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Vehicle-to-infrastructure communication-based adaptive traffic signal control

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Abstract: This study presents a method that combines travel-time estimation and adaptive traffic signal control. The proposed method explores the concept of vehicle-to-infrastructure communication, through which real-time vehicle localisation data become available to traffic controllers. This provides opportunity to frequently sample vehicle location and speed for online travel-time estimation. The control objective is to minimise travel time for vehicles in the system. The proposed method is based on approximate dynamic programming, which allows the controller to learn from its own performance progressively. The authors use micro-traffic simulation to evaluate the control performance against benchmark control methods in an idealistic environment, where errors in sampling vehicle location and speed are not considered. The results show that the proposed method outperforms benchmarking methods substantially and consistently.

1 Introduction

Vehicle-to-infrastructure (V2I) communication is an emerging technological framework that aims for direct data transmission between vehicles and road infrastructure using wireless technology. Data from vehicles may include speed, position, destination and occupancy; data from the infrastructure may encompass congestion, surrounding road conditions, controller status and routing information. The availability of real-time vehicle data with greater detail and accuracy offers new approaches for traffic signal control at intersections. Substantial improvement was seen in several real-world pilot projects. Notable examples include Audi [1] and BMW [2].

This paper explores the concept of using V2I data for travel-time estimation at individual intersections, and proposes a 'vehicle-to-infrastructure communication-based adaptive control' (VICAC) method. The V2I communication assumes the dedicated short-range communication (DSRC) [3] protocol, operating at 5.9 GHz band. The VICAC method aims to minimise vehicle travel time through the controlled intersection. The control algorithm is based on approximate dynamic programming (ADP) [4]. The scopes of this paper are to present a method for travel-time estimation using V2I, and incorporate the estimated travel time to the control algorithm. Performance of the VICAC is analysed in idealised environment, where vehicle behaviour is well defined and modelled using micro-simulation, and errors in sampling vehicle data, including position and speed, are not considered. Impact of probe vehicle localisation data error on traffic signal control is studied in [5, 6]. Both found that data error can affect control performance significantly.

The rest of this paper is organised as follows. A literature review is provided in Section 2. Notations and definitions are introduced in Section 3. Travel-time approximation using V2I data is discussed in Section 4. The problem formulation using ADP is presented in Section 5. Numerical experiments using micro-simulation are presented in Section 6, with conclusions of this paper in Section 7.

2 Literature review

Adaptive traffic control systems, in contrast to fixed-time system, change signal indication at intersections according to real-time traffic. Inductive loop detector is the most common device for measuring real-time traffic. Depending on the configuration of loops, the control system can measure traffic volume, speed, degree of saturation and end-of-queue. Such adaptive systems, including Sydney coordinated adaptive traffic system (SCATS) [7], split cycle and offset optimisation tool (SCOOT) [8], optimised policies for adaptive control (OPAC) [9], PRODYN [10], urban traffic opimisation by integrated automation (UTOPIA) [11] and microprocessor optimised vehicle actuation (MOVA) [12], reported gains of 8–20% in performance against optimised fixed-time system or vehicle actuated system in various experiments and field tests [13–15]. ADP for adaptive traffic signal control was investigated by Cai *et al.*, Cai and Le and Li *et al.* [16–18], with significant gains in performance from benchmark adaptive systems.

In contrast to the fixed location loop detectors, vehicle with V2I communication capability and under DSRC protocol can continuously broadcast its location and speed to traffic controller up to 1000 m from the stopline. This provides scope for enhancing observability of real-time traffic. A few research works were seen on developing advanced control algorithm using V2I facilities. In [19], a decentralised system of adaptive traffic signal controller with V2I communication data is described. To reduce the total queue length, the method optimises the traffic control strategy through dynamic programming with rolling horizon. Reductions up to 24% in delay and increase by 5% in mean speed are reported. An intelligent system of traffic management based on V2I communication is presented in [20]. In this work, for improving traffic flow and avoiding vehicle collision, a fuzzy-based control algorithm considering vehicle gap and speed adjustment is used for traffic management. In [21], ADP with temporal difference learning [22] is studied together with V2I communication for intersection control. The study focuses on comparing temporal difference learning trained neural networks with human trained neural networks in control performance.

With DSRC connectivity among road vehicles, another way to control traffic at intersections is to allow vehicles to organise their right-of-way cooperatively. A self-organised traffic control system using virtual signs in vehicle instead of roadside infrastructure is presented in [23], with up to 60% increase in flow rate. A cooperative traffic control method is presented in [24], where inter-vehicle and vehicle-to-roadside communications enabled by DSRC form *ad hoc* networking and computing grid. The cooperative system schedules the sequence of lane merging at the merge point. A recent study on cooperative control system for traffic intersections was presented [25]. A more general vehicle control algorithm for cooperative driving is studied in [26].

