational parameters such as delay time, congestion, and speed. Emissions were then estimated either by using emission factors or well-established models. The choice of analytical approach depends on the data available to each agency, however, acquiring reliable data is needed to robustly analyze traffic conditions and determine congested regions from the consequential effects of crashes (Wang et al., 2024).

The current study reviews methodologies for estimating the impact of vehicular crashes on emissions, comparing macro and micro models, surrogate safety measures, high-resolution trajectory models, and machine learning models. The review also highlights traffic incident management programs and emerging technologies to reduce crash rates and emissions. Building on this review, TTI researchers implement a methodology in Texas to quantify vehicle emissions from traffic crashes using crash data. Queuing data from ITS sensors and crash data from the Crash Record Information System (CRIS) for 2019-2023 are used to estimate the emission impacts of crashes. Different machine learning models are trained and evaluated to predict emission impacts based on various crash characteristics.

2 LITERATURE REVIEW

Between 1999 and 2006, nearly half of the increase in total U.S. greenhouse gas emissions was attributed to transportation emissions (Hodges and Potter, 2010). The Environmental Protection Agency (EPA) stated that by 2012, transportation had become the second largest emitter of carbon dioxide (CO_2) greenhouse gases, following electricity generation (US EPA, 2019). There's a growing concern regarding the impact of transportation CO_2 emissions, which constitute 95% of transportation greenhouse gas emissions, on public health (US EPA, 2019).

A primary factor contributing to transportation CO_2 emissions is traffic congestion. The costs associated with congestion, in terms of time and fuel consumption, surged from 24 billion dollars in 1982 to 121 billion dollars in 2011 (Schrank et al., 2021). Notably, non-recurring congestion resulting from unforeseen vehicle crashes significantly adds to vehicle CO_2 emissions. This type of congestion, making up quarter of all traffic congestion (Figure 1), arises from stop-and-go driving behaviors, which also escalate the risk of crashes within transportation networks (USDOT, 2006).

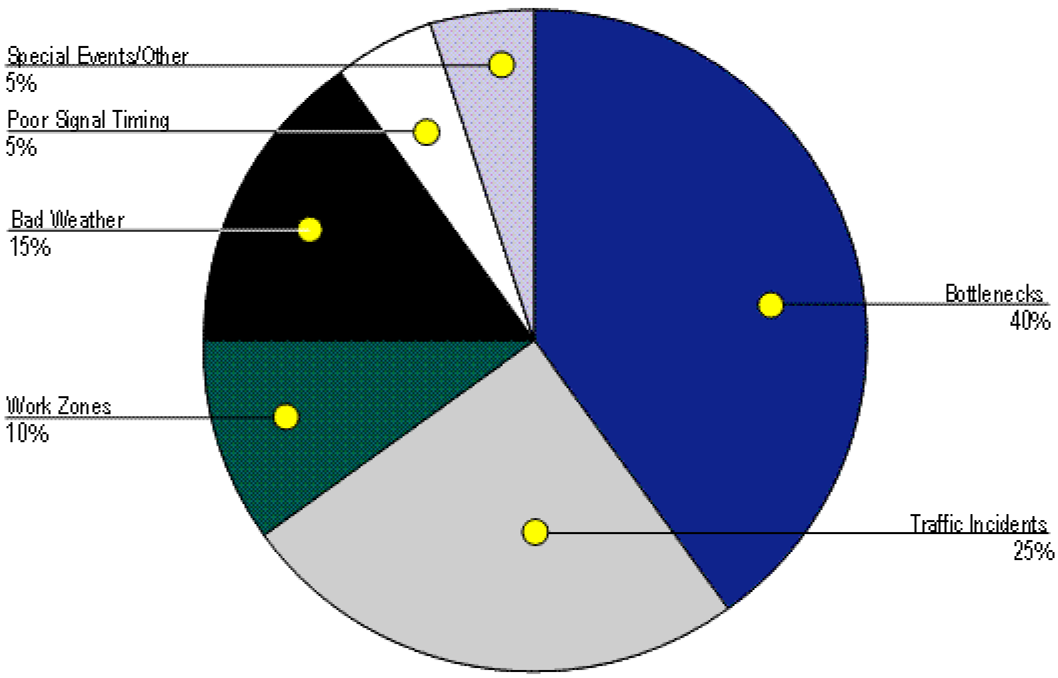

Figure 1 National estimates of congestion by source (FHWA, 2005)

To substantially curb vehicle emissions, the U.S. Department of Transportation (DOT) proposed four key strategies: the adoption of low-carbon fuel, enhancement of vehicle fuel economy, optimization of transportation system efficiency, and the reduction of carbon-intensive travel activity (USDOT, 2010). Among these, the strategy to improve transportation system efficiency stood out due to its additional advantages such as time savings for travelers and cost reductions for shippers on a local scale (USDOT, 2010). This strategy encompasses the implementation of highway operation and management technologies like signal coordination, freeway ramp metering, and real-time traveler information (USDOT, 2010).

However, a lack of criteria for determining the applicability of the U.S. DOT's efficiency strategy in field implementations for emission reductions has been noted. The transportation system faces irregular congestion from unexpected crashes, leading to resultant vehicle emissions. Intriguingly, both vehicle emissions and crashes are often triggered by similar driving behaviors, such as abrupt acceleration or deceleration during car-following or lane changes. For a transportation system, reducing vehicle emissions and enhancing safety could be more effectively achieved by averting non-recurring congestion. This could be done by monitoring crash potentials, understanding the correlation between vehicle emissions and crash potential, and proactively advancing transportation system efficiency improvements.

Roadway crashes are one of the leading causes of fatalities in the United States according to recent statistics from the Center for Disease Control and Prevention. In the last decade (between 2011 and 2020), more than 350,000 people lost their lives as a result of traffic-related crashes. Various federal, state and local agencies have been advocating for Vision Zero. The goal of this program is to eliminate deaths and incapacitating injuries on the U.S. roadway system due to crash impacts. Vision Zero is achievable by implementing a safe system approach where roadway infrastructure can be designed and managed to lower the risk of crash occurrences and to ensure safe mobility for all roadway users. The safe system is proactive in evaluating risk across an entire roadway network and helps in identifying locations that require safety improvement. Agencies applying this methodology can maximize benefits and effectively allocate financial resources by deploying various low-cost countermeasures systematically. Another significant factor that should be considered is the impact of crashes on air pollution and health. Crashes contribute to congestion. Congested conditions increase idling and stop-and-go traffic, hence leading to an increase in vehicular emissions. These traffic-related emissions can have adverse impacts on public health, especially on communities residing near major roads. Locations with a higher risk of crash occurrences can be correlated with higher exposure to traffic-related air pollution due to more congestion. Therefore, adding a sustainability component to the systemic safety approach can be a complementary incentive to efficiently distribute funding to enhance roadway safety. The modeling pathway will apply statistical methods to quantify the extent of congestion caused by crashes. A few key considerations will include crash severity, roadway classification, traffic volume, response time and clearance, and driver behavior. Eventually, the impacts of congestion will be correlated to roadway emissions.

This document intends to review the state of practice evaluating the effect of vehicular crashes on traffic congestion and its relationship to vehicular emissions.

2.1 State of Practice Relating Vehicular Crashes, Traffic Congestion and Emissions

Mobility and safety are paramount priorities in any transportation system (Dias et al., 2009). The aspiration is for improvements in traffic flow and crash reductions to occur concurrently, reflecting the idea that traffic operations and road safety are "two sides of the same coin" (Dias et al., 2009). Newer theories challenge earlier assumptions that there's a positive link between flow and collisions. At low densities, traffic flow improves while speed remains relatively unchanged. However, an uptick in traffic volumes leads to increased vehicle interactions and conflicts (Zhou and Sisiopiku, 1997), potentially raising collision rates (Dias et al., 2009). As density escalates to congestion levels, both flow and speed are significantly curtailed. Lowered flows result in fewer crashes, while reduced speeds lead to less severe crashes (Dias et al., 2009; Noland and Quddus, 2005).

The safety impact on traffic flow is evident: collisions create bottlenecks, exacerbating congestion levels (Dias et al., 2009). On the other hand, the influence of traffic congestion and flow on road safety is less apparent (Marchesini and Weijermars, 2010) and underexplored (Dias et al., 2009), necessitating more empirical data and quantitative analysis of congestion (Wang et al., 2009) to ascertain the nature and extent of this relationship.

Traffic congestion is exacerbating in many urban locales, with traditional peak-period congestion being superseded by all-day congestion (Taylor et al., 2000). Efforts to fathom and diminish the scope, duration, and intensity of congestion (Stipancic et al., 2017) ought to be prioritized (Taylor et al., 2000). The interplay between traffic flow and collisions is likely non-monotonic (Zhou and Sisiopiku, 1997), demanding thorough understanding for effective management of both (Wang et al., 2009).

To establish the relationship between crashes and traffic congestion, scholars have devised numerous models from diverse perspectives, achieving some progress. These models can be broadly categorized into

- macro models - primarily concentrate on the macro impact and predictive prevention of traffic accidents.
- micro models – delve into the detailed aspects of accidents, their causes, influencing factors, and the like.
- Surrogate Safety Measures (SSMs) – uses secondary data to predict relationships between crashes and congestion.
- High resolution trajectory models – uses emerging data sources with GPS and cellular data to analyze vehicle trajectories to estimate effect of crashes.
- Machine learning models – predicts crash severity and hotspots using historic trends.

2.1.1 Macro Models

Macro models generally utilize existing mathematical, statistical or network models to analyze the macro-level traits of crashes. The insights garnered from these models help identify major factors affecting crashes at a macro level, facilitating the proposal of traffic safety control measures (Guo et al., 2018; Song and Li, 2011; Vorko-Jović and Jović, 1992). One study focuses on utilizing an improved K-means clustering algorithm to analyze urban road traffic accidents in Yinzhou, Ningbo, utilizing data collected via a smart mobile application (Guo et al., 2018). The noteworthy aspect of this study is the innovation in overcoming the traditional K-means algorithm's limitations such as slow convergence and low accuracy by improving the algorithm to reduce the influence of outliers. This innovation is instrumental in automatically identifying accident black spots(Guo et al., 2018). The data also provides a rich temporal and spatial analysis of accidents, as well as insights into accident causality based on driving behaviors(Guo et al., 2018). However, the study seems to rely heavily on data collected from a single district and within a specific timeframe which may not provide a comprehensive understanding applicable to broader contexts or different urban settings(Guo et al., 2018).

The second study, centered in Croatia, aims at predicting the injury and death rates of elderly individuals in traffic accidents using a methodological approach that tackles variable selection, intercorrelation, and employs a rank correlation method(Vorko-Jović and Jović, 1992). The essence of this study lies in its effort to build a model from officially accessible data, striving for a realistic preventive approach to mitigate elderly casualties in traffic mishaps(Vorko-Jović and Jović, 1992). The model's predictive accuracy, which supposedly improves over time without modifying other generative factors, is a promising aspect (Vorko-Jović and Jović, 1992). However, the study’s focus on new road construction as a primary preventive measure seems a bit narrow and may overlook other potentially significant factors such as traffic regulation, driver education, or vehicle safety enhancements(Vorko-Jović and Jović, 1992).

The third study aims to address the shortcomings of existing macro prediction models regarding accuracy and convergence speed by introducing a Radial Basis Function in predicting macro-road traffic accidents. This study endeavors to establish a relationship between various factors like population, economic conditions, vehicle count, road mileage, and accident statistics. By employing Matlab for simulation, the study attempts to validate the feasibility and practicality of the proposed model. The emphasis on improving prediction accuracy is crucial for better traffic management and accident prevention. However, the study could potentially benefit from a more diversified data set or a comparative analysis with other prediction models to establish the robustness and reliability of the proposed model in different traffic scenarios or regions(Song and Li, 2011).

Conversely, micro-level models are better suited to elucidate the propagation mechanism of traffic crashes and their impact on traffic flow.

