

Development and Evaluation of Cooperative Intersection Management Algorithm under Connected and Automated Vehicles Environment

Slobodan Gutesa¹, Jyoung Lee², and Dejan Besenski³

Abstract

Recent technological advancements in the automotive and transportation industry established a firm foundation for development and implementation of various connected and automated vehicle solutions around the globe. Wireless communication technologies such as the dedicated short-range communication protocol are enabling information exchange between vehicles and infrastructure. This research paper introduces an intersection management strategy for a corridor with automated vehicles utilizing vehicular trajectory-driven optimization method. Trajectory-Driven Optimization for Automated Driving provides an optimal trajectory for automated vehicles based on current vehicle position, prevailing traffic, and signal status on the corridor. All inputs are 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. The concept evaluation through microsimulation reveals that, even with low market penetration (i.e., less than 10%), the technology reduces overall travel time of the corridor by 2%. Further increase in market penetration produces travel time and fuel consumption reductions of up to 19.5% and 22.5%, respectively.

To improve efficiency and safety of road transportation systems (without adding physical capacity) researchers began to investigate the synergy between the information and communication technologies and the automotive industry. Those modern technologies paved the way for a new automotive revolution supported and initiated by the growing connected vehicle technology. The Fixing America's Surface Transportation (FAST) Act was introduced in 2015 with the goal of providing long-term funding for surface transportation planning and investment (1). As auto manufacturers and academia are responding rapidly by offering various self-driving solutions readily available, United States Department of Transportation (U.S. DOT) issued a primer on connected vehicles environment as a part of the Architecture Reference for Cooperative and Intelligent Transportation (ARC-IT) to provide an overview and discuss relevant issues pertaining to the overall concept implementation (2). Under the Connected Vehicle Pilot Deployment Program, U.S. DOT Joint Program Office (JPO) has selected three pilot sites—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 (3, 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 because of 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, because of the stochastic nature of the vehicular movement, such predictions of

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vehicle arrivals are not sufficiently accurate and can undermine the intersection performance.

Nonetheless, some recent studies show that the pre-determined TOD control approach along with reliable prevailing traffic information can provide an adequate system efficiency (7). Such systems heavily rely on the traffic counts and turning movement data that is naturally associated with a significant level of variation. The connected vehicle concept supported by the data exchange protocols constitute a controlled environment for an instantaneous exchange of information between vehicles and signal controllers (8). This environment opens multiple opportunities for cooperative applications allowing more efficient and reliable vehicle operations (9–11). 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.

The primary idea presented in this paper proposes a new signal control paradigm where the traffic streams are manipulated to conform to the signal control devices. Signal status parameters such as 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 a 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 was developed 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.

This paper is organized as follows. The relevant research in the area of signal control optimization is summarized in the next section. In the following section, the TOAD algorithm is introduced through proposed system architecture and optimization-based control approach. The optimization example section demonstrates the determination of the optimal vehicle trajectories. The section of evaluations includes test-bed development and simulation results. Findings and concluding remarks are addressed in the last section.

Relevant Research

Because of its limited ability to deal with traffic flow fluctuations, the fixed-time control was replaced by more sophisticated solutions such as adaptive traffic control and actuated systems (12–14). 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 time reductions to reach 39.5% in the peak period (12). Similarly, initial travel time savings for the Split, Cycle, Offset Optimization Technique (SCOOT) were estimated to reach 35% (12). Although the adaptive approach has been proven to bring direct benefits to users and agencies, some recent evaluations revealed significantly lower benefits than those initially reported (15, 16). It is also known that all adaptive signal control systems inevitably depend on the projections of vehicle arrivals, and reliability of the detection system. Because of this, and many other known issues, a study conducted by the Federal Highway Administration (FHWA) reported some direct concerns from practitioners whether the adaptive signal control system would resolve the mobility issues as was expected at the early stage of development (17). Some implementation cost analysis performed by U.S. DOT in January 2013 estimated average implementation costs for adaptive signal control technologies (ASCTs) to be between \$46,000 and \$65,000 for a single intersection (18).

Because of the above-mentioned financial and operational constraints of the adaptive systems, researchers focused on alternative methods to improve mobility performance. The benefit of utilizing vehicle-to-infrastructure (V2I) communication to improve operation of fixed-time intersections has been studied extensively over the past decade. The main idea behind the concept is to provide the advisory speed through an on-board device to improve the safety, environmental, and mobility performance of a fixed-time intersection (18–21). In-Vehicle Signal Assistance (ISA) is one of the connected vehicles applications utilizing V2I communications (22). Vehicles equipped with the ISA application receive real-time signal phase and timing (SPaT) data from the intersection where the vehicles approach (22). With the SPaT broadcasted message, the ISA application conveys the current signal status to the driver via a graphical display unit (e.g., an opt-in LCD panel or head-up display, an external smartphone, or tablet PC.)

