Intersection Management Using In-Vehicle Speed Advisory/Adaptation

CVI UTC

CONNECTED VEHICLE/INFRASTRUCTURE UNIVERSITY TRANSPORTATION CENTER (CVI-UTC)

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Intersection Management Using In-Vehicle Speed Advisory/Adaptation

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Connected Vehicle/Infrastructure UTC

The mission statement of the Connected Vehicle/Infrastructure University Transportation Center (CVI-UTC) is to conduct research that will advance surface transportation through the application of innovative research and using connected-vehicle and infrastructure technologies to improve safety, state of good repair, economic competitiveness, livable communities, and environmental sustainability.

The goals of the Connected Vehicle/Infrastructure University Transportation Center (CVI-UTC) are:

- Increased understanding and awareness of transportation issues
- Improved body of knowledge
- Improved processes, techniques and skills in addressing transportation issues
- Enlarged pool of trained transportation professionals
- Greater adoption of new technology

Abstract

In recent years, connected vehicles (CVs) and automated vehicles (AVs) have emerged as a realistic and viable transportation option. Research centers and companies have dedicated substantial efforts to the technology, motivated largely by the potential safety benefits that can be realized through the elimination of human error, the enhancement of mobility via reduction of congestion and optimization of trips, and the associated positive environmental impacts. Both sensors and control mechanisms are needed for this technology to succeed. The goal of this study is to make use of vehicle connectivity via vehicle-to-vehicle (V2V) (i.e., exchanging information between vehicles) and vehicle-to-infrastructure (V2I) (i.e., exchanging information with the infrastructure, including intersection controllers) features, leveraging both connected and automated capabilities, to develop control algorithms/systems that deliver solutions/recommendations for connected automated vehicles (CAVs) [1] as they proceed through intersections. The algorithms developed in this report deliver optimal and/or near-optimal solutions, which required extensive simulations and field experiments for validation.

In the work described in this report, the research group combined mathematical modeling, optimal control theory, and optimization into a simulation framework that allows vehicles to cross an intersection safely, while incurring the least amount of delay. These models feature kinematic, dynamic and static constraints. Different versions of the model were developed, ranging from exact solutions that cannot be implemented in real-time to heuristic solutions that are computationally efficient. The results of the final proposed model were compared to other control techniques already implemented in the field, and demonstrated that a reduction of at least 50% in delay was achievable. An interesting byproduct of this model was the reduction in fuel consumption, and thus emissions, by more than 10%.

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Introduction

Automation has been introduced into an increasing number of transportation related systems that used to require human intervention. Some examples include auto-manufacturing systems, subway systems, and, the subject of this report, systems used in connected automated vehicles (CAVs) which leverage both connected vehicle (CV) and automated vehicle (AV) capabilities [1]. In recent years, computers have become integral components of vehicles, with various tasks, from cruise control to the synchronization of the engine combustion cycle, being handled automatically. The ultimate goal behind this trend is to make vehicles truly automated, with the principal motivation being the expected associated safety, economic, and mobility advantages. At this stage of the automation process, various automated and semi-automated vehicle prototypes do exist. However, the technology implemented is still not mature enough for mass field implementation. Considerable development in algorithms is still required so that vehicles perform as expected when facing any predicted or unpredicted situation.

In this report, a number of algorithms are proposed that address specific concerns and/or operation regimes of CAVs.

In the first section of this report, a method is proposed to optimize the movement of vehicles crossing an intersection while avoiding collisions. This method is called the Intersection Cooperative Adaptive Cruise Control (iCACC) system; it is a comprehensive car model, which includes kinematic and dynamic constraints. This mathematical model was linearized, and the car-following and collision avoidance model were also included. The velocity of each vehicle entering the intersection was adjusted to ensure that it reached the intersection while conflict zones were empty to provide a safe crossing. To achieve this aim, vehicle-to-vehicle (V2V) and (vehicle-to-infrastructure) V2I technologies were required. Vehicle delay, fuel consumption, emissions, and stops were computed in the simulation.

In the second section of the report, a comprehensive and extended car model is proposed to provide a solution as to how CAVs should cross an intersection using some type of reservation scheme. For this solution, a vehicle's behavior was modeled using nonlinear equations of motion, including, for example, bounds on vehicle velocity and accelerations. The conditions of the roadway surface and vehicle tire conditions were also accounted for, and the fuel consumption and CO_2 emissions were computed as part of the results. Simulations were performed for an intersection with one major and one minor street. The traffic inflows ranged from 500 vehicles per hour (veh/h) to a maximum of 1,200 veh/h. The traffic inflows for the minor street ranged from 250 veh/h to 600 veh/h. This section provides a more complex and complete model when compared to the previous section.

In the third section of this report, the movement of CAVs traversing an intersection was optimized using a heuristic approach called the Isolated Intersection Zone Algorithm (IIZA), which is less accurate than the model described in Section 2 but can be implemented in real-time. Specifically, a heuristic distributed algorithm was developed that can be applied in real-time, and which does not require expensive infrastructure investments.

The final section of the report extends the heuristic algorithm to optimize the movement of vehicles traveling through multiple intersections. Two algorithms were developed and compared that extended IIZA such that at each intersection, the four directly neighboring intersections (west, east, north, and south) were considered while scheduling the passage of vehicles through the intersection. The first proposed algorithm, the Networked Intersection Zones Algorithm (NIZA), relied on V2V communication and cooperation of vehicles with no dependence on any infrastructure agents. The second algorithm, the Dual-Layered Algorithm (DLA), defined two layers of traffic control—the lower layer applied IIZA at each intersection, while the higher layer defined a new distributed multi-agent system where each intersection in the network was an agent. Each intersection was modeled as an agent that communicated with the four direct neighboring intersections (west, east, north, and south). An intersection agent communicated with its directly neighboring intersection agents to exchange the traffic states of the four approaches, then broadcasted what it knew about its neighbors to the vehicles in its zone. The vehicles in its zone could then make use of this state information to assist in scheduling their movements through the intersection.

Developed Work

The Intersection Cooperative Adaptive Cruise Control System Concept

Introduction

Numerous wireless-communications-based in-vehicle technologies are currently being deployed by the automotive industry. One of these technologies is the Cooperative Adaptive Cruise Control (CACC) system, which provides better connectivity, safety, and mobility by allowing vehicles to travel in denser platoons via vehicle connectivity The research presented here developed a simulation/optimization tool to optimize the movement of CACC-equipped vehicles as a replacement for traditional intersection control. This system, called iCACC, assumes that the intersection controller receives vehicle requests to travel through an intersection, advising each vehicle on the optimum course of action, thus ensuring no crashes occur, while at the same time minimizing intersection delay. This suggests there is V2I and V2V communication between the vehicles crossing this intersection. The results showed that the proposed iCACC system significantly reduced the average intersection delay and fuel consumption level by 90% and 45%, respectively.

Modeling

In this section, the physics used to model the behavior of a typical vehicle are described. The model used the Rakha-Pasumarthy-Adjerid (RPA) car-following model, which integrates vehicle dynamics and collision avoidance constraints with the Van Aerde steady-state car-following model [2]. The Virginia Tech Comprehensive Power-based Fuel Consumption Model (VT-CPFM) was also used to estimate fuel consumption and CO2 emission levels. In addition, gap acceptance modeling was a vital part of the optimization process for modeling various levels of automation, especially for non-CAVs.

Van Aerde Steady-state Car-following Model

The RPA car following model uses the Van Aerde steady-state car-following model [3] together with vehicle dynamics and collision avoidance models. The RPA car-following model computes the vehicle speed as the minimum of the maximum allowed speed based on vehicle dynamics, the steady-state car-following desired speed, and the collision avoidance speed as:

$$v_n(t+\Delta t) = \min \begin{cases} v_n(t) + \dfrac{F_n(t) - R_n(t)}{m} \Delta t \\ \dfrac{-c_1 + c_3\, v_f + s_n(t+\Delta t) - \sqrt{A}}{2\, c_3} \\ \sqrt{v_{n-1}(t+\Delta t)^2 + 2\, d_{max} \left(s_n(t+\Delta t) - \dfrac{1}{k_j} \right)} \end{cases}$$

$$s_n(t+\ \Delta\, t) =\ s_n\ (t) + \left(\, v_{n-1}(t) - v_n(t) \right) \Delta t + \frac{1}{2}\, a_{n-1}(t) \Delta t^2$$

$$A\ = \left(\, c_1 + c_3\, v_f\ - s_n(t\ +\ \Delta t)\, \right)^2 - 4\, c_3 \left[\, s_n(t\ +\ \Delta t) v_f\ -\ c_1\, v_f\ - c_2\ \right]$$

$$c_1 = \frac{v_f}{k_j\, v_c^2} \left(2\, v_c\ -\ v_f \right)$$

$$c_2 = \frac{v_f}{k_j v_c^2}\ \left(v_f\ -\ v_c \right)^2$$

$$c_3 = \left(\frac{1}{q_c}\ - \frac{v_f}{k_j\, v_c^2} \right)$$

where

- $u_n(t)$ is the speed of vehicle *n* at time *t* (km/h);
- c_1, c_2, and c_3 are steady-state car-following model parameters;
- u_f is the free-flow speed (km/h);
- u_c is the speed-at-capacity (km/h);
- $s_n(t)$ is the spacing at time (t);
- $F_n(t)$ and $R_n(t)$ are the resultant forces acting on vehicle *n* at time *t*;
- k_j is the jam density (veh/km/lane);
- q_c is the capacity (veh/h/lane);

- $s_n(t)$ is vehicle spacing between the following vehicle n and the lead vehicle n-1 (km) at time t;
- $s_n(t+\Delta t)$ is the predicted spacing at time $t+\Delta t$ considering that vehicle n continues at its current speed (km);
- $a_n(t)$ is the acceleration of vehicle n at time t; and
- d_{max} is the maximum acceptable deceleration level the driver is willing to exert (m/s^2).

Modeling Vehicle Dynamics

The vehicle dynamics model is used to capture vehicle acceleration constraints. In doing so, the vehicle speed is computed from the resultant forces acting on the vehicle. These forces include the tractive forces given by

$$F = \min\left(767\ \eta_d\ f_p \frac{P}{v}, m_{ta} g\ \mu\right)$$

and the resistive forces given by

$$R = \frac{r}{25.92} C_d C_h A_f v^2 + mg \frac{c_{r0}}{1000}\left(c_{r1} v + c_{r2}\right) + mgG\ .$$

where

- η_d is the driveline efficiency (unitless);
- P is the vehicle power (kW);
- m_{ta} is the mass of the vehicle on the tractive axle (kg);
- v is the vehicle speed (km/h);
- g is the gravitational acceleration (9.8067 m/s^2);
- μ is the coefficient of road adhesion (a function of the roadway surface condition) or the coefficient of friction (unitless);
- ρ is the air density at sea level and a temperature of 15◦C (1.2256 kg/m^3);
- Cd is the vehicle drag coefficient (unitless), typically 0.30;
- Ch is the altitude correction factor (unitless);
- Af is the vehicle frontal area (m^2); cr0 is rolling resistance constant (unitless);
- cr1 is the rolling resistance constant (h/km);
- cr2 is the rolling resistance constant (unitless);
- m is the total vehicle mass (kg); and
- G is the roadway grade at instant t (unitless).

The vehicle acceleration is calculated as the ratio of the difference in tractive and resistive forces and the vehicle mass (i.e., $a = (F\text{-}R)/m$). The vehicle speed at ($t + \Delta t$) is then computed by solving the differential equation using a first-order Euler approximation as

$$v_{n+1}(t) = v_n(t) + \frac{F_n(t) - R_n(t)}{m}\Delta t$$

Gap Acceptance Model

A gap is defined as the elapsed-time interval between arrivals of successive vehicles in the opposing flow at a specified reference point in the intersection area. The minimum gap that a driver is willing to accept is generally called the critical gap. The iCACC tool models the critical gap for each driver as a stochastic value based on the vehicle capability, the crossing distance, and the weather condition (i.e., rain intensity). In an earlier study [4], it was demonstrated that increasing the rain intensity causes an increase in the critical gap. The critical gap for different rain intensities can be computed using the following equation:

$$t_c = -\frac{\beta_0}{\beta_1}\bar{\tau}_t - \frac{\beta_2}{\beta_1}w - \frac{\beta_3\bar{\tau}_t}{\beta_1\bar{r}}r$$

where t_c is the critical gap; w is the waiting time to accept a gap (s); r is the rain intensity (cm/h); $\bar{r}$ is the average rain intensity at the site; $\bar{\tau}$ is the average travel time to a conflict point and β_0, β_1, β_2, β_3 were estimated to be equal to -5.65, 2.16, 0.065, and -0.11, respectively. In the iCACC tool, the waiting time is set to be zero and the travel time is calculated using the vehicle dynamics model.

Fuel Consumption Model

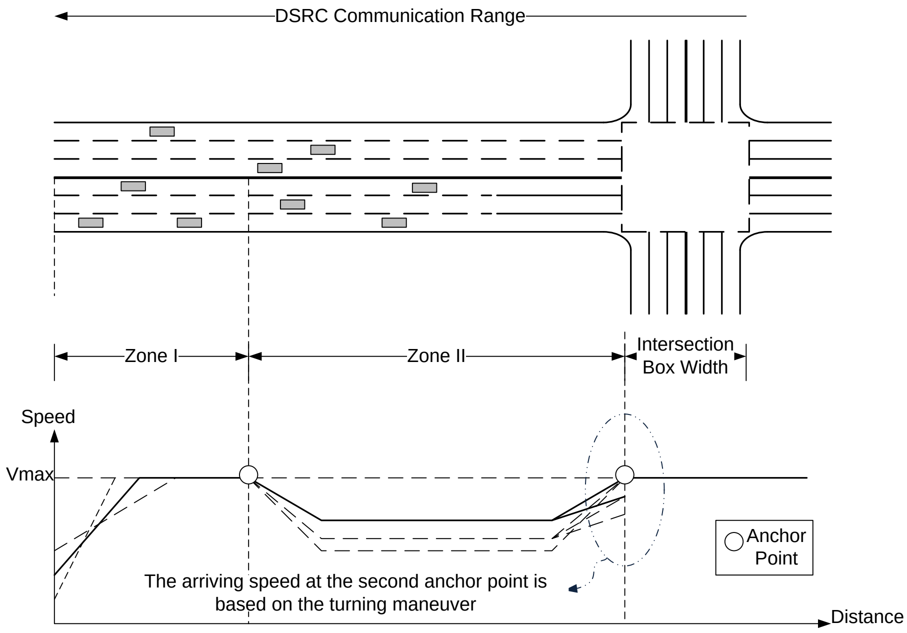
The iCACC tool uses the VT-CPFM (Type 1), taking advantage of its simplicity, accuracy, and ease of calibration [4, 5]. The VT-CPFM utilizes instantaneous power as an input variable and can be calibrated using publicly available fuel economy data (i.e., EPA published city and highway fuel economy ratings). Thus, the calibration of model parameters does not require gathering any vehicle-specific data. The fuel consumption model is formulated as

$$FC(t) = \begin{cases} a_0 + a_1 P(t) + a_2 P(t)^2 & \forall\, P(t) \geq 0 \\ a_0 & \forall\, P(t) < 0 \end{cases}$$

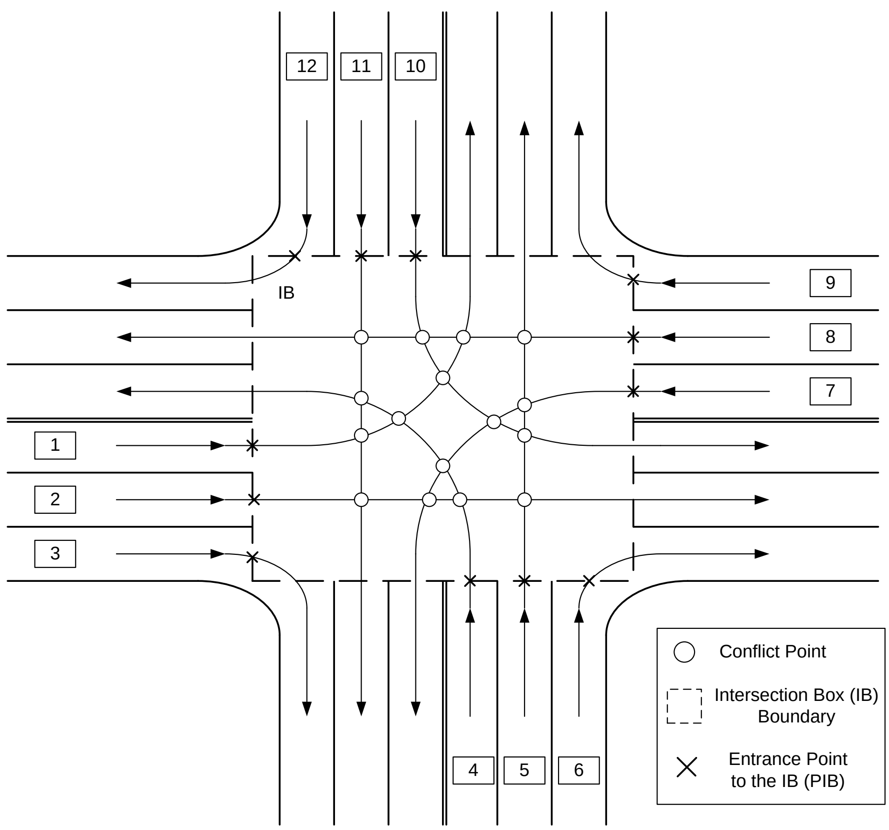
where α_0 is the fuel consumption rate (grams per second [g/s] or liters per second [l/s]) for idling conditions and $P(t)$ is the instantaneous total power in kilowatts (kW). Estimation of the model coefficients (α_1, α_2) uses the fuel consumption rates of the standard fuel economy cycles (i.e., EPA published city and highway fuel economy ratings). Specific model relations for this computation can be found in the literature [5].

The iCACC Simulation/Optimization Module

In this module, three zones are considered in the optimization logic: Zone I, Zone II, and the Intersection Box (IB), as shown in Figure 1 below.



(a)



(b)

Figure 1. (a) The different zones of the optimization process in the iCACC. (b) Vehicle trajectories inside the intersection zone.

