Cooperative and Integrated Vehicle and Intersection Control for Energy Efficiency (CIVIC-E^2)

Yunfei Hou, *Member, IEEE*, Salaheldeen M. S. Seliman, Enshu Wang, Jeffrey D. Gonder, Eric Wood, Qing He, *Member, IEEE*, Adel W. Sadek, Lu Su, *Member, IEEE*, and Chunming Qiao, *Fellow, IEEE*

***Abstract*— Recent advances in connected vehicle technologies enable vehicles and signal controllers to cooperate and improve the traffic management at intersections. This paper explores the opportunity for cooperative and integrated vehicle and intersection control for energy efficiency (CIVIC-E^2) to contribute to a more sustainable transportation system. We propose a two-level approach that jointly optimizes the traffic signal timing and vehicles' approach speed, with the objective being to minimize total energy consumption for all vehicles passing through an isolated intersection. More specifically, at the intersection level, a dynamic programming algorithm is designed to find the optimal signal timing by explicitly considering the arrival time and energy profile of each vehicle. At the vehicle level, a model predictive control strategy is adopted to ensure that vehicles pass through the intersection in a timely fashion. Our simulation study has shown that the proposed CIVIC-E^2 system can significantly improve intersection performance under various traffic conditions. Compared with conventional fixed-time and actuated signal control strategies, the proposed algorithm can reduce energy consumption and queue length by up to 31% and 95%, respectively.**

***Index Terms*— Connected vehicles, fuel economy, intelligent transportation systems.**

I. Introduction

EFFECTIVE intersection control is an enduring problem, raising the age-old question of how the conflicting traffic movement can be best accommodated. On average, American drivers spend 38 hours per year waiting in traffic, which wastes more than 19 gallons of gasoline per vehicle per year. The cost of congestion was reported to be 121 billion dollars in recent years [1]. A large portion of traffic delay is caused by poor traffic signal timing. Despite its important role in traffic management, there is still significant room for improvement. The latest national traffic signal assessment indicates an overall grade of D+ on signal control and operations [2].

Regardless of the operating principles of traffic signal control, there have been typically three inherent assumptions that limited or constrained the level of optimization possible. The *first* assumption is that control had to be exerted on only the infrastructure side (i.e., by controlling cycle length, splits, and offset for the signals). This is because, until very recently, it was not possible to organize individual vehicle movements (i.e., control each vehicle's intersection approach speed). *Second*, the vehicles' arrival was modeled as a network flow, typically measured via aggregate metrics such as flow rates or average number of vehicles. Traditional fixed sensors (e.g., loop detectors, video cameras) can be used for traffic detection, but they are not capable of tracking individual vehicle trajectories in real-time. *Third*, it was typically assumed that once the traffic conflicts have been eliminated, the only objective the designer had to be concerned with was traffic operations efficiency, i.e., minimizing delay or queuing length. Until very recently, traffic signal control algorithms paid little attention to environmental and sustainability related metrics [3]–[9].

Now, however, we are beginning to witness the relaxation of the three constraining assumptions mentioned above. Recent advances in connected vehicle (CV) technologies [10], [11] provide new opportunities to improve traffic management: vehicles and traffic infrastructure will be able to coordinate with each other through vehicle-to-infrastructure and vehicle-to-vehicle communication. The control infrastructure will be able to gather accurate local or global information on traffic. As a result, it will become possible to make better scheduling decisions at a microscopic level. Regarding the third assumption, current global concerns about climate change have underscored the importance of managing traffic to reduce fuel consumption and minimize emissions. Towards this end, there has been some research recently that focused on utilizing CV technologies to reduce emissions and fuel consumption [12], [13].

In this paper, we explore the opportunity for Cooperative and Integrated Vehicle and Intersection Control for Energy Efficiency (CIVIC-E^2) to support a more sustainable trans-

Manuscript received June 29, 2017; revised October 24, 2017; accepted December 2, 2017. Date of publication February 15, 2018; date of current version June 28, 2018. This work was supported in part by the National Renewable Laboratory. The Associate Editor for this paper was K. Wu. *(Corresponding author: Yunfei Hou.)*

Y. Hou was with the Department of Computer Science and Engineering, University at Buffalo, The State University of New York, Buffalo, NY 14260 USA. He is now with the School of Computer Science and Engineering, California State University San Bernardino, San Bernardino, CA 92407 USA (e-mail: hou@csusb.edu).

S. M. S. Seliman, Q. He, and A. W. Sadek are with the Department of Civil, Structural and Environmental Engineering, University at Buffalo, The State University of New York, Buffalo, NY 14260 USA (e-mail: sseliman@buffalo.edu; qinghe@buffalo.edu; asadek@buffalo.edu).

E. Wang, L. Su, and C. Qiao are with the Department of Computer Science and Engineering, University at Buffalo, The State University of New York, Buffalo, NY 14260 USA (e-mail: enshuwan@buffalo.edu; lusu@buffalo.edu; qiao@buffalo.edu).

J. D. Gonder and E. Wood are with the National Renewable Energy Laboratory, Golden, CO 80401 USA (e-mail: jeff.gonder@nrel.gov; eric.wood@nrel.gov).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2017.2785288

portation system. We propose a two-level approach that *jointly determines the traffic signal timing and vehicles' approaching speed*, with the objective being to minimize total energy consumption. More specifically, at the intersection level, *a multimodal energy-efficient traffic signal* (MEETS) control strategy is designed to determine the optimal signal timing by explicitly considering the arrival time and the energy profile of each vehicle. At the vehicle level, *an eco-cruise control* (ECC) strategy is adopted to ensure that vehicles pass through the intersection in a timely and energy-efficient fashion. The novelty of this paper centers on the following contributions: 1) joint consideration of traffic signal control and vehicle speed advisories, 2) joint consideration of multimodal traffic, and 3) evaluation of the energy impact of the proposed system for both current and future traffic.

The remainder of the paper is organized as follows. In Section II, we discuss related work on sustainable intersection control strategies. Section III describes the simple intersection we use for modeling and evaluation and presents our proposed solution, along with an analysis of its complexity. We report the results from simulations in Section IV. Finally, Section V summarizes the main conclusions derived from this study.

II. Related Work

Traditional signal control has always been based on detection information provided via fixed sensors and primarily focused on reducing traffic delay. The advent of the concept of a CV environment and the increased interest in sustainable transportation and mobility introduced four new concepts of advanced intersection control which the current paper attempts to harness. These concepts are briefly reviewed below.

A. Control at the Level of Individual Vehicles

Through vehicle-to-infrastructure communications, vehicles can be detected and tracked at the individual level. With such fine-resolution data made available in a connected environment, more effective traffic signal control plans may be developed [14]–[16]. Good examples of this line of thinking, which motivated the current study, were [17] and [18], where a discrete signal control algorithm, which took into account the arrival time of each individual vehicle, was designed. However, our work is different from theirs in that we focus on minimizing energy consumption, whereas they targeted minimization of evacuation time. Additionally, our algorithm takes into account vehicles' behavior in more detail (i.e., queuing behavior at the intersection). Other previous studies [19]–[23] used CV to adaptively adjust traffic signal timing with traditional flow-based control methods. In comparison, our algorithm is designed to explicitly schedule individual vehicles. In addition, the goal of their control algorithms was to minimize delay or average waiting time, with the energy impact just evaluated as an additional benefit of their control methods.

B. Eco-Signals

The concept of eco-signals has received a significant level of attention recently. The basic premise of this concept is that if a driver has accurate information about the upcoming signal status, the vehicle speed can be adjusted accordingly to avoid vehicle operation associated with increased fuel consumption and emission rate (e.g., stop at a red light, hard acceleration maneuvers). Various vehicle speed control strategies [24]–[29] have been proposed to compute fuel-optimal vehicle trajectories. Both simulation and real-world experiments [30]–[34] showed that eco-signals appear to be an effective approach that can significantly reduce energy consumption. In all those studies, however, signal time plans are assumed to be fixed based on traffic flow, and the control action primarily focuses on adjusting the approaching vehicles' speeds without considering their influence on other vehicles. In other words, previous concepts of eco-signals did not involve the joint control of traffic signals and vehicles' speeds.

C. Reservation-Based Intersections

Connected vehicles, and in particular connected and automated vehicles, can be managed using a concept known as reservation-based intersection control, which does not use any physical traffic signals [15], [35]. Under this concept, concurrent intersection crossing is allowed if no conflict for a reservation is detected. A similar concept is known as virtual traffic lights [36]. This concept depends on vehicles to negotiate with other vehicles about which direction should get a virtual green light. Our algorithm proposed herein shares the vision of increased automation and wide CV technology adoption, but it focuses on the energy aspects of the control objective and utilizes less futuristic assumptions. Although traffic lights can be eliminated for fully automated traffic, in the proposed system, we assume traffic lights will still be used to accommodate human-driven vehicles.

D. Multimodal Traffic Signal Control

Given that modern urban transportation networks involve complex traffic streams composed of multiple travel modes, including passenger cars, buses, pedestrians, bicycles, trucks, light rail, emergency vehicles, and other commercial and private modes of transportation, multimodal traffic signal control has been attracting the attention of researchers [37]–[41]. Different travel modes have their own specific characteristics, including travel speed, volume, priority level, degree of eco-friendliness, and vulnerability. Yet very little is understood about the links among signal control strategies for different modes. The CV environment makes optimal multimodal traffic control a real possibility. Most of the previous studies focused on delay-oriented multimodal signal control. In this paper, we will address multimodal signal control from the standpoint of energy and fuel consumption.

