ABSTRACT

DEVELOPMENT AND EVALUATION OF COOPERATIVE INTERSECTION MANAGEMENT ALGORITHM UNDER CONNECTED VEHICLES ENVIRONMENT

by
Slobodan Gutesa

Recent technological advancements in the automotive and transportation industry established a firm foundation for development and implementation of various automated and connected vehicle (C/AV) solutions around the globe. Wireless communication technologies such as the dedicated short-range communication (DSRC) protocol are enabling instantaneous information exchange between vehicles and infrastructure. Such information exchange produces tremendous benefits with the possibility to automate conventional traffic streams and enhance existing signal control strategies. While many promising studies in the area of signal control under connected vehicle (CV) environment have been introduced, they mainly offer solutions designed to operate a single isolated intersection or they require high technology penetration rates to operate in a safe and efficient manner. Applications designed to operate on a signalized corridor with imperfect market penetration rates of connected vehicle technology represent a bridge between conventional traffic control paradigm and fully automated corridors of the future.

Assuming utilization of the connected vehicle environment and vehicle to infrastructure (V2I) technology, all vehicular and signal-related parameters are known and can be shared with the control agent to control automated vehicles while improving the mobility of the signalized corridor. This dissertation research introduces an intersection management strategy for a corridor with automated vehicles utilizing vehicular trajectory-driven optimization method. The Trajectory-driven Optimization for Automated Driving

(TOAD) provides an optimal trajectory for automated vehicles while maintaining safe and uninterrupted movement of general traffic, consisting of regular unequipped vehicles. Signal status parameters such as cycle length and splits are continuously captured. At the same time, vehicles share their position information with the control agent. Both inputs are then used by the control algorithm to provide optimal trajectories for automated vehicles, resulting in the reduction of vehicle delay along the signalized corridor with fixed-time signal control. To determine the most efficient trajectory for automated vehicles, an evolutionary-based optimization is utilized. Influence of the prevailing traffic conditions is incorporated into a control algorithm using conventional data collection methods such as loop detectors, Bluetooth or Wi-Fi sensors to collect vehicle counts, travel time on corridor segments, and spot speed. Moreover, a short-term, artificial intelligence prediction model is developed to achieve reasonable deployment of data collection devices and provide accurate vehicle delay predictions producing realistic and highly-efficient longitudinal vehicle trajectories.

The concept evaluation through microsimulation reveals significant mobility improvements compared to contemporary corridor management approach. The results for selected test-bed locations on signalized arterials in New Jersey reveals up to 19.5 % reduction in overall corridor travel time depending on different market penetration and lane configuration scenario. It is also discovered that operational scenarios with a possibility of utilizing reserved lanes for movement of automated vehicles further increases the effectiveness of the proposed algorithm. In addition, the proposed control algorithm is feasible under imperfect C/AV market penetrations showing mobility improvements even with low market penetration rates.

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A Dissertation
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Transportation

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May 2018

APPROVAL PAGE

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This dissertation is dedicated to my family
Wife, Marija
Daughter, Ema
Parents, Nada and Milan

Посвећено члановима моје породице
за сву подршку, жртву, стрпљење
и неисцрпна охрабрења

ACKNOWLEDGEMENT

I would like to express my deepest appreciation to those who helped me successfully complete my doctoral study.

First, I would like to thank my advisor Dr. Joyoung Lee for his devoted guidance, encouragement and advice throughout my dissertation research. Without his support as a supervisor and dissertation advisor, this dissertation would not have been possible. I would also like to thank Dr. Lazar Spasovic for providing me with an opportunity to participate in several influential projects through the New Jersey Department of Transportation ITS Resource Center at NJIT. The skills and experience I gained through those projects were of an irreplaceable importance for me. I would also like to thank members of staff in the Department of Civil and Environmental Engineering, Branislav Dimitrijevic and Dejan Besenski for their help and support. Many thanks to Zijia (Gary) Zhong for constructive discussions and knowledge sharing.

I would also like to express my sincere appreciation to the rest of my dissertation committee, Dr. Steven Chien in the Department of Civil and Environmental Engineering at NJIT, Dr. Grace Wang of the Yingwu College of Computing Science at NJIT, and Dr. Parth Bhavsar of Rowan University, for their time and valuable input.

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CHAPTER 1

INTRODUCTION

1.1   Background

To improve efficiency and safety of road transportation systems without adding additional physical capacity, researchers have begun to investigate the synergy between the communication technologies and automotive industry. Those modern technologies paved the way for new automotive revolution supported and initiated by the growing connected vehicle (CV) technology. The Fixing America's Surface Transportation (FAST) Act [1] was introduced in 2015 with the goal of providing long-term funding for surface transportation planning and investment. The authorization of a $305 billion over fiscal years 2016 through 2020 created direct opportunity to improve the performance of nation's surface transportation in terms of mobility, job creation, and promotion of innovations. As auto manufacturers and academia are responding rapidly by offering various self-driving solutions readily available, United States Department of Transportation (USDOT) and other public sectors developed a Connected Vehicle Reference Implementation Architecture (CVRIA) [2] to support and accelerate the implementation of connected vehicles. Under the Connected Vehicle Pilot Deployment Program [3], the USDOT Joint Program Office (JPO) has selected three pilot sites in New York City, New York, Interstate 80 (I-80) in Wyoming, and Tampa, Florida for which they successfully developed the concept of operations (ConOps), Deployment Outreach Plan, and Deployment Readiness Summary [4]. All those efforts are indicating the rising need for efficient and easily implementable control systems that can utilize the connected vehicle environment.

Over the past decade, the contemporary traffic operation and control strategies focused mainly on fixed-time, actuated, traffic responsive pattern selection (TRPS), and Adaptive Traffic Control [5]. The fixed-time control with predetermined time-of-day (TOD) plan is still widely used across the country since it is fairly easy to implement. Where more complex traffic patterns are observed, many agencies opted for adaptive traffic control solutions due to frequently observed day-to-day and hour-to-hour volume variations. Almost all adaptive signal control systems utilize the projections of vehicle arrivals [6]. In many cases, due to the stochastic nature of the vehicular movement, such predictions of vehicles' arrivals are not sufficiently accurate and can undermine the intersection performance.

Nonetheless, some recent studies show that the predetermined time-of-day (TOD) control approach along with reliable prevailing traffic information can provide an adequate system efficiency [7]. Those systems heavily rely on the traffic counts and turning movement data that is naturally associated with a significant level of variation. Collecting such huge amount of data on a daily basis and updating signal control setting would involve unacceptable manpower requirements and significant financial resources [8]. Thus, the connected vehicle and infrastructure environment attributes can be utilized to develop a new traffic control paradigm, where the control system is designed to convey the most desirable speed to individual road vehicles, based on the current state of traffic streams, the state of signalization, and the position of the individual vehicles in real time.

1.2   Problem Statement

To the best of author's knowledge, the previous studies offer solutions that are either developed to operate on a single, isolated intersection or they require a high market penetration of technology. In addition, the majority of reservation-based control algorithms are operating on a first-come-first-served (FCFS) rule. Some studies presented in the next section of this dissertation indicated a variety of scenarios in which traffic signals outperformed the reservation-based control strategies on the arterial roadway. It was found that the fairness of the first-come-first-served reservation rule may disrupt the platoon progression and therefore increase total vehicle delay of an arterial intersection. The main reason can be found in the fact that the vehicles on the local road requested a reservation before vehicles on the arterial submitted their requests, therefore, making the conventional rules of corridor coordination impossible.

None of the existing efforts addressed this drawback. The mobility improvements that were detected are based solely on an isolated intersection testbed often ignoring the corridor-wide context. The same drawback was detected in the area of the trajectory-driven control approach used by several authors. Again, all reviewed studies fail to observe the corridor-wide context or do not offer a viable option for low market penetration conditions.

The SPaT-related studies are divided into two major categories 1) Eco-driving oriented control strategies, 2) Green-wave oriented control strategies. Reviewed studies offer an irreplaceable methodological and practical contribution. The methodology is proven and some proposed solutions are even implemented and tested in the field. However, all the reviewed studies offer a decentralized solution designed for the operation of a single

vehicle (often tested on a testbed consisted of a single isolated intersection) rather than offering a system-wide corridor control.

It is well known that all adaptive signal control systems inevitably depend on the projections of vehicle arrivals, and reliability of the detection system. Since the nature of the vehicular movement is stochastic, the prediction of vehicles' arrivals is often inaccurate. To remedy mentioned problems many authors investigated the utilization of the connected-vehicle environment to replace the conventional detection paradigm. However, if large portion of the traffic stream is not equipped with a proper communication device, the accuracy of the collected parameters (vehicle arrivals, travel time, speeds, queue length etc.) do not represent an adequate replacement of the on-line measure and the low penetration conditions still encounter the same limitation of the conventional on-line optimization.

1.3 Motivation

In the current state of the practice, various sophisticated signal control solutions have been implemented. Introduction of actuated and adaptive systems represent a signal control paradigm where traffic control devices are designed to conform to prevailing traffic conditions. Due to that, the described signal control utilizes complex detection systems and control logic. In contrast to the described paradigm, this research utilizes a connected vehicle environment where communication between vehicles and infrastructure allows development of the new intersection management paradigm. This paradigm assumes instantaneous adjustment of vehicles to given signal timing conditions, produced by control

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devices. Thus, the main motivation is to develop a new, simple, and low-cost solution, functional under the connected and automated vehicles environment.
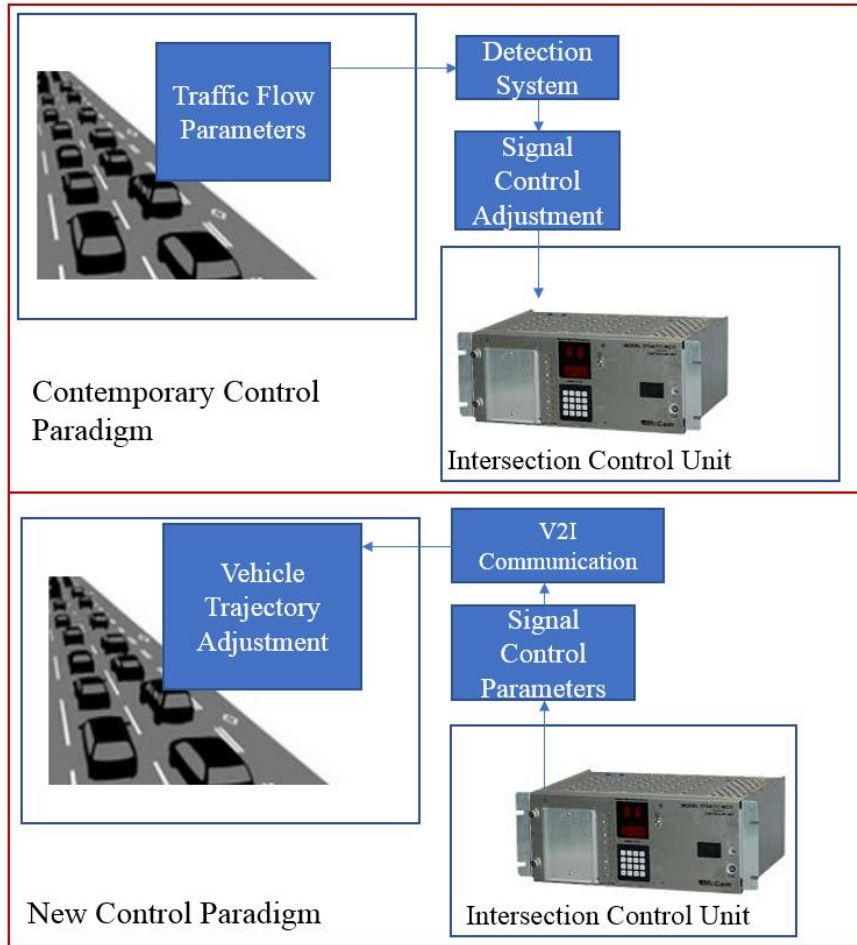
Figure 1.1 The new intersection management concept.

1.4   Goal and Objectives

All existing signal control strategies are sharing one common approach: manipulating and adjusting the signal control devices in the manner that they accommodate prevailing traffic conditions. To that end, many complex systems have been introduced often requiring significant financial investments, maintenance, and implementation costs. Against the existing efforts, the primary goal of this research is to introduce a new signalized corridor

management strategy where the traffic streams are manipulated to conform to the signal control devices. Signal status parameters (i.e., cycle length and remaining green/red time) are continuously captured by the control instance. At the same time, vehicles provide their position through the connected vehicle environment. Both inputs are then used by predictive, trajectory-driven, control algorithm, namely Trajectory-driven Optimization for Automated Driving (TOAD) to adjust the trajectory of each automated vehicle in the system. As the proposed control strategy is designed to manipulate the prevailing traffic flow, rather than adjusting the signal timing and configuration, simple pre-timed devices are sufficient for the successful system operation. It is envisioned that described control strategy allows the gradual introduction of the automated vehicles with no need for replacement of the contemporary signal control devices.

Besides the possibility of utilizing existing conventional control devices, it is also important that the solution is capable of handling the low technology penetration rates. To this end, the following objectives are addressed:

- Objective 1: To develop the control algorithm for automated vehicles utilizing individual vehicular and signal timing information. The information is captured instantaneously and used by the control agent to generate the optimal trajectories for the automated vehicles while respecting the prevailing traffic constraints.

- Objective 2 To develop an artificial intelligence model to predict prevailing traffic conditions to be incorporated into trajectory optimization framework

- Objective 3: To develop the testbed using microsimulation platform and evaluate the performances of the developed control algorithms by comparing them with existing traffic signal control logic under various volume scenarios. The evaluation scenarios include the possibility of utilizing managed lanes reserved for movement of automated vehicles.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the review of existing research efforts in the field automated vehicle-based intersection control, control strategies utilizing Signal Phase and Timing (SPaT) information exchange, and control strategies utilizing on-line optimization. The automated vehicle control is divided into two major categories: 1) reservation-based approach and 2) trajectory-driven approach, while SPaT- related efforts are divided into 1) eco-driving and 2) green-wave oriented control strategies. Utilization of the on-line optimization is observed from the aspect of the conventional and connected-vehicle oriented approach.

2.1   Automated Vehicle-based Intersection Control

An automated vehicle refers to a vehicle that can achieve a safe movement on a roadway facility without the influence of a human driver. With emerging trend of the connected vehicle concept over the past decade, numerous state-of-the-art applications focusing on automated vehicle-based intersection control have been proposed. The following section focuses on the relevant achievements in this area. Based on the exhaustive literature review, the autonomous and automated vehicle-based efforts can be divided in two broad categories: 1) reservation based, and 2) trajectory-driven algorithms and solutions.

2.1.1   Reservation-based Control Algorithms

One among very first studies of the intersection control for autonomous and automated vehicles was conducted by Dresner and Stone [9]. The methodology is focusing on an

intersection reservation system. In the proposed system, driver agents (i.e., vehicles with an onboard unit) "call ahead" to an intersection manager, located at the intersection, to reserve the space-time slot needed to cross the intersection safely. The methodology assumes the existence of an intersection manager program responsible for spatial and temporal manipulation of the vehicles' positions to achieve safe operation of an intersection. The intersection is divided into virtual cells and intersection reservation is produced with respect to spatial and temporal occupancies of the virtual cells where vehicle maneuvers are adjusted to ensure safe operation. Assuming 100% autonomous vehicles, the performance was evaluated for a four-way intersection containing three lanes for each approach under traffic volumes of up to 750 vph. Under given conditions, delay reductions of up to 94% were detected.

Similarly, VanMiddlesworth et al. [10] proposed an intersection control mechanism for autonomous vehicles based on peer-to-peer communication among vehicles where no signals or stop signs are necessary. The control is achieved by making a reservation when a vehicle reaches a predetermined point where it needs to convey information to other vehicles how it intends to cross the intersection. While achieving significantly low average delay (<0.5 sec) for low-volume conditions, the algorithm is not suitable for high-volume conditions and it is outperformed by the conventional signal control if the vehicle arrival rate is above 0.7 vehicles per second.

Road time-space occupancy concept was also utilized by Jin and Wu [11] to develop a multi-agent intersection control. This connected-vehicle based advanced traffic management system (ATMS) assumes communication between vehicles and infrastructure in real time to produce intersection time-space reservations and then provide feedback to

vehicles. The vehicle agents then adjust their trajectories to meet the assigned time slot. The concept was evaluated using microsimulation platform for an isolated intersection where reductions of vehicle emissions were observed. The study does not assess the mobility aspects and requires all vehicle agents to be fully controllable.

A reservation-based intersection control system named autonomous control of urban traffic (ACUTA) was introduced by Li et al. [12] where vehicles in a reservation-based system communicate with centralized intersection controller. The intersection controller regulates the intersection by determining the passing sequence for all the vehicles approaching the intersection. The intersection is divided into a mesh of tiles used for the time-space reservation algorithm. Like previously mentioned studies, the methodology assumes that the vehicle sends a request along with its location, routing, and speed information to the intersection manager. The intersection manager processes the reservation request by computing the time-space occupancies for the intersection tiles to ensure the safe crossing of the vehicle. The evaluation considered an isolated intersection under different volume conditions reporting the increase in the intersection throughput by 33% percent.

Huang et al. [13] developed similar, reservation-based methodology. The new reservation protocol proposed in this study requires the approaching vehicles to update their information at every consecutive time step, based on that information, the system recommends a speed profile for vehicles to follow until they cross the intersection, and prioritizes vehicle requests, in a hierarchical fashion. The prioritizing is based on several factors, including the distances of the vehicles to the stop line. The study reported a reduction of average vehicle delay by 85%, fuel consumption by 50%, and emissions by

39%-50%. Hausknecht et al. [14] expanded the methodology introduced by Dresner and Stone [9] by including different navigation policies which autonomous vehicles can utilize to dynamically alter their planned paths. The methodology also introduces a possibility of dynamically reversing the flow of traffic along lanes in response to minute-by-minute traffic conditions. The proposed algorithm showed about 32% decrease in average vehicle delay for a network of four interconnected intersections.

Ahmane et al. [15] proposed a control logic for an isolated intersection where the right of way information is conveyed through an onboard screen. This reservation-based control approach assumes that all vehicles are equipped with an onboard unit and are able to wirelessly negotiate the right of way. The control policy for controlling an isolated intersection comprises the exchange of the request messages between vehicles. The result of the control policy is a sequence of authorized vehicles allowed to traverse an intersection in the order of First in First Out (FIFO). The control algorithm is utilizing the self-organizing theory where simple, locally established rules lead to global complex behavior. The proposed approach is tested through a real intersection with four ordinary vehicles and a simulation. The simulation considered two levels of traffic flow, 1800 and 2800 vehicles per hour revealing almost 50% of the delay reduction compared to the conventional traffic signal control. Another, reservation-oriented algorithm for driverless vehicles has been proposed by Zhang et al. [16]. The control model assumes autonomous motion with its spatial-temporal and kinetic parameters based on centralized scheduling mechanism. The control approach respects FIFO priority rules but has an ability to flexibly adapt pass requests from emergent vehicles.

Lu et al. [17] proposed a priority-based V2V protocol where vehicles equipped with sensors share their position, speed, and acceleration to establish a sequence of a vehicle passing through an uncontrolled intersection. The set of rules has been introduced depending on the current vehicle position and desired maneuver (i.e left, right, or through) in the intersection. If the approaching car needs to yield other cars, the proposed algorithm finds a proper deceleration value to execute safe yielding. The car brakes automatically using this deceleration value to avoid collision with other cars. Although the methodology utilizes the adjustment of vehicle's trajectory, the methodology has certain similarities with previously mentioned, reservation-based methods as the adjustment of the trajectory is based on the previously determined sequence of vehicles.

Elhenawy et al. [18] developed a game-theory based algorithm to replace conventional signal-based intersection control by utilizing V2I communication. The proposed algorithm is chicken-game inspired and is effective for application in real-time. It assumes vehicles can communicate with a central agent at the intersection to provide their instantaneous speeds and locations. The developed algorithm is designed to control an isolated intersection by resolving the conflict between crossing vehicles considering 100% market penetration of the automated vehicle technology. Although showing promising results, the study did not provide relevant performance evaluation with respect to different volume rates and market penetration level.

Zhu et al. [19] developed a reservation-based algorithm, namely Look-ahead Intersection Control Policy (LICP) where the main idea is to choose a right decision whether a vehicle can receive a passing permission based on the predictive value of total delay if postponing the current reservation request is conducted. The evaluation was

conducted using simulator developed by authors. The evaluation was conducted using different volume rates and comparison between FIFO-based reservation rule. It was determined that LICP can make nearly 25% performance improvement on average intersection delay than the previous FIFO method.

Sharon and Stone [20] studied the possibility of combining reservation-based, first-come-first-served methodology and conventional signal control to allow intersection operation under imperfect market penetration level, namely H-AIM. The H-AIM grants reservation in a first-come-first-served (FCFS) order. The algorithm automatically rejects reservation requests that conflict with regular, signal controlled vehicle's trajectory (active green trajectory). The methodology was evaluated using microsimulation, showing that the protocol can decrease traffic delay for autonomous vehicles even at 1% technology penetration rate.

Although mentioned studies presented promising results for an isolated intersection a comprehensive study conveyed by Levin et al. [21] in 2016 revealed a variety of scenarios in which traffic signals outperformed the reservation-based control strategies on two realistic networks (arterial roadway and downtown city area) in Austin, Texas. It was found that the fairness of the first-come-first-served reservation rule increases total vehicle delay at an arterial road intersection. One of the main reasons why reservation-based logic was outperformed by the conventional signal-based control is that the reservation rule disrupted platoon progression that would occur with timed signals on an arterial roadway. Because vehicles on the local road requested a reservation before vehicles on the arterial submitted their requests, vehicles on the local road have their reservation accepted.

2.1.2 Trajectory Planning Algorithms

In addition to reservation-based control approach, several promising algorithms have been proposed utilizing vehicle trajectory adjustment to achieve safe and efficient intersection control. The trajectory of a vehicle is described using a time-space diagram (frequently used in coordination analysis), that is the predictive position of a vehicle in the observed time window where a known kinematic relationship between vehicle velocity, acceleration, and time are used.

Ding et al. [22] developed a centralized cooperative intersection control (CCIC) approach for the non-signalized intersections under automated vehicle environment. The aim of cooperative intersection control is to guide vehicles passing the intersection using V2X communication technology. The objective of centralized cooperative intersection control is to minimize the intersection delay, fuel consumption, and emission as well as the discomfort level of drivers. Collision avoidance is handled by manipulating the predictive trajectories of individual vehicles. The model assumption is that all vehicles are automated vehicles equipped with the V2X communication device and they follow the instructions absolutely. A microsimulation model of a single four-leg intersection reveals 10.49%-17.61% improvement in throughput and 17.78%-37.81% of gas savings under traffic conditions of 400-900 vehicles per hour per intersection approach.

Lee and Park [23] developed a Cooperative Vehicle Intersection Control Algorithm (CVIC) under the connected vehicles environment. The CVIC algorithm was designed to manipulate individual vehicles' maneuvers so that vehicles can safely cross the intersection without colliding with other vehicles. To that end, a nonlinear, trajectory-driven optimization algorithm was solved using genetic algorithm approach to adjust trajectories

of individual vehicles for the safe crossing. A simulation-based case study implemented on a hypothetical four-way single-lane approach intersection under varying congestion conditions showed that the CVIC algorithm significantly improved intersection performance compared with conventional actuated intersection control detecting 99% and 33% of stop delay and total travel time reductions, respectively.

Similarly, Wuthishuwong et al. [24] developed a V2I control algorithm for an intersection under fully automated traffic conditions. The methodology utilizes intersection distance and time discretization where the trajectory of each vehicle is planned by the vehicle itself based on the returned timing index from the intersection manager. The four-way intersection with a single lane of incoming and outgoing traffic is used as the reference model in the simulation scenario with the traffic flow rate from the minimum 1 vehicle per hour up to the maximum 3,000 vehicles per hour. It was discovered that proposed control algorithm outperforms the traditional traffic light in terms of overall delay and throughput.

2.2 Control Strategies Utilizing Signal Phase and Timing (SPaT) Information Exchange

The benefit of utilizing the vehicle to infrastructure (V2I) communication to improve the operation of conventional, signalized intersections have been studied extensively over the past decade. The main idea behind the concept is to provide the advisory speed through an onboard device to improve safety, environmental and mobility performance of a conventional, signal-based control strategy or utilize SPaT information to manipulate the movement of automated vehicles. While the impact of the SPaT concept on transportation safety has not been extensively studied, the relevant SPaT-related research went into two directions: eco-driving, and mobility-related (also known as the green-wave) approach.

2.2.1 Eco-Driving Oriented Control Strategies

Jiang et al. [25] proposed an eco-driving system for an isolated signalized intersection under partially connected and automated vehicles (C/AV) environment. This system prioritizes fuel efficiency before improving mobility and manipulates the entire traffic flow by optimizing speed profiles of the connected and automated vehicles. The inputs of the optimization algorithm are instantaneous speed for each controlled vehicle, vehicle arrival time and signal phase and timing (SPaT) information from the traffic signal, and the trajectory information of the preceding vehicle. The objective is to minimize total fuel consumption and emissions and maximize comfort while maintaining the throughput at its optimum level. The simulation results for an isolated intersection indicate the proposed system could save fuel by up to 58%, reduce emissions by up to 33% and improve throughput by up to 11%. Although this study provides promising results, it is not clearly addressed how will the optimization methodology affect traffic streams on a signalized corridor. This aspect is crucial since the paradox described by Levin [21] proves that a control strategy performing well on an isolated intersection can be outperformed by the conventional signal control strategy if the innovation undermines coordination of a corridor.

Rakha and Kamalanathsharma [26] developed an eco-driving framework that utilizes vehicle-to-infrastructure (V2I) communication to receive signal phasing and timing (SPaT) information and compute the optimal acceleration rate to minimize fuel consumption while passing through an isolated intersection. A vehicle dynamics model is used to describe the acceleration maneuver and statistical model consisting of linear, quadratic and cubic combinations of speed and acceleration levels using chassis

dynamometer data. The eco-drive model predicts the fuel-optimum speed profile for vehicles approaching an intersection and provides instantaneous speed assuming Dedicated Short-Range Communication (DSRC) connectivity between vehicles and the infrastructure. While mainly focusing on the development of the strategy which yields the most fuel-optimal speed profile for a vehicle approaching a signalized intersection using V2I communication capabilities, the study does not provide detailed performance analysis in different traffic volume and technology penetration conditions.

A field operational testing of an eco-driving technology at a fixed-time signalized intersection was performed by Xia et al. [27]. A communication platform based on a 4G/LTE network link and a cloud-based server were utilized to exchange SPaT information between vehicle and infrastructure. The control logic utilizes SPaT and vehicle position information, calculates a recommended cruise velocity for the vehicle given the constraints of roadway speed limit and surrounding traffic. Based on given information, the algorithm is producing the most fuel-efficient acceleration or deceleration profiles for reaching the desired cruise velocity. It was found in both the simulation experiment and the field operational testing that on average 14% fuel and CO2 savings can be achieved. The optimal speed recommendation was delivered to a driver through an onboard device also used for computation of the recommended speed trajectory.

Similarly, Kundu et al. [28] developed a model for eco-driving to minimize total fuel consumption for a signalized intersection utilizing SPaT information to calculate optimal advisory speed which allows the driver to go through the green light and reduce the stop-and-go driving pattern and thus reducing fuel consumption. Simulation results discovered that the algorithm can reduce fuel consumption by 10% in a journey for a single

fixed platoon of vehicles. Niu and Sun [29] compared two SPaT related models, the eco-driving model, and the green wave speed guidance model. While the first one mainly focuses on the minimization of the fuel consumption and emissions, the second one was designed to minimize the travel time of a vehicle through an isolated intersection. The guided velocity is dynamically adjusted based on the vehicle s spatial-temporal trajectories, in relation to which an optimization-based rolling horizon and a dynamic programming approach were adopted. To determine the effectiveness of the overall strategies, 15 typical drivers took part in the driving simulator studies and it was determined that the fuel consumption and CO_2 emissions can be reduced by 25% and 13% under eco-driving and green wave guidance respectively.

Kamal and Yochimura [30] observed a partially connected vehicle environment where only a fraction of traffic has Dedicated Short-Range Communication (DSRC) connectivity. They also assume that the SPaT information can be broadcasted by the intersection agent when vehicles are within the communication range. The optimization problem is formulated to drive a single vehicle, with respect to signal timing and preceding vehicle constraints. To that end, a cost function with a defined penalty for vehicles violating the red signal state was optimized using the finite horizon approach. The evaluation of the methodology was conducted for a single technology penetration rate of 10%. It was determined that with 10% of technology penetration, the methodology improves fuel economy by 4.5% and reduces travel time by 4.7% on a road section of 1 km with a single, isolated intersection.

