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Utilizing Simulated Vehicle Trajectory Data from Connected Vehicles to Characterize Performance Measures on an Arterial After an Impactful Incident

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UTILIZING SIMULATED VEHICLE TRAJECTORY DATA FROM CONNECTED VEHICLES TO CHARACTERIZE PERFORMANCE MEASURES ON AN ARTERIAL AFTER AN IMPACTFUL INCIDENT

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DEDICATION

To The Lord Almighty God.

To my late father in heaven, Novat Baraba, may his soul rest in peace.

To my beloved family on Earth; my mother, Stella, my brothers, Norran, Nicus, Ebenezer and Joshua, and beloved sister, Dorcus.

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ABSTRACT

Traffic incidents are unforeseen events known to affect traffic flow because they reduce the capacity of an arterial corridor segment and normally generate a temporary bottleneck. Identification of retiming requirements to enhance traffic signal operations when an incident occurs depends on operations-oriented traffic signal performance measurementsWhen effective and real-time traffic signal performance metrics are employed at traffic control centers, delays, fuel use, and air pollution may all be decreased. The majority of currently available traffic signal performance evaluations are based on high-resolution traffic signal controller event data, which gives data on an intersection-by-intersection basis but requires a substantial upfront expenditure. The necessary detecting and communication equipment also involves costly and periodic maintenance. Additionally, the full manifestation of connected vehicles (CVs) is fast approaching with efforts in place to accelerate the adaptation of CVs and their infrastructures. CV technologies have enormous potential to improve traffic mobility and safety. CVs can provide abundant traffic data that is not otherwise captured by roadway detectors or other methods of traffic data collection. Since the observation is independent of any space restrictions and not impacted by queue discharge and buildup, CV data offers more comprehensive and reliable data that can be used to estimate various traffic signal performance measures.

This thesis proposes a conceptual CV simulation framework intended to ascertain the effectiveness of CV trajectory-based measures in characterizing an arterial corridor incident, such as a vehicle crash. Using a four-intersection corridor with different signal timing plans, a microscopic simulation model was created in Simulation of Urban Mobility (SUMO), Vehicles in Network Simulation (Veins) and Objective Modular Network Testbed in C++ (OMNeT++) platforms. Furthermore, an algorithm for CVs that defines, detects and disseminates a vehicle crash incident to other vehicles and a roadside unit (RSU) was developed. In the thesis, it is demonstrated how visual performance metrics with CV data may be used to identify an incident. This thesis proposes that traffic signal performance metrics, such as progression quality, split failure, platoon ratios, and safety surrogate measures (SSMs), may be generated using CV trajectory data. The results show that the recommended approaches with access to CV trajectory data would help both performance assessment and operation of traffic control systems. Unlike the current state of the practice (fixed detection technology), the developed conceptual framework can detect incidents that are not captured by intersection-vicinity-limited detectors while requiring immediate attention.

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LIST OF ABBREVIATIONS

AADT	Annual Average Daily Traffic
AOG	Arrivals On Green
AOR	Arrivals On Red
ATSPMs	Automated Signal Performance Measures
COBYLA	Constrained Optimization By Linear Approximation
CV	Connected vehicle
DAC	Maximum Deceleration to Avoid a crash
EBL	East Bound Left
EBR	East Bound Right
EBT	East Bound Through
FHWA	Federal Highway Administration
GPS	Global Positioning Services
HCM	Highway Capacity Manual
LOS	Level of Service
MAC	Media Access Control
NBL	North Bound Left
NBR	North Bound Right
NBT	North Bound Through
NCV	Non-Connected Vehicle
OD	Origin Destination
OSM	Open Street Map
PAOG	Percentage Arrivals on Green
PAOR	Percentage Arrivals on Red

PCD	Purdue Coordination Diagram
PM	PM Peak
P_r	Platoon ratio
RMSE	Root Mean Squared Error
RSU	Roadside Unit
SBL	South Bound Left
SBR	South Bound Right
SBT	South Bound Through
SSM	Safety Surrogate Measures
SUMO	Simulation Of Urban Mobility
TMCs	Turning Movement Counts
TOD	Time of Day
TraCI	Traffic Control Interface"
TS	Traffic Server
TTC	Time To Collision
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Others
Veins	Vehicles in Network Simulation
WBL	West Bound Left
WBR	West Bound Right
WBT	West Bound Through

CHAPTER I

INTRODUCTION

1.1. Background

Unpredictable traffic incidents, such as vehicle crashes or breakdowns, often disrupt various traffic flow characteristics. About 50% of all commuter traffic in the US is brought on by "nonrecurring" incidents like bad weather and construction zones. 25% of this traffic is completely brought on by stalled vehicles, spilled cargo, road debris, and crashes. Traffic congestion is the most evident outcome of an incident (FHWA, 2020).

The frequency of these incidents has a significant impact on traffic flow (Novat, N, 2022b). For example, lane-blocking incidents have a greater impact on traffic flow than the number of lanes obstructed. The capacity of a road is reduced by around 50% when an incident blocks one of its three lanes (Cheu & Ritchie, 1995; Giuliano, 1989). When two additional lanes are blocked, capacity is reduced by around 80%. Minor lane-blocking incidents can have a big impact on traffic when they're not swiftly resolved. Their effects, meanwhile, are more obvious when traffic is at its worst. If a lane is blocked when traffic flow is at or close to a facility's capacity, the queue of traffic that forms behind the obstruction won't go forward after the obstruction is gone; instead, it will remain in place until the flow of traffic into the queue drops. Significant incidents that result in protracted traffic closures have further negative effects on mobility and, consequently, safety. Intersecting arterial roadways, other collector highways, and even local streets are all impacted by traffic closures (Giuliano, 1989). The capacity to respond to medical emergencies, fires and police call unrelated to the highway incident is impacted by increasing traffic congestion. It is crucial to resolve incidents safely and immediately to lessen their negative effects on traffic and safety.

Although signalized intersections are known to be effective at maintaining traffic build-up by assigning priority at intersections, they also present significant challenges for drivers. The presence of traffic control devices affects delays, collisions, congestion and emissions, and the impact is even heightened when there is a perceived incident on the signalized corridor. The National Transportation Operations Coalition notes that operating traffic signals in the United States have caused 295 million vehicle miles of delay on major roadways (Denney et al., 2012; National Transportation Operations Coalition, 2012). To optimize the performance of these signalized intersections, transportation agencies have been considering the use of detector-based Automated Signal Performance Measures (ATSPMs). Necessary signal timing readjustments are done based on the inferences made from the ATSPMs to optimize the performance of the signalized intersections. ATSPM detector-based approaches can estimate measures such as queue length, arrivals on green and red, etc., by computing cumulative arrival counts and departure counts (Q. Wang et al., 2021).

However, the National Transportation Operations Coalition also documented a cost-benefit ratio that exceeds 40:1 on optimizations made from the use of ATSPMs (National Transportation Operations Coalition, 2012). Also, C. Day et al., (2014) published a report in which controller-based high-resolution data collection costs were presented. It was stated there was a one-time cost of S3,120 for installing detectors, plus an additional $420 per year for maintenance required for a single basic intersection. This represents a 10-year future cost of $7,320 for an agency. Given the multitude of sparsely located signalized intersections in the United States, it would require an exhaustive reach of resources by the local and state departments of transportation (DOTs) to install and maintain the infrastructure necessary for signal optimization at each intersection. In addition to that, they also have the following limitations: (a) detector malfunctions, which could limit traffic detection leading to decreased efficiency when estimating performance measures and (b) Only when a vehicle passes by can stationary detectors offer instantaneous data; otherwise, the status of the traffic must be approximated (Feng et al., 2015).

Fortunately, the development of data collection, mining, and analytical tools has led to the introduction of efficient alternative methods for calculating signal performance indicators from crowd-sourced datasets that can be cost-effective in terms of DOT resource allocation. These performance metrics are created from point-based probing GPS sources using smartphone apps and fleet telematics. Fortunately, the development of data collection, mining, and analytical tools has led to the introduction of efficient alternative methods for calculating signal performance indicators from crowd-sourced datasets that can be cost-effective in terms of DOT resource allocation. These performance metrics are created from point-based probing GPS sources using smartphone apps and fleet telematics. As these datasets continue to grow in both scope and accuracy, their reliability as an alternative data source for signal performance measures tools will certainly increase. One example of these crowd-sourced datasets is the automated probe vehicle trajectory data offered by commercial providers typically containing latitude, longitude, timestamp, speed, heading and a unique trip identifier. Recent studies have explored means of extracting various performance measures from these datasets (Arvin et al., 2020; C. Day et al., 2011; C. M. Day & Bullock, 2016; Waddell et al., 2020). The proposed performance measures eliminate the need to install and maintain expensive infrastructure for physical vehicular detection. However, the probe trajectory data still encounters a low ping frequency challenge due to lower penetration rates and limited connectivity (Waddell et al., 2020). The use and acceptance of traffic-signal performance measures on a greater scale will profit from avoiding the expense of physical detection installation and maintenance.

Additionally, using wireless connections, enhanced data from connected cars (CVs) may explain traffic conditions close to an intersection, which would complement the requirement for detectors and facilitate the broadcast and gathering of probe vehicle trajectory data. This can be achieved through direct communication with other CV environment devices, such as roadside units (RSU), a computing device located on the roadside that provides connectivity support to CVs. With advanced CV technology, data can be exchanged between CV and RSU, and RSUs can channel the information to traffic control centers (TCC) for storage and processing. From CV technology, important real-time traffic data such as queue length can be obtained or estimated more accurately.

Few recent studies have been conducted utilizing CV trajectory data to optimize various signal performance measures (Arvin et al., 2020; Feng et al., 2015; Wang et al., 2021). Past studies have utilized both detector based ATSPMs and a few with secondary vehicle trajectory probe data from a range of mobile communication network devices to explore various signal performance measures. However, the information on the efficiency of these tools in detecting, evaluating, and producing performance measures after an impact from unplanned incidents, such as a roadway crash, is lacking. The development of signal performance metrics has benefited from the use of probe data from a variety of communication devices, but the CV concept vehicles operate as roaming traffic detectors that are not restricted to particular and fixed positions along the road infrastructure.

There are several methods that may be used to build the traffic messages that the CVs will broadcast. For instance, every interval, each CV can send a traffic message that includes its current location and speed. Better yet, the communication is transmitted to the rest of the vehicles in the network to take an alternative course of action, such as slowing down, re-routing, etc. Another advantage is communicating with other roadside features. CVs can collect data, such as real-time traffic signal status, thus making the analysis and characterization of various traffic flow parameters easier from one CV data source.

By using CV as the data source, it will be possible to analyze this data and, as a result, gain a better knowledge of what happens at signalized intersections and corridors. With this data at hand, accurate signal control system input and output conversion into more informative and practical data sets will be feasible under a variety of operational conditions. The quantitative and qualitative performance assessment method that is proposed will formulate a decision support framework for thorough and long-term performance analysis and decision-making when it comes to incident management.

1.2. Study objective

This thesis proposes a conceptual framework for leveraging the capacity of CV technology in detecting incidents on an arterial corridor and using the trajectory data shared by CVs to develop signal performance measures to characterize the spatial-temporal impacts of an arterial incident. The following are the study's specific objectives:

1. To develop a simulation framework for incident creation and detection by CVs on the network.
2. To develop performance measures that use the CV trajectory data to detect and determine incidents.
3. To estimate Safety Surrogate Measures (SSM) from CV trajectory data for incident detection purposes.

1.3. Research questions

This thesis aims to integrate information from CVs data into practical and effective traffic analytical metrics that help in detecting incidents, thereby enhancing its anticipated operational capabilities. To do so this thesis aimed to answer the following questions:

1. How can CVs help collect traffic operation data that is not captured by location-limited detectors for operation conditions reflecting and occurring well in advance of the downstream intersection vicinity?
2. How can CVs generated traffic data be utilized for traffic state characterization especially when an incident occurs on the corridor?
3. Can safety-related metrics have estimated from CV data help in detecting arterial corridor incidents?

1.4. Scope of study

To address the research questions presented in section 1.3, a simulation study was performed on a single four-intersection signalized arterial corridor in downtown Cleveland. The CV trajectory collected from the simulation was used to estimate changes in speed and acceleration, split failure, Arrival on Green (AOG), Arrival on Red (AOR) and platoon ratios. Additionally, two safety-related metrics are incorporated, the Time To Collision (TTC), and Deceleration to Avoid a Crash (DAC), to explain the impact of the vehicle crash incident. The major assumption in this study is that majority (90%) of the simulated vehicles have connectivity capabilities and only 10% are non-connected vehicles.

1.5. Study method

To be able to define an incident scenario (vehicle crash), as well as define the response of the vehicles impacted by the incident in a CV environment, this study uses a microsimulation model developed in a microscopic urban mobility simulator, SUMO (Krajzewicz et al., 2002) coupled with OMNet++ and Veins frameworks for vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) communication. A vehicle crash is induced in the network for CVs to detect the vehicle crash, then an algorithm is developed for CVs to disseminate the traffic flow data to other vehicles on the road and the RSU. Following the vehicle crash data dissemination, another algorithm is developed to make the vehicles that received the information slow down or stop for safety in response to the vehicle crash. Consequently, vehicle trajectory data before and after the crash is extracted from the simulation for further analysis and development of the performance measures.

1.6. Study contribution

The primary addition of this work to the body of literature is an enhanced description of how a signalized arterial corridor approach performance may be affected spatially and temporally by an incident. The trajectory analytics framework uses SSMs to describe a real-time incident to determine how reliably and to what extent data from CVs may be used. Although the current state of practice does offer useful metrics to support traffic management centers in responding to incidents, the means of data collection is still lacking. Not all traffic flow data is captured along the entire corridor, only data within the vicinity of an intersection is captured.