III. Cooperative and Integrated Vehicle and Intersection Control for Energy Efficiency (CIVIC-E^2)

The CIVIC-E^2 system proposed herein is made of two strategies: 1) a traffic signal control strategy, and 2) a vehicle speed control strategy. The entire control model consists of two levels: at the macroscopic/global level, the traffic signal control strategy governs how to dispatch all vehicles within a given communication range approaching the intersection from conflicting directions; at the microscopic/local level, once the signal timing is decided, the vehicle speed control strategy determines the energy-efficient speed for each individual vehicle according to its assigned schedule.

More specifically, given the expected arrival time of each vehicle (arrival time is estimated based on vehicle's cruising speed when entering the communication range) and information on the vehicle's energy profile (the energy profile can be estimated based on the type of vehicle), the traffic signal control strategy aims to optimize signal timing such that each vehicle is explicitly scheduled to cross the intersection in a fashion that would minimize the energy consumption of all the incoming vehicles passing through the intersection. For the vehicle speed control strategy, assuming that the vehicle has received its schedule from the traffic signal control strategy, the goal is to find the speed plan (also known as trace or drive cycle) that minimizes energy consumption for the vehicle while simultaneously allowing the vehicle to pass through the intersection on time and avoid collisions.

The proposed CIVIC-E^2 system is an open platform, since different control algorithms can be implemented at both macroscopic and microscopic levels using a wide variety of strategies. In this paper we propose two specific control strategies for CIVIC-E^2, namely the Multi-modal Energy Efficient Traffic Signal (MEETS) strategy for signal control, and the Eco-Cruise Control (ECC) strategy for vehicle control. These two strategies are described below.

A. Multi-Modal Energy Efficient Traffic Signal (MEETS) Control Strategy

1) Problem Description: In this section, we present the traffic light control strategy of an isolated intersection. At the signal controller, each vehicle is explicitly scheduled to cross the intersection with the objective of minimizing overall energy consumption. The MEETS strategy will suggest a time frame for each vehicle to reach the intersection. Specifically, once a vehicle enters the communication range of the traffic light, it communicates to the traffic controller its information (e.g., speed, direction, location). The traffic signal timing will then be decided according to the arrival time of each individual vehicle with the control objective being to minimize the overall energy consumption for all detected vehicles scheduled to pass the intersection. Each vehicle will receive a schedule from the traffic controller on when to pass the intersection.

From a vehicle's perspective, it would be one of these two cases when approaching a MEETS intersection: 1) keep its current speed, or 2) slow down. In the second case, the ECC onboard the vehicle will calculate its speed plan (ECC will be explained in Section III B). In MEETS, we assume vehicles will not speed up to overtake others near the intersection, this is in part for safety concerns, and it also helps to simplify the optimization problem.

Similar to [17], we assume the following to simplify the modeling of the intersection. In Fig. 1, we assume that the intersection has two roads, each road has one lane, and vehicles on the same road have the same inbound and outbound directions (without left or right turns). Both the vehicles and the traffic controller are equipped with communication devices that are running IEEE WAVE protocols [42]. The traffic controller only needs to listen to the vehicles' basic safety messages, which contain information about the vehicle speed, location, heading, etc. Based on this information, the traffic controller is able to estimate the arrival time of each vehicle. Given that basic safety messages (specified in SAE J2735) are designed to be broadcast at 10 Hz with a transmission range of about 300 meters, no additional protocol is required for the proposed traffic control strategy.

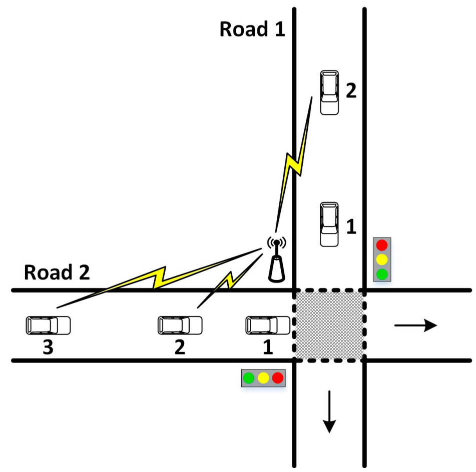


Fig. 1. A simple intersection.

In this model, vehicles coming from the same direction (i.e., inbound road) will leave the intersection in a stringent order according to their arrival time. In other words, passing is not allowed near the intersection and vehicles will be discharged from their respective directions in a first-in, first-out order. Hence, for the q^{th} vehicle on road r, we have: $V_r^1 \prec V_r^2 \prec \ldots \prec V_r^q$ (i.e., V_r^1 is followed by V_r^2 etc.). Other parameters for MEETS strategy are tabulated in Table I.

We use $E(q_1, q_2, r)$ to denote the total energy loss after q_1 vehicles on road 1 and q_2 vehicles on road 2 have passed (i.e., $\mathrm{V}_1^1, \mathrm{V}_1^2, \ldots, \mathrm{V}_1^{q_1}$ and $\mathrm{V}_2^1, \mathrm{V}_2^2, \ldots, \mathrm{V}_2^{q_2}$), and at that time the traffic light is green on road r. Let n_r denotes the total number of vehicles on road r, the problem of finding the energy optimal control strategy becomes:

$$\min\{E(n_1, n_2, 1), E(n_1, n_2, 2)\}$$

With reference to the example in Fig. 1, the objective can thus be expressed as:

$$\min\{E(2, 3, 1), E(2, 3, 2)\}$$

That is to find the minimum total energy loss in two cases: a) when two vehicles have crossed road 1 and three vehicles have crossed road 2, and the final traffic light phase is green on road 1, and b) all vehicles have crossed roads and the final phase is green on road 2.

Intuitively, we can solve the problem by scheduling one vehicle at a time based on the total energy loss in previous

TABLE I
PARAMETERS IN MEETS CONTROL STRATEGY

Variable	Definition
r	The index of road $r = 1, 2$
n_r	The number of vehicles on road r
V_r^q	The q^{th} vehicle on road r
P_r^q	The time for vehicle V_r^q to cross the intersection
A_r^q	The estimated time of arrival for vehicle V_r^q to reach the intersection
$C_r^{r'}$	The time for the traffic light to change from road r to r', including both yellow and all-red time
H	The saturation headway time (when vehicles are stopped)
q_r	The number of vehicles that have already passed road r
τ	The time span of a vehicle in full stop
S_r	The maximum time span of a vehicle in full stop on road r
e	Energy penalty factor, the energy loss for a vehicle to cross the intersection
$T(q_1, q_2, r)$	The total time spent after q_1 vehicles on road 1 and q_2 vehicles on road 2 have passed, with the last vehicle being discharged from road r
$E(q_1, q_2, r)$	The total energy loss after q_1 vehicles on road 1 and q_2 vehicles on road 2 have passed, with the last vehicle being discharged from road r

times. E.g., looking backwards in time, $E(2, 3, 1)$ depends on $E(1, 3, 1)$ and $E(1, 3, 2)$, then $E(1, 3, 1)$ further depends on $E(0, 3, 1)$ and $E(0, 3, 2)\ldots$ Before we present our solution in Section III A. 3), we first describe how energy loss is modeled in the proposed system.

2) Energy Penalty Factor: We use the energy penalty factor e to model the energy loss for a vehicle in crossing the intersection. It is designed to roughly estimate the energy loss from a vehicle having to stop. Note that the ECC design (described in Section III.B) will address more detailed driving behavior influences on energy consumption. In the dynamic programming described in the following section, e is used to compute the minimum total energy loss E, which thus helps in weighting between the different scheduling strategies. The energy penalty factor consists of two parts: 1) the loss of kinetic energy if a vehicle has to stop at the intersection and then reaccelerate back up to speed, and 2) the energy wasted in engine idling during the time of waiting. In particular, for vehicle V_r^q that has a waiting time of τ before entering the intersection, let K_r^q denotes the energy consumption rate (e.g., in terms of kilojoules per second) when idling, and B_r^q denotes the total energy required to regain the cruising speed, the energy loss for a vehicle to cross the intersection is defined as:

$$e = \begin{cases} K_r^q \times \tau + B_r^q & if\ stopped \\ 0 & otherwise \end{cases} \tag{1}$$

K_r^q and B_r^q are determined using the Future Automotive Systems Technology Simulator (FASTSim) [43] for different types and models of vehicles. FASTSim, developed by the National Renewable Energy Laboratory, is a powertrain model that can be used for calculating fuel economy. It also provides comprehensive vehicle models that allow for evaluating both fuel and electricity consumption for advanced vehicles, such as hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and all-electric vehicles (EVs).

We estimate the parameters for e using an empirical approach: For each type of vehicle, B_r^q is estimated by calculating the energy consumption difference between the following two scenarios: 1) the vehicle cruises through the intersection at a constant speed, and 2) the vehicle stops at the intersection and then regains cruising speed. In both scenarios we assume the vehicle travels an equal distance. As to K_r^q, its value depends on the auxiliary load and engines' power output when idling. In our simulation, K_r^q is obtained by feeding a drive cycle with zero speeds into FASTSim.

3) Dynamic Programming: If we consider the approaching vehicles as a set of jobs [44] (i.e., each direction is a job and each vehicle is an operation with precedence constraints) and the intersection as a shared machine, then the problem of finding the minimum total energy loss turns into a scheduling problem. We can find the optimal solution by a forward dynamic programing algorithm. The recursion is as follows:

$$E\left(q_1, q_2, r\right) = \min_{r'=1,2} \left\{ E\left(q_1', q_2', r'\right) + e \right\} \tag{2}$$

where $q_f' = q_f\ for\ f \neq r$, otherwise $q_f' = q_f - 1\ for\ f = r, f \in \{1, 2\}$.

