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System Monitoring of Auto Traffic

Queue Detection and Congestion Impact Assessment

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16. Abstract

The main objectives of this study were to identify available data sets and explore methodologies for improving the detection of bottlenecks, related congestion, and queue formation, as well as formulate methodologies to determine the extent and rate of spread queues, identify their impact area, and look at potential mitigation strategies. Methodologies are provided that evaluate (a) impacts of single construction projects, (b) combined daily impacts of construction projects and incidents on selected segments of the corridor, and (c) a process to find the most appropriate schedule that minimizes the negative impact of construction, utility work or special events that require partial or full closure of a roadway. Finally, this study describes an approach to queue detection using a combination of data available from two different sources (traffic sensors and third-party data providers) and finding the best combination of the two data sources for queue detection

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Executive Summary

The main objective of this study was to identify available data sets and explore methodologies for improving the detection of bottlenecks, related congestion, and queue formation. Additional objectives are to determine the extent and rate of spread of queues, identify their impact area, and look at potential mitigation strategies.

The first chapter of the report includes a review of relevant literature. The second chapter provides a description of the data sources identified and used for illustrating selected methods for congestion and queue analysis. After a review of available datasets, the TTI research team identified the I-35 traveler information database. This database and related data collection system have been successfully used for detecting congestion and queue formation along a 100-mile segment of I-35 in Central Texas. The I-35 data suite incorporates a lane closure database and real-time and archived traffic data from various data sources. Available traffic data include lane-level traffic volumes and spot-speeds from Wavetronix radar sensors, segment travel times and speeds from Bluetooth (and/or WiFi) readers, incident, and traffic jam data as well as segment travel times and speeds from third-party traffic data providers. Both real-time and archived data are available from most of these data sources. The second chapter describes the available data sources and data types on I-35 in Central Texas and provides details on their potential use for different applications, such as queue detection and queue warning. For example, data from Wavetronix sensors have been used for

- Estimating the expected impact (delay and queue length) of planned lane closures.
- Assessing the need for deploying portable queue warning systems for planned closures.
- Find the best schedule for planned closures, i.e., closure time that is expected to have the least negative impact (minimum delay and shortest queues).
- Identifying potential radar sensor issues (e.g., need for equipment adjustment due to change in roadway alignment).

On the I-35 corridor, Bluetooth readers are deployed at an average of 4-mile spacing with a minimum distance of 0.9 mile and maximum distance of 11.5 miles between consecutive readers. Bluetooth-based segment travel times and average segment speeds have been used for

- Assessing the impacts of lane closures, accidents, and special events on the corridor, both separately and in combination.
- Determining mobility-related work zone performance measures at both project- and corridor-levels.

Queue data is also collected by portable queue warning systems deployed for work zones in the I-35 reconstruction project. The portable queue warning system used iCone® portable traffic monitoring devices and have been deployed in two configurations depending on the expected lengths of the longest queues.

Third-party traffic data are also available and offer crowdsourced traffic information and probe vehicle data on the I-35 corridor and a large portion of the connecting roadway network. A major benefit of these crowd-sourced third-party data is that they can be collected without the need for the deployment and operation of physical infrastructure, and they provide broad coverage over the road network. The data include segment travel times and speeds, and information on incidents, road construction, weather and road conditions. The segment travel times and speeds are provided as averages over predefined time intervals (e.g., 1, 5, 10 or 15 minutes). TxDOT and TTI have access to third-party traffic data from WAZE and INRIX. Agencies can access WAZE's crowd-sourced incident data through the Waze for Cities (formerly: Connected Citizen Program). In exchange, they are expected to share their own incident and/or work zone data feed with WAZE. Available INRIX probe data include segment travel times and speeds measured over two types of road segments: TMC

(Traffic Message Channel) segments and XD (eXtreme Definition) segments. Probe data from both segment types may be used for detecting congestion and estimating delays, but data from DX segments typically provide more accurate queue detection.

There are significant differences between the above-mentioned data sources in terms of their data types, spatial coverage, spatial and temporal resolution, and latency. Table 5 provides a comparison of key characteristics of available data sources that may be used for queue detection.

The last chapter describes potential applications and methods of congestion and queue analysis using the data sources identified. Examples illustrating the use of these methods to improve queue detection and minimize the negative impacts of congestion for travelers are also included. The selected applications include:

- Post-event traffic performance assessment and queue analysis.
- Queue detection using data from multiple sources
- Optimal scheduling of road construction activities and special events.

To assess the performance of the I-35 traveler information system, post-event evaluations have been performed for all significant lane closures as well as special events along the corridor. The operational impacts of lane closures or special events may be quantified in terms of travel time delays determined from Bluetooth data and queue analysis using third-party data.

The major steps of a post-event impact analysis of work zone lane closures or incidents are summarized in Figure 18. The method is illustrated by an example of a night-time construction that required the closure of all northbound main lanes of I-35 while traffic was diverted to the frontage roads.

In addition to evaluating the impacts of single construction projects, the method has also been used to determine the combined daily impacts of construction projects and incidents on selected segments of the corridor. This so-called Daily Postmortem (DPM) has been routinely performed to determine 15-minute average travel times and delays over 24-hour periods on three segments between major population centers on the I-35 corridor.

When significant delays are observed, additional congestion analysis are performed to identify the location of bottlenecks and capture the formation and propagation of vehicle queues. For I-35, such congestion and queue analysis have been conducted using data from INRIX's XD segments and the Congestion Scan tool included in the Probe Data Analytics (PDA) Suite of the Regional Integrated Transportation Information System (RITIS) developed by CATT Lab at University of Maryland.

Figure 23 shows the speed heat map of a segment of I-35 on Saturday, October 23, 2021, when a vehicle collision occurred soon after 6 AM at mile marker (MM) 334. Figure 24 captures the main results of queue analysis. The incident-induced congestion and the formation and propagation of queues over time and space can be clearly identified.

The second part of chapter 3 describes an approach to queue detection using a combination of data available from two different sources, traffic sensors and third-party data providers. Data from these two sources have different spatial coverage and temporal resolutions because of the way they are collected, aggregated, and transmitted. Traditional sensors provide average spot data (speed, volume, and occupancy) which are collected for each lane. Third-party data sources provide travel times and average travel speeds over predefined segments without lane-level detail. Data from the two sources also differ in their latencies. Sensor data has a minimum latency of 20 or 30 seconds depending on the data aggregation level. Third party probe data latency typically ranges from 3 to 4 minutes. These differences present some challenges in finding the best combination of the two data sources for queue detection. Table 7 provides a guide for BOQ detection under different scenarios of data availability from sensors and third-party data. The flow chart in Figure 29 shows the BOQ estimation logic using sensor and/or third-party data.

The last section of chapter 3 describes a process to find the most appropriate schedule that minimizes the negative impact of road construction, utility work or special events that require partial or full closure of a roadway. The impact is measured by the expected length of longest queue generated by the lane closure. The objective is to find the optimal schedule (start time) for a planned lane closure of fixed duration. The optimal schedule is defined by the lane closure start time t^* during the week that is expected to create the shortest maximum queue length. The steps to determine an optimal schedule is summarized in Figure 30. The required input includes work zone capacity and a historical time series of vehicle flow rates measured at a point upstream of the planned lane closure. Note that work zone capacity does not have to be constant; the method can easily accommodate capacities that vary over the time of the closure. This methodology was tested and implemented for various lane closure situations across the corridor and provided a simple analytical process to ensure the least impact to the traveling public. The method is illustrated through an example where the optimum schedule for a 16-hour planned lane closure on I-35 was to be determined.

Introduction

Vehicle queues may form upstream of incidents, work zones, entry and exit ramps, lane drops, freeway junctions, and traffic signals. They may also be caused by adverse weather and poor visibility conditions that significantly reduce vehicle speeds and roadway capacity. No matter where and why they form, queues are impactful to traffic, causing delay and increased accident potential. Drivers approaching the back of queues without receiving any warning often have poor perception of the time and distance needed to safely slow down or stop to avoid rear-end collisions with slower or stopped vehicles in front of them. Queues behind horizontal or vertical curves that limit drivers' sight distance are particularly hazardous. Rear-end collisions are among the most common types of crashes, often resulting in fatal or serious injuries.

There is a need to identify available data sources and data sets that may be used for automated queue detection upstream of freeway bottlenecks. There is also a need to develop methodologies to

- assess the impact of lane closures, incidents, and special events, and
- fuse multiple data sources to improve the accuracy and timeliness of queue detection.

The overall goal of this effort is to explore methodologies for improving the detection of bottlenecks, related congestion, and queue formation. Additional objectives are to determine the extent and rate of spread of queues, identify their impact area, and look at potential mitigation strategies.

The first section of the report includes a review of relevant literature. The second chapter provides a description of the data sources identified and used for illustrating selected congestion and queue analysis methods and mitigation strategies. The last section includes examples of how the identified data sources can be used to improve queue detection and minimize the negative impacts of congestion for travelers.

Literature Review

Congestion management and forecasting has been at the forefront of transportation agencies for decades. Lomax et al. defined congestion in their 1997 NCHRP Report 398 as:

- Congestion is travel time or delay in excess of the normally incurred under light or free-flow travel conditions.
- Unacceptable congestion is travel time or delay in excess of an agreed-upon norm. The agreed-upon norm may vary by type of transportation facility, travel mode, geographic location, and time of day.

The two other concepts used in determining congestion are:

- Mobility – the ability of people and goods to move quickly, easily, and cheaply to where they are destined as a speed that represents free-flow or comparably high-quality conditions.
- Accessibility – the achievement of travel objectives within time limits regarded as acceptable (Lomax et al., 1997).

As populations increase and roadway capacities "shrink", the need to develop methods to quickly and accurately identify problems and implement strategies for mitigation becomes more urgent. Historically traffic congestion has been measured using identifiers such as speed, travel time, delays, level of service (LOS), congestion indices and federal level measures. However, as roadways and cities continue to grow they also continue to get "smarter." Transportation agencies are able to utilize data from the smart technologies such as the Internet of Things (IoT), Internet of Vehicles (IoV), vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) to provide critical real-time data for a faster and more accurate assessment of traffic conditions. Transportation infrastructure and vehicle technologies have changed how transportation agencies collect and manage data and disseminate traffic information. Intelligent transportation system (ITS) infrastructures contain sensors, data processing, and communication technologies that enable the transfer of data from vehicle-to-vehicle, vehicle-to-infrastructure, and infrastructure-to-vehicle and tracking of individual vehicles (El Faouzi et al., 2011).

The basic safety message (BSM) is a connected vehicle technology consisting of vehicle position, heading, speed, and other information relating to a vehicle's state and predicted path (see Figure 1). Onboard units (OBUs) installed on vehicles will continually broadcast BSMs. Roadside units (RSUs) also receive and broadcast messages. To enable security in V2X systems, it is important to ensure:

- A message originates from a trustworthy and legitimate device
- A message was not modified between sender and receiver
- Misbehaving units are detected and removed from the system (USDOT 2019).

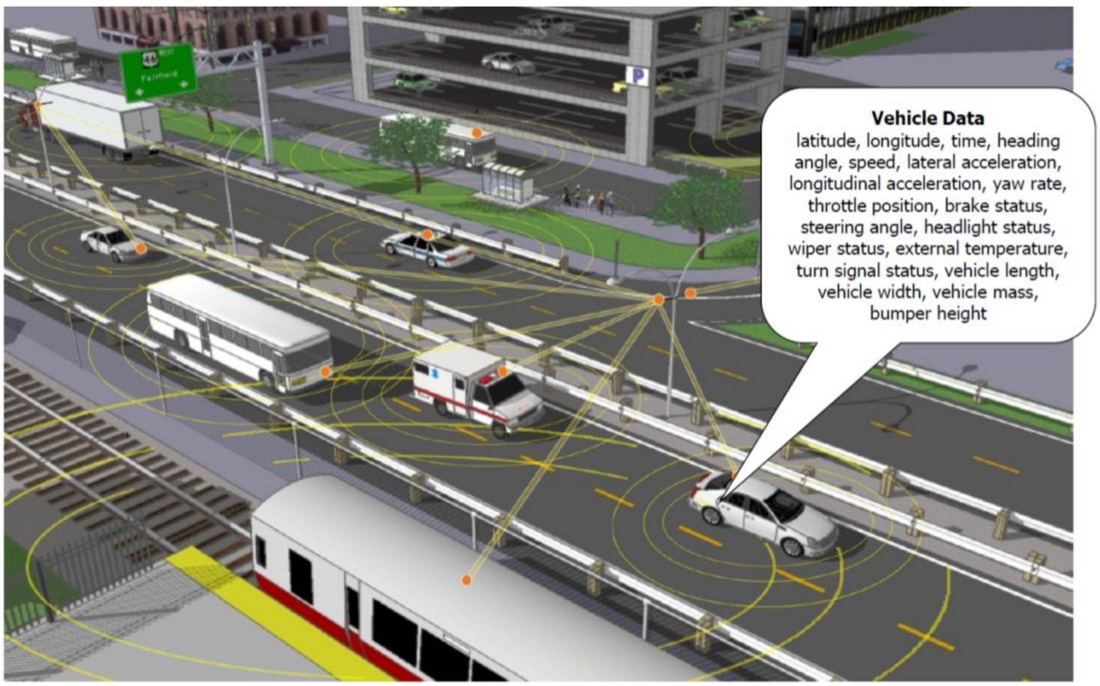

Figure 1. Fully Connected Vehicle (Cronin 2020).

Using cellular data to augment BSM provides the vehicle data needed to support nearly all mobility applications such as:

- Cooperative Adaptive Cruise Control
- Speed Harmonization
- Queue Warning
- Intelligent Traffic Signal System
- Transit Signal Priority
- Mobile Accessible Pedestrian Signal System
- Emergency Communications and Evacuation

- Incident Scene Pre-Arrival Staging Guidance for Emergency Responders
- Incidents Scene Work Zone Alerts for Drivers and Workers
- Next Generation Integrated Corridor Management
- Transit Connection Protection
- Dynamic Transit Operations
- Dynamic Ridesharing
- Freight Traveler Information
- Traveler Information (Cronin 2020).

The USDOT's Dynamic Mobility Applications (DMA) Program was initiated in 2009 to develop and assess bundle type applications that work with CVs to better enable safer, smarter, greener, and more efficient travel. These DMA applications included:

- Enabling Advanced Traveler Information System (EnableATIS)
- Freight Advanced Traveler Information Systems (FRATIS)
- Integrated Dynamic Transit Operations (IDTO)
- Intelligent Network Flow Optimization (INFLO)
- Multi-Modal Intelligent Traffic Signal Systems (MMITSS)
- Response, Emergency Staging and Communications, Uniform Management, and Evacuation (R.E.S.C.U.M.E.) (USDOT DMA).

One of the key components going forward with traffic management on urban street networks includes how use these technologies to identify queue formation and spread in real-time using automated detection systems. This involves methods to determine queue spread, the rate of spread and the potential impacts of the queue as it spreads into the surrounding areas and creates traffic flow delays. The impacts of the queue known as a shockwave are characterized as the boundaries between different traffic states such as different vehicle speeds and densities (i.e., boundary between slow-moving queued vehicles and approaching high-speed traffic) (Pesti et al., 2007). Real-time data collection and analysis method involves combining data from multiple sources to provide an accurate and reliable assessment of real-time (or near real-time) traffic conditions. This method is known as data fusion (DF). Transportation agencies are tasked with gathering and analyzing enormous amounts of traffic data, known as big data, across multiple modalities and domains. These data can include traffic cameras, global positioning system (GPS) or location information, Twitter and vehicular sensors, taxi trajectories data, metro/bus swiping data, bike-sharing data and so on (Adetiloye and Awasthi 2019, Xie et al., 2019). Other multisource data includes Bluetooth® and IP-based (cellular and Wi-Fi) communications, GPS devices, cell phones, probe vehicles, license plate readers, infrastructure-based traffic-flow sensors, and connected vehicles. Table 2 shows some of the applications assembled by El Faouzi and Klein (2016) that includes data fusion algorithms and architecture.

Table 1. Data fusion algorithms and architectures currently applied to ITS (El Faouzi and Klein 2016).

Application	*Data Fusion Algorithm*	*Architecture*
Ramp metering	Fuzzy logic	Sensor level
Pedestrian crossing time	Fuzzy logic	Central-level
Automatic incident detection	Artificial neural network	Sensor level
Automatic incident detection	Bayesian inference	Sensor level
Automatic incident detection	Dempster-Shafer	Sensor level or decision level
Travel time estimation	Inference rules	Sensor level
Travel time estimation	Dempster-Shafer	Sensor level
Travel time estimation	Weighted mean of several travel-time estimators. Weights are a function of the variance or covariance of the estimators.	Sensor level
Travel time estimation	Weighted mean where the weights are a function of the data source reliability.	Sensor level
Travel time estimation	Fuzzy logic	Sensor level
Vehicle and object tracking	Kalman filter	Central level
Lane departure warning	Image processing using edge detection and extraction of other features.	Pixel level
Traffic state estimation	Extended Kalman filter	Central level
Crash analysis and prevention	*k*-means algorithm	Sensor level or decision level
Traffic forecasting and monitoring	Bayesian inference	Sensor level
Traffic forecasting and monitoring	Artificial neural network	Sensor level
Traffic forecasting and monitoring	Kalman filter	Central level
Traffic forecasting and monitoring	Extended Kalman filter	Central level
Traffic forecasting and monitoring	Kernel estimator	Central level
Traffic forecasting and monitoring	Particle filter	Central level
Vehicle position estimation	Unscented Kalman filter	Central level
Vehicle position estimation	Artificial neural network	Central level

Mekker et al. (2017) discuss the high-level function of an email/text queue alert system developed for the Indiana DOT (INDOT) to notify relevant personnel, such as work zone managers, of queues that exceed prescribed thresholds. The algorithm was first deployed in 7 work zones with 13 users receiving text messages. On average, there were 8 text messages per day per work zone. Two case studies from one of the six work zones are presented that demonstrate the functionality of the system by using images captured from existing traffic cameras. Result demonstrated the feasibility of using a system to send targeted alerts to public safety and traffic management personnel to assist with more informed decisions during incidents (Figure 2). The probe vehicle data is collected by a third-party vendor from several sources, including freight, smart phones, and in vehicle GPS. The queue alert system developed in this study utilizes the same real-time probe vehicle data for defining and locating queues as in the previous INDOT tool.

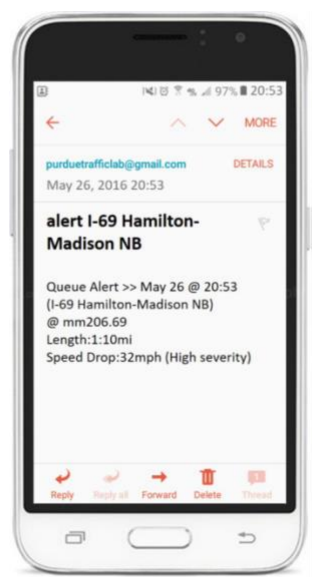

Figure 2 Sample queue alert message (Mekker et. al 2017).

