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Trajectory Analytics for Traffic Signal System Management in Connected Vehicle Environments

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ABSTRACT

With connected vehicle generated (***CVG***) information, traffic stream parameters become straightforwardly quantifiable, enabling traffic state characterization and examination over a variety of operational conditions. Since the observation is independent of any spatial restrictions and unaffected by queue buildup and discharge, ***CVG*** data offer more comprehensive, more reliable inputs to the traffic signal control system. The presented study investigates whether this new information is meaningful and actionable enough to enable advancing traffic operations management and control.

This study formulates a conceptual framework for a high definition analysis platform intended to ascertain the responsiveness of trajectory-based measures in reflecting the experienced operational conditions. To this end, this study establishes a quality of service evaluation method at an intersection approach level by introducing a composite, Time-Space Signal Measure of Effectiveness – ***TSS-MOE -*** and cross-referencing it with high-resolution (Hi-Res) performance indicators. At the same time, graphical representations of time-space-signal (***TSS***) signatures aim to characterize the state of the system to identify the underlying cause of any detected disruptions or poor performance level.

One of the ways to designing more effective signal control strategies is leveraging and synthesizing connected vehicle generated (***CVG)*** information to identify traffic states for the controller to operate in a predictive, yet vehicle-actuated manner. The contribution of this dissertation is twofold: 1) it presents a framework for an advanced, online, signal control logic in a connected environment that utilizes information from CVs to augment high-resolution controller

and/or sensor data, and 2) it applies the trajectory analytics to compare the performance of the new controller schemes with CVG data and functionalities relative to conventional, vehicle-actuated, control.

The framework puts forward a predictive control logic that schedules phases in an acyclic manner over a variable planning horizon. Phase duration is continually evaluated in response to updated requests for service distributed among equipped vehicles and associated performance indicators. Within the same connected control setup, two measures of effectiveness of a decision were compared to determine the upper bound on the potential effectiveness of a more-responsive control strategy. Finally, the trajectory analytics was used to evaluate the effectiveness of the CV technology-based control scheme against the conventional one.

The manner in which the real-time traffic information collected from external data sources (i.e. ***CV***s) is utilized within the same controller logic, would determine which mode of operation is superior i.e. which of the two objectives should be responsible for signal control parameter optimization. This is why the two controller modes were isolated and their performance compared.

The findings indicate that both control system performance assessment and optimization objectives should change with access to CVG data. Unlike the current state of the practice controllers, the developed method is able to handle high and low demand states equally well. The designed connected controller is shown to be robust in handling varying traffic conditions and demand levels.

DEDICATION

Посвећено мом тати!

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Chapter 1. **INTRODUCTION**

Modern surface transportation systems face limited resources in trying to accommodate the growing need for mobility and safety. Finding smarter transportation solutions to advance the system most recently focuses on connected/automated vehicles (CAVs) recognizing their sensing, communication, and computational capabilities.

Current research efforts focus on augmenting traditional control methods with the modern technology of communication among and between vehicles and infrastructure to create a "connected" system. In this "connected" system, individual vehicles can communicate (a defined set of data) with each other through Vehicle-to-Vehicle (V2V) communications and to infrastructure and Traffic Management Center (TMC) through Vehicle-to-Infrastructure (V2I) communications. Connected vehicles (***CVs***) are designed to broadcast and exchange information regarding their performance, state and trajectory – timestamped position, heading, speed, routing, driving style, and preferences via over-the-air (OTA) communication such as dedicated short-range communication (DSRC) protocols or cellular network (C-V2X). These vehicles transmit their location and progression-related information in a high-resolution format and at a fast rate, offering in-depth information about users' travel experience in a transportation system. This technology holds exciting potential as a valuable source of real-time accurate traffic information; its potential availability has been one of the motivating factors for this dissertation.

This research primarily focuses on ***CVG*** information as a data source and the opportunities from analyzing this information. Better insight into signal system operations is achievable by exploiting in-depth information about users' travel experience. Analyzing this data on an approach or corridor level can reveal meaningful relationships, trends, and patterns that can help provide a better driver experience and improve systems quality and reliability. With ***CVG*** information, traffic stream parameters become straightforwardly quantifiable, enabling traffic state characterization and examination over a variety of operational conditions. Since the observation is independent of any spatial restrictions and unaffected by queue buildup and discharge, ***CVG*** data offer more comprehensive more reliable inputs to the traffic signal control system.

This dissertation aims to set up a series of visual and quantitative metrics of performance at signalized intersections, computed when two types of high-definition information are combined.

The first data source consists of connected vehicles generated (***CVG***) trajectory information. Since the observation is independent of any spatial restrictions and unaffected by queue buildup and discharge, ***CVG*** data is superior to conventional sensor data. Furthermore, valuable patterns hidden in vehicle trajectory data uncover driver preferences and style not only when and where but most importantly how the vehicle is driven.

The second source consists of high-resolution data, which refers to fine-granularity data obtainable outside of readily available (aggregated) traffic counts or signal phase durations. Signal controllers with high-definition data logging capability, log phase change events with a tenth-of-a-second resolution timestamp and store the events in temporary data files.

The focus of this dissertation is on examining how the operation of signalized intersections can be improved using Connected Vehicle Generated (***CVG***) information superimposed by signal event status data. To analyze this high-quality information when assessing the quality of signal timing settings, new performance metrics are required since traditional ones no longer suffice the definition of state-representativeness.

The connected (vehicle-traffic signal) system management procedure, designed in this study, adopts the concept of signal indication-coded vehicle trajectory data to support offline performance assessment as well as online signal timing optimization and effectiveness evaluation.

Given the sheer magnitude of vehicle-generated data in a connected environment, methods associated with “big-data” analytics would be increasingly needed in this context.

The quantitative part of the performance assessment framework developed in this study is referred to as the *Trajectory Analytics*. In the context of this study, it represents a set of methods and their conceptual underpinning for the systematic mining of large trajectory data sets to analyze and characterize associated traffic patterns at signalized intersections (or corridors). This study designs quantitative methods that use those patterns for traffic stream properties characterization and performance-based signalized corridor operations management.

This enables signalized approach analysis to be conducted on a user level and then aggregated to a system level by utilizing the most complete set of information related to how the users perceived their travel in response to signal timing and other users along the same route.

Against the available literature, the main contribution of this study consists of characterizing the spatial and temporal extent to which actual traffic conditions might affect signalized approach performance. To ascertain how reliably and to what degree this information can be related, the trajectory analytics framework integrates conventional with newly designed high-resolution phase performance indicators. To this end, this study establishes a quality of service evaluation method at an intersection approach level by introducing a composite Time-

Space Signal Measure of Effectiveness – ***TSS-MOE*** and cross-referencing it with now-obtainable high-resolution (Hi-Res) performance indicators.

The qualitative component of the performance assessment framework i.e. visualizing relevant signal performance data in an easy-to-understand format is critical when identifying the underlying cause of any detected disruptions or poor performance levels. Vehicle trajectory data superimposed with signal phase indication/ duration create distinguishable time-space-signal event signatures that provide insightful diagnostic capabilities to uncover possible reasons for the inferior performance of traffic signal systems. Here, this visualization concept is utilized to determine traffic control operational deficiencies, as well as the extent to which deployed signal phasing/timing successfully responds to prevailing traffic conditions. The practicality of the proposed approach is reflected in reducing the time and effort required by the existing signal design/retiming practice since trajectory-signal signatures distinguish between incidents and retiming opportunities caused by changing traffic conditions.

To this end, the study formulates a conceptual framework for a high definition analysis platform intended to ascertain the responsiveness of trajectory-based measures in reflecting the experienced operational conditions. At the same time, graphical representations of time-space-signal (***TSS***) signatures aim to characterize the state of the system to identify the underlying cause of any detected disruptions or poor performance level.

Trajectory data from connected/autonomous vehicles represent an essential data source for a growing number of applications, including signal control (*1*). Until recently, its exploitation in the realm of adaptive traffic control has been limited since real-time signal control strategies to-date, have relied primarily on infrastructure-based detection (Eulerian) data. Lagrangian observations provide detailed, more accurate, and more reliable information that creates the potential for improved control and management. If higher efficiency is to be achieved at a transportation system level, opportunities for improved performance need to be realized at both major components, freeways, and arterials, concurrently. Higher throughput on freeways in mixed traffic would cause gridlock on the arterial street network unless a considerable improvement in signalized intersection control schemes is achieved (*2*).

It is necessary to derive robust, efficient control schemes that are applicable in a variety of traffic conditions (*3*, *4*). To ease the validation of the models, many researchers employed a simplified road and/or intersection model in simulation-based studies. Due to computational costs, for the sake of online implementation, earlier studies did not reference real-world representative geometric and signal phasing settings. These configurations can be complex, which poses a challenge to the adaptability of the control strategies proposed. To date, optimization of traffic signal timings is based on aggregated performance measures thus not taking full advantage of each vehicle's information (e.g., speed trajectory, turning movement, signal event status) available via vehicular communications. Despite these efforts, a computationally tractable as well as structurally flexible online adaptive traffic signal control strategy is still needed under the Connected Vehicle Environment.

One of the ways to designing more effective signal control strategies is leveraging and synthesizing connected vehicle generated (***CVG)*** information to identify traffic states for the controller to operate in a predictive, yet vehicle-actuated manner. The real-time control is separated into two parts: 1) a framework for an advanced, online, signal control logic in a connected environment that utilizes information from CVs to augment high-resolution controller and/or sensor data, and 2) application of the trajectory analytics to compare the performance of the new controller schemes with CVG data and functionalities relative to conventional, vehicle-actuated, control.

The control algorithm framework puts forward a predictive control logic that schedules phases in an acyclic manner over a variable planning horizon. Phase duration is continually evaluated in response to updated requests for service distributed among equipped vehicles and associated performance indicators. Within the same connected control setup, two measures of effectiveness of a decision were compared to determine the upper bound on the potential effectiveness of a more-responsive control strategy. Within the same control algorithm, two objective functions were tested to identify the advantages of each. The two objectives were: 1) maximizing green time and space utilization and 2) minimizing delay. The first objective was chosen to balance between low and high demand levels since these inherently require different control strategies. The second, because, typically, traffic operations analysis is explained in terms of delay. If the connected vehicle can compute its delay, this attribute would be the objective to minimize.

The manner in which the real-time traffic information collected from external data sources (i.e. ***CV***s) is utilized within the same controller logic, would determine which mode of operation is superior i.e. which of the two objectives should be responsible for signal control parameter optimization.

This study also designed and tested computationally efficient real-time intelligent control algorithms to handle mixed vehicular fleets, aimed at maximizing green time and space utilization. During the transition from no-to-full connectivity-enabled control systems, the idea was to devise and test algorithms that are compatible with the existing infrastructure so that there is no need to replace the traditional traffic controllers. Therefore, it is important to examine whether and to what extent the current infrastructure – sensors, controllers – can add in terms of ***CV***-based traffic control in mixed traffic streams.

Determining when enough real-time traffic information is collected from external data sources (i.e. ***CV***s) to augment controller and/or sensor data and, should determine the controller mode of operation. This is why the two controller modes were isolated and their performance compared. A preliminary assessment of the effectiveness of such control in relation to the state of the practice (conventional) controller logic is provided.

The adopted analysis framework addresses two main questions in terms of CV-based traffic control. The first is to assess to what degree the connected infrastructure – CV data, and functionalities – can add in terms of designing a more efficient (CV-based) traffic control, compared to the conventional NEMA-RBC. The second is to identify ways to advance signal control algorithms by fully leveraging CV sensing, communication and computing capability.

The trajectory analytics method, therefore, quantifies the extent to which CVG data and functionalities can augment typical controller schemes. Comparing two measures of effectiveness of a decision within the same connected algorithm setup provides an upper bound on the potential effectiveness of a more-responsive control strategy. The goal is to evaluate the robustness of CV-based control models and their ability to improve traffic operations in a range of operational conditions and demand levels.

1.1. Motivation

To date, the need to identify, describe and quantify operational conditions of (traffic) system states to manage signal control systems remains the most important task of any traffic management center (TMC). Because of its critical role in the successful operation and management of any signalized system, valid, relevant, and timely information is of utmost importance.

Connected environments offer more information as well as improved data availability, and quality in order to guide better decision making. Obtaining necessary information in a timelier fashion enhances currently established practices and standards, but more importantly, new actionable information adds new functionalities and opportunities to advance operational efficiency.

Furthermore, increased situational awareness and faster and more reliable information mean faster identification of issues and faster response to specific traffic events. This in turn means more effective and efficient management of capacity/demand.

To this end this study proposes to answer the following research questions:

- Can traffic signal system efficiency and mobility be measured and enhanced in innovative and meaningful ways by combining two primary data sources (i.e. by using ***CVG*** and controller log information)?
- To what extent can connected vehicle data and technologies be used to support offline and online performance-based management of signalized facilities?

Realizing potential benefits requires developing advanced analytical methods and traffic control algorithms that utilize these ***CVG*** capabilities. The motivation behind this dissertation is twofold:

- identify, describe, and interpret meaningful patterns in ***CVG*** data to systematically characterize the state of the traffic system.
- utilize knowledge from the initial stage to formulate advanced traffic control schemes and performance evaluation methods for short-term and long-term effective decision making.

With better insight into the system's performance, problem areas can be proactively identified, and relevant information and solutions can be suggested and communicated in real-time.

As a decision support tool, the proposed approach to connected traffic signal system management could form a basis for an "overall" arterial performance assessment platform, consisting of a set of metrics and graphical representations for large multidimensional datasets. A complete picture of the health of the system and its level of performance is only possible by investigating both – qualitative and quantitative aspects thereof.

1.2. Problem Statement and Objectives

A distinctive feature of ***CVs*** that is the focus of this research is their ability to generate and broadcast real-time information through wireless telecommunications. Detailed trajectory information such as link/lane position, speed, turn movement and acceleration can be used to track shapes of vehicle trajectories in time and space and associated properties at a finer scale to better understand interrupted traffic flow dynamics to then improve traffic performance assessment, prediction and control.

The state of the practice for traffic control systems does not incorporate ***CVG*** information. Control schemes rely on aggregated and/or averaged traffic parameters, such as vehicle counts, occupancies and mean speeds, etc. Conventional measurement formats cannot accurately represent traffic signal system states over a variety of traffic conditions. Furthermore, performance assessment only indirectly considers signal timing effectiveness when analyzing signalized approaches. Since control systems' inputs are estimated (depending on the type of control) signal timing effectiveness is limited and as a result, performance evaluation itself is hindered.

To address the issues identified, ***CVG*** traffic data is utilized for reactive and/or predictive analytics under different operational conditions, optimization engines and traffic control applications to enhance systems operational efficiency and impact decisions at two levels - micro i.e. the individual user and macro i.e. system level.

CVG trajectory data is collected and processed, fused with other operational control data, synthesized to produce "information" which is then operated to enable multiple applications. Signal event coded ***CVG*** trajectory information, as the core method proposed, is designed to:

- Ascertain state-responsive trajectory-based measures
- Identify the underlying causes of system inefficiencies and facilitate the development of innovative analytical methods to describe and address these issues
- Integrate individual trajectory-based performance analytics into online signal control strategies design

- Design advanced traffic signal control and management strategies to improve the overall performance of traffic signal systems

The quantitative and qualitative performance assessment method formulates a decision support framework for thorough and long-term performance analysis and decision-making. Consisting of a set of metrics and graphical representations for larges datasets, such a platform would enable proactive management and control of signalized corridors. The evaluation method that standardizes the data formats and performance measurements that are independent of controller operation and is capable of online data archiving. Accordingly, it establishes an analysis framework for comparing intersection/arterial performance on corridors.

Relevant research studies emphasize the importance of understanding and quantifying existing field traffic conditions in the design and fine-tuning of control parameters. Furthermore, diagnosing problems, determining their causes and extent cannot occur without storing and processing relevant data. The key to designing more effective connected signal control strategies lies in leveraging and synthesizing information to identify the type of problem, its underlying cause, and spatial and temporal context.

CVG information as the data source and the opportunities from analyzing this information will enhance our understanding of what is occurring at signalized intersections. With this information readily available, accurate traffic state characterization and examination over a variety of operational conditions are achievable, transforming signal control systems inputs and outputs into more meaningful and actionable data sets.

1.3. Organization

This dissertation is organized as follows. Chapter 1 introduces the thesis and motivation of this dissertation. Chapter 2 provides a literature review of the high-resolution performance measures in partially and/or fully connected signal systems as well as traffic control strategies based on such data and in connected vehicle environment, setting the context in which the new applications were developed. Chapter 3 introduces a conceptual and methodological framework for developing traffic signal system management strategies in connected vehicle environments which serves as a road map for methods and applications introduced in later chapters. Chapter 4 introduces an innovative visualization method using the superimposition of (connected) vehicle trajectory data with signal controller event data. It defines a qualitative performance assessment framework of time-space-signal signatures. Chapter 5 introduces the trajectory analytics framework by defining condition-responsive trajectory-based set of measures. The emphasis is on the newly developed, composite, time-space-signal measure of effectiveness which relates the utilization of green time and space. Building on the previously introduced concepts and measures, chapter 6 presents a real-time communication-based connected controller logic. Within the same connected control setup, two measures of effectiveness of a decision were compared to determine the upper bound on the potential effectiveness of a more-responsive control strategy. Building on findings and methods proposed in chapter 5, chapter 6, evaluates the effectiveness of the CV technology-based control scheme against the conventional one. Considering the novelty of the proposed connected system management framework, within chapter 6, the results analysis and findings were presented and discussed in much detail. Finally, chapter 7 provides concluding remarks.

Chapter 2. **LITERATURE REVIEW**

While detectors are widely deployed for traffic control purposes along signalized arterials, in practice, operational data from traffic signal systems are rarely stored or analyzed. As a result, the current state of the practice severely limits reactive (proactive) traffic systems monitoring and evaluation. In previous studies, high-resolution detector and controller status information was used to visualize and, in a way, determine the quality of vehicular progression based on pre-set signal timing parameters (*5–10*). There were sporadic attempts to design innovative high-definition data-driven intersection performance measures, yet their success was constrained by the type and quality of sensors utilized. Retrievable information is dependent on the actual detection type used, detector position and assumptions made when adjusting for the distance traveled (toward the signal stop bar) from the moment vehicle was first detected – in advance (*11*). In case queue had formed upstream of the (advance) detector, traditional performance measures do not reveal much about the signal's efficiency to serve the demand, especially in oversaturated traffic conditions.

On the other hand, vehicle trajectories provide the most valuable information regarding individual vehicle's position in time and space and respective intersection/controller settings and environment. Such high-resolution information along with signal data will allow for performance measures to be easily calculated on a per phase, approach, intersection, or corridor level and will allow for accurate and detailed traffic state evaluation, particularly during congested traffic conditions.

This research focuses on individual vehicle trajectories because of their capability to capture, describe, and measure nearly every state of the traffic signal system including signalized corridors most challenging one - oversaturation, breakdown, and recovery. As shown in previous applications, trajectory-based measurements are more accurate than those based on aggregated information (*12*).

2.1. Traffic Signal System High-Resolution Data and Performance Measures

Balke et al. (*5*) defined and recommended several performance measures of reliability, efficiency, and safety, considered appropriate to describe the state of the system if fine-granularity data were to be available from the existing infrastructure (controller and detector). These metrics involved calculating, in a given evaluation period, the average number of times a phase was activated, vehicles served per cycle during a given evaluation period, vehicles stopped per cycle during a given evaluation period, probability of a vehicle having to stop at an approach and cycle failures. The same researchers, (*13*) designed a prototype software program, called Traffic Signal Performance Measurement System (TSPMS), which monitored, and stored in a log file, phase, and detector status outputs from the traffic signal controller at individual intersections. The additional utility was designed to enable an analysis of these log files. Based on raw events which included Phase Status, Phase On, Ring Status, and Vehicle Detections, the following performance measures were recommended to practitioners to assess traffic operations and the effectiveness of the signal timing - cycle time, time to service, queue service time, duration of green, yellow, all-red and red interval for each phase, number of vehicles arriving during each interval, as well as yellow and all-red violation rates, and phase failure rate.

In 2007, Smaglik et al. (*6*) designed an integrated, general-purpose, data collection module that timestamps detector and phase state changes in a NEMA (*14*) controller and uses this data to provide quantitative graphics to assess arterial progression, phase utilization, served volumes on a cycle-by-cycle basis and estimate intersection delay. Equivalent hourly volume, volume over capacity ratio (V/C), and arrival type were presented as indicators that quantitatively document progression quality. Certain performance metrics (delay estimates) are conditioned upon the actual detector setup requirements (advanced detection aside from regular stop bar). Around the same time, Dowling (*15*) recommended a set of key system MOEs for assessment of the general health of the transportation system. Several of them relate to an urban arterial street: throughput, mean delay, and "intersections with long queues, turn bay overflows and exit blockages". This basic set of MOEs describes the state of the system, yet the report recommended the use of vehicle trajectories when performing a more detailed intersection or segment analysis and identifying additional, *actionable* performance metrics. Similarly, in 2008, Liu et al. (*7*) presented their SMART-SIGNAL (Systematic Monitoring of Arterial Road Traffic and Signals) system, capable of collecting fine granularity event-based traffic data and generating time-dependent estimates of signal performance metrics in real-time, most significantly intersection queue length and arterial travel time estimates. In 2013, the same authors (*10*), accounting for the deficiencies of their prototype version, added a plug-and-play capability to reduce the effort of customized installation.

Day et al. (*9*) introduced what subsequently became a standard in-vehicle progression quality representation, a tool for visualizing and qualitatively evaluating signal phase performance while identifying existing signal timing deficiencies, named Purdue Coordination Diagram (PCD).

PCD, using advanced detection, plots arrivals of vehicles relative to the green/red indication encountered, upon entering the vehicle detection zone. The time of arrival of each vehicle, corresponding to the time within the cycle is adjusted by the amount of time it would take to travel to the stop bar. Percent arrivals on Green or commonly referred to as Arrivals on Green (AOG), a quantitative measure of the quality of progression, was also associated with the diagram, a metric that infers a vehicle's progression quality with respect to its time of arrival. One limitation is, due to the inherent nature of the state of the practice data, sensing infrastructure and traditional MOEs, that once the queue forms, at the stop bar or beyond the advanced detection zone, the estimates would be erroneous/misleading as to what is occurring with the inbound demand and, consequently, signal timing.

Green Occupancy Ratio - the ratio of the time occupancy during green and red indication duration - was proposed by Smaglik et al. (*16*) as an alternative performance measure of phase utilization. Although the metric was shown to be a reasonable surrogate for V/C ratio (difficult to obtain directly and requires excessive processing to develop the metric) in undersaturated conditions, it reaches a saturated value of 1.0 more rapidly than V/C, as the volume increases, making it challenging for the analyst to identify oversaturation. As a result, does not correlate with delay as well as V/C.

Freije et al. (*17*) introduced and demonstrated the validity, robustness, and effectiveness of the graphical performance measures based on detector occupancy ratios and signal events in verifying cycle failures and other signal timing shortcomings. The authors combine phase termination events with the Green/Red Occupancy Ratio to validate and adjust phase splits when warranted.

Hallenback et al. (*18*), similarly, hypothesized that lane occupancy percentage values, from an advanced sensor, with respect to green and amber indication, could be used to develop a basic arterial performance estimation method. The outcome was an occupancy-congestion level relationship, where thresholds between light, moderate and heavy congestion, were determined as speed ranges.

Prompted by signal operators' needs to troubleshot quickly operational problems of a signalized approach, Sunkari et al. (*19*) designed a toolbox consisting of a monitoring and analysis tool. The monitoring component logs relevant events within the controller cabinet that provide input for analyzing intersection operations (signal status, detector call status, preempt status, and coordination status). These represented analysis inputs for cycle-based reporting format outputs. Signal performance measures of effectiveness included phase time, phase failures, queue clearance time, time to service, etc.

Signal performance visualization aid i.e. "intuitive evaluation of time-space diagrams quality" was suggested by Liu et al. in 2014 (17) as a method for adjusting signal control parameters. The authors proposed calculating through traffic cumulative flow profile at the link entrance, based on the advance detector data. This required vehicle arrival time estimation and depended on whether the queue had propagated onto the advance detectors.

2.2. Oversaturated Conditions

Gettman et al. (*20*) introduced a comprehensive practitioner's guidebook related to the traffic signal system's operations in oversaturated conditions, to detect the type and causes of oversaturation. The second volume of the guidebook listed the quantitative measures of oversaturation intensity (*21*) which determined the overflow queue length at the beginning of red and estimated lost green time due to, either, the overflow queue discharge or approach queue spillback. The authors designed regime-customized strategies and thresholds for traffic-responsive application of pre-configured mitigation strategies.

Liu et al. (*22*) as part of the SMART-SIGNAL initiative, developed a shockwave theory-based method for estimation of long queues, i.e. queues extending past the detector and intersection stop bar. In the event of slight, intermittent, link oversaturation, once the detector is occupied by the queue and cumulative count of vehicle arrivals is not available, such a method was necessary to quantify its extent. The authors identified three breakpoints at which the traffic condition changes within a cycle. Occupancy thresholds were specified to distinguish between said points (detector occupancy time of 3 seconds was considered a trigger which verified that a long queue did form). Once this point was verified to exist, the second one indicated the discharge shockwave passed the detector and the last (third), when the rear end of the queue passed the detector. Timestamps for these points were recorded and if the time gap between two consecutive vehicles was larger than 2.5 seconds, indicated the end of the queue had reached the stop bar.

By utilizing high-resolution information Wu et al. (*23*) developed a spill-over detection algorithm to quantify the spatial and temporal severity of oversaturation. For queues extending beyond the detector, the method by Liu et al. (*22*) was adopted to estimate the residual queue length, which was necessary to quantify the temporal oversaturation severity index (T-OSI) – the ratio between the residual queue discharging time and total available green time, per cycle. Spatial oversaturation severity index (S-OSI), refers to the queue spillback at the upstream intersection caused by the positive value of T-OSI at a downstream intersection, i.e. spatial extent of oversaturation if an approach was unable to discharge vehicles.

The algorithms described previously were prone to estimation errors particularly when multiple cycle failures occur, in case of severely oversaturated short links or platooned vehicles' arrivals (*23*).

Several other authors investigated cycle-by-cycle queue length estimation based on various data sources. By using probe vehicle data with penetration rates ranging from 5 to 100%, Li et al. (*24*) tested a method to reproduce a queue forming and discharging dynamic, based on inflection points. These were defined as trajectory points when a vehicle joins or leaves the queue. A fitted function is then used to estimate the queuing and discharging shockwaves. Signal timing is not known a priori, but estimated in the process, based on which, and the estimated shock-wave profile, the maximum queue length is estimated. Building upon their previous work related to oversaturation severity indices, Hu (*25*) developed a maximum-flow based signal control model to manage oversaturation. The authors formulated a control scheme which decided whether to adjust red or green duration: changing red times aims to eliminate spillover; changing green times aims to clear residual queues.

2.3. Mixed Traffic Environments and Connected/Autonomous Vehicle Environment MOEs

Most up-to-date literature summarizes communication technology-based advancements in intersection signal control into two categories. One utilizes individual vehicle level information from approaching vehicles to advance signal control strategies, while the other provides signal control information to the drivers so that they can optimize their routes. Researchers were predominately focusing on how the performance of currently deployed adaptive traffic signal systems can be improved by using enhanced algorithms based on richer data provided by the connected vehicles (*26*) (*27*). Rare attempts were made to define innovative signal performance quantifiers (*28*).

Christofa et al. (*29*) designed and tested two arterial queue spillback identification methods based on connected vehicles or probe data. The first, gap-based queue spillback detection method was based on the estimation of the distance between the last ***CV***-equipped queued vehicle and the actual end of the queue. The number of non-equipped vehicles that joined the queue after the last ***CV***-equipped was assumed to follow a truncated geometric distribution – the probability of success corresponds to the connected vehicles MPR. The second method, shockwave-based queue spillback detection method, considered additional information on signal settings of the upstream intersection. The stopping time and location of the last ***CV***-equipped vehicle that was served by the upstream intersection were utilized to project the shockwaves arising from vehicles joining the queue. The time and location of the last queued vehicle were calculated based on the kinematic wave theory.

Seeing as the two most important inputs to the existing adaptive signal control systems are the saturation flow rate and the free-flow speed, Bagheri (*26*) proposed the two parameters estimation method, suitable for mixed traffic environments. Feng (*30*) proposed methodologies to process ***CV*** trajectory data then used to design a real-time phase allocation algorithm that inferred the unequipped vehicle's information based on connected vehicle data and traditional vehicle detector data where available.

Khoshmagham (*31*) established and field and simulation-tested an architecture for a real-time performance measurement system that used partial vehicle trajectories data to estimate many traditional as well as derived operational metrics (in the signal control category - arrivals on green and red).

Argote-Cabanero et al. (*32*) devised a methodology to establish minimum penetration rates required for accurate estimates of four arterial MOEs in both, under and oversaturated, traffic conditions. The impact of MPR on the accuracy of MOEs (average speed, delay per unit distance, the number of stops and acceleration noise) had been estimated with the use of real-world and simulated vehicle trajectories. The authors concluded that the level of estimation accuracy for different MOEs, depending on prevailing traffic conditions, required different *CV* technology MPRs**.**

Most recently, Zheng and Liu (*33*) proposed an expectation-maximization procedure to estimate traffic volumes using GPS trajectory data from ***CV*** technology under low market penetration rates (< 10%). The approach also accounted for the encountered traffic signal status to calculate the Poisson arrivals (within cycle) time-dependent factor, similar to the cyclic flow profile from detection-based systems. Arrival rates are assumed to depend on the time in a signal cycle. ***CV*** trajectory information included: projected stop bar arrival time (based on free-flow speed), departure time, and whether the vehicle was stopped or not. The approach only treated undersaturated traffic conditions, assuming no residual queue existed at the beginning of the red interval.

Assuming full information availability (100% MPR of ***CV*** technology), Beak et al. (*28*) analyzed vehicles' speed variation along a corridor. The outcome of the study was a new signal performance measure of effectiveness (MOE), named Smoothness Of the Flow of Traffic (SOFT), which based on the speed profile observed determined how smoothly vehicles were traveling along a corridor. SOFT was defined as the ratio of the sum of the total power distributed over the higher frequencies (variation of speed increases) to the power of zero frequency (average vehicle speed). The lesser the variation in speed, the smoother the travel.

Although safety performance measures of signalized intersection operation are outside of the scope of this research, it is worth noting that Zha (*34*) categorized safety indicators for connected vehicle safety applications.

Traditional measurement formats cannot accurately represent traffic signal system states over a variety of traffic conditions. Furthermore, performance assessment only indirectly considers signal timing effectiveness when analyzing signalized approaches. Since control systems' inputs are estimated (depending on the type of control) its effectiveness is limited and as a result, performance evaluation of modern traffic control systems is hindered.

2.4. Traffic Signal Control in Connected Environment

Traffic signals remain the most common form of traffic control on urban streets and arterials. With connected and autonomous vehicles (CAVs) providing an opportunity to improve throughput and flow stability on freeways, it is important to seek similar performance improvement in urban arterial street operations (*1*). Signal control settings that are responsive to the changing traffic conditions can alleviate traffic congestion and consequently reduce associated delays. Actuated signal control strategies address the drawbacks of pre-timed signals by being reactive to minor changes in the demand. Furthermore, adaptive signals are based on continuous monitoring of arterial traffic conditions and queuing at intersections as well as the dynamic adjustment of the signal timing to optimize one or more operational objectives - minimize delays, maximize throughput, etc.) (*35*, *36*).

As ***CVG*** data provide a much more complete picture of the arterial/intersection traffic states, opportunities to leverage these for control purposes become evident (*37*). Consequently, ***CV***-based signal control strategies rely on more accurate detection and more reliable prediction in the case of rolling horizon approaches (*30*, *38–40*).

Despite adaptive strategies' successful implementation, their performance relies on the continuous and reliable operation of detectors. The advent of V2V and V2I communication through dedicated short-range communications (DSRC) is envisioned as a solution to this problem i.e. detector failures and drawbacks. Moreover, DSRC provides more information related to individual vehicles' travel. Real-time position, and under certain concepts of operations, desired route, destination, etc. are readily available. A comprehensive review of adaptive signal control strategies in a connected vehicle environment was presented by Jing et al. (*4*). Past research distinguishes adaptive signal strategies based on DSRC aimed at minimizing delay or travel time (*41–48*), queue length (*38*, *49–54*), waiting time (*33*, *55*, *56*), (only implicitly) pollutant emissions (*57*), the number of stops (*58*, *59*), fuel consumption (as one objective among multiple) (*43*, *60*), or maximizing throughput (*49*, *61*, *62*) using data acquired through Connected vehicles (***CVs***), V2X communication, or vehicular ad hoc networks.

Relevant literature, presented in this subchapter, summarizes communication technology-based advancements in intersection signal control and enumerates most noteworthy efforts as per the author's opinion.

Gradinescu et al. (*41*) were one of the first to propose a phase sequence/duration optimization, to minimize control delay and/or queue length using car-to-car and car-to-controller communication. The authors utilized Webster's formula (*63*) to derive the amount of required green per movement. By utilizing properties and relative positions of vehicles, researchers attempted to devise vehicle scheduling-based control strategies (*64*).

Given high-resolution vehicle trajectory information, advanced priority and platooning techniques are being re-examined in recent years. Acknowledging the unavailability of connected vehicle information required for signal control purposes, Ren et al. (*65*) instead of measuring the queue length or movement of the back of the queue, utilized variations in speed to detect if the vehicle queue spills back to the upstream intersection. By utilizing real-time information (obtained from speed detectors periodically) and current traffic signal status, the decision tree, upon established triggers, determines which scheme to apply to adjust the predetermined fixed time plan. Early cut-off or return of unused green are recommended as techniques to better serve platoons/queues during oversaturated conditions.

Among conventional studies, the majority determines whether a vehicle belongs to the same platoon as the vehicle immediately preceding it according to a critical value for the inter-platoon headway. As shown in other studies (*66–68*), these parameters should depend on current traffic volume. To minimize disruptions to vehicle platoons, designed algorithms, in one form or another, determine when to switch between phases and calculate certain objective's savings if a phase were to become active vs the opposite happening. For example, in (*66*) the decision whether to switch the current phase's green was made by comparing the computed savings against the delay incurred.

Conventional platooning-based control schemes share common findings: traditional detection undermined the effectiveness of the platoon-based adaptive signal timing since platoon detector positions affected the estimation of platoon size, headway, and speed. Real-time control applications based on platoon recognition methods are rare. Computational complexity as well limits its applicability in a variety of traffic conditions. In recent years, however, platoons of connected vehicles have been the basis of several novel control schemes. Real-time connected vehicles' positions and speeds determine their arrival times when identifying or segmenting a platoon for traffic control purposes.

The review from this point onward will mostly focus on platoon-based signal control in connected vehicle environments.

Wunderlich et al. (*69*) proposed a queue size based maximum weight matching (MWM) control framework, which became the benchmark for many other researchers when developing platoon-based strategies. The algorithm evaluates the size and weight of each queue and schedules phases to maximize throughput. The weights reflect the service urgency of each queue. Its flexible phasing setup provides superior performance in terms of average vehicle delay compared to a sequential dual-ring phase scheme. Accounting for minor shortcomings of their earlier work, additional models were formulated to account for variation in queue discharge rates (*70*). Two main aspects were carefully inspected. 1) whether longer queues discharge rates were lower than those of shorter queues and 2) shared lanes traffic mixture (straight and right/left-turning vehicles) impact on queue clearing times. By leveraging turn information and vehicle lane positions, the newly developed control method selected the next best phase and decided its duration for overall (intersection) throughput maximization, while promoting "fairness". Allocating more green time to those approaches with higher arrival rates, and "occasionally" assigning right of way to lower ones.

Assuming advanced communication between vehicles and traffic controllers, He et al. (*71*) formulated an offline arterial traffic signal optimization framework for multiple travel modes named Platoon-based Arterial Multi-modal Signal Control with Online Data (PAMSCOD). A headway-based platoon recognition algorithm categorized individual vehicle requests and clustered them into platoons by priority level and phase. The procedure assumes first come first serve rule and aggregated vehicles into platoons which request priority to address the issue of computational complexity. Another feature of PAMSCOD was its ability to control the discharge rate from upstream intersections to avoid de-facto red since real-time information regarding queue length and size were considered available. Under the same V2I framework, the authors structured a simplified formulation and a heuristic algorithm for real-time applications (*72*). Multiple priority requests from different modes are explicitly accommodated while simultaneously considering virtual priority requests for coordination and vehicle actuation. When coordination was broken, a penalty would reflect it in the objective function calculation. Connectivity-enabled platoon-based control strategies continue to emerge (*73*). Yang et al. (*74*) tested their switch or extend signal timing logic to reduce platoons' waiting time on a hypothetical four-phase isolated intersection, where segmentation of platoons was based on a preset critical headway threshold. Next (in a fixed sequence) phase's platoon size and clearing time were balanced against the time it took to clear the last queued vehicle times the number of vehicles served if the phase were to stay active.

Other authors proposed variants of a rolling horizon-based phase sequence optimization, originally proposed by Gartner (*75*) as well (*76*). Feng et al. (*76*) developed an adaptive signal control for ***CV***-enabled isolated intersections where a two-level optimization problem that minimizes total vehicle delay and queueing length was solved in real-time. Later the authors, recognizing the traffic controller's complex operational requirements related to coordination, extended this methodology (*77*). Their adaptive signal control in a connected vehicle environment integrated multimodal priority requests, platoon-based coordination requests, and regular vehicle-actuated control. The reason for incorporating regular-vehicle actuation in the "connected" controller logic were the errors of unequipped vehicles positions estimates under low penetration rates. *As the penetration increases, actuation may negatively affect the performance of the adaptive control algorithm since sufficient connected data are available to make better decisions. The analysis in Chapter 6 supports such findings.*

Unlike conventional sensors and signal control systems related deficiencies, queue spillback issues in over-saturated traffic conditions can be addressed using ***CV*** technology (*78*, *79*). As part of a large initiative to design advanced control strategies for connected vehicle environments, Smith et al. (*78*) utilized intelligent transportation systems data to design multiple control strategies - vehicle clustering, queue identification, and monitoring and rolling horizon approach to optimize offsets and splits at signalized intersections.

Lee et al. (*44*) among the three, most relevant concerning this study is described - the vehicle clustering algorithm (VCA). VCA finds a suitable gap among approaching vehicles to determine when to terminate each phase's green. It operates in three stages. The first calculates cumulative waiting times on each red-indication movement, second ensures gap out occurs as soon as the last vehicle has cleared the approach and the third, determines which pseudo-platoon is the closest to the intersection, yet farther than a certain threshold distance. Accordingly, appropriate green-extension times are computed. After the time has elapsed or the maximum time is reached, the right of way is given to the red-indication movement associated with the highest cumulative waiting time.

Outside of conventional approaches to traffic control and building on the previously mentioned queue spillback algorithm in Smith et al. (64), Venkatanarayana et al. (*79*) proposed a procedure to detect queue spillback during oversaturated conditions. The authors devised an algorithm to monitor queue lengths at an intersection in real-time and in response to queue spillback adjust offsets and splits of the upstream intersection by either extending or shortening respective green times. However, the algorithm was proved to be effective by reducing total delay only in a quite simple network with 2 one-way street intersections.

Extending their previous work on fully connected control algorithms, Datesh et al. (*80*) developed an algorithm that determined the end-of-phase time by identifying sharp decreases in vehicle density, calculated based on vehicle's location thus distance to stop bar. The proposed

IntelliGreen Algorithm (IGA) used k-means clustering to determine the optimal point in time to terminate active green. A natural break in the time-to-intersection distribution of the vehicles approaching the green signal partitions the vehicles into two clusters: green and red. The largest time-to-intersection value in the green cluster is set as the remaining green time while the "red cluster" is stopped. However, traffic flow was divided into, at most, two platoons, regardless of the actual arrival pattern.

Similarly, a Schedule-driven Intersection Control strategy (SchIC) was designed to efficiently generate (near) optimal solutions in real-time (*40*). SchIC reduces the search space by exploiting queue size and temporal arrival distribution in the prediction horizon.

Goodall et al. (*39*) proposed a predictive microscopic simulation algorithm (PMSA) for signal control in connected environments that utilized vehicle positions, headings, and speeds. Vehicle trajectory information was imported into a microscopic simulation model to predict future traffic conditions and in a rolling horizon manner, optimize phasing over 15 seconds.

As part of another initiative to design advanced control concepts for connected environments, Skabardonis et al. (*81*), developed and tested through simulation, a queue spillback avoidance strategy to improve mobility based on ***CV*** data. The method was formulated as a platoon-based control method. It comprised of three distinct strategies: green extension, phase termination, and double cycling. Applying the most effective one depends on the associated total delay predicted.

Some recently proposed control methods render traditional traffic lights obsolete. ***CV***/***AV*** environment could also lead to a scenario with no actual traffic controller at the intersection. Starting with (*82*), Autonomous Intersection Management (AIM) methods were designed to control individual vehicles' maneuvers so that vehicles can safely cross the intersection without colliding with other vehicles, therefore establishing intersection control far superior to the conventional traffic signals' mechanisms (*83*) (*84*) (*85*) (*86*). AIM related research is intensifying and more significant work is yet to be recognized. To reduce computational burden and complexity on the controller itself, Jin et al. (*87*) proposed a reservation-based intersection management system. Each platoon's lead vehicle communicates with the intersection by sending the estimated earliest arrival and clearance time of its platoon. After the intersection manager confirms the reservation, the leader will design its trajectory and trajectories of its followers to meet the chosen criteria.

Additionally, there have been limited efforts to design algorithms that optimize signal operations and vehicle trajectories in an integrated manner. Sun et al. (*62*) designed a method that controls lane changing and car-following behavior while optimizing splits to maximize intersection capacity. Under the V2I framework and with full connectivity, Li et al. (*88*) developed and tested a joint vehicle trajectory/ signal control parameter optimization algorithm. The approach was, timing plan enumeration based, accounting for certain restrictions, to reduce combinatorial complexity, and was fundamentally focused on trajectories optimization. In a simplified setup (two-phase, two one-way roads), the proposed method was evaluated under a variety of demand scenarios (undersaturated conditions) and showed modest improvements are achievable compared to vehicle-actuated control. Subsequently, the authors extended the concept to incorporate mixed traffic environments (connected, autonomous and regular vehicles) and real-time optimization of control parameters. Again, the core of the method was the decision of whether to switch or extend the current phase (*89*). Similar work has been done by (*90*), where optimal traffic signal schedules were found by approximate dynamic programming and optimal vehicle speed advice was given after respective green had started, conditioned upon no queue traffic state. The overall procedure was aimed at minimizing both delay and number of stops. Xu et al. (*91*) introduced a method based on cooperation between signals and vehicles' speed. The proposed method optimized actuated cycle lengths while vehicle speeds were optimized on a rolling horizon basis. Vehicle control minimized fuel consumption by optimizing the amount of braking and engine power. However, the study only considered autonomous vehicles.

More recent studies propose dynamic traffic management frameworks to optimize network-level signal control decision variables and departure times of individual connected vehicles to determine their optimal routes. Signal control parameters are updated every control interval, whilst departure times upon vehicle's request. The latter problem is solved as the shortest path problem, where links availability depends on the decisions previously taken by all the other vehicles (*92*). Similar solutions were also suggested for grid subnetworks by (*93*). The authors, however, predicted vehicle turning movement i.e. travel direction according to discrete probability distribution functions and assumed phase sequence and duration were fixed. Control methods reviewed in this study, if tested, proved efficient only under light-demand scenarios, which was to be expected, considering the complexity of the problem and consequently computational effort required to solve the problem in a reasonable amount of time (*40*).

Relevant literature was found to be sparse in addressing the performance of advanced signal control strategies in mixed traffic conditions, at various penetration rates of different vehicle types. It is reasonable to assume that not all vehicles will be connected or automated in the near future. A mixed traffic fleet will certainly exist during the (extended) transition period. Previous studies agree on the fact that the most critical parameter determining the effectiveness of control algorithms is the market penetration rate of connected vehicles. Most of the previous studies referred to offline (optimization) control strategies with a 100% penetration rate of connected vehicles.

Chapter 3. CONCEPTUAL FRAMEWORK

This dissertation proposes to establish an offline and online performance-based management platform for traffic signal systems leveraging connectivity-enabled information. By recognizing opportunities to characterize signalized intersections operational conditions, efficiency, and control schemes more comprehensively and reliably, the study formulates a two-layered decision support tool that operates two interdependent components of an integrated system, i.e. real-time control and performance assessment. The practicality of the proposed approach is reflected in its design which accounts for both, immediate problem detection and solution as well as long-term evaluation of performance for system-level decision making.

The conceptual framework for the connected traffic signal system operations and management, illustrated in , describes the relationship between real-time and offline system components from the system management point of view and its consequences for system users expressed as operational efficiency improvement. The left half of the diagram represents the real-time layer of the system, the right half the offline performance assessment layer of the system.

The conceptual framework presented here is meant to serve as a foundation for organizing and understanding components of the connectivity-enabled traffic signal system management process.

To understand and analyze the system at an individual user as well as any more aggregate level in the environment of connected vehicles and traffic signals, this framework recognizes particular vehicle trajectory-based indicators and their relevance, where assumptions have been made, and where gaps exist in the literature and data. At the highest level, it identifies four main process components, namely: (1) monitoring traffic data i.e. vehicle trajectories and signal events; (2) analysis and problem (area) detection; (3) control strategies design; and (4) immediate solution as well as continuing system performance evaluation.

These interacting components undertake specific tasks to support various aspects of analysis based on relevant information pre-processing. Pre-processing includes (a pre-defined set of ***CVG*** attributes) retrieval and noise removal, labeling, storage, and examination. ***CVG*** data as a source of information represents a rich input for data analytics processes to support both: offline analysis – identifying traffic patterns or operational deficiencies, and online analysis – real-time control and prediction.

User-level evaluation constitutes a single most important element of the entire framework. At this point, real-time control and performance assessment overlap and is the core of both parts of the framework.

However, performance indicators in both system elements are not and could not be the same - as they and their interrelationships on different temporal and spatial scales are complex, differ in functionality, and require different reporting formats. Namely, signal group-level aggregated information and measures are applied when performing system evaluation respective of specific criteria - efficiency, utilization, and reliability. Respectively, user-level information is essential when tracking traffic parameters rate of change in real-time to proactively impact i.e. control traffic operations in real-time.

The real-time component of the system operates on a feedback control principle. Iteratively, it associates specific traffic parameters which are also inputs for the highest-level performance evaluation which then determine the control strategy itself. This recursive procedure enables immediate feedback and correction of solutions, which guarantees even the “incorrect” action is rectifiable instantly. Therefore, effective control is fundamental to achieving efficient traffic operations and, links to supporting largescale transportation services standards. Designing connected systems control strategies and their operational logic aside from rigorous formulation should focus on practicality and transferability thus ease of implementation. It is essential to verify its performance and adaptability in a range of operational conditions, demand levels, and in no to fully connected environments.

The long-term quality of service assessment describes as comprehensively as possible how the system's users are affected and suggest the type of problem-customized solutions.

What distinguishes this study from the state of the practice solutions is that, within both parts of the overall framework, interrelationships between various traffic system states and respective performance quantifiers were captured based on the idea of "causal chains" (analysis and problem detection).

Analyzing the relationship between several success indicators representing various aspects of signalized approach analysis allows one to understand and model these causal chains with one goal in mind – optimizing traffic operations.

Such an approach assumes identification of most representative attributes to retrieve, properties to monitor, assumptions to make, and natural points of intervention.

In many cases data on the state of the system and operational success, indicators are considered misinterpreted or otherwise misleading as to the underlying cause of the problem, which, as a result, hinders the quality of evaluation. Also, one may know about the exhibited symptoms (for example failure to clear the approach) yet not the context of it.

System-level evaluation is intended to assist operators/decision-makers distinguish between specific traffic events and system upgrades warranted by changing traffic conditions. Trajectory/signal analytics applied at a system-level builds a context-sensitive approach to the management of signal systems in connected environments which by integrating various analysis models enables multi-dimensional and continuous monitoring of traffic performance.

The conceptual framework identified contextualized traffic state representativeness as the main pathway to mitigating operational deficiencies and associated outcomes. The full framework is intended to be useful in determining the main points of intervention to help manage a positive outcome, locally and globally as well as immediately and in the long run. These assumptions under various operational scenarios will be systematically assessed and validated in this study.

Therefore, the conceptual framework for a high-resolution data analysis platform formulated in this study is intended to identify the causes of intersection performance deterioration, by defining a set of visual and quantitative operational success indicators. The current state of the practice does not recognize such a method of connected traffic-signal system management.

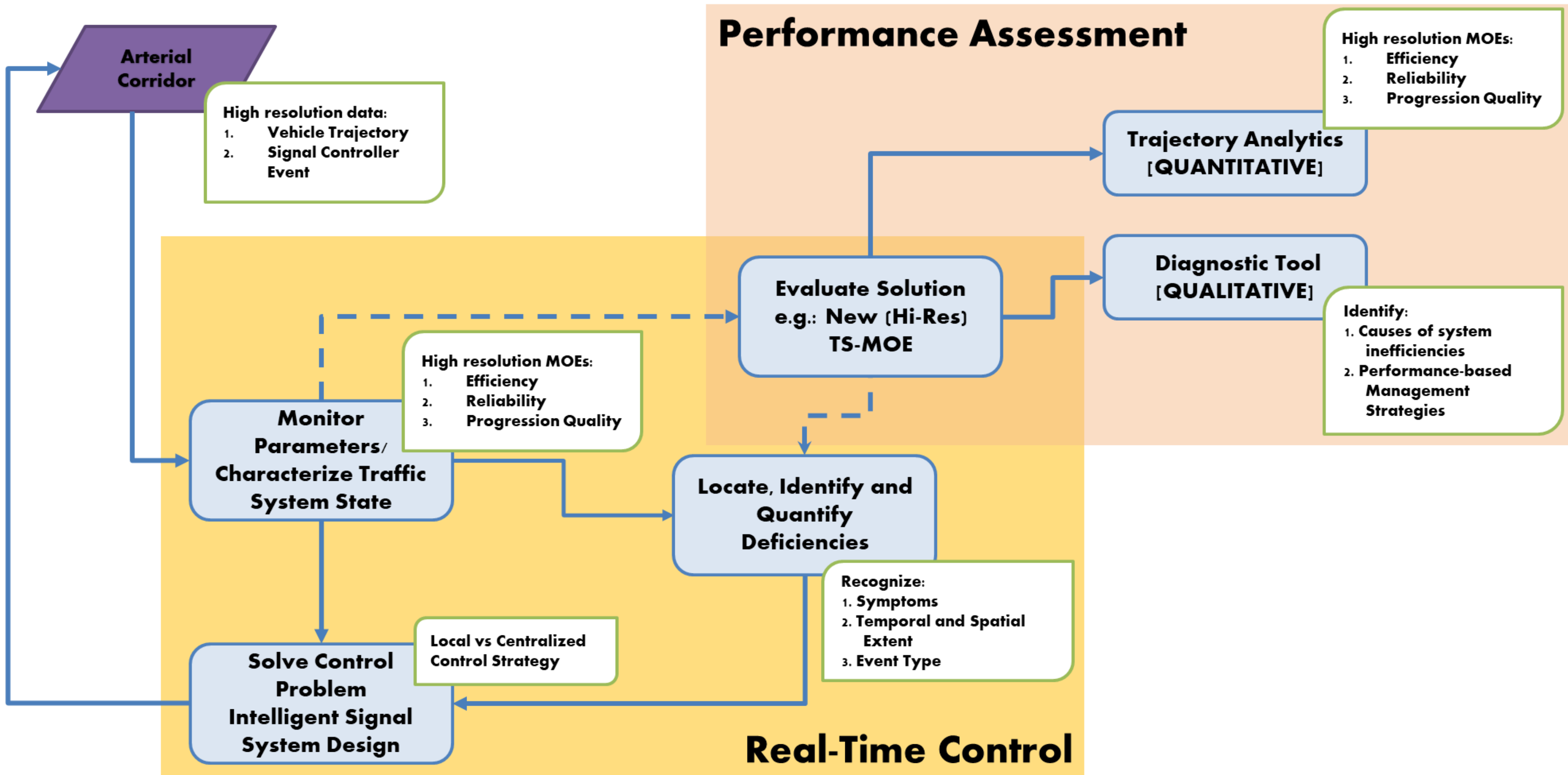


Figure 3-1. Conceptual Framework

3.1. Modeling Framework

The conceptual framework () has been developed to guide the study. This analytical framework allows identification of the main components, their relationships, and feedback mechanisms that affect the connected traffic-signal system management process. However, this study has a limited scope, as it is restricted to the research questions in **1.2**, and therefore focuses primarily on the relevant elements of the framework. Modeling framework **Figure 3-2** consists of three main parts, each of which operates multiple smaller modules: quantitative analysis, qualitative analysis, and real-time control.

