Transportation Research Part C 32 (2013) 193–206

Contents lists available at SciVerse ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Sustainability assessments of cooperative vehicle intersection control at an urban corridor

Joyoung Lee [a,*], Byungkyu (Brian) Park [a], Kristin Malakorn [b], Jaehyun (Jason) So [a]

[a] Department of Civil and Environmental Engineering, University of Virginia, 351 McCormic Road, Charlottesville, VA, USA
[b] Vanasse Hangen Brustlin (VHB) Inc., 101 Walnut Street, Watertown, MA, USA

ARTICLE INFO

Article history:
Received 19 December 2011
Received in revised form 29 May 2012
Accepted 6 September 2012

Keywords:
Intelligent transportation system
Cooperative vehicle intersection control
Safety evaluation
Sustainable transportation
Connected vehicles
Traffic operation

ABSTRACT

Connected Vehicle (CV) technology, formerly known as IntelliDrive, has emerged and is expected to provide unprecedented improvements in mobility. A recent study developed a cooperative vehicle intersection control (CVIC) algorithm for an urban intersection that does not require a stop-and-go style traffic signal and demonstrated significant mobility improvements over an actuated traffic signal control. This paper expanded the algorithm and implemented it to a corridor consisting of multiple intersections. In addition, this paper investigated sustainability aspects of the CVIC system for an urban traffic control system by applying surrogate safety assessment model (SSAM) and VT-Micro model to measure safety and environmental impacts, respectively. A simulation-based case study was performed on a hypothetical arterial consisting of four intersections with eight traffic congestion cases covering low to high volume conditions. When compared to the coordinated actuated control, the CVIC system dramatically reduced the total delay times for the volume cases considered (i.e., from 82% to 100% delay time savings observed). The CVIC system also reduced the number of rear-end crash events by 30–87% for the volume cases considered, indicating that safer driving conditions would be achieved with the CVIC system. Finally, the CVIC system contributed to improving the air quality (i.e., 12–36% CO_2 emission reduction) and saving fuel consumptions (11–37% of gas saving).

© 2012 Elsevier Ltd. All rights reserved.

1. Introduction

With the US Department of Transportation's connected vehicle technology initiative (USDOT, 2011), the transportation system is expected to face a new paradigm shift from an existing reactive/proactive control to possibly a fully cooperative vehicle and infrastructure control. The existing control, which is mostly based on fixed point sensors still requires significant operations and maintenance costs and it is generally understood that such control would not able to cope up with ever-increasing transportation demands. Furthermore, the existing control would not be able to adequately address issues related to crashes, fuel consumption and greenhouse gas emissions in the transportation sector. Given the primary goals of US DOT are to improve mobility, safety, energy and the environment, the effect of the cooperative vehicle and infrastructure control on these key measurements should be well evaluated such that policy goals and connected vehicle technology deployment decisions can be properly established.

As is widely known, the transportation system is one of the critical sectors responsible for greenhouse gas emissions (affecting climate change), oil consumption (contributing to energy crises), and fatalities due to crashes (resulting in a lead-

* Corresponding author.
E-mail addresses: jl9hc@virginia.edu (J. Lee), bpark@virginia.edu (Byungkyu (Brian) Park), kjm8pc@virginia.edu (K. Malakorn), js9pb@virginia.edu (Jaehyun (Jason) So).

0968-090X/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.trc.2012.09.004

ing cause of death for young adults). It is highly expected that several control algorithms relying on fully cooperative controls based on the connected vehicle technology will be developed and evaluated through simulations and eventually implemented in the real world.

In fact, a recent research developed a fully cooperative vehicle intersection control (CVIC) algorithm and evaluated its mobility improvements over the existing actuated control using an isolated intersection (Lee and Park, 2012). In order to consider multiple intersections along the corridor in urban transportation systems and to explicitly assess sustainability measures including fuel consumption, emissions and crashes, earlier research had to be significantly expanded. The purpose of this paper is to examine the sustainability impact of the CVIC system by expanding the algorithm to be implemented at multiple intersections along the corridor.

The remainder of this paper is organized into four sections. The literature review section summarizes the state-of-the-art of cooperative intersection controls for autonomous vehicles and presents the previous research on simulation-based safety, energy and environment evaluations. The methodology section provides the expanded CVIC algorithm in detail and addresses the overall integrated simulation framework to assess the mobility, safety, energy, and environmental impact of the CVIC algorithm. The case study section presents the design of simulation experiments and the results on the mobility, safety, energy and environment measures. Finally, conclusions and recommendations for future research are provided in the concluding remarks section.

2. Literature review

2.1. Cooperative intersection control

With the recent advancement of cutting-edge vehicular wireless communications technologies, cooperative intersection controls have gained increased attention in the research community. This section presents a summary of some of the research efforts to date.

Dresner and Stone (2008) proposed a multi-agent based intersection management algorithm by utilizing an intersection reservation system for autonomous vehicles within a cooperative vehicle and infrastructure system (CVIS) environment. Assuming a hypothetical four-way isolated intersection with three lanes for each approach in which the maximum volume was 750 vph and varying autonomous vehicle ratios such as 100%, 99%, 95%, and 90%, the proposed algorithm showed 99%, 94%, 78%, and 7% of delay time savings, respectively, compared to a pre-timed traffic control system.

de La Fortelle (2010) also proposed an intersection reservation algorithm for fully autonomous vehicles, assuming the perfect CVIS environment. Thus, the author assumed that the intersection in the research not only collects individual vehicles' driving information such as speed and location, but also provides the best reservation solutions for each vehicle such that it can keep crossing the intersection without potential collision risks at the intersection. The author did not include any explicit results in the paper but demonstrated the actual implementation of the proposed algorithm in the field through a video clip (Laraimara, 2010).

Lee (2010) and Lee and Park (2012) proposed an algorithm for a cooperative vehicle intersection control (CVIC) environment and assessed its potential benefits on a hypothetical isolated intersection. The proposed algorithm examined the predictive trajectories of vehicles that would be at risk for coming into conflict with one another at an intersection area. When multiple vehicles on conflicting approaches are projected to cross the intersection area at the same time, with a safe gap constraint between two consecutive vehicles, the algorithm optimizes their trajectories in search of optimal speeds and accelerations that will prevent the occurrence of trajectory overlaps. Comprehensive microscopic traffic simulation-based experiments covering various traffic congestion conditions were performed on a hypothetical isolated intersection. Statistically significant benefits were observed: for mobility 99% and 33% of improvements on stop delays and travel time, respectively, were estimated and about 34% of both CO_2 emission reductions and fuel savings were also reported.

Agbolosu-Amison et al. (2012) quantified the potential benefits of a dynamic gap-out feature for an actuated signal control within the connected vehicle technology. Knowing the arrival time of each vehicle approaching to an intersection, the gap-out was dynamically implemented based on the arrival time of each vehicle. This resulted in efficiency improvements at the actuated control intersections. Assuming 100% market penetration rate of connected vehicle technology deployment, the authors examined the performance of the dynamic gap-out feature on a hypothetical intersection using a simulation-based test-bed and demonstrated approximately 5–20% of benefits can be obtained even for congested conditions.