Federal Highway Administration has procured probe data feeds and provides free access to state and local agencies as National Performance Measures Research dataset (NPRMDS). INRIX is the current provider of NPMRDS data records. Ahsani

et al. (2020) evaluated the reliability of probe-sourced data (INRIX) using two performance measures; congested hour and the number of congested events. Another study looked at a 23 intersection urban corridor in Pittsburgh, PA to evaluate the operational impacts of the SUTRAC (Scalable Urban Traffic Control) Adaptive Signal Control Technology (ASCT) using a combination of real-world GPS floating car runs and private sector probe data from INRIX. The ASCT was found to produce significant improvements in the number of stops made along the corridor. The findings of this study are generally consistent with past evaluations of other ASCTs, indicating that the SURTRAC system is another potential tool for managing congestion on signalized urban arterial networks (Khatak et al. 2020). Zhang et al. (2020) also evaluated the accuracy of the travel time data estimated by Dual loop, Waze, HERE, and INRIX against Bluetooth data. The results show that the INRIX and HERE data closely match the Bluetooth data, both in the trends and values of reported travel time; however, all three vendors' data accuracy deteriorates when the traffic congestion intensifies (Zhang et al. 2020).
The Intelligent Traffic Congestion Monitoring & Measurement System called TrafficMonitor developed by Mandal et al. (2011) uses a probe vehicle that combines active RFID and Global System for Mobile communication (GSM) technologies to trace the travel time of probe vehicle as it passes the roadside devices and create an average trip time. TrafficMonitor measures congestion of a single length of road using the following:

- One active RFID tag to be kept in the probe vehicle
- One wireless router and one wireless coordinator (both acting as RFID readers) to be installed at the roadside
- Two GSM modems (one with coordinator and the other with central monitoring station) for wireless data transmission between gateway and software monitoring system
- Monitoring station software for real-time visualization of traffic congestion and report generation.
- The system can also be connected wirelessly with Variable Message Sign (VMS) to divert the traffic upon automatic detection of congestion on a stretch of a road.

Crowd sourced GPS probe data have become a major source of real-time traffic information applications being used for automatic incident detection, integrated corridor management (ICM), end of queue (EOQ) warning systems, and mobility-related smartphone applications. Wang et al. (2018) evaluated the lag time between the reported incident in the outsourced data feed, and the time at which the traffic is disturbed using high-quality independent Bluetooth/Wi-Fi re-identification data to measure the latency of the vehicle probe data provided by three major vendors.

EOQ warning systems can use a combination of sensors for detecting traffic and an artificial neural network (ANN) model-based algorithm for predicting EOQ location and issuing warning messages displayed on portable variable message sign (PVMS). Khan (2017) synthesized an automated information system that integrates traffic sensors, ANN models, PVMS and potential links with other media for highway work zones which automatically predicts queue-end location and alerts drivers so that rear-end collisions can be avoided. Selected results of ANN models illustrate their application in the queue-end warning system requires a limited number of traffic sensors and relies upon the ANN-based algorithm to perform its function. Limitations of the system design include its reliance on predictive queue-end models rather than traffic sensors to find the EOQ on a real-time basis and it does not have the on-line self-calibration capability necessitating the analyst to intervene during a field demonstration period, archive the sensor data and measure queues.

Pesti et al. (2019) used a microscopic traffic simulation to explore the expected performance and reliability of a work zone queue warning system. Researchers assessed system performance based on queue detection accuracy, distribution of queue estimation errors and the percentage of drivers that encountered queues without receiving any warning. The effect of key design parameters such as speed thresholds for queue detection, detector spacing and speed aggregation intervals, portable changeable message sign (PCMS) location and update intervals were studied using a simulation testbed of a queue warning system for a hypothetical freeway work zone involving the closure of a lane. The results showed that queue warning systems with half-mile spacing between speed sensors detected queues with significantly higher accuracy than systems with 1-mile sensor spacing. It was also found that shorter speed aggregation intervals and shorter PCMS update intervals improved the reliability of the system by reducing the percentage of drivers encountering queues without warning. However too short PCMS update intervals may increase oscillation in queue warning messages.

Another EOQ warning system uses Dedicated Short Range Communications (DSRC). The study conducted by Liu et al. (2017) used only velocity difference information which is one of the key factors for determining s_{sl}, the minimum distance to avoid collision. The proposed model considered the influencing factors of real highway data such as traffic parameters, communication range and penetration rate.

The technique developed Mohammadi et al. (2020) is based on the strength of Bluetooth signals transmitted by both stationary and moving beacons, creating radio maps, and applying an algorithm called k-nearest neighbors (k-NN). They evaluated an intersection and its adjacent streets using four Bluetooth signal scanners and a beacon. Results found up to 90% precision with the stationary beacons with an error of 5 m or less, but the moving beacons were challenging. Two advanced Bluetooth devices were used along a 0.52-mi segment of an urban arterial road in Baton Rouge, LA to assess match rate, travel time, and segment speed to benchmark data sets. They were coupled with classic Bluetooth technology: the demodulator (BT DM), and the low-energy Bluetooth signal additional component (BLE). Results showed the BLE performed better than the BT DM (Cotton et al. 2020).

Liu et al. (2020) used approximately two million records of Bluetooth time-stamped media access control (MAC) data to evaluate their accuracy for travel time. The work shows that accurate Bluetooth-based travel time information on signalized arterial roads can be derived if an appropriate matching method can be selected to smooth out the remaining noise in the filtered travel time estimates. The method used by Advani et al. (2019) to develop Bluetooth MAC Scanner (BMS) based links for the entire Brisbane city network focused on challenges of integrating the Bluetooth scanners and the Open Street Map network used for congestion visualization. The results showed the method is ready to implement for any large city network. A study conducted by Yuan et al. (2020) included a review of case studies regarding the use of Bluetooth for traffic data and included three case studies in Delaware. The overall conclusion is that the Bluetooth technology by itself is not a proper tool for travel time measurements. Some of the issues found with using Bluetooth data are as follows.

- Unknown location of detected vehicle within the detection zone
- Extremely dense data processing
- Communications/power supply complications during sensor deployment
- Oversampling
- Unable to determine traffic volume
- Trip-Chaining
- Low detection/match rates
- No standard for of analysis
- Limited information extraction

- Difficulty of determining reasons for delay

Researchers from the University of Central Florida (Abdel-Aty et al. 2019) developed a decision support system (DSS) for Integrated Active Traffic Management (IATM) for both freeways/expressways and arterials/collectors. The data sources used included HERE, NPMRDS, MVDS (Microwave Vehicle Detection System), AVI (Automatic Vehicle Identification), BlueTOAD, BlueMAC, etc. The results suggested that the developed DSS could successfully reduce traffic congestion and improve travel time reliability.

The Ontario Ministry of Transportation developed their *Transportation Systems Service Books* available on their website http://www.mto.gov.on.ca/english/publications/#corridor. These include Permanent Queue Warning, Roadside Travel Time Information and Traffic Incident Management. Each contain information that includes system costs and life cycle expectancy. The Queue Warning Systems (QWS) found in *the Permanent Queue Warning Service Book* includes the three basic components of detection, processing and information dissemination. Table 2 contains the compiled information (Grewal 2020).

Table 2. Permanent queue warning technologies (Grewal 2020).

	Technology	Advantage	Disadvantages	Description
Detection	In-pavement detectors	Reliable	Maintenance issues	e.g. inductive loops, magnetometers, magnetic detectors
	Radar/Microwave Traffic Sensors	Configurable to changing lane patterns High sample size Can be leveraged for traffic count data	Requires mounting on existing infrastructure or installing new poles	Pole-based sensors utilizing microwave/radar technology to detect vehicle speeds, classification and volume data and they represent a reliable, tested, and non-intrusive approach for permanent deployments.
	Bluetooth Detectors	Low cost Can be leveraged for travel time	Not well suited for standalone queue detection. Sample size constrained to availability of passing Bluetooth devices. Requires the same vehicles to span two or more detection points.	Roadside sensors scan for passing Bluetooth devices as a surrogate to the presence of a vehicle. A second Bluetooth device placed downstream provides comparative data to determine average vehicle speeds.
	Probe Data	Requires no infrastructure Scalable Portable	Still in development and early stages. Unproven for this application. Requires new software to integrate to VMS controller.	Privately sourced vehicle location data through a combination of car manufacturers, commercial fleet trackers and/or cell phones (e.g. INRIX, TomTom, Cellint).

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	Technology	Advantage	Disadvantages	Description
Processing	Queue detection algorithm	This system offers the ability to monitor and override the messages as needed.	MTO's current system is an Advanced Traffic Controller (ATC) based system near the end of its design life. MTO is currently exploring alternative options which may include Software-as-a-Service (SaaS) or server-based systems.	Upon determination of a queue, the appropriate information can be issued to message signs and/or traveler information systems.
Information Dissemination	Static Queue Warning Signs	Low cost Contact closure input allowing for simplified integration	Limited visibility and applications No time or distance information is provided	A static sign advising to "Watch for Slow Traffic" accompanied by flasher beacons. Flasher beacons are actuated when a downstream queue is detected.
	Hybrid Queue Warning Signs	Low cost and lower power compared to other variable message sign options	Combination of static and variable text may hinder readability	Like the static queue warning sign with the addition of a single-line VMS providing the distance to the queue
	Permanent Portable Variable Message Sign	VMS provides additional messaging options Medium cost Large sign face for detailed messaging and high readability across all lanes	Low, roadside deployment may limit visibility to drivers across all lanes Does not provide clean, permanent aesthetics	Portable variable message signs (PVMS) deployed on a concrete pad to provide a "permanent" application
	Overhead Variable Message Sign	Large sign face for detailed messaging and high readability across all lanes Can be used for alternate applications when a queue is not present	High cost	Typically used for multi-purpose applications such as congestion, safety, and traveler information
	Pole-mounted Variable Message Sign	Great readability across all lanes with a higher mounting height Can be utilized for alternate applications when	Moderate to high cost	Permanent, roadside pole-mounted option

	Technology	Advantage	Disadvantages	Description
		the queue is not present Finished design and look		
	Portable Mounted Variable Message Sign (PMVMS)	Great readability across all lanes with a higher mounting height Flexibility in deployment locations Can be utilized for alternate applications when a queue is not present	Originally designed for temporary applications Typically used for construction or special event applications, not providing dedicated queue warning function	Can be deployed on the median, separator or roadside using a temporary concrete barrier system

Queue length and queue discharge rates are key performance measures for urban street networks that consist of signalized intersections that contribute to the traffic shockwave. Urban spatial-temporal traffic flow congestion are characterized by these main components: traffic incidents, work zones, daily flows activity patterns, anomalies of flows activity patterns, weather, special events, traffic control devices, and inadequate capacity (Crawford et al. 2011, Xie et. al 2019). Contributing factors can include left-turn spillback, traffic from side streets, traffic signal timing and queue storage capabilities.

Numerous studies and models examined probe vehicles with sensors and probe data as methods for identifying and/or estimating traffic conditions. A proposed model using a two-way bandwidth maximization approach considers the turning traffic from side streets especially when the traffic volume is relatively high and the spacing between arterial intersections is short. Results showed a reduction in the overall network average delay and number of stops per vehicle (Chen et. al 2019). Zhang et al. (2020) examined a cycle-based EOQ estimation method using sampled vehicle trajectory data under relatively low penetration rates that resulted in desirable accuracy using different scenarios, e.g., under-saturated, oversaturated, and queue spillback conditions. Yin et al. (2018) used low-penetration mobile sensor data as the only input as a queue length estimation method based on the combination of Kalman Filtering and shockwave theory. Yao and Tang (2019) looked at point detector placement method to estimate the cycle-based queue length at signalized intersections considering spillover. Detector data at the upstream intersection approach are used to modify the volume data of the downstream intersection when long queue occurs, and the effect of spillover can thus be formulated analytically using the shockwave theory. An integer-programming model was evaluated to estimate queue length and guarantee the consistent reconstruction of shockwave propagation by comparing the estimated queue length with observed queue length in every signal period based on simulation data. Results demonstrated the model's ability to estimate queue length and the required penetration rate of floating vehicles (Guo et al. 2019). Christofa et al. (2016) developed and tested a queue spillback detection method using CV data and CV data combined with information about the signal settings at the upstream intersection and is based on a kinematic wave theory of traffic. Results show the penetration rate thresholds of CV-equipped vehicles required for accurate queue detection and the proposed signal control strategy improved traffic operations for the upstream cross streets without compromising traffic operations on either direction of the arterial traffic and substantially reduced the variation of the queue length on the critical arterial link. Results of a study conducted using a new arterial coordination control model for two-way arterial progression solely using sampled trajectories shows that the optimization of fixed-time arterial coordination control solely using sample trajectories is feasible (Yao et al. 2019).

Adaptive signal control usually offers high benefits as it relies on real-time traffic flow information as input, such as traffic volume, queue length, delay, travel speed, and travel time. Vehicle trajectory data was used to estimate traffic parameters at signalized intersections based on a framework combining shockwave analysis (SA) and Bayesian Network (BN) (Wang et al. 2020). A real-time adaptive traffic signal control method for managing spillbacks along signalized arterials used partitioning of the arterial to detect critical cluster(s) of consecutive links with oversaturated traffic conditions. Results showed that an advanced queue length detection method and specific focus on queue spillbacks prevention can significantly reduce congestion and arterial total delay (Ramezani et al. 2017). Chen et al. (2015) used an optimization (SO) algorithm to design the most appropriate adaptive signal plan for a highly congested urban network with multimodal traffic, numerous signalized intersections, short links and a grid-type topology. Results showed the proposed signal plans improves traffic conditions as measured by a variety of performance metrics.

Mercader et al. (2019) presented a max-pressure algorithm for traffic signal control that offers scalability, stability, and distribution. The new, modified version improves the practical applicability of the max-pressure controller by considering travel times instead of queue lengths as input. An extended backpressure algorithm (EBP) considers the trade-off of pressure differential and traffic status of downstream links to prevent queue spillback and improve performance of whole traffic network. Results showed that the coordination of neighboring intersections should be considered in the future work due to the impacts of approaching vehicles from upstream links that will generate pressure to the downstream intersections (Hao 2020).

Perimeter control strategies for urban networks commonly use a macroscopic fundamental diagram (MFD) model. Ingole et al. (2019) investigated the side-effects (in terms of the queue, emission, and total time spent) of perimeter control strategy inside-and-outside of the perimeter. Simulation results show significant improvements in the total time spent and mean speed in the network with a minor increase in the queues. Wang et al. (2017) looked at the effect on the MFD from queue spillbacks and presence of the hysteresis loop during the traffic unloading process. Using the MFD Wu et al. (2018) suggest a perimeter control strategy by assigning a special prohibiting phase to the perimeter traffic lights for the roads entering the core area. Simulations show that the average arrival rate and the average flow will be greatly improved with the perimeter flow control strategy and that it can increase the critical density of traffic congestion. A delay balancing strategy at the gated links under perimeter control was evaluated in microscopic simulation for a realistic traffic network and compared with fixed-time only, perimeter control without queue or delay management and perimeter control with relative queue balancing. Results showed that managing the queues at the gated links not only improves the overall network performance but also reduces the possibility of queue propagation to the upstream junctions (Keyvan-Ekbatani et al. 2017).

Cao et. al examined the development of a proposed online approach to detect traffic shockwaves on freeways, particularly the end-of-queue shockwaves, using spacing-based probe vehicles (SPVs) to the trajectories of its leading and/or following vehicles. This approach had four stages: (1) local shockwave (LSW) position detection, (2) LSW speed estimation, (3) grouping of LSWs into a whole shockwave (WSW), and (4) WSW speed estimation. There were two alternatives for stage 2 - the line connection-based method (LCM) and the Lighthill-Whitham- Richards (LWR) model-based method (LWRM). Stage 4 alternatives were the simple average method (SAM) and the hybrid method (HM). A set of NGSIM data are utilized to evaluate the performance of the proposed method. The combination of LWRM+HM outperforms among the four combined methods. Analysis indicates that the proposed method is computationally efficient, accurate, and more importantly it is applicable for sensor data from SPVs with real-world noise (Cao et. al 2018).

The Minnesota DOT (MnDOT) has conducted several studies. As part of their Active Traffic Management (ATM) the MnDOT examined a queue warning system to manage the shockwave affect using two scenarios: (1) high crash rate due to rapidly evolving shockwaves and (2) longstanding queues extending into the freeway mainline. Results showed a 22% decrease in crashes and 54% decrease in near crashes for scenario 1 and a reduction in the speed variance near the queue locations and the speed difference between upstream and downstream locations for scenario 2 (Hourdos et al. 2017). Another MnDOT project looked at the DMAs such as the INFLO bundle applications that target maximizing roadway throughput, reducing crashes, and reducing fuel consumption through the use of frequently collected and rapidly disseminated data drawn from wirelessly connected vehicles, travelers' communication devices, and infrastructure. Dynamic Speed Harmonization (SPD-HARM) and Queue Warning (Q-WARN) were the INFLO bundle applications that were examined. The INFLO SPD-HARM concept uses V2I and V2V communication to detect impending congestion that might require speed harmonization, generate an appropriate target speed recommendation for upstream traffic, and communicate the recommendations to the affected. Recommendations are made through a traffic management center (TMC) or a similar infrastructure-based entity and then communicated to the affected traffic. Unlike the SPD-HARM application which is infrastructure-based entity, the INFLO Q-WARN application uses V2I and V2V communication (in vehicle and/or infrastructure) to detect existing queues and/or predict impending queues and communicate advisory queue warning messages to drivers in advance of roadway segments with existing or developing vehicle queues (Hourdos et. al 2019).

A study conducted in China used License Plate Recognition (LPR) systems at signalized intersections to record individual vehicles' departure time at the stop-line of each approach lane to identify left-turn lane spillback in order to optimize signal controls. Results of the proposed method showed an average identification rate of 90% for all the left-turn phasing schemes, and achieves the highest 96% for the lagging and protected-only left-turn phase (Wu et al., 2019).

Popescu et al. (2017) discuss the collection of traffic data through V2I communications to facilitate automatic detection of traffic incidents in a highway scenario that are based on the use of distance and time for changing lanes, respectively vehicle speed changes over time. The proposed methods outperform alternative Automatic Incident Detection (AID) techniques through higher incident detection rates, about 25% shorter peak queue values and 20% faster dissipation of roadway congestion.