To simplify the notation, the index of the vehicle of interest is omitted. For example, in Fig. 1, to calculate E(2,3,1) we have:

$$E\left(2, 3, 1\right) = \min\{E\left(1, 3, 1\right) + e\left(\mathrm{V}_1^2\right), E\left(1, 3, 2\right) + e(\mathrm{V}_1^2)\}$$

where V_1^2 is the vehicle of interest.

To calculate the total energy loss (i.e., E), we need to keep track of the travel time (i.e., T). We denote the total travel time $T\left(q_1, q_2, r\right)$ in a similar fashion as E (refer to Table I).

Intuitively, $T\left(q_1, q_2, r\right)$ for V_r^q can be calculated by considering four cases (refer to the SCHEDULE() function in Algorithm 1): **Case 1)** when the previous signal is green (at $T\left(q_1', q_2', r\right)$) and there is no waiting/discharging queue, $T\left(q_1, q_2, r\right) = A_r^q + P_r^q$, where A_r^q, P_r^q are the estimated arrival time and intersection crossing time of V_r^q respectively. **Case 2)** when the previous signal is green and there is a waiting queue, $T\left(q_1, q_2, r\right) = T\left(q_1', q_2', r\right) + H + P_r^q$, where H is the saturation headway (i.e., discharge time). Note that the time for V_r^q to leave the waiting queue at the intersection (i.e., the discharging time after the signal turns green) depends on its position in the queue. The recursion lumps saturation headway. For the N^{th} vehicle in the queue, for example, its discharging time is $C_{r'}^r + N \times H$. $C_r^{r'}$ is the sum of yellow and all-red time when traffic signal switches from one road to another. **Case 3)** when the previous signal (at $T\left(q_1', q_2', r'\right)$) is red and the last scheduled vehicle from the opposite direction has passed the intersection, $T\left(q_1, q_2, r\right) = A_r^q + P_r^q$. **Case 4)** when the signal is red and V_r^q needs to wait for the last vehicle from the opposite direction to be cleared, $T\left(q_1, q_2, r\right) = T\left(q_1', q_2', r'\right) + C_{r'}^r + P_r^q$.

Finally, we can calculate the τ, i.e., the time span that the vehicle is in full stop, as:

$$\tau = T\left(q_1, q_2, r\right) - A_r^q - P_r^q \tag{3}$$

Algorithm 1 Intersection Controller

INTERSECTIONCONTROLLER (*Lst1*, *Lst2*)

▷ Input: List of vehicles' estimated time of arrival by directions:

▷ $Lst1 = \left\{A_1^1, A_1^2, \ldots, A_1^{n_1}\right\}$, $Lst2 = \{A_2^1, A_2^2, \ldots, A_2^{n_2}\}$

▷ Output: matrix E

▷ Optimal result is $\min\{E(n_1, n_2, 1), E(n_1, n_2, 2)\}$

1: $E(0, 0, r) \leftarrow 0$, $T(0, 0, r) \leftarrow \infty$
2: INITIALIZEVARIABLES ()
3: **for** $s \leftarrow 2$ **to** $(n_1 + n_2 + 1)$; diagonal traverse, refer to Fig. 2
4:   **for** $i \leftarrow 0$ **to** $(n_1{+}1)$
5:     **for** $j \leftarrow 0$ **to** $(n_2{+}1)$
6:       **if** $(i + j - s = 0)$
7:         **for** $k \leftarrow 1$ **to** 3
8:           SCHEDULE (*i,j,k,E,T*)
9: **return** E

SCHEDULE (q_1, q_2, r, E, T)

▷ Input: q_1, q_2, r, E, T refer to Table I

▷ Output: update $E(q_1, q_2, r)$, $T(q_1, q_2, r)$ in matrix E, T

1: **for each** $r' \in \{1, 2\}$
2:   **if** $A_r^q > T(q_1', q_2', r)$; Case 1), no light change, no waiting
3:     $T(q_1, q_2, r) = \mathrm{A}_r^q + P_r^q$
4:     $E(q_1, q_2, r) = E(q_1', q_2', r)$
5:   **else** ; Case 2), V_r^q needs to wait in queue
6:     $T(q_1, q_2, r) = T(q_1', q_2', r) + H + P_r^q$
7:     calculate e using Eq. 3 and 1
8:     $E(q_1, q_2, r) = E(q_1', q_2', r) + e$
9:   $temp1 = T(q_1, q_2, r)$, $temp2 = E(q_1, q_2, r)$
10: **if** $A_r^q > T(q_1', q_2', r') + C_{r'}^r$; Case 3), switch traffic light from r' to r
11:     $T(q_1, q_2, r) = \mathrm{A}_r^q + P_r^q$
12:     $E(q_1, q_2, r) = E(q_1', q_2', r')$
13:   **else** ; Case 4), wait r' to clear
14:     $T(q_1, q_2, r) = T(q_1', q_2', r') + C_{r'}^r + P_r^q$
15:     calculate e using Eq. 3 and 1
16:     $E(q_1, q_2, r) = E(q_1', q_2', r') + e$
17:     **if** $\tau > S_{r'}$; τ is calculated in line 15
18:       **continue** ; schedule V_r^q and switch light, regardless of E
19: **if** $(q_1, q_2, r) > temp2$; essentially Eq. 2
20:     $T(q_1, q_2, r) = temp1$, $E(q_1, q_2, r) = temp2$
21: **end for each**

$$\begin{bmatrix} * & \# & \blacksquare \\ \# & \blacksquare & \triangle \\ \blacksquare & \triangle & \circ \end{bmatrix} \xrightarrow{diagonal\ traverse} *\#\#\ \blacksquare\blacksquare\blacksquare\ \triangle\triangle\circ$$

(a)

$$\begin{bmatrix} (0,0) & (0,1) & (0,2) \\ (1,0) & (1,1) & (1,2) \\ (2,0) & (2,1) & (2,2) \end{bmatrix} \longrightarrow \begin{array}{l} Stripe\ 0: (0,0) \\ Stripe\ 1: (0,1), (1,0) \\ Stripe\ 2: (0,2), (1,1), (2,0) \\ Stripe\ 3: (1,2), (2,1) \\ Stripe\ 4: (2,2) \end{array}$$

(b)

Fig. 2. (a) An illustration of diagonal traverse. (b) An illustration of elements' index and their corresponding stripe number in a diagonal traverse. Note the sum of indexes of each element in a stripe equals their stripe number. i.e., let i, j, s be the index of row, column and stripe, respectively, then $\mathrm{i} + \mathrm{j} - \mathrm{s} = 0$.

The algorithm to find $\min\{E(n_1, n_2, 1), E(n_1, n_2, 2)\}$ is given above, which iteratively solves the forward dynamic programing problem. In line 1, the initial values of E and T are set to be ∞. Then, in the function INITIALIZEVARIABLES(), we have $T(1, 0, 1) = A_1^1 + P_1^1, E(1, 0, 1) = 0$ and $T(0, 1, 2) = A_2^1 + P_2^1, E(0, 1, 2) = 0$. The other two initial cases: T(0,1,1) and T(1,0,2) are not possible without violating traffic rules, thus are set to ∞. For example, $T(0, 1, 1)$ indicates that no vehicle from road 1 and one vehicle from road 2 have crossed the intersection, but the last vehicle that crossed the intersection was from road 1, which contradicts reality.

Lines 3-8, in the INTERSECTIONCONTROLLER() function look for minimum energy loss by breaking it down to schedule one vehicle at a time. Essentially, it traverses an $\mathrm{n}_1 \times \mathrm{n}_2$ matrix in diagonal strips (as shown in Fig. 2(a)). Each decision depends on the energy loss of two previous results, the SCHEDULE() function handles which previous schedules are required to calculate the next one. Specifically, lines 2-8 in the SCHEDULE() function handle the case that traffic light will not change, i.e., the last vehicle crossing the intersection was from the same road r, and lines 10-16 handle the case that the last crossing vehicle was from an different road r'. To avoid stopping a vehicle for a long time because of the heavy traffic on the other direction, lines 17-18 check the waiting time. If τ exceeds the maximum stopping time S_r, then $E(q_1, q_2, r)$ and $T(q_1, q_2, r)$ will be updated for switching the light regardless of the energy loss. S_r can be set to the maximum green time of road r by default, thus providing an upper bound of vehicles' waiting time.

After finding the optimal E with Algorithm 1, vehicle schedules can be calculated by back tracking the minimum energy loss (i.e., the order of vehicles being scheduled to cross the intersection that produces the optimal E). The traffic light schedule can then be derived by aggregating individual vehicle schedules.

The time complexity of the Algorithm 1 is $O(\mathrm{n}^2)$, since the function SCHEDULE() is called $\mathrm{n}_1 \times \mathrm{n}_2 \times 2$ times and the complexity of SCHEDULE() is $O(1)$. Specifically, lines 3-8 in INTERSECTIONCONTROLLER() diagonally traverse two $\mathrm{n}_1 \times \mathrm{n}_2$ matrices once (as shown in Fig. 2(b)): one matrix for $E(q_1, q_2, 1)$ and the other for $E(q_1, q_2, 2)$.