2.2. Simulation-based safety estimations

It is generally understood that transportation safety is challenging to evaluate, especially where no post crash data is available because new treatments were never deployed. The most straightforward way to evaluate safety would be through surrogate measures. There have been a few research efforts utilizing surrogate safety measures based on individual vehicular data to relate them actual crash data to develop crash prediction models (Son et al., 2011) and to examine the relationships between crashes and surrogate measures (Park et al., 2011). However, obtaining such archived data would either require tremendous effort or be practically impossible. Addressing this challenge, simulation-based safety assessment has gained great

attention and has recently shown proven performances in several related studies. This section summarizes some of those successful research efforts.

Minderhoud and Bovy (2001) proposed two safety surrogate measures extended from Time-to-collision, Time Exposed Time-to-collision (TET), and Time Integrated Time-to-collision (TIT), to assess the safety impacts of future intelligent vehicles. By assuming an autonomous intelligent cruise control (AICC) system (Minderhoud and Bovy, 2001), the authors applied those measures to examine the safety impacts of multiple AICC deployment scenarios (e.g., 50% and 100% market penetration rates and partial and complete human driver interventions). The authors discovered that the AICC system would incur more dangerous conditions but the frequency of such conditions would decrease.

Gettman and Head (2003) proposed a simulation-based safety surrogate assessment model (SSAM). SSAM identifies conflicts by analyzing each vehicle's interaction found in the trajectory records from the microscopic traffic simulation software such as VISSIM (PTV, 2009a) and PARAMICS (Quadstone, 2006). Given the trajectory record of each individual vehicle obtained from the microscopic traffic simulation models, the SSAM program evaluates (i) surrogate measures such as time to collision (TTC), post encroachment time (PET), maximum speeds, and maximum decelerations to determine crash events, and (ii) conflict angles to determine crash types such as rear-end, lane changing, and crossing crashes. The performance of the SSAM program was well validated through simulation-based case studies covering various intersection geometries, traffic conditions, and operational strategies and demonstrated remarkable performances (Gettman et al., 2008).

Ozbay et al. (2008) demonstrated, in a validation study with real-world crash data collected on the New Jersey Turnpike over 10 years from 1996, that surrogate safety measures obtained from microscopic simulation models can be used for potential crash estimations. In the paper, the authors proposed two surrogate measures: (i) a modified TTC (MTTC) extended from TTC to consider the combinations of speeds and acceleration rates between leading and following cars and (ii) a crash index (CI) designed to reflect the severity and possibility of two consecutive vehicles involved in a potential crash. Statistical tests showed that both measures capture the real-world safety conditions with relatively high statistical indicators (e.g., R-squared values of 0.83 and 0.84 for CI and MTTC, respectively).

Pirdavani et al. (2010) examined the safety impacts of speed limit and approaching volume at an unsignalized intersection by analyzing the post-encroachment time (PET) measure obtained from the S-Paramics simulation model (SIAS, 2011). With scenario-based simulation experiments covering various speeds and traffic volumes for major and minor roads, the authors showed that the intersection safety gets worse as both the speed limit and the approaching traffic increases.

Stevanovic et al. (2011) applied SSAM to evaluate the safety performance of Sydney Coordinate Adaptive Traffic System (SCATS), an adaptive traffic control system (SCATS, 2011), by using a VISSIM-based calibrated simulation model covering approximately 12-km long corridor in Park City, Utah. Compared to actuated-coordinated control system, SCATS showed promising performances in both measures of safety, i.e., 12% total conflict reductions, and mobility, i.e., 4% of total delay saving.

2.3. Simulation-based energy and environment estimations

Recently, models for the assessment of the energy and environment impacts of transportation systems have evolved to explicitly capture individual vehicles' dynamic changes of speed and acceleration rates that significantly affect the amount of emission and fuel consumption. Of those models, VT-Micro model (Rakha et al., 2004) has gained significant attention from several researchers performing the evaluation of environmental aspects of traffic management, operations, and ITS strategies. In this section, some selected research efforts are presented.

Park et al. (2009) demonstrated the impacts of stochastic optimization on energy and environment improvements. They used a microscopic traffic simulation model, CORSIM, a genetic algorithm, and the VT-Micro model to assess the benefits.

Park and Lee (2009) examined the environmental aspects of route guidance strategies under connected vehicle environment by incorporating VISSIM and the VT-Micro model. Author also identified the relationships between the amounts of greenhouse gas emission and fuel consumption and the market penetration rates of connected vehicles when the connected vehicle-based route guidance information is deployed.

Kwak et al. (2012) also demonstrated that an urban corridor traffic signal optimization can improve mobility, energy and environment performances. They used a well calibrated TRANSIMS traffic simulation model and the VT-Micro model.

3. Methodology

In order to assess the sustainability impacts covering mobility, safety, energy, and environment, this paper incorporated three distinct components into a single simulation framework. Those components are: (i) a CVIC simulation test-bed based on VISSIM, a commercial microscopic traffic simulator (PTV America, 2009a), (ii) the SSAM software for evaluating the safety impacts of the CVIC, and (iii) VT-Micro model (Rakha et al., 2004), a microscopic level emissions and fuel consumption estimation model. This section presents a high level description of the expanded CVIC algorithm (Lee, 2010; Lee and Park, 2012). In addition, an overall integrated simulation framework is briefly introduced in this section.

3.1. CVIC algorithm

Assuming two vehicles approaching from conflicting streets to an intersection, Fig. 1 illustrates the vehicles' anticipated trajectories that would likely result in a crash in the intersection area. The length of the trajectory overlap, denoted as l, is given by Eqs. (1) and (2). With vehicles' driving information such as locations, speeds, and acceleration/deceleration rates obtaining through the connected vehicle environment, the CVIC system projects individual vehicles' traveling trajectories and identifies whether potential crashes would occur at the intersection or not by examining the overlaps of trajectories. In case trajectory overlaps are detected as shown in Fig. 1, the CVIC system seeks optimal trajectories to avoid the crash.

If $a_n \neq 0$,

$$l = \int_p^q \sqrt{1 + x'(w)^2 dw} \tag{1}$$

otherwise,

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

where l is the length of trajectory overlap, $x_n(t)$ the predicted remaining distance to the intersection stop bar of vehicle n at time t ($=x_n(0) - 0.5a_n t^2 - v_n t$), $x_n(0)$ the current ($t = 0$) remaining distance to the intersection stop bar of vehicle n at time t, p the arrival time at the beginning of intersection, q the arrival time at the end of intersection, lw the intersection length in meters, a_n the acceleration or deceleration rate of vehicle n, v_n the current speed of vehicle n and t is the time.