Another approach at intersections is the use of graph theory which involves the applications of vertex connectivity and edge connectivity in traffic control problems at an intersection. The waiting time of the traffic participants can be minimized by controlling the edges of the edge connectivity and can be achieved by placing traffic sensors on each such edges of the edge connectivity of the transportation network which will provide complete information of the traffic network. As an alternative to above, sensors can also be placed on each vertex of the vertex connectivity of the transportation network for getting complete traffic information of the network (Tanveer 2016). Two vertices are represented as the flow connected by an edge if and only if the flow at the crossroads can be moved simultaneously without causing crashes. Influenced by the volume of traffic flows and the weights of the traffic flow, thus to be created a mathematical model in the form of the total time of all flows function by establishing required conditions, such as minimizing running time of each flow (Setiawan and Budayasa, 2017) shows the direction of the 8 flows labeled *a, b, c, d, e, f, g,* and *h* (Figure 3).

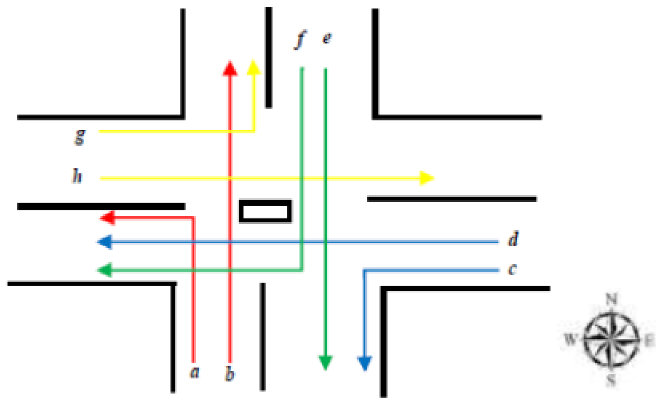

Figure 3. Crossroads Example Darmo Street (Setiawan and Budayasa 2017).

The flows are compatible which can be seen in the following:
1. A flow *a* is compatible with the flows *b, c, e, g, h*
2. A flow *b* is compatible with the flows *a, c, e*
3. A flow *c* is compatible with the flows *a, b, d, e, f, g, h*
4. A flow *d* is compatible with the flows *c, g, h*
5. A flow *e* is compatible with the flows *a, b, c, f, g*
6. A flow *f* is compatible with the flows *c, e, g*
7. A flow *g* is compatible with the flows *a, c, d, e, f, h*
8. A flow *h* is compatible with the flows *a, c, d, g.*

In observation of the crossroads forms are assumptions, including:

- The flow turn left (c) does not follow the light, meaning that the flow can move at any time by the waiting time 0 (zero).
- The flow of the main street Darmo that turn left from the north (e) does not relate directly to the junction for the left turn lane there before the crossroads.
- For other flow turn left (a and g) the movement of currents follow the light.
- There is only one flow turn right (f) (Setiawan and Budayasa 2017).

Traffic flow is always an issue for any roadway. Shelton et al. (2018) examined the potential effects of CV technology on congestion and mobility in a DTATexas context by modeling the traffic impacts of CVs at varying market penetrations on a twelve-mile section of I-35 in Austin at 2035 population levels. Researchers used a multi-resolution modeling (MRM) methodology mobility-focused applications, inspired by cooperative adaptive cruise control (CACC), speed harmonization, and queue warning applications which incorporates macroscopic, mesoscopic, and microscopic models. Figure 4 demonstrates the findings from the simulation-based modeling that showed counter-intuitive results when comparing to the consensus results of previous studies modeling CACC. On a heavily congested network, the effects of the Custom CV application were detrimental to the performance of the freeway in terms of mobility – speeds and total volumes were reduced while total travel times increase.

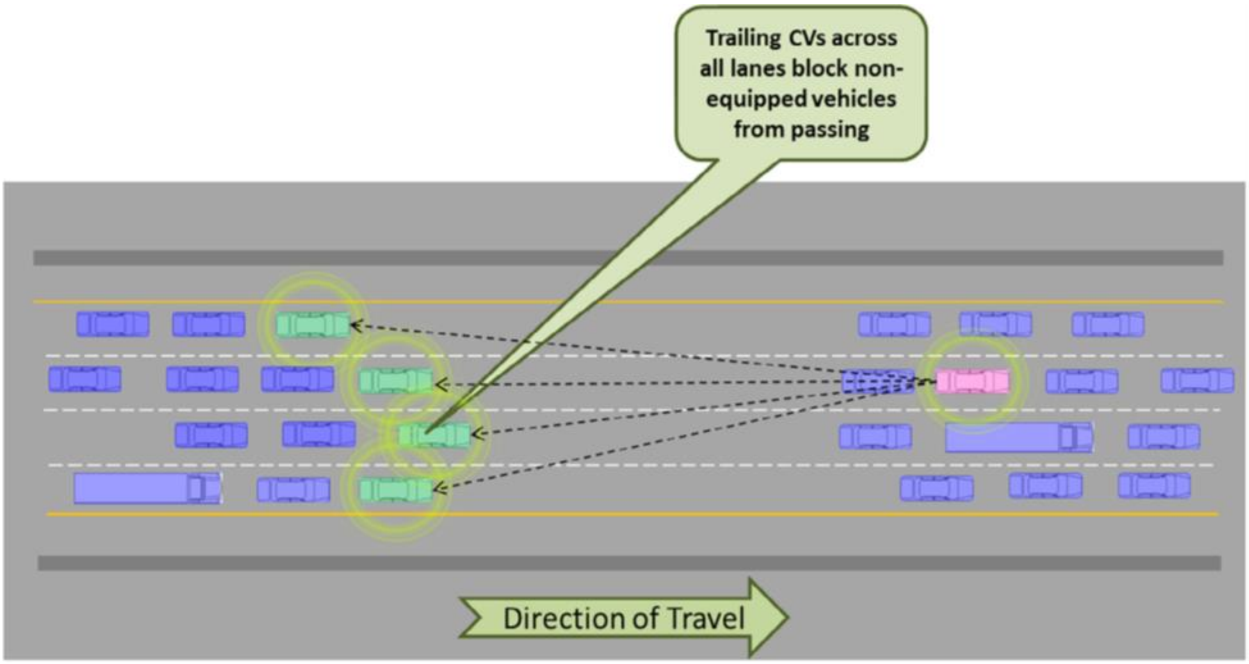

Figure 4. Impacts of CV on congestion (Shelton et. al 2018).

Mekker et al. (2015) looked at 3 years of Indiana crash data and crowd-sourced probe vehicle data to classify crashes as being associated with queueing conditions or free-flow conditions. A new measure of crash rate was developed to account for the presence and duration of queues: crashes per mile-hour of congestion. Resulting trends were as follows:

- Over the 3 years studied, 13% of fatal crashes occurred at the back of a queue.
- 87% of fatal back-of-queue crashes involved at least one commercial vehicle.
- Only 1-2% of the total mile-hours of interstate operated under congested conditions.
- 90% of congested crashes in 2014 had a queue duration ≥ 5 minutes
- 75% of congested crashes in 2014 had a queue duration ≥ 14 minutes
- Overall congested crash rate was 24.1 times greater than the uncongested crash rate
- Rural congested crash rate was 23.8 times greater than the rural uncongested crash rate
- Urban congested crash rate was 20.7 times greater than the urban uncongested crash rate

Gap in Literature

Although the literature extensively covers the various data sources and their use for congestion and queue analysis, only a limited number of studies focused on the combination of multiple data sources for queue detection and queue warning applications. There is a need to identify all challenges of fusing point detector data with crowd-sourced segment data, and to develop algorithms that can improve the accuracy and latency of queue detection under various data availability scenarios.

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Data Identification

After a review of available datasets, the TTI research team identified the I-35 traveler information database and data collection system that has been successfully used for detecting congestion and queue formation along a 100-mile segment of I-35 in Central Texas. The I-35 data suite incorporates a lane closure database and real-time and archived traffic data from various data sources. Available traffic data include lane-level traffic volumes and spot-speeds from Wavetronix radar sensors, segment travel times and speeds from Bluetooth (and/or WiFi) readers, incident and traffic jam data as well as segment travel times and speeds from third-party traffic data providers. Both real-time and archived data are available from most of these data sources. This section describes available data sources and data types on I-35 in Central Texas, and provides details on their potential use for queue detection and queue warning applications.

Data sources on I-35

The Texas Department of Transportation (TxDOT) has undertaken a $2.1 billion reconstruction project of a 100-mile section of the I-35 corridor located between Hillsboro and Salado in Central Texas. During reconstruction, TxDOT in collaboration with the Texas A&M Transportation Institute (TTI) has developed and deployed a traveler information system for providing real-time traffic information to travelers, freight operators and businesses along the corridor, so they can make informed travel decisions and route choices. The traveler information system deployed along the corridor has several advanced field components that provide real-time information on lane closures, travel times to the nearest major destination on the corridor, the existence and location of vehicle queues in advance of work zone lane closures, and available alternate routes. Wavetronix radar sensors, Bluetooth readers and CCTV cameras deployed along the corridor provide real-time data feeds and archived databases for the traveler information system. Bluetooth and Wavetronix locations on the I-35 corridor are shown in Figure 5.

Wavetronix Radar Sensors

As shown in Figure 6, a radar-based Wavetronix uses a sensor installed on a roadside pole. Each radar is capable of lane-by-lane vehicle counts and classification and speed detection. If positioned properly, a single radar can collect the data in both travel directions. The sensor uses a unique pair of radar beams (a speed trap) projected across each traffic lane to detect vehicles and calculate their speeds and lengths on a per lane basis. The most common brand of this type of sensors uses central software that receives sensor data transmitted through messages.

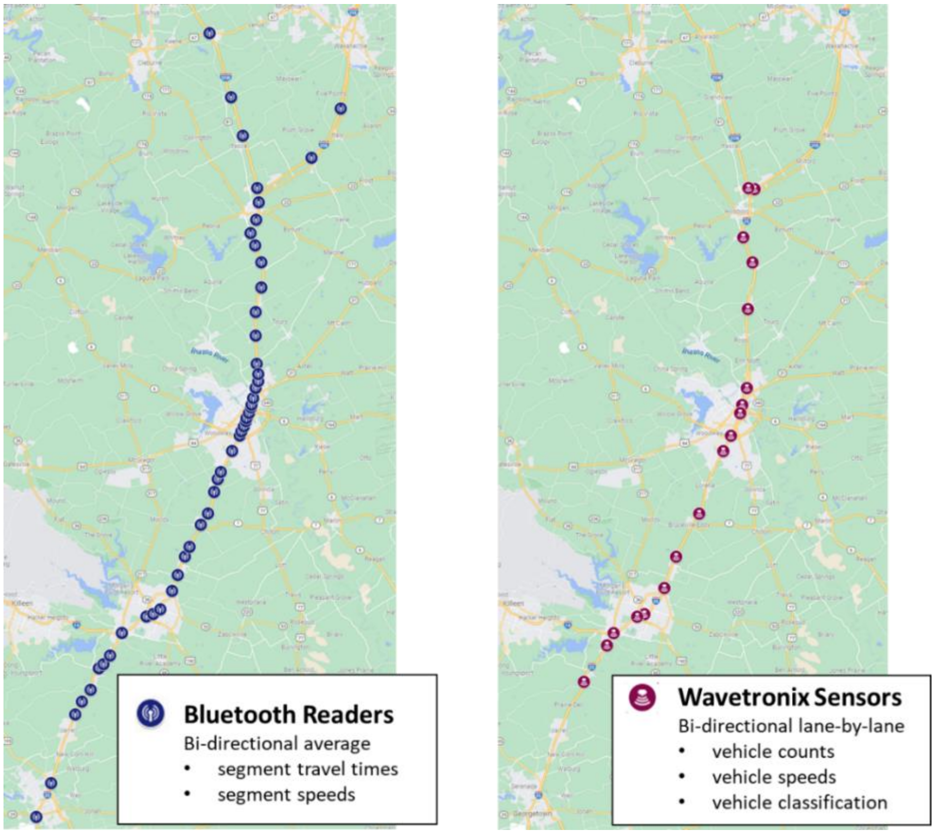


Figure 5. Bluetooth and Wavetronix sensors on the I-35 corridor.

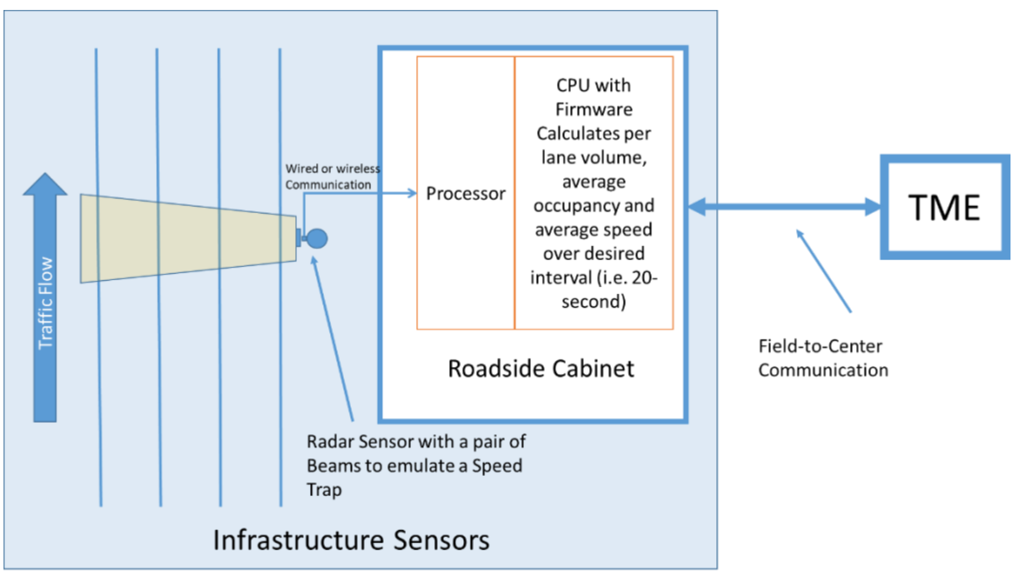


Figure 6. Radar-Based Detection.

Wavetronix data are archived and available in 15-min and 60-min intervals. A sample data set archived in 15-minute intervals is illustrated by Table 3. Six-month average northbound volumes at 15 Wavetronix locations on I-35 are shown by the heat map on Figure 7, and the time series plots on Figure 8 through Figure 10.

Table 3. Sample Wavetronix data archived in 15-minute intervals.

Time	Sensor ID	Location	Volume				Avg Speed MPH	Avg Occupancy	Total Lanes	Num Samples
			Total	Small	Med	Large				
4/7/2021 0:00	9218	IH-35 Southbound at TokioRd-West-MM351.7	161	59	10	92	69	0	3	30
4/7/2021 0:15	9218	IH-35 Southbound at TokioRd-West-MM351.7	141	49	10	82	69	0	3	30
4/7/2021 0:30	9218	IH-35 Southbound at TokioRd-West-MM351.7	127	35	12	80	70	0	3	30
4/7/2021 0:45	9218	IH-35 Southbound at TokioRd-West-MM351.7	135	43	11	81	69	0	3	30
4/7/2021 1:00	9218	IH-35 Southbound at TokioRd-West-MM351.7	132	41	8	83	69	0	3	30

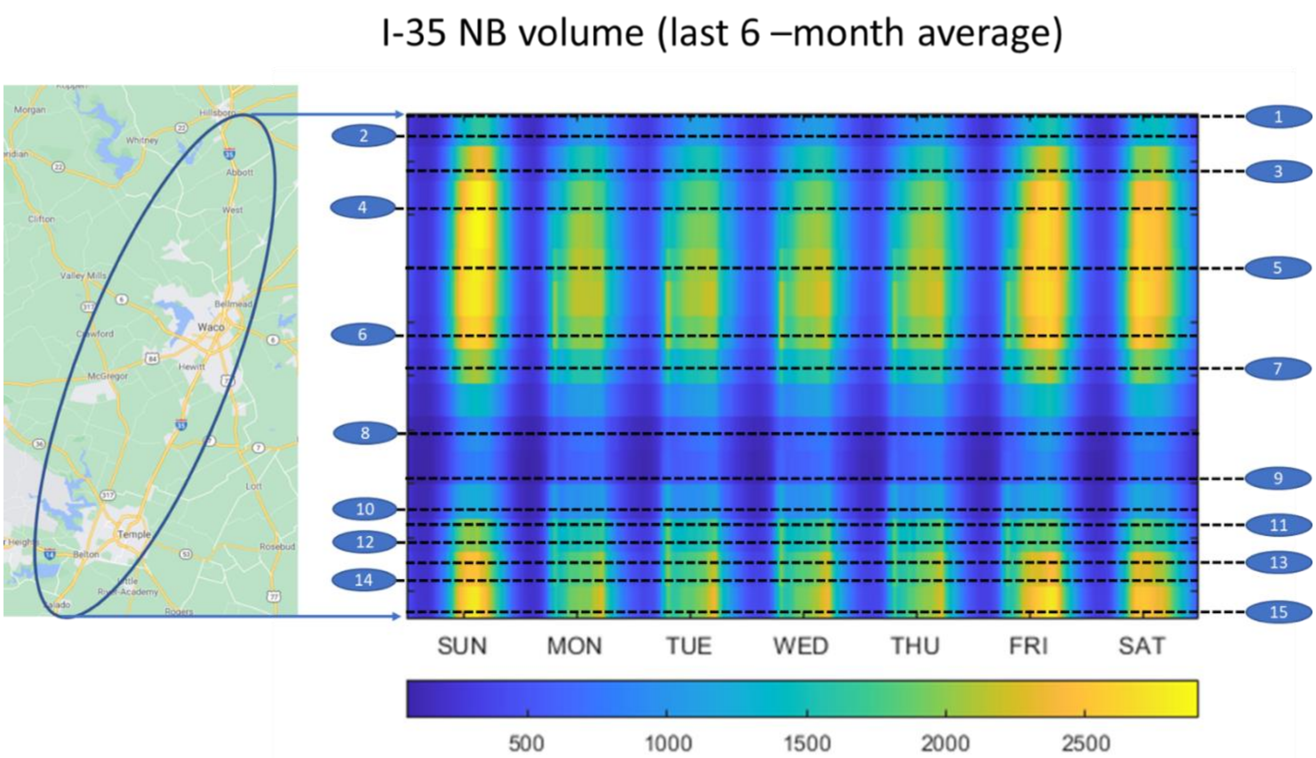


Figure 7. Historical (Six-Month Average) NB Traffic Volumes on the I-35 Corridor.

