Development and Evaluation of a Cooperative Vehicle Intersection Control Algorithm Under the Connected Vehicles Environment

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***Abstract*—Under the Connected Vehicles (CV) environment, it is possible to create a Cooperative Vehicle Intersection Control (CVIC) system that enables cooperation between vehicles and infrastructure for effective intersection operations and management when all vehicles are fully automated. Assuming such a CVIC environment, this paper proposed a CVIC algorithm that does not require a traffic signal. The CVIC algorithm was designed to manipulate individual vehicles' maneuvers so that vehicles can safely cross the intersection without colliding with other vehicles. By eliminating the potential overlaps of vehicular trajectories coming from all conflicting approaches at the intersection, the CVIC algorithm seeks a safe maneuver for every vehicle approaching the intersection and manipulates each of them. An additional algorithm was designed to deal with the system failure cases resulting from inevitable trajectory overlaps at the intersection and infeasible solutions. A simulation-based case study implemented on a hypothetical four-way single-lane approach intersection under varying congestion conditions showed that the CVIC algorithm significantly improved intersection performance compared with conventional actuated intersection control: 99% and 33% of stop delay and total travel time reductions, respectively, were achieved. In addition, the CVIC algorithm significantly improved air quality and energy savings: 44% reductions of CO_2 and 44% savings of fuel consumption.**

***Index Terms*—Connected Vehicles (CV), cooperative vehicle intersection control (CVIC) system, intelligent transportation system (ITS), traffic control, traffic simulation.**

I. Introduction

MOBILITY, sustainability, and safety of transportation systems are all critical topics of interest in the field of transportation. They all significantly affect the economic growth and quality of civilian life. For example, Americans spent 4.8 billion hours of extra time and 3.9 billion gallons of extra gas due to congestion in 2009–an increase of 26%–30% compared with the previous decade [1]. Nationwide, the United States wasted about $115 billion due to congestion, which is a 35% increase from the previous decade [1]. For the same period, while the amount of carbon dioxide (CO_2) emissions produced in the United States slightly decreased by 2% from 5665 Teragrams (Tg) in 1999 [2] to 5508 (Tg) in 2009 [3], the ratios of total CO_2 emission attributable to transportation increased by 1% [3]. On the other hand, the total number of crashes reported in 2009 was 14% lower than that in 1999 [4]. Still, 33 808 people died, and about 2.2 million people were injured in crashes in 2009 [4], which is a traffic safety statistics that remains unsatisfactory.

Connected Vehicles (CV) [5], which was previously called IntelliDrive, provides a two-way wireless communication environment enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. Thus, vehicles equipped with communication devices and infrastructure within the CV environment could not only collect previously unobtainable and high-fidelity traffic data such as individual vehicles' maneuvers, origins/destinations, and trajectories but share such collected traffic information with both other equipped vehicles and infrastructure managers as well. As such, the CV environment would allow urban intersections to be controlled cooperatively with other vehicles and infrastructure.

In fact, cooperation between vehicles and/or between vehicles and infrastructure, based on the CV environment, has received a great deal of attention for its potential benefits. A notable product of cooperation among vehicles is a Cooperative Adaptive Cruise Control [6], [7] system, which is designed to optimally manipulate vehicles' maneuvers based on nearby-vehicles' conditions. Moreover, a Cooperative Vehicle Intersection Control (CVIC) system envisions that vehicles and an intersection controller could cooperatively work together to improve traffic operations at an intersection when all vehicles are fully automated.

It is noted that stop-and-go control at an intersection has been a dominant paradigm. At traffic-light-controlled intersections, vehicles on each approach receiving green signals are ensured safe crossing of the intersection but with the added inconveniences of frequent stops and idling until the right-of-way is obtained. With a CVIC environment, however, an intersection controller would provide each individual vehicle with an adequate maneuver to let it safely pass through an intersection, and thus, traffic operations at intersections could be controlled without stop-and-go-style traffic lights.

This paper presents the development and evaluation of an algorithm for CVIC. The main purpose of this paper is to

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quantify potential upper ceiling benefits of the CVIC algorithm such that a proper decision on infrastructure investments can be made. Assuming a CV environment that enables two-way communications between vehicles and a controller (i.e., infrastructure), individual-vehicles' driving maneuvers are to be manipulated by the controller to safely and quickly cross the intersection. It is noted that this paper differs from previous research such as a Dresner and Stone [8], which proposed a cooperative intersection management system for autonomous vehicles (AVs). The most notable differences are given as follows: 1) the best driving maneuver ensuring the mobility and the safety of each vehicle being determined by globally adjusting the trajectory of the individual vehicle; 2) enhanced treatments handling exceptional cases such as solution failures; and 3) simulation experiments evaluating the performance of the proposed algorithm under varying traffic conditions.

The remainder of this paper is organized into four sections. The literature review section addresses relevant research effort on state-of-the-art CVICs. The methodology section describes how the optimal gap searching logic of the CVIC algorithm is converted to a nonlinear constrained optimization problem and presents the proposed intersection control logic for a CVIC algorithm. The evaluation section presents the designs of simulation experiments and the results of the mobility and sustainability impacts of the proposed algorithm under varying traffic volume conditions. Finally, conclusions and recommendations regarding the issues found in this paper are provided.

II. Literature Review

There have been a few cooperative intersection-control-related studies. This section presents a summary of such research effort.

Initial effort emphasizing the cooperation between vehicles and an infrastructure can be found in intersection control for a personal rapid transit system [9], [10]. The optimal vehicular maneuvers for safe crossing were determined by the selections of proper maneuver combinations, i.e., either accelerating or decelerating a vehicle while maintaining another vehicle's driving maneuver for two vehicles attempting to cross an intersection [10].

Raravi *et al.* [11] proposed a merging algorithm for intelligent vehicles under a cooperative vehicle infrastructure environment. The optimal maneuvers for merging vehicles were obtained by solving an optimization problem, which was formulated based on vehicle kinematics to minimize the maximum of driving time to intersection for every vehicle coming from two conflicting approaches.

