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Comparing & Combining Existing & Emerging Data Collection & Modeling Strategies in Support of Signal Control Optimization & Management

Dr. Mohammed Hadi | Florida International University

Dr. Virginia Sisiopiku | University of Alabama at Birmingham

Mosammat Tahnin Tariq | Florida International University

Rajib Chandra Saha | Florida International University

Dr. Tao Wang | Florida International University

Gokmen Pacal | University of Alabama at Birmingham

STRIDE | Southeastern Transportation Research, Innovation, Development and Education Center

UF | Transportation Institute UNIVERSITY of FLORIDA

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16. Abstract

For decades, traffic signal management agencies have used signal timing optimization tools combined with fine-tuning of signal timing based on field observations in their updates of time-of-day signal timing plans. These traditional signal optimization methods and tools use very limited amount of data and depend on default values in the signal timing optimization/simulation tools to estimate network performance under different signal optimization strategies. In recent years, new data collection technologies are emerging including high resolution controller data, more advanced detection technologies such as video image detection that are based on vehicle tracking and possible integration with microwave detectors, automatic vehicle-based identification technologies, third party crowdsourcing data, connected vehicles, and connected automated vehicles data. The objective of the study is to propose methods and algorithms to combine data collected from existing and emerging sources with enhanced models and optimization algorithms to optimize and manage signal operations. The study developed a method for the calibration and validation of microscopic simulation models of arterial networks utilizing high-resolution controller data combined with a two-level unsupervised clustering technique and multi-objective optimization for simulation model calibration. The study demonstrated the benefits of this methodology. Based on the results from this calibration, the study compared the performance of two signal timing optimization methods based on macroscopic simulation and microscopic simulation with and without fine-tuning their parameters based on high-resolution controller data. The next step was to use a combination of two artificial intelligence approaches, namely Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) to recommend modifications to signal timings during non-recurrent events such as incidents, construction, surge in demands, and device malfunctions. An important aspect of the methodology was the calibration of the utilized mesoscopic simulation-based MRM based on the increase in demands and travel times on alternative routes using data from third party vendors. Another important aspect was the use of microscopic simulation-based optimization of signal timing utilizing a multi-objective optimization that jointly minimizes the delays and maximizes the throughputs considering the whole intersections as well the specific impacted movements on the alternative routes.

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LIST OF AUTHORS

Lead PI:

Mohammed Hadi, Ph.D.
Professor, Department of Civil & Environmental Engineering
Florida International University
(305) 348-0092 | hadim@fiu.edu

Co-PI:

Virginia P. Sisiopiku, Ph.D.
Professor, Department of Civil, Construction and Environmental Engineering
University of Alabama at Birmingham
(205) 934-9912 | vsisiopi@uab.edu

Additional Researchers:

Mosammat Tahnin Tariq
Graduate Student
Department of Civil and Environment Engineering
Florida International University
(786) 479-5724 | mtari006@fiu.edu

Rajib Chandra Saha
Graduate Student
Department of Civil and Environment Engineering
Florida International University
(701) 400-9637 | rsaha005@fiu.edu

Tao Wang, Ph.D.
Research Associate, Department of Civil and Environmental Engineering
Florida International University
(305) 348-1393 | twang@fiu.edu

Gokmen Pacal
Graduate Trainee, Department of Civil, Construction, and Environmental Engineering
University of Alabama at Birmingham
(205) 934-1574 | gokmen@uab.edu

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LIST OF ACRONYMS

AAM	Active Arterial Management
ACO	Ant Colony Optimization
AIMSUN	Advanced Interactive Microscopic Simulator
AMP	Arterial Management Program
ATCSs	Adaptive Traffic Control Systems
ATSPMs	Automated Traffic Signal Performance Measures
CAF	Capacity Adjustment Factor
CART	Classification and Regression Trees
CBD	Central Business District
CCTV	Closed Circuit Television Camera
CHART	Coordinated Highways Action Report Team
CHAID	Chi-square Automatic Interaction Detector
COM	Component Object Model
CORSIM	Corridor Simulation
DI	Disutility Index
DT	Decision Tree
DTA	Dynamic Traffic Assignment
EB	Eastbound
EBL	Eastbound Left
EBT	Eastbound Though
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
FRBS	Fuzzy Rule Based System
GA	Genetic Algorithm
GOR	Green Occupancy Ratio
HCM	Highway Capacity Manual
HCS	Highway Capacity Software

HRC	High Resolution Controller
ID3	Iterative Dichotomizer 3
ITE	Institute of Transportation Engineers (ITE)
ICM	Integrated Corridor Management
ITS	Intelligent Transportation System
MISO	Multiple-Input and Single-Output
MOE	Measures of Effectiveness
MPO	Metropolitan Planning Organization
MRM	Multi-Resolution Modeling
NB	Northbound
NBL	Northbound Left
NBT	Northbound Though
NSGA	Non-dominant Sort Genetic Algorithm
NTOC	National Transportation Operations Coalition
NW	Northwest
OD	Origin and Destination
ODME	Origin Destination matrix estimation
PASSER	Progression Analysis and Signal System Evaluation Routine
PDF	Platoon Dispersion Factor
POG	Percentage Arrival on Green
PSO	Particle Swarm Optimization
PTV	Planung Transport Verkehr
RITIS	Regional Integrated Transportation Information System
RPART	Recursive Partitioning and Regression Decision Tree
SA	Simulated Annealing
SAS	Self-Assessment Survey
SB	Southbound
SBL	Southbound Left
SBT	Southbound Though

SCOOT	Split, Cycle, Offset Optimization Technique
SIGOP	Signal Optimization
SNE	Stochastic Neighbor Embedding
SUR	Split Utilization Ratio
TMC	Traffic management centers
TOD	Time of Day
TRANSYT	Traffic Network Study Tool
TSK	Takagi Sugeno Kang
TSIS	Traffic Software Integrated System
TSM&O	Transportation Systems Management and Operations
TSOOMM	Traffic Signal Operation, Optimization, Maintenance and Management
UDOT	Utah Department of Transportation
USDOT	United States Department of Transportation
VISSIM	Verkehr In Städten SIMulationsmodell
VISTRO	Vision Traffix and Optimization
WB	Westbound
WBL	Westbound Left
WBT	Westbound Though
WisDOT	Wisconsin Department of Transportation

ABSTRACT

For decades, traffic signal management agencies have used signal timing optimization tools combined with fine-tuning of signal timing based on field observations in their updates of time-of-day signal timing plans. These traditional signal optimization methods and tools use very limited amount of data and depend on default values in the signal timing optimization/simulation tools to estimate network performance under different signal optimization strategies. In recent years, new data collection technologies are emerging including high resolution controller data, more advanced detection technologies such as video image detection that are based on vehicle tracking and possible integration with microwave detectors, automatic vehicle-based identification technologies, third party crowdsourcing data, connected vehicles, and connected automated vehicles data. The objective of the study is to propose methods and algorithms to combine data collected from existing and emerging sources with enhanced models and optimization algorithms to optimize and manage signal operations.

The project started with a review of the literature and a comprehensive survey of practice that aimed at documenting current signal timing practices of operating agencies responsible for traffic signal control in small, medium, and large size cities in the Southeast United States. Then, the study developed a method for the calibration and validation of microscopic simulation models of arterial networks utilizing high-resolution controller data combined with a two-level unsupervised clustering technique and multi-objective optimization for simulation model calibration. The study demonstrated the benefits of this methodology. Based on the results from this calibration, the study compared the performance of two signal timing optimization methods based on macroscopic simulation and microscopic simulation with and without fine-tuning their parameters based on high-resolution controller data.

The next step was to use a combination of two artificial intelligence approaches, namely Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) to recommend modifications to signal timings during non-recurrent events such as incidents, construction, surge in demands, and device malfunctions. This was followed by comparing the performance of the resulting plans from the above methods with those obtained using a simulation-based optimization methods to select the signal timing parameters during non-recurrent conditions.

This study also investigated the use of clustering analysis, multi-resolution modeling (MRM), and optimization techniques in the development of plans on alternative routes to accommodate diverted traffic during freeway incidents. An important aspect of the methodology was the calibration of the utilized mesoscopic simulation-based MRM based on the increase in demands and travel times on alternative routes using data from third party vendors. Another important aspect was the use of microscopic simulation-based optimization of signal timing utilizing a multi-objective optimization that jointly minimizes the delays and maximizes the throughputs considering the whole intersections as well the specific impacted movements on the alternative routes.

Keywords: Signal Timing Optimization, Emerging Data Sources, Recurrent Events, Non-recurrent Events

EXECUTIVE SUMMARY

Signal control is a major influencing factor on the mobility and reliability of the transportation system. There have been major investments in installing, operating, and maintaining traffic signal infrastructure. Public agencies have the responsibility to manage and operate this infrastructure in an optimal manner to reduce the impacts of traffic signal on traffic. Signal timing methods and practices utilized by these agencies play a major role in achieving these objectives. Considerable improvements in signal timing methods are possible with the advancement in data collection technologies and the potential for enhancing optimization techniques to utilize the data. This research will develop a framework to utilize data from existing and emerging sources combined with optimization tools to support traffic control optimization and management. This is expected to result in significant reductions in travel time and delays at signalized intersections, increased travel time reliability of motorists, and potentially safety. The framework will allow agencies to achieve these improvements considering their priorities and constraints including the level of the availability of data.

Adequately designed, managed, operated, and maintained traffic signal systems provide substantial operational, environmental, economic, and safety benefits. While technological advancements can enable improvements in traffic signal operation, optimization, maintenance, and management; such benefits cannot be realized unless transportation authorities are ready to embrace the new technologies and adopt them. In order to understand the needs and opportunities for intervention in these systems, it is important to examine the current practices and document the facilitators and barriers that drive those practices. Along these lines, this study developed and conducted a comprehensive survey of traffic signal operation, optimization and management practices in the Southeast United States. Twenty representatives of transportation agencies that operate various-sized traffic signal systems in six states in the Southeast responded to the survey. The study team aggregated the responses by agency size and used the results to document the state-of-practice. Also, current barriers were identified including limitations in available resources (such as funding and staffing levels), and lack of efficient trigger data for retiming signals. The analysis of the survey results highlighted opportunities for refining and improving current practices through the use of emerging data collection and modeling options.

Calibration of traffic simulation models a critical component of simulation modeling when used in assessing or optimizing signal timing parameters. The increased complexity of the transportation network and the adoption of emerging of vehicle and infrastructure-based technologies and strategies have motivated the development of new methods and data collection to calibrate the simulation models. This study proposes the use of high-resolution controller data, combined with a two-level clustering technique for scenario identifications and a multi-objective optimization technique for simulation model parameter calibration.

The evaluation of the calibration parameters resulting from the multi-objective optimization based on travel time and high-resolution controller data measures indicates that the simulation model that uses these optimized parameters produces significantly lower errors in the split utilization ratio, green utilization ratio, arrival on green, and travel time compared to a simulation model that uses software's default parameters. When compared with a simulation model that uses calibration parameters obtained based on the optimization of the single objective of minimizing the travel time, the multi-objective optimization solution produces comparably low

travel time errors but with significantly lower errors in terms of the high-resolution controller data measures.

The efficient design of traffic signal control has been recognized as one of the most cost-effective methods to improve the accessibility and mobility of urban networks. Traffic signal management agencies have used signal timing optimization tools combined with fine-tuning of signal timing based on manually collected field observations in their updates of time-of-day signal timing plans. These traditional signal optimization methods and tools use a very limited amount of data due to the high cost and efforts associated with collecting the data. The adaptation of Automated Traffic Signal Performance Measures (ATSPMs) technology creates an opportunity to calibrate the signal timing optimization tool instead of using default values in the simulation model. This study evaluates the performance of the macroscopic simulation-based optimization tool, TRANSYT-7F (T7F), and microscopic simulation-based optimization using Vissim and multi-objective optimization algorithm in the presence of high-resolution controller (HRC) data. An arterial network consisting of five intersections is coded in both software, and the parameters along with turning movement counts are calibrated using data retrieved from the HRC controllers used in the field. The plans generated by the HRC calibrated models reduce more delays per vehicle and the total number of stops compared to their traditionally calibrated counterparts. In addition, the properly calibrated macroscopic model develops a better plan than the uncalibrated microscopic model for both network and major movement performance. The study highlights the usefulness of the HRC data in signal timing optimization. The agency can use this method to update the current signal control plan or develop new plans.

Events such as surges in demands or lane blockages can create queue spillbacks even during the off-peak periods resulting in delays and spillbacks to upstream intersections. To address this issue, some transportation agencies have started implementing processes to change the signal timing in real-time based on traffic signal engineer/expert operator’s observations of incident and traffic conditions at the intersections upstream and downstream of the congested locations. Decisions to change the signal timing are governed by many factors such as the queue length, conditions of the main and side streets, and potential of spilling back to upstream intersections, the importance of upstream cross streets, and the potential of the queue backing up to a freeway ramp. This study investigates and assesses automating the process of updating the signal timing plans during non-recurrent conditions by capturing the history of the responses of the traffic signal engineers to non-recurrent conditions and utilizing this experience to train a machine learning model. A combination of Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) is utilized in this study to deal with the vagueness and uncertainty of human decisions. Comparing the decisions made based on the resulting fuzzy rules from applying the methodology to previously recorded expert decisions for a project case study indicates accurate recommendations for shifts in the green. The simulation results indicate that changing the green times based on the output of the fuzzy rules decrease the delays due to lane blockages or demand surge.

Non-recurrent events, such as lane blockage incidents or demand surge due to traffic diversion or rerouting, can increase the congestion on signalized arterial streets, resulting in long queues and significant vehicle delays. This study compares two methods for the development of signal timing plans for activation during these events. First, it introduces a multi-objective optimization model to determine the signal timing plans considering the performance on the impacted arterial intersection approaches as well as the whole intersection performance measures.

The multi-objective optimization problem is solved via a simulation-based optimization utilizing the Non-Dominated Sorting Genetic Algorithm (NSGA-III) algorithm to find a set of Pareto optimal fronts. The Pareto optimal fronts allow trade-offs among various objectives of the simulation. Microscopic simulation models are developed and calibrated using high-resolution controller data to better replicate real-world conditions. The performance of the resulting plans is compared with a second approach previously developed by the author that use machine learning to emulate signal timing expert's decisions during non-recurrent events. The evaluation results show that, although both approaches can improve the performance during non-recurrent congestion, the special signal timing plans obtained from the optimization method produced better results.

An important concept of integrated corridor management is the coordinated operation of freeways and arterial streets during incidents. A critical component of this coordination is the activation of special signal timing plans to accommodate the diverted traffic on the alternative routes during incidents on the freeway. This study investigates the use of clustering analysis, multi-resolution modeling (MRM), and optimization techniques in the development of such plans. An important aspect of the methodology is the calibration of the utilized mesoscopic simulation-based MRM based on the increase in demands and travel times on alternative routes during incidents. Another important aspect is the use of microscopic simulation-based optimization of signal timing utilizing a multi-objective optimization that jointly minimizes the delays and maximizes the throughputs considering the whole intersections as well the specific impacted movements on the alternative routes. The evaluation of the signal timing plans resulting from the multi-objective signal timing optimization indicates that the derived special signal timing plans are able to reduce the delays and increase the throughputs in the network and particularly for the traffic movements impacted by the diverted traffic. The degrees of improvements depend on the level of impacts of the diverted traffic on the operations of the alternative routes.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

Signal control is a major influencing factor on the mobility and reliability of the transportation system. There have been major investments in installing, operating, and maintaining traffic signal infrastructure. Public agencies have the responsibility to manage and operate this infrastructure in an optimal manner to reduce the impacts of traffic signal on traffic. Signal timing methods and practices utilized by these agencies play a major rule in achieving these objectives. Considerable improvements in signal timing methods are possible with the advancement in data collection technologies and the potential for enhancing optimization techniques to utilize the data. This study investigated the methods and algorithms to combine data collected from existing and emerging sources with enhanced models and optimization algorithms to optimize and manage signal operations. In addition, the developed methods and algorithms were evaluated by comparing the results with traditional signal timing and optimization methods currently used by transportation agencies.

For decades, traffic signal management agencies have used signal timing optimization tools combined with fine-tuning of signal timing based on field observations in their updates of time-of-day signal timing plans. These traditional signal optimization methods and tools use very limited amount of data and depend on default values in the signal timing optimization/simulation tools to estimate network performance under different signal optimization strategies. Traditionally, signal control optimization and management processes have been based on turning volume data collected for one day and approach volumes collected for three to seven days. The data are then used to prepare inputs to signal optimization models. Agencies normally fine-tune the signal timing after implementation to account for the differences between the model results and the real-word measurements and observations. The agencies then update the signal timings either at predetermined intervals or when getting complains from the public.

Traditional signal optimization methods and tools use very limited amount of data and depend on default values to model network performance under different signal optimization strategies. In recent years, new data collection technologies are emerging including high resolution controller data, more advanced detection technologies such as video image detection that are based on vehicle tracking and possible integration with microwave detectors, automatic vehicle-based identification technologies, third party crowdsourcing data, connected vehicles, and connected automated vehicles data. Data from these technologies will enable better estimation of demands, saturation flow rates, lost time, platoon progression, arrival on green, queue length, delay, split failure, phase termination type, and so on. In particular, there has been a lot of excitement in the signal timing community about the potential use of high-resolution controller data, as formulated in the work by Purdue University (2-4). Studies have proposed using modeling combined with this data to estimate delays and queue lengths (5, 6). High-resolution controller data has already been used to optimize the offsets using what is referred to as Purdue Link Pivot (7). There is also a lot of anticipation of the use of connected vehicle data to support performance measurements and use for signal timing controls. Completed projects by the proposed research team demonstrated the benefits of using connected vehicle data and developed a method to assess the use of connected vehicle data in lieu of or in combination with other data sources (8, 9).

The above mentioned new and emerging data collection technologies combined with more advanced signal optimization models are expected to have transformative changes in improving signal timing optimization and management processes of transportation agencies.

1.2 OBJECTIVES

The objective of this study is to propose and evaluate methods and algorithms to combine data collected from existing and emerging sources with enhanced models and optimization algorithms to optimize and manage signal operations. The results from applying the developed methods and algorithms are compared with traditional signal timing and optimization methods currently used by transportation agencies.

1.3 SCOPE

This study identifies current practices, existing and emerging data collection methods and models that can be used to support signal optimization and management, methods for data fusion and use with developed models to optimize signal control and assess the performance of the project development compared to the traditional methods. The specific scope of this task are:

- Review of current signal optimization and management practices
- Review of Existing and Emerging Models and Data Collection Methods
- Development of Data and Tool Integration Methods
- Evaluation of the Developed Methods
- Documentation and Dissemination of Findings

1.4 OVERVIEW AND REPORT ORGANIZATION

This report consists of eight chapters. This chapter is the introduction which describes the project background and objectives. Chapter 2 presents the literature review. Chapter 3 provides the findings of a comprehensive survey of practice that aimed at documenting current practices that operating agencies responsible for traffic signal control in small, medium, and large size cities in the Southeast United States currently use to manage and optimize traffic control in their regions. Chapter 4 presents and demonstrates an advanced method for the calibration and validation of microscopic simulation models of arterial networks utilizing high-resolution controller data combined with a two-level unsupervised clustering technique for scenario identifications and multi-objective optimization for simulation model calibration identification. Chapter 5 demonstrates the benefits of using high-resolution controller (HRC) data in the calibration of signal timing optimization tools over traditional calibration using turning movement counts only. Chapter 6 presents a combination of two artificial intelligence approaches, namely Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) to recommend modifications to signal timings during non-recurrent events such as incidents, construction, surge in demands, and device malfunctions. Chapter 7 provides the methods to mitigate the impacts of non-recurrent congestion by identifying optimized signal timing plans that consider the travel performance in the critical direction impacted by the non-recurrent events, overall corridor, and the overall intersection performance. Chapter 8 presents a methodology to support the selection of management plans as part of real-time decision support systems (DSS) at traffic management centers.

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CHAPTER 2: LITERATURE REVIEW

2.1 REVIEW OF EXISTING SIGNAL TIMING OPTIMIZATION TOOLS

Several signal timing optimization tools have been developed in the past few decades to generate signal timing parameters. These tools optimize traffic delay and number of stops, as well as other measures of effectiveness to improve travel conditions.

Among the existing tools, Synchro is currently the most widely used signal timing optimization tool used by transportation professionals in the United States. It is a delay-based signal timing design tool, which can compute intersection offsets, as well as cycle lengths and phase splits. The program calculates the cycle length and green splits using Webster's method and calculates the intersection delay using the HCM method *(1)*. This program does not model platoon dispersion effects, spillback effects, or "bottleneck" situations where upstream traffic deficiencies reduce the traffic volumes reaching downstream of the intersections.

Synchro calculates the "Coordinatability Factor", which is used to recommend whether the signals should be coordinated. This factor considers travel time, volume, distance, vehicle platoons, vehicle queuing, and natural cycle lengths. The potential for vehicle queues exceeding the available storage is also considered in determining the desirability of coordination (Henry and Sabra, 2005). The offsets are selected using a quasi-exhaustive search that attempts to minimize delay.

Another software package, the Highway Capacity Software (HCS), is a macroscopic modeling approach that implements the HCM procedures. The HCS can optimize pre-timed signal timing at a single intersection for minimum delay using the SOAP2K tool method and also estimate the actuated phase lengths *(2)*. Currently, the Streets module within HCS 2010 can optimize signal timing for an arterial segment based on the HCM 2010 procedures using a Genetic Algorithm. HCS 2010 can optimize the signal timings based on several objective functions, including the Percent Free-Flow Speed for Level of Service, Overall Delay, Arterial Delay, Arterial Stops, Travel Time, and Travel Speed.

The TRAffic Network StudY Tool (TRANSYT) is a signal timing optimization package developed by the Transport Research Laboratory in the United Kingdom, which is one of the most widely used for signal timing optimization. Version 7 of TRANSYT was "Americanized" by the University of Florida Transportation Research Center for the Federal Highway Administration (FHWA) and named TRANSYT-7F *(3, 4)*. TRANSYT-7F uses a system "performance index" (PI) to optimize signal timing *(5)*. Optimization of the cycle length, splits, and offsets is done by minimizing a Disutility Index (DI), which is a function of delay, number of stops, fuel consumption, and, optionally, queue spillover.

Some of the existing and previously used signal timing optimization tools and their adapted optimization methods and optimized parameters are listed in Table 1.

TABLE 1: EXISTING AND PREVIOUSLY USED SIGNAL TIMING OPTIMIZATION TOOLS

Tools	Source	Methods	Optimization Parameters
MAXBAND	*(6,7)*	Mixed Integer Linear Programming (MILP) method	Bandwidth/progression maximization
MULTIBAND	*(8)*		
PASSER II	*(9)*	Exhaustive search	Cycle length estimation using Webster's method
		Hill-Climbing optimization	Adjust splits by minimizing the delay
		Bandwidth maximization and fine-tuning using interference algorithm for both directions	Optimize phasing sequence and offset
PASSER V	*(10)*	Genetic Algorithm - Based Optimizer and Bandwidth maximization algorithms	Minimizing delay bandwidth/progression maximization
		Interference algorithm and Time space diagram tool	Fine tuning offset
TRANSYT & TRANSYT-7F	*(11)*	Exhaustive search for cycle length, Hill-Climbing and Genetic Algorithm (GA) based optimization methods	Optimize progression bandwidth/function of delay, stops, fuel consumption / and, optionally, queue spillover. A later version considered "throughput measure" and "queuing measures" in objective functions
HCS	*(12)*	SOAP2K tool method, Genetic Algorithm	Split optimization by minimizing Delay
SYNCRO	*(13)*	Exhaustive search technique	Minimizes delay, number of stops and queue size by applying penalties for these measures
SIGOP	*(14)*	Monte Carlo simulation and gradual increment method for offset optimization	Delay, number of stops and excess queue
VISGAOST	*(15)*	VISSIM-based Genetic Algorithm	Optimizes the fitness function combination of delay, travel time, number of stops, and throughput

Tools	Source	Methods	Optimization Parameters
VISTRO	*(16)*	Hill Climbing and Genetic Algorithm	Optimizes the weighted sum of delays and number of stops

2.2 REVIEW OF CURRENT SIGNAL OPTIMIZATION AND MANAGEMENT PRACTICES

Several research and development efforts addressed selecting traffic signal control during oversaturated conditions. Liberman et al. (2000) proposed a real-time traffic control policy to select signal timing based on estimated queue lengths. The goal was to control and stabilize queue lengths and provide equitable service to competing traffic streams by metering traffic at intersections, thus servicing oversaturated approaches while fully utilizing storage capacity and preventing queue spillback from maximizing the throughput that controls the interaction between incoming platoons and standing queues *(17)*.

Researchers investigated the incorporation of knowledge-based artificial intelligent layers to support traffic management *(18-21)*. Some of these studies proposed the use of fuzzy decision support systems used for providing traffic control under different traffic situations *(21,22)*. For example, a knowledge-based decision support system was developed to identify critical traffic states, propose possible changes in the current signal timing plan, and decide which action should be taken *(21)*. Other systems have used "expert" systems, which represent traffic engineers' knowledge *(23-25)*.

Optimization of a traffic signal setting is one of the most important requirements of a successful arterial performance. Choosing an appropriate objective function for optimizing traffic signal timing is critical because the choice will affect the overall network performance. Delay minimization is mostly used as an objective function for signal timing optimization, sometimes combined with the number of stops *(26)*. However, instead of only delay minimization, a combination of delay minimization, system throughput maximization and queue maintenance are crucial for oversaturated conditions *(17) (27-30)*. Signal timing optimization should be dynamic in that the signal timing control strategy and the associated plans should be selected based on the assessed conditions, including the congestion level. It is essential to have accurate congestion condition identification and queue estimation methods based on the collected data to achieve this goal. The following section discusses previous research conducted for signal timing optimization for oversaturated conditions.

Signal optimization for oversaturated conditions has been studied since the 1960s. In early studies, many researchers suggested that the objective function used in oversaturated intersection optimization should be based on maximizing system throughput instead of minimizing delay *(31-34)*.

On the other hand, Michalopoulos and Stephanopoulos *(35)* proposed a so-called ''bang-bang" control model to minimize the delay of oversaturated intersections with queue-length constraints. Michalopoulos and Stephanopoulos developed timing strategies for undersaturated and oversaturated conditions and two-staged timing methods to identify switching over point *(35)*. Chang and Lin extended this work to identify the timing of switching strategies *(36)*. Chang and Sun further extended the model for oversaturated networks by introducing the traffic flow propagation model in an integrated approach with TRANSYT-7F, where TRANSYT-7F identifies signal timings for undersaturated intersections while utilizing the two-stage model for oversaturated intersections *(37)*.

While these methods concentrate on changing timing strategies between undersaturated and oversaturated conditions, other researchers have focused on solely identifying optimum cycle lengths and green times for oversaturated conditions *(38)*. Liberman et al. (2000) proposed a real-time traffic control policy to develop the relationship between the queue and signal timing *(17) (38)*. This proposed queue estimation method uses input-output balancing of the advanced detector's occupancy profile. Lieberman and Chang (2005) used a mixed-integer linear programming approach and heuristic optimization methods to the extent of this methodology. They implemented their method to a grid network by decomposing it into its constituent arterial subsystems in response to user-specified priorities *(30)*.

Girianna and Benekohal (2004) used genetic algorithm optimization to design a discrete-time signal-coordination model for coordinated oversaturated intersections to distribute the queue of the oversaturated intersections and ensure that the queues are reduced or cleared before released platoons arrive at a downstream signal system *(39)*. A quadratic programming approach was used to minimize and balance the link queues for real-time network-wide signal control in large-scale urban traffic networks *(40)*.

Hadi and Wallace (1993) developed a hybrid genetic algorithm approach to be implemented in the TRANSYT-7F program. Their method optimizes cycle length, phase sequence, and offsets, whereas TRANSYT-7F is used to optimize green splits. Hadi and Wallace (1995) proposed an enhancement function to TRANSYT-7F to enable the program to analyze and optimize signal-timing plans under congested conditions. The enhancement improved the program's capability by implementing extensions to the objective function that considers queuing and/or throughput if queue spillback occurs *(5) (41) (42)*.

Park et al. (1999) proposed a genetic algorithm (GA) optimization strategy that includes a combination of delay minimization with a penalty function and throughput maximization based on the TRANSYT-7F model for optimal signal timing and queue management of oversaturated conditions *(43)*. Later, they tested three different optimization strategies and evaluated the strategies for different intersection configurations *(44)*.

Abu-Lebdeh and Benekohal (1997, 2000, 2003) presented a set of dynamic control and queue management algorithms for signal optimization to manage the queue formation and dissipation on oversaturated network links. They maximized the throughput by managing queue formation and dissipation under oversaturated traffic conditions *(45) (46) (29)*. Abu-Lebdeh et al. (2007) presented several models that can capture intersection traffic throughput while explicitly considering the interactions between traffic streams at adjacent signals *(47)*.

Version 13 of TRANSYT included a cell transmission model as an alternative method to its embedded platoon dispersion model, enabling the model to consider the spillback effects and the time-varying flow evolution (Binning et al. 2008). Li (2010) proposed a model to capture traffic dynamics with the cell transmission concept by considering complex flow interactions among different lane groups under oversaturated conditions.

Liu and Chang (2011) developed a genetic algorithm for signal timing optimization during blockage and spillback conditions by minimizing the travel time or maximizing system throughput. They also compared their results with the output from TRANSYT-7F (version 8) and showed that their proposed model works better under congested and high demand traffic conditions *(48)*. Long et al. (2011) developed a traffic control utilizing vehicle movement ban strategies to avoid gridlock situations during incidents in a grid network. They evaluated the control strategies in a simulated environment and found promising results in reducing congestion *(49)*.

2.3 PRACTICE AND NEED FOR SIMULATION MODEL CALIBRATION

Calibration of traffic simulation models is a critical component of simulation modeling. The increasing complexity of the transportation network and the adoption of the emerging vehicle and infrastructure-based technologies and strategies have motivated the development of new methods that utilize new data sources in the calibration. There has been increasing recognition for the need for more detailed and specific guidance for utilizing simulation tools, considering the increasing complexity of simulation modeling. Several states have developed guidelines for utilizing simulation modeling, including a strong emphasis on calibration. The FHWA Traffic Analysis Toolbox documents have provided valuable information regarding the use of traffic analysis tools, including simulation model calibration *(50)*. However, the existing simulation calibration guidance focuses on the use of field-measured macroscopic traffic flow parameters such as average travel times, approach volumes, turning movement counts, and queue lengths as measures of effectiveness (MOEs) to calibrate microscopic driving behavior parameters *(51-54)*. More recently, there has been an increasing interest in using microscopic parameters such as vehicle trajectories in simulation model calibration *(55-57)*.

In practice, the calibration of simulation models has relied on a manual iterative process to adjust the simulation model parameters to allow the model to better represent field traffic conditions. However, several researchers automate the calibration process using optimization-based approaches such as gradient search, simplex-based, and genetic algorithm (GA), aiming to minimize the error between field and simulation traffic parameters *(53) (58-60)*. However, these studies calibrated the models based on macroscopic measures, even when using advanced optimization techniques. Combining the use of more detailed traffic measurements and advanced optimization techniques has the potential to achieve a more accurate and reliable replication of traffic conditions in the simulation model. Such combinations are investigated in this study.

2.4 USE OF HIGH-RESOLUTION CONTROLLER DATA IN SIGNAL TIMING PERFORMANCE MEASURES

Detailed signalized intersection parameters such as the number of vehicles utilizing an intersection, detector occupancy during green time and red time, and percentage of vehicle arrival on green are very important measures used to evaluate the performance of an intersection. Data from existing system detectors have been used to analyze the performance of signalized intersections for a long time. In the past, the most popular type of detector was inductive loop technology, which was installed at intersection approaches. More recently, video image detections at stop lines and microwave detectors for midblock detections have been used due to concerns with the maintenance requirements of inductive loops. Inductive detector failures are common and maintaining them requires lane closures. The use of microwave sensors, video image processing, Bluetooth, or Wi-Fi readers has increased in recent years for the automatic collection of data on arterials.

In recent years, advanced data collection, processing, archiving, and mining techniques have motivated and enabled the retrieval of event-based high-resolution controller data from signal controllers *(61-63)*. This data is being widely used by signal control agencies to assess their signal control performance and identify required changes to the system. The high-resolution controller data provides significant support of the operation and maintenance of traffic signals by allowing the identification of capacity utilization level, determining progression quality, estimating performance measures (volume, delay, and queue length), and assessing detection and communication malfunctions.

There are several studies in which researchers utilize the event-based controller data for the estimation of measures, such as arterial progression quality, which uses the coordination diagram *(64),* split utilization *(65),* green occupancy ratio *(66) (67),* arrival type *(68) (69),* and vehicle arrival on green *(70) (71)*. High-resolution controller data allows the analyst to identify the cause of congestion such as demand exceeding capacity of the whole intersection, bad green time allocations, poor progression, and/or spillback from downstream intersections. In addition, high-resolution controller data will allow automating the data collection of the volume counts and other measures of performance for the intersection turn movements. High-resolution controller data also allows examining the need for maintenance of the detectors and communication. The parameters estimated based on high-resolution controller data can be used for daily operations including basic parameters, detection problems, complaint response/ troubleshooting, signal coordination, and estimating impacts under non-recurrent conditions. They can be also used for off-line modeling and optimization of the signals including estimating approach volumes and turning movement counts, for prioritizing signal improvement needs, and to communicate system status to the decision makers and the public. This section provides a brief description of the data and the derived parameters based on the data. The measures that can be obtained based on high-resolution controller include:

- Capacity and Delay Performance Measures including Signal Timing Parameters, Phase Termination by Type, Volume to Capacity Ratio, Green Occupancy Ratio, Split Failure, Split Utilization Ratio, Yellow and Red Actuations, and Delay and Queue Estimation

- Progression Performance Measures including Arrival on Green and Arrival on Red, Highway Capacity Measures, Purdue Coordination Diagram, Flow Profile Diagram, and Purdue Link Pivot

- Multi-Modal Measures including Pedestrian Measures and Preemption and Priority measures

- Maintenance Support Measures including Communications and Detection Health Monitoring

The FDOT adopted an ATSPM software that was originally developed by the Utah Department of Transportation (UDOT). Agencies in Florida have used the ATSPM software tools, with Seminole County being the first to use the FDOT tool in Florida. Other agencies have used other commercially available tools for this purpose.

One objective of this study is to investigate the use of this data in traffic pattern recognition, and in the calibration and validation of microscopic simulation models. This study hypothesizes that it is possible to capture the multidimensional features of arterial traffic by using various performance measures derived based on high-resolution control data.

Data description

The use of high-resolution data collected by traffic signal controllers has been developed and used for engineering-related performance measures over the past ten years. High-resolution controller data includes signal timing and detection at the highest time resolution of the controller (0.1 seconds), combined with data from other sources to support ATSPM. This data consists of various signal controller events that are logged in 0.1-s intervals based on a standardized set of event parameters and event identification codes. Figure 1 shows a sample of high-resolution event data.

Intersection ID	Date	Time	Event Code	Event Parameter
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:07 AM	81	62
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:07 AM	44	5
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:07 AM	81	54
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:07 AM	81	42
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:08 AM	81	41
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:08 AM	81	49
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:11 AM	82	55
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:11 AM	82	56
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:12 AM	82	53
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:12 AM	82	62
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:12 AM	1	2
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:13 AM	1	6
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:13 AM	82	45
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:13 AM	82	47
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:14 AM	81	45
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:14 AM	82	46
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:14 AM	81	47
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	2	5
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	82	46
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	43	7
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	81	56
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	82	27
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	81	46
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:15 AM	81	53
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:16 AM	82	56
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:17 AM	7	2
459196A1-55B0-4339-B1E1-8868D9A026FA	11/1/2019	12:00:18 AM	7	6

FIGURE 1: EXAMPLE OF HIGH-RESOLUTION CONTROLLER DATA

The high-resolution data consists of signal controller events based on a standardized set of event parameters and event identification codes. The stored parameters include the Timestamp, which contains the date and time of activities, and the Event Code and Event Parameters. The Event Code describes the type of event. The Event Parameters indicate the specific detector or signal phase where the event occurs. The definitions of Event Code and Event Parameter are provided in the Indiana Traffic Signal High-Resolution Data Logger *(72)*.

Utilized Performance Measures

In this study, performance measures based on high-resolution data are utilized for partitioning traffic operational scenarios. This data is also used for simulation model calibration and validation as part of the optimization process. The utilized measures are vehicle throughput, green occupancy ratio, split utilization ratio, and percentage arrival on green in each cycle.