To do this, this study develops a mechanism for evaluating service quality. at a corridor and intersection approach level by introducing a composite CV trajectory diagram and cross-referencing it with other qualitative and quantitative metrics that can characterize the entire arterial corridor. The quantitative and qualitative performance assessment method proposed will formulate a decision support framework for thorough and long-term performance analysis and decision-making. The qualitative component of the performance assessment framework i.e., visualizing relevant signal performance data in an easy-to-understand format is critical when identifying the root cause of any observed interruptions or substandard performance levels. Consisting of a set of metrics and graphical representations for larger datasets, the proposed methodology will enable quick responsive management and control of signalized arterial corridors especially if an impactful incident has occurred.

The metrics provide higher precision in determining the incident's location and time in real-time, making any necessary signal timing modifications, and suggesting other alternative routes. The metrics will provide a sufficient rationale for traffic management centers to dispatch necessary responders (fire, police, medical personnel, etc.) to a precise location of the incident and at the right time to address perceived incidents on the corridor.

1.7. Thesis organization

Chapter I introduces the thesis background, study objectives, study method used, potential study benefits and motivation of this study. Chapter II presents the literature review of the ATSPMs in partially and/or fully connected signal systems on detector-based data and in a CV environment, revising past research in which the applications were developed. Chapter III introduces a methodological conceptual framework for simulating an incident (vehicle crash) and develops ATSPMs for CV trajectory data in explaining the incident, which will serve as a road map for methods and applications to be introduced in later chapters. Chapter IV introduces the trajectory analytics framework by defining a condition-responsive trajectory-based set of measures. The emphasis is on the newly developed, composite, time-space-signal measure of effectiveness, which relates to the utilization of green time and space, platoon ratios, etc. Chapter V presents an innovative visualization tool that superimposes CV trajectory data with SSMs in explaining the vehicle crash, as well as a qualitative and quantitative representation/display of SSMs performance measures. Chapter VI provides concluding remarks and proposes a direction for future studies.

CHAPTER II

LITERATURE REVIEW

This section provides an overview of traffic signal performance measures, different data sources used to develop signal performance measures and current implementation in developing performance measures. The purpose of this literature review is to have a comprehensive understanding of current practices and identify a gap in new methodologies.

2.1. Automated Traffic Signal Performance Measures (ATSPMs)

ATSPMs are metrics that automatically process data to provide an insightful assessment of a given traffic signal in the form of performance measures that rely on traffic signal controller high-resolution data (detector data). The performance of signalized intersections may be measured and displayed by traffic management centers using ATSPM at a reasonable cost. ATSPM enables traffic control centers to promptly identify maintenance issues that impact traffic flow and proactively adjust traffic signal timing. These metrics often include several data visualization reports that may be used to assess how well traffic moves along corridors and to locate wasted green time that can be allocated to other intersecting movements. Additionally, traffic management centers are informed of vehicle and pedestrian detector issues via ATSPM visualizations, saving staff time while doing maintenance. To assess the efficacy of signal timing alterations, system data of vehicle quantities, delays, and speeds are also employed. The TMC staff can make decisions more quickly and more efficiently by using ATSPM technologies. Metrics for the ATSPM include arrivals on red, coordination diagram, pedestrian delay, phase termination, preemption information, split failure, split monitor, and turning movement counts.

The Highway Capacity Manual (HCM) states that the LOS, which is based on control delay, is the typical metric used to evaluate intersection performance. Operational performance measures have been created to assist agencies in adjusting time as more states have included ATSPMs into their regular procedures. Applications include, but are not limited to, tracking phase termination status by time-of-day (TOD), which is important for professionals to assess if certain motions at an intersection require extra split time or if the crossing is full.

The research by Freije et al. (2014), which developed a method to quantify split failures using stop bar detection, is one of the earlier studies on ATSPMs. Wu & Liu (2014) used detector-based data to quantify arrival type, which provides qualitative information on progression. C. Day et al. (2014) developed a graphic called Purdue Coordination Diagram, which provides insight into the level of progression, cycle length and split times at an intersection by plotting vehicle arrivals and phase changes on a time in cycle vs. TOD graph. Wu & Liu (2014) created a shockwave-based queue estimation model using setback detector data to identify whether an approach is overloaded. According to Emtenan & Day (2020), detectors with fixed setbacks that are closer to the stop bar frequently underestimate the number of stops brought on by queues. The accuracy of predicting the number of stops rose along with the detector setback.

2.1.1. The current state of the application of ATSPMs

The usage of ATSPMs has started to become institutionalized in several US jurisdictions. With additional deployments and pilots taking place in at least 44 localities, Indiana, Wichita, Georgia, and Utah are among the first states to deploy ATSPMs. To facilitate easy implementation, the Utah Department of Transportation (UDOT) has created open-source ATSPM software that can be enhanced by the private sector or government agencies (Office of Research-FHWA, 2019). The UDOT and the Georgia Department of Transportation (GDOT) collaborated to take use of their ATSPM deployment expertise. The GDOT ATSPM implementation uses open-source software to make data and analysis easily accessible and adheres to the same fundamental design as that in Utah. The ATSPM system's data collection enables GDOT to manage the signal operation and maintenance (GDOT, 2022). For data reporting and storage, the Pennsylvania Department of Transportation (PennDOT) makes use of open-source software created by UDOT. Additionally, PennDOT gathers and stores high-resolution operational data with tenth-of-a-second timestamps using a mix of contemporary signal controllers and vehicle detection systems. Each signal's contact with a central computer server result in the storage and archiving of data for analysis and reporting (PennDOT, 2022).

2.2. Current CV trajectory probe data metrics

Recently, performance measurements from point-based probe GPS sources have been made available through smartphone apps, fleet telematics, and CVs. Most commercial service providers produce this kind of "trajectory" or "probe" data, which comprises timestamp, latitude, longitude, speed, direction, and a specific trip identification. It eliminates the need to construct and maintain physical detection systems on the road, which is a major advantage of utilizing this data (Carranza, 2021). Studies have shown that using trajectory data, measures including travel time, delay, arrivals on the green, and queue length may be generated (Kidando et al., 2020). Several of the studies are summarized in the sections that follow.

2.2.1. Control delay estimation from probe data

Intersection control delay is a key performance indicator used to measure the quality of service provided at intersections. It is interpreted as a proxy for the quality with which intersection capacity is used, as well as for the levels of fuel consumption and environmental impacts caused by vehicles (H. Wang et al., 2016, N. Novat et al., 2022). Huang et al. (2013) suggested a formula for calculating control delay at signalized intersections using probe data from vehicle trajectories. However, the formula's parameters need to be calibrated for each intersection, so a location-specific pre-analysis must be performed before delay calculations can be performed. Waddell et al. (2020) developed a formula for estimating delay at an intersection using CV trajectories. First, the time it would take a vehicle to pass through an intersection without being stopped or delayed is determined by the speed of the vehicle at the start of its approach. Delay is then determined by subtracting the actual travel time from the ideal travel time without being stopped or delayed.

2.2.2. Travel time estimation from probe data

Travel time is a measure of the length of time necessary for a vehicle to move from one place to another. Li et al. (2019) developed a method to calculate composite travel times on a corridor from trip trajectory data. Trajectories that travel different sections of the corridor are combined to increase the number of start-to-finish trip occurrences. Zhang et al. (2019) utilized vehicle trajectory data and a Trip Information Maximizing Generative Adversarial Network to calculate travel time distributions.

2.2.3. *Arrivals on green (AOG) estimation from probe data*

This is the number of vehicles that were able to progress through the intersection when the signal indication was green. Waddell et al. (2020) used vehicles' computed delay at an intersection to determine if they were stopped while approaching to compute AOG. Vehicles with delays of at least 5 seconds that still arrived during the green phase of the cycle were filtered out.

Another method proposed by Waddellet al. (2020) was to calculate AOG based on the percentage of vehicles that stopped at an intersection. Stopped percentages were calculated by dividing the number of vehicles with speeds under 5 mph for 2 seconds or more, 19 over the total number of vehicles. These two methods produced AOG values 7.2 and 2.5 percent lower than ATSPM AOG, respectively.

Moreover, C. M. Day & Bullock (2016) used CV data to calculate vehicle arrivals at virtual detectors upstream of an intersection, yielding arrival profiles. At the 90% confidence level, a statistically significant goodness-of-fit was found between the simulated arrivals and the actual measurements. After that, the AOG was computed using the green phase times obtained from the controller event logs.

2.2.4. *Queue length estimation from probe data*

This is the number of vehicles waiting in a queue to be served. Hao et al. (2019) obtained queue length from vehicle travel data. First, the stopping distribution of the vehicles was analyzed to determine the penetration rate of the available data. Queue length was then determined by multiplying the number of vehicle trajectories by the penetration rate. Cetin (2012) introduced a technique for estimating queue length at signalized intersections, using shock wave theory and spatial-temporal data on when vehicles enter the end of the queue.

2.3. Research gap

Although there has been more interest in developing new crowd-sourced based traffic signal performance measures, this review warrants an opportunity for more metrics to be produced from CV trajectory data. Previous research has produced a variety of graphics that provide traffic operators with information on the performance of a traffic signal. Nonetheless, these graphics typically only provide information on one or two traffic signal metrics. This necessitates the examination of various graphics to gain a comprehensive understanding of traffic signal operation, especially during saturated conditions, or when there is an incident on the corridor, such as a vehicle crash, work zone, etc.

Chapter IV offers visuals with information on progression quality, traffic delay, arrivals on green, split failures and platoon ratios. Furthermore, the majority of proposed performance measures are centered on an incident occurring upstream of the intersection. The causes of the calculated poor performance are then attributed to the downstream traffic signal. Immediately following, chapter V introduces metrics based on SSMs that help in explaining poor downstream intersection performance due to simulated traffic incident (vehicle crash).

CHAPTER III

METHODOLOGY

This section presents the study's methodology in depth. Discussions include the study site, calibration and validation of data input, and microscopic simulation modeling.

3.1. Study location

To evaluate the suggested methods for simulation model calibration, a real-world arterial signalized section was modeled in SUMO. The simulation model was developed from a corridor with four signalized major intersections located in downtown Cleveland, Ohio, as shown in Figure 1. The four intersections are Carnegie Ave. and East 30th St., Carnegie Ave. and East 36th St., Carnegie Ave. and East 40th St. and Carnegie Ave. and East 46th St., all adjacent to the Cleveland State University and the Wolstein Center for sports and live events.

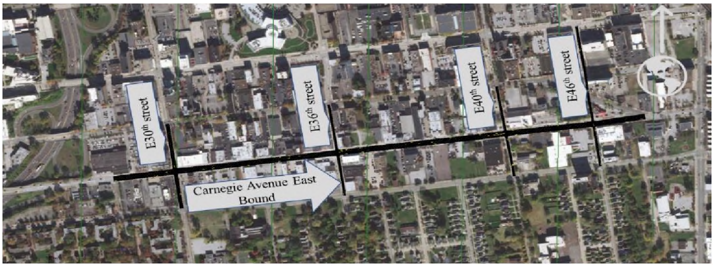


Figure 1. Study location

3.2. Simulation framework

The framework was developed in Veins, SUMO and OMNeT++ 5. The architecture of the framework for communication between the components is shown in Figure 2. The framework is inspired by a study from Sayed (2021), who proposed the connectivity algorithm for CV simulation in Veins, SUMO and OMNeT++ 5. This study builds from Sayed's study (2021) by simulating an incident and expanding the method to collect more traffic flow parameters that are used to produce signal performance measures. The framework consists of a Traffic Server (TS), a Roadside Unit (RSU), and linked cars (CVs). In this approach, RSU is notified via CVs of both emergency and non-emergency situations. CVs are unable to directly reach the main Traffic Server (TS).

RSU determines whether a request is for an emergency occurrence or not after receiving data and requests from the CV. The RSU quickly executes its own Safety Surrogate Measure (SSM) algorithm and delivers the required warning signals to the CV If the request is urgent, RSU sends the notification to the primary TS in the event of non-emergency circumstances. The TS responds to the RSU's message for forwarding and provides the appropriate details. The RSU transmits the CV's reaction after receiving it from the TS. The next section has a thorough overview of the key components.