2.2.2 Green-wave Oriented Control Strategies

Besides described eco-driving strategies, some author focused on utilizing SPaT information to improve mobility (i.e. travel time, intersection throughput). Chen and Chang [31] proposed a framework focusing on cooperative traffic control between vehicle and infrastructure producing optimal signal timing pattern and formation of a green wave on a signalized corridor. With the assumption of 100% technology penetration almost 50% improvement in travel time was detected, however, the impact of the proposed control algorithm on the delay of minor street approaches was not addressed in the study.

Lee et al. [8] developed a control algorithm to minimize the travel time of a vehicle on a signalized corridor with actuated intersections. The algorithm utilizes SPaT data and an onboard unit. The onboard unit is a smartphone device which along with SPaT information from 11 intersections, and the vehicle position obtained from embedded smartphone GPS receiver produces an advisory speed range displayed to the driver. Following the advisory speed, driver minimizes the number of stops along the corridor. The control algorithm was tested in live traffic on a signalized corridor in New Jersey showing up to 25% of travel time reduction.

A study conducted by Katsaros et al. [32] evaluates the application of a traffic light assistant service, namely Green Light Optimal Speed Advisory (GLOSA). Following previously mentioned concept, the methodology utilizes SPaT messages that along with the provision of vehicle parameters through an onboard unit produces optimal speed value to avoid stopping at the signal. The study describes the algorithm operation and reports impact on travel time and fuel consumption based on a simulation model of two signalized intersections under different market penetration scenarios. The study detected a maximum

of 80% reduction in stopping time and up to 7% reduction in fuel consumption in a high traffic density scenario.

Jinjian and Dridi [33] introduced a multi-vehicles green light optimal speed advisory algorithm based on the augmented Lagrangian Genetic Algorithm. The study introduces an optimized method to get the global optimized fuel consumption based on the minimal total running time. This study is processing the multi-vehicles problem by assigning car fleet and car-following model. The main idea is to utilize both signal information, and position of individual vehicles to form fleets of vehicles that can pass an intersection as a group. Firstly, a leading vehicle gets assigned and it searches the most related traffic light cycle, in which it could pass the intersection as fast as possible; then, all vehicles that have the same most related traffic light cycle are assigned to the same car fleet. The simulation was performed for a single fixed-time intersection, revealing significant vehicle delay reductions.

Similarly, Stebbins et al. [34] examined the possibility of utilizing the optimal green light speed advisory trajectories for platoon-based optimization. This algorithm produces the advice given to a vehicle, by optimizing the delay while considering the corridor-wide trajectory. Optimization is achieved through the provision of initial conditions – time until green, distance to the intersection and initial speed. The optimal speed advice also takes into account a suitable safety constraint, ensuring that vehicles are always able to stop before the intersection during a red interval. Platoon formation is proposed through a time-loop technique, which allows accurate identification of the leader even when there are complex interactions between preceding vehicles. A single intersection was simulated with

average traffic flow ranging from 100 to 700 vehicles per hour per lane, providing average delay reduction of 30–50%.

2.3 Intersection Control Strategies Utilizing On-line Optimization

This section provides a review of the research conducted for online signal optimization under conventional and connected vehicle environment.

2.3.1 Conventional On-line Traffic Responsive Control

Due to its limited ability to deal with traffic flow fluctuations, the fixed-time control was replaced by more sophisticated solutions such as adaptive traffic control [35] and actuated systems [36]. Thus, the adaptive signal control strategy gained a significant deal of attention around the globe. One of the very first studies conducted for the adaptive system in Sydney, Australia, namely SCAT, estimated travel times reductions to reach 39.5-percent in the peak period [35]. Similarly, initial travel time savings for the SCOOT (Split, Cycle, Offset Optimization Technique) were estimated to reach 35-percent [37].

One of the first adaptive control algorithms was first introduced by Miller [38] when he proposed a strategy that is based on an online traffic model. The model calculates time wins and losses, based on trial and error methodology and produces criteria for the different stages of the traffic flow. In sequence, a series of adaptive methods were developed. SCOOT minimizes delay by the smooth adaptation of split, cycle time and offset. In contrast to general believing only the offset is optimized on the basis of delay modeling whereas split and cycle time are adapted according to a saturation criterion. With successful trials of SCOOT in different networks, the popularity of the adaptive solutions

increased [39]. Even up to now, SCOOT represents the most established control method with over 170 implementations all over the world.

In the early 80's the Optimized Policies for Adaptive Control Strategy (OPAC) was introduced. OPAC is a demand-responsive adaptive traffic control system developed by the University of Massachusetts [40]. The strategy is operating acyclic, i.e. it does not consider explicitly cycles or offsets. Given prespecified stage schemes, optimal switching times over a horizon are calculated. The optimization is based on delay criteria determined by simplified traffic models. OPAC have been upgraded since its first prototype. OPAC-1 and 2 are utilizing dynamic programming (DP) and an exhaustive search algorithm, respectively. A perfect information on traffic arrival patterns over the entire cycle length is required to obtain optimal signal timing plans.

The Real-time. Hierarchical, Optimized, Distributed and Effective System (RHODES) [41] introduced in late 90's is another online traffic adaptive control strategy introduced by Mirchandani and Head [6]. The methodology introduced an innovative, proactive control where optimal timing plans are created by predicting traffic demands on a downstream intersection. The proactive control is achieved through implementation of a downstream detector located at the preceding intersection allowing short-term volume prediction (i.e., 5 seconds).

A field test performed by Mirchandani et al. [42] for a single intersection, focused mainly on functionality and system responsiveness, but did not provide detailed information with respect to system performance on a signalized corridor. The system performance under different volume and road geometry scenarios was not revealed until today. ACS-Lite is being developed by FHWA to be a cost-effective solution for applying

adaptive control system (ACS) technology to current, state-of-the-practice closed-loop traffic signal control systems [43]. A feature of the system called Time-of-the-Day (TOD) Tuner adjusts plan parameters (cycle, splits, and offsets) based on a long-term historical data. There is also a feature called Run-time Refiner that modifies the cycle, splits, and offsets of the plan that is currently running based on observation of traffic conditions that are outside the normal bounds of conditions that the plan is designed to handle.

A comprehensive performance evaluation was conducted by Shelby et al. [44] for test locations in Gahanna, OH, Houston, TX, Bradenton, FL, and El Cajon, CA and it was revealed that the travel time improvements are ranging between 1-11% for the mentioned location comprising mainly signalized corridors of up to 10 intersections.

Although the adaptive approach has been proven to bring direct benefits to users and agencies, some recent evaluations [45], [46] revealed significantly lower benefits than those initially reported. It is also known that all adaptive signal control systems inevitably depend on the projections of vehicle arrivals, and reliability of the detection system. Due to this, and many other known issues, a study conducted by FHWA [47] reported some direct concerns from practitioners whether the adaptive signal control system would resolve the mobility issues as it was expected at the early stage of development. Some implementation cost analysis performed by the USDOT in January 2013 [48], estimated average implementation costs for adaptive signal control technologies (ASCTs) to be between $46,000 and $65,000 for a single intersection.

2.3.2 On-line Intersection Control under Connected and Automated Vehicles Environment

Several promising studies addressing on-line optimization of signals under connected vehicle environment have been proposed.

Lee et al. [49] proposed utilization of a connected vehicle environment to remedy known limitations of a traffic responsive system. The study presents a cumulative travel-time responsive (CTR) real-time intersection control algorithm based on a stochastic state estimation technique utilizing Kalman filtering that is used in estimating the cumulative travel times under imperfect market penetration rates. The CTR algorithm employs individual vehicles' cumulative travel time (CTT) directly measured (under 100% market penetration rate). The methodology uses elapsed time spent by vehicles from the time they enter the approach link to the moment at the current position of the vehicle on the link, as the real-time measure of the proposed intersection control algorithm. Because the accuracy of information collected from CVs depends on how many vehicles are equipped with the CV devices, the CTR algorithm adopted a Kalman filter–based estimation technique to account for imperfect market penetration conditions. A hypothetical isolated intersection was used for the evaluations with a total of 40 volume scenarios covering the volume capacity ratio ranging from 0.3 to 1.1 and different market penetration levels. At the 100% market penetration rate, the CTR algorithm significantly improved the mobility of an intersection when compared to the actuated controls. The total travel times were decreased by 34% and the average speeds increased by 36%. Lower market penetration rates (30% or less) degraded the performance of an intersection.

Similarly, Goodall et al. [50] proposed a traffic signal control with connected vehicles utilizing decentralized, fully adaptive traffic control algorithm using a rolling-horizon strategy in which the phasing is chosen to optimize an objective function over a 15-s period in the future. The objective function uses either delay only or a combination of delay, stops, and decelerations. To measure the objective function, the algorithm uses a

microscopic simulation driven by present vehicle positions, headings, and speeds. A simulation test-bed consisted of four signalized intersections was developed in the microsimulation platform where the proposed algorithm was compared to the base case scenario (i.e. coordinated actuated signal control). The algorithm showed much greater improvements during unexpected demands, for which the baseline coordinated actuated timing plan is not optimized, particularly in a simulated incident and with annual traffic volume increases when the timing plan is not updated.

Feng et al. [51] developed an algorithm for a real-time adaptive signal control in a connected vehicle environment. The methodology introduces an adaptive signal phase allocation algorithm using connected vehicle data which optimizes the phase sequence and duration by solving a two-level optimization problem. At the upper level, a dynamic program is applied to each barrier group defined as the collection phases between two barriers of a standard NEMA ring barrier structure. The lower level (individual phase) optimization is formulated as a utility minimization problem. The objective can be either minimizing total vehicle delay or queue length based on different operational policies. The arrival flow of each phase at each time step comes from a predicted arrival table. To construct the arrival table, the location and speed of each vehicle on the roadway is estimated from the available connected vehicle data. A single isolated intersection was simulated in a microsimulation platform, for different market penetration and volume rates of 375-667 vehicles per hour per lane. The results show an improvement of the proposed algorithm compared to actuated control when the penetration rate is equal to or greater than 50%. The maximal total vehicle delay reduction of 16.33% was also detected in this study.

Tiaprasert et al. [52] introduced a mathematical model for real-time queue estimation using connected vehicle (CV) technology from wireless sensor networks. The objective is to estimate the queue length for queue-based adaptive signal control using a discrete wavelet transform (DWT) method. The queue estimation comprises following steps: collecting the data from connected vehicles, determining whether a connected vehicle is a stopping or moving, and estimating queue length based on two main cases: 1) no stopped vehicle is detected and 2) stopped vehicle is detected. The simulation assessment of a single intersection including penetration ratios of 10%, 50%, and 80%, and different volume rates showed promising queue estimation accuracy with only 8-10% relative error.

Pandit et al. [53] proposed a method to utilize vehicular ad hoc networks (VANETs) for collecting and aggregating real-time speed and position information on individual vehicles to optimize signal control at traffic intersections. The signal control is formulated as a job scheduling problem, with jobs corresponding to platoons of vehicles. An online algorithm is therefore developed to minimize the delay across the intersection. The main idea behind this method is that the VANET can be utilized to group vehicles into approximately equal-sized platoons, whose crossing time can be further scheduled using the proposed algorithm. The platooning algorithm is an exhaustive search over all the platoon configurations to determine the platoon combination that minimizes the difference between the maximum and minimum green times. In this study, an isolated, four-leg intersection was observed with eight traffic movement groups. The simulation setup included three volume scenarios: heavy with 1700, medium 800, and light with 400 vehicles per hour revealing up to 30% of vehicle delay reduction.

Li et al. [54] developed a signal control optimization algorithm for automated vehicles at isolated signalized intersections. The methodology assumes that vehicle paths and signal control can be jointly optimized based on advanced communication technology between approaching vehicles and a signal controller. A rolling horizon scheme was developed to implement the algorithm and to continually process newly arriving vehicles. At the beginning of the optimization, the algorithm identifies the vehicles inside the communication range and gather the required input information for the intersection controller, based on the optimization period, minimum green time and maximum green time for each approach is calculated, and all the feasible timing plans are enumerated. At last, the algorithm computes the optimum vehicle trajectories and associated minimum average travel time delay of each timing plan. It was discovered that the algorithm can reduce the average vehicle delay by 16.2–36.9% and increase intersection throughput by 2.7–20.2%, depending on the demand scenario.

Arel et al. [55] applied artificial intelligence system to develop a signal control policy based on reinforcement learning (RL) framework. This multi-agent approach is minimizing the average delay, congestion, and likelihood of intersection cross-blocking. Two types of agents are used in this study, a central agent and an outbound agent. While the outbound agents schedule traffic signals by following the longest-queue-first (LQF) algorithm the central agent learns a value function driven by its local and neighbors' traffic conditions using the Q-Learning algorithm with a feedforward neural network for value function approximation. Simulation results demonstrate the advantages of multi-agent-based control over conventional signal control on an isolated single-intersection.

Zohdy et al. [56] introduced a new tool for optimizing the movements of autonomous vehicles through intersections, namely iCACC. The main concept of the proposed tool is to control vehicle trajectories using Cooperative Adaptive Cruise Control (CACC) systems to avoid collisions and minimize intersection delay. The required inputs for the system are entry speed and acceleration of all vehicles, the weather condition (dry or wet) and the intersection geometry (number of lanes, lane width, etc.). The decision of arrival time for each vehicle is made using an optimization module. For vehicle movement control, at each time step, an optimization module is used to optimize the time of arrival of each vehicle at the intersection stop-line. Simulations were executed to compare conventional signal control with iCACC observing delay and fuel consumption. Compared to conventional signal control, the savings in delay and fuel consumption of 91 and 82 percent were detected.

Wenije et al. [57] proposed a new vehicle detection method for signalized intersection using the wireless sensor network (WSN) technology. The algorithm is designed to adjust the duration of each phase, determined by the conditions of the vehicle that the wireless network detected. The basic idea of the algorithm is to calculate the Lane Waiting Queue (i.e., vehicles that waiting on or running on the lane), and the Queue Passing Time (i.e., time needed for all of the vehicles in a queue to pass the intersection) to estimate the optimal value for the duration of the phase. To demonstrate the effect of the proposed algorithm, a single intersection was simulated using microsimulation. On a four-leg intersection with total intersection volume of 6100 vehicles per hour, most vehicles encountered delay less than 60 seconds.

2.4   Chapter Summary and Research Gap

In the first section of the literature review, a brief review of selected reservation-based control algorithms is presented. It was discovered that almost all referenced studies share several common limitations. Their methodology is either developed to operate on a single, isolated intersection or it requires a high market penetration of technology. In addition, majority of reservation-based control algorithms are operating on a first-come-first-served (FCFS) rule.

A comprehensive study conveyed by Levin et al. [21] in 2016 revealed a variety of scenarios in which traffic signals outperformed the reservation-based control strategies on the arterial roadway. It was found that the fairness of the first-come-first-served reservation rule may increase total vehicle delay of an arterial intersection by disrupting the platoon progression. This is mainly because the vehicles on the local road requested a reservation before vehicles on the arterial submitted their requests undermining the conventional rules of corridor coordination.

To the best of authors knowledge, none of the existing efforts addressed this drawback and the presented mobility improvement was detected solely on an isolated intersection testbed often ignoring the corridor-wide context. While many authors utilized the trajectory-driven control approach where vehicles' trajectories are manipulated to ensure safe and efficient operation, again all reviewed studies fail to observe the corridor-wide context or do not offer a viable option for low market penetration conditions that are inevitably present at the early implementation stages.

Various SPaT related studies are also presented in the literature review section. The two major categories were observed 1) Eco-driving oriented control strategies, 2) Green-

wave oriented control strategies. Reviewed studies offer an irreplaceable methodological and practical contribution by introducing utilization of the SPaT concept, however, all the reviewed studies offer a decentralized solution designed for the operation of a single vehicle (often tested on a testbed consisted of a single isolated intersection) rather than offering a system-wide corridor control.

This literature review section also presents relevant studies in the field of conventional and connected-vehicle based on-line optimization. Although the adaptive approach has been proven to bring direct benefits to users and agencies, the operational and cost-related disadvantages have been published [45, 46, 47]. The implementation of the concept across the globe also revealed significantly lower benefits than those that were published while the concept was still in the early development stage. It is well known that all adaptive signal control systems inevitably depend on the projections of vehicle arrivals, and reliability of the detection system. Sine the nature of the vehicular movement is stochastic, the prediction of vehicles' arrivals is often inaccurate. To remedy mentioned problems many authors investigated the utilization of the connected-vehicle environment to replace the conventional detection paradigm. However, if large portion of the traffic stream is not equipped with a proper communication device, the accuracy of the collected parameters (vehicle arrivals, travel time, speeds, queue length etc.) do not represent an adequate replacement of the on-line measure and the low penetration conditions still encounter the same limitation of the conventional on-line optimization.

CHAPTER 3

METHODOLOGY FOR TRAJECTOR-DRIVEN OPTIMIZATION AND CONTROL

This chapter discusses methodologies to develop the TOAD algorithm. The overall architecture is illustrated and described outlining all necessary components of the system. The Trajectory-driven Optimization for Automated Driving (TOAD) is described through theoretical, evolutionary-based formulation of the optimization problem, and the control algorithm framework.

The functionality of the algorithm is demonstrated using a numerical example for a single and a group of automated vehicles. The proof of concept is conveyed through more extensive evaluations presented in the next chapter. The overall methodology with performed activities is presented in Figure 1.
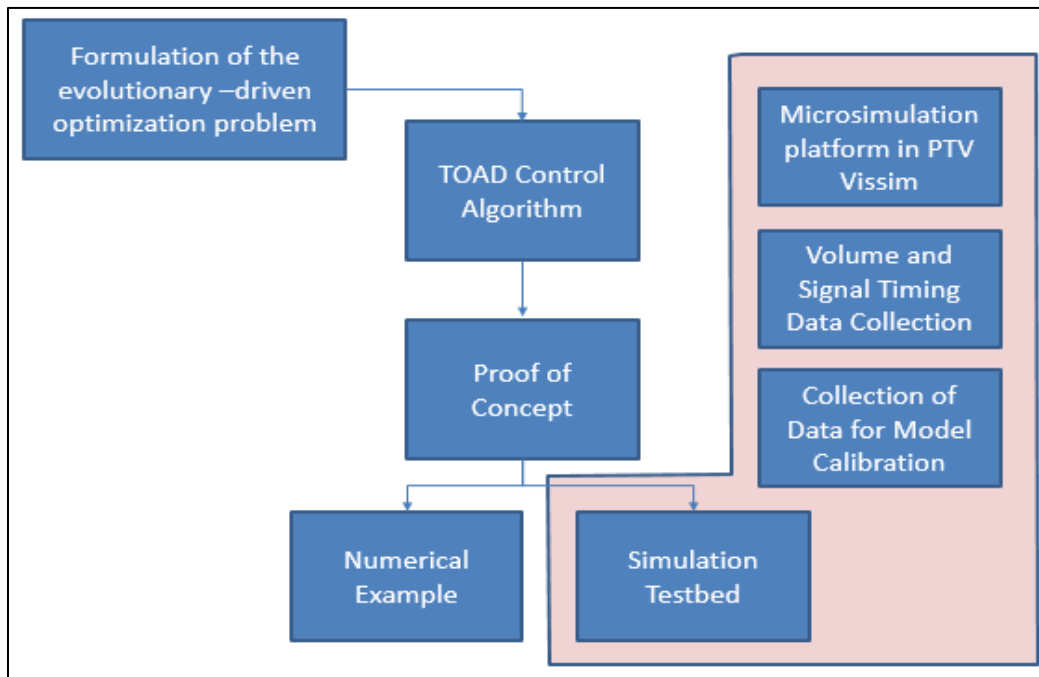
Figure 3.1 The methodology overview.

3.1   Modeling Assumptions

The methodology presented in this dissertation introduces control strategy for a signalized arterial with fixed-timing signals under imperfect market penetration of the connected vehicle technology.   The methodology assumes the provision of vehicular parameters (i.e. speed and position) by utilizing connected and automated vehicle environment (C/AV). Information exchange and proactive adjustment of vehicles' trajectories is handled by the computer system, namely TOAD control agent. The TOAD control agent collects necessary vehicular and signal status information from equipped vehicles and traffic signal controllers to determine the optimal speed for every automated vehicle in the system, while allowing regular, unequipped vehicles, to maintain safe and uninterrupted movement along the corridor. Both automated and unequipped vehicles share the same roadway facility, however, after the proportion of automated vehicles in the traffic stream exceeds a predetermined benchmark point, the inclusion of reserved lanes is possible to increase the effectiveness of the control strategy. It is envisioned that the inclusion of the reserved lanes is achievable by utilizing overhead signs, and left turn movements through the provision of jug-handle configuration.

Figure 3.2 Proposed corridor control architecture.

3.2 Trajectory-driven Optimization for Automated Driving (TOAD) Framework

The methodology assumes that the vehicle trajectory can be defined as a cubic interpolated spline allowing flexible accommodation of the trajectory to the given signal timing obstacles in the time-distance searching space. An example of the trajectory is illustrated in Figure 3.3, where control points $p_1(x, y_1) \dots p_M(x_M, y_M)$ were used for the trajectory interpolation. By respecting interpolation and monotonicity rules [58], the trajectory T will be produced in the field of real numbers giving the sequence of coordinates in the defined coordinate space:

$$T: \quad x^T = (x_1, \dots \dots, x_n); \ y^T = (y_1, \dots \dots, y_n) \tag{3.1}$$

(a) arrival during red interval　　　　　　(b) arrival during green interval

Figure 3.3 Trajectory defined using cubic interpolation.

The main objective of the trajectory optimization is to minimize the sum of all the trajectory curves for vehicles in the control space C. The length of the curve illustrated in Figure 3.3, with n number of elements of the trajectory is therefore calculated as the sum of Euclidean distances between successive x_i and y_i elements of the trajectory as follows:

$$Trajectory\ Length = \sum_{i=1}^{n-1} \sqrt{\Delta x_i^2 + \Delta y_i^2} = \sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} \qquad (3.2)$$

where

$\Delta x =$ change in time

$\Delta y =$ change in distance

In order to maintain cruising condition along the green-band of the corridor, and comply with the posted speed limit the optimization model is formulated for the corridor with N number of vehicles, H number of intersections, and M number of control points for each vehicle trajectory, as presented in Table 3.1. The first and the second group of constraints was designed to adjust the trajectory curve for two possible cases (Figure 3.3), that is

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passing during the green interval, G starting with the predefined beginning of green *(bog)* (Figure 3.3a) or passing during the red interval, R (Figure 3.3b). It is noted that all combinations are possible, for example, a vehicle can pass on the green at the first, but arrives on the red at the second intersection etc. Described transformation allows nonlinear programming algorithms, specifically, Genetic Algorithm [59] to evaluate all possible combinations of a chromosome and determine the best individual that is the most optimal vehicle trajectory to minimize total travel time of the corridor while satisfying defined safety constraints (Table 3.1).

The third group of constraints was introduced to adjust the slope of trajectories so that they do not violate the speed limit of a road section, taking into consideration current distance of a vehicle to intersections. Those distances are denoted as $d_1, d_2 \dots d_M$ representing the distance to the first, second, and M^{th} intersection respectively.

The last group of constraints was designed to prevent the collision of the leading and the following vehicle in the control environment by maintaining the safety headway denoted in Table 3.1 as h, which is possible as the assumption of the model is that all vehicles in the system share their position with the control agent.

Table 3.1 Mathematical Model Formulation for the Corridor-level Control Algorithm

$$MIN \sum_{j=0}^{N} \sum_{j=1}^{M} Length\left(p_{1+(2H+1)j}, p_{2+(2H+1)j}, p_{3+(2H+1)j}, p_{4+(2H+1)j}, p_{5+(2H+1)j}, p_{6+(2H+1)j}, p_{M+(2H+1)j}\right)$$

Subject to: $X_{2+(2H+1)j} - X_{3+(2H+1)j} = 0; \quad X_{2+(2H+1)j} \in G_1 \quad \forall j \in C$ $X_{4+(2H+1)j} - X_{5+(2H+1)j} = 0; \quad X_{5+(2H+1)j} \in G_2 \quad \forall j \in C$ $X_{6+(2H+1)j} - X_{7+(2H+1)j} = 0; \quad X_{6+(2H+1)j} \in G_3 \quad \forall j \in C$ ... $X_{(M-1)+(2H+1)j} - X_{M+(2H+1)j} = 0; \quad X_{M+(2H+1)j} \in G_3 \quad \forall j \in C$	Constraint Group 1 Purpose: control point allocation to represent the "green time arrival" curve, if control point values are inside the red time interval
$-X_{3+(2H+1)j} + bog_1 \leq 0; \quad X_{2+(2H+1)j} \in R_1 \quad \forall j \in C$ $-X_{5+(2H+1)j} + bog_2 \leq 0; \quad X_{4+(2H+1)j} \in R_2 \quad \forall j \in C$ $-X_{7+(2H+1)j} + bog_3 \leq 0; \quad X_{6+(2H+1)j} \in R_3 \quad \forall j \in C$ ... $-X_{H+(2H+1)j} + bog_H \leq 0; \quad X_{(M-1)+(2H+1)j} \in R_H \quad \forall j \in C$	Constraint Group 2 Purpose: control point allocation to represent the "red time arrival" curve, if control point values are inside the red time interval
$d_1/(X_{2+(2H+1)j} - X_{1+(2H+1)j}) \leq Speed\ Limit$ $d_2/(X_{4+(2H+1)j} - X_{3+(2H+1)j}) \leq Speed\ Limit$ $d_3/(X_{6+(2H+1)j} - X_{5+(2H+1)j}) \leq Speed\ Limit$ ... $d_H/(X_{H+(2H+1)j} - X_{(H-1)+(2H+1)j}) \leq Speed\ Limit$	Constraint Group 3 Purpose: constrains the slope of curves to prevent generation of trajectories that would exceed posted speed limit
$(X_{2+(2H+1)j} + h) - X_{2+(2H+1)(j+1)} \leq 0$ $(X_{3+(2H+1)j} + h) - X_{3+(2H+1)(j+1)} \leq 0$ $(X_{4+(2H+1)j} + h) - X_{4+(2H+1)(j+1)} \leq 0$ $(X_{5+(2H+1)j} + h) - X_{5+(2H+1)(j+1)} \leq 0$ $(X_{6+(2H+1)j} + h) - X_{6+(2H+1)(j+1)} \leq 0$ ... $(X_{H+(2H+1)j} + h) - X_{H+(2H+1)(j+1)} \leq 0$	Constraint Group 4 Purpose: constrains the slope of curves to prevent collision of the leading and following vehicle using time headway h.

3.3 TOAD Control Algorithm

The overall optimization framework is illustrated in Figure 3.4. The procedure starts by collecting the distance to all intersections downstream of the vehicle and speed information of the first vehicle $j = 1$ followed by the collection of the current signalization status. The signal status includes the beginning of green *(bog)* for the next several cycles of all corridor intersections as illustrated in the time-space diagram in Figure 3.3. With known position and signalization information the GA algorithm described in the previous section is

executed to manipulate a chromosome consisted of control points $p_1 \ldots p_M$ until the optimal solution comprising the best possible individual is produced. After storing the best individual into the pool of solved trajectories $T_1 \ldots T_n$ its position is further included into the constraint of the next vehicle $j = 2$ to avoid violation of the safety headway *(h)* and collision of the two successive vehicles. The procedure is further continued until the trajectory is determined for the last vehicle $= N$. After creating the most desirable predictive trajectory for the last vehicle, the information is returned to the control agent for the immediate execution after which the new iteration of the control algorithm is started again updating all necessary information and generating updated trajectories for vehicles $j = 1, \ldots, j = N$.
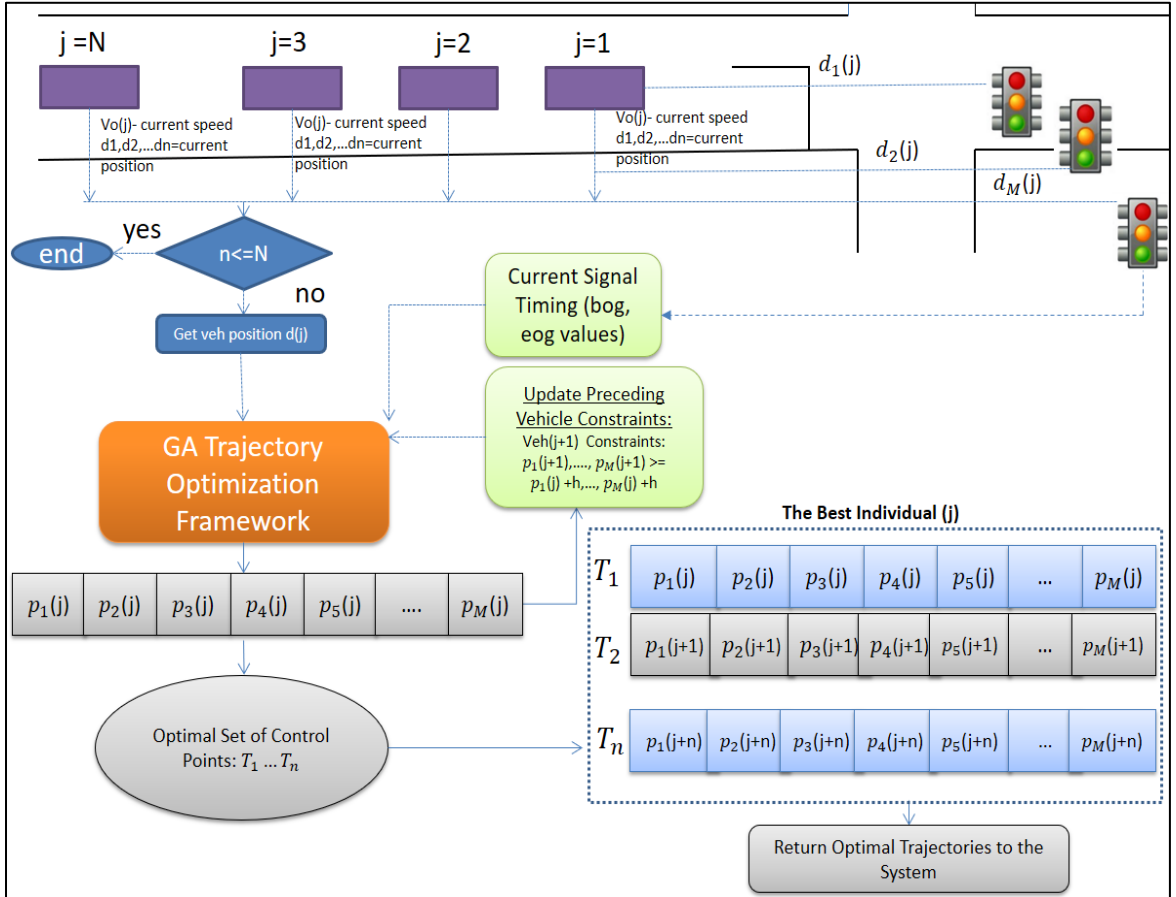
Figure 3.4 Control algorithm framework.