The ideal profile entails traveling the entire intersection zone (IZ) at the speed limit. Zone I is used so that each vehicle can accelerate to the speed limit and maintain that speed for the remainder of the zone (assumed to be 50 meters [m] long in this report). As a result, the end-point of Zone I is considered as the first fixed speed point in the iCACC-optimized profile. This fixed speed point is called the "anchor point." In the absence of conflicting vehicles, a vehicle should be able to cross Zone II and the IB at the same maximum speed. For optimization purposes, the speed may be reduced in Zone II in order to avoid conflicts with other vehicles. Zone II was assumed to be 150 m long in this study. At the end of Zone II, all vehicles travel at the movement-specific maximum possible speed while traversing the intersection. This ensures that the speed of all vehicles equals the speed limit at the first anchor point and the maximum movement speed at the second anchor point. In other words, the speed at the second anchor point is based on the movement at the intersection. I.e., the left turn movement is assumed to have a lower speed than the through movement. The second anchor point is assumed to be located at the intersection stop-line.

The iCACC system adjusts the vehicle speed profile in Zone II so that all vehicles traverse the IB at their respective maximum movement speed without colliding with other vehicles. As an example, Figure 1 (b) shows the 16 conflict points in a four-legged, three-lane approach intersection. Ideally, if the vehicle does not decelerate and/or stop in Zone II, it will arrive at the stop line at the shortest time possible (i.e. Optimum Time [*OT*]). However, to avoid conflicts with other vehicles, vehicles may need to decelerate, and in some cases come to a complete stop, as is the case with traditional intersection control (e.g., at a traffic signal, stop sign, etc.). Therefore, the vehicle arrives at the stop line at the Actual Time (*AT*). By minimizing the summation of the difference between *AT* and *OT* for all vehicles, the iCACC system minimizes the total intersection delay.

Consequently, the decision of arrival time for each vehicle is made using an optimization module. In optimizing the vehicle trajectories, this module also optimizes the time of arrival of each vehicle at the intersection stop-line at each time step (i.e. optimization loop). The main objective of the optimization problem is to minimize the amount of delay (*D*) required to be added to the *OT* to avoid conflicts with crossing vehicles. This optimization problem is formulated as

$$Min: \sum_{i=1}^{\Omega^1} D_i$$

Subject to:

$$(OT_i + D_i) - (OT_j + D_j) \geq H_{\min}(l_{im} l_{jm}); \quad i \neq j, \forall i, j \in \Omega, \forall m \in \Psi$$

$$\left|(OT_i + D_i + \tau_{mn}) - (OT_k + D_k + \tau_{nm})\right| \geq \Delta\tau(l_{im} l_{kn} c_{mn}); \quad i \neq k, \forall i, k \in \Omega^1, \forall m, n \in \Psi$$

$$(OT_i + D_i + \tau_{mn}) \geq \max\left[(OT_f + D_f + \tau_{mn}), (OT_p + D_p + \tau_{nm})\right]; \forall i \in \Omega^1, \forall f, p \in \Omega^0, \forall m, n \in \Psi$$

$$D_i \geq 0; \quad \forall i \in \Omega$$

Where

i, j, f, p is the vehicle identification number.

D_i is the time difference between the optimum time (OT) and the actual time (AT) for vehicle i; for the ideal case D_i is zero (no deceleration occurs in Zone II).

OT_i is the optimum arrival time of vehicle i at the entrance point to the IB (PIB). OT_i is estimated assuming that each vehicle accelerates to the maximum speed in Zone I and continues to travel at that maximum speed until PIB. (The arrival time is calculated based on the mathematical equations presented in the following sub-section).

Ω^0 is the set of vehicles that entered the IZ in the last time step that are still in the IZ in the current time step.

Ω^1 is the set of vehicles that enter the IZ in the current time step.

Ω is the set of vehicles in the IZ in the current time step ($\Omega = \Omega^0 + \Omega^1$).

m,n is the lane identification number.

Ψ is the set of lanes at the intersection.

l_{im} = 1 if vehicle i enters the IB from lane m; and=0 otherwise, with $\sum_{m\in\Psi} l_{im} = 1$.

c_{mn} = 1 if vehicle i from lane m has a conflict point with vehicles traveling on lane n; and = 0 otherwise, with $\sum_{m,n\in\Psi} c_{mn} = 1$.

τ_{mn} is the travel time from the PIB of lane m entering into IB to the conflict point of lane n. Distance to each conflict point is based on the intersection geometry. It is assumed that all vehicles will be running at maximum speed in the IB. Thus, τ_{mn} is fixed for all vehicles from the same lane m to the same conflict point mn (to facilitate the optimization process). It should be noted that the maximum speed may be different for different movements.

$\Delta\tau$ is the duration of time that a vehicle occupies the conflict point—in other words, the safety interval between two consecutive vehicles occupying the same conflict point. To simplify the model formulation and calculation, the research group assumed $\Delta\tau$ to be identical for all vehicles. This assumption can be relaxed for future testing.

H_{min} is the minimum headway between vehicles in the same lane.

Results

In validating the proposed iCACC algorithm, four different scenarios for intersection control were tested: traffic signal controlled, all way stop-controlled (AWSC), roundabout controlled, and iCACC controlled. The case study intersection consisted of four approaches and each approach had two lanes with shared movements. Each lane was 3.5 m wide with a speed limit of 35 mph (approximately 16 meters per second [m/s]).

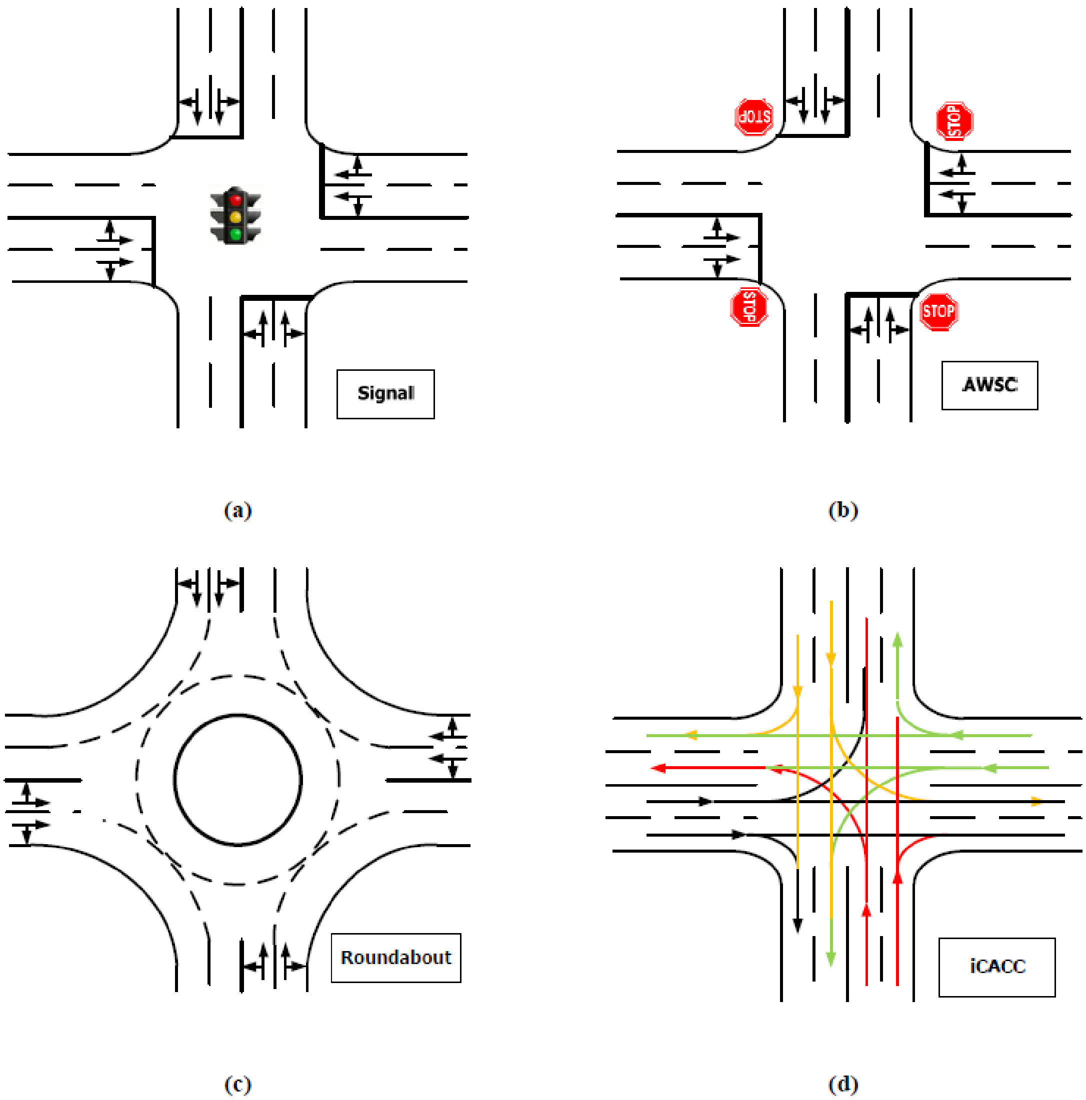


Figure 2. Different intersection scenarios: (a) traffic signal (b) AWSC (c) roundabout (d) iCACC.

In calibrating the vehicle dynamics and fuel consumption model parameters, the physical and mechanical characteristics of a 2010 Honda Accord with a 177 horsepower engine were used.

The analysis assumed that the vehicle traveled on a good flat asphalt surface (grade 0%) and the current weather condition was dry. Table 1 summarizes the specifications and the parameters used for testing the proposed CAV application. The major street volume ranged between 500 to 2,000 veh/h/approach and the minor street volume ranged between 250 to 1,000 veh/h/approach. INTEGRATION micro-simulation software was used for simulating the three conventional intersection control scenarios: signal control, AWSC control, and roundabout control. The entrance time of each vehicle to the IZ, their initial speed, and their acceleration were picked using a random number generator.

Table 1. The Simulation Input

	Parameter	**Value**
Optimization Inputs	Exchanged Information Rate	0.1 (sec)
	Number of Optimization Iterations	30
	Optimization Horizon	20 (sec)
The Physical Parameters of the Tested vehicle (2010 Honda Accord)	Power of Engine (P)	177 Hp
	Transmission Efficiency (μ)	0.92
	Total Weight (W)	1453 kg
	Mass on Tractive Axle (mta)	785 kg
	Air Drag Coefficient (Cd) and Altitude factor (Ch)	0.3 and 1
	Frontal Area (Af)	2.32 m2
	Rolling Resistance Coefficient	Cr0 = 1.75, Cr1=0.0328 and Cr2=4.575
	EPA Estimates	City/ Combined/Highway 21/25/31 MPG

The iCACC scenario was simulated in MATLAB using the "moving horizon optimization" concept at each time step (i.e., 30 seconds) to speed-up the optimization process. In other words, at each time step, the new entering vehicles to the IZ were optimized with the expected entering vehicles in the following time step. Consequently, by using the moving horizon concept, the optimization process took less time, as the preliminary optimization results were used in the following time step as the initial input to the optimization process.

Two measures of effectiveness were computed: the average vehicle delay and the average vehicle fuel consumption level. Delay incurred by a vehicle was computed as the deviation in time to cover the distance under consideration. This value was averaged across all vehicles for the four scenarios for the 16 traffic demand cases, as shown in Figure 3. Fuel consumption estimates were made using the VT-CPFM model calibrated for the test-vehicle. Inputs for the model were instantaneous speed vectors for vehicles derived from the MATLAB simulation and trajectories extracted from the INTEGRATION software. The average fuel consumption required for the vehicles to pass through the intersection was also computed the same way for all 16 scenarios, as shown in Figure 4.

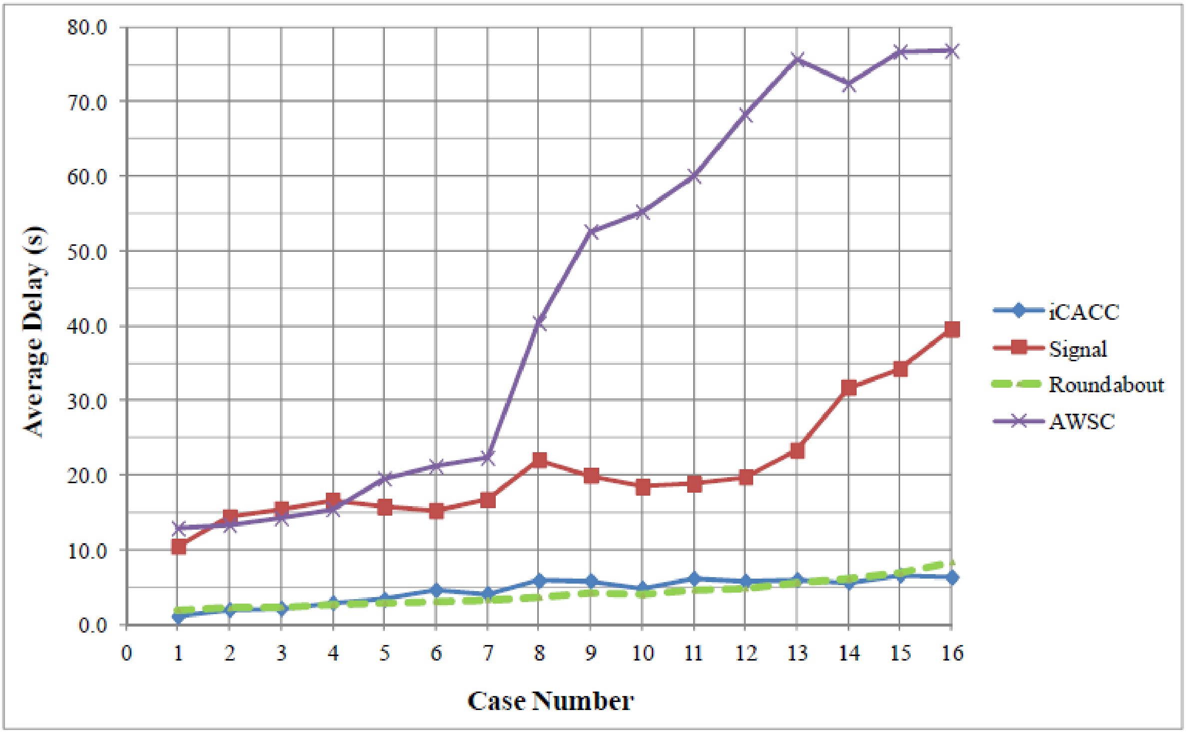


Figure 3. Comparison between different scenarios, average delay comparison per vehicle (seconds).

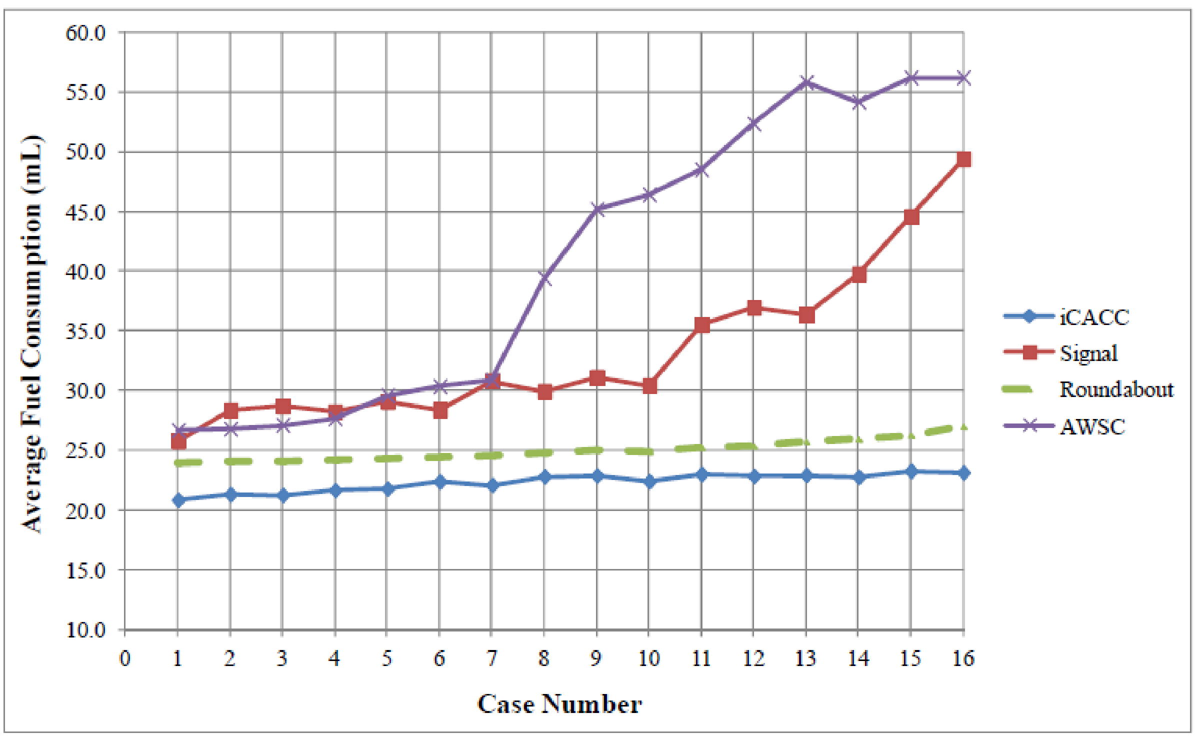


Figure 4. Comparison between different scenarios, average fuel consumption per vehicle (milliliters).

a

Figure 3 and Figure 4 compare the benefits of iCACC intersection control over conventional signalized intersection control in terms of delay and fuel consumed on a per-vehicle basis for the different traffic demand scenarios. The intersection and vehicles simulated in all cases were similar in all geometric and physical aspects. The AWSC produced the highest average delay per vehicle followed by the signal control scenario. The roundabout and iCACC scenarios showed the least average delay per vehicle. The average delay value for the roundabout scenario was almost consistent with the iCACC scenario for each of the traffic demand scenarios. Consequently, it appears that by reducing the number of conflict points (i.e. roundabout), the impact on the average delay was nearly the same as managing/optimizing the movement of crossing vehicles considering a larger number of conflict points (i.e., iCACC). In the case of fuel consumption, the iCACC scenario showed higher savings over the conventional scenarios. The simulation results show that fuel consumption for the iCACC scenario was, on average, 33%, 45%, and 11% lower than the fuel consumption for the traffic signal control, AWSC control, and roundabout control scenarios, respectively.