Real-time control is centered around high temporal-resolution computations of operational parameters at the user-level. At the same time, user-level information is being stored for long-term operations evaluation, which consists of two parts: quantitative and qualitative.

It is performed by utilizing lower temporal-resolution data formats of signal group-based summary statistics and visualized performance measures. The study utilizes traffic system parameters which are vehicle and signal group-based and for this information to be meaningful and actionable in real-time a feedback loop continuously checks and evaluates system states, quantifies performance to optimize control system parameters. The overlap between the online and offline components occurs at the user level evaluation stage. This boundary represents their interdependency since neither component can operate without individual vehicle level information. This module is essential and feeds information back into both performance-based control settings optimization (via solution evaluation) and user-level computations of success indicators (quantitative evaluation) to support trajectory-based analytics.

As for the performance assessment layer of the full framework, the focus is on qualitatively and quantitatively describing the state of the system and pinpointing associated deficiencies concerning distinct aspects of signalized intersection analysis.

As common knowledge tells us both, demand and supply, settings affect the state of the system under consideration and may generate significant fluctuations in the quality of service offered.

Time of day, weekly or seasonal demand variability or pattern changes, whether a regular seasonal change or more complex interaction will need to be evaluated separately from the interaction with the control scheme, so that the impact of a control strategy - through particular intervention, can be separately identified. It is also important to characterize inherent systems variability to understand which traffic system state changes require or can be subjected to management.

Trajectory Analytics represents a comprehensive set of quantitative high-definition signalized approach performance measures defined as most representative of the traffic system state. It establishes efficiency, reliability, and progression quality indicators to be applied at various levels of analysis for different purposes, from individual vehicles, isolated intersections phases to arterials, and networks.

A complete picture of system state can only be observed if multiple indicators are cross-referenced and even then, in certain circumstances, causes of deteriorated performance can remain unknown.

So, the various indicators and aspects of the assessment address specific traffic event contexts, and the overall analysis attempts to tie these together focused on the type of issue and its extent.

Addressing diverse types of problems and accordingly, their scales inherently would require local vs global-scale mitigation strategies.

The qualitative component of the analytical framework defines a diagnostic tool, which through summary graphics and traffic state visual signatures, systematically locates and identifies the type of problem, while defining its spatial and temporal context.

The real-time component of the modeling framework assumes adaptive traffic controller logic. This work identifies a control algorithm that leverages synthesized information from two distinct data sources - ***CVG*** and signal controller event data - to manage connected and mixed traffic environments proactively and reactively.

The real-time control component of the proposed framework consists of three main modules and an evaluation module as external short-term information storage. Traffic state monitoring, as well as problem detection and analysis, integrate ***CVG*** information into the design of control logic. The intelligent traffic controller is able to receive and process the information ***CV***s are transmitting. This means that the controller is aware of the inbound traffic configuration at each updating interval - frequency of information update and is capable of computing traffic performance metrics.

By feeding vehicle-based computations as inputs to the control system, controller logic is designed to optimize phasing sequence and duration in an acyclic manner. This is necessary to quantify the quality of service, hence the severity of the problem, prompting reallocation of green time, or some more elaborate control strategy. Recognizing exhibited symptoms in an umbrella-type environment, by tracking specific criteria at adjacent intersections (pairs of intersections), controller logic is devised to distinguish whether a strategy needs to consider the interaction between adjacent signals. This means that for a defined set of parameters (criteria to check) at a local level, on a global level proposed heuristic recognizes the type of problem and its spatial and temporal extent.

Accordingly, by using inputs and measures on a corridor-wide level rather than on an isolated intersection level, a more efficient control strategy can be realized. Addressing these operational challenges can be prohibitive computationally for real-time applications, which is why the proposed method reduces the effort, by diagnosing the issue's causes and magnitude. Furthermore, when justified, arterial-level implicit coordination is considered between pairs of intersections and not as a universal solution.

The control problem is solved in real-time, generating traffic event-tailored strategies with local adjustments to be applied, if warranted. The proposed concept explicitly considers micro-level vehicle-following behavior and identifies discontinuities in traffic patterns, which differentiates between control strategies type and controller mode of operation.

The proposed method puts forward a control logic which proactively determines the next best phase to serve and continually adjusts its phase duration in real-time reacting to the prevailing demand pattern. The methodology proposed is conceived to enable data-driven verification of whether the implemented solution had worked.

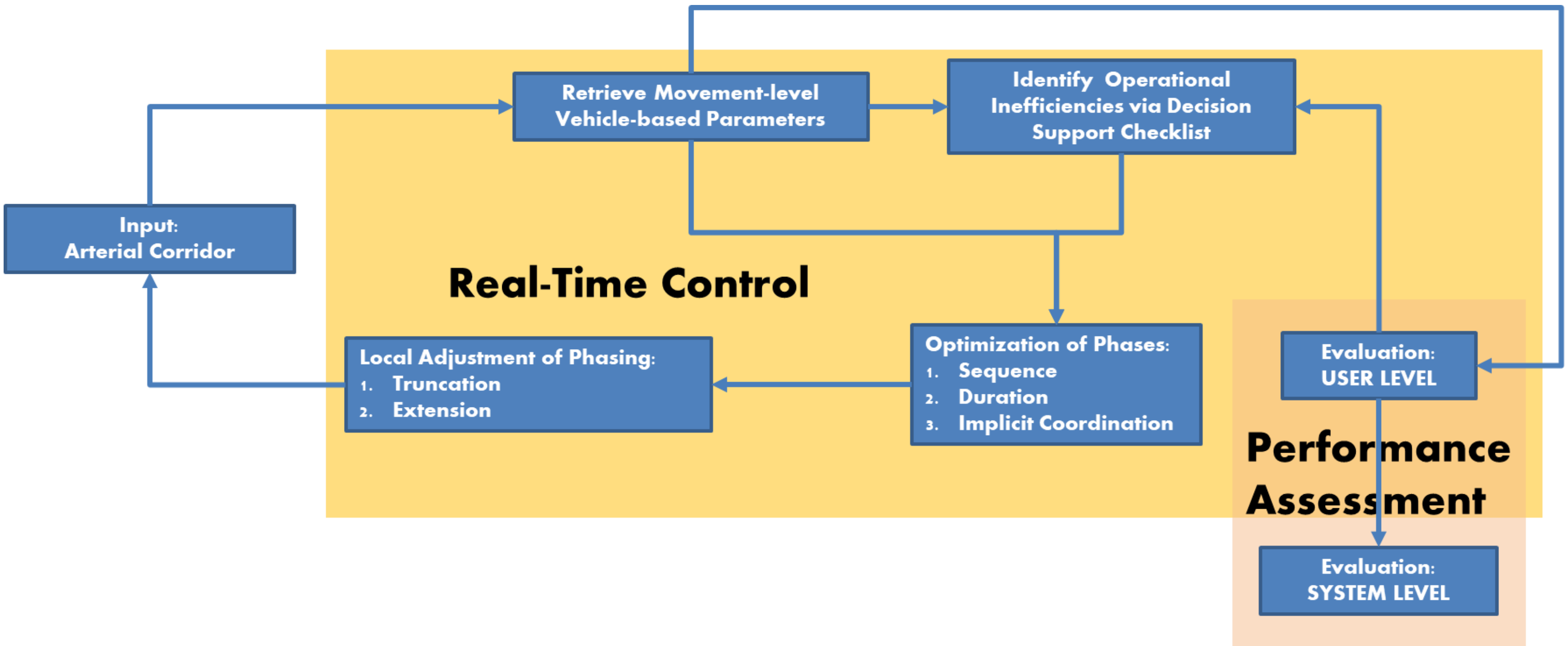


Figure 3-2. Modelling Framework

Chapter 4. QUALITATIVE PERFORMANCE ASSESSMENT

As any traffic management center is concerned whether their system is performing well and, if not, why not, it is critical to troubleshot operational problems quickly. Therefore, it is important to make sure a relevant set of success indicators reflects the actual condition of the transportation system.

Excessive demands and suboptimal traffic signal control timings are major reasons for traffic delays in urban traffic networks. Relevant research studies emphasize the importance of understanding and quantifying existing field traffic conditions in the design and fine-tuning of signals. Yet, reviewed studies do not give insight into how one would utilize these newly available systematic and robust data to evaluate signalized intersection's performance. Modern traffic signal systems require a set of performance indicators and visualization aids to characterize the state of the system, document traffic operations and assess signal timing effectiveness accurately and comprehensively. Diagnosing problems, determining their cause, and designing appropriate strategies cannot occur without storing and processing relevant data.

Vehicle trajectories do not suffer from typical sensor-based limitations. Besides, approach-based traditional performance indicators may not be transferable to all the states of a system, viz. undersaturated, saturated, and oversaturated. With traditional measures, it can be evident that phase failure had occurred but why and how severely it cannot be inferred. Through visualizing and processing of vehicle trajectories, associated with each green phase, the number of consecutive phases that had shown "failed" performance levels and causes thereof can be studied closely.

While the delay is the single most important MOE used to date, labeling an intersection approach with LOS C doesn't distinguish whether vehicles were waiting to get served at the stop bar or were queued as soon as they entered an approach far upstream. While the former is often expected, the latter could be the consequence of something more critical – insufficient roadway capacity, incident, etc. The visualization method presented in this section allows us to visualize and quantify both states.

The two components of the proposed framework: Trajectory Analytics along with (respective) TSS signatures introduce a decision support tool which, by diagnosing the issues and roots thereof, enables proactive management of signalized corridors.

4.1. Concurrent and Nonconcurrent Phasing

Conventional traffic signal control for 4-leg intersections uses the standard National Electrical Manufacturers Association – NEMA (*14*) signal phases, as shown in **Figure 4-1** below. For each leg of the intersection, there are three movements: a left-turn movement, a through movement, and a right-turn movement. Typically, the right-turn movement for a given intersection leg is permitted to be concurrent with the intersection leg's through movement. Therefore, there are a total of 8 signalized phases at a conventional 4-leg intersection. The 8 phases are divided into the main street and side street phases, as indicated in **Figure 4-1**. The phases are further divided into 2 rings. Both rings, {1, 2, 3, 4}, and {5, 6, 7, 8}, consist of self-conflicting phases. Two phases are non-conflicting if they are on the same side of the barrier and in different rings. For example, phase 1 may be active with either phase 5 or phase 6. Each column shown in the phase table on the right-side portion of Figure 1 represents a dual-ring signal phase. A typical cycle consists of serving the 8 individual phases with 4 dual-ring phases. The main street movements are usually served before the side street movements and are also given a larger “split” of the total cycle length time than the side street movements. The left-turn movements on each side of the barrier usually precede the through and right-turn movements.

Adopting a standard NEMA (*14*) ring barrier controller (RBC) dual-ring eight-phase structure (**Figure 4-1**), non-concurrent phasing refers to a phasing configuration where **NO** other non-conflicting movement is allowed the right of way at the same time as the protected or permissive (left) phase.

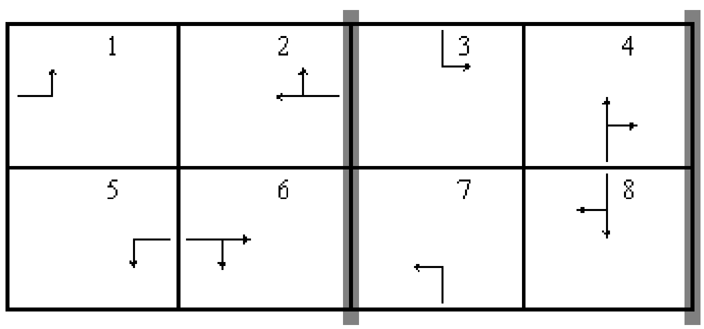


Figure 4-1. Standard NEMA dual ring barrier controller (RBC)

For non-concurrent phasing, per phase numbering in **Figure 4-1**, following are the turn types and associated movements:

- Protected Left
    - 1, 3, 5, and 7
- Protected + Permissive
    - 1&6, 3&8, 5&2, 7&4

- Permissive Left
    - 2, 4, 6, 8

For non-concurrent phasing, opposing directions' TSS diagrams are not required. Whereas, in the case of concurrent phasing, another non-conflicting movement is allowed the right of way at the same time as protected or permissive left. Accordingly, for concurrent phasing, the following are the turn types and associated movements:

- Protected Left
    - 1&3, 5&7
- Permissive Left
    - 2&6, 4&8

4.2. Visualization of phase performance

Visualization is the zeroth step in the overall Trajectory Analytics framework. This study proposes a ***visualization technique*** of the high-resolution data within a color-coded time-space diagram by superimposing individual signal phase duration and indication over individual vehicle trajectories. This enables visualization of the amount of "cycle" time vehicles spent moving vs stopped while considering the speed of progression.

It uses an effective idea of illustrating and capturing how much time vehicles spent, given pre-determined signal settings, moving, or queued, either due to signal indication being red or because of oversaturation. This allows one to understand not only where and when but ***HOW*** the vehicle behaved along its route and respective of external factors.

This framework fundamentally tries to capture signal performance under oversaturated conditions of traffic flow. It intends to enable a straightforward and comprehensive representation of signal (phase's) green time utilization when serving known demand levels by addressing the gap in the literature and/or methods available.

Several visualization tools have been used in signalized approach analysis each of which quantifying some aspect of the experience of a driver traversing a signalized intersection. The two most relevant in the context of this research are briefly described below.

4.2.1. Purdue Coordination Diagram

Purdue Coordination Diagram (*11*), using advanced detection, plots arrivals of vehicles relative to the green/red indication encountered, upon entering the vehicle detection zone. The time of arrival of each vehicle, corresponding to the time within the cycle is adjusted by the amount of time it would take to travel to the stop bar. PCD provides a graphical method to illustrate the stage of a cycle at which vehicles arrive at an intersection. For a specific approach of an intersection, the arrivals can be plotted on a time scale, where each dot represents an individual vehicle arrival.

By calculating statistics such as Percent Arrivals on Green or commonly referred to as Arrivals on Green (AOG), a quantitative measure of the quality of progression, was also associated with the diagram. A metric that infers a vehicle's progression quality with reference to its time of arrival or at a corridor level the quality of coordination, based on the objective of providing smooth flow along a corridor.

One limitation is, due to the inherent nature of the state of the practice data, sensing infrastructure and traditional MOEs, that once the queue forms, at the stop bar or beyond the advanced detection zone, the estimates would be erroneous/misleading as to what is occurring with the inbound demand and, consequently, signal timing.

If one is to apply the concept presented above on the Hi-Res trajectory data, the outcome would look like the one presented in the graph in **Figure 4-2**. Advance detection naturally would not exist as such since vehicle position information is obtainable at each updating interval. For this illustration updating interval was 0.2 seconds (as it can be higher too).

Focusing on **Figure 4-2** it is evident that vehicle arrivals are random, but also that their respective timestamps relative to the green indication encountered fall below the green line. This assumes an extremely high AOG value.

However, looking at **Figure 4-3** which essentially plots the same data but filtered by vehicle clearing time, one notices some vehicles still at the stop bar between ~1400 and ~1800 seconds. Some percentage of AOG effectively showed as served was not, and we can only be aware of such occurrences if we have access to trajectory data. Since the timestamp reference and accordingly distance to stop bar adjustment do not correctly capture what had occurred respectively to green time utilization.

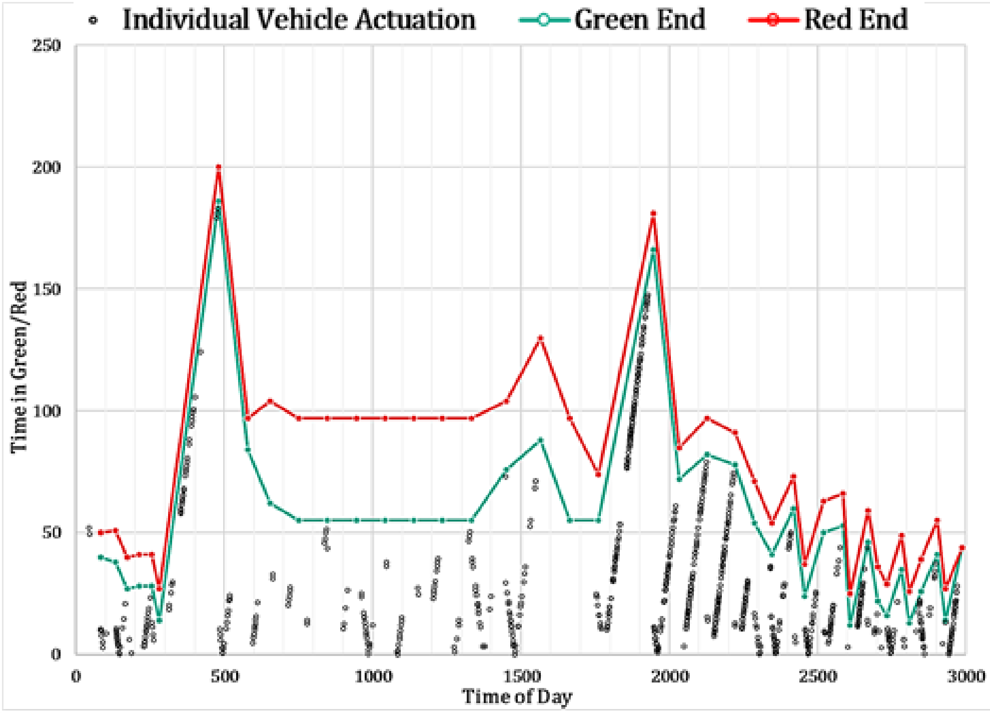


Figure 4-2. Hi-Res Purdue Coordination Diagram (phase 2 arrivals)

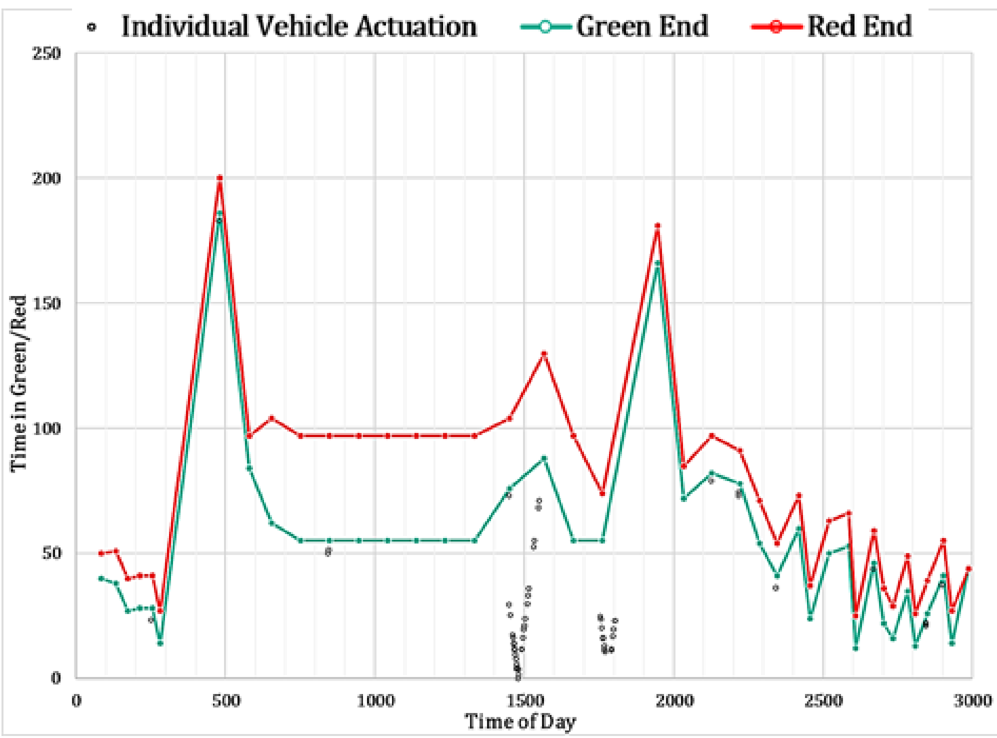


Figure 4-3. Hi-Res Purdue Coordination Diagram (phase 2 unserved)

In circumstances when oversaturation or atypical behavior occurs, this representation while considered a benchmark in signalized approach analysis today, cannot offer much actionable information nor insight into operations. Yet with traditional infrastructure-based detection data formats, these techniques developed into the application of overlay plots and distribution analysis to assess accuracy based on repeatable traffic patterns and motivated this research.

4.2.2. Cumulative Number of Vehicles Arriving and Departing vs Time

There is another graph that allows one to glean even more information regarding traffic operations. **Figure 4-4** shows a plot of the total number of vehicles vs time. In each chart (a and b) two curves are shown: a plot of arriving vehicles and a plot of departing vehicles. The x-axis is time, and the y-axis contains the vehicle numbers according to the order of their arrival. The time axis is divided into periods of effective green and effective red. Vehicles are assumed to arrive at a uniform rate of flow, hence the constant slope of the curve. Assuming no preexisting queue, arriving vehicles depart instantaneously when the signal is green - the departure curve is the same as the arrival curve.

When the red indication begins, vehicles begin to queue as none are being discharged. Thus, the departure curve is parallel to the x-axis during the red interval. When the next effective green begins, vehicles queued during red depart from the intersection at a saturation flow rate. For stable conditions i.e. traditionally undersaturated operations, the departure curve catches up with the arrival curve before the next red interval begins. This means no residual queue is left at the end of the effective green. The model explained is based on the assumptions of stable flow and the arrival function that is uniform.

Please refer to the bottom chart in **Figure 4-4**, the plot depicts a control strategy that stabilizes flow conditions, unlike the one presented in **Figure 4-4** – top chart.

Overflow queue/delay occurs when the capacity of an individual phase or series of phases is lesser than the demand or arrival flow rate, as in the previously mentioned example. The top plot shows that consecutive green intervals fail to serve the demand, and the residual, or unserved, the queue of vehicles continues to grow throughout the analysis period (time interval between 3800-4500 seconds).

The most significant reference of queueing theory application to signalized intersections behavior and it was introduced to transportation by Moskowitz (*94*) and Gazis and Potts (*95*); Gordon Newell (*96*) demonstrated its full potential.

Queueing theory is the theory of congested systems and provides a foundation for the optimization of signal timing. Usually, it only handles steady-state stochastic problems. In the case of signalized intersection approaches however, we will look at dynamic systems.

Graph of cumulative vehicles versus time is considered pivotal, with many researchers using it as the basis of their distributed, non-cyclic, or adaptive traffic control strategies.

While this graph may not seem informative at first, a second look reveals its insights. For a given time, the difference between the arrival pattern and the service pattern is the queue length. For a given vehicle, the difference between the service pattern and the arrival pattern is the vehicle delay. The area of the triangle is equivalent to the total delay for all the vehicles.

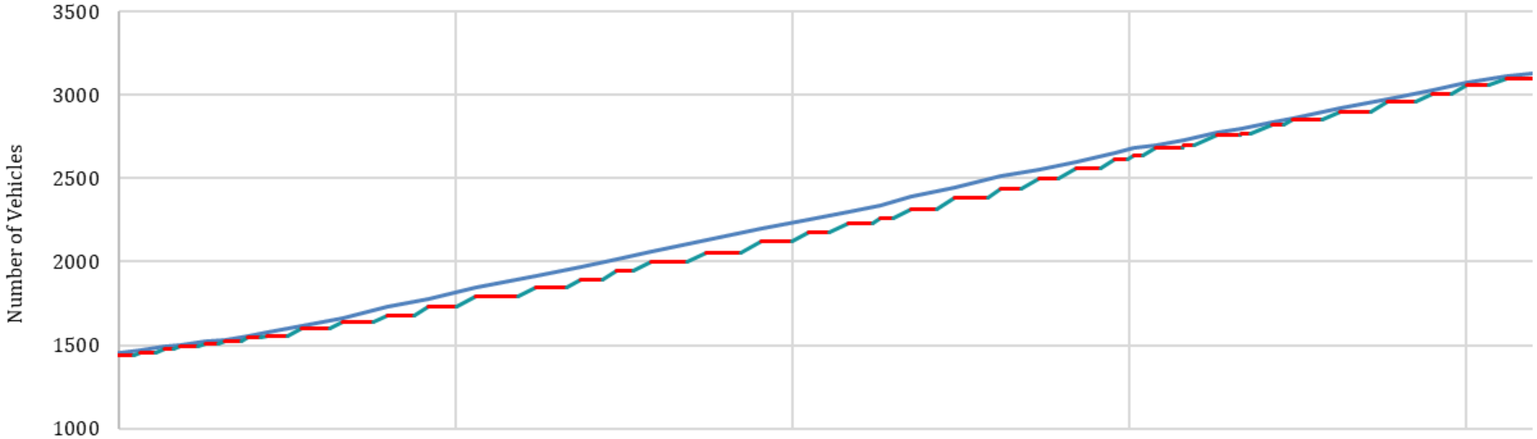
The example in **Figure 4-4** represents two control strategies that demonstrate differences in control parameters and setup robustness to serve the prevailing demand. The graph on the top as it is evident represents a case where the queue is not being discharged adequately.

Performance evaluation at a signalized approach typically is explained in terms of delay as it is directly perceived by the user, by applying the queueing theory. Inconsistency between these models and what is occurring at the intersection approach when demand exceeds capacity (at v/c>=1.0) leads to delay and other MOEs calculations using such models to not be accurate as the models are explained on the theoretical basis only.

Plotting cumulative vehicle arrivals/ departures vs time reveals relationships between users' behavior aggregate properties and control systems parameters. However, it neglects the in-depth information about the driver experience traversing a signalized intersection.

If one is to investigate how the driver experiences the system, disaggregated information is required. Rather than to validate whether the assumptions made at an aggregate level hold, analysis of such information would enable system-level performance evaluation but from the system's user perspective.

With ***CV*** trajectory information the actual path of the vehicle is known and recognizably includes a stop at a red signal, accounting for decreased speed, stops and acceleration, and deceleration.



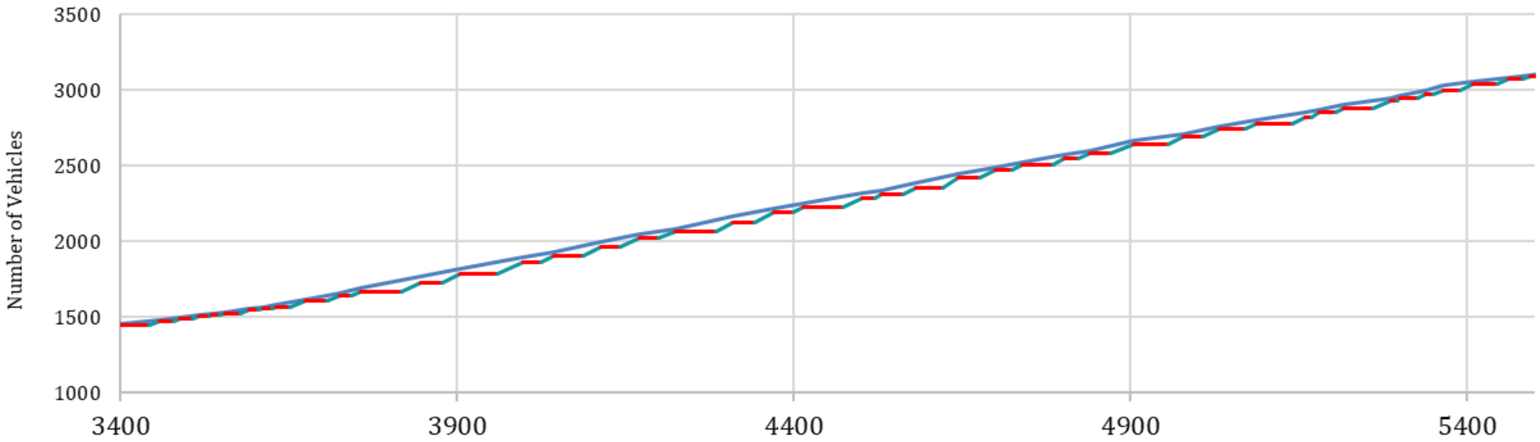


Figure 4-4. Hi-Res Cumulative Arrival/Departure Curve vs Time - Control Strategy 1 (top) and 2 (bottom)

4.2.3. Time-Space Signal Representation

Visualizing relevant signal performance data in an easy-to-understand format is critical when identifying problem areas and causes of problems. The zeroth step of the proposed method entails visualizing individual trajectories as they progress through a signalized approach and along a corridor, on a detailed, disaggregate level.

The proposed visualization technique introduces a concept of a time-space-signal (TSS) signature to visualize, large, multidimensional, data sets in an easy-to-understand manner. Finding a balance between the level of detail and the conciseness in traffic/signal state-representativeness was a major challenge throughout this research effort. State-representative graphical aids offer insight into various aspects of the signal system's operations and assist in identifying underlying causes of any detected disruptions or inferior performance levels.

To generate a time-space-signal (TSS) diagram of a vehicle - first, the vehicle's trajectory is plotted on standard time and space diagram. Next, signal status is superimposed by color-coding trajectory segments with the signal indication. The process is repeated for all vehicles on the approach. Signal indications correspond to the desired movement that the vehicle encounters at the immediate downstream signal. This allows for approach phasing settings to account for the aforementioned categories, queueing, and delay of vehicles and their propagation.

Each portion of the vehicle's trajectory is color-coded with the associated phase's indication at each time step at each green/red interval. The same approach can be taken at each intersection approach along the route that a vehicle may have taken. The method thus enables visualization of the amount of green and red time vehicles spent moving vs being stopped while considering the speed of progression. At this point, it is easy to recognize major/minor approach progression or lack thereof, along a corridor.

The time-space diagram is a graph that describes the relationship between the location of vehicles in a traffic stream and the time as the vehicles progress along the corridor. The diagram in **Figure 4-5 a)** is an example of a time-space diagram.

Typically, time is drawn on the horizontal axis and distance from a reference point on the vertical axis. The trajectories of individual vehicles in motion are portrayed in this diagram by sloping lines, and stationary vehicles are represented by horizontal lines. The slope of the line represents the speed of the vehicle. Reductions in speed cause the slopes of the lines to flatten, while increases in speed cause the slopes to become greater. Acceleration causes the time-space curve for the accelerating vehicle to bend until the new speed is attained. Curves that cross indicate that the vehicles both shared the same position at the same time. Unless passing is permitted, crossed curves indicate collisions.

Aside from location in space and time, signal display changes as individual vehicles perceived them are shown in the graph in **Figure 4-5 b)**, as vehicles traverse the corridor. The illustration on the left-hand side shows a conventional time-space diagram that cannot account for the contribution of the turning vehicles to progression and does not capture the reaction of vehicles to the controller indication on an individual level. On an approach level, control settings are accounted for at an individual vehicle-level – the type of left phasing protected vs permissive, lead vs lagging left, actual (perceived) green, and red time duration.

Since phasing and durations are known, identifying the reasons for poor progression is straightforward and explicable. It is easy to observe and comprehend when traffic is blocked by the through traffic or approach spillback, granted other intersection approaches are accounted for.

Vehicle stopped time counts towards progression inefficiency, regardless of signal indication. The worst case, naturally, is experienced during oversaturation or similar conditions, when even with green indication, the vehicle is not moving.

Important to note is that available green time (unlike with conventional time-space diagram) does not refer to the actual (effective) green duration, which is the same for all vehicles, but to the green-colored portion of trajectory, which is unique for each vehicle.

This visualization can be applied at an individual vehicle level, measuring how well the vehicle utilized the available green time and space under specific signal control and operational conditions, or any other more aggregate spatial and/or temporal level.

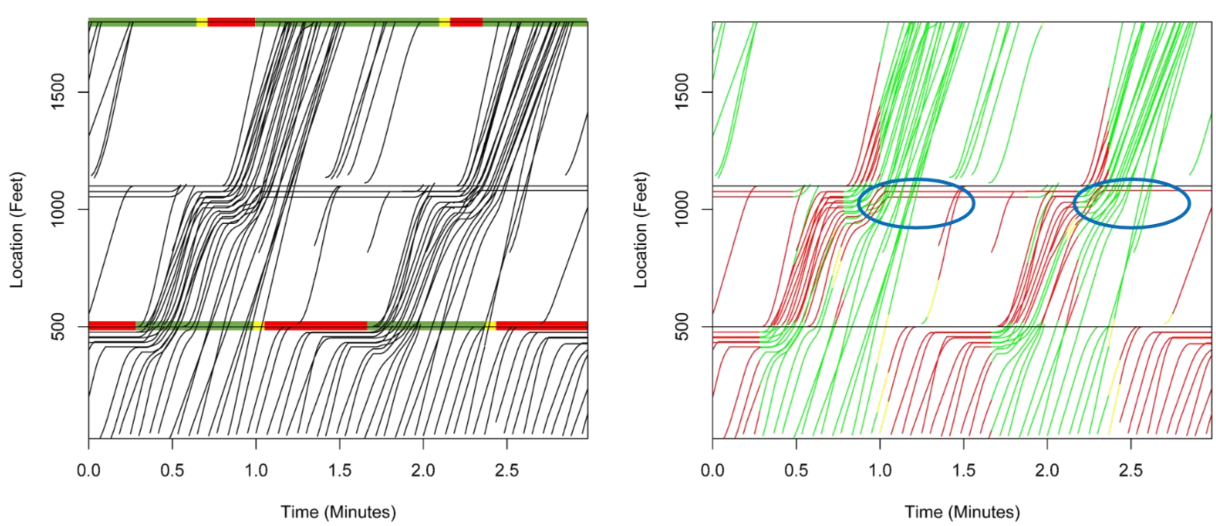


Figure 4-5. Conventional Time-Space Diagram a) vs. Signal Indication-coded Vehicle Trajectories b)

The technique can be used to gain insight into operations at two levels: (1) individual intersection or (2) route level. As the analysis is vehicle-based it is pertinent to the evaluation of individual phases performance as well as the corridor-level quality of progression assessment.

This study proposes to quantify the quality of service of a signal (phase), i.e. progression along a corridor or ***any pre-defined path***, by identifying a measure of utilization of green time and space, which would capture and describe the state of signal performance reliably and comprehensively and be applicable in a variety of traffic conditions.

4.3. Defining A Time-Space-Signal (TSS) Signature

Time-space-signal (TSS) signatures represent graphical summaries of large, multidimensional, data sets that offer diagnostic capabilities in uncovering possible reasons for traffic signal systems inferior performance or detected disruptions.

TSS diagrams recognize distinctive trajectory-signal signatures that characterize specific system states with respect to demand and type of control and operational conditions. Observing trajectories in response to signal indication enables one to identify signal system's deficiencies related to phasing and split duration, spillback, overflow queuing, intersection blocking, etc. (**Table 4-1**) and permits for specific state-representative success indicators interrelationships to be analyzed and understood. **Table 4-1** describes typical oversaturation types of traffic events on signalized corridors.

When suspecting a problem at a subject intersection, the following information should be considered and processed to identify the problem and respective source. Depending on the traffic event type (**Table 4-1)**, the analysis may require information related to intersections upstream and downstream of the subject intersection.

Identifying the type of problem is critical, especially when formulating mitigation strategies. The problem might be rooted at a location far upstream/downstream of the target intersection and its impact may extend spatially and temporally over several adjacent ones. For this reason, additional approaches may need to be considered depending on the phasing setup and event type.

Table 4-1. Signalized approach typical traffic events

Oversaturation Symptom		***Description***
Overflow Queue	:	Part of the queue not served during a single cycle
Approach Spillback (de facto red)	:	Upstream queue physically blocks downstream vehicles
Storage Bay Spillback	:	Turning queue fills storage bay and physically blocks
Storage Bay Blocking	:	Through queue physically block turning movement from the storage bay
Starvation	:	Traffic demand is restricted from using full downstream roadway capacity
Cross Intersection Blocking	:	Queue extends into an intersection and blocks progression of crossing vehicles

Trajectory-based signalized approach analysis illustrated in **Figure 4-5** requires the following information:

- ***Controller Data***:
    - Signal phasing
    - Type of left turn
        - Permitted
        - Protected (and Permitted)
    - Signal indication duration
- ***Vehicle Trajectory Data***:
    - Demand (presence of vehicles on approach)
    - Movement of vehicles:
        - Left
        - Through
        - Right
    - Speed
    - Position to identify if the lane is blocked
    - Upstream approach demand to identify approach spillback or eliminate it as cause

- ***<u>TSS of concurrent (left) phase (if applicable)</u>***:
    - If a phase is concurrent with another – the concurrent phase's TSS diagram might be required to distinguish whether the intersection is blocked or not when both (through/left) approaches' lights display green, but vehicle speeds are close to 0.

A practical and straightforward approach was designed to visualize and analyze individual phases' green time utilization in a considerable number of operational scenarios. And while TSS plots provide a good visual insight into operations, as such they do not support quantitative assessments. To develop performance measures from vehicle trajectories, the trajectories must be represented mathematically and not just visually. Numerical and robust performance metrics supplementing the graphical system state summary can include phase failures (lost green time), the number of arrived, served, queued or unserved vehicles, the proportion of vehicles arriving on green as well as the proportion of vehicles to stop per SG duration.

The examples in **Figure 4-6** and **Figure 4-14** only serve to demonstrate that computing and interpreting, even the most comprehensive set of Hi-Res performance measurements do not help distinguish whether insufficient green time was the cause of failed performance or left-turning traffic was blocking the through movement's progression.

The underlying causes of signal system's inferior performance levels can only be identified by associating a distinct TSS signature which visualizes traffic conditions as materialized i.e. experienced by the users of the system.

The TSS signatures in **Figure 4-14** corresponds to the representation in **Figure 4-6**. As shown in this example, assessing operational success is straightforward in undersaturated conditions.

Referring to the TSS graph on the right (in **Figure 4-14**) - even though green durations seem sufficient, the number of unserved vehicles and in turn number of phase failures is increasing while the number of served vehicles is decreasing,

The TSS diagram, even with no quantifiable measure associated indicates inbound demand levels as high, queue length as increasing with every green and no significant variation in green durations. Moreover, the diagram also reveals that left turns are protected, that the controller is operating in some pre-timed manner, but also those left-turning vehicles are blocked by many through moving vehicles.

However, one should be cautious in such circumstances as well, since available green times and arriving demand (relying on measured values alone) might not reveal that the approach link is severely oversaturated, and vehicles are unable to enter the approach link.

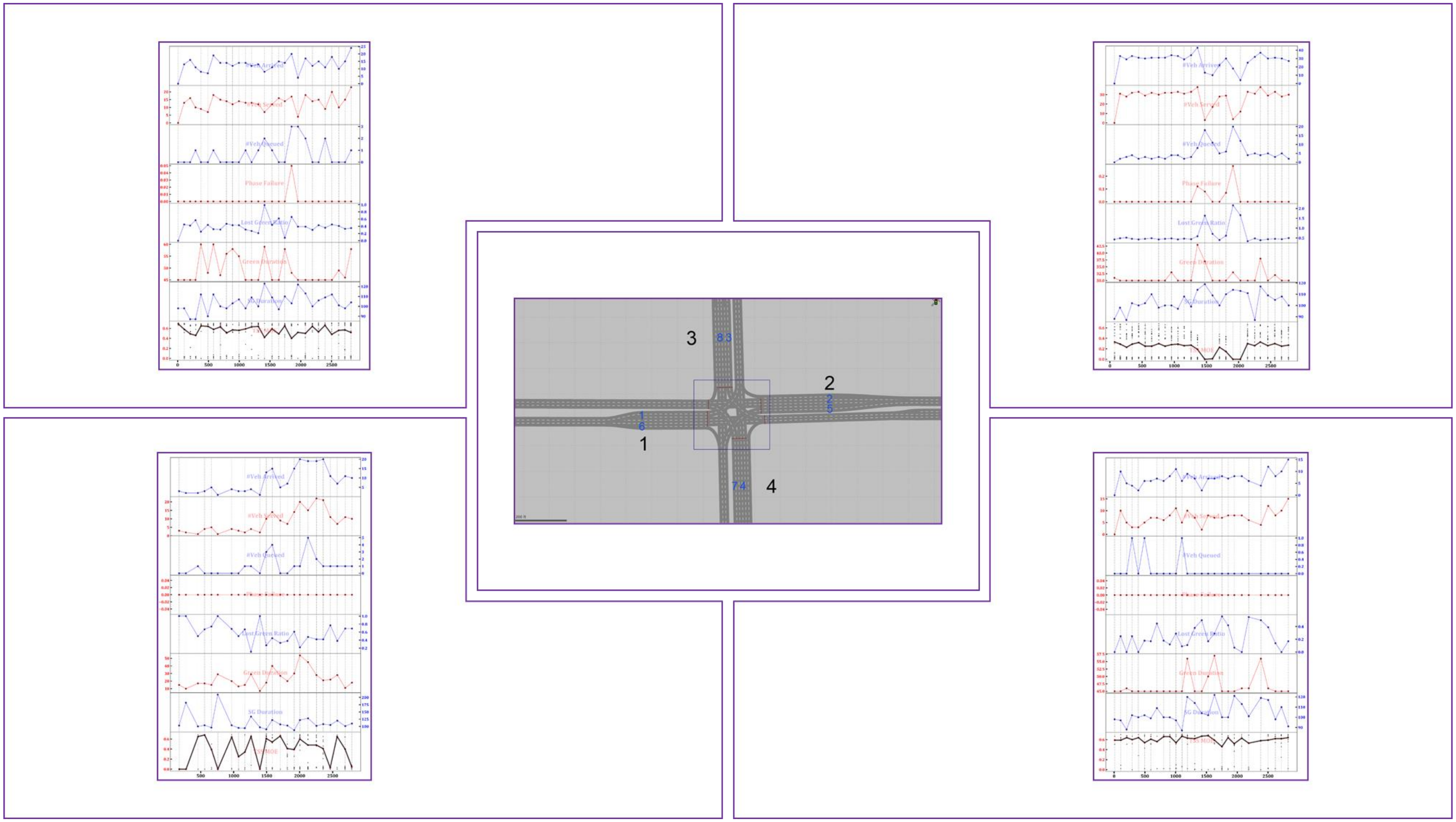


Figure 4-6. Quantifiable Measures without Associated TSS Signature

4.4. Identification of Problem Areas and Associated Causes

Tools and measures found in literature and the current state of the practice deal with assessing the signalized approach's condition, without discovering the issues and their causes. TSS signatures along with Event Characterization Stepwise Procedure (**Figure 4-7**) establish cause and effect relationships between performance indicators and traffic system attributes. If green time is being under or overutilized, the visualization tool is expected to help uncover the cause. Visually distinctive TSS diagrams emerge as signatures of each of the cases investigated. Different cases in this context represent different traffic events defined by controller phasing and timing, demand, and intersection configuration settings.

TSS diagrams provide comprehensive summary graphics related to individual phase performance and help identify signal system deficiencies, such as inadequate split allocation, phase failures, signal or intersection phasing configuration, excessive demand, presence of non-recurrent events, etc.

As with any other cause-effect relationship, the first step in establishing causality is demonstrating association; between the independent variable or the type of event type and the dependent variable(s) or the exhibited symptoms. The second assumes temporal precedence – the cause occurring before the effect while the third validates that whenever the cause occurs, the effect must also occur. The third criterion or non-spuriousness is the most challenging to validate for implementation in real-world conditions.

Specific scenarios, corresponding to the cases presented in the following section, demonstrate that TSS diagrams offer valuable insight into traffic operations, establishing the cause and effect relationships between operational conditions representative parameters and corresponding event types.

Causality in the context of qualitative analysis in this section is considered in a slightly broader context. It is not that different event types associate a distinct set of defined parameters to relate system behavior, but that symptoms corresponding to a specific event type may partially or completely overlap with other event types. However, operational conditions parameters describe the outcome of a specific type of traffic event unambiguously, meaning no to sets of criteria to check are identical.

As a result, a customized control strategy can be identified and implemented to alleviate performance degradation, both spatially and temporally. Since different traffic events exhibit different symptoms, by defining a set of parameters to check within a systematic stepwise procedure and more importantly their associated visual TSS signatures, their temporal and spatial extent can be determined.

Since phasing and corresponding durations are known, along with vehicle location, status, and speed, determining why left-turning traffic underperformed is straightforward and explicable. It is easy to observe and comprehend when and why traffic is blocked by the through traffic or prevented from progressing due to approach spillback.

Please note that other intersection approaches need to be accounted for depending on the phasing structure and/or event type.

A conditional flowchart in **Figure 4-7** establishes a decision support checklist which enables identifying causes of poor progression based on exhibited (associated) symptoms. Parameters representing the causational flowchart criteria are derived based on TSS data only. No other information was used. It should be noted that additional, event type representative TSS signatures can be identified and that the list of cases explained below is not exhaustive. **Figure 4-7** exemplifies the most characteristic and most frequently occurring ones.

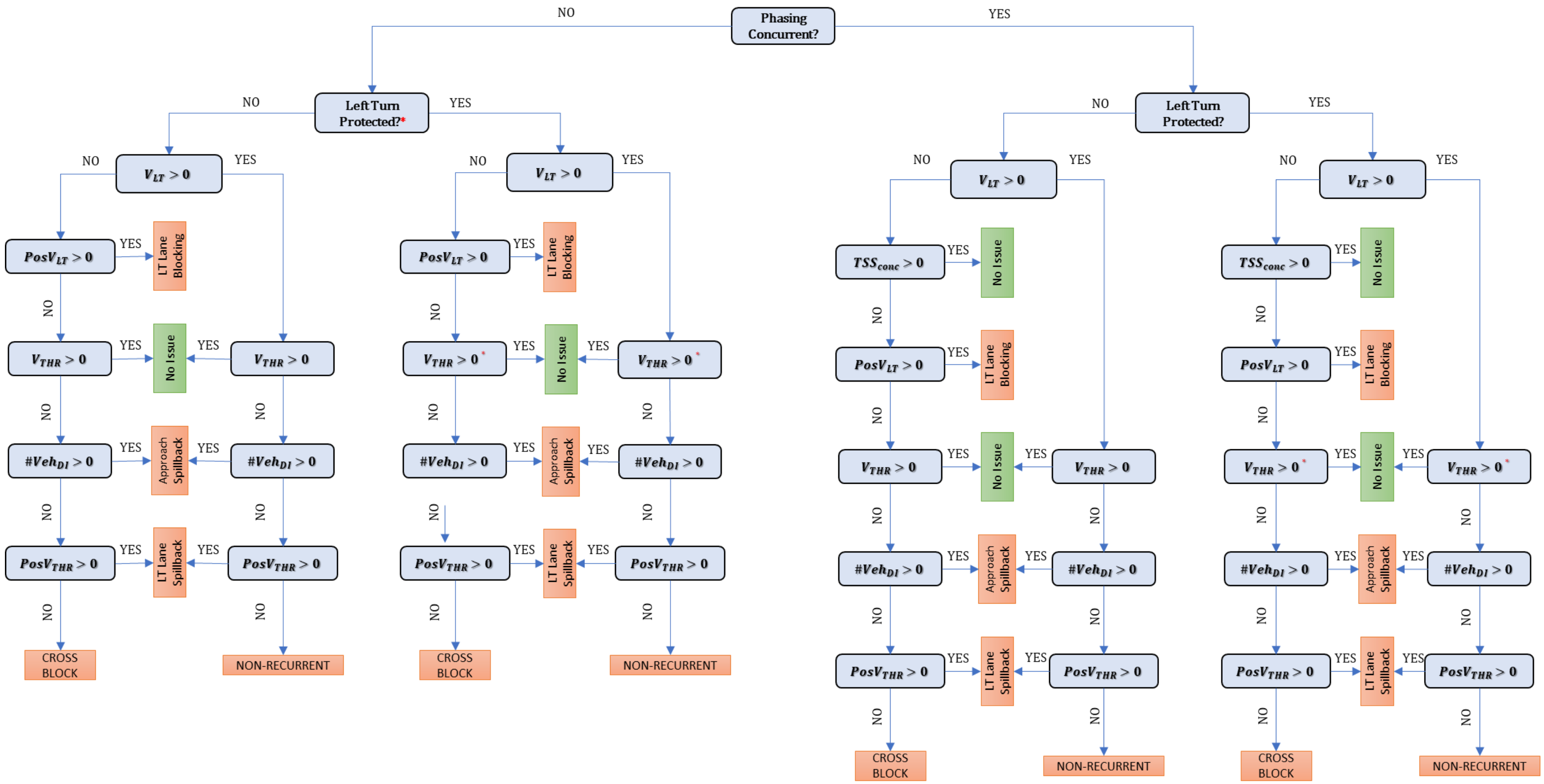


Figure 4-7. Event Characterization Stepwise Procedure

Referring to the flowchart in **Figure 4-7**, conditioned upon the following sets of checks, the state of a system, for non-concurrent phasing, can be categorized as follows:

Check 1. Indication is green

Check 2. Position of left and through/right-turning vehicles is (near) stop bar

Check 3. Speed of through traffic is zero, but not the speed of left-turning vehicles

If checks 1-3 hold *then proceed to identify the cause of flow disruption as follows:*

Check 4. Vehicles are present on an outbound link

→ *Case 1: Approach Spillback (**Figure 4-9**)*

Check 5. Speeds are practically zero, at opposing approaches

→ *Case 2:* Cross-*blocking (**Figure 4-10**)*

Check 6. No demand on outbound link whereas vehicle position not at the stop bar

Check 7. Left turning vehicle's position beyond the length of the turning bay

→ Case *3: Bay (Lane) Blocking (**Figure 4-11**)*

Check 8. If through vehicle's position extends beyond the length of the turning bay

→ *Case 4:* Bay *(Lane) Spillback **(Figure 4-12**)*

In case left-turn phasing (movement) is concurrent with another: aforementioned checks apply in addition to concurrent phase's TSS diagram: Concurrent phases $\boldsymbol{TSS_{conc}}$ diagram confirms the presence and/or progression of vehicles in the opposite direction (of concurrent phase).