3.4   Numerical Example

This numerical example illustrates the procedure of evaluating the fitness of an individual for the proposed evolutionary optimization algorithm. Let there be a signalized corridor with three signalized intersections and a speed limit of 55 mph (24.8 m/s) Assumed green interval of each intersection is 20, 30, and 25 seconds, followed by the red interval of the same length, for intersections one to three respectively. The lengths of the corridor links are 1,640 ft (500 meters), between intersections one and two, and 1,312 ft (400 meters) between intersections two and three.

There is a vehicle 2,788 ft (850 meters) from the stop bar of the first intersection.

This example illustrates evaluation of the feasibility for a given trajectory for the vehicle with initial values $x_1 = 0$, $x_2 = 110$, $x_3 = 110$, $x_4 = 155$, $x_5 = 155$, $x_6 = 210$, $x_7 = 227$

Due to the described corridor geometry following distance values are known:

$$y_1 = 0, \ y_2 = 850, y_3 = 850, \ y_4 = y_5 = 850 + 500, \ y_6 = y_7 = 850 + 500 + 400$$

For the first vehicle $j = 0$ and H=3 since there are three intersections downstream of the vehicle. Therefore, decision variables will be indexed as follows for the constraint group 1. This constraint group 1 (Table 3.1) is being utilized for the vehicle arrival during the green interval at intersections 1 and 2. Correspondingly, the constraint group 2 is utilized at intersection 3 as the vehicle arrives within the red interval at this intersection:

$$X_{2+(2*3+1)*0} - X_{3+(2*3+1)*0} = 0; X_{2+(2*3+1)*0} \in G_{1u} \quad \forall j \in C$$
$$X_{4+(2*3+1)*0} - X_{5+(2*3+1)*0} = 0; X_{5+(2*3+1)*0} \in G_{2u} \quad \forall j \in C$$
$$X_{6+(2H+1)*0} - X_{7+(2*3+1)*0} = 0; X_{6+(2*3+1)*0} \in G_{3u} \quad \forall j \in C$$

or

$$X_2 - X_3 = 0; X_2 \in G_{13}$$
$$X_4 - X_5 = 0; X_5 \in G_{23}$$
$$-X_7 + bog_{35} \leq 0; X_6 \in R_{35}$$

The signal timing constraints are defined as follows:

1) $x_2 - x_3 = 0$, and $x_2 = 110\ sec \in G_{13} = [100,120]$ which is the green interval of the

third cycle at intersection 1,

2) $x_4 - x_5 = 155 - 155 = 0\ sec$, and $x_3 = 155\ sec \in G_{23} = [150,180]$ which is the

green interval of the third cycle at intersection 2

3) $x_7 \geq bog_{35} = 225\ sec$, since $x_6 \in R_{35} = [200,225]$ which is the red interval of the

fifth cycle at intersection 3

The observed individual satisfies signal timing constraints (constraint groups 1 and 2).

In order to assure the compliance with the posted speed limit, following constraints are

evaluated (constraint group 3):

$$d_1/(X_{2+(2H+1)j} - X_{1+(2H+1)j}) \leq Speed\ Limit$$
$$d_2/(X_{4+(2H+1)j} - X_{3+(2H+1)j}) \leq Speed\ Limit$$
$$d_3/(X_{6+(2H+1)j} - X_{5+(2H+1)j}) \leq Speed\ Limit$$

Therefore, this set of constraints is also satisfied because of the following:

$$1)\ x_2 - x_1 = 110\ sec\ and\ 110\ sec \geq \frac{850\ m}{24.8\frac{m}{s}}$$

$$2)\ x_4 - x_3 = 110\ sec\ and\ 45\ sec \geq \frac{500\ m}{24.8\frac{m}{s}}$$

$$3) \, x_6 - x_5 = 110 \sec and \, 55 \sec \geq \frac{400 \, m}{24.8 \frac{m}{s}}$$

A cubic interpolated curve will be calculated by respecting the interpolation and

monotonicity rules for the control points:

$$p_1(0,0), \quad p_2 = p_3(110,850), \quad p_4 = p_5(155,1350), \quad p_6(210,1750), \quad p_7(227,1750),$$

and it is resulting in the interpolated cubic curve with 46 interpolation points illustrated in

Figure 3.5.
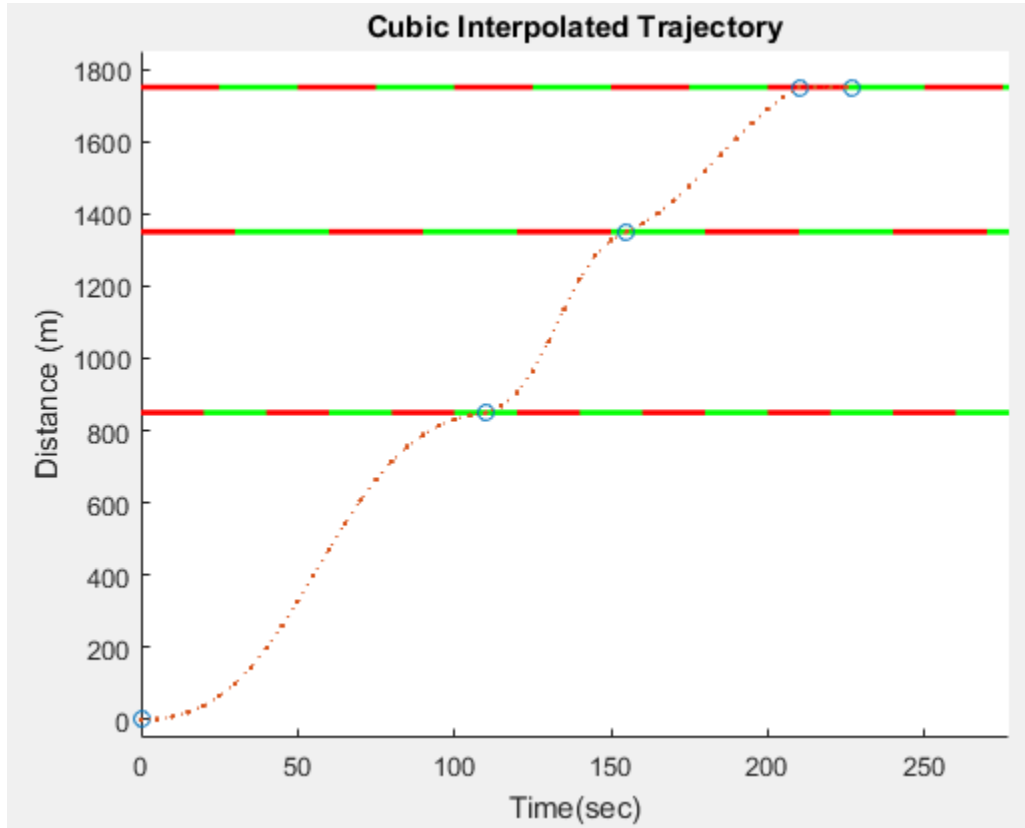
Figure 3.5 Evaluated cubic interpolated trajectory.

Therefore, the fitness function value will be calculated for the given trajectory as follows:

$$Trajectory\ Length = \sum_{i=1}^{46}\sqrt{\Delta x_i^2 + \Delta y_i^2} = \sum_{i=1}^{n-1}\sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} = 1760.02$$

As the preceding vehicle does not exist in this numerical example the fourth group of constraints is not presented, but it is utilized in the control algorithm when information about the preceding vehicle is available.

The problem formulated in the previous section was also demonstrated using a realistic scenario where a platoon consisted of N=25 vehicles is passing through the same corridor. This time MATLAB 2015b [60] was used due to the complexity of the optimization problem.

The leading vehicle of the platoon was 2,788 ft (850 meters) from the stop bar of the first intersection, and the last vehicle was 3,215 ft (980 meters) from the stop bar. Vehicles in-between had assumed headway of 10-16 ft assigned randomly.

The problem was successfully solved using Genetic Algorithm (GA) programmed in MATLAB 2015b [60] with the population size of 50. The program successfully returned an optimal solution after evaluating 43 generations and 1344 different individuals, with CPU time less than 120 seconds. It is noted that this numerical example represents only one iteration of the TOAD control algorithm. For the evaluation purpose, the same solution will be executed in the second-by-second fashion, every time updating vehicle speed and positions. The optimal solutions with corresponding vehicular trajectories are illustrated in Figure 3.6.
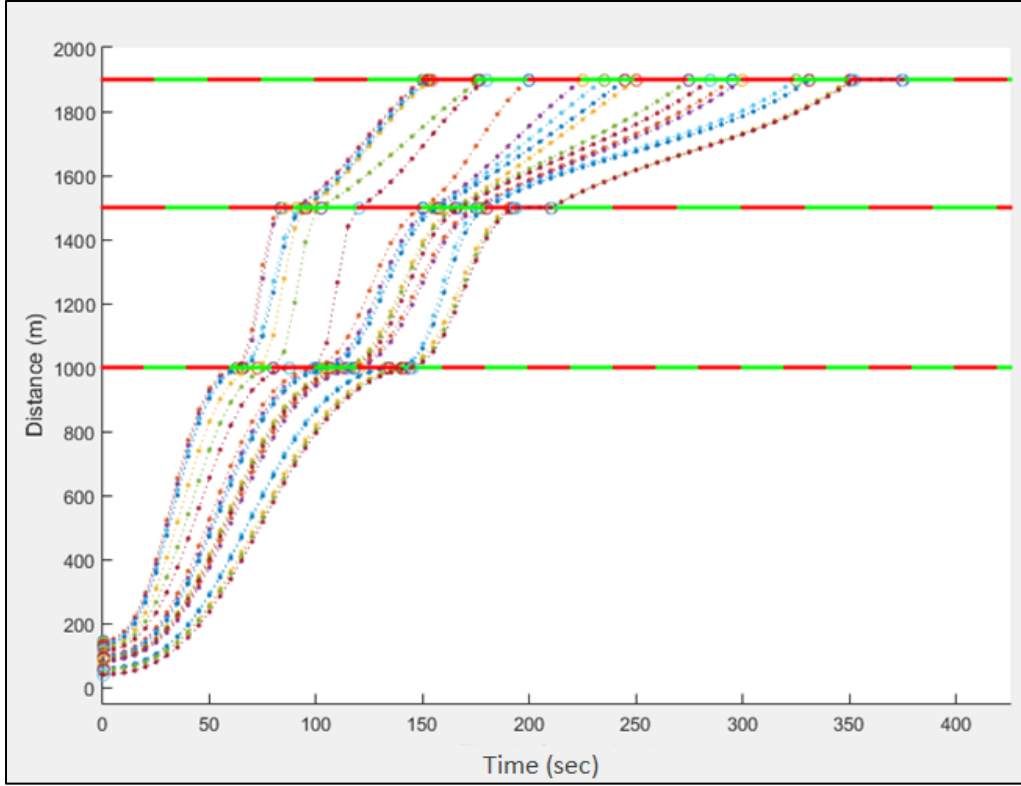
Figure 3.6 Optimal trajectories for a platoon of 25 automated vehicles.

3.5   Proof of Concept and Test Bed Development

The simulation test-bed used in this paper integrates 1) calculations and optimization solver; 2) microscopic traffic simulator. While microscopic simulator provides vehicular information for each individual vehicle in the network (i.e. distance to the stop bar, current vehicle speed, and signalization status), optimizer solves a non-linear optimization problem with the data input obtained for each individual vehicle. To adequately implement both tasks mentioned above, the optimizing task is handled by MATLAB [60] and microscopic traffic simulator PTV VISSIM [61] where the exchange of information between MATLAB and VISSIM is conveyed through Common Object Model (COM) [62]. As illustrated in Figure 3.7, the executive code written in Microsoft C# serves as a control agent instance,

synchronizes information flow, combines parameters obtained from both platforms, and executes the optimal trajectories determined by the algorithm in the microsimulation.
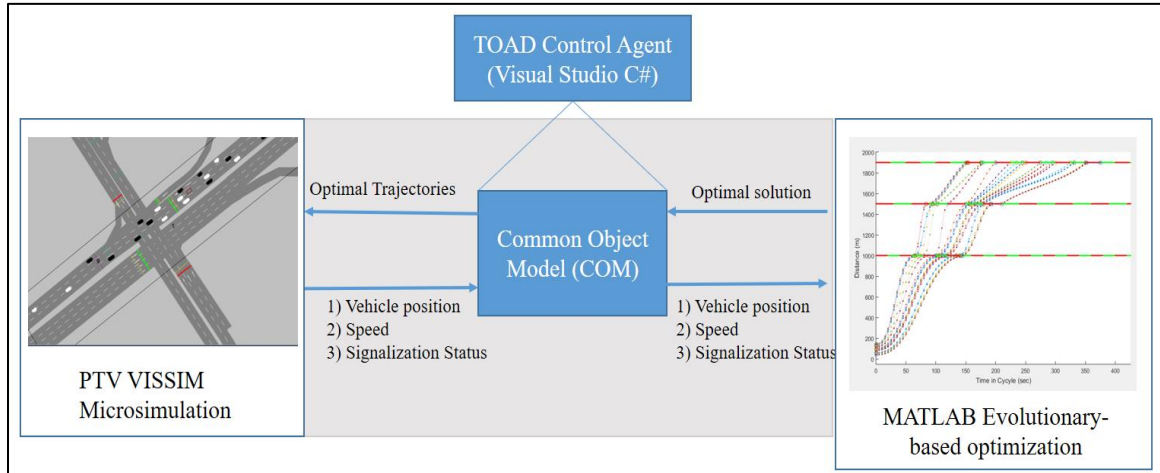
Figure 3.7 Simulation test bed framework.

3.5.1   Test Bed 1: US-1 in Princeton, NJ

The first test bed location (Figure 3.8) selected for the system evaluation is located in Princeton Township, New Jersey. A section of US-1 in Mercer County, between Carnegie Center Boulevard and Ridge Road, is about 5 miles long, with mainly six lanes in two directions. Coordinated intersections include jug-handle ramps with no left turns allowed from the mainline (i.e., US 1). The roadway has a speed limit of 55 mph. The corridor has numerous jughandle ramps allowing restriction of left turns from the mainline of the corridor.
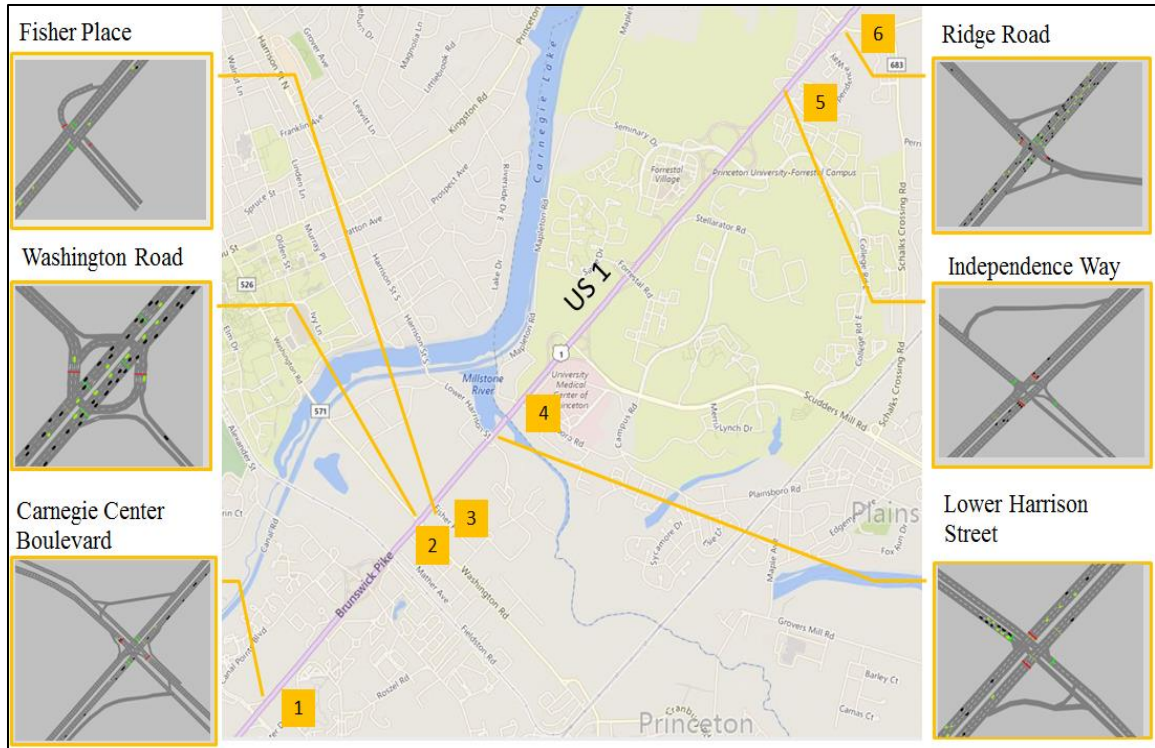
Figure 3.8 VISSIM model for selected test corridor in Princeton, New Jersey.

The VISSIM simulation model was developed and calibrated using multiple traffic counts and travel time data sources. The developed simulation model was calibrated and fine-tuned to represent the actual field conditions. Travel time was selected as an index of comparison. The field travel time data obtained from GPS equipped probe vehicles were used as ground truth travel time. VISSIM provides a possibility of using 25 different variables for the purpose of calibration; however, the number of combinations for the 25 parameters is enormous. Therefore, the Quasi Monte Carlo (QMC) algorithm was applied to reduce the number of combinations down to a reasonable level. After multiple simulation runs were conducted using QMC based parameter sets, the parameter values were calibrated and selected as illustrated in Table 3.2. The travel time results obtained from the calibrated VISSIM model were compared again to the ground truth travel times.

Table 3.2 Calibrated Parameter Values

Accepted deceleration (own)	-0.58
Accepted deceleration (trailing vehicle)	-7.48
Amber behavior alpha	1.51
Amber behavior beta 1	-0.26
Amber behavior beta 2	0.68
Maximum cooperative deceleration	-11.37
Deceleration reduction distance (own)	171.47
Deceleration reduction distance (trailing vehicle)	329.16
Look ahead distance (maximum)	268.65
Look ahead distance (minimum)	251.69
Look back distance (maximum)	405.13
Look back distance (minimum)	89.17
Maximum deceleration (own)	-3.97
Maximum deceleration (trailing vehicle)	-8.54
Minimum headway	2.00
Safety distance reduction factor (lane change)	0.48
Safety distance reduction factor (signals)	0.32
Safety distance reduction factor end (signals)	194.46
Safety distance reduction factor start (signals)	215.53
Temporary lack of attention - sleep duration	1.37
Temporary lack of attention - sleep probability	0.13
W74ax: Average standstill distance (Wiedemann 74)	3.61
W74bxAdd: Additive factor for security distance	4.09
W74bxMult: Multiplicative factor for security distance	2.34
Desired Speed Distribution Number	2.10

The comparison between the ground truth and the simulation data is presented in Figure 3.9.
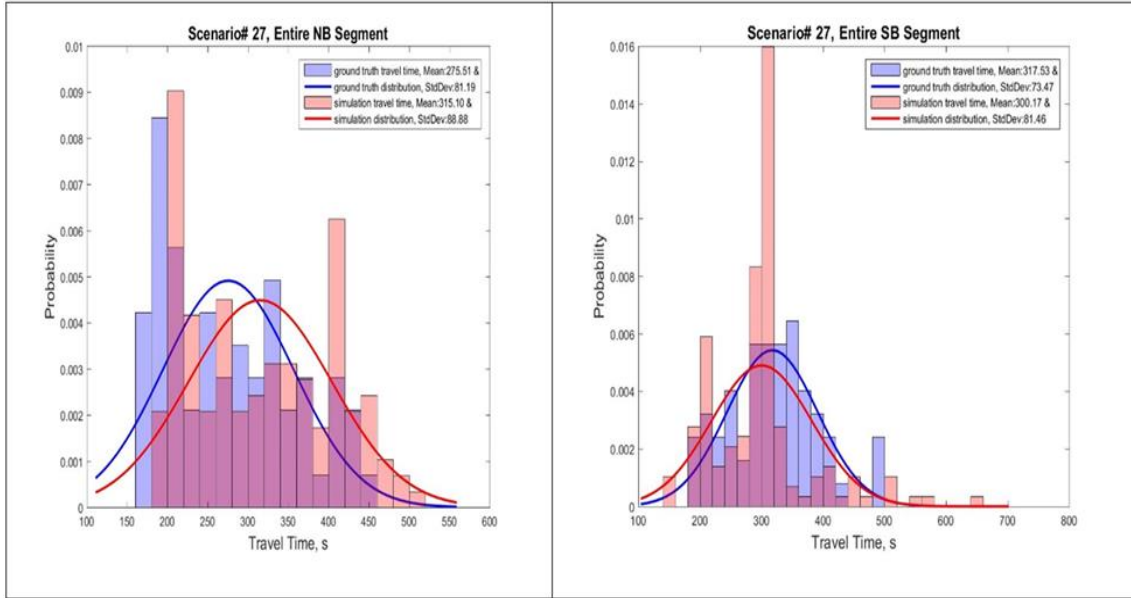
Figure 3.9 Comparison between ground truth and simulation travel time results.

3.5.2 Test Bed 2: US-1 in Woodbridge, NJ

Due to the different geometrical and traffic volume characteristics, the second testbed was developed to provide additional proof of the algorithm functionality. This corridor is characterized by different lengths of the corridor links, and slightly different volume rates in the observed time period. In addition, this corridor contains an isolated intersection and an intersection without a jughandle ramp. The second test corridor is presented in Figure 3.10. The test bed selected for the system evaluation is located in Woodbridge Township, New Jersey. A section of US-1 in Middlesex County, between Gill Lane and Prince Street, is about 4 miles long, with mainly seven lanes in two directions (four lanes north-east, and three lanes south-west direction). Coordinated intersections include jughandle ramps with no left turns allowed from the mainline (i.e., US 1). The roadway has a speed limit of 55 mph. Traffic volume and signal timing data were obtained directly from the New Jersey Department of Transportation (NJDOT).
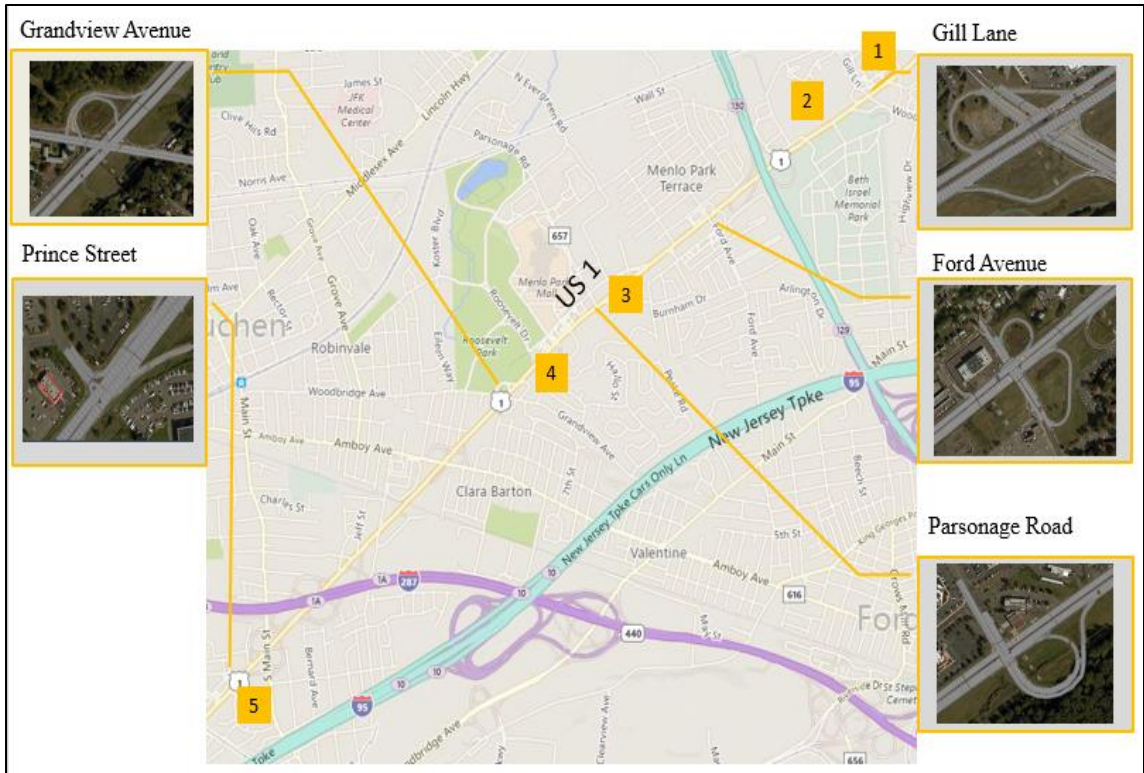
Figure 3.10 VISSIM model for selected test corridor in Woodbridge, New Jersey.

3.6 Experimental Scenarios

The simulation results comprise eleven different market penetration conditions (0%-100%, in 10% increments) and were examined with five consecutive simulation runs for both testbed locations. Some more detailed information about simulation scenarios and simulation results are provided in the following section. To assess benefits of the proposed control strategy, the mobility performance measures (average total travel time for the whole network) were collected and compared with base-case conditions.

3.7 Simulation Results for Testbed in Princeton, New Jersey

To properly estimate potential benefits of proposed TOAD control algorithm, the real-world volume, turning movement, and signal timing data was obtained for a typical weekday and a time period from 1 PM to 3 PM. Eleven different market penetration

conditions (0%-100%, in 10% increments) were examined with five consecutive simulation runs totaling in 55 simulation runs. The average corridor travel time measurements comprise values of both southbound and northbound directions. The aggregated simulation results are illustrated in Figure 3.11.
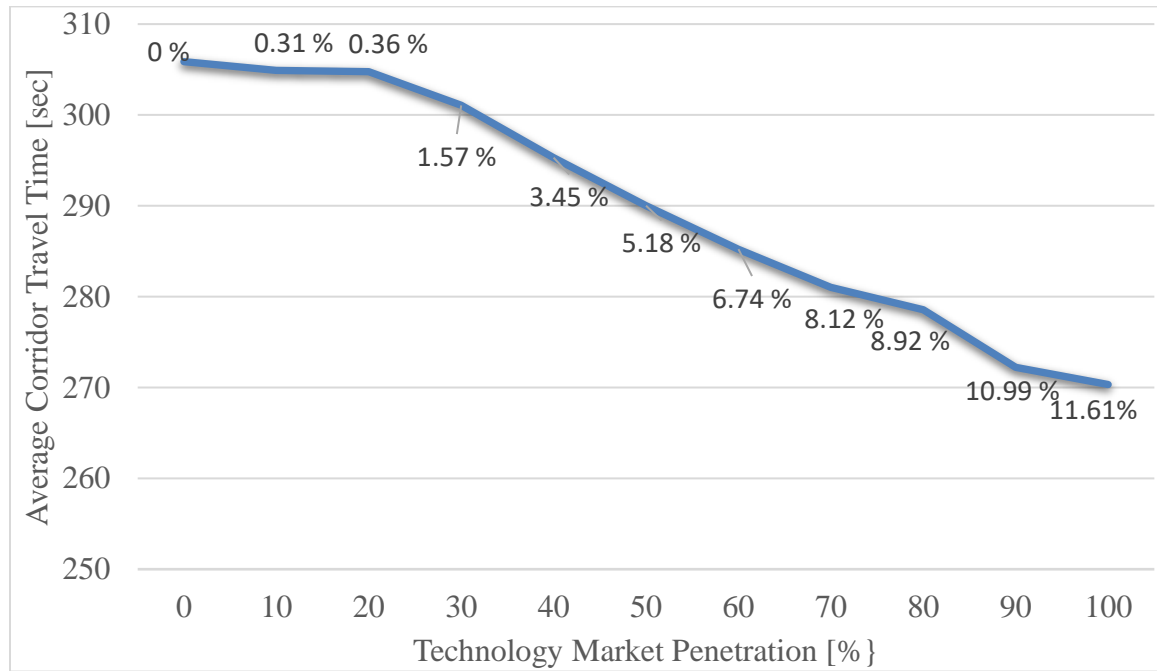
Figure 3.11 Simulation results for different market penetration and lane configurations

During the evaluation, it was observed the overall travel time of the corridor decreases with an increased market penetration rate of TOAD control strategy. Low market penetration rates (i.e. 0%-30%) of automated vehicles produced marginal reductions in overall corridor travel time ranging from 0.3% to 1.5%. Benefits are more visible with the percentage of automated vehicles higher than 30% resulting in 3.4% reduction in travel time with 30% of automated vehicles in the traffic stream. The travel time savings for a corridor with 100% of automated vehicles achieved almost 12% of travel time reduction

under given volume conditions presented in Table 3.3. Most of the intersections on this corridor except US1 at Fisher Place operated under the level of service B.