Besides SPaT-related studies, many authors examined potential benefits of different control systems under connected and automated vehicle (CAV) environment. To that end, several promising algorithms for the autonomously controlled vehicle have been invented in past several years where the trajectories of vehicles are manipulated to safely cross an intersection and minimize the intersection delay (23–26). In addition, several studies optimizing the phases of a signal using the information from connected vehicles were introduced (27–29). The common limitation of the above-mentioned work is the assumption of a 100% penetration rate of equipped vehicles.

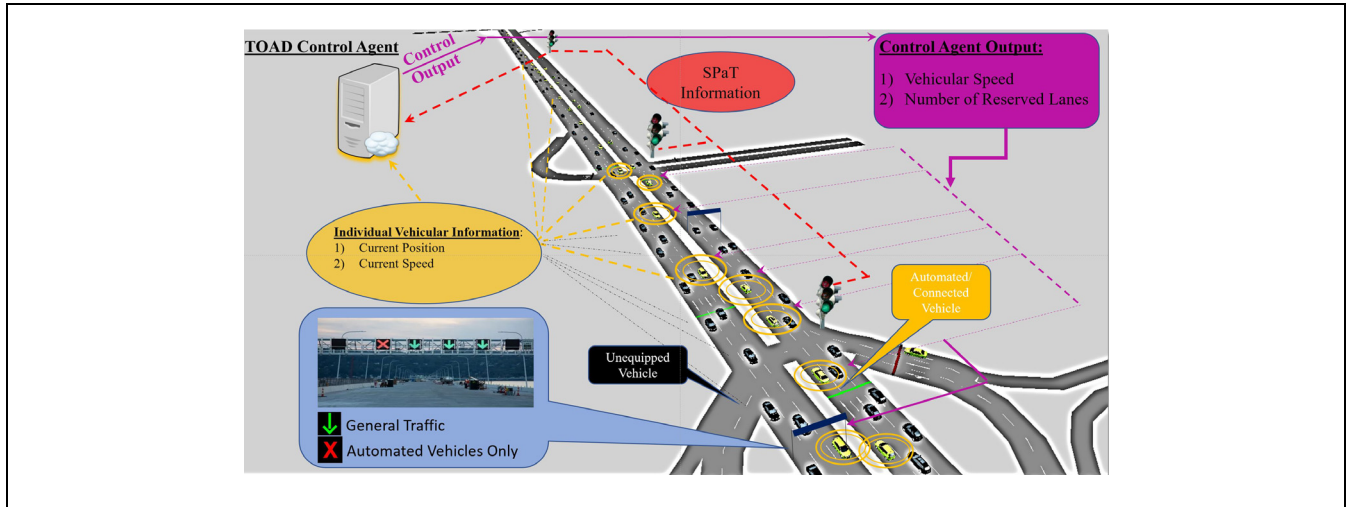


Figure 1. Proposed corridor control architecture.

Against the existing efforts, the main contribution of this study is to introduce a new signal control paradigm for CAVs with imperfect market penetration rate. The idea proposes a solution where the traffic streams are manipulated to conform to existing signal control devices in the field. The TOAD algorithm produces the most desirable speed to automated vehicles in the signalized corridor, with respect to the current state of traffic streams, the state of signalization (SPaT), and the position of the individual vehicles in real time. The proposed solution does not require any additional investments into control and detection systems; thus, simple pre-timed devices are sufficient for the system implementation under CAV environment.

Methodology

Proposed Control Architecture

The methodology presented in this paper introduces control strategy for a signalized arterial with fixed-time signals under imperfect market penetration of the CAV technology. The methodology assumes the provision of vehicular parameters such as speed and position by utilizing CAV environment (Figure 1). The computer system, namely TOAD control agent, handles both information exchange and proactive adjustment of vehicles' trajectories. 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 CAV 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, allowing automated vehicles to operate on a

conventional signalized corridor with imperfect market penetrations.

Trajectory-Driven Optimization

The majority of signal timing applications are evaluated through the time-space diagram as the primary measure of the control strategy operation. To that end, a control algorithm generates optimal, time-distance, vehicular trajectories for all automated vehicles in the system.

The assumptions of the model are the following: (1) all CAVs are completely controlled by the TOAD agent, and follow generated trajectory with 100% compliance; (2) other vehicles from the general traffic are not controlled by TOAD; (3) the corridor utilizes fixed-timing plan with optimized parameters (i.e., cycle, split, offset) according to existing traffic conditions; (4) the prevailing traffic conditions are incorporated into the trajectory prediction and are collected using mid-block detectors. The final output of the proposed control algorithm are longitudinal speed profiles delivered to each individual automated vehicle in the control space.