Check 9. Vehicles observed on phase 2 (e.g. concurrent phases 2&6/4&8 with permissive lefts)

→ *Case 5: NO issue*

This case represents traffic conditions where the speed of left-turning vehicles on phase 6 (e.g. permissive left turns for phases 2&6) is effectively zero while through vehicles are progressing unimpededly. Effectively progression of left-turning vehicles is restricted due to moving vehicles' presence in the opposing direction.

Check 10. For phases 1&5 or 3&7, (concurrent protected lefts), the shape of the $\boldsymbol{TSS_{conc}}$ diagram will distinguish whether intersection blocking or opposing direction spillback is the reason for either approach not clearing.

→ *Case 6: Opposing Direction Spillback (**Figure 4-13**)*

When referencing a specific traffic event, one should note that its extent will vary, in time and space, depending on the actual problem encountered. The localized effect can be observed if insufficient green is allocated to a movement and correspondingly solution may be a local adjustment of signal timing/phasing. Conversely, if demand levels are high and green time inadequate, the outbound link of a downstream approach could be saturated, preventing vehicles to clear the target approach, even with more than an adequate amount of green time awarded.

Assessing the cause and impact of oversaturation, both spatially and temporally, with traditional measurement formats and indicators is challenging and unreliable, and in case of severe oversaturation – unfeasible. The method presented is intended to enable an in-depth analysis of oversaturated traffic conditions.

Furthermore, the severity of phase performance degradation is captured through various indicators' variation in the range of values, whereas the bottleneck location, type of problem as well as its physical extent can only be done via a graphical summary of traffic system's state **Figure 4-14**. A set of associated time-dependent trajectory-based MOEs is recorded to accompany the qualitative state summary and potentially establish trends between multiple MOEs and TSS representations.

4.5. Numerical Experiments Results

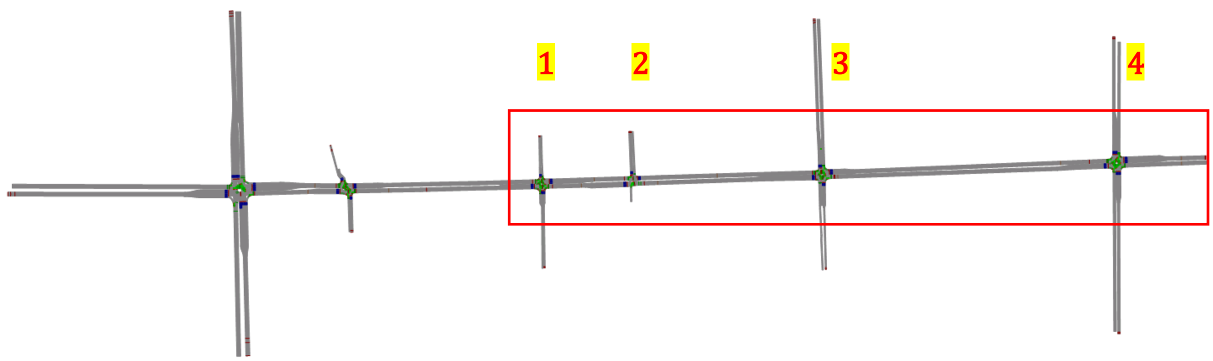


Figure 4-8. Microsimulation Testbed Setup – numbering refers to specific scenarios

A testbed setup was done in a microscopic simulation setting. Broward Boulevard, located in Fort Lauderdale, Florida, corridor segment consisting of 4 signalized intersections was modeled and calibrated in VISSIM (*97*) to represent field conditions as realistically as possible.

The testbed was running SYNCHRO (*98*) optimized TOD signal timing plans for peak periods and regular vehicle actuated (free-running) during off-peak periods. The robustness and effectiveness of the proposed method were examined under different demand levels and operational scenarios.

It should be noted that controlled experiments were conducted to investigate the feasibility and applicability of the proposed approach. Controlled experiments involving high-resolution vehicular information were designed to correspond to the most frequently encountered traffic event types with a focus on oversaturation and how the system state changes in such circumstances.

Demand levels were divided into three categories: low, medium, and high, each being 30 minutes long. A 2-hour long simulation horizon was designed to represent the demand build-up from low (off-peak conditions), then medium to oversaturated (AM or PM peak) and then reverting to medium, to represent recovery after oversaturation dissipates. Major approaches are East and West (Broward Blvd.).

Hi-Res trajectory information visualization algorithm generates time-space signal graphical summaries over consecutive demand periods referencing actual intersection approaches performance. It associates a label corresponding to one of the cases presented in the examples below.

Trajectory-based analytics performed on the same data finalizes the analysis of a signalized approach by looking into various aspects of signal system operations via graphical representation and associated measures of effectiveness.

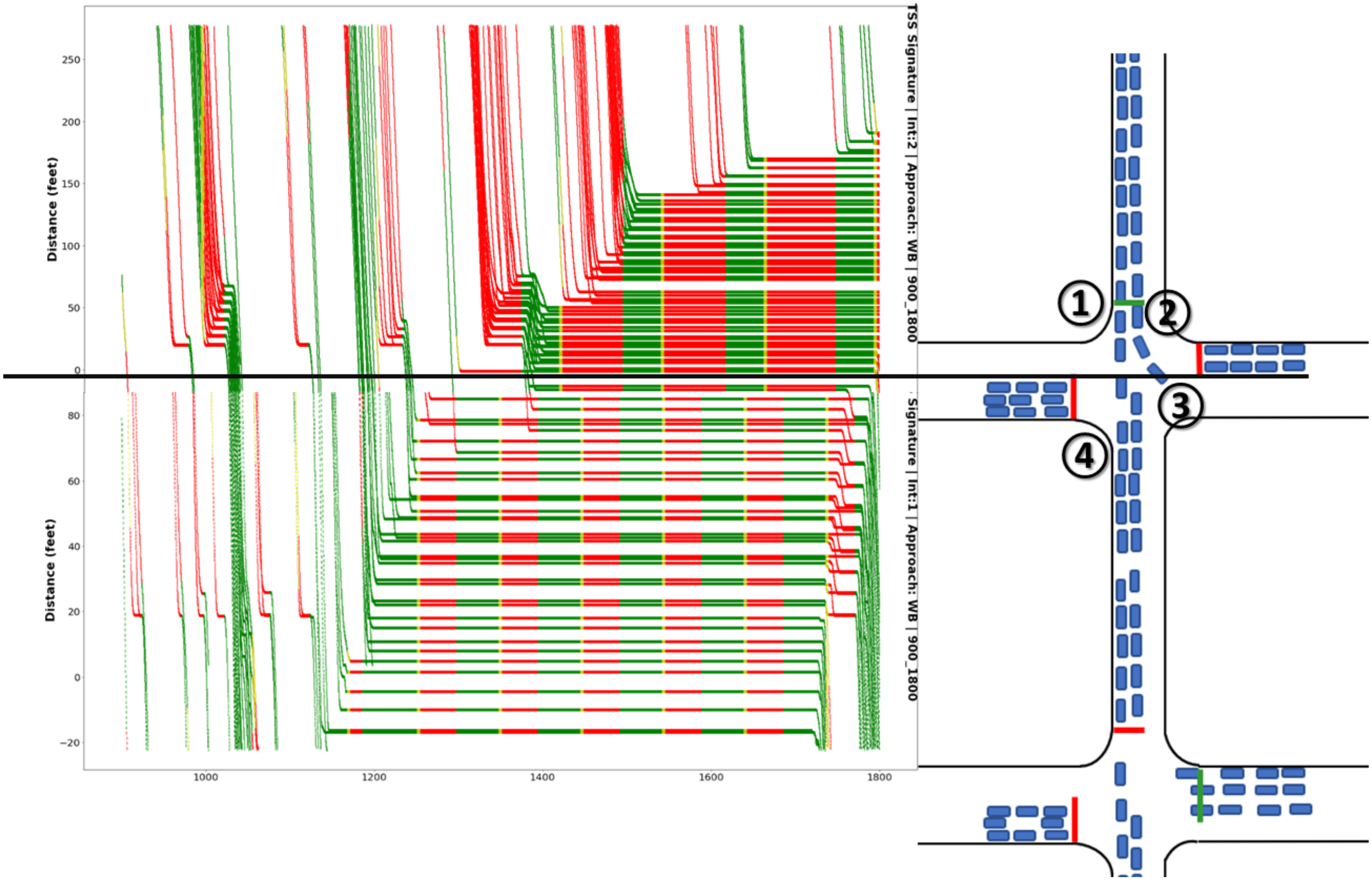


Figure 4-9. TSS signature – Case 1: Approach Spillback

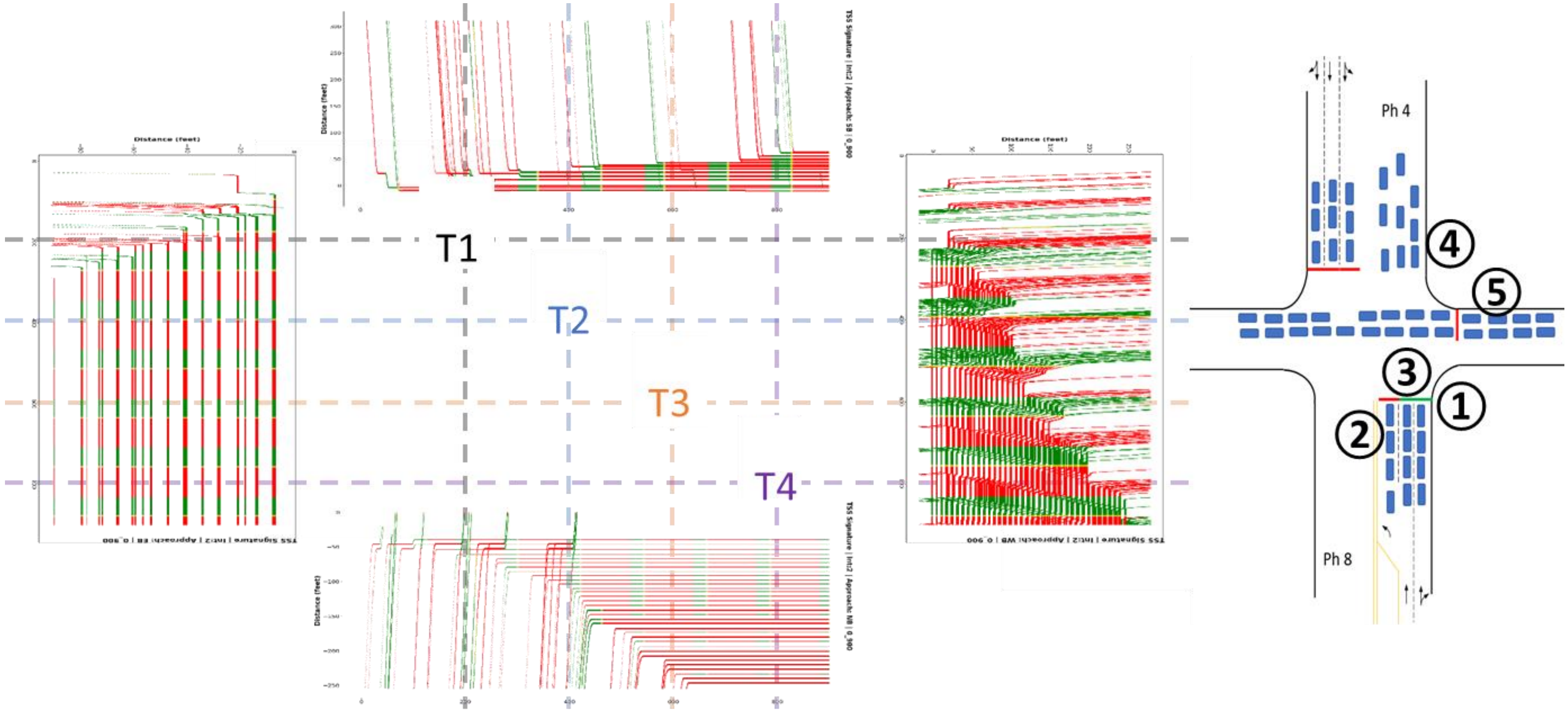


Figure 4-10. TSS signature – Case 2: Intersection Cross-Blocking

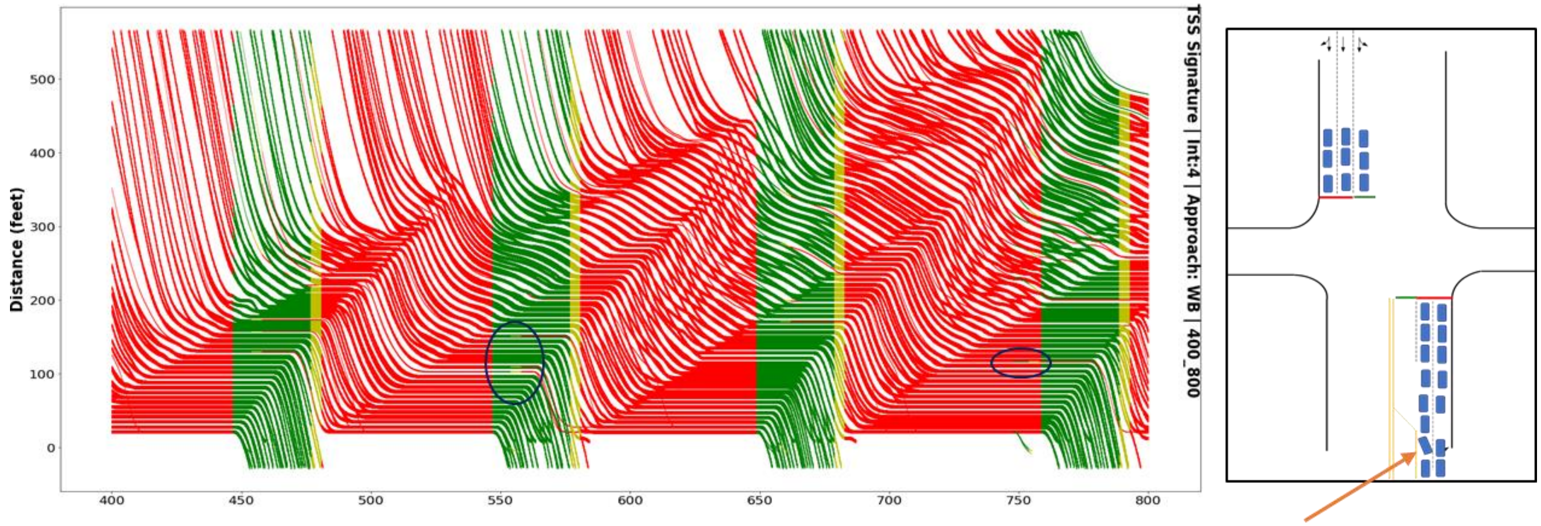


Figure 4-11. TSS signature – Case 3: Left Turn Bay Blocking

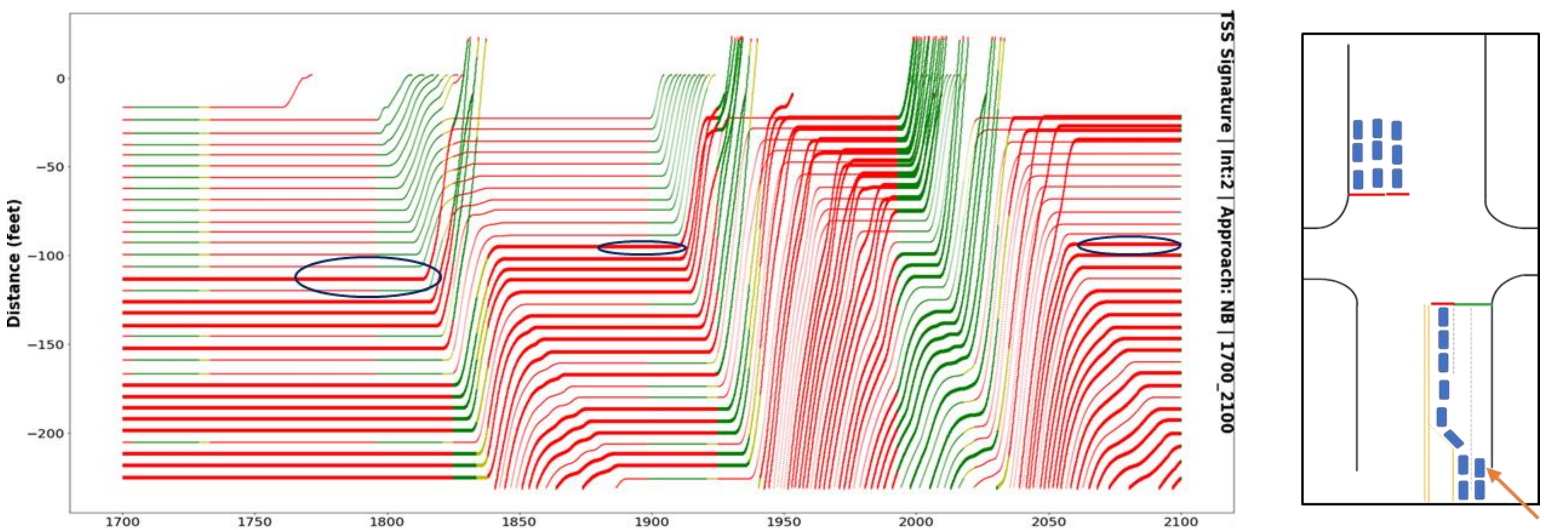


Figure 4-12. TSS signature – Case 4: Left Turn Bay Spillback

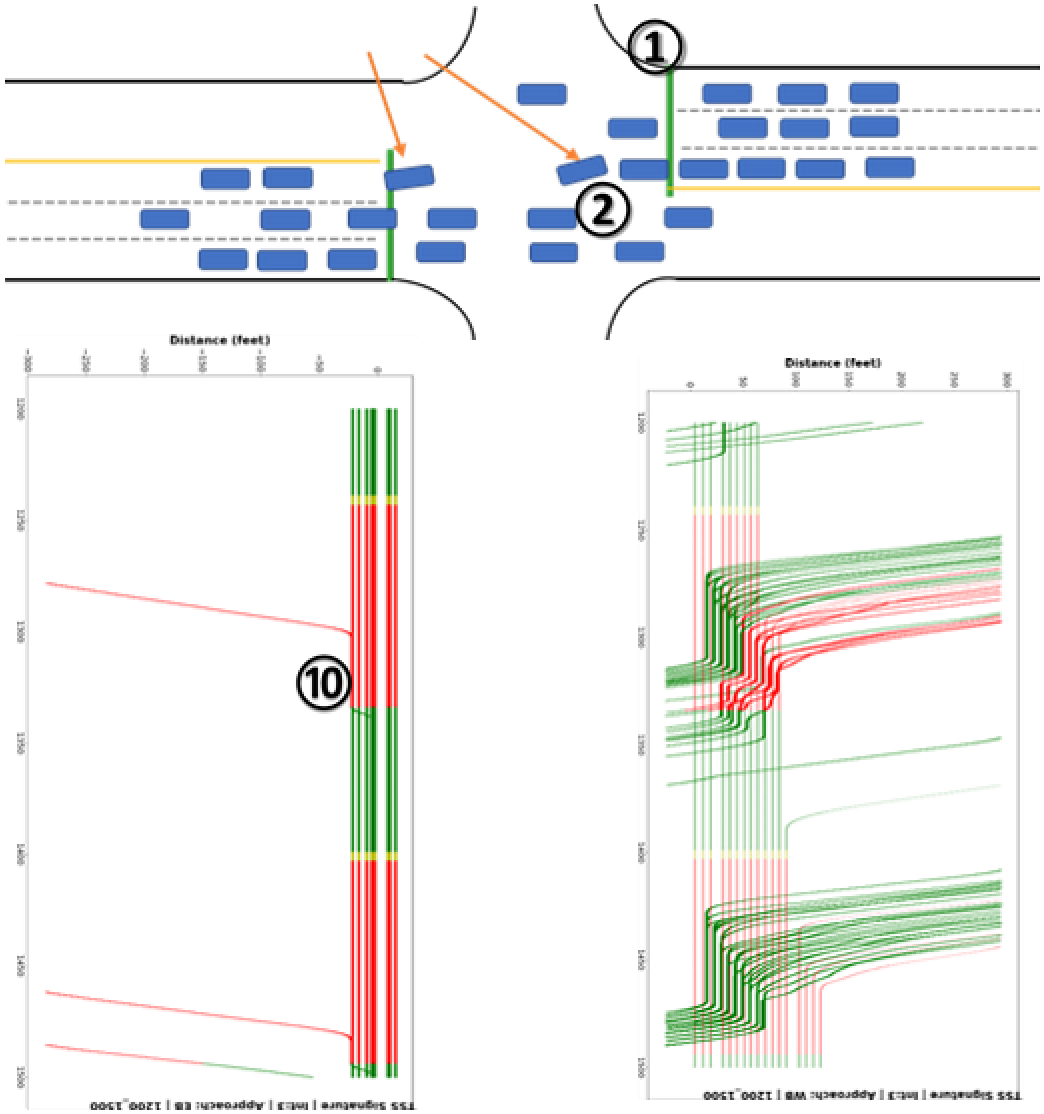


Figure 4-13. TSS signature – Case 6: Concurrent Phasing - Approach Spillback

Figure 4-9 represents the case of approach spillback, operational conditions at two westbound (WB) approaches are presented where, due to spillback, through traffic is prevented from progressing. The effects are severe since its spatial extent is significant as well as temporal. From the TSS signature, it can be observed that vehicles experienced several phase failures before being able to clear the approach. Although inbound traffic demand does not seem heavy, just by observing trajectories, we can conclude phase failure occurred. Referring to **Figure 4-8**, through traffic at intersection **2** spills back, affected by the traffic upstream – at intersection **1**. However, also evident is an extreme degree of disruption on the target approach since vehicles are unable to move to pass the stop bar over consecutive intervals. The controlled experiment, in this case, represents freight railway crossing preemption immediately upstream of intersection **1**.

TSS graphical summary in **Figure 4-10**, references the traffic state on the right side of the figure and establishes cross-blocking as the event type. In this case, two opposing directions' TSS diagrams would have sufficed. Here, WB-EB and NB-SB, both, are presented for illustration purposes only. Neither left nor through vehicles on either (NB/SB) approach can travel, due to excessive demand cross-section blocking in the WB direction. The controlled experiment, in this case, represents physical blocking of the cross-section of intersection **2**.

Figure 4-11 for a protected left setup, illustrates a case where heavy through traffic demand is blocking left turners from reaching the stop bar. As can be seen in the corresponding TSS signature's circled areas. Consequently, left phase utilization is unsatisfactory. Free-running type of operation would not even register a call on a phase being placed (due to distance) and in other circumstances (TOD or coordinated) green time would have been unutilized, measured performance levels would not infer such operational conditions. The controlled experiment, in this case, represents excessive inbound demands at intersection 4 corresponding to the special event type of occurrence (athletic events or concerts for example).

Figure 4-12 demonstrates the opposite case of the one represented in **Figure 4-11**. At the NB approach left-turning vehicles are spilling back and for this reason, blocking through moving ones from progressing. The through moving vehicles are positioned further upstream (relative to regular operations) – circled areas in **Figure 4-11** TSS signature. This means through vehicles are not able to place a call on the corresponding phase, due to the heavy demand of the left turning movement. The controlled experiment, in this case, represents excessive left turn demand at intersection 4 due to rerouting.

Figure 4-13 represents traffic conditions in which at intersection 3, WB left-turning traffic cannot turn due to the approach spillback in the opposite direction, i.e. EB. As shown in **Figure 4-13** opposing approach experiences spillback, from an upstream intersection. According to **Figure 4-13** TSS signature(s), EB traffic is effectively preventing WB left-turning vehicles to progress, and since through traffic is unimpededly crossing the stop bar and no other reason for such behavior is evident, EB approach spillback is occurring. The controlled experiment represents inadequate phasing configuration at intersection 3. WB and EB both have permitted lefts while concurrently running in the NEMA-RBC setup.

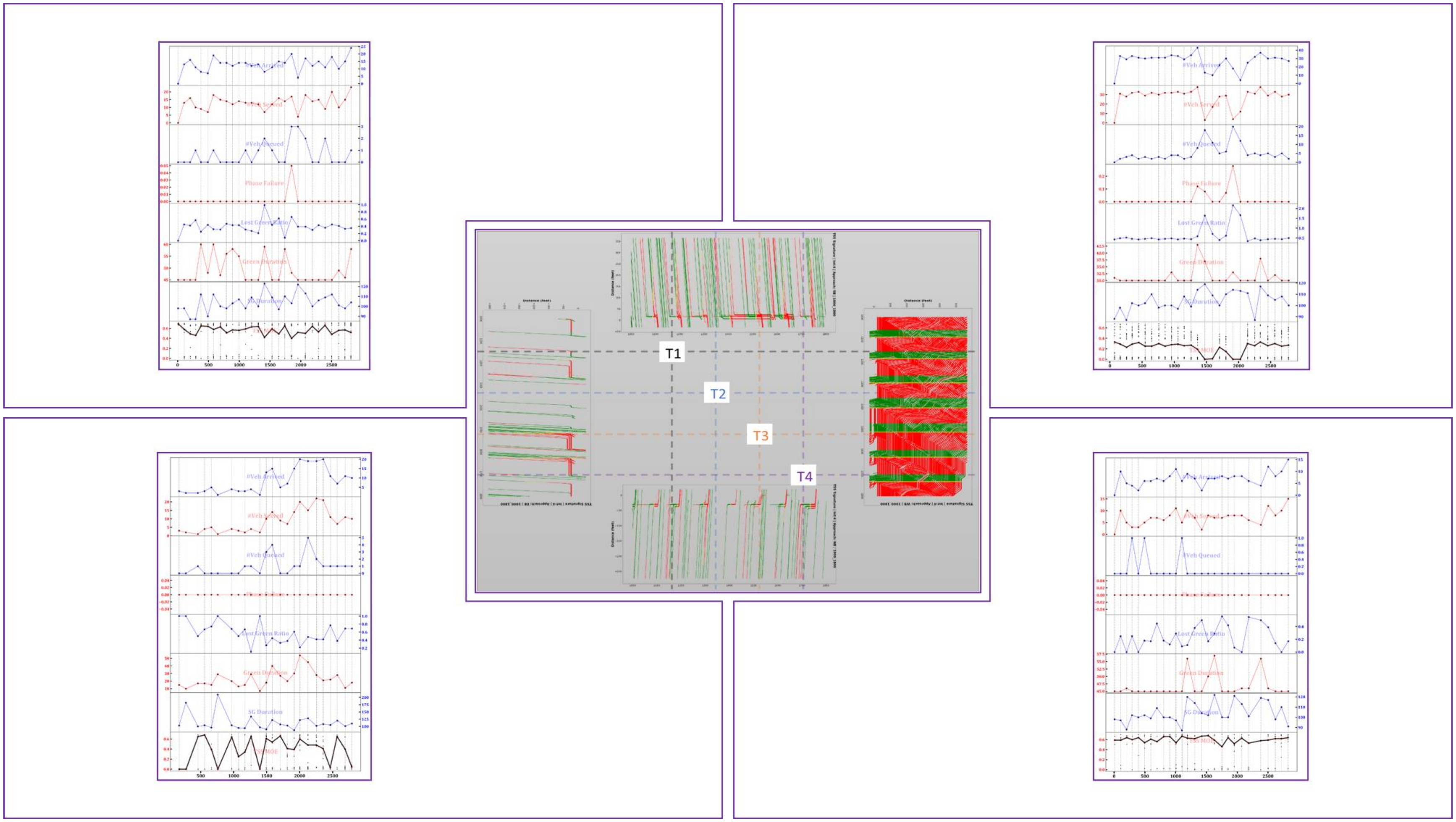


Figure 4-14. Quantifiable Measures along with Associated TSS Signature

4.6. Conclusion

This chapter presented a diagnostic tool aimed at determining traffic control operational deficiencies, as well as the extent to which deployed signal timing plans successfully respond to prevailing traffic conditions. A practical and straightforward approach was proposed to visualize and analyze individual phases' green time utilization in a considerable number of operational scenarios. The goal was to present recognizable Time-Space Signal Event Signatures and associated set of parameters, which can streamline the system's monitoring, management, and fine-tuning of field solutions when traffic conditions change.

Even though models are based on simulated traffic data, they are readily applicable to real-world trajectories. The formal framework introduced in this chapter is universal and could be applied to any intersection/signal configuration as well as the controller type of operation.
The practicality of this method is reflected in reducing the time and effort required by the existing signal design/retiming practice since trajectory-signal signatures distinguish between incidents and retiming opportunities caused by changing traffic conditions. Implementation of such decision support tools would allow systems engineers and operators to quickly assess the historical operation of a traffic signal and prioritize problematic intersections/approaches.

Chapter 5. QUANTITATIVE PERFORMANCE ASSESSMENT: TRAJECTORY ANALYTICS

Signal performance measures help agencies effectively manage traffic signals without the need for extensive manual field data collection. Regardless of the type of signal control, key system parameters, such as demand, queue formation, and discharge, as well as delay are not correctly capturing various operational conditions or traffic states since the information is obtained from detectors placed at the stop-bar.

This means control system inputs are being estimated, which in turn, limits the effectiveness and hinders performance evaluation of modern traffic control systems. To overcome this issue, obtain more reliable traffic parameters and by extension state-representative performance indicators, several state agencies began investing resources into the development of performance measures based on the high-resolution signal/detector event data. Reliably and accurately measuring what was previously estimated, on an aggregated/averaged level, provides further insight into the system's operational characteristics.

Archived, time-stamped, individual detector activations, and signal phase status/events have been referred to as *high-resolution data*. In this study, high-resolution data refers to also vehicle trajectory information, and the term can be applied to any fine granularity data that is obtainable outside of readily available (aggregated) traffic counts or signal phase durations.

Here, each vehicle trajectory record consists of a position, identification number, speed, direction, turn status and a timestamp of the moment when the information was created.

As stated in ***4.3*** the method superimposes individual signal phase indication and duration over individual vehicle trajectories. Color-coding each portion of each trajectory enables visualization of the amount of cycle time vehicles spent moving vs stopped while considering the speed of progression. By aggregating discrete vehicle trajectories by color, in time and space, a total number of served vehicles during one phase can be quantified while detailing how these were served (ex. queued vs not).

The study proposes to establish the quality of service evaluation method at an intersection (or arterial corridor/network) level by introducing an alternative, composite measure of effectiveness and cross-referencing it with now-obtainable Hi-Res performance indicators. The proposed rate of utilization of available green time and space incorporates multiple aspects of signal performance assessment: utilized vs available green, quality of progression (speed), as well as the impact of oversaturation. It can be applied at an individual vehicle level, measuring how well the vehicle is utilizing available green time and space under specific signal control operational conditions, or any other more aggregate level.

The Trajectory Analytics evaluation method, therefore, stands for the set of methods and their conceptual underpinning for the systematic mining of large trajectory data sets to analyze and characterize the associated traffic and behavioral patterns in the network. Its application to signal system performance evaluation is the basis of this effort.

For this study thus evaluation of the proposed framework simulation data obtained from the microsimulation tool VISSIM (*97*) was used. The authors believe the proposed trajectory-based signal performance assessment can improve the state-of-the-practice of traffic signal operations by identifying a performance metric which is meaningful and actionable to practitioners as well as researchers and tells how well the vehicles are utilizing both available time and space, given preset signal timing settings (*99*). The study further proposes to establish the merit of the proposed MOE when optimizing signal control parameters as well as its potential applicability in signal re-timing practices.

“Perfect” (full) information was assumed. A real-world application would challenge the approach undertaken due to imperfect data and associated uncertainty as well as necessary map matching of trajectory data. The MOE itself as well is expected to undergo further refinement and evaluation. Its current form requires real-world rationalization and adjustment respective of real-world data.

5.1. The Core Concepts of the Method

Traffic engineering practice widely utilizes *Time-Space (TS)* Diagrams, such as SYNCHRO’s (*98*), to estimate the appropriateness of signal timing parameters in the signal design/retiming process. Multiple attempts have been made to relate the TS diagram to the quality of signal control operation (*7*, *11*, *98*, *100*). Although intuitively useful, these are not associated with a tangible and robust measure of the quality of service.

In many cases data on the state of the system, and operational success indicators, are considered misinterpreted or otherwise misleading as to the underlying cause of the problem, which, as a result, hinders the quality of evaluation. Also, we may know about the exhibited symptoms (for example failure to clear the approach) yet not the context and extent of it.

The zeroth step of the proposed method entails visualizing individual trajectories as they progress through a signalized approach, on a detailed, disaggregate level. Signal indication-coded trajectories as part of signalized approach analysis form distinguishable traffic state visual signatures which aside from location in space and time, capture vehicles' performance respective to individual phase indication and operational conditions experienced. As explained in ***4.3***, this qualitative component of the proposed approach systematically locates and identifies the type of problem, while characterizing its spatial and temporal extent.

5.1.1. Experiment Setup

To test and demonstrate the validity of this multistep methodology, the study developed a simulated testbed using VISSIM (*97*), a microscopic traffic simulation software, to emulate real-world scenarios. Real-world, 4-legged, 8-phase signalized intersection of Broward Boulevard and Federal Highway (US-1) in Fort Lauderdale, Florida was modeled in a microsimulation environment for this study (**Figure 5-1**). The testbed was running SYNCHRO (*98*) optimized TOD signal timing plans for peak periods and regular vehicle actuated (free-running) during off-peak periods.

Demand levels were divided into three categories: low, medium, and high, each being 30 minutes long. A 2-hour long simulation horizon was designed to represent the demand build-up from low (off-peak conditions), then medium to oversaturated (AM or PM peak) and then reverting to medium, to represent recovery after oversaturation dissipates. Major approaches are East and West (Broward Blvd.). Evaluation periods included both morning and evening peaks as well as the off-peak periods to capture various demand levels and operational conditions.

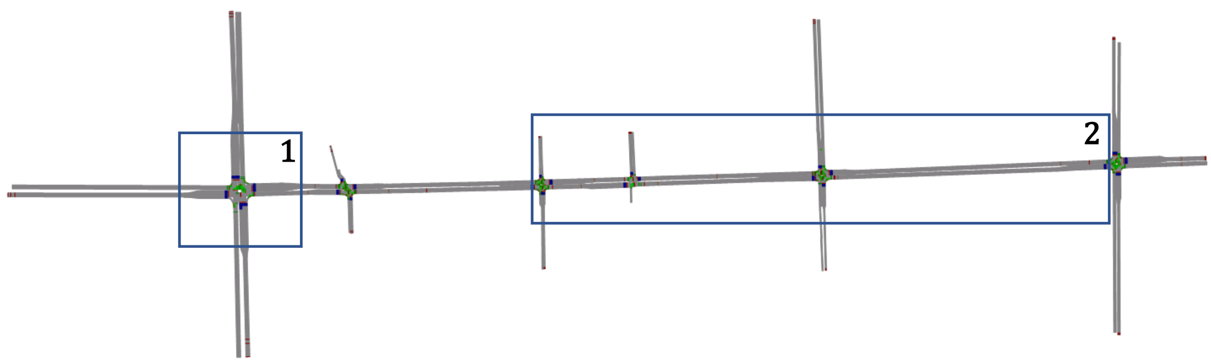


Figure 5-1. VISSIM testbeds - isolated intersection location labeled 1 and corridor labeled 2

Hi-Res performance measures algorithm calculates and outputs the metrics while the visualization algorithm generates corresponding TSS signatures over consecutive demand periods. The robustness and effectiveness of the proposed method were examined under different demand levels and operational scenarios. It should be noted that controlled experiments were conducted to investigate the feasibility and applicability of the proposed approach. System-level performance assessment overall considers the intersection approach's/ movement's operational efficiency. Depending on the level of analysis, performance assessment can consider multiple levels from isolated intersections phases to arterials and networks. In the isolated intersection case – like in the example here, only subject intersection (movement/phase) is evaluated.

Simulation outputs were used as the source of data in a format that corresponds to real-world Hi-Res data (signal status and vehicle positions) at a transmission rate of 10 Hz.

5.1.2. 3 – Stage Method

This study establishes a 3-step method to analyze the state and performance of a signalized approach before establishing a new composite ***TSS-MOE***.

Step1: Retrieve Data

High-resolution data, broadly, refers to fine granularity data that is obtainable outside of readily available (aggregated) traffic counts or signal phase durations. Traffic signal controllers with high-definition data logging capability, log phase change events with a tenth-of-a-second resolution timestamp and store the events in temporary data files in the controller. Event-based data logging means that only signal status and time at which there is a status change is recorded.

Due to the lack (unavailability) of real-world high-resolution (Hi-Res) data at this stage, relevant information was obtained from the simulation runs. Raw signal and trajectory data at a frequency of 10 Hz was retrieved as the testbed’s simulation output. Data formats are designed to correspond, as closely as possible, to real-world “connected” traffic signal systems standards. Vehicles' positions (and a defined set of attributes) in time and space, at every time step, were recorded. Accordingly, signal status was superimposed (at individual vehicle level) with the indication corresponding to the intended movement (movement-phase pair), at the immediate downstream signal.

On approach level, control settings can be accounted for at individual vehicle-level – the type of left phasing protected vs permissive, lead vs lagging left, actual (perceived) green, and red time duration.

Trajectory-based signalized approach analysis requires the following information:

- *High-Resolution Vehicle Trajectories* –
  - Individual vehicle ID
  - Time Stamp
  - Position (X and Y Coordinate)
  - Intended turn movement at the downstream intersection, i.e. turn left, through or turn right)
  - Speed
  - Acceleration

- *High-Resolution Signal Controller* (or Signal Phase and Timing or SPaT) –
  - Signal phasing, e.g. lead or lag phase, protected or permissive left turns
  - Phase duration, i.e. beginning and end of each indication at each cycle
  - Phase indication at each time step observed

Step 2: Performance Indices

While the trajectory-signal plots provide a good intuitive insight into operations, they do not, as such, support quantitative assessments. To develop performance measures from vehicle trajectories, the trajectories must be represented mathematically, not just visually.

Trajectory-based assessment of signal performance consists of identifying several discernible trajectory sections: efficient green and red – the vehicle is moving on green/red, the slope of the trajectory i.e. speed relative to that of the uninterrupted flow, and inefficient green/red – the vehicle is effectively not moving on either green or red. Through trajectory color-coding, these states are discernable and free of assumptions or need for an estimation regarding behavior or performance metrics calculations.

The information used to construct time-space-signal (TSS) diagrams can be converted into quantifiable performance measures. Each of the recorded MOEs is computed by quantifying these portions within each vehicle trajectory and aggregating them over time and/or space.

All indicators calculated at an individual trajectory level are then aggregated to represent measures of efficiency on a per-signal group basis.

Aggregate measures refer to signal group (SG)-based quantities such are the ones described in **Table 5-1**. **Table 5-2** specifies the measures that are computed as cumulative on an individual vehicle level, then aggregated per SG duration. These vehicle-based measurements could also be aggregated to any other more aggregate level.

Movement-level vehicle-based computation of performance metrics is the core of the conceptual groundwork proposed. Hi-Res performance indicators, presented in **Table 5-1** and **Table 5-2** are computed as per their definitions.

Table 5-1. Signal Group-based Hi-Res Performance Indicators and Corresponding Definitions

Hi-Res Performance Indicator		***Definition of Performance Indicator***
Arrived Veh	:	Number of arriving vehicles between two consecutive green ends*
Served Veh	:	Number of served vehicles between two consecutive green ends*
Unserved Veh	:	Number of queued vehicles at the end of green
Demand	:	Unserved plus Arrived
Prop of Vehicles Arrived on Green (prop **ASoG**)	:	Proportion of vehicles arrived and served during two consecutive green ends
Prop of Vehicles to Stop	:	Proportion of vehicles that had to stop (on green)
Progression Ratio	:	Proportion of vehicles arrived on green that did not stop on green
Green Duration	:	Time difference between the end and beginning of each green indication
*SG Duration	:	Time difference between two consecutive green ends

** Please note right-turning vehicles can be served during red if allowed

Veh = Vehicle

SG = Signal Group

Table 5-2. Vehicle-based Hi-Res Performance Indicators and Corresponding Definitions

Hi-Res Performance Indicator		***Definition of Performance Indicator***
Total Time	:	Total travel time
Total Distance	:	Total distance traveled
Time in Queue	:	Time spent queued (not moving)
Green in Queue	:	Time spent queued during green indication
Green Distance	:	Distance traveled during green indication
Avg. Speed in Green	:	Average speed during green indication
Green Time Available	:	Total amount of green observed (over multiple SG durations)
Green Time Utilized	:	Total amount of green time vehicle spent effectively moving (over multiple SG durations)
Phase Failure	:	Number of entire green indications encountered before served
Number of Stops	:	Number of stops
TSS-MOE (per Veh)	:	Utilization of time and space (per **Equation 5-1**)

**Please note right-turning vehicles can be served during red if allowed

*** Measures computed as cumulative per vehicle as well as per SG duration

Veh = Vehicle

SG = Signal Group

To-date, traffic stream parameters, are being derived from detectors placed at the stop bar and/or approach, which, further, impacts the accuracy of key control system metrics, as such (V/C, delay, and queue length, etc.). On the other hand, by using surrogate measures, and/or by coupling several metrics, researchers were trying to identify phase failure occurrences from detector activations and force offs vs gap outs from signal event logs (*16, 17*).

The objective was to establish a set of trajectory-based performance measures that characterize signal capacity utilization, quality of progression, and effectiveness through quantifiable parameters.

Lost Green Time (per vehicle and per phase) – is defined as a measure of phase performance degradation. It is quantifiable as the amount of green time during which a vehicle was not able to clear an intersection despite the traffic signal displaying a green indication.

On a vehicle level, Lost Green Time as the ratio of green time utilized vs green time available is calculated as the ratio of green time vehicle spent effectively progressing over the cumulative green time duration available to that vehicle. This measure per SG represents a cumulative value over several SG durations (case when a vehicle required more than one to clear the approach).

Signal Group (SG duration)-based reporting format is used to represent results as generically as possible, making it applicable to any type of controller operations. SG duration is defined as the elapsed time between two consecutive green (indication) ends for a single phase. The green time of an actuated phase is related to the number of vehicles that arrived in the preceding red. The algorithm that calculates and outputs MOEs (on an SG basis) defines the SG duration as the sum of preceding red and current green duration.

The performance assessment framework is designed as SG duration based since no notion of “cycle length” as such exists, and the method applies to any type of controller operation. Such an approach underscores that a single phase can fail (experience single or multiple phase failures) whereas no significant degradation in performance can be observed on other approaches.

Phase failure, therefore, refers to an integer number of green indications a vehicle experiences on an approach before clearing said approach.

If a vehicle is stopped over multiple SG durations, it is considered to have experienced a single stop, while respective stop duration will accumulate the time accordingly.

Cross-referencing multiple performance metrics, along with a newly developed composite ***TSS-MOE*** measure, is proposed as the method to assess potential operational deficiencies of a signalized approach. This approach was taken to define easy-to-understand classes of operational success indicators which can be related to the state of the practice standards in traffic signal system performance assessment.

The number of stops and stop durations per vehicle is calculated based on specific vehicle trajectory speed criteria, relative to signal timing settings. It is possible to distinguish between the stops during green and red i.e. over the entire SG duration. The number of stops and the proportion of stopped vehicles on each green is also recorded and considered applicable when determining the quality of progression.

Any other indicator that was used in the analysis was derived based on the elementary ones described in **Table 5-2.**

*Step 3: Compute Composite Time-Space Signal Measure of Effectiveness – **TSS-MOE***

Single vehicle's ***TSS-MOE*** can be defined as in **Equation 5-1** below:

$$\boldsymbol{TSS\text{-}MOE} = \underbrace{\left(1 - \frac{t_{int}^{V=o}}{TS_{int}}\right)}_{①} . \underbrace{\left(\left(\frac{Dist_{int}}{TS_{int}}\right) \Big/ SL_{int} \right)}_{②} . \underbrace{\left(1 - \frac{t_{int}^{V=o,Green}}{TS_{int}^{Green}}\right)}_{③} . \underbrace{\left(\frac{1}{PF_{int}}\right)}_{④} \qquad \textbf{Equation 5-1}$$

where:

$t_{int}^{V=o}$	:	Stopped time regardless of indication
$t_{int}^{V=o,Green}$	:	Stopped time during green indication
TS_{int}	:	Total time spent (total travel time)
$Dist_{int}$	:	Distance traveled
TS_{int}^{Green}	:	Green time available over the entire trajectory
SL_{int}	:	Speed limit
PF_{int}	:	An integer number of green indications observed before served

A newly developed Time-Space Signal (TSS) index assesses the utilization of time and space dimensions of a signalized approach. The index synthesizes information from *vehicle trajectory* and *signal-phase and time* (or SPaT) data into a quantifiable traffic state-responsive parameter.

The utilization of green time and space – or time-space-signal measure of effectiveness (***TSS-MOE***) - attempts to contextualize the most relevant causal factors of inferior signalized approach performance by quantifying their relative contributions. It accounts for negative contributions of prevailing demand levels, inadequate phase timing, and offset between adjacent intersections. In such a manner it incorporates multiple aspects of signal performance assessment by designing proxies that relate efficiency measures of 1) observed demand patterns, 2) quality of progression, 3) green time efficiency, and 4) impact of oversaturation.

Figure 5-5 shows the correlation matrices (average correlation and standard deviation in parenthesis) of the four components of the ***TSS-MOE***. It was computed first on a user level, under **Equation 5-1**, then aggregated to movement per approaches, then to intersection level, as indicated by callout boxes.

In **Figure 5-5,** white boxes correspond to the respective approach's left-turning movement and blue to through movements. The correlation matrix in the middle represents the overall (intersection's) correlation between the four elements. The strength of the between-component relationship varies, depending on the operational conditions. Furthermore, negative correlation (between third and fourth component) is indicative of circumstances in which high on green utilization succeeds earlier experienced phase failure(s). In the examined experiment these represent low demand conditions in which queued vehicles wait to get served.

The first term represents the moving proportion of trajectory; the second term relative speed (to the speed limit - could be greater than 1, thus capped by the speed limit as the maximum); the 3rd parenthetical term establishes the proportion of green time vehicle spent effectively moving; and the final term is the inverse of the number of entire green durations encountered.

Each term measures efficiency, although the entire expression (**Equation 5-1**) was conceived as utilization since a maximum of 1, in each of these dimensions, is assumed and some ratio of it is being utilized.

Please note that available green time does not refer to the actual (effective) green duration, which is the same for all vehicles, but to the green-colored portion of trajectory, which is unique for each vehicle.

In **Equation 5-1**, the first two components can be interpreted as space utilization, whereas the last two represent green time utilization efficiency and settings robustness. The form of **Equation 5-1** corresponds to an individual vehicle's performance indicator. Subscript $\boldsymbol{int}$ is used to denote a single (intersection) movement/phase pair.

It was designed in such a manner so it can be applied at an individual vehicle level, measuring how well the vehicle utilized the available green time and space under specific signal control and operational conditions, or any other more aggregate spatial and/or temporal level.

The terms in **Equation 5-1** are ratios, each had been normalized. Hence, they are dimensionless components contributing to a unitless MOE. Since individual contributions are normalized, proposed ***TSS-MOE*** is dimensionless, and its value ranges between a lower bound of zero and an upper bound of 1.

The higher the value the better the utilization of green time and space, where attaining 1.0 is optimal. A value of zero represents operational conditions in which the vehicle has not effectively moved over its entire trajectory.

Vehicle stopped time counts towards progression inefficiency, regardless of signal indication. The worst case, naturally, is experienced during oversaturation or similar conditions, when even with green indication, the vehicle is not moving. The greater the on-green performance, or the lower the phase failure value is, the more reliable service is.

What distinguishes this measure (and approach) from others is that it recognizes the system's operational success from the user's perspective and carries over the information going from one "signal cycle" to another. The information is cumulative in time and in space which is the opportunity that arises thanks to connected environments. And from an evaluation standpoint, it becomes evident that not demand-based green time allocation, but its utilization determines the quality of service.

In certain circumstances (under-saturation) data from the stop bar detector alone is sufficient to estimate the "intersection approach" performance, but not overall arterial performance (*18*). While the delay is the single most important signalized approach performance indicator, the level of service (LOS) of C does not distinguish whether vehicles were waiting to get served at the stop bar or were queued as soon as they entered the approach link.

Individual total delay and time spent in a queue can be observed and measured by processing vehicle's positions in time and space along a corridor while accounting for the slope of its trajectory. The slope of trajectory was considered to distinguish between the slow and fast-moving vehicles' contribution to the ***TSS-MOE***– refer to **Figure 5-2.**

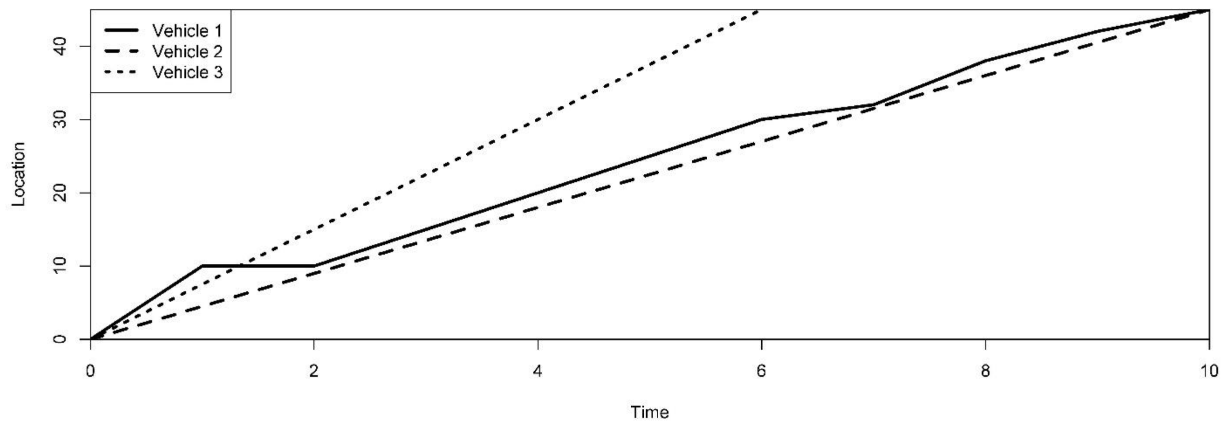


Figure 5-2. Difference in Slope of Trajectories for Three Representative Cases

If in a given evaluation period a vehicle has not moved, its negative contribution to the ***TSS-MOE*** is captured through the overall time spent on a link (intersection, corridor, etc.). However, if a vehicle was moving slowly or was stuck in stop-and-go traffic, the number of entire green durations a vehicle had to wait before it was served, increases the negative penalty, and reduces the ***TSS-MOE,*** respectively. In this study, the quality of service refers to the manner vehicles were served immediately upon entering the approach respective of the signal indication. When aggregating at a corridor level, a *single vehicle's* ***TSS-MOE*** *value is, in a manner, weighted by its respective travel time, so the contribution of vehicles traveling shorter distances (spending less time in the system) would not be overestimated, and vice versa, in the overall (aggregated)* ***TSS-MOE*** *measurement*. The aggregate measure, therefore, scales the contribution of each vehicle. Please refer to the analysis in section ***5.2.1*** for corridor-level calculations and the interpretation of results.