2.1.2 Micro Models

Micro-level simulation analysis includes traffic flow dynamics models (Dadashova et al., 2012), car-following models (Brill, 1972; Chen and Xi'an, 2006; Zhai et al., 2016), and cellular automata (CA) models (Kong et al., 2015). The CA model, particularly popular due to its computer-friendliness and flexibility to modify rules to mimic real traffic conditions (e.g., crashes, lights, ramps, bottlenecks, etc.), maintains the nonlinear behavior and other physical attributes of traffic flow (Wolfram, 1983). The classic one-dimensional cellular automaton traffic flow model is the Nagel–Schreckenberg (NaSch) model (Meng and Weng, 2011), mainly applied in highway crash simulations (Bentaleb et al., 2014; Moussa, 2003). However, urban road networks, being complex two-dimensional systems with numerous intersections in varied directions, demand two-dimensional CA models. Biham, Middleton, and Levine introduced the first two-dimensional traffic scenario CA model (i.e., the BML model) in 1992 (Biham et al., 1992), later refined by several scholars to study urban road traffic crashes considering factors like average vehicle speed, traffic signals, etc. (Marzoug et al., 2015; Xiao-ming and Ying-hong, 2010). In 1999, Chowdhury and Schadschneider proposed the ChSch model, coupling the one-dimensional NaSch model and the two-dimensional BML model, yielding positive results in studying urban road traffic (Chowdhury and Schadschneider, 1999).

Golob et al. investigated the link between highway accidents, weather, lighting, among other factors, concluding that collision type is strongly correlated with median traffic speed and temporal variations in speed in certain lanes (Golob and Recker, 2004, 2003). Aljanahi et al. highlighted a reduction in crash rates with an increased percentage of heavy vehicles on roads, holding the speed distribution constant (Aljanahi et al., 1999). Hiselius reached a similar conclusion regarding the decrease in crashes with an increase in truck numbers on roads (Hiselius, 2004). Zhu et al. modeled a highway traffic scenario with an accident-induced blockage, noting that the accident car caused a local jam and vehicle clustering in the bypass lane (Zhu et al., 2009). Qian et al. analyzed highway traffic flow under lane control post-accident, finding that blocked time and blocked section length significantly affected traffic flow within a certain density range (Qian Yong-Sheng et al., 2011). Research has shown that enhancing roadway width, pedestrian facilities, and access management are effective in curbing road traffic crashes (Berhanu, 2004). Charging vehicles for central city access during peak hours has also been proven to significantly reduce crash numbers and rates (Green et al., 2016). Several studies have analyzed the effect of adverse weather (Jaroszweski and McNamara, 2014), road conditions, and building environment on crashes (Snyder, 1971; Vieira Gomes, 2013;

Zhang and Zhi-gang, 2000), as well as the externality of traffic crashes and its connection with hourly traffic flow (Cedar and Livneh, 1983; Ceder, 1982; Dickerson et al., 2000; Martin, 2002).

The aforementioned studies have delved into the characteristics, predictions, impacts, and evaluations of traffic crashes from different angles, yielding notable results. However, these studies are predominantly geared towards highway traffic flow, whereas urban road networks, with their intricate weave of roads, numerous intersections, signal lights, and complex traffic organization, present a different challenge. Some scholars have aimed to extend highway traffic crash research to urban networks. For instance, Nagatani posited that crash locations induce traffic congestion, delaying rear vehicles' forward movement with crash delay time being a key determinant of impact range (Takashi Nagatani, 1993a, 1993b; T. Nagatani, 1993). Yao et al. introduced the susceptible-infected-susceptible (SIS) model to prevent widespread delays in urban road traffic networks caused by disruptive traffic crashes (Yao et al., 2017). Yet, these studies mainly scrutinize the impact of crashes on urban road networks from a macroscopic standpoint, lacking a detailed analysis intertwined with the traffic flow phase. Pressing questions concerning the effects of crash sites, occurrence time, road traffic density, and other factors on traffic flow in urban road traffic networks remain.

2.1.3 Surrogate Safety Measures (SSMs)

SSMs could offer an enhanced or complementary insight into the relationship between congestion, flow, and safety, along with the causative processes. SSMs encompass any non-crash measures that are physically and predictably related to crashes (Tarko, 2018), aiming to lessen reliance on crash data Laureshyn et al., 2009) and address challenges associated with crash-based methods such as reactivity (Agerholm and Lahrmann, 2012), extended collection periods (Lee, Hellinga, et al., 2006), and inaccuracies in collision databases (Kockelman and Kweon, 2002).

Various methodologies exist for surrogate safety analysis including event-based techniques, behavioral techniques, and techniques grounded on measures of traffic flow. Event-based techniques consider traffic conflicts, road user interactions, or evasive maneuvers, gauged through human observation, video-based sensors, and other techniques (Sayed, Zaki, et al., 2013). Behavioral techniques aim to identify individual driver behaviors like yielding (Dingus et al., 2006). Traffic flow techniques, employing measures of volume, speed, or density to estimate risk (Yan et al., 2008), typically require roadside point sensors, including loops, radar, or other sensors (Golob et al., 2004; Lee et al., 2009; Oh et al., 2001). Although traffic flow-based indicators have succeeded on freeways, deploying roadside sensors across urban networks is impractical and costly (Herrera et al., 2009).

2.1.4 High resolution vehicle trajectory models

High-resolution vehicle trajectory data can help in determining crash potential with regards to the amount of congestion a crash might cause. Vehicle trajectory data is instrumental in facilitating such analysis as it provides insights into driver behavior and vehicle interactions. Notably, the Federal Highway Administration (FHWA) has made vehicle trajectory datasets available through the Next Generation Simulation (NGSIM) project, which has been the foundation for several traffic engineering studies. The prevailing methodologies in this domain can be grouped into two: identifying the factors that influence vehicle interactions and modeling microscopic traffic events like car-following (Hamdar and Mahmassani, 2008; Kesting and Treiber, 2008; Talebpour et al., 2011) and lane-changing (Choudhury et al., 2006; Thiemann et al., 2008; Toledo et al., 2007).

Micro-simulation modeling for conflict analysis has gained traction, particularly for evaluating experimental modifications to existing road networks. An initial phase of conflict analysis via simulation modeling was carried out by a study from Bachmann et al., which devised a refined definition of conflict to address unrealistic conflict scenarios. This study explored the evaluation of a truck-only highway in Canada to gauge its impact on traffic conflicts (Bachmann et al., 2011). The findings indicated an uptick in car lane-change conflicts due to increased maneuverability and presence on the truck-free highway, despite a reduction in truck-related conflicts.

In examining conflicts, vehicle trajectory data were utilized to delve into traffic conflict potential at a more granular level in previous studies. Oh and Kim (2010), Meng and Weng (2011) proposed methods to assess rear-end crash risks (Meng and Weng, 2011; Oh and Kim, 2010). Laureshyn et al. (2010) suggested a theoretical framework employing surrogate safety measures derived from trajectory data(Laureshyn, Svensson, et al., 2010). Yang and Ozbay (2011), and Kuang et al. (2015) estimated traffic conflict risks for merging vehicles and proposed a probabilistic causal model to measure rear-end crash risk using a collision risk index reflecting freeway traffic state at traffic speed disturbance respectively(Kuang et al., 2015; Yang et al., 2011). Li et al. (2013) assessed driving risk based on traffic characteristics of freeway interchange entrance areas, discovering a decrease in speed difference and crash risk with an increase of the front car on the acceleration lane (Xin-wei et al., 2013).

Furthermore, vehicle emissions and measurements depicting the environmental impacts of transportation-related operations and control strategies (Park et al., 2011; Tao et al., 2011; Wu et al., 2010) and policies (Lee, 2011; Lee et al., 2009) have been estimated based on vehicle trajectory data. Unlike macroscopic emission estimations based on aggregated representative link speeds, microscopic emission models grounded on vehicle trajectories yield more precise estimates (Lee, 2011).

In a recent attempt, Silva et al. aimed to measure injury severity and vehicle emissions (Silver et al., 2010). However, the authors analyzed crash potential and vehicle emissions independently for each crash case, without considering vehicle interactions in the traffic stream and any numerical correlation between them. Consequently, there's a paucity of studies exploring numerical estimation methods to measure vehicle emissions and crash potential and correlate them based on individual vehicle trajectory data.

2.1.5 Machine Learning models

Also, different machine learning models have also been used in various studies to relate vehicle crashes to congestion. Abou-Amouna et al. aimed at identifying and analyzing significant factors affecting road accidents in Qatar, projecting the total number of road accidents in 2022 (Abou-Amouna et al., 2014). They found multiple linear regression (MLR) and artificial neural network (ANN) models to be most suitable, concluding that MLR (projecting 355,226 accidents) outperformed ANN (projecting 216,264 accidents) due to ANN's incapacity to handle large range variations in data (Abou-Amouna et al., 2014).

Oyetunji et al. fashioned a road traffic accident predictive model using the naive Bayes' model to forecast road traffic accidents in Nigeria with the objective of prevention or reduction. The model exhibited a reliability of 89.83% accuracy, utilizing selected dependent variables like road condition, road dimension, human factors, and vehicular factors (Oyetunji et al., 2017). Park et al. constructed a predictive model using the Hadoop framework for processing and analyzing extensive traffic data, coupled with a sampling method to tackle data imbalance issues (Park et al., 2016). The experiment reported accuracy and true positive rate of 76.35% and 40.83% respectively, aligning closely with outcomes from other research(Park et al., 2016). Ghadge et al. employed a machine learning algorithm to predict road bumps using data collected through an accelerometer sensor and GPS for location plotting on Google map (Ghadge et al., 2015). They utilized the K-means clustering algorithm for analyzing training data and the random forest classifier for validation, achieving promising results (Ghadge et al., 2015).

In another realm, Yuan et al. employed big data covering motor vehicle crashes in Iowa from 2006 to 2013, alongside a detailed road network and various weather attributes at 1-hour intervals (Z. Yuan et al., 2017). They utilized four classification models, specifically, support vector machine (SVM), decision tree, random forest, and deep neural network (DNN) (Zhuoning Yuan et al., 2017). To counter the issue of imbalanced classes, they applied an informative negative sampling approach and addressed spatial heterogeneity challenge by incorporating SpatialGraph features through Eigen analysis of the road network (Zhuoning Yuan et al., 2017). Their findings showed significant enhancement in model performance with random forest and DNN generally outperforming the other models (Zhuoning Yuan et al., 2017). Various other studies in different countries like India and the United States employed machine learning models to analyze factors such as road geometry and weather conditions for accident prediction (Berhanu et al., 2023; Kavoosi et al., 2020). Wang et al. utilized floating car trajectory data and two modeling methods to predict crash occurrences on urban expressways, with the SVM model significantly outperforming the binary logistic regression model in crash prediction(Wang et al., 2019). Numerous other studies have further emphasized the effectiveness of machine learning algorithms like multiple linear regression models, artificial neural networks, random forest, and deep neural networks in accident prediction (Berhanu et al., 2023). These algorithms can scrutinize vast amounts of traffic data to accurately predict accident likelihood or traffic congestion, demonstrating promising prospects in accident mitigation. Through these predictive models, the potential for reducing accident occurrence and severity by alerting drivers to avoid hazardous areas or take necessary precautions is highlighted, ultimately contributing to safer road environments.

2.2 Key Takeaways and Future Research

The literature review on vehicular crashes and their effects on emissions reveals important trends and methodologies in traffic safety research. Traffic flow and safety are closely linked, with higher vehicle densities often leading to increased collision rates due to the rise in interactions and conflicts. Congestion tends to reduce both speed and flow, which may result in fewer and less severe accidents.

A comparison of different model types, presented in the Table 1, highlights their strengths and limitations in evaluating crash impacts on emissions.

Macro models offer broad trend insights but struggle with localized variability. Micro models provide detailed accuracy in specific scenarios but demand extensive computational resources. Surrogate Safety Measures (SSMs) can effectively assess risk without relying on actual crash data but require calibration and validation. High-resolution trajectory models reveal precise vehicle interactions but need high-quality data. Finally, machine learning models are adaptable for predicting crashes but depend on substantial training data and clear output interpretation.

Innovative methodologies such as clustering algorithms, probabilistic models, and big data analytics hold promise in understanding the diverse factors influencing road safety. However, further research is required to refine numerical estimation methods that can accurately link vehicle emissions and crash potential based on trajectory data.