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 such trajectory is illustrated in Figure 2, where control points $p_1(t_1, y_1) \dots p_M(t_M, y_M)$ were used for the trajectory interpolation. By respecting interpolation and monotonicity rules, the trajectory T will be produced in the field of real numbers giving the sequence of coordinates in the defined coordinate space (27):

$$T : t^T = (t_1, \dots, t_n); y^T = (y_1, \dots, y_n)$$

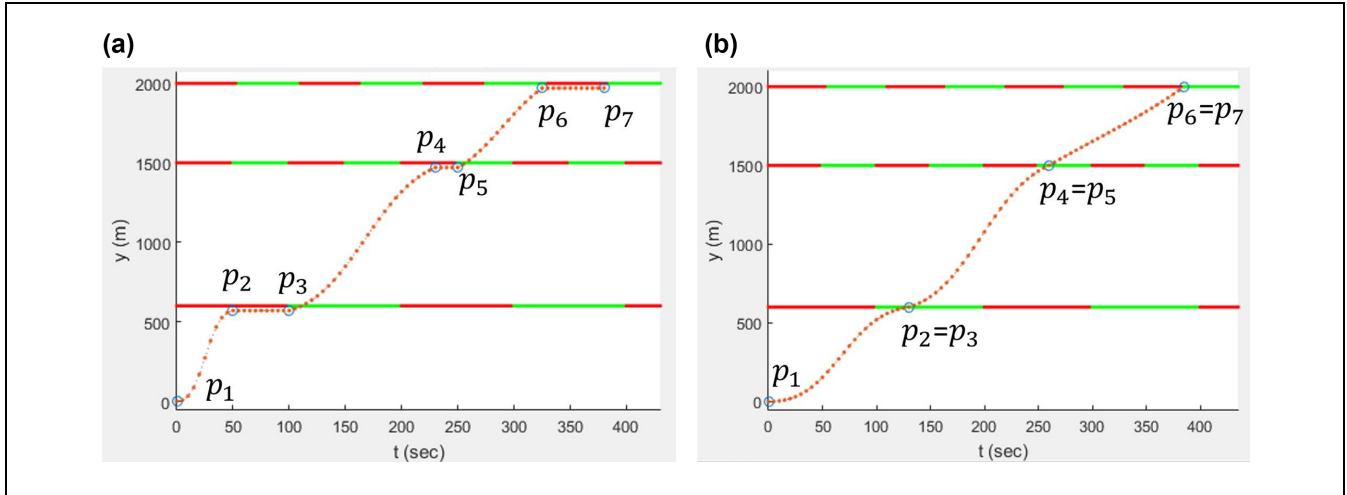


Figure 2. Trajectory defined using cubic interpolation: (a) arrival during red interval, and (b) arrival during green interval.

Table 1. The Artificial Neural Network Model Design

Training algorithm	Levenberg-Marquardt
Initialization function	Nguyen-Widrow
Hidden layers	1
Output layers	1
Hidden layer neurons	25
Validation range (mean squared error)	-1.41 to 1.18 s

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 2, 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:

$$\begin{aligned} \text{Trajectory Length} &= \sum_{i=1}^{n-1} \sqrt{\Delta t_i^2 + \Delta y_i^2} \\ &= \sum_{i=1}^{n-1} \sqrt{(t_{i+1} - t_i)^2 + (y_{i+1} - y_i)^2} \end{aligned}$$

where

Δt = change in time

Δy = change in distance

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, and M number of control points for each vehicle trajectory, as presented in Table 1.

The first and second groups of constraints are designed to adjust the trajectory curve for two possible cases (Figure 2), that is, passing during the green interval, G , starting with the predefined beginning of green (*bog*) (Figure 2a) or passing during the red interval, R (Figure 2b). It is noted that all combinations are possible, for example, a vehicle can pass on the green at the first, but arrive on the red at the second intersection, and so forth. Such a transformation allows nonlinear optimization techniques, for example, genetic algorithm (GA), to evaluate all possible combinations and determine the best individual (31). Determined individual is the most optimal vehicle trajectory to minimize total travel time of the corridor while satisfying defined safety constraints (Table 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 fourth group of constraints was included to prevent vehicles from traveling faster than the prevailing traffic in the mixed-traffic mode where no reserved lanes for automated vehicles are provided. This group of constraints adjusts speed of a vehicle j , on a distance d from the downstream intersection M . The prevailing speed constraint is based on the reading from the nearest downstream speed detector D and is a result of a short-term prediction of vehicle delay. 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 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. The objective function is defined as length

of a curve approximated using H number of control points $p(t, y)$.

$$\min \sum_{j=0}^N \sum_{i=1}^M \text{Length}(p_{1+(2H+1)j}, p_{H+(2H+1)j})$$

The first constraint is designed with the purpose of control point allocation to represent the “green time arrival,” if control point values are inside the red time interval where the slope between intersections (M) and the subsequent intersection ($M+1$) is defined using H number of control points for each vehicle j .

$$t_{M+(2H+1)j} - t_{(M+1)+(2H+1)j} = 0; t_{M+(2H+1)j} \in G_3 \forall j \in$$

The second constraint is defined similarly with control point allocation to represent the “red time arrival” curve, if control point values are inside the red time interval was defined as follows:

$$-t_{M+(2H+1)j} + bog_M \leq 0; X_{(M+1)+(2H+1)j} \in R_H \forall j \in C$$

where for intersection M its beginning of green is denoted as bog_M and red interval length as R_H . The third constraint, which constrains the slope of curves to prevent generation of trajectories that would exceed posted speed limit, is correspondingly defined as:

$$d_M / (t_{H+(2H+1)j} - t_{(H-1)+(2H+1)j}) \leq \text{Speed Limit}$$

where d_M is remaining distance of a vehicle j to intersection M . The fourth constraint whose purpose is to constrain the slope of a curves to prevent collision of the leading and following vehicle (j) and ($j+1$) using time headway h is defined as follows:

$$(X_{M+(2H+1)j} + h) - X_{(M+1)+(2H+1)(j+1)} \leq 0$$

And finally, the final constraint, with the purpose to constrain the slope of curves in accordance to the prevailing traffic conditions causing predicted delay (d).

$$(X_{M+(2N+1)j} + d) - X_{(M+1)+(2N+1)j} \leq 0$$

More details in relation to short-term prediction of prevailing traffic conditions and determination of the predicted delay (d) is provided later in a separate section of this paper.