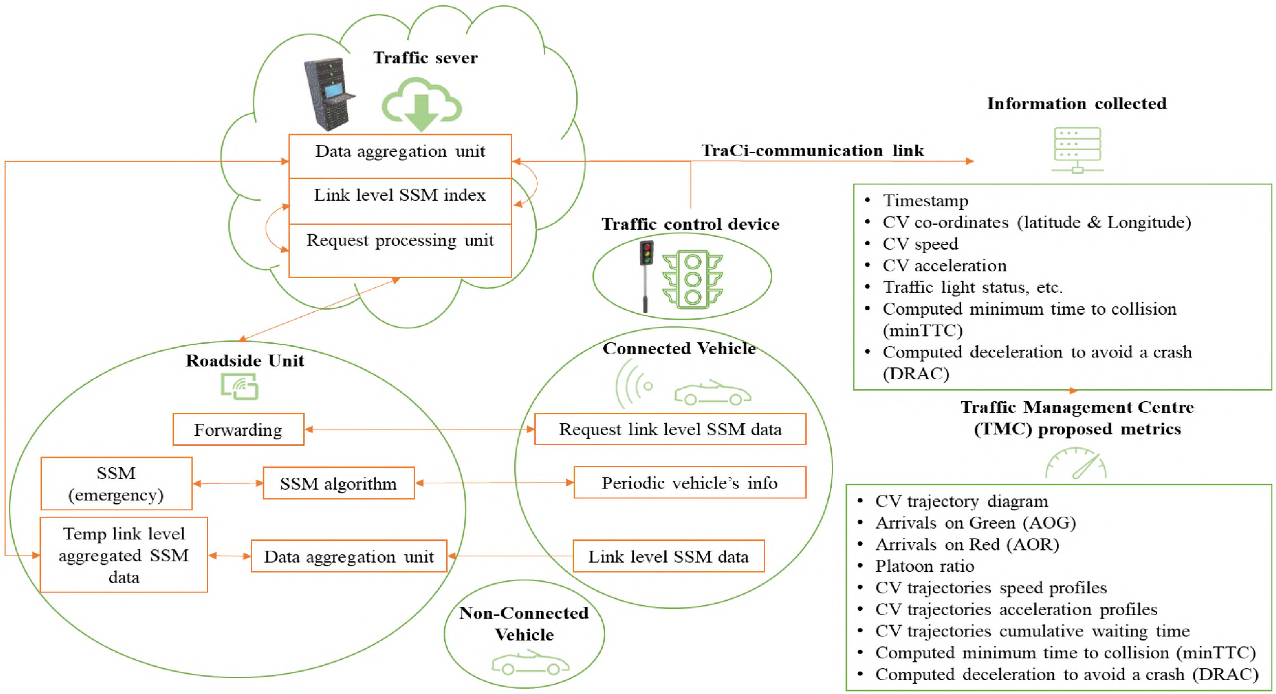


Figure 2. Study framework and V2X communication flow

3.3. Connected Vehicle (CV)

In this design, a CV is a vehicle with an RSU-compatible onboard communication device. A CV is presumed to have basic vision or LIDAR technology that can identify and gauge the foe vehicle's distance. Depending on the rate of distance change, CV determines the speed of the front vehicle. The speed and distance of the foe vehicle were determined using Equation 1.

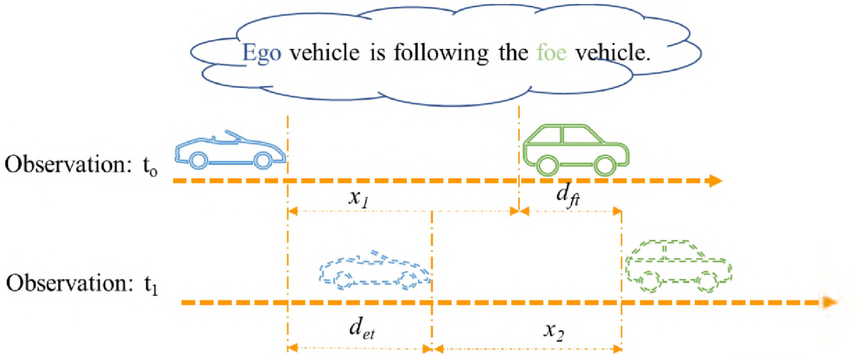


Figure 3. Foe vehicle speed estimation by CV.

Change in time, $\Delta_t = t_1 - t_0$

Ego vehicle drive-distance, $d_{et} = (v_{et_0}) \times t + ({}^{1}/{}_{2} \times a_{et_0} \times t^2)$ Equation 2

Foe speed at time t, $v_{ft} = {}^{d_{et}}/{}_{t}$

In order to provide the SSM to the RSU within its communication range, the CV estimates the speed of the opposing vehicle for each time stamp.

An NCV is defined in this framework as a vehicle that does not have any communication equipment capable of communicating via any communication method. As a result, the NCV cannot be managed using this framework. The activity of the CV, on the other hand, will have an effect on the state of an NCV. The arriving NCV will slow down or stop, for instance, if a CV stops in a lane.

A CV module was constructed, consisting of csuCV.cc, csuCV.h, and csuCV.NED files, to manage CVs via the TraCi API of SUMO and broadcast a signal in real-time to other CV, RSU, and TS. Signal transmission is automated. The module's main features are the "handlePositionUpdate" and "onWSA" functions. For each timestamp, the "handlePositionUpdate" function updates every CV in the network. This function implements all of the SSM algorithms as well as the data transfer messages from a CV. The "onWSA" features are used to validate incoming messages from other CVs, RSUs, and TSs. It will behave based on the message type after receiving it. Each message contains distinct characteristics that are utilized to distinguish across message types. APPENDIX A presents primary algorithm specified in "handlePositionUpdate."

3.4. Roadside Unit (RSU)

The roadside unit (RSU) in this study is a communication and data processing device that can exchange information directly with CVs and TSs within its communication range. It consists of three functional units:

1. Unit for data processing and storing.

Less severe incident CV data is processed by the data processing unit, which also momentarily stores the processed data before sending it to the TS. It erases its temporary data after transferring data to the TS.

2. Incident warning messages sending unit based on SSM index.

The unit that implements the SSM algorithm and sends alert messages applies the SSM algorithms to the kinematics of the CV that have been received for each time step, and it then transmits the warning message for upcoming conflicts to the CVs that are nearer those conflicts.

3. Message transmission unit

The RSU in the message forwarding unit sends the TS the CV's request for non-emergency incidents, and similarly, it transmits the CV's reaction from the TS. No messages in this unit are encrypted by the RSU. This unit's primary responsibility is to send the message to the proper node right away (CV).

For an RSU to receive messages from the TS and CVs to issue a warning signal to the CVs, and send data to the TS, a module called "csuRSU" needs to be created. It likewise contains of "csuRSU.cc," "csuRSU.h," and "csuRSU.NED" files, much like a CV's module does. RSU is a stationary device that only activates in response to a signal or a programmed event, such as transferring data to TS at regular intervals. The "onWSM" function defines the algorithms for data processing (saving the SSM data) and warning message (sending an incident warning message to CVs).

3.5. Traffic Server (TS)

The primary data processing serving as a proxy for a traffic management center, with advanced computational ability and significant storage, is the traffic server (TS). TS and RSU have a direct communication link for information exchange. It has a request processing unit and an SSM data aggregation unit. The SSM data aggregation unit develops an aggregated SSM index and saves it in a permanent database after collecting data at predetermined intervals from all RSUs within its communication range.

The "onWSM" function developed a separate module for a TS named "TS" to collect data from an RSU and communicate corridor segment level SSM data to a CV through an RSU. The files "csuTS.cc," "csuTS.h," and "csuTS.NED" are included in this module.

3.6. Simulation setup

This section presents the process of the simulation parameters via simulation from all software (SUMO, Omnet++ and Veins), which explains the simulation data input to the model, the connectivity and communication between software, as well as the simulation calibration and validation steps.

3.6.1. Simulation setup in SUMO

The simulated real-world traffic network is the experiment study location presented in Figure 1, which was obtained from OpenStreetMap. SUMO has an integrated module known as OSMWebWizard that scraps data from OpenStreetMap. Utilizing OSMWebWizard has the advantage that the majority of network characteristics, including lane information, speed limits, traffic signals, etc., are also taken directly from OpenStreetMap.

To be able to use with SUMO, the OSM file was then transformed into a net.xml file. The.rou.xml, poly.xml,.sumo.config, and launched.xml files from.net.xml files are additional files that are also necessary for simulation in SUMO. The routing file, or.rou.xml, contains the vehicle's profiles, including its travel trajectories. Physical infrastructure, including structures and natural features, is provided in the.poly.xml file. For OMNeT++ and Veins to provide the network blockage effect, this file is required. The sumo.config file is the simulation file, and it starts the simulation, builds typologies for all the files, and sets the simulation settings. The SUMO simulation is executed and controlled by the launched.xml file in the Veins. The Krauss car-following model in SUMO was utilized in this experimental investigation.

3.6.2. *Simulation setup in Veins and OMNeT++ and*

The required SUMO files are made, and then the simulation settings for OMNeT++ Table 1 are produced. Every one-second simulation step, the built framework updates the state of the network and traffic simulations in OMNeT++ and SUMO, respectively. The SUMO configuration file must provide a total simulation time of 3600 seconds. The obstacle module, which creates a stumbling barrier in packet loss and transmission, is activated. Periodic messages are not started in the car module so that CVs couldn't generate needless messages.

The CV module is in charge of controlling periodic messages. Each specified number of received messages triggers the RSU to transmit a temporary aggregated SSM to the TS (for instance, relay SSM messages to TS when there are 10 messages received, and then reset the database.). Only when the RSU makes a request does the TS module react. Table 1 lists the simulation parameters (CV, RSU, NIC, and RSU) for each of the modules utilized in OMNeT++. Settings marked with an asterisk indicate the simulation's default values.

Table 1. Simulation parameters in OMNeT++

Module	**Description of parameters**	**Value**
General parameters for Simulation	Time for simulation	3600 s
	Module for obstacles	active
	Simulation time step update interval	1s
	*TraCi Communication port	9999
CV module	*Antenna Position above the ground	3 m
	*Send beacon periodically	active
	*Beacon sending interval	10 s
RSU Module	*Antenna Position above the ground	3 m
	*Send beacon periodically	active
	*Beacon sending interval	10 s
TS Module	*Antenna Position above the ground	3 m
	*Send beacon periodically	inactive
	*Maximum communication boundary (meter)	300 m
	*Transmission power	20 mW
	*Bitrate transfer	6 Mbps
	*Minimum power level	-110 dBm

* Default parameter values

3.7. SUMO microscopic model building, calibration and validation

The simulation must initially be built by entering fundamental simulation data, such as network layout, trip demand, vehicle characteristics, and traffic control systems (traffic signal timing data). These inputs have a direct impact on how well the micro-simulation models function, hence it is important to evaluate their reliability while calibrating and validating the models.

The calibration of driving behavior models using real-world data is the next phase. A model must be calibrated by having its outputs compared to observable data and then changing model parameters until the results are within an acceptable error range. One of the driving behavior models that govern how cars move through traffic and must be customized for a specific location is car-following (or acceleration).

The final step is to modify the calibration phase settings to take the effects of network-level congestion into consideration. The local characteristics must be represented in the driving behavior models, and area validation must be done as well (intersection-by-intersection).

Model calibration is usually followed by an iterative procedure called model validation. To determine if parameters obtained from calibration are reliable, model validation is necessesary, it is typically carried out using a separate data set of the broader region inside the modeling network. Model validation is the last step to determine whether each component accurately replicates observed trip characteristics and whether the model's overall performance is reasonable.

3.7.1. Simulation building and input data

Traffic volumes, signal timings, vehicle trajectory data, and geometry data were all used as simulation inputs. The StreetLight data provider offered traffic volume information as intersection turning movement counts (TMCs). APPENDIX E Geometric information constituting network data including the lane widths, turning radius and number of lanes, were extracted from Open Street map (OSM) through SUMO's OSM web wizard tool (a python script used to scrap and import open Street map data to SUMO simulation platform). The intersections obtained from the OSM web wizard also come with randomized traffic volume data and signal timing data. Travel time data from StreetLight was used for general calibration and validation process of the model. Intersection lights signal timing data was manually collected on-site.

3.7.1.1. Real-time time calibration data from StreetLight

Traditionally, one of the most important and common sources of data for quantifying travel behavior used for simulation model calibration and validation has been site-collected trip surveys. Discharge and approach headways, travel time and intersection turning movement counts (TMCs) are common traffic metrics collected on-site.

However, alternative means for retrieving travel data, such as Bluetooth media access control (MAC) address matching, have recently emerged. Although not as detailed as trip surveys, data from these alternative technologies allows for the cost-effective collection of a considerably larger sample. Moreover, tracking individual vehicle trips via smartphones has now become a common data source, as opposed to matching unique identifiers (e.g., MAC addresses) between two stations. Hand used devices (e.g., smartphones) with tracking capacity i.e global positioning services (GPS) allow the collection of high-resolution location data to infer trip time, trip length, route and possible travel mode. To take advantage of these data sources, this study replicates the task of collecting data from the site by using crowd-sourced speed, travel time and TMCs data from StreetLight - an application that provides valid estimates of different vehicle trip metrics. Streetlight uses extensive geospatial data generated by mobile phones to calculate ODs, trip purposes, travel times, and TMCs. Data obtained from Streetlight (Travel speed, Travel time and TMCs) was used to calibrate and validate the car following model.

3.7.2. *Calibration through an optimization algorithm*

The calibration of the traffic simulation model is the stage of transportation system modeling intended to define the values of the model's parameters to have the least amount of variance between the observed traffic data and those anticipated by the model. The following optimization framework may be used to formulate this.:

$$\min_{\beta,\gamma} f\left(O^{obs}, O^{sim}\right)$$

$Constrainted\ to:$

$$\underset{\beta.i}{l} \leq \beta_i \leq \underset{\beta.i}{u} = 1 \dots O \quad such\ that \quad \beta_i \leq \beta_j \quad i \neq j \qquad \text{Equation 3}$$

Where β_i is a vector of the model parameters that are associated with m various simulation elements such as different road types and vehicle classes etc. The intention or objective function is to measure the distance between the simulation and observed traffic measurements O^{obs} and O^{sim} such that $\underset{\beta.i}{l}$ and $\underset{\beta.i}{u}$ are the lower and upper bounds of the calibration parameters. O^{sim}= S(β_i , …, β_m), in which S(β_i , …, β_m) is the micro-simulation model.

The Root Mean Square Error (RMSE) function serves as the objective function. (Equation 4), This represents the residuals' standard deviation also known as prediction errors. Residuals are a measure of how far apart the observed and simulated trip durations are from the regression line data points, and RMSE is a measure of how evenly distributed these residuals are. What is the difference between the network's observed travel time and the travel time that results from optimizing the values of these parameters?

$$RMSE = \frac{1}{N}\sum_1^N \sqrt{(x_i - y_i)^2} \qquad \text{Equation 5}$$

Σ = summation, $(x_i - y_i)^2$= differences of observed and simulated travel time, squared, N = sample size.