Ultimately, the variety of approaches demonstrates the multi-dimensional nature of crash and congestion studies. Advancing predictive models with machine learning and big data will enhance proactive measures for road safety and efficient traffic management.

Table 1 Comparison of Different Methodologies to Estimate Impact of Crashes on Emissions from Literature

Model Type	Application Areas	Strengths	Potential Limitations
Macro Models	- Accident trend analysis; - Safety measure evaluation	- Effective for broad pattern recognition and macro-level insights; - Can inform policy and strategic planning	- Limited in handling local variability and micro-level interactions; - Data-intensive, requiring extensive historical data
Micro Models	- Detailed traffic simulation; - Crash mechanism analysis	- High accuracy in modeling specific scenarios like car-following and lane changes; - Useful for detailed traffic engineering studies	- Computationally intensive; - Requires detailed data on traffic dynamics and driver behavior
Surrogate Safety Measures (SSMs)	- Crash risk assessment; - Traffic management improvement	- Useful for ongoing monitoring without needing crash occurrences; - Can be implemented with less invasive methods like video analysis	- Indirect measure of safety, may not capture all risk factors; - Requires calibration and validation against real crash data
High Resolution Trajectory Models	- Detailed traffic behavior analysis; - Crash potential assessment	- Provides insights into precise vehicle movements and interactions; - Allows for the simulation of interventions and their impact on traffic flow	- Dependency on high-quality trajectory data; - Analysis complexity requires advanced data processing capabilities
Machine Learning Models	- Crash prediction; Traffic congestion analysis; - Road safety hotspot identification	- Adaptable to various types of data and capable of handling complex variable interactions; - Can improve over time with new data	- Needs substantial and diverse training data to achieve high accuracy; - Model outputs can be opaque, making interpretation challenging

3 METHODOLOGY

This section details the comprehensive methodology used to quantify the air quality benefits of TxDOT's Traffic Incident Management (TIM) programs by analyzing incident-related emissions. The methodology is divided into several key steps, including data collection, data matching and preparation, emission prediction, and analysis.

3.1 Data Collection

Two primary datasets were used in this study, queuing data and Crash Record Information System (CRIS) data.

3.1.1 Queuing Data:

The queuing data was obtained from ITS sensors and covered incidents from 2019 to 2023. Each incident was divided into 5-minute intervals, and the roadway segments affected by the incident were identified. For each interval, the length, volume, and speed of the segments were recorded. The entire affected length (queue) was calculated by summing the lengths of all affected segments. Weighted volumes and speeds were calculated for each segment by dividing the segment length by the queue length and multiplying by the volume or speed of the segment. The weighted speeds were summed and compared to emissions tables for NO_X and VOC to determine incident emission rates. The total emissions for each incident were determined by summing all the time interval emissions. Historical data was used to determine the additional emissions caused by the incident.

The data was originally in JSON format, containing nested tables with detailed information about each traffic incident. There is a seperate json file for every month.

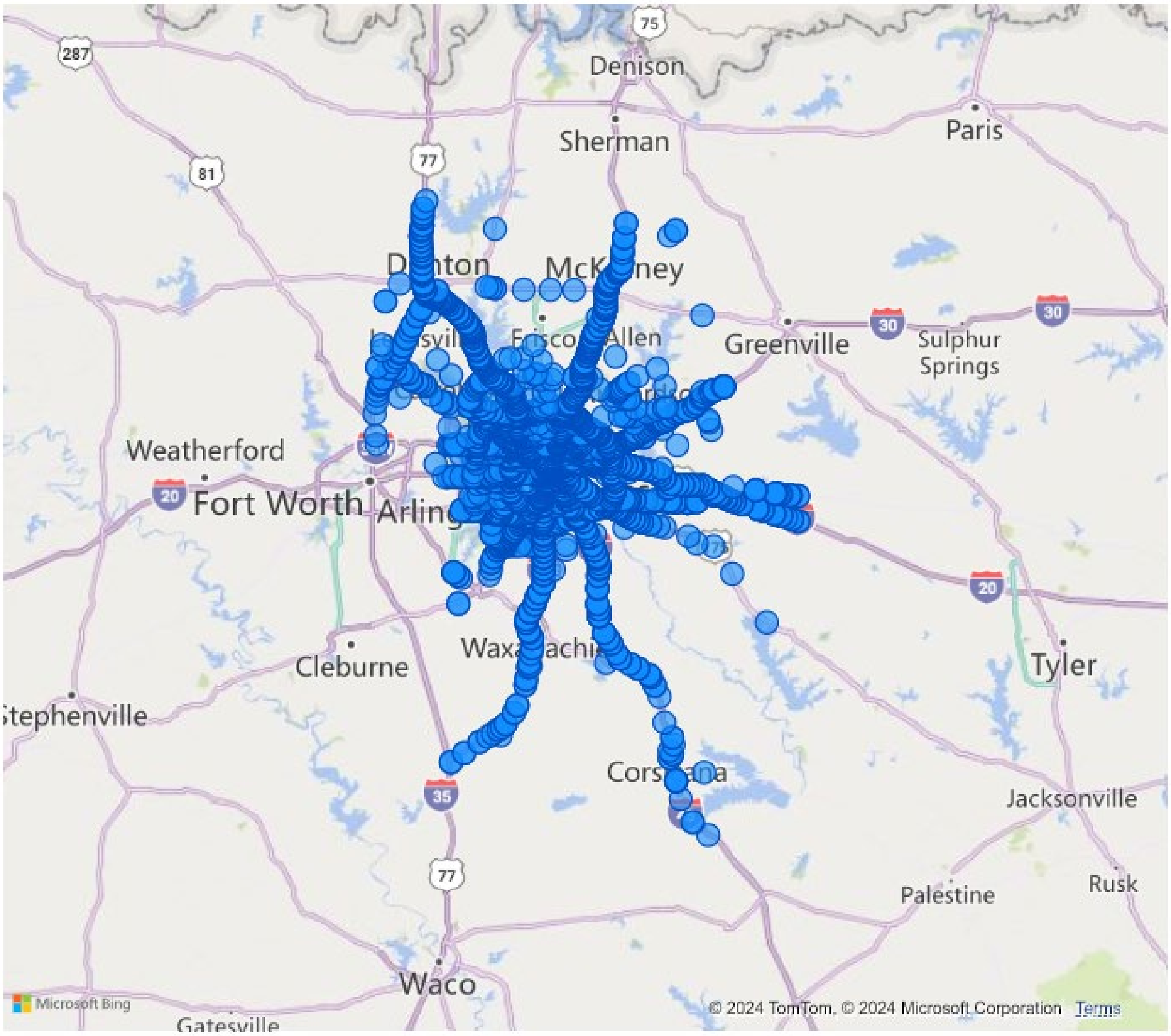

Figure 2 Map showing all the incidents captured by the Queuing Data

The following tables were nested in the JSON files

- **Event Data:** Includes high-level details of each incident.
  - Columns: EventID, DetectedTime, ClosedTime, Duration, RoadwayName, Direction, CrossStreet, Latitude, Longitude, Type, AffectedLanes, ImpactedLinks, TotalEmissionNOX, TotalEmissionVOC, EmissionNOXDiff, EmissionVOCDiff, PrimaryLinkVolume, TotalVolume, VolumeDifference, WeightedAvgSpeed, EventLink
- **Emission Data:** Contains time-segmented emission data related to each event.

  - EventID, Date, SegmentsNOX, SegmentsVOC, SegmentsNormalNOX, SegmentsNormalVOC

- **Link Data**: Provides detailed information about each affected road segment.
  - Columns: EventID, Date, LinkID, Length, Volume, Speed

A python script was developed to process each JSON file and extract these nested tables and save them as separate CSV files (Event_Data.csv, Timestamp_Data.csv, Link_Data.csv). Figure 2 shows the map summarizing all the events collected from the final combined queing data for 2019 to 2023. There was a total of 86573 incidents collected from the queing data.

3.1.2 Crash Data:

This data was obtained from TxDOT's Crash Record Information System (CRIS). The dataset included extensive crash data with various traffic and roadway parameters. The following data fields were extracted for all the crashes from 2019 to 2023 for the counties overlapping the queing data – Denton, Collin, Tarrant, Dallas, Johnson, Ellis Hill and Navarro.

- **General Information:** Crash ID, Crash Date, Crash Time, City, County, Latitude, Longitude
- **Traffic and Roadway Parameters:** $1000 Damage to Any One Person's Property, Adjusted Average Daily Traffic Amount, Adjusted Percentage of Average Daily Traffic For Trucks, Adjusted Roadway Part, Average Daily Traffic Amount, Average Daily Traffic Year, Commercial Motor Vehicle Flag, Construction Zone Flag, Contributing Factors, Crash Death Count, Crash Month, Crash Severity, Day of Week, Direction of Traffic, Fatal Crash Flag, Highway Number, Highway System, Hour of Day, Light Condition, Median Type, Number of Entering Roads, Number of Lanes, On System Flag, Outside Shoulder Width on Divided Highway, Percentage of Combo Truck Average Daily Traffic, Percentage of Single Unit Truck Average Daily Traffic, Population Group, Property Damages, Right Curb Type, Right of Way Usual Width, Right Shoulder Type, Road Class, Roadbed Width, Roadway Alignment, Roadway Type, Rural Flag, Rural Urban Type, Speed Limit, Surface Condition, Weather Condition

Figure 3 shows the map summarizing all the events collected from the CRIS data for 2019 to 2023. There was a total of 563,489 incidents collected from the CRIS database.

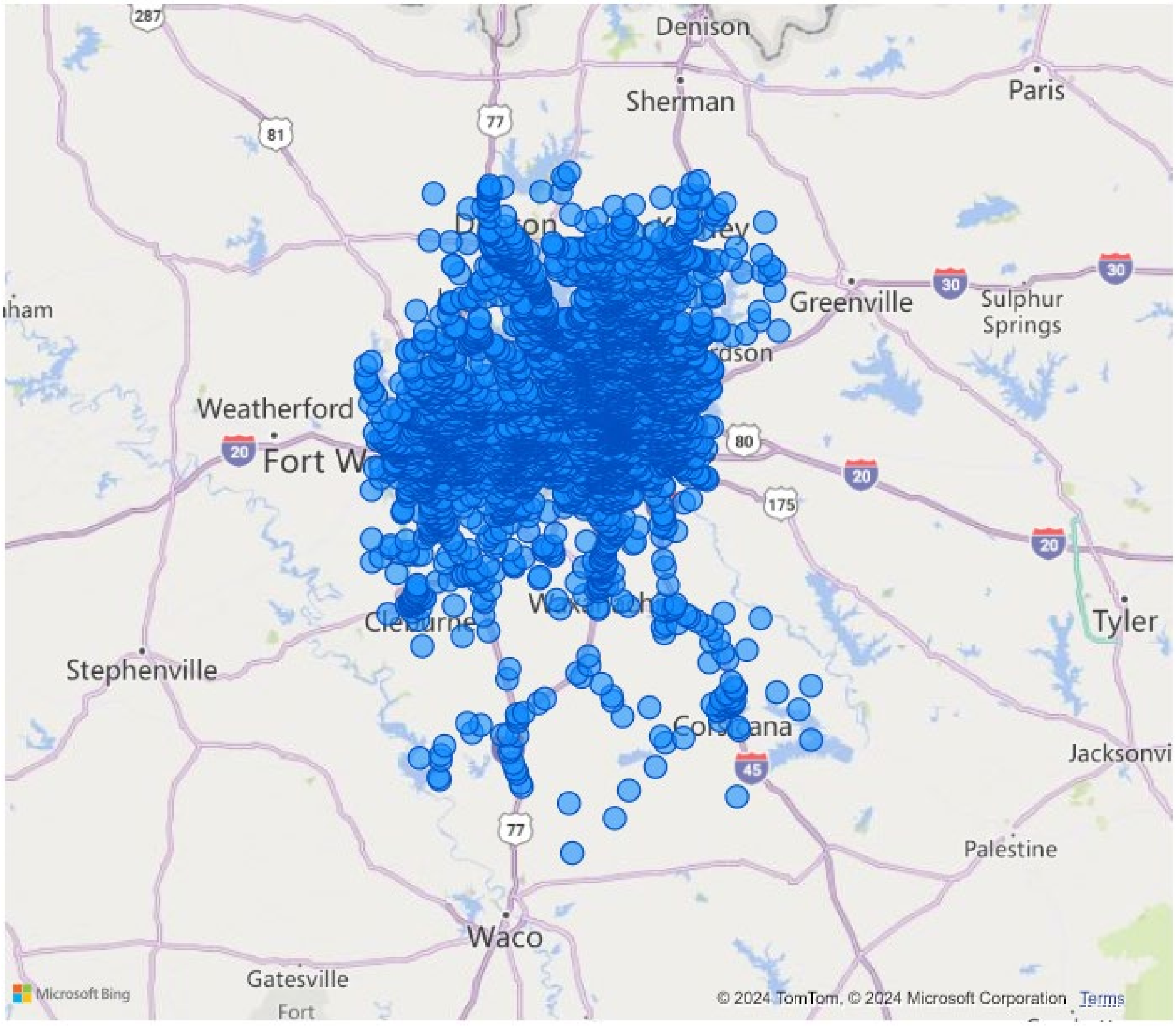

Figure 3 Map showing all the incidents captured by the CRIS Data

3.2 Data Processing

3.2.1 Matching CRIS and Queuing Data

Another python script was used to match the queuing data with the CRIS crash data. The process involved the following steps:

- **Data Merging:** The queuing data and CRIS crash data were merged based on spatial and temporal proximity. The Haversine distance was calculated to determine the distance between incidents and crashes.