Optimization Example

The problem formulated in the previous section was demonstrated using a realistic scenario where a platoon consisting of 25 vehicles passed through a signalized corridor with three signalized intersections and speed limit of 55 mph (88.51 km/h). Assumed green interval of each

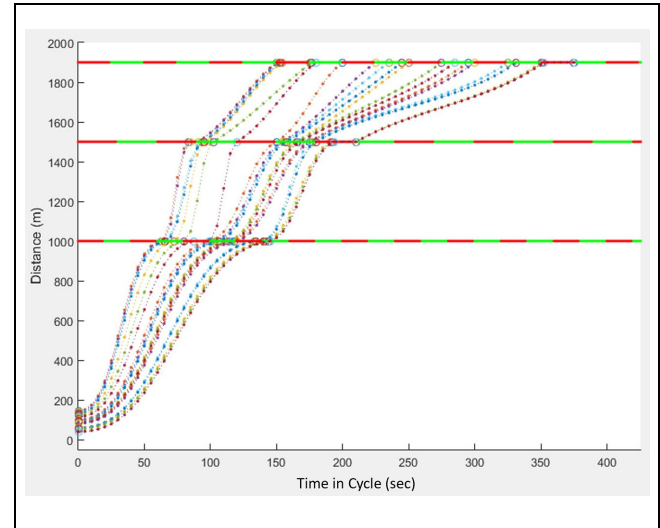


Figure 3. Optimal trajectories for a platoon of 25 automated vehicles.

intersection was 20, 30, and 25 s, followed by the red interval of the same length, for intersection one to three, respectively. The lengths of the corridor links were 1,640 ft (500 m) between intersections one and two, and 1,312 ft (400 m) between intersections two and three, as indicated in Figure 3. The leading vehicle of the platoon was 2,788 ft (850 m) from the stop bar of the first intersection, and the last vehicle was 3,215 ft (980 m) from the stop bar. Vehicles in between had assumed headway of 10–16 ft assigned randomly.

The problem was successfully solved using GA programmed in MATLAB with the population size of 50 (32). The program successfully returned an optimal solution after evaluating 43 generations and 1,344 different individuals, with CPU time less than 120 s. 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.

The overall optimization framework is illustrated in Figure 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 bog for the next several cycles of all corridor intersections as illustrated in the time-space diagram in Figure 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 $p_1 \dots p_M$ until the optimal solution comprising the best possible individual is produced. After storing the best individual into the pool of solved