In general, on a vehicle-by-vehicle basis, the iCACC algorithm reduced vehicle delay significantly when compared to conventional intersection control scenarios. In the case of high-volume intersections, the iCACC optimization algorithm compromised the no-stop constraints and thus reverted to the “First in First Out” (FIFO) concept. In other words, once the system could not find a feasible solution for the optimization process, it managed the movement of vehicles based on the priority of entering the IZ. This study demonstrates the promising potential of iCACC intersection control when connected and eventually CAVs enter the market, as it not only mitigates crash risk but also reduces total intersection delay and fuel consumption.

Inclement Weather Analysis

Most of the literature on the effects of weather have focused on collision risk, traffic volume variations, signal control, travel pattern, and traffic flow parameters [6, 7]. In addition, there have been limited studies that directly address how adverse weather affects traffic flow variables, including speed, flow, density, capacity, and gap acceptance [8–10]. However, it is hard to find studies that characterize individual driver behavior for non-equipped vehicles under adverse weather conditions in conjunction with CAVs.

The iCACC system captures inclement weather impacts on both driver behavior and vehicle dynamics. The iCACC system has the ability to model driver behavior in non-CAVs by adjusting the critical gap based on the weather condition and the travel time needed to cross (using the vehicle dynamics model). The objective of this section is to extend the previous analysis and investigate the impact of inclement weather on the intersection performance under different levels of market penetration (LMP) of CAVs and levels of congestion. The evaluation of the iCACC system was made considering three different volume scenarios for maximum volume-to-capacity (v/c) ratios of 0.2, 0.5, and 0.8. The simulated LMP ranged from 20% to 100%. Given that that the LMP is not anticipated to be high in the near future, the research evaluated the performance of the intersection for various LMPs. Obviously, by increasing the LMP, the iCACC was able to reduce the delay and fuel consumption level by controlling the movements of the accessible CAVs. Consequently, at a 100% LMP, the potential benefits are provided if full deployment of iCACC is achieved.

The results demonstrate that in case of low volumes (v/c=0.2), the impact of introducing the iCACC intersection controller was relatively small when compared to more congested conditions. For the high volume case (v/c=0.8), the iCACC was able to significantly reduce the delay and fuel consumption level. For dry condition scenarios, as would be expected, the delay and fuel consumption levels were lower than rainy and snowy condition scenarios. Plots in Figure 5 and Figure 6 illustrate the variation in the average delay and fuel consumption values with the increase in the LMP corresponding to different weather conditions. The impact of weather condition was captured in various models: vehicle dynamics (coefficient of friction and rolling resistance coefficients), car-following (free-flow speed, speed at capacity, and capacity) and the gap acceptance models (critical gap and follow-up time).

In general, weather causes a variety of impacts on traffic management during and after weather events. However, the linkages between inclement weather conditions and CAV systems remain tenuous. The primary concern of this analysis was to understand how drivers make their decisions at intersections for various LMP of connected systems under different weather conditions.

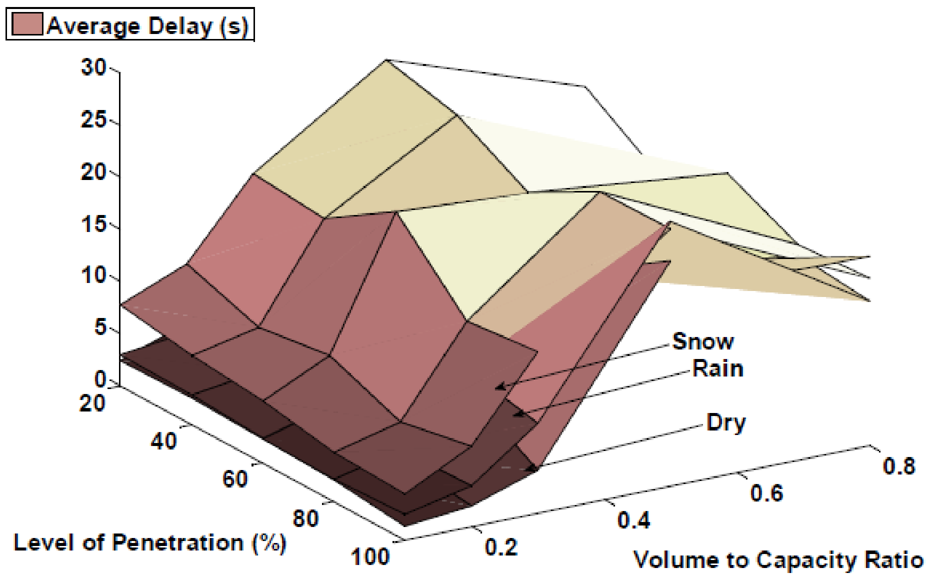


Figure 5. The impact of LMP, v/c, and weather conditions on average delay per vehicle (seconds).

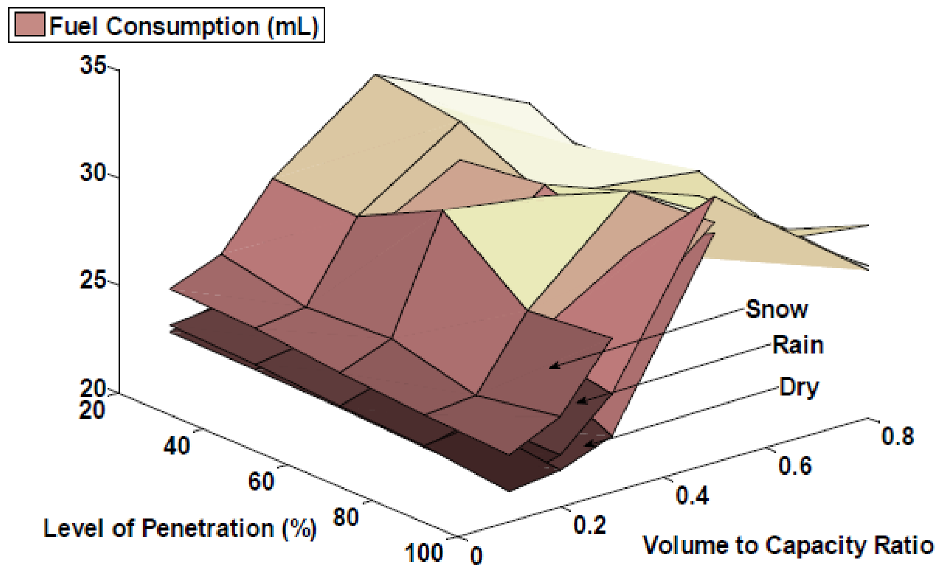


Figure 6. The impact of LMP, v/c, and weather conditions on average fuel consumption (milliliters) per vehicle.

Conclusions

The research presented here proves that through iCACC, the movement of CAVs can be optimized while ensuring no crashes occur, and at the same time can minimize intersection delay. These recommendations are made in real-time each time step (fast optimization). The proposed system was tested and compared to different intersection control approaches using multiple traffic volume combinations. The results show that the proposed iCACC system significantly reduced the average intersection delay and fuel consumption level by 90% and 45%, respectively. Additionally, the research demonstrated how the impact of inclement weather and LMP of CAVs could impact the results. Despite the value in these findings, more work is still needed to extend the logic to deal with higher levels of congestion, and to extend the system to consider multiple intersections.

Optimal Intersection Control for Connected Automated Vehicles

Introduction

Automated technologies within vehicles have become increasingly present in the marketplace, and will likely become more prevalent over time. CAVs are already present on the roads and fully-autonomous vehicles are likely to be deployed within the next few years. Consequently, substantial research efforts are being dedicated to the development of systems and technologies for the implementation of these CAVs. This effort is mainly motivated by the potential safety benefits that would be provided through the elimination of human error, the enhancement of mobility through the reduction of congestion, and the enhancement of the environment through reduction in CO_2 emissions. Algorithms are needed to deliver optimal and/or near-optimal solutions for situations CAVs may face, and consequently, extensive simulations and field experiments are needed in order to develop a mature technology.

One of the challenges researchers need to address is how a CAV would traverse an intersection optimally and in a cooperative manner so that the delay and environmental impacts are minimized. In this report, the research group attempts to address this need using optimal control theory. The developed model is an optimization problem subjected to dynamical constraints (i.e. ordinary differential equations governing the motion of a vehicle) and static constraints (i.e. maximum achievable velocities). The solution that minimizes the trip time is obtained by virtue of Pontryagin's minimum principle. This solution is expected to be the true optimum to deliver the lowest possible delay that satisfies the previously mentioned constraints. This logic was simulated and compared to the operation of an intersection controlled by a roundabout, AWSC, and a traffic signal. The results demonstrated that an 80% reduction in delay was achievable compared to the best of these three other intersection control strategies. An interesting byproduct of this new logic was the slight reduction in fuel consumption, from an average of 68 centiliters for the non-optimized solutions to 62 centiliters for the optimized solution, and a reduction in CO2 emissions, from 152.7 g for the roundabout to 26.81 g for the optimized solution.

Study Objective

In this study, a novel algorithm was developed to compute an optimal solution for each possible scenario an CAV may encounter while traversing a roadway intersection. This algorithm uses an optimal control theory that guarantees the true optimality of the solution. The features of this solution include

1. A dynamic system describing the motion of the vehicle using vehicle characteristics such as engine power, mass, fuel consumption modeling, and physical acceleration and deceleration constraints that account for roadway surface and vehicle tire conditions.
2. Accounting for weather conditions.
3. Accounting for singular cases where the vehicle has to stop at the intersection.

Model Description

In this model, the research group considered the intersection given in Figure 7. Each vehicle represented in this figure has three possible routes: through, left, or right. These routes proceed through "conflict zones." A number of vehicles will share these zones and thus the solution to the proposed problem will feature an occupancy time slot allocation for each zone. For a given vehicle, the general dynamics are depicted in Figure 8. The corresponding equations of motion are

$$\begin{aligned} \dot{x} &= V\,Cos(\theta) \\ \dot{y} &= V\,Sin(\theta) \\ \dot{V} &= \alpha_1 \\ \dot{\theta} &= \frac{\alpha_2}{V} \end{aligned}$$

where $\alpha_1$and α_2 are control inputs that govern the rate of change of the vehicle velocity V and its orientation θ with respect to the horizontal axis. To simplify the notation, the state vector is used

$$X = \begin{pmatrix} x \\ y \\ V \\ \theta \end{pmatrix}$$

and the control vector

$$\alpha = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix}$$

and re-write the equations of motion as

$$\dot{X} = f(X, \alpha)$$

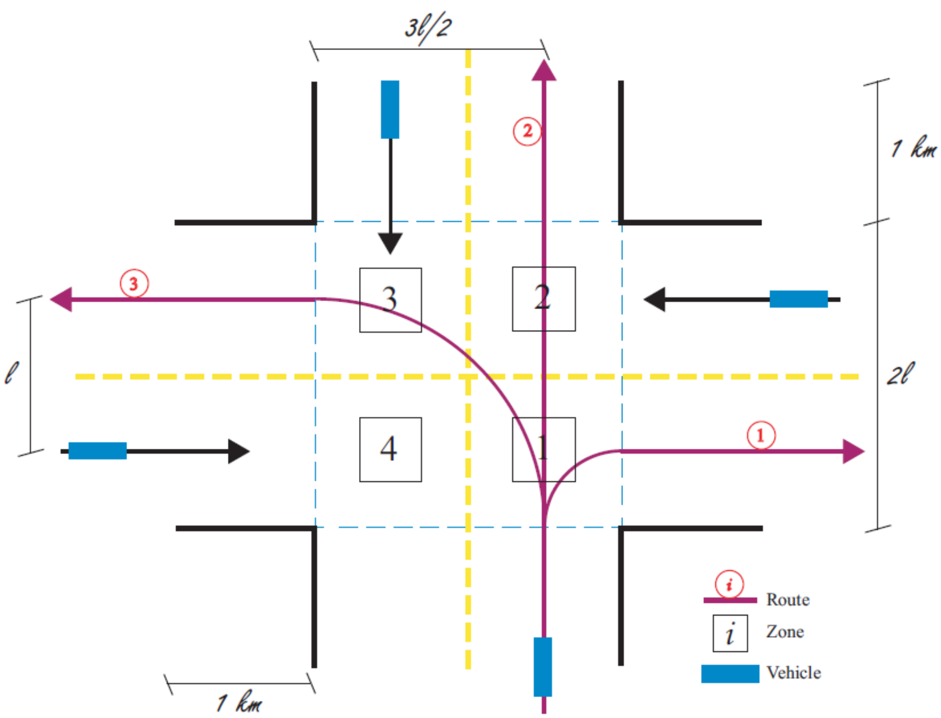


Figure 7. Schematics of a typical intersection.

As part of this research effort, an attempt was made to find the control vector α such that the given initial $X(t_0) = X^0$, the car dynamics evolved according to the equation of motion, and ultimately the research arrives at the final state $X(t_f) = X^1$ while minimizing the cost function

$$P[\alpha(\ )] = \int_{t_0}^{t_1} r(X, \alpha) dt$$

where t_i and t_f are initial and final time. This is referred to as the time optimal control problem. For a typical car there are a number of physical and kinematic constraints due, in part, to the presence of other vehicles on the road. For this study, these constraints are (1) acceleration constraints, (2) a car-following model including collision avoidance, and (3) time constraints.

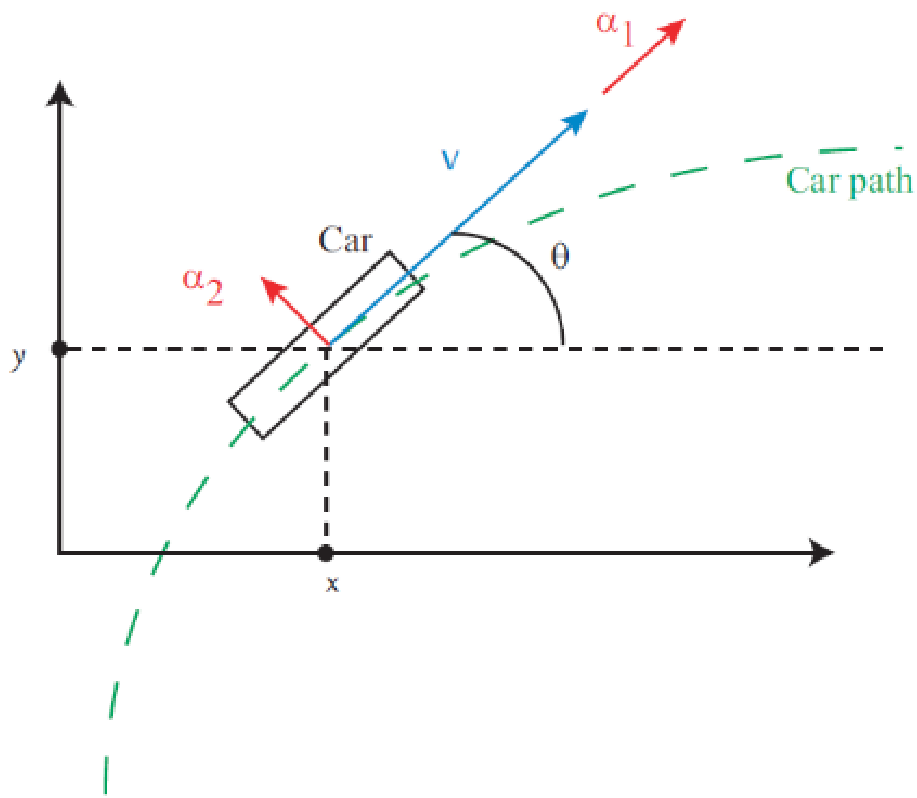


Figure 8. Schematics of a vehicle in motion along a path.

Acceleration Constraints

For a typical vehicle, the maximum vehicle acceleration is computed as

$$\alpha_{1max} = \frac{F - R}{m}$$

where F is the traction force; $R = R_a + R_r + R_g$ is the resistive force sum of the aerodynamic resistance, the rolling resistance and the grade resistance; and m is the vehicle mass.

The traction force is defined as

$$F = \min\left(767\, \eta_d\, f_p \frac{P}{v}, m_{ta} g\, \mu\right)$$

where η_d is the drive-line efficiency, f_p is the driver throttle input $0 < f_p < 1$, P is the vehicle power, v is the vehicle velocity, m_{ta} is the vehicle mass on the tractive axle, μ is the coefficient of road adhesion and g is the gravitational acceleration.

The aerodynamic resistance force is defined by

$$R_a = \frac{1}{2}\,\rho\, C_d C_h A_f v^2$$

where ρ is the fluid density, C_d is the car drag coefficient, C_h is the altitude correction factor and A_f is the frontal area of the vehicle subjected to the flow.

The rolling resistance force is defined by

$$R_r = m\, g\, \frac{c_{r0}}{1000}(c_{r1}v + c_{r2})$$

where c_{r0}, c_{r1} and c_{r2} are the rolling resistance constants.

The grade resistance force is defined by

$$R_g = m\, g\, G$$

where G is the roadway grade. In this work, the research group neglected the grade resistance force by assuming G=0.

The maximum deceleration that can be experienced by a vehicle in this work is assumed to be $5\, m.s^{-2}$. Consequently, the constraint associated with the tangential acceleration is given by

$$-5 \leq\ \alpha_1(t) \leq \frac{F - R}{m}$$

When the vehicle is making a turn, the minimum radius of curvature R_d is given by

$$R_{dmin} = \frac{v^2}{g(e + f_s)}$$

where e is the super elevation and f_s is the coefficient of side friction. Consequently,

$$-g(e + f_s) \leq\ \alpha_2(t) \leq g(e + f_s)$$

Car Following Model: Collision Avoidance

In order to model the behavior of a vehicle with respect to its peers on a lane, the research group used the previously described RPA [2, 11] car-following model. The model combines the Van Aerde steady-state car-following model with collision avoidance constraints for non-steady state conditions. The RPA model predicts the velocity of a vehicle in order to remain within a safe distance with respect to the vehicle ahead of it. Details of this model were presented in Van Aerde's steady-state car-following model, as described in the previous section.

The computed value of $v_n(t+\Delta t)$ can also be cast as a constraint on the spacing between two consecutive vehicles

$$d \geq \bar{d} = \begin{cases} \max\begin{cases} c_1 + \dfrac{c_2}{v_f - v} + c_3 v \\ \dfrac{v^2 - \bar{v}^2}{2\, d_{max}} + c_1 + \dfrac{c_2}{v_f} \end{cases} & if\ v > \bar{v} \\ c_1 + \dfrac{c_2}{v_f - \frac{1}{2}(v_c + v_f)} + \dfrac{1}{2} c_3 (v_c + v_f) \end{cases}$$

where, v is the velocity of the vehicle under consideration and $\bar{v}$ is the velocity of the vehicle directly ahead of it in the same lane.