To identify the signal system's deficiencies: cross-referencing multiple performance metrics, along with a newly developed composite measure, is proposed as the method to assess potential operational deficiencies of a signalized approach.

Relative significance of each is weighted by cross-referencing with proposed Hi-Res indicators to establish criteria that categorize ***TSS-MOE*** into ranges broadly corresponding to under, saturated, and oversaturated traffic conditions. This approach was taken to define easy-to-understand classes of operational success which can be related to the state of the practice standards to date used in traffic signal system performance assessment tools.

5.2. Results and Discussion

5.2.1. Corridor Level Analysis

This approach by adopting a TS-diagram-like graphical illustration, determines and associates a measure of time and space utilization on an individual signal (phase) level and then aggregates it on an arterial level.

This study proposes to quantify the quality of service of a signal (phase), i.e. progression along a corridor or ***any pre-defined path***.

This is possible because the analysis is performed on a vehicle i.e. route level. If a chosen path is an arterial, then the signal status is superimposed at the individual vehicle level, coloring the trajectory with the signal indication corresponding to the intended movement that the vehicle encounters at the immediate downstream signal. Therefore, by definition, the ***TSS-MOE*** can be applied at any level of analysis - approach, intersection, corridor, or even network level.

TSS-MOE information is cumulative over phases for a single controller and a route. If one is to investigate performance over consecutive adjacent intersections, phasing information is updated as soon as the vehicle crosses the stop-bar onto the next approach. Multiple approaches performance is recorded and then *averaged over an entire trajectory since the first two components of the **TSS-MOE** are cumulative over the trajectory and are calculated independently of signal control settings***.**

The example below demonstrated how the evaluation method would be applied to a corridor level analysis as opposed to the link (approach) level. It illustrates a simple 3-intersection progression quality measurements cross-referenced with an average corridor-level ***TSS-MOE***. Analysis in this section refers to different controller types of operations, for a corridor testbed in **Figure 5-1** labeled 2.

Figure 5-3 and **Figure 5-4** represent evening peak and off-peak corridor level ***TSS*** diagrams, respectively, illustrating vehicle progression over time and space on one of the test bed's corridors. Signal type on the righthand side of the figures shows the actuated type of control as circles and fixed time as squares.

From **Table 5-3**, it can be observed that ***TSS-MOE*** does not follow the same trend as the conventional performance metrics. While higher average delay (and stopped time) thus lower average speeds would quantify a specific level of service category, proposed ***TSS-MOE***values would not necessarily do the same.

Note the entries highlighted in red, where based on the conventional measures for the period 3 link 3 should be ranked as the worst-performing one. However, this is not the case if we look at the ***TSS-MOE*** value. Even though link delay is the highest and its speed is the lowest, its time and space utilization is greater than that of link 1. This is because the time spent on the link is more efficiently utilized by the larger number of vehicles within the available green time interval.

Similar conclusions can be drawn when assessing corridor level performance. Conventional metrics would classify the second-time period as the worst-performing one in terms of delay, stopped time, and speed, whereas the ***TSS-MOE***ranking says otherwise.

Similar trends can be observed when looking at the results in **Table 5-4** for the off-peak signal control parameters' settings. **Figure 5-4** demonstrates signal indication coded vehicle trajectories during off-peak along the same corridor.

Link-level metrics would classify link 3, during the third evaluation period as the least operationally efficient, characterized by the highest average stopped time delay of 45.1s, the average delay of 45.0s, and the lowest average speed of 8.3 mph. However, according to the ***TSS-MOE***it is ranked second-best among the three links.

Link 3 associated green times are long enough thus can serve the demand better, so the overall time and space utilization are greater.

Corridor-level performance attributes quantify the second evaluation period as the worst one in terms of experienced operational conditions - average stopped time of 49.9s, the average delay of 57.5s, and an average speed of 14.5 mph.

Yet, the ***TSS-MOE***showed the first evaluation period as the one with the lowest utilization of green time and space. If we look at the second and third analysis period, we observe remarkably similar trends, but neither is ranked as the lowest in terms of ***TSS-MOE.***

This quick preliminary corridor-level analysis prompted a more detailed, disaggregated look into the performance assessment and consequently determining the most relevant success indicators as well as causal factors contributing to performance degradation.

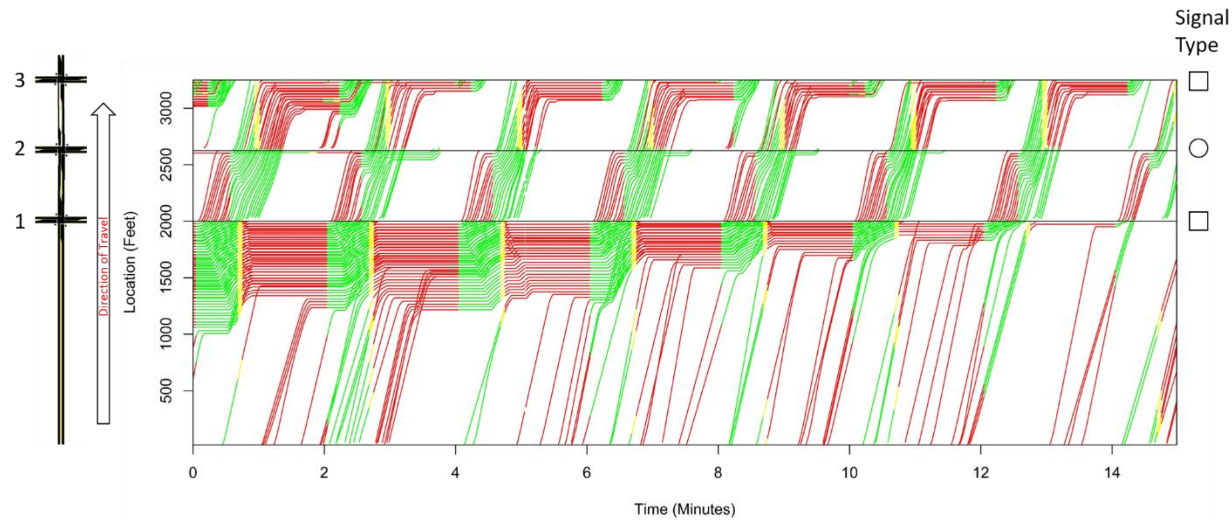


Figure 5-3. Corridor TSS Diagram during Evening Peak

Table 5-3. Hi-Res MOEs - Evening Peak Evaluation- a) Link Level, b) Corridor Level

Period	Link	MOE	Average Stopped Time	Average Delay	Average Speed
1	1	0.111	111.277	145.673	4.276
	2	0.821	10.882	14.316	17.068
	3	0.613	33.694	36.436	8.416
2	1	0.816	105.667	121.513	5.661
	2	0.923	5.706	6.946	21.802
	3	0.336	48.947	50.708	7.961
3	1	0.63	24.889	29.868	15.151
	2	0.952	6.192	6.824	22.407
	3	0.751	37.328	37.481	8.687

a)

Period	Corridor/Direction	MOE	Average Stopped Time	Average Delay	Average Speed
1	BB/EB	0.203	99.042	125.097	6.349
2	BB/EB	0.234	103.66	116.128	7.644
3	BB/EB	0.816	48.679	52.519	13.802

b)

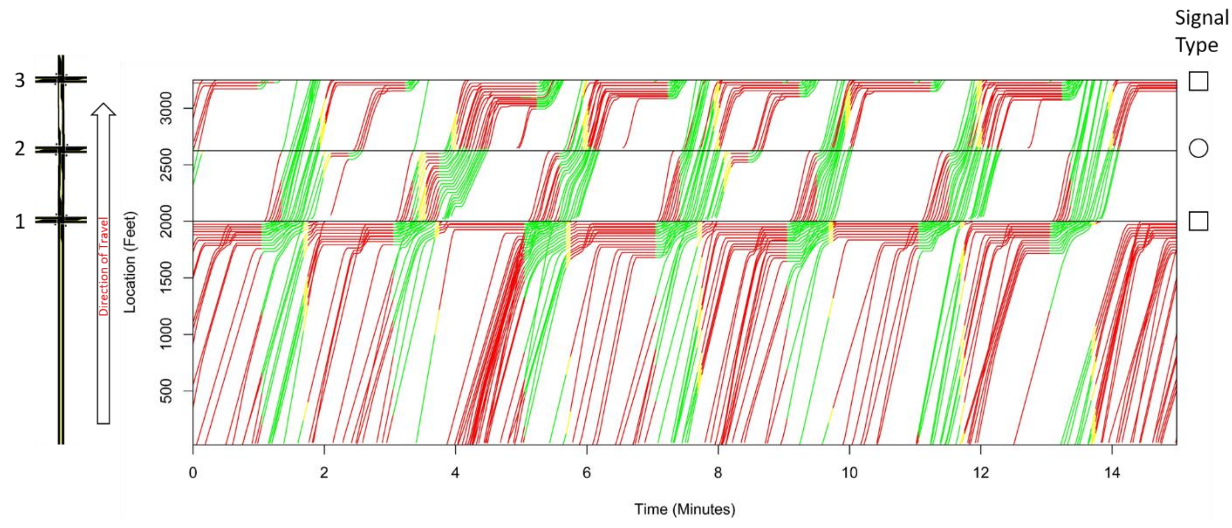


Figure 5-4. Corridor TSS Diagram during off-Peak

Table 5-4. Hi-Res MOEs - Off-Peak Evaluation- a) Link Level, b) Corridor Level

Period	Link	MOE	Average Stopped Time	Average Delay	Average Speed
1	1	0.159	35.507	37.099	16.679
	2	0.891	6.814	9.34	20.265
	3	0.108	30.809	30.899	10.535
2	1	0.241	36.767	45.854	14.34
	2	0.901	2.738	3.78	25.322
	3	0.417	29.753	30.467	10.167
3	1	0.289	37.134	33.885	17.582
	2	0.975	0.979	1.102	31.826
	3	0.351	45.118	45.021	8.286

a)

Period	Corridor/Direction	MOE	Average Stopped Time	Average Delay	Average Speed
1	BB/EB	0.364	48.733	51.322	15.671
2	BB/EB	0.517	49.922	57.513	14.465
3	BB/EB	0.587	53.132	49.611	15.755

b)

5.2.2. Movement Level Analysis

The x-axis defines a time window which is the same for all MOEs, where each point represents an event (individual signal group duration). Since the study presents a Signal Group based analysis of a signalized approach's performance, each figure represents an identical time frame (simulation time). Considering the amount of information compiled in a single chart the author, for clarity reasons, dropped the x-axis from representations.

Analysis and results in this section refer to a fully vehicle-actuated controller mode of operation – free running, for an isolated intersection testbed in **Figure 5-1** labeled 1.

Please note that in case a vehicle is unable to clear the approach over several consecutive SG durations, cumulatives of ***TSS-MOE*** components are computed, and accordingly, the negative impact is accounted for on an individual vehicle level as well as any other aggregate level.

Figure 5-6 *is presented to offer additional insight into operations and pinpoint potential reasons for inferior performance or detected disruptions, besides validating quantitative deliverables and interpretation thereof.* Based on TSS representations in **Figure 5-6**, it can be observed that the westbound (WB) approach experiences the highest demand, while the other 3 approaches, east (E)-, south (S)-, and north (N)- bound, operate under lighter traffic conditions. The example intersection is chosen to demonstrate the validity of the method proposed since it captures different operational conditions depending on the approach analyzed. WB through movement is served by signal group (SG) 8, while the opposing direction SB and NB and are served under SG 6 and 2, respectively. *Since NB and SB represent similar operational conditions,* *and only a single example was used to exemplify both.* The subject controller operates an 8-phase configuration with protected left turns in a vehicle actuated mode.

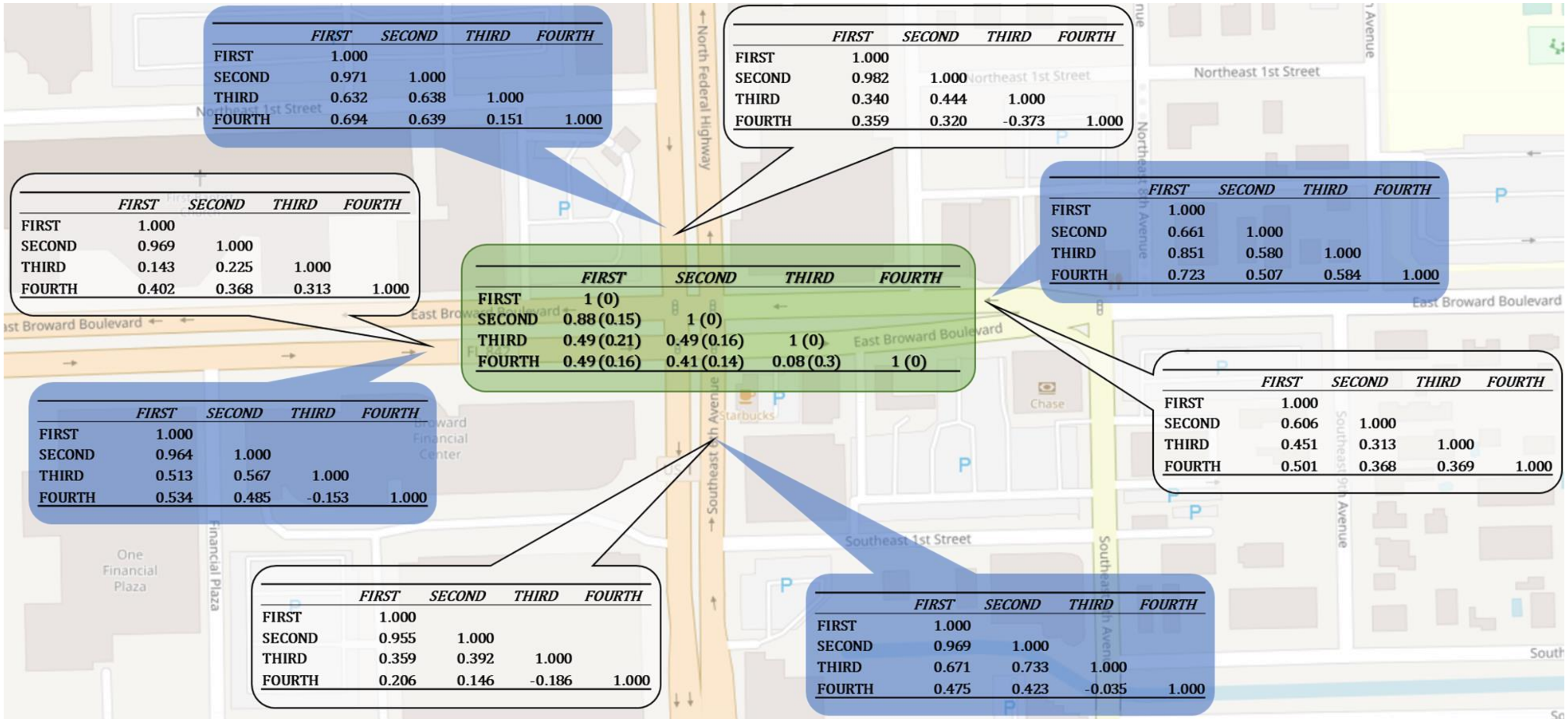
Figure 5-7 through **Figure 5-9** demonstrates that the proposed ***TSS-MOE*** does not follow the trend of any of the Hi-Res performance indicators and also that Hi-Res performance indicators when considered independently (or any combination of 2) fail to represent operational conditions accurately. **Figure 5-7** represents a low demand scenario corresponding to SG 6. Solely relying on the number of vehicles served vs. arrived, the level of service could be evaluated as satisfactory with almost no queued vehicles (except for point 1 in **Figure 5-7**) at the end of each green over the entire evaluation period. For such general observations, Hi-Res MOEs are sufficient, but they fail to capture atypical traffic patterns and, over a variety of conditions, their onset, and magnitude.

Point 1 in **Figure 5-7**, showed, despite queue build-up, the number of served vehicles had increased, and the allotted green was sufficient to serve a pa***RT***of the queue.

Focusing on point 2 on the graph to the right in **Figure 5-7**, the TSS MOE recognizes, irrespective of the high ASoG, that on a low-demand approach, underutilized green time indicates through movement wasn't timed properly relative to the reference green time at the upstream approach (offset time between adjacent intersections). Essentially, inbound demand is arriving either too early or too late at the subject approach. At point 3, again ASoG is high, but green time is not utilized efficiently, i.e. the discrepancy between green available and utilized is increasing, indicating poor progression again, since no other parameter value is unusual.

The most noteworthy finding indicates that demand-based green time allocation does not guarantee a high rate of green time and space utilization even in regular operational conditions.

In "normal" operational conditions (**Figure 5-7)**, green utilized and green available are expected to follow similar trends. This is because signals are either timed for the demand or are actuated by the prevailing demand. **Figure 5-7** through **Figure 5-9**, confirms the similarity in trends throughout most of the evaluation period. However, whenever there is non-recurrent or atypical behavior (events such as approach spillback or grid locking), these trends deviate considerably. More specifically green available is underutilized, confirmed by low values of green utilized. To better understand what is occurring with the amount of allocated green for a specific movement and to determine the effectiveness of signal timing correctly, measuring green time available and utilized is required.



	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.971	1.000		
THIRD	0.632	0.638	1.000	
FOURTH	0.694	0.639	0.151	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.982	1.000		
THIRD	0.340	0.444	1.000	
FOURTH	0.359	0.320	-0.373	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.969	1.000		
THIRD	0.143	0.225	1.000	
FOURTH	0.402	0.368	0.313	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.661	1.000		
THIRD	0.851	0.580	1.000	
FOURTH	0.723	0.507	0.584	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1 (0)			
SECOND	0.88 (0.15)	1 (0)		
THIRD	0.49 (0.21)	0.49 (0.16)	1 (0)	
FOURTH	0.49 (0.16)	0.41 (0.14)	0.08 (0.3)	1 (0)

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.964	1.000		
THIRD	0.513	0.567	1.000	
FOURTH	0.534	0.485	-0.153	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.606	1.000		
THIRD	0.451	0.313	1.000	
FOURTH	0.501	0.368	0.369	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.955	1.000		
THIRD	0.359	0.392	1.000	
FOURTH	0.206	0.146	-0.186	1.000

	FIRST	SECOND	THIRD	FOURTH
FIRST	1.000			
SECOND	0.969	1.000		
THIRD	0.671	0.733	1.000	
FOURTH	0.475	0.423	-0.035	1.000

Figure 5-5. Correlation matrices by 1) approach for a) left-turning movements (white), b) through movements (blue), and 2) overall intersection

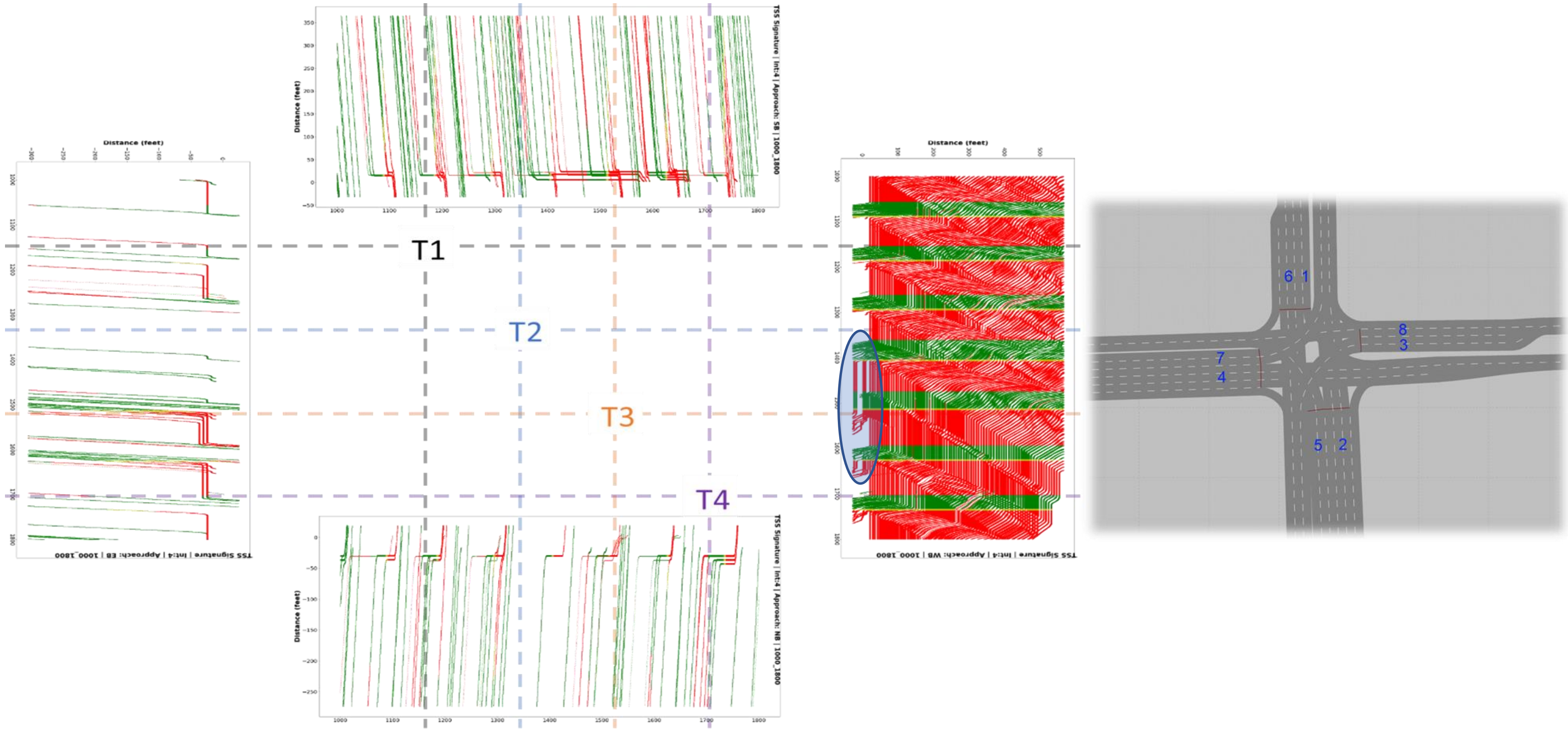


Figure 5-6. on the left a) TSS signatures of signalized approaches on the right b) VISSIM isolated intersection testbed

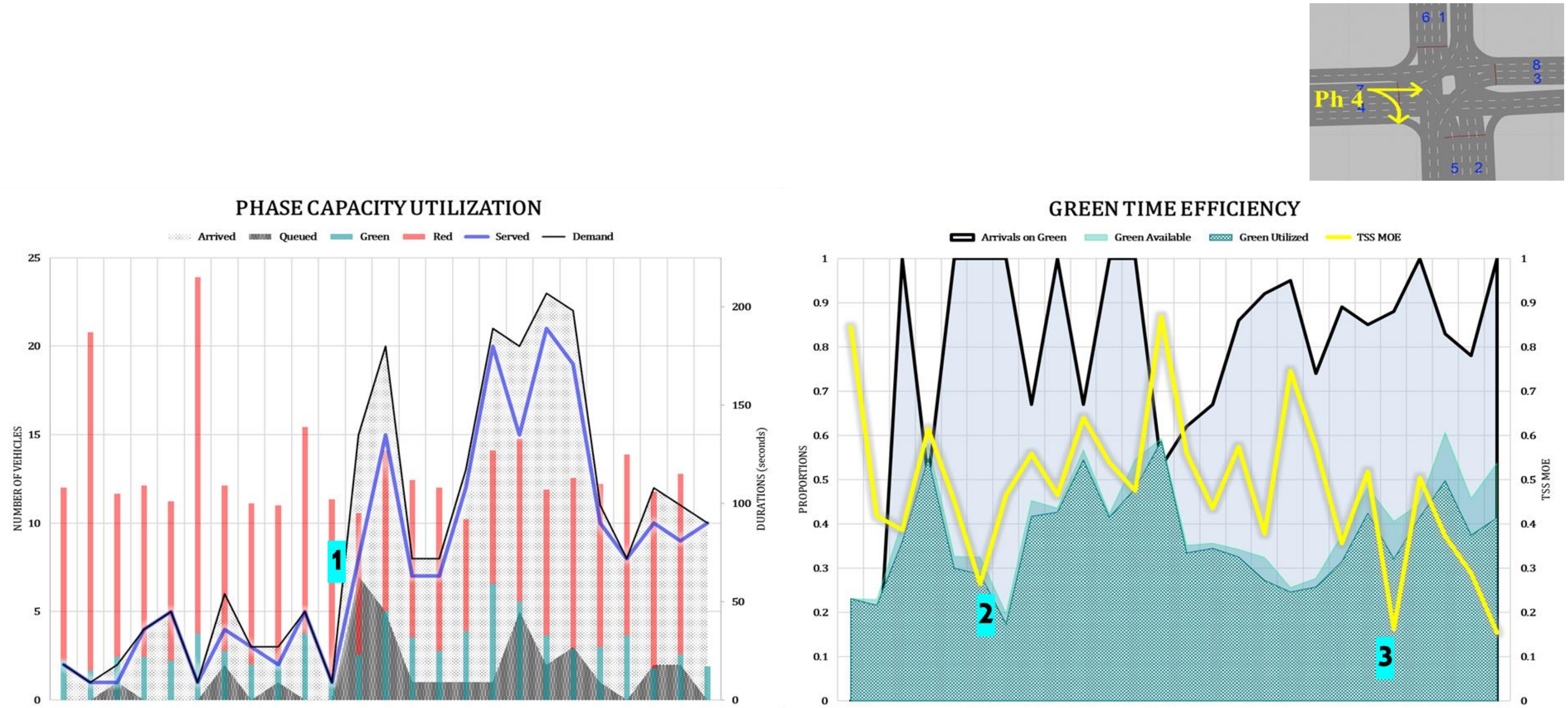


Figure 5-7. Hi-Res Performance Assessment for SG4

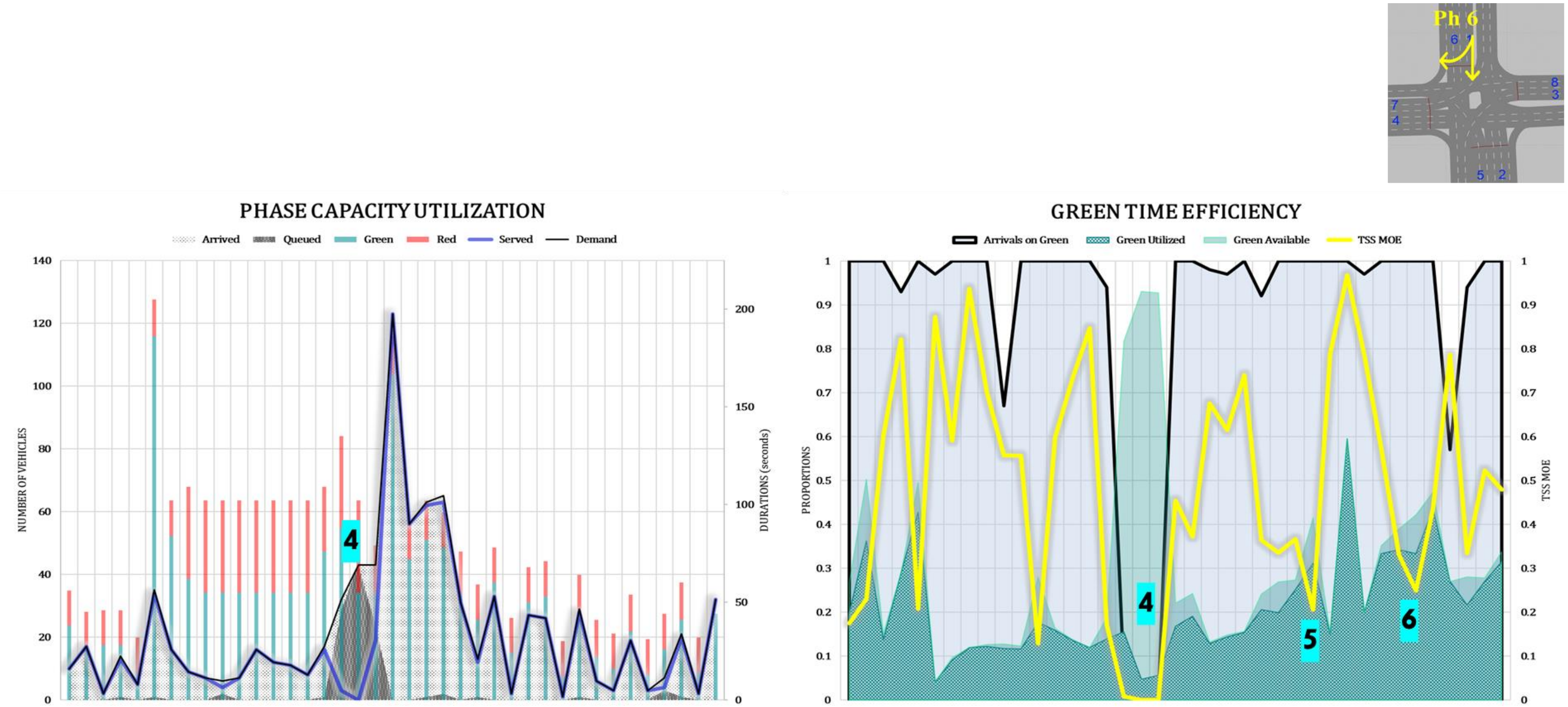


Figure 5-8. Hi-Res Performance Assessment for SG6

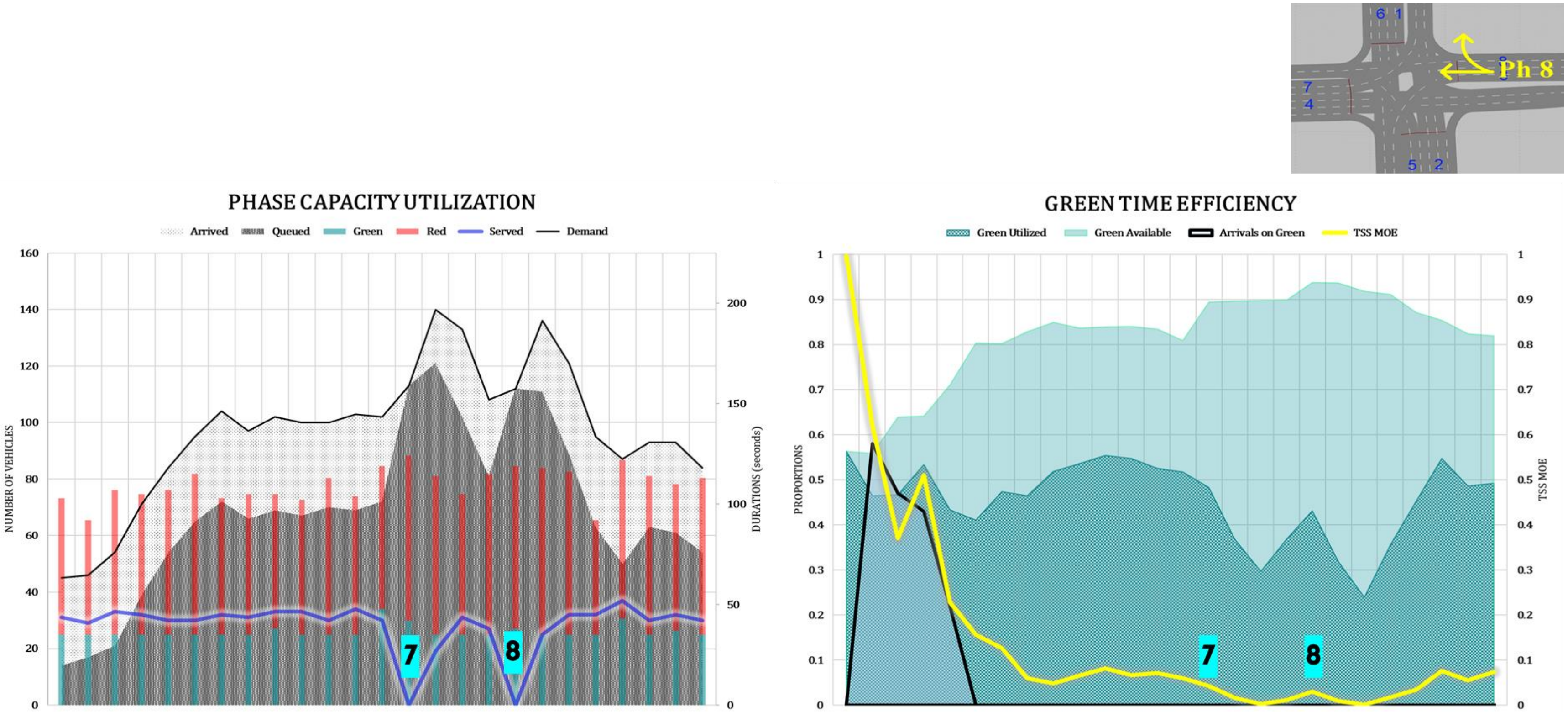


Figure 5-9. Hi-Res Performance Assessment for SG8

The large discrepancy between green utilized and green available, corresponding to point 4 in **Figure 5-8**, indicates that vehicles were unable to utilize the allotted green (even though it was available). Such a discrepancy indicates an issue not related to green duration sufficiency. Referring to the left side of the figure, the drop in the number of served vehicles accompanied by queue build up confirms unfavorable operational conditions and is reflected in the TSS MOE trend, as it drops. Interesting to note is that TSS MOE and arrivals on green, both, capture the reduction in demand, yet the TSS MOE starts to drop earlier. The TSS MOE is able to respond to changed traffic states sooner since user experience is considered cumulatively and carried over from one green onset to another. **Figure 5-8** point 4 *represents states of rather light traffic when demand exists and green is available (meaning no issue related to controller operation), yet queue builds up while no vehicle is served. The **TSS-MOE** value of 0 tells us that no vehicle was effectively moving throughout the entire SG duration.*

Unlike other Hi-Res performance indices, taken individually or jointly, ***TSS-MOE*** can capture these occurrences. A greater concern is whether these would infer the opposite of what was observed.

Focusing on point 5 on the graph to the right in **Figure 5-8**, the TSS MOE recognizes that queued vehicles from previous “cycles” (point 4) are being served. There is an accumulation of unutilized green time even though arrivals on green (prop ASoG) are increasing. Queue formation on a low-demand approach along with underutilized green time implies that through movement wasn’t timed properly relative to the reference green time at the upstream approach (offset time between adjacent intersections). The inbound demand is arriving either too early or too late at the subject approach.

At point 6, prop ASoG is high but green time is not utilized efficiently, i.e. the discrepancy between green available and utilized is increasing, indicating poor progression, since no other parameter value is unusual. Please note *our methodology utilizes vehicle count as they enter and exit the approach links within a single "cycle" if it is reasonable to assume a vehicle can physically clear said approach within that green. Analysis proposed utilizes connected vehicles' positions to detect their presence on the approaches regardless of their distance from the stop bar.*

Arrivals on green (in this study prop AOG) had been computed to reference one of the previously established success indicators that estimate service level quality, recognizing the higher the arrivals on green the better the service. However, the figures above demonstrate that such a quantifier does not represent traffic conditions nor assesses operational success accurately. For example, at points 5 and 6, high prop AOG is recorded, yet poor progression is observed, referring to discrepancy between green time available and utilized.

Figure 5-9 reveals that the WB approach experiences a steady queue buildup after which the queue remains about the same size over multiple consecutive green durations. Since the beginning of the evaluation period, it is evident that arriving vehicles outnumber the served ones, indicating allocated green time is not enough to serve the demand. Since green time utilization is consistently low, the TSS MOE is respectively decreasing, and as the number of queued vehicles increases.

At points 7 and 8 in **Figure 5-9**, ***TSS-MOE*** approaches zero as the number of served vehicles drops to zero. While arrivals on green would infer the lack of inbound demand altogether, ***TSS-MOE*** documents the presence of vehicles on the approach as well as green time availability, yet vehicles are not being served (graph on the left in **Figure 5-9**). Such circumstances indicate that aside from overflow queuing, the target approach is experiencing another more extreme issue. The most right diagram in Figure 5-6 confirms there is an approach spillback from an upstream intersection which obstructs SG8 through movement (shaded area on the most right TSS graph). As can be observed, after traversing the stop bar, vehicles are stopped and obstruct the progression of other vehicles on the same approach.

In the example above, movement-level ***TSS-MOE*** was computed to demonstrate its applicability to different operational conditions. This experiment demonstrates even Hi-Res MOEs (independently or cross-referenced) fail to represent the state of the system adequately and that innovative composite measures might do a better job with connected data. The experiment also showed that irrespective of the demand level, the amount of available green time cannot compensate for its inefficient utilization, which is something current practice is attempting in such circumstances – extend the green time available. On an aggregated level this means a larger number of vehicles spend more of their available green time – not moving.

5.3. Conclusion

An abundance of information at an individual vehicle level enables measuring traffic signal performance parameters more reliably and comprehensively. To analyze this high-quality information when assessing the quality of signal timing settings, new performance metrics are required since traditional no longer suffice the definition of state-representativeness. Combining the two, high-definition traffic signal controller and vehicle trajectory data, provides a clear framework for performance analysis and decision-making, enabling a series of (visual and quantitative) performance metrics, to be generated.

As a ***decision support tool***, depending on the nature of the analysis (identifying causes of inferior performance, traffic state characterization, service level evaluation) some or all the parameters represented in the figures above should be examined. Still, a ***complete picture*** of the health of the system and its level of performance is only possible by investigating time-space signal visual signatures along with associated performance measurements.

This study proposed a signalized approach ***performance evaluation*** method that showed potential in assessing green time and space utilization within a controlled simulation environment. To validate and extend the concept's applicability to real-world problems, future work would require information available from real-world connected vehicles' trajectories.

Definitions of performance metrics and mathematical/statistical methods thereof, are yet to be standardized. However, improvement of state-of-the-practice is imminent since traffic engineers would be able to directly measure what they previously could only estimate and model, as this research demonstrated.

From both a scientific merit standpoint as well as practical applicability, the proposed Trajectory Analytics framework fills an important methodological and practical gap whose time has come.

The evaluation method that standardizes the data formats and performance measurements that are independent of controller operation, and capable of online data archiving would establish a platform for comparing intersection/arterial performance on corridors.

Chapter 6. REAL-TIME TRAFFIC SIGNAL CONTROL

Through wireless communication, connected vehicles can exchange information with the infrastructure and among themselves, potentially generating rich data streams that can provide the basis for advanced effective management of vehicular flows through junctions and along arterials. How such information could be used for this purpose requires a fundamental view of signal-based control in a mixed traffic environment with full or only partial connectivity. This section examines the manner in which CV-transmitted information could provide the basis for adaptive signal control at intersections and develops a methodology to accomplish this purpose; it also provides a preliminary assessment of the effectiveness of such control when only a fraction of the vehicles in the traffic stream are connected.

Detailed trajectory information such as link/lane position, speed, turn movement, and acceleration can be used to track shapes of vehicle trajectories in time and space and associated properties at a finer scale to better understand interrupted traffic flow dynamics to then improve traffic performance assessment, prediction, and control.

Better insight into signal system operations is achievable by exploiting in-depth information about users' travel experience. Since the observation is independent of any spatial restrictions and unaffected by queue buildup and discharge, ***CVG*** data offer more comprehensive more reliable inputs to the traffic signal control system.

This study seeks to establish a novel real-time communication-based intelligent controller logic, which solves a phase allocation problem in real-time, based on the most comprehensive high-resolution data obtainable. Assuring applicability in a variety of traffic conditions and intersection/signal configurations, special consideration was given to traffic operations during oversaturation and how the system behaves in such circumstances. This study proposes an efficient and generic adaptive signal control algorithm for mixed-connectivity traffic environments, aimed at maximizing green time and space utilization. Such an objective was chosen to balance between low and high demand levels since these inherently require different strategies - achieving smooth flow vs congestion alleviation strategies when the smooth flow is not feasible.

This framework is intended to address two main questions in terms of ***CV***-based traffic control, i.e., mixed vehicle flow (connected or not) and combined regular and/or connected vehicle traffic control. To this end, the CVG data-based control algorithm that included regular vehicle actuation in the reactive component of the controller logic was formulated to quantify the improvement achievable if both types of observations were utilized as inputs to the controller.

During the transition from no-to-full connectivity-enabled control systems, the idea is to devise and test algorithms that are compatible with the existing infrastructure so that there is no need to replace the traditional traffic controllers. The methodology assesses the extent to which ***CVG*** data and functionalities can augment typical controller schemes relative to might have been possible through the use of ***CVG***-adaptive signal control.

Determining when enough real-time traffic information is collected from external data sources (i.e. ***CV***s), will determine which mode of operation is superior. This is why the two controller modes were isolated and their performance compared.

6.1. Problem Formulation and Methodology

One of the ways to designing more effective signal control strategies is leveraging and synthesizing connected vehicle generated (***CVG)*** information to identify traffic states for the controller to operate in a predictive, yet vehicle-actuated manner.

Many of the reviewed studies on traffic control in connected environments do not characterize real-world representative geometric, traffic, and control characteristics. These configurations can be complex, which poses a challenge to the adaptability of the models. At the same time, these studies showed that CVs market penetration rate was a critical parameter in determining the effectiveness of the associated signal control algorithms. It was thus essential to verify the performance and adaptability of the proposed strategy under different penetration rates of CVs while representing real-world operational conditions.

In a connected (vehicle-traffic signal) system, vehicle-based computations of performance indicators are integrated into the design of control system parameters. To this end, a connected (vehicle-signal) control algorithm that utilizes CVG information as inputs is formulated, and the resulting improvement quantified. This novel real-time communication-based intelligent controller logic solves a phase allocation problem in real-time, in a predictive manner, adjusting phase duration in response to the prevailing CV demand on all approaches. Within the same control algorithm, two objective functions were tested to identify the advantages of each. The two objectives were: 1) maximizing green time and space utilization and 2) minimizing delay. The first objective was chosen to balance between low and high demand levels since these inherently require different control strategies. The second, because, typically, traffic operations analysis is explained in terms of delay. If the connected vehicle can compute its delay, this attribute would be the objective to minimize.

The manner in which the real-time traffic information collected from external data sources (i.e. ***CV***s) is utilized within the same controller logic, would determine which mode of operation is superior i.e. which of the two objectives should be responsible for signal control parameter optimization. This is why the two controller modes were isolated and their performance compared.

The adopted analysis framework addresses two main questions in terms of CV-based traffic control. The first is to assess to what degree the connected infrastructure – CV data, and functionalities – can add in terms of designing a more efficient (CV-based) traffic control, compared to the conventional NEMA-RBC. The second, to identify ways to advance signal control algorithms by fully leveraging CV sensing, communication and computing capability.

The trajectory analytics method, therefore, quantifies the extent to which CVG data and functionalities can augment typical controller schemes. Comparing two measures of effectiveness of a decision within the same connected algorithm setup provides an upper bound on the potential effectiveness of a more-responsive control strategy. The goal is to evaluate the robustness of CV-based control models and their ability to improve traffic operations in a range of operational conditions and demand levels.

A prerequisite of such an approach is the application of the devised procedure for segmentation and clustering of traffic flows based on ***CV*** trajectory data, presented in Mittal et al. (*101*).

Given most recent ***CVG*** data, signal group status and estimated temporal gaps in platoon arrivals, group CVs into platoons and aggregate ***TSS-MOE*** and other **PI**s to platoon level. Next, priority ranking of platoons is carried out, in terms of associated (lowest) ***TSS-MOE*** value to determine the subset of critical platoons to form Candidate Phases – those overlapping in arrival and departure times determine the phases which flag immediate requests for service).

The priority rank sets up, on conflicting approaches, platoons with the earliest time-to-intersection as critical platoons. From these, candidate phases are identified, and the opportunity cost calculation is performed to weight the additional travel time of unserved against the travel time savings of served platoons.[1]

TSS-MOE-based signal control optimization logic is the key aspect of the contribution that needs to be further extended and explained - please refer to reference (*102*) for details on MOEs functional form and characteristics presented in **Equation 5-1**). A newly developed Time-Space Signal (TSS) index assesses the utilization of green time and space dimensions of a signalized approach. The index synthesizes information from *vehicle trajectory* and *signal-phase and time* (or SPaT) data into a quantifiable traffic state-responsive parameter.

What distinguishes these measures (and approach) is that they reflect the system's operational success from its users' perspective. The information is cumulative in time and space and carries over from one "signal cycle" to another. The aggregate measure scales the contribution of each vehicle. Single vehicle's **TSS-MOE** value is weighted by its respective travel time, so the contribution of vehicles traveling shorter distances (spending less time in the system) would not be overestimated, and vice versa, in the overall (aggregated) **TSS-MOE** measurement.

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[1] Refers to subset of previously prioritized platoons i.e. Candidate Phases, not **ALL** platoons on **ALL** approaches

The proposed algorithm is expected to demonstrate responsiveness to different traffic vehicular mixes, demand levels, and fluctuations in arrival patterns. Special consideration was given to traffic operations during oversaturation and how the system behaves in such circumstances. If an approach is the heaviest in terms of delay or demand, or both - ***TSS-MOE*** will reflect it and assign the right of way accordingly. This is another reason for the objective function choice, i.e. recognizing such circumstances inherently, not treating a movement preferentially a priori. In cases of non-standard intersection/signal phasing configurations, NEMA-RBC phasing standards would apply, and the number of workable phasing scenarios might increase if the 5^{th} approach existed, yet controller logic would remain the same.

The overall system architecture will be presented in the following subsection. Next, an extension of the dual-ring traffic controller is introduced, followed by a description of the signal timing optimization method utilized.

6.2. Connected Controller Conceptual Framework

An adaptive signal control algorithm for connected and mixed-connectivity traffic environments is proposed, aimed at maximizing utilization of green time and space. As part of the quality of service evaluation method this measure was used to diagnose performance levels, and here, the same measure, as it will be demonstrated, can be used for control purposes – to develop more efficient traffic control strategies.

An intelligent vehicle-actuated controller logic computes vehicle-based performance metrics to optimize control parameters in real-time. The method puts forward a predictive control logic that determines the next best phase to serve and continually evaluates its duration in response to the prevailing CV demand pattern and associated performance indicators on all approaches of the intersection. This control scheme assumes movement-based analysis built on NEMA-RBC dual-ring phasing configuration, due to which prerequisite compatibility between movements and controller phases is required.

Figure 6-1 represents a high-level architecture of a connected traffic signal control framework, based on the information received through – 1) communication among the controller and CVs, 2) CV and regular detection of inbound vehicles. V2I communication enables CVs to share their ***CVG*** data such as position, speed, turning movement with respect to the immediate downstream signal, and timestamp when this information was recorded. The overall modeling framework for real-time advanced traffic control applications in mixed traffic environments comprises of three interactive components (**Figure 6-1**) – 1. Traffic State Monitoring 2. Phase Planner (PP) and 3. Real-Time Regulator (RT).

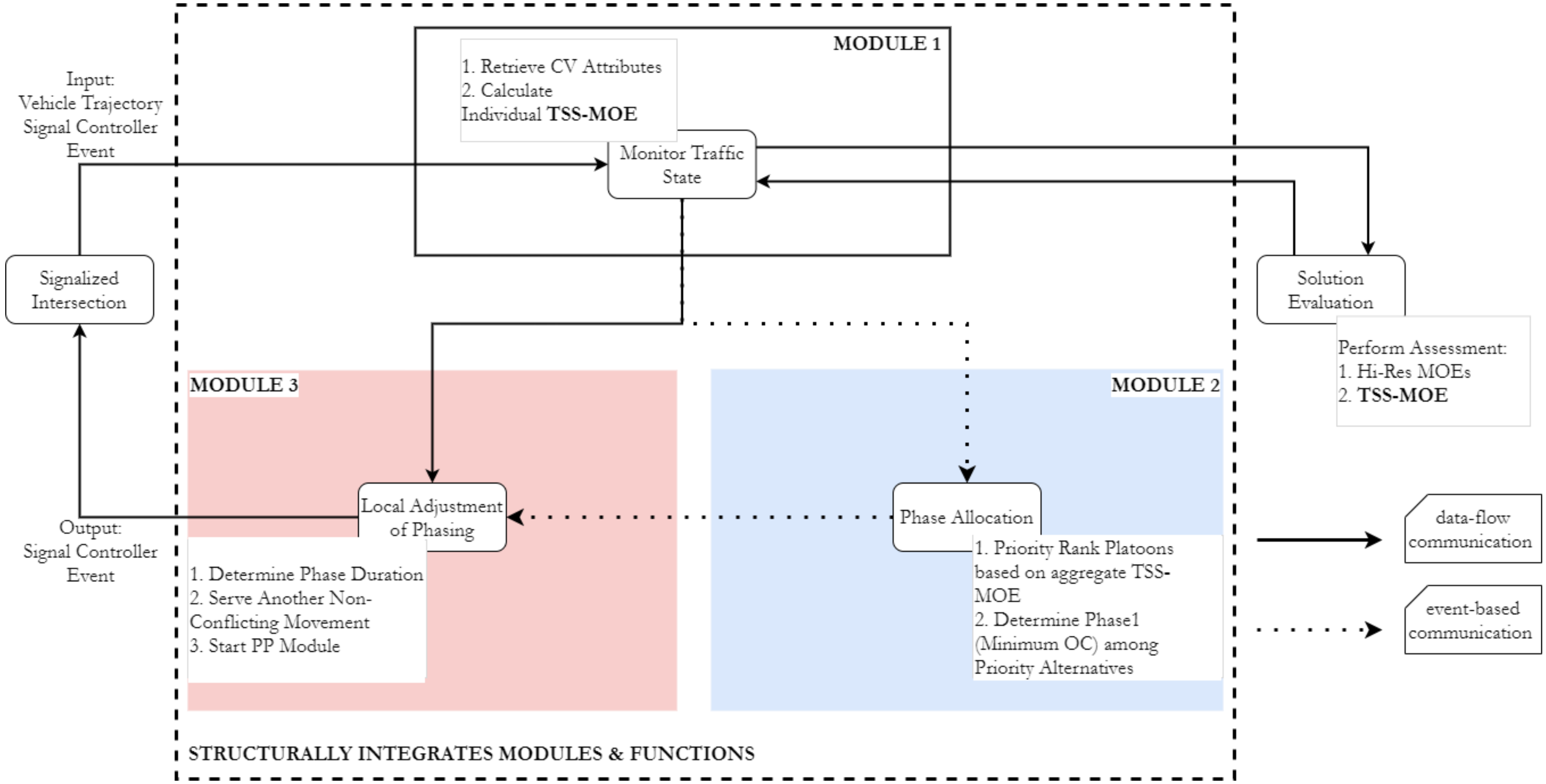


Figure 6-1. Real-Time Control Conceptual Framework

As part of an integrated and interdependent structure, the system allows for communication between modules. In a continuous process, CVs periodically transmit information related to their position speed and routing information, and the timestamp this information was recorded.

This ***CVG*** data support calculations of relevant performance measurements for phase allocation to determine the next phase in module 2. This information is then communicated to module 3 where local adjustment of phasing and duration is performed.

While data flow between module 1 and module 3 is continuous, module 2 exchanges information with the other 2 once specific criteria are met, meaning it is event-based.