To seek the optimal trajectories, the CVIC algorithm utilizes non-linear constraint optimization techniques, which are designed to solve an optimization problem given in Eqs. (3)–(6). The optimization techniques used in this paper are Active-set Method (ASM; Nocedal and Wright, 2000), Interior Point Method (IPM; Nocedal and Wright, 2000), and Genetic Algorithm (GA; Goldberg, 1989) and those techniques are sequentially invoked to solve the problem in the control logic that will be discussed in the next section. With optimal acceleration/deceleration rate for each vehicle approaching the intersection, the overlapping trajectory for each vehicle is adjusted to safely cross the intersection without stops or the need for a traffic signal. It is noted that the optimization techniques (e.g., ASM, IPM and GA) do not always find feasible solutions and sometimes produce infeasible solution. In case of infeasible solution, the CVIC algorithm goes into a recovery mode, a traffic signal-based special period designed to be quickly returned to normal optimization-based control mode. The recovery mode is briefly presented in Section 3.1.2.

$$\text{Min } TL = \sum_{i=1}^{P}\sum_{k=1}^{L_i}\sum_{m=1}^{N_{ik}}\sum_{j=1}^{P}\sum_{l=1}^{L_j}\sum_{n=1}^{N_{jl}} \int_p^q \sqrt{1 + x'_{ikm}(w)^2 dw} \tag{3}$$

such that,

$$a_{ikm} \geqslant \max(a_{\min}, -v_{ikm}^2/2x_{ikm}(0), (u_{\max}^2 - v_{ikm}^2)/2(x_{ikm}(0) - x_{ikm}(t))) \quad \forall\, i,k,m \tag{4}$$

$$a_{ikm} \leqslant \min(a_{\max}, (u_{\min}^2 - v_{ikm}^2)/2(x_{ikm}(0) - x_{ikm}(t))) \quad \forall\, i,k,m \tag{5}$$

$$S(0.5(a_{i,k,m} - a_{i+1,k,m})R^2 - (a_{i,k,m}h - v_{i,k,m} + v_{i+1,k,m})R + S > 0 \quad \forall\, i,k \quad \textit{and} \quad m = 1,2,\ldots N_{i,k} - 1 \tag{6}$$

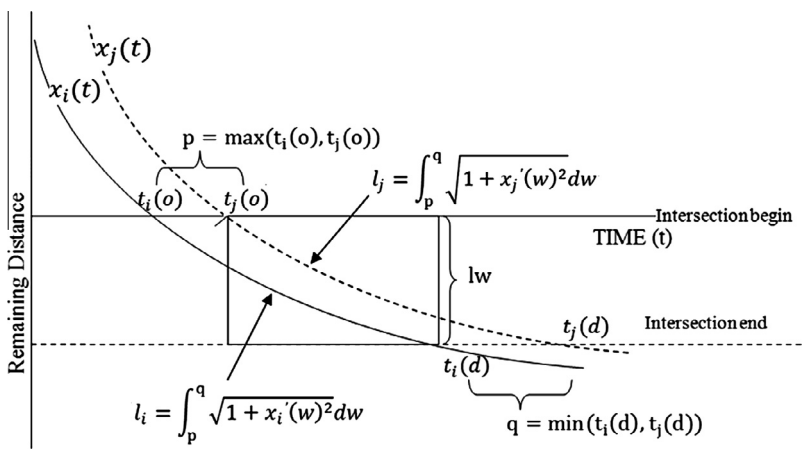

Fig. 1. Illustration of Vehicle Trajectory Overlap at an intersection (Lee, 2010).

where P is the total phase numbers, i, j the phase number indices (1 if phases are conflicted, 0 otherwise), k, l the lane identifier, m, n the vehicle identifier, L_i, L_j the total number of lanes of phase i, j, respectively, N_{ik}, N_{jl} the total number vehicles on lane k and l of phase i and j respectively, p the arrival time at the beginning of intersection (=max($t_{i,k,m}(o)$, $t_{j,l,n}(o)$)), q the Arrival time at the end of intersection (=min($t_{i,k,m}(d)$, $t_{j,l,n}(d)$)), $t_{i,k,m}(o)$, $t_{j,l,n}(o)$ the arrival times at the beginning of the intersection of vehicle $m(n)$ on lane $k(l)$ in phase $i(j)$, $t_{i,k,m}(d)$, $tl_{j,l,n}(d)$ the arrival times at the end of the intersection of vehicle $m(n)$ on lane $k(l)$ in phase $i(j)$ and $u_{\max}$, $u_{\min}$ are the maximum and minimum speeds.

$$S = 0.5a_{i,k,m}h^2 - v_{i,k,m}h - x_{i,k,m}(0) + x_{i+1,k,m}(0)$$

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

3.1.1. Implementation of the CVIC algorithm

In this paper, an Intersection Control Agent (ICA) is assumed to collect individual vehicular information and disseminate the best maneuvers to the vehicles crossing an intersection (see Fig. 2). With the collected information, ICA performs optimization processes to obtain safe acceleration/deceleration rates in the order of ASM-, IPM-, and GA-based optimizers, assuming that the time required for performing the optimization process takes less than 100 ms. If one of such optimizers finds an acceptable solution, then ICA disseminates it to the vehicles to keep them crossing the intersection, and its solution is recorded in a solution database for future use. Fig. 3 illustrates the overall implementation logic of the CVIC algorithm in the simulation test-bed.

In case none of the optimizers finds safe solutions, ICA recalls previous acceptable solutions that were successfully optimized in the latest time step. If no new vehicles have entered the streets, the previous solution will work perfectly. Otherwise, ICA investigates potential trajectory overlaps caused by the newly entered vehicles. If the trajectories 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 given, the optimizer searches for the earliest trajectory overlap and

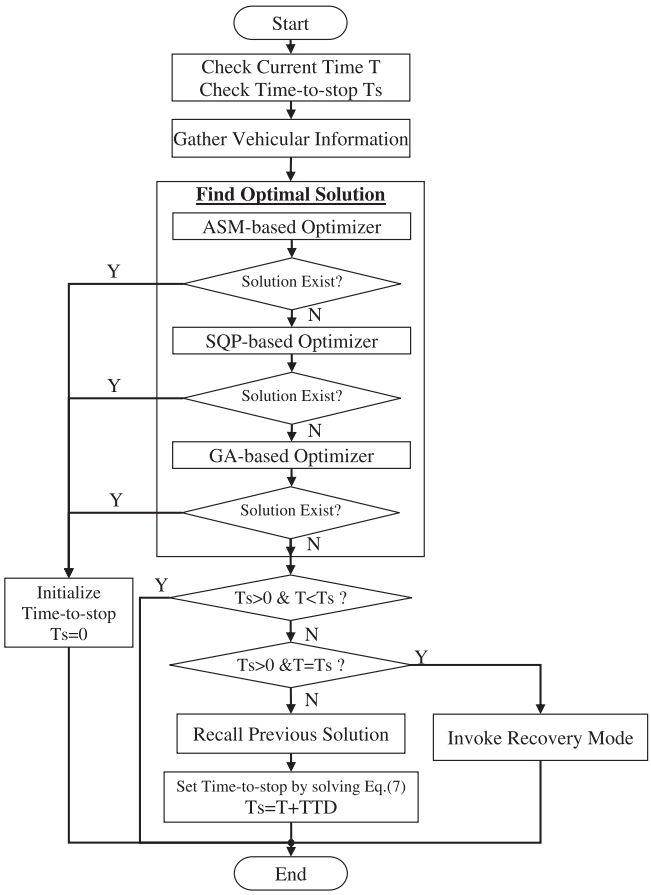

Fig. 2. Overall implementation logic of the CVIC algorithm (Lee, 2010).