4) MEETS for a Typical Four-Leg Intersection: Although we introduced the MEETS algorithm using a simple two-way intersection, the control strategy can be readily adopted to a common intersection controller. For a standard 8-phase controller of a typical four-leg intersection (as shown in Fig. 3) [47], given its current ring-and-barrier settings, MEETS can be implemented with the following modifications: 1) consider vehicles that can pass during the same signal phase as a set of vehicles traveling in the same direction. For example, in Fig. 3, vehicles from direction 1,5 can be treated as if they are on the same road; 2) set the dynamic programming process to follow the sequence in the ring-and-barrier diagram. For example, if direction 1,5 is considered as road 1 and direction 2,6 is considered as road 2, then the iterative process in the INTERSECTIONCONTROLLER() function needs to consider one vehicle on road 1 first then one on

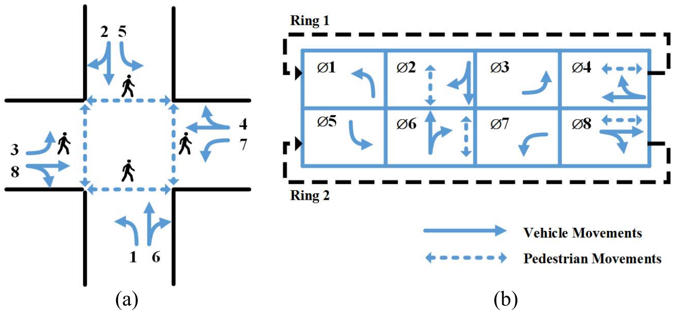


Fig. 3. (a) Typical vehicle and pedestrian movement at a four-leg intersection, (b) Standard ring-and-barrier diagram.

road 2; and 3) decide constant values in Table I according to the intersection specifications, such as setting vehicle crossing time base on the width of the intersection and traveling speed.

In general, when there are k signal sequences (i.e., $k = |r|$), the algorithm takes $O(n^k \cdot k)$ to calculate the optimal signal timing. Given that the algorithm can finish in polynomial time, it can be deployed in real-world intersections.

B. Eco-Cruise Control (ECC) for Speed Planning

In CIVIC-E^2, the objective of the vehicle speed planning step is to guarantee that a vehicle would arrive at the intersection as scheduled by the traffic controller while simultaneously minimizing its energy consumption. This problem is similar to the aforementioned eco-signals problem studied in the literature and surveyed in Section II.B; the difference, however, stems from how the traffic controller operates. In CIVIC-E^2, each vehicle is scheduled to cross the intersection at a specific time (or a small time window) whereas for eco-signals applications, each vehicle's arrival time is loosely restricted by the signal period, i.e., the eco-signals application can choose anytime within a green cycle for the vehicle to pass the intersection. Although several previous studies have shown that a heuristic algorithm will work reasonably well for eco-signals, we need a systematic way to meet the time requirement in CIVIC-E^2.

In the following section, we propose an ECC strategy for speed planning. Given the scheduled time to pass the intersection (the output from MEETS) and the position of the vehicle in front (information collected from onboard sensors or the wireless channel), ECC uses a Model Predictive Control (MPC) algorithm to guarantee the timely arrival of a vehicle. Specifically, our control algorithm is inspired by the work on predictive cruise control by Asadi and Vahidi [27]. The major difference between our proposed ECC strategy and predictive cruise control is that we explicitly consider reducing energy consumption in the control objectives.

1) Minimize Energy Consumption Approaching a Traffic Light: Similar to Section III.A.2, we consider energy consumption in terms of the mechanical work that is applied to a vehicle when passing the intersection. Using physical work instead of gas consumption allows us to compare the energy use of different types of vehicles. The mechanical work for a certain drive cycle (speed trajectory) can be separated into the work that has been used to approach the intersection, denoted as $W_{approach}$, and the work that has to be supplied after crossing the stop bar, denoted as W_{rest}. Hence, the objective of minimizing the mechanical work is to:

$$\min.\ W_{approach} + W_{rest}$$

If a vehicle needs to slow down, we use W_{brake} to denote the braking work. Let E_0 be the initial kinetic energy of the vehicle, and E_1 be the energy when the vehicle reaches the stop bar, we have the following energy equilibrium when a vehicle crosses the stop bar:

$$E_1 - E_0 = W_{approach} + W_{brake} \tag{4}$$

Without loss of generality, we assume that after crossing the intersection, vehicles will get back to their cruising (initial) speed, thus the final energy of a vehicle is again E_0. We thus have the following:

$$W_{rest} = E_0 - E_1 \tag{5}$$

With Eq. 4 and Eq. 5, the new objective can be rewritten as:

$$\min.\ -W_{brake} = -\int x f_{brake}(t)\mathrm{d}t$$

where x is the travel distance and $f_{brake}(t)$ is the braking force at time t. In the following section, this objective is incorporated in the cost function of the MPC method.

2) Model Predictive Control: Simple vehicle dynamics are used in the modeling process. Let f_{engine}, f_{brake}, f_{road} be the force of engine, braking force, and the road force, respectively. For a vehicle with a mass of m kg that traveled x meters, the longitudinal dynamics are:

$$m\frac{d^2x}{dt^2} = f_{engine} - f_{brake} - f_{road} \tag{6}$$

where f_{road} lumps the road forces, including aerodynamic drag and rolling resistance.

$$f_{road} = C_d v^2 + \mu m g$$

and where C_d is the drag coefficient, μ is the coefficient of rolling resistance, and g is the gravitational acceleration.

The major design priority in ECC is to make sure vehicles arrive at the intersection according to the scheduled deadline, otherwise a missed deadline may cause cascading effects on the remaining vehicles. In the control objective, we target at minimizing the difference between the reference speed ($v_{target}(t)$) and the output speed, i.e., to control a vehicle to follow a reference speed that guarantees the timely arrival. The reference speed is calculated according to the vehicle's distance to the intersection (to the stop bar) and the remaining time to the scheduled arrival time. The reference speed is updated in each prediction horizon based on vehicle's position at that time. The drive cycle obtained by $v_{target}(t)$ may not necessarily be the energy optimal speed trajectory, but ECC provides a systematic way to guarantee the arrival

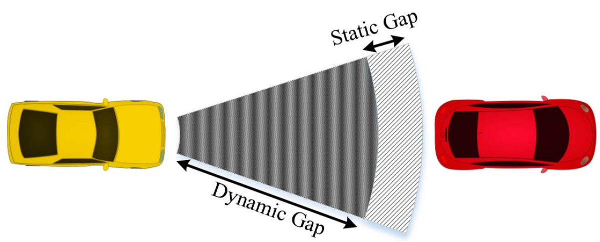


Fig. 4. An illustration of the safety constraint in ECC.

time. Because the reference speed is adjusted according to the scheduled arrival time, as long as the vehicle eventually follows the reference speed, it will arrive at the intersection on time.

In an effort to reduce the energy consumption for a vehicle, we target at minimizing the physical work that has been used for braking. Intuitively, only braking is costly according to Eq. 4. As we discussed in Section III.B.1, to minimize the mechanical work applied to the vehicle, we need to minimize the mechanical work for braking.

With the objectives of speed tracking and reducing mechanical work for braking, the control performance index at each step k is defined as:

$$J(k) = \sum_{j=k}^{k+P-1} \{w_1(v(j) - v_{target}(j))^2 + w_2[f_{brake}(j) \times (x(j) - x(j-1))]^2\}$$

where w_1, w_2 are penalty weight for each term, and P is the number of prediction steps in the future.

Additionally, the following constraints should be satisfied over the future prediction horizon. Let j be the time index, $\forall j \in \{k, k+1, \ldots, k+P-1\}$: 1) speed limit: $0 \leq v(j) \leq v_{max}$, where v_{max} denotes the maximum speed limit. It is decided based on the local speed limits; 2) bounds on the traction force: $0 \leq f_{engine}(j) \leq f^{max}_{acceleration}$, $0 \leq f_{brake}(j) \leq f^{max}_{deceleration}$, where the maximum force of acceleration, i.e., $f^{max}_{acceleration}$ and the maximum force of deceleration $f^{max}_{deceleration}$ can be estimated based on the vehicle's dynamics (e.g., by assuming the maximum deceleration is $1g$); and 3) the minimum safe distance between this vehicle and the vehicle in front of it, which should be a function of the vehicle speed, and is chosen as: $x_{front}(j) - x(j) \geq \alpha v(j) + \beta$ [45] where α, β are constants, α is often referred to as the "dynamic gap," which provides extra separation distance between vehicles with increasing speeds, whereas β is a "static gap," which determines the minimum gap needed when the vehicles are stopped (refer to Fig. 4). We assume that at each time step, the distance between the current vehicle and the preceding vehicle, denoted by $x_{front}()$, is known by the ECC controller. This information can be collected by technologies used in an Adaptive Cruise Control, or through wireless communication.

3) Solve ECC With MATLAB: The proposed MPC problem can be solved using MATLAB's MPC Toolbox, making it easy to deploy ECC to physical devices. In doing so, we introduce the following two modifications or assumptions to linearize the proposed model:

1) In the vehicle model, we treat f_{road} as a measured disturbance to approximate road force (i.e., use v from the last prediction period). With this, Eq. 6 can be written in the following state-space discretized form:

$$z(k+1) = Az(k) + B_u u(k) + B_w w(k)$$
$$y(k) = Cz(k)$$

where $z = [x\ v]^T$ is the state vector, $u = [f_{engine}\ f_{brake}]^T$ is the control input, $w = [f_{road}]$ is the measured disturbance. $A, B_u, C \in \mathbb{R}^{2\times2}$, $B_w \in \mathbb{R}^{2\times1}$ are the discretized systems matrices. The main outputs of interests are $y = [x, v]^T$.