Time constraint

Since the vehicles cross a shared intersection with other vehicles, it is imperative that specific time slots are assigned to each vehicle. In this work, only the time after which a zone z_i is free (i.e. t_{zi}) is considered and therefore a vehicle must arrive at the zone z_i at a time $t_{zone\ entry}$ to satisfy

$$t_{zone\ entry} \geq t_{zi}$$

Given the constraints defined in the previous section, the time optimal control problem [13, 14] solved in this work for each vehicle was

$$\begin{array}{ll} \textbf{minimize} & P[\alpha(.)] = \int_{t_i}^{t_f} dt = t_f - t_i \\ \textbf{subjected to} & \\ & \dot{X} = f(X, \boldsymbol{\alpha}) \end{array}$$

$$\begin{array}{ccccc} t_{z_i} & \leq & t_{zone\,entry} & \leq & \infty \\ -5 & \leq & \alpha_1 & \leq & \frac{F-R}{m} \\ 0 & \leq & v & \leq & \sqrt{Rd\, g\,(e + f_s)} \\ \overline{d} & \leq & d & \leq & \infty \end{array}$$

When the previous system of equations is solved using Imperial College London Optimal Control Software (ICLOCS) [15] and a solution is obtained, the fuel consumed along the vehicle trajectory using the VT-Micro model can be computed:

$$FC(t) = \begin{cases} e^{\sum_{i=0}^{3}\sum_{j=0}^{3} L_{ij}^{e}\, v^i a^j} & for\ a \geq 0 \\ e^{\sum_{i=0}^{3}\sum_{j=0}^{3} M_{ij}^{e}\, v^i a^j} & for\ a < 0 \end{cases}$$

where L_{ij}^{e} are the model coefficients at speed power i and acceleration power j for positive accelerations, M_{ij}^{e} are the model coefficients at speed power i and acceleration power j for negative accelerations, v is the instantaneous speed, and a is the instantaneous acceleration. In this work, the Oakridge National Lab model parameters were used.

Results and Discussion

Using the model described above, various simulations were performed for an intersection considering various levels of congestion. The intersection used in this work had a major roadway and a minor roadway, where the arrival rates on the minor roadway were always half the flow of the major arterial. The flows along the major arterial ranged from 500 to 1,200 veh/h, with 10% of vehicles turning left and 20% turning right at the intersection. The base saturation flow rate of the roadway was 1,700 veh/h/lane. Given that the capacity of a signalized approach is much less than the saturation flow rate, the intersection experienced over-saturation delay in a number of scenarios. This work presents two versions of the introduced logic. The first version, Optimal Control Time (OCT), attempts to obtain a solution that reduces the delay regardless of the control effort (i.e. aggressive acceleration levels). The cost function was

$$P[\alpha(\quad)] = \int_{t_0}^{t_f} dt$$

The second version, Optimal Control Effort (OCE), aims at obtaining the same results while minimizing the control effort (i.e. avoiding aggressive acceleration levels). In this case, the cost function was

$$P[\alpha(\quad)] = \int_{t_0}^{t_f} (1 + \alpha_1(t)^2 + \alpha_2(t)^2) dt$$

The results of the introduced logic were compared to the results obtained when the intersection was controlled by a roundabout, a traffic signal, or AWSC. Note that a two-phase plan was used to control the traffic signal since it provided better results compared to a three-phase plan. The results of the roundabout, traffic signal, and AWSC approaches were obtained using INTEGRATION software with the same input to make vehicles cross the intersection using optimal control. It should be noted that the INTEGRATION software also uses the RPA car-following and acceleration model embedded in the proposed algorithm.

Figure 9, Figure 10, Figure 11, and Figure 12 present the mean delay, stops, fuel consumption, and CO2 emissions for the entire intersection. The results suggest a general improvement in these variables for both versions of the control system (i.e., OCT and OCE).

Figure 9 illustrates that the OCT resulted in lower delays, far better than the roundabout, and demonstrates that it was the best among the other intersection control strategies. The OCE was the next best approach, and was also better than the roundabout. In this figure, the benefits of the proposed approach are clear, showing that a true optimality was obtained. Specifically, the delays of approximately 2 seconds for OCT and of approximately 6 seconds for OCE were significantly lower than the delay of 76 seconds for the roundabout controlled intersection.

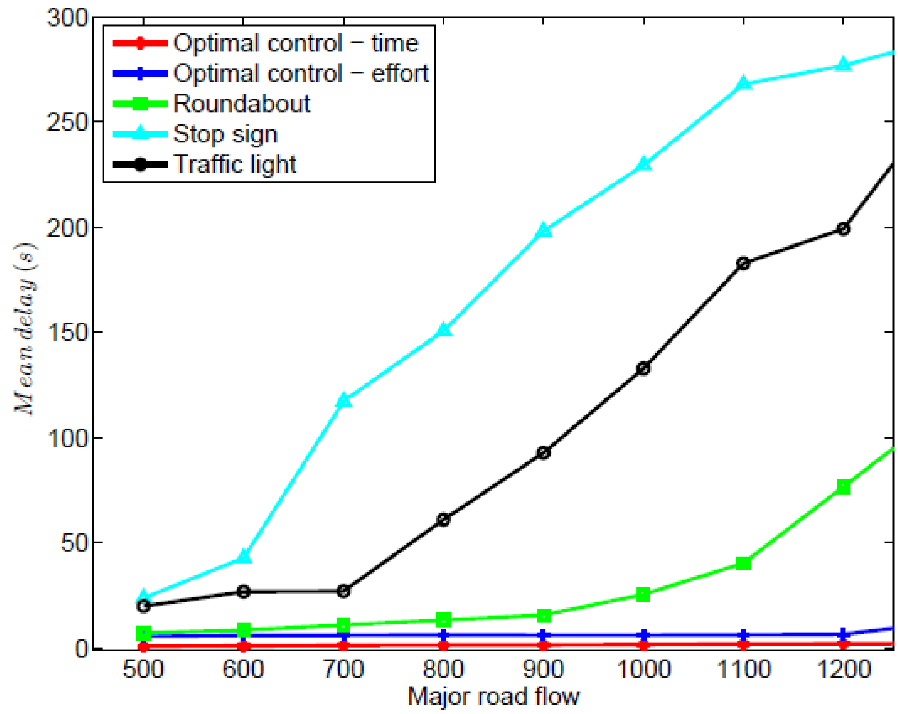


Figure 9. Mean delay in seconds for an intersection equipped with various control mechanisms and various flow rates.

Figure 10 illustrates the mean fuel consumption computed for all vehicles traversing the intersection. Here, results show that the AWSC intersection produced the highest fuel consumption levels (i.e. an average of 27 milliliters [mL]). The consumption generated by the proposed algorithm was insensitive to the demand level (approximately 0.117 liters [L] for OCT and 0.133 L for OCE). The intersection equipped with a traffic light resulted in a fuel consumption of 0.280 L, and the roundabout equipped intersection resulted in a fuel consumption level of 0.226 L.

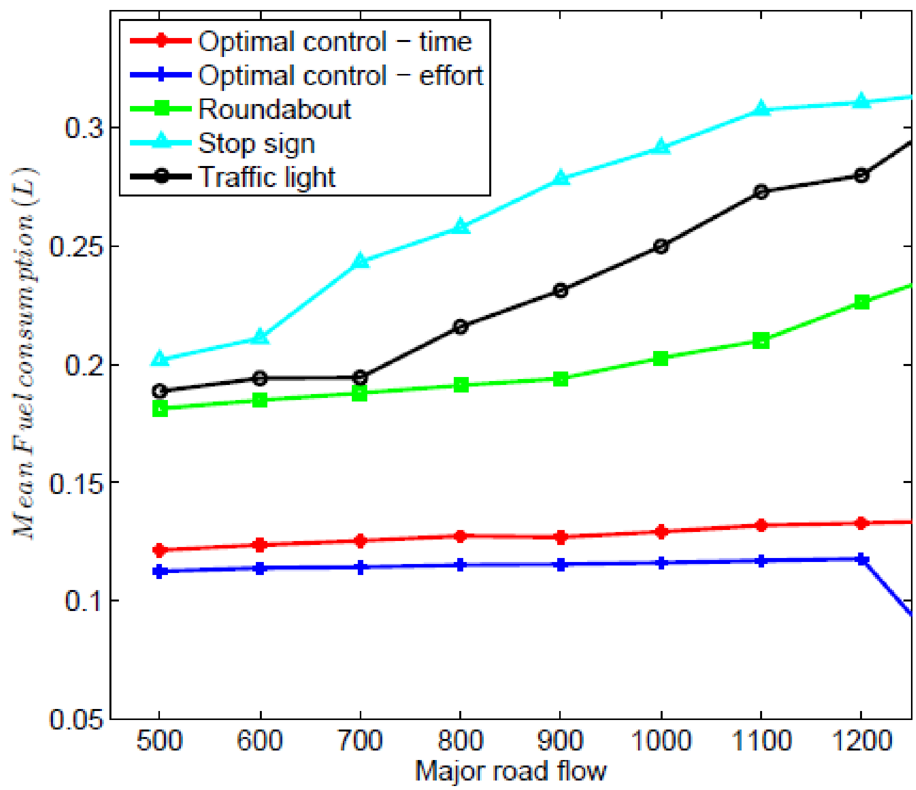


Figure 10. Mean fuel consumption in liters for an intersection equipped with various control mechanisms and various flow rates.

Figure 11 presents the mean computed stops, showing that the computed stops for the proposed algorithm remained fairly constant (i.e., approximately 0.4 stops for OCT) in comparison with the roundabout, for which stops increased from 0.3 to 0.95. For the OCE, the value of the stops also remained constant, but at a value of 0.55. The value of the stops for the AWSC intersection were slightly below 1, as the high demand levels resulted in the queue spilling back to the entrance point, causing vehicles to enter the control zone at lower velocities and thus incur fewer stops.

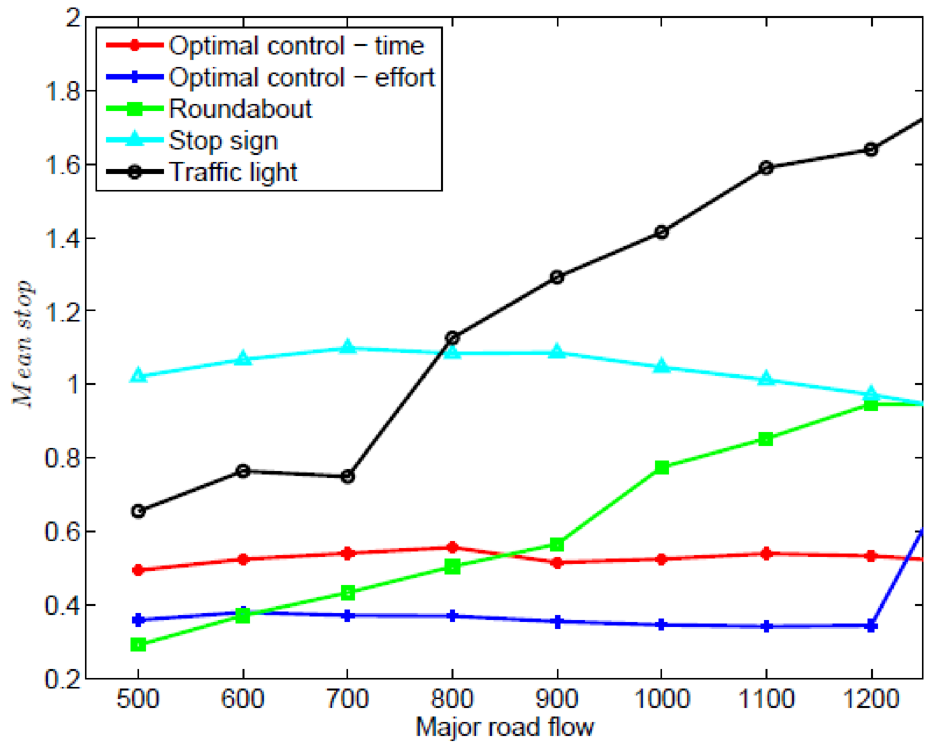


Figure 11. Mean stop for an intersection equipped with various control mechanisms and various flow rates.

Figure 12 shows the computed mean CO2 emissions for the vehicles and for the different intersections. The proposed algorithm resulted in lower CO2 emissions (i.e., 265 g for OCT and 286 g for OCE) compared to other control algorithms. The roundabout produced the least CO2 emissions compared to the other control strategies (i.e., 446 g).

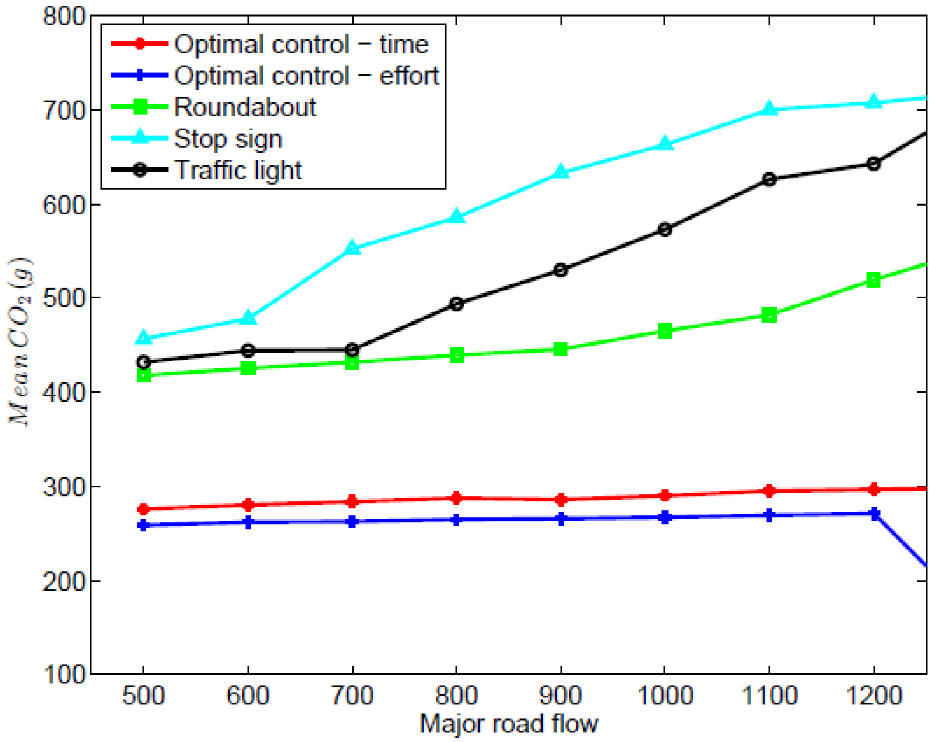


Figure 12. Mean CO2 emissions in grams for an intersection equipped with various control mechanisms and various flow rates.

Figure 13 presents box plots showing the delay for different flow rates and different approaches. These plots were obtained by considering all the data for each vehicle; the data of an individual vehicle was considered as a realization. The realizations for the proposed algorithm lie within a narrow region, demonstrating that not only was the mean travel time low, but that the variability in the travel times was also low.

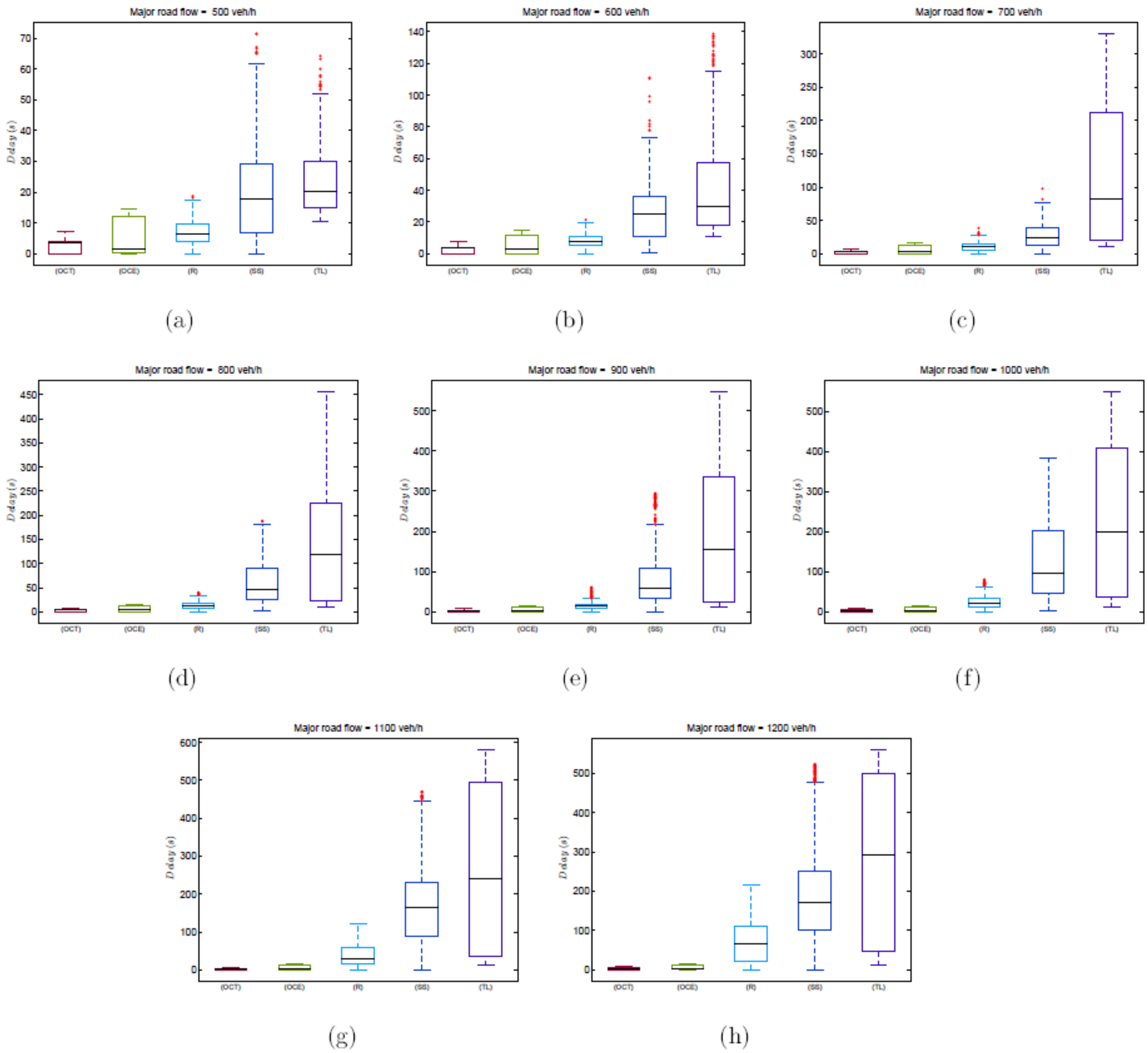


Figure 13. Box plots for the delay experienced by the vehicles crossing the four-way intersection equipped with the new logic, the roundabout, the stop sign and the traffic signal and for different major axis flow rates: (a) 500 veh/h (b) 600 veh/h (c) 700 veh/h (d) 800 veh/h (e) 900 veh/h (f) 1,000 veh/h (g) 1,100 veh/h (h) 1,200 veh/h.