The prevailing traffic state – captured via Hi-Res explanatory variables is calculated based on information transmitted by CVs only, and here on out will be referred to as the ***CVG*** data. In a continuous process, CVs periodically transmit information related to their status (every 0.2 seconds). Each record contains current position, speed, the direction of travel, and a timestamp of the instance when this data was transmitted. The direction of travel refers to the routing information i.e. turning movement with respect to the immediate downstream signal.

At the start of the planning module execution, ***CVG*** data is retrieved from the "real-world" i.e. ***RT*** module as the most up-to-date information on traffic configuration. ***CVG*** data forms core information for the ***PP*** module estimation of platoon progression.

If the ***PP*** module can be referred to as the planning or predictive part of the control framework then the ***RT*** can be referred to as the reactive component of the same system. The overall conceptual framework can be then seen as the combination of both predictive and reactive. The connected controller stores (over time and space) and processes relevant information only when needed yet it reacts to continually updated requests, re-distributed among equipped vehicles.

Via real-time feedback loop, the controller verifies whether the implemented solution is still "optimal" considering what is occurring on other approaches.

The connected controller framework is referred to as the "smart" or "intelligent" controller because it uses an intelligent transportation system's information to control signal phasing. It is actuated on both connected and regular vehicle sensing infrastructure since this study presents the control logic that uses information from both. Flexibility in the context of this study refers to sequence as well as phase duration variability. At this point, it is necessary to point out that other control methods do not achieve the same kind of "flexibility".

The control scheme proposed in this study assumes a flexible phasing sequence, which is vehicle trajectories (data)-driven. There is no notion of cycle length as such. The devised controller logic is generic thus transferable to any intersection configuration and controller type of operation without restrictions on the number of approaches, type of vehicles, etc. The method focuses on operational logic and ease of implementation.

The following are the low-level controller components:

a.) Controllers' detection capability needed to monitor regular vehicles assumes relevant sensors observation availability along inbound directions – regular detection at the stop bar

b.) Traffic controller receives desired turn directions of ***CVs***

c.) The controller estimates movement-based ***CV*** demand and respective aggregated cumulative traffic metrics and most importantly ***TSS-MOE***

d.) ***PP*** or phase planning module (as seen in blue in **Figure 6-5**) utilizes vehicle-based performance metrics on an aggregated level to optimize control parameters i.e. generate optimal settings; and e.) Optimized SPaT is implemented in ***RT*** for local adjustment of phasing and duration (see **Figure 6-5**).

This framework formulates an advanced, online, signal control logic for mixed traffic environments utilizing the information from ***CVs*** only (1) and to augment controller/sensor data (2). A prerequisite of such an approach is the application of the devised procedure for segmentation and clustering of traffic flows based on ***CV*** trajectory data. Unlike conventional gap-out platooning methods, utilizing a critical headway threshold of 2.5 seconds to distinguish between platoons, platooning in this study adopts a concept first proposed in Mittal et al. (*101*). The platooning function was applied in the planning stage to group vehicles per movement/phase. Depending on their inter-vehicular variation, the proposed concept explicitly considers inherent discontinuities in traffic patterns.

6.3. Traffic State (Parameter) Monitoring Module

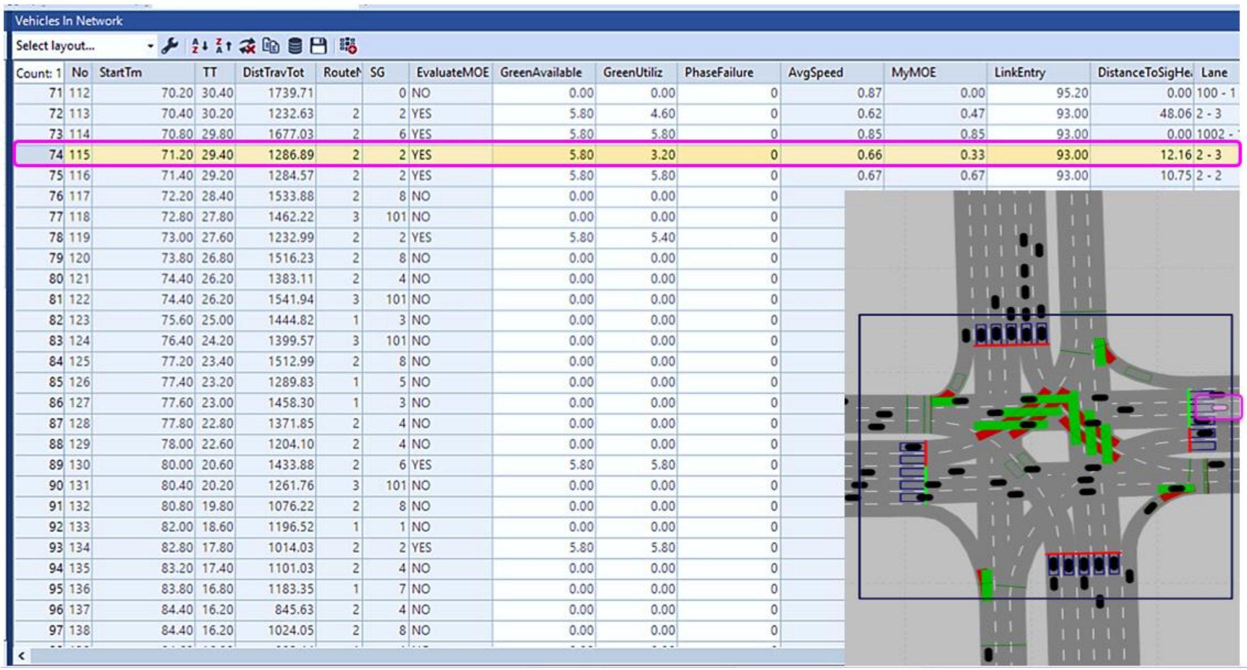
The traffic state monitoring module assumes high-frequency continuous updating of the state of the system or traffic parameters in terms of ***CV*** trajectories data on inbound approaches. Hi-Res explanatory variables defined in the monitoring module are at the core of both planning and real-time module.

The architecture in **Figure 6-1** is designed to take full advantage of ***CV*** sensing, communication, and computation capabilities.

In that regard, the computational burden on the controller itself is lessened since it is redistributed among equipped vehicles. In this setup, ***CV***s are assumed to record specific events such as the onset of green/red and calculate relevant indicators such as time in green/red which are then communicated to the connected controller.

The traffic controller is assumed to record the intersection's traffic configuration and state. The state of the system is being monitored within a prespecified distance[2]. This study designs a decentralized (local) logic where the connected controller maps positions of ***CV*** vehicles (X and Y coordinate) onto the physical roadway layout corresponding to movement/phase lane groupings. Please note that routing information corresponds to the turn indication at the immediate upstream approach. As the controller is aware of the actual traffic configuration, it can compute performance indicators on an individual vehicle level and then aggregate them over space and time on all approaches.

[2] The distance is variable and adjustable depending on the actual physical corridor/intersection configuration



Count: 1	No	StartTm	TT	DistTravTot	RouteN	SG	EvaluateMOE	GreenAvailable	GreenUtiliz	PhaseFailure	AvgSpeed	MyMOE	LinkEntry	DistanceToSigHe	Lane
71	112	70.20	30.40	1739.71		0	NO	0.00	0.00	0	0.87	0.00	95.20	0.00	100 - 1
72	113	70.40	30.20	1232.63	2	2	YES	5.80	4.60	0	0.62	0.47	93.00	48.06	2 - 3
73	114	70.80	29.80	1677.03	2	6	YES	5.80	5.80	0	0.85	0.85	93.00	0.00	1002 -
74	115	71.20	29.40	1286.89	2	2	YES	5.80	3.20	0	0.66	0.33	93.00	12.16	2 - 3
75	116	71.40	29.20	1284.57	2	2	YES	5.80	5.80	0	0.67	0.67	93.00	10.75	2 - 2
76	117	72.20	28.40	1533.88	2	8	NO	0.00	0.00	0					
77	118	72.80	27.80	1462.22	3	101	NO	0.00	0.00	0					
78	119	73.00	27.60	1232.99	2	2	YES	5.80	5.40	0					
79	120	73.80	26.80	1516.23	2	8	NO	0.00	0.00	0					
80	121	74.40	26.20	1383.11	2	4	NO	0.00	0.00	0					
81	122	74.40	26.20	1541.94	3	101	NO	0.00	0.00	0					
82	123	75.60	25.00	1444.82	1	3	NO	0.00	0.00	0					
83	124	76.40	24.20	1399.57	3	101	NO	0.00	0.00	0					
84	125	77.20	23.40	1512.99	2	8	NO	0.00	0.00	0					
85	126	77.40	23.20	1289.83	1	5	NO	0.00	0.00	0					
86	127	77.60	23.00	1458.30	1	3	NO	0.00	0.00	0					
87	128	77.80	22.80	1371.85	2	4	NO	0.00	0.00	0					
88	129	78.00	22.60	1204.10	2	4	NO	0.00	0.00	0					
89	130	80.00	20.60	1433.88	2	6	YES	5.80	5.80	0					
90	131	80.40	20.20	1261.76	3	101	NO	0.00	0.00	0					
91	132	80.80	19.80	1076.22	2	8	NO	0.00	0.00	0					
92	133	82.00	18.60	1196.52	1	1	NO	0.00	0.00	0					
93	134	82.80	17.80	1014.03	2	2	YES	5.80	5.80	0					
94	135	83.20	17.40	1101.03	2	4	NO	0.00	0.00	0					
95	136	83.80	16.80	1183.35	1	7	NO	0.00	0.00	0					
96	137	84.40	16.20	845.63	2	4	NO	0.00	0.00	0					
97	138	84.40	16.20	1024.05	2	8	NO	0.00	0.00	0					

Figure 6-2. Traffic State Monitoring Simulation Setup

6.4. Signal Control Planner Module – Phase Planning (PP)

Module 2 or phase planning module sets up a phase allocation problem, which is essentially a platoon-phase scheduling problem and prerequisites grouping the vehicles into platoons based on their temporal and spatial proximity. ***PP*** schedules the next phase by minimizing the opportunity cost of serving a critical platoon at the expense of other unserved platoons. The following control problem is the core of the control logic i.e. its planning module:

Given:

$\boldsymbol{CVG}\ data,\ Signal\ Group\ Status$

$veh_{\boldsymbol{ph}} - set\ of\ CV_s\ in\ (platoon - phase)\ ph$

$t_{ph}^{a} - time\ of\ arrival,\ \ t_{ph}^{d} - time\ of\ departure\ of\ ph$

$TSS - MOE_{cv},\ \ TT_{cv},\ \ \forall cv \in veh_{\boldsymbol{ph}}$

$$MOE_{ph} = \sum_{cv \in veh_{ph}} \frac{TSS - MOE_{cv}}{TT_{cv}} - performance\ index\ of\ ph$$

$Priority_{ph} = \ rank\left(MOE_{ph},\ t_{ph}^{a},\ \ t_{ph}^{d}\right)$

$Can_{\widetilde{ph}}\ \subseteq\ Priority_{ph}$

$$\widetilde{ph} = \begin{cases} ph \in\ Can_{\widetilde{ph}} & if\quad t_j^a <\ t_{j'}^d\ \ \wedge\ \ t_j^d > t_{j'}^a \\ ph \notin\ Can_{\widetilde{ph}} & otherwise \end{cases} \qquad \forall\ j, j'\ \in ph\ \ j' \neq j$$

Variable: x_i

Objective Function:

$$minimize\left(\frac{Cost_i}{C_{ii}}\right) \times x_i$$

$$x_i = \begin{cases} 1 & if\ \ phase\ i\ selected \\ 0 & otherwise \end{cases} \qquad \forall i\ \in Can_{\widetilde{ph}}$$

$$\textstyle\sum_i x_i = 1 \qquad \forall i\ \in Can_{\widetilde{ph}}$$

$$C_{ji} = \left(\ t_i^d - t_j^a\right) \times N_j \qquad Opportunity\ Cost\ for\ phase\ j\ if\ phase\ i\ is\ selected$$

$$Cost_i = \sum_{\substack{j \in Can_{\widetilde{ph}} \\ j \neq i}} C_{ji} \qquad Total\ Opportunity\ Cost\ for\ unserved\ phases\ if\ phase\ i\ is\ selected$$

$Vehicles\ respect\ laws\ of\ physics$

$Drivers\ follow\ Wiedemann\ 74\ car\ following\ model\ (enhanced\ for\ \boldsymbol{CV}_s)$

$No\ frequent\ switching\ between\ phases\ in\ real - time\ module^*$

$Upper\ bound\ on\ gap - out\ distance\ in\ real - time\ module^*$

Figure 6-3. Control (Phase Planning) Problem Formulation

The platooning method applied here is the so-called platoon self-identification method – a novel approach for partitioning vehicles into platoons named Adjusted Spatial Longitudinal Variation (ASLV) clustering, designed by Mittal et al. (*101*).

Signal Control Planner or Phase Planning (***PP***) module aims to dynamically optimize signal control settings when supplied with real-time traffic information. The solution method is based on a platoon-phase heuristic in **Figure 6-3** that has been designed to decide phase allocation in an acyclic manner.

The ***PP*** module estimates traffic conditions according to ingested ***CVG data*** from the ***RT*** module. Based on this information, signal group status is determined for the immediate next time step. ***CVG data*** is the "current state of the system" and characterizes the real-world traffic conditions. As soon as the most up to date ***CVG data*** from ***RT*** is available, the new ***PP*** "cycle" starts i.e. vehicles are grouped into platoons and an aggregate ***TSS-MOE*** is attributed to each.

The most critical platoons in terms of ***TSS-MOE*** thus all feasible phasing scenarios are identified to form the subset $Can_{\widetilde{ph}}$.

Here, the phase combinations consist of any two non-conflicting signal groups. The connected controller builds on NEMA-RBC dual-ring phasing configuration, due to which prerequisite compatibility between movements and controller phases is required.

"Feasible phasing scenarios" refer to potential phase combinations that account for and give the right of way to the movement if: (1) it is the worst-performing in terms of ***TSS-MOE*** (compared to that of any other movement and is considered to be the reference movement) and (2) the time of arrival and departure is estimated to be overlapping with that of the reference movement. Each phasing scenario that satisfies these two conditions serves critical inbound demand. For each platoon or $\widetilde{ph}$, $\widetilde{ph} \in Can_{\widetilde{ph}}$, corresponding ***TSS-MOE*** function value, MOE_{ph}, is recorded and the earliest time of arrival as well.

This subset of platoons is to be evaluated each time phase planning is called to assign NextPhase. At this point, the opportunity cost of serving one at the expense of another among the highest-ranked platoons is calculated and determines which movement groups should be given the right of way. If identical ***TSS-MOE*** is attributed to two distinct platoons on conflicting approaches, the one with the higher number of vehicles would be prioritized.

$Can_{\widetilde{ph}}$ are not pre-established but generated whenever multiple-phase combinations are identified by the algorithm as phasing alternatives to manage prevailing demands. The purpose of vector $Can_{\widetilde{ph}}$ is to limit the search space and reduce computational effort.

Priority ranking of movements (aggregate cumulative ***TSS-MOE*** value) governs the “optimal” next phase selection; however, the control problem is then solved by minimizing the opportunity cost for the overall system. To determine which phase to serve next, from the (highest*) priority ranked (or candidate phases), the opportunity cost is calculated relative to time savings if one movement is to be discharged instead of another (already ranked as priority i.e. $\widetilde{ph} \in Can_{\widetilde{ph}}$).

Multiple criteria decision-making approach was chosen to identify, compare, and evaluate the alternatives since the two main criteria (objectives) are conflicting.

To achieve a more efficient control strategy the opportunity cost calculation was formulated to weigh the priority ranking in terms of ***TSS-MOE*** according to estimated arrival times against the additional travel time incurred. Opportunity cost in this study is defined as the additional waiting time incurred by a non-served movement due to the right of way afforded to the served one. Overall opportunity cost is then aggregated over all unserved movements (platoons) to give the total cost of serving a movement platoon at the expense of all others.

The opportunity cost function decides whether it is "reasonable" for a platoon to cross the intersection unimpeded, given the information on respective signal groups indication status.

Since signal group status is known and the vehicles are assumed to be progressing at currently attained speeds, based on the distance from the stop bar, arriving $\boldsymbol{CV}$s can either 1) be served during the current green or 2) stopped to wait for the next green indication.

For each $\boldsymbol{CV}$ platoon, distance to stop bar and the required range of speeds is known, thus arrival and clearing times. Vehicles are projected to attain their "current" speed within the moving platoon when estimated whether they will reach the stop bar after the onset of green. If the first arriving vehicle is anticipated to arrive after the onset of next red, they will be stopped thus increasing overall travel time along the route. Opportunity cost varies with the movement's clearing time. The estimated time required to serve the movement is defined as the time difference between the exit of the last vehicle and the arrival of the first vehicle in the platoon.

Such rationale was necessary for two reasons: 1) another movement (immediate request or queue formed) can be served if the estimated arrival time of the critical platoon allows for it and 2) there was no need to account for (thus increase computational burden on the controller) platoons arriving after the critical regardless of their respective $\boldsymbol{TSS\text{-}MOE}$.

The movement-phase for which this opportunity cost is minimal is the $NextPhase$ i.e. phase to change the status to green in $\boldsymbol{RT}$ and signal groups status information is fed to $\boldsymbol{RT}$.

Considering NEMA-RBC non-conflicting phasing combinations, the algorithm then continues to find a potential concurrent phase, $Phase_2$, if warranted by the demand thus state indicators calculations.

Another platoon can be served along with the optimal platoon as long as their phases are not conflicting. To determine if multiple platoons that can be served together, the opportunity cost function is called again conditioned upon 1) signal groups concurrency and 2) temporal proximity.

Main, primary phase or $Phase_1$ is associated with the lowest opportunity cost (and ideally ***TSS-MOE)*** value and corresponds to the platoon that should be served next. For this phase, a concurrent one is determined, $Phase_2$, corresponding to NEMA-RBC phasing nomenclature for dual-rings. Since each phase can run concurrently with either of the 2 non-conflicting phases, the one performing worse will be selected to run with the primary phase this is to say as its concurrent $Phase_2$.

If there is no ***CV*** demand on either nonconflicting phase, only $Phase_1$ will be given the right of way.

6.5. Real-Time Module

The ***RT*** module represents the actual real-world timeline for the implemented connected controller. The microsimulation model emulates real-world traffic and operational conditions and runs at the same rate as the actual physical system.

Since the connected controller can receive the information from ***CVs*** at every updating interval, it capable of monitoring and computing signal control performance metrics for said vehicles. For a preset frequency of information update, traffic state attributes are estimated for each movement-phase pair and being transferred, dynamically, from one system component to the other.

At the start of ***PP*** module execution***, CVG*** information is communicated from monitoring and ***RT*** to ***PP,*** and platoon progression (and associated features) estimation initializes. At the end of execution, the ***PP*** module generates “optimal” phasing advice for the ***RT*** module to implement in real-time. These two data exchanges are executed continuously in real-time.

As soon as the phase’s status changes to active, the ***RT*** takes over and continues updating individual vehicle’s ***TSS-MOE*** and other explanatory variables, while simultaneously reevaluating the solution implemented. While executing previously communicated optimal SPaT, an ongoing local evaluation:

1. decides when to terminate currently active phase
2. decides the optimal strategy within the transitioning logic
3. decides whether to call the ***PP*** module

The core of the ***RT*** module is the so-called local adjustment of phasing.

Local adjustment of phasing lessens the computational efforts on the controller as it only considers immediate approaches to the intersection or immediate requests as opposed to the overall ***CV*** inbound traffic. Unlike the planning module that looks ahead and accounts for inbound demand's projected arrivals, the ***RT*** module considers only the demand that is either 1) queued or 2) arriving within at most 5 seconds of currently active green.

In such a manner, ***RT*** tries to clear the queue before the platoon arrives, yet it does not extend the green unless most up to date ***CVG*** data-based calculations warrant such actions. Similarly, the transitioning logic determines whether another concurrent phase is to become active, swap ranks, or terminate all active phases. Addressing these operational challenges can be prohibitive computationally for real-time applications, which is why the proposed method reduces the effort, by valuing immediate requests and their magnitude within the presented transitioning mechanisms rules.

The flowchart in **Figure 6-4** conditions a heuristic to recognize the immediate request for service at each approach/movement as well as respective weights after termination criteria are satisfied. If among those requesting immediate service is the currently active one green is extended if it can run with another that is performance-wise critical the same applies, yet phase swapping occurs. This way the newly labeled Phase1, since it requires more green time, will be evaluated whether to continue, in the next time step and determine whether the ***PP*** module will be called. If such action occurs a flag is recorded to avoid alternating between the same 4 (**directional)** phases, multiple times while the unserved direction experiences further degradation in performance.

Also, swapping between Phase1 and Phase2, solves the problem of extremely short greens, if another phase compatible with Phase1 is activated, but criteria for Phase1 termination are met with the next update information update.

The rule-based approach also determines whether some other two phases should initiate instead of the current ones. NextPhase function within the ***PP*** module is called and whether Phase1 and Phase2 will be reassigned depends on the weight on the immediate request, but also the opportunity cost calculation.

Phase Planning takes place once currently active signal groups meet the termination criteria and decide the optimal action for the immediate next ***time step*** based on the measured parameters.

Even if the NextPhase determines a specific movement as critical it does not mean its immediate request will warrant its actuation in the next time step.

The algorithm (in real-time) continuously checks, with a frequency of 0.2 seconds, whether active phase(s) requires additional phase time, given that additional vehicles might arrive before the phase has terminated. If this is the case, the green will be extended to service inbound vehicles, conversely, if the demand has cleared the intersection earlier than expected, the green terminates.

After the minimum green time is reached the phase *gaps out* if no inbound ***CV*** is observed or the first arriving vehicle is positioned further than the prescribed distance to stop bar. It should be noted that the concept is considering a distance *gap out*. The extension is enabled if vehicles are still incoming, but no other movement is critical.

The controller continuously monitors ***CV***s within the predefined distance from the controller, so it can measure their utilization of green time and space as experienced by individual vehicles.

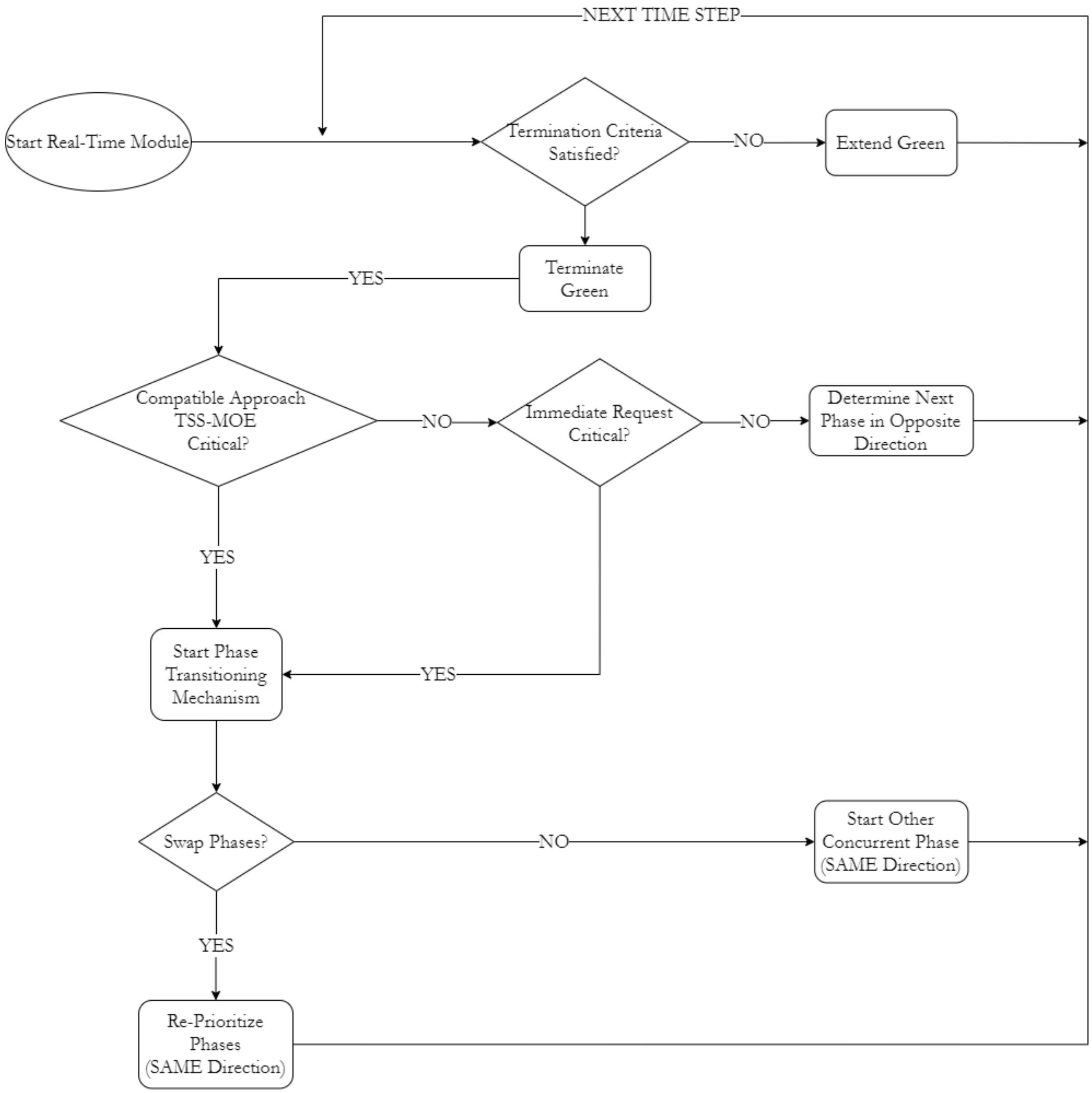


Figure 6-4. Real-Time Module Flow of Information and Processes

Addressing these operational challenges can be prohibitive computationally for real-time applications, which is why the proposed method reduces the effort, by valuing immediate requests and their magnitude within the presented transitioning mechanisms rules.

By using ***CVG*** inputs and measures the ***RT***'s transitioning mechanism rather than switching between individual phases, considers non-conflicting groupings of movements when deciding on the next action in real-time. If among those requesting immediate service is the currently active one green is extended if it can run with another that is performance-wise critical the same applies, yet phase swapping occurs. This way the newly labeled Phase1, since it requires more green time, will be evaluated whether to continue, in the next time step and determine whether the ***PP*** module will be called. If such action occurs a flag is recorded to avoid alternating between the same 4 **directional** phases, multiple times while the unserved direction experiences further degradation in performance.

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The controller continuously monitors CVs within the predefined distance from the controller, so it can measure their utilization of green time and space as experienced by individual vehicles.

The control scheme proposed in this study assumes a flexible phasing sequence, which is vehicle trajectories (data)-driven. There is no notion of cycle length as such, the controller is unrestricted when scheduling platoon-based phases. The method does not require complex mathematical and/or statistical models and ***focuses on operational logic and ease of implementation***. Devised controller logic is generic thus transferable to any intersection configuration and controller type of operation without restrictions on the number of approaches, type of vehicles, etc.

6.6. Platoon-Phase Scheduling Heuristic

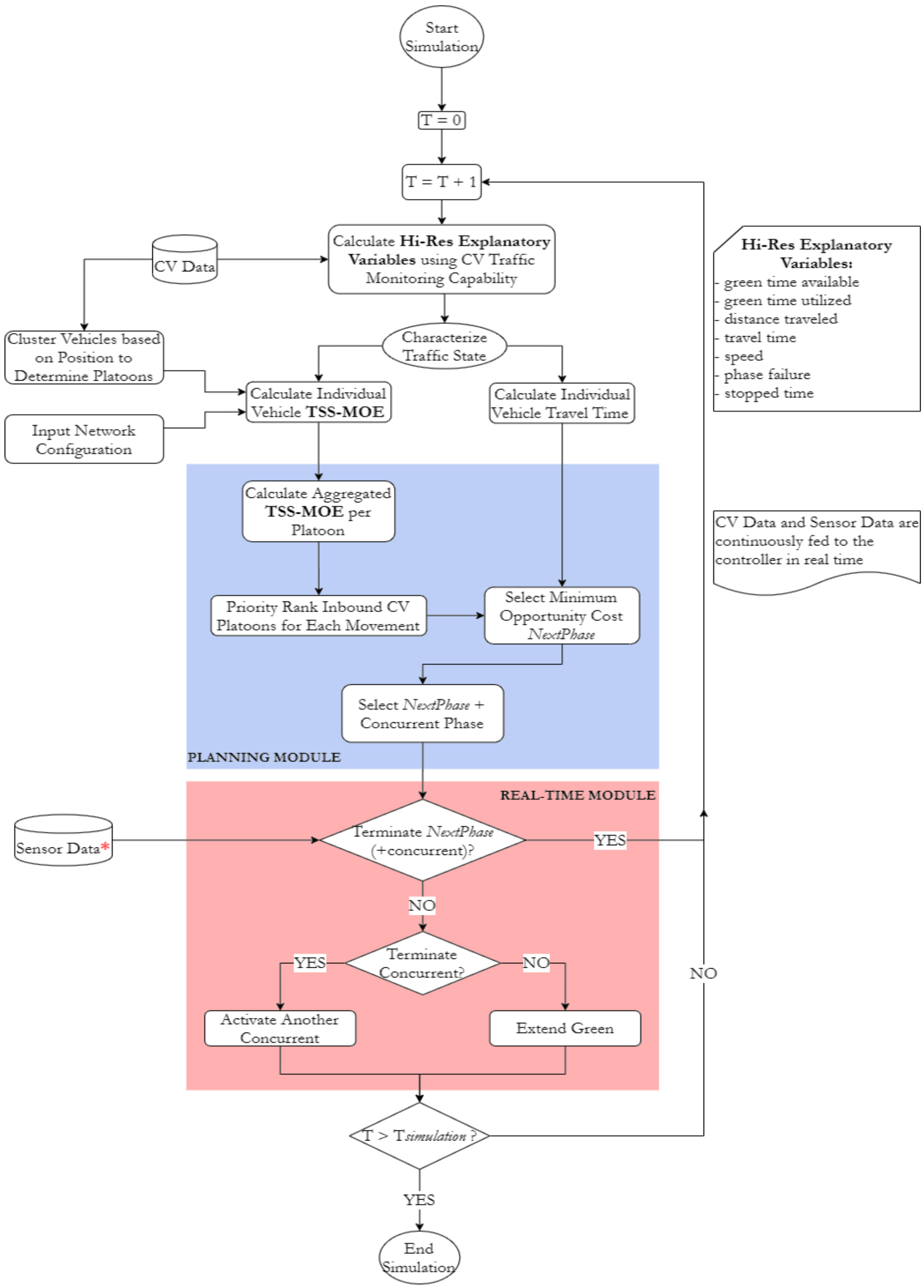


Figure 6-5. Control Algorithm – Platoon-Phase Scheduling Heuristic

Real-Time Control Algorithm (**Figure 6-5**) represents the flow of information between the monitoring predictive and real-time component and the iterative nature of the process.

The solution method is based on a **heuristic that has been designed to schedule phases in an acyclic manner and over a planning horizon.**

After the monitoring module supplies the information, the planning schedules the $NextPhase,$ its output prompts respective signal groups status information to be fed to $\boldsymbol{RT}$. $\boldsymbol{RT}$ applies the changes and continues to react to updated requests for service distributed among equipped vehicles. Once modules have transferred respective outputs these steps are iterated until the preset time frame is exhausted.

In the case of ***CV+RV*** operational logic, regular vehicle information augments ***CVG*** data to determine phase duration in real-time – similar to the NEMA-RBC free-running controller type of operation. Hence, sensor data in the figure refers to, both, ***CV*** and ***RV*** information. In the case of ***CV*** only based sensing, the controller considers ***CV*** data only. And sensor data is ***CV*** data.

Since the three modules, Monitoring, Real-Time (***RT***), and Planning (***PP***), are interacting with one another each time ***PP*** is called from the ***RT***, the ***PP*** solves the platoon-phase scheduling problem as described below at two stages. First, for each of the identified platoons, corresponding arrival times are determined. Individual vehicle ***TSS-MOE*** is computed weighted by respective ***TT*** then aggregated per platoon and used as the basis of the optimization procedure. Then, for the highest-ranked i.e. most critical in terms of ***TT*** weighed ***TSS-MOE***, opportunity cost calculation is performed to identify the minimum over all the (Candidate Phase) platoons.

The decision variable, in the control problem which minimizes the “opportunity cost” function, is the next phase to change status to active. However, the heuristic is designed to operate concurrency phasing groups since these (phases) time together.

Based on the prevailing traffic state on all inbound approaches, the ***PP*** computes opportunity costs of each alternative in $Can_{\widetilde{ph}}$ to determine control settings associated with the optimal objective function value.

The ***RT*** module conducts required calculations for local adjustment of phasing at three levels termination, transitioning, and feedback evaluation. Unlike with regular vehicles, ***CV*** trajectory uncertainty is eliminated, since at each time step, ***CVG*** data is transmitted, and ***RT*** updates relevant attribute values on an individual level. The control parameters are being optimized considering restrictions such as distance-based extension time. The method is conceived to enable data-driven verification of whether the implemented solution had worked via a control feedback loop. In such a way the algorithm determines whether one of the active phases is to be terminated and another concurrent given the right of way. Conditioned upon the main phase still being the critical one, the heuristic activates another compatible phase while it continues to update individual vehicle’s properties and check the immediate requests at every 0.2 seconds.

RT in real-time updates movement-level ***TSS-MOE*** and calls ***PP*** every time the main phase i.e. $Phase_1$ is about to terminate. It evaluates whether $Phase_1$ or $Phase_2$, or both, should continue running. If $Phase_1$ is to be terminated (and/or $Phase_2$) ***RT*** calls ***PP*** to start the procedure of determining the highest priority ranked movement-phase pairs. If overall reevaluated as required to stay active $Phase_1$ status does not change. ***RT*** also verifies whether $Phase_1$ should at current timestep become $Phase_2$ since another compatible phase was determined as critical. The ***PP***

verifies (based on the data from the real-time component) whether another conflicting movement became the least efficient one and if confirmed, the main phase is terminated regardless of the inbound demand on said phase.

6.7. Communication Between Modules

The controller consists of two modules that communicate by exchanging vehicle and signal information continuously. The ***PP***, as well as the ***RT*** module in its core, operate the monitoring/ performance assessment function(s) based on which both determine and execute phase allocation and adjustments, respectively.

The ***RT*** and ***PP*** module run in parallel. Whereas ***RT*** keeps track of ***CV*** trajectory properties in response to signal control parameters received from PP, the ***PP*** itself does not run unless called from the RT. After the monitoring module supplies the information, the planning module schedules the $NextPhase$. Its output prompts respective signal groups' status information to be fed to ***RT.*** ***RT*** applies the changes and continues to react to updated requests for service distributed among equipped vehicles. Once modules have transferred respective outputs the steps are iterated until the preset time interval is exhausted.

The ***RT*** and ***PP*** module run in parallel. Whereas ***RT*** keeps track of ***CV*** trajectory properties in response to signal control parameters received from ***PP***, the ***PP*** itself does not run unless called from the ***RT***.

Two modules, Real-Time (***RT***) and Phase Planning (***PP***) are interacting with one another at the "beginning" of each ***RT***'s NextPhase() function call and the "end" of each ***PP*** module execution. The exchange of relevant information occurs only if specific criteria are met to terminate the main phase or Phase1.

Defining control functions and their integration within structural system components was a central task in the algorithm development process since it required establishing the relationships and rules between said functions.

The real-time control scheme represents an integrated entity which defined the relationships and rules between the following functions:

- Get***CVG***Data()

    Defines and retrieves connected vehicle attributes at every time step

- ***TSS-MOE***Update()

    Calculates individual TSS_MOE based on Get***CVG***Data()

    Calculates and updates other individual performance indicators

- PlatoonVehicles()

    Groups based on position in time/space and proximity to other vehicles based on Get***CVG***Data()

- OpportunityCost()

    Computes opportunity cost for $\widetilde{ph}$ in $Can_{\widetilde{ph}}$ and finds minimum among alternatives

- NextPhase()

    Priority Ranks platoons per movement based on aggregate ***TSS-MOE***

    Forms $Can_{\widetilde{ph}}$ ****conditioned upon platoon arrival times***

    Identifies $Phase_1$ based on OpportunityCost()

- REAL-TIME

    Structurally integrates functions to:

        Determine Phase Duration in Real-Time

        Serve Another Non-Conflicting Movement/Platoon (if possible)

        Call NextPhase()

The first two functions constitute the controller's monitoring capability, the second two planning, and the last defines how they are interrelated and executed in real-time.

As soon as the most up-to-date ***CVG*** data is ingested, given current (from ***RT***) signal group state information i.e. green, yellow, or red at the time of information retrieval, the ***PP*** module first executes the user-level performance assessment (user-PA or ***TSS-MOE)*** algorithm. Next, by calling $\mathrm{PlatoonVehicles()}$, the function $\mathrm{NextPhase()}$ groups ***CVs*** and aggregates performance indicators to the movement i.e. platoon level as current state explanatory variables. It performs multi-criteria ranking of platoons (objective function first then the time of arrival and departure) to compute overall opportunity cost of serving each alternative in the $Can_{\boldsymbol{ph}}$. It returns the new next phase(s) that should change status.

The ***RT*** component of the controller retrieves the output of the planner module which is the next optimal main phase and its compatible companion phase and changes its(their) status while terminating currently active phases. It is important to recognize the existence of an overlap (monitoring/ user-level PA component) between the two modules. The ***RT*** module operates its control logic after the green for the next optimal phase starts running.

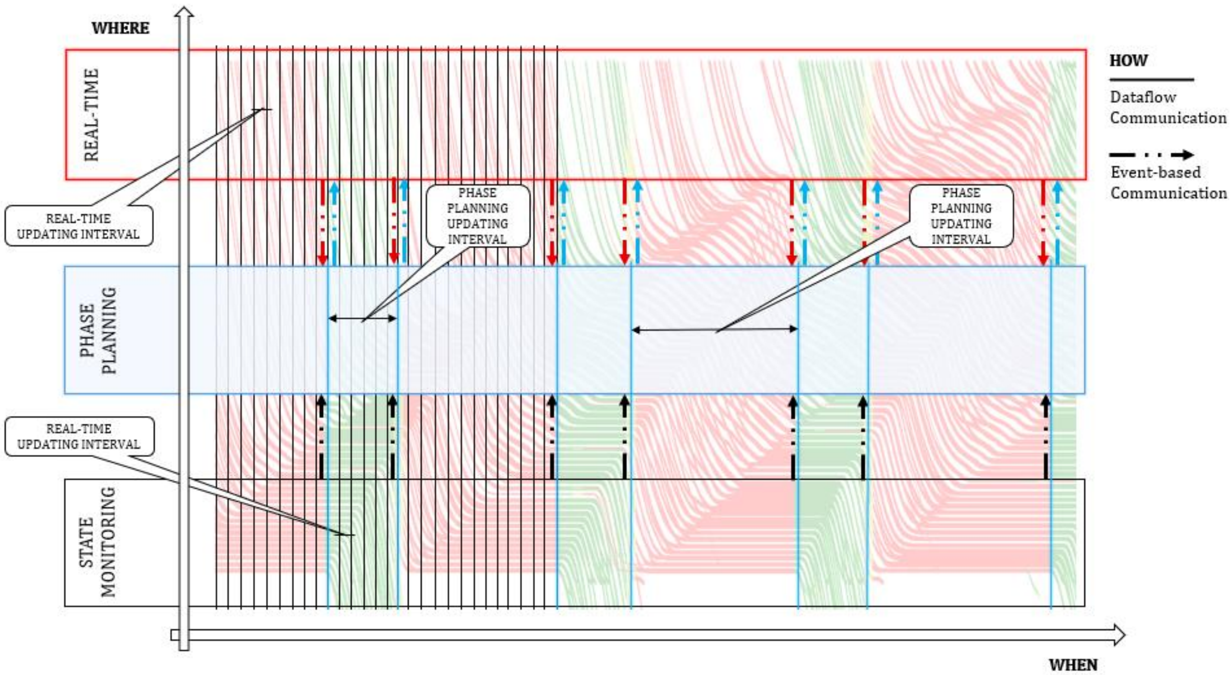


Figure 6-6. Communication between modules

Between-module communication frequency varies as it depends on multiple factors (**Figure 6-6**). Transferring state variables from monitoring and exchange of information between ***RT*** and ***PP*** and vice versa occurs every phase planning updating interval. This communication happens every time there is a signal group status change that needs to be recorded and by design is variable. The frequency of ***PP*** calculations is event driven.

State monitoring and real-time module are communicating continuously with a small timestep - real-time updating interval of 0.2 seconds. The frequency of information update is adjustable although here preset and constant.

In this study, the controller is assumed to record and process signal group status and trajectory information with a 0.2-second frequency.

6.8. Testbed Setup and Implementation

To evaluate the feasibility and effectiveness of the two proposed control strategies, ***CV*** only and ***CV*** supplemented with regular vehicle (detector) data in the real-time module, the connected controller's experimental testbed was set up in a microscopic simulation environment.

Presently, the lack of available connected vehicle information is an issue when relying on these in signal control-related applications. Demonstrating the effectiveness of the control concept was one of the main goals of this research. For this reason, conceptual design, experiments, and evaluation in a mixed vehicle environment of connected and regular vehicles, with high-resolution vehicular information, were performed in a microscopic simulation setting.

Modeling setup prerequisites an integrated microsimulation environment, operating three separate yet interdependent controller components: (1) Monitoring traffic state, (2) Real-Time, emulating real-world and running in real-time, representing the ***RT*** module, and (3) Planning (***PP***) module, running as requested, predicting ***CV*** progression and computing signal performance measurements and timing plans, representing the ***PP*** module. The ***RT*** and ***PP*** module are run together. The simulation framework was designed in VISSIM because of its capability to replicate controller logic reliably as well as its flexible application programming interface (***API*)**. The ***API*** was used to allow customization and interfaces to external software packages for advanced applications. The proposed architecture for the simulation experiments and the main logic for a ***TSS-MOE***-based traffic signal control was coded in Python 2.7 with the library NumPy namely to handle arrays efficiently. COM-enabled Python-VISSIM interface allows for external scripting of controller logic which is what the focus was in this study.

The isolated intersection control strategy and the proof of concept were established on a complex intersection/roadway/controller configuration so transferability to other configurations would not pose a challenge. NEMA phasing standards would apply even if the number of feasible phasing scenarios increases (for example if a 5^{th} approach existed) and the ***external*** controller logic would remain the same.

The optimal solution is generated by choosing when requested, one out of 8 possible (at most) scenarios, which is a small size problem executed in real-time. The simulation model runs at a faster rate than the actual physical system. Even faster execution time algorithms can help further cut down the simulation and optimization time, which is important if large network scaling of computational effort is required.

A real-world intersection of SR7 and Broward Blvd, in Fort Lauderdale, Florida, was modeled and calibrated in VISSIM (*97*), to represent field conditions as realistically as possible (). A 4-legged intersection with 8 protected phases located in a busy urban setting represents an isolated intersection testbed in this study (**Figure 6-7**).

As previously mentioned, a microscopic traffic simulation model of the real-world corridor was used to emulate real-world roadway geometry and traffic conditions as well as the signal controller setup. Regular vehicles are assumed to follow Wiedemann's - a standard car-following model. This car following behavior was modified for ***CVs*** to represent enhanced operational features of these vehicles. Parameters such as look ahead distance, lane changing, reaction times, following headways, etc. were modified based on recommendations given in (*103*). The scope of the study was not modeling nor investigating these behavioral parameters and other than information exchange with the controller no other functionality was explicitly modeled.

To understand the signal phasing optimizer's operation, it is relevant to illustrate the physical layout of the crossing, number of phases, and compatible grouping combinations. The description of the "individual movements" of the dual-ring 8-movement controller as "phases" has blurred into commonly communicated terminology of "movement number" being synonymous as "phase number". Most signal designs and all controllers sold today provide eight standard phases within the signal controller (*104*).

The isolated intersection control strategy and the proof of concept were established on a complex intersection/roadway/controller configuration so transferability to other configurations would not pose a challenge. NEMA phasing standards would apply even if the number of feasible phasing scenarios increased (for example if a 5th approach existed) and the ***external*** controller logic would remain the same.

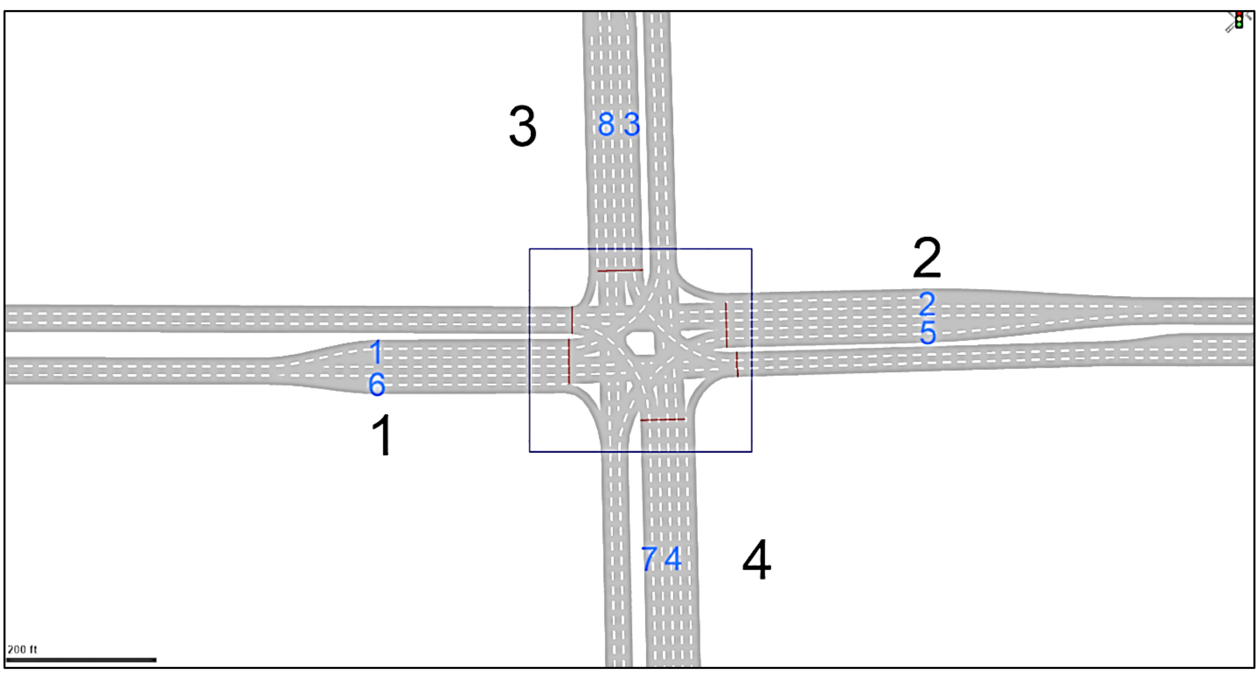
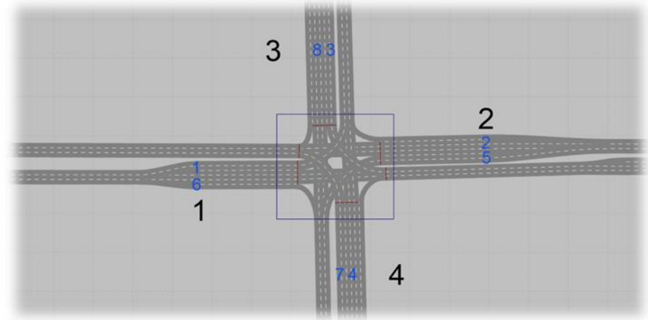


Figure 6-7. Phasing Configuration Numbering and Layout

Baseline testbed calibration and validation were rigorously performed as part of another research effort that included a larger study area (*105*). Broward Boulevard was chosen as a testbed for its heavy congestion, low overall traffic performance, and poor level of service in the network. A real-world intersection of SR7 and Broward Blvd, in Fort Lauderdale, Florida, was modeled and calibrated in VISSIM (*97*), to represent field conditions as realistically as possible (identical to the one in **Figure 5-1** - intersection marked 1. A 4-legged intersection with 8 protected phases located in a busy urban setting represents an isolated intersection testbed in this study (**Figure 6-7**).

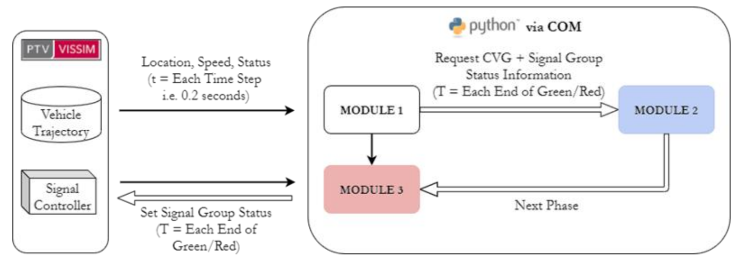
REAL-WORLD INTERSECTION OPERATING NEMA-RBC CONTROLLER

MICROSIMULATION MODEL



TRAFFIC COMPOSITION AND DEMAND LEVELS

Case	Traffic mix		Demand Level	
	Connected	*Regular*	*Case*	*Flow*
2	20.0%	80.0%	Low	1800
3	30.0%	70.0%	Medium	2400
4	40.0%	60.0%	High	3600
5	50.0%	50.0%	**Demand Factors**	
6	60.0%	40.0%	*Dir*	*%*
7	70.0%	30.0%	EB	100%
8	80.0%	20.0%	WB	100%
9	90%	10.0%	NB	70%
10	100.0%	0.0%	SB	50%



SIMULATION FRAMEWORK

Figure 6-8. Modeling Framework

6.9. Sensitivity Analysis –Frequency of Information Update

Developing the control algorithm and investigating its effectiveness required observing its execution in a microsimulation setup. While it was evident early on that gap-out distance will have to be considered (and tweaked) respective of actual intersection configuration, frequency of CV information update proved more significant and impactful on the overall system performance. Conducted sensitivity analysis found that the frequency of 0.2 seconds suffices the objective. Anything higher frequency did not add to the impact but increased computational burden.