2) In the objective function, we use w_2' to approximate $[x(j) - x(j-1)]$. w_2' is decided upon from the last prediction period. We thus have: $J(k) = \sum_{j=k}^{k+P-1} \{w_1(v(j) - v_{target}(j))^2 + w_2' f_{brake}(j)^2\}$. Note that when $f_{brake} \gg 0$ the vehicle is decelerating, then using the previous $x(j) - x(j-1)$ in the objective essentially involves minimizing the upper bound of the physical work of braking.

IV. Performance Evaluation

In this section, we compare the performance of the proposed sustainable control strategy with traditional fixed-time and actuated control signalization strategies. An isolated two-way intersection (refer to Fig. 1) is modeled in VISSIM version 5.40, and vehicle behaviors are controlled by VISSIM's Wiedemann74 model with default parameters. The proposed MEETS strategy is implemented by overwriting VISSIM's signal controller via a COM interface. Average vehicle cruising speed is set to 30 mph to mimic an urban environment. Given the communication range of a connected vehicle is about 300 m, the link distance of each road is assumed to be equal to 600 m. Both low and high traffic volume scenarios are tested: let the flow rate of the i^{th} road be $flow_i$ vehicles/hour/lane, in an urban two-way intersection setting, based on our simulation we find $flow_1 = 300$, $flow_2 = 400$ is a good representation of the low volume case, and $flow_1 = 600$, $flow_2 = 800$ for the high volume case. Energy penalty factors are estimated based on traces collected from VISSIM with stop-and-go behaviors (e.g., we find the average acceleration/deceleration rate is about $2.68 m/s^2$ for the default vehicle behavior model).

Fixed-time and actuated signal control strategies are used as baseline for this study. For all the simulation experiments, the fixed-time and actuated signal timing are optimized using Synchro version 9.1, which is a classical signal timing program for minimizing stops and queues with flow-based inputs. Signal timing parameters used in the case studies are tabulated in Table II. In the following results, the MEETS strategy refers to the case where the vehicles are not controlled by the ECC control algorithm. This means that only the signal control part of CIVIC-E^2 is implemented, and vehicle behavior follows VISSIM's car-following model.

We use two metrics to compare the performance of the different signal control strategies: the length of the waiting

TABLE II

TIME PARAMETERS

Low Traffic Volume			High-Traffic Volume			High-Traffic Volume with 5%Trucks		
	Road 1	Road 2		Road 1	Road 2		Road 1	Road 2
Fixed-Time:			**Fixed-Time:**			**Fixed-Time:**		
Green Time	18 s	19 s	Green Time	26 s	36 s	Green Time	29 s	38 s
Yellow Time	3 s	3 s	Yellow Time	3 s	3 s	Yellow Time	3 s	3 s
All-Red Time	1 s	1 s	All-Red Time	1 s	1 s	All-Red Time	1 s	1 s
Actuated:			**Actuated:**			**Actuated:**		
Min. Green	8 s	8 s	Min. Green	8 s	8 s	Min. Green	8 s	8 s
Vehicle Extension	2 s	2 s	Vehicle Extension	3 s	3 s	Vehicle Extension	3 s	3 s
Max. Green	18 s	19 s	Max. Green	26 s	36 s	Max. Green	29 s	38 s

TABLE III

POWERTRAIN PARAMETERS USED IN FASTSIM

Vehicle Model	2012 Ford Fusion	Class 8 Straight Truck	2012 Ford Fusion HEV	2012 Nissan Leaf
Frontal Area	2.12 m^2	9.5 m^2	2.12 m^2	2.74 m^2
Coefficient of Drag	0.39	0.8	0.33	0.32
Coefficient of Rolling Resistance	0.007	0.0085	0.008	0.009
Simulated Mass	1,644 kg	15,075 kg	1,823 kg	1,701 kg
Accessory Load	700 W	3,500 W	300 W	280 W
Rated Engine Power	131 kW	212 kW	116 kW	N/A
Rated Motor Power	N/A	N/A	78 kW	80 kW
Simulated Composite EPA Fuel Economy	8.7 L/100 km (27 mpg)	60.2L/100 km (4 mpg)	5.7L/100 km (41 mpg)	21.6 kWh/100 km (347 Wh/mi)

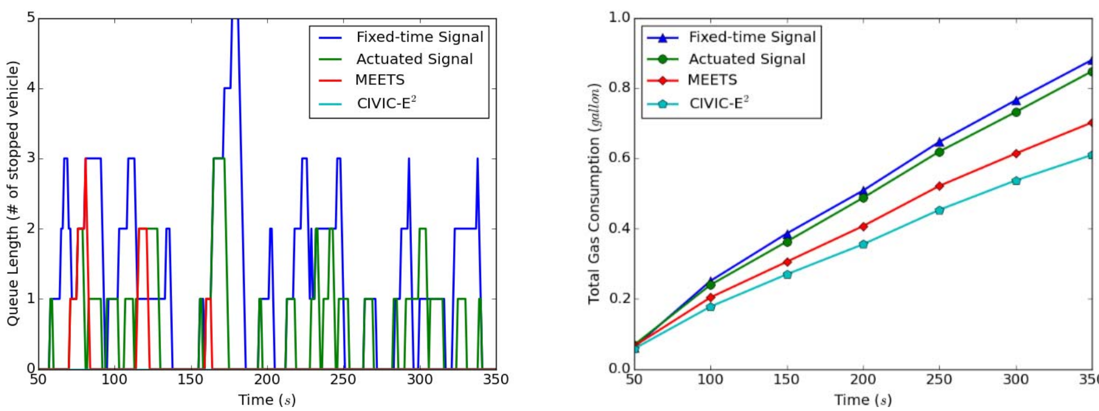


Fig. 5. Performance in the low traffic flow scenario. (a) Queue length of different strategies over time, (b) Total gas consumptions of different strategies over time.

queue (i.e., the number of stopped vehicles) at each second, and the aggregated energy use for all vehicles in the network sampled each 50 seconds. Energy use in this analysis is performed using FASTSim. For each testing scenario, all vehicles have the same total travel distance, i.e., from entering the communication range to leaving it). The speed profiles generated by VISSIM are simulated in FASTSim assuming mid-size sedans and Class 8 trucks for passenger vehicles and heavy-duty vehicles, respectively. The relevant parameters of these powertrain models are shown in Table III.

We first evaluated the performance in the low traffic flow scenario. Fig. 5 shows that the proposed CIVIC-E^2 strategy can significantly reduce queue length and energy consumption when compared with the fixed-time and actuated strategies. Specifically, compared to the fixed-time strategy, the CIVIC-E^2 system can reduce fuel consumption by 31%. This result tends to confirm the hypothesis that explicitly considering energy saving in intersection control is an effective sustainable mobility approach. As we expected, the actuated control strategy outperformed the fixed-time control strategy and reduced the number of vehicles stopped at the intersection. However, actuated signal control works in a passive manner, i.e., it needs vehicles to trigger loop detectors before switching the signal, which led to at least one vehicle being stopped (refer to Fig. 5 (a)). Under MEETS and with vehicle information from vehicle-to-infrastructure communication, the signal phases can be switched in a proactive manner to further reduce the number of stopped vehicles.

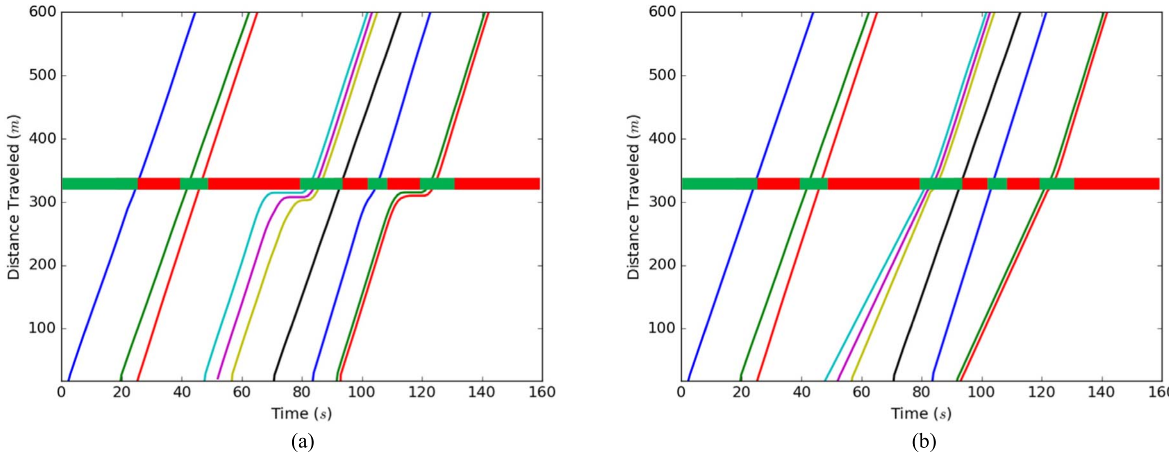


Fig. 6. Comparison of the driving behavior of 10 vehicles in the low traffic flow scenario. (a) Vehicle traces without ECC, (b) Vehicle traces with ECC.