- **Filtering Data:** Rows with missing or zero coordinates were filtered out. Crashes within a specific time (30 minutes) and distance (500 m) range from the incidents were identified and matched. This process ensured that each incident was paired with the nearest relevant crash.
- **Summarizing Emission Data:** Emissions from the queuing data were summarized to calculate total emissions for each incident, and the difference between actual and historical emissions provided the additional emissions caused by each incident. Emission data was summarized, and additional emissions caused by the incidents were calculated. Emission levels were categorized into quintiles: Very Low, Low, Medium, High, and Very High.

The matched data was saved into a CSV file (merged_data_with_emission_levels.csv), which included the variables from both datasets.

3.3 Development of Predictive Classification Model

A python script was developed to preprocess the data and build the emission prediction model with the following steps.

3.3.1 Data Preprocessing

Initially, the merged dataset was loaded from a CSV file. Relevant features were selected based on domain knowledge and their potential impact on emissions. Missing values in the dataset were filtered out to have consistent dataset to ensure the model could handle the data without errors. Categorical columns were identified for one-hot encoding, while numerical columns were standardized. This process ensured that all data was in a format suitable for machine learning model training.

3.3.2 Encoding and Scaling

Categorical variables were converted to binary vectors using one-hot encoding. Numerical variables were standardized to have a mean of 0 and a standard deviation of 1. The encoded categorical variables and scaled numerical variables were then concatenated to form the final feature matrix. This step ensured that the data was uniformly scaled and encoded, which is crucial for the performance of the machine learning model.

3.3.3 Splitting Data

The preprocessed data was split into training and testing sets to evaluate the model's performance. This step ensured that the model could be trained on a portion of the data and tested on a separate portion to assess its accuracy and generalization capabilities.

3.3.4 Handling Imbalanced Classes

The SMOTE (Synthetic Minority Over-sampling Technique) was applied to balance the classes in the training set. This technique addresses class imbalance by oversampling the minority class, ensuring that the model does not become biased towards the majority class.

3.3.5 Model Training

Various machine learning models were used to train and evaluate the emission prediction model. These models included:

- **Logistic Regression:** A baseline model to compare performance against more complex models. Logistic regression provided insights into the linear separability of the data.
- **XGBoost Classifier:** Known for its robustness and performance, XGBoost was used to train the model on the balanced training set. The model was evaluated using a classification report that provided metrics such as precision, recall, and F1-score for each emission level category.
- **Random Forest Classifier:** Another popular model for classification tasks, Random Forest was used to build and evaluate the prediction model. The model was also trained on the balanced dataset and evaluated using similar metrics.
- **Gradient Boosting Machine (GBM):** GBM was used to improve prediction accuracy by combining weak learners to form a strong learner.
- **Neural Networks:** A fully connected neural network model was also trained and evaluated to capture intricate patterns in the data.
- **Grid Search with Cross-Validation (GridSearchCV):** GridSearchCV was used to fine-tune hyperparameters for all models to achieve the best performance.

3.3.6 Model Evaluation

The trained models were evaluated on the test set to assess its performance. The evaluation included generating a classification report that provided metrics such as precision, recall, and F1-score for each emission level category. This thorough evaluation allowed for an assessment of the model's accuracy and its ability to correctly classify emission levels.

Figure 4 summarizes the different steps adopted in the methodology of this study.

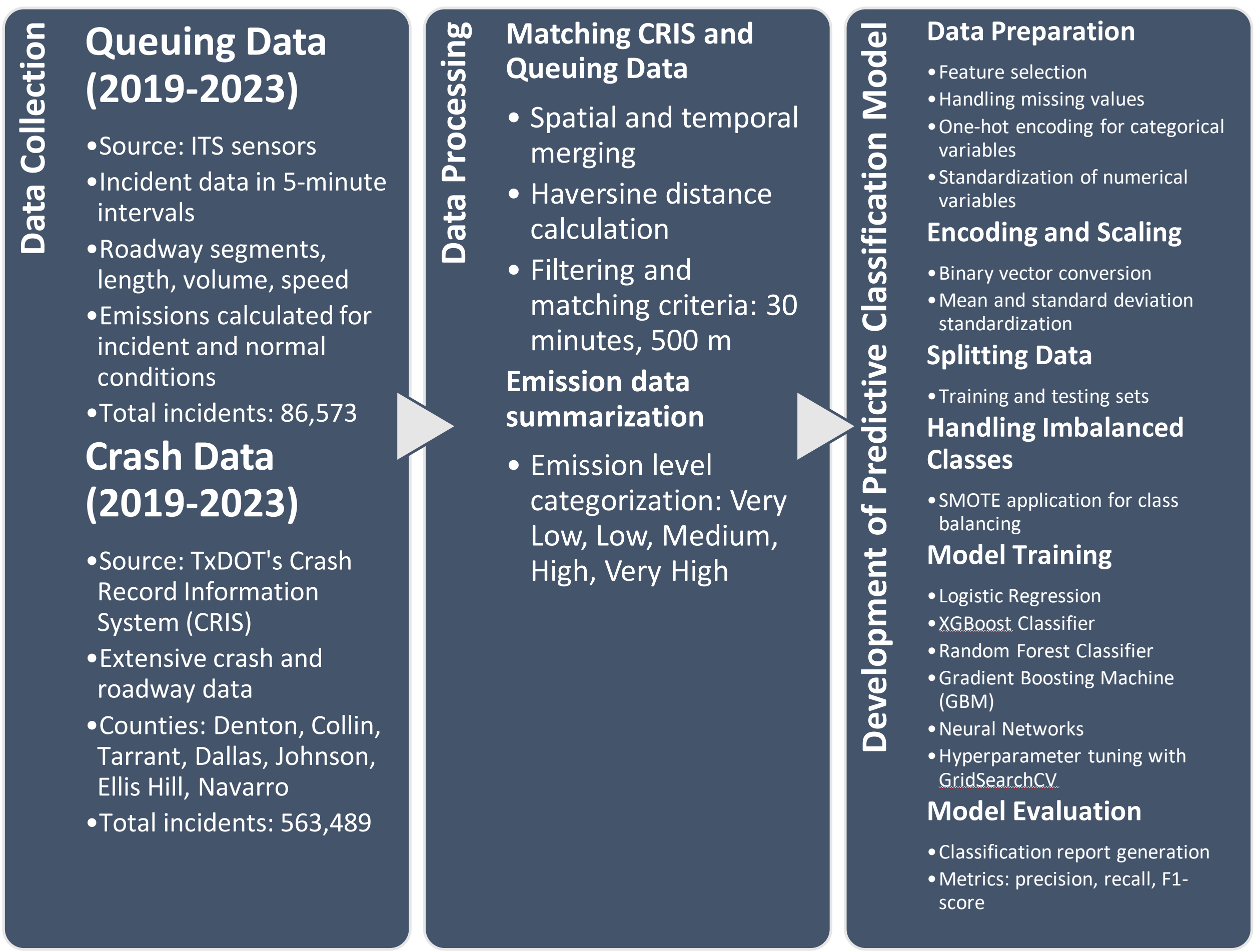

Figure 4 Overview of Methodology

4 RESULTS AND DISCUSSION

4.1 DATA EXPLORATION

4.1.1 CRIS Data

The data exploration of CRIS data provide valuable insights into the distribution of traffic incidents based on crash severity, time, and road class as summarized in the following figures .

- Annual and Monthly Trends: The annual distribution highlights that the majority of incidents result in no injuries, with a consistent pattern observed across the years. The monthly distribution shows a spike in incidents during October.
- Daily Patterns: The hourly distribution underscores the higher frequency of incidents during late afternoon and early evening hours, correlating with peak traffic times.
- Road Class Analysis: The road class distribution illustrates that interstates and US & state highways experience the highest number of incidents, predominantly resulting in no injuries.

Figure 5 shows the number of incidents per year, broken down by the severity of the crash. The severity categories include "Not Injured," "Possible Injury," "Suspected Minor Injury," "Suspected Serious Injury," "Fatal Injury," "Unknown," and "Unknown Injury." The chart highlights the prevalence of different severity levels over the years, with "Not Injured" being the most common outcome. There was a dip in the number of incidents during year 2020. This may be due to reduced mobility because of COVID-19 pandemic.

Figure 6 presents the number of crashes each month, categorized by crash severity. The chart indicates that the distribution of crash severities remains relatively consistent throughout the year, with a noticeable increase in incidents during October. The most common severity category is "Not Injured.".