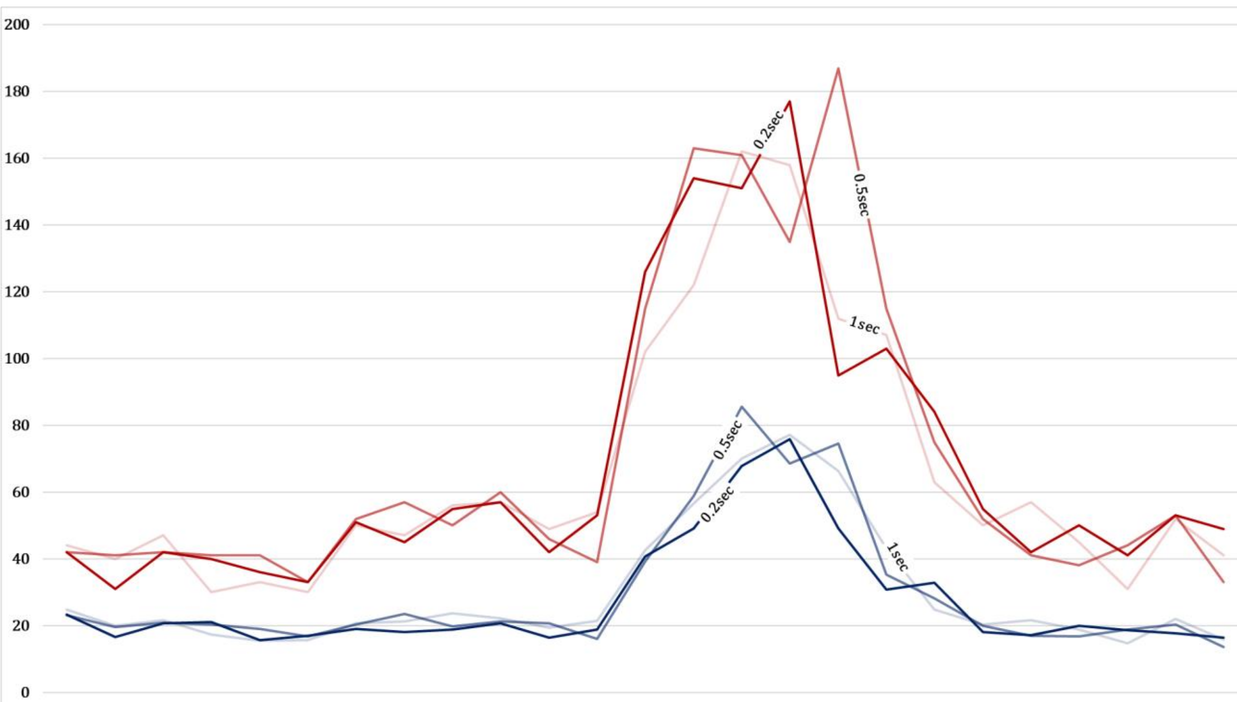


Figure 6-9. Queue Length (red) and Average Delay (blue) Variation at three updating intervals - 0.2, 0.5 and 1 second

It was relevant to investigate the sensitivity of the formulated logic relative to the updating interval - **Figure 6-9**. Please note this refers to the actual frequency of ***CVG*** data transmission in the ***RT*** module. ***PP*** module, as it was discussed previously, is being called from the ***RT*** module when warranted and ***PP*** logic is only then executed and based on the current timestep logged up to date ***RT*** information. Otherwise, the ***PP*** module will not perform calculations locally nor update phasing, unless explicitly called from the ***RT*** module.

6.10. Results and Discussion

The results reporting format is devised as a comparison between two control strategies* formulated in this study and also against the baseline conventional vehicle-actuated NEMA-RBC controller logic:

- Connected vehicle sensing-based controller logic (***CV*** only)

Stands for the controller logic which is operating based on ***CV*** information transmitted by said vehicles. The controller does not recognize RVs as such i.e. does not sense their presence on the approach.

- RV information in addition to ***CV*** is used to determine real-time phasing and duration (***CV+RV***)

Regular vehicle information in addition to ***CV*** is used to determine real-time phasing and duration (***CV+RV***)

*The planning module is the same in both cases – the next phase is determined based on ***CV*** only data due to algorithm design requirements – computing vehicle level ***TSS-MOE.*** The real-time module is different in that it accounts for both vehicle types when determining phase duration.

Two algorithms were formulated to quantify the improvement achievable if both infrastructure-based detection and CV observations were utilized as inputs to the controller. It was not evident if and to what degree the current infrastructure – sensors, controllers – can add in terms of CV-based traffic control in mixed traffic streams. A methodology was devised to assess the extent to which ***CVG*** data and functionalities augmented typical controller schemes in serving observed demands relative to might have been possible through the use of CV-adaptive signal control.

This way, an upper bound on the potential effectiveness of a more-responsive control strategy is provided, when warranting the deployment of CV-only based traffic control.

During the transition from no-to-full connectivity-enabled control systems, the idea was to devise and test algorithms that are compatible with the existing infrastructure so that there is no need to replace the traditional traffic controllers. The proposed controller should easily connect to and control the legacy signal controller, regarding it as one of the peripheral devices. To achieve this goal, the system's software architecture is designed as shown in **Figure 6-1**, and it represents a layered functional structure of the connected controller.

The controller mode of operation depends on whether the real-time traffic information is sufficient or not to provide superior operational efficiency given identical external conditions.

It was then considered important to compare the combined regular and connected vehicle information-based traffic control with the connected sensing-based to isolate the advantages of each. An integrated microscopic simulation platform was used to evaluate the impact of the two alternative control strategies' phasing/timing concepts in a controlled experimental setting i.e. (preset identical operational conditions).

An integrated microscopic simulation platform was used to evaluate the impact of the two alternative control strategies' phasing/timing concepts in a controlled experimental setting i.e.

(preset identical operational conditions). Due to the control model's formulation, the 100% MPR case, should and is reporting identical outcomes concerning inspected aspects of performance.

The robustness and effectiveness of the proposed control method were examined for different MPRs and demand level combinations and assessed against the corresponding baseline of SYNCHRO (*98*) optimized signal timing plans. Isolated intersection control methods were evaluated for various market penetration rates (**MPR**s) of connected vehicles under different demand levels (**Table 6-1**). Baseline controller logic is characterized by a regular NEMA-RBC vehicle-actuated controller mode of operation for an isolated intersection.

Table 6-1. Traffic composition and demand levels

Case	***Traffic mix***		***Demand Level***	
	C	**R**	**Case**	**Flow**
2	20.0%	80.0%	Low	1800
3	30.0%	70.0%	Medium	2400
4	40.0%	60.0%	High	3600
5	50.0%	50.0%	***Demand Factors***	
6	60.0%	40.0%	**Dir**	**%**
7	70.0%	30.0%	EB	100%
8	80.0%	20.0%	WB	100%
9	90%	10.0%	NB	70%
10	100.0%	0.0%	SB	50%

Demand levels were divided into three categories: low, medium, and high, each representing a 30-minute interval. Overall a 2-hour long simulation horizon was designed to represent the demand build-up from low (off-peak conditions) to medium to oversaturated (AM or PM peak) and reverting to medium, to capture the recovery stage after the oversaturation dissipates. East and West directions (Broward Blvd.) are considered major approaches with a 100% demand factor of the respective demand level. Please refer to the representation of demand levels and traffic mixes in **Table 6-1**. Overall, (5 random seeds of) 9 different MPRs of connected vehicle mixes were tested over a 2-hour long horizon with three demand levels. The chosen high demand level is unrealistically high and was chosen to test the capabilities of the strategy under extreme conditions.

The results show that once 30% MPR of CVs is achieved, fixed infrastructure can be completely disregarded (as in current controller operational logic dependent on fixed-location detectors). CV only control scheme outperforms consistently the CV+RV one, with respect to each recorded (conventional and newly designed **Hi-Res**) MOEs, except the average number of stops. The results and discussion in the following section are separated into two parts depending on the analysis type:

- **Hi-Res** MOEs and ***TSS-MOE***
- Conventional MOEs (queue length, delay, number of stops, speed)

6.10.1. Control Strategies Comparison – Hi-Res MOEs and *TSS-MOE*

To demonstrate the advantages of CVG data and related applications in terms of developing more efficient signal control algorithms, the ***TSS-MOE*** (**Equation 5-1**) based control was compared against the delay-based one.

The results present a comprehensive Hi-Res data-based performance evaluation effort conducted over three different traffic control strategies.

1. Conventional vehicle-actuated controller logic.

(Please note that the authors had no access to more advanced adaptive traffic control algorithms, therefore evaluated what is the state of the practice in controller operations. A more sophisticated control algorithm could yield improvements in terms of various performance aspects over the NEMA-RBC conventional functionalities and logic.

1. Delay-based control.
2. ***TSS-MOE*** based control.

Envisioned as the condition-responsive traffic control solution, the ***TSS-MOE*** based phase allocation and duration adjustment are built on the same principles as the CV delay-based one. The only difference is the objective function, in both the predictive and reactive parts of the controller. The solution to the control problem is based on the heuristic which sets up the flow of information and processes to alternate the right of way based on the platoon-level associated ***TSS-MOE*** value and subsequent opportunity cost calculation function output.

If one is to examine the ***TSS-MOE*** based optimization worthiness in the context of platoon-based phase scheduling, it seems logical to evaluate it against the benchmark in current signal timing design practice i.e. minimizing delay. Since this study operates specific ***CVG*** data formats and on these derived capabilities, it was relevant to investigate the level of improvement within the same controlled setting and the same control algorithm while varying the objective. Under certain concepts V2I of operations, the connected traffic stream can be assumed to record and calculate individual vehicle delay. This delay can then aggregate to the same level as in the ***TSS-MOE*** based case i.e. platoon level.

The platoons are ranked by priority of service and candidate phases are determined based on accumulated platoon-level delay. As the opportunity cost function is the same, the output of the ***PP*** module, ideally, should be the phase number for which the accumulated delay is the highest.[3] Similarly, in the ***RT*** module, instead of ***TSS-MOE***, movement-level accumulated delay terminates the phase, drives the active phases priority swapping, and requests the *NextPhase* execution.

The connected controller is claiming advanced operational features not only due to CVG data superiority, but also new applications based on such input's explicit integration into the control logic.

Traffic signal control design recognizes that different traffic states require different control strategies. The ***TSS-MOE***-based solution outperforms the delay-based one due to its ability to capture system performance-user experience relationship, contingent upon traffic conditions.

[3] Since the same algorithm rules apply, the ranking, critical platoons/phases and opportunity cost are identified in the same manner

Unlike delay, the relative contribution of the predominant causal factor(s) of inferior performance is reflected and weighted as such via the state-responsive trajectory-based quantifier. The worst performing aspect carrying the largest weight in the composite measure prompts the reallocation of green time, or some more elaborate control strategy.

To reiterate, operational logic is the same in both controllers, the same connected controller mechanism as described, the only difference is the objective function that drives the phase allocation and adjustment of phasing in real-time.

To evaluate the feasibility and effectiveness of the two proposed control strategies against the conventional NEMA-RBC controller, the connected controller's experimental testbed was set up in a microscopic simulation environment. The proof of concept was established on a complex intersection/roadway/controller configuration so transferability to other configurations would not pose a challenge. A real-world intersection of SR7 and Broward Blvd, in Fort Lauderdale, Florida, was modeled and calibrated in VISSIM , to represent field conditions as realistically as possible. An isolated intersection testbed is a 4-legged intersection with 8 protected phases located in a busy urban setting.

Modeling and simulation framework prerequisites an integrated microsimulation environment, operating three separate yet interdependent controller components: (1) Monitoring traffic state, (2) Real-Time, emulating real-world and running in real-time, representing the ***RT*** module, and (3) Planning (***PP***) module. The proposed system architecture for the simulation experiments and the connected controller logic was coded in Python 2.7 with the library NumPy namely to handle arrays efficiently. COM-enabled Python-VISSIM interface allows for external scripting of controller logic.

The analysis compares, for three controller types, averaged and aggregated per direction, outputs over 5 random seeds for the fully connected stream (100% MPR). The recorded measures were reported at two levels: Hi-Res MOEs were aggregated per interval (300seconds) and per SG duration throughout the oversaturation period. SG-based reporting was not appropriate when comparing different strategies as a common denominator was necessary, so the 5-minute analysis interval was chosen. However, since aggregated values could misrepresent the traffic condition during oversaturation, insight into the system's behavior on an SG-basis was also presented.

Each of the four graphical representations refers to a different operational aspect of the signal system effectiveness. The system's operational success was evaluated from its users' perspective i.e. the manner in which the travelers experienced the system.

Each figure consists of two parts. The left side records the operational success in the WB-EB direction (heavy demand approach) whereas the right one, the NB-SB direction (light demand), over the same time interval.

The top chart on either side references the conventional vehicle-actuated controller, the middle - the delay-based control scheme while the bottom chart ***TSS-MOE*** based algorithm's performance in terms of various operational success indicators.

The testbeds are identical in every aspect including the arrival rate of vehicles – thus it was easy to assess the dissimilarities in terms of control scheme's effectiveness and robustness.

Figure 6-10 compares the strategies in terms of phase capacity utilization via the number of arrived, served, and queued vehicles over each 300-second interval. Green and red bars represent the average green and red times - they sum to the average signal group duration within the overall 300-second analysis period. Reported quantities are computed based on definitions in **Table 5-1**.

Referring to **Figure 6-10** and **Figure 6-11**, both connected controllers, relative to the conventional one, exhibit:

1. Shorter green times and overall SG durations
2. Oversaturation effect is “narrower” with significantly shorter queues (3600-5400seconds)
3. Served vehicles profile similar to that of arrived, as opposed to what is observed in the top chart
4. The ***TSS-MOE*** control algorithm (bottom charts) demonstrates consistently short queue lengths throughout the oversaturated period
5. On average, green/red times and their temporal profiles that are comparable

A closer look at **Figure 6-11** reveals that the ***TSS-MOE*** control algorithm handles low and high demand conditions in a similar manner. With even shorter greens and SG durations (compared to delay-based), the algorithm minimizes the leftover queue when the demand is the heaviest.

Figure 6-12 relates green time efficiency in terms of green time available, green time utilized, arrivals on green and cumulative, aggregate and average ***TSS-MOE*** per each 300-second interval. Green times are expressed as ratios or portions of the entire (effective) green time allocated to the movement. Reported quantities are computed based on definitions in **Table 5-2**.

Referring to **Figure 6-12** and **Figure 6-13**, the connected controllers, relative to the conventional demonstrate:

1. Arrivals on green profile that are more consistent and robust during oversaturation
2. The discrepancy between green available and green utilized as less prominent, contained within a narrower time window and with less green time being underutilized
3. Regardless of the demand level and time interval, the ***TSS-MOE***-based one outperforms the other two, with its minimum ***TSS-MOE*** value of around 0.3 during oversaturation peak
4. In either direction, the bottom chart's ***TSS-MOE*** temporal profile differs from that of the other two strategies i.e. the drop is less significant and discontinuous

The "cycle-to-cycle" performance during oversaturation in **Figure 6-13,** offers a more significant insight. Even though the delay-based connected controller recovers after approximately 30 minutes, extremely low ***TSS-MOE*** and the green time underutilization for the major direction were recorded. Significant improvement is observed only in the case of a ***TSS-MOE*** based connected controller.

Figure 6-14 and **Figure 6-15** represent the state of the system in terms of stopped delay. Dark green/red bars are aggregate cumulatives of stop durations, averaged per interval. The charts measure stops duration against the corresponding average green and red interval duration.

Focusing on the 3600-5400 seconds interval, the maximum total stop delay is higher than 85 seconds, around 30 seconds and around 18 seconds, in the three cases, respectively, for the same 300-second interval.

Figure 6-14 demonstrates that:

1. For connected controllers, throughout the evaluation period, stop delay is significantly reduced
2. The impact of ***CV***-based strategies is especially evident in oversaturated conditions
3. Stopped in green time, as well as stopped time due to red indication were reduced proportionately
4. For the ***TSS-MOE*** based controller, further reduction in terms of stop delay is observed

Figure 6-15 breaks down the green time activation further and, in the ***TSS-MOE*** based case, demonstrates less frequent switches between phases together with lesser waiting times. Compared to the delay-based control scheme, the one built to maximize ***TSS-MOE*** reduces both green and, red indication induced, stop delay, especially in high-demand circumstances (left side graph in **Figure 6-15**).

Figure 6-16 and **Figure 6-17** requires clarification related to the property reported. Progression ratio is defined as the ratio of ASoG vehicles that were served without being stopped on Green. It is built on the same notion as the platoon ratio (*106*) and can be considered as the Hi-Res version of said parameter.

Results in **Figure 6-16** show that:

1. Quality of progression was improved, as were both, ASoG and Progression Ratio
2. The ***TSS-MOE*** outperforms the delay-based controller
3. For the conventional controller, due to its logic design drawbacks, green times that are respectively twice as long, do not add to the progression quality

4. As the number of stopped vehicles rises, so does the number of phase failures
5. ***CV***-delay based logic keeps a larger number of vehicles accumulated on approaches before triggering two consecutive executions of the ***PP*** module. Furthermore, a larger number of vehicles is stopped on unserved approaches while the green on served is extended due to vehicle presence

Interesting to note in **Figure 6-17** is that the number of phase failures decreased during oversaturated conditions in the case of ***TSS-MOE***-based logic, which at first may seem counterintuitive. However, the objective function was designed to re-prioritize inferior performance contributing factors as condition changes and as the demand increases. In this manner, contributing factors are weighted differently, thus drive the solution depending on the traffic condition.

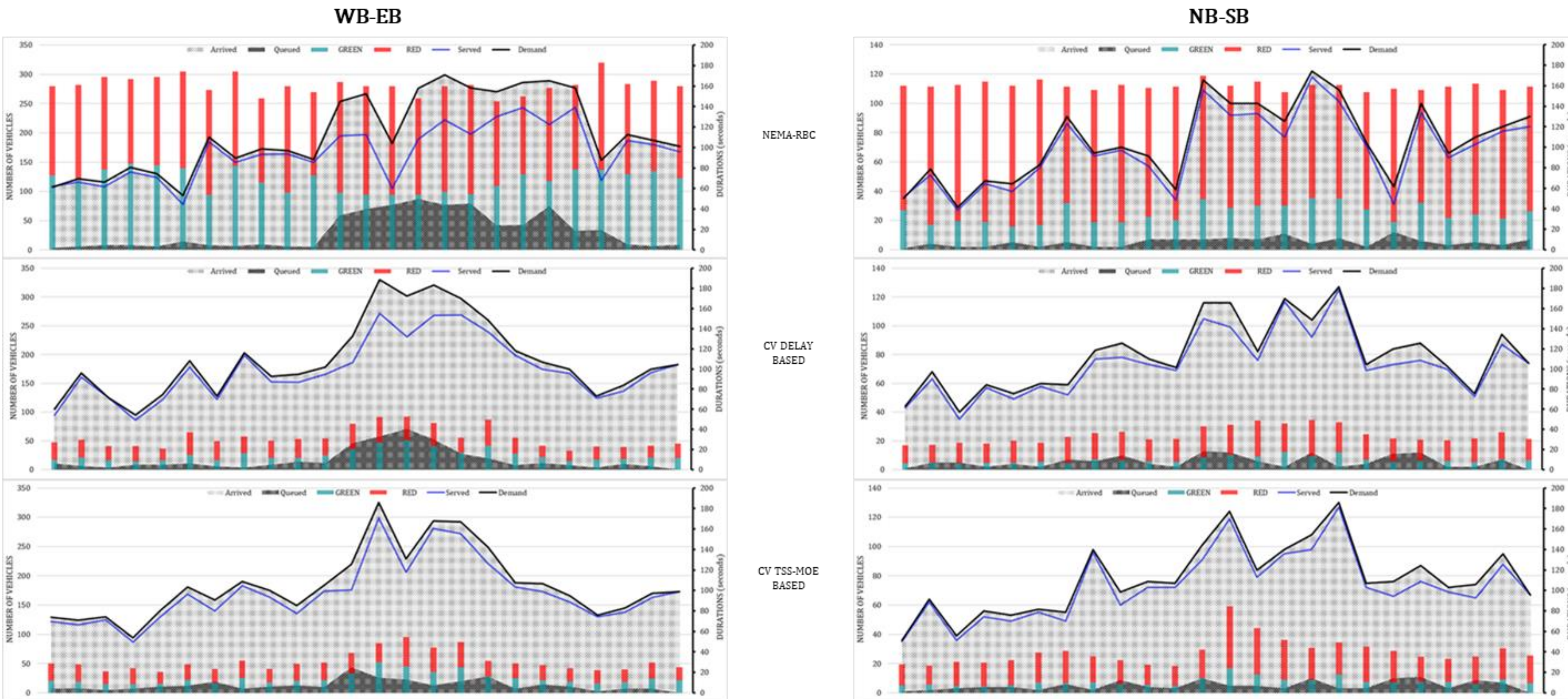


Figure 6-10. Phase Capacity Utilization Comparison between CV Strategy (top chart) and RV Strategy (bottom chart)

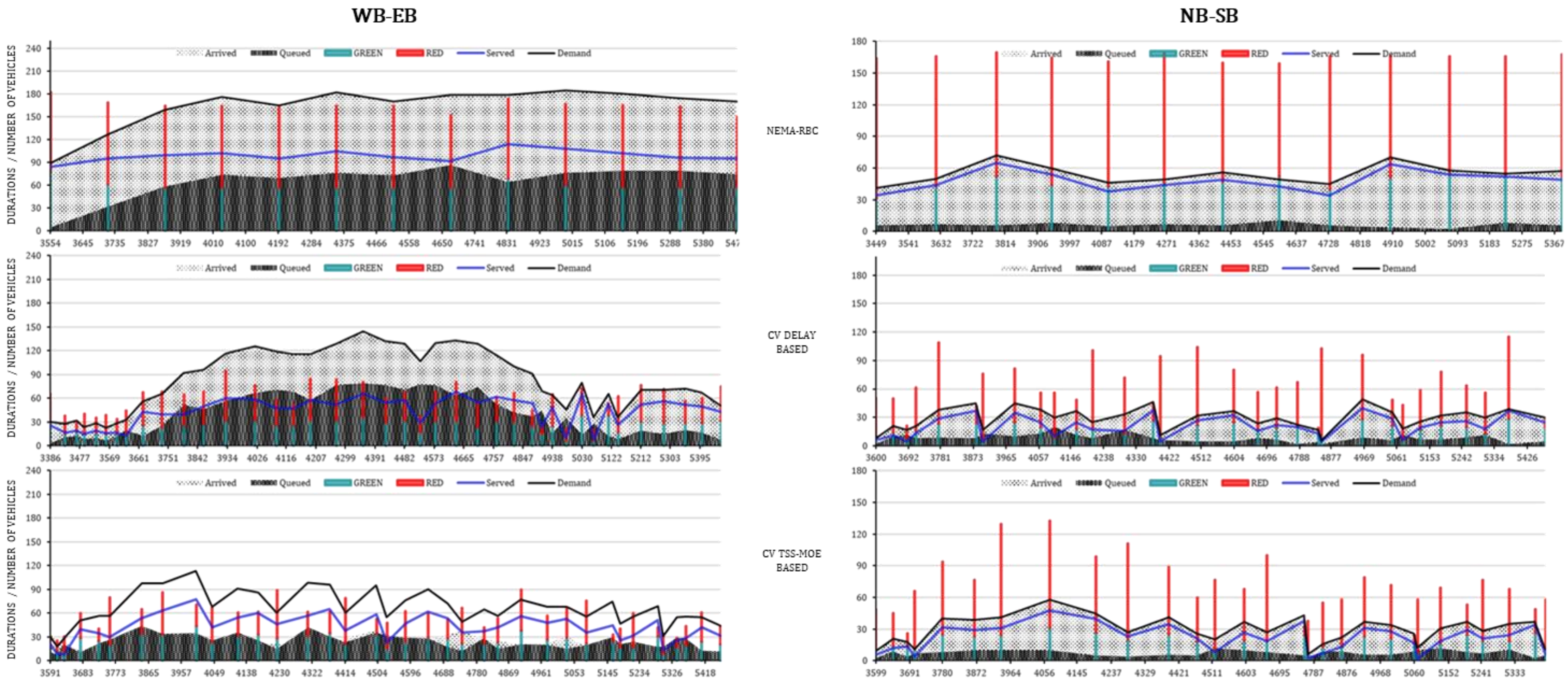
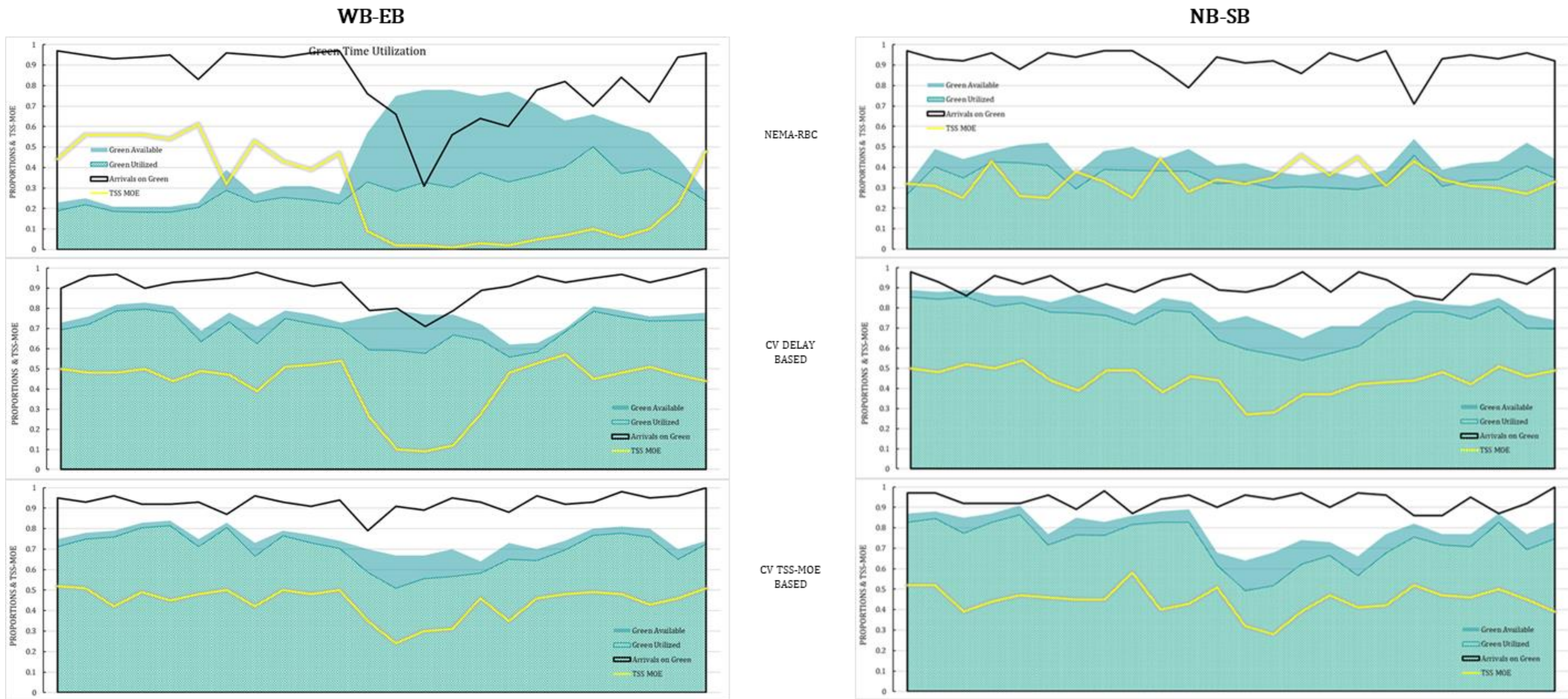
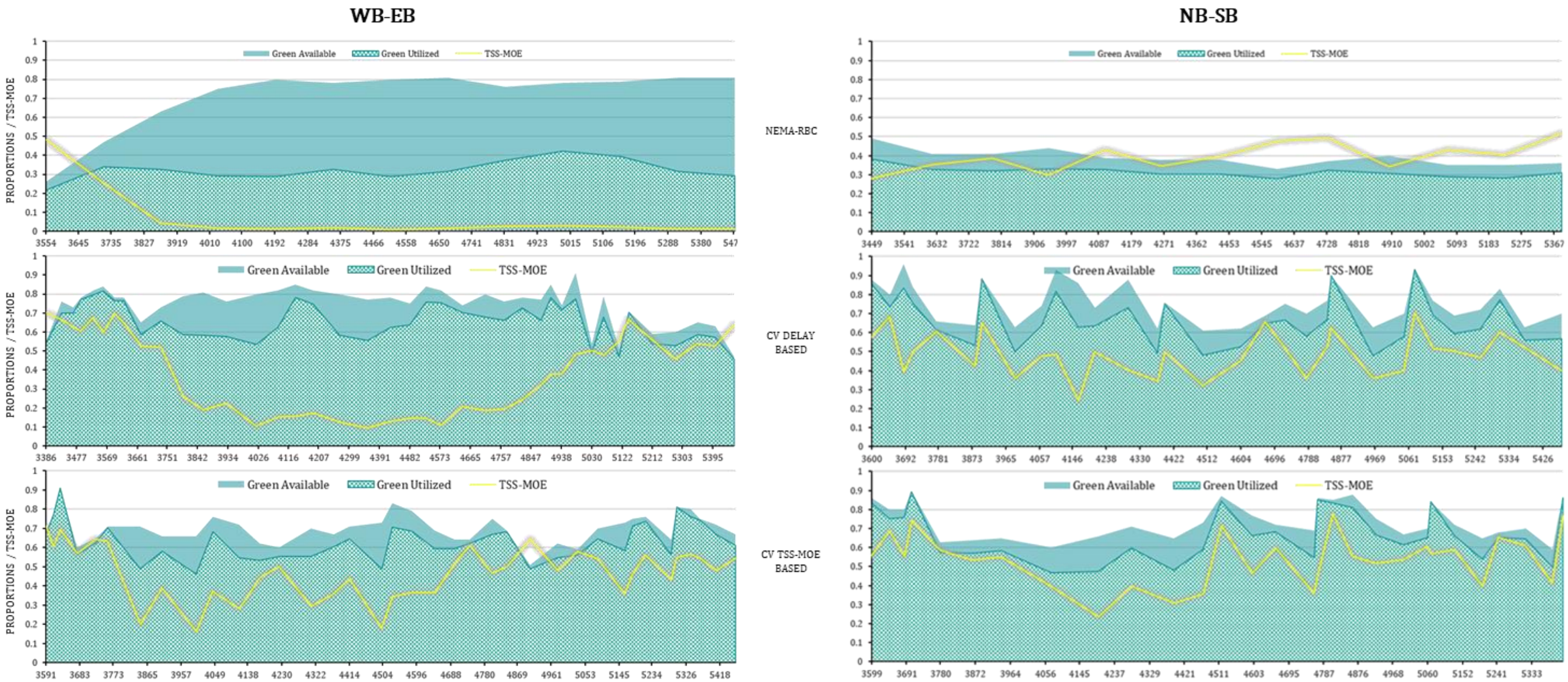


Figure 6-11.Phase Capacity Utilization Comparison between CV Strategy (top chart) and RV Strategy (bottom chart)



a) b)

Figure 6-12. Green Time Utilization Comparison a) major approach and b) minor approach



a) b)

Figure 6-13. Green Time Utilization Comparison a) major approach and b) minor approach

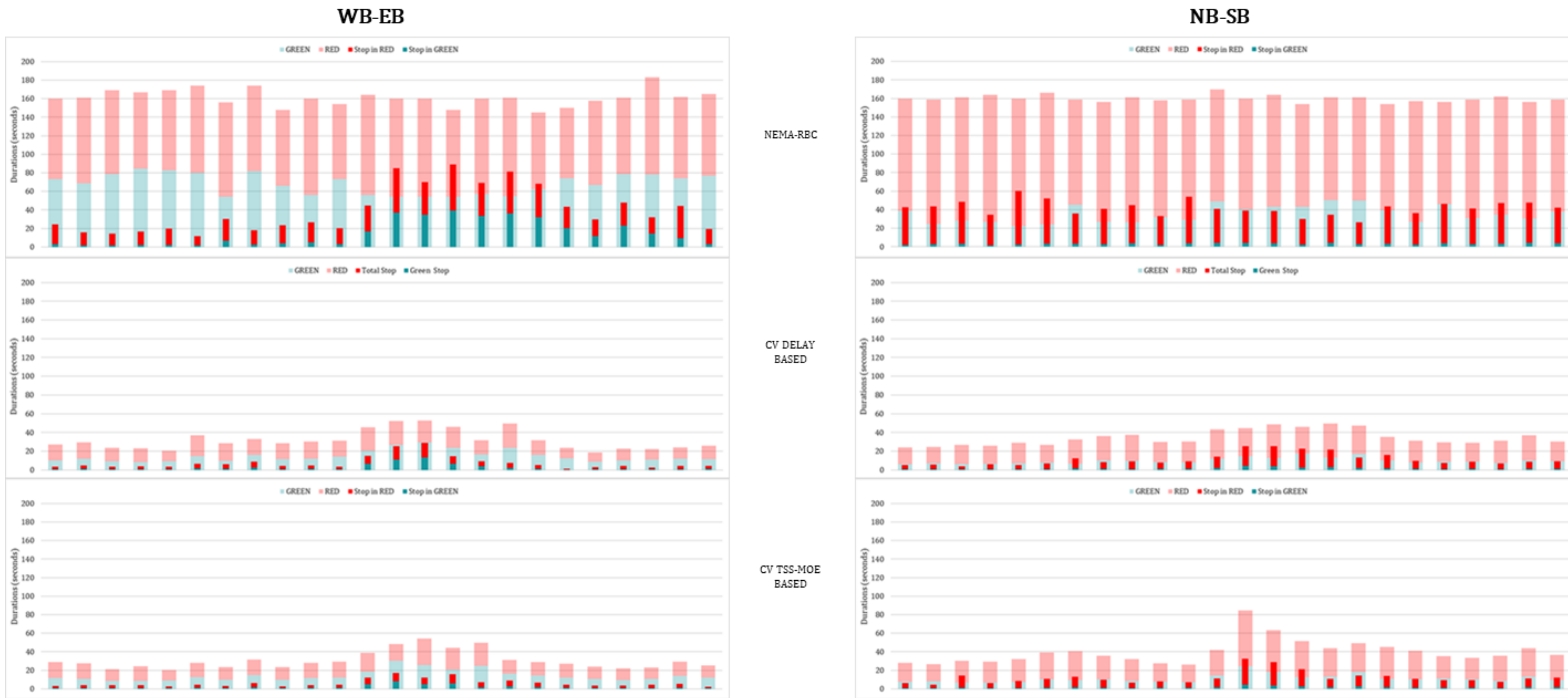


Figure 6-14. Quality of Progression (Stop Delay) Comparison between Strategy 1 (top chart) and strategy 2 (bottom chart)

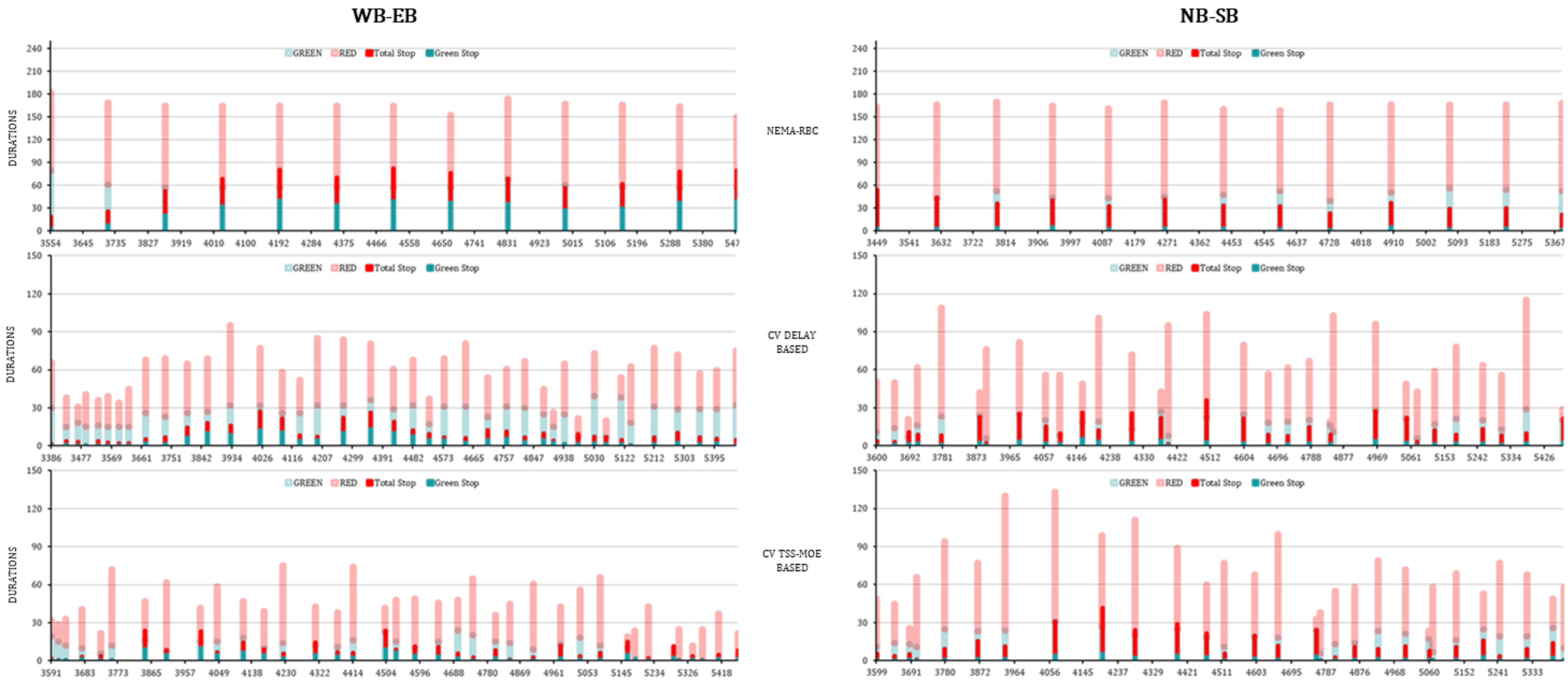


Figure 6-15. Quality of Progression (Stop Delay) Comparison between Strategy 1 (top chart) and strategy 2 (bottom chart)

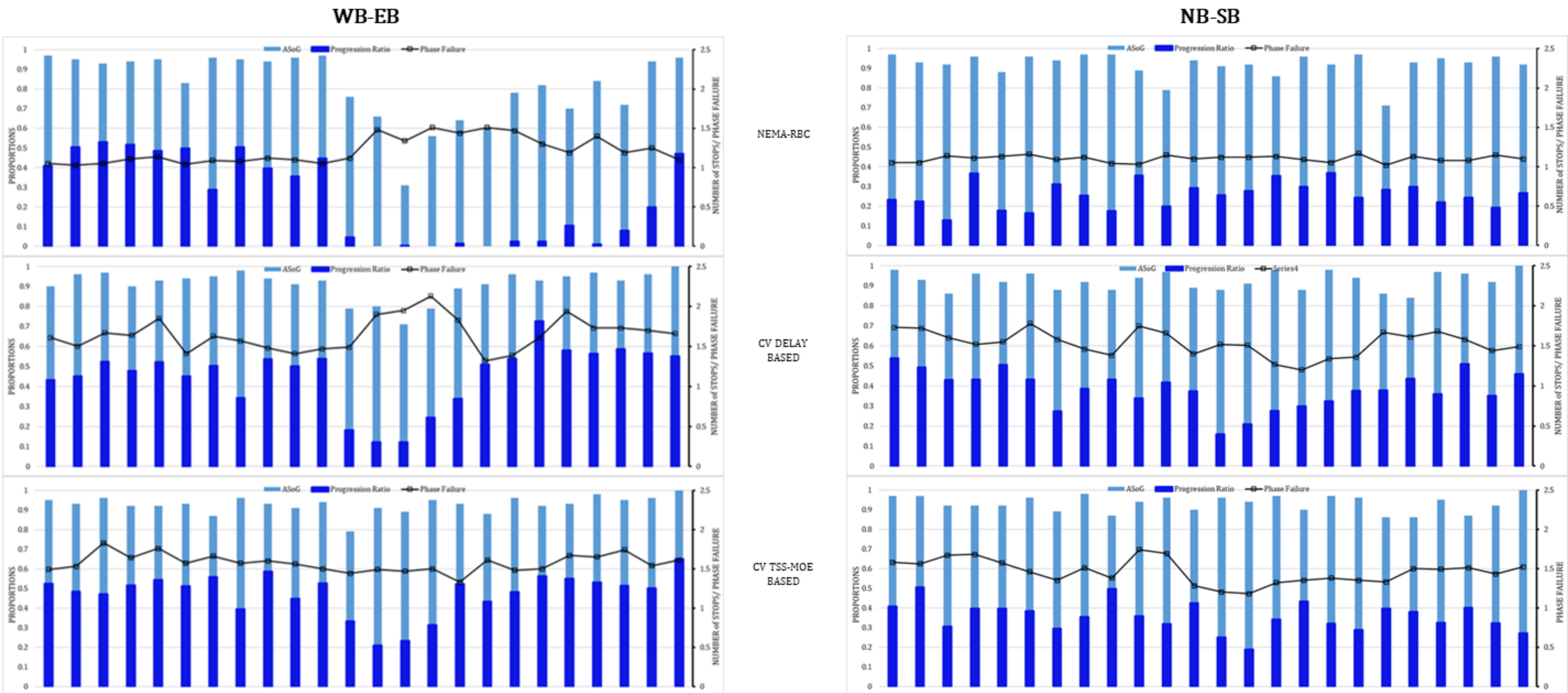


Figure 6-16. Phase Failure Comparison between Strategy 1 (top chart) and strategy 2 (bottom chart)

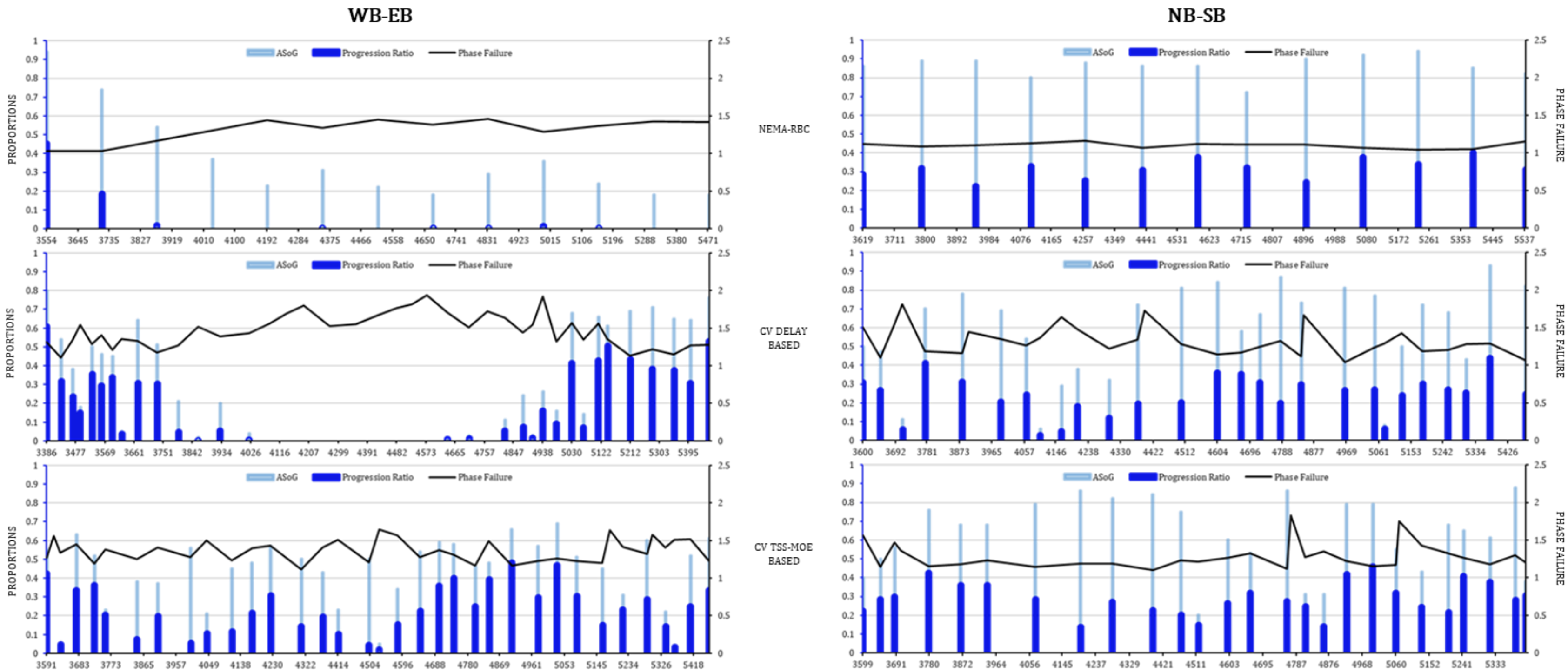


Figure 6-17. Phase Failure Comparison between Strategy 1 (top chart) and strategy 2 (bottom chart)

6.10.2. Control Strategies Comparison – Conventional MOEs

Assessment of the performance was conducted by analyzing conventional MOEs for two reasons:

1.) Impartial validation of the effectiveness of the proposed smart controller logic
2.) Referencing the state of the practice indicators for easier interpretation when the state of the practice controller logic is considered as the base case

By observing the difference in performance between the ***CV*** only and ***CV***+RV optimal settings, the degree of robustness is quantified for the ***CV*** (only) based phasing/timing. Accordingly, an upper bound on the potential improvement when operating a fully connected adaptive control can thus be estimated.

The results presented focused on a detailed-level analysis that considered various objectives. Based on a specific objective, the results offered a slightly different perspective on the same issue. The differences in performance for various MOEs over the range MPRs offered an insight into ***CVG***-based optimization worthiness.

This study was primarily focused on quantifying reductions and benefits at an intersection level, due to the massive amount of data that was processed and analyzed on an individual approach level.

Signalized intersection analysis presented in terms of average performance (queue length, delay, number of stops, and speed) during the analysis period was done at two levels:

- Overall system

- Per vehicle class

To validate the effectiveness of the method proposed it was important to demonstrate it benefits the entire system as well as each vehicle class (RVs and ***CV***s both). The premise was that a reliable and robust method should demonstrate improvements for both categories.

The results for traditional MOEs also recorded temporal profiles per interval so their distributions and patterns are distinguishable.

- Cumulative and relative delay analysis per MPR
- Temporal distributions of the absolute and relative difference in performance per demand level and per MPR

The mean PI values (per vehicle) were averaged over 5 random seeds and per analysis interval (300 seconds). The average for the entire analysis period (~ 2hr) for each of the ***MPR***s is presented in **Figure 6-18** through **Figure 6-25**.

For consistency reasons throughout this section, the figures will represent ***CV***+***RV*** strategy as blue-colored while ***CV*** only as orange-colored shapes in various chart types (box plots, lines, and bars).

Figure 6-18 through **Figure 6-25** depicts box plots of four measures of effectiveness (MOEs) for each of the MPRs investigated at an intersection level. The most left box (no color fill just the outline), when included, represents the baseline case performance i.e. conventional vehicle-actuated controller. The blue box for each MPR (in each plot) represents the aggregated (over 5 random seeds) and then averaged vehicle-level MOE value and corresponds to the ***CV***+***RV***

control scheme's effectiveness in serving the demand. Correspondingly, the orange box represents the averaged MOE value for the ***CV*** only case. Each measure’s median is depicted as the horizontal solid line inside the box, while the X marks the mean.

Please note that for **Figure 6-23** through **Figure 6-25** same color convention was applied when representing different vehicle classes. Blue stays representative of the ***CV***+***RV***, whereas orange of the ***CV*** only method. Note that the light shade records **RV**s performance, while dark illustrates ***CV***s performance for each method, respectively. Please note queue length results cannot be reported per vehicle class.

Referring to **Figure 6-18** through **Figure 6-22** the connected controller logic significantly outperformed the baseline in terms of queue length is evident. The ***CV*** only method the ***CV***+***RV*** alternative, starting with 30% ***MPR***. Furthermore, there is less variation for the ***CV*** only cases over the same range of ***MPR***s.

The strategy proves to be effective in reducing average delay as well, as can be observed in **Figure 6-18** through **Figure 6-22**. Average vehicle delay reduction is found to be significant. The two strategies exhibit similar trendlines regarding average speed as well. **Figure 6-18** through **Figure 6-22** shows rising averages with the increase in ***CV***s ***MPR***.

Although the two methods perform rather comparably, the ***CV***+***RV*** strategy is outperforming the alternative regularly in terms of the average number of stops. Even higher ***MPRs*** of ***CV***s (as high as 50% and higher) do not guarantee the ***CV*** only framework’s operational superiority as was the case with other PIs.

The highest magnitude improvement is recorded in terms of queue length, while the trend in the average delay, as well as average speed, was similar but less significant. If focusing on the trend the average number of stops is showing, although there is a reduction with the increase in ***CV***s ***MPR*** for both cases, the reduction achieved going from 20 to 30 and 30 to 40 ***MPR*** for the ***CV*** (only) framework is drastically more significant. This may be due to the controller design logic which at this point does not include a function that handles the lack of specific traffic data formats i.e. estimates regular vehicles presence and position within the traffic stream. Their impact on traffic operations is neglected - i.e. regular vehicles do not exist in the case of ***CV*** only connected controller - when timing the active "optimal" phase, which, in turn, affects the transitioning between active phases.

As for the overall performance, figures above established a global, positive, trend remarking considerable improvement in 3 out of 4 MOEs; average queue length, overall delay, and speed. Traffic operations analysis showed that the connected controller outperformed the conventional one in all tested scenarios, with more than 50% reduction (increase) in queue length and overall delay and speed, respectively.

The results show that once 30% ***MPR*** of ***CV***s is achieved, fixed infrastructure can be completely disregarded (i.e. fixed-location detectors and controllers). ***CV*** only control scheme outperforms consistently the ***CV***+***RV*** one, with respect to each recorded MOE, except the average number of stops. The results also point out the importance of shortening the green times (and by extension cycle times). Since shorter "cycles" mean lesser waiting times for the unserved approaches and in turn the entire system.

Exhibited trends per vehicle type (b) charts in figures below) are consistent with the trends for all vehicles together in **Figure 6-23 a), Figure 6-24 a)** and **Figure 6-25 a)** which aggregates results for the two classes, yet it was important to point out that both vehicle types properties showed improvement and not one at the expense of the other.

The goal of this research was to evaluate the robustness of the designed “connected signal” control in handling varying traffic conditions. By assessing relative reduction/improvement for each ***MPR*** scenario and aggregating savings over the entire analysis period, the ***MPR*** cutoff point which offered significant savings was identified. While it is reasonable to assume the ***CV*** only strategy might underperform when the traffic stream consists of predominantly regular vehicles only (*case2* through *case6*), at first, it seemed counterintuitive that the opposite occurs when only 30 % of the fleet is connected.

This could be attributed to the logic design. Including actuation in the connected controller logic negatively affected the performance of the control algorithm since sufficient **CVG** data was available to provide superior operational efficiency given identical external conditions. 30% of connectivity-enabled vehicles in the traffic stream improve operational conditions for all system users i.e. overall and per vehicle class as well. ***CV*** only control scheme outperforms consistently the ***CV***+***RV*** one, with respect to each recorded MOE, except the average number of stops. The results indicate that once 30% ***MPR*** of ***CV***s is achieved, fixed infrastructure can be completely disregarded (i.e. fixed-location detectors and legacy controllers).

The focus of the analysis was on traffic operations during oversaturation, and how the system behaves in such circumstances.