To better illustrate the effect of ECC in CIVIC-E^2, Fig. 6 shows traces of the first 10 vehicles passing through the intersection. All of these vehicles are traveling to the same direction. In Fig. 6, the green-and-red bar shows the signal timing calculated by the MEETS, which has dynamic cycle length and split. Two scenarios have been compared: 1) vehicles traveling without utilizing ECC (Fig. 6 (a)), their driving behavior is controlled by the Wiedemann74 model in VISSIM, and 2) vehicles controlled by ECC (Fig. 6 (b)), their driving behavior is simulated with MATLAB. As can be seen, without ECC, at around 60 seconds into the simulation time, stopped vehicles start accumulating at the intersection. In comparison, with the same signal schedule, stopping can be avoided when ECC is active (Fig. 6 (b)). By proactively adjusting their speed once entering the communication range of the intersection, vehicles with ECC result in further reductions in fuel use.

Moreover, to determine if the proposed ECC strategy can be readily implemented in real time, we recorded the total computational time for solving the MPC optimization problem. The algorithm was implemented in MATLAB R2014b, and run on an AMD Phenom II X6 3.00 GHz processor with 8 GB of memory. For a simulation trip of the aforementioned scenario (each trip is 600 meters), the average CPU time for running the optimization of one vehicle is 2.029s (standard deviation = 0.369s), which appears to be quite reasonable.

Fig. 7 (a-d) shows the results in the high traffic flow scenario. When compared with the Fixed-time strategy, CIVIC-E^2 systems managed to reduce fuel consumption by around 28%. In Fig. 7 (a, b), it can be seen that the proposed CIVIC-E^2 strategy performed the best in terms of both queue length and total fuel consumption. These results indicate that CIVIC-E^2 appears to be effective for both high and low traffic flow scenarios. In contrast, when one compares the fuel use between actuated and fixed-time control strategies, the actuated strategy no longer outperforms the fixed-time strategy under the high traffic flow case. As can be seen from Fig. 7 (b), the difference between actuated and fixed-time signal control is not that significant. This is mainly due to the high flow rate in both directions, which leads to a scenario where the loop detectors are always activated by vehicles; in that case, the actuated control strategy works as if it were a fixed-time strategy.

In Fig. 7 (c, d) we replace 5% of the overall vehicles with Class 8 trucks to evaluate the control strategies with multimodal traffic (i.e., in the presence of trucks). Other parameters were kept the same as in the all-passenger vehicle case. Vehicle arrival times were the same in both these two cases, thus resulting in a similar performance in terms of queue length (refer to Fig. 7 (a) and (c)). One may have also expected similar results in terms of fuel consumption; however, in Fig. 7 (d), the actuated control strategy appears to have resulted in greater fuel use than the fixed-time strategy. This is mainly because a greater number of heavy-duty vehicles were stopped in the actuated case due to insufficient green light extension time (although the total number of stopped vehicles in the actuated case is less than those in the fixed-time case), and the heavy-duty vehicles' fuel consumption accounts for a very large percentage of the total fuel consumption. To justify this explanation, Fig. 7 (d) shows the total number of stopped trucks during the simulation period. Overall, our tests clearly show that CIVIC-E^2 can effectively improve traffic flow, minimize queue length, reduce fuel use, and support multimodal traffic.

The remainder of our experiments focused on evaluating the energy impact of the CIVIC-E^2 system in traffic streams of the future, which are likely to include a significant percentage of hybrid and electric vehicles. A recent published report [46] presents a scenario where by the year 2030, 77% of road traffic consists of electrified vehicles, i.e., HEVs, PHEVs, and EVs. In Fig. 8, two vehicle compositions are evaluated: 1) a conventional vehicle (Con.V)-dominant scenario where all vehicles are assumed to be Con.Vs, and 2) an xEV (including EVs, HEVs, and PHEVs)-dominant scenario that, based on estimates from [46], was assumed to consist of 19% HEVs, 56% PHEVs, 1.9% EVs, and 23.1% Con.Vs. To simplify the simulation of PHEVs, we assumed that such vehicles behaved like an EV for two-thirds of the time and behaved as an HEV for one-third of the time. Vehicle models used in the FASTSim simulation were a 2012 Ford Fusion, a 2012 Ford Fusion HEV, and a 2012 Nissan Leaf for the Con.V, HEV, and EV,

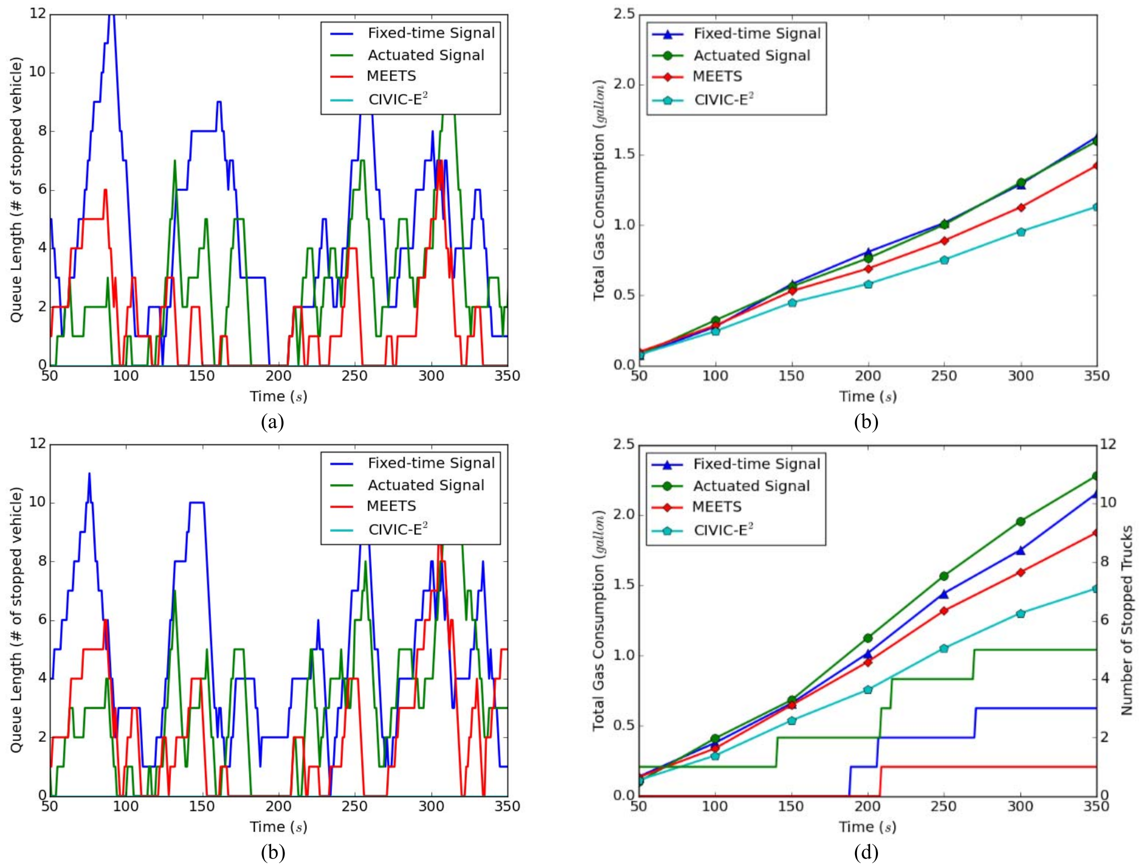


Fig. 7. Performance in the high traffic flow scenario. (a, b) traffic consists only of passenger vehicles, (c, d) traffic includes 5% Class 8 trucks.

respectively (parameters used for EV and HEV simulations are tabulated in Table III).

Fig. 8 confirms that CIVIC-E^2 has the potential to reduce energy consumption for both current and future traffic streams. In the xEV-dominant scenario, when compared with the fixed-time traffic signal control strategy, the proposed CIVIC-E^2 system was able to reduce average gasoline consumption by 17% and electricity consumption by 14%. Although major fuel savings are likely to come from vehicle electrification, the results confirm our observation that CIVIC-E^2 is an efficient approach to further reduce energy consumption for a variety of vehicle technologies at intersections.

Finally, we evaluated how different penalty factors e would affect the system performance results. In previous simulations, all passenger vehicles were assumed to have the same energy penalty factors in MEETS (trucks were given a higher penalty in proportion to their energy consumption). However, because xEVs usually consume less energy compared to Con.Vs (due to their advanced powertrains such as regenerative braking), we were interested in answering the following two questions: 1) how would different penalty factors assigned to account for stopping of xEVs vs. Con.Vs affect energy consumption? and 2) whether the CIVIC-E^2 system, with reduced penalty values for stopping xEVs, might result in longer delay for those vehicles? Given that it is difficult to quantitatively compare energy use between the Con.V and the xEV (because xEVs consume both gasoline and electricity), we compare two test

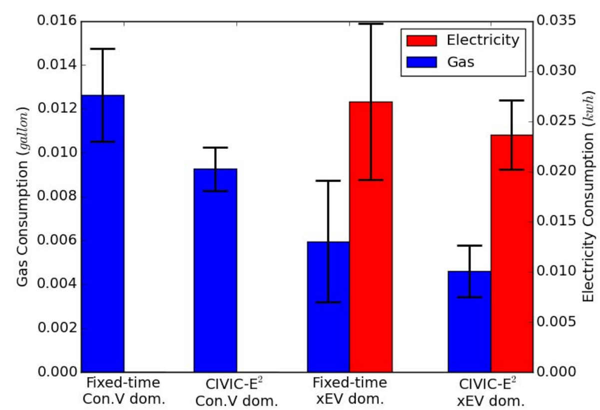
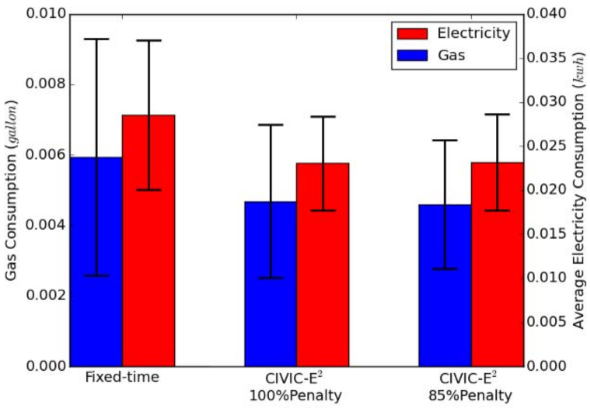