The high-resolution controller data provides the opportunity for cycle-by-cycle estimation of the throughputs. Having a separate detection channel per lane is required if lane-by-lane detection of the throughput is needed. The Green Occupancy Ratio (GOR) is a performance measure that reflects the degree of green utilization in each phase. It is defined as the stop bar detector occupancy during the green interval *(66)*. Higher values of GOR reflect higher utilization of the green time. This value increases to values above 0.5 in the peak periods.

The Split Utilization Ratio (SUR) measures are derived for each intersection movement, which allows for the assessment of the congestion level in all intersection approaches. SUR is defined as the ratio of the number of vehicles passing the detector to the maximum number of vehicles that can pass during the effective green time *(64)* and can be calculated as follows:

$$X_k = \frac{h_k \times N_k}{g_k} \tag{2-1}$$

where

X_k = Split utilization ratio of phase k,
N_k= The vehicle counts at phase k,
h_k = Saturation headway of phase k (seconds), and
g_k = Effective green time of phase k (seconds).

The Percent Arrivals on Green (POG) is calculated as the proportion of vehicles that arrive at the green signal indication versus the proportion of vehicles that arrive at the red signal *(65)*. This measure reflects the progression of traffic.

Equipment Needs and Influences

This section describes the equipment needed to support high-resolution controller data collection and processing including detection, controllers, and central software and the influence of the type of equipment.

Detection: When estimating performance measures based on high-resolution controller data, no detection is needed for signal timing measures such as cycle length, green time, g/C ratio, and even capacity (if the saturation flow rate is assumed to be known). However, the volumes and capacity utilization measurements require stop line detectors or advanced detectors. Progression quality measures require advance (setback) detectors, on the main street through movements, located 350 ft to 400 ft in advance of the stop line. It is desirable to have detection on every lane at the intersection. In addition, if the detector location is upstream of the left or right turning bay, then it will not be possible to differentiate between the through and turning movements. Furthermore, current detection technologies cannot differentiate between different movements on a shared lane. Another important component is the setting of the detection units. There are two types of detection outputs: presence and pulse (counts). The presence type is the utilized default in most cases and allows the estimation of occupancy. With this output, the presence state is active as long as there is a portion, one, or more vehicles on the detection zone. If the detector is long, this data is not sufficient to produce counts since more than one vehicle can be on the detector without being sensed and pulse or count outputs is needed. Pulse or count data is based on activating a state when a new vehicle arrives. For long detection zones, the detection unit has to utilize an algorithm based on the sensor response to estimate the arrival of new vehicles.

Controllers: Advanced new generation controllers allow the logging of high-resolution controller data. These controllers do not require external data logger devices to collect the data (see next section regarding external data loggers). However, other controllers such as the older 170 controllers will require a data logger in the cabinet to log the data from the controller and upload the data to the central software

Central Software: A software is required for high-resolution controller data acquisition and processing. In general, the ATSPM software is expected to support the downloading, normalizing, archiving, interpreting, and displaying the signal data logged by the controller and the derived measures.

2.5 IDENTIFICATION AND PARTITIONING OF TRAFFIC OPERATIONAL CONDITIONS

Clustering analysis is an unsupervised machine learning method that is capable of classifying each data point into a specific group. Clustering analysis is the most practical method for the identification of traffic patterns that are representative of traffic conditions in support of analysis, modeling, and simulation (AMS) *(73-76)*. This type of analysis has been recommended for the development and calibration of simulation, particularly those used to assess transportation system operations and management strategies. Partitioning the field traffic conditions allows agencies to better plan, design, and evaluate new technologies and traffic operation strategies (Saha et al., 2019). The most extensive example of the utilization of clustering analysis in transportation engineering is its use in the AMS testbed effort funded by the FHWA (76) (77).
Recent guidance provided in the updated Traffic Analysis Toolbox Volume III (FHWA) recommends using clustering to identify operational scenarios for use in calibration, such as different congestion levels, incident conditions, and weather conditions *(78).* In this study, clustering analysis is performed using parameters derived based on high-resolution controller data and travel time data to identify traffic patterns that represent field traffic conditions.

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CHAPTER 3: TRAFFIC SIGNAL OPERATION, OPTIMIZATION, MAINTENANCE AND MANAGEMENT PRACTICES IN THE SOUTHEAST US

3.1 INTRODUCTION

Traffic congestion is an issue of increasing concern in the United States. Across the country, drivers spend on average 97 hours trapped in congestion every year while the annual cost of congestion is estimated at $87 billion or an average of $1,348 per driver [1]. Outdated traffic signal control, lack of signal optimization, and/or poor signal management are responsible for 5 percent of overall total congestion and more that 11% of recurring congestion [2]. Furthermore, poorly designed, located, operated, and maintained traffic signals lead to negative impacts on air quality and increase in fuel consumption. An estimated 4.3 billion dollars can be saved annually nationwide should well-managed, optimized, and controlled traffic signal systems were in place. Moreover, according to the U.S. Department of Transportation's Intelligent Transportation Systems Joint Program Office the benefits of investments in signal timing outweigh the costs by 40:1 or more [3].

In recent years, new data collection technologies are emerging that can assist in improved traffic signal operation, optimization, maintenance, and management (TSOOMM). These include high resolution controller data; advanced detection technologies such as video image detection, automatic vehicle-based identification technologies; third party crowdsourcing data; connected vehicles, and connected automated vehicles data. Moreover, advances in signal optimization methods and models offer new tools that can be used to improve TSOOMM, leading into significant benefits in system performance. However, potential gains can be realized only if the transportation agencies embrace the advanced technologies and tools and choose to utilize them for traffic signal systems in their regions.

This study conducted a comprehensive survey of practice that aimed at documenting current practices that operating agencies responsible for traffic signal control in small, medium, and large size cities in the Southeast United States currently use to manage and optimize traffic control in their regions. The findings reported in this study provide valuable insights about a) current operating, signal retiming, and management practices of agencies, b) the reasons that drive those practices; and c) opportunities and barriers for adopting new approaches to improve the current state-of-the-art through the use of emerging data collection sources and advanced signal optimization options.

3.2 PREVIOUS SURVEY EFFORTS ON TRAFFIC SIGNAL OPERATION, OPTIMIZATION, MAINTENANCE AND MANAGEMENT (TSOOMM)

The first systematic effort to assess the state of traffic signal operation in the United States took place in 2005, when the National Transportation Operations Coalition (NTOC) conducted a self-assessment survey (SAS) of agencies operating traffic signals across the United States. The goal was to bring attention to the state of signal operation, to create awareness of the congestion-reducing benefits of good traffic signal operation, and to make a case for additional investment in traffic signal operation. The survey responses were used to develop the first National Traffic Signal Report Card [4]. A total of 378 agency representatives from 49 states fully completed the survey. Respondents were asked to rate (on a scale of 1 to 5) each question based on the performance of their agency. Six topics were explored in the questionnaire, namely signal operation in coordinated systems, signal operation at individual intersections, specialized operation for traffic signals, detection systems, management, and maintenance of traffic signals. Based on the responses received, the overall national performance of traffic signal systems was graded as D- receiving a score of 62 out of 100. The report concluded that the rating was not surprising and pointed to limited funding and staff, poor management, delayed re-timing signal plan, and lack of adequate data for traffic signal timing plans as some of the fundamental issues resulting in this performance rating.

In 2007, a second self-assessment survey was carried out across the United States and Canada by NTOC and a total of 417 agencies responded. These agencies operated various-sized traffic signal systems representing 47 states and 45 percent of the nation's traffic signals [5]. Similarly to the 2005 survey, the second survey effort was intended to assess the state of traffic signal management and operation practice, identify deficiencies in traffic signal systems and highlight ways to improve operations. The questionnaire used contained precisely the same six sections as the first SAS; however, questions were improved to provide more clarity and some of the questions within the self-assessment were rearranged. Besides, the scoring methodology was included; thus, respondents could determine their score and associated letter grade. The responses from the 2007 SAS reaffirmed the findings of the 2005 survey and resulted to a National Traffic Signal Report Card score of 65 out of 100 points (equivalent to a D letter grade). According to the 2007 survey findings, one-third of the respondents stated having minimal or no management of traffic signal operations, and almost one-half reported not having enough staff or resources committed to monitor or manage traffic signal operations on a regular basis. In addition, traffic monitoring and data collection received the lowest score ratings, irrespectively of the type of agency or signal system size. The findings confirmed that agencies had limited resources and thus were forced into difficult choices about how to utilize them. A proactive, integrated program management approach that includes the principles of continuous improvement, asset life-cycle costs and resource allocation for traffic signal operations was seldom seen as an option [5].

Subsequently, NTOC undertook a third SAS in 2011, which collected responses from 241 agencies of various sizes across the US and Canada (representing approximately 39 percent of all traffic signals in the US) [6]. The results and findings from the third SAS were used to determine the scores for the 2012 National Traffic Signal Report Card. The survey used the same methodology as the earlier SAS tools, but further improvements were made to remove some irrelevant questions, add details to some of the questions, modify and expand the summary information, describe the scoring methodology, and connect the questions more to the outcomes of objectives-based traffic signal operations programs. Topic areas covered in the 2011 SAS included management, traffic signal operations, signal timing practices, traffic monitoring, and data collection, and maintenance. The results showed a slight improvement in terms of management, signal timing practices, and maintenance leading to a 2012 National Traffic Signal Report Card score of 69 out of 100, which is equivalent to a D+ letter grade [6].

The three NTOC SAS efforts discussed above provided a broad overview of the state of practice in traffic control across the USA and Canada in an aggregated manner. However, the survey findings were not categorized based on agency size or population nor provided details about the unique issues and barriers for TSOOMM at the regional or state levels. These issues are essential to characterize the current state of traffic signal operations and draw conclusions regarding effective countermeasures to address needs at the local and regional levels and need further consideration.

In other noteworthy efforts, Gordon at al. conducted a survey of traffic signal operations and maintenance practices across the USA in 2008 for the purpose of developing a formal guideline to estimate the staffing and resources required to operate and maintain traffic signal systems effectively [7]. Responses from 7 agencies operating traffic signals including cities, counties, and state DOTs were received and analyzed. The main subject areas covered in the survey included the classification of signal system characteristics, redundancy characteristics of system traffic detection, timing plan characteristics, operations characteristics, maintenance practices, and staff size and qualifications. The overarching issues of concern revealed by the survey responses were the qualifications of staff, lack of utilization of advanced technologies, failure of signal retiming on a regular basis, and inadequate funds. Although the questionnaire covered a wide variety of subjects, the limited number of survey responses and the heterogeneity of those responses did not allow for a comprehensive analysis of findings and performance of meaningful comparisons and assessments.

In 2010, Gordon led a National Cooperative Highway Research Program (NCHRP) Synthesis study [8] that documented findings from a comprehensive literature review and a series of project case studies. As part of this effort, the authors carried out a survey to document practices that states were using to re-evaluate the timing of signalized intersections. The survey solicited additional statistical and anecdotal information from agencies involved in the case studies that were not addressed in prior surveys. The questions asked revolved around retiming tools and personnel qualifications, field implementation of timing plans, resource appropriation for retiming, evaluation of signal timing performance, and management issues of signal timing. A total of 17 agencies were approached, 7 of which provided responses. According to the survey results, around half of the transportation agencies reported that they did not routinely collect and analyze traffic data for signal timing, and that existing traffic data collection programs did not evaluate the quality of data collected. Also, detector data were often not used routinely to determine the need for retiming. Besides, the appropriate number of timing plans were deemed inadequate for the requirement [8]. While the NCHRP Synthesis report provide valuable information regarding traffic signal retiming practices, the survey conducted as part of this effort was limited in scope focusing only on signal retiming. Furthermore, it drew conclusions from a limited number of responses; thus, overall, cannot provide a broad picture for signal control, optimization, and management practices.

The earlier studies summarized above focused on national wide surveys and had not been updated recently to consider new and emerging data collection methods and the availability of new software for signal timing optimization. Moreover, regional differences were not considered. To address these gaps, this study developed a new questionnaire survey tool and used it to document current practices, existing limitations and needs, and future considerations of agencies located in the Southeast United States and are responsible for TSOOMM. The research team identified transportation agency representatives responsible for TSOOMM in six states in the Southeast (i.e., Georgia, North Carolina, Tennessee, South Carolina, Alabama, and Florida) and distributed the survey to them in 2019. The following sections discuss the study methodology, results, and conclusions from this effort.

3.3 METHODOLOGY

To obtain information about transportation agencies' current practices related to TSOOMM in the Southeast United States, the project team developed a survey questionnaire in accordance with the Institute of Transportation Engineers (ITE) Manual on Transportation Engineering Studies [9] using the Qualtrics platform. The survey questions focused on the number and type of signals managed by the agency, practices related to the signal retiming process, tools and methods employed in signal optimization, data used for evaluation of signal performance, and plans for using emerging technologies for enhancing current practices in the future. More specifically, the questionnaire survey included 16 questions that solicited information on the following topics:

- Characteristics of agencies participating in the survey (e.g., type, size and location of agency, and the number and types of traffic signals managed by an agency)
- Signal retiming practices (e.g., retiming frequency and triggers used to initiate the retiming process)
- Resources used in support of signal control optimization and management (e.g., use of formal guidelines and use of simulation, analysis, and/or optimization software)
- Data collection strategies (e.g., types of data used for signal timing and utilization of emerging data sources).

Moreover, the survey participants were asked about the adequacy of available resources (such as funding, staffing, training, etc.) in support of their work and were given an opportunity to provide comments using an open-ended question format.

The Qualtrics Research Core tool was used to prepare the questionnaire as it provided a user-friendly platform. Several capabilities of the survey tool were utilized, including closed-ended, multiple-choice, checkbox, open-ended, demographic, and rating scale questions.

After the survey questionnaire was developed, it was pretested and fine-tuned prior to use to ensure that it was easy for survey participants to understand the questions and provide answers. Then, an approval was obtained from the Institutional Review Board (IRB) for Human Use to proceed with the survey. Upon approval, the questionnaire survey was emailed to representatives of selected state, county, and local transportation, and public works departments in the Southeast region that owned and operated traffic signals along with a request to provide feedback regarding current practices of their agency. Care was placed into soliciting input from jurisdictions of different sizes ranging from large (i.e., serving a population greater than 450,000) to small (i.e., less than 65,000).

Returned responses were carefully screened and incomplete and/or duplicate responses were discarded. Details about the responses obtained, and study findings and conclusions are presented next.

3.4 RESULTS AND INTERPRETATION

Twenty detailed responses were received from representatives of the surveyed transportation agencies that operate various-sized traffic signal systems in six states in the Southeast (namely Georgia, North Carolina, Tennessee, South Carolina, Alabama, and Florida). Inspection of the responses indicated that three of the responses were duplicates and had to be omitted. After discarding these three responses, seventeen detailed responses were utilized for further analyses. These responses represent six large, six medium and five small city agencies managing collectively over 9,600 traffic signals. Large city agencies were considered as those with jurisdiction size greater than 450,000 people, whereas medium and small agencies refer to those with jurisdiction size between 65,000 and 450,000 and less than 65,000, respectively. The following paragraphs present summaries of the survey results organized in table format for easy reference. The responses were aggregated by jurisdiction size and subtotals were provided, when appropriate. Survey responses are anonymous except for survey respondents' comments.

3.4.1 Characteristics of Agencies Participating in the Survey

Based on the survey responses, the total number and percentage of coordinated signals, isolated signals, and signals connected to central software that are managed by responding agencies are shown in Table 2.

TABLE 2: SYSTEM NETWORK CHARACTERISTIC

Population	Agency Type	Coordinated Signals		Isolated Signals		Signals Connected to Central Software
		Total Number Reported	Percent[1]	Total Number Reported	Percent[1]	Total Number Reported
> 450,000	Large	5350	75.54%	1732	24.46%	6175
65K-450K	Medium	932	63.02%	547	36.98%	1296
< 65,000	Small	447	83.24%	90	16.76%	173
	Total	**6729**	**73.96%**	**2369**	**26.04%**	**7644**

Notes: [1] Shows the percent of coordinated or isolated signals by agency type.

As can be seen, nearly three quarters of the signals managed by the agencies responding to the survey are coordinated while isolated signals account for the rest (26%). Moreover, the study participants representing large and medium-size agencies reported that the vast majority of their signals are connected to central software (over 85%) while small agencies reported only one out of every 3 traffic signals being connected centrally.

Table 3 illustrates the number and percent of different types of traffic controllers used (namely fixed time, actuated, traffic responsive, adaptive) by jurisdiction size. It can be observed that actuated signals are by far the most common type of signals used by agencies represented in this survey, regardless of agency size (81.95%). On the other hand, traffic responsive and adaptive signals have a small share (4.94% and 5.57%, respectively) across all agency sizes combined.

Recently, many state-of-the-art signal strategies have been introduced and implemented by various agencies across the United States. Examples include special plans for special events management, arterial incidents response, and freeway incidents response. According to the survey responses from agencies in the Southeast, advanced signal strategies utilized by agencies are summarized in Table 4.

TABLE 3: TYPE OF TRAFFIC CONTROLLERS

Agency Type	Fixed time		Actuated		Traffic responsive		Adaptive		Total Number of Signals Reported
	Total Number Reported	Percent[1]	Total Number Reported	Percent[1]	Total Number Reported	Percent[1]	Total Number Reported	Percent[1]	
Large	361	4.93%	6365	86.97%	102	1.39%	491	6.71%	**7319**
Medium	267	15.01%	1177	66.16%	335	18.83%	0	0.00%	**1779**
Small	99	18.20%	360	66.18%	39	7.17%	46	8.46%	**544**
Total	**727**	**7.54%**	**7902**	**81.95%**	**476**	**4.94%**	**537**	**5.57%**	**9642**

Notes: [1]Shows the percent of the fixed time, actuated, traffic responsive or adaptive by agency type

TABLE 4: ADVANCED SIGNAL STRATEGIES EMPLOYED BY AGENCIES

Advanced signal strategies	Agency Type, Total Number of Agencies Reporting			Total, n=17
	Large, n=5	Medium, n=6	Small, n=6	
Transit signal priority	4	1	1	**6**
Freight signal priority	1	-	-	**1**
Railroad-highway grade crossing signal priority	4	3	1	**8**
Emergency vehicle preemption	4	5	5	**14**
Special plans for special events management	5	4	4	**13**
Special plans for arterial incidents response	3	-	1	**4**
Special plans for freeway incidents response	3	-	3	**6**
Other (Requested details)	3	-	1	**4**

The findings summarized in Table 4 indicate that emergency vehicle preemption and special plans for special events management are the most prevalent strategies used by agencies in the Southeast, regardless of the justification size. In addition, some large agencies reported utilizing drawbridge preemption and reversible-lane control, which were entered in the “Other” category.

3.4.2 Signal Retiming Practices

A broad literature review conducted as part of this study revealed that retiming traffic signals improves mobility and contributes significant benefits in terms of reduced delay, fuel consumption, and emissions (Gordon et al. [7], Tarnoff and Ordonez [10], Gordon [8], Skabardonis [11], Chien et al. [12], Sunkari [13]). Koonce et al. [14] suggested that signal retiming should take place every 3 to 5 years, and even more often should there be considerable shifts in traffic volumes or any changes in roadway conditions. Therefore, this survey of practice solicited information about agency current practices with respect to signal retiming. The reported responses are provided in

Table 5.

Table 5: Traffic Signals Retiming Frequency

Frequency	Percentage by Agency Type: Large	Medium	Small	Total (All Agencies Combined)
Every year	0.0%	16.7%	16.7%	**11.8%**
Every 2 years	0.0%	16.7%	0.0%	**5.9%**
Every 3-5 years	20.0%	16.7%	50.0%	**29.4%**
Every 5 years or more	40.0%	33.3%	0.0%	**23.5%**
When getting feedback from travelers	20.0%	16.7%	16.7%	**17.6%**
Other (Requested details)	20.0%	0.0%	16.7%	**11.8%**

The survey responses revealed that the majority of large and mid-size agencies in the Southeast that responded to the survey retime their traffic signals every five years or more. One of the large agencies reported that they retime the traffic signals when it is needed. It can also be seen from

Table 5, that half of the small agencies retime their signals every 3 to 5 years.

Table 6 summarizes the factors considered by agencies in the Southeast when deciding on retiming traffic signals. Some of these factors include a review of available data, field observations, feedback from travelers, and retiming based on a regular schedule.

Table 6: Main Factors of Retiming Signals

Factors	Percentage by Agency Type: Large	Medium	Small	Total (All Agencies Combined)
Based on the review of data (requested the data source)	20.0%	33.3%	20.0%	**23.8%**
Based on field observations (requested details)	0.0%	16.7%	30.0%	**19.0%**
Based on feedback from travelers	20.0%	0.0%	20.0%	**14.3%**
Retiming is scheduled at regular intervals	20.0%	16.7%	20.0%	**19.0%**
Other (Requested details)	40.0%	33.3%	10.0%	**23.8%**

Two large agencies, two mid-size, and one small agency reported that they combine several of the factors listed in Table 6, when making signal retiming decisions. Also, the survey requested participants to specify the data source considered if they base their decisions on the review of data. Based on the participants' answers, the reviewed data includes traffic counts, origin and destination (OD) data, Metropolitan Planning Organization (MPO) travel time studies, Automated Traffic Signal Performance Measures (ATSPMs), and intersection movement counts. Furthermore, agencies that reported making decisions about signal retiming based on field observations, were asked to elaborate. The following comments were made by the agencies in response to this request for details:

- Observation of general congestion
- Date of last timing update

- The agency is required to re-evaluate all signals over a set period. If through observation, it determines that a signal needs timing updates, then the signal is re-timed. The agency also evaluates the signals if it receives feedback from travelers, but this occurs less frequently
- Observation of traffic flow

Table 7 summarizes different types of triggers used by the agencies to retime the signals. These triggers include geometric changes, traffic demand changes, installation of new traffic signals in the area, and new development in the area. Changes in traffic demand are the most common trigger, followed closely by installation of new traffic signals in the area, geometric changes, and new development.

TABLE 7: TRIGGERS USED TO INITIATE THE RETIMING PROCESS

Triggers	Number by Agency Type			
	Large, n=5	Medium, n=6	Small, n=6	Total, n=17
Geometric changes	2	5	6	**13**
Traffic demand changes	5	5	6	**16**
Installation of new traffic signals in the area	5	6	3	**14**
New development in the area	4	4	5	**13**
Other (Requested details)	1	0	1	**2**

3.4.3 Resources Used in Support of Signal Control Optimization and Management

The survey participants were also asked if their agencies use formal guidelines for signal control optimization and management. Their responses are summarized in Table 8. It can be seen that the majority of agencies surveyed (58.8%) rely on national or statewide guidance. Only a small number of agencies reported having their own guidelines, but 17.6% of the agencies expressed an interest in developing a set of guidelines in the future.

TABLE 8: DEPLOYED FORMAL GUIDELINES FOR SIGNAL CONTROL OPTIMIZATION AND MANAGEMENT

Options	Percentage by Agency Type			Total (All Agencies Combined)
	Large	Medium	Small	
Yes, my agency has established guidelines and/or manuals for signal control optimization & management	0.0%	0.0%	16.7%	**5.9%**
Yes, my agency has some guidelines and/or are currently in the process of developing a set of guidelines	0.0%	16.7%	0.0%	**5.9%**
My agency uses national or statewide guidance	80.0%	50.0%	50.0%	**58.8%**
No, my agency has no guidelines but is using national guidelines	0.0%	16.7%	0.0%	**5.9%**
No, my agency has no guidelines but is interested in developing a set of guidelines	20.0%	16.7%	16.7%	**17.6%**
No, my agency has no guidelines and/or is not interested in developing guidelines	0.0%	0.0%	16.7%	**5.9%**

Furthermore, the survey requested information regarding current practices with respect to the use of signal optimization software or techniques. A summary of the responses obtained from representatives of agencies in the Southeast responsible for TSOOMM is provided in

Table 9.

TABLE 9: UTILIZED SIGNAL OPTIMIZATION SOFTWARE OR TECHNIQUE

Type of Software or Techniques	Number by Agency Type Large, n=5	Medium, n=6	Small, n=6	Total, n=17
SYNCHRO	5	5	5	**15**
TRANSYT-7F	0	0	0	**0**
PASSER-V	0	0	0	**0**
MAXBAND	0	0	0	**0**
Tru-Traffic	3	0	1	**4**
My agency performs optimization based on high-resolution controller data	1	2	1	**4**
My agency uses manual time-space diagrams	2	1	1	**4**
My agency uses manual fine-tuning for retiming	3	4	3	**10**
Other (Requested details)	1	0	1*	**2**

Note: * HCM-based method/tool

It is clear from the responses received that SYNCHRO is the most popular software for signal optimization in the Southeast, with 15 out of 17 responding agencies reporting using the software at the time of the survey. Ten agencies also reported engaging in manual fine-tuning and two reported using the Highway Capacity Manual methodologies for signal optimization. It was interesting to see that none of the agencies that responded to the survey utilized TRANSYT-7F, PASSER-V, and MAXBAND at present. Once very popular for signal optimization use, these software packages are no longer mainstream and have been replaced by other options.

The survey participants were also asked to report on their use of simulation or computational models in support of signal control optimization and management. Table 10 clearly shows that SimTraffic is the most widely used computational model with 10 out of 17 agencies surveyed reporting using it. Highway Capacity Software (HCS) and VISSIM/VISUM were used by 5 and 4 agencies, respectively. There is no use of TSIS/CORSIM and AIMSUN, and only one large agency reported the use Transmodeler. In addition, two mid-size and two small responding agencies indicated they do not use any simulation models as part of their practice.

TABLE 10: USED SIMULATION OR COMPUTATIONAL MODELS IN SUPPORT OF SIGNAL CONTROL OPTIMIZATION AND MANAGEMENT

Simulation or Computational Models	Number by Agency Type Large, n=5	Medium, n=6	Small, n=6	Total, n=17
TSIS/CORSIM	0	0	0	**0**
VISSIM/VISUM	1	1	2	**4**
SimTraffic	5	4	1	**10**
Highway Capacity Software (HCS)	1	2	2	**5**

AIMSUN	0	0	0	**0**
Transmodeler	1	0	0	**1**
Other (Requested details)	0	0	0	**0**
No, my agency does not use any simulation models	0	2	2	**4**

3.4.4 Data Collection Strategies

The survey solicited information regarding the types and sources of data currently used for evaluating signal performance. As illustrated in Table 11, agencies responding to the survey use a variety of data types for evaluating signal performance. Intersection crash data and results from simulation or computational tools are the most prevalent data types considered. Some of the large and mid-size agencies report using travel time measurements/delays based on third-party vendors (INRIX, HERE, TomTom, etc.), whereas none of the small size agencies surveyed reported the utilization of such data. Furthermore, one large agency reported that they use travel time runs/field observations, and two small size agencies stated that they use "manual observations of the corridor and individual signal performance (delays, queuing, etc.)" and "Manual counts and HCS procedures."

TABLE 11: DATA EMPLOYED FOR EVALUATING SIGNAL PERFORMANCE

Data Types	Number by Agency Type			Total, n=17
	Large	Medium	Small	
High-resolution controller/ATSPMs	3	2	2	**7**
Travel time measurements/ delays based on Bluetooth/Wi-Fi	3	1	3	**7**
Travel time measurements/ delays based on third party vendor (INRIX, HERE, TomTom, etc.)	2	1	0	**3**
Intersection crash data	4	3	2	**9**
Simulation or HCS models	3	3	2	**8**
Other (Requested details)	2	0	2	**4**

In addition, the survey participants were asked if their agency implemented emerging data collection strategies such as high-resolution controller data in support of signal control optimization and management. Table 12 summarizes the answers received.

TABLE 12: EMERGING DATA COLLECTION STRATEGIES

Options	Percentage by Agency Size			Total (All Agencies Combined)
	Large	Medium	Small	
Yes, full scale implementation	0.0%	16.7%	0.0%	**5.9%**
Yes, on few intersections	20.0%	16.7%	33.3%	**23.5%**
Planned, not implemented yet	20.0%	16.7%	0.0%	**11.8%**
Not planned, being considered	60.0%	33.3%	0.0%	**29.4%**
Not planned, or not aware	0.0%	16.7%	50.0%	**23.5%**
Not planned, or not interested in implementing	0.0%	0.0%	16.7%	**5.9%**

As seen from Table 13, the majority of large and mid-size agencies responded that the use of emerging data collection practices in support of signal optimization is not currently done but it is being considered for the future. However, the majority of small size agencies reported that they have no plans for using emerging data collection options, or their agencies are not aware of such practices and/or not interested in implementing.

To understand motivations and obstacles associated with the use of new sources of data in support of signal timing and optimization, survey participants were asked their opinion on whether or not it is worth to invest on emerging technologies for signal optimization (such as high-resolution controller data and connected vehicle data) in their regions. The responses summarized in Table 13 indicate that representatives of large agencies are extremely supportive of such investment. Mid-size agencies are also in support with two thirds of the reporting agencies embracing investment on emerging technologies in support of signal optimization. Small-size agencies are more cautious but are still overall supportive.

TABLE 13: PERCEIVED VALUE OF THE INVESTMENT IN EMERGING TECHNOLOGIES FOR SIGNAL OPTIMIZATION (SUCH AS HIGH-RESOLUTION CONTROLLER DATA AND CONNECTED VEHICLE DATA)

Options	Percentage by Agency Size			Total (All Agencies Combined)
	Large	Medium	Small	
Yes	100.0%	66.7%	50.0%	**70.6%**
Somehow	0.0%	33.3%	33.3%	**23.5%**
No	0.0%	0.0%	16.7%	**5.9%**

Survey participants were also asked if their agency has sufficient resources at present (e.g., technical staff and an adequate budget) or not in order to meet signal optimization and management needs. The respondents' opinions are summarized in Table 14.

TABLE 14: AGENCY RESOURCES TO MEET SIGNAL OPTIMIZATION AND MANAGEMENT NEEDS

Options	Percentage by Agency Size			Total (All Agencies Combined)
	Large	Medium	Small	
Yes, my agency has sufficient resources to meet current and future needs	0.0%	16.7%	33.3%	**17.6%**
My agency has limited resources; additional resources will be needed in order to adequately meet future needs	80.0%	50.0%	66.7%	**64.7%**
No, my agency does not have sufficient resources; lack of resources hinders efforts to improve signal optimization and management at the present time	20.0%	33.3%	0.0%	**17.6%**

According to Table 14, the majority of agencies representatives surveyed think that their agency has limited resources. About 20% of representatives of large agencies and 33.3% of representatives of mid-size agencies feel that their agency does not have sufficient resources and that the lack of resources hinders efforts to improve signal optimization and management at present. They also feel that additional resources will be needed in order to adequately meet future needs.

To gain a more in depth understanding about the resources needed and agency priorities, the survey further asked: "If your agency needs additional resources, please rank the following resources based on need from highest priority to lowest priority". The responses obtained from representatives of large, medium, and small size agencies are depicted in Figure 2, Figure 3, and, Figure 4, respectively.

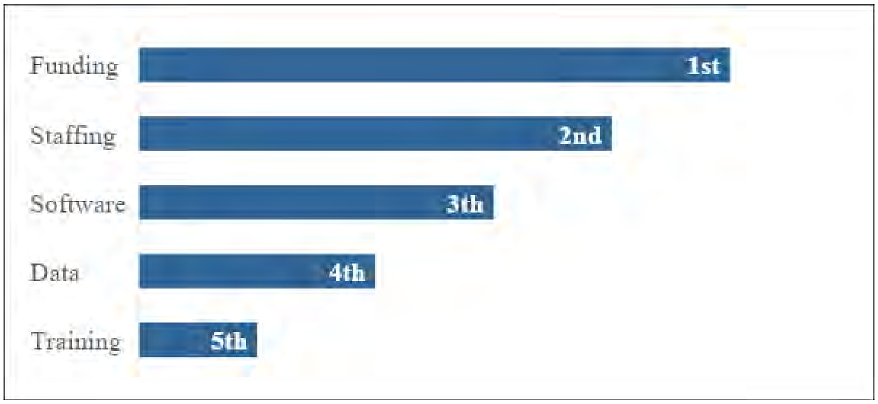

FIGURE 2: LARGE AGENCIES' PARTICIPANT OPINION, RANKING FROM HIGHEST PRIORITY TO LOWEST PRIORITY

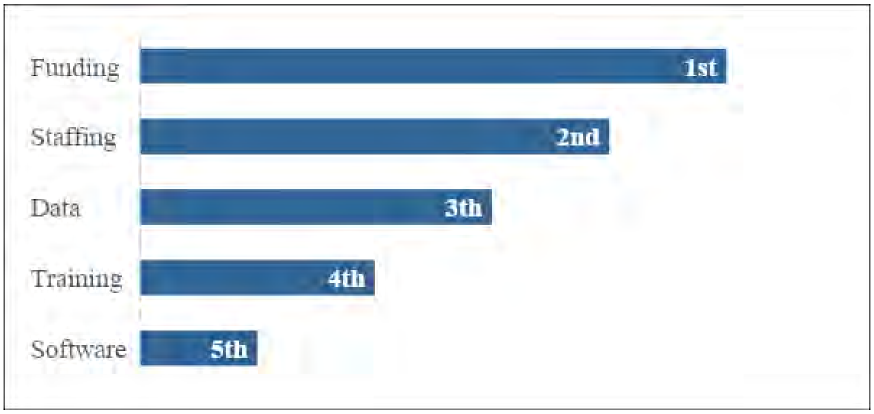

FIGURE 3: MID-SIZE AGENCIES' PARTICIPANT OPINION, RANKING FROM HIGHEST PRIORITY TO LOWEST PRIORITY

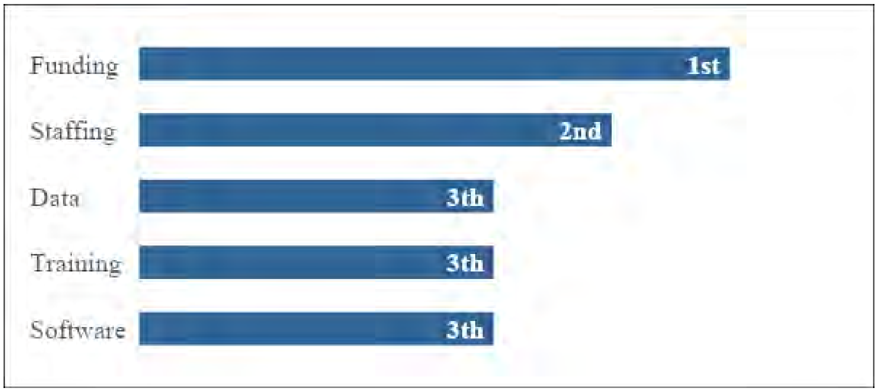

FIGURE 4: SMALL AGENCIES' PARTICIPANT OPINION, RANKING FROM HIGHEST PRIORITY TO LOWEST PRIORITY

The results in Figures 1 through 3 show that funding and staffing are ranked as the top two priority issues regardless of agency size. This is consistent with earlier findings from nationwide surveys that reported resource limitations related to funding and staff as being the most significant factors contributing to suboptimal signal retiming and optimization [6], [7].

3.5 CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

This study collected and analyzed questionnaire survey responses from 17 transportation agencies responsible for TSOOMM of over 9,600 traffic signals in the Southeast US. The findings shed light on current signal timing practices and software resources used for signal control optimization and management. Moreover, the survey results document types and sources of data used for evaluating signal performance along with stated preferences related to the value of the investment in emerging technologies for signal optimization and the adequacy of resources. The following conclusions can be given based on the analysis of the responses to the survey conducted in this study:

- The responding agencies reported that nearly 74% of the traffic signals that they manage are coordinated. Large and mid-size agencies surveyed also reported that the majority of their signals are connected to the central controller (87%).
- Large majorities of the signals managed by the agencies surveyed are actuated/semi actuated. The numbers of traffic responsive and adaptive signal controls are still relatively low.
- Most of the agencies surveyed have implemented emergency vehicle preemption and special plans for special event management. Furthermore, large agencies reported that they utilize drawbridge preemption, and reversible-lane control. Eight out of the 17 agencies surveyed reported using railroad-highway grade crossing signal priority.
- Most of large and mid-size agencies retime their traffic signals every five years or more while half of the small agencies retime their signals more frequently, typically every three to five years.
- The agencies surveyed reported making signal retiming decisions based on review of data, field observations, feedback from travelers, or they retime at regular intervals. One-third of the agencies reported combining several of the above-mentioned considerations.