Table 3.3 Traffic Conditions on the Test Corridor in Princeton, NJ

Intersection	Ridge Road	Independence Way	Lower Harrison Street	Fisher Place	Washington Road	Carnegie Center Boulevard
LOS	B	B	B	C	B	B
V/C Ratio	0.42	0.45	0.38	0.45	0.43	0.41

Table 3.4 summarizes average corridor travel times for TOAD-equipped and unequipped vehicles. Expectedly, the TOAD vehicles achieved lower travel times by 0.1-6.0% depending on market penetration level. The difference between equipped and unequipped vehicle's travel time is larger as market penetration level increases. Also, the travel time of both vehicle types decreases with market penetration rate as TOAD vehicles generally influence the movement of unequipped vehicles. This influence is present at higher market penetration rates when automated vehicles are predominant in the traffic stream and unequipped vehicles are often forced to follow automated vehicles while facing indirect benefit of the TOAD optimization. For small market penetration levels, the difference between automated and unequipped vehicles is smaller as the prevailing nature of unequipped vehicles in the stream obstruct automated vehicles, further decreasing compliance with optimal trajectories generated by control agent.

Table 3.4 Average Travel Times for Different Vehicle Types (seconds)

Market Penetration	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Equipped Vehicles	n/a	304.7	302.3	296.6	294.0	286.4	280.4	277.0	275.3	270.5	270.3
Unequipped Vehicles	305.8	304.9	305.4	304.9	296.2	293.6	292.5	290.4	291.4	287.8	n/a
Difference (%)	n/a	0.1	1.0	2.7	0.7	2.4	4.2	4.6	5.5	6.0	n/a

In addition to described benefits, it is also evident from Table 3.4 that travel time for unequipped vehicles decreases with market penetration of automated vehicles. The decrease in travel time of unequipped vehicles is an indirect benefit. Equipped vehicles make influenece on unequiped vehicls, and this infuelnce is higher as market penetration increases. One example of the infuelnce are unequiped vehicles following equiped vehicles, which is further rsulting in decreased number of stops. This allows unequiped vehicles to indirectly benefit from the TOAD management strategy, however, automated vehicles still outperform unequipped vehicles. Another reason for the indirect benefit of unequipped vehicles is the overall mobility improvement of the signalized facility where corridor throughputs, number of stops, and vehicle delay decrease with market penetration rate, allowing more vehicles to be served with less delays. This represents an important fact from the aspec of equity, allowing TOAD management strategy to be implemented without negative impact on unequipeed vehicles.

3.8 Simulation Results for Testbed in Woodbridge, New Jersey

Just as in the previous case, a typical weekday and a time period from 1 PM to 3 PM was observed. Again, eleven different market penetration conditions (0%-100%, in 10% increments) were examined with five consecutive simulation runs, totaling in 55 simulation runs. The results include average corridor travel time measurements of both southbound

and northbound directions. Traffic conditions used for the test, are presented in Table 3.6. Again, the low market penetration rates (i.e. 0%-30%) of automated vehicles produced marginal reductions in overall corridor travel time ranging from 0.04% to 0.4 % depending. The improvement becomes visible after 30% technology penetration and it gradually increases until the corridor achieves 100% of market penetration. Under 100% of market penetration and under the described traffic conditions the highest possible travel time reductions are 9%. Average corridor-wide travel times for different market penetration reveals similar trends to those observed at the first test location, however, the magnitude of the travel time reductions is slightly lower for the test location in Woodbridge.
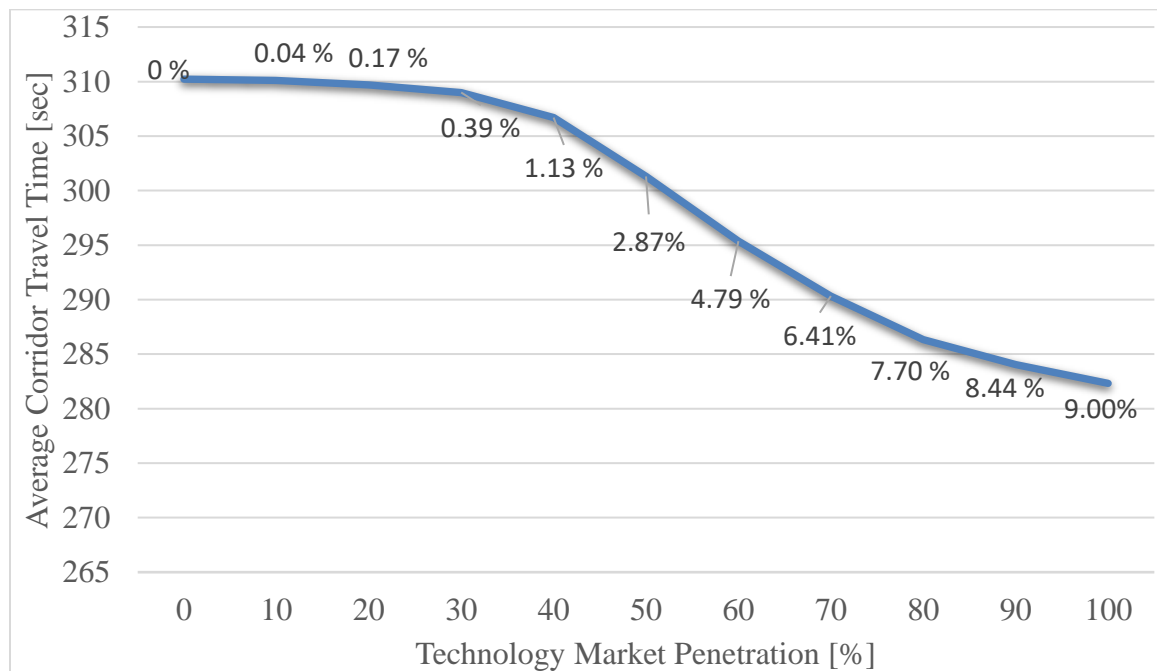

Figure 3.12 Simulation results for different market penetration and lane configurations

By observing differences between the two vehicle types, presented in Table 3.5, it is again confirmed that this difference is more visible as market penetration increases.

Although the second testbed location has different geometrical and signal timing characteristics, this finding is consistent with the one detected on the first testbed locations.

Table 3.5 Average Travel Times for Different Vehicle Types (seconds)

Market Penetration	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Equipped Vehicles	n/a	308.9	303.8	304.4	298.0	294.6	285.6	284.0	283.0	282.2	282.3
Unequipped Vehicles	310.2	310.2	311.2	311.0	305.0	302.0	298.0	300.0	299.5	300.3	n/a
Difference (%)	n/a	0.4	2.4	2.1	2.3	2.4	4.2	5.3	5.5	6.0	n/a

It can be inferred from Table 3.5 that travel time of unequipped vehicles decrease with market penetration of automated vehicles. Although the decrease is marginal for unequipped vehicles, it assures this vehicle group is not affected by proposed management strategy, confirming previously described equity aspect of the TOAD control methodology.

Traffic conditions correspond to those observed at the first test bed location and include the level of service of B and C. The detailed intersection performance and volume conditions applied in the simulation are summarized in Table 3.6.

Table 3.6 Traffic Conditions on the Test Corridor in Woodbridge, NJ

Intersection	Gill Lane	Ford Avenue	Parsonage Road	Grandview Avenue	Prince Street
LOS	B	C	B	C	B
V/C Ratio	0.39	0.49	0.45	0.49	0.40

It must be noted that the benchmark point when the reserved lane is introduced is extremely important. For the observed locations, the inclusion of a dedicated lane in conditions where the number of automated vehicles in the traffic stream is low (e.g., 5-10 %) will most likely undermine the system performance. The main reason can be

found in a fact that, in described conditions, the general traffic would operate with significantly reduced capacity, while automated vehicles have not yet started achieving visible travel time reductions on a corridor level. On the other hand, correct manipulation of the lane configuration will result in significantly better operation of the corridor as illustrated in Figure 12 and 13.

3.9   Chapter Summary

This chapter describes methodology applied to develop a trajectory-driven control algorithm for automated driving on the signalized corridor. The algorithm designed to work with imperfect market penetration rates was tested through series of simulations. The proposed algorithm was successfully simulated on two test bed locations indicating up to 12% of corridor-wide travel time reductions. It was also discovered that the proposed algorithm provides visible results only after technology penetration reaches 30%. The optimization methodology presented in this chapter does not utilize information about prevailing traffic conditions for better vehicle arrival prediction. The inclusion of prevailing traffic conditions into the proposed framework is necessary to achieve more realistic and more accurate vehicle trajectories. This parameter was not included in this initial control algorithm assessment, therefore, the methodology to detect, predict, and incorporate the parameter is presented in the next chapter of this dissertation.

The comparison between equipped and unequipped vehicles revealed improvement for both vehicle groups. The mobility improvement of unequipped vehicles is caused by an indirect influence of equipped vehicles and it increases with market penetration of the technology. Application of the TOAD algorithm improves overall mobility performance

of the facility by decreasing average travel time, vehicle delay, and increasing overall throughput. All this produces better performance of both equipped and unequipped vehicles allowing TOAD control management to achieve it's benefits without affecting user equity.

CHAPTER 4

PREVAILING TRAFFIC CONDITIONS AND ARTIFICIAL INTELLIGENCE MODEL

4.1 Short-term Prediction of Prevailing Traffic Conditions and Trajectory Adjustment

The inclusion of predicted vehicle delay is essential for a realistic trajectory generation. Without predicted vehicle delay, application of the generated trajectory is challenging as the vehicle cannot fully achieve assigned speed profile due to the influence of downstream traffic. The prevailing traffic conditions can be directly measured using conventional data collection devices such as loop detector, Remote Traffic Microwave Sensor (RTMS), video detection, Bluetooth or Wi-Fi sensors. Those devices provide instantaneous information with respect to prevailing traffic volumes, spot speed, or travel time.

Although prevailing traffic conditions devices are highly accessible in the current state of technology, it is often not possible to have data collection devices densely deployed. Devices that are not densely deployed provide information suitable for the vehicle control, only to automated vehicles that are in the near proximity to those sensors. Vehicle located far from data collection points (i.e. 1-2 miles upstream) would not receive accurate information as traffic conditions are likely to change by the time they arrive at the data collection point.

In order to have a reasonable number of data collection points, but still, provide accurate information about prevailing traffic conditions it is necessary to incorporate a short-term prediction of the traffic parameters for vehicles entering the control space. That way, the costs of having densely deployed detectors can be significantly decreased.

To adequately adjust predicted vehicle trajectory to prevailing traffic conditions on downstream links a predicted vehicle delay information can be incorporated into existing trajectory generation framework. Figure 4.1 illustrates an ideal vehicle trajectory and an adjusted (realistic) trajectory altered with respect to predicted vehicle delay on downstream link. When the predicted delay is not included in the constraint function, the maximum velocity is equal to the free flow speed. This would often result in the undermined performance of the control algorithm as the algorithm will assume speeds that are not achievable in the given traffic conditions. The described trajectories would be additionally corrected by the fourth constraint group from Table 3.1 in order to avoid collision with the preceding vehicle, but would not provide an ideal trajectory prediction.

4.1.1   Application of Artificial Neural Networks for Short -term Prediction

Artificial neural network (ANN) algorithms are frequently used to perform nonlinear statistical modeling used for developing predictive models. This type of statistical models generally offer ability to implicitly detect complex nonlinear relationships between dependent and independent variables, and ability to detect all possible interactions between predictors [63].

Although prediction problem described in this section can be solved using some of the most widely used models (i.e. ARIMA time-series, Box-Jenkins, Kalman filtering, etc.), some studies indicate varying performance during congested periods [64]. Aforementioned models also include the smoothing of input data over long time intervals (i.e., 5 minutes) which can produce poor performance in short-term predictions [65]. On the other hand, numerous studies successfully applied ANN models for short-term

prediction of traffic flow parameters [65] [66] [67] showing sufficiently high prediction accuracy suitable for traffic operations and signal control.

To allow accurate short-term prediction of vehicle delay, an Artificial Neural Network (ANN) trained with available traffic stream factors is designed and presented in the following section. This short-term prediction model alleviated two potential challenges of the TOAD algorithm:

1) The necessity for the dense detector deployment,

2) Improved trajectory prediction.

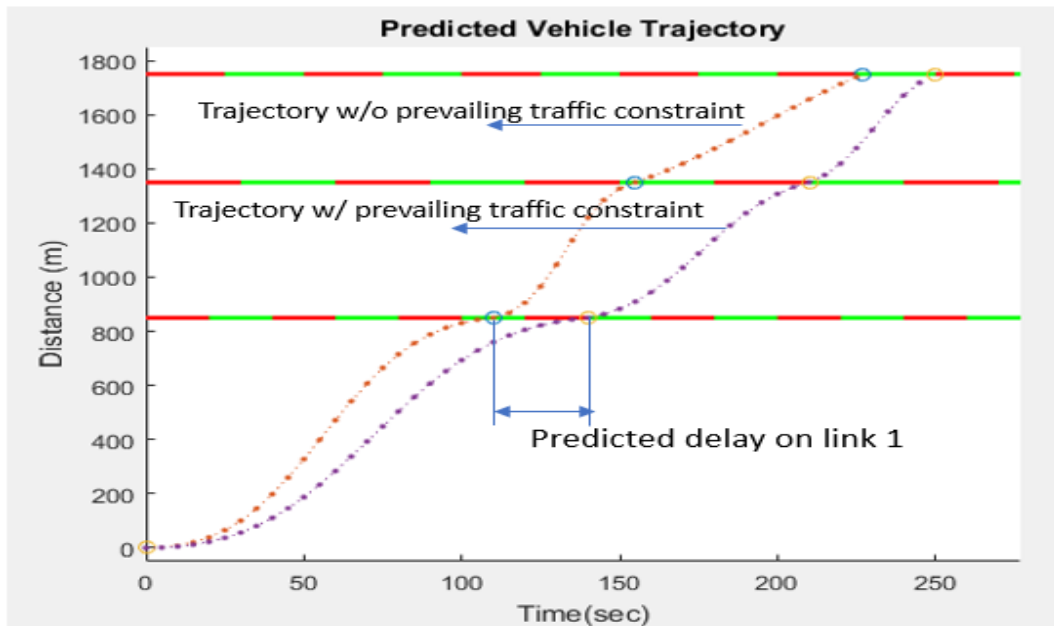**Figure 4.1** Trajectory with and without prevailing traffic constraints.

4.2   Neural Network Model for Short Term Vehicle Delay Prediction

To adequately estimate delays caused by prevailing traffic conditions, an Artificial Neural Network, specifically Multilayer Layer Perceptron (MLP) Network has been trained with known traffic flow and signalization parameters. MLP is a supervised learning algorithm

that utilizes a training dataset also known as a set of features and a target parameter to be predicted. The input features form a set of neurons further transformed in the hidden layer with weighted linear summation followed by a non-linear activation function. The purpose of the developed model is to predict delay over the horizon of 200 seconds, allowing described adjustment of the vehicle trajectory. MLP networks solve problems stochastically allowing accurate solutions for non-linear function approximation, regression, and classification tasks. Since delay prediction is based on real-time information for spot speed, volume rate, travel time, number of lanes, and signalization status, the model uses those parameters as a set of neurons to represent input features. A comprehensive training set includes a wide range for all input features covering all possible traffic scenarios that a vehicle may encounter in the observed signalized corridor. The comprehensive training set also contains all possible combinations of the input features resulting in a wide range of the target feature (vehicle delay) making this prediction problem adequate for classification algorithms.

4.2.1   Initial ANN Model Design

In MLP neural network models, the inputs are multiplied by weights followed by the summation and addition of the constant bias term. The result is further used by the activation function that is either hyperbolic tangent *(tanh)* or a sigmoid function. As described before, the short-term prediction using ANN model is achieved using the following parameters obtained from the microsimulation model for signalized corridor:

1. Spot speed obtained from loop detector or RTMS device

2. Vehicle counts from loop detector or RTMS device

3. Travel time obtained from Bluetooth or Wi-Fi sensors

4. And signal setup (i.e. green interval length) obtained from the controller

To successfully predict vehicle delay based on provided input parameters, a multilayer network with several nodes connected in series and parallel needs to be formed as illustrated in Figure 4.2.
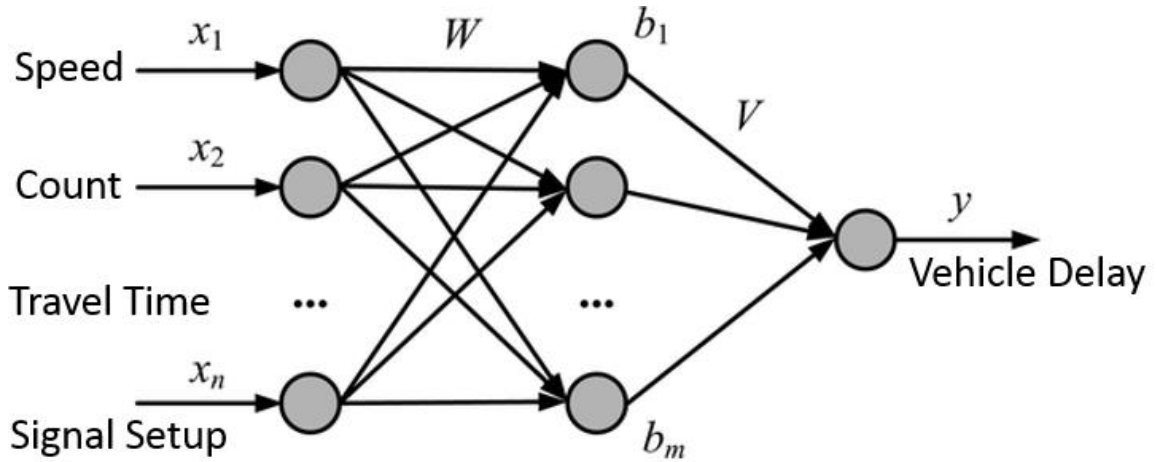

Figure 4.2 Multilayer MLP network for the proposed ANN model.

To produce an accurate neural network allowing satisfactory MLP network performance, the training and preparation of the network represent a data fitting task, where parameters to be updated are weights *(W)* and biases *(b)*. Determination of the two parameters is achieved using learning or teaching algorithm. Two most frequently used methods are back-propagation and Levenberg-Marquardt algorithms. The task can only be completed using a set of high fidelity training parameters that will provide a robust parameter estimation. The procedure of network training used for the prediction of vehicle delay comprises the following steps:

1) Step 1: Aggregation and collection of the training data

2) Step 2: Model training (including determination of network size, training algorithm, and training performance)

3) Step 3: External validation using experimental setup for testing in microsimulation platform

Some more details with respect to the determination of the measured dataset are described in the following section.

4.2.2 Aggregation of the ANN Training Set

Training set for the vehicle delay prediction model was generated using microsimulation model in PTV VISSIM. The network geometry used for this purpose correspond to the network previously used in simulation assessment.

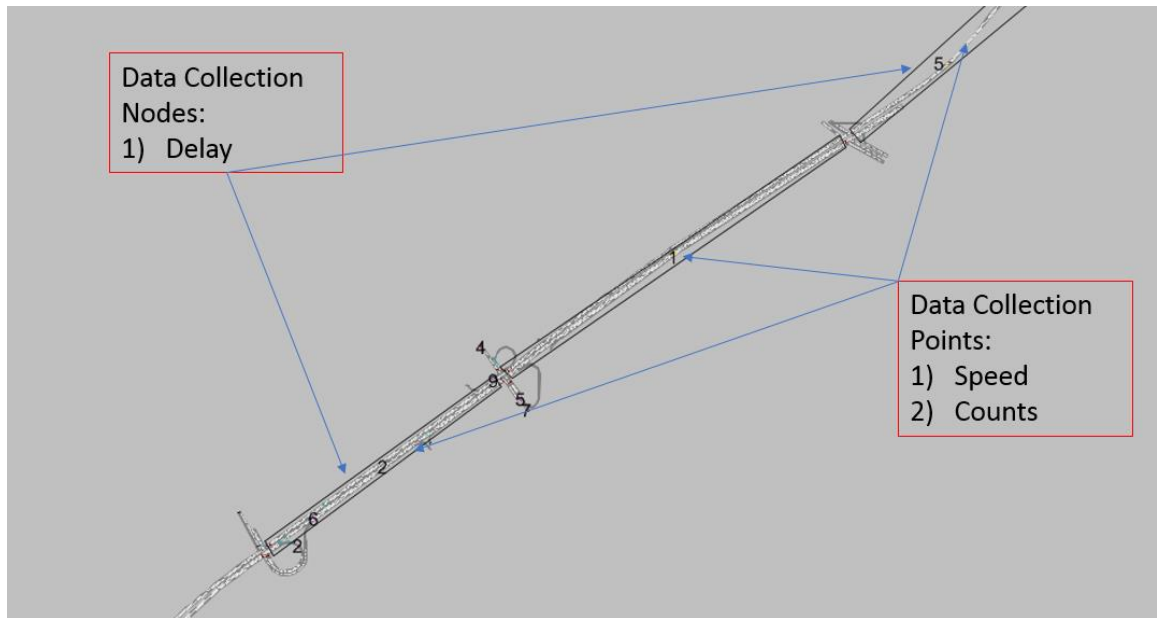**Figure 4.3** Network segment for training set data collection in PTV VISSIM.

To collect all necessary training set parameters, the simulation setup was formed as illustrated in Figure 4.3. The data collection nodes were placed on each corridor segment to collect vehicle delay for all evaluated scenarios. Travel time measurements were also deployed to measure travel time values for each corridor segment. Data collection points

were in the middle position of every link to collect vehicle counts and spot speed for each

corridor segment. To produce a comprehensive training set, a wide variety of input and

output parameters had to be covered. Therefore, the training set was generated through

following scenarios:

Table 4.1 Scenarios for Training Set Generation

Simulation Factor	Range	Increment	Scenarios / Factor
Input Volume Rate	100-6500 veh/h	100	65
Green interval length	10-100 sec	10	10
		Total Number of Scenarios	650

As presented in Table 4.1, volume rates ranging from 100 to 6500 veh/hr with an

increment of 100 vehicles per hour produced 65 different simulation scenarios. The green

interval for the mainline approaches ranging from 10 to 100 seconds in 10-second

increment was applied to all 65 volumes scenarios totaling in 650 simulation runs. The

main purpose of such an intensive scenario generation was to cover training parameter

ranges to the greatest possible extent. Through 650 microsimulation scenarios, a wide

variety of parameter values were covered: the range of values, for each model input, is

illustrated in Figure 4.4. In addition to the four training inputs, the data set also covered

mainline green interval length from 10-100 seconds in 10-second intervals. As illustrated

in the individual value plot presented in Figure 4.4, the dataset covers almost all delay

values from 0 to 2000 seconds and spot speeds from 10 to 100 kilometers per hour. Travel

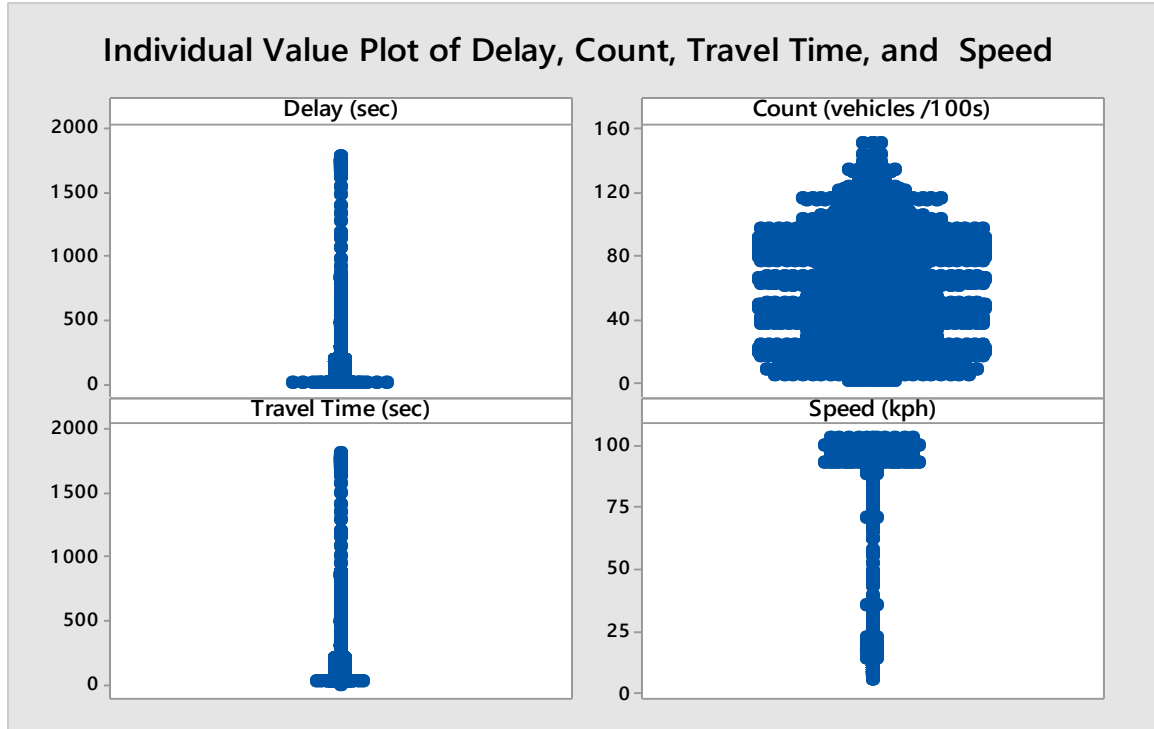times are covered for values between 30 and 1900 seconds per link.

Figure 4.4 Individual value plot for collected training parameters.

4.2.3 Definition of Network Size and Training Performance

The first step of the training procedure was to initiate an ANN network with some small number of hidden layers which can later be increased depending on training performance. With some initial network size, the weight and bias values are also initiated through random assignment. The size of validation and test samples were assumed to be 15% of the original dataset for each, leaving 70% of the dataset to be used for actual training.