Figure 14 and Figure 15 are also box plots, in this case showing the stop values and fuel consumption for all vehicles within the simulation. The significance for these plots is that the realization for the roundabout controlled intersection R lies within a narrow region.

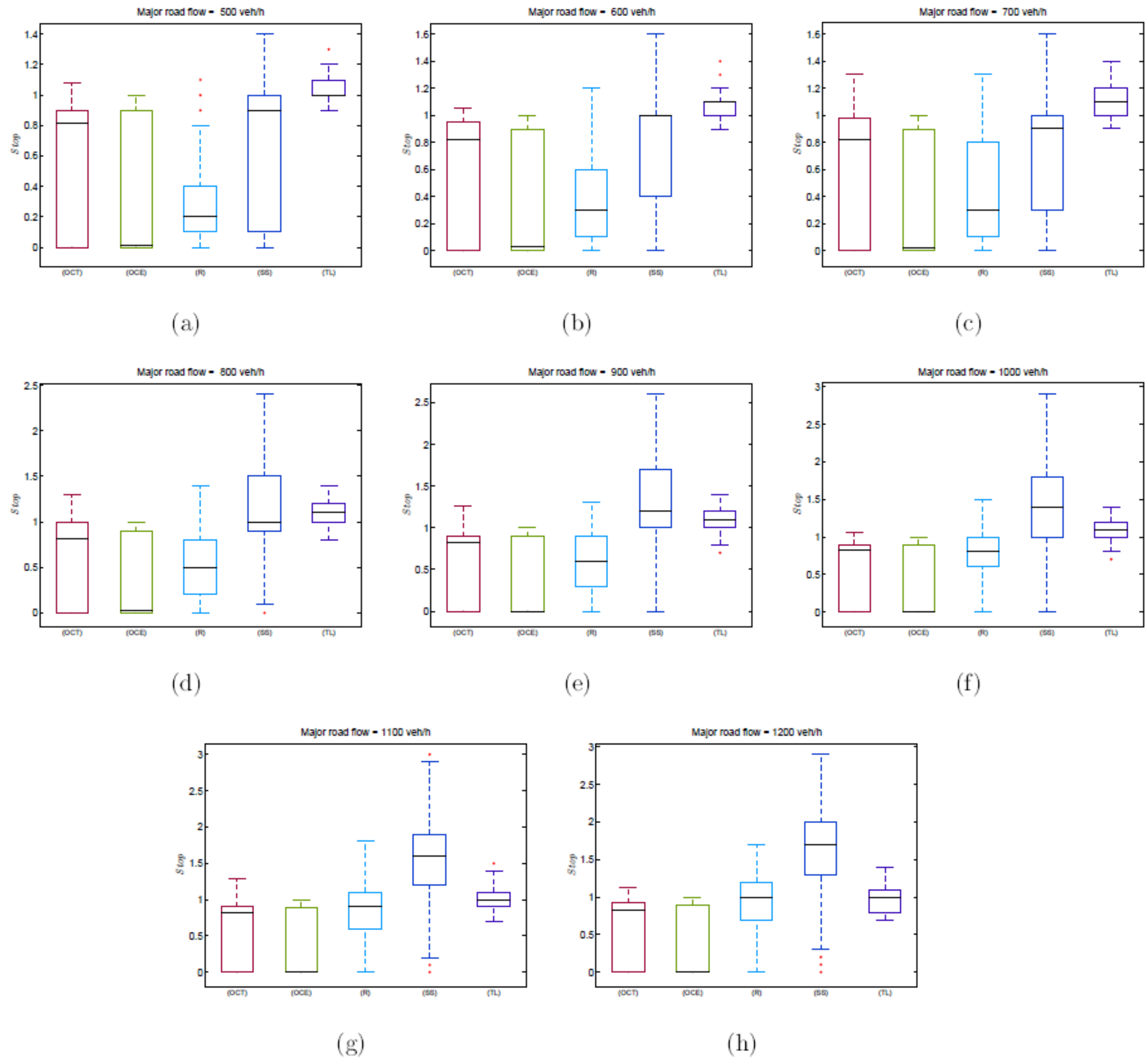


Figure 14. Box plots for the stop experienced by the vehicles crossing the four-way intersection equipped with the new logic, the roundabout, the stop sign and the traffic signal and for different major axis flow rates: (a) 500 veh/h (b) 600 veh/h (c) 700 veh/h (d) 800 veh/h (e) 900 veh/h (f) 1,000 veh/h (g) 1,100 veh/h (h) 1,200 veh/h.

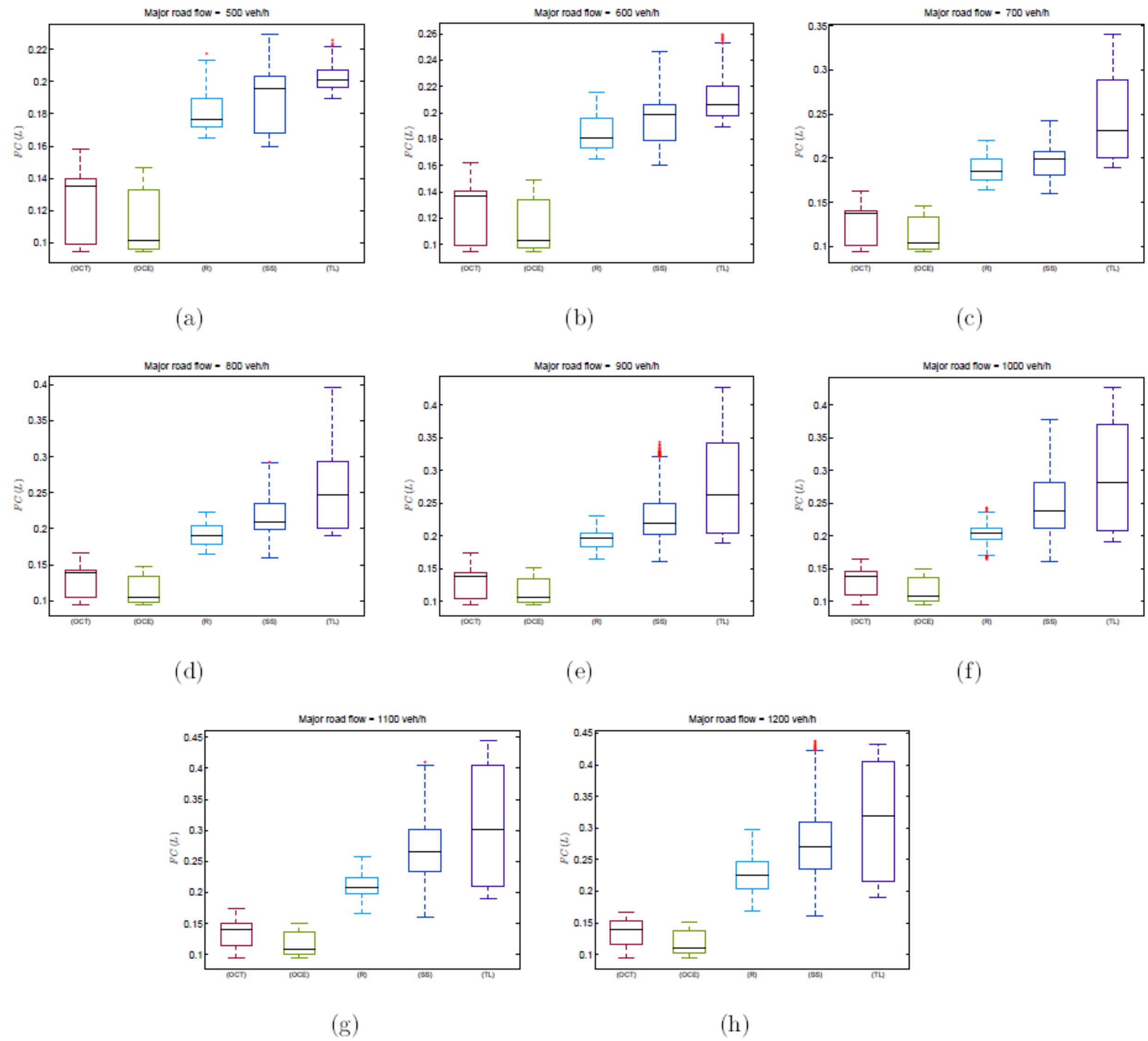


Figure 15. Box plots for the fuel consumption of the vehicles crossing the four-way intersection equipped with the new logic, the roundabout, the stop sign and the traffic signal and for different major axis flow rates: (a) 500 veh/h (b) 600 veh/h (c) 700 veh/h (d) 800 veh/h (e) 900 veh/h (f) 1,000 veh/h (g) 1,100 veh/h (h) 1,200 veh/h.

Figure 16 shows box plots illustrating the CO2 emissions for all the vehicles crossing the intersection. The proposed algorithm produced lower CO2 emissions (i.e. 318 g median for OCT and 253 g for OCE) compared to the roundabout, for example (520 g as median). Note also that the realizations of these simulations for the proposed algorithm are confined to a lower values region: the 25^{th} and 75^{th} percentile are 255 g and 341 g respectively for OCT, and the 25^{th} and 75^{th} percentile are 234 g and 315 g respectively for OCE in comparison to the roundabout, where the 25^{th} percentile is 470 g and the 75^{th} percentile is 565 g. These values were generated for the mainline flow of 1,200 veh/h.

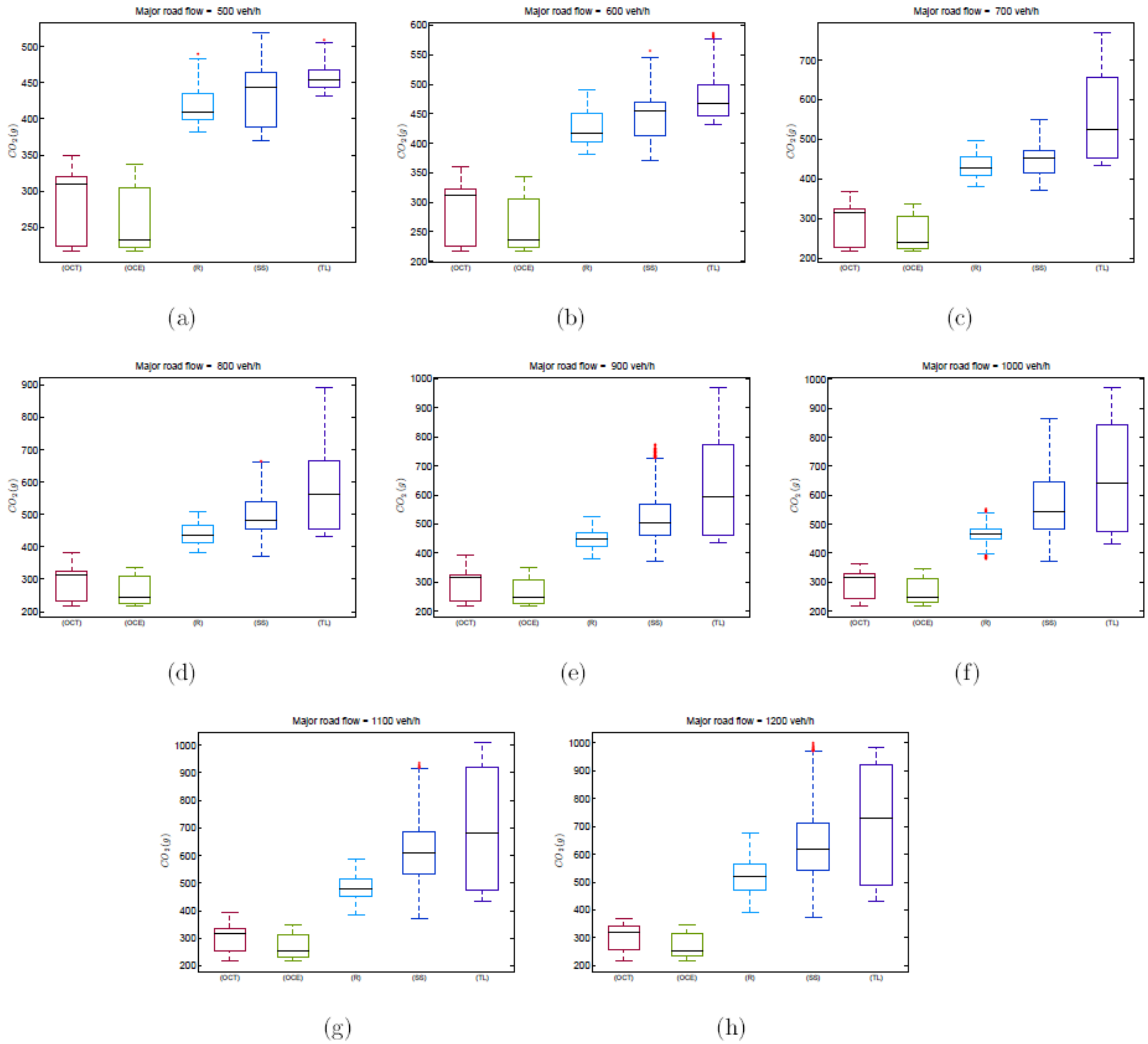


Figure 16. Box plot for the CO2 emissions of the vehicles crossing the four-way intersection equipped with the new logic, the roundabout, AWSC, and the traffic signal and for different major axis flow rates: (a) 500 veh/h (b) 600 veh/h (c) 700 veh/h (d) 800 veh/h (e) 900 veh/h (f) 1,000 veh/h (g) 1,100 veh/h (h) 1,200 veh/h.

The proposed algorithm does have one main disadvantage, which is the high computational cost associated with the nonlinear optimization. Specifically, a set of four vehicles approaching the intersection takes somewhere between 2–5 minutes to solve for. This drawback makes the algorithm unsuitable for real-time applications. Other simplified versions, however, are currently being developed in another study and will be compared to the algorithm presented here.

Conclusion

A novel intersection management algorithm derived from optimal control theory was developed for the control of CAVs. The developed algorithm was tested and compared to other intersection control strategies, including a roundabout controlled, an AWSC (i.e., stop sign controlled), and a traffic signal controlled intersection. The results demonstrated that the proposed algorithm outperformed the other intersection control strategies, producing lower delays and CO2 emissions with reductions of up to 80% and 10%, respectively, relative to the best intersection control strategy (in this case the roundabout).

One of the major disadvantages of the proposed algorithm is the high computational cost associated with finding the optimum solution, which makes the algorithm impractical for real-time implementations.

Consequently, additional research is needed to develop faster heuristic algorithms that are more suitable for real-time applications. It should be noted, however, that the proposed algorithm could be used to evaluate the accuracy of these heuristic algorithms given that the solutions generated using this algorithm represent the best that can be achieved.

A Fully-distributed Heuristic Algorithm for Control of Connected Automated Vehicle Movements at Isolated Intersections

Introduction

Traffic at intersections contributes significantly to both congestion and safety problems. Studies show that about 40% of car accidents in the U.S are related to intersections and about half of these accidents are caused by inadequate driver decisions. The work proposed in this section of the report focuses on the management of traffic at intersections using an algorithm that models the traffic as a multi-agent system using a fully-distributed protocol where vehicles coordinate to pass through the intersection without collision and with minimum delay.

The choice of proposing a fully-distributed protocol is a reasonable one. V2V would allow vehicles to exchange information (including positioning and trajectory data), which is expected to significantly reduce accidents and crashes, especially those caused by human errors, as well as alleviate traffic congestion. With the implementation of CAV technologies, a protocol requiring vehicles at an intersection to continuously exchange coordination messages, like the ones proposed in this section of the report, could soon be easily implemented in real vehicles on roadways, as well as on intersection infrastructure.

Related Work

One of the key research efforts in this area is the work of Dresner and Stone [16, 17], where a centralized multi-agent reservation-based intersection control protocol was presented for CAVs. The protocol simply depended on a central management agent that used the FIFO method to reserve time slots for vehicle agents requesting to pass through the intersection. The importance of Dresner and Stone’s work is that it provided a simple feasible approach and showed how it significantly reduced the delay experienced by traditional traffic signals. Other researchers have built on their work. For example, Zhu et al. [18] also used a centralized reservation-based protocol, proposing a look-ahead intersection control policy (LICP) using the FIFO method. Using this approach, when a vehicle makes a request to reserve a time slot, the controller agent predicts the total delay if the request is allocated, and the total delay if it is postponed. Based on these two predicted values, the controller makes its decision. The use of LICP was shown to achieve up to 25% performance improvement over the FIFO scheme. However, the reliance on a central agent for traffic control was also shown to cause a bottleneck when the number of vehicles increased in the vicinity of an intersection.

Au et al. [19] built on the work of Dresner and Stone in a different way. Instead of limiting the system to CAVs, they proposed a centralized reservation-based protocol that accommodates human-driven and CAVs in addition to fully-automated vehicles. This is the only protocol in the literature that enabled smooth interaction between all types of vehicles.

The proposed algorithm in this work builds on that of Zohdy et al. [20–22], who used centralized multi-agent modeling, and proposed and tested a number of techniques to manage the passage of CAVs through the intersection. In [19], an Optimization Simulator for Driverless vehicles at Intersections (OSDI) was built into the central controlling agent, which used a heuristic optimization algorithm that continuously adjusted the vehicles' trajectories to minimize the occupancy time in areas of conflict in the intersection. The algorithm significantly reduced the delay for a simplified scenario of four vehicles passing through the IZ. In [21–23], a game theory framework and an optimization framework were used to develop a heuristic algorithm for CAVs equipped with CACC, achieving significant reduction in vehicle delay compared to traditional intersection control schemes, such as traffic lights or stop signs. The analysis presented here considered flows of CAVs, lane sharing, and also considered superimposing the logic on the control of roundabouts.