- The majority of agencies use national or statewide guidelines for signal optimization and management, irrespective of agency size.
- SYNCHRO is a very popular signal optimization software utilized by 15 out of 17 agencies surveyed. None of the 17 agencies that responded to the survey currently utilizes TRANSYT-7F, PASSER-V, and MAXBAND.
- SimTraffic is the most used simulation model by survey participants, irrespective of agency size. VISSIM/VISUM and Highway Capacity Software (HCS) are also utilized but to a much lesser extent.
- Agencies reported using a variety of data types for evaluating signal performance with intersection crash data and outputs from simulation models being the most prevalent data type used.
- The majority of large and mid-size agencies reported that even though they do not currently utilize emerging data collection strategies such as high-resolution controller data in support of signal control optimization and management, such strategies are being considered for future use. On the contrary, the majority of small size agencies indicated that their agencies are not planning and/or are not aware or interested in such data collection strategies.
- Large agencies reported being much more interested in investing resources toward emerging technologies for signal optimization (such as high-resolution controller data and connected vehicle data) in their regions than small agencies.
- The majority of agencies surveyed feel that they have limited resources (e.g., technical staff and budget) in order to properly handle signal optimization and management needs. They also stated that additional resources will be needed in order to adequately meet future needs. Such results are in agreement with those from previous survey efforts [4]–[8] that also identified lack of funding as the biggest issue of concern that almost all types of agencies involved in TSOOMM are facing.

The consensus of survey participants regarding limited finding resources may also explain why some agencies have limited ability to collect data, invest in software and emerging technologies, retime signals more frequently, and increase staffing. The findings also heighten the importance of well-managed traffic signal operations as a means for optimizing traffic operations and reducing related congestion.

According to the scope of the study, the results from this survey of practice focused on agencies engaged in TSOOMM in the Southeastern States. While this was done by survey design, it may also be viewed as a limitation of this study. In terms of future work, it is recommended to expand the scope of this research and conduct a comprehensive survey of practice soliciting feedback from transportation agencies responsible of TSOOMM across the nation. Analysis of responses on a region-by-region basis (West, Midwest, Northwest, Southeast, and Southwest) is recommended to facilitate a better understanding of potential similarities and differences in current practices based on geographical region. In addition, in future work, it is suggested to include self-assessment as part of the survey instrument. The self-assessment would allow agencies to benchmark their own performance and compare their practices with those of other agencies as well as with commonly accepted best practices. Finally, further research can focus on the integration of traditional and emerging data from different sources for signal timing optimization purposes. It is recommended that a framework be developed considering the variations in the capability, maturity, and resources available to different agencies.

The work presented in this study was the first study documenting TCOOMM practices in the Southeast in the era of emerging technologies. One valuable contribution of the study is that transportation agencies can use the findings of the survey to compare their practices with other agencies in the Southeast and gain useful knowledge that will assist them in improving signal timing, optimization, and management in the future. Moreover, the survey identified current gaps and barriers that may be addressed through additional research and training to further assist agencies in taking full advantage of existing and new data and technology resources in the future

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CHAPTER 4: USING HIGH-RESOLUTION CONTROLLER DATA IN THE CALIBRATION OF TRAFFIC SIMULATION MODELS

4.1 INTRODUCTION

Microscopic traffic simulation tools are now commonly used to support various business processes of the transportation agencies. The use of simulation models and the complexity of these models are expected to increase with the increasing need to assess the emerging vehicle and infrastructure-based technologies and strategies such as active traffic and demand management, connected and automated vehicles, and cooperative driving automation.

Traffic simulation tools are usually set with default values of user-adjustable parameters. However, the models with the default values rarely replicate local traffic conditions. Thus, a calibration and validation process is necessary to minimize the deviation between the simulation results and field observations before using the models for alternative analysis. When a microscopic simulation model is used without proper calibration and validation, the simulation results are inaccurate and unreliable and thus cannot be used to support the agency's decisions.

Traditionally, the calibration of traffic simulation models has been based on macroscopic traffic parameters such as traffic volumes and demands, spot speeds, travel times, and where available queue lengths. The models are usually calibrated for an average peak and/or off-peak hour or period that are supposed to represent typical traffic conditions on the modeled network. However, the recent guidance provided by the updated Traffic Analysis Tool Box Volume III, produced by the Federal Highway Administration (FHWA) recommends the use of clustering to identify operational scenarios for use in calibration such as different congestion levels, incident conditions, and weather conditions *(1).*

Conventional traffic data collection and utilization methods aggregate traffic measurements such as vehicle flow, speed, and occupancy in 15 min to one-hour intervals. On arterial networks, day-to-day as well as cycle-to-cycle variations in the measurements are important, including the measurements of volumes, vehicle platoon arrivals, discharge rates, and green time utilization. These measurements at the signalized intersections significantly affect the estimation of network performance. In recent years, new data collection technologies are emerging that can be used to support better development and calibration of simulation models, including multi-scenario simulations. These data sources include high-resolution controller data, vehicle trajectories based on advanced detection technologies and/or image processing, automatic vehicle identification (AVI) technologies, third-party vendor data, and connected and automated vehicle data. These data sources can support the estimation of more detailed, accurate, and microscopic parameters of the traffic flow and associated control to enhance traffic simulation modeling quality.

High-resolution controller data provides timestamps for vehicle arrival and departure and records signal status changes within a 0.1-sec resolution. Therefore, this data allows the estimation of vehicle arrivals and departures, green time utilization, signal control timings, and other parameters. This data can be used for more detailed calibration and validation of simulation models. However, despite the great interest in collecting and using this data by signal control agencies, there has been no effort to investigate its use in simulation model calibration. This study proposes the use of high-resolution controller data in combinations with the commonly used traffic data in the calibration and development of simulation models. The data was used first to identify operational scenarios for use in the model based on clustering analysis. A microscopic simulation model was then developed and calibrated for the scenarios using a multi-objective optimization technique based on travel time and high-resolution controller-based measurement. The evaluation of the calibration based on the multi-objective function indicates that the proposed optimization technique is able to better replicate intersection measures assessed based on high resolution controller data such as green occupancy ratio, green utilization, and arrival on green, while producing comparable errors in travel time to those obtained when optimizing the calibration parameters based on travel time measurements alone.

4.2 BACKGROUND ON SIMULATION MODEL CALIBRATION

Calibration of traffic simulation models is a critical component of simulation modeling. The increasing complexity of the transportation network and the adoption of emerging of vehicle and infrastructure-based technologies have motivated the development of new methods that utilize new data sources in the calibration. There has been increasing recognition of the need for more detailed and specific guidance for utilizing simulation tools considering the increasing complexity of simulation modeling. Several states have developed guidelines for utilizing simulation modeling in their states, including a strong emphasis on calibration. The FHWA Traffic Analysis Toolbox documents have provided valuable information regarding the use of traffic analysis tools, including simulation model calibration *(1)*. However, the existing simulation calibration guidance focuses on the use of field-measured macroscopic traffic flow parameters such as average travel times, approach volumes, turning movement counts, and queue lengths as measures of effectiveness (MOEs) to calibrate microscopic driving behavior parameters *(2,3,4,5)*. More recently, there has been an increasing interest in using microscopic parameters such as vehicle trajectories in simulation model calibration *(6, 7, 8)*.

In practice, the calibration of simulation models has relied on a manual iterative process to adjust the simulation model parameters to allow the model to better represent the traffic conditions. However, several researchers automate the calibration process using optimization-based approaches such as gradient search, simplex-based, simultaneous perturbation stochastic approximation (SPSA), Bayesian optimization, and genetic algorithm (GA), aiming to minimize the error between field and simulation traffic parameters *(4,9,10,11,12,13)*. In the absence of microscopic data, macroscopic data can be utilized to calibrate simulation models by optimizing field and simulation measures. Travel time (10,11,14), traffic counts (12,13), traffic density (15), vehicle speed (12,13,15), , traffic flow rate (16), occupancy (17), Origin-Destination (OD) demand data(18) has been previously used to calibrate simulation models.

However, these studies calibrated the models based on macroscopic measures, even when using advanced optimization techniques. Combining the use of more detailed traffic measurements and advanced optimization techniques has the potential of achieving more accurate and reliable replication of traffic conditions in the simulation model. Such combinations are investigated in this study.

4.3 CASE STUDY NETWORK

The case study segment used to demonstrate the proposed method to calibrate the simulation models based on high-resolution controller data consists of five intersections, from NW 22nd Avenue to NW 7th Avenue on NW 119th Street in Miami-Dade County. This segment is around 1.5 miles in length. This segment is selected because it faces moderate to high demands all day long and is often congested during peak hours. Also, advanced data sources such as high-resolution controller data, travel time data based on Bluetooth reader measurements, traffic counts, and incident data are available for the segment.

The signal timing plans input into the model were the same as the semi-actuated time-of-day plans implemented in the real-world. The signal phase timing was obtained from Miami-Dade County and verified using the high-resolution controller data. Vehicle inputs at the entry points of the network and the static routes were coded as the traffic volume extracted from high-resolution data, which were verified for correctness based on the turning movement counts taken for one day in the peak periods. The desired speed distribution in the eastbound (EB) and westbound (WB) direction was coded according to the speed limits of each link in the segment. In addition, reduced speed areas are placed for the turning movements of the roadway intersections to reflect the turning speeds. Figure 5 shows an illustration of the study simulation model over the Open Street network.

FIGURE 5: MICROSCOPIC SIMULATION NETWORK OF CASE STUDY SEGMENT

4.4 PERFORMANCE MEASUREMENTS BASED ON HIGH-RESOLUTION DATA

In recent years, advanced data collection, processing, archiving, and mining techniques have motivated and enabled the retrieval of event-based high-resolution data from signal controllers *(19,20, 21)*. This data has started to be widely used by signal control agencies to assess their signal control performance and identify required changes to the system. As stated earlier, the main objective of this study is to investigate the use of this data in the calibration and validation of microscopic simulation models. This study hypothesizes that using various performance measures derived based on the high-resolution control data to capture multidimensional features of arterial traffic, and it will be possible to achieve a better quality of the model.

There are several studies in which researchers utilize the event-based controller data for the estimation of measures such as arterial progression quality using coordination diagram *(22),* split utilization *(23)*, green occupancy ratio *(24,25)*, arrival type *(26,27)*, vehicle arrival on green *(26,28)*. This section provides a brief description of the data and the derived parameters based on the data.

4.4.1 Data Description

High-resolution controller data includes signal timing and detection at the highest time resolution of the controller (0.1 seconds). This data has been used in combination with data from other sources to support the estimation of what is now commonly known as Automated Traffic Signal Performance Measures (ATSPM). The high-resolution data consists of signal controller events based on a standardized set of event parameters and event identification codes. The stored parameters include the Timestamp that contains the date and time of activities, Event Code, and Event Parameters. The Event Code describes the type of event. The Event Parameters indicate the specific detector or signal phase where the event occurs. The description of the data is provided in the Indiana Traffic Signal High-Resolution Data Logger *(29)*. The recorded phase numbers (k=

1 to 8) correspond to the numbering scheme of the eight-phase, dual-ring NEMA traffic signal controller. The numbering was set to ensure that the phase number correspond the same movement for different signal controller. For example, all eastbound left-turn phases are coded as Phase Number 1.

4.4.2 Utilized Performance Measures

In this study, at first clustering of the operational traffic conditions is done utilizing the green occupancy ratio and travel times. For each operational condition, the travel time, split utilization ratio, and movement throughput are used in the calibration. The green occupancy ratio and percentage arrival on the green are used in the validation.

The high-resolution controller data provides the opportunity for cycle-by-cycle estimation of the throughputs. Having a separate detection channel per lane is required if lane-by-lane detection of the throughput is needed. The Green Occupancy Ratio (GOR) is a performance measure that reflects the degree of green utilization in each phase. It is defined as the stop bar detector occupancy during the green interval *(24)*. Higher values of GOR reflect higher utilization of the green time. This value increases to values above 0.5 in the peak periods.

The Split Utilization Ratio (SUR) measures are derived for each intersection movement to allow the assessment of congestion level in all directions. SUR is defined as the ratio of the number of vehicles passing the detector to the maximum number of vehicles that can pass during the effective green time *(22)* and can be calculated as follows:

$$S_k = \frac{h_k \times N_k}{g_k} \tag{1}$$

Where:
S_k = Split utilization ratio at phase *k*,
N_k = The vehicle counts at phase *k*,
h_k = Saturation headway at phase *k* (sec.), and
g_k = The effective green time at phase *k* (sec.)

The Percent Arrivals on Green (POG) is calculated as the proportion of vehicles that arrive on the green signal versus the proportion of vehicles that arrive on the red signal *(23)*. This measure reflects the quality of progression of traffic.

4.5 CLUSTER ANALYSIS FOR PARTITIONING OPERATIONAL CONDITIONS

Clustering analysis is the most practical method for the identification of traffic patterns that are representative of traffic conditions in support of analysis, modeling, and simulation (AMS) *(30)* studies *(31,32,33,34)*. Clustering analysis has been recommended for the development and calibration of simulation, particularly those used to assess transportation system operations and management (TSMO) strategies. Partitioning the field traffic conditions allows agencies to better plan, design, and evaluate new technologies and strategies for traffic operation (*33,35)*.

In this study, clustering analysis is used for pattern recognition to model representative traffic operational scenarios for a more accurate estimation of arterial network performance measures. The pattern recognition was accomplished by first clustering the whole day travel time measurements at 15 minute-resolution for both directions of the case study segment. In this clustering, normal (incident-free) day travel time data for one month was used. Then, the GOR values were included in the next level of clustering. This study uses K-means clustering, which has been widely used in transportation engineering research. One crucial aspect of clustering is to determine the number of clusters to use in the clustering that further categorized the travel-time clusters based on the GOR. This study utilizes a method referred as the Elbow method to determine the required number of clusters *(36)*. The Elbow method is an empirical method that provides an objective approach to determine the optimal number of clusters. The method determines the number of clusters based on the total within-cluster sum of square (WSS) for each number of clusters *(36)*. A graph is drawn between the total WSS and the number of clusters, and the location of the bend in the plot is considered as an indicator of the appropriate number of clusters. In this study, it was determined that four different clusters are the best number for the travel time-based clustering.

Figure 6 shows the four separate clusters derived using the K-means methods and their centers based on travel time only. Cluster 2 mainly represents data between 7:00 AM and 9:00 AM with heavy eastbound traffic, Cluster 1 represents moderate traffic in both directions during the midday and post the peak period in the PM (between 7:00 PM and 9:00 PM), Cluster 3 represents night traffic, while Cluster 4 represents the PM peak period traffic between 3:00 PM and 7:00 PM that is heavy in the westbound direction. Obviously, the traffic can change significantly within each of these periods, between days, and from cycle-to-cycle. Thus, further portioning is needed for the data based on high resolution controller data, as explained next.

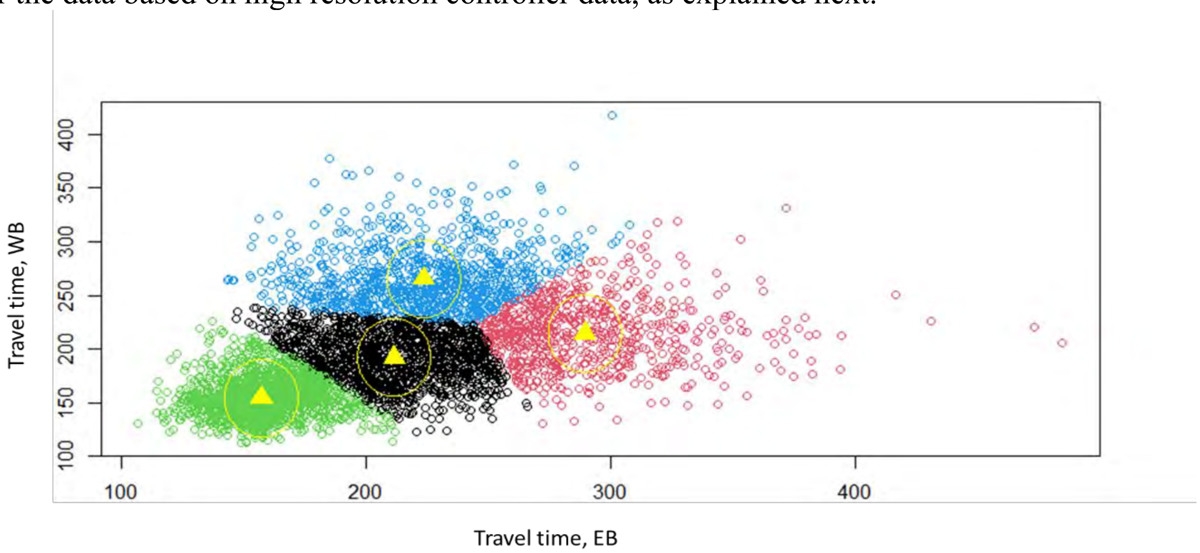


FIGURE 6: TRAVEL TIME CLUSTERS

Further partitioning of the traffic patterns is done by K-means clustering based on the GOR for the 7:00 AM to 9:00 AM peak period utilizing event-based controller data. Table1 presents the resulting categorization of traffic conditions in the AM peak based on the GOR of all major movements and the associated travel times of the study segment. In this study, we present the calibration and validation of a microscopic simulation model for the case study utilizing the

VISSIM (Verkehr in Städten – SIMulationsmodell) microscopic simulation tool for one of the categories in Table 15 (Category 2).

TABLE 15: CATEGORIZATION OF TRAFFIC BASED ON THE GREEN OCCUPANCY RATIO

Category	**No of Data Points**	**Travel Time, seconds (Average)**		**Through Movement Cluster Center GOR**		**Left Turn Cluster Centers GOR**	
		EB	**WB**	**EBT**	**SBT**	**EBL**	**SBL**
Category 1	8	300.1	223.01	0.636	0.775	0.84	0.94
Category 2	22	279.65	215.74			0.84	0.77
Category 3	5	276.6	205.26			0.77	0.62
Category 4	16	265.5	213.57	0.556	0.772	0.79	0.87
Category 5	19	280.15	217.51			0.80	0.72
Category 6	18	281.7	198.03	0.613	0.658	0.80	0.77

Note: EB= Eastbound movement, WB= Westbound movement, EBT= Eastbound Through movement, SBT= Southbound Through movement, EBL= Eastbound Left turn movement, SBL= Southbound Left turn movement.

4.6 SIMULATION MODEL CALIBRATION

This study uses an optimization process to calibrate the simulation model based on a combination of traffic measurements, including those derived based high-resolution controller data. GA has become a widely used optimization technique in transportation engineering research. It is a heuristic optimization technique that is motivated by Darwin's principles of natural selection, survival of the fittest, and evolution *(37)*. GA is widely used because of its robustness, computational efficiency, and ability to find solutions near the globally optimal solution *(37) (38)*. The calibration in this study utilizes a multi-objective optimization technique using the NSGA III algorithm, which is a variation of the GA *(39,40)*. Unlike the basic GA, the NSGA-III belongs to a set of multi-objective algorithms aiming to find the Pareto front of compromised solutions of all objectives rather than integrating all objectives together in one objective function *(41)*. A solution belongs to the Pareto set if there is no other solution that can improve at least one of the objectives without the degradation of any other objective. NSGA-III was found to be able to maintain a better spread of solutions and converge better in the obtained non-dominated front *(41, 42)*. This study compared the utilization of GA to calibrate the simulation model based on a single variable (travel time) with the use of NSGA-III based multi-objective optimization to calibrate the model with the use of additional parameters estimated based on high resolution controller data.

The utilized procedure for development and calibrating microscopic simulation models consists of five main steps: microscopic performance measures estimation based on field data, traffic pattern recognition, model development, model calibration by optimizing driver behavior parameter to minimize the difference between the field and simulated performance measures, and finally model validation.

4.7 CALIBRATION PROCESS

Various performance measures were estimated for the Category 2 scenario, as identified in Table 16. For example, using high resolution controller data, the vehicle throughputs for each lane per cycle was calculated based on Detector On code (Event Code 82) that is encoded when a vehicle enters a detector and detector off code (Event Code 81) that is encoded when a vehicle exits a detector. Occupancy was measured by the time difference between consequent Event Code 82 to Event Code 81, which shows the amount of time the detector was occupied. The green time is calculated using Event Code 1(Phase Begin Green), Event Code 7 (Phase Green Termination) for each phase and so on.

The vehicle inputs at the entry points of the simulation network and the relative flows associated with the static routes were coded based on the traffic volumes extracted from high-resolution data, which were verified using one-day turning movement counts, as mentioned above.

Simulation models were developed and calibrated for a one-hour analysis period. The study optimized the VISSIM parameters that affect driver behaviors and traffic performance characteristics to improve the microsimulation model's ability to replicate real-world traffic scenarios. VISSIM provides two car following models to select from, the Wiedemann 74 and Wiedemann 99. The Wiedemann 74 model is generally used for urban traffic and merging areas, whereas the Wiedemann 99 is generally used for freeway traffic with no merging areas *(43)*. The driver behavior parameters for lane changing, signal control parameters, and the car following model according to Wiedemann 74 model were optimized in this study using the NSGA-III algorithm. The specific optimized parameters and the associated ranges of their values were selected in accordance with the VISSIM-specific guidelines of the Wisconsin State Department of Transportation (WSDOT) Traffic Engineering, Operations and Safety Manual (TEOpS) *(43),* as presented in Table 16.

TABLE 16: LIST OF ADJUSTED DRIVER BEHAVIOR PARAMETERS

Parameter Type	Parameters	Minimum Value	Maximum Value	Default Value	Unit	Parameters Description
Car Following Model	Average Stand Still Distance	3.28	6.56	6.56	ft.	Average desired distance between two cars. Higher value means larger standstill distance and lower capacity
	Additive part of safety distance	2	2.2	2	ft.	Used for desired safety distance. Higher value means larger standstill distance and lower capacity
	Multiplicative part of safety distance	2.8	3.3	3	Ft.	Used for the computation of the desired safety distance. Higher value means larger standstill distance and lower capacity
Lane Change	Maximum deceleration - Own (ft/s2)	-15	-12	-13.12	ft/s^2	Upper bound of deceleration for own vehicles. Higher absolute value means more aggressive lane changing behaviors
	Maximum deceleration - Trail (ft/s2)	-12	-8	-9.84	ft/s^2	Upper bound of deceleration for trailing vehicles. Higher absolute value means more aggressive lane changing behaviors
	Waiting time before diffusion (s)	60	99999	60	sec.	The maximum amount of time a vehicle can wait at the emergency stop distance for a necessary change of lanes. Higher

						value means more tolerance on vehicles waiting at the emergency stop distance for necessary lane changes.
	Minimum Headway	1.5	2	1.64	ft.	The minimum distance between two vehicles that must be available after a lane change, so that the change can take place.
Signal Control	Factor	0.6	1	0.6		Higher value reduces the safety distance between vehicles close to the signal stop bar

Performance measurement, as outputs of the simulation, were collected using the simulation evaluation window in the Python COM interface as well as the output performance evaluation files, including the detection, signal phasing, and timing log files as follows.

- Vehicles throughput is collected based on data collection points specified at the stop line detector locations.
- Vehicle travel time is collected directly from vehicle travel time measurements in the simulation.
- Green time is measured using the ‘signal state run time’.
- The total number of vehicles passing each detector is collected based on detector log

The detection and signal phasing timing log files are processed with the combination of these files providing 0.1 sec data that emulate real-world signal controller high resolution event-data.

4.8 OPTIMIZATION OF CALIBRATION PARAMETERS

As stated earlier, this study investigates the performance of the use of the NSGA-III algorithm in multi-objective optimization to calibrate the simulation model with the use of additional parameters estimated based on high resolution controller data compared to the utilization of GA to calibrate the simulation model based on a single variable (travel time) in the calibration. The multi-objective optimization problem of the calibration can be stated as follows:

$$\text{minimize} \quad f(x) = [f_1(x), f_2(x), f_3(x) \dots \dots \dots, f_M(x)] \qquad (2)$$

subject to:

$$x_i^L \leq x_i \leq x_i^U \qquad (3)$$

where,
M= Number of objective functions, (In this study M=3, which are travel time, split utilization ratio, and throughput),
f(x)= Objective function values,
i= Number of decision variables,
x_i = Decision variables (Adjustable microsimulation parameters),
x_i^L= Lower bound of decision variables,

x_i^U= Upper bound of decision variables.

The decision variables in this optimization are the driver behavior parameters listed in Table 16, and the lower bound and upper bound of each parameter in the optimization algorithm are set based on the values in Table 16. The objective function values are directly calculated based on the simulation results collected from the COM interface of the utilized tool and the field data for Category 2 traffic pattern. The objective functions are calculated as below:

$$f_1 = \frac{|TT_{Field} - TT_{simulation}|}{TT_{Field}} \tag{4}$$

$$f_2 = \frac{|S_{Field(k)} - S_{simulation(k)}|}{S_{Field(k)}} \tag{5}$$

$$f_3 = \frac{|Throughput_{Field(k)} - Throughput_{simulation(k)}|}{Throughput_{Field}(k)} \tag{6}$$

where,
TT_{Field} = Field-measured travel time,
$TT_{Simulation}$ = Simulation travel time,
$S_{Field(k)}$= Field- measured Split utilization Ratio at phase k,
$S_{Simulation(k)}$= Simulation Split utilization Ratio at phase k,
$Throughput_{Field(k)}$= Field- measured throughput at phase k, and
$Throughput_{Simulation(k)}$= Simulation throughput at phase k.

The whole multi-objective optimization process is shown in the flowchart in Figure 7.

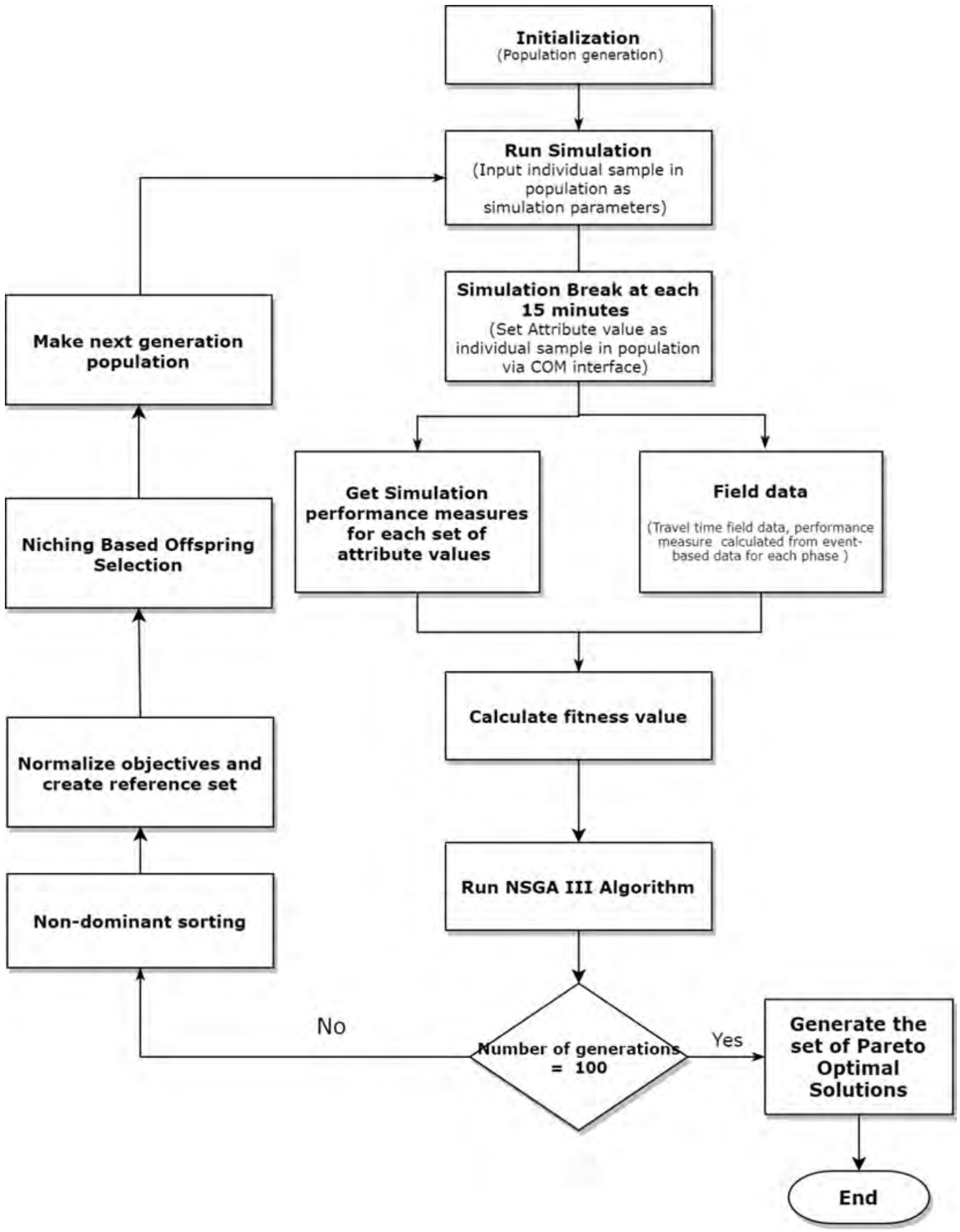
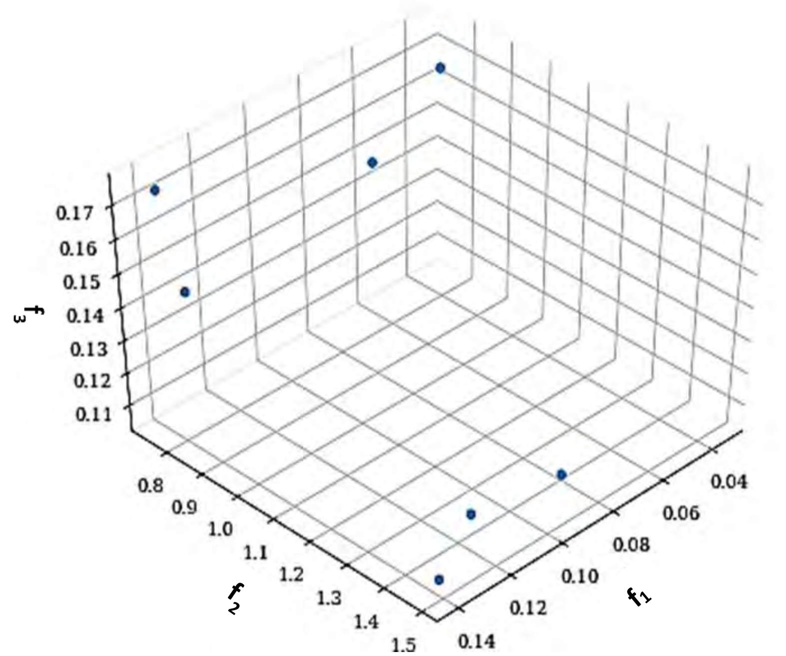


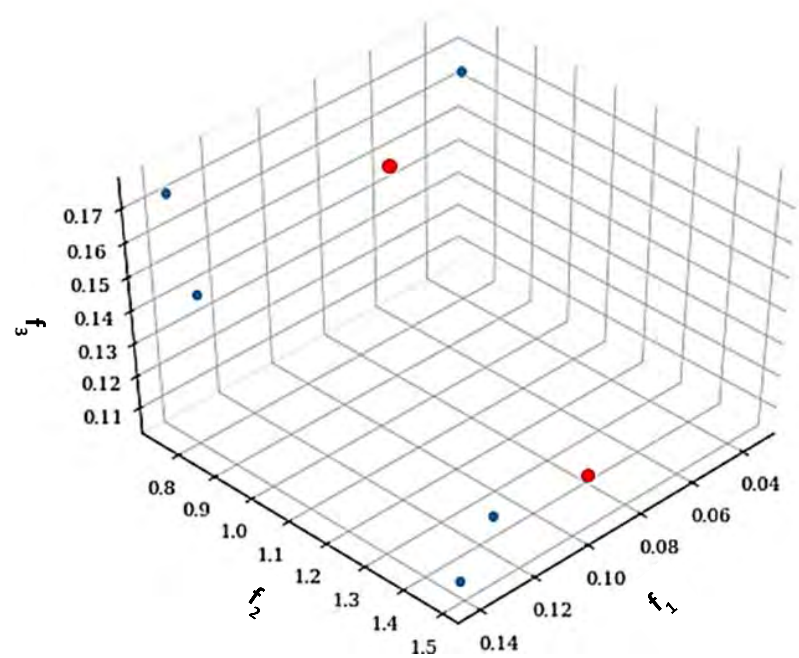
FIGURE 7: NSGA III OPTIMIZATION PROCESS USING THE VISSIM COM INTERFACE

4.9 CALIBRATION RESULTS

As stated earlier, the NSGA III algorithm uses a non-dominant sorting procedure and finds a set of Pareto optimal solutions rather than a single optimal solution. The Pareto-optimal solutions are the sets of solution trade-offs when all the objectives are considered. Figure 8 shows the 3D scatter plot of the final set of the Pareto optimal solution. Figure 8-a shows the Pareto optimal solution from NSGA III algorithm with 7 different sets of objective function values. Each set represents trade-offs of solutions between the three objective function values used in this study (Equations 4, 5 and 6). Figure 8-b shows the selected two pareto optimal sets in red dot for further evaluation. These two sets are referred to as NSGA Set-I and NGSA Set-II in the remaining of this study. Table 17 shows the decision variables or driver behavior parameters for both solution sets. Table 17 also shows the GA optimization results using the travel time objective function (f_1 in Equation 4).



(a)



(b)

FIGURE 8: PARETO OPTIMAL SOLUTION FROM NSGA III OUTPUT

TABLE 17: OPTIMAL SOLUTIONS AND CORRESPONDING DECISION VARIABLES

Pareto Optimal Set	Objective Function Values		Average Stand Still Distance (ft)	Additive Part of Safety Distance (ft)	Multiplicative Part of Safety Distance (ft)	Maximum Deceleration - Own (ft/s^2)	Maximum Deceleration - Trail (ft/s^2)	Waiting Time Before Diffusion (s)	Minimum Headway (ft)	Safety Distance Factor
Set-1	f_1	0.07003	5.963	2.1904	2.828	-14.7358	-11.54	64.85	1.9154	0.738
	f_2	0.82222								
	f_3	0.15684								
Set-2	f_1	0.09005	5.7823	2.1858	2.844	-14.7247	-11.545	64.60	1.8154	0.738
	f_2	1.46651								
	f_3	0.11334								
GA optimization results using only f_1 in equation 4										
	f_1	0.1075	4.9889	2.09	3.18	-13.122	-9.0464	94.76	1.8121	0.8641

As an example of the results, Table 18 presents the variation in the performance measures resulting from utilizing the simulation parameters based on the three solutions presented in Table 17. The compared performance measures are the travel times and the split utilization ratio (SUR). Table 18 shows that the parameters from all three optimization solutions produced significantly closer travel times compared to the model with the existing parameters. The travel time errors from the three solutions are comparable. However, the utilization of the parameters provided by the NSGA-III Set-1 solution in the simulation produced significantly more accurate results in term of the SUR parameter estimated based on high resolution controller data. This shows that the utilization of the NSGA-III Set-1 optimized parameters is able to accurately balance the objective functions providing less error in the split utilization ratio estimates.

TABLE 18: COMPARISON OF PERCENTAGE ERROR IN THE TRAVEL TIME AND SUR W/O CALIBRATED MODELS

Performance measures	Directio n	With default parameter value	GA minimization of travel time error	NSGA III, Set-1	NSGA III, Set-2
Error (%) in Travel Time	EB	20.25	9.76	4.40	8.14
	WB	5.85	4.40	7.58	5.96
Error (%) in SUR	EBT	75.53	36.18	7.89	9.21
	WBT	24.25	40.00	12.50	10.00
	SBT	17.48	19.75	13.58	19.75
	NBT	63.30	95.00	12.50	35.75

4.10 MODEL VALIDATION

Validation is the process of determining the degree to which a simulation model is an accurate representation of the real world from the perspective of the intended uses of the model. The simulated and field-observed data sets were further compared to check how the simulation model can replicate the existing traffic conditions based on additional measures not used in the calibration. The model validation was performed using additional high resolution controller intersection-based performance measures that were not used in the optimization, including the green occupancy ratio (GOR) and percent arrival on green (POG). These performance measures ensure the model's ability to replicate vehicle progression and congestion level. Table 19 shows that NSGA-III Set-1 and NSGA-III Set 2 based simulation provide a better representation of the real-world measurements of these parameters, compared to the use of the default model parameters and the parameters optimized using GA based on travel time. However, Table 19 shows that for the cross-street movements (southbound and northbound) the NSGA III Set –based simulation provides significantly lower error than NSGA III Set 2-based simulation, confirming that the NGSA III Set 1 solution provides the best set of parameters based on the calibration and validation results.