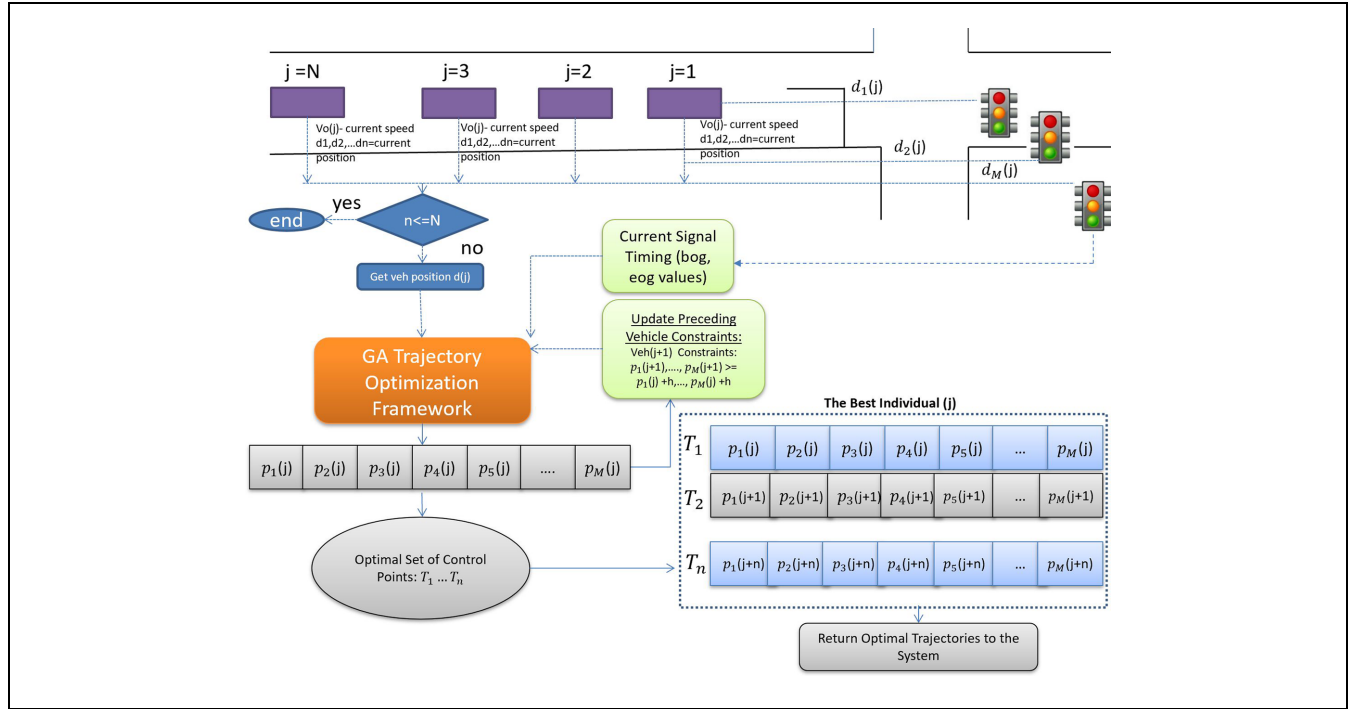


Figure 4. Control algorithm framework.

Note: bog = beginning of green; eog = end of green.

trajectories $T_1 \dots T_n$ 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 immediate execution after which the new iteration of the control algorithm is started again updating all necessary information and generating updated trajectories for vehicles $j = 1, \dots, j = N$.

Short-Term Prediction of Prevailing Traffic Conditions

Without predicted vehicle delay, application of the generated trajectory is challenging, as the vehicle cannot fully achieve assigned speed profile because of the influence of downstream traffic. Although traffic control devices are highly accessible in the current state of technology, it is often not possible to have data collection devices densely deployed. 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. To allow accurate short-term prediction of vehicle delay, a multi-layer perceptron artificial neural network (MLPANN) trained with available traffic stream factors is designed

and presented in this section. The purpose of the developed model is to predict delay over the horizon of 200 s, allowing described adjustment of the vehicle trajectory. MLPANN solves problems stochastically allowing accurate solutions for non-linear function approximation, regression, and classification tasks. The MLPANN model is trained using the following parameters obtained from the microsimulation model for signalized corridor:

- 1) Spot speed obtained from fixed point sensors (e.g., loop detector, CCTV camera, microwave sensor)
- 2) Vehicle counts from fixed point sensors
- 3) Travel time obtained from Bluetooth or Wi-Fi sensors
- 4) Signal setup (i.e., green interval length) obtained from the controller.

The MLPANN network was trained using Levenberg-Marquardt algorithm and the training set was created using microsimulation platform. The training parameters for a signalized corridor cover the following value ranges:

- 1) Vehicle delay: 0–1,900 s/corridor link
- 2) Mid-block detector vehicle counts (0–160 vehicles/100 s)
- 3) Link travel time: 0–1,900 s
- 4) Traffic flow speed: 0–100 km/h.

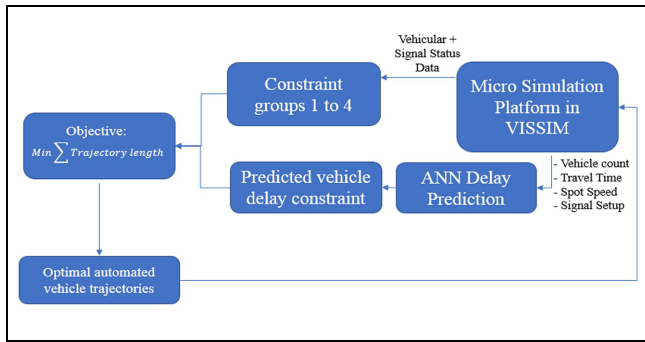


Figure 5. Integration of predicted vehicle delay into microsimulation test-bed.

Note: ANN = artificial neural network.

The trained network integrates into existing microsimulation test-bed and its prediction result is predicted delay, that additionally constrains the slope of the predicted vehicle trajectory (Figure 5). This additional constraint provides more realistic predictions of the vehicle arrival at the stop bar.

Evaluations

Design of Simulation Test-Bed

The simulation test-bed used in this paper integrates: (1) an external server for calculation and optimization; and (2) a microscopic traffic simulator. While the 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 and

microscopic traffic simulator PTV VISSIM where the exchange of information between MATLAB and VISSIM is conveyed through Common Object Model (COM) (32–34). As illustrated in Figure 6, 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.

The test-bed selected for the system evaluation is located in Princeton Township, New Jersey (Figure 7). A section of US-1 in Mercer County, between Carnegie Center Boulevard and Ridge Road, is about 5 mi long, with mainly six lanes in two directions. Coordinated intersections include jug-handle ramps with no left turns allowed from the main line (i.e., US 1). The roadway has a speed limit of 55 mph. 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 for further research.