Isolated Intersection Zone Algorithm

The Isolated Intersection Zone Algorithm (IIZA) is a heuristic distributed coordination algorithm proposed for the management of vehicles traversing an intersection. The algorithm exploits the fact that drivers approaching an uncontrolled intersection typically make rational decisions while proceeding or yielding without having complete information about all oncoming vehicles from all approaches. Considering an intersection of four approaches, each a single lane, the proposed algorithm assumes the four leading vehicles communicate with each other at each time step to schedule their entry time to the intersection. In each time step, one of the four vehicles will be responsible for updating the schedule if needed. If the scheduling agent identifies a conflict that may lead to a collision between two or more vehicles, the arrival times of some of the vehicles are altered by sending messages from the scheduler to update their trajectory to ensure they arrive at the correct time. Priority is always given to vehicles on the more congested lanes when the scheduler identifies a conflict. Other than the four leading vehicles, a vehicle communicates only with its two neighboring vehicles (the one preceding and the one following it) at each time step.

The goal of IIZA is to optimize the movement of CAVs traversing an intersection. The solution proposed here focuses on how to achieve this in a feasible manner. IIZA uses a fully-distributed approach: there is no central agent controlling the traffic approaching the intersection; instead, each vehicle in the proximity of the intersection is modeled as an agent. All agents cooperate using a heuristic distributed coordination algorithm. A distributed algorithm seems to be more reasonable in real-world applications for a number of reasons, as follows:

1. The use of a central agent to control traffic may result in congestion within the system and thus act as a bottleneck as the volume of traffic increases in the intersection vicinity. For example, an intersection in a downtown area of a big city during the peak period may have hundreds of vehicles heading to the intersection from different approaches at the same time.
2. A technique requiring installation of some device at each intersection to control the traffic is much more expensive compared to a distributed approach. Furthermore, both central and distributed approaches will require a vehicle to be equipped with almost the same communication devices whether they need to communicate with an infrastructure agent or with other vehicles in close proximity to them.
3. Another important reason to favor distributed systems is related to safety issues and how the system will respond to failures in the central agent unit. Distributing the traffic control among the vehicles themselves allows for a truly fault-tolerant system.

Modeling Agent States

Every vehicle is modeled as an agent that has a role in coordinating with other agents (vehicles) to order the passage of all vehicles without collisions and with the minimum possible delay. As summarized in Figure 17, a vehicle passes through a number of states until it successfully and safely passes the intersection.

1. A vehicle that is far from the IZ (more than 200 m away from intersection) is in state “Out.” It simply proceeds without any actions related to intersection traffic control.
2. As the vehicle passes the edge of the IZ (within 200 m from the intersection), it moves to state “Last.”
    a. As soon as it enters this state, a vehicle calculates the time it could reach the intersection if it continued to travel at its current speed if not delayed by other conflicting vehicles.
    b. It sends its properties and the time it calculated in a broadcast message to cars ahead of it in the lane.
    c. The vehicle later receives a reply from the vehicle preceding it so it knows the agent it will be following, and at each time step the vehicle is updated with any change in the properties of the preceding car so it can follow without colliding.
3. A vehicle moves from Last state to “Mid” state when it receives a message from a vehicle announcing it is the new last in the lane, it receives the properties of the new car following it, and replies with its properties so the new last can follow it. Meanwhile, the Mid agent still follows the vehicle in front of it. So, at every time step, every vehicle in a lane updates the vehicle immediately following it. Accordingly, at each time step, each vehicle needs to receive an update from the one ahead of it and check if it needs to change its properties (for example, if it needs to decelerate) and then send its potentially updated properties to the vehicle following it.
4. A vehicle becomes in “Head” state when it receives a message from the preceding vehicle that that vehicle has passed the intersection.
    a. The new Head communicates with other Head agents in other approaches.
    b. It listens to any messages from every newly arriving Last so it knows all vehicles behind it.

Every time unit, one of the Head vehicles from the different approaches of the intersection becomes the "Scheduler." The Scheduler is responsible for making sure that all vehicles in the IZ arrive and pass the intersection at different non-conflicting times. Only the Heads communicate with each Head, giving the most updated arrival times of following vehicles.

Scheduling Algorithm

The scheduling of vehicles is designed to minimize the overall average delay of vehicles in the intersection area by avoiding the formation of waiting vehicle queues. To achieve this in a distributed manner, the following algorithm is executed every time step.

1. For each approach, the Head vehicle checks, based on the current time, if it is its turn to be the Scheduler for this time step.
2. Each Head sends the partial schedule it holds for vehicles behind it in the lane. Any vehicle in a lane that alters its speed and time to reach the intersection conflict area sends a message with its new arrival time to the Head, so each Head knows the number of vehicles in its lane and holds a sorted list of times when those vehicles will reach the intersection.

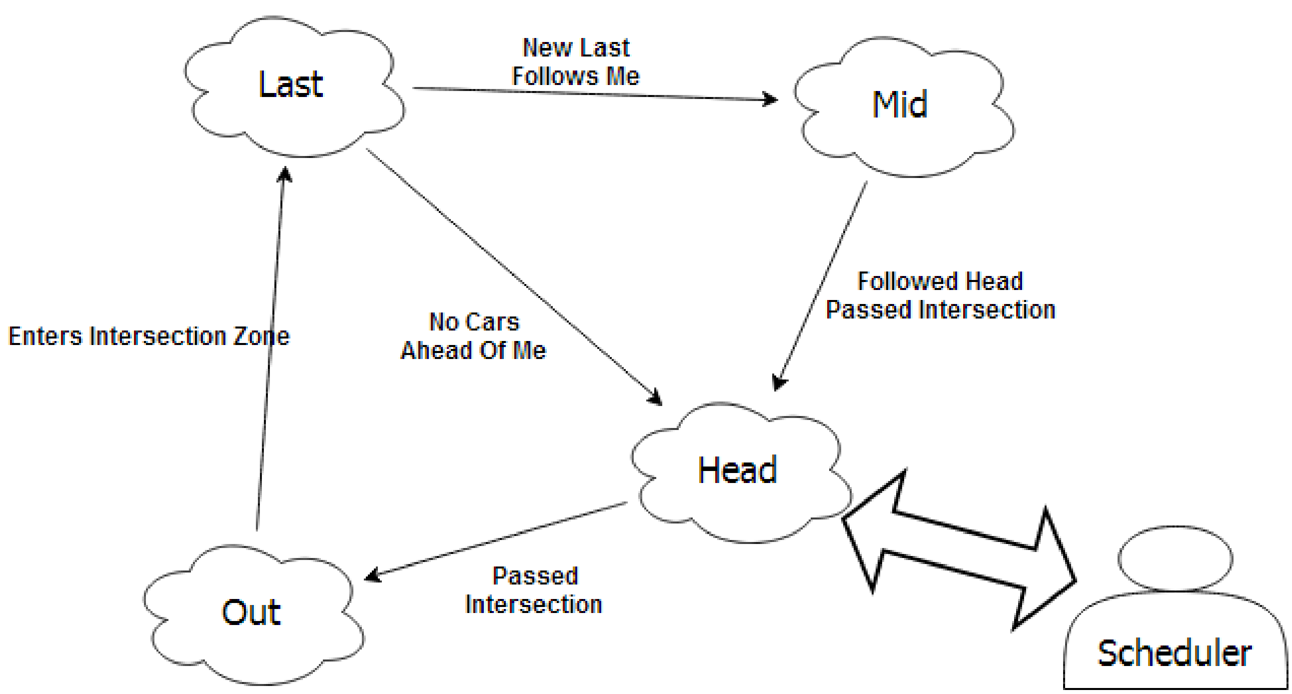


Figure 17. Agent state diagram.

3. The current scheduler receives the messages from the other Heads. These messages give a complete picture of the expected times of arrival of all vehicles from all approaches.
4. The Scheduler agent performs the following steps:
   a. Merges the sorted lists of various approaches into a global list of arrival times of all vehicles near the intersection

b. For each traffic lane, determines the number of vehicles in each approach; approaches with more vehicles are given higher priorities.
c. Sends to each Head an array with values representing how much delay is required from each vehicle in each approach.
d. Sends to each Head the partial schedule for its approach. The Head identifies whether there are any nonzero values associated with any vehicles. If such values exist, the Head forwards the delay orders from the Scheduler to the vehicles that need to delay. Each of these vehicles receives the order and decelerates to a speed that will allow it to enter the intersection at its reserved time.

At the next time step, another Head will be responsible for scheduling. The previous steps are repeated. It may take a vehicle few time steps to receive its final permitted time of entry to the intersection based on the traffic in all lanes.

Simulated Experiments and Results

The proposed algorithm IIZA was implemented in MATLAB and the following experiments were performed.

Experiment Set 1

A two-lane cross-intersection was simulated. Each approach was a single lane heading towards the intersection. For this experiment, it was assumed that all vehicles would enter the IZs with speeds varying between 30 and 40 mph (approximately 12 to 18 m/s). Intersection traffic was randomly generated, allowing for a maximum gap of 10 seconds between two consecutive vehicles in a lane. It was assumed that all lanes had similar traffic, so the number of simulated vehicles was evenly divided among the four lanes.

The experiment began by simulating four vehicles (one vehicle per lane) and running two algorithms: the distributed approach developed in this work, and the FIFO centralized approach discussed in the related work section. The average delay and the maximum delay of both approaches were obtained for the four-vehicle scenario. The experiment was repeated 10 times and the overall average delay and maximum delay for the two compared algorithms were recorded.

The number of vehicles considered in the simulation was increased in steps. Each step involved 10 runs of randomly generated traffic when the number of vehicles was increased by four (one added vehicle to each lane). The last 10 runs included 100 vehicles.

The results of this experiment are summarized in Figure 18 and Figure 19. Figure 18 shows how the average delay [seconds per vehicle [s/veh]) experienced by a vehicle decreased using the distributed prioritized scheme compared to the central FIFO approach. The reduction in the average delay increased gradually until it reached about 40% at the 100-vehicle simulations.

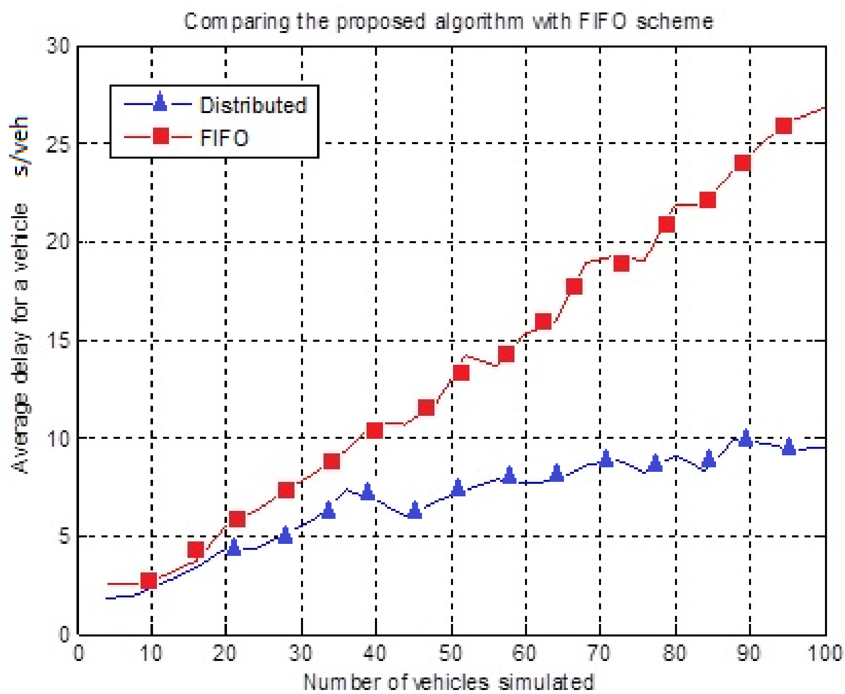


Figure 18. Average delay of IIZA algorithm compared to FIFO.

Comparing the maximum delay experienced by a vehicle, on the other hand, did not show the same significant reduction, as can be seen in Figure 19. However, simulations with a larger number of vehicles still showed that the distributed prioritized approach was better than the central FIFO approach.

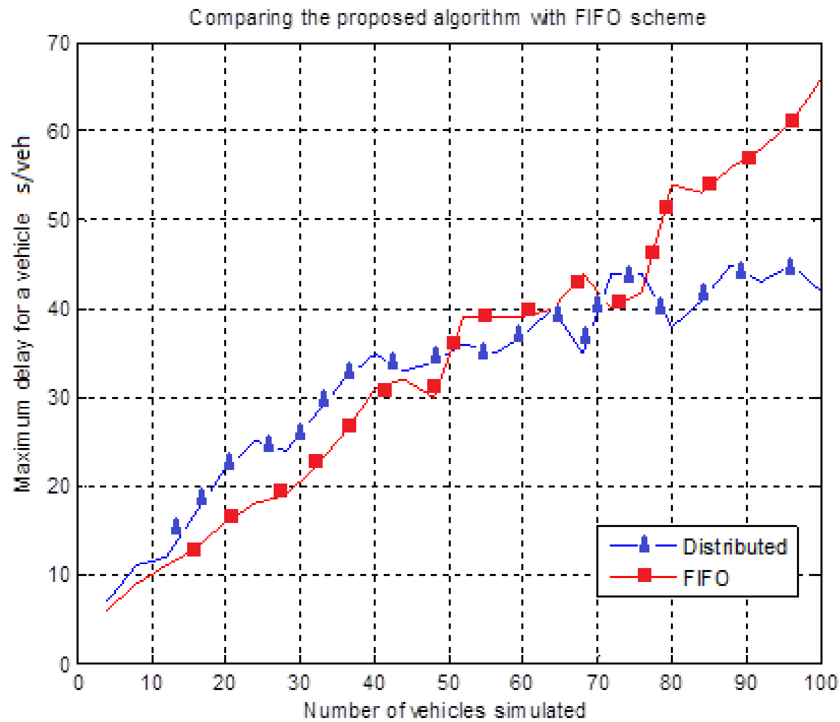


Figure 19. Maximum delay of IIZA algorithm compared to FIFO.

Experiment Set 2

In order to assess the effect of heavier traffic on both approaches, the same set of simulated experiments was repeated with heavy traffic. Instead of allowing for a 10-second gap between two consecutive cars, the maximum allowed gap was reduced to a range of 1–5 seconds. The same trend discussed above was noticed for the average delays resulting from both approaches as shown in Figure 20. The maximum delays seen in this experiment were significantly reduced for the proposed distributed approach, as can be seen in Figure 21.

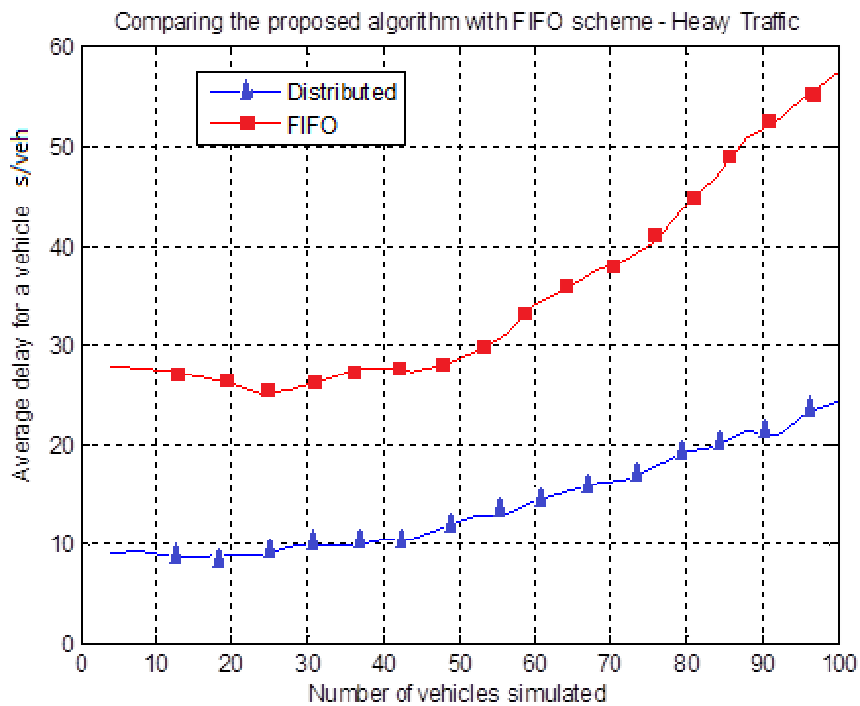


Figure 20. Comparing average delay of the two methods with heavy traffic.

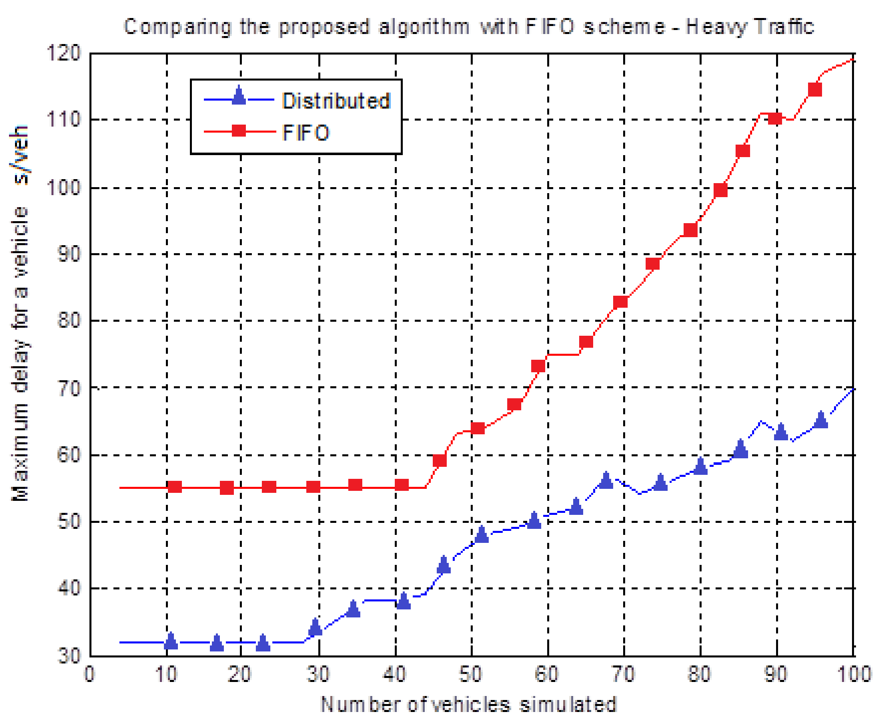


Figure 21. Comparing maximum delay of the two methods with heavy traffic.