TABLE 19: COMPARISON OF PERCENTAGE ERROR IN THE GOR AND POG W/O CALIBRATED MODELS

Performance measures	Direction	With default parameter value	GA minimization of travel time error	NSGA III, Set-1	NSGA III, Set-2
Error (%) in GOR	EBL	47.62	44.05	14.29	11.90
	EBT	41.82	30.82	13.21	7.23
	WBL	39.47	26.32	10.53	13.16
	WBT	53.18	18.18	11.36	13.64
	SBL	38.96	45.45	10.39	18.18
	SBT	47.10	46.32	15.25	21.31
	NBL	50.91	54.55	7.27	21.82
	NBT	33.33	25.42	3.75	18.48
Error (%) in POG	EBL	19.64	18.18	8.23	5.12
	EBT	21.71	20.22	2.97	7.25
	WBL	68.04	65.62	4.78	4.09
	WBT	18.69	19.95	1.86	1.69

4.11 CONCLUSIONS

This study successfully developed and demonstrated an advanced method for the calibration and validation of microscopic simulation models of arterial networks utilizing high-resolution controller data combined with a two-level unsupervised clustering technique for scenario identifications and multi-objective optimization for simulation model calibration identification. The study introduced for the first time the use of several new parameters to calibrate and validate simulation models, including the split utilization ratio, green utilization ratio, arrival on green, in combination with other commonly used measures like vehicle travel time and throughput. The utilized multi-objective optimization technique belongs to a set of multi-objective optimization algorithms that aim to find the Pareto front of compromised solutions of all objectives rather than integrating all objectives together in one objective in the optimization.

The clustering analyses successfully categorized the traffic patterns based on segment travel time and the movement GOR values. The evaluation of the calibration parameters resulting from the multi-objective optimization based on travel time and high-resolution controller data measures indicate that the simulation model that uses these optimized parameters produces significantly lower errors in the split utilization ratio, green utilization ratio, arrival on green, and travel time compared to a simulation model that uses the default parameters of the simulation model. When compared with a simulation model that uses calibration parameters generated from the optimization of the single objective (minimizing the travel time only), the multi-objective optimization solution produces comparably low travel time errors but with significantly lower errors in terms of the high-resolution controller data measures.

In this study, the calibration process is conducted on a small network model that deals with a corridor with a series of intersections. Calibrating microscopic signal controller performance measures of medium networks of up to 100 intersections and large-scale networks are probable to show unacceptable errors. In this case one might calibrate the model using network-level macroscopic data such as traffic count, travel time, vehicle speed, traffic density, etc., and optimize these parameters as a multi-objective problem.

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CHAPTER 5: ANALYSIS OF PERFORMANCES OF TRAFFIC SIGNAL OPTIMIZATION IN THE PRESENCE OF HIGH-RESOLUTION CONTROLLER DATA

5.1 INTRODUCTION

The efficient design of traffic signal control has been recognized as one of the most cost-effective methods to improve accessibility and mobility of urban networks *(1)*. The inadequate design of traffic signal plans will significantly impact congestion *(2)*. For decades, traffic signal management agencies have used signal timing optimization tools combined with fine-tuning of signal timing based on field observations in their updates of time-of-day signal timing plans. These traditional signal optimization methods and tools use a very limited amount of data. The users of these tools, in many cases, utilize the default values of the traffic flow models used by the signal timing optimization tools to estimate network performance under different signal optimization strategies. Traditionally, signal control optimization and management processes have been based on movement volume data collected for one day and approach volumes collected for three to seven days. Agencies normally fine-tune the signal timings after implementation to account for the differences between the model results and the real-world measurements and observations.

The adoption of emerging technologies such as probe vehicles, Bluetooth-based technology, high-resolution controller, and so on provide the agency an abundance of data that have been increasingly used in recent years to estimate ATSPMs. This data creates an opportunity to calibrate the signal timing optimization tool instead of using default values. Moreover, the high-resolution data can also better capture the subtle changes in the field and replicate the real-world scenario. The utilization of these data in the modeling can reduce the differences between real-world and the model results. Considering the above, this study compared the performance of two signal timing optimization methods in the presence of the high-resolution controller (HRC) data. For this purpose, the macroscopic simulation-based optimization tool, TRANSYT-7F, and microscopic simulation-based (using Vissim) and multi-objective optimization algorithm were used in the study. The parameters of both models were calibrated, utilizing HRC data. The study then evaluated the optimized plans with or without calibration using HRC data.

The contribution of the work in this chapter is two folds. Most previous studies utilize link volume or turning movement counts to calibrate the model for simulation-based signal timing optimization. This study demonstrates the variation of performance of the optimization when calibrated using other important parameters of the simulation model besides turning movements or link counts. In another aspect, the study assesses the effectiveness of two different resolutions of the simulation model in signal timing optimization in the presence of HRC data.

5.2 LITERATURE REVIEW

The methods for traffic signal timing (i.e., cycle length, split, offset, phase sequence) design have evolved through the years. Most existing optimization tools use analytical methods or macroscopic simulation to assess the system performance during optimization. Among the tools that have been used in the United States, the most widely known are PASSER-II *(3),* MAXBAND *(4),* TRANSYT-7F *(5)*, Synchro *(6),* HCS-GA *(7)*.

TRANSYT-7F was developed based on the British TRANSYT tool and uses a system "Performance Index" (PI) to optimize signal timing *(8)*. The software optimizes the cycle length, splits, and offsets by minimizing a "Disutility Index" (DI), a function of delay, stops, fuel consumption, and, optionally, queue spillover. Two additional objective functions related to "throughput measure" and "queuing measures" were added in the software to allow better optimization of congested conditions. The tool performs optimization using a combination of hill-climbing and Genetic Algorithm (GA) based optimization methods *(5, 8)*. For better optimization's results, the users are supposed to input saturation flow and platoon dispersion factor (PDF) based on field measurements in addition to turning movement count, although the measurements of saturation flow rates and PDF is not usually done. Farzaneh and Rakha revealed in a study that proper calibration of the recursive platoon dispersion model is important to achieve and maintain a good signal timing plan *(9)*. In the absence of field data, the tool assumes a default value of 0.35, based on empirical studies performed by the Transport and Road Research Laboratory in the United Kingdom *(10)*. Research *(11-13)* suggests that the value in Table 20 could be used to obtain reasonable estimates for the PDF in the absence of field data.

TABLE 20: EMPIRICAL PDF VALUE SUGGESTED BY THE TRANSYT-7F MANUAL (11-13)

PDF	Roadway Characteristics	Description of Conditions
0.5	Heavy friction	Combination of parking, moderate to heavy turns, moderate to heavy pedestrian traffic, narrow lane width. Traffic flow typical of urban CBD.
0.35	Moderate friction	Light turning traffic, light pedestrian traffic, 11-to-12-foot lanes, possibly divided. Well-designed CBD of fringe arterial.
0.25	Low friction	No parking, divided, turning provision, 12 ft lane width. Suburban high-type arterial.

Based on the availability of the field data, various efforts have been taken to calibrate the PDF. Farzaneh and Rakha used data obtained from INTEGRATION simulation software for a single intersection for estimating the PDF *(9)*. Bie et al. used 4-hour video data of an intersection that were processed later using computer software to estimate the platoon dispersion factor *(14)*. Bonneson et al. also utilized video data from ten urban sites to collect the data and calibrate the dispersion factors *(15)*. Shen et al. developed a method to dynamically estimate the PDF for each time window considering the real-time collection of the speed of the vehicle in an upstream point and estimate the platoon dispersion factor for each time frame *(16)*. The utilization of the dynamic dispersion factor in the model outperforms the model with the static dispersion factor. However, the method needs additional detectors that involve cost. Other studies in the literature describe methods of calibrating this model by various means *(9, 17, 18)*. Most prior studies report results of machine-assisted manual data collection means *(17,18)*. However, extensive calibration is seldom done in practice because the data collection procedures are labor-intensive. Day et al. (2011)

demonstrated that high-resolution event data logged by traffic signal controllers at two neighboring intersections could be used in tandem to measure platoon distributions by correlating downstream vehicle arrivals with upstream beginning-of-green times *(19)*. Day & Bullock (2012) introduced a method to estimate the PDF using high-resolution data *(20)*. Since the high-resolution data has a better capacity to capture the platoon in the intersection automatically, this study conceived the use of this method to estimate the PDF in the field and calibrate the platoon dispersion model in the utilized tool.

Besides the commercial use of the TRANSYT-7F, many signal timing studies in the literature utilized this tool as the base model to compare the results with their proposed methods of optimization *(21-23)*. Among all of these studies, very few of them have gone through the detailed calibration of the model to include PDF and saturation flow calibration. The TRANSYT-7F software is used as the macroscopic model-based optimization tool in this study. The reason for selecting this tool is that it allows the user to provide additional calibration parameters to better model local traffic conditions. In contrast, other commonly used optimization software allows the modification of the movement saturation flow rates but not the platoon dispersion parameters. This study investigated the calibration of the PDF and saturation flowrates that are used as inputs to the tool using HRC data and evaluated those parameters' effect in the signal timing optimization.

Although macroscopic simulation-based methods have flexibility in use with no computational burden, well-calibrated microscopic simulation is the best available tool to represent real-world traffic behavior. Microscopic simulation provides the ability to account for system variability that stems from heterogeneity in driving behavior, the existence of different vehicle classes with different capabilities and characteristics, and the fluctuations in demand. Signal plan optimization methods are expected from using this level of detail in assessing system performance during the optimization. Recognizing this advantage, studies have investigated optimizing the signal timing in an integrated manner in microscopic simulation environments *(24-28)*.

As example of using optimization based on microscopic simulation, Rouphail et al. used the CORSIM simulation tool (*24*). The authors used the model default values for the distribution of driver types, spillbacks probabilities, and queue discharge headways *(24)*. Park & Schneeberger used a Vissim model as part of a GA-based optimization of signal control *(25)*. Stevanovic et al. (2007) calibrated a Vissim model based on turning movement counts, saturation flow rates, desired speed decisions, and control delay collected for nine days in a three weeks' period during am peak, midday peak, and afternoon peak *(26)*. In another study of simulation-based optimization, Zheng et al. (2019) calibrated three driving-behavior-related parameters of the Vissim model *(29)*. The data used for the calibration are link counts and travel time of the links collected for 30 minutes in a single day. Similarly, there are many other studies that use field-measured macroscopic traffic flow parameters such as average travel times, approach volumes, turning movement counts, and queue lengths as measures of effectiveness (MOEs) to calibrate microscopic driving behavior parameters *(30-32)*. More recently, there has been an increasing interest in using microscopic parameters such as vehicle trajectories in simulation model calibration *(33, 34)*. As described earlier, this study developed a multi-objective optimization-based calibration methodology for the microscopic simulation model calibration using HRC data. The calibrated model produced significantly lower errors in the split utilization ratio, green utilization ratio, arrival on green, and travel time compared to a simulation model that uses the simulation model's default parameters.

This chapter discusses this use of this calibrated model to optimize signal timing to examine the advantages of the calibrated model using HRC data.

5.3 METHODOLOGY

The study objectives include the demonstration of the performance of traffic signal plans developed using simulation-based optimization models with or without calibration of the models' parameters with HRC data and assessing the utilization of two different resolutions of the simulation models in signal timing optimization.

The study assesses six signal timing optimization scenarios to develop the traffic signal plans to realize the objectives. Four scenarios are based on macroscopic modeling, and two scenarios are based on microscopic modeling. The scenarios differ in the calibration process. As previously mentioned, TRANSYT-7F is used as the macroscopic tool in the study. Two input parameters to the tool, the PDF and saturation flow rates estimated using HRC data, are input to the model in addition to inputting turning movement's counts. Scenario I represents the macroscopic model with only inputting turning movement counts. Scenarios II and III represent macroscopic models calibrated with the saturation flow rate and PDF, respectively. Scenario IV represents the macroscopic model calibrated with saturation flow rate and PDF. Scenario V represents the microscopic model with the default parameters. Scenarios VI represents the microscopic model calibrated with HRC data using the procedure described earlier in this document. For Scenario VI, eight parameters of the Vissim microscopic simulation model, estimated using HRC data, are calibrated to replicate the real-world condition. Scenario VI is also used to evaluate the performance of the signal plans developed for all the scenarios as a base model. Below is a list of the scenarios:

- **Scenario I**: Macroscopic model calibrated with turning movements counts only
- **Scenario II**: Macroscopic model calibrated with turning movements counts and saturation flow rate
- **Scenario III**: Macroscopic model calibrated with turning movements counts and PDF
- **Scenario IV**: Macroscopic model calibrated with turning movements counts, saturation flow rate, and PDF
- **Scenario V**: Microscopic model calibrated with turning movements counts only
- **Scenario VI**: Microscopic model calibrated with turning movements counts and HRC data

5.3.1 Case Study Area

The analysis is performed using a real-world arterial network in Miami-Dade County. The arterial is around 1.5 miles in length and consists of five signalized intersections (with 19 signal phases) and eight non-signalized minor intersections, from NW 22nd Avenue to NW 7th Avenue on NW 119th Street. The major movement is in the east-west direction. This segment is selected because it faces moderate to high demands all day long and is often congested during peak hours. In addition, advanced data sources such as high-resolution data, travel time data based on Bluetooth reader measurements, traffic counts, and incident data are available for the segment. The existing semi-actuated time-of-day based signal timing plans are used as the initial input to the models. Figure 9 shows an illustration of the case study network over the Open Street Map.

FIGURE 9: CASE STUDY NETWORK

5.3.2 High-resolution controller (HRC) Data

One of the important aspects of the study is the utilization of the High-resolution controller (HRC) data obtained from the controllers' presence in the field. HRC data is event-based data with a temporal fidelity of 0.1 s. *(35)*. The data is recorded through a data logger software interface in the controller and capture all detection and phase events at a given intersection. The obtained data has a specific format consisting of three columns: "Timestamp," "Event Type," and "Parameter." The description of the data is provided in the Indiana Traffic Signal High-Resolution Data Logger *(35)*. The data used in the study is collected for November 2019 for the case study area.

5.3.3 Macroscopic Model Calibration

This study calibrates two critical parameters in TRANSYT-7F, the PDF and saturation flow rate. The HRC data allows the estimation of both the PDF and saturation flow rates for use in the model.

The TRANSYT-7F (T7F) software incorporates the Robertson platoon dispersion model *(10)*. It is a recurrence equation that estimates the downstream arrival flow at a specific time step based on the combination of upstream departure flow and the downstream arrival flow in the previous time step. The equation of the Robertson model is

$$q'_{(i+T)} = F * q_i + (1 - F) * q'_{(i+T-1)} \tag{7}$$

where

q_i = flow for ith bin of upstream departure platoon,
q'_i= flow in ith bin of downstream departure platoon,
T = average travel time (in units of bins), and
F = smoothing factor given by

$$F = \frac{1}{1+\alpha\beta T} \tag{8}$$

Where α and β are calibration constants; α is the platoon dispersion factor (PDF) ($0 \leq \alpha \leq 1$), and β represents the ratio of the leading vehicle travel time and average travel time of the entire platoon ($0 \leq \beta \leq 1$) (*15, 30*). In this study, α and β are not estimated separately but together as a product of αβ. The PDF, α is then calculated for the value of β as 0.8, as stated in Manar and Baass (1996) *(36)*.

The PDF in the study is estimated following the method developed by Day & Bullock (2012). Following the method, this study measures the platoon in all the internal links of the five signalized intersections of the case study from 07:00 AM to 09:00 AM. Only through movements in the East-West directions (the main street thru movements) are considered in the study to measure and model the platoon and to estimate the PDF. First, the vehicle counts is divided uniformly among the time steps within the cycle. This uniform departure profile is then varied on different values α and β as shown in Equations 7 and 8 to get a similar pattern to the platoon arrivals in the field. The best-modeled platoon is identified based on the goodness of fit using a non-parametric Kolmogorov–Smirnov (K-S) test. The details of the K-S test can be found in *(37)*. In this method, the cumulative frequency distributions of the measured and modeled platoons are estimated and used to calculate the D-statistics, a measure of the maximum vertical distance between the measured and modeled cumulative frequency diagrams. This value is then compared with the Smirnov's statistical table's critical D-value to calculate the 90% confidence interval *(37)*. After identifying the best fit modeled platoon, the best fit Robertson parameters are estimated by running through all the possible values of T and αβ using an exhaustive search with a granularity of 1 second for T and 0.01 for αβ.

5.3.4 Saturation Flow Rate

The field measured saturation flow rate is another factor calibrated in the model. It is measured using HRC data for through movements. The study utilizes the Highway Capacity Manual *(38)* stated method to measure the saturation headway in the field. The saturation headway is measured as the time difference between successive vehicles crossing the stop line at the intersection after the beginning of the green period. As stated in HCM, saturation headway is measured for each vehicle from the fourth vehicle after the start of green time in each cycle. The saturation flow rate is then estimated using Equation (9).

$$s = \frac{3600}{h} \tag{9}$$

Where,

S = saturation flow rate, vehicles per hour of green per lane (veh/hg/ln)

h=saturation headway, seconds/vehicle (s/veh)

Besides the field measured saturation headway, the study also measures the saturation headway for both the calibrated and non-calibrated Vissim models and compare the results with the field measured value.

5.3.5 Microscopic Simulation Model Calibration

The PTV Vissim software is used to develop a microscopic simulation model for the case study segment. The study utilizes the method developed by the authors to calibrate the microscopic simulation model based on data from multiple sources, including HRC data (Tariq et al., 2021). The microscopic driving behavior parameters of the model are calibrated using a multi-objective optimization-based approach based on minimizing the deviation from real-world measurements of three parameters: minimization of the differences in travel time, spilt utilization ratio, and throughput between the simulation model and real-world data. The optimization allows the selection of the values of driver behavior parameters in Vissim, including the Average Stand Still Distance, additive part of safety distance, Multiplicative Part of Safety Distance, Maximum Deceleration-Own, Maximum Deceleration-Trail, Waiting Time before Diffusion, Minimum Headway, and Safety Distance Factor. The above-mentioned study demonstrates that the optimized parameters produce significantly lower errors in the split utilization ratio, green utilization ratio, arrival on green, and travel time compared to a simulation model that uses the simulation model's default parameters and when optimizing the parameters based on travel time difference only. The details of the methodology are described elsewhere (Tariq et al., 2021). The optimum parameters obtained for the case study model are shown in

Table 21.

TABLE 21: VISSIM CALIBRATION PARAMETERS FOR STUDY AREA

Average Stand Still Distance (ft)	Additive part of safety distance (ft)	Multiplicative part of safety distance (ft)	Maximum deceleration - Own (ft/s2)	Maximum deceleration - Trail (ft/s2)	Waiting time before diffusion (s)	Minimum Headway (ft)	Safety Distance Factor
5.963	2.1904	2.828	-14.7358	-11.54	64.85	1.9154	0.738

5.3.6 Traffic Signal Plan Development

The traffic signal plan is developed utilizing a multi-objective optimization technique. The objective functions used in the optimization include the maximization of intersection throughput and the minimization of the control delay of all the intersections movements in the study network. The objective functions and subjected constraints used in the optimization are the following.

$$\text{Minimize } f_1(d) = \left(\sum_1^i \sum_1^m (d * V)_{i,m}\right) / \sum_1^i \sum_1^m V_{i,m} \tag{10}$$

$$\text{Maximize } \mathrm{f}_2(\mathrm{N}) = \sum_1^i \sum_1^m N_{i,m} \tag{11}$$

Where,

$d_{i,m}$= Average delay for movement m, at intersection i

$V_{i,m}$= Number of vehicles for movement m, at intersection i

$N_{i,m}$= Total throughput for movement m, at intersection i

Decision Variables: $S_{i,k}$= green split for phase k, at intersection i

The objective functions are subjected to the following constraints.

$$\mathrm{C_i} = \mathrm{Cexist_i} \quad \forall \mathrm{i} \in \mathrm{I} \tag{12}$$

$$\mathrm{gmin_{i,k}} < \mathrm{g_{i,k}} < \mathrm{gmax_{i,k}} \qquad \forall \mathrm{i} \in \mathrm{I}, \forall \mathrm{k} \in \mathrm{K_i} \tag{13}$$

Where,

$\mathrm{C_i}$=cycle length of intersection i

$\mathrm{Cexist_i}$= existing cycle length at the intersection i

I= set of all intersections of the alternative route

$\mathrm{g_{i,k}}$= green duration for phase k, at the intersection i (Decision Variable)

$\mathrm{gmin_{i,k}}$= minimum green time associated with phase k, at the intersection i

$\mathrm{gmax_{i,k}}$= maximum green time associated with phase k, at the intersection i

K= set of all phases available at the intersection i

The objective functions and the constraints are used to estimate the optimum phase split for all movements in all the intersections. In the optimization, the existing cycle lengths are kept the same. Both the macroscopic and microscopic simulation models are utilized to estimate the values of the objective function while the optimization problem is solved using a Genetic Algorithm (GA) and one of its variations, NSGA-II, respectively.

The GA is selected in the study because it was found successful in optimizing the signal timing plan. The theoretical foundation of GA is originally developed by Holland (1975). It is a heuristic optimization technique that imitates the biological processes of reproduction and natural selection to solve for the 'fittest' solutions *(39)*. Unlike GA, the NSGA-II belongs to a set of multi-objective algorithms that strive to find the Pareto front of compromised solutions of all objectives rather than integrating all objectives together *(39)*. NSGA-II was found to be able to maintain a better spread of solutions and converge better in the obtained non-dominated front *(39)*. As with GA, the algorithm performs crossover and mutation. However, a selection operator is used to create a mating pool by combining the parent and offspring populations and selecting the best individuals following the process of the non-dominated sorting and crowding distance sorting *(39)*.

In TRANSYT-7F, both the objective functions are optimized together using the GA embedded in the software. Unlike T7F, the Vissim based microscopic model does not have an inbuilt optimization method. Hence, the NSGA-II algorithm is developed using the Python programming language and access in the simulation through the Component Object Model (COM) interface available in Vissim.

The GA optimization is run for 20 generations consisting of 10 individuals in each optimization generation through the COM. The crossover rate and mutation rate are used 0.5 and 0.1, respectively.

5.4 RESULTS AND DISCUSSIONS

5.4.1 Macroscopic Model Calibration Results

As stated earlier, this study applied the method developed by Day & Bullock (2012) for calibrating PDF of T7F model using HRC data. The measured and modeled platoon of one of the internal links in major movement direction is shown in Figure 10. The best-modeled platoon was estimated using the K-S test for a 90% confidence interval. The critical D-value required for the K-S test was estimated from the measured and modeled platoon's cumulative frequency curves shown in Figure 11. The highest difference between the cumulative frequency is 0.136 and obtained for the 15th Bin, which is termed as the critical D-value. The K-S test parameters and Robertson's parameters of the modeled platoon are shown in Table 22. The confidence interval of the fitness of the measured platoon is 91%, as observed from the table. The PDF, α for the movement, was estimated as 0.10 considering the travel time factor β as 0.8.

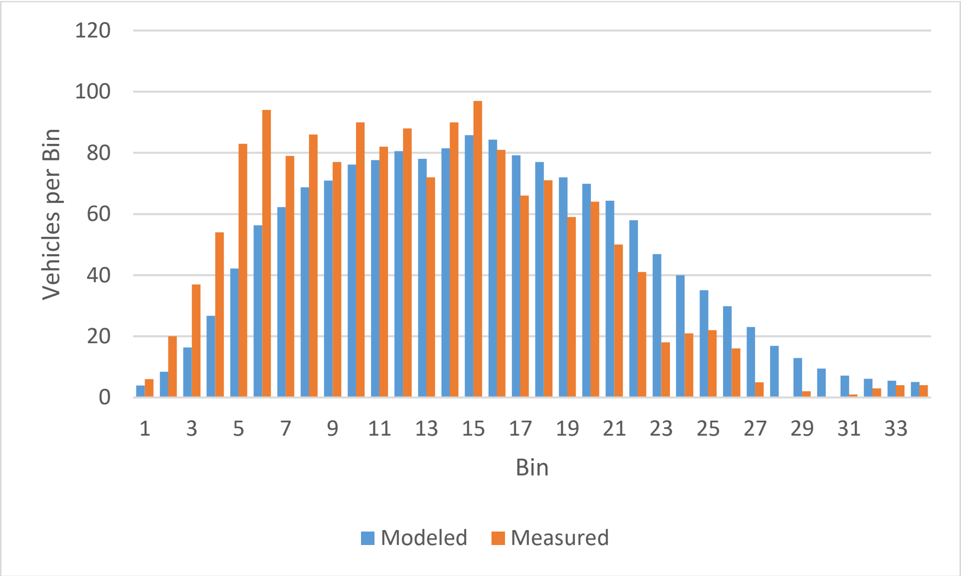


FIGURE 10: MEASURED AND MODELED PLATOON IN THE EAST BOUND DIRECTION OF NW 119TH ST – NW 17TH AVE INTERSECTION

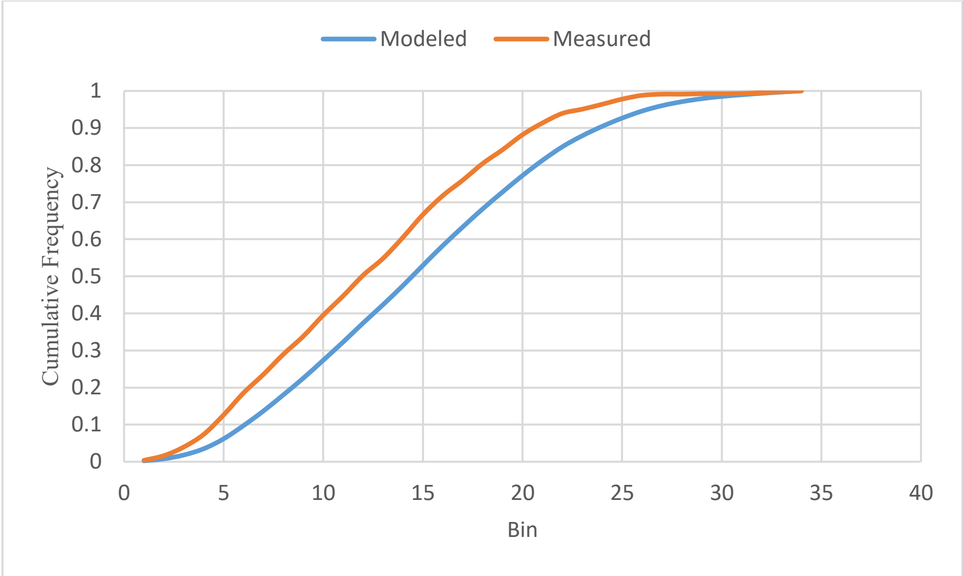


FIGURE 11: CUMULATIVE FREQUENCY OF MEASURED AND MODELED PLATOON FOR EB DIRECTION OF NW 119TH ST – NW 17TH AVE INTERSECTION

TABLE 22: K-S TEST AND ROBERTSON PARAMETERS FOR EB DIRECTION OF NW 119TH ST – NW 17TH AVE INTERSECTION

K-S test parameters		Robertson Modeled Platoon Parameters	
D	0.136	**F**	0.26
Z	0.561	**T**	43
L(z)	0.087577	**αβ**	0.08
P	0.912	**α**	0.10

The product of **αβ** and PDF, **α** for all other movements are shown in Table 23. It was found that the PDF for each movement at each intersection is different from others as well as different from the default value of 0.35. The table also shows that the PDF obtained from the field is different than the recommended value in the TRANSYT-7F manual.

TABLE 23: PDF FOR ALL THE INTERNAL LINKS IN THE MAJOR MOVEMENT DIRECTIONS

Intersection's Name	Movement	αβ	β	PDF, α
NW 119th St - NW 22nd Ave	WB	0.16	0.8	0.20
NW 119th St - NW 17th Ave	EB	0.08	0.8	0.10
	WB	0.069	0.8	0.09
NW 119th St - NW 12th Ave	EB	0.09	0.8	0.11
	WB	0.09	0.8	0.11

Intersection's Name	Movement	αβ	β	PDF, α
NW 119th St - NW 10th Ave	EB	0.14	0.8	0.18
	WB	0.31	0.8	0.39
NW 119th St - NW 7th Ave	EB	0.28	0.8	0.35

*EB= East Bound
*WB= West Bound

5.4.2 Saturation Flow

The distribution of saturation headways for the through movements measured in the field and in the Vissim models (with and without calibration using HRC data) are shown in Figure 12 to Figure 14, respectively. The headways were highly variables within a range of 1.0 seconds to 3.0 seconds for all three cases. However, the median value of the headway for the real-world and HRC calibrated Vissim model was found 2.1 seconds while it was found 2.0 seconds for the Vissim model calibrated without HRC data. This study considered the median value of 2.1 seconds as the saturation headway and used it to calibrate the TRANSYT-7F model.

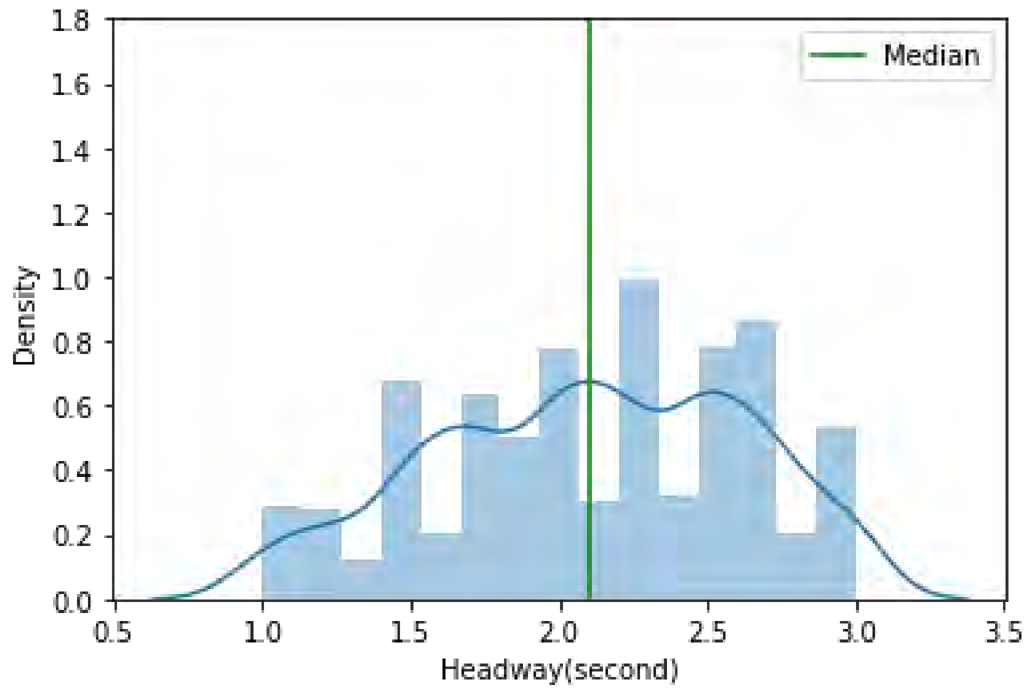


FIGURE 12: SATURATION HEADWAY DISTRIBUTION IN THE REAL-WORLD

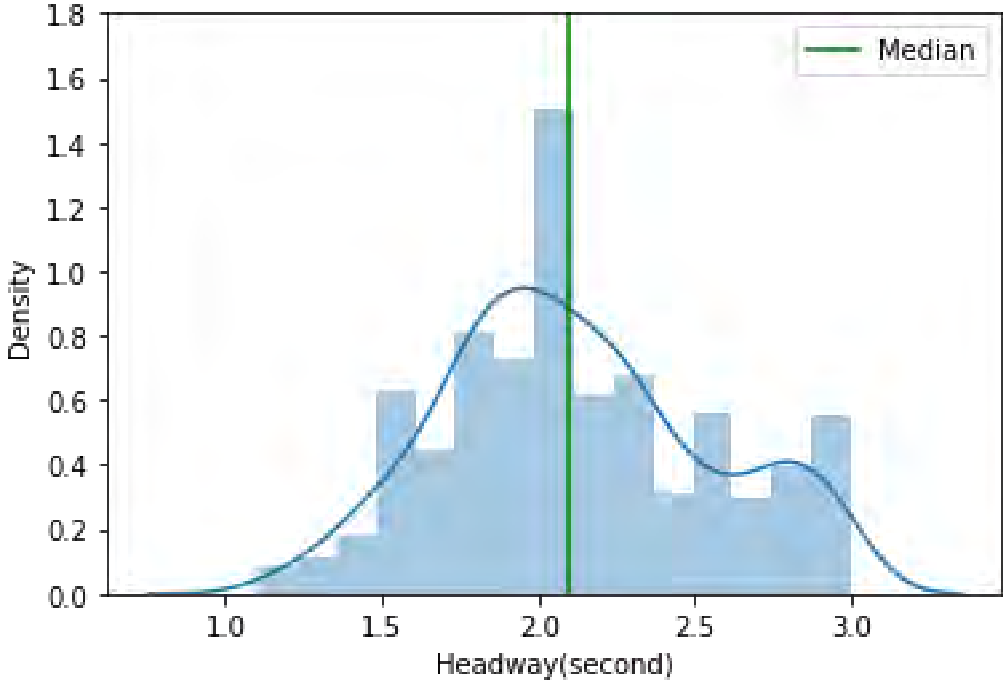


FIGURE 13: SATURATION HEADWAY DISTRIBUTION MEASURED IN VISSIM MODEL CALIBRATED WITH HRC DATA

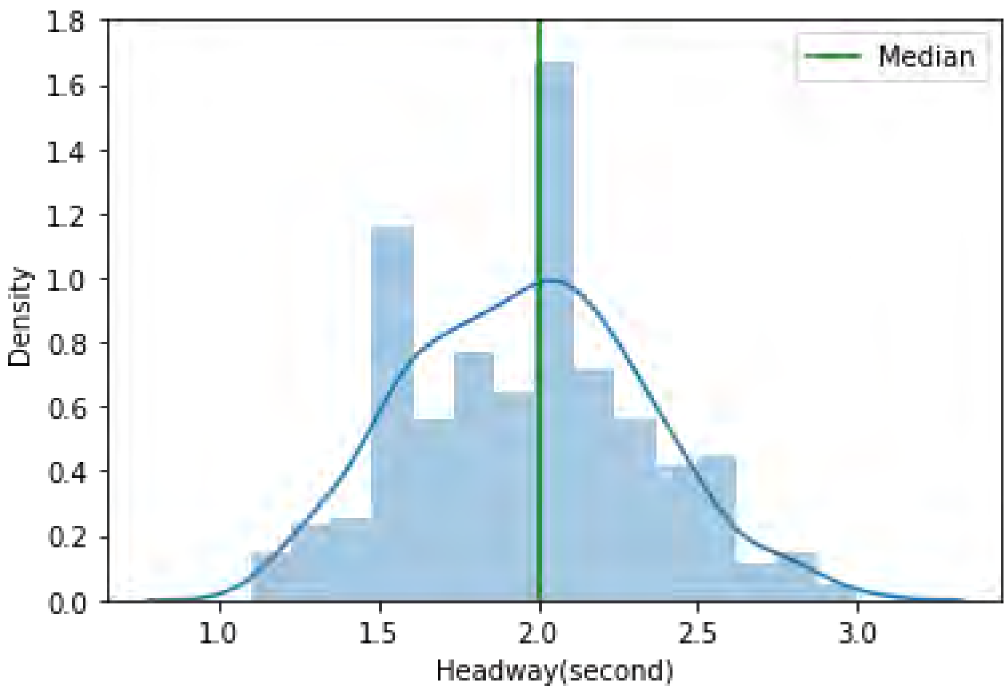


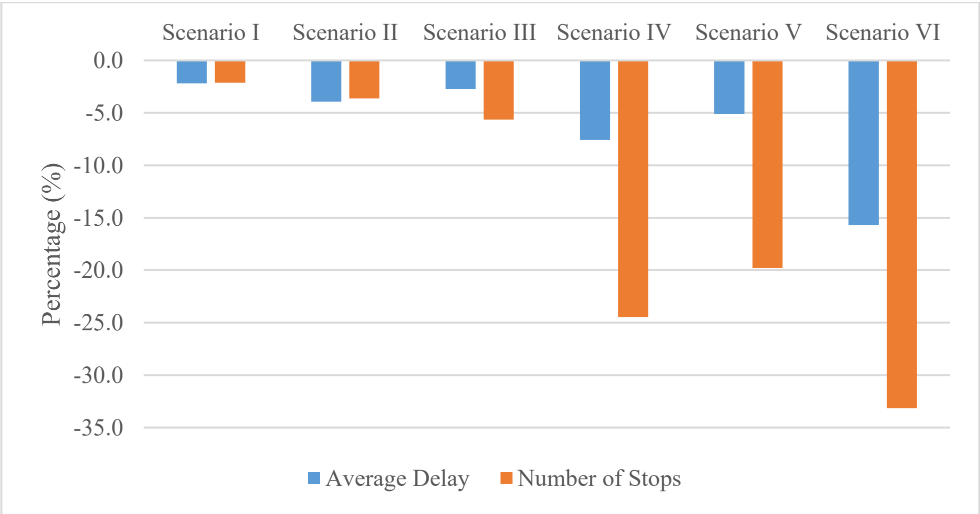
FIGURE 14: SATURATION HEADWAY DISTRIBUTION MEASURED IN VISSIM MODEL WITHOUT CALIBRATION USING HRC DATA

5.4.3 Evaluation of the Plans

The signal control plans developed for all six scenarios were evaluated using the base model. The detailed calibration parameters used in the study are shown previously in Table 20. The overall network performance as well as major movement performance were evaluated after deploying the newly developed plans in the base model.