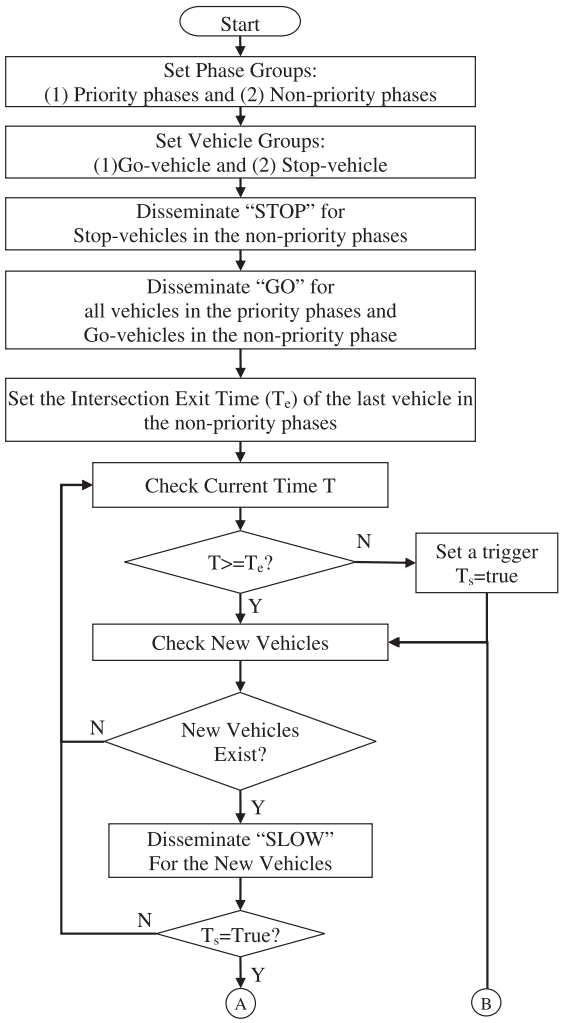

Fig. 3(a). Recovery mode logic (continued to Fig. 3(b)) (Lee, 2010).

identifies the vehicle pairs involved in the overlap. With these vehicle pairs, ICA determines phases to be proceeded (i.e., namely priority phase) and to be stopped (i.e., namely non-priority phase) by comparing the total number of vehicles. After determining phases to be stopped and a boundary vehicle, a car determined to be stopped in the non-priority phases, ICA estimates the time-to-decelerate (TTD) of the boundary vehicle by solving Eq. (7). If the obtained TTD is positive, it indicates that it is safe to keep vehicles moving with previously obtained optimal solutions for the period of TTD seconds. Thus, while the vehicles are manipulated by previous solutions, ICA can have additional opportunities to retry optimization processes for the TTD period. Nevertheless, if ICA fails to find safe solutions until this time, then it provides the boundary vehicle with decelerating guidance and the intersection goes into a recovery mode, a special period designed to handle such solution failures.

$$\mathrm{TTD} = \begin{cases} -v_n/a_n + \sqrt{d_{\max}(d_{\max} - a_n)(2a_n x_n(0) + v_n^2)}/a_n(a_n - d_{\max}), & a_n > 0, a_n \neq d_{\max} \\ -v_n/a_n - \sqrt{d_{\max}(d_{\max} - a_n)(2a_n x_n(0) + v_n^2)}/a_n(a_n - d_{\max}), & a_n < 0, a_n \neq d_{\max} \\ v_n/2d_{\max} + x_n(0)/v_n, a_n = 0 & \\ 0, & a_n = d_{\max} \end{cases} \tag{7}$$

where $x_n(0)$ is the current ($t = 0$) remaining distance to the intersection stop bar of vehicle n, a_n the acceleration or deceleration rate of vehicle n, v_n the current speed of vehicle n and $d_{\max}$ is the maximum deceleration rate.

3.1.2. System recovery mode

During the recovery mode, vehicles on the stopping phases are categorized into two groups based on the position of the boundary vehicle: the group of vehicles geometrically located before the boundary vehicle, named as a go-group, and the

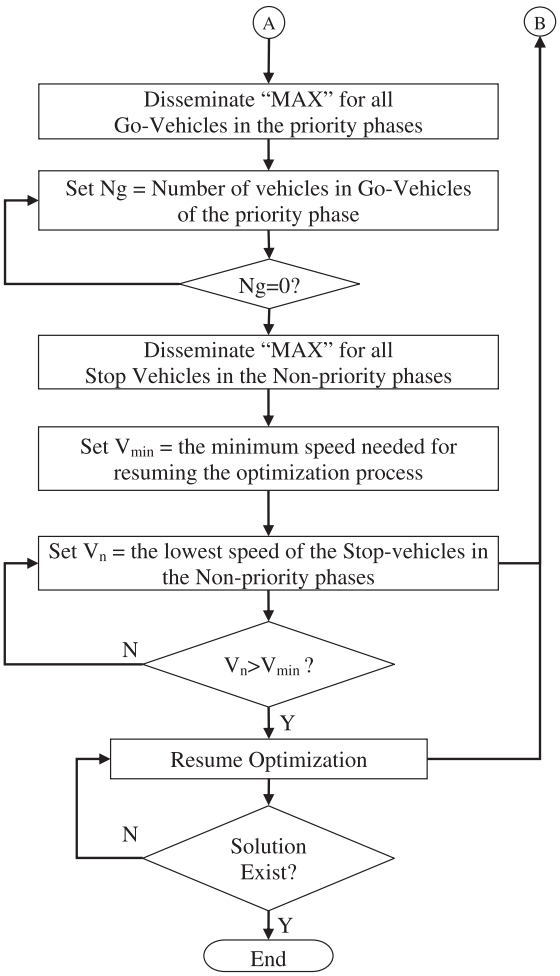

Fig. 3(b). Recovery mode logic (continued from Fig. 3(a)) (Lee, 2010).

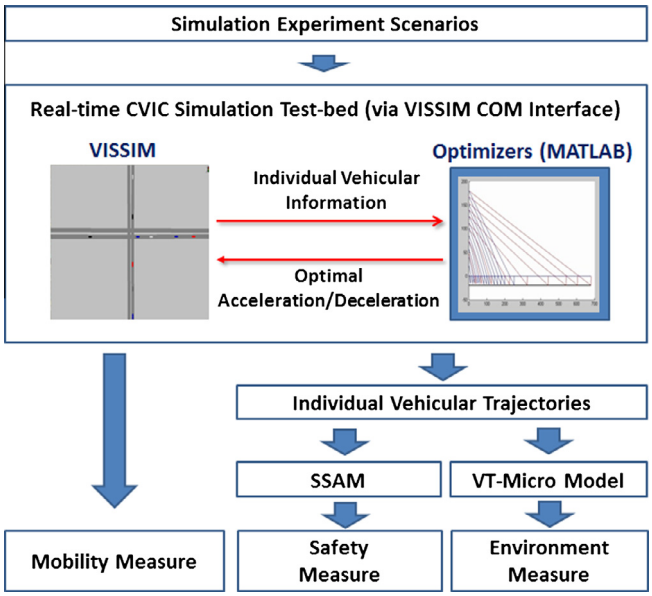

Fig. 4. Overall simulation framework.