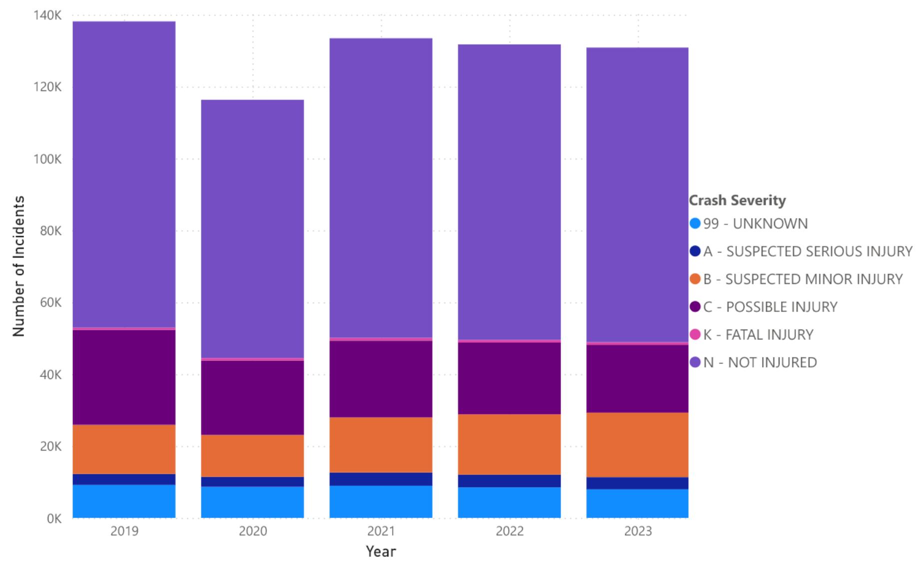

Figure 5 Annual Distribution of Incidents by Crash Severity

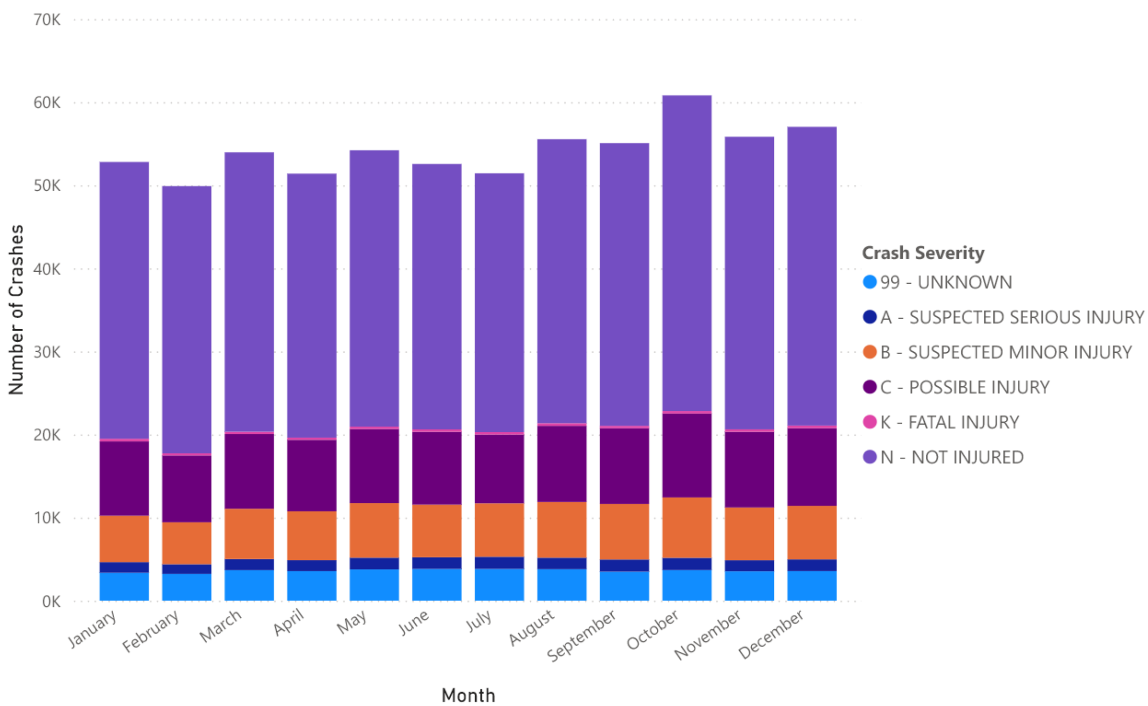

Figure 6 Monthly Distribution of Crashes by Crash Severity

Figure 7 shows the number of incidents for each day of the week, categorized by crash severity. The chart illustrates that Friday has the highest number of incidents, followed by Monday through Thursday, with Saturday and Sunday having fewer incidents. As with other figures, "Not Injured" is the most common outcome.

Figure 8 depicts the distribution of traffic incidents throughout the day, categorized by crash severity. The chart reveals that the number of incidents peaks during the late afternoon and early evening hours (15:00 to 18:59). The majority of incidents result in "Not Injured" outcomes, with fewer incidents resulting in serious or fatal injuries.

Figure 9 shows the number of incidents by road class, with each bar segmented by crash severity. The chart demonstrates that the majority of incidents occur on interstates and US & state highways, with "Not Injured" being the most frequent severity category. Incidents on farm-to-market roads, city streets, and other road classes are significantly fewer in number.

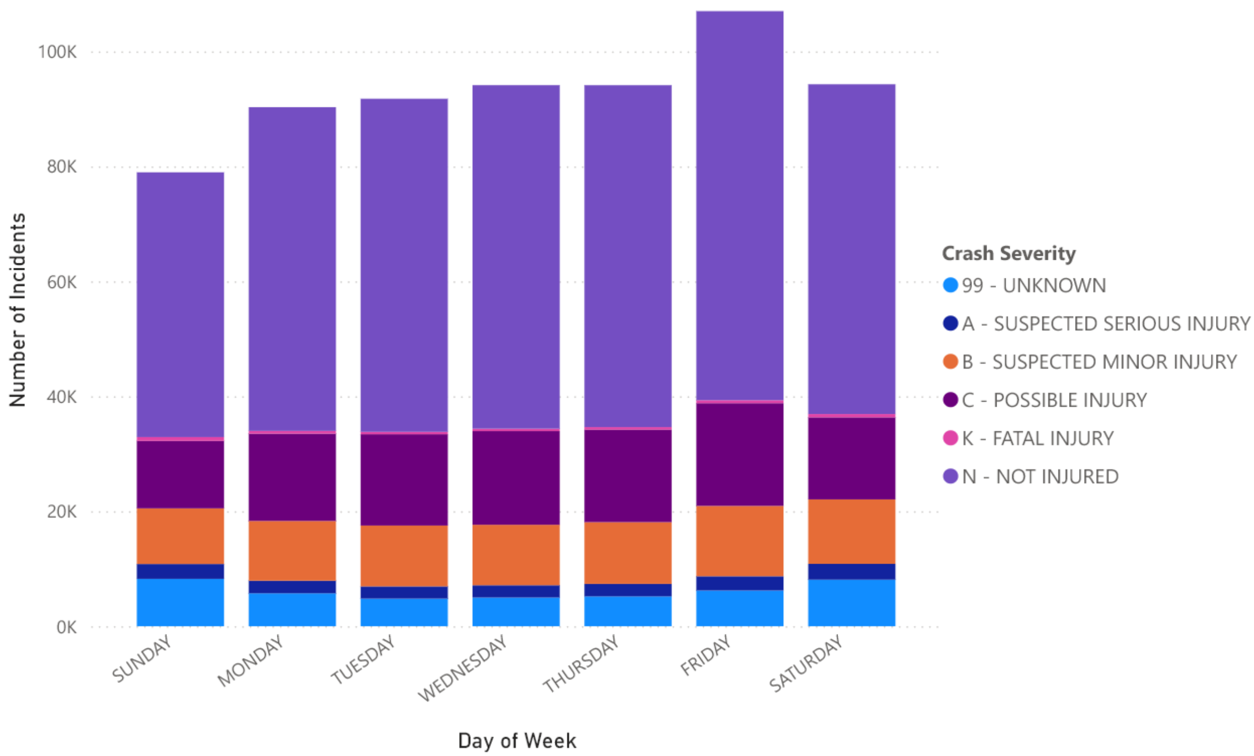

Figure 7 Weekly Distribution of Incidents by Crash Severity

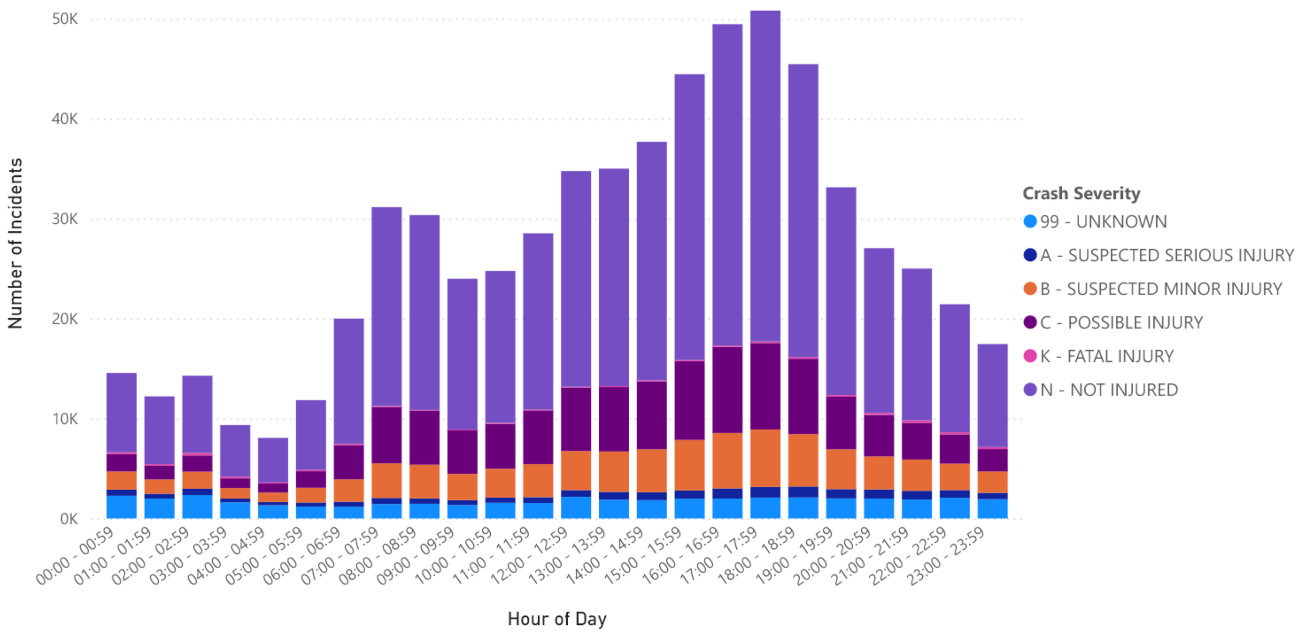

Figure 8 Hourly Distribution of Incidents by Crash Severity

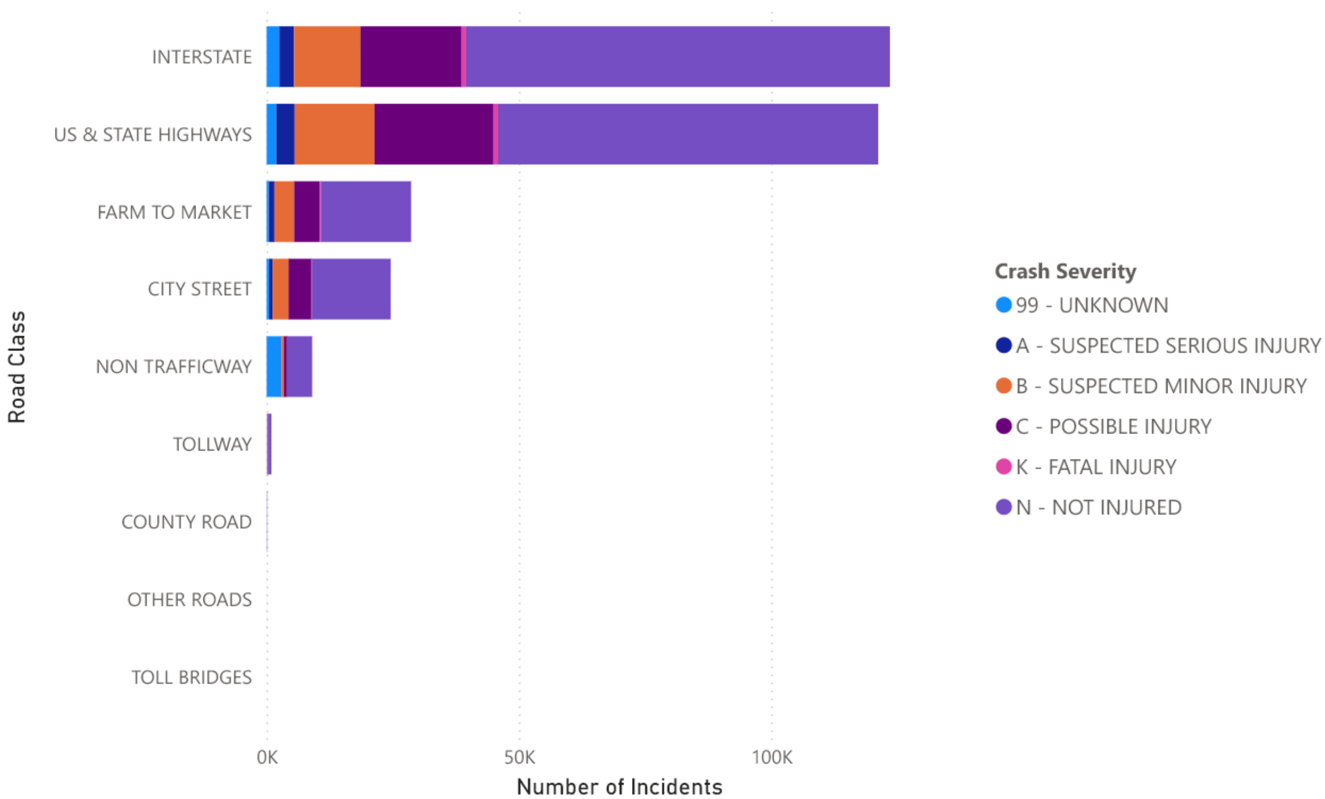

Figure 9 Distribution of Incidents by Road Class and Crash Severity

4.1.2 Queuing Data

The data exploration figures for the queuing data provide valuable insights into the distribution of traffic incidents based on incident type, time, and road class.