Dresner and Stone [8] developed an intersection management algorithm for AVs by utilizing a cell-based intersection reservation system that they proposed. In [9], by allowing an intersection manager program to coordinate the reservation requests of temporal/spatial cell occupancies from every AV, the right-of-way ensuring safe crossing for each AV is granted. A simple system recovery algorithm was also proposed to manage unexpected dangerous events such as vehicle malfunctions and crashes.

Milanés *et al.* [12] proposed a fuzzy-based intersection control logic for such AVs and successfully demonstrated its performance with an autonomous car and a manual driven car on an actual secured test bed in Spain. While the manual driven car showed the significant fluctuations of the speed when crossing the intersection, the autonomous car maintained its speed resulting in no stops at the intersection.

Glaser *et al.* [13] presented a scenario-driven trajectory adjustment algorithm for AVs' adaptive cruise control system. The proposed algorithm estimates the crash possibilities of a total of nine trajectory adjustment scenarios, i.e., including lane changing and speed adjustments for lateral and longitudinal movements, respectively, by using safety surrogate measures such as a time to collision and a post-encroachment time measured in real time.

Milanés *et al.* [14] demonstrated the intersection crossing of three actual AVs developed by Spain, France, and The Netherlands, respectively, on a test site facilitating a vehicular wireless communications network in France. With a two-way single-lane approach, a cooperative control logic designed to manipulate the maneuvers of the AVs significantly improved the speeds of all the autonomous cars, compared with two-way stop sign operation.

Recently, air traffic management system has utilized the cooperative trajectory adjustment technique. Alonso-Ayuso *et al.* [15] proposed a cooperative collision avoidance system for airplanes. To this end, the authors presented a mixed-integer linear optimization approach to find the best flying trajectory such that each airplane can prevent any potential collisions and minimize their flying distance.

The cooperation between vehicles and an intersection has been emphasized since the 1960s as it presents promising benefits expected from safety and mobility improvements at the intersection. Despite such promising benefits addressed by relevant studies reviewed in this section, treatments for exceptional cases occurring from system malfunctions, communications drops, or incidents were not clearly presented in those studies. In addition, most of those studies, except for [8], were performed with only a few test vehicles, which are insufficient to cover varying traffic congestion cases. In the next section, it is presented how the CVIC algorithm handles such challenges that have appeared in previous research.

III. Methodology

A. Predictive Trajectory-Based Optimal Safe Gap Adjustment Logic

At a yield-sign-controlled intersection, drivers may go through the intersection without stopping, particularly when traffic volume is very light. This is because a driver would be able to recognize sufficient gap to safely cross the intersection based on his/her visual observation, assuming adequate sight distance is provided. However, such human observations would not be adequate to determine the safety gap, particularly for congested traffic conditions.

Fig. 1 shows time-space diagrams describing the projected trajectories of two vehicles, which are denoted by A and B,

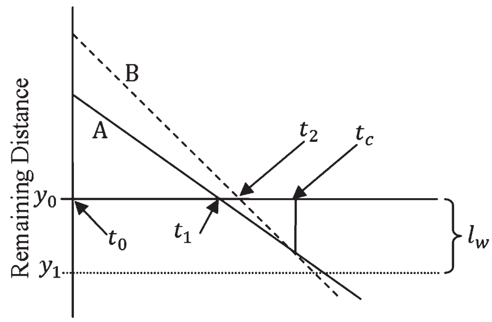

Fig. 1. Insufficient gap case by vehicle trajectories.

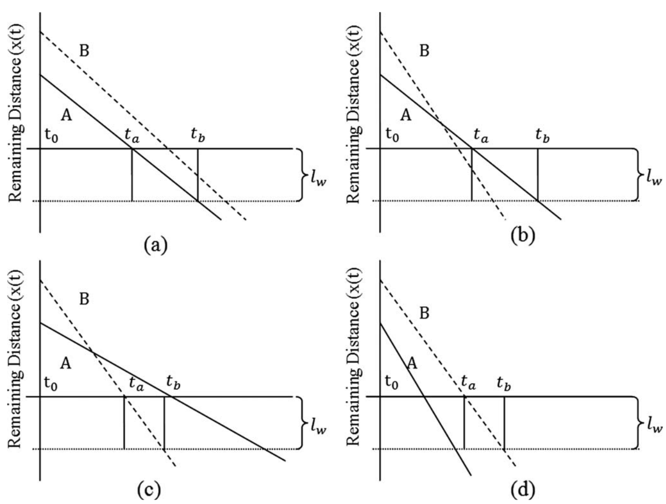

Fig. 2. Possible sufficient gap combinations.

approaching from two conflicting movements at time $t = t_0$. The y-axis indicates the remaining distance from the current vehicle position to the beginning and end of the intersection, which are denoted as y_0 and y_1, respectively. Note that l_w is the intersection length. The x-axis depicts the time horizon marked with t_0, t_1, and t_2 indicating the starting time and the intersection-entering times of the vehicles A and B. In this case, the trajectories of vehicles A and B are predicted to be intersected (i.e., potential collision) at time t_c, indicating an insufficient gap.

If the manipulation of vehicles based on the projected vehicular trajectories is feasible (i.e., a Cooperative Vehicle Infrastructure System), the insufficient-gap case in Fig. 1 might be adjusted to make a sufficient gap, as shown in Fig. 2.

Note that the initial positions of vehicles A and B at time t_0 in Fig. 2(c)–(d) are identical, and t_a and t_b on the x-axes indicate the intersection-entering and -exiting times of a vehicle. For example, Fig. 2(a) describes that vehicle A arrives and exits the intersection at times t_a and t_b, resulting in the creation of a rectangular area. Since none of two trajectories shown in solid and dashed lines within the rectangular area intersect each other in Fig. 2, no collisions would be expected at the intersection area. However, unlike Fig. 2(c) and (d), the two trajectory lines in Fig. 2(a) and (b) exist, in part, at the intersection at the same time. In other words, vehicle B would be within the intersection area before vehicle A completely leaves the intersection, thereby resulting in potential danger for both vehicles while crossing the intersection, even though a collision is not expected. Accordingly, such situations, in addition to the insufficient gap shown in Fig. 1, should be avoided by properly adjusting the trajectories as shown in Fig. 2(c) or (d). To this end, this paper converts such a trajectory adjustment problem to a nonlinear constrained optimization problem that is addressed in the next section.