Conclusions

The proposed IIZA algorithm was successfully implemented. Simulations were run for various numbers of vehicles in each lane. The applied rotating scheduling proved to be successful, as no collisions resulted in any of the simulation experiments. The prioritized assignment of time slots was more successful than the centralized FIFO scheme. As more vehicles were simulated, the reduction in the average delay became clearer. Also the maximum delay experienced by any vehicle was significantly reduced compared to FIFO.

One further advantage is the fact that the proposed algorithm's communication requirements are applicable and reasonable for real intersections. The cost of running IIZA is promising, as there is no need to install any infrastructure devices.

Two Algorithms for Traffic Optimization of Automated Vehicles at Multi-Intersection Networks

One important way to improve traffic at an intersection is to provide the optimizer with knowledge about traffic at close-by intersections. This way, the optimizer can prioritize conflicting requests in a way that better avoids delaying vehicles in approaches that might be congested. The hypothesis investigated in this section of the report is that augmenting an algorithm for an isolated intersection with information about its directly neighboring intersections can significantly reduce average delays experienced by vehicles proceeding through the network of intersections.

Building on the distributed algorithm for isolated intersections proposed by the authors in [23], two novel multi-intersection algorithms are proposed here. Simulation results show that both algorithms achieve significant reduction in both average delay and maximum delay experienced by simulated traffic.

Related Work

There are several research efforts in the literature that address traffic management of CAVs at isolated uncontrolled intersections. As discussed in a previous section of this report, Dresner and Stone proposed a simple centralized intersection control protocol for CAVs based on FIFO priorities [16]. AIM is a multi-agent time reservation system consisting of an intersection manager (controller) and vehicle agents. When a vehicle approaches the intersection, it requests a time-space slot to cross the intersection. Upon receiving the driver agent request, the controller simulates the vehicle crossing the intersection and, based on the output trajectories, the controller makes decisions that avoid conflicts. Zhu et al. [18] proposed a central algorithm where the controller evaluates the total delay if a request is allocated and if it is postponed and makes the decision that results in a smaller delay. Zohdy and Rakha proposed a centralized algorithm [21] where the controller uses a custom simulator to continuously adjust vehicle trajectories to minimize occupancy time in an intersection conflict zone. They also proposed a centralized algorithm using game theory framework [22] to be used with vehicles equipped with CACC.

Some researchers proposed distributed algorithms for traffic management at uncontrolled intersections. One interesting scheme is proposed by Khoury [24], where CAVs at an intersection make localized access decisions based purely on sensing information rather than requiring V2V or V2I communication. The scheme averts collision, but is less optimal than other available algorithms. Guangquan et al. [25] proposed another distributed algorithm where passing vehicles exchange information and follow a predefined set of rules to resolve conflicts at the intersection. Other examples of proposed distributed methods are [26] and [27]. The drawback of these algorithms is the requirement that each vehicle communicates with all other vehicles at each time step.

Wuthishuwong and Traechtler [28] proposed a multi-intersection algorithm where traffic information is exchanged using infrastructure-to-infrastructure communication (I2I). Their algorithm is based on the concept of the green wave, which attempts to maintain a continuous stream of vehicles passing through the intersections. Fei et al. [28] proposed a genetic algorithm approach designed to find an optimal or near-optimal vehicle passing sequence at each intersection in a multi-intersection network.

Proposed Algorithms

The two algorithms proposed in this paper extend IIZA, the focus of this report's previous section, such that at each intersection, the four directly neighboring intersections (west, east, north, and south) are considered while scheduling the passage of vehicles through the intersection. The first proposed algorithm is NIZA, which is briefly discussed in the introduction to this report. This algorithm still depends on V2V communication and cooperation of vehicles with no dependence on any infrastructure agents. The second algorithm is DLA, also briefly discussed in this report's introduction, which defines two layers of traffic control; the lower layer applies IIZA at each IZ, while the higher layer defines a new distributed multi-agent system where each intersection in the network is modeled as an agent that communicates with the four directly neighboring intersections (west, east, north, and south) to exchange traffic states of the four approaches in the IZ. This neighboring intersection information is then broadcast to the vehicles in its zone so that they can make use of it to schedule their movements through the intersection. Accordingly, DLA requires V2V, V2I, and I2I communication to optimize traffic in a network of intersections. The following subsections discuss each of these algorithms—IIZA, NIZA, and DLA—in more detail.

Isolated Intersection Zone Algorithm (IIZA)

As established earlier, IIZA is a fully-distributed algorithm that assumes traffic consisting of CAVs. It allows vehicles to successfully pass the intersection without collision and aims at optimizing the traffic in the intersection by minimizing the delay experienced by vehicles. In order to achieve this, IIZA gives priority to vehicles in approaches with heavier traffic to try to avoid the formation of long queues of vehicles waiting in the IZ. It does not require the installation of any central infrastructure agent in the intersection to manage traffic. Rather, vehicles in the intersection are intelligent agents that cooperate to schedule their passage through the conflict zone using a designed communication protocol.

IIZA for isolated intersections has two advantages:

1. It is fully distributed, depending only on passing vehicles to optimize traffic at an intersection with no need of infrastructure agents, which can make it feasible to implement with reasonable cost.
2. It tries to minimize V2V communication required to achieve successful traffic control and optimization. It also uses a heuristic algorithm for scheduling vehicles that is not computationally demanding.

One major disadvantage of IIZA is that it only considers the traffic around the intersection within a radius of 200 m. This limitation is due to restraints imposed by current wireless technology (i.e. DSRC) used in vehicular networks. Since IIZA uses incomplete information for optimization of the traffic at the intersection, it doesn't maximize optimization and delay reduction as it could if more information were fed to the vehicles while they optimize their movement through the intersection. The following subsections discuss two ways to overcome this disadvantage by incorporating information from neighboring intersections.

Networked Intersection Zones Algorithm (NIZA)

NIZA extends IIZA to allow vehicles at an intersection to use historical information from neighboring IZs to estimate the traffic state beyond the 200 m limit. The main objective of NIZA is to achieve this goal without losing the two aforementioned advantages of IIZA. NIZA extends IIZA with no increase in communication requirements, and continues to depend solely on the vehicles to manage their movements without any need for any infrastructure agents installed at the intersections.

For the purpose of this study, the research group designed a 4x4 grid network of intersections. Figure 22 shows the network of intersections, where four horizontal major roads intersect with four vertical minor roads. The network was composed of 16 intersections, labeled 1–16 in Figure 23.

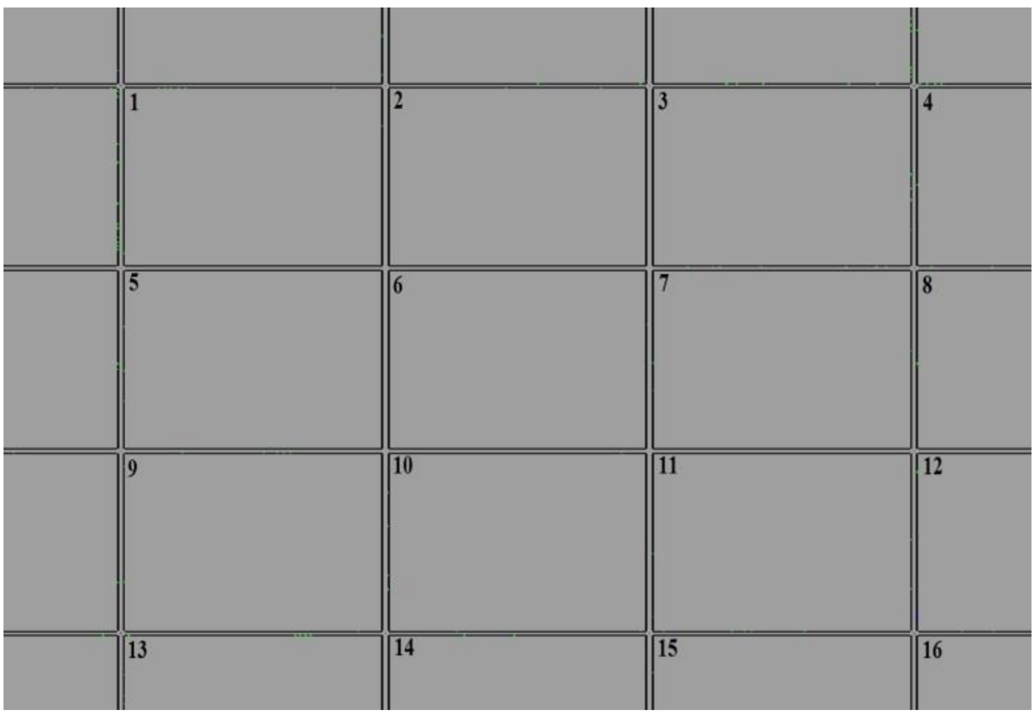


Figure 22. A 4x4 grid network of intersections.

Following is a description of how NIZA extends IIZA. When a Head vehicle of an approach passes an intersection conflict area, it stores the number of vehicles behind it in the same approach for later use. When the vehicle enters the next IZ in its route through the network, it will be in state Last, and will provide the Head vehicle in that approach to the IZ with the history value stored for number of vehicles in the previous intersection when it left that intersection. This value is used by NIZA as an estimate of the traffic in an extra 200 m behind the Last vehicle in the approach. The goal here is to double the radius of the zone considered for traffic optimization at an intersection. Information about traffic within 200 m from the center of intersection is now augmented with an estimate of the traffic level in the following 200 m.

The difference between IIZA and NIZA can be understood by thinking of IIZA as an algorithm that can only see the traffic in a narrow 200 m slice of the road (the IZ). NIZA can see an additional 200 m slice of traffic, so its estimation in more congested approaches should be more accurate than IIZA. Note, however, that NIZA still uses incomplete information; even if the estimates for 400 m are accurate, there is still unseen traffic between intersections that is not captured by the values transferred between intersections. Yet, NIZA is still advantageous in that it works without requiring any central infrastructure agents to be installed at the intersections. The processing is still fully distributed, and NIZA computational and communication requirements are the same as those for IIZA. This means that any improvement in delay reduction realized by NIZA will be achieved for free.

Dual-Layered Algorithm DLA

Instead of considering only two 200 m slices of the road as NIZA does, DLA is a multi-intersection algorithm that uses historical traffic information at an intersection at carefully chosen times to estimate current traffic on whole road sections between two intersections.

For example, in Figure 23, the road section between two intersections is shown as five 200-m slices, and assumes the distance between intersections 1 and 2 is 1 km.

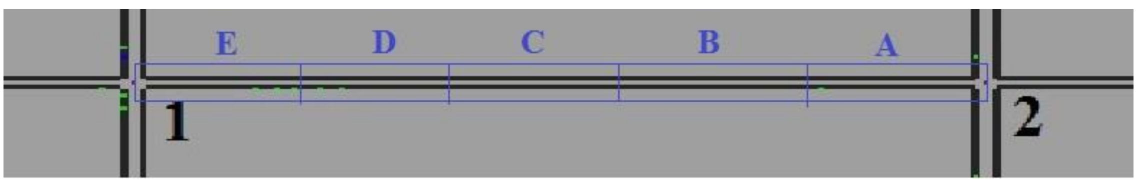


Figure 23. Road slices between two intersections.

Considering the through traffic from intersection 1 towards intersection 2, vehicles around intersection 2 know the traffic state only in slice A out of the five slices. Using IIZA, only this limited knowledge is employed while optimizing the traffic. Using NIZA, vehicles at intersection 2 add an estimate of traffic in slice B to what they know about traffic in slice A. Using DLA, the vehicles at intersection 2 will be supplied with more estimates of traffic in the remaining slices C, D, and E. Estimated traffic at road slices far from intersection 2 can be made by using the history of through traffic in the same direction at the IZ of intersection 1.

Assuming vehicles proceed between intersections 1 and 2 with an average speed s_{av}, the number of vehicles in the IZ of intersection 1 heading to slice E at time t can be used to estimate the number of vehicles in slice E at time $t + 200/ s_{av}$. This number can also be used to estimate the number of vehicles in slice D at time $2(t + 200/s_{av})$ and so on.

Vehicles at intersection 2 need the values of traffic from the neighboring intersection 1 at these times in the past to estimate current traffic in each of the slices between the two intersections.

DLA assumes there are two layers of multi-agent systems working together. The lower layer is composed of the vehicles in an IZ applying IIZA. This lower layer is responsible for managing traffic locally at an intersection. The upper layer is a multi-agent system of intersection agents. For example, for the network in Figure 22, there will be 16 agents. DLA requires each intersection agent to do the following every time step:

1. Store the traffic volume in each direction within its IZ for later use by adjacent intersections. This can easily be done by simply listening to the exchanged messages between the Head vehicles using a modified version of IIZA.
2. Exchange traffic information in its zone with the four directly neighboring intersection agents.
3. Broadcast historic values of neighboring intersections' traffic that represent current estimates of traffic beyond the IZ. Vehicle agents of lower level can use these broadcasted estimates to optimize the traffic through the intersection.

Simulated Experiments and Results

The proposed algorithms, NIZA and DLA, were implemented using MATLAB. A 4x4 grid network of intersections similar to the one in Figure 22 was used. Simulations were run to compare the algorithms and compute the delays in the network. The distance between any two adjacent intersections was 1 km. The horizontal roads represented major roads with heavier traffic while the vertical roads were minor roads. Vehicles were allowed on the major roads at double the rate (veh/h) of arrival of vehicles on minor roads. Origin-Destination demands for an hour of traffic (5,040 vehicles) were submitted to the INTEGRATION simulation program. The vehicle initial conditions (initial speed, time, and coordinates when entering the network) and vehicle routes generated by INTEGRATION were used as inputs to the MATLAB simulator built to test the algorithms proposed in this study.

Figure 24, Figure 25, and Figure 26 show the resulting delays for each vehicle in the network during the simulated one-hour of traffic using IIZA, NIZA, and DLA. The delay of a vehicle in an IZ was the difference between the time it actually spent in the IZ and the time it needed to pass the IZ if it was the only car present. The delay of a vehicle shown in the figures represents the sum of its delay times in all network intersections in the vehicle's route.

Figure 24 illustrates the improvement NIZA achieved compared to IIZA.

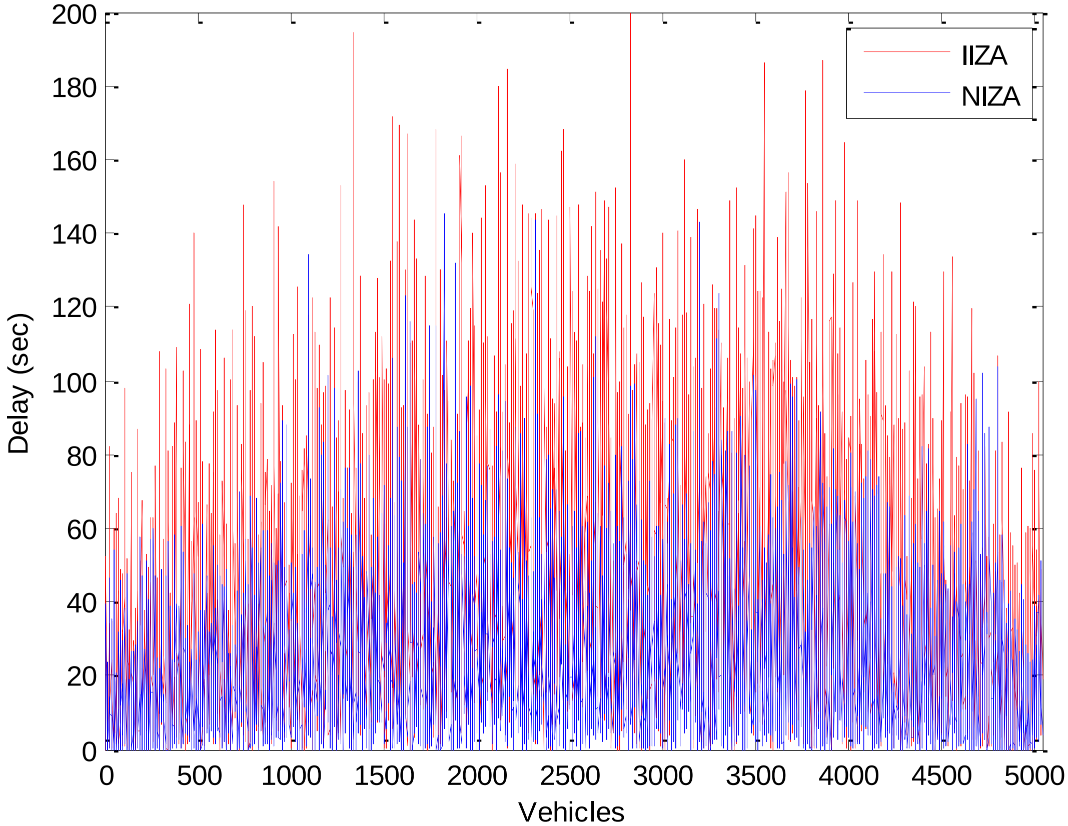


Figure 24. NIZA delay compared to IIZA delay.

Figure 25 illustrates the clear reduction in delay when using DLA compared to IIZA.