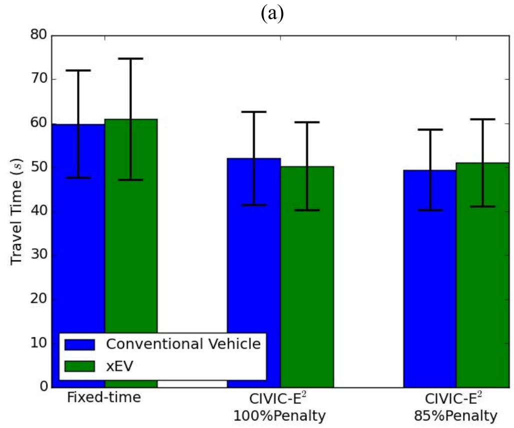
Fig. 8. Average and standard deviation of energy consumption per vehicle in the low traffic flow scenario.

cases: 1) CIVIC-E^2 100% penalty in which the Con.V and xEV are set to have the same penalty factor, and 2) CIVIC-E^2 85% penalty in which the value for an xEV's penalty factor is assumed to be equal to 85 % of that for a Con.V. In other words, the algorithm assumes that, if stopped, an xEV uses 15% less total energy than a Con.V uses.

Fig. 9 shows the results with different penalty factors for the xEV-dominated traffic stream. In the scenarios investigated, the use of different penalty factors does not appear to significantly affect the test results: the average energy consumption



(a)



(b)

Fig. 9. Sensitivity test in the high traffic flow scenario. (a) Average and standard deviation of energy consumption, (b) Average and standard deviation of travel time (600/800 veh/ln/hr).

(Fig. 9 (a)) and the average travel times (Fig. 9 (b)) are very close. Two factors contribute to this result: First, with CIVIC-E^2, not many vehicles need to be stopped even in the high traffic volume case. Secondly, because the future traffic stream was assumed to consist mainly of xEVs (about 77%), there were not many cases where a Con.V needed to compete with an xEV for intersection crossing. It is worth noting however, that since energy consumption and travel time depend on several factors such as vehicle speed and trip length, further study is required to confirm this result.

V. Conlusions

In this work, we proposed a Cooperative and Integrated Vehicle and Intersection Control for Energy Efficiency system for managing traffic to reduce fuel consumption and minimize emissions. In the proposed CIVIC-E^2 algorithm, the traffic signal timing and vehicle approach trajectories are jointly controlled with the objective of minimizing energy consumption. We also proposed a two-level control approach for CIVIC-E^2: at the global level, the MEETS control strategy is presented to find the optimal signal timing by explicitly considering the arrival time and energy profile of each vehicle; at the local level, an ECC algorithm is designed to ensure approaching vehicles follow the assigned schedule and cross the intersection with minimum energy consumption. Our findings clearly show that CIVIC-E^2 has the potential to reduce energy consumption by up to 31%, as well as to significantly improve traffic flow at signalized intersections, by reducing queue length by up to 95%. Additionally, the results demonstrate that CIVIC-E^2 can further improve the efficiency of future traffic streams consisting of significant percentages of electrified vehicles.

To extend the current work, future research should: 1) consider lane-changing behavior and allowing for signal preemption for approaching emergency vehicles, 2) consider coordination between multiple intersections along a corridor or in a transportation network, and 3) incorporate an analytical model for energy consumption, thus improving the speed advisory strategy.

Acknowledgement

This work received support from a Laboratory-Directed Research and Development project at the National Renewable Energy Laboratory (NREL). NREL is managed for the U.S. Department of Energy by the Alliance for Sustainable Energy under Contract No. DE-AC36-08GO28308. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

References

[1] D. Schrank, B. Eisele, and T. Lomax, "TTI's 2012 urban mobility report," Texas A&M Transp. Inst., Texas A&M Univ. Syst., Dec. 2012.

[2] *National Traffic Signal Report Card*, Nat. Transp. Oper. Coalition, U.S. Dept. of Transport., 2012.

[3] N. M. Rouphail, H. C. Frey, J. D. Colyar, and A. Unal, "Vehicle emissions and traffic measures: Exploratory analysis of field observations at signalized arterials," in *Proc. 80th Annu. Meeting Transp. Res. Board*, Washington, DC, USA, 2001, pp. 1–26.

[4] S. Hallmark and R. Guensler, "Comparison of speed-acceleration profiles from field data with NETSIM output for modal air quality analysis of signalized intersections," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1664, pp. 40–46, Jan. 1999.

[5] X. Li, G. Li, S.-S. Pang, X. Yang, and J. Tian, "Signal timing of intersections using integrated optimization of traffic quality, emissions and fuel consumption: A note," *Transp. Res. D, Environ.*, vol. 9, no. 5, pp. 401–407, 2004.

[6] L. Zhang, Y. Yin, and S. Chen, "Robust signal timing optimization with environmental concerns," *Transp. Res. C, Emerg. Technol.*, vol. 29, pp. 55–71, Apr. 2013.

[7] H. Rakha, K. Ahn, and A. Trani, "Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions," *Transp. Res. D, Environ.*, vol. 9, no. 1, pp. 49–74, 2004.

[8] A. Stevanovic, J. Stevanovic, J. So, and M. Ostojic, "Multi-criteria optimization of traffic signals: Mobility, safety, and environment," *Transp. Res. C, Emerg. Technol.*, vol. 55, pp. 46–68, Jun. 2015.

[9] H. Rakha and Y. Ding, "Impact of stops on vehicle fuel consumption and emissions," *J. Transp. Eng.*, vol. 129, no. 1, pp. 23–32, 2003.

[10] T. L. Willke, P. Tientrakool, and N. F. Maxemchuk, "A survey of inter-vehicle communication protocols and their applications," *IEEE Commun. Surveys Tuts.*, vol. 11, no. 2, pp. 3–20, 2nd Quart., 2009.

[11] G. Araniti, C. Campolo, M. Condoluci, A. Iera, and A. Molinaro, "LTE for vehicular networking: A survey," *IEEE Commun. Mag.*, vol. 51, no. 5, pp. 148–157, May 2013.

[12] B. Zhou, J. Cao, and H. Wu, "Adaptive traffic light control of multiple intersections in WSN-based ITS," in *Proc. IEEE 73rd Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.

[13] K. Pandit, D. Ghosal, H. M. Zhang, and C. N. Chuah, "Adaptive traffic signal control with vehicular Ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 4, pp. 1459–1471, May 2013.

[14] R. Florin and S. Olariu, "A survey of vehicular communications for traffic signal optimization," *Veh. Commun.*, vol. 2, no. 2, pp. 70–79, 2015.

[15] L. Joyoung and P. Byungkyu, "Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 1, pp. 81–90, Mar. 2012.

[16] N. J. Goodall, B. L. Smith, and B. B. Park, "Traffic signal control with connected vehicles," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2381, pp. 65–72, Dec. 2013.

[17] F. Yan, M. Dridi, and A. El Moudni, "Control of traffic lights in intersection: A new branch and bound approach," in *Proc. Int. Conf. Service Syst. Service Manage.*, 2008, pp. 1–6.

[18] C. Li and S. Shimamoto, "An open traffic light control model for reducing vehicles' CO_2 emissions based on ETC vehicles," *IEEE Trans. Veh. Technol.*, vol. 61, no. 1, pp. 97–110, Jan. 2012.

[19] V. Gradinescu, C. Gorgorin, R. Diaconescu, V. Cristea, and L. Iftode, "Adaptive traffic lights using car-to-car communication," in *Proc. IEEE 65th Veh. Technol. Conf. (VTC-Spring)*, Apr. 2007, pp. 21–25.

[20] S. I. Guler, M. Menendez, and L. Meier, "Using connected vehicle technology to improve the efficiency of intersections," *Transp. Res. C, Emerg. Technol.*, vol. 46, pp. 121–131, Sep. 2014.

[21] N. Maslekar, M. Boussedjra, J. Mouzna, and H. Labiod, "VANET based adaptive traffic signal control," in *Proc. IEEE 73rd Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.

[22] Y. Feng, K. L. Head, S. Khoshmagham, and M. Zamanipour, "A real-time adaptive signal control in a connected vehicle environment," *Transp. Res. C, Emerg. Technol.*, vol. 55, pp. 460–473, Jun. 2015.

[23] N. Maslekar, J. Mouzna, M. Boussedjra, and H. Labiod, "CATS: An adaptive traffic signal system based on car-to-car communication," *J. Netw. Comput. Appl.*, vol. 36, no. 5, pp. 1308–1315, 2013.

[24] R. K. Kamalanathsharma and H. Rakha, "Multi-stage dynamic programming algorithm for eco-speed control at traffic signalized intersections," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst.-(ITSC)*, Oct. 2013, pp. 2094–2099.

[25] M. Alsabaan, K. Naik, and T. Khalifa, "Optimization of fuel cost and emissions using V2V communications," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 1449–1461, Sep. 2013.