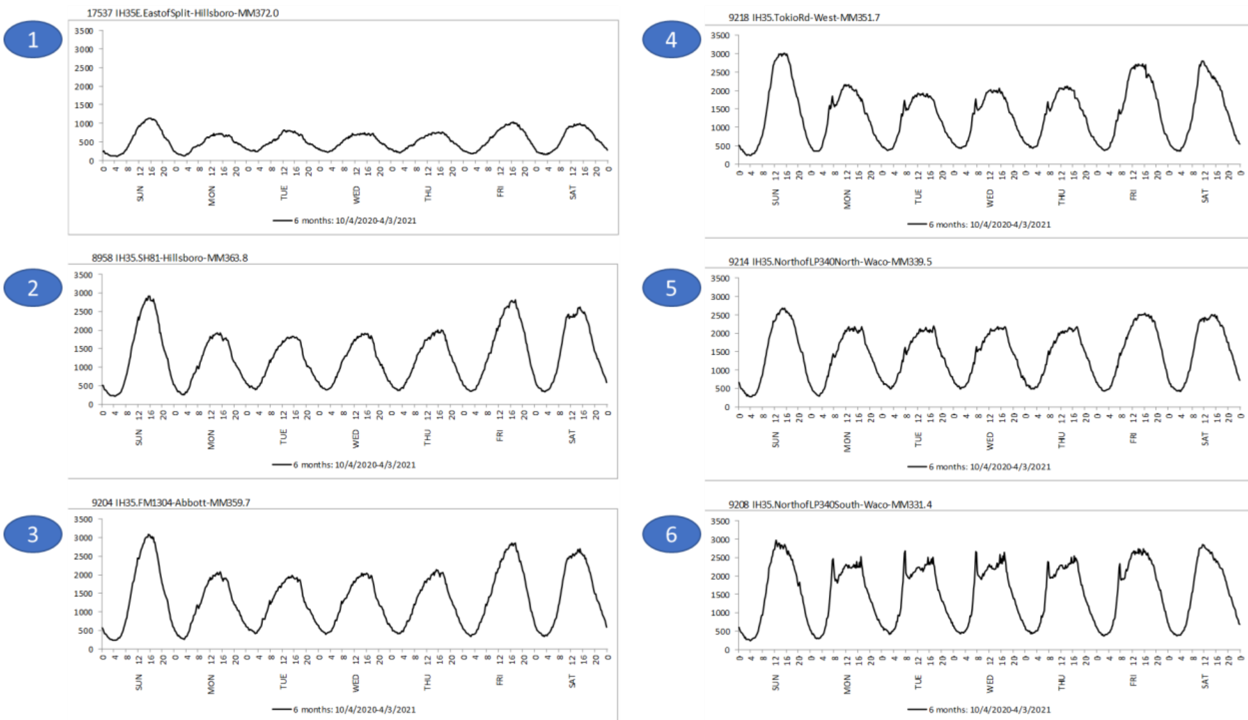


Figure 8. Six-Month Average NB Traffic Volumes at Wavetronix Stations 1 through 6.

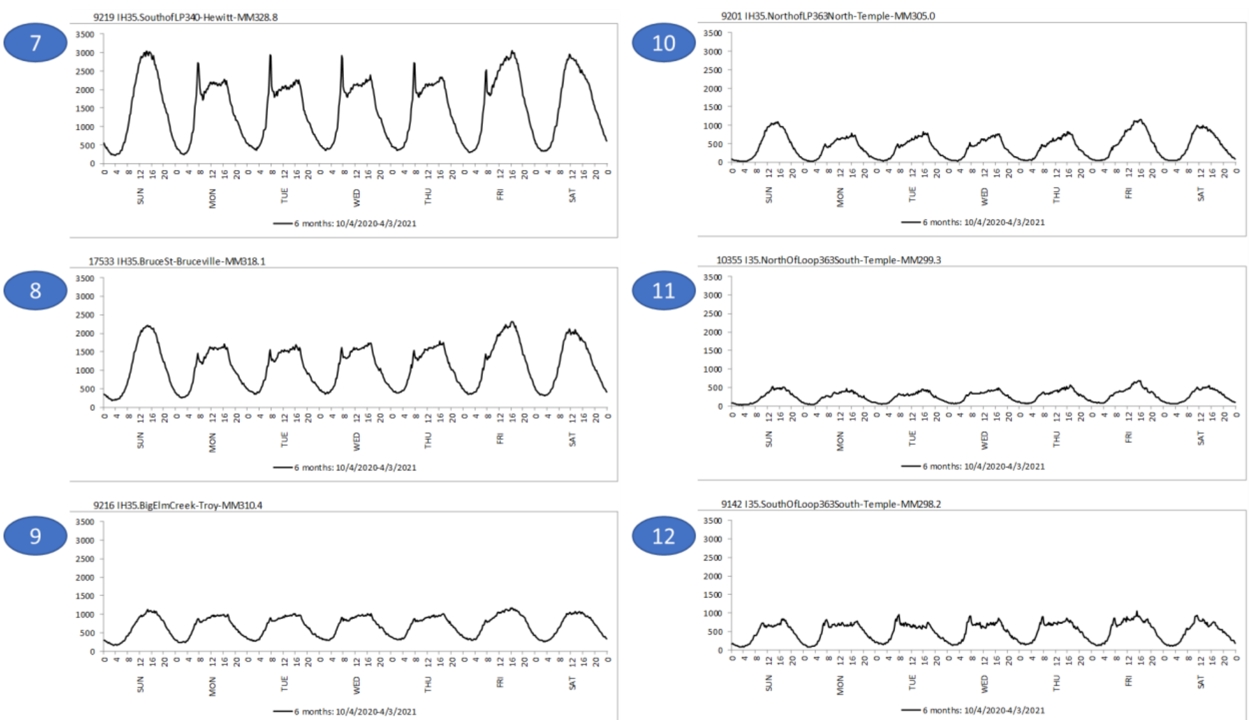


Figure 9. Six-Month Average NB Traffic Volumes at Wavetronix Stations 7 through 12.

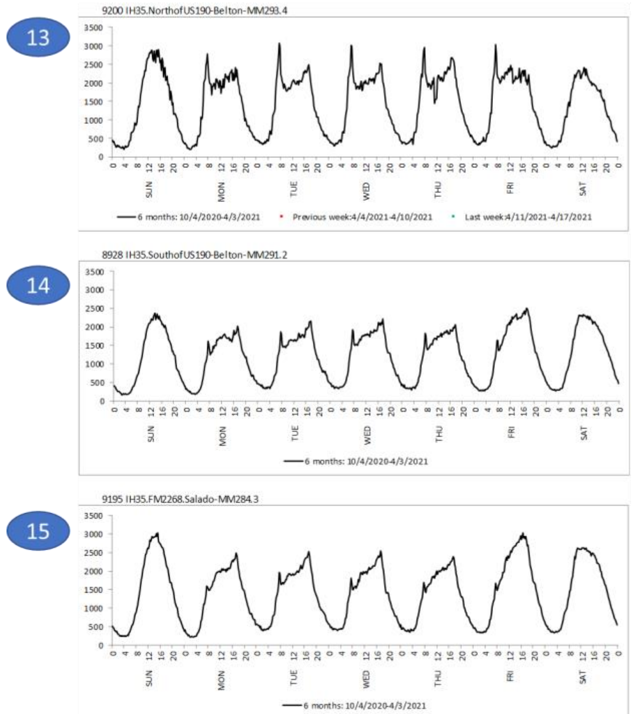


Figure 10. Six-Month Average NB Traffic Volumes at Wavetronix Stations 13 through 15.

Data from Wavetronix sensors have been used for

- Estimating the expected impact (delay and queue length) of planned lane closures.
- Assessing the need for deploying portable queue warning systems for planned closures.
- Find the best schedule for planned closures, i.e., closure time that is expected to have the least negative impact (minimum delay and shortest queues).
- Identifying potential radar sensor issues (e.g., need for equipment adjustment due to change in roadway alignment).

Bluetooth-based Segment Travel Time and Speed

On the I-35 corridor, Bluetooth readers are deployed at an average of 4-mile spacing with a minimum distance of 0.9 mile and maximum distance of 11.5 miles between consecutive readers. Each BT-reader unit reads MAC addresses of passing-by mobile BT devices (vehicle-based or hand-held devices of occupants) and records the observation time and location, and wirelessly transmits them to TTI's database server. Figure 11 illustrates this system.

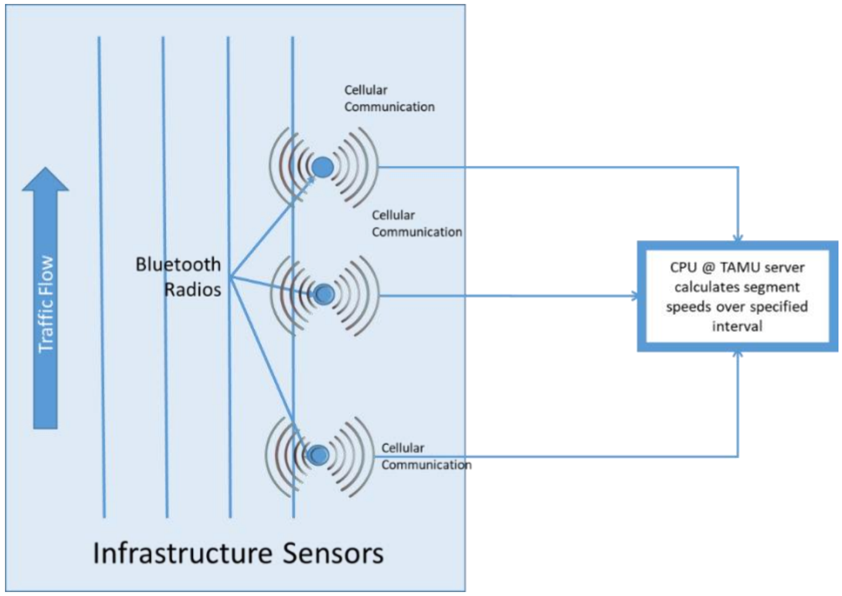


Figure 11. Bluetooth-based Segment Travel Time and Speed Data Collection.

The central computer software uses an address-matching algorithm to identify vehicles detected at adjacent stations and uses respective detection times and known distance between field devices to calculate the segment travel time for these vehicles. After calculating the travel times between designated pairs of Bluetooth readers and applying appropriate filters to remove outliers and invalid data, the data are archived and stored on the server. The archived data include travel times of individual vehicles with matched Bluetooth MAC addresses, and average segment travel times and speeds in 15-min intervals. Bluetooth-based post-event analyses of freeway work zones and incidents on the I-35 project have been used for

- Assessing the impacts of lane closures, accidents, and special events on the corridor, both separately and in combination.
- Determining mobility-related work zone performance measures at both the project- and corridor-levels.

Data from Existing Queue Warning Systems (iCone)

The TxDOT in collaboration with TTI have been deploying portable queue warning systems for work zones in the I-35 reconstruction project. The portable queue warning system used iCone® portable traffic monitoring devices. An iCone® is a self-contained, battery-powered unit that consists of a radar detector, GPS antenna, cellular and backup satellite communication capabilities, and processor.

The deployment procedure starts with the prediction of queues that a lane closure was expected to create. An input-output analysis is performed using traffic demands calculated from

- historical volumes measured on the approach to the work zone and
- the estimated reduced capacity of the lane closure.

If a queue was expected to occur, then a queue warning system is deployed at that location. The queue warning systems have been deployed in two configurations depending on the expected lengths of the longest queues. The first configuration consists of speed sensors installed at the lane closure taper and at 0.5, 1.5, and 2.5 miles upstream of the taper; a PCMS is placed at 3.5 miles upstream of the taper, as illustrated by Figure 12.

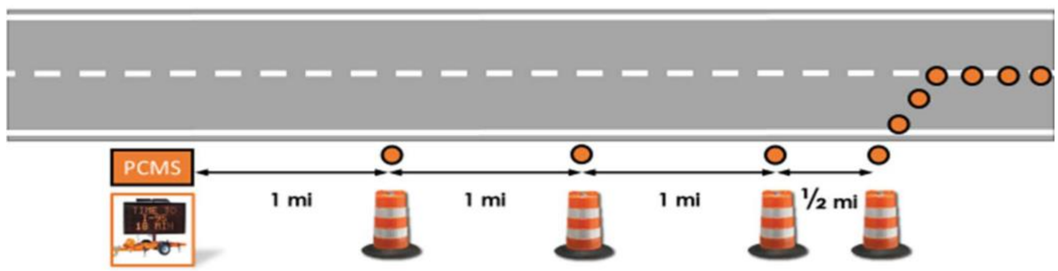
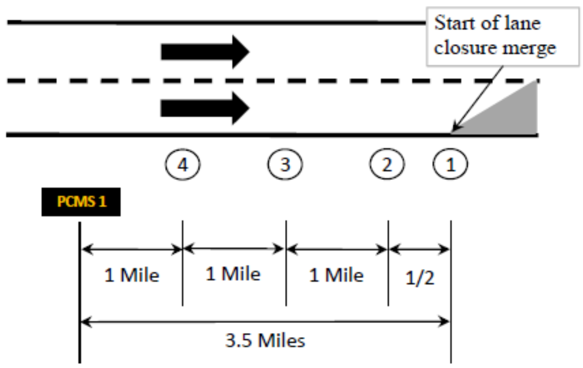


Figure 12. iCone Deployment Configuration Layout.

When queues longer than 3 miles are expected, additional sensors are installed at 3.5, 4.5, 5.5 and 6.5 miles upstream of the taper, and an additional PCMS is placed at 7.5 miles upstream of the taper. Message selection logics for the two queue warning system configurations are shown in Figure 13 and Figure 14, respectively.



PCMS 1	Q	(4)	(3)	(2)	(1)
{Blank}	= 0	F	F	F	F
SLOW TRAFFIC 3 MILES	= 0.25	F	F	F	M
SLOW TRAFFIC 2 MILES	= 1	F	F	M	!S
SLOW TRAFFIC 1 MILE	= 2	F	M	!S	!S
SLOW TRAFFIC AHEAD	= 3	M	!S	!S	!S
STOPPED TRAFFIC 3 MILES	= 0.25	F	F	F	S
STOPPED TRAFFIC 2 MILES	= 1	F	F	!F / S	S / A
STOPPED TRAFFIC 1 MILE	= 2	F	!F / S	S / A	S / A
STOPPED TRAFFIC AHEAD	>= 3	!F / S	S / A	S / A	S / A

(1)	iCone Traffic Sensor
PCMS	Portable Changeable Message Sign

Notes

- Location of the iCones and the PCMS can be adjusted based on site conditions (ramp locations, other static signing, overpasses, etc.)
- Free Flow/Slow/Stopped traffic trigger speeds are adjustable on a per iCone basis
- Displayed message text is configurable on a per PCMS basis
- "Q" is the calculated queue length from iCone-1, in miles, and resolves to the mid-points between iCones.
- **Condition tables may not cover all possible cases.** Please refer to the specific deployment's logic and settings for details.

Symbol	Condition	Avg Speed (V)
F	Free Flow	40mph < V
!F	Non Free Flow	V <= 40mph
M	Moderate / Slow	25mph <= V <= 40mph
!S	Non Stopped	25mph <= V
S	Stopped	V < 25mph
A	Any	0 <= V

iCone
End Of Queue Warning
(Type 1)

Figure 13. Message Selection for Queues up to 3 miles (Source: iCone).

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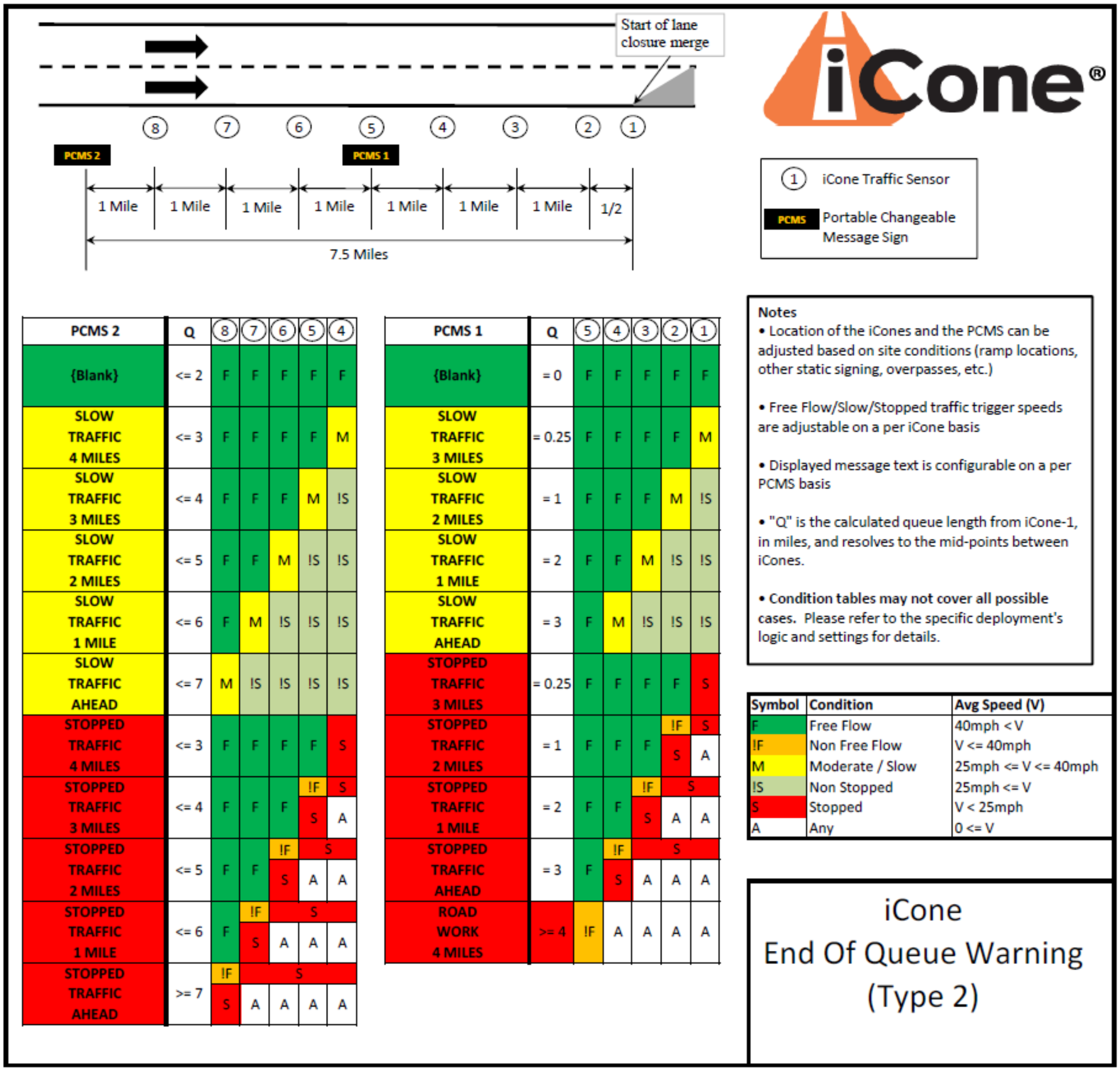

Figure 14. Message Selection for Queues up to 7 miles (Source: iCone).

Third-Party Traffic Data

Third-party traffic data providers offer crowdsourced traffic information and probe vehicle data over a large portion of the roadway network. The data may include segment travel times and speeds, and information on incidents, road construction, weather and road conditions. The segment travel times and speeds are provided as averages over predefined time intervals (e.g., 1, 5, 10 or 15 minutes). TxDOT and TTI have access to third-party traffic data from WAZE and INRIX. A major benefit of these crowd-sourced third-party data is that they can be collected without the need for the deployment and operation of physical infrastructure, and they provide broad coverage over the road network.