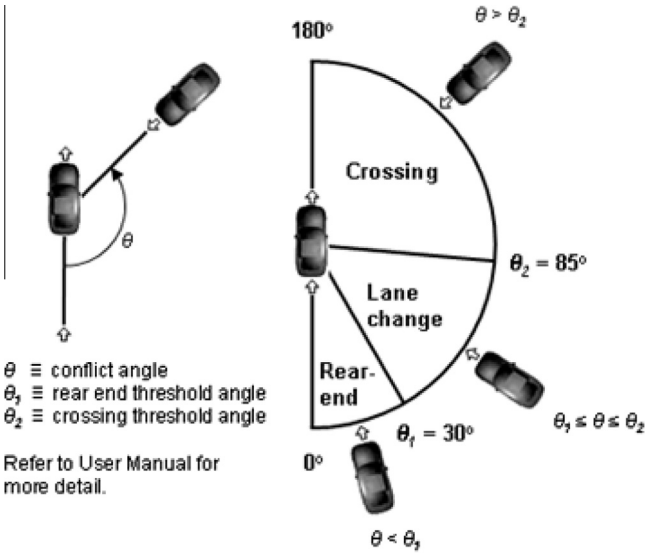

Fig. 5. SSAM conflict angle (Gettman et al., 2008).

group of vehicles behind the boundary vehicle including itself, named as a stop-group. The controller disseminates a "GO"-command to all vehicles in the priority phases and vehicles in the go-group in the non-priority phases until the boundary vehicle completely stops at the stop bar. The vehicles with the GO-command move with their previously obtained acceleration or deceleration rates that allow them to safely pass through the intersection, whereas vehicles in the stop-group decelerate with the decelerating guidance by 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 phases are guided to keep going with the maximum speeds by "MAX" command from the controller. Meanwhile, ICA keeps checking new vehicles entering onto the green phases, and, if new vehicles are present, the controller disseminates "SLOW" command to guide the vehicles to have a low enough speed (e.g., 25 k/h) to create an adequate gap between the groups of high-speed and low speed-vehicles on the priority phases. By making sufficient gaps between the two groups on the priority phases, the stopped vehicles on the non-priority phases can start crossing the intersection. This procedure continues until the last vehicle in the high-speed group exits the intersection. Then, the controller gives the GO command to the vehicles in the non-priority phases to make the vehicles on those roads move, and resumes the optimization process by terminating the recovery mode. Fig. 3 presents a diagram for the recovery mode implementation in the test-bed.

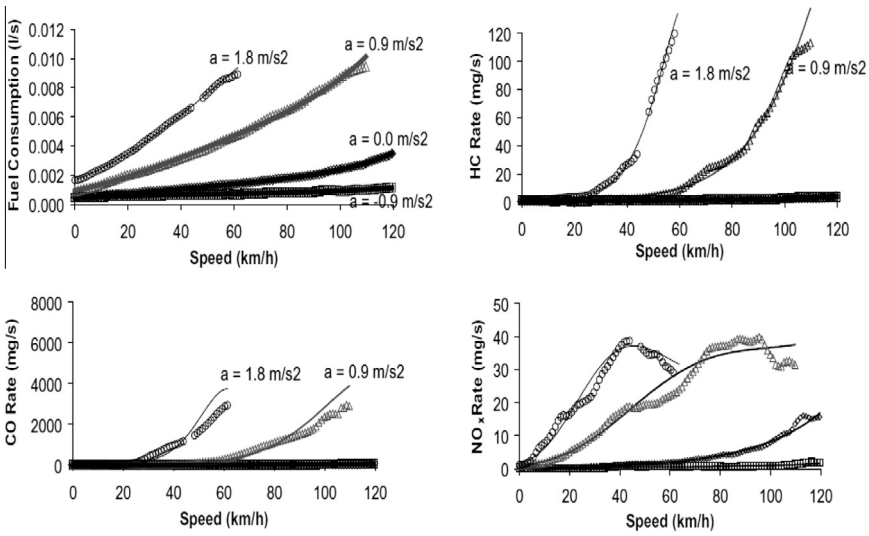

Fig. 6. Examples of the final VT-Micro model (Rakha et al., 2004).

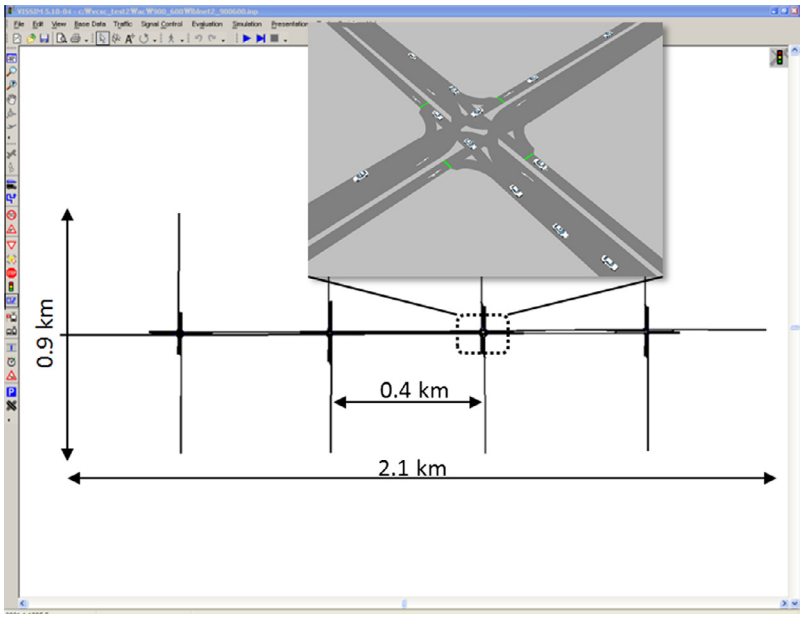

Fig. 7. Hypothetical test network for the case study.

Table 1
Volume condition scenario.

Scenario	Directional (EB and WB) major approach volume (vph)	Directional (SB and NB) minor approach volume (vph)	Overall v/c ratio
1	900	500	0.97
2	900	600	1.01
3	800	500	0.92
4	800	400	0.90
5	600	500	0.88
6	600	400	0.78
7	400	400	0.71
8	400	300	0.61

Table 2
Algorithm parameters.

Parameter	Value
Min. speed	25 k/h
Max. speed	105 k/h
Max. acc.	4 m/s^2
Max. dec.	−3 m/s^2
Min. headway	1 s

3.2. Simulation framework

In order to evaluate the mobility, safety, and environmental impacts of CVIC, the simulation test-bed should incorporate proper methods that deal with such measures into a single framework. To this end, this paper employed VISSIM and its COM interface (PTV, 2009b) which enabled real-time data exchanges between individual vehicles in VISSIM and optimal driving obtained by external optimizers to solve a non-linear constrained problem. The simulation test-bed was developed under the Visual C# programming environment and the optimization methods were implemented using MATLAB's script language.

While the mobility measures such as total travel time, delay, and throughputs are directly obtainable from VISSIM with no third party programs, both the safety and the environment metrics must be evaluated by indirect methods, such as SSAM for safety and VT-Micro model for environment, through a post process. Fig. 4 shows the overall framework describing how to integrate those models into the simulation test-bed.

Table 3
Mobility improvements.