With this initial setup, the training is conducted, and the mean squared error (MSE) is recorded to determine the performance of the training. The error is basically computed using validation and training datasets and is an essential indicator of the training performance. The complete training framework is illustrated in Figure 4.5.
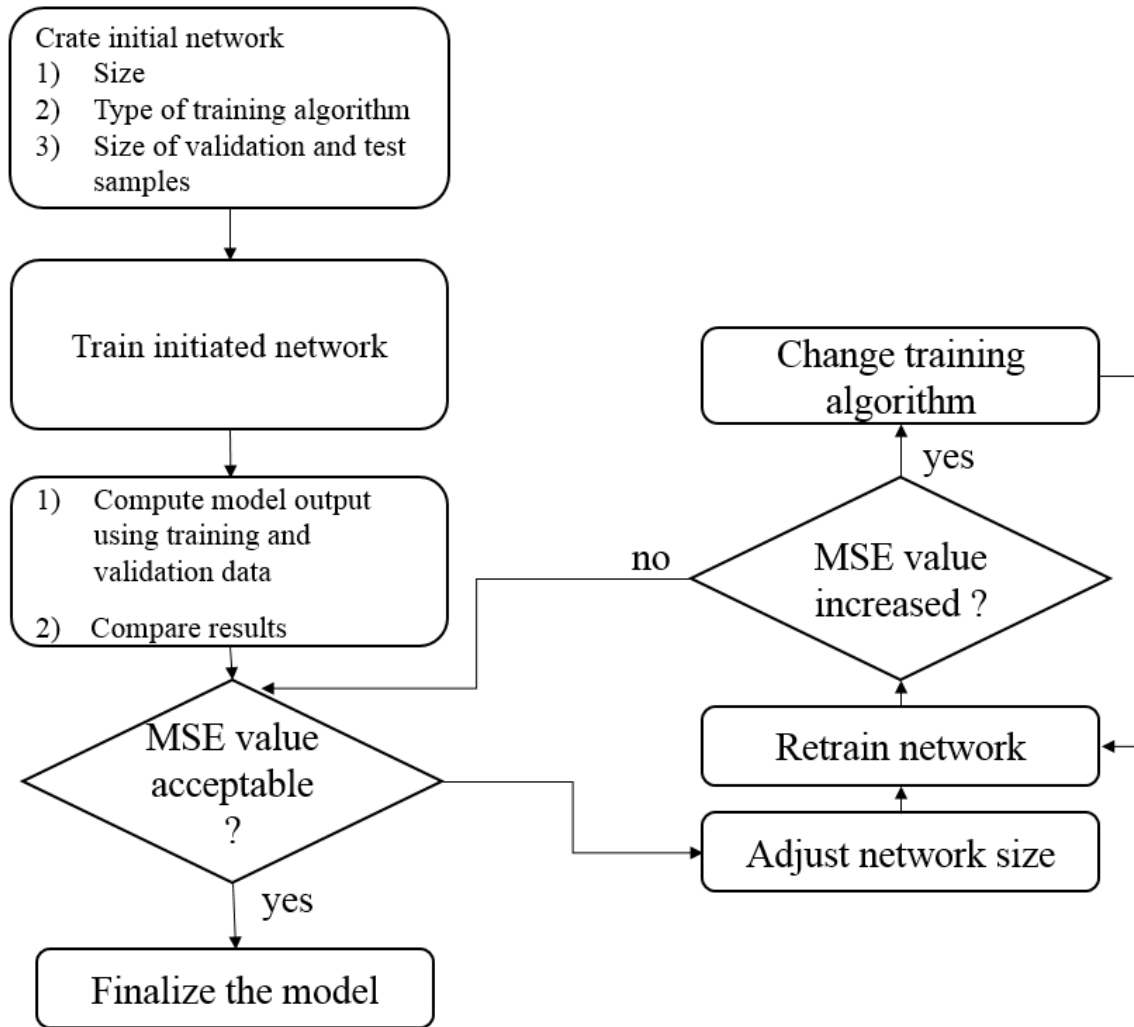
Figure 4.5 Network training framework.

After an initial training is conducted, the MSE value is compared with some
arbitrarily determined threshold. If the MSE value is below the expected threshold the next
step is to increase the network size (number of hidden layers) followed by retraining of the
network. Once the assigned network size is tested it is necessary to check if there is a rising
trend in MSE value of the model. If that is the case, the framework suggests trying another
training algorithm while keeping the record of all previous training iterations. The same
steps are repeated for different training algorithm finding the best possible performance.

Once the optimal point for network size and training algorithm type is found, the model is finalized. For this purpose, three different training algorithms were tested including:

1) Levenberg-Marquardt Training Algorithm

2) Bayesian Regularization Algorithm

3) Scale Conjugate Gradient Approach

Figure 4.6 illustrates the performance of the described training algorithms for different network size. It was discovered that the best training performance was achieved using the Levenberg-Marquardt Training Algorithm producing the following final outcome:

1) MSE= 0.1

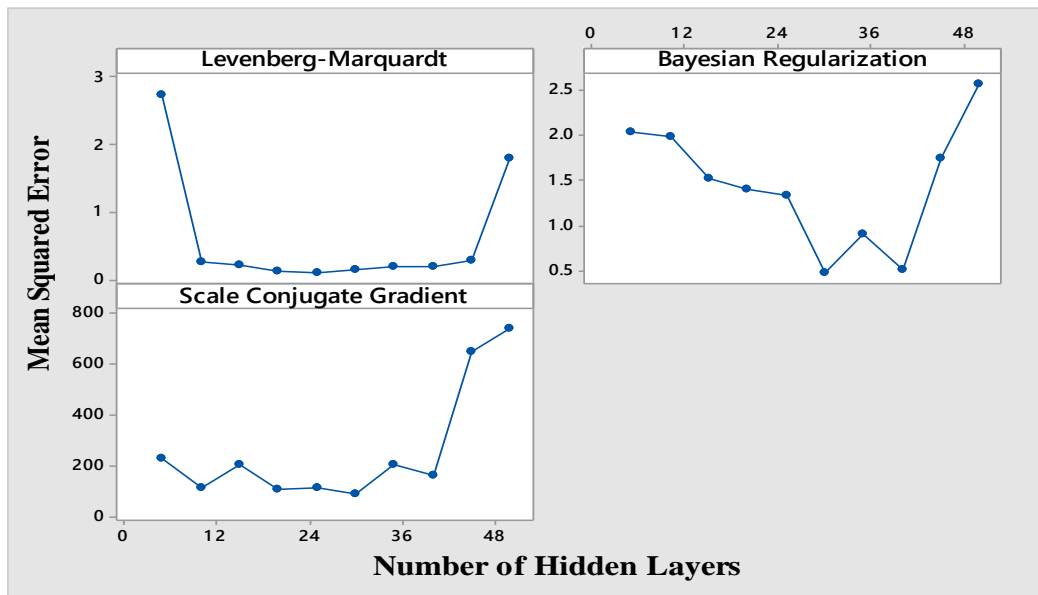2) 633 training epochs

3) 25 hidden layers

Figure 4.6 Training performance for different training algorithm types.

Optimal network size for this training algorithm was achieved using 25 hidden layers, and a further increase in network size gave no improvement in terms of model accuracy. The second-best training algorithm for the delay prediction was Bayesian

Regularization, while Scale Conjugate approach achieved significantly less effective training performance.

Figure 4.7 illustrates training performance of described network setup. The smallest MSE value was achieved at 633rd iteration.
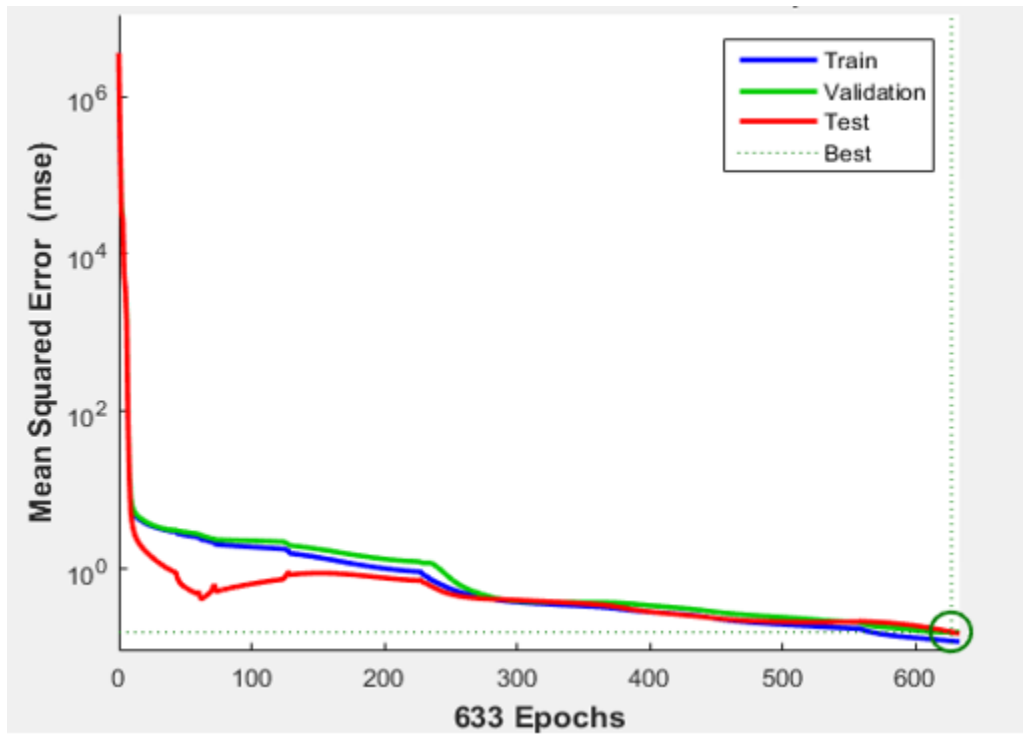

Figure 4.7 Training performance using Levenberg-Marquardt algorithm.

Figure 4.8 illustrates the distribution of absolute training error. It can be inferred from the graph that the error ranges from -1.41 to 1.18 seconds. However, the majority of records had an absolute error of -0.0005 seconds and -0.23 seconds, respectively.
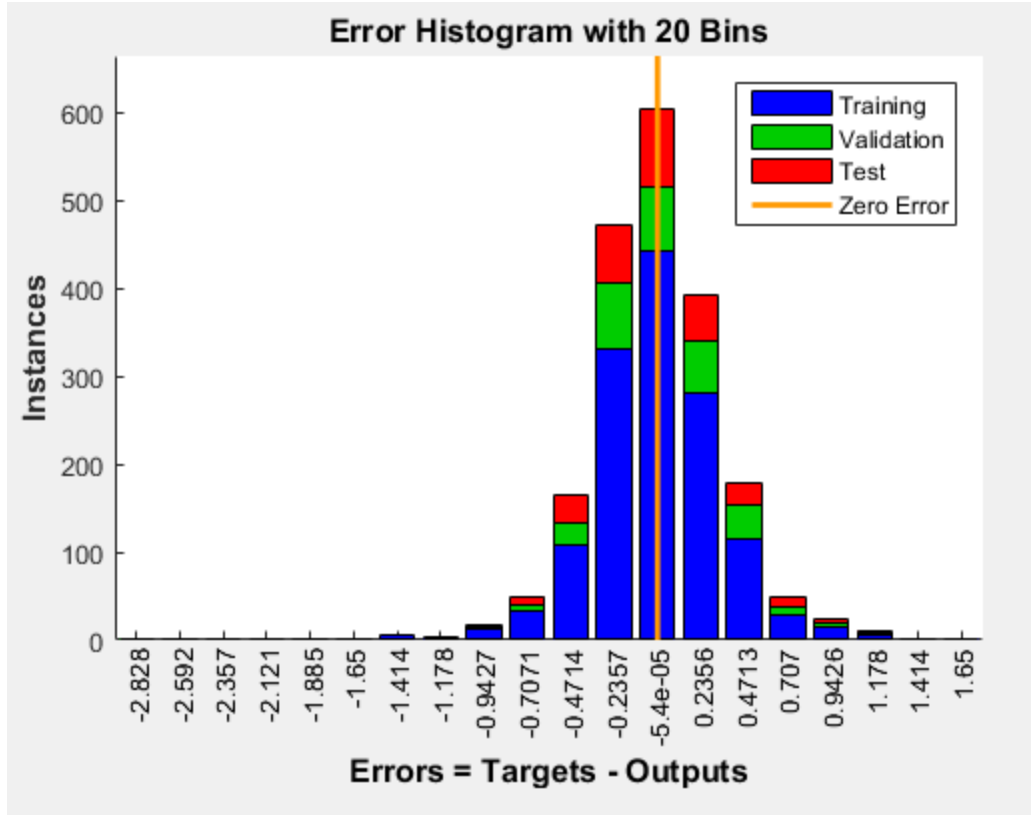
Figure 4.8. Distribution of absolute validation errors for Levenberg-Marquardt algorithm.

4.2.4 External Model Validation Assessment

External validation performed through microsimulation assumes the exposure of the trained network to an experimental setup with various traffic and signal timing conditions. The validation assessment reveals the possibility of the model to achieve an adequate generalization as it is tested with data inputs different from those utilized for training.

The experimental setup in through microsimulation include the following elements:

1) Microsimulation model for signalized corridor in PTV VISSIM

2) VISSIM data collection tool (i.e., evaluation node) for the collection of individualized vehicular parameters (i.e., vehicle delay)

3) Travel time measurements for each corridor link

4) One mid-block detector (data collection measurement) for retrieval of vehicle counts and speeds

5) ANN model for prediction of the delay caused by prevailing traffic conditions
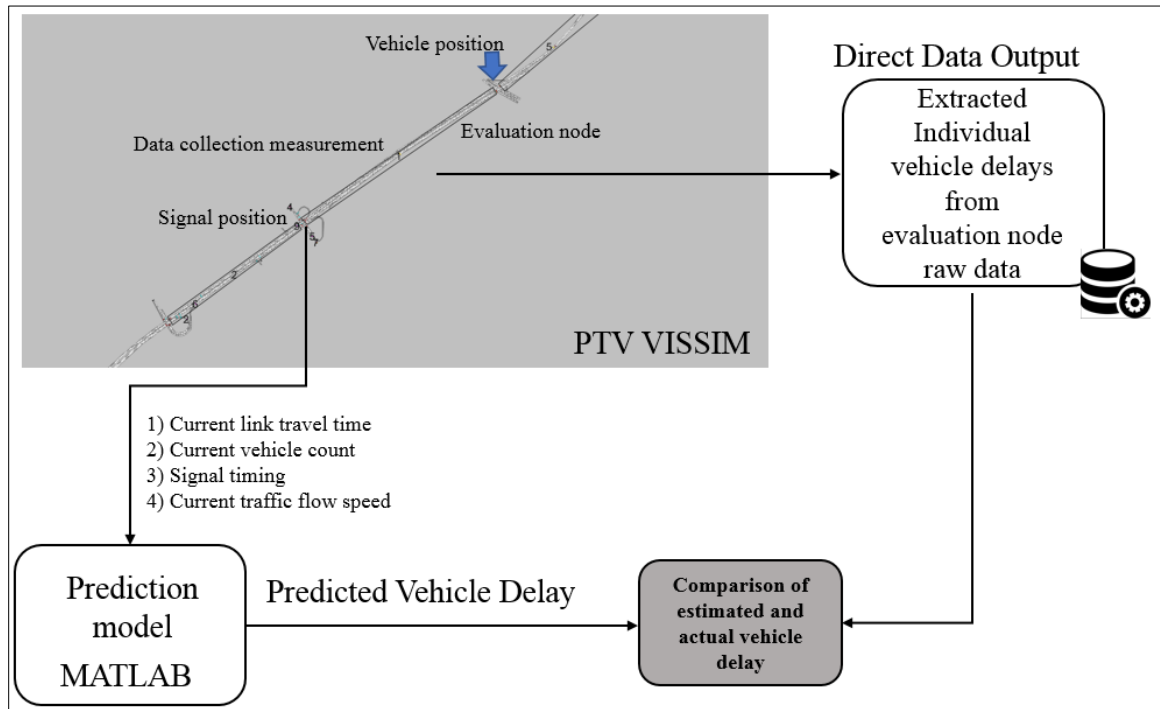
Figure 4.9 Experimental setup for the model validation in VISSIM.

The experimental setup allows instantaneous collection of vehicular data. In particular, the delay experienced by each individual vehicle is of special interest for this evaluation. Such data is obtained through VISSIM direct data output features where individualized data is stored in an external database. Once the vehicle enters the corridor, a prediction model is initiated and predicted delay value together with vehicle ID number is recorded. Such information is later used for the comparison of predicted versus actual vehicle delay. Once the simulation is completed, it was possible to compare individual vehicular record that stores information for delay experienced on every evaluation node in

the network. With known vehicle ID, the predicted delay value delivered to a vehicle upon his entrance to the VISSIM network was compared to the actual delay experienced by the vehicle and detected by the evaluation node located downstream of the entry point.

After 3600 seconds of simulation with calibrated simulation model described in Chapter 3, the comparison revealed an excellent correlation between predicted and measured vehicle delay. With isolated vehicular data, the regression plot illustrated in Figure 4.10 was created showing the R-squared value of 0.99.

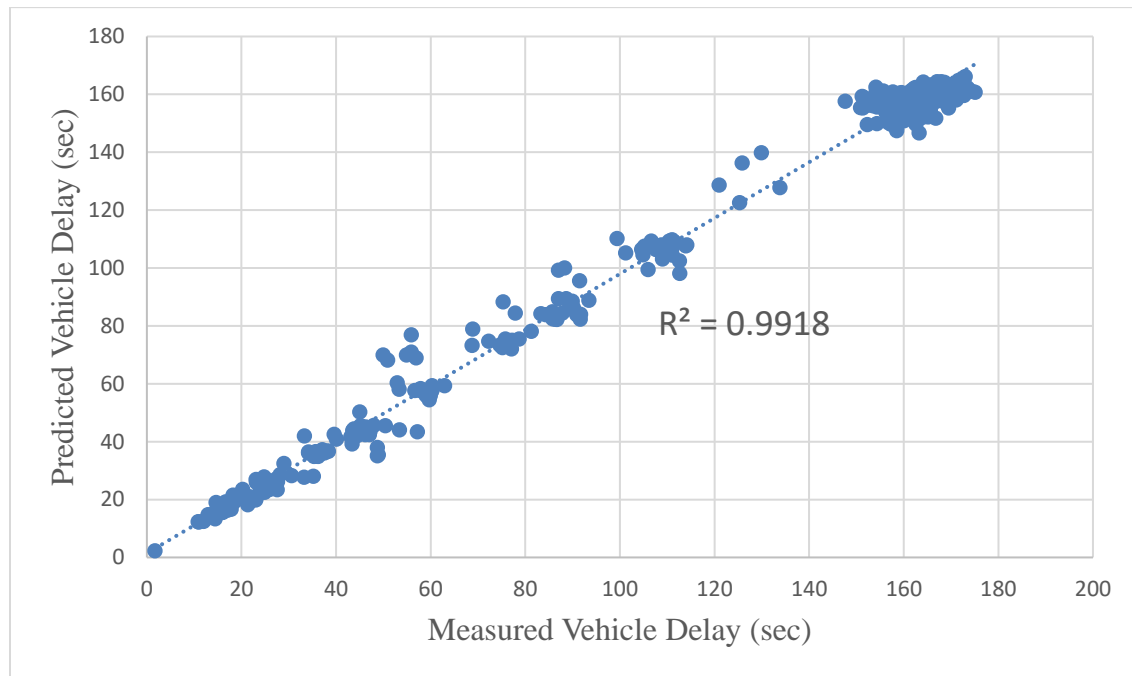**Figure 4.10**. Correlation between predicted and measured vehicle delay values.

The described procedure confirmed the correctness of the model training process. The next step in the evaluation of the proposed control strategy assumes integration of the prediction tool into existing control algorithm for automated vehicles. The predicted vehicle delay can be added to the constraint function of existing TOAD algorithm. Some

more details regarding integration of the prediction model and its impact on overall performance of the TOAD control algorithm are presented in the next section.

4.3   Integration of the Prediction Model into Existing TOAD Algorithm

The delay caused by prevailing traffic on a signalized corridor is integrated into existing TOAD algorithm structure to constrain the range of possible trajectories. The purpose of incorporating such a constraint is to provide a more accurate prediction of vehicle arrival, therefore making optimization more effective. Trajectories generated without consideration of the prevailing traffic are applicable in the simulation, however, such predictions are assuming that no vehicle delay is present along the corridor.

With the inclusion of the predicted vehicle delay, the algorithm receives more accurate information regarding vehicle arrival at the intersection stop bar, eliminating the correction of the trajectory in the later update iteration of the algorithm. The integration of the prevailing traffic prediction requires the following activities:

1) Inclusion of the vehicle delay produced by the prediction model into existing constraint function

2) The inclusion of the real-time data collection from the mid-block and travel time detectors to feed the prediction model in every simulation step of the microsimulation platform.

The formulation of the optimization model presented in Table 3.1 in Chapter 3 is based on the adjustment of control points of the interpolated trajectory curve with respect to four groups of constraints (i.e., signal timing, speed limit, and preceding vehicle constraints). An additional constraint can now be added to adjust control points to conform

with prevailing traffic conditions. With known predicted delay while using the same

notation presented in Table 3.1 in Chapter 3, the constraint can be defined as follows:

$$X_{2+(2N+1)j} - \theta_1 \leq 0$$
$$X_{4+(2N+1)j} - \theta_2 \leq 0$$
$$X_{6+(2N+1)j} - \theta_3 \leq 0$$
$$. . .$$
$$X_{M+(2N+1)j} - \theta_M \leq 0$$

Where,

$X_{M+(2N+1)j}$ represent a time dimension of the M-th control point for trajectory covering

N number of intersections and vehicle j, defined in Chapter 3

θ_M represent a predicted vehicle delay on the corridor link corresponding to control

point M.

The overall information flow with integrated vehicle delay prediction is illustrated
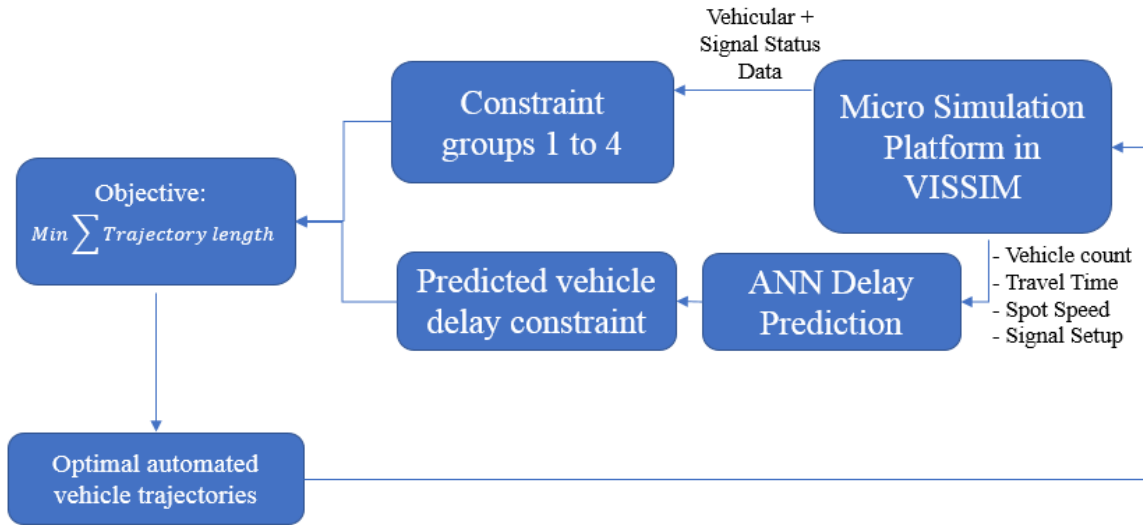
in Figure 4.11.

Figure 4.11 Information flow for optimization algorithm with predicted delays.

4.4   Inclusion of the Left-Turn Trajectories into the Existing Control Framework

The optimization method presented in Chapter 3 does not distinguish left turning vehicles as a separate group of controlled vehicles. Their trajectories were optimized with respect to the state of the signalization for through movements and distances to the stop bar of the major street approach. In such control setup, vehicles making left turns are exiting the control space, and are removed from the system once they step on the links representing the minor street. Such concept was improved by including information about vehicles static route into the existing control logic. The routing information is shared with the control agent once the vehicle accepts routing decision assigned to the left turn. Such vehicle signal timing information is followed by the corrected remaining distance to the stop bar of the jughandle ramp since left turns are executed through them throughout the whole corridor. To calculate remaining distance to the stop bar in this special case, the total length of jughandle (l_{jg}) is added to the remaining distance to the jughandle ramp (d_{jg}) as illustrated in Figure 4.12. The new, adjusted remaining distance calculates as:

$$d = l_{jg} + d_{jg} \qquad\qquad (4.1)$$

Aforementioned information improves the accuracy of the predicted arrival time for left turning vehicles. By adjusting their trajectory adequately, this group of vehicles utilizes signal status for the opposing phase allowing them to minimize the overall travel time and stopping condition as much as possible. The described adjustment is illustrated in Figure 4.13 where the final control point is assigned by respecting jughandle geometry and the corresponding signal timing phase serving the minor street link (i.e. jughandle approach).
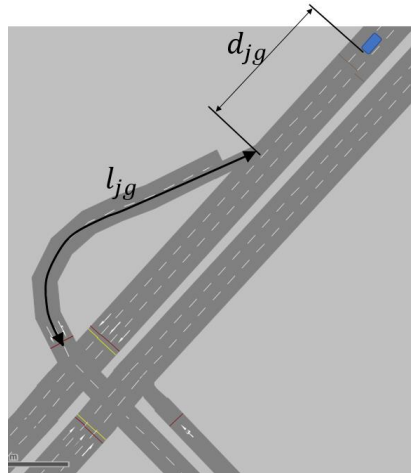
Figure 4.12 Remaining distance for left turns.

In the simulation environment, the routing information is retrieved using route number attribute of the vehicle object through VISSIM COM.
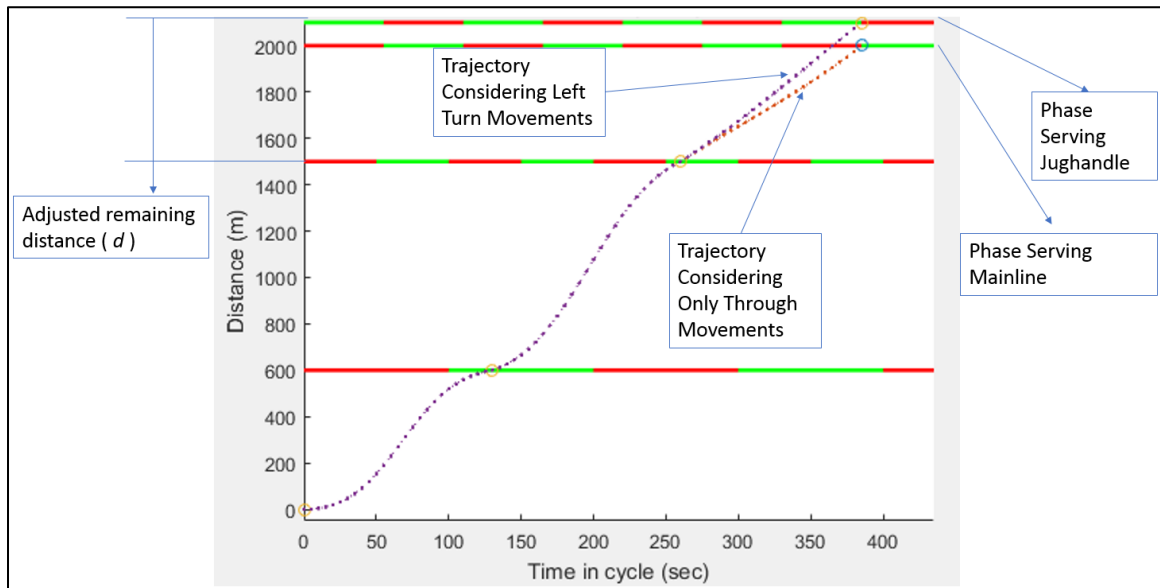

Figure 4.13 Optimal trajectory of a left turning vehicle.

4.5   Evaluation Results for TOAD Algorithm
with Inclusion of Prevailing Traffic Conditions

Chapter 3 summarized findings for the TOAD algorithm where no prevailing traffic conditions were included in the process of generating optimal vehicle trajectories. In this assessment, some general findings indicate substantial reductions in average corridor-wide travel time as technology penetration increases. It was also discovered that inclusion of the reserved lane for movement of the automated vehicle further increases benefits of the developed control strategy.

With similar evaluation scenario setup, the performance assessment can be performed for the TOAD algorithm with integrated delay prediction model. Performing analysis using two microsimulation models presented in Chapter 3, with identical input parameters allow side-by-side comparison of the two control algorithms. The same test-bed setup was enhanced with the delay prediction model as described in section 4.3. Evaluation of this setup will reveal the influence of delay prediction and its inclusion into trajectory generation.

4.5.1   Simulation Results for Testbed in Princeton, New Jersey

The results for the testbed in Princeton were evaluated under two congestion levels. The first one represents less congested conditions where the most of intersections operate under the level of service (LOS) of C as summarized in Table 4.2. Such uncongested conditions provide generally fewer control delays and insignificant vehicle queues on signalized intersections.

Table 4.2 Traffic Conditions and LOS values for Corridor in Princeton, NJ

Intersection	Ridge Road	Independence Way	Lower Harrison Street	Fisher Place	Washington Road	Carnegie Center Boulevard
LOS	B	B	B	C	B	B
V/C Ratio	0.42	0.45	0.38	0.45	0.43	0.41

The second, more congested condition includes LOS E on most corridor intersections. Those traffic conditions include significant delays and queues on signalized intersections. Such conditions are summarized in Table 4.3.