Simulation Results

To properly estimate potential benefits of proposed TOAD control algorithm, the traffic volume scenarios

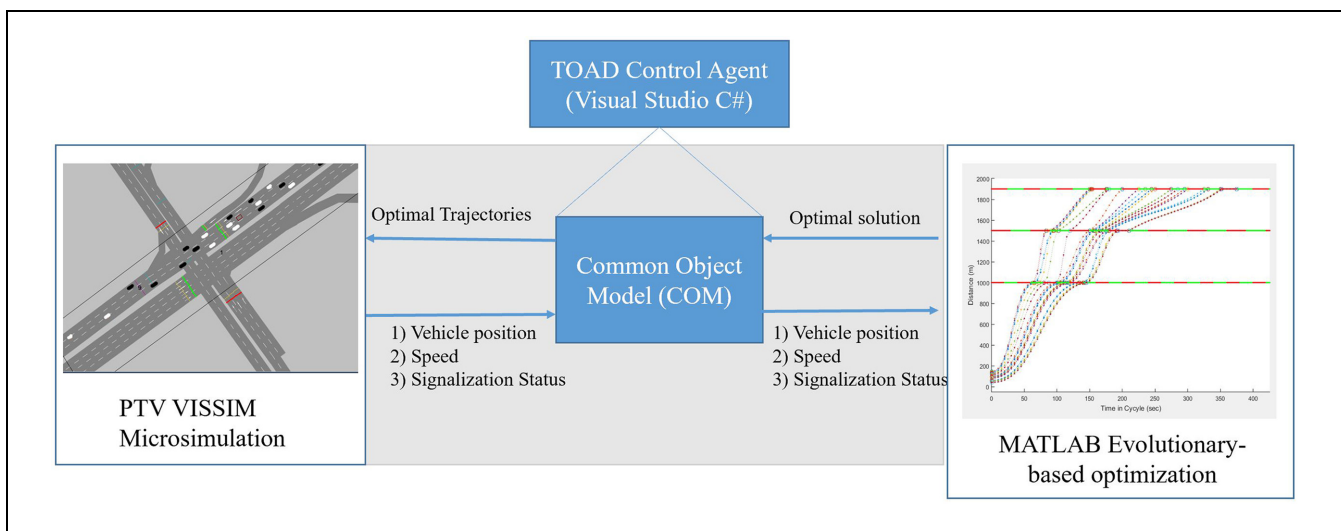


Figure 6. Simulation test-bed framework.

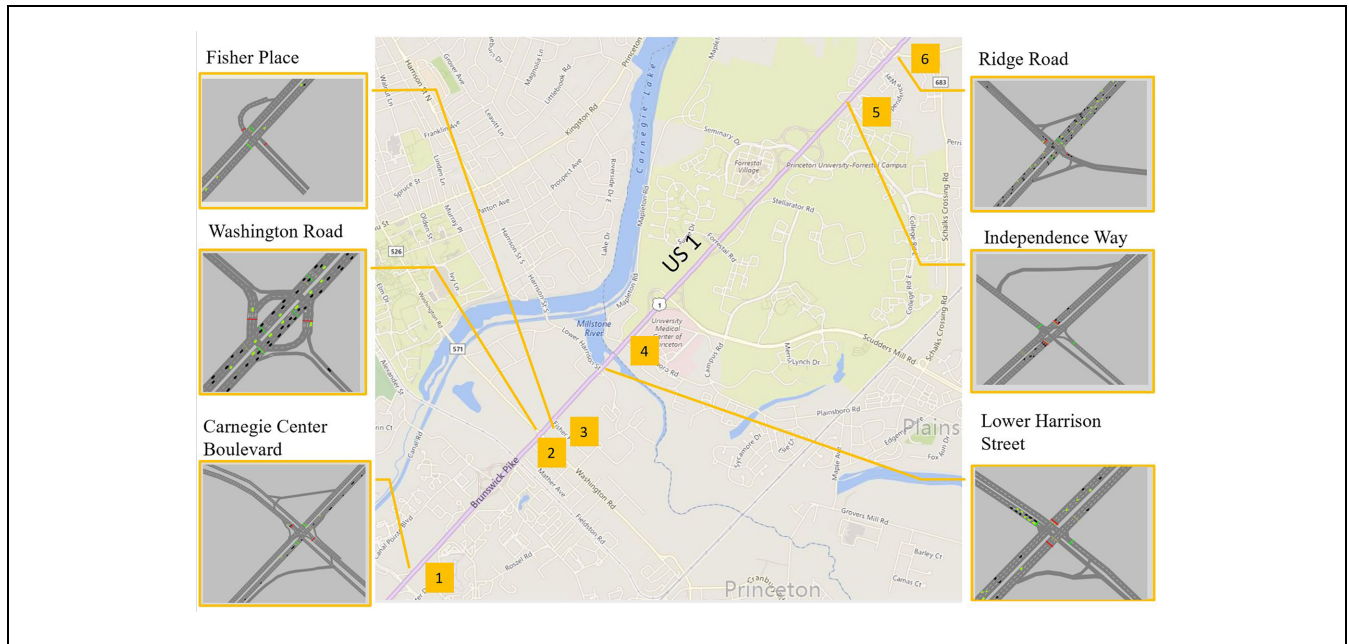


Figure 7. VISSIM model for selected test corridor in Princeton, New Jersey.