The RMSE objective function was selected since it is frequently used in calibration studies of traffic simulators and provides an average error in absolute terms without taking into account whether there are systematic variations. (Hollander and Liu, 2008).

3.7.3. Constrained Optimization By Linear Approximation (COBYLA) Method

The COBYLA algorithm was used to find optimal car-following model parameters. When there are no derivatives, Powell created COBYLA in 1994 as an iterative approach for nonlinearly restricted optimization computations. By interpolating at the vertices of a simplex, each iteration creates linear approximations to the goal and constraint functions, and a trust zone bound limits each change to the variables. When there are no derivatives, Powell created COBYLA in 1994 as an iterative approach for nonlinearly restricted optimization computations. By interpolating at the vertices of a simplex, each iteration creates linear approximations to the goal and constraint functions, and a trust zone bound limits each change to the variables. When there are no derivatives, Powell created COBYLA in 1994 as an iterative approach for nonlinearly restricted optimization computations. By interpolating at the vertices of a simplex, each iteration creates linear approximations to the goal and constraint functions, and a trust zone bound limits each change to the variables.

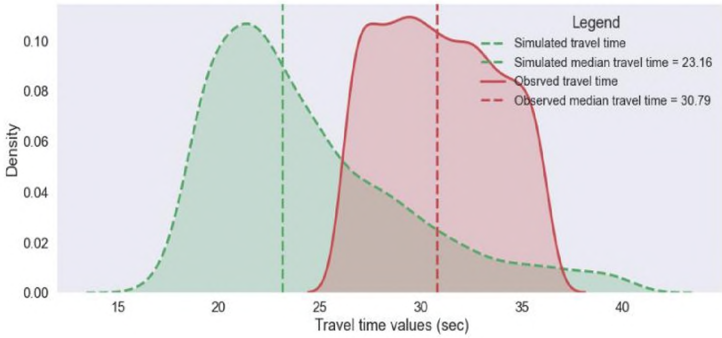
A set of $n+1$ values of the function is maintained by the algorithm in parameter space with an approximate solution x_i, and a radius p_i. A linear approximation on the n+1 points is used to estimate the objective function and constraint functions, and their values are equal. By constraining the linear approximations of the constraint functions to be non-negative, this results in a linear program that can be solved. However, since the linear approximations are probably only accurate close to the existing simplex, the additional criterion that the solution, will become $x_i + 1$, must be within p_i from x_i; p_i only decreases never increase. It is quite simple to convert it to a global optimization technique by repeating the process beginning from randomly selected points. With this strategy, the initial deterministic approach gains stochastic features. The SciPy community's implementation (Jones et al., 2001) was utilized. After implementing the calibration algorithm, the calibrated parameters are presented in Table 2 with reference from the default value and the range of the allowable values of the specific parameters.

Table 2. Calibrated parameters

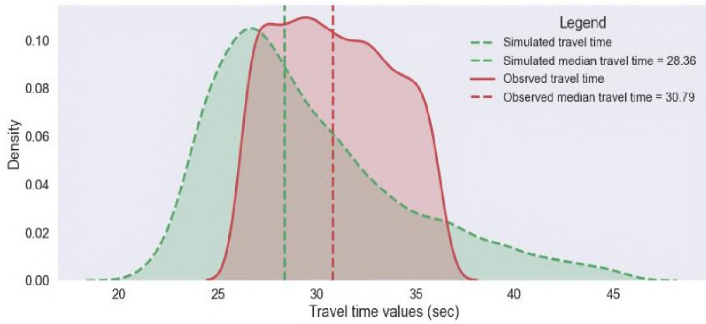
Attribute	**Default (seconds)**	**Range**	**Optimal value (seconds)**	**Description**
Minimum gap	2.5	>= 0	2.5	The minimum gap when standing (m)
Acceleration	1.5	>= 0	1.505	The acceleration ability of vehicles (in m/s^2)
Deceleration	4.5	>= 0	2.715	The deceleration ability of vehicles (in m/s^2)
Emergency deceleration	4.5	>= deceleration	4.65	The maximum deceleration ability of vehicles in case of emergency (in m/s^2)
Sigma	0.5	[0,1]	0.1	The driver imperfection 0 being perfect driving
Tau	1	>= 0	1.1	The driver's desired minimum time headway.

3.8. Simulation validation with travel time comparison

The calibrated model was used to estimate the travel times along the Carnegie Ave. and E 30th St., and Carnegie Ave. and E 36th St., in the network and the results are summarized in Figure 4 (a) and (b). Through floating vehicle measurements inside the flow of traffic in one direction, trip time observations were made. The travel distribution and median values before and after model calibration were used for comparison threshold and as a means for simulation validation. The median travel time along the segment before model calibration (23.16 sec) is less than the median travel time obtained from StreetLight data (30.79 sec). The median of travel after model calibration (28.36 sec) was observed to be much closer to that obtained from filed StreetLight data (30.79 sec).



(a) Before calibration



(b) After calibration

Figure 4. Plot distribution of (a) default simulation travel times and (b) calibrated simulation travel times, both compared with field travel times

CHAPTER IV

CV TRAJECTORY-BASED PERFORMANCE MEASURES

This section describes how to use CV vehicle trajectory data from the simulation to determine the arrival on green (AOG), split failures and platoon ratio performance measures, with a special focus on detecting and explaining upstream corridor incidents. The section also summarizes the practical application and uses of the proposed performance measures.

4.1. Signal-coded CV trajectory diagram

This study proposes the use of a CV trajectory time-space diagram, which is signal color-coded. This graphical representation helps determine traffic progression along the corridor. Figure 5 shows the color-coded time-space diagram indicating a series of trajectories of vehicles traveling eastbound pm Carnegie Ave. (filtered to one lane of through traffic only), and traffic signal status for the first 15 minutes (15:30 – 15:45) of the peak hour (15:30 – 16:30). When through traffic or approach spillback is impeding traffic, it is possible to see and interpret the performance, provided that the trajectories from intersecting approaches are also considered.

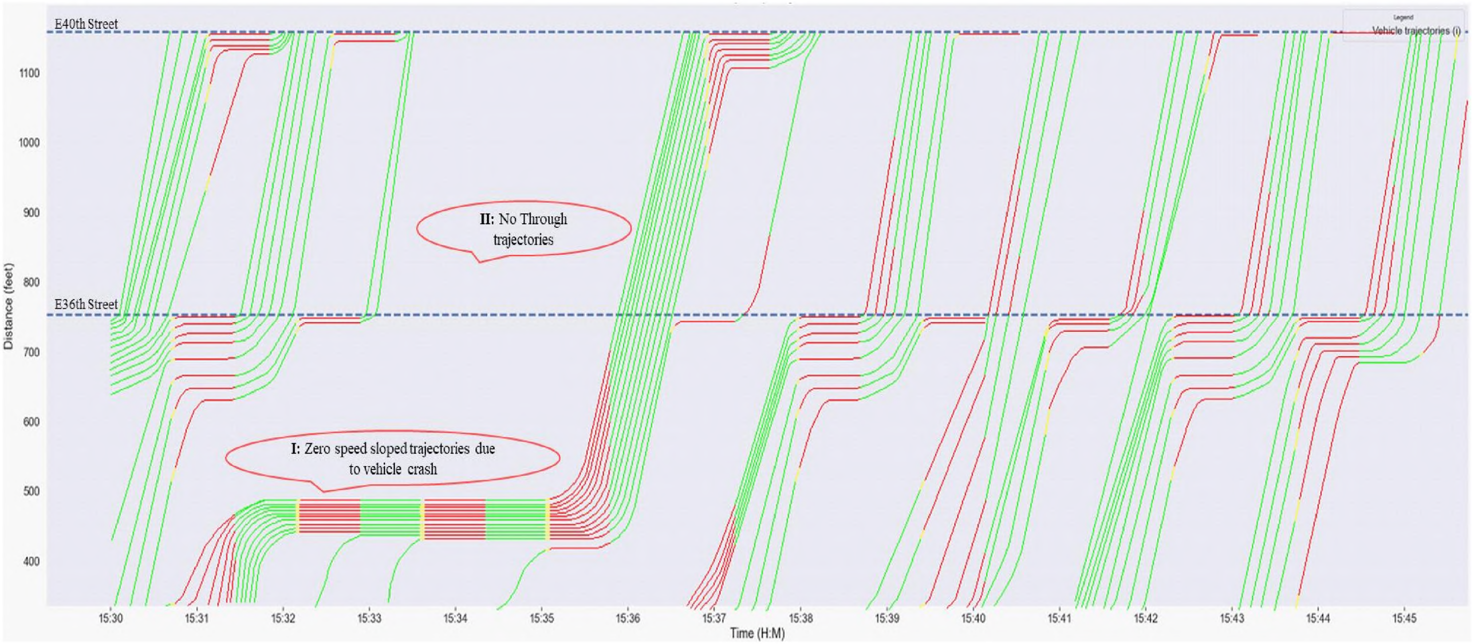


Figure 5. Signal-coded CV trajectory diagram

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A crash was simulated and defined to last for 4 minutes. As shown in Figure 5, callout I, trajectories that experienced disrupted progression as a result of a crash occurring have zero sloped (zero-speed) trajectories at a mid-block area (crash location). Furthermore, the impact of the incident on the preceding corridor section can be seen on the corridor section between E40th and E36th Street as no trajectories are seen during that time frame (callout II).

Although signal status may contribute to CVs stopped time and delay the adverse impact is when there is excessive delay and longer queues such as due to an incident, and the vehicles are not moving even though the light is green. It's crucial to note that, unlike in a conventional time-space diagram, "available green time" refers to the green part of the trajectory, which varies depending on the vehicle, rather than the actual (effective) green length, which is the same for all vehicles. This visualization, when used at a more aggregate spatial or temporal level, can be used to assess how well a single vehicle utilized the available green time and space while operating under precise signal control and operational circumstances.

4.2. Signal performance-based measures

In general, motorists anticipate enough green progression time so that they can proceed through one cycle of synchronized signals and arrive within the green phase of a downstream intersection. They do not have to stop downstream of the signal thus unimpeded by downstream queues due to poor signal performance or an incident on the road.

In current practice, AOG and split failures are estimated using conventional detector-based data. However, it is difficult to determine the impact of upstream incidents using detector-based data because they are constrained to capture actuations within the vicinity of the downstream intersection. Using simulated CV trajectory data, these two operational performance metrics can be viewed holistically from the perspective of each CV trajectory. The objective was to establish a set of trajectory-based performance measures that characterize signal capacity utilization, quality of progression, and effectiveness through quantifiable parameters.

4.2.1. Arrivals on Green and Arrivals on Red

AOG highlights the proportion of vehicles that arrive at a signalized intersection during the green portion of the signal's cycle while the AOR metric is the number of vehicles that arrive in the red phase. These metrics also indicate the effectiveness of coordinated intersections. Low AOG values indicate poor progression of traffic between intersections along the corridor.

The simulation framework was designed to collect the status of the downstream signal at every simulation time step. The signal status was coupled with other CV trajectory data to compute the proportion of trajectories that were served during the allocated green time (The number of trajectories at the position of the stop bar when the signal indication was green). This approach is different from other studies including the recent study by Saldivar-Carranza et al. (2021). Saldivar-Carranza et al. (2021) estimated the AOG from probe data as a ratio of trajectories that had no stops during the approach and the total number of trajectories. While the assumption may be valid in estimating AOG, it may be difficult to infer trajectories that experienced split failures and whether the stop was due to the signal status or a mid-block incident. Therefore, coupling the arrivals metrics with actual signal status is essential, especially in explaining incidents from the perspective of signal performance measures. Qualitatively, trajectories that arrived on green or any other signal indication can be directly inferred from the CV trajectory diagram in Figure 7.

To quantify the impact of the vehicle crash using the AOG and AOR performance measures, the distribution of CV trajectory arrivals on the green and red signal indication on Carnegie Ave. eastbound through movement at the intersection on E 36th St. are presented in Figure 6. The plot represents percent AOG and percent AOR against time in 90-second cycle length bins. Since vehicles were prompted to stop as a result of the crash, no vehicles arrived at the intersection on E 36th St. from when the vehicle crash began to when it ended, hence the AOR and AOG percentages are both 0%.