Case	Measure	CVIC		AC		p	Improvement (%)
		Mean	Std. dev.	Mean	Std. dev.		
1	Average speed (km/h)	48.4	2.4	40.7	0.2	0.002	19
	Number of stops	1123.6	977.8	4826.2	287.5	0.001	77
	Total delay time (h)	3.5	4.1	19.3	0.8	0.001	82
	Total travel time (h)	66.4	4.3	79.1	2.3	0.001	16
2	Average speed (km/h)	44.4	3.1	40.2	0.3	0.040	10
	Number of stops	2598.4	1162.2	4229.6	130.2	0.034	39
	Total delay time (h)	0.9	2.1	20.8	0.7	0.000	96
	Total travel time (h)	76.4	6.1	84.9	1.5	0.033	10
3	Average speed (km/h)	50.8	1.3	40.3	0.1	0.000	26
	Number of stops	442.8	271.3	4302.4	192.4	0.000	90
	Total delay time (h)	0.5	0.9	18.2	0.4	0.000	97
	Total travel time (h)	59.2	2.1	73.7	1.2	0.000	20
4	Average speed (km/h)	51.6	0.5	42.0	0.2	0.000	23
	Number of stops	170.0	78.3	3691.4	198.4	0.000	95
	Total delay time (h)	0.0	0.0	15.1	0.4	0.000	100
	Total travel time (h)	53.3	1.7	66.7	0.7	0.000	20
5	Average speed (km/h)	52.0	0.5	40.3	0.2	0.000	29
	Number of stops	129.6	84.7	3340.6	77.4	0.000	96
	Total delay time (h)	0.0	0.0	14.4	0.2	0.000	100
	Total travel time (h)	50.1	0.7	61.5	0.6	0.000	19
6	Average speed (km/h)	52.1	0.5	41.7	0.1	0.000	25
	Number of stops	98.0	85.5	2824.8	43.1	0.000	97
	Total delay time (h)	0.0	0.0	12.3	0.1	0.000	100
	Total travel time (h)	44.7	1.1	56.2	0.2	0.000	21
7	Average speed (km/h)	51.8	0.2	40.9	0.3	0.000	27
	Number of stops	6.8	5.5	2360.0	59.9	0.000	100
	Total delay time (h)	0.0	0.0	9.5	0.2	0.000	100
	Total travel time (h)	35.8	1.1	44.1	0.7	0.000	19
8	Average speed (km/h)	51.6	0.3	42.2	0.3	0.000	22
	Number of stops	7.0	6.9	1927.4	31.8	0.000	100
	Total delay time (h)	0.0	0.0	7.7	0.1	0.000	100
	Total travel time (h)	29.9	0.7	37.5	0.6	0.000	20

For safety assessment, once the simulations of CVIC are completed, the resulting trajectory data of each individual vehicle is run through the SSAM software to assess safety using surrogate measures. For example, if both the TTC and the PET of a pair of vehicles in the trajectory data are found to be within their threshold values and their conflict angle is less than 30 degrees, the SSAM program identifies it as a surrogate rear-end crash event as depicted in Fig. 5. Note that the crash event does not indicate an actual crash but the likelihood of a potential crash. That is, if the SSAM program identifies either TTC or PET is less than its corresponding threshold, it counts such instance as a unsafe condition, not an actual crash. Thus, it is not necessary to obtain trajectories including an actual crash to estimate the safety performances. While the safety condition varies depending on the use of TTC and PET threshold values, it does not matter as the focus of this paper is assessing relative differences in safety, not actual or absolute crashes. This paper employed 1.5 s and 5 s of TTC and PET threshold values, respectively, based on the previous research (Hyden, 1987; Sayed et al., 1994).

The VT-Micro Model, which has a two-regime regression model form as in Eq. (8), estimates four emission matters such as Carbon Monoxide (CO), Carbon Dioxide (CO_2), Nitrogen Oxide (NOx), and Hydro Carbon (HC), and fuel consumption. The VT-Micro model was developed with rich data obtained from 60 light duty vehicles and trucks by conducting 1300–1600 individual measurements for each vehicle, thereby resulting in higher fidelity (i.e., R^2 in excess of 0.92 for all MOEs) compared to existing macroscopic model based on the driving cycles as shown in Fig. 6 (Rakha et al., 2004). Thus, unlike planning level emission/fuel consumption models such as EMFAC (Air Resources Board, 2011) and MOVES (US EPA, 2001), utilizing aggregated profiles of vehicles' driving cycle such as stops, starts, and movements with constant speeds and acceleration and deceleration rates at each level, the VT-Micro model is sufficient to accurately account for the amount of emissions and fuel consumption resulting from individual vehicles' driving behaviors.

$$\ln(\mathrm{MOE}_e) = \begin{cases} \sum_{i=0}^{3}\sum_{j=0}^{3}(L_{i,j}^{e} \times S^i \times a^j) & \text{for } a \geqslant 0 \\ \sum_{i=0}^{3}\sum_{j=0}^{3}(M_{i,j}^{e} \times S^i \times a^j) & \text{for } a < 0 \end{cases} \tag{8}$$

Table 4
Safety impacts of the CVIC.

Case	Control	Mean TTC (s)	Mean PET (s)	Rear-end crash events
1	CVIC	0.82	1.23	732
	AC	1.41	3.08	951
	Improvement (%)	−42	−60	30
	t-Value	44.51	41.94	1.86
2	CVIC	0.76	1.79	536
	AC	1.23	3.08	796
	Improvement (%)	−38	−42	33
	t-Value	37.34	40.41	1.88
3	CVIC	0.70	1.51	268
	AC	1.24	3.07	679
	Improvement (%)	−44	−51	61
	t-Value	30.81	36.22	7.36
4	CVIC	0.56	1.04	172
	AC	1.25	3.07	549
	Improvement (%)	−55	−66	69
	t-Value	31.48	42.57	14.03
5	CVIC	0.53	0.99	109
	AC	1.26	3.07	492
	Improvement (%)	−58	−68	78
	t-Value	26.62	34.85	26.26
6	CVIC	0.47	0.88	94
	AC	1.26	3.04	372
	Improvement (%)	−63	−71	75
	t-Value	26.85	34.50	10.06
7	CVIC	0.28	0.30	37
	AC	1.28	3.13	287
	Improvement (%)	−78	−90	87
	t-Value	24.95	56.62	18.50
8	CVIC	0.25	0.27	29
	AC	1.29	3.12	217
	Improvement (%)	−81	−91	87
	t-Value	24.19	52.90	28.17

[a] Tested at 95% of confidence level.

where MOE is the CO, CO_2, NOx, HC and fuel, $L^e_{i,j}$ and $M^e_{i,j}$ the model coefficients for each MOE, S the speed (km/h) and a is the acceleration rate (m/s^2).