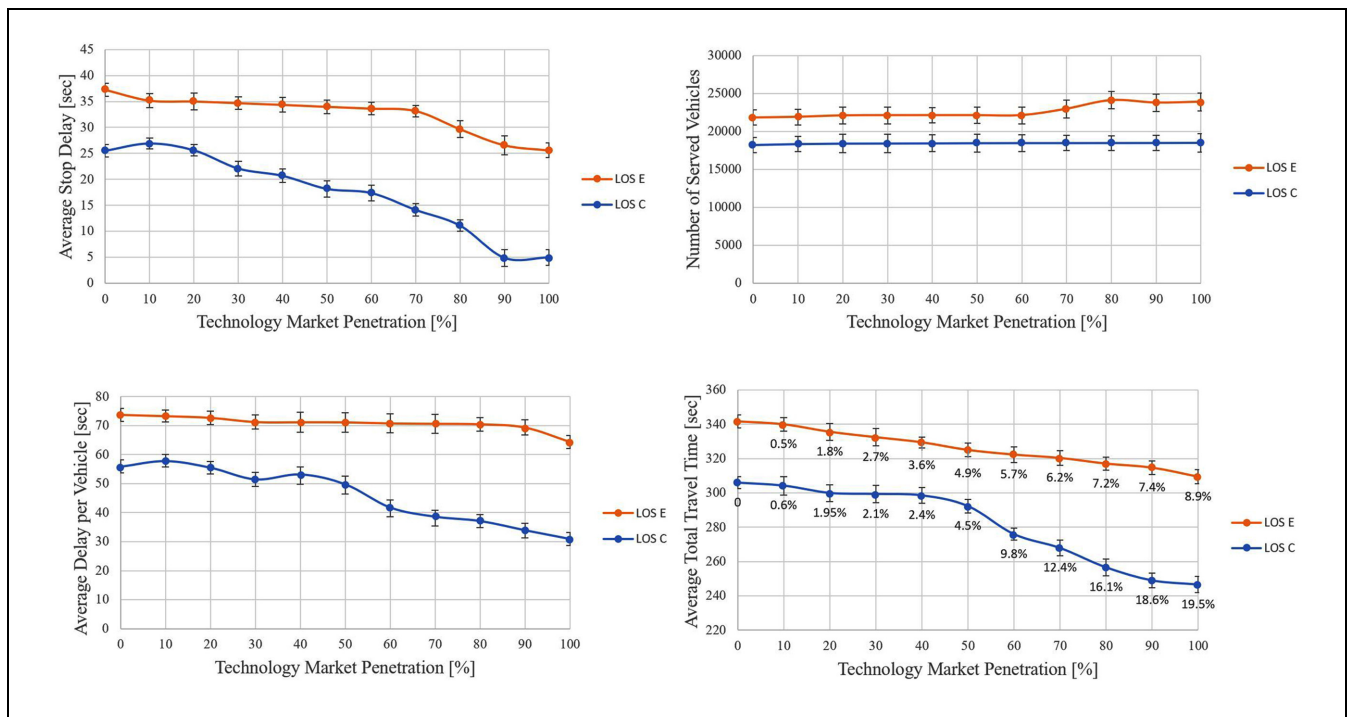


Figure 8. Corridor performance under different volume and market penetration levels.

included stable (i.e., level of service [LOS] C) and unstable traffic conditions (i.e., LOS E). Eleven different market penetration conditions (0%–100%, in 10% increments) were examined with five consecutive simulation runs for both volume scenarios, resulting in 110

simulation runs. The aggregated simulation results are illustrated in Figure 8.

It is obvious from Figure 8 that all observed parameters decrease with the increase in market penetration rate. The low market penetration rates (i.e., 0%–20%) of

Table 2. Simulated Results for Total Fuel Consumption in Liters/Hour and Percent Reductions under Uncongested Conditions

	Intersection 1	Intersection 2	Intersection 3	Intersection 4	Intersection 5	Intersection 6
0%	30.4	19.9	31.3	9.6	10.4	22.9
10%	−0.3%	0.0%	−1.3%	0.0%	−1.0%	−0.4%
20%	−2.3%	−4.5%	−2.2%	−3.1%	−1.9%	−1.3%
30%	−7.2%	−7.0%	−5.8%	−6.3%	−2.9%	−1.3%
40%	−8.9%	−9.5%	−7.3%	−7.3%	−4.8%	−2.2%
50%	−12.5%	−11.1%	−8.3%	−9.4%	−6.7%	−2.6%
60%	−14.5%	−14.6%	−10.5%	−10.4%	−6.7%	−5.7%
70%	−16.8%	−16.1%	−11.8%	−11.5%	−7.7%	−7.4%
80%	−20.7%	−18.1%	−13.7%	−12.5%	−8.7%	−8.7%
90%	−21.1%	−19.6%	−15.0%	−13.5%	−10.6%	−9.6%
100%	−22.4%	−19.6%	−20.1%	−15.6%	−11.5%	−10.9%