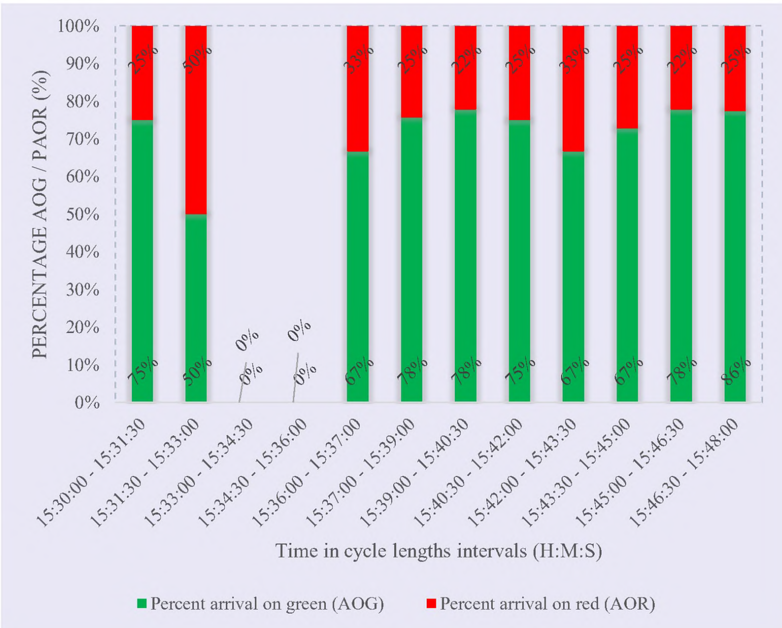

Figure 6. Distribution of CV trajectories AOG and AOR

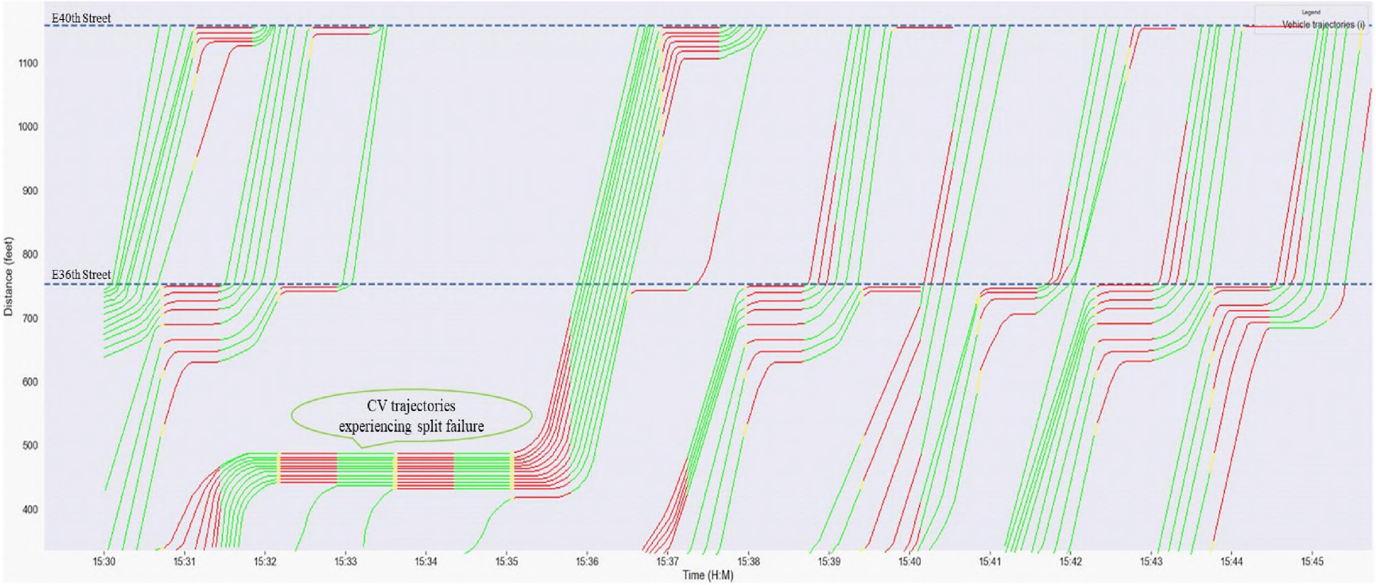

Figure 7. Signal-coded CV trajectory diagram indicating split failure

4.2.2. Split failure

When a traffic signal doesn't provide a certain movement of vehicles enough green time to cross the intersection, it results in a split failure, which makes them wait more than one cycle length. Split failures on an approach indicate that the approach is operating beyond its capacity. Agencies must be able to reallocate green time to improve system operation by being able to track the spatial-temporal occurrences of the split failures.

When a CV trajectory has lengthy stops and fails to advance as it approaches an intersection, it can be classified as having undergone a split failure using the CV trajectory diagram. The CV trajectory diagram is shown in

Figure 7, for Carnegie Ave. eastbound through movement at the intersection on E 36^{th} St., is presented, CVs experiencing split failure can be seen with trajectory signal coded green, as they failed to progress to the intersection due to the incident.

4.2.3. Approach platoon ratio

To measure the effectiveness of progression on a signalized corridor approach, the platoon ratio, abbreviated as R_p, is utilized. The platoon ratio is the proportion of the percentage of the overall cycle's green interval that is made up of CV trajectories that arrive during the green phase. This is given by.

$$R_p = P * \frac{C}{g} \qquad \text{Equation 6}$$

where P= proportion of all CV trajectories during the green time, C = cycle length, and g = effective green time.

Platoon ratios can be between 0.5 and 2.0. It is employed in the estimation of approach capacity and delays. There are six different arrival categories, with 1 being the worst platoon situation and 6 being the best platoon condition. The progression quality and platoon ratio are close approximations. For instance, the following correlation between platoon ratio and the arrival has been proposed by (HCM, 2022) which is as shown in Table 3. In this instance, as shown in Figure 8, the platoon ratio is calculated as the ratio of trajectories arriving during the green phase to the fraction of the overall cycle's green period.

Table 3. Relationship between arrival type and platoon ratio

Arrival type	**Range of platoon ratio R_p**	**Default value (R_p)**	**Progression quality**
1	$\leq$ 0.50	0.333	Very poor
2	> 0.50 - 0.85	0.667	Unfavorable
3	> 0.85 - 1.15	1	Random arrivals
4	> 1.15 - 1.50	1.333	Favorable
5	> 1.5 - 2.00	1.667	Highly favorable
6	> 2	2	Exceptional

Table 3's arrival type identification can be used to determine the platoon ratio. The arrival type has values between 1 and 6. The HCM gives the following descriptions of each sort of arrival.

Arrival type 1 is distinguished by a dense platoon that makes up more than 80% of the movement group's volume and arrives at the start of the red period.

A dense platoon arriving in the center of the red period or a scattered platoon with 40 to 80 percent of the movement group's volume arriving throughout the red interval are both examples of arrival type 2.

Arrival type 3 designates any of two circumstances. A platoon comprising less than 40% of the movement group volume arrives partially during the red interval and partially during the green interval if the signals enclosing the segment are synchronized. This arrival type is characterized by platoons arriving at the subject junction at various moments in time, making arrivals appear to be random if the signals are not synchronized.

A platoon that is either scattered and contains 40 to 80 percent of the mobility group volume or one that is fairly packed and arrives in the middle of the green period defines arrival type 4. This sort of arrival is frequently connected to average-length segments that advance well in the intended direction of travel.

A dense platoon comprising more than 80% of the movement group volume arrives at the beginning of the green interval, which is the hallmark of arrival type 5.

Figure 8 presents the distribution of percentage AOG, percentage AOR, and platoon ratios of the CV trajectories against time in 90-sec intervals for Carnegie Avenue and E36th Street intersections. The impact of the incident can be seen as the values for percentage AOG, percentage AOR, and platoon ratios are zero.

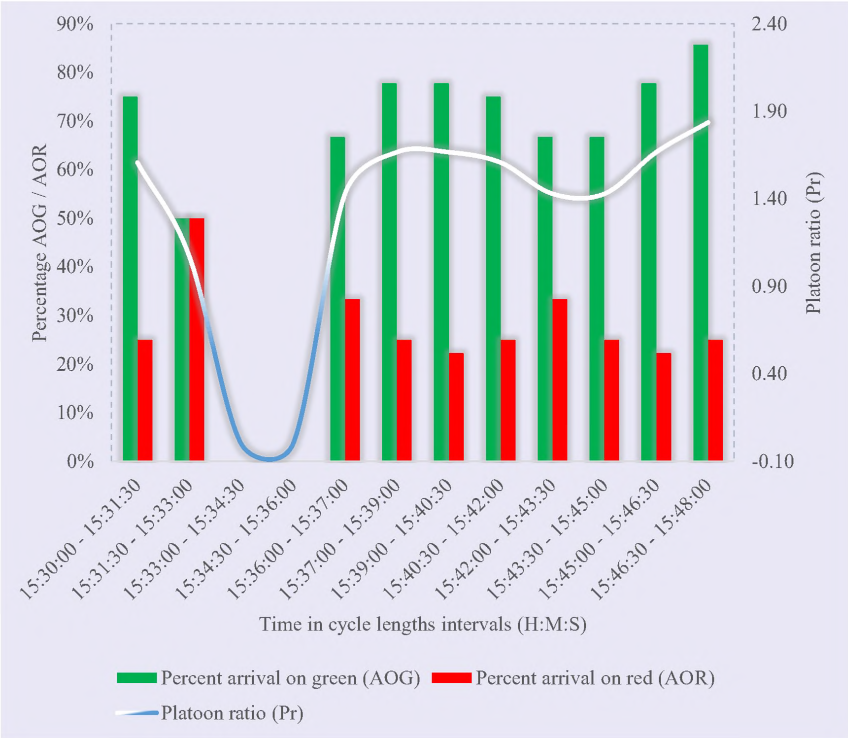

Figure 8. Distribution of platoon ratios

4.3. Approach speed and acceleration

Speed is the distance covered by the CV in the unit of time, while acceleration is the rate of change of the velocity with respect to time. As shown in Figure 9 and Figure 10, the speed and acceleration of the respective CV were queried and recorded for each simulation time step within the simulated peak hour. during an incident, it's expected that CVs slow down and consequently stop hence the respective velocity and acceleration would be close or equal to zero. The average velocities and acceleration values of the trajectories are seen to decrease, and the decrease is observed to last from when the crash occurred to when it cleared (15:32 to 15:36).

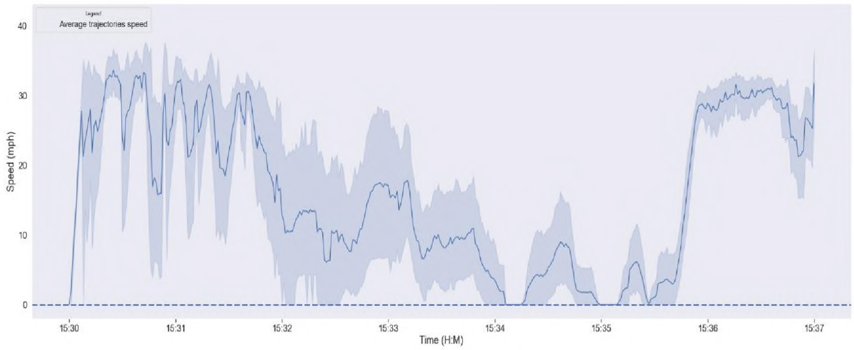

Figure 9. Average CV trajectories speed diagram

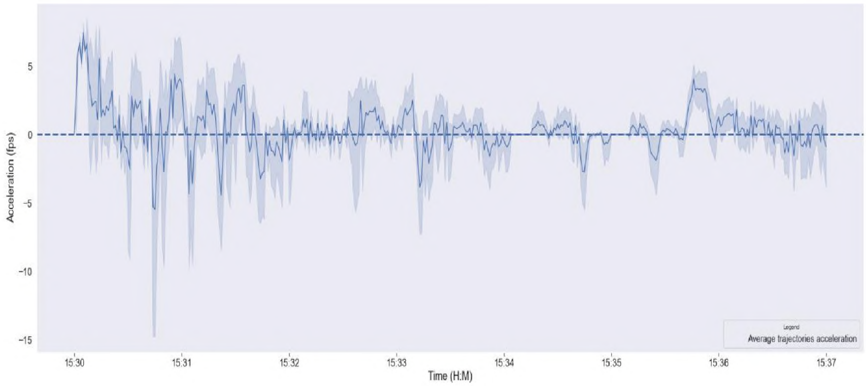

Figure 10. Average CV trajectories acceleration diagram

4.4. Approach waiting time

The duration of waiting is the period during which the vehicle's speed was less than or equal to 0.1 m/s (0.22 mph). Consequently, Figure 11 shows the average waiting time of all trajectories on Carnegie Avenue eastbound through movement at the intersection on E36th Street, which was determined by calculating the total time the CV trajectories recorded zero velocity (slope). It can be seen that during the incident the average waiting times of all trajectories increased. However, it can be argued that CVs could have been waiting due to yellow-red time or left-right turns at intersections. To take this into account a threshold region was suggested (callout I in Figure 11) which represents the length of red and amber time (90 sec) at the downstream signalized intersection (East 36th intersection). This is the total time CVs would stop while waiting for conflicting movements to go through the intersection, therefore any recorded waiting times that were are higher than the threshold region warrants an incident or underperformance of the corridor signals.

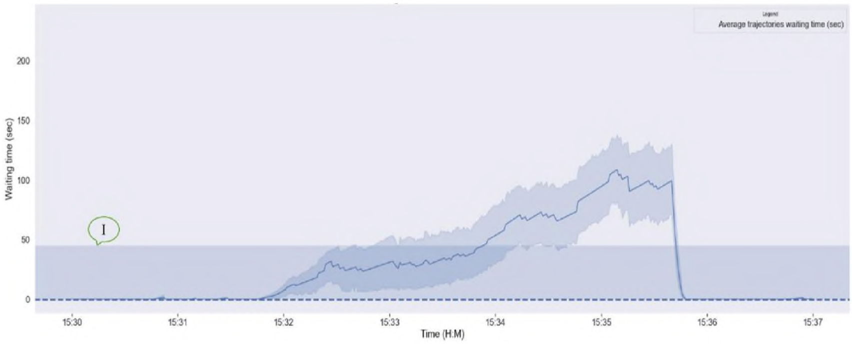

Figure 11. Average CV trajectories waiting time diagram

4.5. Summary

To visualize and assess the corridor/signalized intersection performance in a variety of operating circumstances, a useful and simple framework was developed. Color-coded CV trajectory diagrams can identify distinctive trajectory-signal diagrams that represent different traffic states in terms of demand, signal status, and operational circumstances. It is possible to see issues in a signal system's phasing and split duration, spillback, overflow queuing, intersection blocking and incidents. by reviewing the trajectories that CVs take while overlapping with a signal indication in a diagram.