B. Assumptions

To quantify the potential benefits of the CVIC algorithm, several assumptions are made.

1) All vehicles are fully automated and equipped with a communication device, resulting in 100% market penetration.
2) Communication performances are assumed to be perfect, resulting in no packet drops or any packet transmission delays.
3) An intersection is equipped with a controller that is specially designed to find the best maneuvers for all vehicles crossing the intersection.
4) All vehicles crossing the intersection are manipulated by the intersection controller that disseminates guidance information for safe and rapid crossing.
5) With respect to the communication protocol, every vehicle transmits its driving information through the Basic Safety Message [16], [17] every 100 ms, and the controller does its guidance information through the Ala Carte Message [16], [17], as defined in Wireless Access in Vehicular Environments/Dedicated Short Range Communications [18], [19] standards.
6) All vehicles travel on a level terrain, resulting in no gravity acceleration effects while accelerating or decelerating.
7) Frictions between a tire and the ground are trivial enough to ignore, thereby resulting in no considerations of the friction effects for the derivations of objective function and constraints.
8) Passenger cars only: Trucks, bicycles and pedestrians are not considered in this study.

C. Derivation of a Nonlinear Constrained Optimization Problem

1) Objective Function: The curves in Fig. 3 indicate the individual vehicles' predictive trajectories if the vehicles maintain their current acceleration/deceleration rates at $t = 0$. Note that the dashed-line curves indicate vehicles on the major street and the solid-line curves are for vehicles on the minor street. As noted, the x-axis represents the time, and the y-axis is for the remaining distance from a vehicle to the beginning of an intersection, as defined in (1). Thus, the horizontal distance between two curves represents headway (in seconds), and the vertical distance between them represents distance gap (in meters). Note that the acceleration and deceleration rates are referred to by symbol "a" from now on: If the sign of "a" is

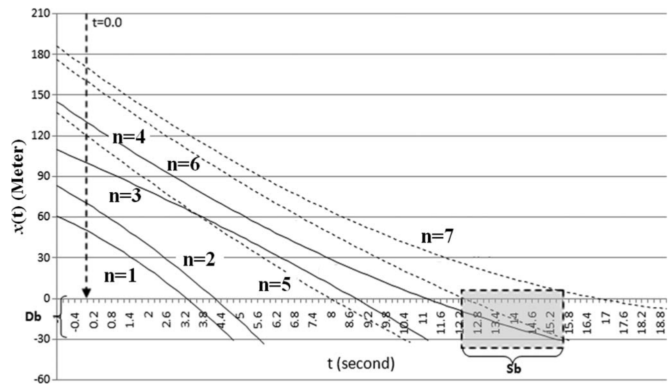

Fig. 3. Vehicular trajectories.

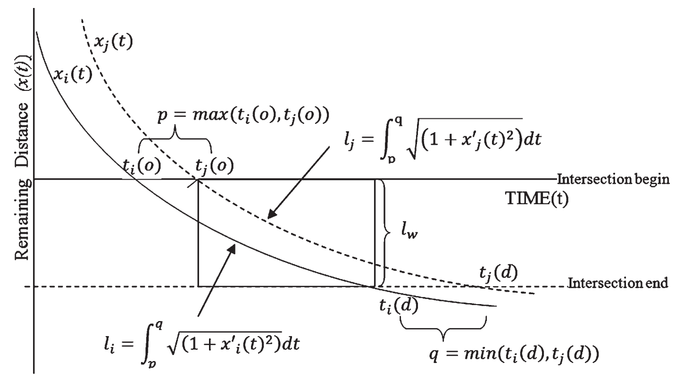

Fig. 4. Trajectory overlaps.

positive, it means an acceleration; otherwise, it is a deceleration. That is

$$x_n(t) = x_n(0) - 0.5a_n t^2 - v_n t \tag{1}$$

where

$x_n(t), x_n(0)$	predicted and current remaining distance to the intersection stop bar of vehicle n at time t, respectively;
a_n	acceleration or deceleration rate of vehicle n;
v_n	current speed of vehicle n;
t	time.

The shaded box area, which is denoted as S_b in Fig. 3, depicts a situation in which two conflicting vehicles from each street are crossing the intersection at the same moment, thereby resulting in an overlap, which must be avoided. Fig. 4 shows the overlapping situation in Fig. 3 in detail. The length of the overlap is defined as the curves in the boxed area and formulated as (2a) and (2b). Since the lengths of both the dashed curve and the solid curve are same, one of the two curves is selected, e.g., l_i, as the overlapping length. That is

if $a \neq 0$

$$l = \int_p^q \sqrt{(1 + x'(t)^2)\, dt} \tag{2a}$$

Otherwise

$$l = \sqrt{(q-p)^2 + (l_w - x(p))^2} \tag{2b}$$

where

p	arrival time at the beginning of intersection (see Fig. 4);
q	arrival time at the end of intersection (see Fig. 4);
l_w	intersection length in meters.