Table 4.3 Traffic Conditions and LOS Values for Corridor in Princeton, NJ

Intersection	Ridge Road	Independence Way	Lower Harrison Street	Fisher Place	Washington Road	Carnegie Center Boulevard
LOS	D	E	C	E	E	E
V/C Ratio	0.72	0.95	0.68	0.95	0.95	0.95

Total average stop delay decreases with increased technology penetration rate. As it can be seen in Figure 4.14 the reductions in average stop delays are more intensive under LOS C. The slope of the LOS C curve is higher compared to LOS E; this is due to decreased capabilities of the trajectory optimization in congested roadway conditions. While under LOS C, the average stop delay curve decreases gradually, the same curve representing LOS E is almost flat between market penetration rate 10% to 70%. After this point reductions are more visible since the majority of vehicles in a signalized corridor are automated vehicles controlled by TOAD.
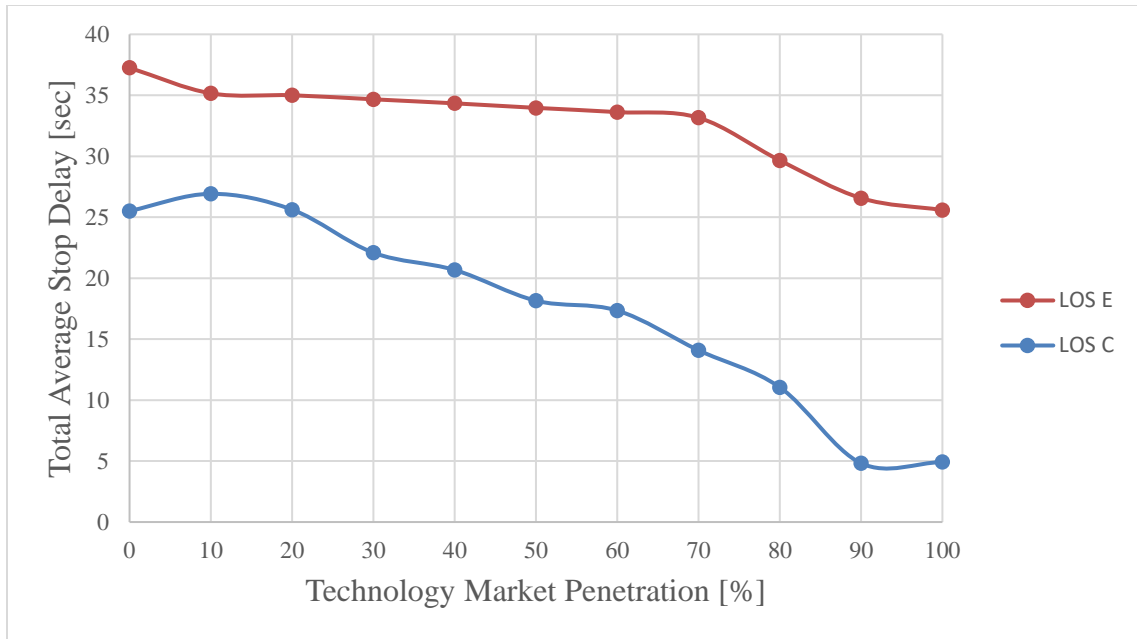
Figure 4.14 Total average stop delay for testbed in Princeton, NJ.
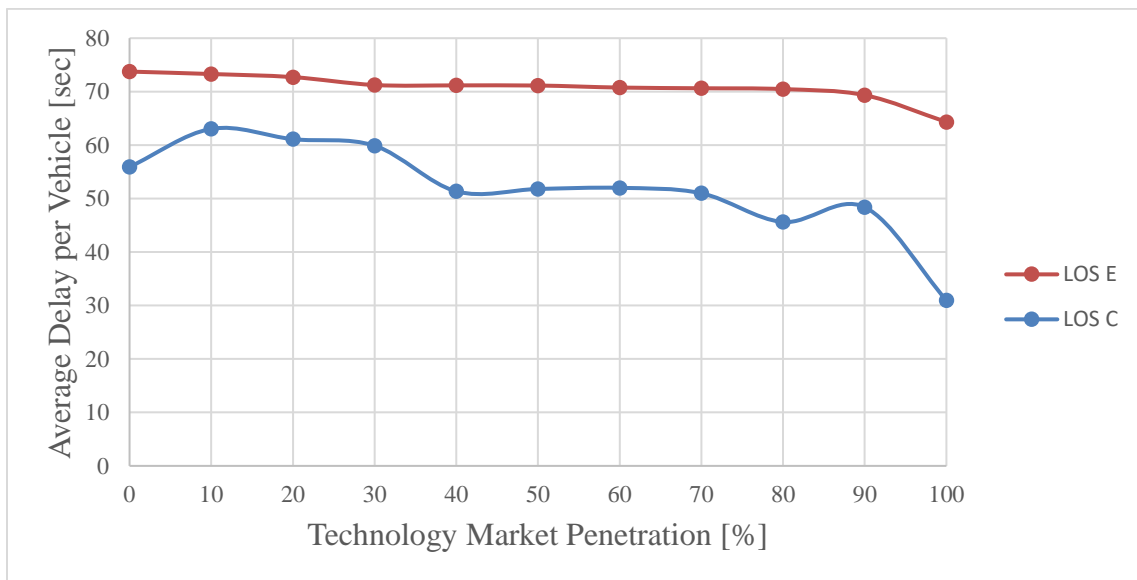
Figure 4.15 Total average delay for testbed in Princeton, NJ.

Average delay per vehicle was also observed and is illustrated in Figure 4.15 for the two traffic conditions. The trend of average delay curves is similar to the one observed for average stop delay. The curve is nearly flat under LOS E indicating low possibilities for vehicle delay reduction due to congestion and is more intensive under LOS C.

Figure 4.16 Total number of served vehicles for testbed in Princeton, NJ.

The impact of TOAD algorithm on an overall number of served vehicles is also visible under both traffic conditions.

Figure 4.17 Total average travel time for testbed in Princeton, NJ.

It is clear from Figure 4.16 that a total number of served vehicles increases with market penetration of TOAD technology and is more visible under LOS C.

The impact on overall corridor travel time is illustrated in Figure 4.17. Under uncongested corridor conditions, travel time reductions can reach 19.5% compared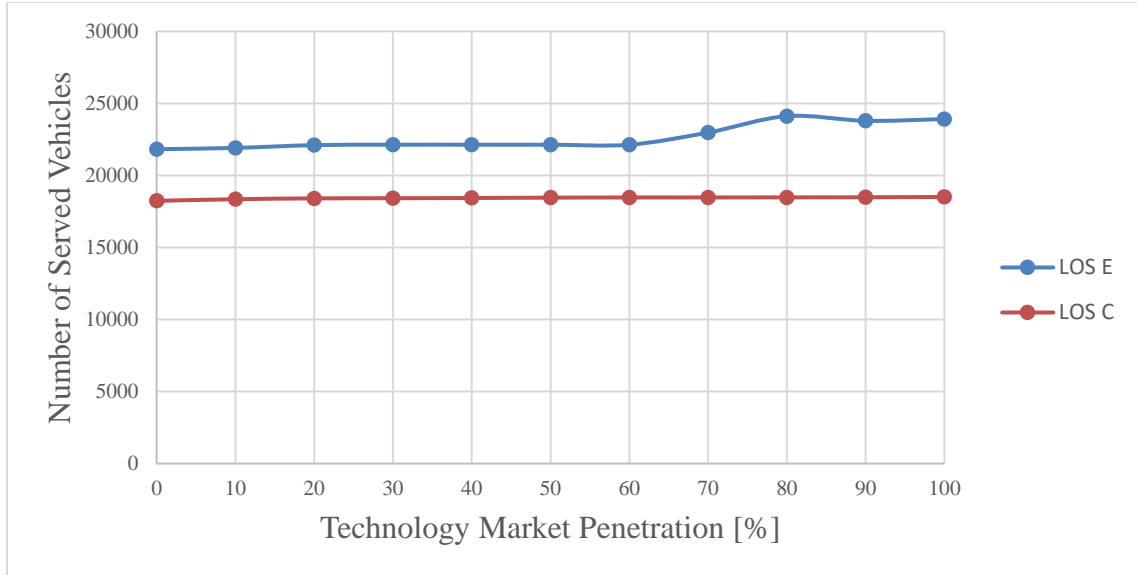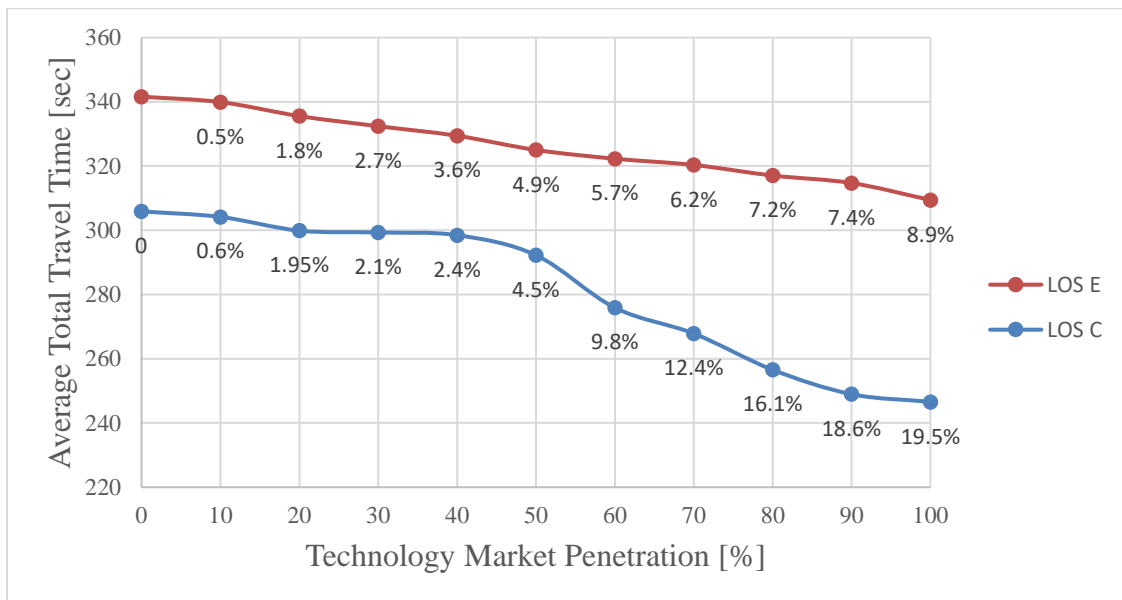 to base case scenario. Under same conditions, the benefits become more intensive after the market penetration rate reaches 50%. The same trend is more or less gradual under LOS C but is also characterized by the lower magnitude of travel time reductions that reached 8.9% with 100% of automated vehicles in the corridor. The main reason for this is that V/C ratios of the corridor presented in Table 4.3 are mostly around 0.95 which represent congested conditions which allow very limited possibilities for optimization.

Although benefits are significantly smaller under congested conditions, they still allow application of TOAD algorithm and produce improvements. In addition, even low market penetrations produce some level of travel time reductions indicating the possibility of TOAD algorithm to work under imperfect market penetration conditions.

4.5.2 Simulation Results for Test-bed in Woodbridge, New Jersey

The algorithm was additionally tested on the second test bed location, again exposing it to two traffic conditions described in Tables 4.4 and 4.5. The conditions summarized in Table 4.4 include mostly uncongested traffic conditions where V/C ratios generally range from 0.39 to 0.49 and level of services are mainly B or C. Such traffic conditions correspond to those observed on the first testbed locations allowing confirmation of findings summarized for the Princeton testbed site.

Table 4.4 Traffic Conditions and LOS Values for Corridor in Woodbridge, NJ

Intersection	Gill Lane	Ford Avenue	Parsonage Road	Grandview Avenue	Prince Street
LOS	B	C	B	C	B
V/C Ratio	0.39	0.49	0.45	0.49	0.40

Table 4.5 summarizes more congested corridor conditions with frequent stops and significant queues. V/C ratio and LOS values are similar to those observed on the first testbed location.

Table 4.5 Traffic Conditions and LOS Values for Corridor in Woodbridge, NJ

Intersection	Gill Lane	Ford Avenue	Parsonage Road	Grandview Avenue	Prince Street
LOS	D	E	E	E	D
V/C Ratio	0.71	0.92	0.95	0.93	0.73

It is again confirmed that the average stop delay decreases with market penetration. Figure 4.18 shows the lower magnitude of stop delay reductions for LOS E and generally higher stop delay values. Average delay per vehicle is also similar. The slop of LOS E curve in Figure 4.19 is lower compared to the slope of the curve under LOS C again indicating reduced possibilities for TOAD optimization under highly congested conditions. Although reductions are lower under LOS E for both average stop delay and average vehicle delay, the decreasing trend is visible, and benefits exist even under lower market penetration rates.
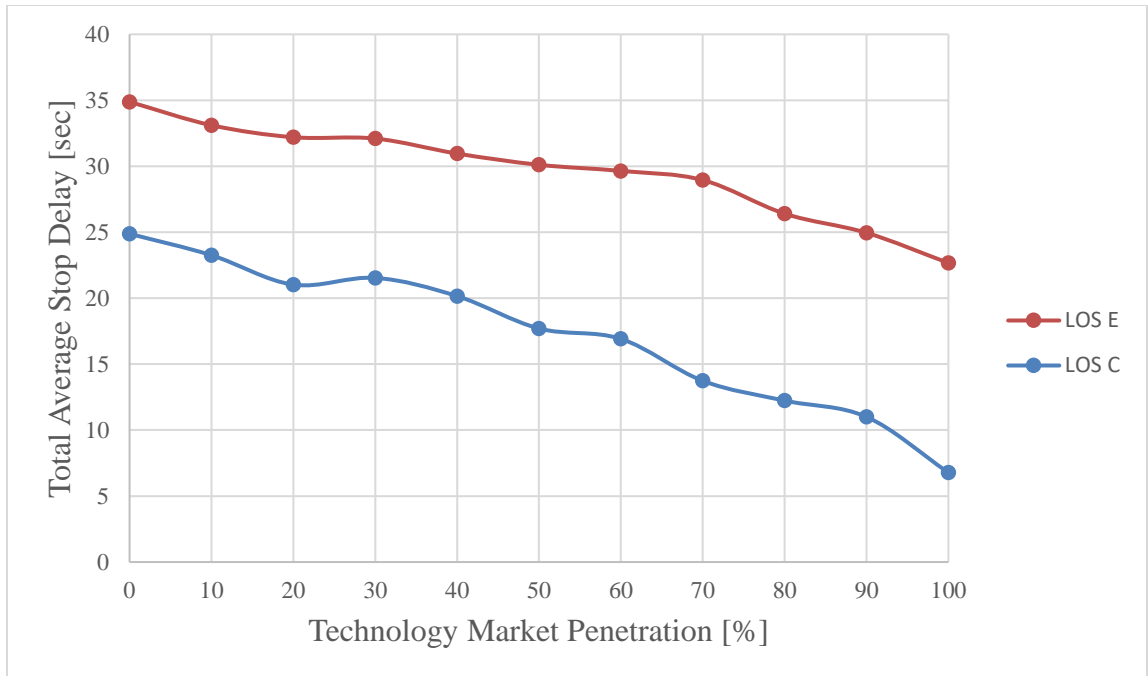
Figure 4.18 Total average stop delay for testbed in Woodbridge, NJ.
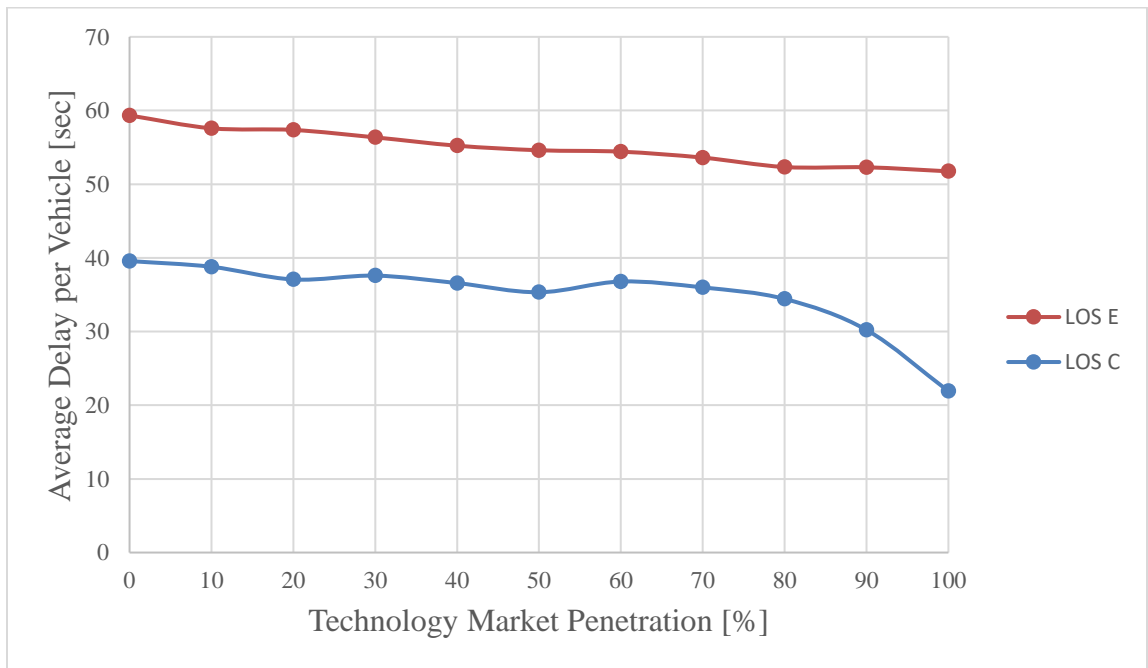
Figure 4.19 Total average delay for testbed in Woodbridge, NJ.

Increase in throughput revealed similar trend as it was detected on the first test bed location. The number of served vehicles is generally higher under LOS E and some more visible increase occurred after market penetration reached 60%. The same curve for LOS C is approximately flat as it was already observed on testbed location in Princeton.

The maximal travel time savings were achieved under 100% of automated vehicles, reaching almost 19% compared to the base case scenario. The travel time reductions are much more visible under LOS C and are generally increasing faster after the market penetration exceeds 50% which is again similar to what was detected on the first testbed location. The travel time reductions are less visible under congested conditions and in the best-case scenario with 100% of automated vehicles, they can reach nearly 9.5%.
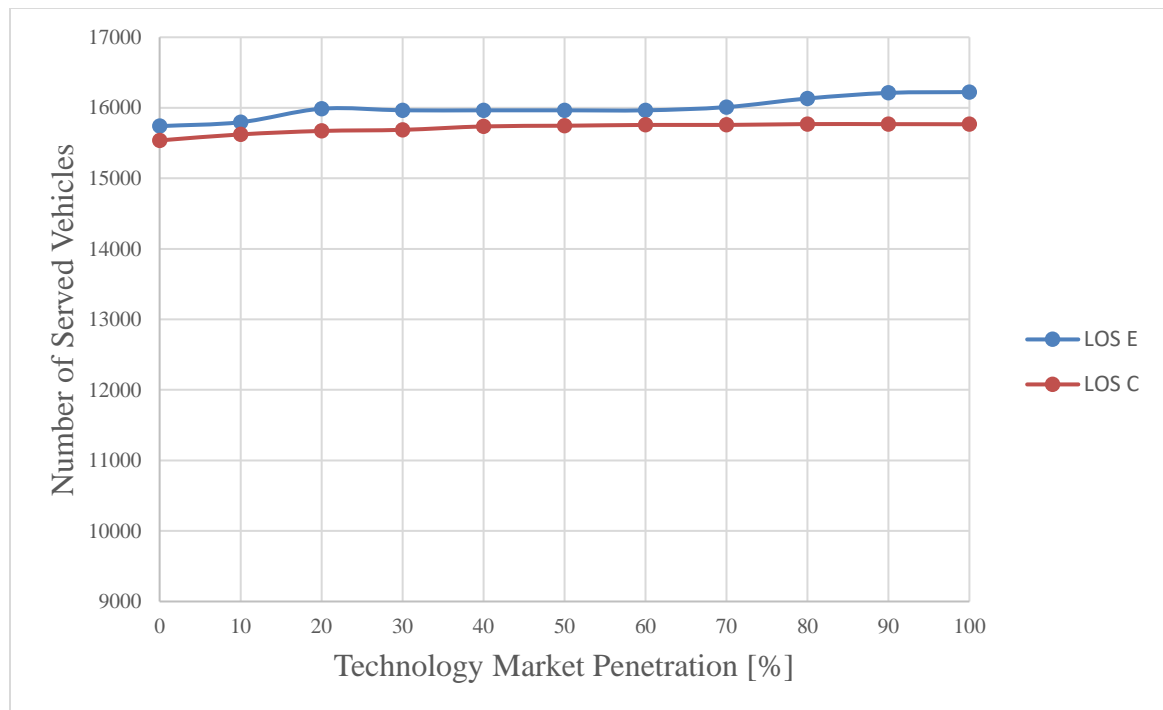
Figure 4.20 Total number of served vehicles for testbed in Woodbridge, NJ.
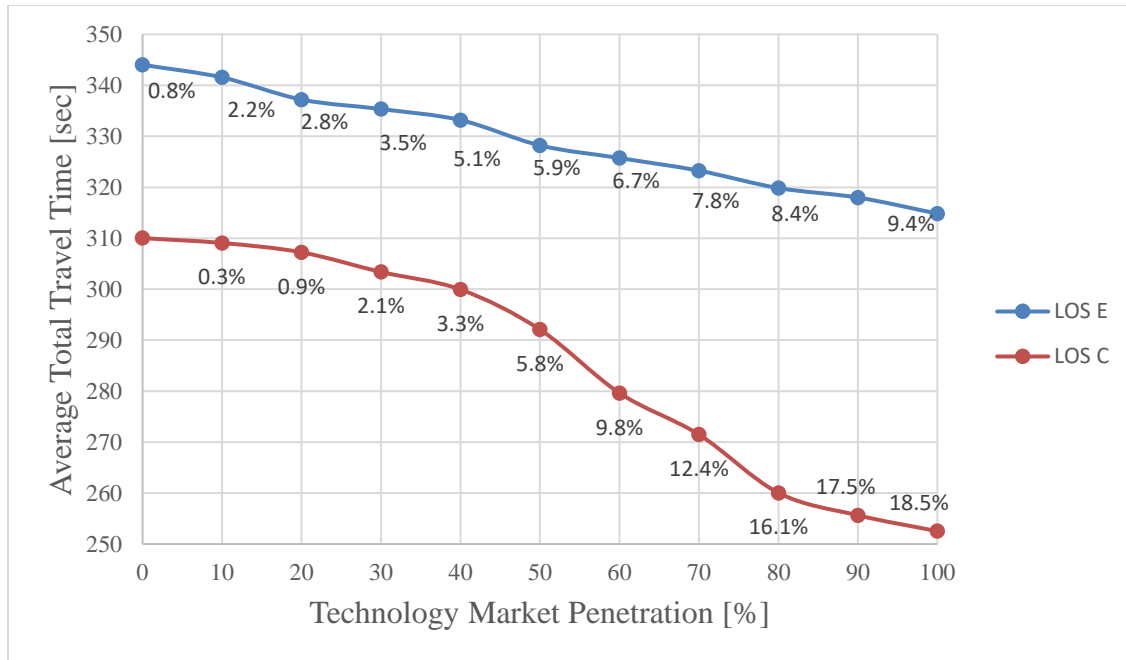
Figure 4.21 Total average travel time for testbed in Woodbridge, NJ.

4.6   Chapter Summary

This chapter introduced a methodology for the inclusion of prevailing traffic conditions into previously defined TOAD control management strategy. To achieve low-cost and reasonable sensor deployment, the short-term prediction described in this chapter was applied. The capabilities of the TOAD algorithm assessed through series of simulations revealed potential mobility improvements under any market penetration level.

Under two different corridor traffic conditions, the inclusion of prevailing traffic conditions allowed better optimization by generating more accurate predictions of vehicle arrivals on the signalized corridor. Under perfect market penetration level, it was discovered that the methodology can bring up to 19.5% in travel time reductions. When some highly congested conditions are applied, benefits can drop to approximately 8.4% but are still present even under low market penetration rates.

In addition to travel time reductions, the TOAD methodology with artificial neural network model for short-term prediction of prevailing traffic conditions significantly reduces average stop delay, average vehicular delay, and increases overall corridor throughputs.

Although findings presented in this chapter indicate significant mobility improvements under described corridor layout, further improvement of the mobility can be archived through the application of reserved lanes for automated driving. The operational characteristics and potential benefits of the reserved lane strategy are introduced in the next chapter of this dissertation.

CHAPTER 5

APPLICATION AND EFFECTIVENESS OF RESERVED
LANES FOR AUTOMATED VEHICLES

The concept of reserved lanes for automated vehicles assumes the inclusion of such lanes into existing signalized corridor using overhead gantries. The reserved lanes allow TOAD vehicles to be segregated from the general traffic in order to eliminate the interaction between two vehicle groups. The lane reservation concept allows smooth integration of automated vehicles assuming road users are well familiar with similar lane assignment concepts such as High Occupancy Vehicle (HOV) lanes, high-occupancy toll (HOT) lanes, or eco-lanes. The possibility to integrate reserved lanes for automated vehicles from the aspect of their efficiency and geometrical design is presented in this chapter. The efficiency of such lanes is evaluated under identical traffic conditions presented in Chapter 4. Comparison between mobility performance measures for the corridor with and without reserved lanes gives insight into the applicability of the concept under different traffic conditions.

5.1   Corridor Design for Automated Driving with Reserved Lanes

To adequately integrate reserved lanes into signalized arterial, the optimal lane group to be used are inner lanes (i.e. left-most lanes). The main reason for described lane assignment is that the left-most lane allows uninterrupted movement of automated vehicles in cases where unequipped vehicles are making right turns at intersections or access points of the corridor.

To apply such lane assignment strategy, the signalized corridor must be equipped with jughandle intersections as left-most lanes cannot be used for left turns. Therefore, all vehicles are assumed to make left turns using jughandles, and automated vehicles making left turns must leave reserved lane and become a part of general traffic in order to access jughandle ramp. Jughandle ramps on signalized corridors are frequently applied traffic regulation strategy as it is well known to improve intersection capacity. This strategy along with reserved lanes for automated driving can further improve mobility performance of a signalized corridor.

■ Automated (Controlled) Vehicles
■ Unequipped Vehicles
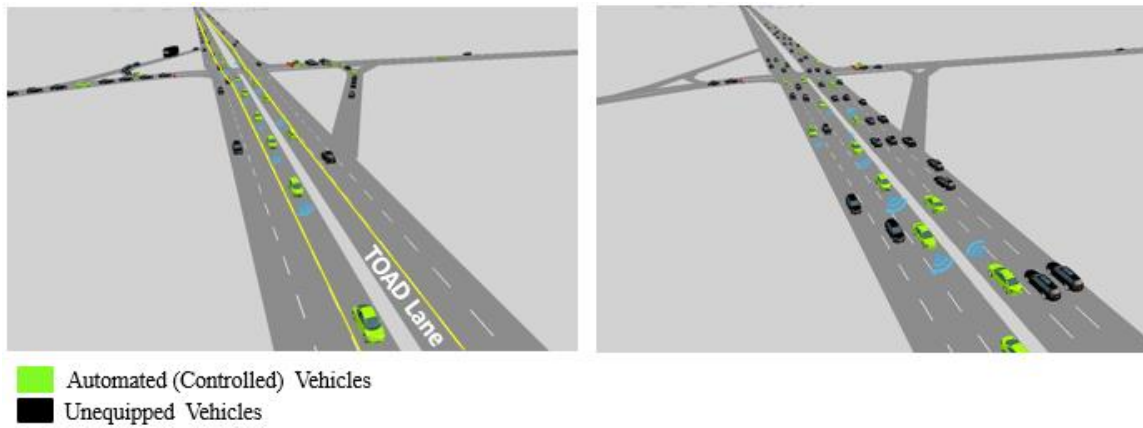
(a) With reserved lane for TOAD (b) Without reserved lane for TOAD

Figure 5.1 Simulation of the TOAD control strategy in PTV VISSIM.

5.2 Evaluation Scenarios for Signalized Corridor with Reserved Lanes for Automated Driving

As it was described in Chapter 4, the simulation results comprise eleven different market penetration conditions (0%-100%, in 10% increments) and were examined with five consecutive simulation runs but this time for additional two cases: 1) with reserved, and 2) without reserved lanes for automated vehicles under the peak and off-peak traffic

conditions. Simulation for eleven different market penetration conditions for both lane configurations was repeated five times, every time changing random seed parameter. Thus, this evaluation required a total of 110 simulation runs.