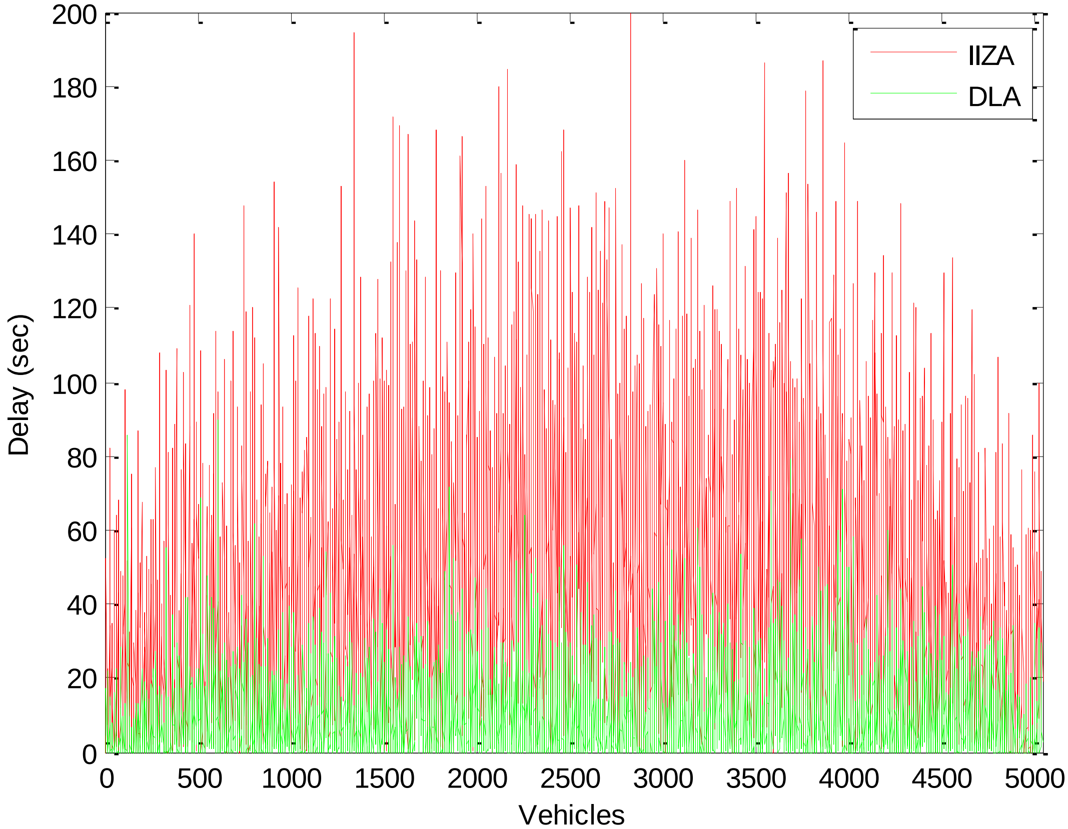


Figure 25. DLA delay compared to IIZA delay.

Figure 26 puts the three algorithms in one figure to make it clear how DLA is, as expected, more optimized than NIZA. Note that despite the increased optimization, it is important to keep in mind that it might also be costly to implement this algorithm.

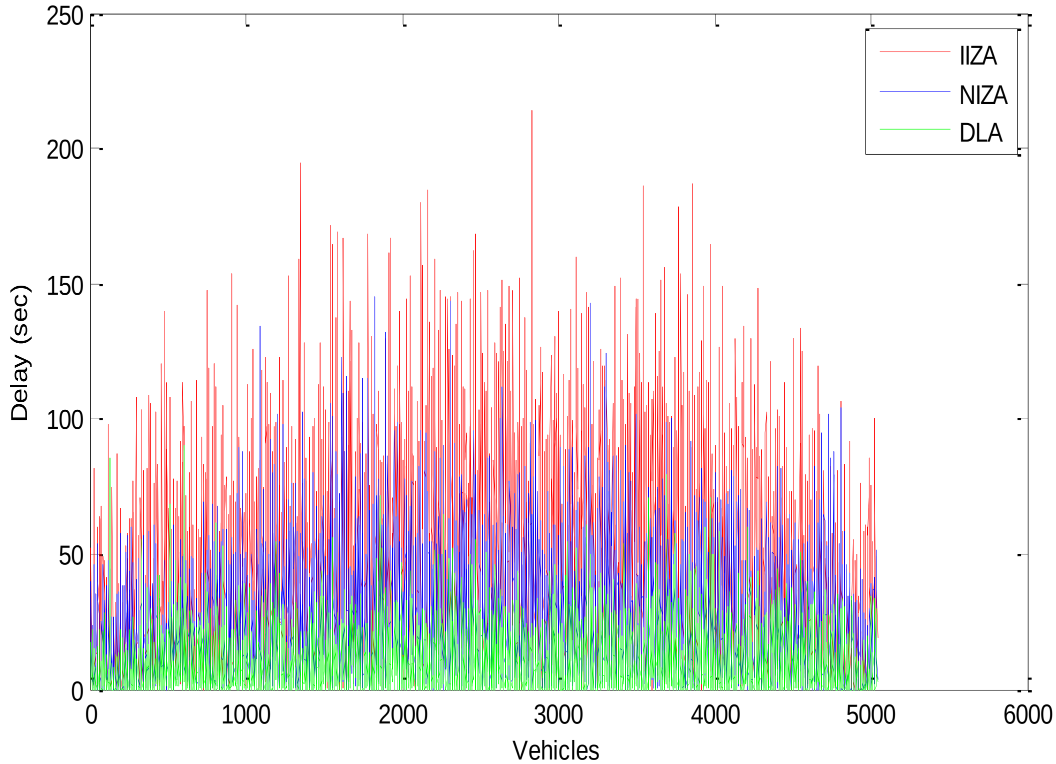


Figure 26. DLA delay compared to delay for both NIZA and IIZA.

Figure 27 shows the average and maximum delays found for simulated vehicles when using each of the three tested algorithms. NIZA achieved 46% reduction in average delay of vehicles compared to IIZA. DLA achieved 79% reduction in average delay compared to IIZA. The maximum delay experienced by vehicles was reduced by 32% when using NIZA and by 58% when using DLA.

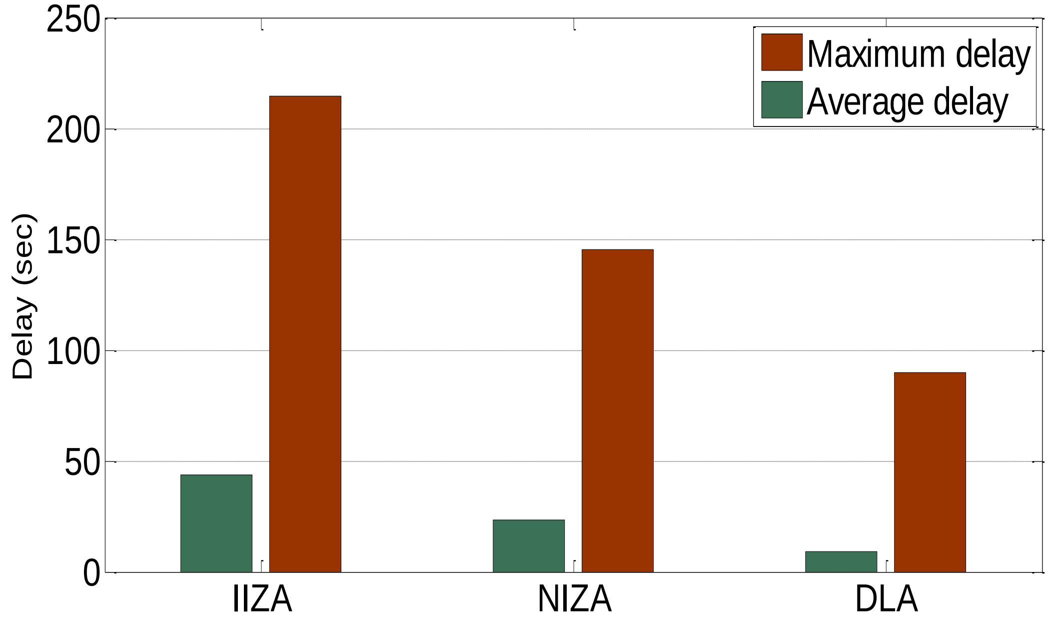


Figure 27. Average and maximum delays of IIZA, NIZA, and DLA.

Conclusions and Future Work

Two novel algorithms for traffic control of CAVs at interconnected intersections were proposed. Even a small extension of an algorithm for isolated intersections reduced the delay at intersections significantly. The NIZA algorithm was less optimal than DLA algorithm. However, it still allowed indirect communication between neighboring intersections by letting a vehicle store traffic information when it was at the first intersection for later use when it entered the next IZ. NIZA was easy to implement and its computational and communication requirements were reasonable. Installing infrastructure intersection agents to exchange I2I traffic information proved to be efficient and produced the least delay. The DLA algorithm showed how IZ traffic could be used to estimate traffic in other road segments away from the intersection. The presence of infrastructure agents could enhance other transportation functions such as vehicle routing to avoid congested intersections, etc.

Future extensions to the proposed work include further testing of the multi-intersection algorithms during various scenarios, testing at different intersection network sizes and topologies, and tuning the algorithms accordingly. Using the framework of DLA for re-routing the vehicles in the network for enhancement of network mobility is another objective.

Conclusions

This report investigates different technologies to be implemented in CAVs. These technologies focus primarily on roadway intersection management using V2V and V2I communication. A comprehensive vehicle optimization and modeling framework, including complex equations of motion and nonlinear dynamic and kinematic constraints, was implemented. The resulting system uses different approaches to solve a complex optimization problem. The four sections of this report provide different optimization algorithms with different fidelity levels.

The results discussed herein demonstrate a general improvement in vehicle delay, fuel consumption, and vehicle emissions. The results in the first section show that the approach used produces a significant delay reduction of up to 90% and up to 45% savings in fuel, which implicitly reduces emissions. The results of the second section, the high fidelity modeling approach, indicate that this approach produces a delay reduction of 80% when compared to the best of the other intersection controllers (the roundabout) and a reduction in emissions of up to 60% in comparison to the roundabout. The results in the third section of the report demonstrate that the proposed algorithms achieve a reduction in delay compared to signalized intersections while allowing the system to be run in real-time. The results presented in the final section demonstrate the benefits of considering multiple intersections in the optimization process.

Study Conclusions

In this report, a number of algorithms are proposed that address specific concerns and/or operation regimes CAVs at roadway intersections.

In the first section of this report, the iCACC system, a method optimizing the movement of vehicles crossing an intersection while avoiding collisions, was proposed. The iCACC system is a comprehensive car model that includes kinematic and dynamic constraints. This mathematical model was linearized, and the car-following and collision avoidance model were also included. The velocity of each vehicle entering the intersection was adjusted to ensure that the vehicle reached the intersection while conflict zones were empty to provide a safe crossing. To achieve this aim, V2V and V2I technologies were required. Vehicle delay, fuel consumption, emissions, and stops were computed in the simulation.

In the second section of the report, a comprehensive and extended car model was proposed to provide a solution as to how CAVs should cross an intersection using some type of reservation scheme. For this solution, a vehicle's behavior was modeled using nonlinear equations of motion, including, for example, bounds on vehicle velocity and accelerations. The conditions of the roadway surface and vehicle tire conditions were also accounted for, and the fuel consumption and CO_2 emissions were computed as part of the results. Simulations were performed for an intersection with one major and one minor street. The traffic inflows ranged from 500 veh/h to a maximum of 1,200 veh/h. The traffic inflows for the minor street ranged from 250 veh/h to 600 veh/h. This model provides a more complex and complete model when compared to the iCACC system described in the previous section.

In the third section of this report, the movement of CAVs traversing an intersection were optimized using a heuristic approach called IIZA, which is not as accurate as the model described in Section 2, but has the advantage that it can be implemented in real-time. Specifically, a heuristic distributed algorithm was developed that can be applied in real-time, and which does not require expensive infrastructure investments.

The final section of the report extended the heuristic algorithm to optimize the movement of vehicles traveling through multiple intersections. Two algorithms were developed and compared to extended IIZA such that at each intersection, the four directly neighboring intersections (west, east, north, and south) were considered while scheduling the passage of vehicles through the intersection. The first proposed algorithm, NIZA, relies on V2V communication and cooperation of vehicles with no dependence on any infrastructure agents. The second algorithm, DLA, defined two layers of traffic control—the lower layer applied IIZA at each intersection, while the higher layer defined a new distributed multi-agent system where each intersection in the network served as an agent. Each intersection was modeled as an agent that communicated with the four direct neighboring intersections (west, east, north, and south) to exchange the traffic states of the four approaches. Each agent then broadcast what it knew about its neighbors to the vehicles in its zone; they could then make use of this state information to assist in scheduling their movements through the intersection.

References

1. Smith, Egan. Connected Automated Vehicles and Intelligent Transportation Systems, in Proceedings of the American Association of State Highway and Transportation Officials (AASHTO) Conference on 21st Century Mobility for Freight and Passenger Transportation, 2015. Retrieved from http://scoe.transportation.org/Documents/AASHTO%20Conference%20on%2021st%20Century%20Mobility%202015/Egan_Salt%20Lake%20presentation.pdf.

2. Rakha, H., P. Pasumarthy, and S. Adjerid, A simplified behavioral vehicle longitudinal motion model. *Transportation Letters: The International Journal of Transportation Research,* Vol. 1, 2009, pp. 95-110.

3. Rakha, H. and B. Crowther, Comparison of Greenshields, Pipes, and Van Aerde Car-Following and Traffic Stream Models. In *Transportation Research Record: Transportation Research Board, No. 1802,* TRB, National Research Council, Washington, D.C., 2002, pp. 248-262.

4. Zohdy, I., S. Sadek, and H. Rakha. Empirical Analysis of Wait time and Rain Intensity Effects on Driver Left-Turn Gap Acceptance Behavior. In *Transportation Research Record: Journal of the Transportation Research Board*, *No. 2173*, TRB, National Research Council, Washington, D.C., 2010, pp. 1-10.

5. Rakha, H. and R. Kamalanathsharma. Eco-driving at Signalized Intersections using V2I Communication. In *14th International IEEE Annual Conference on Intelligent Transportation Systems,* 2011, pp. 341-346.

6. Rakha, H., K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck. Virginia Tech Comprehensive Power-Based Fuel Consumption Model: Model development and testing. *Transportation Research Part D-Transport and Environment,* Vol. 16, No. 7, 2011, pp. 492-503.

7. Cools, M., E. Moons, and G. Wets. Assessing the impact of weather on traffic intensity. *Weather, Climate, and Society*, Vol. 2, No. 1, 2010, pp.60-68.

8. Datla, S.K. and S. Sharma. Association of Highway Traffic Volumes with Cold and Snow and Their Interactions. In *Transportation Research Board 87th Annual Meeting* (No. 08-0843), 2008.

9. Brilon, W. and M. Ponzlet. Variability of Speed-Flow Relationships on German Autobahns. In *Transportation Research Record: Journal of the Transportation Research Board, No. 1555,* TRB, National Research Council, Washington, D.C., 1996, pp. 91-98.

10. Rakha, H., M. Farzaneh, M. Arafah, and E. Sterzin. Inclement Weather Impacts on Freeway Traffic Stream Behavior. In *Transportation Research Record: Journal of the Transportation Research Board, No. 2071*, TRB, National Research Council, Washington, D.C., 2008, pp.8-18.

11. Rakha, H., I. Zohdy, S. Park, and D. Krechmer, Microscopic Analysis of Traffic Flow in Inclement Weather, Part 2 (Report No. FHWA-JPO-11-020). Federal Highway Administration, U.S. Department of Transportation, 2009.

12. Zohdy, I. H. and H. Rakha. Intersection management via vehicle connectivity: The intersection cooperative adaptive cruise control system concept. *Journal of Intelligent Transportation Systems*, 2014, pp.1-16.

13. Stengel, R. F. *Optimal Control and Estimation*. Dover Publications, New York, 1994.

14. Kirk, D. E. *Optimal Control Theory: An Introduction*. Dover Publications, New York, 2004.

15. Van Wyk, E. J., P. Falugi, and E. C. Kerrigan. Imperial College London Optimal Control Software (ICLOCS) (Solves nonlinear optimal control problems with constraints.), http://www.ee.ic.ac.uk/ICLOCS/, 2010.

16. Dresner, K. and P. Stone. A multiagent approach to autonomous intersection management. *Journal of artificial intelligence research,* Vol. 31, 2008, pp. 591-656.

17. Dresner, K. and P. Stone. Traffic intersections of the future. In *Proceedings of the National Conference on Artificial Intelligence* (Vol. 21, No. 2, pp. 1593). Menlo Park, CA; Cambridge, MA; London: AAAI Press; MIT Press, 1999.

18. Zhu, M., Li, X., Huang, H., Kong, L., Li, M. and Wu, M.Y. LICP: A look-ahead intersection control policy with intelligent vehicles. In *2009 IEEE 6th International Conference on Mobile Adhoc and Sensor Systems*, pp. 633-638, 2009.

19. Au, T-C. S. Zhang, and P. Stone. Semi-autonomous intersection management. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2014, pp. 1451-1452.

20. Zohdy, I., and H. Rakha. Optimizing Driverless Vehicles At Intersections. In *19th ITS World Congress,* Vienna, Austria, 2012.

21. Zohdy, I. H., R. K. Kamalanathsharma, and H. Rakha. Intersection management for autonomous vehicles using iCACC. In *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, 2012, pp. 1109-1114.

22. Zohdy, I. H., and H. Rakha. Game theory algorithm for intersection-based cooperative adaptive cruise control (CACC) systems. In *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*, 2012, pp. 1097-1102.

23. Hassan, A. A. and H. A. Rakha. A Fully-Distributed Heuristic Algorithm for Control of Autonomous Vehicle Movements at Isolated Intersections. *International Journal of Transportation Science and Technology*, Vol. 3, No. 4, 2014, pp. 297-310.

24. Khoury, J. Passive, decentralized, and fully autonomous intersection access control. In *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, 2014, pp. 3028-3033.

25. Guangquan, L., L. Lumiao, W. Yunpeng, Z. Ran, B. Zewen, and C. Haichong. A rule based control algorithm of connected vehicles in uncontrolled intersection. In *Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on*, 2014, pp. 115-120.

26. Makarem, L. and D. Gillet. Fluent coordination of autonomous vehicles at intersections. In *Systems, Man, and Cybernetics (SMC), 2012 IEEE International Conference on*, 2012, pp. 2557-2562.

27. VanMiddlesworth, M., K. Dresner, and P. Stone. Replacing the stop sign: Unmanaged intersection control for autonomous vehicles. In *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems-Volume 3*, International Foundation for Autonomous Agents and Multiagent Systems, 2008, pp. 1413-1416.

28. Wuthishuwong, C. and A. Traechtler. Coordination of multiple autonomous intersections by using local neighborhood information. In *Connected Vehicles and Expo (ICCVE), 2013 International Conference on*, 2013, pp. 48-53.

29. Fei, Y., M. Dridi, and A. El Moudni. Autonomous vehicle sequencing problem for a multi-intersection network: A genetic algorithm approach. In *Advanced Logistics and Transport (ICALT), 2013 International Conference on*, 2013, pp. 215-220.