Table 3. Simulated Results for Total Fuel Consumption in Liters/Hour and Percent Reductions under Congested Conditions

	Intersection 1	Intersection 2	Intersection 3	Intersection 4	Intersection 5	Intersection 6
0%	47.1	30.9	48.5	14.9	16.1	35.5
10%	−0.4%	−0.3%	−0.8%	−0.1%	−0.1%	−0.6%
20%	−1.3%	−1.9%	−1.6%	−0.7%	−1.2%	−0.8%
30%	−3.2%	−4.5%	−4.5%	−1.3%	−1.9%	−1.4%
40%	−4.5%	−5.5%	−4.7%	−2.0%	−1.9%	−1.4%
50%	−5.9%	−6.5%	−5.4%	−2.7%	−2.5%	−2.3%
60%	−7.9%	−8.1%	−6.6%	−3.4%	−5.0%	−2.8%
70%	−9.3%	−9.7%	−7.2%	−4.0%	−5.6%	−3.1%
80%	−9.8%	−10.0%	−7.6%	−4.0%	−6.2%	−3.4%
90%	−10.2%	−10.4%	−8.5%	−4.0%	−6.8%	−3.7%
100%	−11.0%	−11.3%	−9.1%	−4.7%	−7.5%	−3.8%

automated vehicles produced marginal reductions in overall corridor travel time ranging from 0.5% to 1.95% depending on corridor congestion level. Under uncongested traffic conditions, some significant travel time reduction is visible after 50% of market penetration, achieving up to 19.5% of travel time reductions under the 100% market penetration scenario. Under congested conditions, the travel time reductions are lower and did not exceed 9%. This is mainly because of reduced potential of the TOAD algorithm in congested conditions where automated vehicle have less freedom to comply with the optimal speed. Similar trends and influences of the congestion are detected for the average number of stops, and average vehicular delay. The total number of served vehicles increases with market penetration of TOAD technology in both traffic condition scenarios.

The environmental impacts of the TOAD algorithm are examined using the vehicle fuel consumption and emission model introduced by Rakha et al. (35). Although some intersections produced generally higher magnitudes of fuel consumption, the reductions generally range between 0.1% and 20% depending on market penetration rate.

Tables 2 and 3 summarize fuel consumption on corridor intersections under different market penetration conditions. Expectedly, the fuel consumption decreases with increase in market penetration of automated vehicles where reductions are ranging from 0.3% to 22.4% in uncongested and 0.1% to 11.3% in congested conditions. The magnitude of reduction is also of interest. While intersections 1–3 have the highest fuel reductions, on intersections 4–6 reductions are slightly lower because of different intersection geometry, arrival type, and signal timing settings. The impact of congestion on fuel savings is obvious and is lower under congested traffic conditions.

Concluding Remarks

The increasing need for mobility yielded significant technological changes in contemporary transportation. While notable advances have been made in the field of intersection control over the past few decades, contemporary intersection control strategies inevitably depend on the prediction of various traffic flow parameters that are highly stochastic in their nature. Consequently, it is

expected that a new emerging concept of connected vehicles can provide unbiased, real-time traffic stream information.

The FAST Act and the Advanced Transportation and Congestion Management Technologies Deployment Program are just two out of many notable U.S. DOT efforts that aim to incorporate connected vehicle concept into reality. To that end, many research and implementation activities were conducted to promote and improve connected vehicle concept. Specifically, intersection control for autonomous vehicles, and other cooperative driving solutions, represent an innovative way to change existing intersection control paradigm. Although scientifically and conceptually adequate, those solutions require either 100% market penetration of technology, or substantial time and cost resources to achieve detectable benefits to road users and community.

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 a series of simulation scenarios and it was discovered that, even with low market penetration, the technology reduces overall travel time of the corridor by 2% and 1.8% under congested and uncongested traffic conditions, respectively. Further increase in market penetration rate reduces overall travel time of the signalized corridor by almost 19.5% and fuel consumption by 20%.

It is worth clearly noting that besides the mobility improvement, the TOAD control strategy utilizes existing fixed-time controllers eliminating significant initial investments. Using artificial intelligence model, the costs of the traffic detection system is minimized allowing application of a single mid-block detector per corridor link. Moreover, the strategy is easily implementable under existing infrastructure conditions, allowing a smooth transition from the contemporary signal control into CAV environment. Further extension of this work would include recovery from pedestrian and preemption calls. This can be achieved by readjusting optimization constraints using preemption parameters to adjust vehicle trajectory prediction. Furthermore, the extension should also address implementation of the algorithm on the network level. To that end, a route choice and route assignment aspects should be incorporated into the control algorithm and optimization framework

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Gutesa, J. Lee, D. Besenski; data collection: S. Gutesa, J. Lee; analysis and interpretation of results: S. Gutesa; draft manuscript preparation: S. Gutesa, J. Lee, D. Besenski. All authors reviewed the results and approved the final version of the manuscript.

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