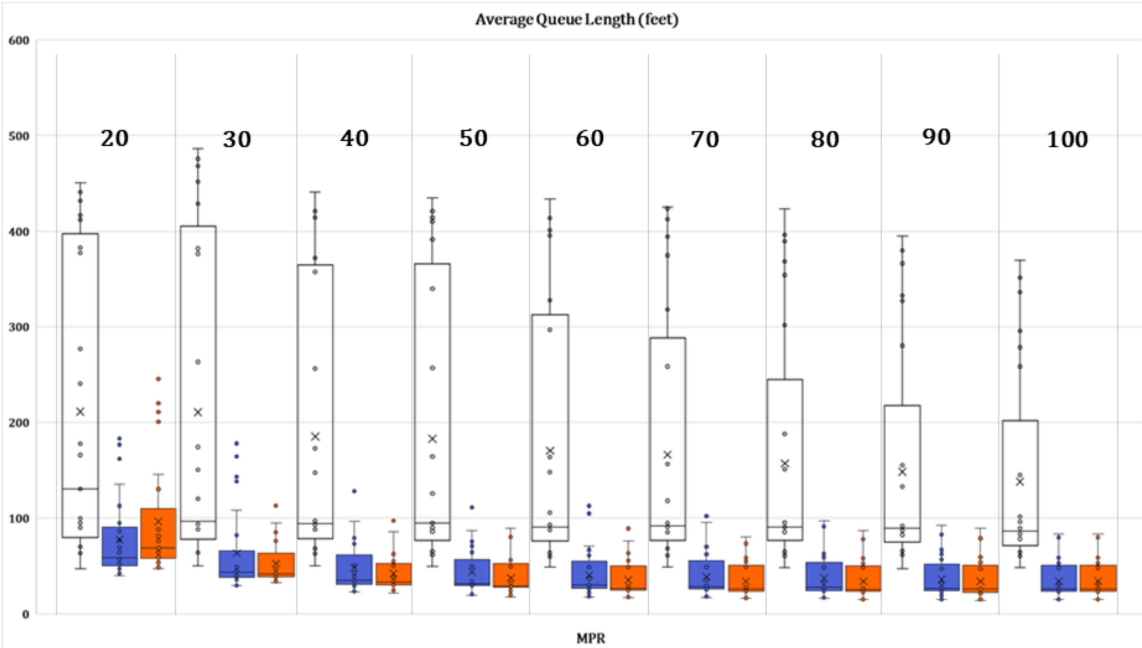


Figure 6-18. Average Queue Length Comparison RV vs CV+RV vs CV

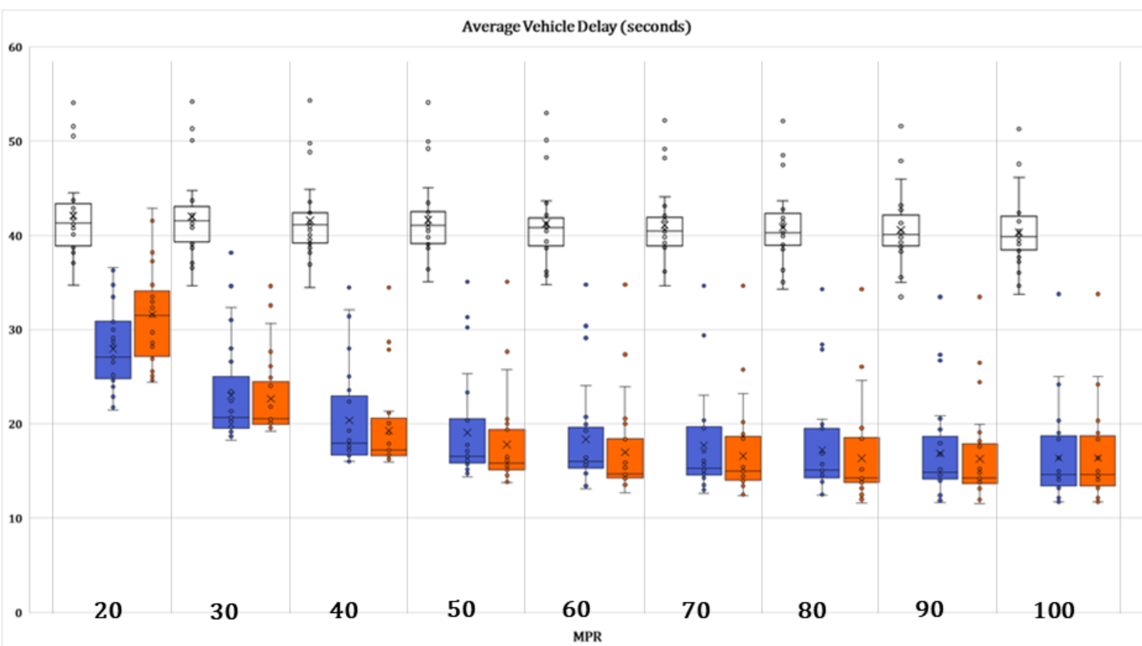


Figure 6-19. Average Vehicle Delay Comparison RV vs CV+RV vs CV

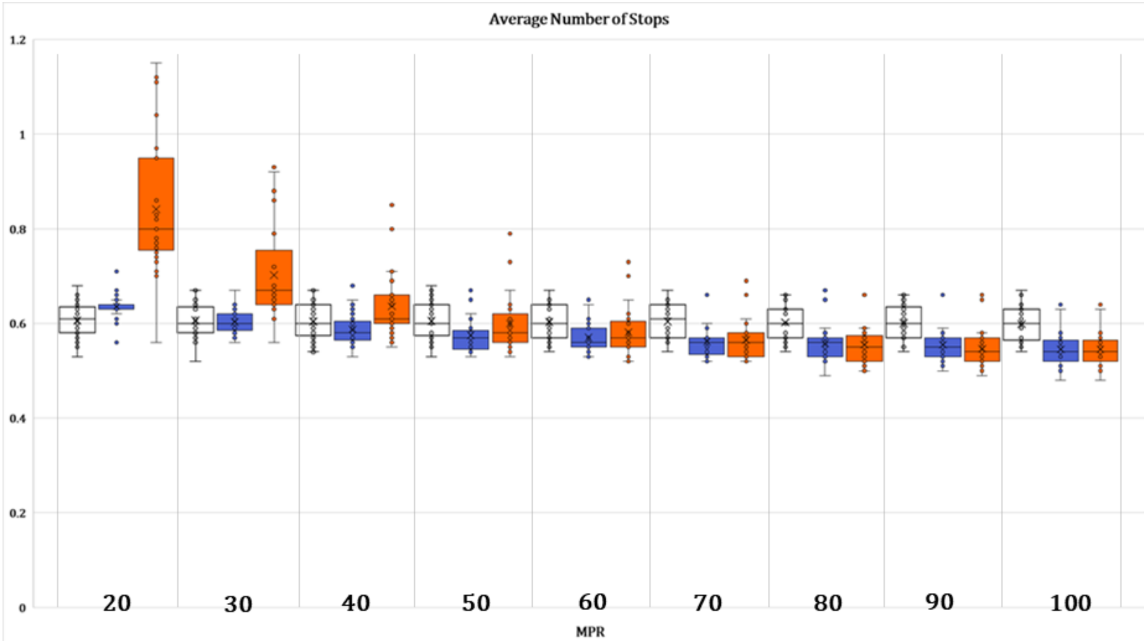


Figure 6-20. Average Number of Stops Comparison RV vs CV+RV vs CV

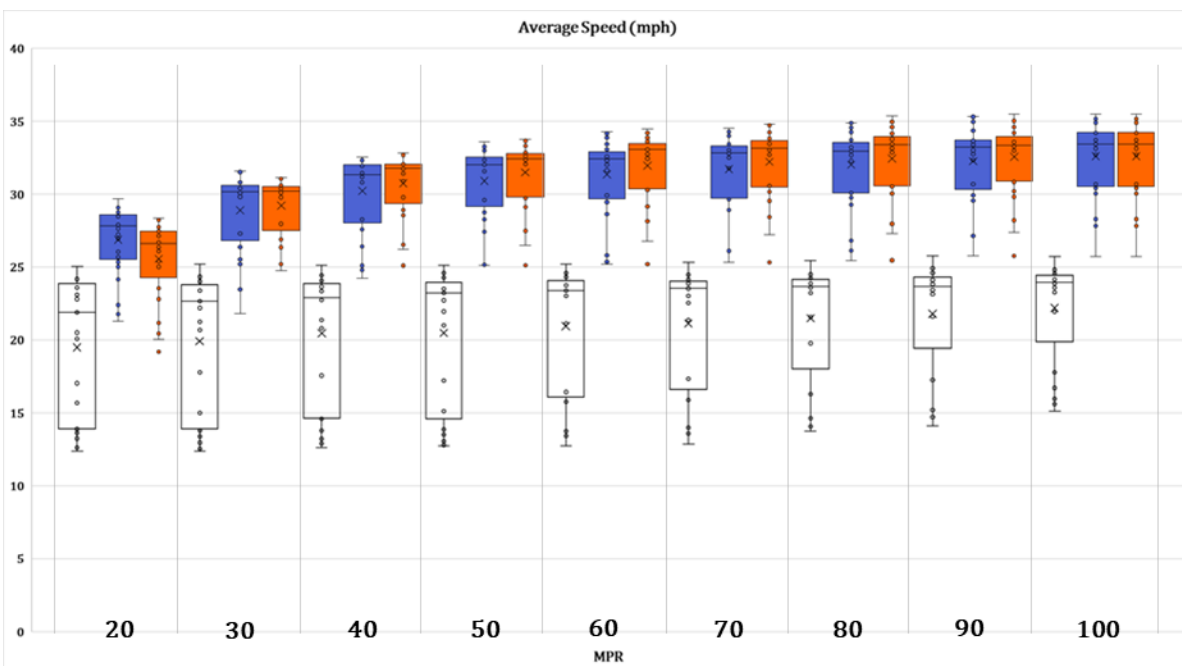


Figure 6-21. Average Speed Comparison RV vs CV+RV vs CV

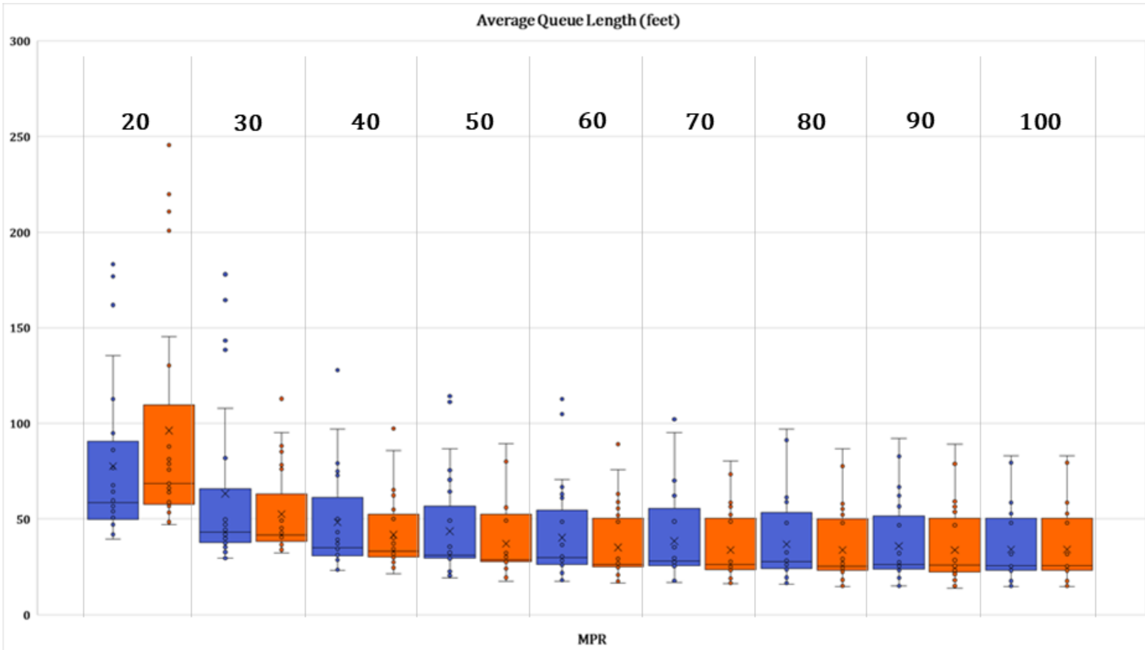
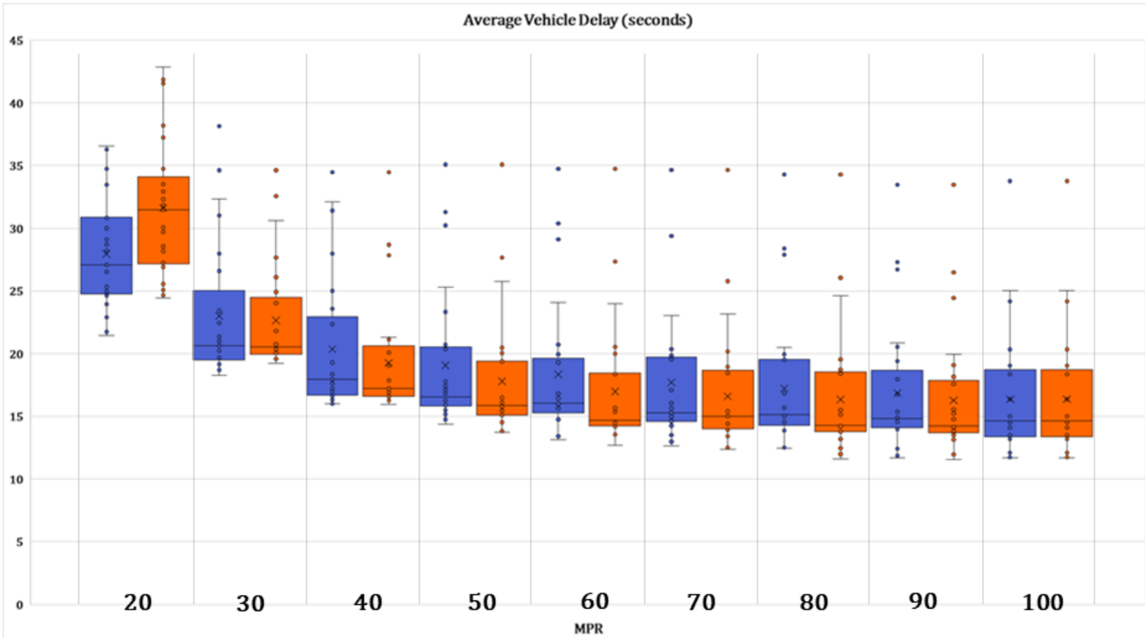
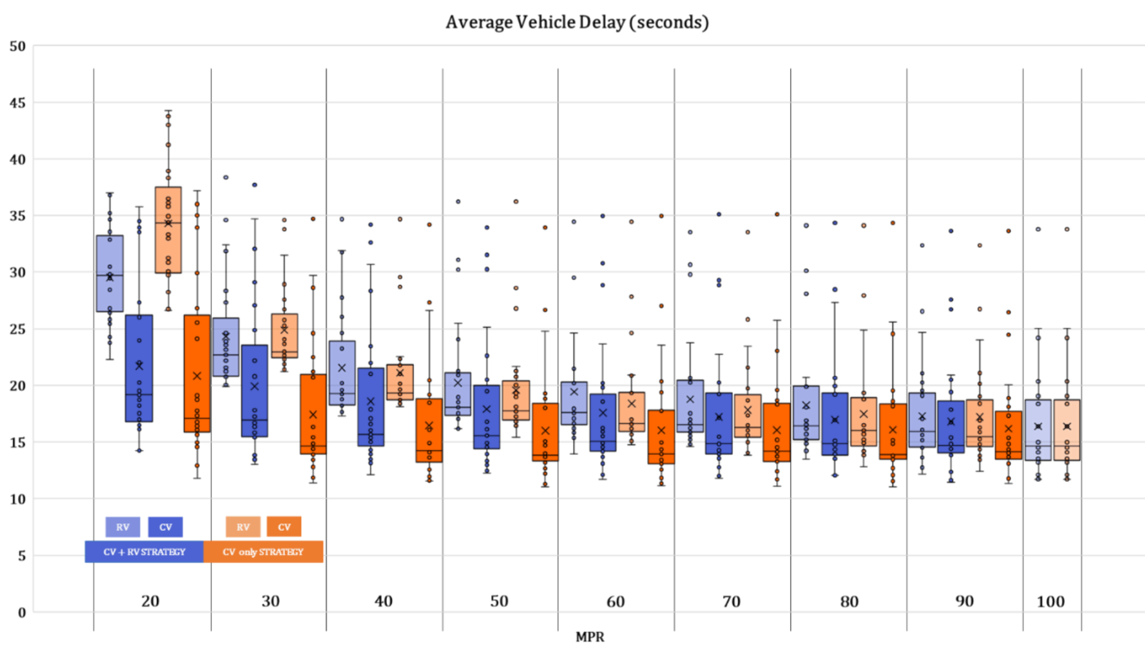


Figure 6-22. Average Queue Length Comparison CV+RV vs CV

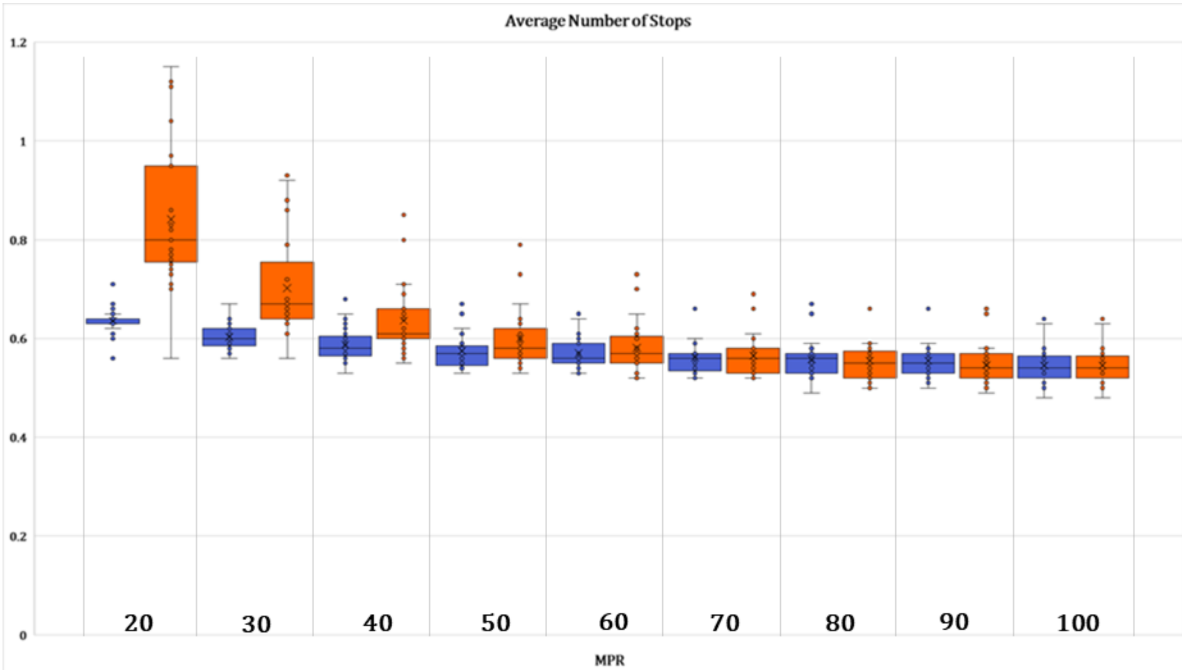


a)

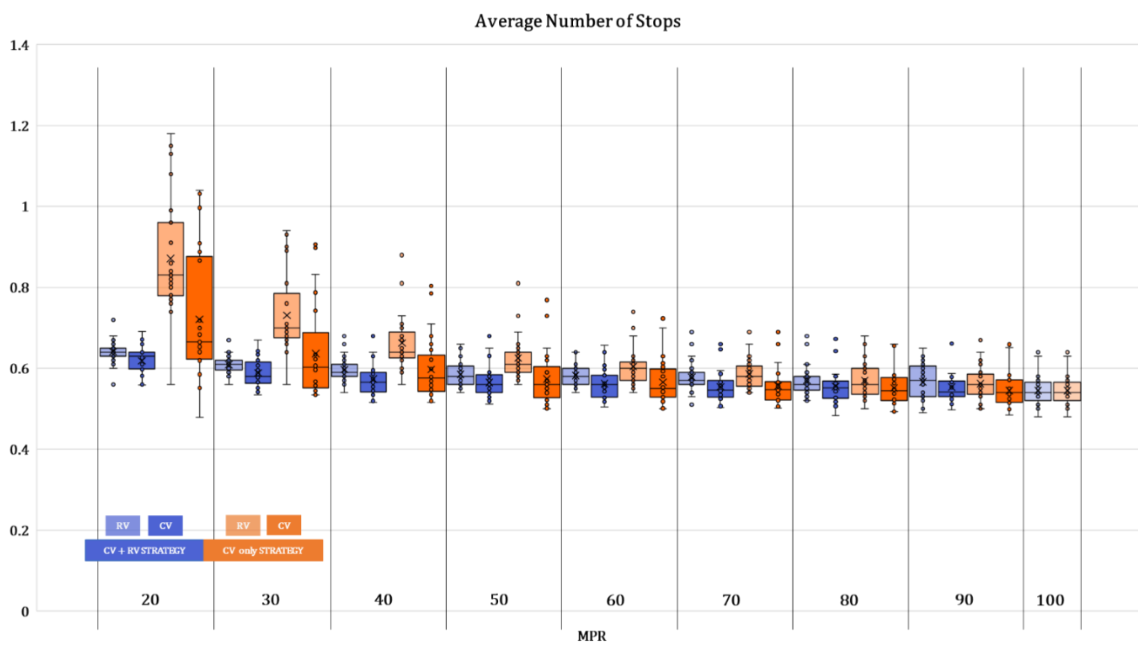


b)

Figure 6-23. Average Vehicle Delay a) all vehicles and b) per vehicle class

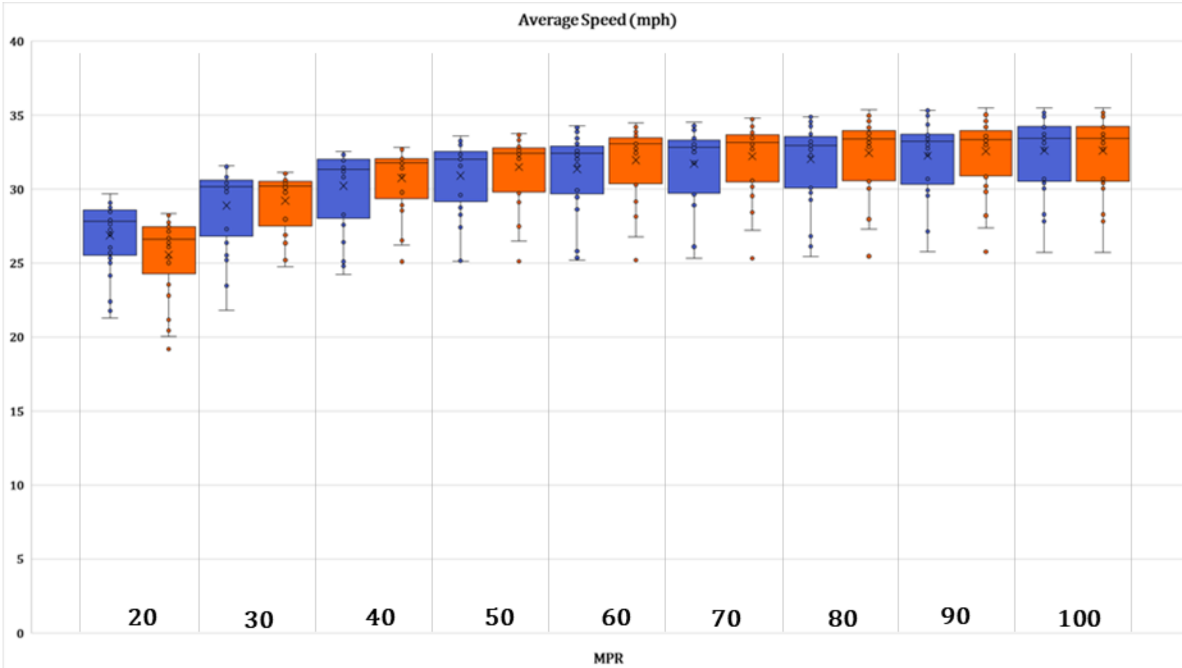


a)

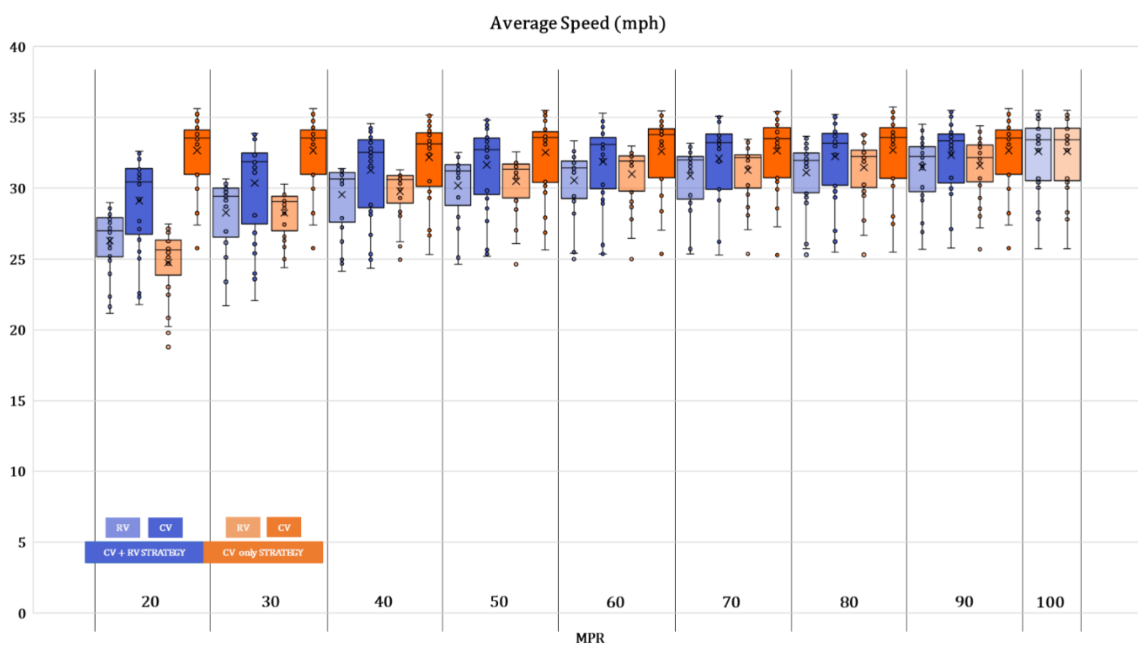


b)

Figure 6-24. Average Number of Stops a) all vehicles and b) per vehicle class



a)



b)

Figure 6-25. Average Vehicle Speed a) all vehicles and b) per vehicle class

As CVG information becomes available, accurate traffic state characterization over a variety of operational conditions will transform signal control system inputs and outputs into more meaningful and actionable data sets. The study utilizes a high definition analysis framework, presented in ***Chapter 5*** to assess the improvement realized when the state-responsive trajectory-based measures are integrated into the signal control design.

What distinguishes these measures (and approach) is that they reflect the system's operational success from its users' perspective. The information is cumulative in time and space and carries over from one "signal cycle" to another.

Traffic operations analysis in terms of reported attributes showed that the ***TSS-MOE*** logic outperforms the delay-based controller logic. Unlike the accumulated delay-based strategy, however, the green time and utilization one benefits from the functional form of its objective function.

The delay-based scheme prioritizes vehicles waiting longer; the higher the number of vehicles waiting longer, the higher the priority. The ***TSS-MOE*** objective is able to inherently recognize the predominant contributing factor among the 4 terms of **TSS-MOE** which conditions the solution choice. This means the objective self-adjusts from queue management during oversaturation to smoothing the progression during light traffic conditions. An extra layer of efficiency and robustness is realized, as the system regardless of the demand level, is able to consistently utilize green time and space capacity, without worsening performance in terms of delay.

The findings indicate that both control system performance assessment and optimization objectives should change with access to CVG data. Unlike the current state of the practice controllers, the developed method takes full advantage of CV's sensing, communication, and computing capability and handles high and low demand states equally well.

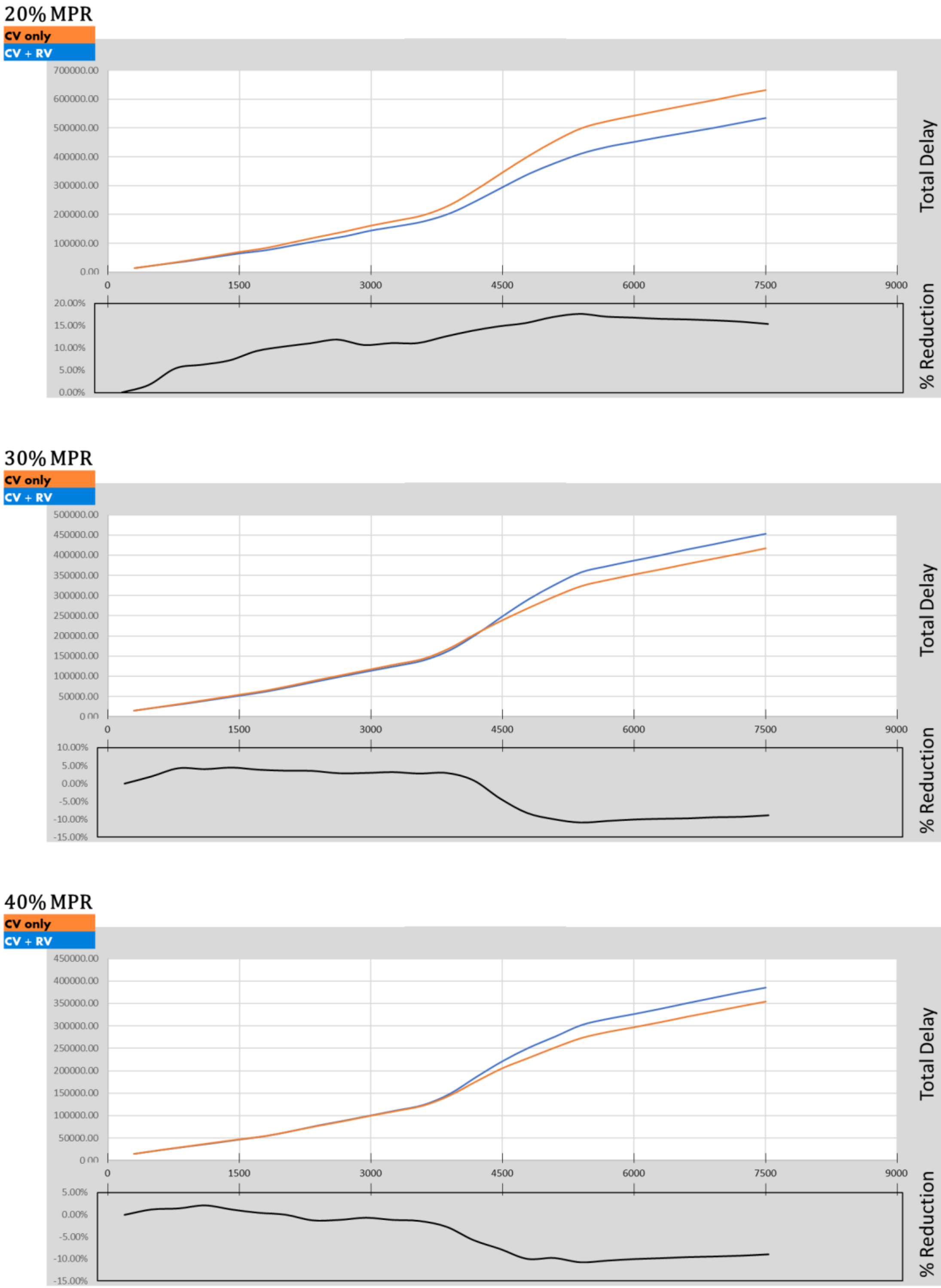


Figure 6-26. Cumulative Delay Comparison 20%, 30% and 40% CV MPR

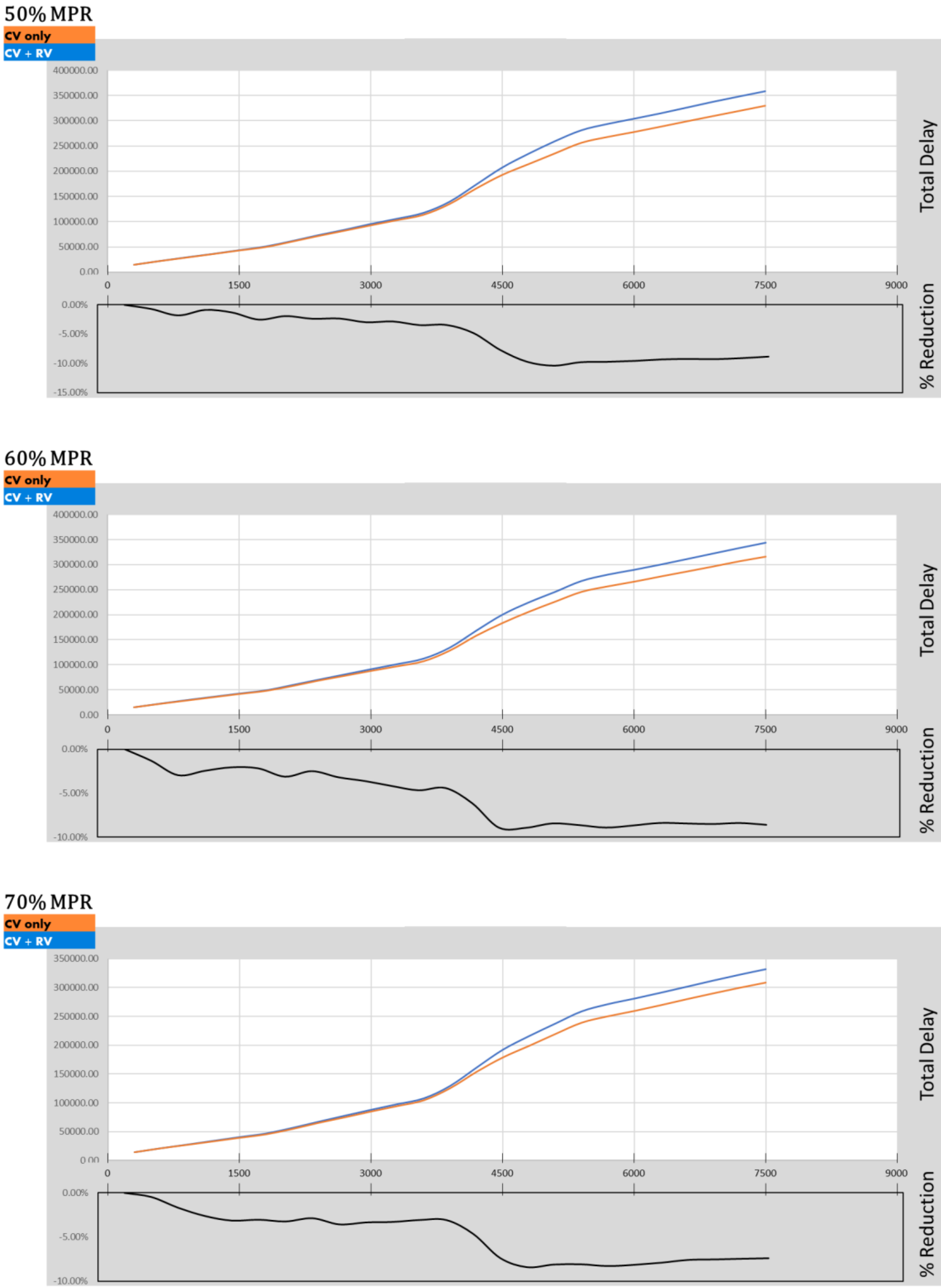


Figure 6-27. Cumulative Delay Comparison 50%, 60% and 70% CV MPR

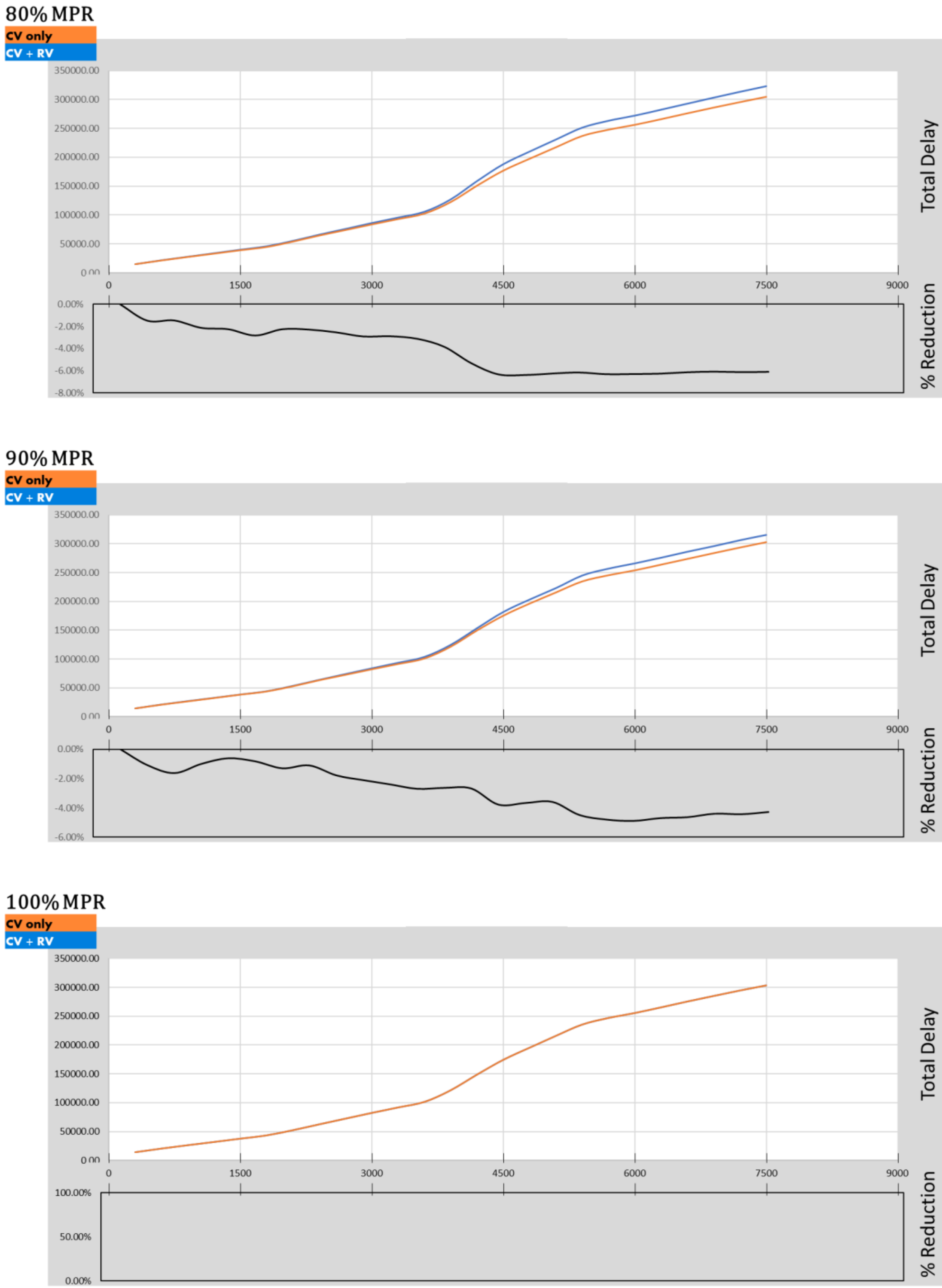


Figure 6-28.Cumulative Delay Comparison 80%, 90% and 100% CV MPR

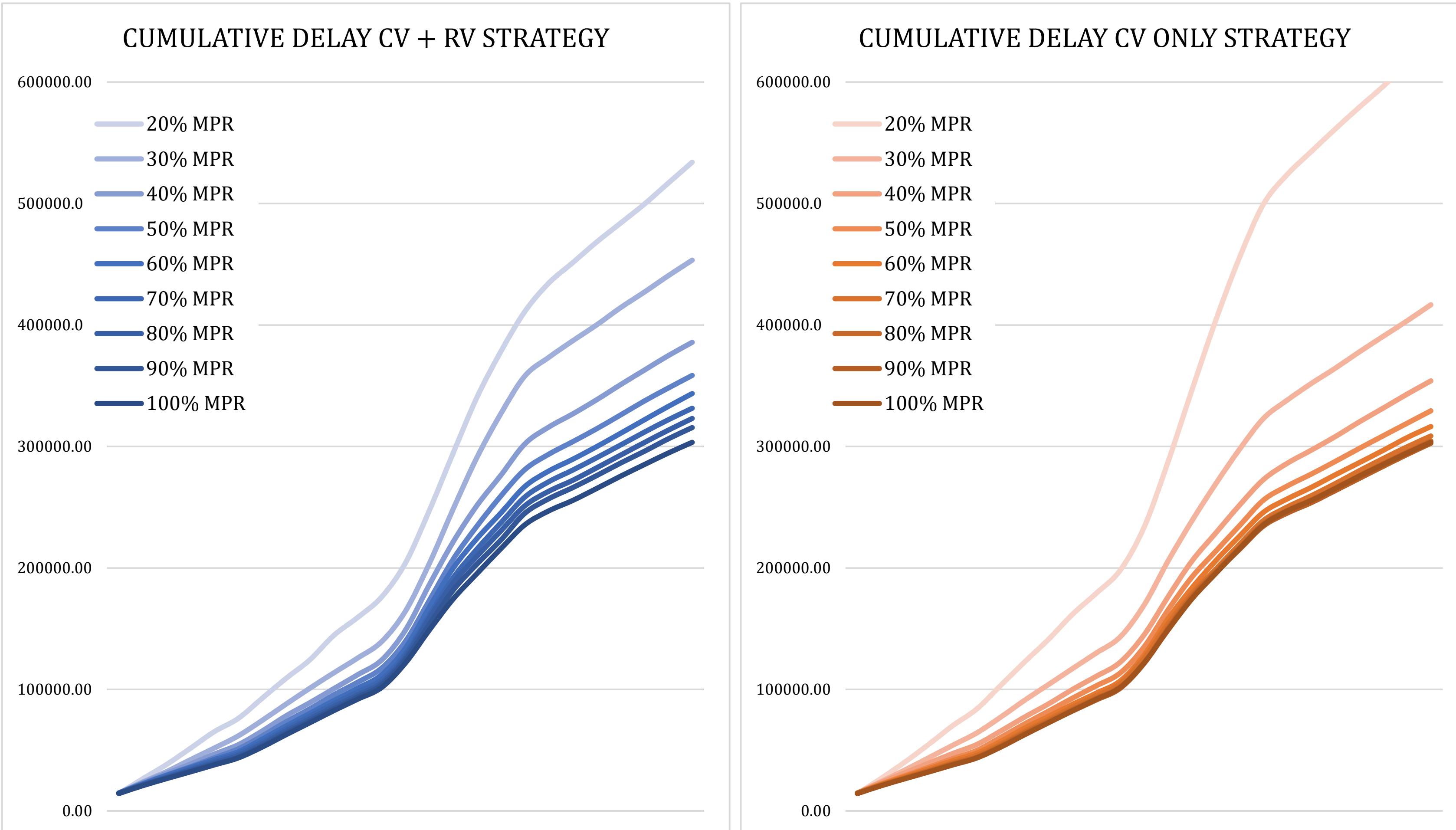


Figure 6-29. Cumulative Delay Decrease with Increase in CV MPR

Cumulative graphs per MPR (**Figure 6-26** through **Figure 6-28**) also compare the relative reduction in delay. The operational success of the two strategies is presented in relative terms (bottom of each chart) – percent change in the performance metric relative to the CV+RV performance over time. CV+RV was considered as the lower bound. **Figure 6-29** demonstrates a tighter spread (MPR above 40%) for CV only strategy resulting delay compared to the CV+RV one.

The difference in cumulative delay is decreasing as the MPR increases. With higher values of MPRs (50% and above) for the CV only strategy, cumulative delay remains relatively the same – please refer to **Figure 6-29**.

As described in this section the increase in volume was significant and affected traffic signal operations adversely in the baseline setup. Yet, with a sizeable increase in volume, both control schemes offered considerable improvements compared to the NEMA-RBC controller operation and, at times, drastically lower intersection delays. Overall, depending on the directional flow symmetry, a more significant improvement in performance was realized on a more burdened approach.

MOEs Temporal Profiles

To isolate the effect of congestion, the temporal profiles of the most relevant MOEs were also studied. It was important to assess the success of the designed control scheme in improving the state of the system during the loading, oversaturation as well as the recovery period and establish the global trend respective of the period and the MPR. ***CV*** only and ***CV***+***RV*** signal timing reported results were compared to the conventional and each other in absolute and relative terms. The same four conventional measurement formats presented in ***6.10.2*** were reported as the most relevant success indications of the current state of traffic operations. The results are aggregated per approach, over a 45- minute evaluation period, for each of the cases reported. The average queue length (**Figure 6-30**), the average number of stops (**Figure 6-31**), average speed (**Figure 6-32**) and average vehicle delay (**Figure 6-33**), of ***CV***+***RV*** vs ***CV*** only signal timing, are presented and discussed, in that order, in this section. The results are aggregated per approach, over a 45-minute evaluation period, for each of the cases reported.

Figures represent temporal distributions over the entire analysis period. Results were reported over 5 separate analysis periods – the first one (0-1500 seconds) represents demand loading, the second low to medium demand level (1500-3000 seconds), the third (3000-4500 seconds) medium to high demand level, the fourth (4500-6000 seconds) oversaturation and the last one (6000-7500 seconds) represents demand recovery (after oversaturation reducing demand to "normal"). In each plot, negative values mean that either connected controller strategy - ***CV*** only or ***CV***+***RV*** - performed better than the baseline.

The charts in **Figure 6-30** through **Figure 6-37** represent temporal distributions of absolute value[4] averages (blue bars – ***CV***+***RV***, orange bars – ***CV*** only control scheme) and respective relative changes in queue length, delay, number of stops, and speed over the reference case. Within one 1500-second interval, each of the 9 cases is presented. Each corresponding to an ***MPR*** % of ***CV***s in ascending order from left to right starting with the most left corresponding to *case2* i.e. 20% ***MPR*** of ***CV***s. The overall findings (comparing the four charts illustrate similar trends relative to the increase in the ***MPR***. Figures indicate the most significant improvements occurred during the oversaturated period.

Most noteworthy, referring to the figures in this section, is that on average (intersection-level) MOEs improve with the increase in MPR and with the increase in the demand.

The oversaturation period – according to the state of the practice and research is expected to be the most challenging in the signalized approach analysis. However, the most significant savings were achieved during this period for each ***MPR***. Important to note is the form of the objective function itself, which, by design (**Equation 5-1**), balances two main objectives smooth progression and queue discharge.

Figure 6-31 shows 1) a different trend and 2) the negative impact ***CV*** (only) strategy has on the average number of stops. Unlike the other three MOEs in **Figure 6-31** demonstrates ***CV*** only scheme's inability to reduce the said parameter. Although the multi-objective function does not account for the number of stops in either case, due to the ***CV***+***RV*** scheme's capability do detect

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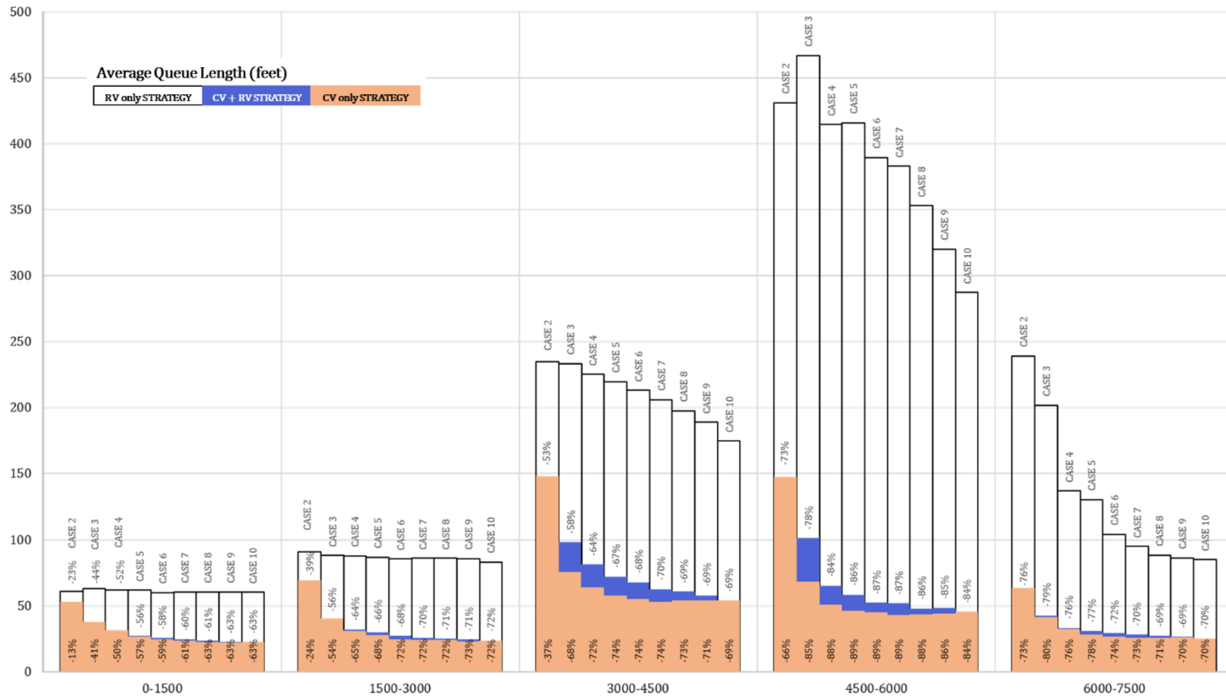
[4] **Technical:** the actual magnitude of a numerical value or measurement, irrespective of its relation to other values

RVs, thus extend the green until gap out occurs, it is reasonable to assume such operational functionality led to such outcomes. SG-based progression ratio for the ***CV***+RV based scheme is higher compared to that of the ***CV*** only one. The reason being the former controller's capability to detect ***RV***s and accordingly extend the green, enabling the progression of a higher number of vehicles overall.

Looking at the charts in **Figure 6-30** through **Figure 6-37**, 20% is the only ***MPR*** for which the ***CV***+***RV*** is outperforming the ***CV*** only control scheme. Already with 30% ***MPR*** of ***CV***s, a significant improvement is recorded throughout the analysis period in each 1500-second interval. Not only this but after the 40% mark, the incremental gains are rather constant and do not vary much, indicating that a traffic stream with only 30% of connectivity-enabled vehicles smooths the flow for all system users and does significantly better in terms of system performance.

Figure 6-34 through **Figure 6-37** represents the average vehicle delay distribution over demand levels and traffic mixes but at an approach level. It was necessary to seek similar improvements at an approach level since the supposition was that the objective function inherently recognizes the quality of service regardless of the number of vehicles or a/symmetry in demand.