5.4.4 Network Performances

The reduction in average delay per vehicle and the total number of stops in the network due to the implementation of new signal plans compared to a base Vissim model with existing timing plans for all scenarios is shown in Figure 15. All the new plans developed through optimization for the scenarios improve the overall network performance compared to the base model plan, as observed from the figure. Although the network performance improved for all scenarios, the variations in the results among the different scenarios are quite significant. The calibrated network (Scenarios II, III, IV, and VI) seems to produce a better plan than its non-calibrated counterpart (Scenarios I and V) based on both delay and the total number of stops measurement. The lowest improvements of the network were observed for the non-calibrated macroscopic model (Scenario I). The most significant improvements were observed with the microscopic model calibrated with HRC data (Scenario VI). The signal plans developed using the Vissim model calibrated with HRC data reduced the average delay by as high as 15% and reduced the total number of stops by as high as 33% compared to the base model. These values for the calibrated TRANSYT-7F model are 8% and 24%, respectively. The calibration of either saturation flow rate or the PDF of TRANSYT-7F by themselves (Scenarios II and III) resulted in improvements that are significantly lower than the calibration of both parameters together. The comparison between macroscopic and microscopic modeling shows that the microscopic model is capable of producing better signal control plans than the macroscopic model, although the calibrated macroscopic model produced good improvement in the performance. However, a comparison between Scenarios IV and V shows that the macroscopic model can produce better signal control plans than the uncalibrated microscopic model in terms of both delay and number of stops reduction if appropriately calibrated.

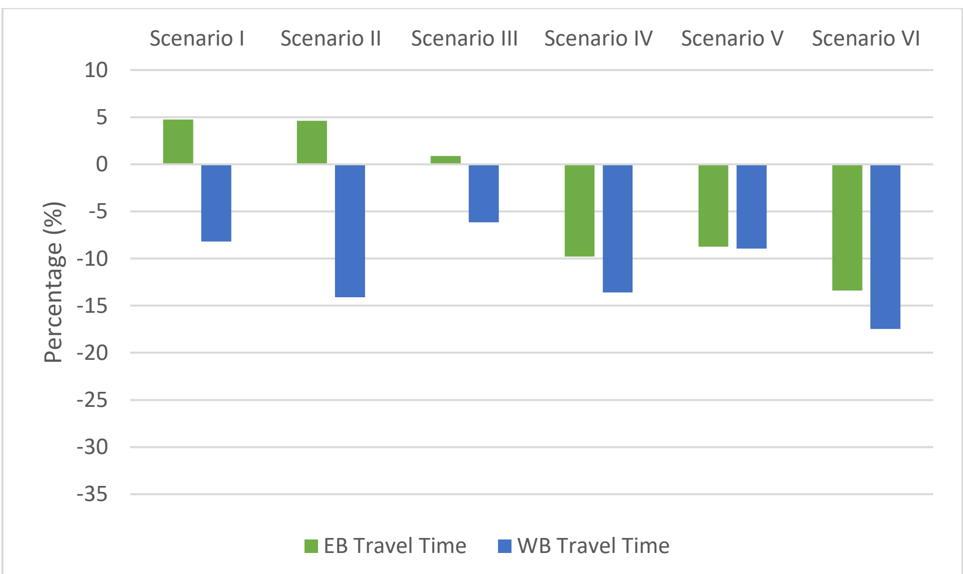


Note: N.B. (- ve) sign represents a reduction

FIGURE 15: OVERALL PERFORMANCE OF THE OPTIMIZED PLANS AGAINST THE BASE MODEL

5.4.5 Major Movements performance

The performances of the network's major movements for the new plans were also evaluated for all the scenarios and are shown in Figure 16. The figure depicts that for Scenarios IV, V, and VI, the travel times for both the major movements (both directions on the main street) were reduced compared to the base model, while for the other three scenarios, the travel time of the westbound (WB) movement reduced but that for the eastbound (EB) movement increased. The models calibrated with HRC data produced better traffic control plans for the major movements. The comparison among the scenarios (Scenarios I-IV) related to the macroscopic model shows that the plans developed when both parameters are calibrated reduced travel time for both movements. In contrast, calibrating one parameter or no parameters reduced the travel time for one movement but increased it for the other movement. Overall, the plan developed using the calibrated Vissim model (Scenario VI) reduced travel time as high as 13% and 17% for EB and WB, respectively. The values are 10% and 14% for the calibrated TRANSYT-7F model (Scenario IV). The Vissim model without calibration with HRC data (Scenario V) reduced travel time for both movements; however, the reduction is lower than the calibrated TRANSYT-7F model (Scenario IV).



Note: N.B. (- ve) sign represents a reduction, EB= eastbound, WB= westbound

FIGURE 16: TRAVEL TIME REDUCTION IN THE MAJOR MOVEMENTS FOR ALL SCENARIOS

5.5 CONCLUSIONS

This study demonstrated the benefits of the use of HRC data in the calibration of signal timing optimization tools over traditional calibration using turning movement counts only. A macroscopic signal optimization tool was used to simulate the scenarios and generate an optimized signal plan. Two parameters, the PDF and saturation headway, were calibrated for traffic signal plan optimization. NSGA-II, a multi-objective optimization method based on Vissim simulation, was utilized to generate signal plans for both scenarios (e.g., calibration with HRC and calibration using turning movement count only). All the plans were evaluated using the Vissim simulation model calibrated using HRC data.

The evaluation of signal timing plans showed an overall improvement of the network compared to the existing traffic signal plan. The plans generated by the calibrated models reduce more delays per vehicle and the total number of stops compared to their traditionally calibrated counterparts. Similarly, the travel time reduction on the major movements was also significantly higher for the plans generated for HRC calibrated models than the plans generated by traditionally calibrated models. Moreover, the properly calibrated macroscopic model developed a better plan than the uncalibrated microscopic model for both network and major movement performance.

The study provides a different perspective on the use of HRC data and highlights the usefulness of the HRC data in signal timing optimization. The agency can use this method to update the current signal control plan or develop new plans. Considering the benefits of this new technology, the agency can plan its investment policy in HRC technology.

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CHAPTER 6: COMBINING MACHINE LEARNING AND FUZZY RULE-BASED SYSTEM IN AUTOMATING SIGNAL TIMING EXPERT'S DECISIONS DURING NON-RECURRENT CONGESTION

6.1 INTRODUCTION

Improving arterial network performance has become a major challenge that is significantly influenced by signal timing control. In recent years, agencies have started focusing on arterial systems by supporting Active Arterial Management (AAM) strategies *(1)*. The activation of special traffic signal plans during non-recurrent events is an important component of AAM and can provide significant benefits in terms of performance metrics of the transportation systems. Most existing signal controllers in use today are still pre-timed operating either as fixed-time or traffic-actuated. With these systems, transportation agencies operate the signal control systems based on time of day (TOD). The TOD plans are prepared using historical traffic flow data collected for different times of the day and fine-tuned based on field observations. Such plans lack the consideration of non-recurrent congestion due to incidents and other lane blockage events and surges in demands due to special events. In some cases, agencies have deployed adaptive signal control technology. However, such implementations are still limited, and the adaptive signal control may not be as effective under all congested conditions, particularly under congested conditions with long queues.

With non-recurrent events that cause a reduction in capacity or increase in demand, congestion can occur and extend to upstream intersections from the bottleneck location. In these conditions, the vehicle queues continue to grow from cycle to cycle, either due to insufficient green times that cannot meet the demands or because of blockages that prevent traffic from efficiently using the assigned green times. Spillbacks to upstream intersection results in parts of the green times intervals at the upstream intersection being constrained by the downstream queue, as vehicles leaving the upstream intersection start joining the downstream. During the red interval(s) of the upstream feeding links to the downstream link, the queue starts decreasing due to the reduction in the arrivals at the back of the queue, creating some queuing capacity accommodating the flows from the upstream links in the next green phase. During the first parts of the upstream link green phases, referred to as the "unconstrained green", the vehicles will be able to leave the stop lines of the feeding links at the saturation flow rates of these links until the queue due to the downstream incident spillbacks to the upstream signal again. The rest of the green time is referred to as the 'constrained green'. As a result of this constraint, the queues can interrupt the flows on the arterial network and can also spillback to freeway ramps, consequently creating congestion on freeway facilities. Thus, it is critical to actively change the signal timings to address the lane blockages and the surges in demands on arterial networks.

Some agencies have hired traffic signal engineers/expert operators to actively manage the traffic signal controls during non-recurrent events such as incidents, surges in demands, work zones, and signal malfunctions. These agencies have started implementing processes to change signal timing in real-time based on traffic signal engineer/expert operator's observations of incident and traffic conditions at the intersections upstream and downstream of the congested locations including observing the queue formation based on videos received from closed-circuit television (CCTV) cameras and travel time maps produced using public agency data or third-party providers. The decisions to change the signal timing are based on observations such as the conditions of the main and side streets, comparison the queue spillback situation with historical queues, and the effects of queues on the upstream intersections.

In order to maintain coordination, in many cases, these expert operators keep the same cycle length between intersections, while changing the green to cycle ratio (g/C) in the congested direction at the downstream of the incident location by taking green times from other intersection movements without violating the minimum vehicular and pedestrian greens. If the incident is very severe and the congestion cannot be mitigated with increasing the green times within the same cycle, the traffic signal engineer may decide to change the cycle length and put the intersection out of coordination. This process of changing signal timing by human is time-consuming and expensive requiring processes to capture and identify the event and incident characteristics, downloading the existing timing, observing the traffic network conditions, designing new timing plans, and implementing the new plans. In addition, the expert signal engineers/expert operators may change jobs causing an important loss in the acquired knowledge and experience. The experts also do not provide the service 24 hours a day/ 7 days a week at the traffic management centers (TMC). Thus, there is a need to automate the decisions to change signal timing plans.

This part of the project investigates automating the process of updating the signal timing plans during non-recurrent conditions by capturing the history of the responses of the traffic signal engineers to non-recurrent conditions and utilizing this experience to train a machine learning model. This study intends to automate expert's decisions using machine learning techniques, facilitating a proactive, consistent, and easily implementable approach to addressing traffic congestion during non-recurrent events. A combination of Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) is utilized in this study to deal with the vagueness and uncertainty of human decisions. The method results in rule based-decision system to identify needed changes to the signal control during incidents based on the past cases of the expert's decisions to change signal timing. This utilization is designed to capture the cognitive uncertainties associated with human thinking and perception, as related to an expert implementing signal timing changes in non-recurrent conditions. The benefits of the implementation of the method developed in this study are assessed using simulation analysis for three case study scenarios.

6.2 LITERATURE REVIEW

One of effective strategies of non-recurrent events is to give priority to specific movements that are impacted by the events in order to minimize the delays to these movements and the overall delay in the network. The Federal Highway Administration (FHWA) identified anticipating and responding to planned and unplanned events as an important issue and emphasizes the need for automating the selection of pre-planned signal timing plans for managing the special events by identifying incident lane closures and increased volume thresholds *(2)*. State and local transportation agencies have reached the same conclusion. For example, the Florida Department

of Transportation (FDOT) District 5 documented in the District's ITS master plan that during non-recurrent traffic conditions, there is a need to identify incident details through CCTV cameras, emergency responder agency contacts, and other sources to allow traffic signal engineer to determine if the conditions warrant an alternate signal timing plan based on the severity of incidents and the percentage of lanes blocked *(3)*. The FDOT District 4 Arterial Management Program (AMP) uses operators to change the signal timing plans during non-recurrent events in both Broward and Palm Beach Counties. The estimated Benefit-Cost (B/C) ratios of the program for Palm Beach County and Broward county were 7.76 and 5.03, respectively in 2016. *(4-6)*
An important application of special signal timing plan implementation that have been addressed in the literature is the sudden increase in demand due to freeway incidents that causes traffic diversion to alternative routes. Such application is considered a critical component of integrated corridor management (ICM). The benefit assessment of the Maryland CHART program reported in 2011 that the application of diversion special signal timing plans to accommodate diversion on to parallel arterials during freeway incidents resulted in a total delay time reduction by of 33.56 million vehicle-hours, as well as a total fuel consumption reduction of 6.49 million gallons *(7)*.
As part of the Dallas US-75 ICM corridor, incident signal timing plans were developed to flush the diverted vehicles to arterials during freeway incidents *(8)*. A clustering analysis was first conducted to classify incidents into different groups based on different traffic and incident attributes *(8)*. And then probable diversion was estimated using a simulation-based dynamic traffic assignment model Signal timing plans were developed for those identified clusters and prioritized based on their impacts on freeway and the surrounding roadway network delays. A database was created that includes criteria-based expert rules for response plan recommendations *(8)*.

Most of the signalized intersections within the San Diego I-15 ICM network are operated utilizing actuated signal control *(9)*. During a congested event, some intersections along the alternative routes switch to an alternative signal plan to provide additional green time to accommodate the increased traffic. The decision to activate the plans is supported by real-time simulation model. Changing signal timing plan during freeway and arterial major incidents was also proposed in the concept of operation of the I-210 ICM project *(10)*. Signal timing changes were modeled in two of the four evaluation scenarios *(11)*. In those two scenarios, signal timing plans along the arterial were modified to increase the capacity of the main approaches by increasing the cycle length and the relative green time for the main direction while the green time for the side streets was kept constant. Saha et al. *(12)* developed methods for the selection of special signal timing plans to accommodate traffic diversion during freeway incidents to arterial streets.

Several research and development efforts addressed selecting traffic signal control during oversaturated conditions. Liberman et al. *(13)* proposed a real-time traffic control policy to select signal timing based on estimated queue lengths. The goal was to control and stabilize queue lengths and to provide equitable service to competing traffic streams by metering traffic at intersections servicing oversaturated approaches, while fully utilizing storage capacity, preventing queue spill-back, and maximizing throughput by controlling the interaction between incoming platoons and standing queues. *(13)*.

A good example of adaptive signal control that explicitly considers oversaturated condition is the "gating" strategy implemented in the Split, Cycle, and Offset Optimization Technique (SCOOT) system. Gating provides a feature to terminate upstream movement phases to reduce the upstream traffic flow to high congestion intersections, thus preventing spill backs *(14)*. Another strategy that has been proposed to control queues at the congested intersections is to provide a 'reverse offset' instead of a forward offset between intersections. The reverse offset reference determining signal timings at an upstream intersection based on the start of green of the downstream considering the time required for the recovery shockwave to move to the upstream intersection, reducing the decrease in capacity at the upstream intersection due to spillback. *(15)*

Research have been done on incorporating knowledge-based artificial intelligent layer in support of traffic management *(16) (17) (18) (19)*. Some of these studies proposed the use of fuzzy decision support systems for providing traffic control under different traffic situations *(19) (20*). For example, a knowledge-based decision support system was developed to identify critical traffic states, propose possible changes in the current signal timing plan, and then decide which action to be taken *(19)*. Other systems are considered to be expert systems representing traffic engineer's knowledge *(21) (22) (23)*.

6.3 ALGORITHM REVIEW

As stated earlier, a combination of Decision Tree and Fuzzy Rule-Based System are used in this study to automate the decisions made by TMC signal engineers/ expert operators when they observe and identify non-recurrent congestion. Decision Tree (DT) is one of the most popular and effective supervised machine learning techniques for prediction and classification problems. To find solutions, a decision tree makes estimation of the outcome variable based on a training data set. DT can work with high dimensional data, can be developed in an efficient manner, and produce results that are easy to present and understood by human *(24)*. DT can produce sets of decision rules by converting the resulting tree structure to 'if' and 'then' rules. If the condition of the first rule is true, then it uses the prediction of the first rule. If not, then it goes to the next rule and checks if it applies and so on.

There are many algorithms available for the development of the decision trees; with the most widely used being Iterative Dichotomizer 3 (ID3), C4.5 which is a successor of ID3, Classification and Regression Trees (CART), and Chi-square Automatic Interaction Detector (CHAID) *(25)*. In general, the DT algorithms search for the dominant attribute from all attributes. Then, this most dominant attribute is put on the top of the tree as the top-level decision node. This search is repeated for the other attributes at the next levels of the Decision Tree. In the tree development process, the algorithms assess a measure of the effectiveness of partitioning the Decision Tree. There are three popular impurity quantification methods that can be used as alternative measures of effectiveness: Entropy or information gain, Gini Index, and Classification Error *(26)*.

Often, in the case of human decision rule definitions, as in this study, the rules cannot be delimited by sharp boundaries and also is associated with one-to-many relations or ambiguousness. The Fuzzy Rule-Based System (FRBS) extends the problem of classification and prediction to consider the vagueness and uncertainty in data more efficiently based on the fuzzy logic and fuzzy sets theory *(27) (28)*. There is another advantage of FRBS in that an expert can augment the rules in the system. In this study, all the rules are extracted from the Decision Tree and there are no additional rules that have been added to the system. However, agencies may decide to augment the derived rules with additional rules as they apply the method in the real-world.

Many researchers have used binary decision trees to extract the linguistic rules for developing FRBS models and creating a discrete set of fuzzy classes or class membership functions *(29) (30)*. The overlap percentages of the fuzzy classes can be chosen empirically considering that decisions made based on the tree are fuzzier and soft when overlap is large *(30) (31)*. The process of representing binary trees as crisp logical rules and transforming these rules into a fuzzy model involves four steps. The first step is to create the Decision Tree by minimizing impurity in the data. Second, membership class/functions are created reflecting the intervals of input and output variables considering the crisp characteristic set generated by the Decision Tree. The third step is to formulate simplified fuzzy rules based on the rules generated by the partitioning of the tree and the characteristic points of the fuzzy sets. The final step is to run the fuzzy interface engine to predict crisp output class from the fuzzy class for any new sample of dataset *(32)*.

Two popular FRBS models are the Mamdani model and the Takagi Sugeno Kang (TSK) model. The Mamdani model is a multiple-input and single-output (MISO) system. This type of model consists of a fuzzy logic-based inference engine and linguistic variables in both the antecedent (input) and consequent (output) parts of the rules *(33) (34)*. The TSK model is similar to the Mamdani model, except that the consequent part in the TSK model are represented by a function of input variables *(35) (36)*. In this paper, the Mamdani-type FRBS model is used due to the ease of interpretability of the model.

6.4 METHODOLOGY

An important component of this research is to capture the decisions of the traffic signal engineers at the TMC in changing signal timing parameters during non-recurrent congestion as part of the Arterial Management Program (AMP) practice by modifying the timing plans to temporarily create capacity during congested periods. In such cases, the signal timing plans are modified in real-time based on traffic signal engineer/expert operator's observations of incidents, prior experience, and the prevailing traffic conditions at upstream and downstream intersections. The goal of this study is to automate the decision-making process of the traffic signal engineer/expert operators to offer a proactive, consistent, and easily implementable solution.

The proposed methodology includes utilizing the Fuzzy Rule-Based decision system that is supported by the Decision Tree machine learning approach to capture and automate the traffic signal engineer's decision. Developed model incorporate complex, but yet reasonable decisions arrived by traffic signal engineers/experts. The steps for constructing the rule-based decision system are shown in Figure 17. As indicated in Figure 17, this construction is composed of the Decision Tree generation and Fuzzy Rule-Based System development.

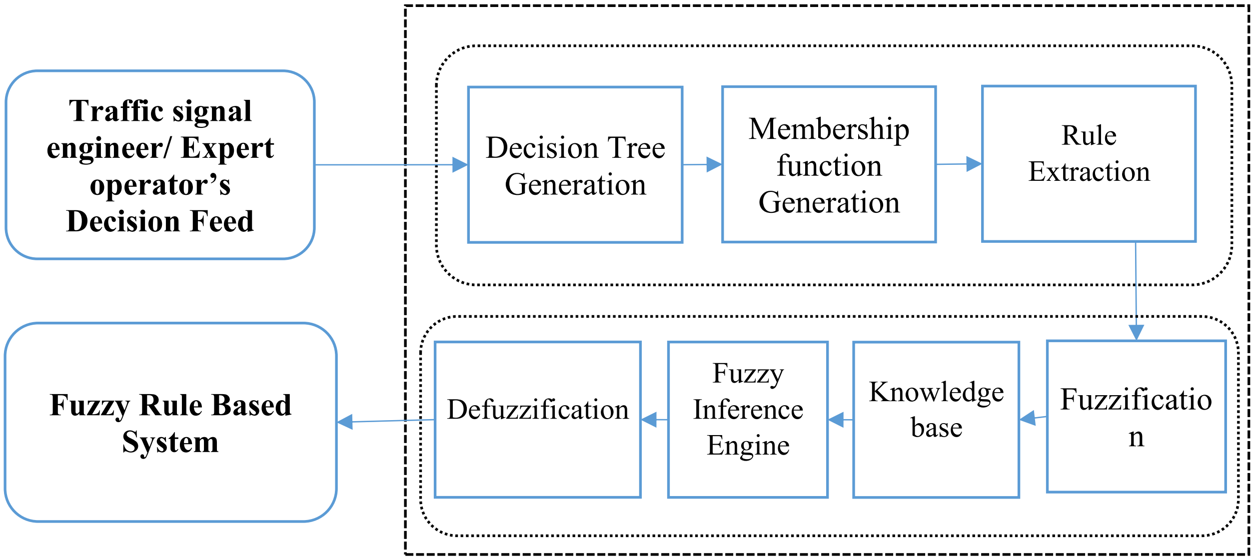


FIGURE 17: PRINCIPAL STEPS OF THE FUZZY RULE-BASED DECISION SYSTEM UTILIZED IN THIS STUDY

The first step of the methodology is the Decision Tree formation, which provides the structure of the partitioning and classification of the data with regard to traffic signal engineer's decisions in changing the timing parameters. The utilized impurity measure for the subset selection of the developed decision tree is the Gini Impurity Index. The Gini Impurity Index measures the probability of an element in the subset to be mislabeled, assuming it is randomly labeled according to the distribution of all the classes in the set. DT also eliminates variables that do not contribute to the prediction of the output from inclusion in the tree utilizing a procedure referred to as feature selection. This is important since having irrelevant features in a dataset can decrease the accuracy of the developed model. The resulting Decision Tree with the remaining features and derived structure is then utilized for the induction of the knowledge base or rule base system by converting the Decision Tree structure into crisp if-then rules. These crisp rules are extracted based on the DT results and capture the traffic signal engineer's decisions. The next step is to fuzzify these crisp rules considering the uncertainties in the assessment of the traffic signal engineers with respect to the input and output parameters.

As mentioned earlier, the Madman model is utilized in this study to develop the FRBS in this paper. The Madman model consists of four major steps: namely fuzzification, knowledge base creation, fuzzy rule inference, and defuzzification. Fuzzification is the process of converting the input variables into fuzzy sets. This step requires the use of membership functions that represent the degree of truth in fuzzy logic and can be developed from the expert's opinion or learned from statistical data. Instead of precise set of bi-valued logic or boundaries, the membership functions or fuzzy sets have indeterminate boundaries. In this study, the membership functions are developed using the expert's database that contain input variables recorded based on real-world events including queue length, upstream intersection importance, demand increment ratio, incident start period, and lane blockage data and the output variable, which is the increment in the g/C ratio as decided by the expert based on the input variables in real-world operations. Also, the linguistic terms of the input variables are converted to fuzzy numbers in this stage. The dataset used for the developed model contains the cases involving green time modifications only. In these cases, the

cycle length and offset were not changed in order to maintain the progression. Thus, this study does not consider the cases when the cycle length was changed.
The knowledge base in the fuzzy logic system is composed of a database and a rule base. The database includes the fuzzy-set membership functions. The rule base represents the reasoning of human experts in a set of if-then rules, which are extracted from the Decision Tree as crisp if-then rule with antecedent and consequent parts. When a rule is formatted as "IF A THEN B" where A and B are fuzzy sets, then A is called the antecedent and B is called the consequent parts of the fuzzy rule.

The fuzzy rule inference engine converts the fuzzy input to fuzzy output using the if-then rules. It establishes the rule strength of the antecedent part according to the combination of the membership functions and fuzzy rules. Then, it determines the consequent rule based on the rule strength and the output membership function. The defuzzification converts the fuzzy output of the inference engine to a crisp output. This process is done by aggregating all the qualified consequents of the rules to get the defuzzified outputs.

The methodology developed in this study is a general process that can be applied by traffic management centers anywhere to recommend changes to the green time splits during non-recurrent events while keeping the cycle length constant. Figure 18 shows a step-by-step description of the process to be used for the application development.

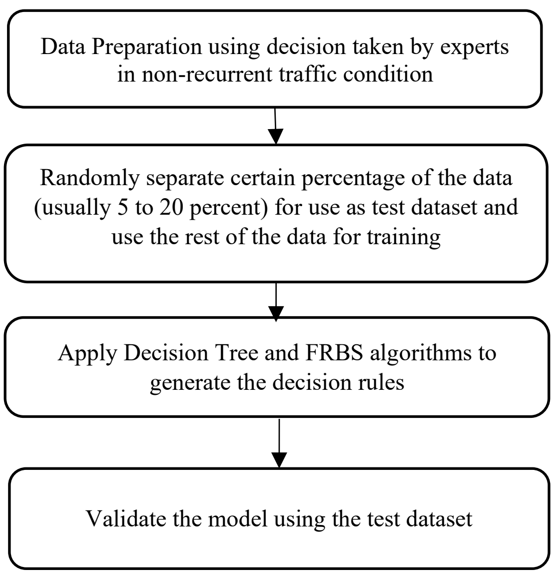


FIGURE 18: STEP BY STEP PROCESS FOR THE APPLICATION DEVELOPMENT

6.5 DATA PREPARATION

In order to capture and automate the decisions to change signal timing in non-recurrent conditions, the collection and preparation of data related to traffic signal engineer/ expert operator's decision is a crucial step. In this step, the decision data set was prepared by first identifying the required data items. This identification was made based on scheduled meetings with the TMC traffic signal engineers to establish the conditions that resulted in decisions to change the green time splits of the signals and the parameters required to identify these conditions. The dataset contains 91 lane blockage incidents and 45 demand surge scenarios when signal engineers modified the green times, and nine demand surcharge and lane blockage scenarios when the green times were not changed. The next step was to collect the required data items. The identified and collected data contains the following parameters: "queue length", "demand increment ratio", "capacity reduction ratio", "and upstream intersection importance", "spillback to the upstream intersection", "congestion or incident start period". Description of each input parameter is stated in Table 24.

TABLE 24: DETAILS OF THE PARAMETERS CONSIDERED IN THE SIGNAL TIMING EXPERT'S DECISION

Parameters	**Description**	**Unit**
Queue length	The queue length is the length of the queue of a congested movements due to non-recurrent congestion.	Feet
Demand increment ratio	The "demand increment ratio" is calculated as the ratio of the increase in the hourly demand compared to the normal day hourly demand.	Unitless
Capacity reduction ratio	The "capacity reduction ratio" is calculated based on the capacity adjustment factors for incident zones suggested in the Second Strategic Highway Research Program, (SHRP 2) L08 project deliverables *(37)*	Unitless
Upstream intersection importance	The is a score of the upstream intersection cross street's importance ratio ranging from 1 to 3, where 3 indicates the highest importance. This score reflects the increased expert operator tendency to change the green times, if the cross-street movements of the upstream intersection of the bottleneck location are major improvements.	Unitless
Spillback to the upstream intersection	The observed spill back to the upstream intersection is utilized as a categorical variable taking the values 'yes' or 'no'.	Unitless
Congestion or incident start period	Congestion or incident start period is categorized variable taking the values 'morning' (between 7:00 am and 10:00 am), 'midday' (between 10:00 am and 4:00 pm) and 'evening' (between 4:00 pm and 7:00 pm).	Unitless

The output or consequent part of the developed model is the percentage increment in the g/C ratio in the congested direction, where g is the effective green time and C is the cycle length. The percentage increment in the g/C ratio is calculated as:

$$\text{Percentage increment of } \frac{\mathrm{g}}{\mathrm{C}} \text{ratio} = \frac{Modified\,\frac{g}{C}\,ratio - Normal\,\frac{g}{C}\,ratio}{Normal\,\frac{g}{C}\,ratio} \text{x } 100 \qquad (14)$$

6.6 DEVELOPMENT OF DECISION TREE

A Decision Tree is developed in this study for feature selection and for extracting the crisp logical rules based on traffic signal engineer's decisions and to feed the resulting crisp rules into the FRBS algorithm, as described in the next section. In this study, the Recursive Partitioning and Regression Trees (RPART) method is implemented to derive the Decision Tree based the traffic signal engineer's data feed. RPART is a function that implements the Classification and Regression Tree (CART) algorithm, which is a popular algorithm for the development of decision trees. It is used to build Decision Tree in a binary form *(38)*. In the implementation of RPART in this study, the 'rpart' and 'rpart.plot' functions in R studio are utilized for the extraction of the logical rules by partitioning the dataset.

When developing a Decision Tree, RPART first selects the variable that best splits the dataset into two groups. The subsets are then again partitioned using the same process. This method is recursive, which means that the process continues to partition the subsets arising from the previous split until there is no more improvement that can be made to the tree *(39)*. The Gini Impurity Index is used for the subset selection when building the Decision Tree *(38)*. The Gini Impurity Index measures the probability of an element in the subset to be mislabeled, assuming it is randomly labeled according to the distribution of all the classes in the set. As such, it estimates the heterogeneity of the classes in a subset created by the split. The Gini Impurity Index is scored between 0 to 1, with 0 being the best and 1 being the worst. If all the elements in a set are in the same class, the Gini Impurity Index is 0. If there are equal number of elements of the two classes in a subset, the Gini Impurity Index is 1/2 *(26)*. The development of the decision tree in this model uses the Gini rule for splitting and two parameters referred to as 'minsplit' and complexity parameter ('cp)' as the control parameter of the nodes. This model minimizes the gini index in a recursive pattern. The 'minsplit' parameter is the minimum number of observations that must exist in a node in order for a split to be attempted. A 'minsplit' of 3 is used in the Decision Tree the model. The complexity parameter 'cp' in 'rpart' function is the minimum improvement in the model needed at each node. It is the amount by which splitting that node improved improves the relative error. For example, if splitting the original root node dropped drops the relative error from 1.0 to 0.5, so the CP cp of the root node is calculated as 0.5. A Ccpomplexity parameter of 0.01 is used in the development of this study developed DT. So this means that, when splitting a node is found to only result in an improvement of 0.01 or less, so the tree building at that node stops there.

The building of the decision tree also eliminates the noncontributing variables to the prediction of the output with the aim of improving the prediction performance of the model. In the development of this study, among the potential six input variables, the Decision Tree selects five contributing features which are "queue length", "demand increment ratio", "capacity reduction ratio", "incident start period" and "upstream intersection importance".

Figure 19 shows the Decision Tree generated in this study. The RPART algorithm first divides the dataset depending on the queue length, then the subset that has queue length lower than 6,057 ft. was further divided into subgroups based on the demand increment ratio and capacity reduction ratio. When the queue length is larger of 6.057 ft, the subsets were divided in terms of upstream intersection cross street importance as well as incident start period, demand increment ratio, and capacity reduction ratio in the next levels. It should be mentioned that the summation of the minimum green times required for pedestrian phases and vehicular movement phase are not violated by the signal timing experts. This and other constraints on the signal timing changes can be added as rules in the fuzzy rule-based system.

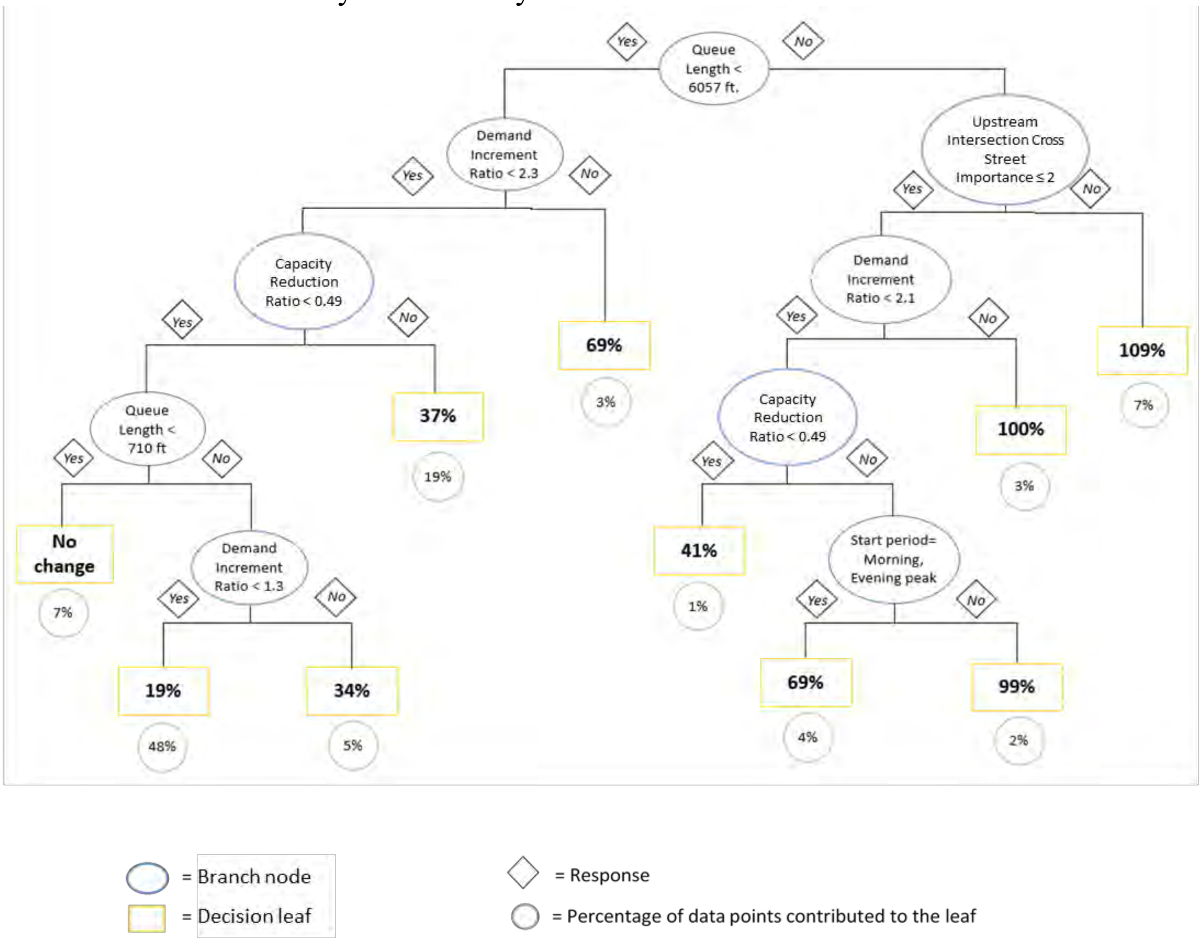


FIGURE 19: DECISION TREE GENERATED BASED ON THE TRAFFIC SIGNAL ENGINEER/EXPERT OPERATOR'S DECISIONS

6.7 DEVELOPMENT OF FUZZY RULE-BASED SYSTEM

A Fuzzy Rule-Based System is developed in this study by using the 'frbs.gen' function in the R studio. The 'frbs.gen' function performs inference based on human knowledge. The purpose of this function is to build a FRBS model manually from user-given inputs or knowledge of human experts without a learning process *(40) (41)*. As stated earlier, developing the knowledge base consists of developing the rule base and data base with the rule base representing the reasoning of human experts in a set of if-then rules. In the Madman model, there are two parts in each rule, the antecedent and the consequent part, which are separated by then ("->"). This study generates the rule base by creating fuzzy if-then rules from the Decision Tree, developed as described in the previous section, instead of creating rules as manual inputs from the experts or users, allowing better estimation. All the rules are initially extracted from the Decision Tree as sets of simplified crisp rules. The extracted crisp rules are shown in Table 25 below.