- **Annual and Monthly Trends**: The annual distribution highlights that "Collision" is the most frequent incident type, with a consistent pattern observed across the years. The monthly distribution shows a spike in incidents during October.
- **Daily and Weekly Patterns**: The hourly distribution underscores the higher frequency of incidents during early morning and late afternoon hours, correlating with peak traffic times. The weekly distribution shows that incidents peak on Fridays.

Figure 10 shows the number of incidents per year, broken down by the type of incident. The incident types include "Collision," "Disabled Vehicle," "Abnormal Congestion," and several others. The chart highlights the prevalence of different incident types over the years, with "Collision" being the most common.

Figure 11 presents the number of incidents each month, categorized by incident type. The chart indicates that the distribution of incident types remains relatively consistent throughout the year, with a noticeable increase in incidents during certain months such as October. The most common incident type is "Collision."

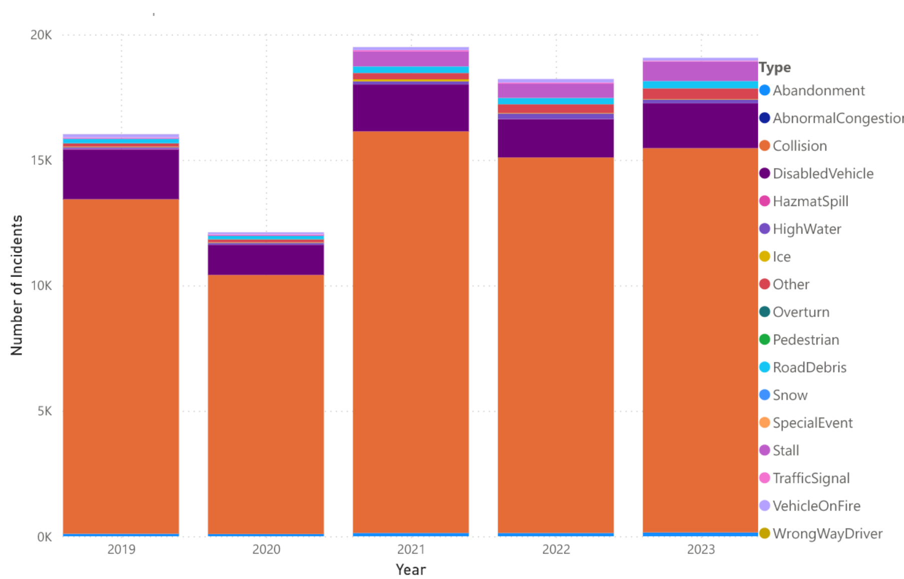

Figure 10 Annual Distribution of Incident Types for Queuing Data

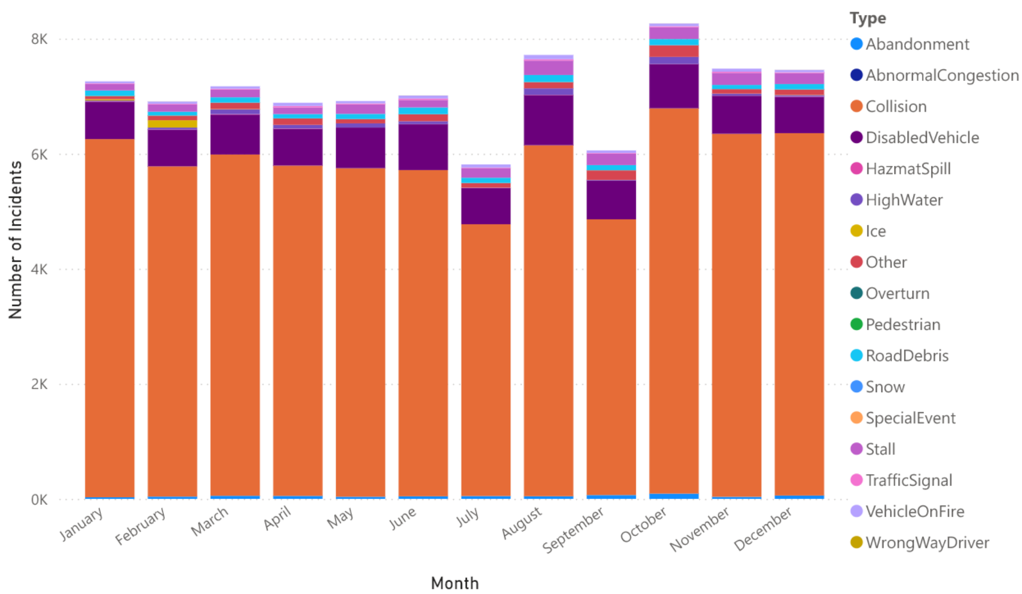

Figure 11 Monthly Distribution of Incident Types for Queuing Data

Figure 12 shows the number of incidents for each day of the week, categorized by incident type. The chart illustrates that Friday has the highest number of incidents, followed by other weekdays, with Saturday and Sunday having fewer incidents. "Collision" is the most common type of incident.

Figure 13 depicts the distribution of traffic incidents throughout the day, categorized by incident type. The chart reveals that the number of incidents peaks during the early morning and late afternoon hours, correlating with peak traffic times. The majority of incidents are "Collisions.".

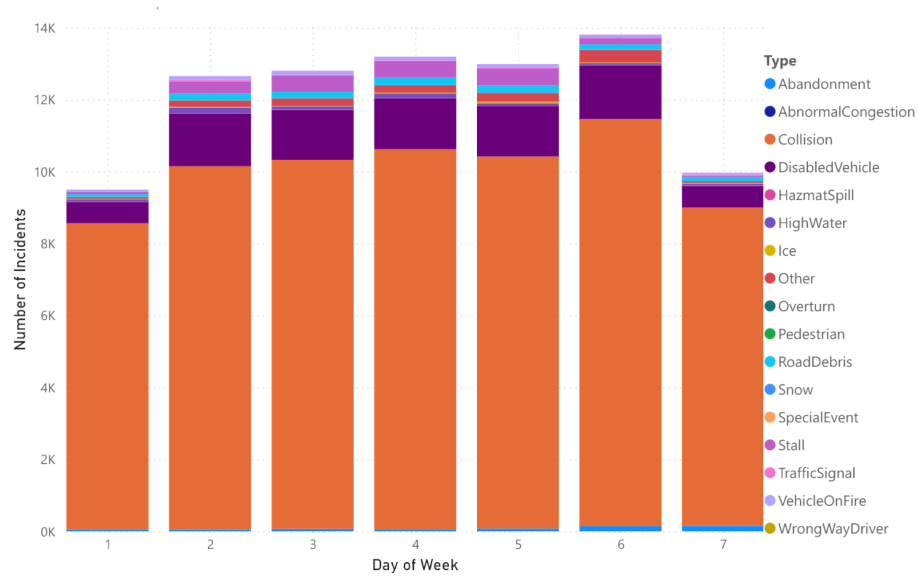

Figure 12 Weekly Distribution of Incident Types for Queuing Data

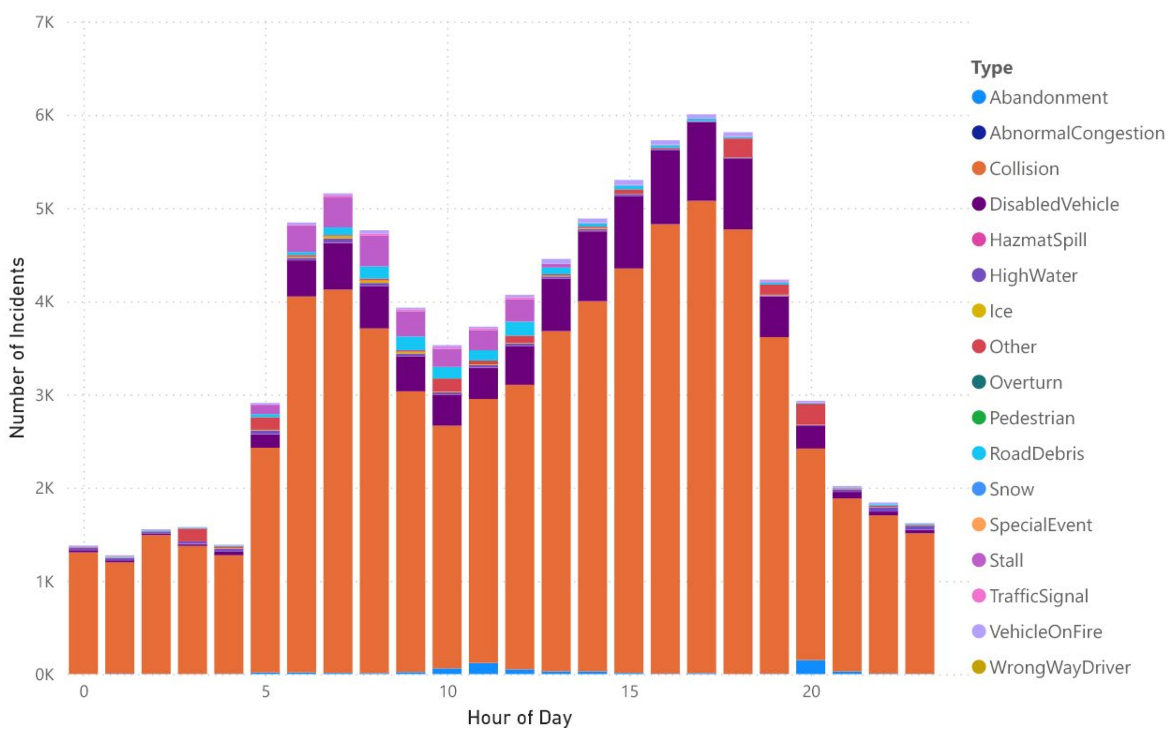

Figure 13 Hourly Distribution of Incident Types for Queuing Data

4.2 Impact of Crashes on Emissions

This section presents an analysis of the impact of traffic crashes on NOx emissions, using queuing data from various crash events. The primary metric examined is the NOx emission increase (g/day) compared to normal historic traffic conditions for each crash event. The data is aggregated and analyzed by the hour of the day, day of the week, month, roadway, and incident type to identify patterns and peak times for increased emissions due to traffic incidents.

The analysis utilizes data from the queuing data table, which includes detailed descriptions of crash events, including the increase in NOx emissions (EmissionNOXDiff) compared to normal traffic conditions. A custom measure was created to calculate the average daily increase in NOx emissions. This measure aggregates the total increase in NOx emissions per day and averages it over the distinct count of days on which events were detected.

The analysis reveals distinct patterns in NOx emissions corresponding to the time of day, day of the week, month, roadway, and incident type.