Waze Data

Agencies can access WAZE's crowd-sourced incident data through the Waze for Cities (formerly: Connected Citizen Program). In exchange, they are expected to share their own incident and/or work zone data feed with WAZE. Data sharing with partners of the Waze for Cities program has the following mechanisms:

- Data are available for partners through a localized XML or JSON data feed that is updated every two minutes.
- Partners can define a data collection polygon to delineate the area where data must be collected from.
- A web-interface called Traffic View Tool is available. Using this web-interface partners can access real-time user-reported incidents and estimated travel times along preselected routes.
- Waze also offers email updates on unusual traffic that can be sent to anyone in the partner organization.

Figure 15 shows the data collection polygon for the I-35 corridor.

A Waze data feed contains the following data types:

- Traffic incidents: jams, accidents, hazards, construction, potholes, roadkill, stopped vehicles, objects on road, missing signs reported by our community of mobile users.
- System-generated traffic jams: location and speed data associated with slowdowns below average speed for a particular segment for the time of day/day of week identified by analyzing user GPS signals.

Each alert gets reliability and confidence scores (based on a scale of 0 to 10) based on other user's reactions (e.g., 'Thumbs up', 'Not there' etc.). Higher scores indicate more reliable reports.

Waze generates traffic jam information by processing the following data-sources:

- GPS location-points sent from users' phones (users who drive while using the app) and calculations of the actual speed vs. average speed (on specific time-slot) and free-flow speed (maximum speed measured on the road-segment).
- User-generated reports - reports shared by Waze users who encounter traffic-jams. These appear as regular alerts.

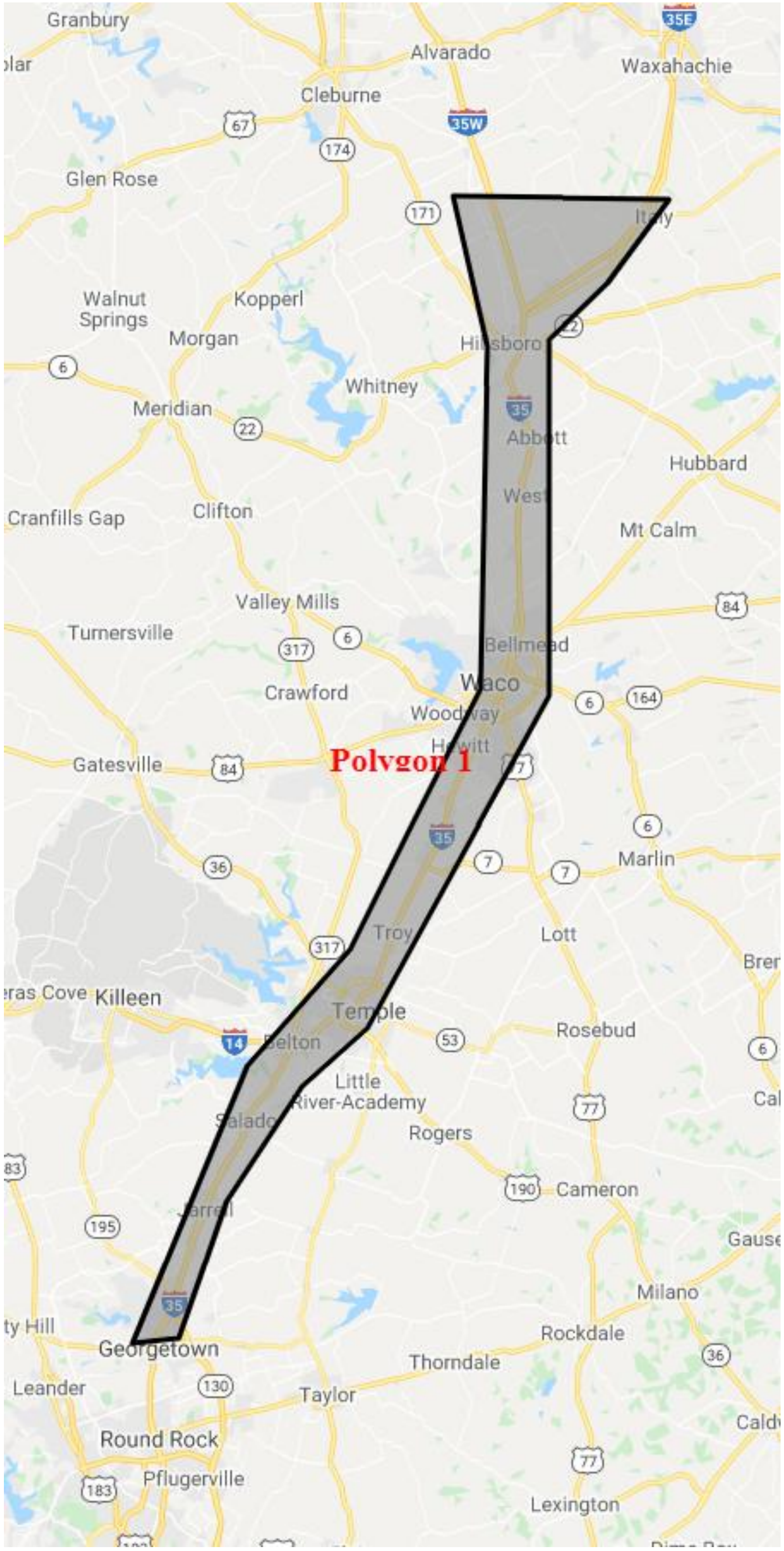

Figure 15. WAZE Data Collection Polygon for the I-35 corridor in Central Texas.

INRIX Data

INRIX probe data include segment travel times and speeds measured over two types of road segments: TMC (Traffic Message Channel) segments and XD (eXtreme Definition) segments. TMC segments generally cover a stretch of road from one exit or entrance ramp to the next, and there is a large variation in their lengths. DX segments cover more roadway miles than TMC segments, and generally with greater granularity. The distributions of TMC and DX segment lengths along the I-35 corridor in Central Texas are shown in Figure 16, and basic segment length statistics are shown in Table 4.

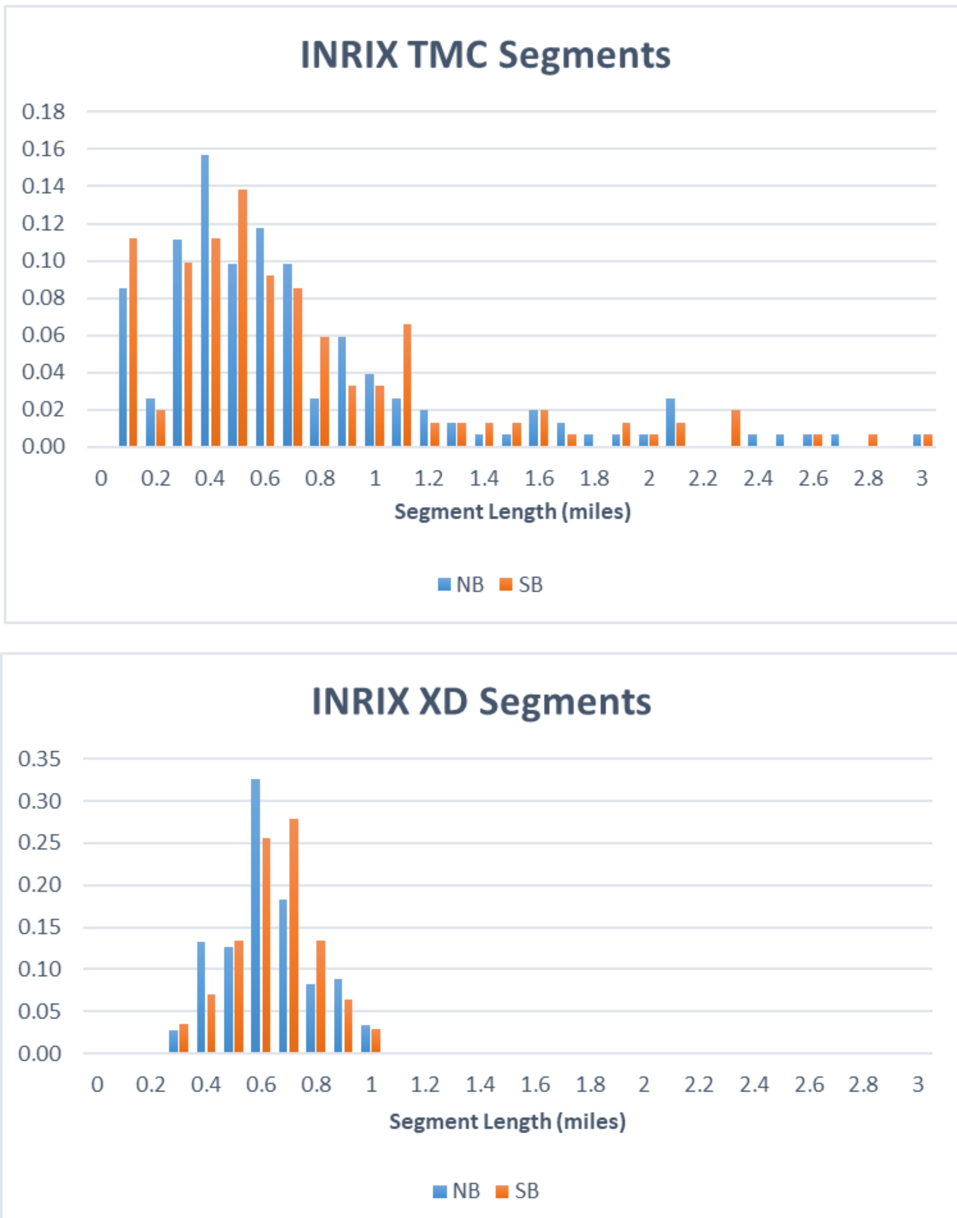

Figure 16. Distribution of INRIX TMC and XD Segment Lengths on I-35 in Central Texas

Table 4. INRIX segment lengths statistics on I-35 in Central TX.

	TMC segment length (miles)		**XD segment length (miles)**	
	NB	SB	NB	SB
Minimum	0.012	0.010	0.263	0.245
Maximum	2.023	2.931	0.965	0.992
Average	0.634	0.685	0.579	0.596
Std. Dev.	0.494	0.581	0.160	0.154

Probe data from both segment types may be used for detecting congestion and estimating delays, but data from DX segments typically provide more accurate queue detection.

There are significant differences between the above-mentioned data sources in terms of their data types, spatial coverage, spatial and temporal resolution, and latency. Table 5 provides a comparison of key characteristics of available data sources that may be used for queue detection.

Table 5. Comparison of Data Sources Available for Queue Detection

Data source characteristics	**Data Source**			
	Sensor Data	**Bluetooth/WiFi**	**Waze**	**INRIX**
Application for congestion and incident detection and queue warning	Most common. Widely used in major cities and on freeway corridors	More and more common because of its cost-effectiveness	Many state and local agencies use it through the “Waze for cities” partnership program.	More and more agencies use it for congestion and queue detection. (e.g., INDOT & Purdue used INRIX data to detect BOQ in work zones).
Data types	Spot speed, Volume, and Occupancy aggregated over selected time intervals (e.g., 20-sec, 30-sec, 1 min)	Segment travel times and speeds	Alerts, traffic jams, and irregularities	Segment travel times and speeds.
Queue detection	Queued state of a sensor location is determined using pre-defined speed or occupancy thresholds BOQ is detected by comparing threshold-based	Queued state of a BT or WiFi segment is determined using pre-defined speed or travel time thresholds.	Alerts can identify potential bottleneck locations. Traffic jam may also identify congested segments.	Agencies can develop their own queue detection logic that uses the segment speeds obtained from a third-party data provider

Data source characteristics	Data Source			
	Sensor Data	Bluetooth/WiFi	Waze	INRIX
	queued states of consecutive sensor locations			Proprietary Queue Detection logic developed by the third-party data provider may also be available (e.g., INRX's Dangerous Slowdown application)
Lane-by-lane queue detection	YES – using high-definition microwave radars, loop detectors, or video image processing.	N/A	N/A	Until recently it was not possible, but new developments of INRIX AI Traffic may include some lane-level detection capability in the future
Queue detection accuracy	Accuracy depends on sensor spacing and data aggregation interval If shockwave speed is known, accuracy can be improved	Queue detection accuracy depends on segment length and number of vehicles detected	Can provide approximate locations of traffic slowdowns but cannot detect the locations of BOQ.	Queue detection accuracy depends on segment length (INRIX DX segment < 0.5 mile) and number of vehicles detected.
Queue information timeliness	Depends on length of time interval for data aggregation and warning message update.	Depends on length of BT/WiFi segments and time interval for data aggregation.	Waze data feed is updated in every 2 minutes. Detection of traffic jams may take much longer.	Information may have a latency of 3-5 minutes.
Queue prediction ability	Locations, times and length of queues under recurring congestion can be predicted using archived historical data.	Short-term prediction of BOQ location may be possible based on shockwave speed observed during queue formation.	N/A	Locations, times and length of queues under recurring congestion can be predicted using historical data archived by the third-party data provider.

Data source characteristics	Data Source			
	Sensor Data	**Bluetooth/WiFi**	**Waze**	**INRIX**
	Short-term prediction using shock wave estimates is also possible			
Spatial coverage	Covers major corridors and arterials. Spacing typically varies between 0.5 – 1 mile.	Covers a selected few corridors and major arterials.	Covers all roadways where third-party provides service and collects traffic related data	

Congestion and Queue Analysis

This section includes examples using data from the I-35 corridor to illustrate how the data sources identified in Task 2 may be used to (1) improve the detection of congestion and formation of queues, and (2) minimize the negative impacts of congestion for travelers. The selected applications include:

- Post-event traffic performance assessment and queue analysis.
- Queue detection using data from multiple sources
- Optimal scheduling of road construction activities and special events.

The first and third applications use archived historical data, while the second application uses real-time data.

Post-Event Traffic Performance Assessment and Queue Analysis

Regular feedback on the performance of the traveler information system along the I-35 corridor is essential to the goal of reliable system operation. To provide this feedback post-event evaluations have been performed for all significant main lane and freeway closures as well as special events along the corridor. The impacts of lane closures or special events are quantified in terms of travel time delays determined from Bluetooth data and queue analysis using third-party data.

Travel Time and Delay Estimation

Travel time delay (D) over a single Bluetooth segment is calculated as:

$$D = t_{BT} - L_{BT}/v_{FF} \quad (1)$$

where

t_{BT} : observed travel time over the Bluetooth segment
L_{BT} : length of Bluetooth segment
v_{FF} : free-flow speed

To estimate delay over a roadway segment consisting of multiple Bluetooth segments, the travel times obtained for each consecutive Bluetooth segment needs to be aggregated first. The Bluetooth segment aggregation process is illustrated using a simple example consisting of four Bluetooth readers numbered as 0, 1, 2, and 3 in the direction of travel (from right to left), as shown in Figure 17. The temporal variations of segment travel times are defined by functions $t_1(.)$, $t_2(.)$ and $t_3(.)$ for BT segments 1, 2, and 3, respectively. If a vehicle arrives at the last Bluetooth reader (3) at time τ, then its travel time through Bluetooth segment 3 is $t_3(\tau)$, and the aggregated travel time T over all three Bluetooth segments can be calculated as:

$$T = t_3(\tau) + t_2[\tau - t_3(\tau)] + t_1\{\tau - t_3(\tau) - t_2(\tau - t_3(\tau))\} \quad (2)$$

where

$t_3(\tau)$: lag between travel times in Bluetooth segments 3 and 2
$t_2(\tau - t_3(\tau))$: lag between travel times in Bluetooth segments 2 and 1

This aggregation process takes into account the dynamically changing travel time lag in each Bluetooth segment.

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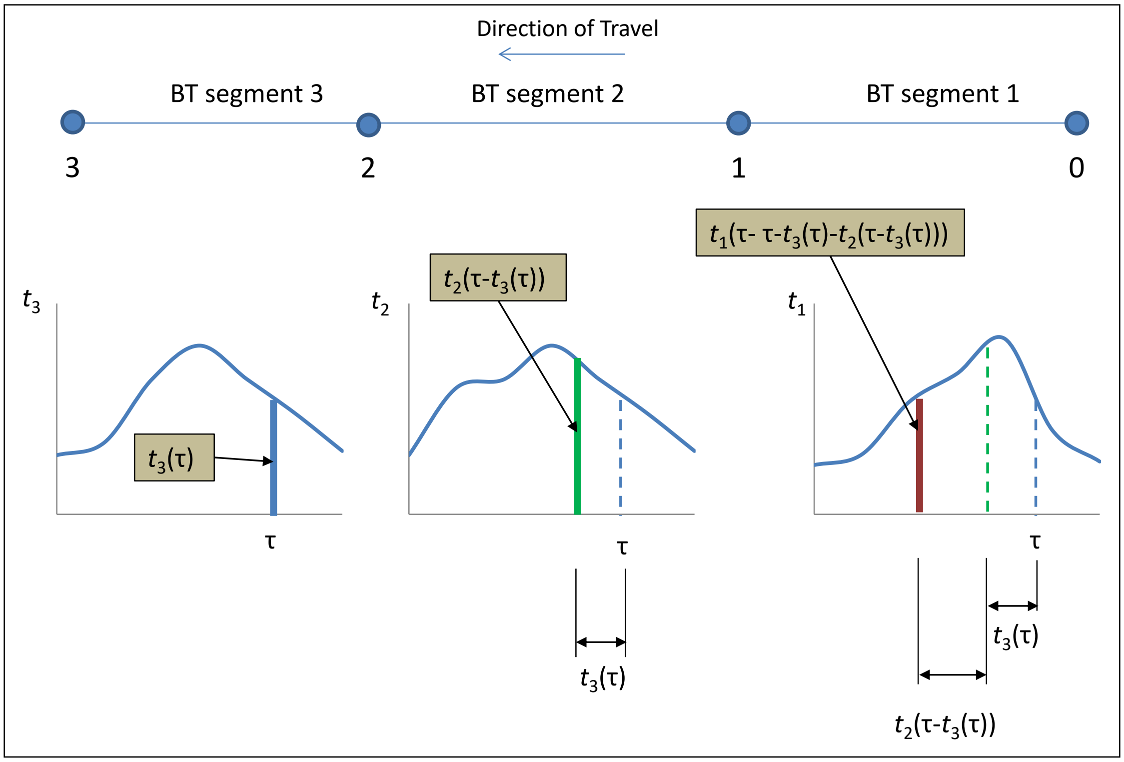

Figure 17. Aggregating Bluetooth Travel Times over Consecutive Segments

The major steps of a post-event impact analysis of work zone lane closures or incidents are summarized in Figure 18. Figure 19 illustrates the application of this method for assessing the impact of a night-time construction on I-35 north of Temple, TX. The road construction required the closure of all northbound main lanes of I-35 while traffic was diverted to the frontage roads. The travel time and delay graphs on Figure 19 show that the maximum delay caused by the freeway closure exceeded 2 hours, and occurred at approximately 11:15 pm. The speed profiles (scatter plots with green dots) for the four Bluetooth segments indicate that there was significant congestion and queuing between 6:30 pm and 3:30 am.