TABLE 25: EXTRACTED CRISP RULES FROM THE DECISION TREE

Incident Period		Upstream Intersection Cross Street Importance		Queue Length		Demand Increment Ratio		Capacity Reduction Ratio			Increment in g/C Ratio
dont_care	and	dont_care	and	Small	and	Not Large	and	not Two-lane Blockage	and	->	No Change
dont_care	and	dont_care	and	Medium	and	None	and	not Two-lane Blockage	and	->	Small
dont_care	and	dont_care	and	Medium	and	Small	and	not Two-lane Blockage	and	->	Small
dont_care	and	dont_care	and	Medium	and	Medium	and	not Two-lane Blockage	and	->	Medium
dont_care	and	dont_care	and	Medium	and	Not Large	and	Two-lane Blockage	and	->	Medium
dont_care	and	dont_care	and	Medium	and	Large	and	dont_care	and	->	Large
dont_care	and	not Very Important	and	Long	and	Not Large	and	not Two-lane Blockage	and	->	Medium
Morning, Evening Peak	and	not Very Important	and	Long	and	Not Large	and	Two-lane Blockage	and	->	Large
Midday	and	not Very Important	and	Long	and	Not Large	and	Two-lane Blockage	and	->	Very Large
dont_care	and	not Very Important	and	Long	and	Large	and	No Blockage	and	->	Very Large
dont_care	and	Very Important	and	Long	and	dont_care	and	dont_care	and	->	Very Large

Note: This table is formatted according to the FRBS coding requirement of the knowledge base step. The term "not" is used to negate a linguistic term, and "dont_care" is used to ignore some input variables

The membership functions are designed based on the developed Decision Tree to transform the crisp inputs into degrees of membership in the fuzzy functions to represent the linguistic terms of the fuzzy sets. This again allows a more accurate representation of expert's knowledge. The membership functions are created by defining the shapes and parameters of the functions of the input and output variables. Triangles and Trapezoid shapes of the membership functions, which are the most widely used function shapes, were used in this study. The membership parameters and number of linguistic terms/ labels to include were derived based on the partitioning of the developed Decision Tree. For example, RPART partitioned the queue length in the Decision Tree into three labels as: small (less than 710 ft), medium (less than 6,057 ft), and large (more than 6,057 ft). The membership function of the queue length in the fuzzy rule base is labeled in the same manner. The developed membership functions of the input and output variables are shown in Figure 20. In Figure 20, the values on the x-axes represent the values of the input and output variables used in the decision and the y-axes represents the probability of a variable value being a member of each of the fuzzy classes.

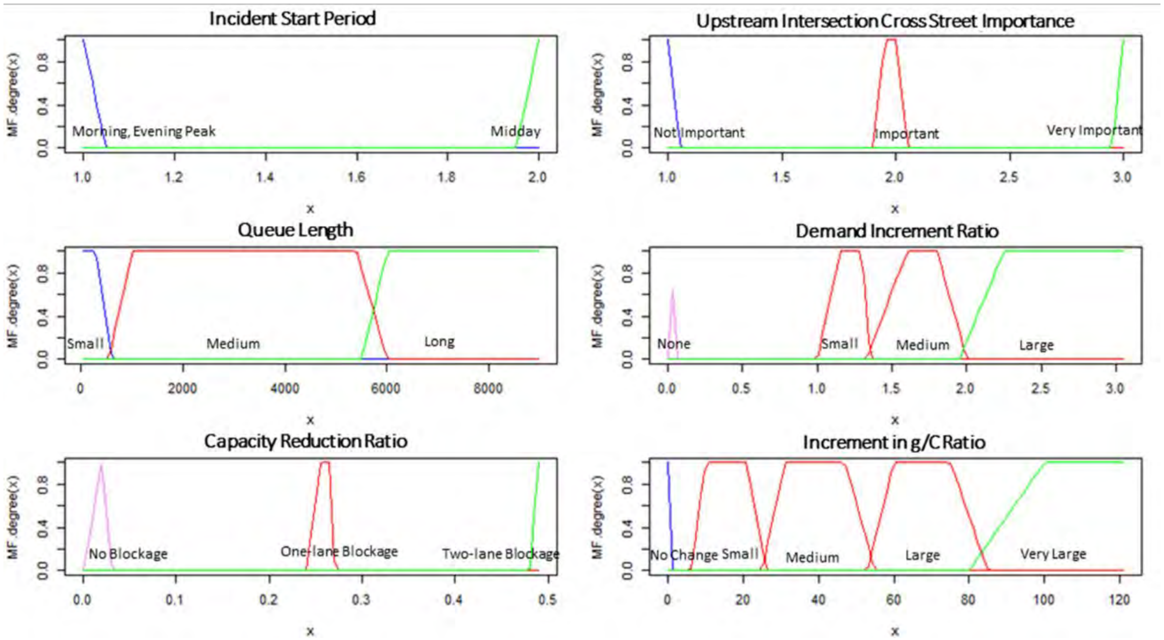


FIGURE 20: MEMBERSHIP FUNCTIONS OF THE DERIVED KNOWLEDGE BASE

In the final step of developing the FRBS system, the 'frbs.gen' inference engine is used in the R programming. For fuzzy inference, the Madman model is used to perform the inference operation using the fuzzy if-then rules. The defuzzification process is done to obtain the crisp values from the fuzzy output set using the weighted average method (WAM) in the defuzzification.

6.8 VALIDATION OF THE MODEL

Model validation is an important part of developing any machine learning model. Validation is performed to test the accuracy of the model. 10 percent of the data points were randomly selected as the test sample that was not included in training the model. The accuracy of the model was calculated using the following formula:

$$\text{Accuracy of the model (\%)} = \frac{\text{Number of Correct Prediction}}{\text{Total Number of Prediction}} \text{ x } 100 \qquad (15)$$

The overall accuracy of the model was found to be 77% with 5% mean absolute error. The Mean absolute error is calculated as the absolute value of the difference between the model output value (g/C ratio increase (%)) and the actual change in g/C (%) as implemented by the expert. Table 26 shows the result of model validation.

TABLE 26: MODEL VALIDATION RESULTS

Predicted Increase in g/C Ratio (Numerical Value)	True Increase in g/C Ratio (Numerical Value)	Predicted Increase in g/C Ratio (Linguistic Term)	True Increase in g/C Ratio (Linguistic Term)	Validation
60%	69.2%	Large	Large	Correct
10%	26.7%	Small	Medium	Incorrect
100%	102.6%	Very Large	Very Large	Correct
31%	34.0%	Medium	Medium	Correct
31%	30.0%	Medium	Medium	Correct
60%	68.0%	Large	Large	Correct
0.1%	0.0%	No Change	No Change	Correct
31%	22.3%	Medium	Small	Incorrect
100%	100.0%	Very Large	Very Large	Correct
10%	11.5%	Small	Small	Correct
10%	26.7%	Small	Medium	Incorrect
31%	28.7%	Medium	Medium	Correct
0.1%	0.0%	No Change	No Change	Correct
Accuracy of the Model				77%
Mean Absolute Error				5%

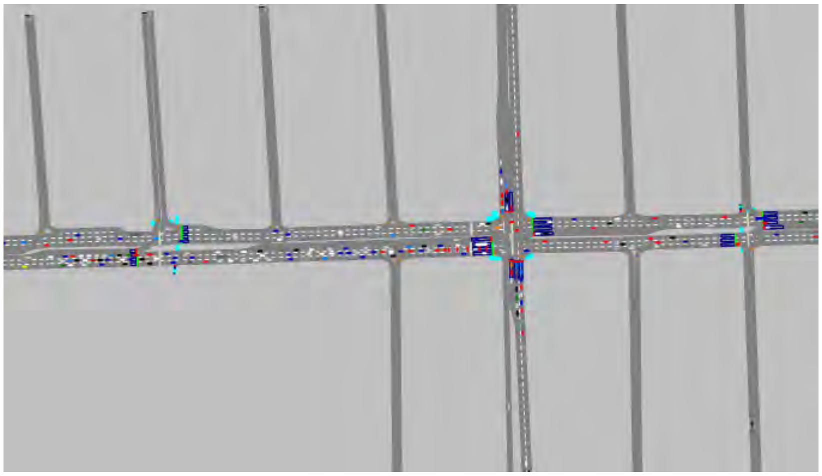
6.9 BENEFIT ASSESSMENT

The benefits of the implementation of the method developed in this study to decide on changing signal timing during non-recurrent congestion were assessed and the results are presented in this section. The assessment involved the estimation of the delay change of the movements impacted by the event and the other movements of the impacted intersection(s). The evaluation of the retiming strategies was done for an arterial network modeled in the PTV's Verkehr In Städten SIMulationsmodell (VISSIM) microscopic simulation tool. The simulation model was used to assess traffic signal operation with and without implementing the timing modifications. The considered timing modifications only involve changing the green time of the movements impacted by the event, and the cycle length and offset were not changed to maintain the progression. Three real-world scenarios were selected from the real-world expert database and simulated in VISSIM. Scenario 1 involves one-lane blocked out of three lanes. Scenario 2 involves two-lane blocked out of three lanes. Scenario 3 is an increase in demand scenario and is modeled by increasing the demand ratio to 1.54.

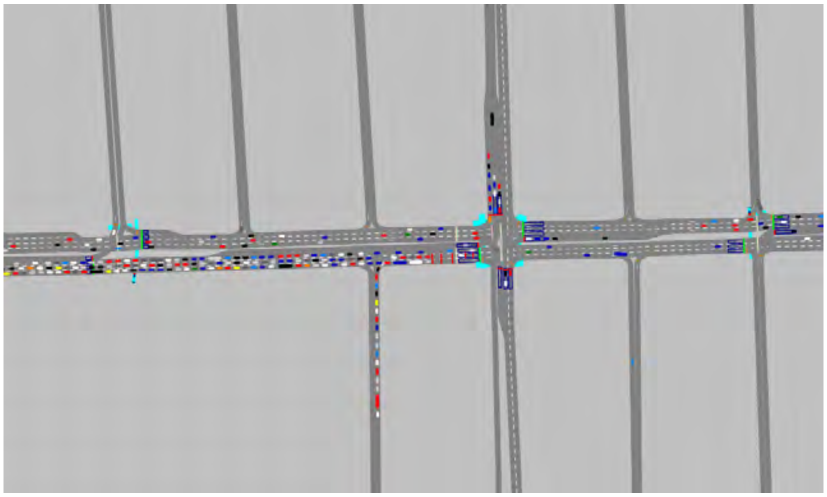
The simulation model was initially calibrated using collected volume, travel time, and queuing data utilizing the calibration procedure recommended in the Traffic Analysis Toolbox Volume 3 developed by the Federal Highway Administration *(42)*. The model was then further calibrated for each of the three scenarios by comparing the model to the data recorded by the signal timing engineer'. The simulated segment with and without incidents were calibrated first to produce the signalized intersection movement capacities per the Highway Capacity manual (HCM) procedures and the capacity adjustment factors for incident zones suggested in the SHRP 2 L08 project *(37)*. The simulated queue length and dynamic animations of the three scenarios were observed to ensure that they reflect the real-world conditions for the three scenarios. The simulation model was run for 10 times with different seed numbers for each simulated condition considering the stochasticity of the simulation model outputs. The simulation was run for an analysis period of 3600 seconds and with a warm-up period of 1800 seconds that was not included in the performance estimation. The delay on all approaches for each scenario were estimated as the average from the ten runs and compared with the results from simulating the base conditions of not changing the signal timing.

6.9.1 Base Scenario Modeling

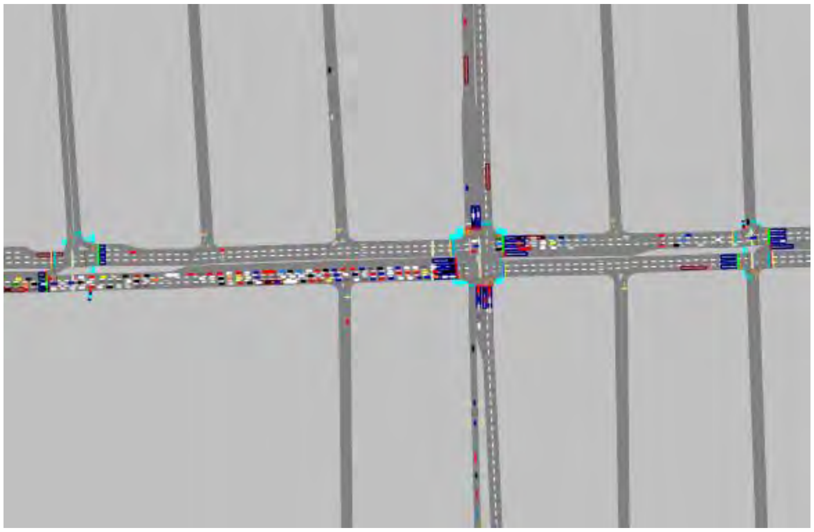
The data associated with the real-world scenarios were obtained from the traffic signal engineer's database and used as inputs to estimate the g/C ratio utilizing the developed FRBS model. When there is one-lane blockage out of three lane roads and the queue length is medium, the model recommended a g/C increment ratio (increase) of 20 percent. For the second scenario with two-lane blocked lanes out of three lanes and a medium queue length, the model prediction is 37 percent increment in the g/C ratio. Scenario 3 involves demand increment from 1,722 veh/hr to 2,655 veh/hr or demand increment ratio of 1.54 and the FRBS model predicted 31 percent increment of the g/C ratio for this scenario. The illustrations of the three scenarios in the VISSIM simulation models are shown in Figure 21.



SCENARIO 1: ONE LANE BLOCKED OUT OF THREE LANES



SCENARIO 2: TWO LANE BLOCKED OUT OF THREE LANE



(C) SCENARIO 3: DEMAND SURCHARGE

FIGURE 21: ILLUSTRATION OF THE VISSIM SIMULATION MODEL (A) SCENARIO 1: ONE LANE BLOCKED OUT OF THREE LANES, (B) SCENARIO 2: TWO LANE BLOCKED OUT OF THREE LANES AND (C) SCENARIO 3: DEMAND SURCHARGE

6.9.2 Signal Re-Timing based on FRBS Prediction

For Scenario 1, the effective green time in the incident direction was increased from 77 sec. to 92 sec. in the simulation according to FRBS output. This was done by taking 14 percent of green time from the left turn and 25 percent from the through movements of the cross-street approaches, while maintaining the same cycle length. The decisions of how to reduce the green times of non-impacted movements by the event was made based on the volume to capacity ratio of each of these movements. In the case of when two-lanes are blocked out of three lanes in scenario 2, the effective green time was increased from 77 sec. to 105 sec. in the incident direction by taking 30% and 43% green time taking from the cross street left turn and through movement respectively. In Scenario 3, the effective green time was increased from 77 sec. to 105 sec., which was done by taking 24 percent of green time from the left turn and 37 percent from the through movements of the cross-street approaches. The signal timing changes are shown in Table 27.

TABLE 27: CHANGES TO SIGNAL TIMING MADE BASED ON FRBS OUTPUT

Scenarios 1 Green Time (Sec)								
Movement	WL	WT	SL	NT	EL	ET	NL	ST
Normal signal timing	28	77	30	45	28	**77**	30	45
Modified signal timing	28	92	26	34	28	**92**	26	34
Scenarios 2 Green Time (Sec)								
Movement	WL	WT	SL	NT	EL	ET	NL	ST
Normal signal timing	28	77	30	45	28	**77**	30	45
Modified signal timing	28	105	21	26	28	**105**	21	26
Scenarios 3 Green Time (Sec)								
Movement	WL	WT	SL	NT	EL	ET	NL	ST

Normal signal timing	28	77	30	45	28	**77**	30	45
Modified signal timing	28	101	23	28	28	**101**	23	28

6.9.3 Delay and Queue Length Estimation

The delay is estimated using simulation and compared for the no signal updates and signal updates for all three evaluation scenarios (one-lane blockage, two-lane blockage, and surge in demand). The delay results based on VISSIM simulation modeling is shown in Table 28. Table 28 shows that when there is one lane blockage in the incident direction, the simulation results show an average reduction in delays of 95.4 sec/veh and 95.2 sec/veh for the effected approach (EB) and the whole intersection respectively. In the case of two-lane blockage incidents, the delay reduction for the impacted direction (the EB) is 110.6 sec/veh and the overall reduction in average delay is 84.3 sec/veh. For the surge in demand in Scenario 3, signal retiming reduces the delay of the affected direction by around 130 sec/veh and the average delay by about 109.6 sec/veh.

TABLE 28: DELAY AND QUEUE LENGTH IMPACT OF UPDATING THE GREEN TIME BASED ON FRBS OUTPUT

Events		Critical Direction (EB)	Opposing Direction (WB)	Cross Street (SB)	Cross Street (NB)	Overall Intersection
One Lane Blockage	Change in Average Delay (s/veh)	-95.4	-3.0	+1.6	+1.6	-23.8
	Change in Queue Length (ft)	-1112	-136	+273	+257	-718
Two Lane Blockage	Change in Average Delay (s/veh)	-110.6	+12.2	+7.6	+6.5	-45.2
	Change in Average Queue Length (ft)	-741	-257	+418	+420	-160
Demand Increment Ratio of 1.54	Change in Average Delay (s/veh)	-130.0	+8.2	+5.9	+6.3	-27.4
	Change in Average Queue Length (ft)	-2075	-234	+426	+414	-1469

Note: '-'sign indicates reduction and '+' sign indicates increment in delay and queue length

6.10 CONCLUSIONS

This study utilized a combination of two artificial intelligence approaches: Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) to recommend modifications to signal timings during non-recurrent events such as incidents, construction, surge in demands, and device malfunctions. The developed methodology learns from the decisions made by signal engineers/expert operators to change signal timings by extending greens during incidents and produce fuzzy rules that can be used to automate the process. Comparing the decisions made based on the resulting fuzzy rules from applying the methodology to previously recorded expert decisions for the project case study indicates accurate recommendations for shifts in the green time (about 77% accuracy or 5.38% mean absolute error). The comparison was done for 10 percent of the data points randomly selected as the test sample that was not included in training the model.

The simulation results indicate that changing the green times based on the output of the fuzzy rules decrease the delays due to lane blockages or demand surge.

The model developed in this study can be used in traffic management centers to support the update of signal timing during non-recurrent conditions on the arterials. In addition, the model can be used when incidents on a freeway cause traffic to divert from the freeway to the parallel arterials resulting in a sudden increase in traffic demands on the arterials.

This study successfully captures and automates expert decisions in implementing signal timing changes during non-recurrent conditions. Although in the cases of very bad congestion, the experts may decide to change the cycle length, the current work only consider the scenarios where the operators do not need to change cycle lengths. As the current model output only recommends the changes in green time to the prominent direction of movement, an expert might still need to decide on how decreasing the green times should be distributed to other approaches at the intersection. It is recommended that the developed model is further integrated with other data and tools available to improve signal timing such as Automated Traffic Signal Performance Measures (ATSPMs) based on high-resolution controller data and signal timing optimization tools. As stated earlier, the Recursive Partitioning and Regression Decision Tree (RPART) and Fuzzy Rule-Based System (FRBS) approaches have the advantage in that they can be augmented with additional rules. Thus, new rules could be developed based on manual expert rules inputs, ATSPMs data, simulation results, and/or optimization results to augment the rules derived based on Decision Tree training of past decisions by the experts.

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CHAPTER 7: SIGNAL TIMING STRATEGIES TO MITIGATE NON-RECURRENT CONGESTIONS

7.1 INTRODUCTION

In recent years, transportation agencies have increased their focus on implementing Active Arterial Management Program (AAM) strategies to manage the performance of arterial streets. The activation of special traffic signal plans during non-recurrent events is an essential component of AAM and can provide significant benefits in terms of performance metrics of the transportation systems. Most of the existing signal controller systems in the United States operates based on time of day. These plans are prepared using historical traffic flow data collected for different times of the day and fine-tuned based on field observations. Such plans lack the consideration of non-recurrent congestion due to incidents and other lane blockage events, as well as surges in demands due to special events. In some cases, agencies have deployed adaptive signal control technology. However, such implementations are still limited, and the adaptive signal control may not be as effective under all conditions, particularly under heavily congested conditions with long queues.

Non-recurrent events cause reduction in capacity or increase in demand; thus, congestion can occur and extend to upstream intersections from the bottleneck location. In these conditions, the vehicle queues continue to grow from cycle to cycle, either due to insufficient green times that cannot meet the demands or because of blockages that prevent traffic from efficiently using the assigned green times. The queues can interrupt traffic flows on the arterial network and can also cause spillback to freeway ramps, consequently creating congestion on freeway facilities. Thus, it is critical to actively change the signal timings to address the lane blockages and the surges in demands on the arterial networks.

To mitigate the adverse effect of non-recurrent events such as incidents, surges in demands, and work zones; some agencies have hired traffic signal engineers/expert operators to actively manage the traffic signal controls during these events based on observing of incident and traffic conditions at the intersections upstream and downstream of the congested locations. In the previous chapter, the authors of this study developed an artificial intelligent model, using a DT and FRBS, to automate the process of updating the signal timing plans during non-recurrent conditions based on the recorded history of the traffic signal engineer's responses to non-recurrent events (Tariq et al, 2020). This model is referred to in the remaining of this chapter as the DT & FRBS model. The previous chapter showed that the DT & FRBS model is effective in minimizing vehicle delay and long queue formation. However, since the development of the model was based on the expert's decisions, the model only recommends the changes in green time to the movements that are impacted by events. The DT & FRBS model does not optimize the overall shifts in the green times between intersection movements. For this purpose, simulation-based optimization techniques are needed to improve signal-timing decisions. These techniques can be enhanced with the use of micro-simulation tools and the availability of detailed ATSPMs based on high-resolution controller data.

Signal timing optimization for oversaturated conditions has been studied since the 1960s. However, there are limited studies on optimizing signal control for non-recurrent congestions such as lane blockage and demand surcharge caused by the diversion from freeway incidents or vehicle rerouting, work zone, etc. This study examines methods to design and activate signal timing strategies and associate plans to mitigate detected and/or predicted non-recurrent congestion conditions. The study proposes methodology and algorithms to combine data collected from existing and emerging sources with enhanced models and optimization algorithms to optimize and manage signal operations during non-recurrent events. The performance of the resulting plans from utilizing the simulation-based optimization approach is compared with the results of the selection of the signal timing utilizing the DT & FRBS in terms of its ability to reduce delays and increase throughputs during the non-recurrent events.

7.2 BACKGROUND OF PROPOSED METHOD

7.2.1 Optimization Methods

Various optimization techniques have been used in signal timing optimization. With the evolution of technology and high computation power, heuristic algorithms are being applied to signal timing optimization problems including genetic algorithm (GA), particle swamp optimization (PSO), ant colony algorithm (ACA), and so on. Signal optimization algorithms techniques generate signal timing plans by maximizing or minimizing the value of the fitness or objective function of the optimization. The objective function can include delay, travel time, throughput, number of stops, and/or other measures and are evaluated using simulation or analytical models (Hadi and Wallace, 1993; Park et al., 2000; Jia et al., 2019; He and Hou, 2012).

Genetic Algorithm (GA) has become a widely used optimization technique in transportation engineering research. GA is motivated by Darwin's principles of natural selection, survival of the fittest, and evolution and is widely used because of its robustness, computational efficiency, and ability to find a solution near to the globally optimal solution (Whitley, 1994; Goldberg, 1989; Beasley et al., 1993). GA can be modified to deal with multiple objectives by incorporating the concept of Pareto domination in its selection operator and applying a niching pressure to spread its population out along the Pareto optimal trade-off surface. The Non-dominated Sorting Genetic Algorithms (NSGA-II and NSGA-III) are multi-objective algorithms based on GA. The NSGA-II algorithm is used when there are two objective functions to be optimized. The NSGA-III is applied for more than two objective function problems and is used in this study. Unlike the basic GA, the NSGA-III algorithm belongs to a set of multi-objective algorithms aiming to find the Pareto front of compromised solutions of all objectives rather than integrating all objectives together in one objective function (Yuan et al., 2014).

A solution belongs to the Pareto set is found, if there is no other solution that can improve at least one of the objectives without the degradation of any other objective. Previous studies demonstrated that NSGA-III is able to maintain a better spread of solutions and converge in the obtained non-dominated front (Yuan et al., 2014, Mishra et al., 2002). With this type of optimization, the boundary defined by the set of all points mapped from the Pareto-optimal set is called the Pareto-optimal front and solutions in the Pareto-optimal front define the best trade-off between the competing objectives (Horn et al., 1994; Deb, 2001).

7.2.2 Signal Timing Optimization

As stated earlier, the objective functions in the optimization are evaluated using simulation or analytical models. Synchro optimizes signal timing plans by minimizing the delays evaluated using an analytical model. TRANSYT-7 F (Wallace et al., 1998) and Synchro (Synchro, 1999) are examples of programs for optimizing signal timings, and both use macroscopic-deterministic models for evaluating the objective functions. An enhancement to TRANSYT-7F allowed optimizing signal-timing plans under congested conditions by implementing additional objective functions to select from and by enhancing the traffic flow model to simulate spillback conditions (Hadi and Wallace, 1995) (Wallace et al., 1998). The Streets module in the Highway Capacity Software (HCS) can optimize signal timing for an arterial segment utilizing objective functions evaluated based on the Highway Capacity Manual (HCM, 2010) procedures using GA.

During non-recurrent events, lane blockages or sudden demand surges can impact capacity, demands, arrival types, and platoon formations. In general, currently utilized optimization tools cannot replicate the microscopic and stochastic behavior of the vehicles especially during heavy congestion. Micro-simulation tools can provide an alternative to evaluate the objective function that are able to replicate the congestion, if properly calibrated. (Ma and Abdulhai, 2002; Kim et al., 2005).

Choosing an appropriate objective function for optimizing traffic signal timing is critical because the choice will affect the overall network performance. Delay minimization is mostly used as an objective function for signal timing optimization, sometimes combined with the number of stops (Eriskin et al., 2017). Signal timing optimization for oversaturated conditions has been studied since the 1960s. In early studies, many researchers suggested that the objective function used in oversaturated intersection optimization should be based on maximizing system throughput instead of minimizing delay (Gazis and Potts, 1963; Gazis, 1964; Gordon, 1969; Singh and Tamura, 1974; Mcshane et al., 1978). However, more recent studies recommended a combination of delay minimization, system throughput maximization, and queue management for oversaturated conditions (Hadi et al., 1999; Abu-Lebdeh and Benekohal, 2003; Lieberman et al., 2000; Lieberman and Chang 2005).

An early consideration of oversaturated conditions in adaptive signal control was implemented in the Split, Cycle, and Offset Optimization Technique (SCOOT) system. SCOOT implements “gating” strategy to terminate upstream movement phases and reduces the upstream traffic flow to congested intersections, thus preventing spillbacks (Wood, 1970). Another strategy that has been proposed to control queues at congested intersections is to provide a “reverse offset” instead of a forward offset between intersections (Quinn, 1992). The reverse offset refers to determining the offset at the upstream intersection based on the start of green at the downstream intersection with the consideration of the time required for the recovery shockwave to move to the upstream intersection (Quinn, 1992).

Several research and development efforts addressed selecting traffic signal control during oversaturated conditions. Lieberman et al. (2000) proposed a real-time traffic control policy to select signal timing based on estimated queue lengths. The goal was to control and stabilize queue lengths and provide equitable service to competing traffic streams by metering traffic at upstream intersections, thus servicing oversaturated approaches while fully utilizing storage capacity and preventing queue spillback from maximizing the throughput that controls the interaction between incoming platoons and standing queues. Saha et al. (2020) developed methods for the selection of special signal timing plans to accommodate traffic diversion during freeway incidents to arterial streets. Although several existing studies on signal timing optimization address recurrent congested conditions, solutions to the non-recurrent congestion problem on arterial streets still need to be explored.

7.2.3 DT & FRBS MODEL

This section presents an overview of the machine learning model (DT & FRBS), presented in the previous chapter, that automates the signal timing modification decisions by TMC Engineers (Tariq et al., 2020). This system is a combination of Recursive Partitioning and Regression RPART and FRBS that deals with the vagueness and uncertainty of human decisions. The method results in a rule based-decision system to identify the changes that need to be made to the signal control during incidents based on past cases of the experts' decisions to change the signal timing. The developed method is designed to capture the cognitive uncertainties associated with human thinking and perception related to an expert implementing signal timing changes in non-recurrent conditions. The decisions to modify the signal timing are based on the conditions of the main, side streets and upstream intersection, comparison of the queue spillback situation with historical queues, traffic congestion level, event characteristics. Figure 22 shows a screen capture of the signal timing modification tool based on the DT & FRBS model.

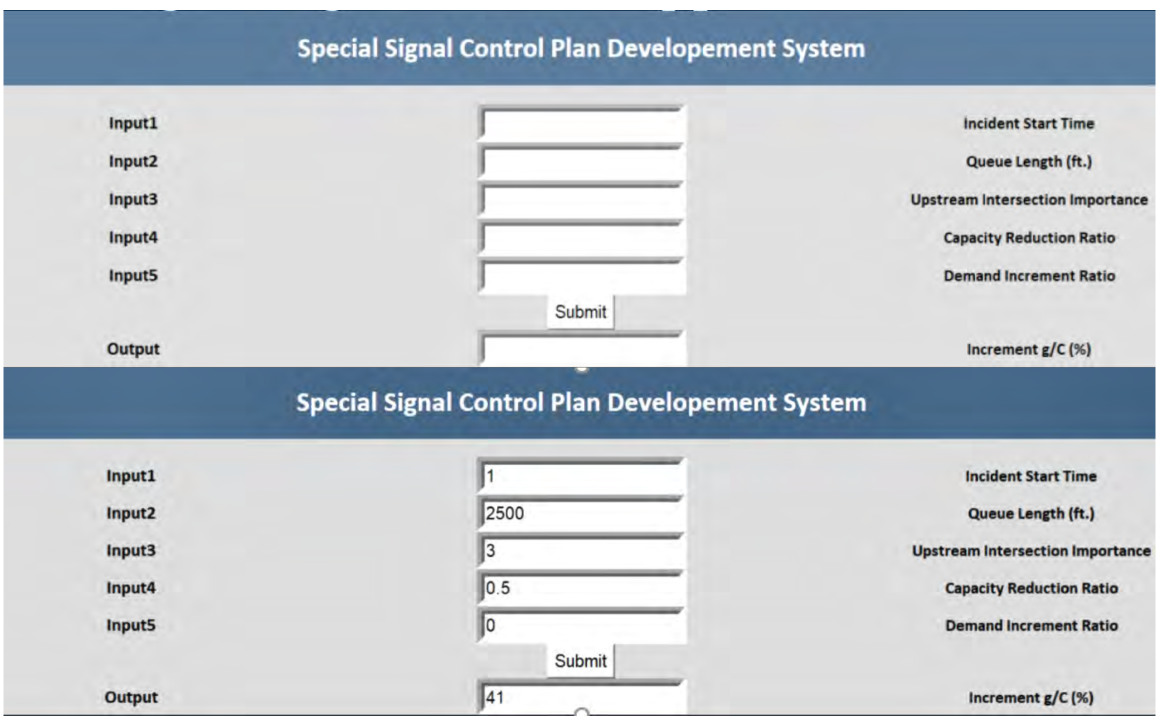


FIGURE 22: SPECIAL SIGNAL TIMING MODIFICATION TOOL

7.3 METHODOLOGY

This section presents the methodology utilized in this study to optimize the signal timing during congested conditions. First, traffic patterns are categorized using cluster analysis based on different measures including ATSPM measures. Second, microscopic simulation models are calibrated for each of the traffic condition scenario resulting from clustering. Then, it provides the details of the optimization methodology used to optimize the signal timing for each scenario.

7.3.1 Traffic Condition Partitioning

To account for the day-to-day variation in traffic condition, this study partitioned the traffic conditions on the subject systems based on the collected data utilizing cluster analysis. This will allow the simulation of traffic and optimization of signal control for each of the patterns in the case that there is high variability of traffic conditions in the year, independent of the non-recurrent events that are the subject of the study. This study uses K-means clustering to partition traffic based on travel time measurements as well as the Green Occupancy Ratio (GOR) measurements. GOR is a measure that is derived based on high-resolution controller data that reflects the degree of green utilization in each phase. It is defined as the stop bar detector occupancy during the green interval. Higher values of GOR reflect higher utilization of the green time.

One crucial aspect of clustering is to determine the number of clusters to use in the clustering. This study utilizes a method referred as the Elbow method to determine the required number of clusters (Ketchen and Shook, 1996). The Elbow method is an empirical method that provides an objective approach to determine the optimal number of clusters. The method determines the number of clusters based on the total within-cluster sum of square (WSS) for each number of clusters (Ketchen and Shook, 1996). A graph is drawn between the total WSS and the number of clusters, and the location of the bend in the plot is considered as an indicator of the appropriate number of clusters.

7.3.2 Microscopic Simulation Modeling

This study utilizes microscopic simulation-based optimization for developing a signal timing plan. In this study, PTV's Verkehr in Städten SIMulationsmodell (VISSIM) microscopic simulation tool is used for generating the micro-simulation traffic models. In the calibration of the model, this study utilizes a recently proposed calibration method that accounts for ATSPM measurements, as part of the simulation model parameter calibration. In this method, the calibration of driver behavior parameters in the simulation model and validation of the model are performed using multi-objective optimization technique based on travel time and high-resolution controller-based measurement, as described in an earlier chapter of this document (Tariq et al., 2021). The calibrated and validated simulation models are then used in the signal timing optimization, as described next.

7.3.3 Signal Time Optimization

As stated earlier, this study utilizes simulation-based optimization to select the signal timing plan parameters. Calibrated simulation models were created for various non-recurrent event scenarios in the VISSIM simulation platforms, as explained in the previous section.

Choosing an appropriate objective function for optimizing traffic signal timing is critical because the choice will affect the overall network performance. As mentioned earlier, selecting the parameters of traffic signals in arterial corridors for congested conditions is a multi-objective problem, in which optimizing the solution based on one objective can often work to the detriment of another. Intersection delay minimization for signal timing optimization is by far the most widely used objective function. However, signal timing optimization based on network delay may not ensure utilizing intersection capacity to the fullest in congested conditions such as those during non-recurrent events. In this study, the NSGA-III multi-objective optimization technique is applied to find the best signal timing plans during non-recurrent events. Calibrated VISSIM models are used for the optimization of signal timing for different types of incident and demand surge scenarios. The VISSIM COM-interface was used with NSGA-III optimization operator in optimizing the signal control based on the evaluation of the objective function using microscopic simulation.

7.3.3.1 Optimized Objective Functions

Three measures of effectiveness are selected in this study for the optimization problem. The objective functions used in the optimization problem include the travel time in the critical direction of the corridor, intersection delay, and average throughput of all phases. The measures are evaluated based on the VISSIM simulation model results collected from the COM interface.

Delay is defined as the difference between the actual travel time and the travel time at free-flow conditions. Throughput is the total number of vehicles released from each link during a specific period of time. Throughput maximization increases the system's ability to process more vehicles, but it may cause queue formation at downstream intersections, especially when the downstream intersections have less capacity than demand. Minimizing the travel time of the critical direction of the corridor can also minimize the possibility of queue formation along the subject's direction.

Non-recurrent events generally form long queues, and in some cases, cause spillback to the upstream intersections. Choosing the objective function in optimizing signal control for such condition is crucial. The designed objective functions should give priority to the critical direction (direction of the special events). At the same time, it should not deteriorate the cross-street traffic conditions. The objective functions utilized in the optimization are cited below:

$$f_1(g) = \text{Corridor Travel Time of the critical direction} \quad (16)$$

$$f_2(g) = \text{Intersection delay} \quad (17)$$

$$f_3(g) = \text{Average throughput of all movements} \quad (18)$$

where

$f_1(g)$, $f_2(g)$, $f_3(g)$= Objective function values,

g= green split in each phase.

7.3.3.2 Model Formulation and Solution algorithm

A knowledge-driven evolutionary algorithm NSGA-III is proposed in this study to select the optimized signal timing plans solutions. The NSGA-III algorithm is a non-dominated sorting type GA algorithm that is capable of optimizing many objective functions at once. The non-dominated solution set is a set of all of the solutions that are not dominated by any member of the solution set.

The Pareto-optimal set is the entire feasible decision space of the non-dominated sets from NSGA-III. The final optimized solutions are found from the boundary of all mapped points of the Pareto-optimal set. The NSGA-III algorithm optimizes the fitness value in a minimization sense. For this reason, in order to maximize the throughput as one objective function, the negative value of the average throughput is minimized using the NSGA-III operator. The fitness function used in NSGA-III for signal timing optimization is stated in Equation 19.

$$\text{minimize} \quad f(g) = [\, f_1(g),\ f_2(g), -f_3(g)\,] \tag{19}$$

subject to:

$$C_m \leq C \leq C_c \tag{20}$$

$$g_i^L \leq g_i \leq g_i^U \tag{21}$$

$$g_1 + g_2 = g_5 + g_6 \tag{22}$$

$$g_3 + g_4 = g_7 + g_8 \tag{23}$$

where
i= Phase number,
g= Vector of effective green time at each phase i (seconds),
$f_1(g)$= Corridor travel time of the critical direction (seconds),
$f_2(g)$= Intersection delay (seconds/vehicle),
$f_3(g)$= Vehicle throughput,
C_m= Minimum Cycle Length (seconds),
C_C= Maximum or Critical Cycle Length (seconds),
C= Cycle Length (seconds),
g_i= green split at phase i (seconds),
g_i^L = Lower bound of green time at phase i (seconds),
g_i^U = Upper bound of green time at phase i (seconds),
g_1= Eastbound Left (EBL) phase split (seconds),
g_2= Westbound Through (WBT) phase split (seconds),
g_3= Southbound Left (SBL) phase split (seconds),
g_4= Northbound Through (NBT) phase split (seconds),
g_5= Westbound Left (WBL) phase split (seconds),
g_6= Eastbound Through (EBT) phase split (seconds),
g_7= Northbound Left (NBL) phase split (seconds), and
g_8= Southbound Through (SBT) phase split (seconds).