Although CV trajectory graphs offer a useful visual understanding of queue spillback at intersections, they do not provide quantitative estimates. It is necessary to complement the visual presentation of vehicle trajectories with performance metrics. Examples of such metrics include phase failures, the number of vehicles served, queued, or unserved vehicles, the percentage of vehicles arriving on the green, as well as the percentage of stopped vehicles.

Despite being based on simulated traffic data, the proposed performance measures can easily be applied to actual world CVs trajectory. The CV trajectory diagrams differentiate between traffic incidents and normal traffic conditions. This diagram is anticipated to help traffic operators identify underperforming intersections or approaches and deploy necessary countermeasures.

CHAPTER V

CV SAFETY-BASED PERFORMANCE METRICS

As vehicle technology keeps getting better, newer vehicles are equipped with advanced safety features which aim at reducing the crash occurrence or its likely severity. As a result, applications of the traffic conflict approach to evaluate safety condition in road corridors has gained more attention among researchers. Click or tap here to enter text. A traffic conflict is an observable situation in which two or more road users are so close to each other in space and time that there is a risk of a collision if their movements stay the same. A detailed analysis and integration of traffic conflicts with signal performance measures can give us a better insight into crash occurrence and thus leads to more efficient traffic safety measures. The traffic conflict indicators can be used as safety surrogate measures (SSM).

5.1. SSM-based performance measures

The time to collision (TTC), the declaration to avoid a crash (DAC), post encroachment time (PET), deceleration rate (DR), gap time (GT), and proportion of stopping distance (PSD), are examples of SSM that have been used in the literature (Khoda Bakhshi & Ahmed, 2022; Yao et al., 2022). The main advantage of using SSM as an alternative safety measure is that data for analysis are more readily available because these events occur more frequently compared to actual crashes.

Even more, there is no need to wait for crashes to occur. This thesis used two SSMs which are TTC and DAC. Different types of encounters, e.g., crossing, merging, or lead/follow situations, may imply different calculation procedures for safety measures. TTC and DAC metrics are used due to the nature of this study the simulated crash, a rear-end crash in the following vehicle colliding with the leading vehicle. TTC and DAC have been used in literature to explain a rear-end crash in the following vehicle colliding with the leading vehicle traffic conflicts (Bidkar et al., 2022; H. Zhang et al., 2022).

5.1.1. Time to Collision (TTC)

The TTC represents the time that a vehicle would take to collide with another vehicle if the current relative velocity at a given point was maintained (Sayed et al. 1994). When a potential conflict is in progress, the TTC value decreases over time, and the critical measure of conflict severity becomes the TTC value when the vehicles finally collide. A standard safety limit has been proposed of 1.50 seconds, this is an indicator of potentially unsafe conflict (Rvd, 1991). Figure 12 presents an illustration of TTC when two vehicles collide or are experiencing a conflict, two trajectories front vehicle v_f and rear vehicle v_i that converge at a point (point of collision). The time towards the collision has two components reaction time (time t_2 to t_3) and time to collision (TTC) (time t_3 to t_4). The TTC is calculated for all follow-lead situations for which the follower is faster than the leader. The TTC metric was computed as follows:

$$TTC = \frac{d}{v_f - v_i} \qquad \text{Equation 7}$$

Where v_f is the speed of a rear vehicle, v_i is that of the front vehicle, and d is the space gap (distance) between the two vehicles.

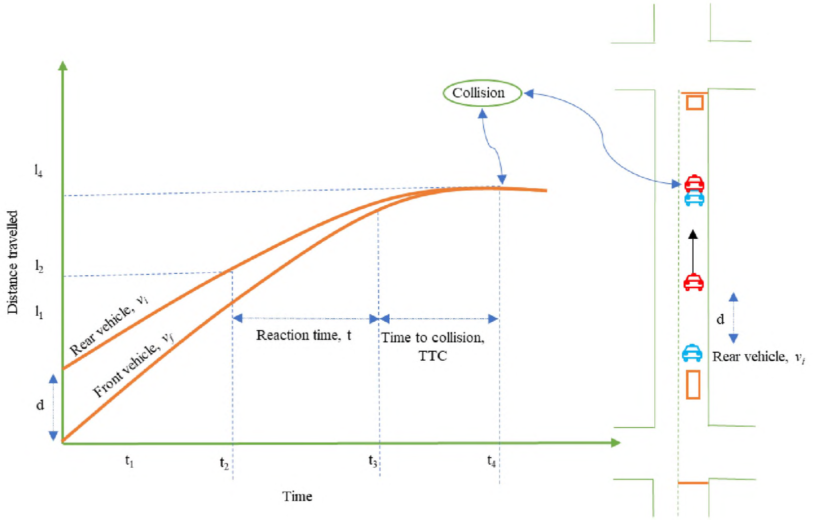

Figure 12. TTC illustration on trajectory collision diagrams

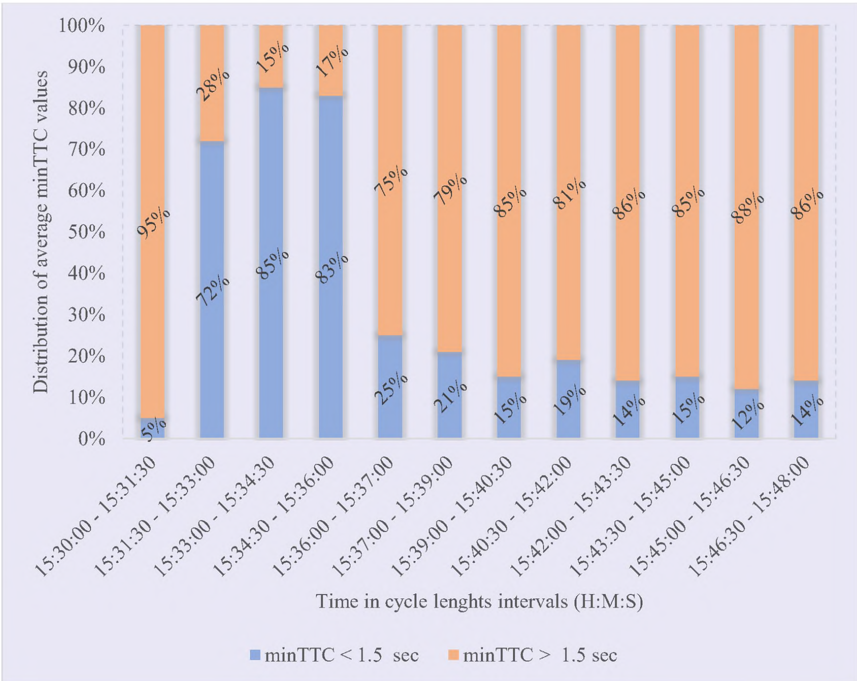

Figure 13. Average TTC distribution v/s time in cycle slice of the 90s

Figure 13 presents the distribution of the TTC values against time in the E36th Street intersection's cycle length of 90 sec. The TTC values have been binned into two groups namely, safer values with TTC greater than 1.5 seconds and unsafe values indicating higher chances of collision with TTC less than 1.5 seconds. It can be seen that the distribution of average TTC values during the incident duration appears to be higher i.e., 72%, 85% and 83%. Generally, under normal traffic conditions without any vehicle crash incident, the distribution of average TTC values greater than 1.5 sec appears to be greater than 75%. This represents a safe time when drivers will typically stop with minimal likelihood to collide with another vehicle. Traffic operators can benefit from the use of this surrogate performance measure in conjunction with other CV trajectory measures to determine critical areas that require attention.

5.1.2. Deceleration to Avoid a Crash (DAC)

DAC is defined as the minimum required deceleration rate that a vehicle has to apply to avoid a crash with the leading vehicle. In a lead/follow scenario when the follower vehicle's speed is higher than the leader vehicle's speed, the DAC (maximum deceleration to prevent an accident) is defined in Equation 8.

$$DAC = \frac{0.5 * Speed\ difference^2}{space\ gap} \qquad \text{Equation 8}$$

Figure 14, represents the distribution of DAC values of CV trajectories in the corridor between E30th and E36th intersection Streets along the Carnegie Avenue East Bound traffic. DAC values have been binned into 4 ranges; similar groups of DAC values have been used by Fazekas et al. (2017). This study adopts DAC values greater than 3.4 m/s^2 which is the safe deceleration value for stopping sight distance in AASHTO to indicate hard braking for sudden stopping. It can be observed that the distribution of DAC values that are greater than 3.4 m/s^2 during the incident duration from 15:31 to 15:35 appears to be the highest. This threshold category is observed to have lower distributions at other times before and after the incident. Similarly, this surrogate tool will help traffic operators to detect incident occurrences in a more precise manner when used with other performance measures the time and location of an incident causing disruption can be accurately determined.

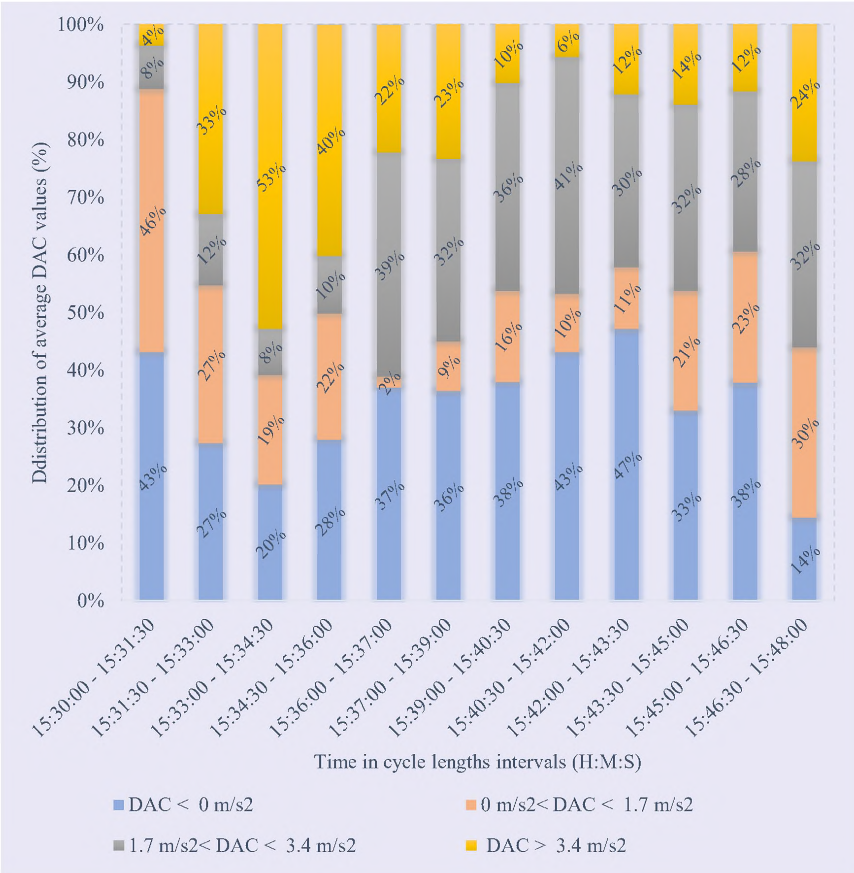

Figure 14. Average DAC distribution v/s time in cycle lengths

5.2. Summary

The metrics TTC & DAC were examined explaining the impact caused by a vehicle crash on traffic from a safety perspective. When the provided SSM metrics in this section are used in conjunction with the metrics provided in Chapter IV traffic management centers will be able to explain a variety of traffic conditions and respond to incidents proactively. Two SSM metrics were considered the TTC and DAC to detect and explain the simulated rear-end crash. Traffic operation centers will be able to detect a potential incident by observing variations in the distribution of the SSM values with respect to time. When there is a higher distribution of SSM values that lie outside of the safety margins of the proposed SSM threshold values there is a possibility of a potential incident that needs to be handled and an optimization of signal controller timings is warranted. However, the observed values for TTC and DAC can be limited to the type of car-following behavior that was used in the simulation (Kraus car-following model) and the calibration approach. Due to this limitation, the threshold used may differ, for this case, a comparative study against real-world TTC and DAC data is warranted It should be noted that different conflicts can be explained with different SSMs as for this thesis a lead/follow situation was simulated and TTC and DAC were the suitable metrics. For other situations like crossing and merging other metrics such as PET can be used. In current practice, SSM is not integrated as a method for real-time incident detection and management. This study provides a great avenue where such efforts can be implemented.

CHAPTER VI

CONCLUSIONS AND RECOMMENDATION

Due to their ability to continuously collect traffic data along the highway, CVs are likely to have an impact on traffic control systems. Incorporating CV data into traffic control will improve efficiency in traffic control operations and can be used for proactive maintenance of traffic operations. The main goal of this thesis was to explore CV data and develop performance measures that can be used to assess the evolution of traffic conditions especially after an incident has occurred.

In previous studies, high-resolution detector and traffic signal controller status data were used to visualize and, in a way, measure the quality of vehicle movement based on pre-set signal timing parameters as well as using high-resolution ATSPM data. Researchers and traffic operators have developed high-definition data-driven performance measures for intersections. They have been successful, but their work is limited by the type and quality of sensors they use. Information can be retrieved depending on the type of detection used, the position of the detector and the assumptions made when adjusting for the distance traveled toward the stop bar. If a queue is formed upstream of the advance detector due to an incident, like a vehicle crash, traditional performance measures don't effectively show how well the signal meets demand.