4. Case study

4.1. Assumptions

The CVIC algorithm is implemented within the cooperative vehicle infrastructure environment powered by connected vehicles. In order to quantify the potential benefits of the proposed algorithm, several assumptions are made:

a. All vehicles are assumed to be equipped with a communication device, resulting in 100% market penetration.
b. Communication is assumed to be perfect, resulting in no packet drops or any packet transmission delays.
c. An intersection is equipped with a controller specifically designed to find optimal maneuvers for all vehicles within a predefined radius across the intersection.
d. All vehicles across the intersection are manipulated by the intersection controller that disseminates guidance information for safe and rapid crossing.
e. With respect to the communication protocols, every vehicle transmits its driving information at every 100 ms, and the controller sends its vehicular maneuver information at the same interval as defined in SAE-J2735 (SAE, 2009).
f. All vehicles travel on a level terrain, resulting in no gravity acceleration effects when accelerating or decelerating.
g. Frictions between a tire and the ground are trivial enough to ignore, thereby resulting in no considerations on the friction effects for the derivations of objective function and constraints.

Table 5
Environment improvements.

Case	Measure	CVIC		AC		p	Improvement (%)
		Mean	Std. dev.	Mean	Std. dev.		
1	Emissions CO_2 (kg)	808.4	81.5	1094.8	36.5	0.001	26
	Fuel consumption (kg)	373.6	40.5	508.5	17.4	0.001	27
	Fuel economy (k/l)	8.1	0.8	6.3	0.03	0.000	22
2	Emissions CO_2 (kg)	991.9	113.9	1131.4	20.1	0.051	12
	Fuel consumption (kg)	464.5	57.1	523.0	9.4	0.083	11
	Fuel economy (k/l)	6.9	0.6	6.6	0.02	0.047	5
3	Emissions CO_2 (kg)	681.6	50.6	1009.7	17.0	0.000	33
	Fuel consumption (kg)	310.6	25.9	468.4	7.8	0.000	34
	Fuel economy (k/l)	9.5	0.6	6.3	0.03	0.000	33
4	Emissions CO_2 (kg)	606.0	21.4	923.4	11.8	0.000	34
	Fuel consumption (kg)	275.5	10.2	428.5	5.8	0.000	36
	Fuel economy (k/l)	10.1	0.5	6.6	0.03	0.000	35
5	Emissions CO_2 (kg)	551.3	18.8	833.2	10.0	0.000	34
	Fuel consumption (kg)	248.3	10.0	385.5	4.7	0.000	36
	Fuel economy (k/l)	10.5	0.4	6.4	0.04	0.000	39
6	Emissions CO_2 (kg)	493.2	16.6	762.8	3.1	0.000	35
	Fuel consumption (kg)	222.2	8.2	352.6	1.5	0.000	37
	Fuel economy (k/l)	10.5	0.2	6.7	0.05	0.000	37
7	Emissions CO_2 (kg)	389.0	11.8	606.8	11.9	0.000	36
	Fuel consumption (kg)	173.9	5.4	280.8	5.7	0.000	38
	Fuel economy (k/l)	10.5	0.2	6.4	0.1	0.000	39
8	Emissions CO_2 (kg)	333.1	8.0	516.9	9.4	0.000	36
	Fuel consumption (kg)	150.0	3.7	239.0	4.3	0.000	37
	Fuel economy (k/l)	10.3	0.1	6.6	0.1	0.000	36

4.2. Experiments set-up

A hypothetical arterial network, consisting of four single-lane intersections, was created by using the VISSIM program. The test network has a 2.1-km long major street expanding eastbound and westbound. Each intersection along the corridor is spaced at about 400 meters apart. Fig. 7 shows the test network modeled in the VISSIM program.

To examine the mobility, safety, energy and environment impacts under varying traffic congestion conditions, eight different volume cases were developed and tested. Table 1 shows specific details about each volume case. Five repetitions of each volume case were simulated. Each repetition was 35 simulation-minutes long, including a 5-min warming-up period. To compare the performance of the CVIC, the coordinated actuated control system was used for each volume case with the same number of replications and simulation period. The timing plans for the coordinated actuated intersection controls were developed by the Synchro program (Husch and Albeck, 2004), which was used as a base case for comparison. Note that the volume to capacity ratio (v/c) for each volume scenario presented in Table 1 was estimated with the optimal timing plans obtained from the Synchro program, assuming the corridor was operated by a coordinated actuated control.

In assessing safety performances, this paper employed (i) a time to collision (TTC) and (ii) a post encroachment time (PET) as safety surrogate measures. TTC is a measure of seconds that vehicles would have to continue behaving as they are to collide with one another. PET is the time required for the lead vehicle to leave a position and the following vehicle to occupy that position. Obviously, shorter PETs are more dangerous. As noted earlier, the energy and environment performances were evaluated through the VT-Micro program, and the mobility measures were directly obtained from the VISSIM simulation program.

Several parameters required to implement the CVIC algorithm are summarized in Table 2. It is worth noting that, according to a guideline published by the Federal Highway Administration (Dowling et al., 2004), the maximum acceleration is defined as 10 ft/s^2, which is approximately 3.05 m/s^2 in metric. Taking into consideration the advancement of vehicular technologies, we slightly relaxed the maximum acceleration rate to be 4.0 m/s^2 assuming that it would be achievable. Regarding the maximum deceleration rate, despite the FHWA guideline (Dowling et al., 2004) suggesting -15 ft/s^2 (or approximately -4.6 m/s^2) for the maximum deceleration rate which would cause uncomfortable driving conditions for drivers, we decided to use -3 m/s^2 for the maximum deceleration rate. The impacts of the parameters on the performance of the CVIC algorithm are not examined in this paper. It can be further investigated in a future research.

4.3. Results

Table 3 summarizes the mobility benefits of the CVIC system applied to the hypothetical arterial network. Compared to the actuated control (AC) system, the CVIC system dramatically reduced the total delay times between 82% and 100%

depending on volume cases. Note that the total delay times are defined as a sum of the standstill times due to congestion at the intersection. Taking into consideration that the CVIC system is designed to keep vehicles crossing the intersection without any risks of crashes, such huge savings obtained from the total delays confirms the promising benefits of the CVIC system.

While such promising benefits were realized in mobility, the CVIC system appeared to decrease the intersection safety. As summarized in Table 4, the average TTC of the CVIC system was less than that of actuated control for each volume case. Similarly, the PET values of the CVIC were all less than the actuated controls. It is noted that smaller TTC and PET indicate a more dangerous situation. However, the number of rear-end crash events for each volume case was significantly reduced as shown in Table 4. It is also noted that the number of rear-end crash events indicates the likelihood of potential crashes and it increases when both TTC and PET are less than the maximum thresholds, which are 1.5 and 5 s, respectively. It is worth noting that approximately 20,000 traffic conflict events account for an actual crash (Gettman et al., 2008). Thus, while the CVIC incurred more dangerous situations, its frequencies were remarkably reduced, resulting in safer conditions. This is likely because the CVIC is designed to manipulate the maneuver of each individual vehicle to guarantee its safety condition even when crossing the intersection at high speeds. Note that the crossing events are not considered for the evaluation as they appeared insignificant in terms of the number of observations for both the actuated and the CVIC, accounting for approximately 2% of the rear-end crash events.

The CVIC algorithm improved air quality and energy consumption as summarized in Table 5. The improvements ranged from 12% to 36% of CO_2 emission reductions for the volume cases considered. In addition, it was assessed that about 11–37% of fuel savings were expected. Obviously, such benefits would result from the congestion reductions at the corridor.