Thus, the optimal acceleration/deceleration rates can be obtained by solving the objective function in the following that minimizes the length of overlapping;

$$Obj.Fun = Min(\text{total length of overlapped trajectories}). \tag{3}$$

2) Constraints: Since vehicles interact with each other while traveling, several constraints are required to ensure safety. These include the following: 1) maximum acceleration or deceleration rates; 2) maximum and minimum speeds; and 3) minimum headways between two consecutive vehicles in the same lane.

a) Maximum acceleration/deceleration rates: The maximum acceleration and deceleration rates should depend on the drivers and/or the performance of the vehicles. However, 4.0 and -3.0 m/s^2 are considered, for this paper, as the general maximum acceleration and deceleration rates, respectively, i.e.,

$$a \geq a_{\min}(= -3.0 \text{ m/s}^2) \tag{4a}$$

$$a \leq a_{\max}(= 4.0 \text{ m/s}^2). \tag{4b}$$

In addition to the maximum and minimum acceleration rates coming from the driving behaviors and/or vehicles' performances, the other constraint to ensure correct movements of vehicles must exist; obviously, vehicles are not allowed to drive backward at any time. From (1), four different trajectories can be derived, depending on the signs and magnitudes of acceleration rates. That is, when accelerating (i.e., $a > 0$) or maintaining current speed (i.e., $a = 0$), the trajectories have convex and linear function forms, respectively, always resulting in unique solutions since the current speed and position denoted as v and $x(0)$ in (1) are always positive. However, when decelerating (i.e., $a < 0$), the function form must be concave, possibly resulting in no feasible solutions. Thus, for the trajectory function in (1) to have real roots, the discriminant of (5a) must be positive, resulting in an additional constraint in (5b), i.e.,

$$t = a^{-1}(-v \pm \sqrt{v^2 + 2ax(0)} \tag{5a}$$

$$a \geq -v^2/2x(0). \tag{5b}$$

Obviously, the discriminants of the accelerating and constant speed cases are positive.

b) Maximum and minimum speeds: The maximum and minimum speeds also affect the rates of acceleration and deceleration. The proper acceleration rates satisfying the maximum and minimum speeds are obtained as follows:

$$a_{n\_\max} = \left(u_{\max}^2 - v_n^2\right) / \left(2\left(x_n(0) - x_n(t)\right)\right) \tag{6a}$$

$$a_{n\_\min} = \left(u_{\min}^2 - v_n^2\right) / \left(2\left(x_n(0) - x_n(t)\right)\right) \tag{6b}$$

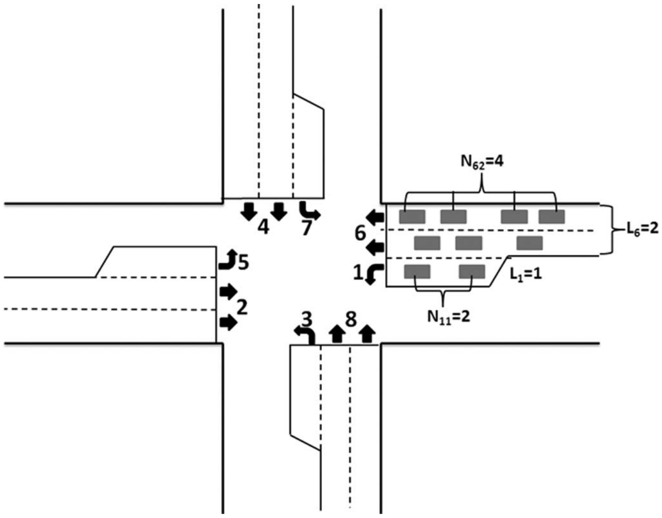

Fig. 5. Example of notation for an intersection condition.

where

$u_{\max}$ maximum speed;
$u_{\min}$ minimum speed;
$a_{n\_\max}$ maximum acceleration rate of vehicle n;
$a_{n\_\min}$ maximum deceleration rate of vehicle n.

c) Minimum headway: In the interest of traffic safety, two consecutive vehicles are encouraged to maintain a safe headway distance. Assuming two trajectories obtained by two consecutive vehicles, which are denoted as $x_n(t)$ and $x_{n+1}(t)$, respectively, and an h-s headway, which is denoted by h, the final form of two consecutive vehicles' minimum headway constraint is derived in

$$S\,(0.5(a_n - a_{n+1})\,R^2 - (a_n h - v_n + v_{n+1})R + S > 0 \quad (7)$$

where

$$S = 0.5 a_n h^2 - v_n h - x_n(0) + x_{n+1}(0)$$
$$R = a_{n+1}^{-1}\left(-v_{n+1} + \sqrt{v_{n+1}^2 + 2a_n x_{n+1}(0)}\right).$$

3) Optimization Problem Formulation for an Intersection: With the objective function and the constraints in (8), this section proposes a generalized optimization formulation for an isolated four-leg intersection by using NEMA phase numbers, as shown in Fig. 5. Notice that each number with arrows indicates the NEMA phase number. The number of lanes for each phase is denoted by L_i, and the number of vehicles on a certain lane in a certain phase is denoted by N_{ij}. Thus, Fig. 5 shows four vehicles travelling on the second lane of phase 6, which consists of two lanes.

From (2), giving an example of the calculation of overlap length drawn by two vehicles approaching from phases i and j, respectively, the total length of overlaps including all phases are formulated by (8). Since it is unnecessary to consider nonconflicting phases when summing up the overlap length of phase i, corresponding counter phases would be selected based on a conflict map describing the relationship between phases. The map is described in Table I, and cells with a value of 1 mean that phases i and j have a conflicting relationship. Thus,