This research aimed to integrate CV trajectory data into the transportation system to enhance existing operational capabilities by proposing new and effective performance metrics with a focus on incident detection. Therefore, this thesis is focused on achieving the following objectives:

1. To formulate a simulation framework for generating and detecting network incidents by CVs.
2. To develop performance metrics that utilize the CV trajectory data to detect and identify incidents.
3. To estimate safety surrogate measures (SSM) for incident detection using CV trajectory data.

The findings indicate that unlike the current state of practice, the developed method takes advantage of CV's sensing, communication, and computing capability and handles high and low-demand states equally well. A new traffic trajectory visualization tool was introduced that provides a visualization of a vehicle experience on a corridor with respect to downstream signal status and interpretation of the impact of the incident simulated. The proposed performance measures tools provide for means for assessing the proportion of vehicles arriving on green and on red, locations with an insufficient allocation of green time can also be readily visualized.

Characterization of individual trajectory quality of progression level of service (LOS) and proportion of trajectories in a particular LOS are provided. Furthermore, the platoon ratio (P_r) distribution in comparison to percentage arrivals in green (AOG) and percentage arrivals in red (AOR) is proposed. More tools on kinematic changes of the trajectories for speed, acceleration and waiting time on the corridor are also presented. This is the first study to integrate safety surrogate measures with signal performance measures to detect conflicts and interpret the likelihood of an incident affecting the quality of progression. present the changes in proportions of minimum time to collision (TTC) and decelerations to avoid crash values (DAC) against time in cycle length intervals.

All presented metrics have been estimated from CV trajectory data and real-time signal controller status. To a considerable extent, CV environments will rely on big data analytics. What this means is that we now have access to cutting-edge data and techniques, as well as novel capabilities and prospects for coming up with more efficient signal performance measures. The focus of the described thesis has been on the development of effective, rigorous, and implementable strategies for the management of urban signalized arterials. What differentiates these measures and the proposed approach from the current state of practice is that they reflect the system's operational situation from its user's perspective respective (CV trajectory). The presented information is cumulative in time and space and carries over from one "signal cycle" to another.

Decision-makers, traffic control operators and respective practitioners need a deeper understanding of the potential impacts of CVs to realize sustainable, affordable, and efficient urban transportation management systems. Timely, important, and challenging, this research is necessary because CVs are predicted to significantly impact transportation systems.

Despite the contribution of the study findings, this study was limited to the following factors: Although a careful calibration and validation approach was used in the simulation experiment, like most traffic simulation studies it is nearly impractical to calibrate all parameters to the likes of a real-world condition. Future studies can consider a more robust calibration model which considers more driving behavior parameters. For instance, as research on CVs is constantly growing other studies can employ the use of car-following behaviors that have more recent adaptation to CVs. While this study used the COBYLA optimization algorithm future studies can use more recent and robust optimization algorithms.

Furthermore, more research is needed to test this approach on a variety of networks and traffic conditions and to find a good composite, for example, consider more lane configurations, different kinds of intersections, etc. Also, considering that certain conflicts (e.g., crossing) may have more severe impacts than others (e.g., rear-end) and consequently affect traffic flow and signal operations differently there is a need to investigate the use of a ''safety (performance) index'' which would use various 'severity weights' assigned to various conflict types.

REFERENCES

Arvin, R., Khattak, A. J., Kamrani, M., & Rio-Torres, J. (2020). Safety evaluation of connected and automated vehicles in mixed traffic with conventional vehicles at intersections. *Https://Doi.Org/10.1080/15472450.2020.1834392*, *25*(2), 170–187. https://doi.org/10.1080/15472450.2020.1834392

Balaji, P. G., German, X., & Srinivasan, D. (2010). Urban traffic signal control using reinforcement learning agents. *IET Intelligent Transport Systems*, *4*(3), 177–188. https://doi.org/10.1049/IET-ITS.2009.0096/CITE/REFWORKS

Balakrishna, R., Antoniou, C., Ben-Akiva, M., Koutsopoulos, H. N., & Wen, Y. (2007a). Calibration of Microscopic Traffic Simulation Models: Methods and Application. *Https://Doi.Org/10.3141/1999-21*, *1999*, 198–207. https://doi.org/10.3141/1999-21

Balakrishna, R., Antoniou, C., Ben-Akiva, M., Koutsopoulos, H. N., & Wen, Y. (2007b). Calibration of Microscopic Traffic Simulation Models: Methods and Application. *Https://Doi.Org/10.3141/1999-21*, *1999*, 198–207. https://doi.org/10.3141/1999-21

Barnston, A. G. (1992). Correspondence among the correlation, RMSE, and Heidke forecast verification measures, refinement of the Heidke score. *Weather and Forecasting*, *7*(4), 699–709. https://journals.ametsoc.org/view/journals/wefo/7/4/1520-0434_1992_007_0699_catcra_2_0_co_2.xml

Benekohal, R. F., & Zhao, W. (2000). Delay-based passenger car equivalents for trucks at signalized intersections. *Transportation Research Part A: Policy and Practice*, *34*(6), 437–457. https://doi.org/10.1016/S0965-8564(99)00026-9

Bidkar, O., Arkatkar, S., & Joshi, G. (2023). *Investigating Surrogate Safety Measures Under Varying Roadway and Traffic Conditions Using Vehicular Trajectory Data*. 285–299. https://doi.org/10.1007/978-981-19-4204-4_17/COVER

Board, T. R., of Sciences Engineering, & Medicine. (2022). *Highway Capacity Manual 7th Edition: A Guide for Multimodal Mobility Analysis*. The National Academies Press. https://doi.org/10.17226/26432

Carranza, E. D. S. (2021). *Scalable Operational Traffic Signal Performance Measures from Vehicle Trajectory Data*. https://doi.org/10.25394/PGS.14371691.V1

Cetin, M. (2012). Estimating Queue Dynamics at Signalized Intersections from Probe Vehicle Data. *Https://Doi.Org/10.3141/2315-17*, *2315*, 164–172. https://doi.org/10.3141/2315-17

Cheu, R. L., & Ritchie, S. G. (1995). Automated detection of lane-blocking freeway incidents using artificial neural networks. *Transportation Research Part C: Emerging Technologies*, *3*(6), 371–388. https://doi.org/10.1016/0968-090X(95)00016-C

Ciuffo, B., Punzo, V., & Torrieri, V. (2008). Comparison of Simulation-Based and Model-Based Calibrations of Traffic-Flow Microsimulation Models: *Https://Doi.Org/10.3141/2088-05*, *2088*, 36–44. https://doi.org/10.3141/2088-05

Cunto, F., & Saccomanno, F. F. (2008). Calibration and validation of simulated vehicle safety performance at signalized intersections. *Accident Analysis & Prevention*, *40*(3), 1171–1179. https://doi.org/10.1016/J.AAP.2008.01.003

Day, C., Brennan, T., Hainen, A., Remias, S., Premachandra, H., Sturdevant, J., Richards, G., Wasson, J., & Bullock, D. (2011). Reliability, Flexibility, and Environmental Impact of Alternative Arterial Offset Optimization Objective Functions. *Transportation Research Record*. https://docs.lib.purdue.edu/civeng/10

Day, C., Bullock, D., Li, H., Remias, S., Hainen, A., Freije, R., Stevens, A., Sturdevant, J., & Brennan, T. (2014a). *Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach*. https://doi.org/10.5703/1288284315333

Day, C., Bullock, D., Li, H., Remias, S., Hainen, A., Freije, R., Stevens, A., Sturdevant, J., & Brennan, T. (2014b). *Performance Measures for Traffic Signal Systems: An Outcome-Oriented Approach*. https://doi.org/10.5703/1288284315333

Day, C. M., & Bullock, D. M. (2016a). Detector-Free Signal Offset Optimization with Limited Connected Vehicle Market Penetration: Proof-of-Concept Study: *Https://Doi.Org/10.3141/2558-06*, *2558*, 54–65. https://doi.org/10.3141/2558-06

Day, C. M., & Bullock, D. M. (2016b). Detector-Free Signal Offset Optimization with Limited Connected Vehicle Market Penetration: Proof-of-Concept Study. *Https://Doi.Org/10.3141/2558-06*, *2558*, 54–65. https://doi.org/10.3141/2558-06

Denney, R. W., Curtis, E., & Olson, P. (2012). *The 2012 National Traffic Signal Report Card presents the aggregate response to the self-assessment survey from 225 local and state agencies in the*.

Der-Horng, L., X, Y., & Parsuvanathan, C. (2001). *Parameter Calibration for PARAMICS Using Genetic Algorithm.*

Dowling, R., Skabardonis, A., Halkias, J., McHale, G., & Zammit, G. (2004). Guidelines for Calibration of Microsimulation Models: Framework and Applications. *Https://Doi.Org/10.3141/1876-01*, *1876*, 1–9. https://doi.org/10.3141/1876-01

Emtenan, A. M. T., & Day, C. M. (2020). Impact of Detector Configuration on Performance Measurement and Signal Operations. *Https://Doi.Org/10.1177/0361198120912244*, *2674*(4), 300–313. https://doi.org/10.1177/0361198120912244

Fazekas, A., Hennecke, F., Kalló, E., & Oeser, M. (2017). A Novel Surrogate Safety Indicator Based on Constant Initial Acceleration and Reaction Time Assumption. *Journal of Advanced Transportation*, *2017*. https://doi.org/10.1155/2017/8376572

Feng, Y., Head, K. L., Khoshmagham, S., & Zamanipour, M. (2015). A real-time adaptive signal control in a connected vehicle environment. *Transportation Research Part C: Emerging Technologies*, *55*, 460–473. https://doi.org/10.1016/J.TRC.2015.01.007

FHWA. (2013). *Signalized Intersections Informational Guide Second Edition.* http://safety.fhwa.dot.gov/.

Freije, R. S., Hainen, A. M., Stevens, A. L., Li, H., Smith, W. B., Summers, H., Day, C. M., Sturdevant, J. R., & Bullock, D. M. (2014). Graphical Performance Measures for Practitioners to Triage Split Failure Trouble Calls.

Https://Doi.Org/10.3141/2439-03, *2439*, 27–40. https://doi.org/10.3141/2439-03

GDOT. (2022). *Georgia Department of Transportation GDOT traffic signal program overview traffic signal systems capability maturity self-assessment Level 1 Level 2*. USDOT FHWA. https://ops.fhwa.dot.gov/tsmoframeworktool/tool/tssc/

Giuliano, G. (1989). Incident characteristics, frequency, and duration on a high volume urban freeway. *Transportation Research Part A: General*, *23*(5), 387–396. https://doi.org/10.1016/0191-2607(89)90086-1

Hollander, Y., & Liu, R. (2008). The principles of calibrating traffic microsimulation models. *Transportation*, *35*(3), 347–362. https://doi.org/10.1007/S11116-007-9156-2/TABLES/3

Hourdakis, J., Michalopoulos, P. G., & Kottommannil, J. (2003a). Practical Procedure for Calibrating Microscopic Traffic Simulation Models. *Https://Doi.Org/10.3141/1852-17*, *1852*, 130–139. https://doi.org/10.3141/1852-17

Hourdakis, J., Michalopoulos, P. G., & Kottommannil, J. (2003b). Practical Procedure for Calibrating Microscopic Traffic Simulation Models: *Https://Doi.Org/10.3141/1852-17*, *1852*, 130–139. https://doi.org/10.3141/1852-17

Hourdakis, J., Michalopoulos, P. G., & Kottommannil, J. (2003c). Practical Procedure for Calibrating Microscopic Traffic Simulation Models: *Https://Doi.Org/10.3141/1852-17*, *1852*, 130–139. https://doi.org/10.3141/1852-17

Huang, J., Li, G., Wang, Q., & Yu, H. (2013). Real time delay estimation for signalized intersection using transit vehicle positioning data. *2013 13th International Conference on ITS Telecommunications, ITST 2013*, 216–221. https://doi.org/10.1109/ITST.2013.6685548

Jha, M., Gopalan, G., Garms, A., Mahanti, B. P., Toledo, T., & Ben-Akiva, M. E. (2004). Development and Calibration of a Large-Scale Microscopic Traffic Simulation Model: *Https://Doi.Org/10.3141/1876-13*, *1876*, 121–131. https://doi.org/10.3141/1876-13

Jones, E., Oliphant, T., & Peterson, P. (2001). *SciPy: Open-Source Scientific Tools for Python*. https://www.semanticscholar.org/paper/SciPy%3A-Open-Source-Scientific-Tools-for-Python-Jones-Oliphant/307827ec09187e9c6935e8ff5fd43eeefb901320

Khoda Bakhshi, A., & Ahmed, M. M. (2022). Bayesian extreme value analysis of kinematic-based surrogate measure of safety to detect crash-prone conditions in connected vehicles environment: A driving simulator experiment. *Transportation Research Part C: Emerging Technologies*, *136*, 103539. https://doi.org/10.1016/J.TRC.2021.103539

Kidando, E., Kitali, A. E., Moses, R., & Ozguven, E. E. (2020). Real-time visualization of operational performance measures of arterial highway using open crowdsourced data. *Advances in Transportation Studies*, *51*, 47–62. https://doi.org/10.4399/97888255337504

Kim, K. O., & Rilett, L. R. (2001). Genetic-algorithm-based approach for calibrating microscopic simulation models. *IEEE Conference on Intelligent*

Transportation Systems, Proceedings, ITSC, 698–704. https://doi.org/10.1109/ITSC.2001.948745

Kim, K. O., & Rilett, L. R. (2003). Simplex-Based Calibration of Traffic Microsimulation Models with Intelligent Transportation Systems Data: *Https://Doi.Org/10.3141/1855-10*, *1855*, 80–89. https://doi.org/10.3141/1855-10