5. Concluding remarks

This paper examined the mobility, safety, energy and environment aspects of the CVIC system under the Connected Vehicles environment. Based on the simulation results, the CVIC system, when compared to coordinated actuated signal, dramatically improved the mobility, the safety, the energy and the environmental performances of the urban corridor. With a hypothetical urban corridor modeled in a simulation test-bed, the CVIC algorithm outperformed conventional coordinated-actuated control system, resulting in 82–100% of delay time reductions and 16–20% of total travel time improvements. Taking into consideration that such dramatic improvements were obtained from the adjustments of the driving maneuver of each individual vehicle to ensure high speed crossing at an intersection, the CVIC system would likely result in more dangerous situations in terms of the safety aspect as indicated by lower TTC and PET values (see Table 4). However, the CVIC system significantly reduced the frequency of such dangerous situations when compared to coordinated actuated signal control, resulting in 30–87% of rear-end crash events reductions. Such huge safety improvements obviously came from the managed movements of individual vehicles ensuring the safety gap between vehicles provided by the CVIC system. In addition, the CVIC system improved air quality and fuel consumption, realizing up to 36% and 37% reduction of greenhouse gas emission and fuel consumption, respectively.

In this paper, perfect wireless communication conditions for the Connected Vehicles environment were assumed such that there were no communication packet drops and no communication delays, which might not be true in the real world. Given that the safety of Connected Vehicles applications would be dependent upon the quality of wireless communications, that aspect must be addressed in future research to ensure more realistic safety assessments.

With respect to the assessment of safety, this paper was not able to address the severity of crashes based on their types (e.g., rear-end, side-swipe, or angle crashes). This is because it is challenging to measure the severities of crashes under the current state-of-the-art and practice of simulation-based safety assessment models. It might be handled with an advanced modeling technology incorporating vehicle dynamics model and human factors in the near future.

Finally, while the case study was demonstrated on a corridor with a single through lane for each approach, the CVIC can handle a generic intersection with multi-lanes and left-turn bays as shown in the objective function in Eq. (3). Although this paper did not perform additional case studies for multi-lanes and coordinated intersections, the implementations for such case studies are recommended for future research.

References

Agbolosu-Amison, S., Yun, I., Park, B., 2012. Quantifying benefits of cooperative vehicle infrastructure system using a dynamic gap-out feature at an actuated signalized intersection. KSCE Journal of Civil Engineering 6 (3), 433–440.

Air Resources Board (ARB), 2011. <http://www.arb.ca.gov/homepage.htm> (accessed 14.12.11).

de La Fortelle, A., 2010. Analysis of reservation algorithms for cooperative planning at intersections. In: 13rd International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 445–449.

Dowling, R., Skabardonis, A., Alexiadis, V., 2004. Traffic Analysis Toolbox: Guidelines for Applying Traffic Microsimulation Software, vol. III. FHWA, FHWA-HRT-04-040.

Dresner, K., Stone, P., 2008. A multiagent approach to autonomous intersection management. Journal of Artificial Intelligent Research 31 (1), 591–656.

Gettman, D., Head, L., 2003. Surrogate measures of safety from traffic simulation models. Transportation Research Record 1840, 104–115.

Gettman, D., Pu, L., Sayed, T., Shelby, S., 2008. Surrogate Safety Assessment Model and Validation: Final Report. Report No. FHWA-HRT-08-051.

Goldberg, D., 1989. Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Professional.

Husch, D., Albeck, J., 2004. SYNCHRO 6 User Guide. Trafficware.

Hyden, C., 1987. The Development of a Method for Traffic Safety Evaluation: The Swedish Conflicts Technique. Department of Traffic Planning and Engineering, Lund University, Sweden.

Kwak, J., Park, B., Lee, J., 2012. Evaluating the impacts of traffic signal optimization on vehicle emissions and fuel consumption. Transportation Planning and Technology 35 (2), 145–160.
Laraimara, 2010. Cooperative Crossroad Management Using Vehicle-to-Vehicle Communications. <http://www.youtube.com/v/JkS0D_Vz3o> (accessed 14.12.11).
Lee, J., 2010. Assessing the Potential Benefits of IntelliDrive-Based Intersection Control Algorithms. Ph.D. Dissertation. University of Virginia, Charlottesville, VA.
Lee, J., Park, B., 2012. Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. IEEE Transactions on Intelligent Transportation System 13 (1), 81–90.
Minderhoud, M.M., Bovy, P.H.L., 2001. Extended time-to-collision measures for road traffic safety assessment. Accident Analysis and Prevention 33 (1), 89–97.
Nocedal, J., Wright, S., 2000. Numerical Optimization. Springer.
Ozbay, K., Yang, H., Bartin, B., Mudigonda, S., 2008. Derivation and validation of new simulation-based surrogate safety measure. Transportation Research Record 2083, 105–113.
Park, B., Lee, J., 2009. Assessing sustainability impacts of route guidance system under cooperative vehicle infrastructure environment. In: IEEE International Symposium on Sustainable Systems and Technology (ISSST), pp. 1–6.
Park, B., Chen, Y., Hourdos, J., 2011. Opportunities for preventing rear-end crashes: findings from the analysis of actual freeway crash data. Journal of Transportation Safety and Security 3 (2), 95–107.
Park, B., Yun, I., Ahn, K., 2009. Stochastic optimization for sustainable traffic signal control. International Journal of Sustainable Transportation 3, 263–284.
Pirdavani, A., Brijs, T., Bellemans, T., Wets, T., 2010. Evaluation of traffic safety at un-signalized intersections using microsimulation: a utilization of proximal safety indicators. International Journal of Advances in Transportation Studies, A 22, 43–50.
PTV, 2009a. VISSIM Traffic Simulation User Manual: Version 5.10.
PTV, 2009b. VISSIM COM Interface User Manual: Version 5.10.
Quadstone, 2006. PARAMICS V5.2 Programmer User Guide. Quadstone Limited.
Rakha, H., Ahn, K., Trani, A., 2004. The VT-micro framework for modeling of hot stabilized light duty vehicle and truck emissions. Transportation Research Part D: Transport and Environment 9 (1), 49–74.
SAE, 2009. SAE J2735 Dedicated Short Range Communications (DSRC) Message Set Dictionary.
Sayed, T., Brown, G., Navis, F., 1994. Simulation of traffic conflicts at unsignalized intersections with TSC-Sim. Accident Analysis and Prevention 26 (5), 593–607.
SCATS, 2011. <http://www.scats.com.au/> (accessed 14.12.110.
SIAS, 2011. <http://www.sias.com/ng/sparamicshome/sparamicshome.htm> (accessed 14.12.11).
Son, H., Kweon, Y., Park, B., 2011. Development of crash prediction models with individual vehicular data. Journal of Transportation Research Part C: Emerging Technologies 19, 1353–1363.
Stevanovic, A., Kergaye, C., Haigwood, J., 2011. Assessment of surrogate safety benefits of an adaptive traffic control system. In: 3rd International Conference on Road Safety and Simulation, pp. 14–16.
US EPA, 2001. Motor Vehicle Emission Simulator (MOVES), <http://www.epa.gov/otaq/models/moves/index.htm> (accessed 14.12.11).
USDOT, 2011. Connected Vehicle Research. <http://www.its.dot.gov/connected_vehicle/connected_vehicle.htm> (accessed 14.12.11).