TABLE I
PHASE CONFLICT MAP

i \ j	1	2	3	4	5	6	7	8
1	-	1	1	1	0	0	1	1
2	1	-	1	1	0	0	1	1
3	1	1	-	1	1	1	0	0
4	1	1	1	-	1	1	0	0
5	0	0	1	1	-	1	1	1
6	0	0	1	1	1	-	1	1
7	1	1	0	0	1	1	-	1
8	1	1	0	0	1	1	1	-

the general form of the optimization problem is now formulated as follows:

$$MinTL = \sum_{i=1}^{P}\sum_{k=1}^{L_i}\sum_{m=1}^{N_{ik}}\sum_{j=1}^{P}\sum_{l=1}^{L_j}\sum_{n=1}^{N_{jl}}\int_{p}^{q}\sqrt{(1 + x'_{ikm}(t)^2)\,dt} \quad (8a)$$

such that

$$a_{ikm} \geq \max\left(a_{\min}, \frac{-v_{ikm}^2}{2x_{ikm}(0)}, \frac{u_{\min}^2 - v_{ikm}^2}{2\,(x_{ikm}(0) - x_{ikm}(t))}\right) \quad \forall\, i, k, m \quad (8b)$$

$$a_{ikm} \leq \min\left(a_{\max}, \frac{u_{\max}^2 - v_{ikm}^2}{2\,(x_{ikm}(0) - x_{ikm}(t))}\right) \quad \forall\, i, k, m \quad (8c)$$

$$S\,(0.\,5(a_{i,k,m} - a_{i+1,k,m})\,R^2 - (a_{i,k,m}h - v_{i,k,m} + v_{i+1,k,m})R + S > 0 \quad \forall\, i, k \text{ and } m = 1, 2, \ldots, N_{i,k} - 1 \quad (8d)$$

where

P total phase numbers;
i, j phase number indices (see Table I for the relationship);
k, l lane identifier;
m, n vehicle identifier;
L_i, L_j total number of lanes of phases i and j, respectively;
N_{ik}, N_{jl} total number vehicles on lanes k and l of phases i and j, respectively;
p see (2) $(= \max(t_{i,k,m}(o), t_{j,l,n}(o)))$;
q see (2) $(= \min(t_{i,k,m}(d), t_{j,l,n}(d)))$;
$t_{i,k,m}(o)$, $t_{j,l,n}(o)$ arrival times at the beginning of the intersection of vehicle $m(n)$ on lane $k(l)$ in phase $i(j)$;
$t_{i,k,m}(d)$, $tl_{j,l,n}(d)$ arrival times at the end of the intersection of vehicle $m(n)$ on lane $k(l)$ in phase $i(j)$.

and

$$S = 0.5a_{i,k,m}h^2 - v_{i,k,m}h - x_{i,k,m}(0) + x_{i+1,k,m}(0)$$
$$R = a_{i+1,k,m}^{-1}\left(-v_{i+1,k,m} + \sqrt{v_{i+1,k,m}^2 + 2a_{i,k,m}x_{i+1,k,m}(0)}\right).$$

4) Solving Constrained Nonlinear Optimization Problems: The optimization problem presented in (8) is considered as a nonlinear constrained programming (NCP) problem. To solve such an NCP problem, this paper employed the Active Set Method (ASM) [20] based on sequential quadratic programming and the Interior Point Method (IPM) [20] as analytical techniques based on the calculation of the Karush–Khun–Tucker [20] conditions. Given an initial solution, both algorithms begin their iterative process to search for the next solution. Thus, the final solution is most likely affected by the initial solution. However, these algorithms would produce different solutions although they started with the same initial point. In other words, given the same initial point, even if ASM fails to find an acceptable solution, it does not mean that IPM would find an unacceptable solution either.

It is generally understood that evolution-based heuristic methods such as the genetic algorithm (GA) [21], [22] or the shuffled-frog leaping [23] algorithm would have a better chance of finding an acceptable solution than ASM or IPM, although it would need a longer time. Thus, in addition to such analytical techniques, this paper also employed GA to obtain better solutions.

Taking into consideration that the purpose of the CVIC algorithm proposed in this paper is to ensure safe crossing of an intersection without any collision risks, using all of the optimization algorithms would improve the chance of finding acceptable solutions. Thus, in this paper, the optimal solution that ensures safe crossing is to be sequentially solved by the three solution algorithms. It is noted that the three solution algorithms could have been implemented in parallel and the first acceptable solution found could have been implemented.

D. Control Algorithm

This section describes the overall framework of the CVIC algorithm. To handle possible system malfunction cases such as infeasible solutions, a system recovery control logic is presented.

1) Control Logic Framework: This paper assumes that there is an intersection control agent (ICA) that is particularly designed to gather individual vehicular information and provide the best maneuvers to the vehicles crossing an intersection under the CV environment. The ICA performs a sequence of optimization processes to obtain acceptable acceleration/deceleration rates with ASM-, IPM-, and GA-based optimizers. While this paper assumes a centralized system through ICA, a decentralized system that uses cooperative vehicular movements without ICA could be achieved.

Individual vehicles' current acceleration/deceleration rates are used as the initial solution required for implementing both ASM and IPM optimizations. If an optimizer finds an acceptable solution ensuring the safety and the mobility of each vehicle, then the entire optimization process terminates, and its solution is recorded in a solution database for implementation. If none of the optimizers finds acceptable solutions, the ICA recalls a previous solution from the database that was successfully optimized in the latest time step.

With the previous acceptable solution, the ICA constructs up-to-date vehicular trajectories of existing vehicles. To construct the trajectories of newly entered vehicles, their current acceleration/deceleration rates are used. If the trajectories of

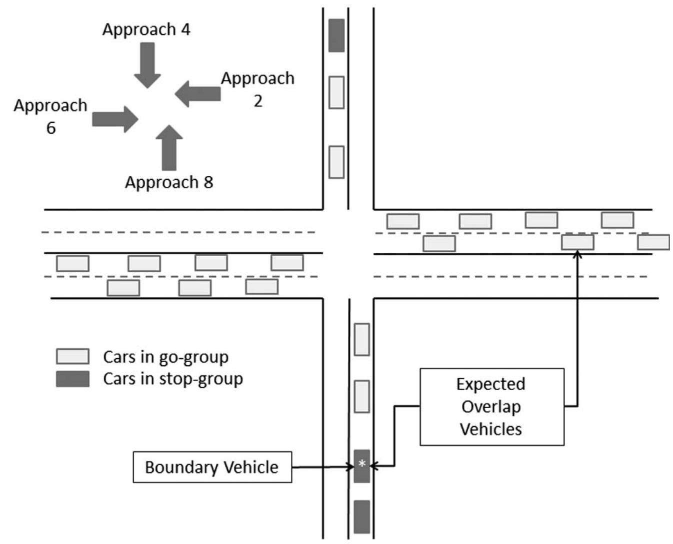

Fig. 6. Example of vehicle grouping for the recovery mode.