Kim, S.-J., Kim, W., & Rilett, L. R. (2005). Calibration of Microsimulation Models Using Nonparametric Statistical Techniques: *Https://Doi.Org/10.1177/0361198105193500113*, *1935*(1), 111–119. https://doi.org/10.1177/0361198105193500113

Krajzewicz, D., Hertkorn, G., Rössel, C., & Wagner, P. (2002). *SUMO (Simulation of Urban MObility) - an open-source traffic simulation.*

Kundé, K. (2002). *Calibration of mesoscopic traffic simulation models for dynamic traffic assignment.* https://dspace.mit.edu/bitstream/handle/1721.1/84839/51873834-MIT.pdf?sequence=2

L. Ding. (2003). *Evaluation of ITS Technologies in South Jersey Priority Corridor Project (Doctoral dissertation, Rutgers University* [The State University of New Jersey]. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C36&q=L.+Ding%2C+%E2%80%9CEvaluation+of+ITS+Technologies+In+South+Jersey+Priority+Corridor+Project%E2%80%9D%2C+Master+Thesis%2C+Rutgers%2C+The+State+University+of+New+Jersey%2C+2003.&btnG=

Li, H., Mackey, J., Luker, M., Taylor, M., & Bullock, D. M. (2019). Application of High-Resolution Trip Trace Stitching to Evaluate Traffic Signal System Changes. *Https://Doi.Org/10.1177/0361198119841043*. https://doi.org/10.1177/0361198119841043

Ma, J., Dong, H., & Zhang, H. M. (2007). Calibration of Microsimulation with Heuristic Optimization Methods: *Https://Doi.Org/10.3141/1999-22*, *1999*, 208–217. https://doi.org/10.3141/1999-22

Ma, T., & Abdulhai, B. (2002a). Genetic Algorithm-Based Optimization Approach and Generic Tool for Calibrating Traffic Microscopic Simulation Parameters: *Https://Doi.Org/10.3141/1800-02*, *1800*, 6–15. https://doi.org/10.3141/1800-02

Ma, T., & Abdulhai, B. (2002b). Genetic Algorithm-Based Optimization Approach and Generic Tool for Calibrating Traffic Microscopic Simulation Parameters: *Https://Doi.Org/10.3141/1800-02*, *1800*, 6–15. https://doi.org/10.3141/1800-02

Mahut, M., Florian, M., Tremblay, N., Campbell, M., Patman, D., & McDaniel, Z. K. (2004). Calibration and Application of a Simulation-Based Dynamic Traffic Assignment Model: *Https://Doi.Org/10.3141/1876-11*, *1876*, 101–111. https://doi.org/10.3141/1876-11

National Transportation Operations Coalition. (2012). *2012 National Traffic Signal Report Card | National Operations Center of Excellence.* https://transportationops.org/publications/2012-national-traffic-signal-report-card

NHTSA. (2018). *Fatality Analysis Reporting System (FARS) | NHTSA*. https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars

Novat, Norris, Emmanuel Kidando, Boniphace Kutela, Angela E. Kitali, A (2022) Comparative study of collision types between automated and conventional vehicles using Bayesian probabilistic inferences, Journal of Safety Research, 2022, ISSN 0022-4375, *https://doi.org/10.1016/j.jsr.2022.11.001.*

Novat, N., Mwende, S., Shita, H., & Mbiaji, G. (2022). Predicting Drivers' Injury Occurrence in Vehicle Crashes Occurring at Horizontal Curve and Grade Combination Segments. Institute of Transportation Engineers. ITE Journal, 92(8), 41-50. https://www.proquest.com/scholarly-journals/predicting-drivers-injury-occurrence-vehicle/docview/2697724589/se-2.

Older, S. J., & Shippey, J. (1977). Proceedings: first Workshop on Traffic Conflicts, Oslo, 1977. *Proceedings of the First Workshop on Traffic Conflicts*, 1–15.

Park, B., & Qi, H. (2005). Development and Evaluation of a Procedure for the Calibration of Simulation Models: *Https://Doi.Org/10.1177/0361198105193400122*, *1934*, 208–217. https://doi.org/10.1177/0361198105193400122

Park, B., & Schneeberger, J. D. (2003). Microscopic Simulation Model Calibration and Validation: Case Study of VISSIM Simulation Model for a Coordinated Actuated Signal System: *Https://Doi.Org/10.3141/1856-20*, *1856*, 185–192. https://doi.org/10.3141/1856-20

PennDOT. (2022). *Pennsylvania Department of Transportation* penndot traffic signal program overview traffic signal systems capability maturity self-assessment level 1. Usdot fhwa. https://ops.fhwa.dot.gov/tsmoframeworktool/tool/tssc/

Powell, M. J. D. (1994). A Direct Search Optimization Method That Models the Objective and Constraint Functions by Linear Interpolation. *Advances in Optimization and Numerical Analysis*, 51–67. https://doi.org/10.1007/978-94-015-8330-5_4

Powell, M. J. D. (1998). Direct search algorithms for optimization calculations. *Acta Numerica*, *7*, 287–336. https://doi.org/10.1017/S0962492900002841

Qin, X., & Mahmassani, H. S. (2004). Adaptive Calibration of Dynamic Speed-Density Relations for Online Network Traffic Estimation and Prediction Applications: *Https://Doi.Org/10.3141/1876-09*, *1876*, 82–89. https://doi.org/10.3141/1876-09

Rvd, H. (1991). TIME-TO-COLLISION AS A CUE FOR DECISION-MAKING IN BRAKING. *TRB*, 19–26. https://trid.trb.org/view/347440

Saldivar-Carranza, E., Li, H., Mathew, J., Hunter, M., Sturdevant, J., & Bullock, D. M. (2021). Deriving operational traffic signal performance measures from vehicle trajectory data. *Transportation Research Record*, *2675*(9), 1250–1264. https://doi.org/10.1177/03611981211006725

SAYED, M. A. (2021). A Simulation Framework for Traffic Safety with Connected Vehicles and V2X Technologies. *Theses and Dissertations*. https://dc.uwm.edu/etd/2724

Sayed, T., Brown, G., & Navin, F. (1994). Simulation of traffic conflicts at unsignalized intersections with TSC-Sim. *Accident Analysis & Prevention*, *26*(5), 593–607. https://doi.org/10.1016/0001-4575(94)90021-3

Schultz, G. G., & Rilett, L. R. (2004). Analysis of Distribution and Calibration of Car-Following Sensitivity Parameters in Microscopic Traffic Simulation

Models: *Https://Doi.Org/10.3141/1876-05*, *1876*, 41–51. https://doi.org/10.3141/1876-05

Toledo, T., Ben-Akiva, M. E., Darda, D., Jha, M., & Koutsopoulos, H. N. (2004). Calibration of Microscopic Traffic Simulation Models with Aggregate Data: *Https://Doi.Org/10.3141/1876-02*, *1876*, 10–19. https://doi.org/10.3141/1876-02

United States. Federal Highway Administration. Office of Research, D. and T. (2019). *Public Roads: Autumn 2019*. https://doi.org/10.21949/1503647

Waddell, J. M., Remias, S. M., Asce, A. M., & Kirsch, J. N. (2020). Characterizing Traffic-Signal Performance and Corridor Reliability Using Crowd-Sourced Probe Vehicle Trajectories. *Journal of Transportation Engineering, Part A: Systems*, *146*(7), 04020053. https://doi.org/10.1061/JTEPBS.0000378

Waddell, J. M., Remias, S. M., Kirsch, J. N., & Kamyab, M. (2020). Replicating Advanced Detection using Low Ping Frequency Probe Vehicle Trajectory Data to Optimize Signal Progression: *Https://Doi.Org/10.1177/0361198120923654*, *2674*(7), 528–539. https://doi.org/10.1177/0361198120923654

Wang, H., Zhang, G., Zhang, Z., & Wang, Y. (2016). Estimating control delays at signalized intersections using low-resolution transit bus-based global positioning system data. *IET Intelligent Transport Systems*, *10*(2), 73–78. https://doi.org/10.1049/IET-ITS.2014.0246

Wang, Q., Yuan, Y., Yang, X. (Terry), & Huang, Z. (2021). Adaptive and multi-path progression signal control under connected vehicle environment.

Transportation Research Part C: Emerging Technologies, *124*, 102965. https://doi.org/10.1016/J.TRC.2021.102965

Wu, X., & Liu, H. X. (2014). Using high-resolution event-based data for traffic modeling and control: An overview. *Transportation Research Part C: Emerging Technologies*, *42*, 28–43. https://doi.org/10.1016/J.TRC.2014.02.001

Yao, Y., Zhao, X., Li, J., Ma, J., & Zhang, Y. (2022). Traffic safety analysis at interchange exits using the surrogate measure of aggressive driving behavior and speed variation. *Https://Doi.Org/10.1080/19439962.2022.2098439*. https://doi.org/10.1080/19439962.2022.2098439

Zhang, H., Hou, N., Ding, N., & Jiao, N. (2023). Using multicolor perceptual markings as a rear-end crash risk mitigator: A field investigation. *Accident Analysis & Prevention*, *179*, 106881. https://doi.org/10.1016/J.AAP.2022.106881

Zhang, K., Jia, N., Zheng, L., & Liu, Z. (2019). A novel generative adversarial network for estimation of trip travel time distribution with trajectory data. *Transportation Research Part C: Emerging Technologies*, *108*, 223–244. https://doi.org/10.1016/J.TRC.2019.09.019

Zhao, Y., Zheng, J., Wong, W., Wang, X., Meng, Y., & Liu, H. X. (2019). Estimation of Queue Lengths, Probe Vehicle Penetration Rates, and Traffic Volumes at Signalized Intersections using Probe Vehicle Trajectories. *Https://Doi.Org/10.1177/0361198119856340*.

APPENDIX E: INTERSECTION EVENING PEAK TURNING MOVEMENT COUNTS

	E 30th SB			Carnegie Ave WB			E 30th NB			Carnegie Ave EB				
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Total	Total %
3:30pm	19	123	64	33	329	25	27	125	20	32	228	23	1,048	25.14%
3:45pm	19	105	61	35	363	40	30	128	17	30	221	29	1,078	25.86%
4:00pm	17	94	65	35	320	42	29	114	16	41	215	21	1,009	24.21%
4:15pm	16	113	62	31	379	35	24	97	17	28	205	26	1,033	24.78%
Hourly Total	71	435	252	134	1,391	142	110	464	70	131	869	99	4,168	100.00%
Hourly Total %	9.37%	57.39%	33.25%	8.04%	83.44%	8.52%	17.08%	72.05%	10.87%	11.92%	79.07%	9.01%		
PHF	0.93	0.88	0.97	0.96	0.92	0.85	0.92	0.91	0.88	0.8	0.95	0.85		

APPENDIX E: INTERSECTION EVENING PEAK TURNING MOVEMENT COUNTS

	E36th SB			**Carnegie Ave WB**			**E36th NB**			**Carnegie Ave EB**				
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Total	Total %
3:30pm	6	33	14	4	319	10	3	11	3	10	243	5	661	25.50%
3:45pm	5	32	16	6	351	10	3	9	1	8	240	4	685	26.43%
4:00pm	4	19	17	6	315	8	3	10	1	11	219	4	617	23.80%
4:15pm	3	16	18	3	331	7	3	8	3	10	221	6	629	24.27%
Hourly Total	18	100	65	19	1,316	35	12	38	8	39	923	19	2,592	100.00%
Hourly Total %	9.84%	54.64%	35.52%	1.39%	96.06%	2.55%	20.69%	65.52%	13.79%	3.98%	94.09%	1.94%		
PHF	0.75	0.76	0.9	0.79	0.94	0.88	1	0.86	0.67	0.89	0.95	0.79		

APPENDIX E: INTERSECTION EVENING PEAK TURNING MOVEMENT COUNTS

	E40th SB			Carnegie Ave WB			E40th NB			Carnegie Ave EB				
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Total	Total %
3:30pm	3	79	13	2	310	1	8	23	2	8	234	11	694	25.66%
3:45pm	4	48	19	3	333	2	9	25	2	10	240	8	703	25.99%
4:00pm	3	54	18	3	297	2	11	34	2	11	207	6	648	23.96%
4:15pm	2	49	15	4	314	2	13	25	3	9	219	5	660	24.40%
Hourly Total	12	230	65	12	1,254	7	41	107	9	38	900	30	2,705	100.00%
Hourly Total %	3.91%	74.92%	21.17%	0.94%	98.51%	0.55%	26.11%	68.15%	5.73%	3.93%	92.98%	3.10%		
PHF	0.75	0.73	0.86	0.75	0.94	0.88	0.79	0.79	0.75	0.86	0.94	0.68		

APPENDIX E: INTERSECTION EVENING PEAK TURNING MOVEMENT COUNTS

	E46th SB			**Carnegie Ave WB**			**E46th NB**			**Carnegie Ave EB**				
	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Left	Thru	Right	Total	Total %
4:30pm	1	24	5	4	293	3	2	8	1	5	220	3	569	23.43%
4:45pm	3	36	7	4	325	4	2	9	3	3	239	5	640	26.36%
5:00pm	3	29	9	4	292	2	3	9	3	4	243	4	605	24.92%
5:15pm	1	24	9	2	297	2	2	9	4	5	255	4	614	25.29%
Hourly Total	8	113	30	14	1,207	11	9	35	11	17	957	16	2,428	100.00%
Hourly Total %	5.30%	74.83%	19.87%	1.14%	97.97%	0.89%	16.36%	63.64%	20.00%	1.72%	96.67%	1.62%		
PHF	0.67	0.78	0.83	0.88	0.93	0.69	0.75	0.97	0.69	0.85	0.94	0.8		