Table 5.1 Evaluation Scenarios for Assessment of Reserved Lanes

Simulation Scenario Factors	Level
Inclusion of the reserved lanes	1) With reserved lanes for TOAD 2) Without reserved lanes for TOAD
Volume rates	1) Peak period volumes 2) Off-peak period volumes
Technology market penetration	From 0% to 100% in 10% increment

5.3 Lane Configuration under Different Market Penetration and Volume Conditions

Throughout simulation assessment, it was discovered that the best lane configuration setup depends on current traffic and market penetration levels. Specifically, under LOS A to C, the first reserved lane can be introduced as soon as market penetration level reaches 10% and additional reserved lane can be introduced with 50% of automated vehicles in the corridor. Under more congested conditions (i.e. LOS C to E) it is not recommended to assign any reserved lanes until the market penetration exceeded 60%. At this point, it is recommended to include two reserved lanes for automated vehicles. The reason for not including reserved lane before 60% market penetration can be explained using Figures 5.10 and 5.18. By observing those figures, it can be inferred that inclusion of reserved lanes before mentioned threshold might provide lower benefits compared to corridor without lane reservation.
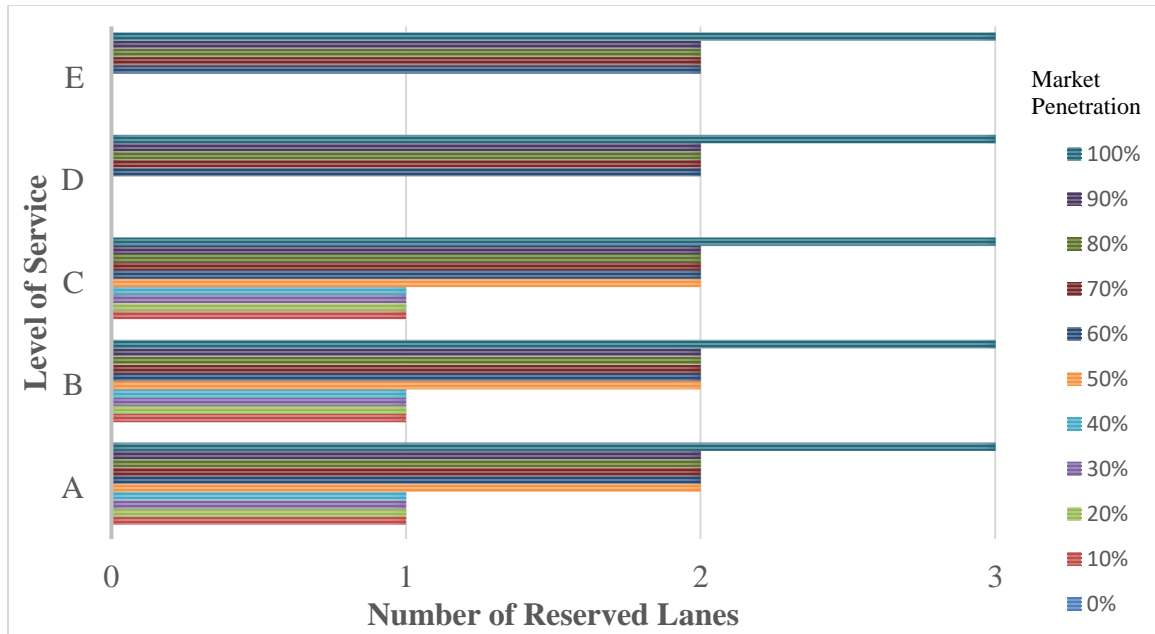
Figure 5.2 Recommended lane configuration for different traffic and market penetration levels

The main reason for lower benefits under unstable traffic conditions is an oversaturation of lanes assigned to general traffic under low market penetration levels. In such conditions, every time one or two lanes are assigned to automated vehicles, the lanes assigned to general traffic will be exposed to undesirable V/C ratios further influencing the average corridor travel time. The same conflict does not occur under lower LOS values, as the volume rates of the corridor are generally lower, making this limitation of the lane assignment strategy less visible.

5.3.1 Evaluation Results for Testbed in Princeton, New Jersey

Under traffic conditions described in Table 4.2, the total average stop delay for entire network was collected for both cases, with and without reserved lanes for automated driving. It can be inferred from the graph that overall trend of the average delay decreases with increased market penetration. The delay for the corridor with reserved lanes under 20-

40% of automated vehicles had similar values. For market penetration values from 40% to 60% the delay significantly decreases and again becomes evenly distributed between 60-80%. The reason for described fluctuation in the stop delay can be found in the lane configuration adjustment. Once the number of lanes changes, the decrease in stop delay cannot be achieved instantly, and generally occurs once the reserved lane produces an appropriate level of utilization.

In case of the corridor without reserved lanes, the decrease in stop delay is gradual in its nature and does not contain significant fluctuations.
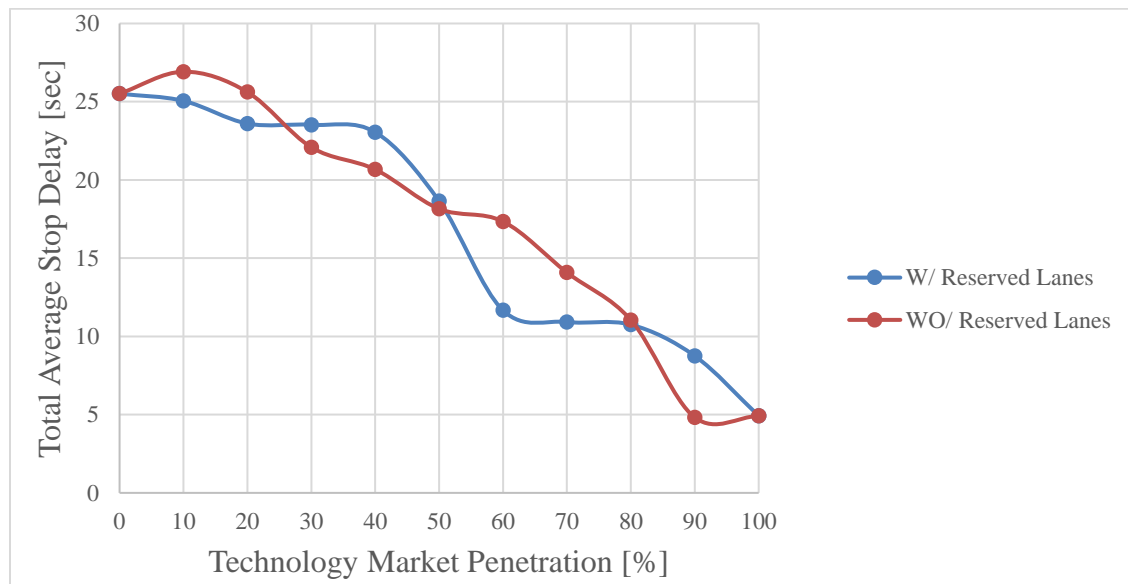
Figure 5.3 Total average stop delay for testbed in Princeton, NJ, under LOS C.

A decreasing trend was detected for the average delay as well. The overall average delay is lower for a corridor with reserved lanes. Similar fluctuations as described for the average stop delay were observed. Again, the overall nature of the average delay curve for the corridor without reserved lane comprises gradual decrease with no distinctive fluctuations.
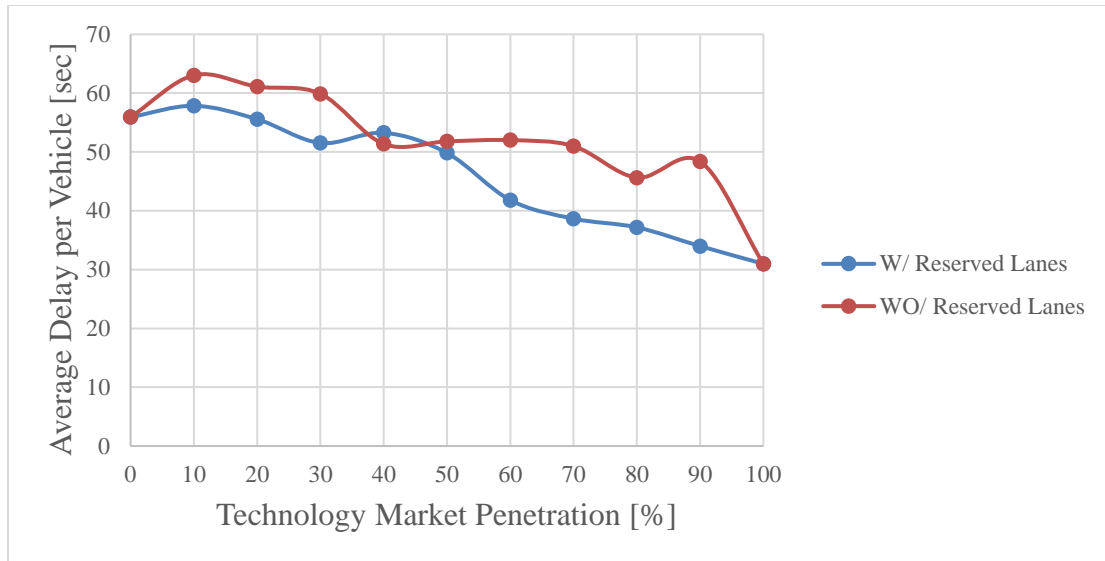
Figure 5.4 Average delay per vehicle for testbed in Princeton, NJ under LOS C.

The total number of served vehicles increased with a number of automated vehicles in the traffic stream. This trend was expected since decreased stop delay and a total number of stops provides better corridor progression. In addition, the more automated vehicles are present in the traffic stream, the less start-up lost time is experienced leading to increase in intersection throughputs along the corridor. Again, a certain level of fluctuations was detected for the corridor with reserved lanes due to described change in a number of lanes reserved for such vehicles. The number of served vehicles is slightly higher for the corridor without reserved lanes. Since the overall utilization of such lanes fluctuates so does the overall throughput.
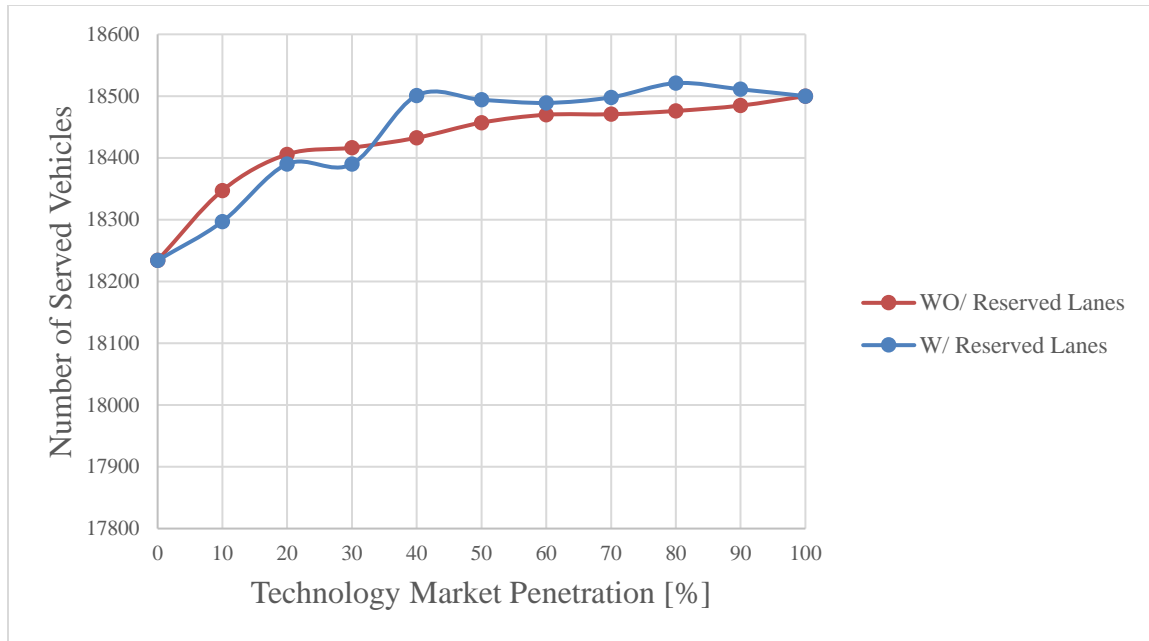
Figure 5.5 Total average number of served vehicles for testbed in Princeton, NJ, under LOS C.

The described mobility performance measures such as average stop delay, average vehicle delay, and increased throughput values are inevitably leading toward a decrease in overall travel time of the corridor. Nonetheless, the introduction of reserved lanes further increases the effectiveness of the proposed control algorithm. Figure 5.6 illustrates the average total travel time for described corridor under different market penetration rates. Expectedly, the overall travel time decreases as a number of automated vehicles increases. Although benefits are marginal for low market penetration levels from 0-20% the overall functionality of the strategy is confirmed. Some more visible travel time reductions can be expected for market penetration rates higher than 20%. The trend of the travel time curves for the corridor with and without reserved lanes under given traffic conditions differs for market penetration levels from 20% to 80%. While the curve for the corridor without such lanes is almost flat for market penetrations 20-50%, the curve for the corridor with reserved

lanes contains a certain level of decrease. Some more abrupt decrease is detected for market penetration rates higher than 50% in both lane configuration cases. For market penetration rates higher than 80%, the detected benefits are similar for both lane configuration cases as a result of a generally high number of automated vehicles in the traffic stream.
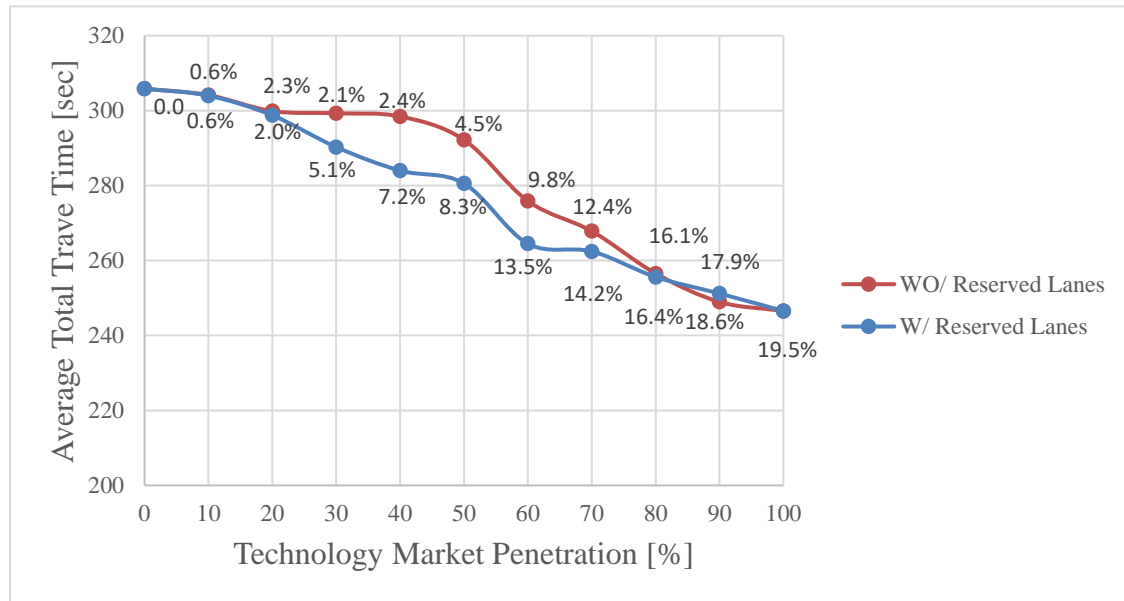
Figure 5.6 Total average travel time for testbed in Princeton, NJ under LOS C.

Some more congested traffic conditions summarized in Table 4.3 changed the overall magnitude of the mobility parameters. The reductions in total average stop delay decreased from 80% to only 32% under congested traffic conditions. The overall trend also changes significantly. The curve representing average stop delays with reserved lanes is generally lower compared to the one representing case without reserved lanes. Also, both curves gave significantly lower reductions in market penetration rates from 0-60%. After this point, the reductions are significantly higher revealing the influence of unequipped vehicles that are less present in higher market penetration cases.
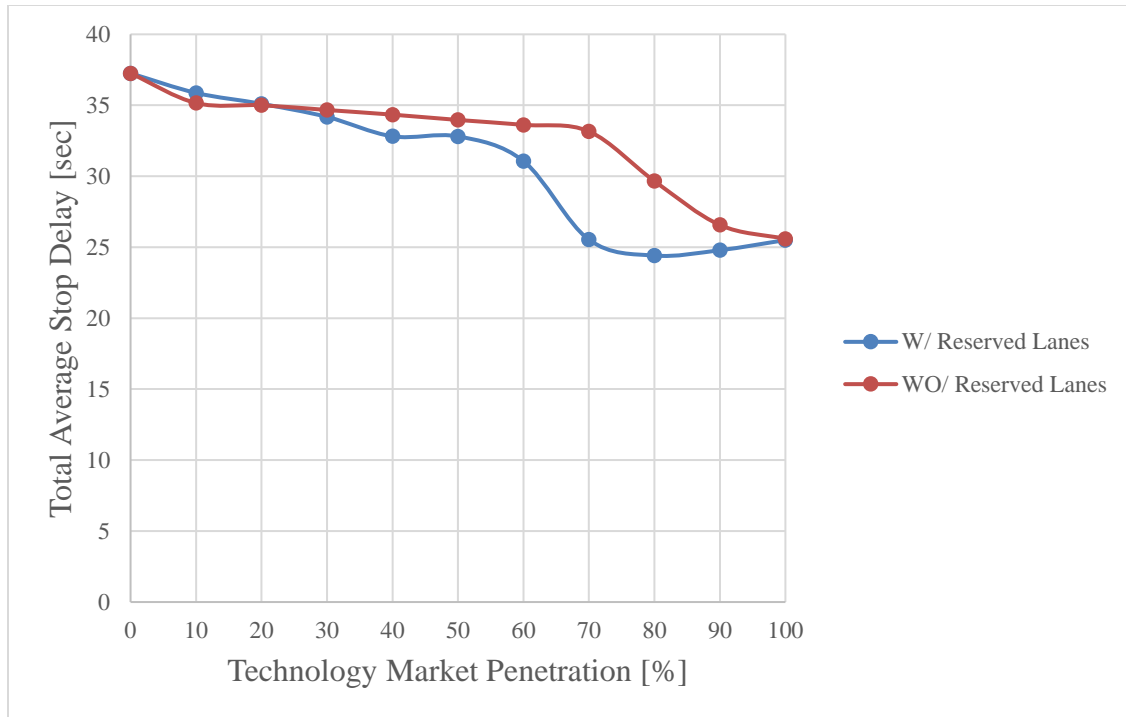
Figure 5.7 Total average stop delay under LOS E for testbed in Princeton, NJ.

The total average delay revealed similar trends. The total reductions under LOS C of 47% are now 13% which can also be described as the influence of generally congested corridor conditions. In such conditions, possibilities for generating more efficient vehicle trajectory are lower, as well as possibilities for lane changing. In general, delays are lower for the corridor with reserved lanes but the slope is significantly lower compared to the same curve generated under LOS C. The benefits for market penetration rates under 30% are almost similar, while after 30% they become more distinctive. An abrupt drop in average delay occurred after 80% of automated vehicles for the corridor without reserved lanes, while the overall trend of the same curve for the corridor with reserved lanes decreases gradually with increase in penetration level of automated vehicles.

Figure 5.8 Total average delay under LOS E for testbed in Princeton, NJ.

Under LOS E the overall number of served vehicles increased by 8.5%. The LOS C revealed a slightly lower increase of 1.4% with 100% of automated vehicles in the traffic stream.
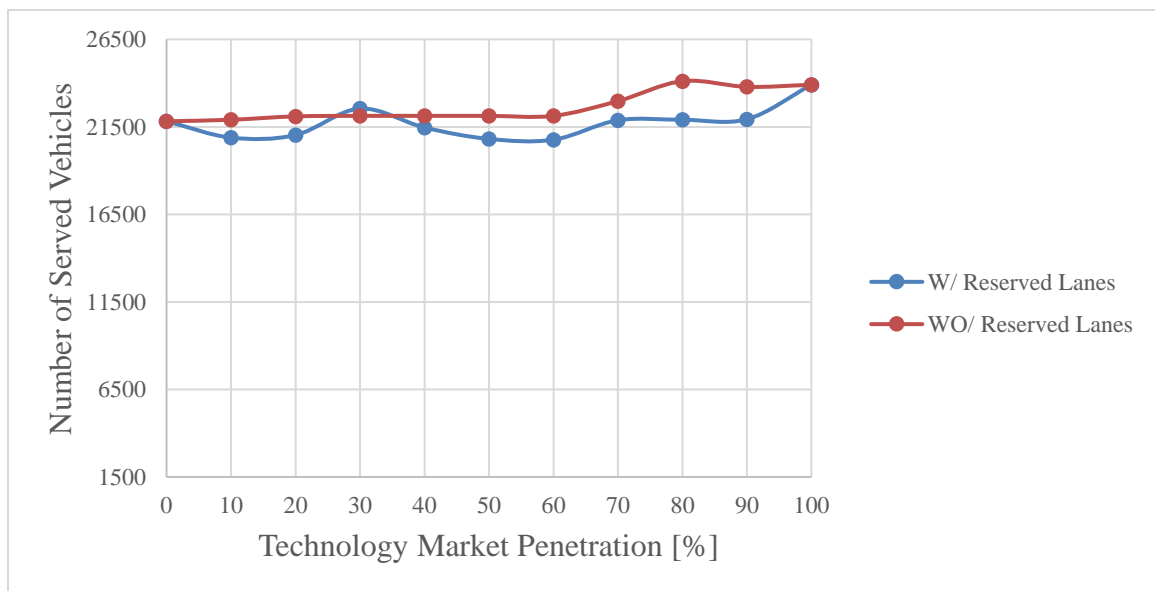
Figure 5.9 Total number of served vehicles under LOS E for testbed in Princeton, NJ.

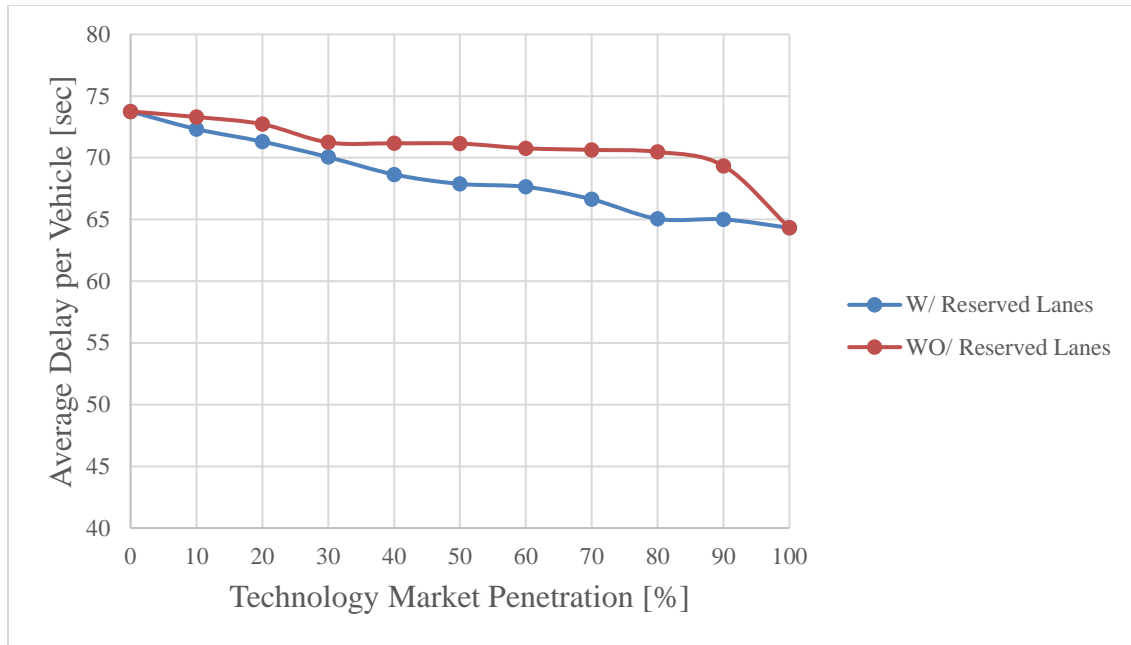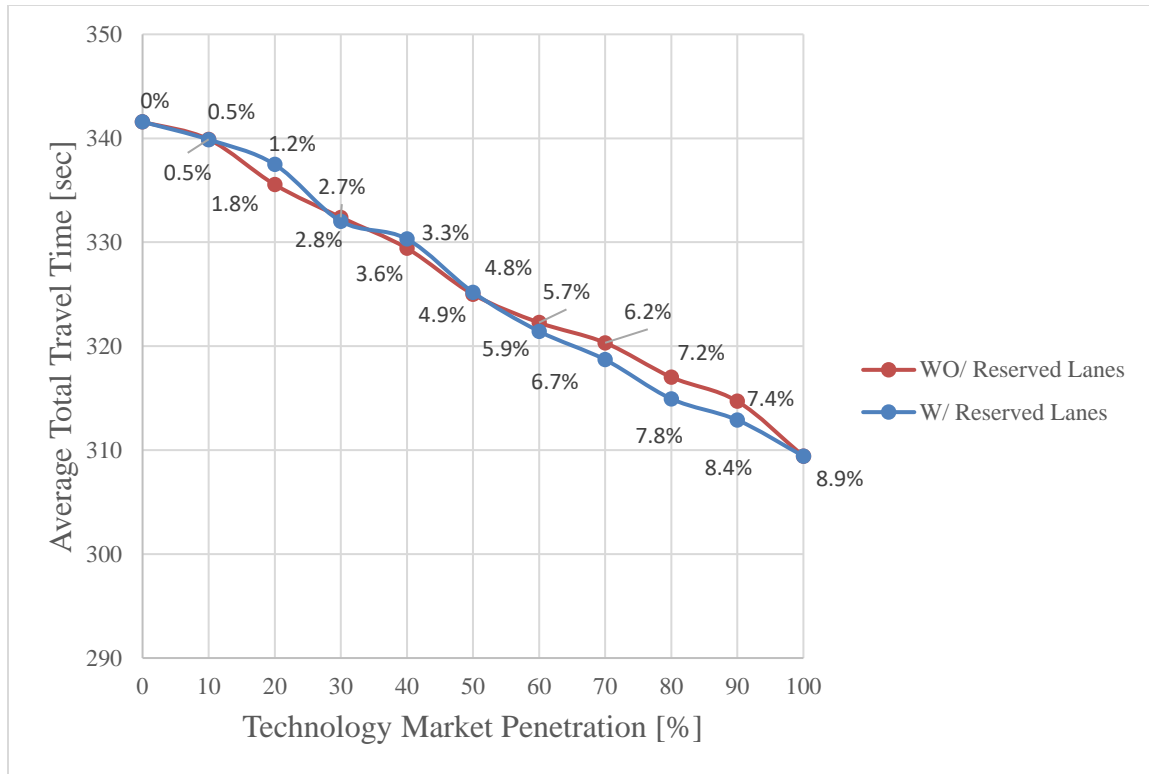**Figure 5.10** Average total travel time under LOS E for testbed in Princeton, NJ.

The congested corridor conditions not only decreased overall mobility improvements but also decreased the effectiveness of the reserved lanes. It can be inferred from Figure 5.10 that travel time curve for the corridor with and without reserved lanes achieved similar trends. Although the concept of reserved lanes is still more effective for market penetration higher than 60%, the difference in travel times is much more visible compared to uncongested conditions presented in the first part of this section. The main reason for the reduced effectiveness of the reserved lanes with respect to overall mobility performance lays in the fact that under congested traffic conditions general traffic suffers once a separate lane is assigned to automated vehicles due to reduced capacity. The same capacity reduction is less visible under uncongested traffic conditions as overall V/C ratios are lower allowing general traffic to operate with fewer constraints. With this finding, it is

highly questionable if the concept of reserved lanes can be applied under highly congested traffic conditions.

5.3.2   Evaluation Results for Testbed in Woodbridge, New Jersey

The second testbed location generally confirmed findings outlined in the previous section. The influence of automated vehicles decreased total average stop delay of the entire network. The maximum reduction under 100% market penetration reached 72% under uncongested traffic conditions described in Table 4.4. The overall reduction is higher for a corridor with reserved lanes although it becomes slightly lower under market penetrations 80-90%. Also, certain fluctuations are present in the case with reserved lanes due to reasons described in the previous section. Again, the total stop delay reductions are more gradual for the corridor without reserved lanes.
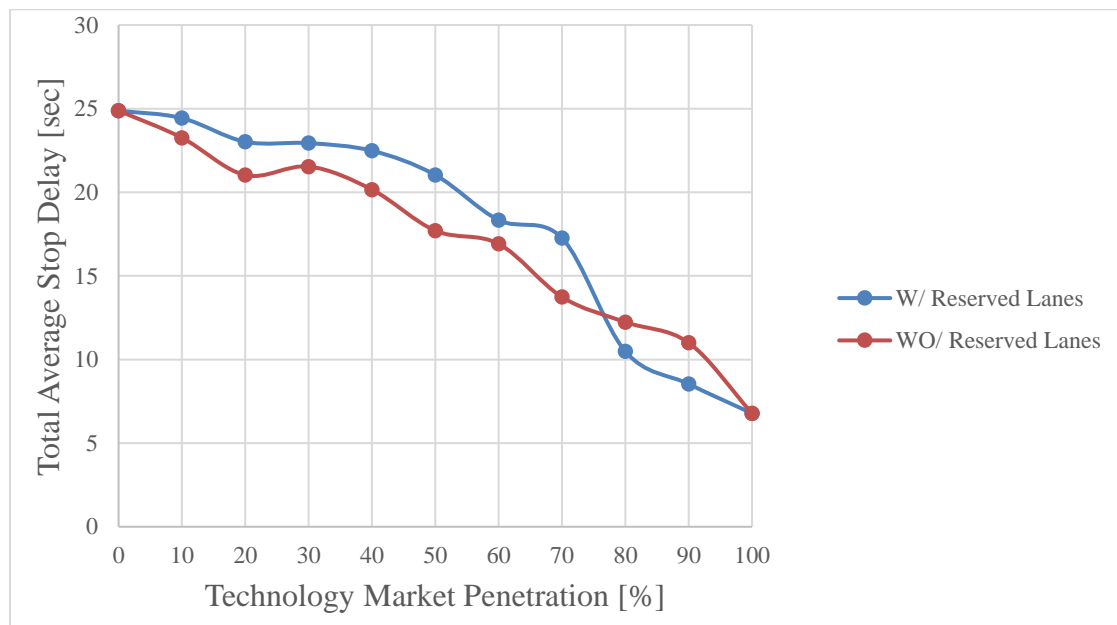
5.11 Total average stop delay for testbed in Woodbridge, NJ under LOS C.