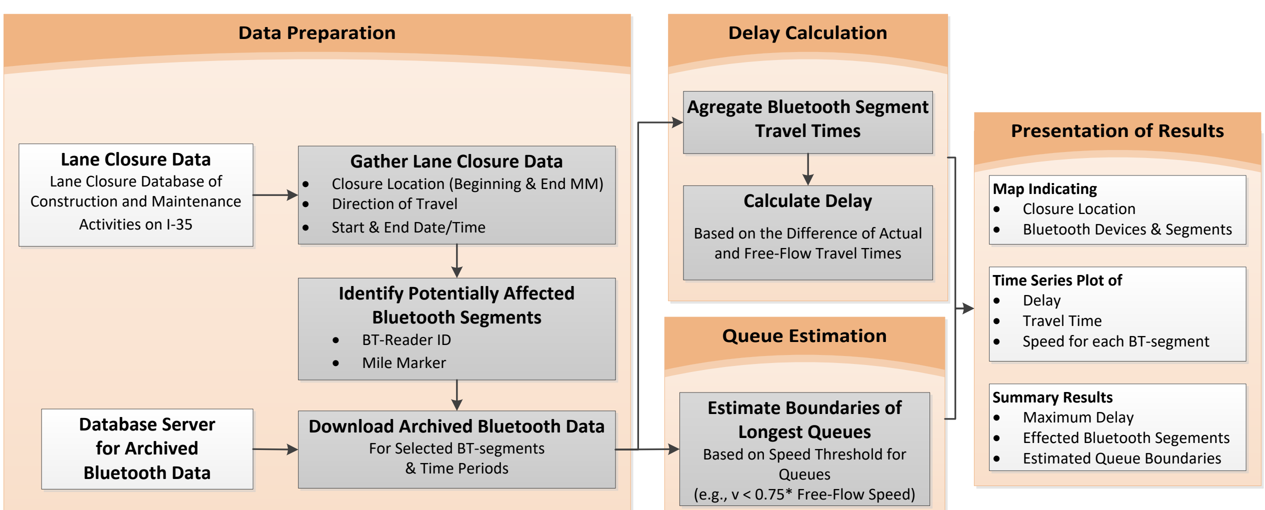

Figure 18. Steps of Post-Event Impact Analysis

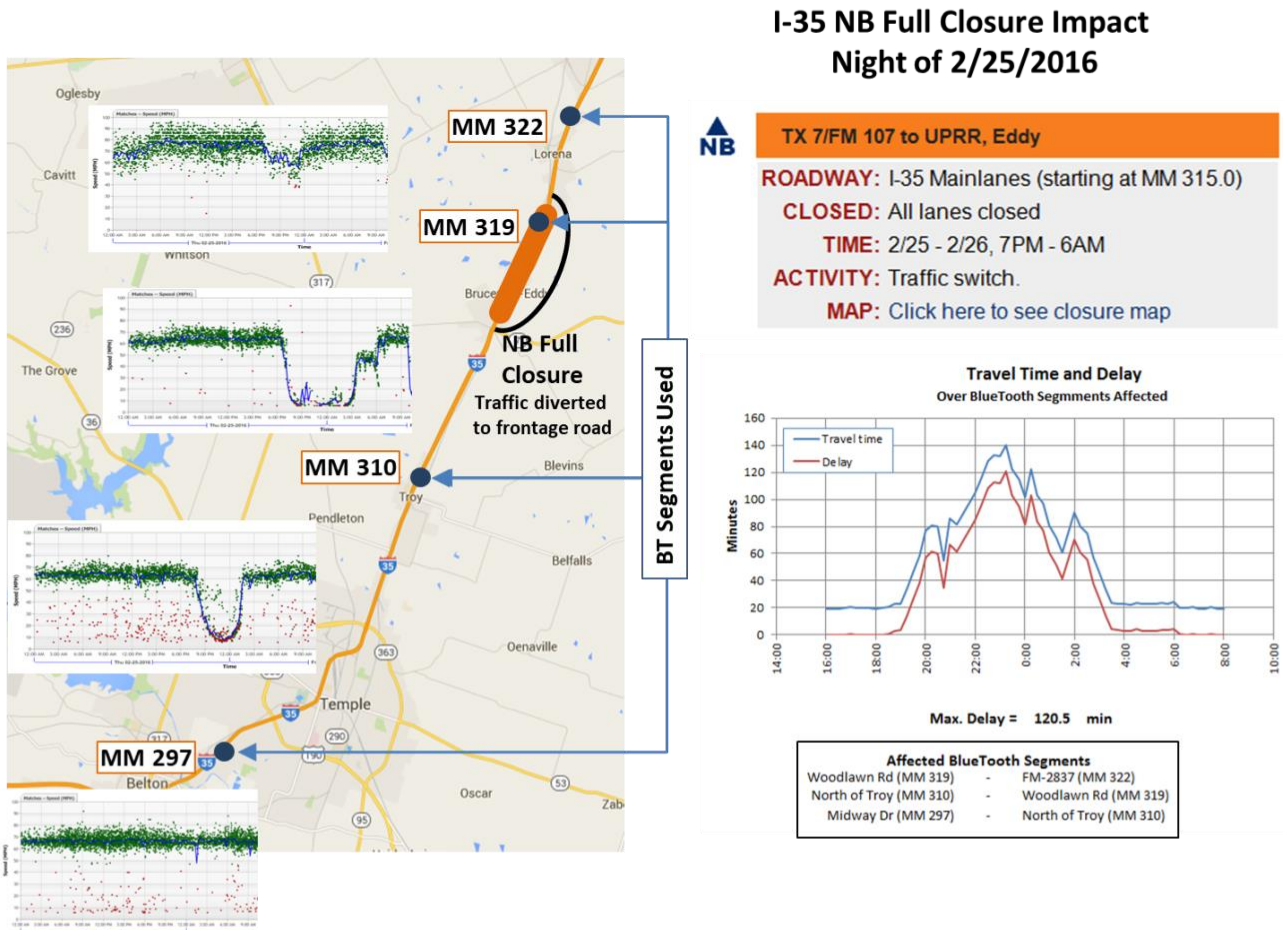

Figure 19. Impact of a Freeway Closure on I-35 NB

In addition to evaluating the impacts of single construction projects, the method has also been used to determine the combined daily impacts of construction projects and incidents on selected segments of the corridor. This so-called Daily Postmortem (DPM) has been routinely performed to determine 15-minute average travel times and delays over 24-hour periods on the following three segments:

- between Hillsboro and Waco,
- between Waco and Temple,
- between Temple and Salado.

Figure 20 shows the major steps of DPM, and Figure 21 illustrates its application for a Saturday on October 23, 2021.

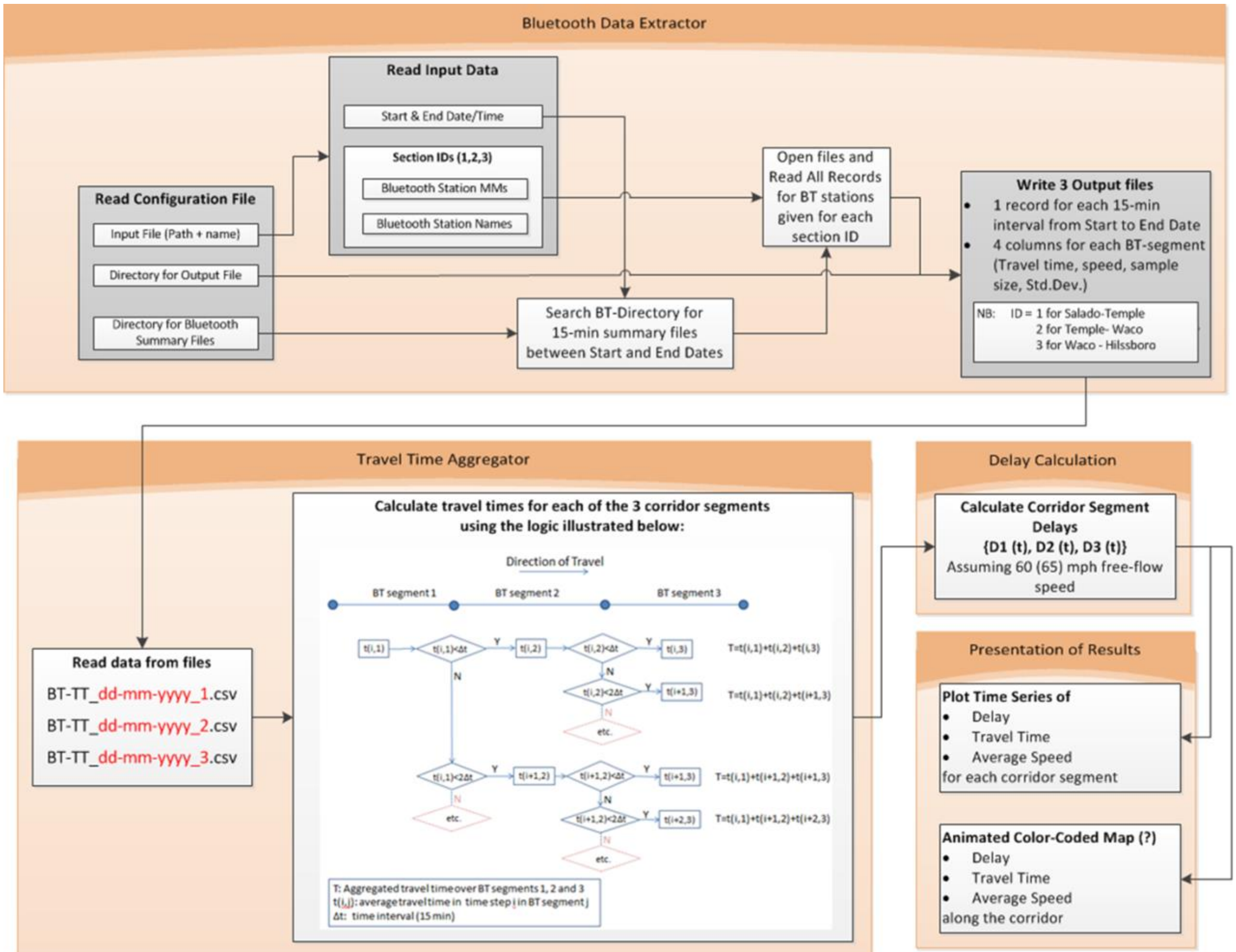

Figure 20. Major Steps of Daily Postmortem.

Figure 21 includes 24-hour time series plots and maximum values of travel times, delays and travel-time index (TTI) for all three segments, as well as letter grades “A” through “D” that characterize traffic conditions in each direction on the entire corridor. Grades are assigned based on delay thresholds defined in Table 6.

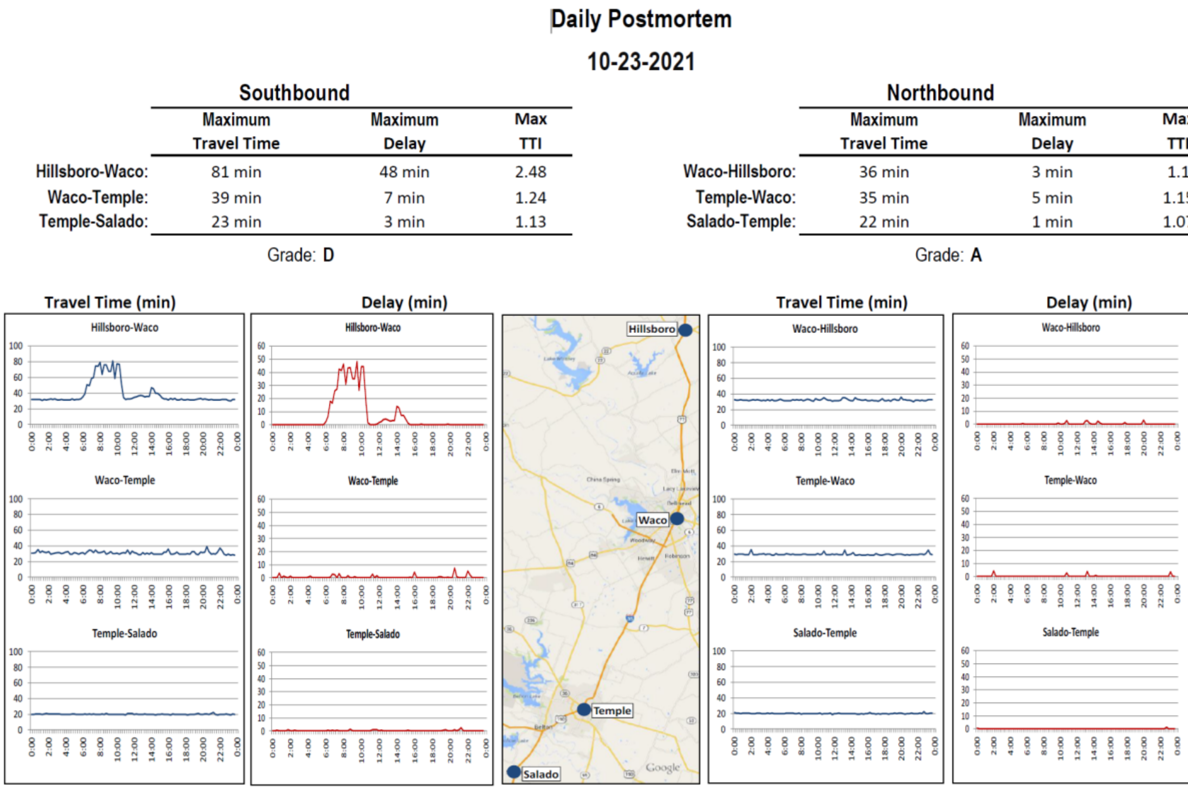

Figure 21. Illustration of a Daily Postmortem for I-35

Table 6. Delay-Based Traffic Condition Grades in Daily Postmortem

Grade	Max. Delay		
A	0 min	< D <=	10 min
B	10 min	< D <=	20 min
C	20 min	< D <=	30 min
D	30 min	< D <=	60 min
F	60 min	< D	

The DPM results in Figure 21 indicate delays considerably higher than usual on the southbound segment between Hillsboro and Waco.

Congestion and Queue Analysis

When significant delays are observed, additional congestion analysis may be performed to identify the location of bottlenecks and capture the formation and propagation of vehicle queues. For I-35, such congestion and queue analysis have been conducted using data from INRIX's XD (eXtreme Definition) segments and the Congestion Scan tool included in the Probe Data Analytics (PDA) Suite of the Regional Integrated Transportation Information System (RITIS) developed by CATT Lab at University of Maryland (Ref: https://pda.ritis.org/suite/). The speed heat map in Figure 22 shows traffic conditions for a typical Saturday when no major incident occurred, and no construction activities took place on I-35 Southbound between Hillsboro and Waco. Figure 23 shows the speed heat map of the same roadway segment for Saturday, October 23, 2021, when a vehicle collision occurred soon after 6 AM at mile marker (MM) 334. The incident-induced congestion and queuing can be clearly identified by the dark-red area indicating speeds below 10 mph on the left side of Figure 23.

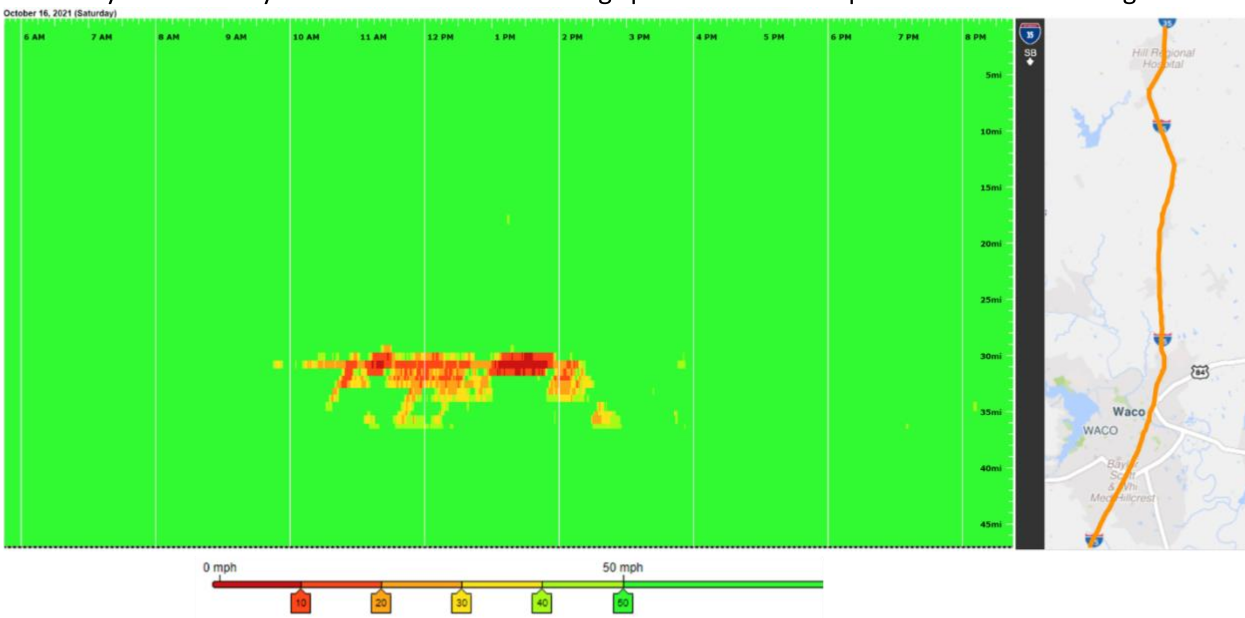

Figure 22. Speed Heat Map Showing Typical Saturday Traffic Conditions on I-35 SB between Hillsboro and Waco on Saturday, Oct 16, 2001.