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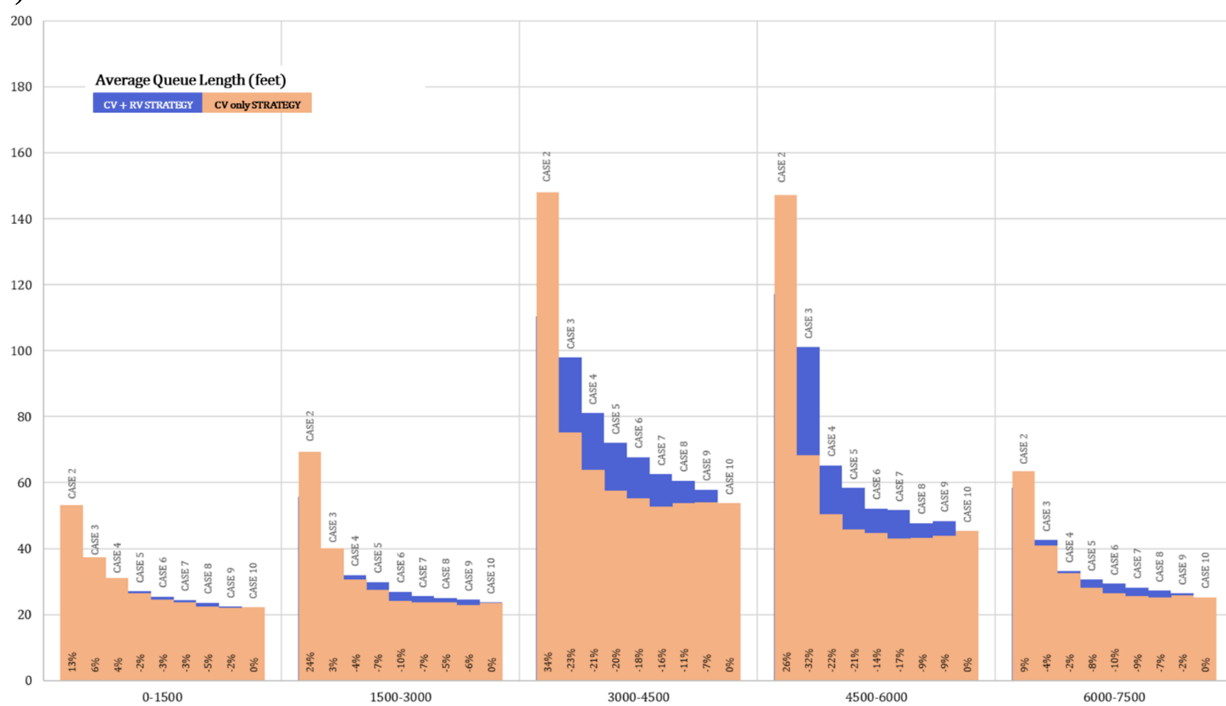
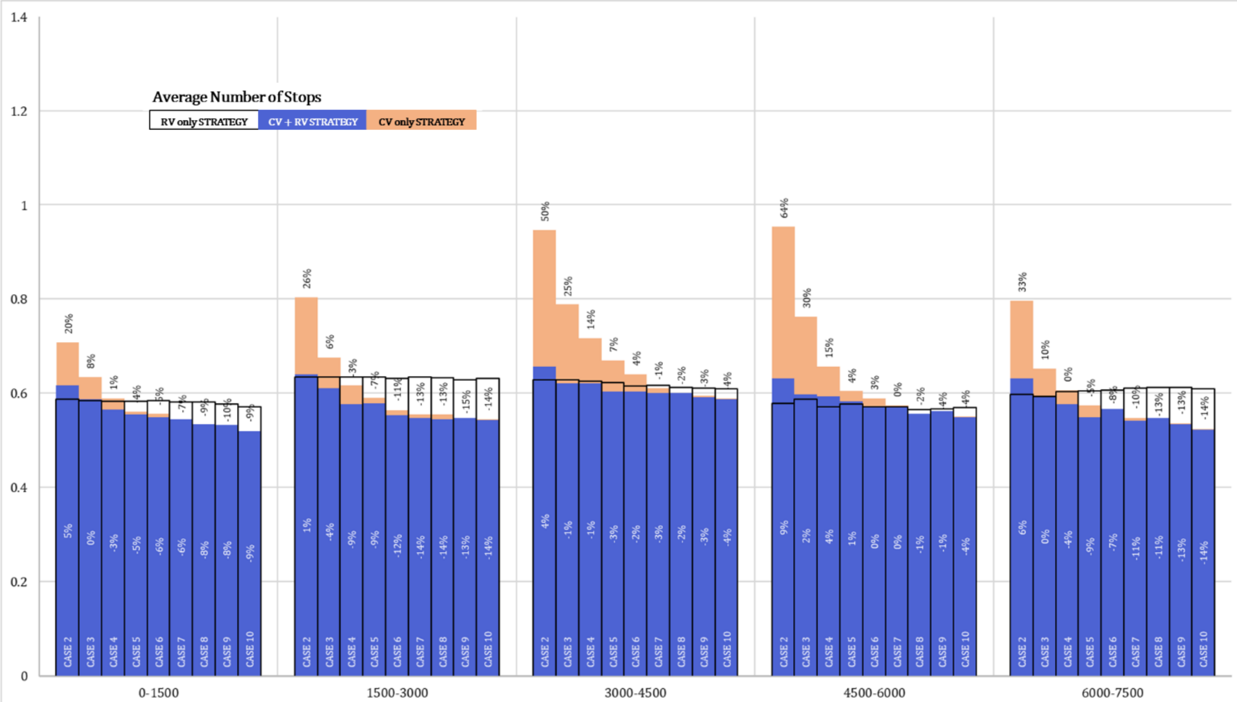


b)

Figure 6-30. Average Queue Length per Demand Level per MPR a) all three controller types and b) CV+RV vs CV only



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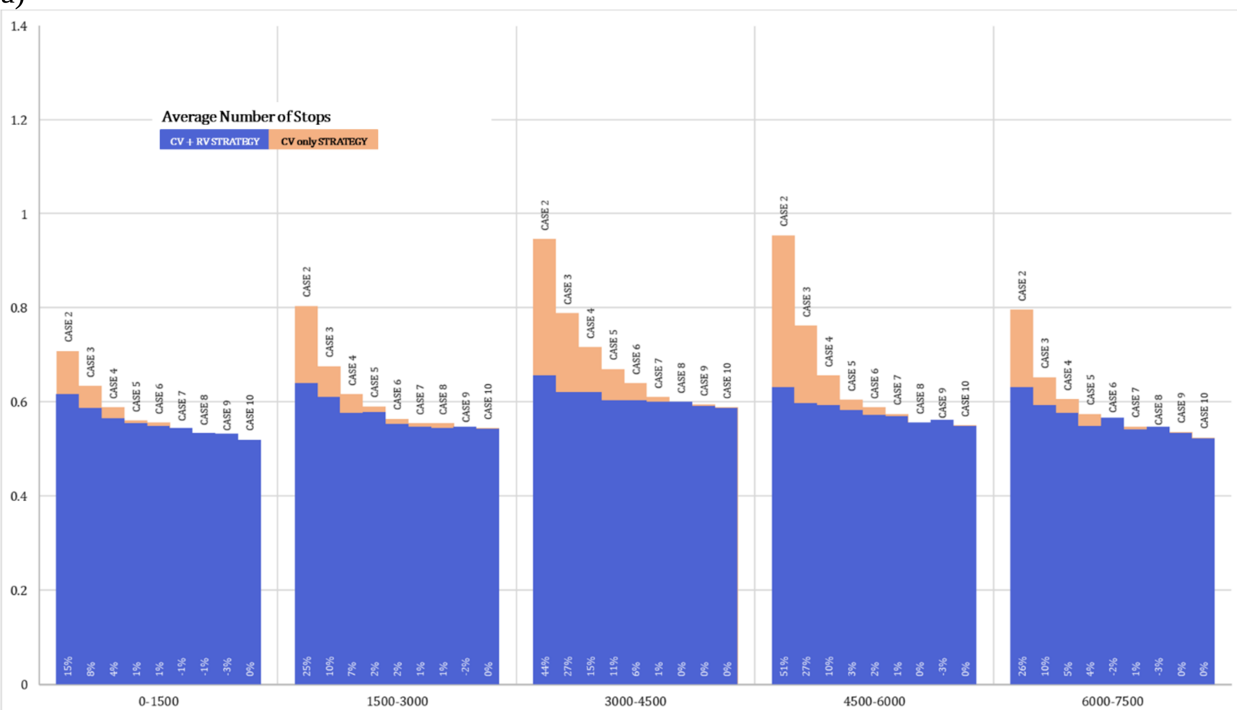
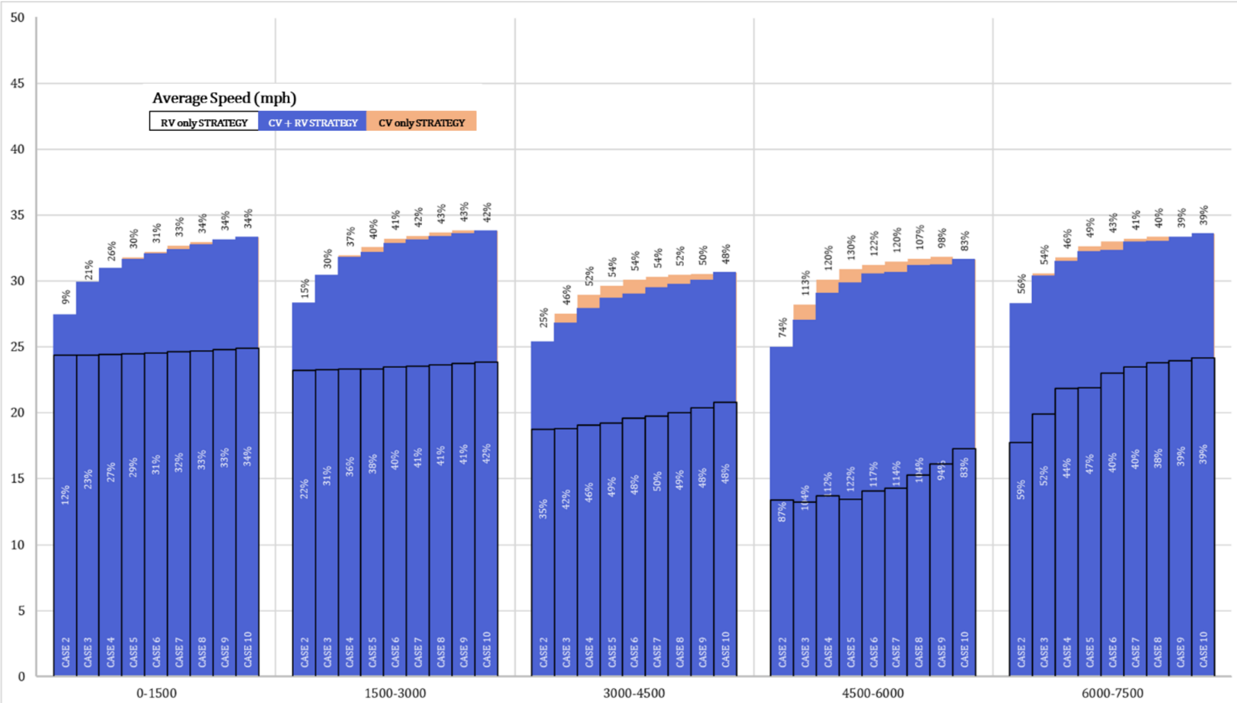


b)

Figure 6-31. Average Number of Stops per Demand Level per MPR a) all three controller types and b) CV+RV vs CV only



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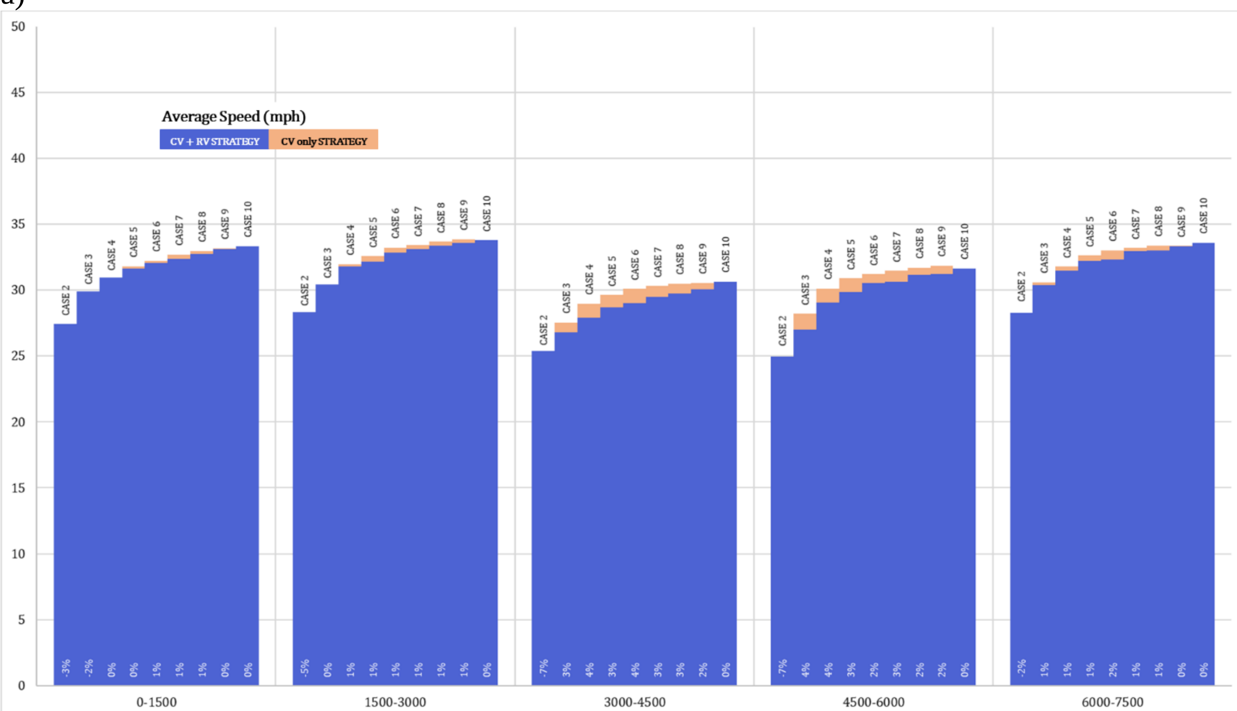
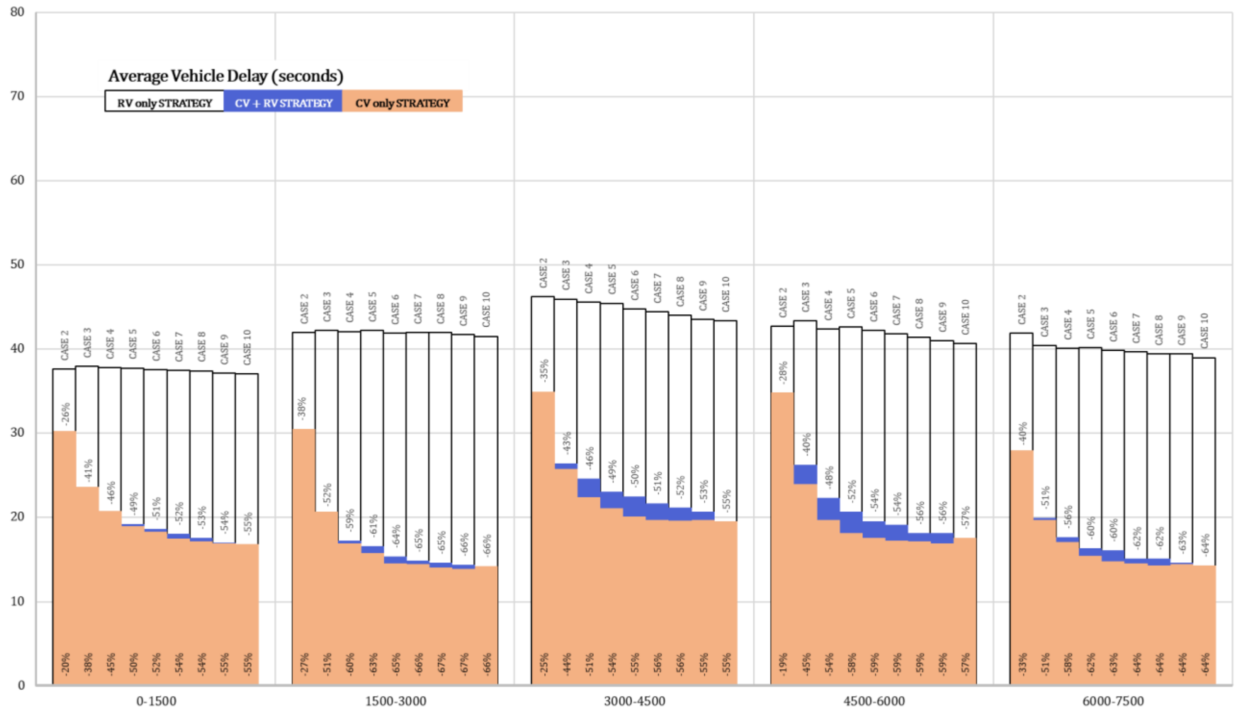
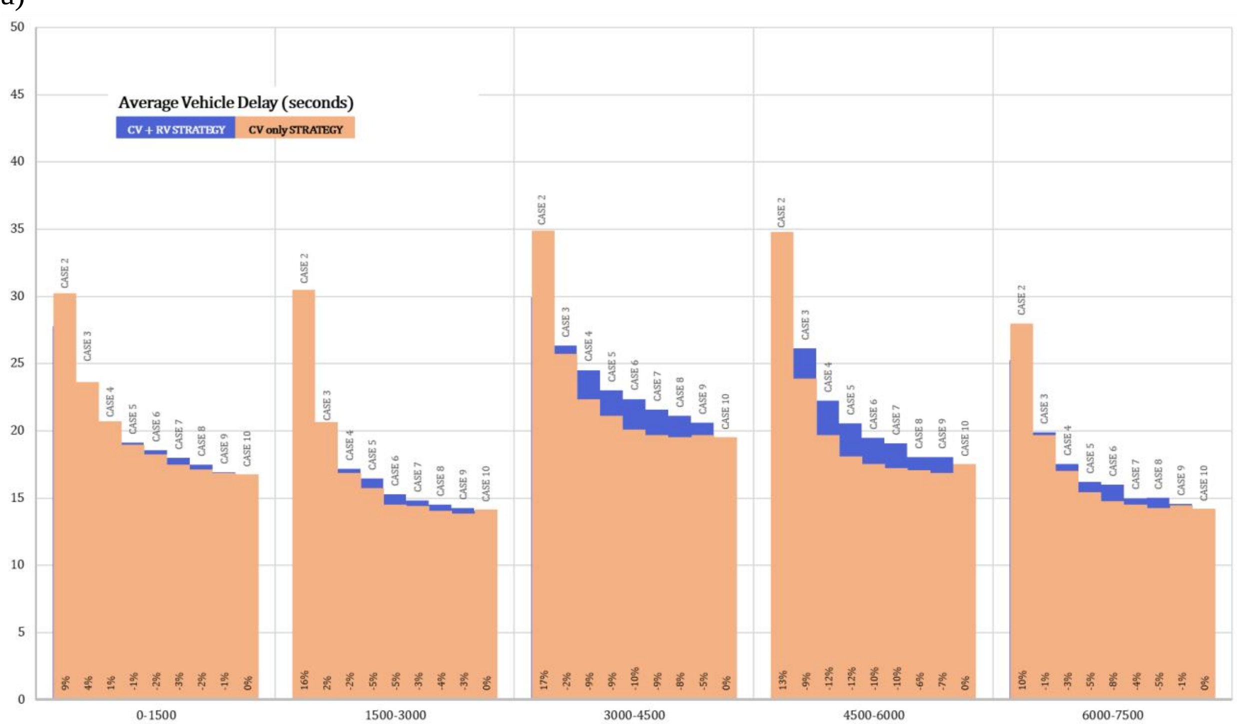


b)

Figure 6-32. Average Speed per Demand Level per MPR a) all three controller types and b) CV+RV vs CV only

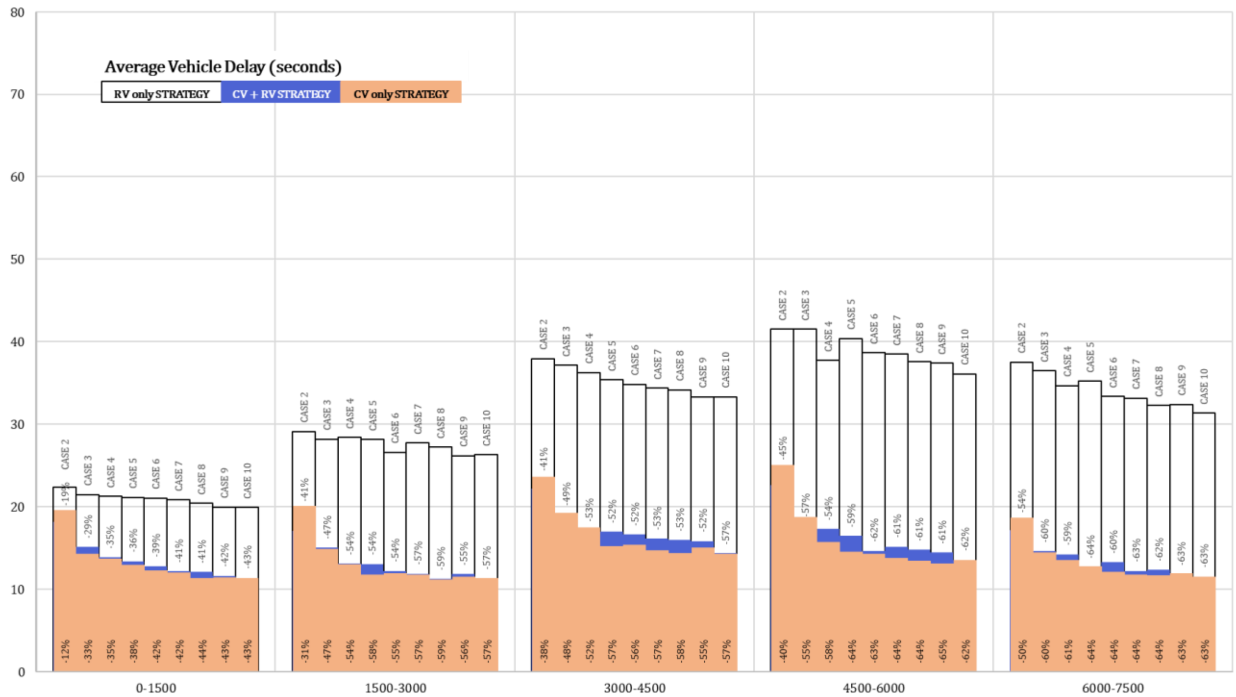


a)

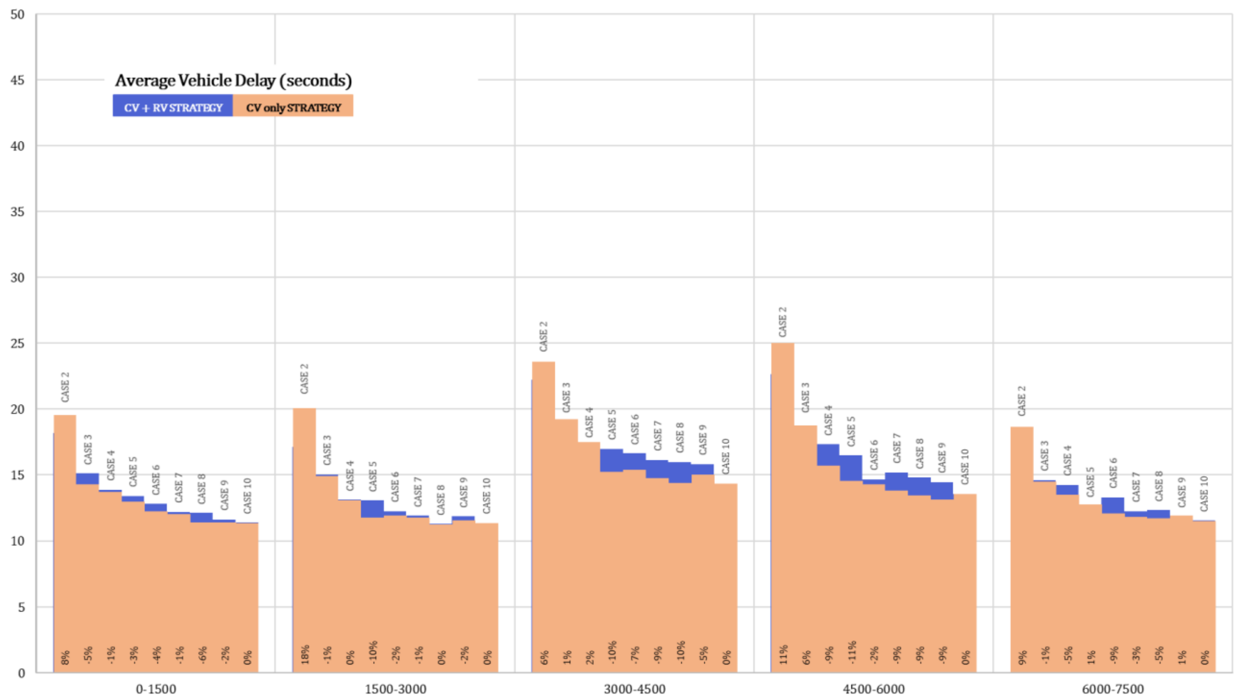


b)

Figure 6-33. Intersection Average Delay per Demand Level per MPR a) all three controller types and b) CV+RV vs CV only

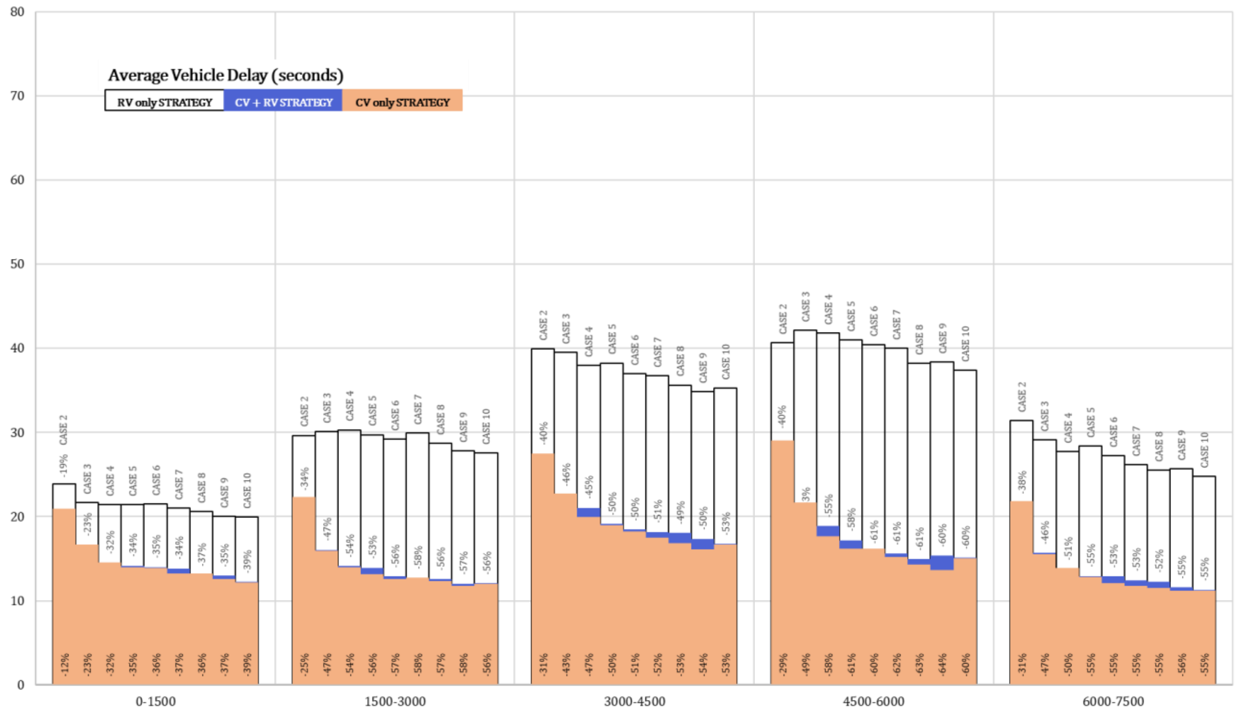


a)



b)

Figure 6-34. Eastbound Approach Delay a) all three controller types and b) CV+RV vs CV only



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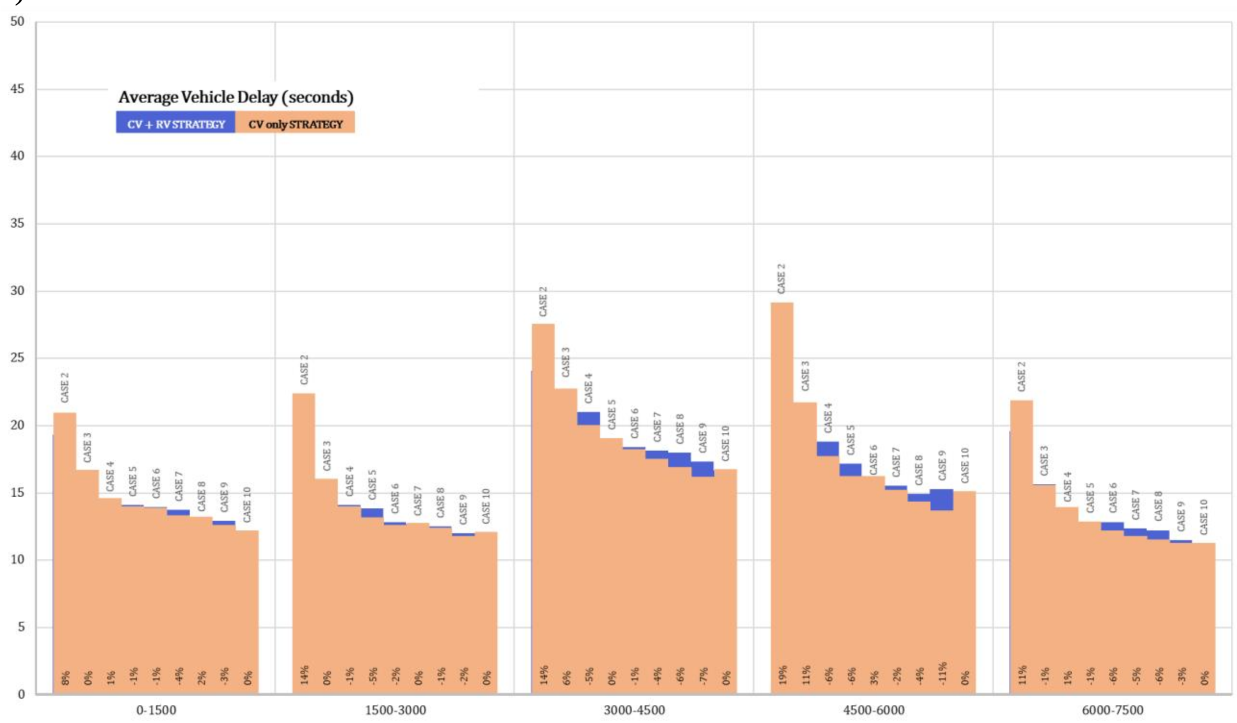
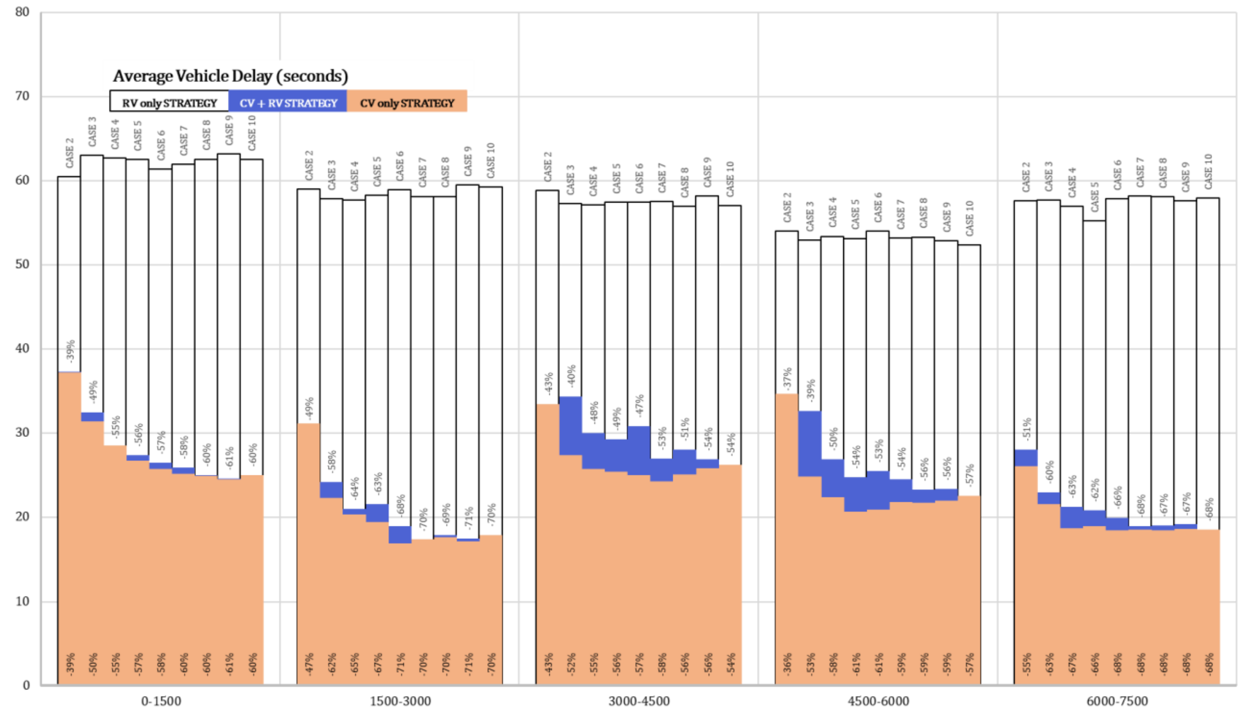


b)

Figure 6-35. Westbound Approach Delay a) all three controller types and b) CV+RV vs CV only



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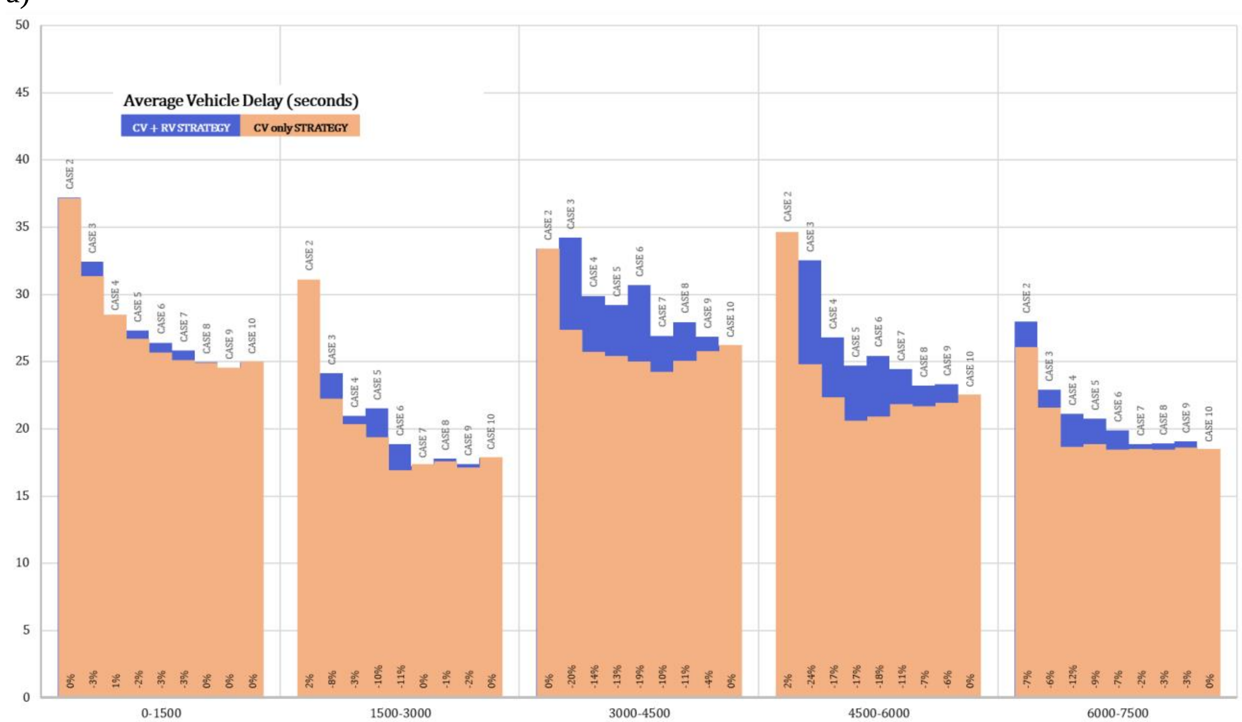
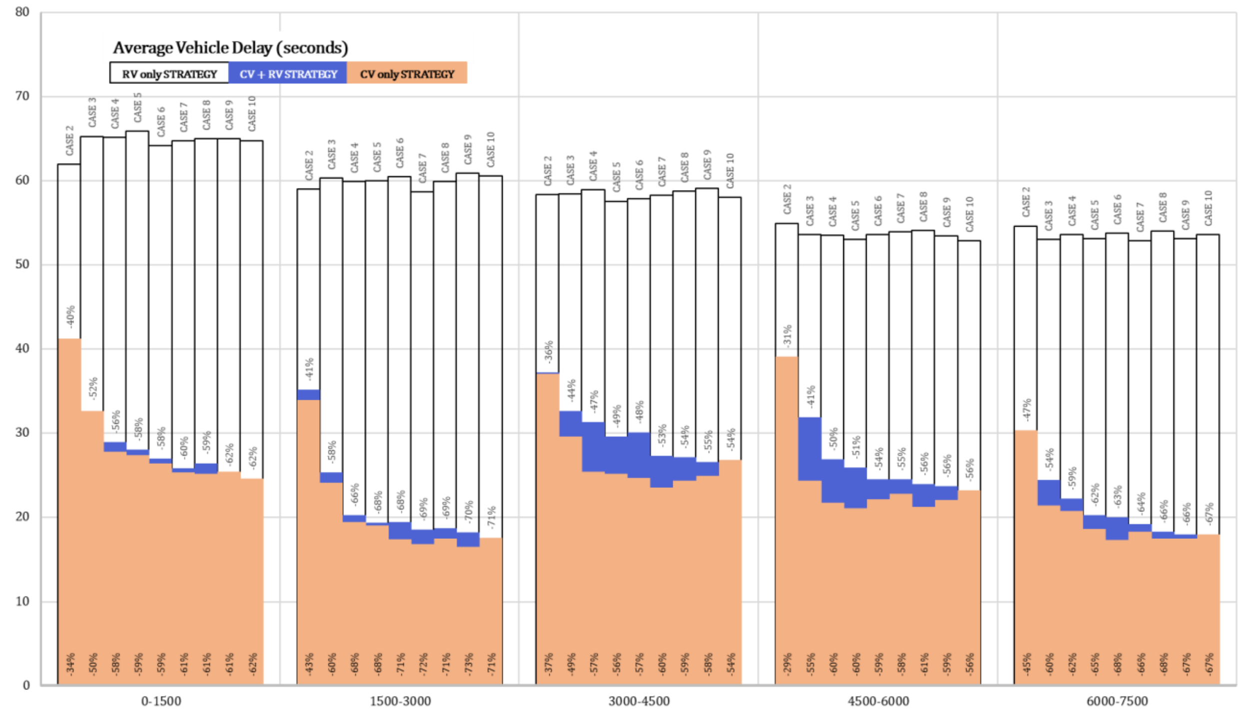
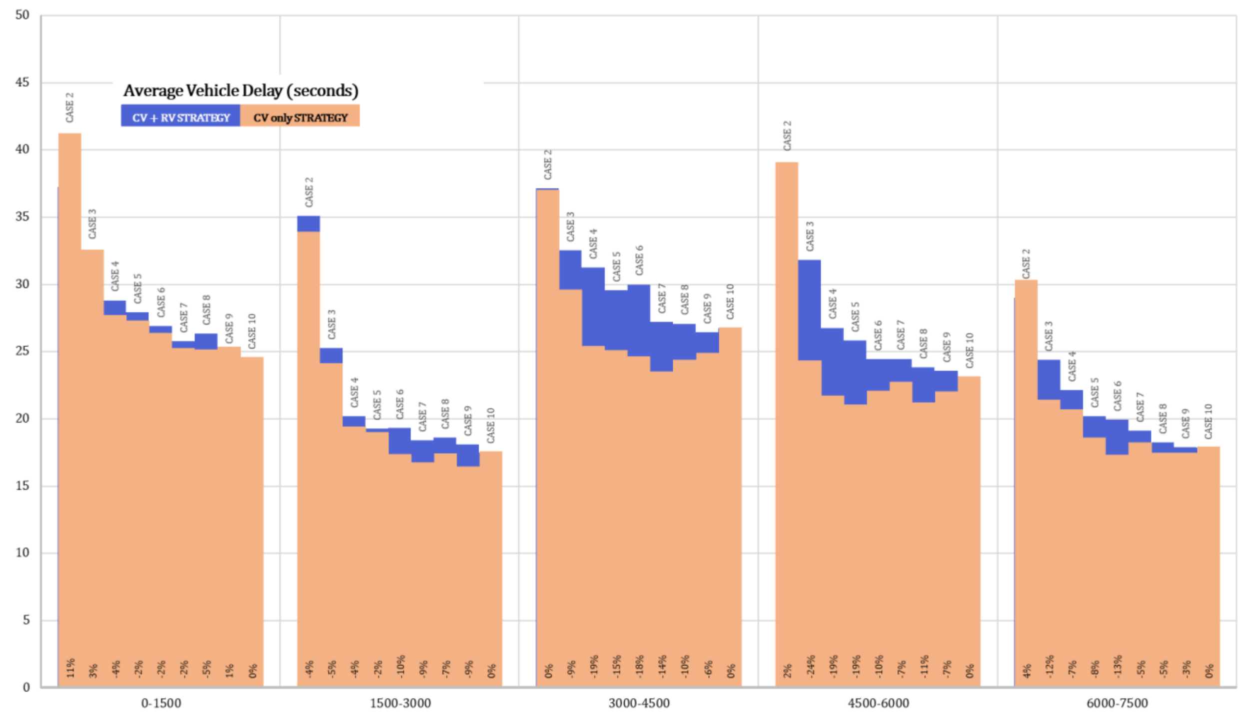


b)

Figure 6-36. Northbound Approach Delay a) all three controller types and b) CV+RV vs CV only



a)



b)

Figure 6-37. Southbound Approach Delay a) all three controller types and b) CV+RV vs CV only

6.11. Conclusion

This study develops a novel communication-enabled smart signal control logic for traffic environments where connected vehicles and regular vehicles coexist. The connected (vehicle-signal) controller, based on the high-fidelity and high-resolution information communicated to the controller, predicts traffic demand, and determines optimal signal phasing and timing.

The study outlines a comprehensive microscopic simulation-based modeling framework to implement and evaluate the novel connectivity-enabled traffic control scheme under varying demand levels and concentrations of vehicle types. The controller logic, aside from conventional input parameters, is capable of processing individual vehicle information related to the experience with respect to operational conditions and immediate downstream signal indication. As a result, the controller logic would potentially allow for "conditional" coordination among consecutive intersections while distributing the computational burden (locally) to individual intersections, running said controller logic.

The connected controller consists of the following low-level elements:

a) Prevailing and near-future traffic demand is estimated by processing connected vehicle generated data exchanged with the controller.
b) Based on vehicle trajectories provided by connected vehicles, the signal controller determines the arrival times of all approaching vehicles and solves the control problem to determine the next SPaT.
c) A newly developed concept of time-space-signal measure of effectiveness forms the basis of a decentralized predictive signal control algorithm. ***CV***s are presumed to calculate and transmit ***TSS-MOE*** related information (as presented in ***5.1*****Error! Reference source not**

found.). This information is the input to the objective function and eliminates the need to pre-specify major vs minor directions.

d) The control problem is solved by minimizing the opportunity cost of serving a platoon at the expense of the (other) unserved platoons. Recorded real-time traffic state recognizes the worst traffic flow conditions (in terms of demand or delay or both) and affords the right of way accordingly.

The goal of this research was to evaluate the robustness of the designed “connected signal” control in handling varying traffic conditions. By assessing relative reduction/improvement for each ***MPR*** scenario and aggregating savings over the entire analysis period, the ***MPR*** cutoff point which offered significant savings was identified. While it is reasonable to assume the ***CV*** only strategy might underperform when the traffic stream consists of predominantly regular vehicles only (*case2* through *case6*), at first, it seemed counterintuitive that the opposite occurs when only 30 % of the fleet is connected.

This could be attributed to the logic design. Including actuation in the connected controller logic negatively affected the performance of the control algorithm since sufficient **CVG** data was available to provide superior operational efficiency given identical external conditions. 30% of connectivity-enabled vehicles in the traffic stream improve operational conditions for all system users i.e. overall and per vehicle class as well. ***CV*** only control scheme outperforms consistently the ***CV***+***RV*** one, with respect to each recorded MOE, except the average number of stops. The results indicate that once 30% ***MPR*** of ***CV***s is achieved, fixed infrastructure can be completely disregarded (i.e. fixed-location detectors and legacy controllers).

The focus of the analysis was on traffic operations during oversaturation, and how the system behaves in such circumstances.

The generality of the controller logic allows for easy transferability to any combination of roadway layouts and/or controller types. The control strategy was developed with the aim to migrate it to real-world applications.

Chapter 7. **CONCLUSION**

CVs and AVs are likely to impact traffic control and traffic flow in significant ways, due to their sensing, communication, and computational capabilities. Incorporating these vehicle capabilities into traffic control models is an important task for the traffic systems community.

This analysis focused on exploring the potential of connected vehicles (CVs) technology related to the design of control strategies and relevant assessment techniques. The aim is to integrate these into practical and effective transportation system components, thereby enhancing its existing operational capabilities. To do so this study aimed to answer the following questions:

- *How can connected vehicle data and technologies be used to support offline and online performance-based management of traffic signal systems?*
- *How can connected vehicle generated traffic data be utilized for traffic state characterization and reactive and/or predictive analytics with respect to different operational conditions?*
- *How can connectivity help isolate the underlying causes of system inefficiencies and facilitate the development of innovative analytical methods to describe and address these issues?*

Big data analytics is expected to play a major role in connected environments. The implication is the availability of new information and methods, new functionalities and opportunities to enhance the state of the practice standards and set new ones. The core of the research described has been the design of robust, rigorous yet practical approaches to urban signalized arterial management, with emphasis on applications and (real-world) transferability. Computationally efficient real-time intelligent controller algorithms were designed to manage CV and mixed vehicular fleets at isolated intersections.

It is also necessary to increase the behavioral realism of CV/AV fleet operational models by explicitly incorporating advanced operational features of these vehicles as more research on their behavior becomes available. Existing modeling frameworks largely ignore the ability of traffic management agencies to adapt to continually-evolving system needs and goals. State of the practice signal system management assumes decision support software is to be advanced to help operators and engineers increase efficiency. With robot vehicles, the control algorithms will not just provide decision support, they will control CV/AVs in real-time. And as the technology of these vehicles matures and the theories are reinforced, control strategies may evolve in ways that are difficult to anticipate. Fully connected environments may make certain infrastructure needs obsolete and a new era of control strategies may come about. While logical, these hypotheses should be tested using advanced transportation models that explicitly incorporate the unique aspects of CV/AVs and model the system dynamics of travelers in complex multi-modal transportation systems.

The results raise the question of the merit of any new method or application deployment. Would it be cost-beneficial to deploy connected signals if only some performance indicators reflect significant improvements in performance? However, how would one determine an acceptable threshold that would warrant such actions? These questions will require further investigation in future studies.

However, designed control parameters are as optimal as the related traffic information is reliable. The goal of this research was to evaluate the robustness of the designed “connected signal” control in handling varying traffic conditions. By assessing relative reduction/improvement for each ***MPR*** scenario and aggregating savings over the entire analysis period, the ***MPR*** cutoff point which offered significant savings was identified. While it is reasonable to assume the ***CV*** only strategy might underperform when the traffic stream consists of predominantly regular vehicles only (*case2* through *case6*), at first, it seemed counterintuitive that the opposite occurs when only 30 % of the fleet is connected.

This could be attributed to the logic design. Including actuation in the connected controller logic negatively affected the performance of the control algorithm since sufficient **CVG** data was available to provide superior operational efficiency given identical external conditions. 30% of connectivity-enabled vehicles in the traffic stream improve operational conditions for all system users i.e. overall and per vehicle class as well. ***CV*** only control scheme outperforms consistently the ***CV***+***RV*** one, with respect to each recorded MOE, except the average number of stops. The results indicate that once 30% ***MPR*** of ***CV***s is achieved, fixed infrastructure can be completely disregarded (i.e. fixed-location detectors and legacy controllers).

The focus of the analysis was on traffic operations during oversaturation, and how the system behaves in such circumstances.

The generality of the controller logic allows for easy transferability to any combination of roadway layouts and/or controller types. The control strategy was developed with the aim to migrate it to real-world applications.

With CVG information readily available, accurate traffic state characterization over a variety of operational conditions will transform signal control system inputs and outputs into more meaningful and actionable data sets. The study utilizes a high definition analysis framework, presented in ***Chapter 5*** to assess the improvement realized when the state-responsive trajectory-based measures are integrated into the signal control design.

What distinguishes these measures (and approach) is that they reflect the system's operational success from its user's perspective. The information is cumulative in time and space and carries over from one "signal cycle" to another.

Traffic operations analysis in terms of reported attributes demonstrated that ***TSS-MOE*** one outperforms the delay-based controller logic. Unlike the accumulated delay-based strategy, however, the green time and utilization one benefits from the functional form of its objective function.

The delay-based scheme prioritizes vehicles waiting longer; the higher the number of vehicles waiting longer, the higher the priority. The ***TSS-MOE*** objective is able to inherently recognize the predominant contributing factor among the 4 terms of **TSS-MOE** which conditions the solution choice. This means the objective self-adjusts from queue management during oversaturation to smoothing the progression during light traffic conditions. An extra layer of efficiency and robustness is realized, as the system regardless of the demand level, is able to consistently utilize green time and space capacity, without worsening the performance in terms of delay.

The findings indicate that both control system performance assessment and optimization objectives should change with access to CVG data. Unlike the current state of the practice controllers, the developed method takes full advantage of CV's sensing, communication, and computing capability and handles high and low demand states equally well.

Designed signal control algorithms are myopic in that they do not consider advanced information about vehicle locations at upstream intersections. Future work is intended to advance these algorithms into robust heuristics that jointly consider adjacent intersections approaches when scheduling the right of way, thus addressing atypical behavior or traffic patterns in a more than local, yet less than centralized manner. This would represent a significant advancement in the field of centralized corridor-level control strategies, and how we perceive coordination.

To attain sustainable, affordable and efficient urban transportation systems, decision-makers must increase their understanding of the potential impacts of CVs and AVs. As CVs and AVs are expected to significantly disrupt transportation systems, this research is especially timely and important, as well as challenging.

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