[26] T. Guan and C. W. Frey, "Predictive fuel efficiency optimization using traffic light timings and fuel consumption model," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst.-(ITSC)*, Oct. 2013, pp. 1553–1558.

[27] B. Asadi and A. Vahidi, "Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 707–714, May 2011.

[28] H. Xia, K. Boriboonsomsin, and M. Barth, "Dynamic eco-driving for signalized arterial corridors and its indirect network-wide energy/emissions benefits," *J. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 31–41, 2013.

[29] G. De Nunzio, C. Canudas de Wit, P. Moulin, and D. Di Domenico, "Eco-driving in urban traffic networks using traffic signal information," in *Proc. IEEE 52nd Annu. Conf. Decision Control (CDC)*, Dec. 2013, pp. 892–898.

[30] T. Tielert, M. Killat, H. Hartenstein, R. Luz, S. Hausberger, and T. Benz, "The impact of traffic-light-to-vehicle communication on fuel consumption and emissions," in *Proc. Internet Things (IOT)*, 2010, pp. 1–8.

[31] Y. Zhao, A. Wagh, Y. Hou, K. Hulme, C. Qiao, and A. W. Sadek, "Integrated traffic-driving-networking simulator for the design of connected vehicle applications: Eco-signal case study," *J. Intell. Transp. Syst.*, vol. 20, no. 1, pp. 75–87, 2014.

[32] M. Haberl and M. Fellendorf, "Eco-driven signal control and eco-driving of hybrid city buses," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2015, pp. 779–784.

[33] S. Matsumoto, T. Park, and H. Kawashima, "A comparative study on fuel consumption reduction effects of eco-driving instructions strategies," *Int. J. Intell. Transp. Syst. Res.*, vol. 12, no. 1, pp. 1–8, 2013.

[34] X. Haitao, W. Guoyuan, K. Boriboonsomsin, and M. J. Barth, "Development and evaluation of an enhanced eco-approach traffic signal application for Connected Vehicles," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2013, pp. 296–301.

[35] K. Dresner and P. Stone, "A multiagent approach to autonomous intersection management," *J. Artif. Intell. Res.*, vol. 31, no. 1, pp. 591–656, 2008.

[36] M. Ferreira, R. Fernandes, H. Conceição, W. Viriyasitavat, and O. K. Tonguz, "Self-organized traffic control," in *Proc. 7th ACM Int. Workshop Veh. InterNETworking*, 2010, pp. 85–90.

[37] Q. He, K. L. Head, and J. Ding, "Multi-modal traffic signal control with priority, signal actuation and coordination," *Transp. Res. C, Emerg. Technol.*, vol. 46, pp. 65–82, Sep. 2014.

[38] Q. He, K. L. Head, and J. Ding, "PAMSCOD: Platoon-based arterial multi-modal signal control with online data," *Transp. Res. C, Emerg. Technol.*, vol. 20, no. 1, pp. 164–184, 2012.

[39] E. Christofa, I. Papamichail, and A. Skabardonis, "Person-based traffic responsive signal control optimization," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 1278–1289, Sep. 2013.

[40] W. Ma, Y. Liu, and X. Yang, "A dynamic programming approach for optimal signal priority control upon multiple high-frequency bus requests," *J. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 282–293, 2013.

[41] B. Cesme and P. G. Furth, "Self-organizing traffic signals using secondary extension and dynamic coordination," *Transp. Res. C, Emerg. Technol.*, vol. 48, pp. 1–15, Nov. 2014.

[42] R. A. Uzcategui, A. J. D. Sucre, and G. Acosta-Marum, "Wave: A tutorial," *IEEE Commun. Mag.*, vol. 47, no. 5, pp. 126–133, May 2009.

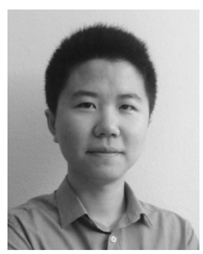
[43] A. Brooker, J. Gonder, L. Wang, E. Wood, S. Lopp, and L. Ramroth, "FASTSim: A model to estimate vehicle efficiency, cost and performance," SAE Tech. Paper 0148-7191, 2015.

[44] X.-F. Xie, S. F. Smith, L. Lu, and G. J. Barlow, "Schedule-driven intersection control," *Transp. Res. C, Emerg. Technol.*, vol. 24, pp. 168–189, Oct. 2012.

[45] A. Vahidi and A. Eskandarian, "Research advances in intelligent collision avoidance and adaptive cruise control," *IEEE Trans. Intell. Transp. Syst.*, vol. 4, no. 3, pp. 143–153, Sep. 2003.

[46] T. Stephens, A. Birky, and J. Ward, "Vehicle technologies program government performance and results Act (GPRA) report for fiscal year 2015," Argonne Nat. Lab. (ANL), Lemont, IL, USA, Tech. Rep. ANL/ESD-14/3, 2014.

[47] "Traffic signal timing mannual," Fed. Highway Admin., Washingtion, DC, USA, Tech. Rep. FHWA-HOP-08-024, 2008. [Online]. Available: https://ops.fhwa.dot.gov/publications/fhwahop08024/chapter4.htm#4.2



Yunfei Hou (M'10) received the Ph.D. degree in computer science from the University at Buffalo, The State University of New York, Buffalo, NY, USA, in 2016. He is currently an Assistant Professor with the School of Computer Science and Engineering, California State University, San Bernardino, CA, USA. His current research interests include applications in transportation cyber-physical systems and data and information analysis for transportation engineering.

Salaheldeen M. S. Seliman is currently pursuing the Ph.D. degree with the Department of Civil, Structural and Environmental Engineering, University at Buffalo, The State University of New York, Buffalo, NY, USA. His research interests include traffic flow modeling and control with connected and automated vehicles.

Enshu Wang is currently pursuing the Ph.D. degree in computer science and engineering with the University at Buffalo, The State University of New York, Buffalo, NY, USA. His research interests include data mining and vehicular cyber-physical systems.

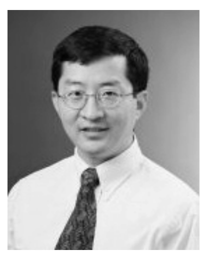
Jeffrey D. Gonder received the B.S. degree in mechanical engineering from the University of Colorado and the M.S. degree in mechanical engineering from Penn State University. He joined the National Renewable Energy Laboratory (NREL) in 2005, where he has led both simulation and hardware testing projects to study energy consumption from conventional, hybrid, plug-in, and fuel cell vehicles and the influence of driving behavior, optimal vehicle design and control, and connectivity/automation technologies on fuel efficiency. His team conducts research on advanced vehicles, alternative fueling infrastructure, and evolving mobility systems and focuses on transportation-relevant "big data" both in the support of NREL research and by hosting data resources for external researcher access.

Eric Wood is currently a Research Engineer with NREL, Golden, CO, USA. He is with the NREL's Transportation and Hydrogen Systems Center, where he focuses on integrating real-world travel data into the analysis of vehicle, infrastructure, and energy storage systems. Interfacing closely with the NREL's Transportation Secure Data Center, he employs quality control, statistical analysis, and data visualization to turn "big data" into quantifiable trends and actionable analysis.

Qing He (S'10–M'13) received the B.S. and M.S. degrees in electrical engineering from Southwest Jiaotong University in 2003 and 2006, respectively, and the Ph.D. degree in systems and industrial engineering from The University of Arizona in 2010. From 2010 to 2012, he was a Post-Doctoral Researcher with the IBM's T. J. Watson Research Center. He has been the Stephen Still Assistant Professor in transportation engineering and logistics with the Civil Engineering and Industrial Engineering Departments, University at Buffalo, The State University of New York, since 2012. His research interests include traffic signal control and freeway operations, railway predictive maintenance for both rolling stock failure and track deterioration, transportation data analytics, and supply chain management and logistics. He is a member of the Transportation Research Board Standing Committee in both Freeway Operations and Traffic Signal Systems. He received the IBM Faculty Partnership Award in 2012 and 2014, respectively.

Adel W. Sadek was an Associate Professor with the School of Engineering, The University of Vermont, where he held a secondary appointment with the Department of Computer Science. He is currently a Professor of civil, structural and environmental engineering with the University at Buffalo. He is also the Director of the University at Buffalo's Institute for Sustainable Transportation and Logistics, the Director of the Transportation Informatics Tier I University Transportation Center, and the Chair of UB2020's Strategic Strength in Extreme Events. He was a recipient of the National Science Foundation CAREER Award and the 2011 IBM Smarter Planet Faculty Innovation Award.

Lu Su (M'08) received the M.S. degree in statistics and the Ph.D. degree in computer science from the University of Illinois at Urbana–Champaign, Champaign, IL, USA, in 2012 and 2013, respectively. He was with the IBM T. J. Watson Research Center and the National Center for Supercomputing Applications. He is currently an Assistant Professor with the Department of Computer Science and Engineering, University at Buffalo, The State University of New York, Buffalo, NY, USA. His research interests include cyber-physical systems, wireless and sensor networks, and mobile computing.



Chunming Qiao (F'10) is currently the Director of the Laboratory for Advanced Network Design, Analysis, and Research, University at Buffalo. He has pioneered research on optical Internet and in particular, optical burst switching. He was the Chair of the IEEE Technical Committee on High Speed Networks and the IEEE Subcommittee on Integrated Fiber and Wireless Technologies, which he founded. He was elected an IEEE Fellow for his contributions to optical and wireless network architectures and protocols.