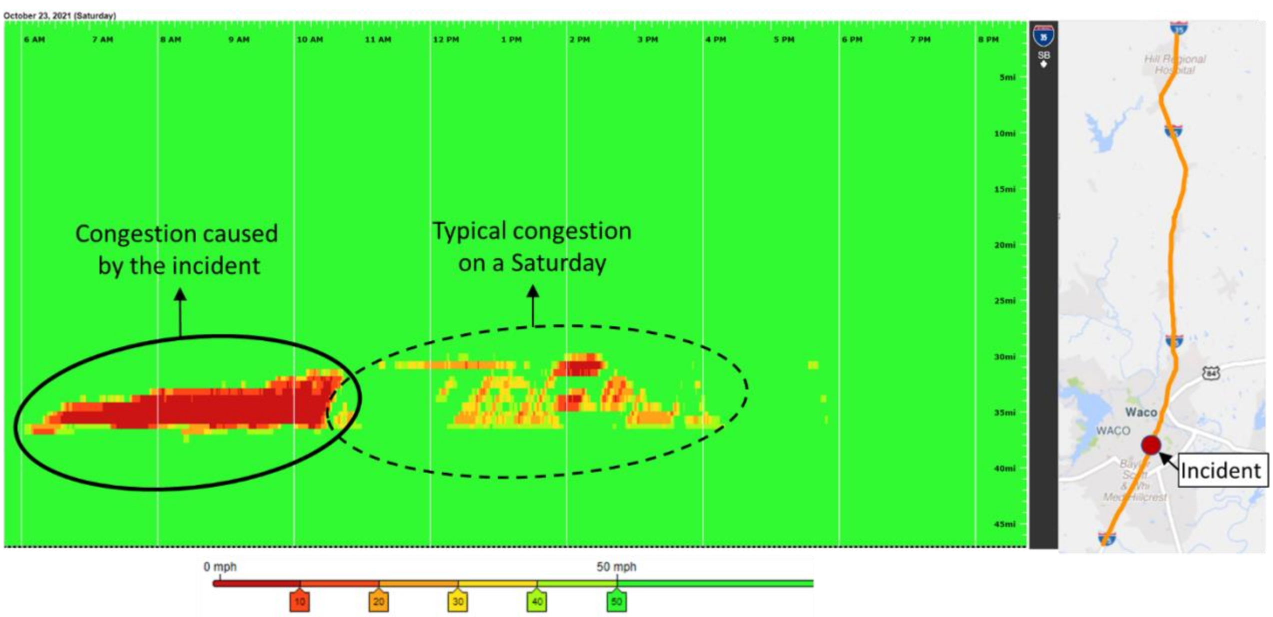

Figure 23. Speed Heat Map Showing Unusual Congestion on I-35 Southbound between Hillsboro and Waco on Saturday, Oct 23, 2001.

Figure 24 captures the main results of queue analysis. A vehicle queue began forming upstream MM 334 about 10-15 minutes after 6 AM and propagated upstream at a speed of approximately 6 mph, reaching a queue length of about 3 miles within the first 30 minutes. As traffic volumes increased, the queue slowly grew to lengths of 3.5 to 4.5 miles between 7:45 AM and 9:45 AM. The maximum queue length was 5.5 miles between 10 AM and 10:25 AM. The queue cleared and traffic returned to normal conditions at about 10:40 AM, 15-20 minutes after the incident was cleared. Figure 24 also makes it possible to identify the position of back of queue on the map at any time during the queuing process.

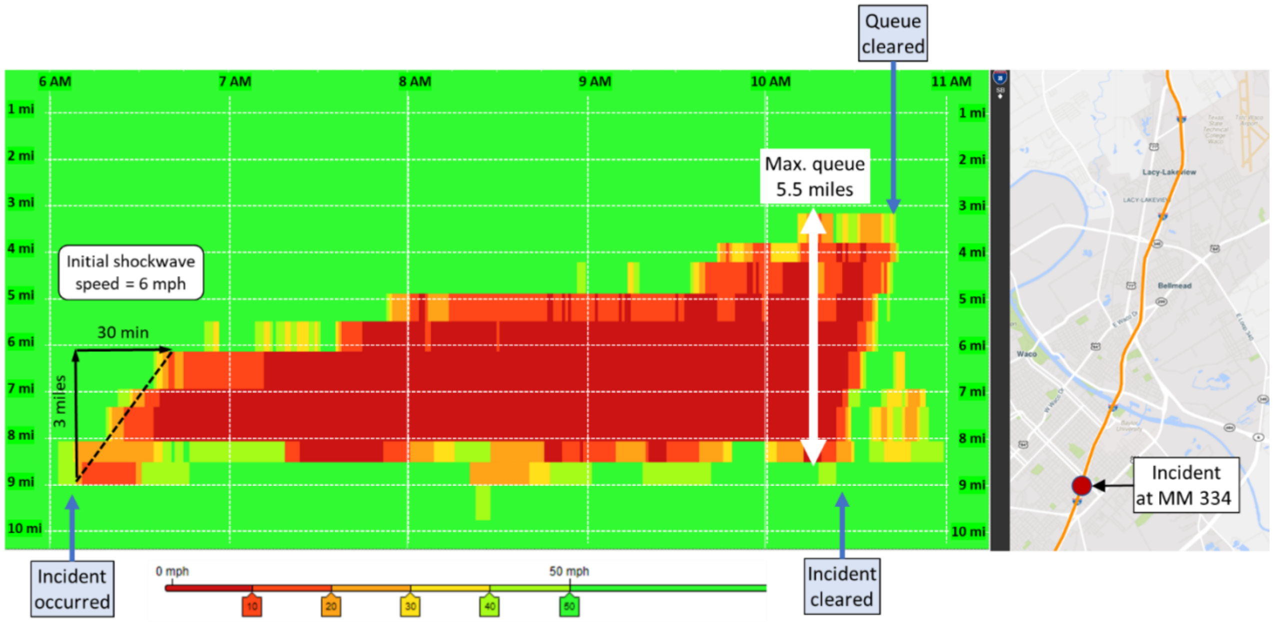

Figure 24. Queue Analysis Using Speed Heat Map on I-35 Southbound in Waco on Saturday, Oct 23, 2001.

Queue Detection Using Data from Multiple Sources

This section describes an approach to queue detection using a combination of data available from two different sources, traffic sensors and third-party data providers. Data from these two sources have different spatial coverage and temporal resolutions because of the way they are collected, aggregated, and transmitted. Traditional sensors provide average spot data (speed, volume, and occupancy) which are collected for each lane. Third-party data sources provide travel times and average travel speeds over predefined segments without lane-level detail. Data from the two sources also differ in their latencies. Sensor data has a minimum latency of 20 or 30 seconds depending on the data aggregation level. Third party probe data latency typically ranges from 3 to 4 minutes. These differences present some challenges in finding the best combination of the two data sources for queue detection.

To address these challenges, a two-step approach is proposed, that is performed in each time step of the queue detection process:

- Step 1: Determine queue parameters from each available source separately

  Determine the locations of Back of Queue (BOQ) and Front of Queue (FOQ), and calculate shock wave speeds using data measured in the current time step or predicted using data from previous time steps.
- Step 2: Choose the best queue parameter estimates from Step 1

Select the best estimates of BOQ, FOQ and shockwave speed for the given time step. Details of the approach are described and illustrated below.

Queue Estimation from Each Available Source

Queue Estimation from Sensor Data

Estimation of BOQ and FOQ from sensor data is illustrated through a queueing example shown in Figure 25. The top part of this figure shows a three-lane freeway segment with ten sensor stations (SS), which measure lane-by-lane speeds. An incident just upstream of SS 2 blocks the two right lanes (lanes 2 and 3) causing the formation of a queue. Average speeds measured at individual sensors are compared to a pre-defined queue threshold (e.g., 15 mph) to determine if traffic flow at a sensor location is queued or not. Red colored bars indicate sensors where traffic is queued. Green colored bars are used for sensors where the average speed is above the queue threshold.

Figure 25 shows a situation with differing queue characteristics in the three lanes. Lane 1 has the shortest queue, which extends upstream of SS 3. In Lane 2, the BOQ is located upstream of SS 7. However, at this instant in time, average speeds of vehicles at SS 5 are above queue threshold. Thus, there are two distinct queues in this lane. Lane 3 has the longest queue that propagated upstream beyond SS 8.

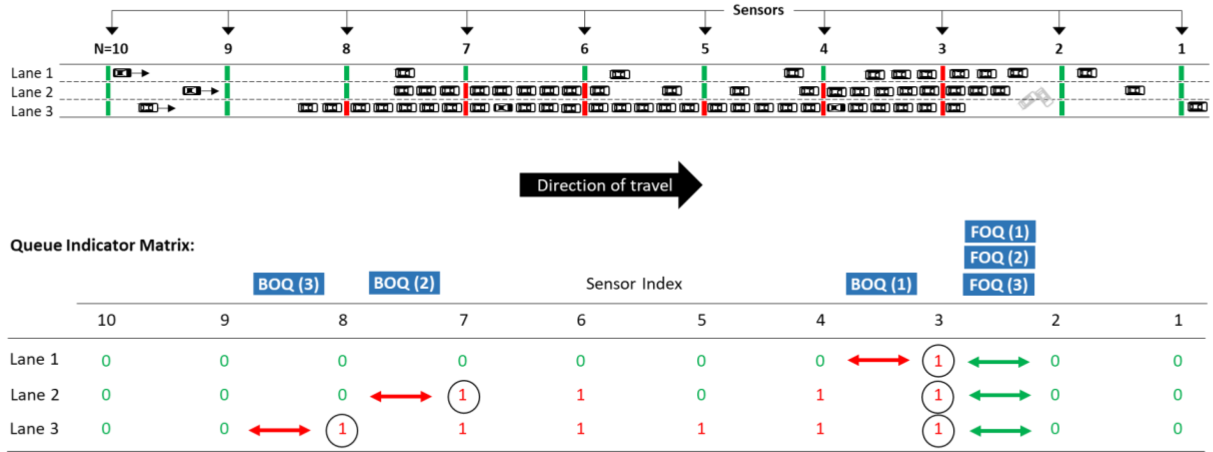

Figure 25. Queue Detection Using Infrastructure Sensor Data.

For numerical processing, queue conditions can be captured by a queue indicator matrix shown at the bottom of Figure 25. The rows of the matrix, represent lanes, and columns represent sensor stations. Cell values of 1 and 0 indicate queued and non-queues states, respectively. The matrix is depicting the current state of the roadway system shown in the top part of the figure. For queue warning purposes, BOQ in each lane is the most upstream position (cell) with a value of 1. The red lines with double arrowheads indicate that the actual queue at this time can be anywhere between this location and the next upstream sensor. The FOQ in each lane is the most downstream cell with a value of 1. The horizontal green lines with double arrowheads indicate that the actual FOQ position at this time can be anywhere between this location and the next downstream sensor.
The flow chart in Figure 26 captures the above-described process for a single time-step of BOQ and FOQ estimation using sensor-based spot speeds. This logic consists of two nested loops. The outer loop steps through all lanes, while the inner loop steps through all detector stations for the current lane. It determines the queued state of each sensor and updates cell values of the queue indicator matrix. BOQ and FOQ for the current lane are updated when all calculations for the corresponding row are complete.

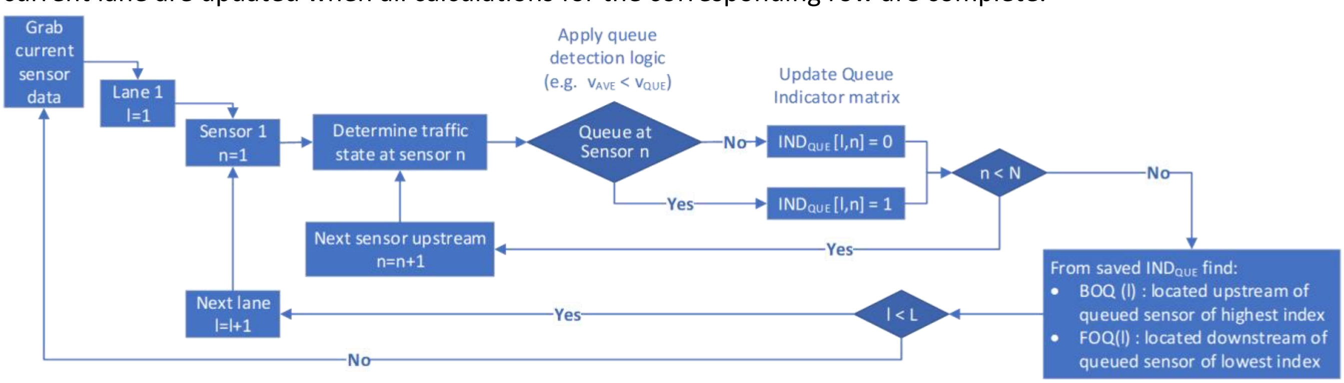

Figure 26. A Single Time Step of Queue Detection Using Sensor Data.

Queue Estimation from Third-Party Data

Queue estimation using third-party data is illustrated in Figure 27. This is the same roadway and queueing example shown in Figure 25. There are eight segments where third-party probe data are collected and available. Probe vehicles that are detectable by the third-party traffic data provider are indicated by green color. A roadway segment is identified by a red arrow if traffic in the segment is queued, and green arrow if traffic is non-queued. Average segment speeds are compared to a pre-defined queue threshold to determine if traffic in that segment is queued or not. Since segment travel times and speeds are averaged across all lanes, queue detection at lane-level is not possible. Figure 27 shows that segments 2, 3, and 5 are in a queued state.

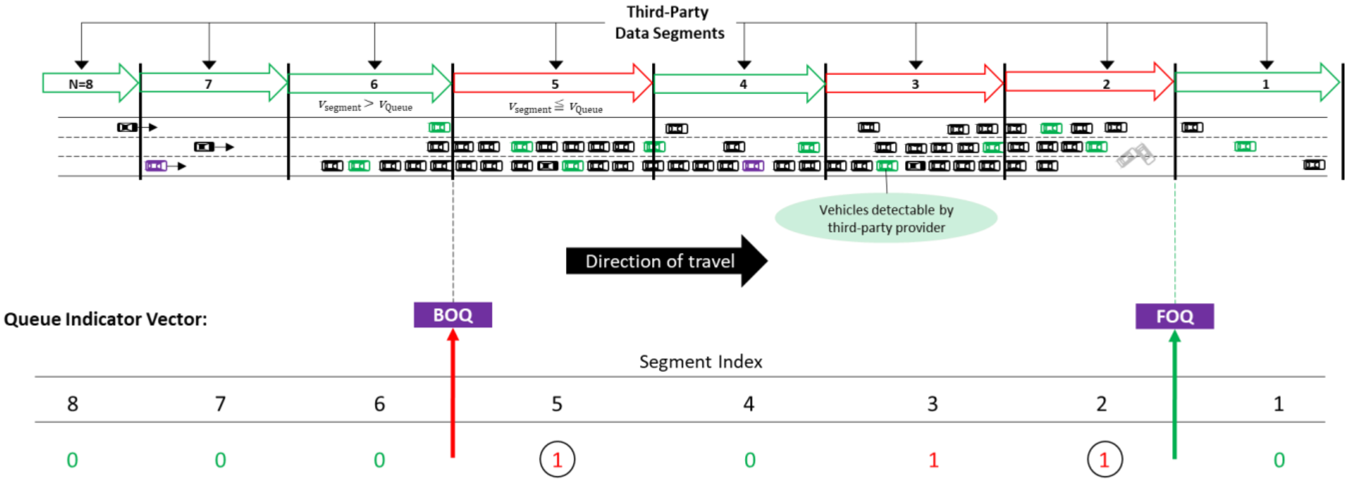

Figure 27. Queue Detection Using Third-Party Data.

Queued and non-queued segments may be represented by a queue indicator vector with values of 1 and 0. Here, three cells, corresponding to the segments indicated by red arrows, have values of one. BOQ location is at the upstream end of the most upstream queued segment. FOQ is at the downstream boundary of the most downstream queued segment. As in the case of sensor data, this information may be combined with positions of previously detected BOQ and FOQ locations to calculate shockwave speeds.

The flow chart in Figure 28 shows a single time step of queue detection using third-party data. This logic is similar but simpler than the one described above for spot sensors. In certain time steps, segment data analysis may not detect any change. In fact, there might be several contiguous time steps without any detected change in queue conditions.

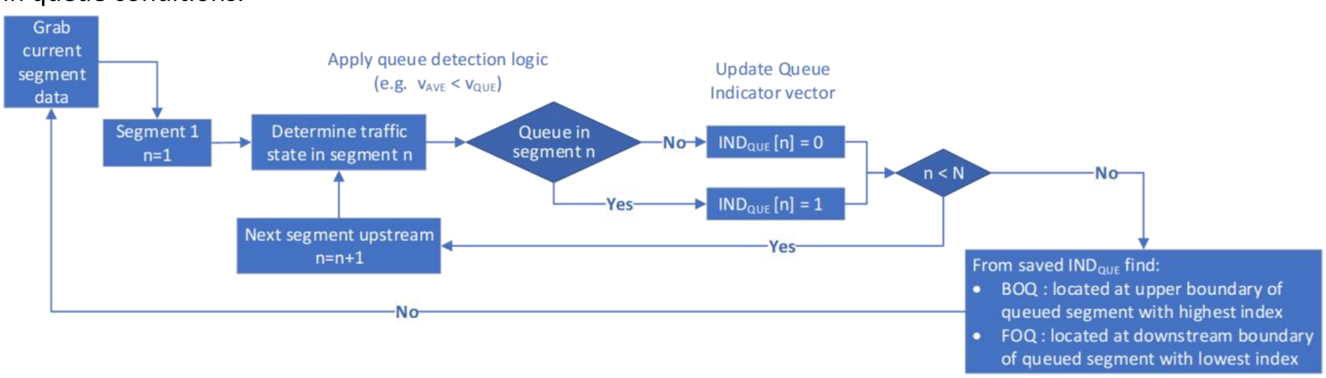

Figure 28. A Single Time Step of Queue Detection Using Third-Party Data.

Queue Estimation and Prediction

In the second step of queue detection, the most likely position of BOQ is determined by comparing queue estimates available from the two data sources in each time step. When all sensors are working as intended, and current queue estimates from sensor data are available, sensor data are preferable to third-party data. Sensor data allow queue estimation at lane-level, while third-party data do not. Also, latency of queue detection using third-party data is typically longer than using sensor data. However, when timely queue estimates from sensors are not available, third-party segment data may be used. Table 7 provides a guide for BOQ detection under different scenarios of data availability from sensors and third-party data.

Table 7. Data Availability Scenarios Considered in Queue Detection.