such vehicles are expected to result in rear-end crashes with leading vehicles, the acceleration/deceleration rates of the following vehicles are adjusted to prevent potential crashes. Once the new trajectories are developed, the optimizer searches for the earliest trajectory overlap and identifies the vehicle pairs involved in the overlap. With this vehicle pair, the ICA determines a priority approach and a nonpriority approach based on a comparison of the total number of vehicles. For example, if the two vehicles located on approaches 2 and 6 are expected to end up an overlap, as shown in Fig. 6, then approaches 4 and 8 would be selected as the nonpriority approaches as fewer vehicles are on those approaches, and the vehicle determined to be stopped in the nonpriority approaches is marked as a boundary vehicle. After determining approaches to be stopped and the boundary vehicle, the ICA estimates the time to decelerate of the boundary vehicle by solving the following:

$$t_s = \begin{cases} \frac{v}{a} + \frac{\sqrt{d_{\max}(d_{\max}-a)(2ax(0)+v^2)}}{a(a-d_{\max})}, & \text{if } a>0 \text{ and } a \neq d_{\max} \\ \frac{v}{a} - \frac{\sqrt{d_{\max}(d_{\max}-a)(2ax(0)+v^2)}}{a(a-d_{\max})}, & \text{if } a>0 \text{ and } a \neq d_{\max} \\ \frac{v}{2d_{\max}} + \frac{x(0)}{v}, & \text{if } a=0 \\ 0, & \text{if } a=d_{\max} \end{cases} \tag{9}$$

and provides the boundary vehicle with decelerating guidance, and the intersection goes into recovery mode, which is a special period designed to handle such solution failures, and rapidly returns to optimization-enabled mode.

2) Implementation of Recovery Mode: During the recovery mode, vehicles on the stopping approaches are categorized into two groups based on the position of the boundary vehicle, i.e., the group of vehicles geometrically located before the boundary vehicle, which is named a go group, and the group of vehicles behind the boundary vehicle including the vehicle itself, which is named a stop group. The ICA disseminates a "GO" command to all vehicles in the priority approaches, as well as vehicles in the go group of the nonpriority approaches. The vehicles with the "GO" command move with their previously

TABLE II
SUMMARY OF MOEs

MOE Category	MOE	Unit
Mobility Measure	Total Travel Time	Vehicle-hour
	Total Stop Delay	Hour
	Maximum Throughput	Vehicles
Sustainability Measure	Carbon Dioxide(CO_2)	Ton
	Fuel Consumption	Liter

obtained acceleration or deceleration rates, which allow them to safely pass through the intersection, whereas vehicles in the stop group decelerate with the decelerating guidance given by the ICA. Once the last vehicle before the boundary vehicle completely leaves the intersection, meaning that no potential conflicts are expected at the intersection area, vehicles on the priority approaches are guided to keep going with the maximum speeds by a "MAX" command from the ICA. Meanwhile, the ICA keeps checking new vehicles entering onto the priority approaches, and if the new vehicles are present, it disseminates a "SLOW" command to guide the vehicles to have a low-enough speed (i.e., 25 km/h) to create an adequate gap between the groups of high- and low-speed vehicles on the priority approaches. By making sufficient gaps between the two groups on the priority approaches, the stopped vehicles on the nonpriority approaches can start crossing the intersection. This procedure continues until the last vehicle in the high-speed group crosses the intersection. Then, the ICA gives the "GO" command to the vehicles in the nonpriority approaches to make the vehicles on those approaches move and resumes the optimization process by terminating the recovery mode, if possible.

IV. Evaluation and Results

A. Simulation Test Bed

This paper developed an integrated simulation test bed incorporating VISSIM [24] for microscopic-level vehicular simulation and MATLAB [25] for the implementation of ASM, IPM, and GA optimizations through the VISSIM's COM interface [26].

1) MOEs: The use of corresponding measures of effectiveness (MOEs) is crucial for the evaluation of system performance. In this paper, two types of MOEs were selected: 1) mobility measures and 2) sustainability measures. The mobility measures selected are the following: 1) total stopped delay time; 2) total travel time; and 3) total throughputs.

To investigate the environmental impacts, a microscopic emission/fuel consumption model, i.e., the VT-Micro Model [27], was employed in this paper. The VT-Micro Model estimates emissions and fuel consumption using instantaneous vehicular speeds and accelerations. In this paper, carbon dioxide (CO_2) and fuel consumption were selected for the sustainability measures. All MOEs with respective units are summarized in Table II.

2) Evaluation Experiments Design:

a) Test intersection design: As an exploratory research to assess the potential benefits of the CVIC algorithm, this paper focused on a single lane hypothetical isolated intersection

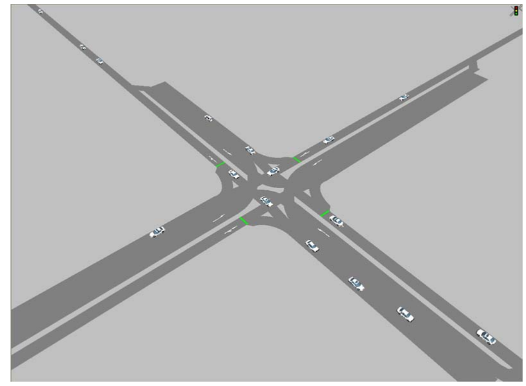

Fig. 7. Hypothetical intersection for the experiments.