The NSGA-III algorithm with the three objectives in Equations 16, 17 and 18 are utilized to generate optimum signal timing plans. The following steps are used in the optimization process to calculate the fitness function values based on VISSIM simulation results. The entire process is performed using the Python COM interface.

- Each of the generated population in the NSGA-III algorithm, which represents a signal timing plan, is used as signal control inputs to the simulation model.
- After using each timing plan generated by the NSGA-III, the VISSIM outputs are used to estimate the performance measures with the plan.

- The fitness values are then calculated for the individual populations (signal timing plans) for use in the optimization process.

The signal timing optimization algorithm is constrained by the minimum and maximum cycle lengths, minimum and maximum green times, and phase sequence (ring and barrier settings). Equation 20 represents the constraint for the cycle length. The minimum and maximum cycle lengths are calculated according to Webster's method (Chaudhary et al., 2002). The barrier is used to separate the east-west movements from the north-south movements to avoid operating conflicting movements at the same time. Equations 22 and 23 ensure the correct ring and barrier setting of the controller, where the northbound and southbound movements start at the time that the eastbound and westbound movement end, and vice versa. The minimum and maximum green time constraint is stated in Equation 21. The minimum and maximum green times of all approaches by the controller settings in the time-of-day plans.

7.4 CASE STUDY

The case study segment used to demonstrate the proposed method consists of five intersections, from NW 22nd Avenue to NW 7th Avenue on NW 119th Street in Miami-Dade County. This segment is around 1.5 miles in length. This segment is selected because it faces moderate to high demands all day long and is often congested during peak hours. Also, advanced data sources such as high-resolution controller data, travel time data based on Bluetooth reader measurements, traffic counts, and incident data are available for the segment.

The signal timing plans input into the model were the same as the semi-actuated time-of-day plans implemented in the real-world. The signal phase timing was obtained from Miami-Dade County and verified using the high-resolution controller data. Vehicle inputs at the entry points of the network and the static routes were coded as the traffic volume extracted from high-resolution data, which were verified for correctness based on the turning movement counts taken for one day in the peak periods.

The desired speed distribution in the eastbound (EB) and westbound (WB) direction was coded according to the speed limits of each link in the segment. In addition, reduced speed areas are placed for the turning movements of the roadway intersections to reflect the turning speeds.

7.5 ANALYSIS AND RESULTS

This section shows the analysis results and the evaluation and comparison of the generated signal timing plans.

Table 29 represents traffic pattern clusters of the morning peak hours of the case study corridor utilizing K-means clustering based on travel time and GOR measurements.

TABLE 29: CATEGORIZATION OF TRAFFIC BASED ON THE GREEN OCCUPANCY RATIO

Category	No of Data Points	Average Travel Time, (seconds)		Through Movement Cluster Center GOR		Left Turn Cluster Centers GOR	
		EB	WB	EBT	SBT	EBL	SBL
Category 1	8	300.1	223.01	0.636	0.775	0.84	0.94
Category 2	22	279.65	215.74			0.84	0.77
Category 3	5	276.6	205.26			0.77	0.62
Category 4	16	265.5	213.57	0.556	0.772	0.79	0.87
Category 5	19	280.15	217.51			0.80	0.72
Category 6	18	281.7	198.03	0.613	0.658	0.80	0.77

The calibrated VISSIM model for Cluster Category 1 in

Table 29 was first used to evaluate the effectiveness of regular time-of-day signal timing settings under non-recurrent congestion. This evaluation involved simulating three non-recurrent congestion scenarios in the eastbound (EB) direction upstream of the NW 119th Street and 17th Avenue intersection. The three scenarios are:

1. One out of three-lane blockage;
2. Two out of three-lane blockage; and
3. Demand surge (increment to 1.3 times of the regular demand).

The Corridor Travel Time (seconds/vehicle), Intersection Delay (seconds/vehicle), Throughput (vehicles), and Queue Length (feet) are evaluated using the simulation model outputs. Table 30 shows the performance of the evaluated regular TOD signal timing for all three non-recurrent scenarios compared to normal traffic conditions. The results show significant increase in intersection delays, corridor travel times, and queue lengths upstream of the critical approach during the investigated non-recurrent events.

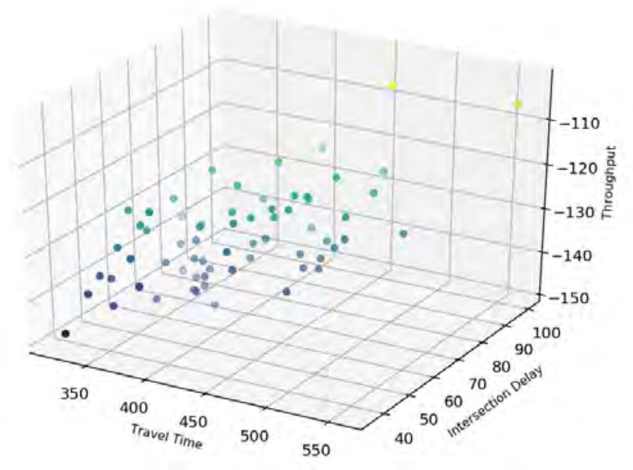
TABLE 30: SIGNAL TIMING PERFORMANCE MEASURES WITH REGULAR TOD TIMING PLAN

Traffic Conditions	Signal Timing Strategies	Phase Split (sec)								Approach Delay (sec/veh)				Corridor Travel Time (sec/veh)	Average Intersection Delay (se/veh)	Throughput (veh)	Queue Length (ft)
		EBL	WBT	SBL	NBT	WBL	EBT	NBL	SBT	EB	SB	WB	NB				
Normal Traffic Condition	Regular Timing Plan	26	88	22	64	26	88	26	64	26.72	27.09	13.87	7.6	297.64	18.82	142	86.76
One Lane Blocked										263.19	35.8	26.06	7.58	557.54	83.16	114	1084.16
Two Lane Blocked										288.15	51.71	30.57	4	622.38	93.61	115	1685.05
Demand Surge										189.02	44.3	332.5	2.81	587	67.17	147	1401.9

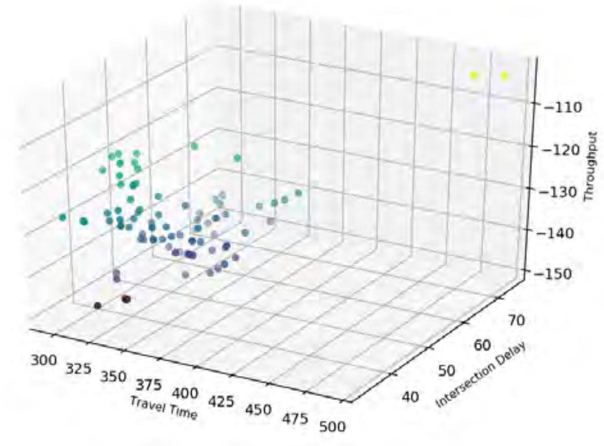
Note: EBL= Eastbound Left turn, WBT= Westbound Through movement, SBL= Southbound Left turn, NBT= Northbound Through movement, WBL= Westbound Left turn, EBT= Eastbound Through movement, NBL= Northbound Left turn, SBT= Southbound Through movement, EB= Eastbound movement, SB= Southbound movement, WB= Westbound movement, NB= Northbound movement.

7.5.1 NSGA-III optimization results

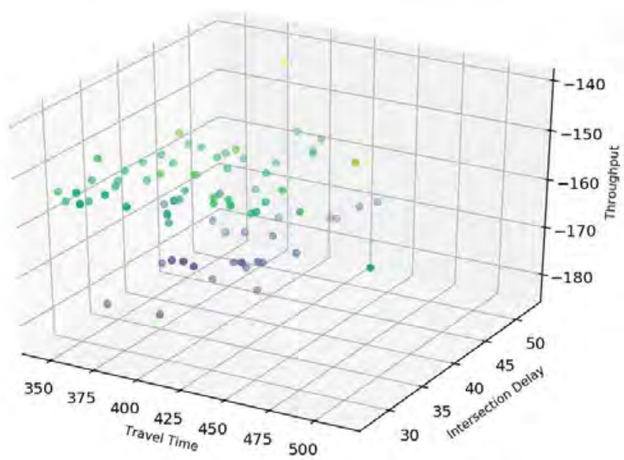
NSGA-III algorithm minimizes the fitness value. The fitness value is linked to the objective function of the optimization problem in each generation by selecting the best offspring from the previous generation. Figure 23 shows the minimization of the fitness value in each generation for the three aforementioned non-recurrent conditions. An important measure of effectiveness for the non-recurrent traffic conditions is the queue length upstream of the incident or critical intersection. Figure 24 to Figure 26 show the change in this measure in the process of optimizing the fitness value in the NSGA-III generations. The trend lines in each plot show that the queue length gradually decreased with the decrease in the travel time and intersection delay and the increase in throughput.



a) **One Lane Blockage**

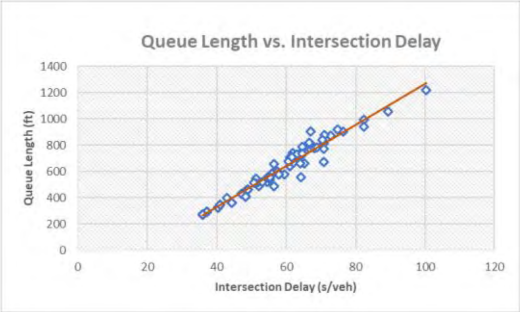


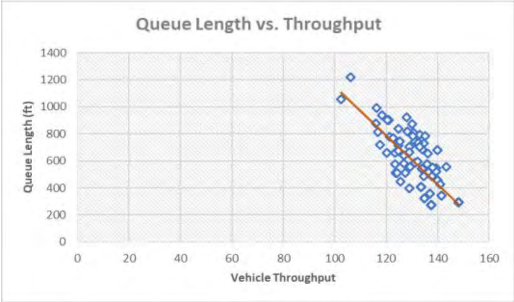
b) **Two Lane Blockage**



c) **Demand Surge**

FIGURE 23: PLOT OF THE RESULTED OBJECTIVE FUNCTIONS IN EACH NSGA-III GENERATIONS





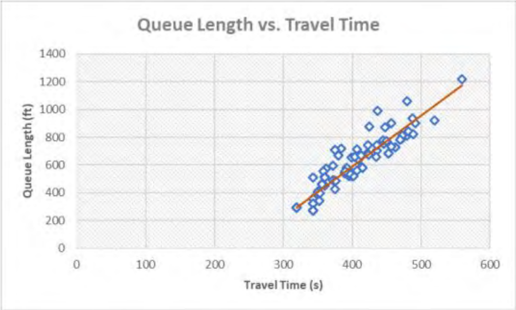
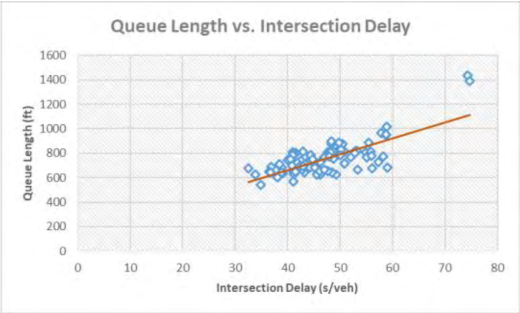
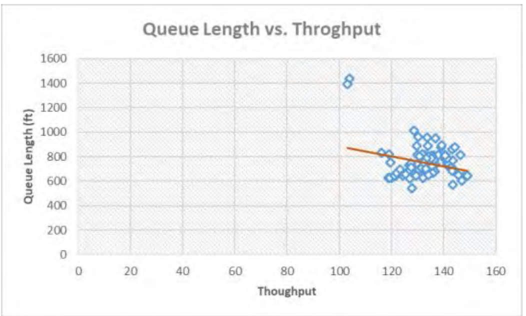


FIGURE 24: QUEUE LENGTH VS. NSGA-III FITNESS VALUES (ONE-LANE BLOCKAGE)





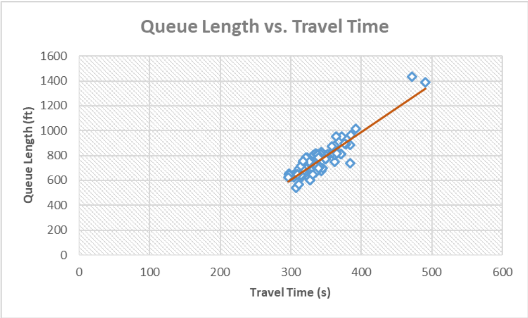
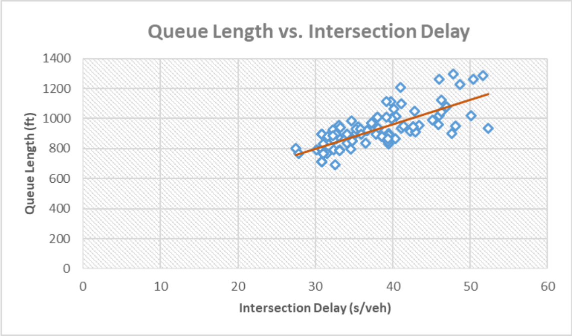
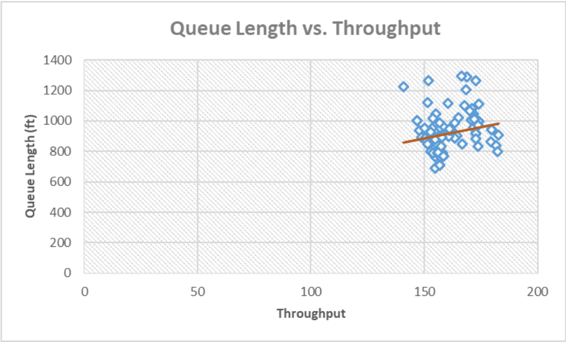


FIGURE 25: QUEUE LENGTH VS. NSGA-III FITNESS VALUES (TWO-LANE BLOCKAGE)





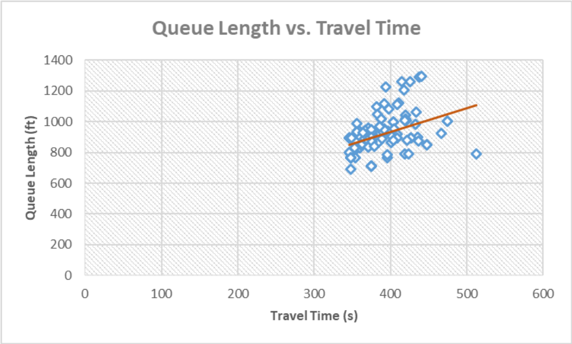


FIGURE 26: QUEUE LENGTH VS. NSGA-III FITNESS VALUES (DEMAND SURGE)

The NSGA-III algorithm provides optimal Pareto sets as outputs of the optimization process. Each set in the Pareto-optimal front resulted in the best tradeoff between competing objectives. For example, if one Pareto-optimal set results in the lowest travel time, it may have higher intersection delays or lower throughput than the other sets. Understanding the roadway conditions and agency objectives and priorities is important for selecting a solution from the Pareto sets. Table 31 presents the resulted Pareto sets from the optimization for each investigated non-recurrent condition. Among the Pareto-optimal sets, a special signal-timing plan for each non-recurrent condition is chosen to cause lower delay to the competing movements and the critical movements compared to the other solutions. In the case of the one-lane blockage incident, the optimization procedure decreased the cycle length to 107 seconds, which is almost half of the regular signal timing settings, possibly indicating that double cycling can be effective when the capacity of an approach is reduced.

TABLE 31: PARETO OPTIMAL SETS FOR NON-RECURRENT CONGESTION CONDITIONS

Non-Recurrent Congestions	Phase Split (sec)								Vehicle Delay (sec/veh)				Corridor Travel Time (sec/veh)	Intersection Delay (sec/veh)	Throughput (veh)	Queue Length (ft)
	EBL	WBT	SBL	NBT	WBL	EBT	NBL	SBT	EB	WB	SB	NB				
One Lane Blocked	19	59	8	20	19	59	8	20	90.64	13.53	43.02	1.038	343.05	37.06	137	273.04
	17	**59**	**9**	**22**	**17**	**59**	**8**	**21**	**92.95**	**9.246**	**41**	**0.92**	**319.51**	**36.03**	**148**	**294.32**
Two Lane Blocked	17	165	10	12	17	165	10	12	104.75	11.29	8.71	30.34	331.37	36.52	145	649.4
	22	**166**	**10**	**13**	**22**	**166**	**10**	**13**	**100.52**	**12.28**	**4.28**	**21.36**	**309.7**	**36.80**	**149**	**645.6**
Demand Surge	**17**	**181**	**8**	**20**	**17**	**181**	**8**	**20**	**81.17**	**10**	**17.43**	**15.63**	**347.55**	**31.057**	**159**	**768.4**
	15	181	8	20	15	181	8	20	77.58	8.23	23.74	13.90	375.31	30.86	157	712.09
	17	185	8	20	17	185	8	20	85.24	10.89	23.51	4.48	353.04	31.03	158	831.35
	17	161	8	20	17	161	8	20	87.38	8.19	27.15	13.56	378.89	34.07	182	838.07
	17	161	8	21	17	161	8	21	85.19	6.35	33	13.7	345.71	34.56	183	798.23

** Bold values are selected solutions from the Pareto sets*
Note: EBL= Eastbound Left turn movement, WBT= Westbound Through movement, SBL= Southbound Left turn movement, NBT= Northbound Through movement, WBL= Westbound Left turn movement, EBT= Eastbound Through movement, NBL= Northbound Left turn movement, SBT= Southbound Through movement, EB= Eastbound movement, SB= Southbound movement, WB= Westbound movement, NB= Northbound movement.

7.5.2 Comparison of the Developed Models

This section compares the results of the assessment of the optimization method to those of the assessment of the previously developed DT & FRBS model based on signal timing experts' decisions. The developed DT & FRBS tool was used to estimate the needed increment in the g/C ratio for the non-recurrent conditions, as shown in Table 32. The output from this model recommended a 20 percent increase in the g/C ratio for the one out of three-lane blockage condition, and a 31 percent increment in the g/C ratio for the two out of three-lane blockage and the demand increment traffic situations. Table 33 compares the recommended special signal timing plan from both the optimization and DT and FRBS model. The DT and FRBS model output are able to improve the performance measures for the impacted movements by the special events by increasing the green time in the subjected direction. However, the optimization results show that the special signal timing plan obtained from the optimization produced better performance than those from the DT & FRBS system for all of the non-recurrent conditions, as indicated below:

TABLE 32: OUTPUT FROM THE DT & FRBS MODEL

Traffic Conditions	Period	Upstream Cross Street Importance	Queue Length (ft)	Volume Increment Ratio	Capacity Reduction Ratio	DT FRBS Prediction (g/C Increment Percentage)	Old g/C	New g/C	New Green Time (sec)	NSGA-III Estimation (g/C Increment Percentage)
One Lane Blocked	AM	Major	1084	0	0.26	20	0.44	0.53	106	11
Two Lane Blocked	AM	Major	1685	0	0.49	31.0	0.44	0.58	116	34.7
Demand Surge	AM	Major	1401	1.6	0	31.0	0.44	0.58	116	36

TABLE 33: COMPARISON OF THE OPTIMIZED SIGNAL TIMING SETTINGS AND DT & FRBS MODEL

Traffic Conditions	Signal Timing Strategy	Phase Split (sec)								Vehicle Delay (sec/veh)				Corridor Travel Time (sec/veh)	Intersection Delay (sec/veh)	Throughput (veh)	Queue Length (ft)
		EBL	WBT	SBL	NBT	WBL	EBT	NBL	SBT	EB	SB	WB	NB				
One Lane Blocked	Regular Timing Plan	26	88	22	64	26	88	26	64	263.19	35.8	26.06	7.58	557.54	83.16	114	1084.16
	DT & FRBS	26	106	17	51	26	106	17	51	186.93	50.18	21.95	9.11	429.45	67.04	121	782.96
	After Optimization	17	59	9	22	17	59	8	21	92.95	41	9.25	0.92	319.51	36.03	148	294.32
Two Lane Blocked	Regular Timing Plan	26	88	22	64	26	88	26	64	288.15	51.71	30.57	4	622.38	93.61	115	1685.05
	DT & FRBS	26	116	15	43	26	116	15	43	261.19	49.37	22.43	8.55	493.92	85.4	130	1132.57
	After Optimization	22	166	10	13	22	166	10	13	100.52	12.28	4.28	21.36	309.69	36.80	149	645.6
Demand Surge	Regular Timing Plan	26	88	22	64	26	88	26	64	189.02	44.3	32.5	2.81	587	67.17	147	1401.9
	DT & FRBS	26	116	15	43	26	116	15	43	138.88	50	14.51	8.51	467.3	52.98	153	988.97
	After Optimization	17	181	8	20	17	181	8	20	81.17	17.43	10	15.63	347.55	31.06	159	768.4

Note: EBL= Eastbound Left turn movement, WBT= Westbound Through movement, SBL= Southbound Left turn movement, NBT= Northbound Through movement, WBL= Westbound Left turn movement, EBT= Eastbound Through movement, NBL= Northbound Left turn movement, SBT= Southbound Through movement, EB= Eastbound movement, SB= Southbound movement, WB= Westbound movement, NB= Northbound movement.

- For the one out of three-lane blockage incident, the DT & FRBS model decreased the queue length upstream of the incident by 28 percent, whereas the optimized signal plan decreased the queue length by 73 percent. In addition to reducing the queue length, the improvements in the travel time, intersection delay, and throughput values were higher with the optimized signal plan than the DT & FRBS recommended signal plan.

- For the two out of three-lane blockage incidents, the DT & FRBS model decreased the queue length upstream of the incident by 33 percent compared to a reduction of 62 percent with the optimized signal plan. Except for the northbound approach, the performance of the signal timing is better for intersection approaches with the optimized signal plans.
- For the demand surge condition, the queue length decreased by 30 percent when utilizing the DT & FRBS model, while the optimized signal timing plans reduced the queue length by 45 percent. The other performance measures are better with the optimized signal timing, except for the northbound direction delay, which is slightly higher with the optimization method.

7.5.3 Model Transferability Assessment

This study investigated temporal transferability of the developed signal timing plan to other days in the year with similar non-recurrent events, considering that the optimization was performed for the traffic operational condition of a specific day in a cluster. This assessment is conducted by examining the difference in the performance of the special signal plans developed for non-recurrent events when optimized with the demands of a specific day compared to the performance of the plans optimized using the demands for a different day. The NSGA-III optimization is performed utilizing the demands for a day that is categorized in Category 2 (Plan 2) and for a day that is categorized in Category 1 (Plan 1) to assess the temporal transferability of the optimization model (see Table 30). The study analyzed the difference in the performance of these two plans in terms of the conditions of Category 2. The assessment results shown in Table 34 indicate that there are only small differences between the performances of the Category 2 representative day of the two plans, indicating a good transferability of the plans between the two investigated categories.

TABLE 34: EVALUATION OF OPTIMIZATION MODEL TRANSFERABILITY

Traffic Conditions	Signal Timing Strategies	Phase Split (sec)								Corridor Travel Time (sec/veh)	Intersection Delay (sec/veh)	Throughput (veh)	Queue Length (ft)
		EBL	WBT	SBL	NBT	WBL	EBT	NBL	SBT				
Normal Traffic Condition	Regular Timing Plan	26	88	22	64	26	88	26	64	279.03	22.28	138	64.18
One Lane Blocked	Regular Timing Plan	26	88	22	64	26	88	26	64	566.69	98.57	124	1128.66
	Plan 2*	17	57	10	22	17	57	10	22	329.71	40.44	134	279.83
	Plan 1*	17	59	9	22	17	59	8	21	361.34	46.87	132	287.67
Two Lane Blocked	Regular Timing Plan	26	88	22	64	26	88	26	64	470.4	67.15	124	1149.93
	Plan 2*	16	163	8	18	16	163	8	18	333.26	38.60	144	690.39
	Plan 1*	22	166	10	13	22	166	10	13	335.31	46.29	141	729.84
Demand Surge	Regular Timing Plan	26	88	22	64	26	88	26	64	521.56	59.44	163	1359.20
	Plan 2*	14	186	8	20	14	186	8	20	440.67	26.35	165	668.46
	Plan 1*	17	181	8	20	17	181	8	20	462.60	28.75	161	675.02

**Plan 1 is the optimized signal plan for Category 1 traffic scenario, and Plan 2 is the optimized signal plan for Category 2 traffic scenario.*
Note: EBL= Eastbound Left turn, WBT= Westbound Through movement, SBL= Southbound Left turn movement, NBT= Northbound Through movement, WBL= Westbound Left turn movement, EBT= Eastbound Through movement, NBL= Northbound Left turn movement, SBT= Southbound Through movement.

7.6 CONCLUSION AND RECOMMENDATIONS

This study investigated methods to mitigate the impacts of non-recurrent congestion by identifying optimized signal timing plans that consider the travel performance in the critical direction impacted by the non-recurrent events, overall corridor, and the overall intersection performance. A critical component of the method is identifying traffic operational conditions based on accurate and detailed measurements of traffic flow conditions. An important aspect of the method is using a microscopic simulation-based optimization model to derive the plans and use detailed data, including high-resolution controller data, to calibrate the simulation model. Given that the calibrated simulation models are able to replicate field traffic operational conditions, the NSGA-III multi-objective optimization technique is implemented to generate optimized signal timing.

The evaluation of the methodology developed in this study showed that the optimized signal timing plan improved the intersection and overall corridor performance in terms of queue length, overall throughput, intersection delay, and corridor travel time. This study compares the recommended special signal timing plans from the optimization method developed in this study with those obtained using the DT & FRBS models developed by the authors in a previous study. The evaluation shows that although the use of the DT & FRBS model is able to improve the evaluated performance measures, the signal timing plans obtained from optimization produced better results for all three investigated non-recurrent conditions. The benefit assessment of the developed special signal timing plans is performed using simulation models in this study. It is recommended to further evaluate the methodology in a real-world environment. The methodology developed in this research can be also further extended by optimizing the signal timing plans in real time. This study explores the lane blockage scenario due to incidents just upstream of the stop line of the subjected approach. Further analysis is needed for methods to develop signal timing plans for incidents at other locations of the segment.

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CHAPTER 8: INTEGRATED APPROACH FOR OPTIMIZING TRAFFIC MANAGEMENT PLANS DURING FREEWAY INCIDENTS

8.1 INTRODUCTION

Coordinated freeway and arterial operation is a critical component of integrated corridor management (ICM). An important concept of such coordinated operation is the implementation of operational plans to accommodate the diverted traffic on the alternative routes during incidents on the freeway. With this concept, the coordinated operation intends to manage the traffic jointly on the freeway and arterial facilities during incidents to improve mobility, reliability, and safety. Such coordination requires the identification of the diversion scenarios, including determining the utilization of each alternative route by the diverted traffic under different scenarios and the identification and activation of special signal timing plans to accommodate the diversion. Wrong identification and prediction of the diversion parameters will result in wrong decisions that will impact the effectiveness of the coordinated operation. Such wrong decisions, for example, can result in the switching of green time to non-deserving intersection movements, which, in turn, causes unnecessary delays to other movements. At intersections with high traffic demands, the consequences of the wrong decisions could be severe *(1)*. Implementing the incorrect response during the incident could also worsen the congestion on the directly impacted freeway and its surrounding highway network *(2)*.

Proactive traffic management strategies require the prediction of the system behavior in real-time and activating plans accordingly. With the increasing emphasis on active traffic management (ATM), some agencies have employed expert operators at traffic management centers (TMCs) to manage the traffic signal control actively during non-recurrent events *(3)* since the existing TOD signal control plans, developed based on normal day traffic, fails to respond to these changing conditions. The decisions made by such operators, however, are still reactive. Moreover, it is challenging for the operators to select the best plans given the many changing parameters in real-time operations during non-recurrent events *(4)*. Adaptive traffic control systems (ATCS) have been developed and implemented to react to the inherent traffic variations occurring from cycle to cycle, thus operate more efficiently than TOD-based systems. It has been reported that ATCS can reduce the delay during the incident conditions *(5)*. However, the ATCS performance under sudden demand surge and when the signal intersection approaches have long queues are uncertain. The oversaturation of an intersection or a movement negatively affects the performance of the ATCS system and may result in under allocation of green times to critical oversaturated movements *(6,7)*. In addition, the existing ATCS systems deal with only the current traffic conditions as measured by the traffic sensors; thus, they are still reactive systems.

A Multi-Resolution Modeling (MRM) framework that combines the different levels of modeling, i.e., macroscopic, mesoscopic, and microscopic modeling, was found effective in developing incident responsive signal control plans *(8)*. The dynamic traffic assignment (DTA) technique in the mesoscopic level of this framework has the capability to simulate time-varying traffic diversion during incidents, whereas the microscopic level provides the necessary details of the traffic stream to develop signal control strategies. Since, the incident induced diversion is a dynamic event and influenced by many factors such as incident attributes, traffic conditions, advanced traveler information systems, alternative route conditions, and signal status *(9-11),* an MRM framework can play a role in predicting diversion to support the traffic management during incidents.

This study investigates the use of clustering analysis, multi-resolution modeling (MRM), and optimization techniques in the development of such plans. An important aspect of the methodology is the calibration of the utilized mesoscopic simulation-based MRM based on the increase in demands and travel times on alternative routes using data from third party vendors. Another important aspect is the use of microscopic simulation-based optimization of signal timing utilizing a multi-objective optimization that jointly minimizes the delays and maximizes the throughputs considering the whole intersections as well the specific impacted movements on the alternative routes.

8.2 REVIEW OF LITERATURE

ICM is an effective TSM&O strategy for managing the congestion along the urban corridors *(12,13)*. In the U.S.-75 ICM implementation in Dallas, TX, the probable shift of the traffic due to the incident was modeled using a mesoscopic simulation model that was calibrated using historical incidents and traffic data *(14)*. The appropriate response plan for the predicted conditions based on real-time mesoscopic simulation was selected from a library of plans based on expert rules. Similarly, the I-15 ICM in San Diego, CA, activates a plan from a predefined set of signal changes for the diversion routes based on a microscopic simulation model prediction of performance *(14)*. Several other studies also utilized simulation models, sometimes combined with dynamic traffic assignment (DTA), to design and assess traffic signal plans to promote coordination between arterial and freeway operations during incidents *(15,16)*.

8.2.1 Modeling of Incidents and Diversion

The lane blockage due to incidents creates a temporary bottleneck by reducing the capacity of the road. The reduction in capacity is not linearly proportional to the number of blocked lanes. A study by Smith et al. (2003) found a 63% capacity reduction for one out of three lanes blocked and a 77% reduction for two out of three lanes blocked on the freeway *(17)*. The Highway Capacity Manual *(18)* recommends the use of capacity adjustment factor (CAF) of 0.74 and 0.52, respectively, for these conditions. The reduction in capacity triggers the diversion in varying percentages depending on various factors such as incident characteristics, traffic status on the affected facility and alternative routes, signal plan on the alternative routes, time-of-day, origin-destination, and so on. These time-varying and complex phenomena can be modeled utilizing a multi-resolution modeling (MRM) framework. The MRM refers to a modeling framework that combines microscopic, mesoscopic, and macroscopic representations of traffic flow usually combined with DTA. The MRM approach addresses issues that are beyond the capabilities of macroscopic models, mesoscopic models, and microscopic models by themselves *(19)*.

In most implementations, MRM links a mesoscopic-based DTA model to both the regional travel demand models (macroscopic) and localized high-detailed models (microscopic). The MRM framework was successfully applied to support and ATM strategies, including during incident on arterials *(8)*, managed lane operations *(20)*, integration of signal timing estimation modeling, and DTA *(21)*, integrated active traffic operation evaluation *(22)*, and so on. This study utilizes MRM to identify the path-level diversion scenario demands and associated impacts on the alternative routes during incidents ion the freeway.

8.2.2 Traffic Signal Plan Development

Effective traffic signal plan development depends on the optimization of signal design elements (i.e., split, cycle length, phase sequence, and offset) individually or in combination against single or multiple objectives functions subject to the underlying constraints. The objective functions widely used include minimization of delay, minimization of travel time, maximization of throughput, maximizing the throughput-minus-queue, minimization of the number of stops, maximizing the number of completed trips, maximizing the weighted number of completed trips alone or in combination *(23-26)*. The choice of the objective function largely governed by the demand patterns associated with the subjected intersections and agency priorities with regard to the performance measures. For example, the agency may decide that the dissipation of queues and the removal of blockages under oversaturated conditions are prioritized over the minimization of travel time *(27)*. Hajbabaie & Benekohal (2013) recommended weighted trip maximization, maximization of throughput-minus-queue, trip maximization, and total delay as the objective functions for oversaturated conditions *(28)*.

Some studies aggregated multiple objectives together and performed a single objective optimization *(24)* while other studies performed multi-objective optimization and developed a Pareto front for selecting the optimal solution. Sun et al. (2003) demonstrated the efficiency of optimizing the average delay and the average number of stops in a multi-objective optimization for stochastic arrivals of traffic *(29)*. Kesur (2010) investigated and suggested the use of multi-objective optimization when there are multiple optimization variables as the method improved the optimization efficiency over the single objective optimization *(30)*. Ezzat et al. (2014) found better results from multi-objective optimization over single objective optimization for oversaturated conditions *(31)*. Other studies that used multi-objective optimizations include *(32-37)*.

8.2.3 Optimization Techniques

Heuristic optimization techniques such as Genetic Algorithm (GA) *(38,39)*, Simulated Annealing (SA) *(40)*, Ant Colony Optimization (ACO) *(41)*, Particle Swarm Optimization (PSO) *(42)* have been successfully applied to solve the traffic signal optimization and produce near-optimal solutions. Among the heuristic algorithms, only the GA, was successfully applied in traffic signal control optimization tools available for practical applications *(39)*. Initially, GA was used along with macroscopic simulation to optimize the signal. A study by Rouphail et al. (2000) revealed that a signal timing plan based on a direct signal optimization using a stochastic and microscopic simulation model produces better performance than that of a macroscopic simulation-based method *(43)*.

Later, Stevanovic et al. (2007) developed a program that utilized GA optimization in a micro-simulation interface to optimize the signal timing directly *(44)*. The authors showed that signal plans produced by the program are effective and continually outperformed those produced by traditional optimization tools that are based on analytical traffic models. Branke et al. (2007) used Non-dominated Sorting Genetic Algorithm II (NSGA-II), a multi-objective optimization, for developing signal timing plans using microscopic simulation *(32)*. The microscopic simulation-based NSGA-II algorithm was found successful in maximizing throughput and minimizing the queues in oversaturated conditions than traditional signal optimization tools *(45)*.

Stevanovic et al. (2013) used VISSIM based NSGA-II multi-objective optimization for signal plan development, considering mobility and safety together *(36)*. The authors used throughput as the measure of mobility and the number of conflicts as a measure of safety. The results demonstrated a 7% decrease in conflicts while maintaining the same throughput compared to the initial level. In another study, Stevanovic et al. (2015) incorporated environment measure as a third objective along with mobility and safety and developed a Pareto Front to select a better signal plan *(37)*.

8.3 METHODOLOGY

The analysis methodology of this study consists of three steps: i) Identification of diversion impact scenarios ii) MRM of the diversion scenarios to estimate path-level demands, and iii) Traffic signal plan development for each diversion impact scenarios using the path level demands resulting from DTA. An important aspect of the methodology is the calibration of the utilized mesoscopic simulation-based MRM based on the increase in demands and travel times on alternative routes using data from third party vendors. Another important aspect is the use of microscopic simulation-based optimization of signal timing utilizing a multi-objective optimization that jointly minimizes the delays and throughputs considering the whole intersections as well the specific impacted movements on the alternative routes. The details of the steps are discussed in the subsections that follow. The methodology was developed and demonstrated using incident and traffic data from January 2017 to December 2018, excluding holidays and weekends on Interstate-95 (I-95) facility in Broward County, FL, and the alternative routes. The traffic detector data for I-95 was retrieved from the regional data warehouse, maintained in the Regional Integrated Transportation Information System (RITIS). Incident data for the analysis horizon was retrieved from the incident management database maintained by the Florida Department of Transportation (FDOT) District IV. The incident data used in the models were incident start time, the number of blocked lanes, severity, and location. The travel time data for both the freeway and alternative routes were estimated using data from HERE, a private-sector travel time data provider.