BOQ determined using measured data from		**BOQ predicted using shockwave speeds estimated from**		Comment
Sensors	**3rd Party**	**Sensors**	**3rd Party**	
BOQ_{SEN}	**BOQ_{3RD}**	**Pred-BOQ_{SEN}**	**Pred-BOQ_{3RD}**	
X	Any	Any	Any	
-	X	-	Any	
-	X	X*	Any	*Age of **Pred-BOQ_{SEN}** > Latency in 3rd party data.
-	X	X**	Any	**Age of **Pred-BOQ_{SEN}** <= Latency in 3rd party data.
-	-	X	Any	
-	-	-	X	
-	-	-	-	Cannot update BOQ position
X	Available for current time step			
X	Use this for BOQ determination			
-	Not available for current time step			
Any	Either available or not available			

At any time during queue detection, a BOQ estimate may be available from data measured in the current time step (first two columns) or it may be predicted using data from previous time steps (second two columns). Table rows represent different scenarios depending on the availability of BOQ and predicted BOQ in a queue calculation time step, and the green shaded cells indicate recommended BOQ selection. The first row represents all cases where sensor-based queue estimates are available for the current time-step, and estimates from other data sources may or may not be available. In such cases, use sensor-based estimates for BOQ and shockwave speeds for prediction. Rows 3 and 4 desribe scenarios when sensor-based BOQ estimate is not available, but sensor-based BOQ prediction is available for the current time step. In such cases, the following logic is recommended for BOQ selection based on the age of predicted BOQ:

IF (Age of Pred-BOQ_{SEN} > 3rd party data latency) THEN
    BOQ = BOQ_{3RD}
ELSE
    BOQ = Pred-BOQ_{SEN}
ENDIF

Other rows describe scenarios with different combinations of available queue estimates and predictions from various data sources. The last row accounts for the case when there is no queue estimate available for the current time slice from any of the data sources. This scenario can occur under uncongested conditions without any queue, or when queue started forming but not yet detected by either of the two data sources. A legend provided at the bottom of the table describes the meanings of cell entries.

The flow chart in Figure 29 shows the BOQ estimation logic using sensor and/or third-party data. In this illustration, the queue detection application runs from T_Begin through T_End, using a calculation time-step of Δt. The length for Δt should not be less than the time it takes to receive and process input data. Processing time includes the time required for data checks, data aggregation, queue detection/prediction and queue warning message generation.

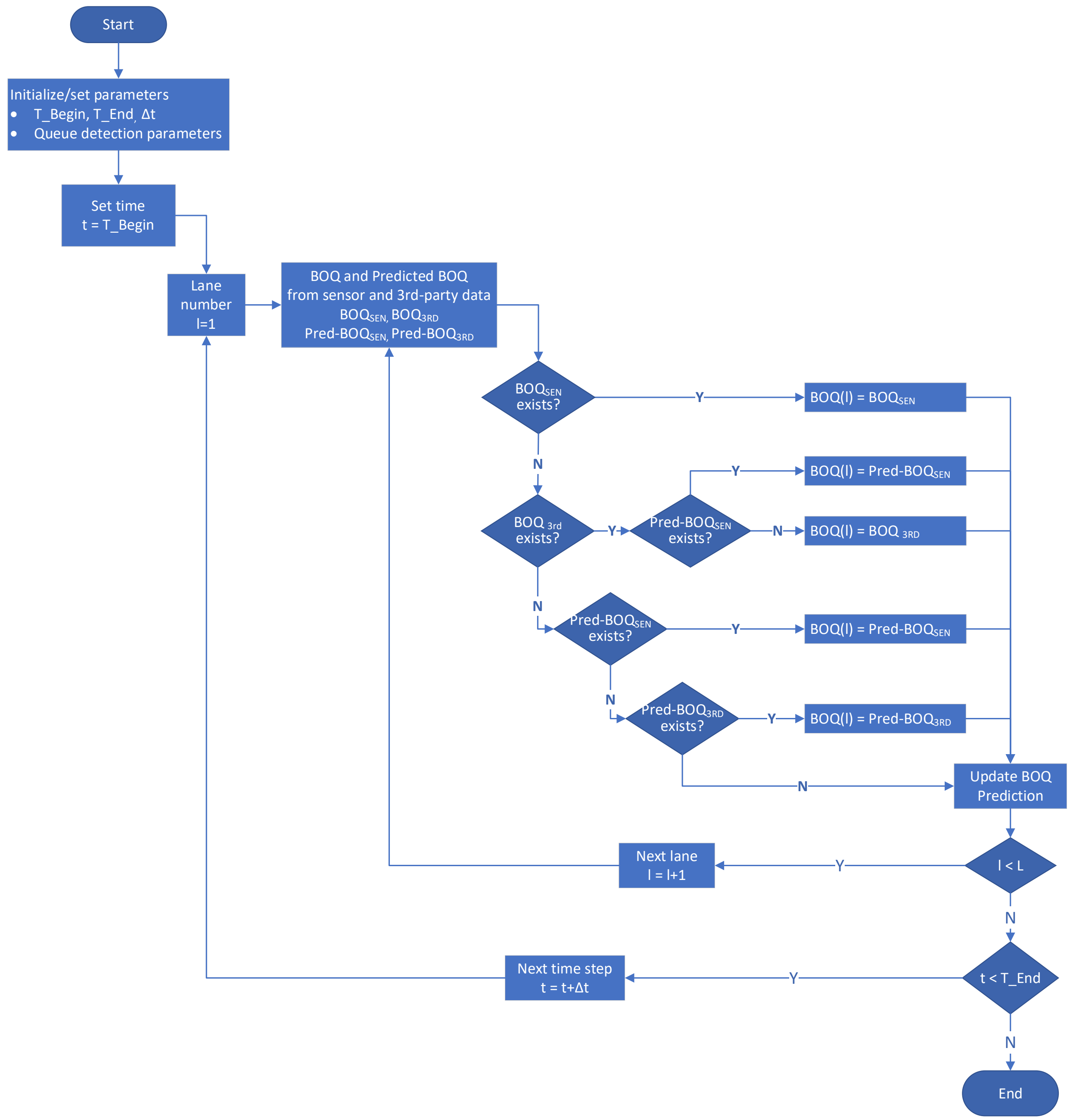

Figure 29. Flow Chart for BOQ Estimation from Sensor and Third-Party Data.

Optimal Scheduling of Road Construction Activities and Special Events

Road construction, utility work or special events often require the closure of one or more roadway lanes for a certain time period. The impacts of such closures depend on the number of lanes closed, the closure time and duration. The number of lanes to be closed and the duration of the closure is typically determined by the nature of the required work or event, but there is often some flexibility in the timing/scheduling of closures. There have been several studies focusing on the optimization of road construction and maintenance projects. For example, S. Chien and P. Shonfeld (2001) developed a method to optimize work zone lengths on four-lane highways where one lane in one direction at a time is closed. Their model finds the work zone length that minimizes the total cost, including agency cost, accident cost, and user delay cost.

This section describes a process to find the most appropriate schedule that minimizes the negative impact of construction, utility work or special events that require partial or full closure of a roadway. The impact is measured by the expected length of longest queue generated by the lane closure. The next subsection describes the lane closure scheduling method and algorithm followed by an illustrative example.

Method and Algorithm

The objective is to find the optimal schedule (start time) for a planned lane closure of fixed duration (*T*). The optimal schedule is defined by the lane closure start time t^* during the week that is expected to create the shortest maximum queue length (i.e., the minimum number of vehicles stored in the queue $S(t^*)$):

$$S(t*) = \underset{\forall t_i \in week}{MIN} \left\{ \underset{t_i \le t_{ij} \le t_i + T}{MAX} \left[S(t_{ij}) \right] \right\} \tag{2}$$

The number of vehicles in queue $S(t_{ij})$ is calculated for all possible lane closure start times during the week. The calculation is performed by running an input-output analysis in a dual loop. In the outer loop, different lane closure start times (t_i) are assigned, starting from Sunday 12 AM and incremented through the entire week in selected time steps (e.g. 1 hour or 15 minutes). The inner loop calculates the number of queued vehicles for the entire lane closure duration *T*, and then finds the maximum number vehicles stored in the queue:

$$\begin{aligned} &S(t_{ij}) = S(t_{ij-1}) + I(t_{ij}) - O(t_{ij}); \quad t_i \le t_{ij} \le t_i + T \;; \quad \forall t_i \; for \; entire \; week \\ &O(t_{ij}) = Min\left[S(t_{ij-1}) + I(t_{ij}) \;,\; C\right] \end{aligned} \tag{3}$$

where

- $S(t_{ij})$ = number of vehicles stored in queue at time t_{ij}
- $I(t_{ij})$ = number of arriving vehicles in the time step starting at time t_{ij}
- $O(t_{ij})$ = number of departing vehicles in the time step starting at time t_{ij}
- C = work zone capacity

The steps to determine an optimal schedule is summarized in Figure 30.

The required input includes work zone capacity and a historical time series of vehicle flow rates measured at a point upstream of the planned lane closure. Note that work zone capacity does not have to be constant; the method can easily accommodate capacities that vary over the time of the closure.

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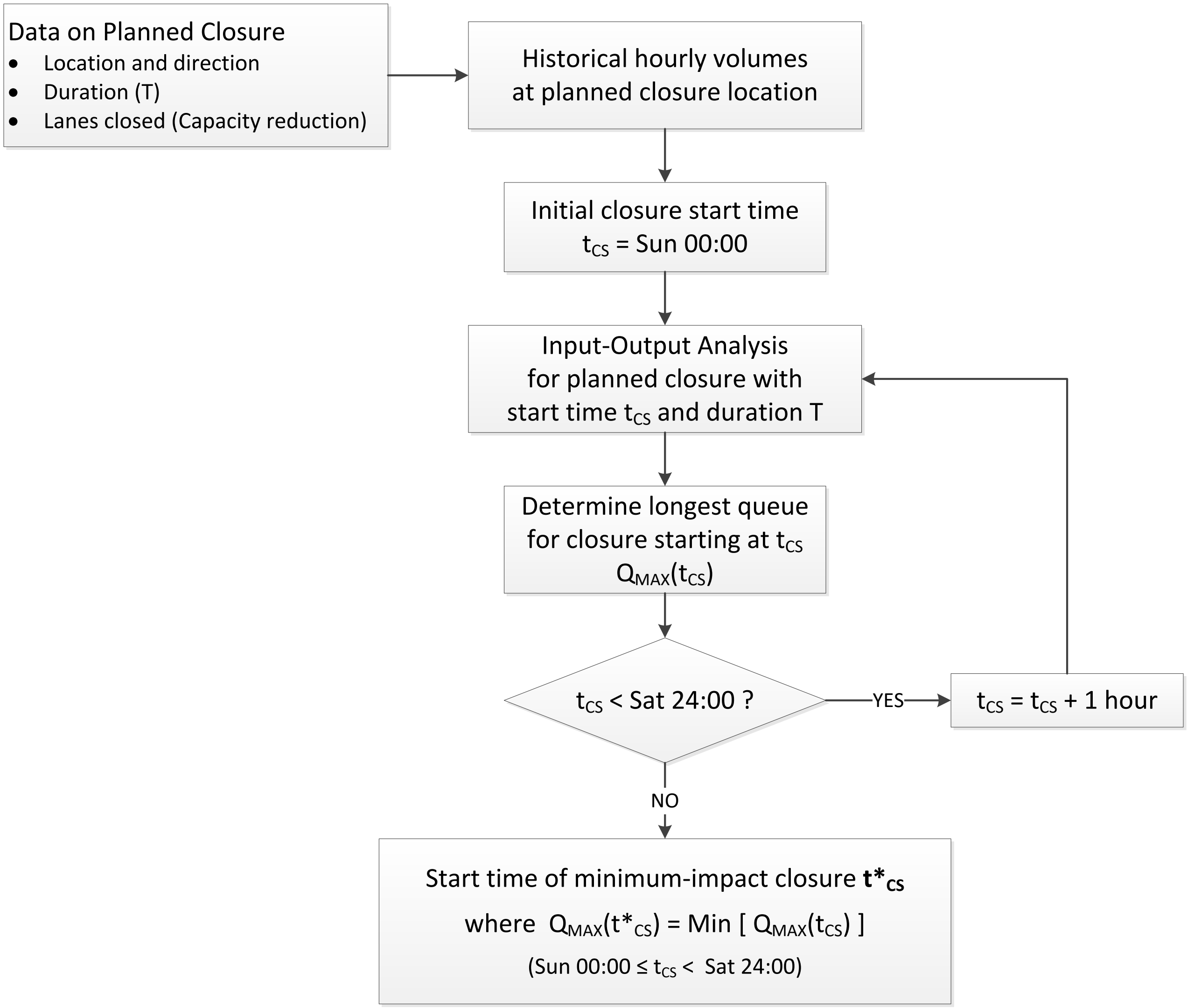

Figure 30. Logic for Determining Optimal Closure Schedule.

Lane Closure Scheduling Example

To illustrate the use of the method, a 16-hour planned lane closure is considered. One of the two northbound main lanes of I-35 is to be closed, and the best closure start time (i.e. the one that is expected to create the shortest queues) is to be determined. The last six months of hourly traffic volumes collected by a Wavetronix radar sensor located a few miles upstream of the planned closure is used to calculate an average time series of hourly traffic volumes for a week.

The volume time series is shown in Figure 31. Three work zone capacities (1100, 1300 and 1500 vphpl) were considered in the calculation of the expected queues.

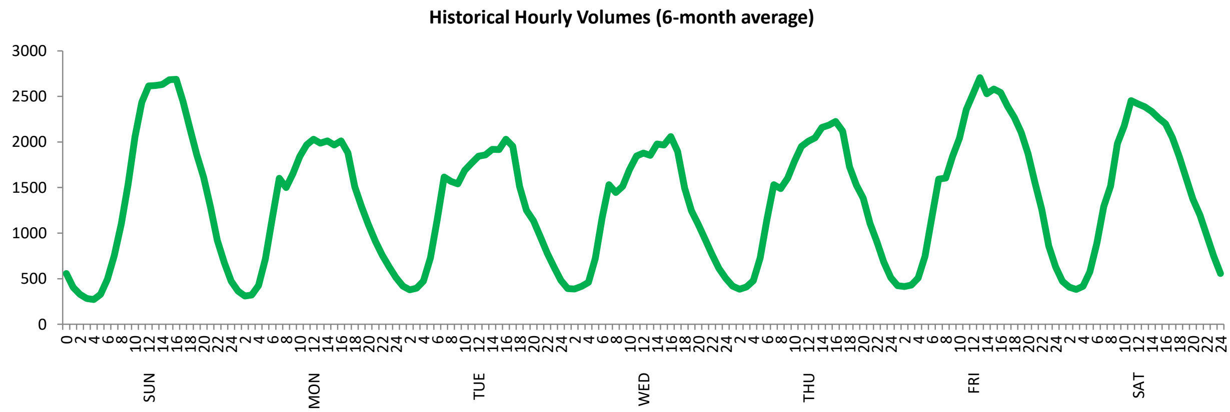

Figure 31. Historical Hourly Traffic Volumes Upstream of the Planned Lane Closure

The queues generated by a 16-hour long work zone lane closures starting at any time during the week were determined for all three work zone capacity scenarios. The longest queues (expressed as the maximum number of queued vehicles) for any closure start time are plotted in Figure 32. The best closure times with the least impact (i.e., shortest maximum queue) are at 6 pm on Monday, Tuesday, Wednesday, or Saturday night. Lane closures starting at these times are expected to create the shortest queues.

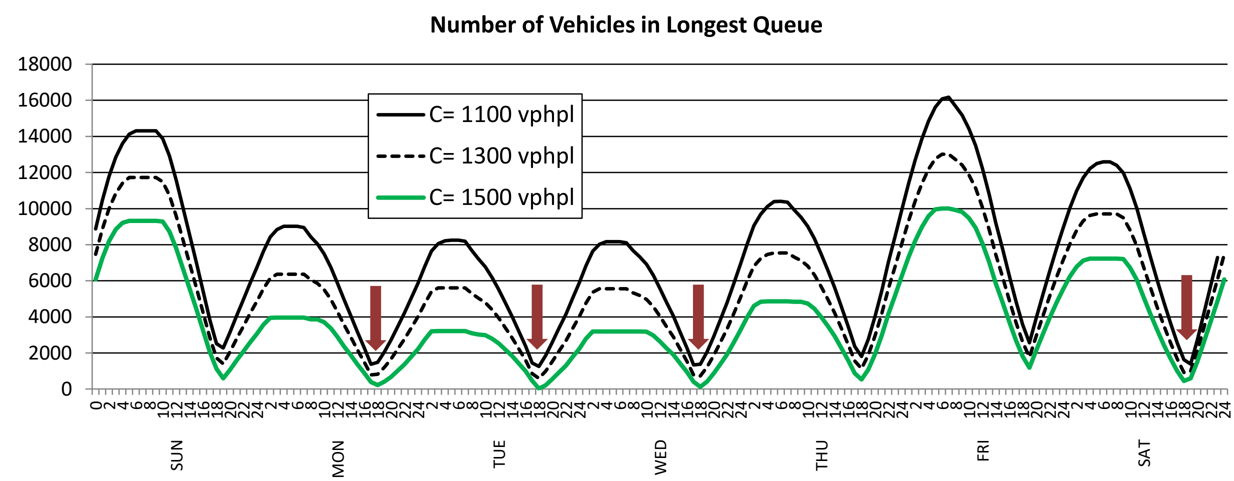

Figure 32. Maximum Queue Lengths vs. Start Time of a 16-hour Lane Closure.

This methodology was tested and implemented for various lane closure situations across the corridor and provided a simple analytical process to ensure the least impact to the traveling public under exceptional closure conditions.

Summary and Conclusion

This study identified available data sources and data sets that may be used for automated queue detection upstream of freeway bottlenecks. It also explored methodologies to assess the impact of lane closures, incidents and special events, and improve the detection of vehicle queues in real-time, and determine their extent and speed of propagation.

After a review of relevant literature, the data from the I-35 traveler information database was used for exploring potential applications and methods of congestion and queue analysis. The selected applications included:

- Post-event traffic performance assessment and queue analysis.
- Queue detection using data from multiple sources
- Optimal scheduling of road construction activities and special events.

Input data for these applications included traffic volumes and spot speeds collected by traffic sensors, and segment travel times and speeds from INRIX XD segments and Bluetooth readers.

It was found that average segment travel times determined using Bluetooth address matching were quite effective in estimating delays caused by lane closures or incidents. However, they were not appropriate for queue detection because of the relatively long distances between Bluetooth readers.

Segment travel times and speeds obtained from INRIX XD segments and averaged over 1-minute intervals have significantly improved the accuracy and timeliness of queue detection. In addition to their higher resolution, another major benefit of INRIX XD segment data is that they can be collected without the need for the deployment and operation of physical infrastructure, and they provide broad coverage over the road network. Therefore, they can also be used for queue detection and queue warning in areas where traffic sensors are either not available or not functioning properly.

One limitation of crowd-sourced third-party data, such as INRIX segment data, is that they are averaged over all lanes, and therefore cannot be used for detecting imbalanced queues where some lane(s) may be queued while traffic in other lanes flows freely. If queue detection at lane level is desired, then additional data source is needed. For example, INRIX XD segment data may be combined with spot speeds from sensors that monitor traffic speeds in each lane separately. Data from these two sources have different spatial coverage and temporal resolutions because of the way they are collected, aggregated, and transmitted. Traditional sensors provide average spot data for each lane. The two data sources also differ in their latencies. Sensor data has a minimum latency of 20 or 30 seconds depending on the data aggregation level. Third party probe data latency typically ranges from 3 to 4 minutes. These differences present some challenges in finding the best combination of the two data sources for queue detection. A queue detection system fusing sensor and third-party data was described in chapter 3. Such hybrid approach can improve the accuracy and timeliness of queue detection.

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