Maximal reductions in average delay under 100% market penetration are 45% and again have a decreasing trend as market penetration increases. The reductions are generally

higher for the corridor with reserved lanes which confirmed findings from the first testbed location.
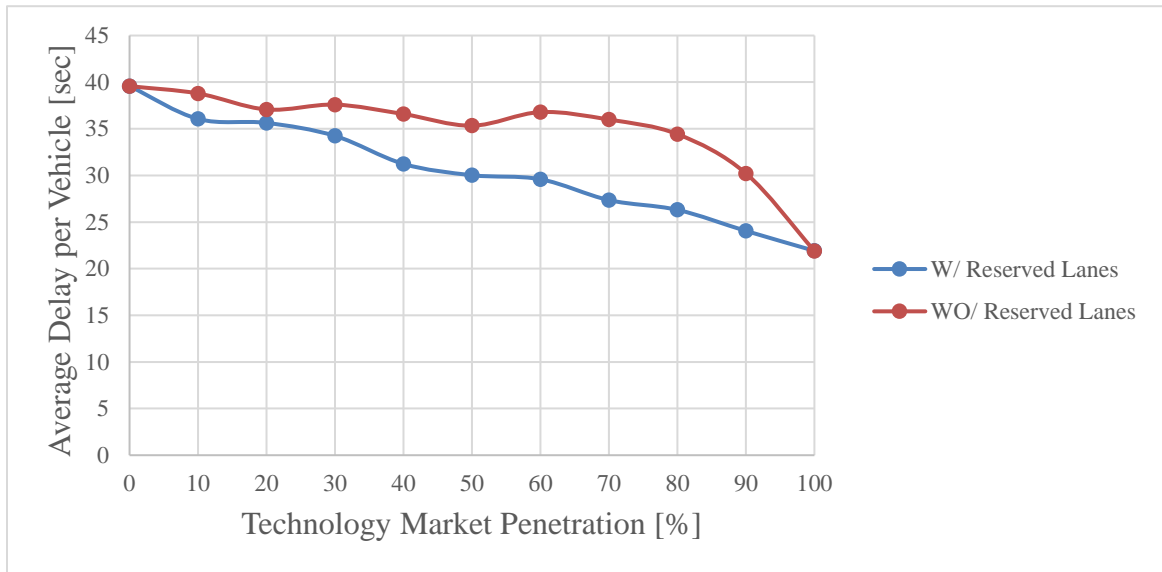
5.12 Total average delay for testbed in Woodbridge, NJ under LOS C
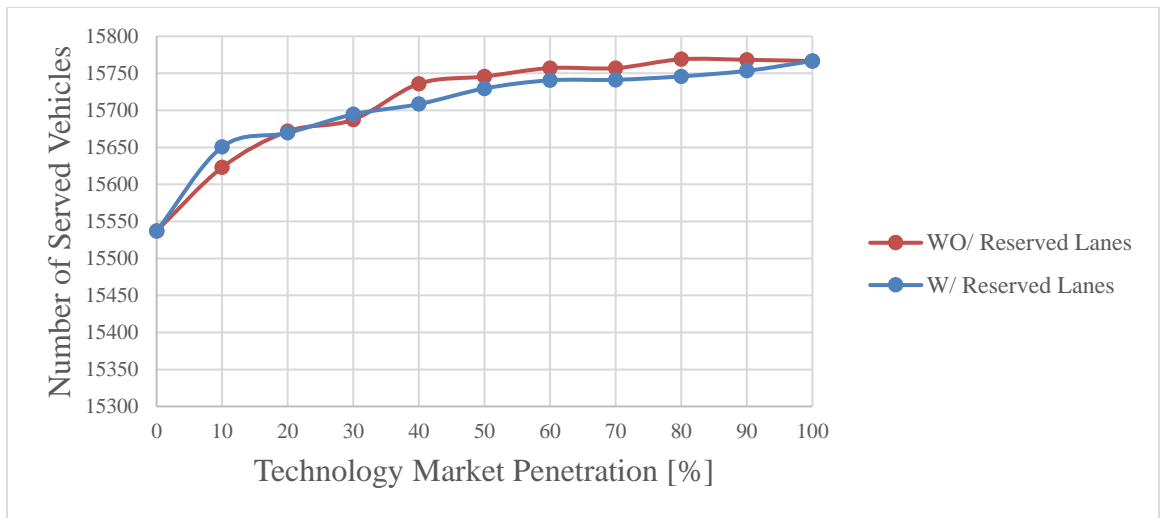
5.13 Total number of served vehicles for testbed in Woodbridge, NJ under LOS C.

The total number of the served vehicle increased by 8.7% under uncongested conditions described in Table 4.4. The increase in vehicles served for market penetration

from 0-90% is higher with reserved lanes although both cases with and without reserved lanes revealed rising trend.
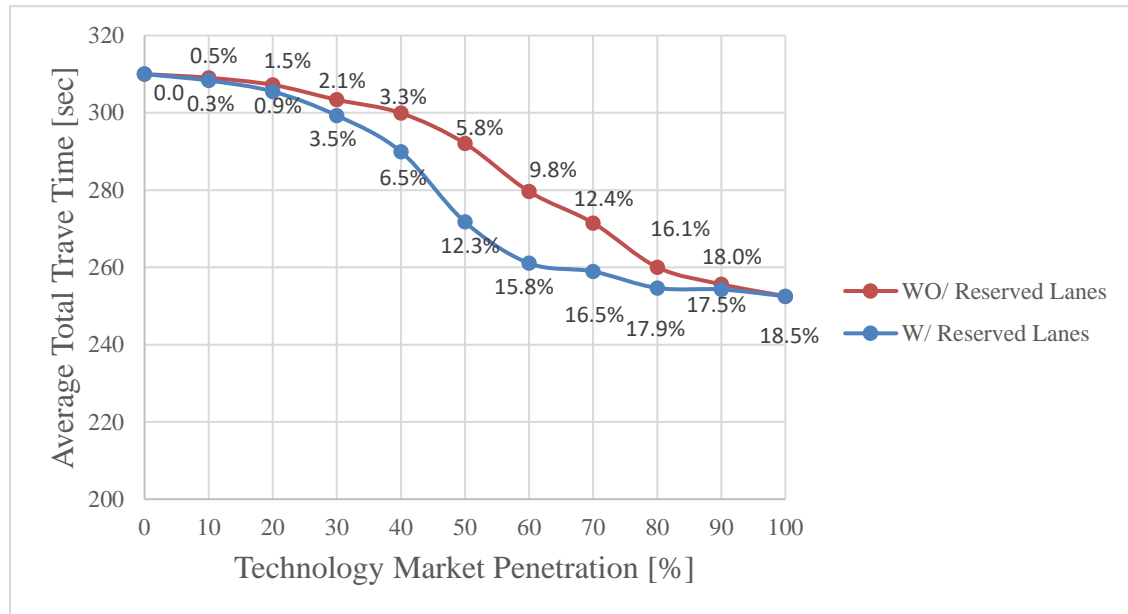
5.14 Average total travel time for testbed in Woodbridge, NJ under LOS C.

The lower market penetrations achieved marginal travel time reductions, however, uninterrupted corridor operation was achieved. Similar to previous testbed location, the benefits become more visible for market penetration rates higher than 20% of automated vehicles in the traffic stream. Again, the effect of reserved lane strategy is visible and provides a further increase of the algorithm effectiveness for market penetrations between 20% and 80%. The travel times for corridor with and without reserved lanes are similar once market penetration reaches 90%. Under 100% the entire corridor is occupied by equipped vehicles, so the travel time values are equal under 100% market penetration.

Further increase in corridor congestion level (Table 4.5) revealed similar changes in observed parameters as those observed for the testbed in Princeton, New Jersey. The average stop delay decreases with market penetration, and it is more intensive for the

corridor with reserved lanes after the market penetration achieved 30%. Under 10% of automated vehicles, the average stoop delay is slightly higher for the corridor with reserved lanes.
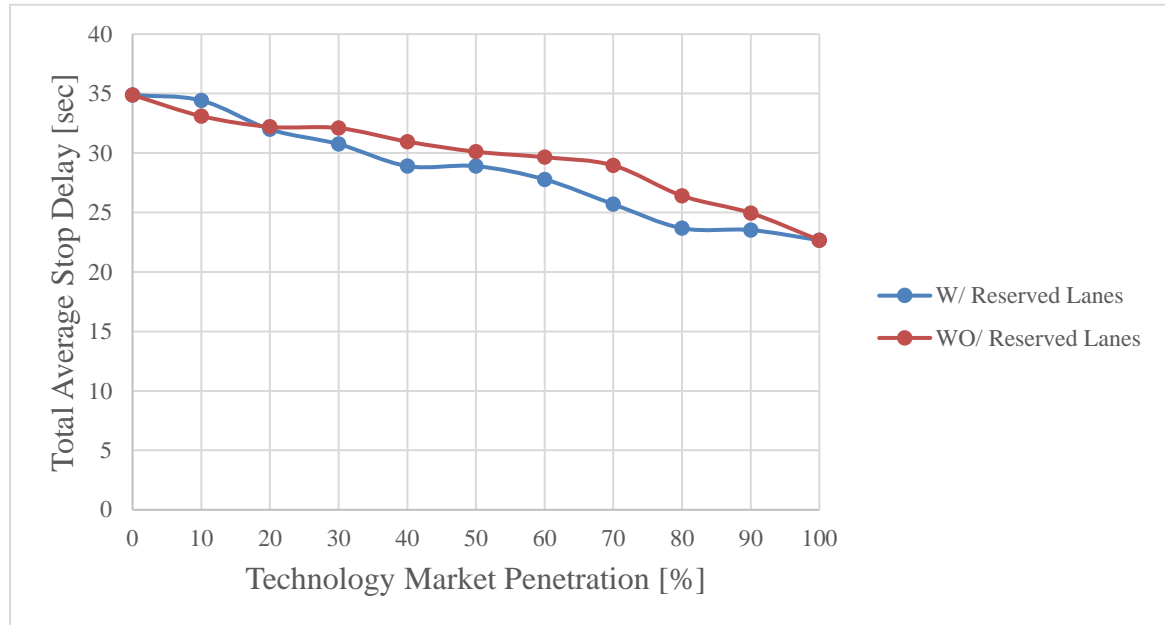
Figure 5.15 Total average stop delay for testbed in Woodbridge, NJ under LOS E.

The average delay per vehicle increased due to an increased level of congestion on the corridor, but so did the overall reductions in average delay. Under LOS C such reductions were 72%. Under congested corridor conditions, such reductions dropped to 34% for 100% market penetration of automated vehicles.

The total average vehicle delays also increased under congested conditions. The magnitude of the average delay reductions also decreased. While under LOS C the maximal reduction under 100% market penetration was 45%, under congested conditions the reduction was 12%. The reductions are higher for the corridor with reserved lanes just as it was observed on the first testbed location in Princeton, New Jersey. The average delay values for different market penetration rates are illustrated in Figure 5.16.
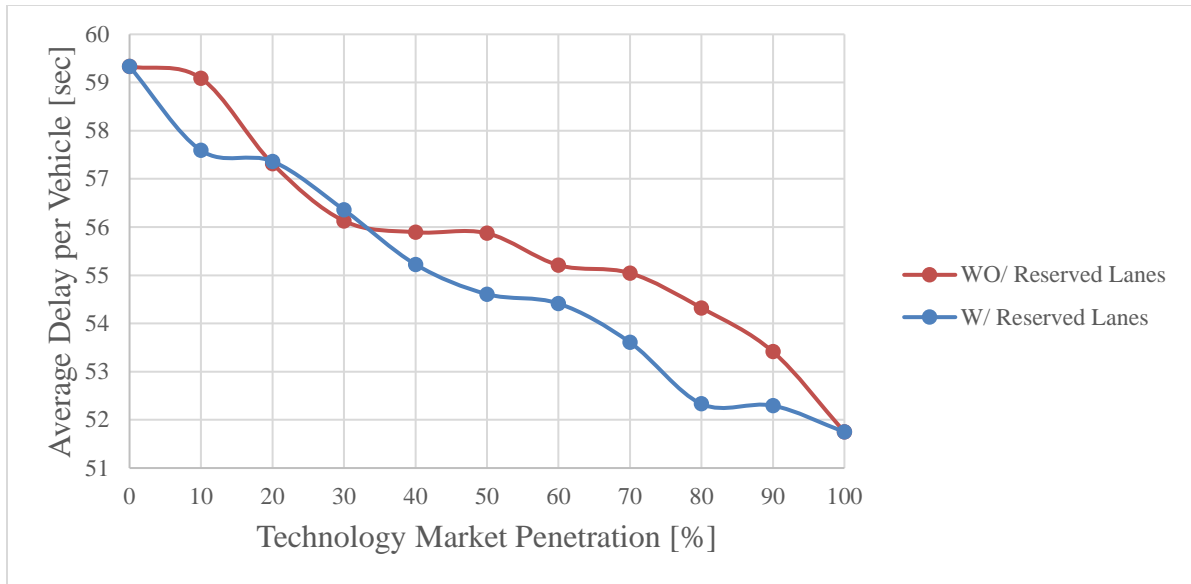
Figure 5.16 Total average delay for testbed in Woodbridge, NJ under LOS E.

The increase in throughput is visible under congested traffic conditions. Again, on the corridor with reserved lanes, the throughput is slightly lower and the maximal increase in throughput under 100% of automated vehicles is around 7%.
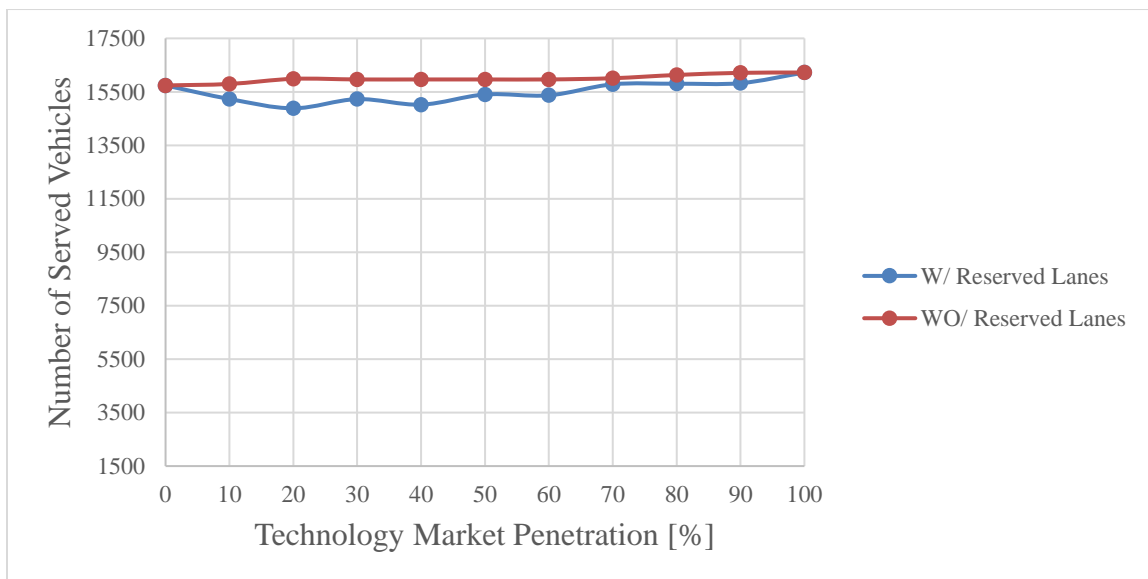
Figure 5.17 Total vehicles served for testbed in Woodbridge, NJ under LOS E.

Once again, the performance of the corridor with reserved lanes under congested traffic conditions on the signalized corridor in Woodbridge showed significantly lower benefits of reserved lanes compared to uncongested conditions. The findings with respect to corridor travel times correspond to those detected on the first testbed locations and are illustrated in Figure 5.18.
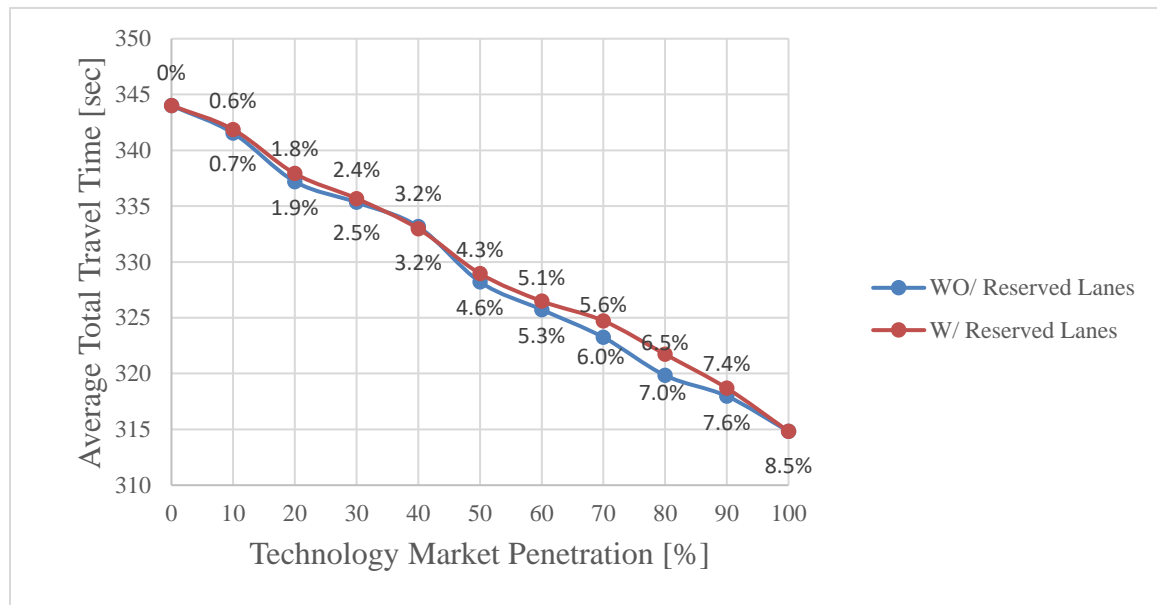
Figure 5.18 Average total travel time for testbed in Woodbridge, NJ under LOS E.

5.4   Chapter Summary

This chapter investigated the impact of the lane reservation strategy on overall performance of the proposed corridor management. To that end, several traffic stream parameters such as stop delay, average vehicle delay, number of served vehicles, and total average travel time of the entire network were observed.

Under the low market penetration conditions, with less than 20% of automated vehicles in the stream, the inclusion of the reserved lane did not provide any improvements (0.5% to 0.6%). By further increasing the market penetration to 30% of automated vehicles

in the corridor, the travel time savings of the corridor with no reserved lane for automated vehicles are lower (2.1% for the first and the second testbed location) than those of the corridor with reserved lanes (0.3.5 % - 5.1 % for the first and second testbed locations respectively). Under stable traffic conditions (i.e., LOS C), a further increase in market penetration levels brings additional benefits ranging from 2.4-19.4% and 3.3-18.5% for market penetrations of 40-100% for the first and second testbed location respectively, with no reserved lanes for automated vehicles.

The findings also imply that for the signalized corridors observed in this study, under given traffic conditions, the benchmark point for the introduction of a reserved lane is 30% of automated vehicles in the system. The simulation methodology also detected that the second reserved lane for automated vehicles should be included when the proportion of automated vehicles exceeds 50%. Under those lane configuration cases, total reductions in total corridor travel times are ranging from 5.1% to 19.4% and 6.5% to 18.5% for market penetrations of 40-100% for the first and second testbed location respectively. This additional benefit is a product of physical separation of the two vehicle groups allowing TOAD algorithm to produce additional benefits for automated vehicles operating in isolated conditions where the influence of unequipped vehicles is excluded.

Congested traffic conditions (i.e., LOS E) are also examined in this chapter for both lane configuration cases. It was discovered that additional benefits produced by lane reservation strategy produced fewer improvements in such traffic conditions. Although all observed traffic stream parameters such as stop delay, average vehicle delay, number of served vehicles and total average travel time generally decrease as market penetration decreases, the inclusion of reserved lanes brings marginal improvements for market

penetrations above 60%. For the first test bed location the travel time reductions with reserved lanes is ranging from 5.9% to 7.4% (5.1% to 7.4% for the second testbed location) for market penetrations of 60-90% while the travel time reductions for the corridor without reserved lanes are ranging from 5.7% to 7.8% (5.3% to 7.6% for the second testbed location). For market penetration levels below 60%, both corridors showed insignificant differences between travel time results for cases with and without reserved lanes.

It is also clear that congested traffic conditions decrease overall travel time reductions produced by TOAD algorithm. Total travel time reductions with 100% market penetration decrease from 19.5% to 8.5% under LOS C and LOS E respectively. Such reduced benefits under significantly congested conditions still provide noticeable benefits and allow an uninterrupted operation of automated vehicles under imperfect market penetration rates.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

This chapter summarizes findings, research contributions and recommendations for further research.

6.1   Conclusions

The TOAD control algorithm proposed in this study recommends the utilization of existing fixed-time signal control devices under connected vehicle environment. Under connected vehicle environment, all vehicular and signal-related parameters are known and can be shared with the control agent to control automated vehicles while improving the mobility of the signalized corridor. Since the whole concept of connected vehicles is likely to be initiated gradually, the TOAD control strategy was designed to work under imperfect market penetration level of automated vehicles technology. The control algorithm was tested through series of simulation scenarios and it was discovered that even with low market penetration, the technology reduces overall travel time of the corridor.

The evaluation was conducted for different traffic conditions. Under stable traffic conditions with LOS C and V/C ratio between 0.38 and 0.49, the reductions in stop delay of almost 80% can be achieved. The total vehicle delay also decreases and it can be reduced by up to 47% while throughputs can be increased by 8.7%. The total travel time decreases with market penetration of automated vehicles and under described conditions, those reductions can reach 19.5% with 100% market penetration. The algorithm is also functional

with low market penetration rates 10-20% where travel time reductions of approximately 1.5% are detected.

The TOAD algorithm also achieves benefits even under unstable flow conditions examined in this dissertation research. Such unstable conditions include LOS E with V/C ratios ranging from 0.68 to 0.95. Travel time reductions under congested conditions reached 8.4% with 100% of automated vehicles in the corridor. Although some marginal reductions (i.e 0.6-0.9%) were detected for market penetration rates of 10-20%, the finding imply the algorithm is still functional even with low market penetration of the technology..

Further inclusion of lanes specifically reserved for the movement of automated vehicles brings additional benefits. For market penetrations between 20 and 80%, a TOD algorithm together with reserved lanes can reduce travel times by 3.5-17.9% which is higher than reductions for the corridor without reserved lanes ranging from 1.5 to 16.1%. Under unstable traffic conditions, lane reservation is less effective and clear benefit of such lanes are visible after the market penetration reached 60% before this point the performance of the corridor with reserved lanes is close to the one without such lanes. Even with minor reductions in travel time, utilization of reserved lanes for automated vehicles might serve as a measure to further foster the application of connected and automated vehicles on signalized arterials.

The inclusion of prevailing traffic conditions into trajectory prediction is of an essential importance. This dissertation research conducted simulation assessment for the TOAD algorithm without the inclusion of predicted vehicle delay where significantly lower benefits were detected. The TOAD algorithm without short-term prediction of vehicular delays, based on real-time readings from the mid-block detectors gained travel time

reductions of 0.04% to 11.61% for market penetration levels from 10 to 100% which is significantly lower than results achieved with the integration of the artificial intelligence model described in Chapter 5.

It is worth clearly noting that besides the mobility improvement, the TOAD control strategy utilizes existing fixed-time controllers eliminating significant initial investments. Through series of simulations, it was also concluded that such system can work with minimal investments in detection systems (approximately one mid-block detector for each signalized intersection). Moreover, the strategy is easily implementable under existing infrastructure conditions, allowing a smooth transition from the contemporary signal control into connected and automated vehicle environment.

6.2   Research Contributions

This dissertation research made several contributions in the field of automated and connected vehicle modeling. The key contributions are as follows:

1. This dissertation research has developed a control algorithm for automated vehicles tested and evaluated through microsimulation platform.

    a) It was discovered that the algorithm allows the introduction of automated vehicles into existing signalized corridor while achieving better mobility performance of the corridor.

    b) The algorithm is applicable even under low market penetration rates and does not require additional investment into signal-control devices.

    c) The TOAD algorithm produces its mobility improvements without affecting mobility performance of unequipped vehicles in a signalized corridor.

2. The developed simulation framework is suitable for testing of other connected vehicle applications such as eco-driving on a signalized corridor.

3. This dissertation has developed a framework for the evaluation of reserved lanes for automated vehicles and answered several relevant questions such as:

   a) Efficiency of reserved lanes under different traffic conditions

   b) Impact of such lanes on overall mobility performance of a signalized corridor with the possibility of automated driving.

4. Finally, this dissertation research offers a low-cost solution with insignificant investments into detection system, as developed artificial intelligence model provides a short-term prediction of traffic parameters necessary for vehicle control while minimizing the number of deployed sensors.

6.3 Recommendations

The methodology presented in Chapters 3 to 5 assume existence of the connected vehicle environment where all communicational, legislative, and technological aspects are fulfilled. Even with all necessary prerequisites, the introduction of the automated vehicles is expected to start gradually, where only few automated vehicles are present in the early stage of the new, connected vehicle, era, eventually leading toward massive implementation. With respect to that, it is recommended to implement the management strategy for signalized corridors presented in this dissertation in two phases:

Phase 1: The "start-up" phase, where the new connected vehicle technology is introduced but has not reached higher technology penetration rates (i.e., $< 10\%$)

Phase 2: The mature phase, where the recommended management strategy is well accepted and high technology penetration rates exist (i.e., > 10%)For both implementation phases it is necessary to include following roadway features:

1) Contemporary intersection signal control devices (i.e. pretimed signal control)
2) Mid-block loop detectors for retrieval of vehicle counts and speed
3) A pair of Wi-fi or Bluetooth sensors for travel time measurements on each corridor link.
4) Centralized control agent (i.e. computing unit)

Existence of the lane reservation is also essential but is only recommended for the mature phase after which the overhead gantries need to be installed. Although lane reservation is recommended as soon as the implementation reached phase 2 (market penetrations >10%), under congested traffic conditions (Table 6.2) it is not recommended to use lane reservation before technology penetration reaches 60% due to performance constraints described in Chapter 5.

Table 6.1 Implementation Roadway Features for Uncongested Conditions

Technology Penetration	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Reserved Lanes	No	Yes									
Signal Control	Pretimed										
Overhead Gantry	No	Yes									
Detection System	Wi-Fi (Bluetooth), Mid-block										

Table 6.2 Implementation Roadway Features for Congested Conditions

Technology Penetration	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Reserved Lanes	No						Yes				
Signal Control	Pretimed										
Overhead Gantry	No	Yes									
Detection System	Wi-Fi (Bluetooth), Mid-block										

6.4   Future Research

The modeling framework and control algorithm can be improved in several ways. Various microsimulation platforms apply different lane-changing and car-following models. Recently, the Intelligent Driving Model (IDM) gained significant interest in the area of evaluation and modeling of connected and automated vehicles. Such car following model can be incorporated into existing TOAD control strategy and can be used as an essential component of the trajectory prediction. The model is suitable for the mentioned task as it already defines the impact of the leading vehicle and allows adjustment of vehicles' acceleration based on the behavior of the leading vehicle, following headway, and the current speed of the following and leading vehicle. Such set of parameters is already available in the existing modeling framework presented in this research.

The existing control algorithm for automated vehicles can be further improved by utilizing a lane-changing model for driving under mixed conditions. Such model, included into existing control algorithm might further improve lane utilization parameters of a signalized corridor which is further expected to improve the overall capacity of the signalized corridor.

The existing control algorithm can further be improved from the aspect of lane configuration. Additional methodology can be developed to determine an online control logic for determination of number of reserved lanes based on real-time data for market penetration of automated vehicles, corridor performance (V/C ratio, vehicle counts, etc.)

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