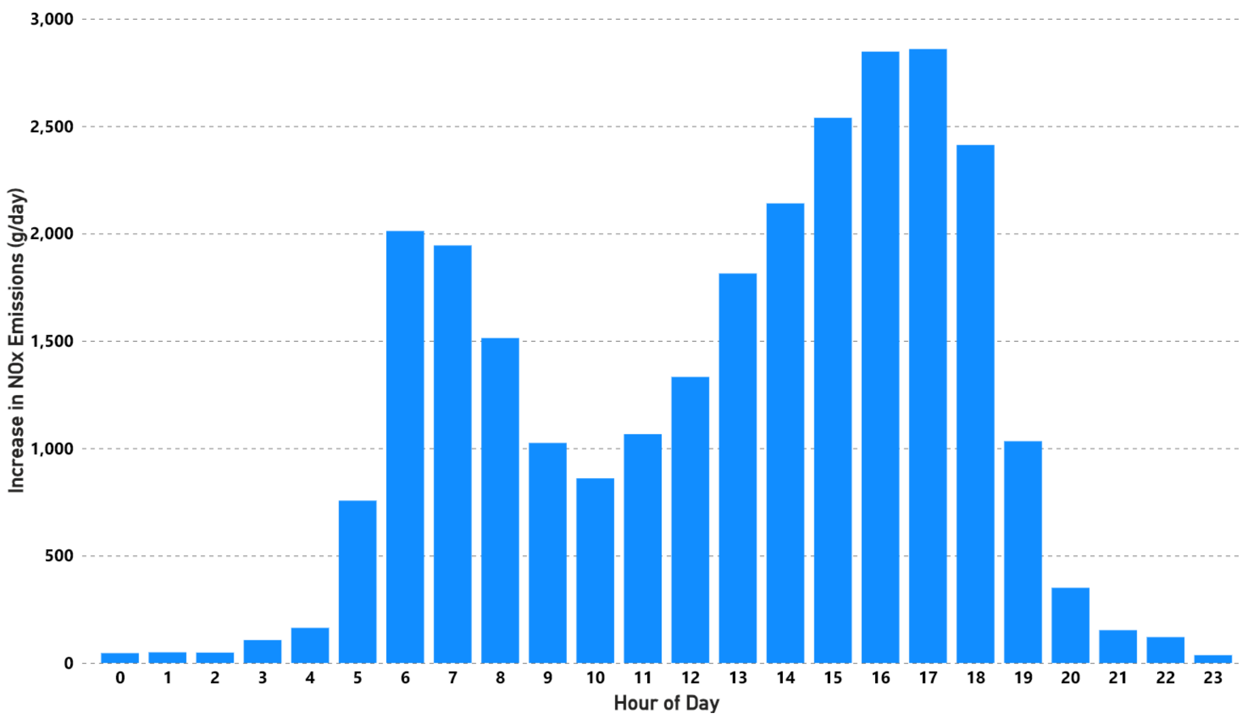

Figure 14 Increase in NOx Emissions (g/day) by Hour of Day

The analysis by hour of day (Figure 14) shows significant peaks in NOx emissions during morning (around 7 AM) and evening (3 PM to 6 PM) rush hours, correlating with high traffic volumes and frequent incidents. Lower emissions are observed during late night and early morning hours (midnight to 5 AM).

When examining the day of the week (Figure 15), higher emissions are observed from Monday to Friday, with a notable peak on Friday. Emissions are lower on Saturday and Sunday, reflecting reduced traffic volumes and fewer incidents.

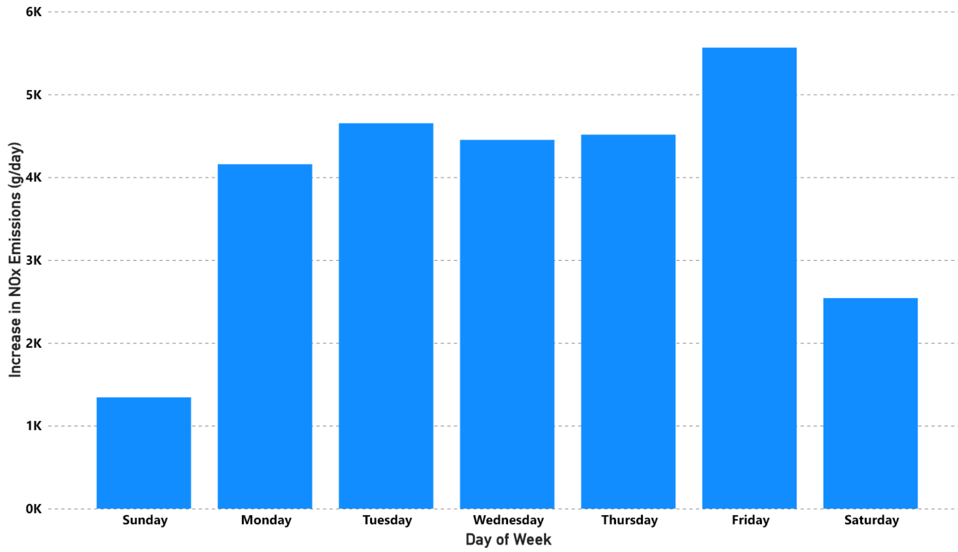

Figure 15 Increase in NOx Emissions (g/day) by Day of Week

The monthly variation in NOx emissions (Figure 16) shows variability throughout the year, with peaks in October, December, and February. Lower emissions are seen in the middle months, particularly in April and May.

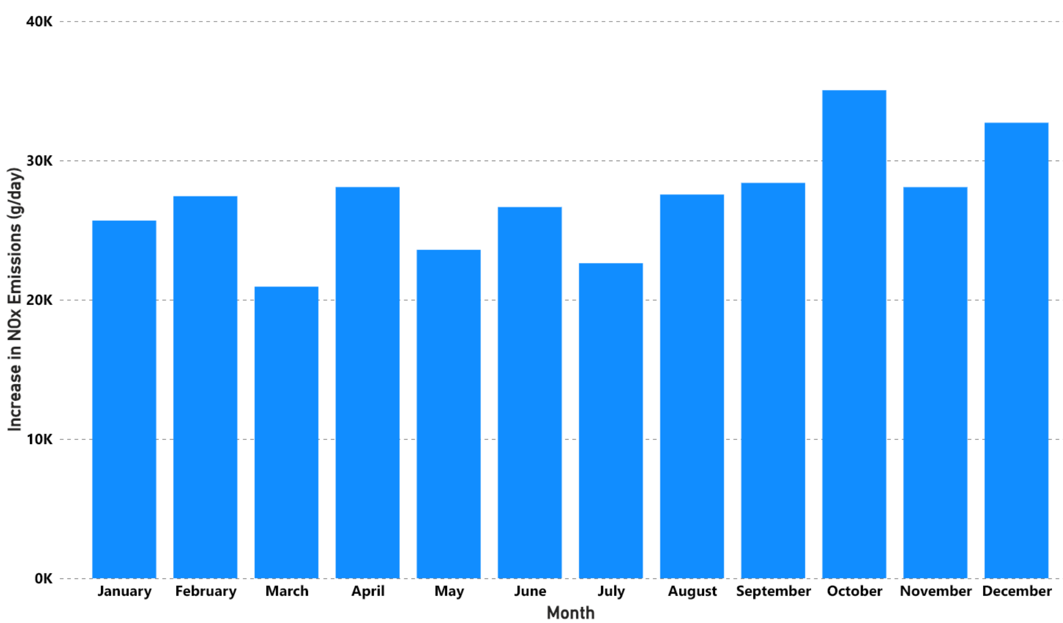

Figure 16 Increase in NOx Emissions (g/day) by Month

Analysis by roadway (Figure 17) indicates that major highways such as IH635, US75, IH35E, IH20, and IH30 experience the highest emissions due to crashes. Significantly lower emissions are observed on minor roads, indicating fewer incidents or less impact per incident.

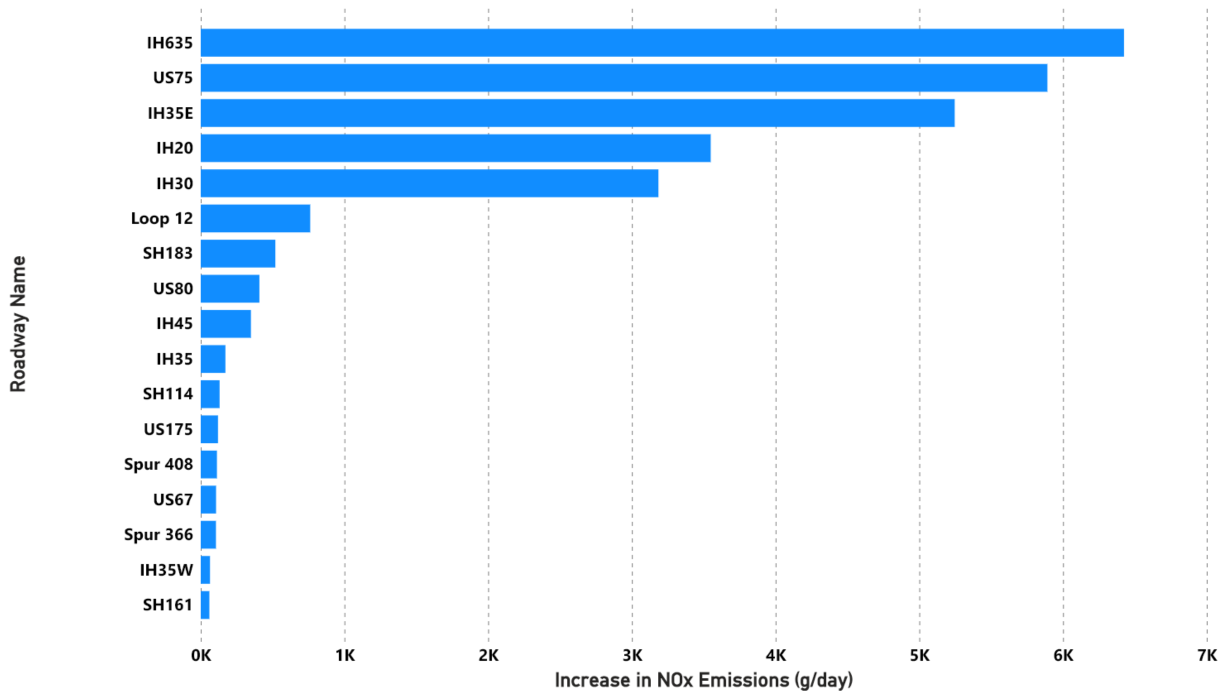

Figure 17 Increase in NOx Emissions (g/day) by Roadway

The impact of different types of incidents on NOx emissions (Figure 18) reveals that collisions are the primary contributor to increased NOx emissions, significantly outpacing other incident types. Disabled vehicles are the second-highest source of emissions, though far lower than collisions. Other incident types (stalls, vehicle fires, high water, etc.) contribute relatively minor increases in emissions.

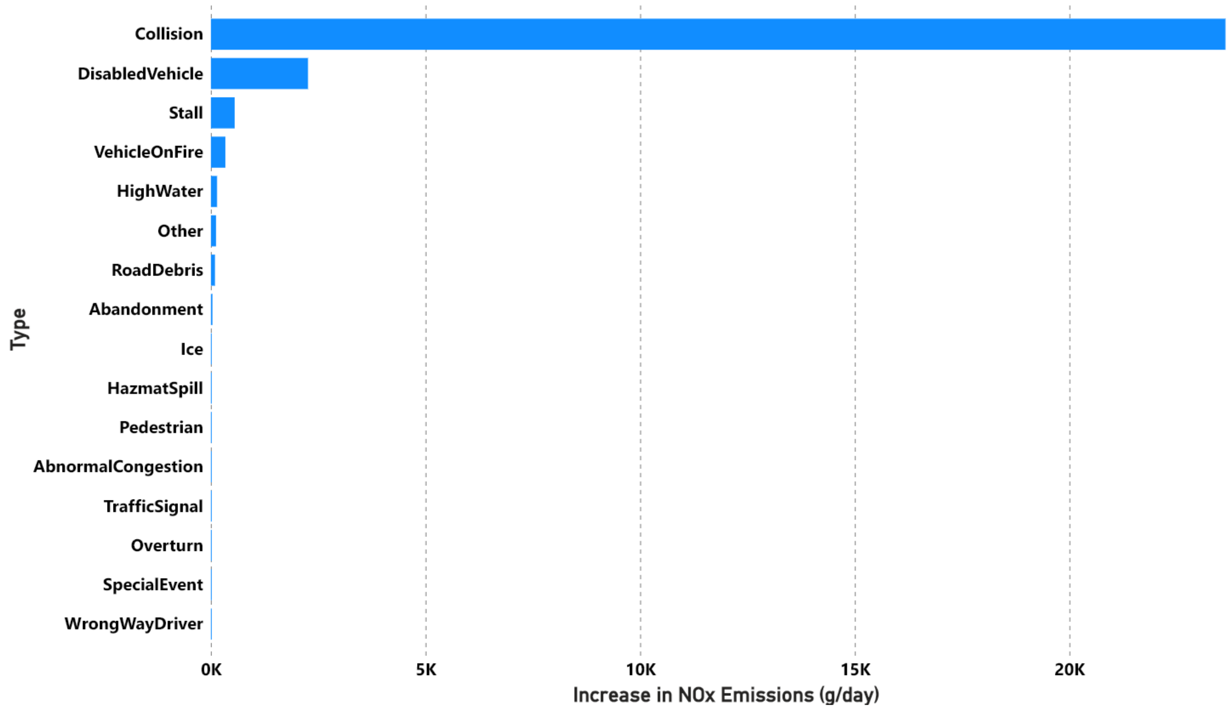

Figure 18 Increase in NOx Emissions (g/day) by Incident Type

The results indicate clear temporal and categorical patterns in the impact of crashes on NOx emissions. Morning and evening rush hours, weekdays, and certain months exhibit higher emissions due to increased traffic incidents. Major highways see the most significant impact, and collisions are the predominant incident type driving emissions increases.