TABLE III
ALGORITHM PARAMETER COMPARISON

Parameters	This Paper	Raravi *et al.*[*11*]	Drenser and Stone[*8*]
Min Speed	25 KPH	0 KPH	0 KPH
Max Speed	105 KPH	97 KPH	90 KPH
Max Acc.	4 m/s^2	4 m/s^2	Not Specified
Max Dec.	-3 m/s^2	-4 m/s^2	
Min Headway	1 second	Not Applicable	

without left turns, as shown in Fig. 7. However, note that the algorithm was originally designed to be applicable for any generic intersection, as shown in (8).

b) Volume scenarios and traffic signal timing plans: For the performance evaluations, a total of 40 volume scenarios covering the volume-to-saturation-flow ratio (v/s) of each street, ranging from 0.1 to 0.7, were created using the Latin-Hypercube Design (LHD) approach [28]. LHD is an experimental design approach that achieves maximum coverage of the vector space defined by the v/s ratio ranges and their levels by ensuring that minimum correlations among factors are considered. Assuming that all vehicles in the test network are passenger cars, and 1900 vehicles per hour is the saturation flow used for this experiment, the performances of the intersection were evaluated by an actuated control (AC) system, in which optimal timing plans were developed by Synchro [29]. With the optimal timing plans, the v/s ratios were converted to the corresponding v/c ratios for all volume scenarios. With a 30-min simulation period, each scenario was replicated 30 times with different random seeds. Thus, a total of 1200 simulations were implemented.

c) Algorithm parameters: Several parameters required to implement the proposed algorithm must be determined before the implementation. Such parameters include the following: the maximum and minimum speeds, the maximum acceleration and deceleration rates, and the minimum headway. These parameters must be set, depending on the traffic states, control strategies, or a safety concern, but in this paper, those are fixed as summarized in Table III. Note that, comparing to the studies conducted by Raravi *et al.* [11] and Dresner and Stone [8], the specified parameter values would be acceptable.

TABLE IV
SUMMARY OF THE OVERALL GAINS OF THE CVIC ALGORITHM

Measure	Measure (Unit)	CVIC	AC	Gain
Mobility Measures	Average total stop delay time (Hour)	0.1	12.1	99%
	Average total travel time (Hour)	25.1	37.2	33%
	Average total throughput (Vehicle)	1449	1342	8%
Sustainab-ility Measures	Carbon Dioxide (CO_2) (ton)	263.7	471.0	44%
	Fuel Consumption (Liter)	120.9	215.2	44%

B. Results

1) Overall Performance Comparisons: The overall performances of the CVIC algorithm compared to AC are summarized in Table IV. It is noted that AC is the most widely deployed system in the U.S. The CVIC algorithm dramatically reduced the total stopped delay times by 99%. The total travel times and throughputs were also improved by 33% and 8%, respectively. Note that the total stopped delay times are defined as a sum of the standstill times due to congestion at the intersection. Taking into consideration that the proposed algorithm is designed to keep vehicles crossing the intersection without any risks of crashes, such huge savings obtained from the stopped time delays demonstrate the promising benefits of the CVIC algorithm.

The CVIC algorithm significantly improved air quality and energy savings: A 44% reduction of CO_2 emission was estimated, and a 44% reduction in fuel consumption was expected. Obviously, such benefits would result from the reduction of congestion at the intersection.

2) Performance Comparisons by Varying Congestion Conditions: The impacts of the CVIC algorithm under varying congestion conditions were examined as shown in Fig. 8. For the total stopped delay, the CVIC algorithm outperformed the ACs over all traffic conditions. It is apparent that the CVIC algorithm contributed to reduced green house gases and fuel consumption, as shown in Fig. 8(d) and (e).

Despite the promising benefits observed under oversaturated conditions, the total travel times and the total throughputs showed marginal improvements under uncongested conditions, i.e., a v/c of 0.9 or less. To investigate such challenging performances, t-tests $(\alpha = 0.05)$ used to statistically examine the difference of means between two control methods, were conducted. Fig. 9 shows the p-values of the total travel time [i.e., Fig. 9(a)] and total throughputs [i.e., Fig. 9(b)] under varying v/c ratios. As clearly shown in Fig. 9(a), while the gains obtained from the CVIC algorithm are statistically significant when the v/c ratios are 0.9 or higher, no gains were observed when v/c is less than 0.9. The total throughputs are similar to the cases of the total travel time, but its boundary v/c ratio was 1.0. Taking into consideration that the v/c ratio of each volume scenario was estimated by the optimized timing plans for the ACs, v/c ratios less than 1.0 mean that the capacity of intersection is adequate to treat the approaching demands. Thus, the total throughputs of ACs under such 1.0-v/c-ratio cases