8.3.1 Identification of Diversion Impact Scenarios

The first step is to use clustering to identify representative scenarios to develop special signal timing plans for. The clustering is based on the percentage change in travel time (Δ-Travel Time) on the potential alternative routes for six 15-minute intervals after the occurrence of the incident. A method was developed by the authors *(46)* to estimate the Δ-Travel Time as the difference between the predicted travel times on the alternative routes with and without the incident at 15-minute intervals, 15 to 90 minutes after the incident. The method utilized a long-short term memory (LSTM) based models for predicting travel time in the alternative routes during normal and incident conditions to allow the estimation of Δ-Travel Time. The details of the method can be found elsewhere *(46)*.

The clustering method used in this study is the K-means algorithm, which is a widely used method for data analysis *(47)*. One of the important aspects of clustering is to determine an adequate number of clusters to discern all the frequent patterns. There are several empirical methods available to identify the required number of clusters, such as the Elbow Method, Average Silhouette Method, and Gap Statistics Method. In this study, the optimal number was selected using the Elbow Method. With this method, a graph is drawn between the sum of square error (SSE) measure and the number of clusters, and the location of the bend in the plot is used as an indicator of the appropriate number of clusters *(48)*.

Besides the Elbow method, the study also utilized the t-distributed stochastic neighbor embedding (t-SNE) method *(49)*, a data visualization technique to verify the optimum number of clusters determined in Elbow method. t-SNE is a dimension reduction technique that uses equality of the conditional probabilities that represent similarities between the data points with high-dimension and low dimension based on the Euclidean distances in the dimension reduction. It is a variation of the stochastic neighbor embedding (SNE), which uses Student-t distribution to compute the similarity between two points in the low-dimensional space *(49)*. The method has been successfully implemented in different fields *(50,51)*.

8.3.2 Multi-Resolution Modeling

The next step is to identify the path-level demands on alternative routes associated with each of the clustered diversion scenarios since the available real-world data do not allow the estimation of these path-level demands. The utilized MRM approach emphasizes the importance of calibrating the percentage diversion of traffic to alternative routes and the impacts on the alternative route travel times in the mesoscopic simulation based DTA component of the MRM, as described in this section.

The MRM of the study corridor (I-95 in Broward County) uses a combination of the regional demand model, mesoscopic simulation-based DTA, and microscopic simulation. The regional demand forecasting model is the Southeast Florida Regional Planning Model (SERPM) that utilizes the Cube-Voyager software *(52,53)*. The SERPM model was used in the study to extract the initial network and the initial Origin-Destination (O-D) matrix for the case study area. The study area network and the O-D matrix obtained from the SERPM planning model were imported to the VISUM *(54)* software to develop a mesoscopic simulation model for use in combination with DTA. At this level, the model was calibrated for both normal and incident conditions. The geometry and traffic signals were input to the model. The Least Square O-D matrix estimation (ODME) module in VISUM was used to produce O-D demands that provide a good match to the turning movement counts for normal conditions. The parameters used as inputs to the ODME are traffic detector counts retrieved from RITIS and turning movement counts obtained from the FDOT District IV.

Figure 27 shows the calibration procedure carried out in this study with and without incident events. The real-world data used in the calibration of the mesoscopic simulation-based DTA model for incident conditions are traffic counts collected by traffic sensors on the freeway mainline, travel time data from a third-party vendor (HERE), and path-specific O-D traffic data from another third-party vendor (StreetLight). The path-based O-D traffic data contains an origin zone, a destination zone, and a path that the traffic uses to reach the destination. As an example, as shown in Figure 28(b), the data used in this analysis are originated from Zone 1 and go to the destination Zones 2, 3, and 4 using any of the alternative routes between the zones during incidents. Incident attributes such as the start time, incident duration, number of blocked lanes, and incident location, were coded in the model. The capacity reductions due to incident lane blockages were replicated in the model through the adjustment of the model parameters to meet the recommended reduced capacity due to incidents in the HCM 2016 *(18)*. The path-based O-D traffic and the travel time on the alternative routes were assessed in combination with the capacity reduction. The calibration was performed through an iterative process and continued until calibration criteria met. After calibration, the resulting path-based O-D traffic volumes and travel times were verified against the criteria set in the Traffic Analysis Toolbox (TAT) Volume III, published by FHWA *(55)*.

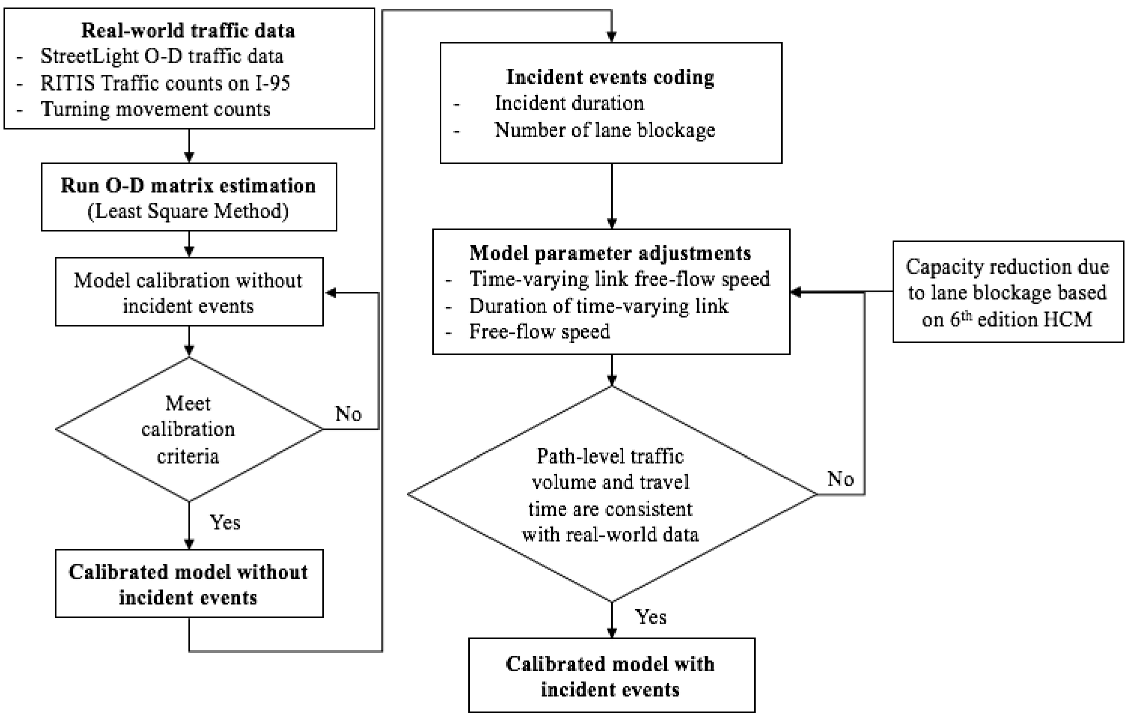
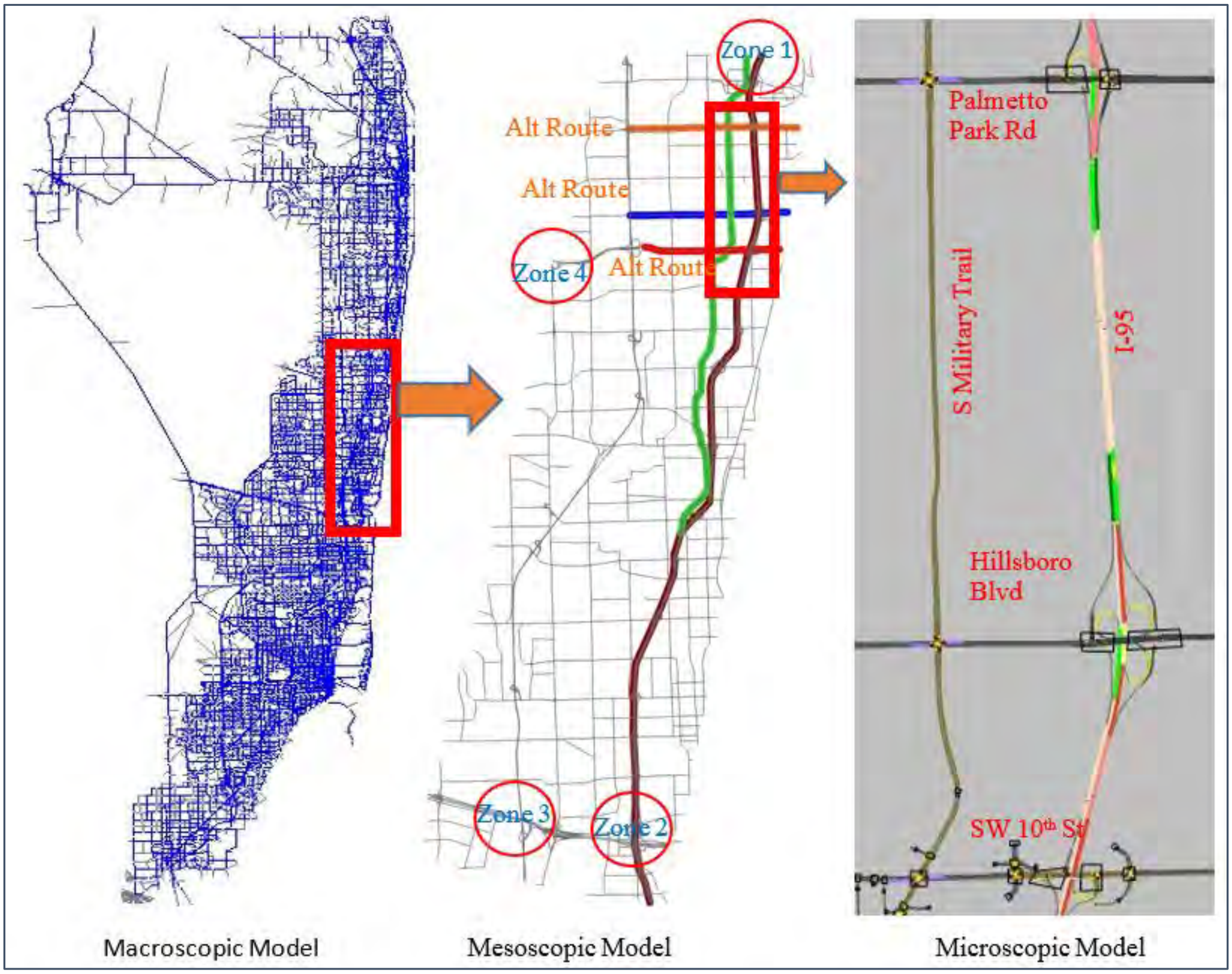


FIGURE 27: MESOSCOPIC MODEL CALIBRATION PROCEDURE

The diverted traffic volumes forecasted by the mesoscopic model were fed to a microscopic model coded in VISSIM *(56)* for detailed analyses of the performance of intersection movements. The coded network was calibrated following the methodology and criteria set in the FHWA TAT Volume III *(55).* In accordance with these criteria, both the traffic flows and travel times of the individual links of the model were within 15% of the observed values in the field in all cases. The calibrated model was used to develop and assess signal plans for the identified scenarios. Figure 28 shows the networks for the three modeling levels.



(a) SERPM Modeled Area **(b) Subarea surrounding Broward County** **(c) I-95 and major arterials**

FIGURE 28: NETWORKS FOR THE THREE LEVELS OF MODELING

8.3.3 Traffic Signal Plan Development

A microscopic simulation-based multi-objective optimization was utilized to develop the signal plans corresponding to different diversion scenarios that arise during incidents in the freeway. The calibrated microscopic model in the previous step was used in the optimization, and the NSGA-II algorithm *(57)* was used to solve the optimization problem. Since diversion can create congested intersection movement(s) with long queues, the objective functions used in the optimization include the maximization of throughput for the impacted movements by diversion as well as the minimization of the overall delay of all the intersections movements along the diverted path. The objective functions and subjected constraints used in the optimization are the following.

$$\text{Minimize } f_1(d) \tag{24}$$

$$\text{Maximize } f_2(N) \tag{25}$$

Where,
d= Average delay in the alternative route
N= Total throughput in the alternative route

The objective functions are subjected to the following constraints.

$$C_i = Cexist_i \quad \forall i \in I \tag{26}$$
$$gmin_{i,k} < g_{i,k} < gmax_{i,k} \qquad \forall i \in I, \forall k \in K_i \tag{27}$$

Where,
C_i=cycle length of intersection i
$Cexist_i$= existing cycle length at the intersection i
I= set of all intersections of the alternative route
$g_{i,k}$= green duration for phase k, at the intersection i
$gmin_{i,k}$= minimum green time associated with phase k, at the intersection i
$gmax_{i,k}$= maximum green time associated with phase k, at the intersection i
K= set of all phases available at the intersection i

In the optimization, the existing cycle lengths, minimum green splits for all phases, and offsets were kept the same as the existing values to ensure no violation of progression and pedestrian crossing requirements.

The theoretical foundation of GA was originally developed by Holland (1975). It is a heuristic optimization technique that imitates the biological processes of reproduction and natural selection to solve for the 'fittest' solutions *(58)*. Unlike GA, the NSGA-II belongs to a set of multi-objective algorithms that strive to find the Pareto front of compromised solutions of all objectives rather than integrating all objectives together *(57)*. The Pareto optimality concept was originally introduced by Francis Ysidro, and then generalized by Vilfredo Pareto *(59)*. A solution belongs to the Pareto set if there is no other solution that can improve at least one of the objectives without degradation of any other objective. NSGA-II was found to be able to maintain a better spread of solutions and converge better in the obtained non-dominated front *(57)*. As with GA, the algorithm performs crossover and mutation. However, a selection operator is used to create a mating pool by combining the parent and offspring populations and selecting the best individuals following the process of the non-dominated sorting and crowding distance sorting *(57)*.

The Component Object Model (COM) interface was used to implement the simulation-based optimization in combination with the VISSIM microscopic simulation using Python programming language to run the simulation and NSGA-II algorithm. The procedure was run for 25 generations consisting of 20 individuals in each optimization generation through the COM.

8.4 RESULTS AND DISCUSSIONS

This section presents a discussion of the analyses and interpretation of the results of the clustering analysis and scenarios selection, simulation model calibration, and the evaluation of the benefits of special traffic signal control plans against the normal day plan.

8.4.1 Determination of Number of Clusters

The optimal number of clusters was determined using the Elbow method. Initially, the t-SNE method was used to visualize the data to see the intrinsic patterns in the dataset. As stated earlier, t-SNE reduces the dimension of the data into two dimensions. Figure 29 shows the reduction of the Δ-Travel Times on the W Palmetto Park Rd for all 15-minute timesteps after the occurrence of all incidents to two dimensions using the t-SNE method. The figure depicts the presence of intrinsic clustering patterns in the dataset. In the Elbow method, the sum of square error (SSE) was plotted against the number of clusters obtained using the K-means clustering, as shown in Figure 30. The location of the kink in the elbow in Figure 30 indicates that twelve clusters are the optimal number of clusters to represent the impacts of diversion on the alternative routes during incidents. The twelve clusters were further analyzed next to identify the distinct scenarios for the signal control plans development.

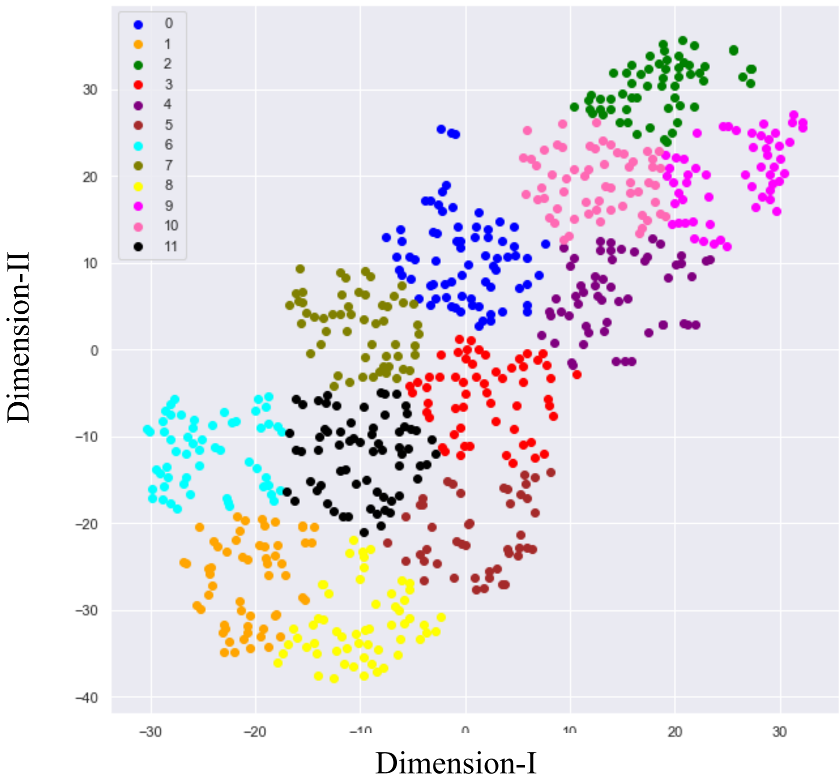


FIGURE 29: VISUALIZATION OF DATA IN LOW DIMENSION USING T-SNE

FIGURE 30: ELBOW PLOT

8.4.2 Selection of Scenarios for Plan Development

Table 35 shows the average Δ-Travel Times for the 12 selected clusters for the six 15-minute timesteps after the occurrence of the incidents. The analysis of the clusters indicates that the average Δ-Travel Time in Cluster 1 and Cluster 8 for all timesteps is within 25% of the normal day travel time and is within the natural variation of the day-to-day traffic. Thus, no new signal plans were developed for these two clusters, and they were excluded from further analysis. The remaining ten clusters show distinct patterns of Δ-Travel Time. The patterns do not only vary across the clusters but also across the timesteps. This happened because some incidents cause immediate diversion of traffic to the alternative routes while other incidents induced diversion at a later stage of the incidents based on the incident and traffic characteristics such as incident location relative to the freeway off-ramp exit to the alternative route, severity, number of lane blockage, traffic demands, and so on. The incident characteristics associated with each cluster are also shown in Table 35. For Clusters 1, 8, and 10, the incidents mostly occurred during the Midday or Evening periods, the severity of the incidents was low, and the locations were far from the exit to the alternative routes. The effect of the incidents on the alternative route travel times was very high when it happened during the AM or PM peak and close to the off-ramp exit to alternative routes, as in Clusters 2 and 3. Medium to high severity incidents grouped in Clusters 5, 11, and 12 affected the alternative routes during AM, PM peak, and Midday when the location of the incidents was far from the alternative routes. Cluster 6 reflects low to medium severity incidents during the PM peak, and Cluster 7 includes diversion during the Midday when the incidents occurred close to the exit to the diversion routes.

The variation of the average Δ-Travel Time across timesteps and clusters, as shown in Table 35, requires different signal timing plans to accommodate the varying diverted traffic demands and impacts. Typical incidents associated with each of the clusters were coded in the PTV VISUM mesoscopic model to simulate the associated scenarios and utilize the dynamic traffic assignment of the model to estimate the demands on each link of the alternative routes. The demands were then imported from VISUM to VISSIM to allow the optimization of the signal timing plan for each scenario within the microscopic model environment, as described earlier.

Please, note that although the clustering results are presented for all time periods in Table 35, the modeling and the optimization analyses presented in the remaining of this study are only for the AM peak period.

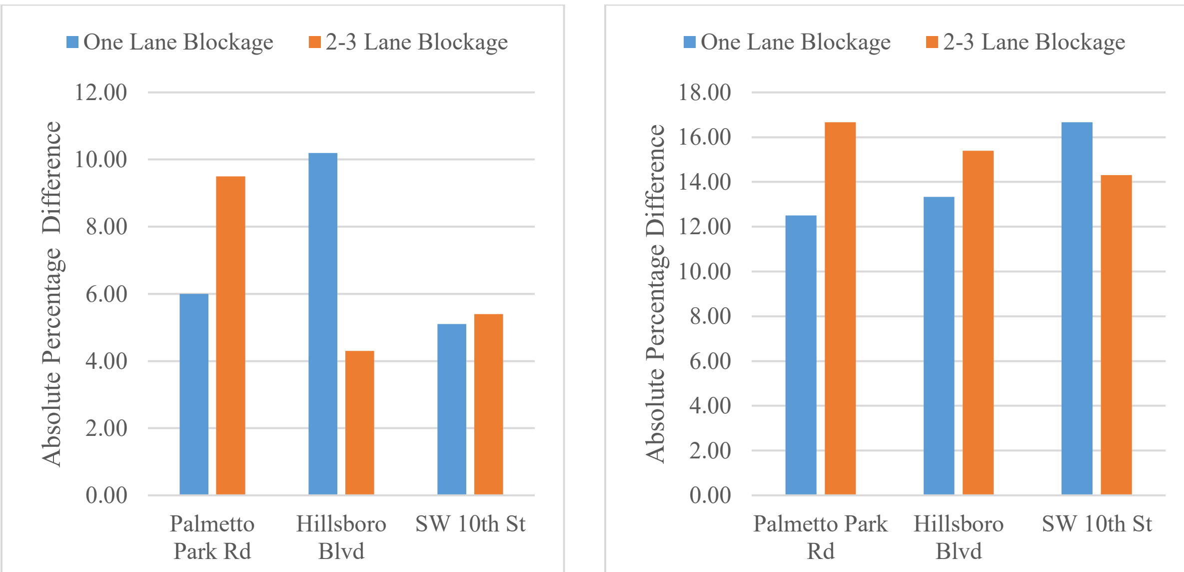
TABLE 35: AVERAGE Δ-TRAVEL TIME AND SIGNAL PLAN FOR SCENARIOS

	Avg. Δ-Travel Time (%) in different timesteps						Incident Characteristics	Analysis Scenarios
	1st Step	2nd Step	3rd Step	4th Step	5th Step	6th Step		
Cluster 1	X	X	X	X	X	X	Period: Midday & Evening Location: Far from the alternative routes Severity: Low	
Cluster 2	33.7	39.7	79.9	193.1	210.2	211.2	Period: AM and PM peak Location: Close to the alternative routes Severity: Low	Scenario I
Cluster 3	103.4	60.4	49.4	32.6	32.5	X	Period: AM and PM peak Location: Close to the alternative routes Severity: Medium to high	Scenario II
Cluster 4	29.2	62.3	82.1	27.8	X	X	Period: AM and PM peak Location: Far from the alternative routes Severity: Low	Scenario III
Cluster 5	X	X	28.2	43.6	31.3	147.5	Period: Midday Location: Close to the alternative routes Severity: Medium to high	
Cluster 6	103.2	126.3	136.2	126.7	67.4	65.8	Period: PM peak Location: Far from the alternative routes Severity: Low to medium	
Cluster 7	X	29.5	36.8	59.5	125.5	111.1	Period: Midday Location: Close to the alternative routes Severity: Low	
Cluster 8	X	X	X	X	X	X	Period: Midday & Evening Location: Far from the alternative routes Severity: Low	
Cluster 9	60.8	X	X	X	X	X	Period: AM and PM peak Location: Far from the alternative routes Severity: Low	Scenario IV
Cluster 10	X	X	25.1	28.2	27.5	30.1	Period: Midday & Evening Location: Far from the alternative routes Severity: Low	
Cluster 11	49.0	70.1	100.0	133.0	125.2	71.3	Period: AM and PM peak Location: Far from the alternative routes Severity: Medium to high	Scenario V
Cluster 12	51.4	46.1	47.7	46.4	54.9	61.5	Period: Midday Location: Far from the alternative routes Severity: Medium to high	

Note: 'X' ≤ 25%

8.4.3 Simulation Model Calibration Results

An important aspect of this study is to calibrate the simulation models not only to reflect normal conditions but the diversion during incident conditions. The calibration results of the mesoscopic model for the normal condition meet the FHWA TAT Volume III and are not presented here. More interesting are the results of the calibrate the model for the incident conditions considering the travel times and path-based demands on the diversion routes, as obtained based on data from third party vendors. The values of these variables for the three-diversion links between I-95 and S Military Trail were close to the criteria set by the FHWA TAT Volume III. Figure 31(a) shows that the difference between the model and real-world travel times for one lane blockage and two to three lanes blockage incidents were below 15%, as specified by the FHWA TAT Volume III. In the case of path-based traffic (Figure 31(b)), the modeled volume of the SW 10th St link for one lane blockage incidents and the Palmetto Park Rd link for 2-3 lane blockage incidents were slightly over 15%.



a) Difference in travel time **b) Difference in path-based traffic**

FIGURE 31: MODELED AND REAL-WORLD TRAVEL TIME AND PATH-BASED TRAFFIC DIFFERENCE DURING INCIDENTS

8.4.4 Pareto Front

The Pareto front, which is used in the optimization of the signal timing in this study, considers a set of non-dominated solutions to achieve an optimal trade-off between the competing objectives. The Pareto fronts in the signal timing optimization of all scenarios are shown in Figure 32. The fronts in this study consist of two competing objectives: average delay and overall throughput. The Pareto fronts for different plans moved upward compared to the Pareto front for the normal conditions, as the developed solutions for the incident diversion scenarios were able to increase the throughput without adversely affecting the average delay. The solutions at the two ends of each front signify the two extreme solutions corresponding to their objectives. Although the solutions in the middle of the front are optimal solutions based on both objectives; in special scenarios, agencies may decide to prioritize one objective over another, such as prioritizing the throughput on the alternative route compared to the total delay of the intersections.

The movement of the Pareto Front from the initial generation to the final generation of the Genetic Optimization of the signal timing plan associated with Scenario IV is shown in Figure 33. The approximated Pareto front for five selected generations showed the improvement of the solutions from one generation to the other. The solution in the final generation is far better than the first generation in terms of the objectives functions value and component variables, which confirms the success of the multi-objective optimization.

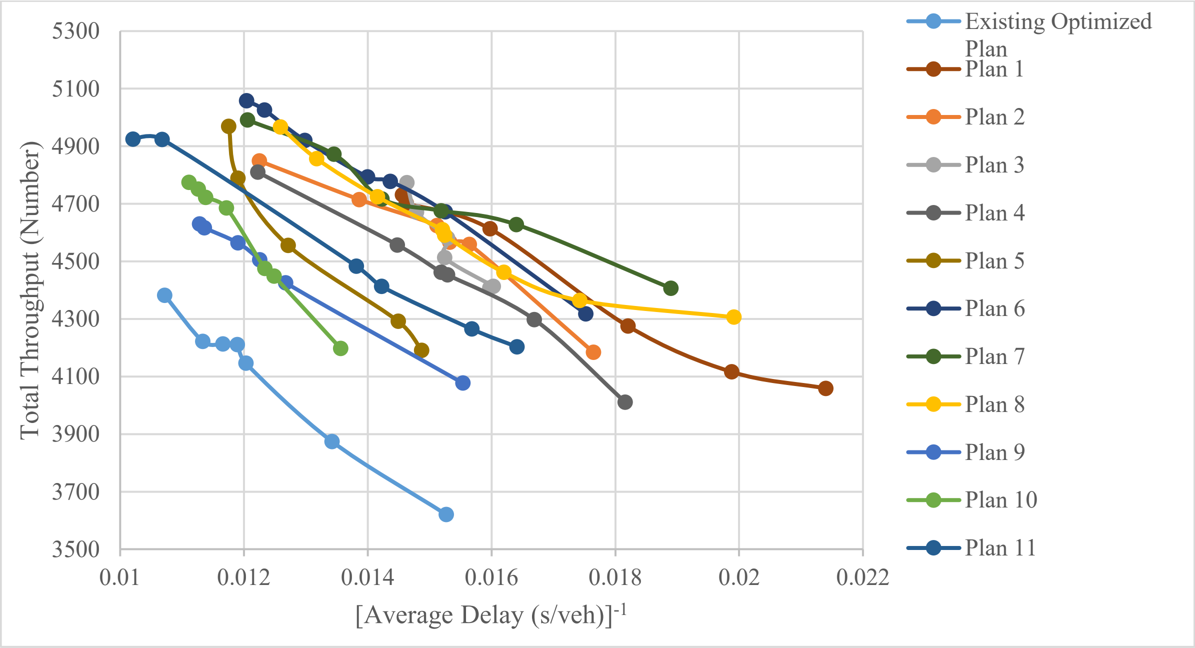


FIGURE 32: APPROXIMATED PARETO FRONT FOR ALL SCENARIOS

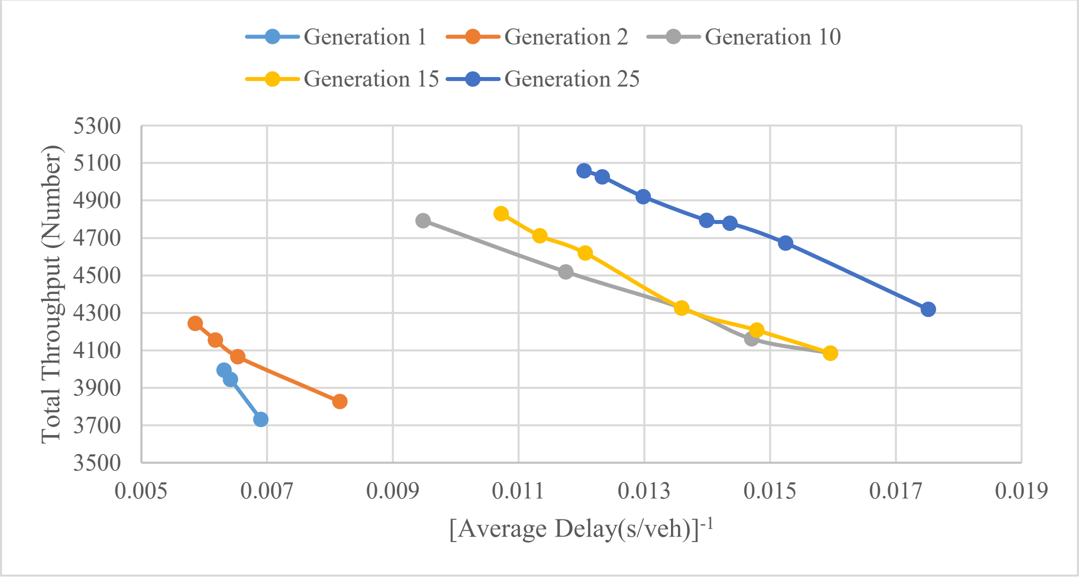


FIGURE 33: PARETO FRONT FOR DIFFERENT GENERATIONS

8.4.5 Evaluation of the Plan

The optimized plans for each scenario were evaluated to assess their performance using the microscopic simulation model. For this comparison, the plan that gives the maximum throughput for each scenario was selected from their corresponding Pareto front. This was done to accommodate the demand surge resulting from the diversion. The plan that provides the maximum throughput during the normal condition (without considering the diverted demand) was identified from the corresponding Pareto front as the base scenario for comparison. The evaluation was performed at both the network and diversion route movement levels. The diversion route movements included in the comparison are the west-bound left turn movement at the W Palmetto Park Rd-S Military Trail intersection and the south-bound through movements of two downstream intersections: Hillsboro Blvd-S Military Trail and SW 10th St-S Military Trail.

The percentages changes in both delays and throughputs due to the newly developed plans for all scenarios are shown in Figure 34. The developed plans for all scenarios increased the throughput while reducing the overall delay compared to the values obtained for the base scenario plan. However, the improvement in performance for the diversion route movements was far more significant than those for the overall network. For Scenario I, the throughput increased by 13% and 72% with the optimized plans compared to the base scenario plan, for the whole network and the diversion route movements, respectively. For the same scenario, the overall delay for the entire network and the diversion route movements was reduced by 17% and 54%, respectively. The changes in delay and throughput for Scenario IV was the lowest as the diversion impacted one timestep only. The increase in throughput and reduction in delay were higher for Scenario II than those for Scenario III due to the longer duration of impact on the diversion route in Scenario II. Although all six timesteps were impacted due to diversion in Scenarios I and V, the reduction in delay and increase in throughput were higher for Scenario I than those for Scenario V because of the high severity of the impact in case of Scenario I.

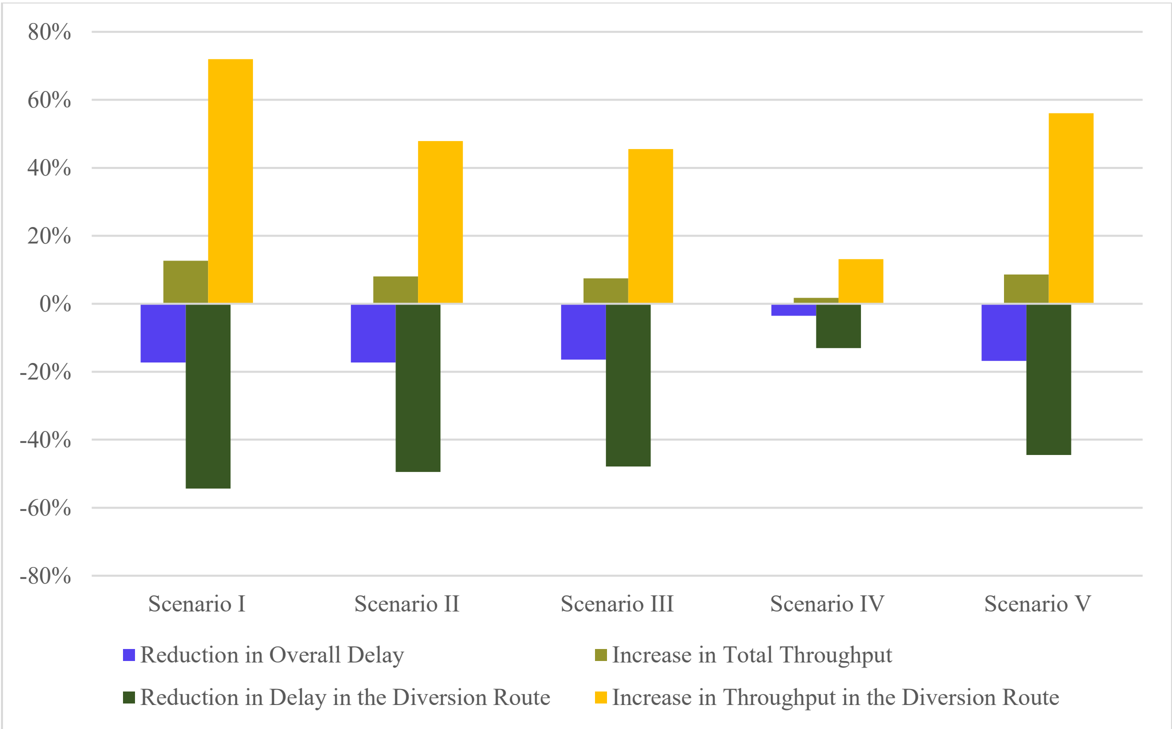


FIGURE 34: EVALUATION OF DERIVED TRAFFIC SIGNAL CONTROL PLANS FOR SCENARIOS

8.5 CONCLUSION

This study developed a methodology to support the selection of management plans as part of real-time decision support systems (DSS) at traffic management centers. The developed method can be applied for managing the traffic in the events of diversion from freeways to arterial streets during incidents on the freeway. The methodology identifies diversion impacts utilizing clustering analysis based on the increase in travel time on the alternative routes following the occurrence of incidents. The scenarios resulting from clustering are modeled utilizing an MRM modeling approach to estimate the demands on the diversion routes. The MRM is calibrated based on path-level demand data obtained from a third-party vendor. These demands were then used as inputs to microscopic-based optimization of signal timings to derive special signal timing plans to activate in the events of diversion. The proposed multi-objective optimization method provides the agency with the opportunity to prioritize different objectives in the optimization based on the prevailing condition, available resources, and purpose.

The evaluation of the signal timing plans resulting from the multi-objective signal timing optimization indicates that the derived special signal timing plans are able to reduce the delays and increase the throughputs in the network, particularly for the traffic movements utilized by the diverted traffic. The degrees of improvements depend on the level of impacts of the diverted traffic on the operations of the alternative routes.

The MRM approach used in this study provides the agency the opportunity of modeling different incidents, associated diversion of traffic, and the resulting impacts. The utilized approach emphasizes the importance of calibrating the percentage diversion of traffic to alternative routes and the impacts on the alternative route travel times in the mesoscopic simulation based DTA. This study successfully demonstrated this calibration. The use of emerging data sources, including those from third-party vendors, high-resolution controller data, and connected vehicles, will provide the needed information for such calibration.

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