These findings emphasize the importance of targeted traffic management and incident response strategies, particularly during peak periods and on major roadways. By mitigating incidents, especially collisions, during high-impact times and locations, significant reductions in NOx emissions can be achieved, contributing to better air quality and environmental health.

Next, the queuing data was matched with CRIS data to get the impact of other parameters in the CRIS database on the emissions overall. Following plots are based on the merged dataset, where 24,290 out of 86,583 events from the queuing data were matched to the CRIS data based on temporal and spatial proximity. These incidents were characterized as emissions per incident as we want to know which variables influence the emissions which will be predicted in the next step.

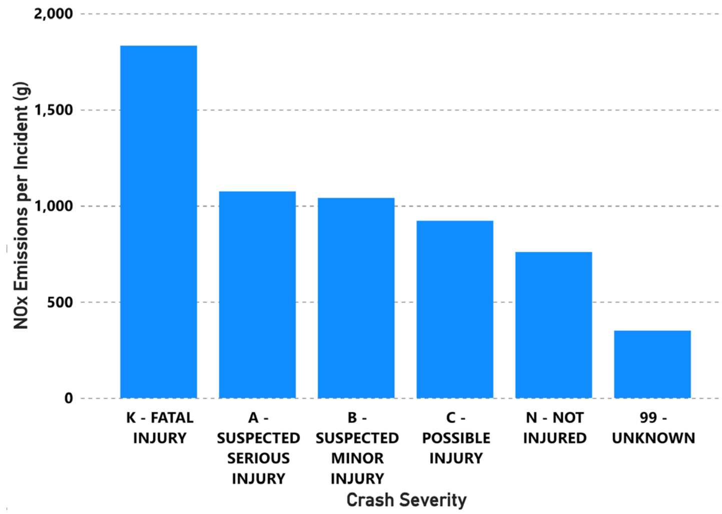

Figure 19 Increase in NOx Emissions per Incident (g) by Crash Severity

Figure 19 shows the average NOx emissions per incident categorized by crash severity. Incidents resulting in fatal injuries have the highest average emissions, followed by suspected serious injuries, minor injuries, possible injuries, and non-injury incidents. The data suggests that more severe crashes lead to higher emissions, likely due to longer incident durations and more extensive traffic disruptions.

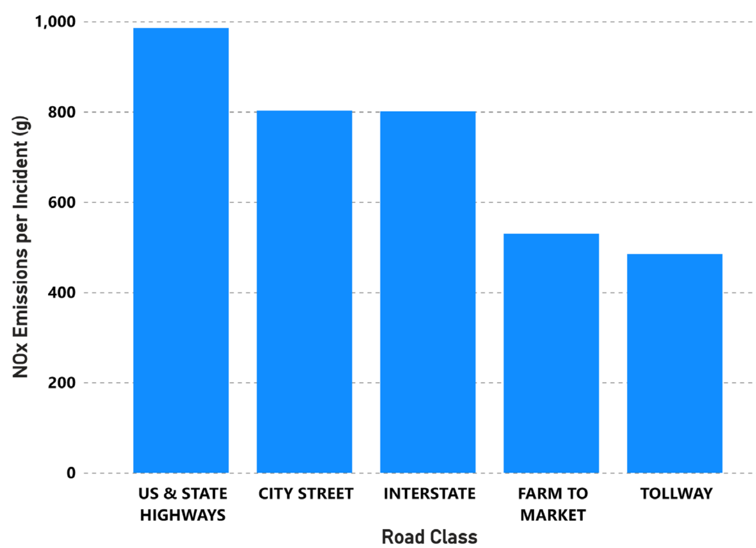

Figure 20 Increase in NOx Emissions per Incident (g) by Roadway class

Figure 20 illustrates the average NOx emissions per incident for various road classes. The chart highlights that US & state highways have the highest average emissions, followed by city streets and interstates. Farm-to-market roads and tollways show lower average emissions. This indicates that major roads, which typically handle higher traffic volumes, tend to have higher emissions during incidents.

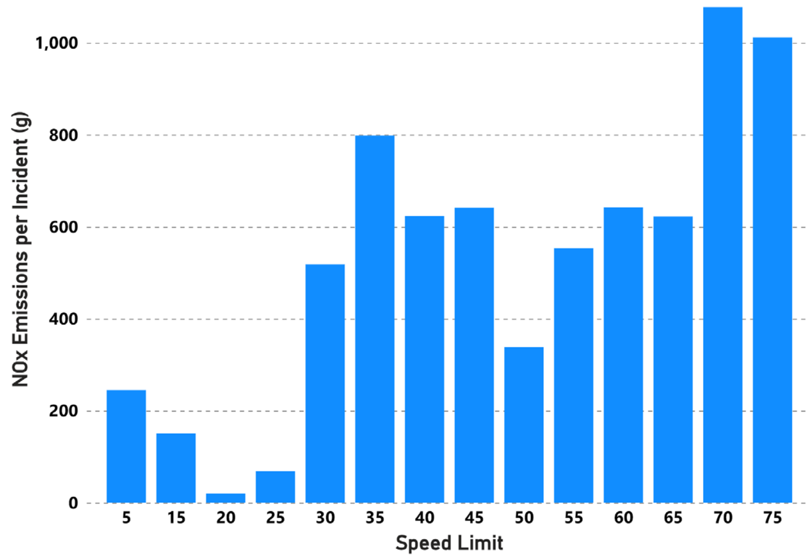

Figure 21 Increase in NOx Emissions per Incident (g) by posted Speed Limit

Figure 21 displays the average NOx emissions per incident for different speed limits. The data reveals that incidents occurring at higher speed limits tend to have higher emissions, with notable peaks at 35 mph, 65 mph, 70 mph, and 75 mph. This trend can be attributed to the fact that high-speed highways typically have a larger capacity, and an incident can cause free-flowing traffic to accumulate in volume, resulting in increased emissions compared to normal conditions.

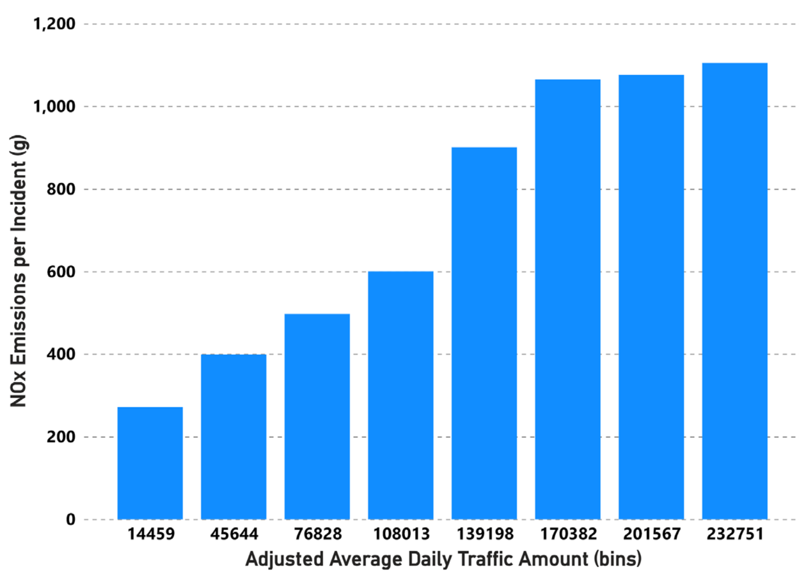

Figure 22 Increase in NOx Emissions per Incident (g) by AADT volume

Figure 22 presents the average NOx emissions per incident for different bins of adjusted average daily traffic amounts. Higher traffic volumes correspond to higher average emissions, indicating that more congested roads contribute to increased emissions during incidents. This relationship highlights the impact of traffic density on emission levels.

4.3 Predictive Model to Estimate the Emission Impact of Crashes

The objective of this analysis was to predict the Emission Level of traffic incidents using various traffic and crash-related features. The merged dataset consisted of multiple traffic and crash-related features alongside the Emission Level. Emission level column was created by categorizing the increase in NOx emissions into five groups based on the quintiles: Very Low, Low, Medium, High, and Very High. Table 2 Summary of NOx Emissions by Emission Level Category shows the average increase in NOx emissions (in grams) for each emission level category, along with the standard deviations and the number of events in each category. The total number of events used to train the model is provided in the last row.

Table 2 Summary of NOx Emissions by Emission Level Category

Emission Level	Average of Increase in NOx Emissions (g/incident)	Standard Deviation of Increase in NOx Emissions (g/incident)	Number of Events
Very Low	1.64	2.16	4979
Low	37.44	24.48	4742
Medium	233.78	96.08	4860
High	762.35	232.02	4852
Very High	3225.52	4026.92	4857
Total			24290

Initially, a subset of relevant features was chosen, including Adjusted Average Daily Traffic Amount, Crash Month, Crash Severity, Day of Week, Duration, Hour of Day, and Road Class. Categorical variables were then one-hot encoded, and numerical features were standardized. The dataset was split into training and testing sets in an 80:20 ratio, and SMOTE (Synthetic Minority Over-sampling Technique) was applied to balance the classes in the training set.

Different classification algorithms were trained. Of the tested models, XGBoost classifier was chosen for its robustness and efficiency. The model was trained on the balanced training set, and feature importance was determined using SelectKBest with ANOVA F-value and feature importance scores from the trained XGBoost model. The most significant features included Hour of Day, Duration, and Adjusted Average Daily Traffic Amount. The classification report for the XGBoost model is summarized in the Table 3.

The model achieved an overall accuracy of 42%, with Very High and Very Low emission levels showing relatively better precision and recall compared to other levels. Precision, recall, and F1-scores varied across different emission levels, indicating varying model performance. This analysis provides a foundation for further refinement and potential inclusion of additional relevant features to improve prediction accuracy.

Table 3 Classification Report for XGBoost Model

EmissionLevel	Precision	Recall	F1-Score	Support
Very Low	0.54	0.55	0.55	977
Low	0.33	0.25	0.28	958
Medium	0.31	0.28	0.29	943
High	0.33	0.34	0.33	995
Very High	0.5	0.66	0.57	985
Accuracy	0.42			4858
Macro Avg	0.4	0.41	0.41	

5 SUMMARY AND CONCLUSIONS

This report investigates the impact of traffic crashes on NOx emissions and evaluates the air quality benefits of TxDOT's Traffic Incident Management (TIM) programs using data from queuing systems and the Crash Record Information System (CRIS) from 2019 to 2023. Key findings reveal that traffic incidents significantly affect NOx emissions, with distinct patterns based on the time of day, day of the week, month, roadway type, and incident type. Peak emission periods occur during morning and evening rush hours, with weekdays, particularly Fridays, showing higher emissions than weekends. Major highways, such as IH635, US75, IH35E, IH20, and IH30, have the highest NOx emissions due to crashes, with collisions being the primary contributor, followed by disabled vehicles. The severity of crashes also plays a significant role, with fatal and serious injury crashes leading to higher emissions.

The methodology involved merging queuing and CRIS data based on spatial and temporal proximity and employing various machine learning models to predict the emission impact of crashes. The models used included Logistic Regression, XGBoost, Random Forest, Gradient Boosting Machine (GBM), and Neural Networks, with XGBoost providing the best precision. However, the model's overall accuracy was only 42%, indicating the need for further refinement. Future studies will focus on incorporating more data points and exploring additional relevant features to improve prediction accuracy. The results underscore the importance of effective TIM programs and the need for targeted traffic management and incident response strategies to mitigate the environmental impact of traffic incidents.

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