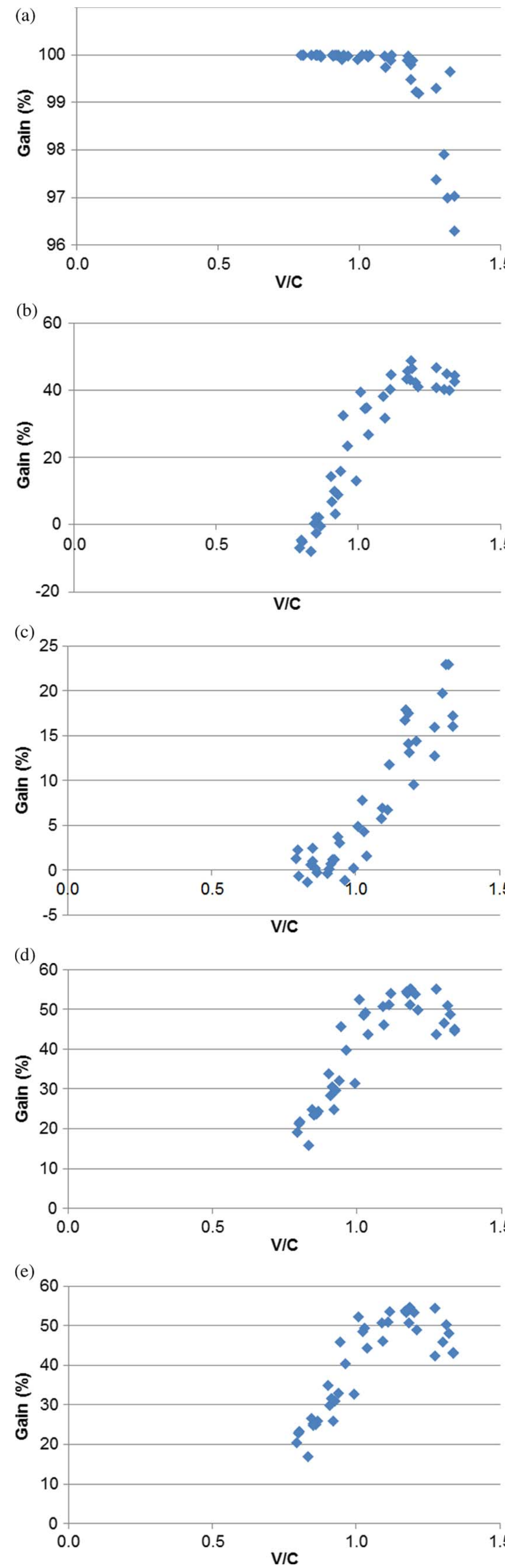

Fig. 8. Gain comparisons under varying v/c ratios. (a) Total stopped delay. (b) Total travel time. (c) Total throughputs. (d) CO_2. (e) Fuel consumption.

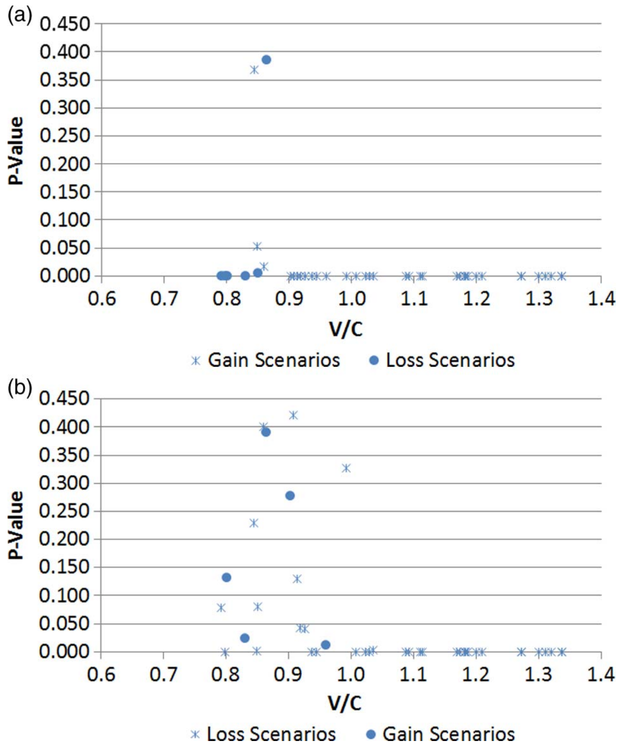

Fig. 9. t-test comparisons under varying v/c ratios. (a) Total travel time. (b) Total throughputs.

would be similar to those of the CVIC algorithm, as clearly shown in Fig. 9(b).

Under uncongested conditions, i.e., the v/c is 0.8 or less, cars maintain free-flow speeds, although they need to stop at the intersection if the intersection is operated by an AC. On the contrary, in the CVIC algorithm, the design of which compels vehicles to cross the intersection without waiting at the stop bar, vehicles are manipulated to maintain the optimal speeds to cross the intersection. However, when the optimal speeds are below the free-flow speeds, the travel times of CVIC vehicles are longer than those of the ACs, particularly when traffic conditions are uncongested; Fig. 9(a) proves such an interpretation. However, it is noted that the travel times under uncongested conditions could be improved by adjusting the control parameters, such as the minimum speed, the maximum deceleration rate, or the minimum time headways, which are fed by fixed values for the simulation experiments in this section.

V. Conclusions and Recommendations

A. Conclusion

This paper has presented the CVIC algorithm under the following assumptions: 1) All vehicles are fully automated. 2) Optimal controls are developed and implemented for real-time control. 3) No communication latencies exist between vehicles and infrastructure. Based on a simulation-based study at a four-leg intersection with a single lane at each approach, the potential improvements of the CVIC algorithm over conventional AC system were evaluated under varying traffic congestion conditions. Results have shown that the CVIC algorithm outperformed the conventional system in both mobility and sustainability.

The stopped delay have been reduced by 99%, and the total travel times and total throughputs have also been improved by 33% and 8%, respectively. In addition, the CVIC algorithm has resulted in 44% reductions of CO_2 and 44% savings of fuel consumption. Results have also shown that the CVIC algorithm outperformed the AC when the intersection was being operated under oversaturated conditions. While the travel time savings have been approximately 18% at most under moderate congestion conditions (i.e., v/c ratio of 1.0 or less), about 60% of travel time reduction has been observed when the v/c ratio was 1.0 or higher.

B. Recommendations for Future Research

While this paper has demonstrated the performance of the proposed CVIC algorithm using a four-way intersection with a single through lane at each approach, the algorithm itself has already been formulated for general intersection with multiple lanes and turning movements. Future research should consider evaluating the proposed CVIC algorithm for a typical four-leg intersection with multiple lanes and turning movements. In addition, future research should consider expanding the algorithm to include multiple intersections along the corridor or the network and conduct simulation based evaluations.

This paper has assumed a central control system embedded within the roadside equipment, parallel computations of three optimization methods, and perfect V2I communications within 150-m radius. Future research should consider validating the feasibility of these assumptions. Furthermore, before deploying the proposed CVIC algorithm in the real world, several factors should be carefully considered and evaluated through physical and simulation test beds. These factors including system architecture (i.e., central, distributed, or hybrid controls), protocols on V2V and/or vehicle-to-infrastructure communications, solution algorithm, and computation power should be determined to ensure that the feasibility of the real-time implementation is guaranteed.

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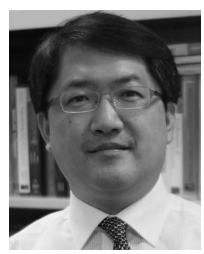

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