Although using vehicle localisation data for traffic signal control is an emerging technology, using such data for online travel-time estimation has been vigorously studied. The state-of-the-art in travel-time estimation of this sort is to use probe vehicles with mobile communication and global positioning system [27–30]. An extensive field evaluation of temporal–spatial data from mobile phones for travel-time estimation is presented in [31], where time-stamped geo-position data are sampled at the frequency of every 3 s, and instantaneous velocity data are produced at the same frequency. This resolution of data together with 2–3% penetration of dedicated mobile phones in driver population proves adequate for real-time traffic monitoring. However, for distributed roadside controller, a higher frequency in data sampling and higher degree of stability in data transmission is required; hence the development of DSRC channel.

The reviewed research works showed that adaptive traffic signal control systems are superior in performance against fixed-time or vehicle actuated systems, and further development on adaptive control algorithms, ADP in particular, provides additional gains in performance. On the other hand, the advent of V2I communication and availability of real-time vehicle localisation data provide scopes for enhancing observability of traffic. These scopes have been explored for higher accuracy of travel-time estimation, and are currently being investigated for traffic signal control. The research work presented in this paper will bridge the development on both sides, and propose an adaptive control algorithm based on ADP, with estimated travel time as performance measurement.

3 Notations and definitions

We define the following terms to facilitate further discussion:

Definition 1: The 'travel time', τ, for a vehicle is the time it takes to travel from entry position until it leaves the control system.

Definition 2: The 'position', d, of a vehicle is the distance from its current location to the stopline measured along the lane in which it is travelling.

Definition 3: The 'waiting time', r, of a vehicle is the accumulated time at standstill.

Definition 4: The 'vehicle state', $\boldsymbol{z}$, is a two-dimensional (2D) vector with components speed and position.

Definition 5: The 'traffic state', $\boldsymbol{q}$, consists of the vehicle states of all vehicles in the system.

Definition 6: The 'controller state', $\boldsymbol{s}$, is vector of binary entries, indicating whether the signal is green (0) or red (1) for each approaching lane.

Definition 7: The 'system state', $\boldsymbol{x}$, consists of the traffic state and controller state.

Other notations used in this paper include:

$\boldsymbol{u}$ action vector; v vehicle cruising speed; α discount factor; δ remaining travel time; λ probability threshold; μ_r average waiting time; $J(\boldsymbol{x})$ true value function associated with state $\boldsymbol{x}$; $\tilde{J}(\cdot)$ approximation to $J(\boldsymbol{x})$; $g(\cdot)$ immediate cost function.

4 Travel-time approximation

In this section, we discuss the approximation of travel time for detected vehicles. For a vehicle approaching to the stopline at a traffic intersection, the remaining travel time can be predicted using

$$\delta = \frac{d}{\bar{v}} + \bar{r} \tag{1}$$

where d is the distance to stopline at the instant of data transmission, the mean value of v is taken over vehicles that have completed their trip through the system in the last 5 min, and the expected waiting time $\bar{r}$ (ignoring lost green time) is given by

$$\bar{r} = E[r] \simeq p\left(s^+ = 1|s\right)\mu_\mathrm{r} \tag{2}$$

where s is the traffic signal (0 for green and 1 for red or inter-green) at the current time, s^+ is the traffic signal when the vehicle arrives at stopline and μ_r is the average waiting time occurred during red or inter-green period in the last 5 min. The sampling frequency for the approaching vehicles is every 0.2 s. Without constraints on minimum/maximum red/green time, the transition probability is approximated by

$$p\left(s^+ = 1|s\right) = \begin{cases} \lambda & \text{if } \dfrac{d}{\bar{v}} \geq T_h \\ \alpha_1 \dfrac{d}{\bar{v}} & \text{if } \dfrac{d}{\bar{v}} \leq T_h \text{ and } s = 0 \\ 1 - \alpha_2 \dfrac{d}{\bar{v}} & \text{if } \dfrac{d}{\bar{v}} \leq T_h \text{ and } s = 1 \end{cases} \tag{3}$$

where T_h is the threshold ($T_h = 40$ s in this work) on remaining travel time beyond which the current state becomes irrelevant to the expectation of s^+. According to (3), as vehicles move closer to the stopline, the probability

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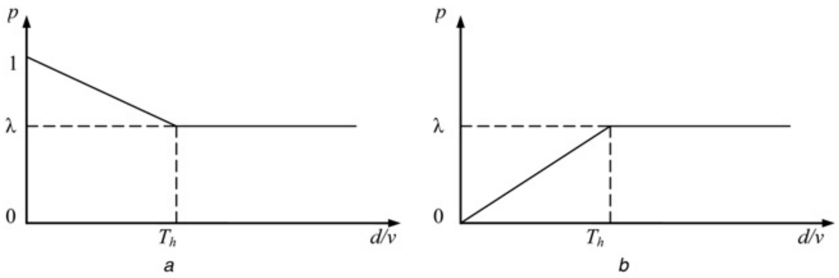

Fig. 1 *Probability distribution of traffic signal transition, d is the vehicle distance to downstream stopline, v is the speed of the vehicle and T_h is the threshold on remaining travel time*

a $p(s^+ = 1 \mid s = 1)$
b $p(s^+ = 1 \mid s = 0)$

of signal remaining unchanged increases asymptotically to 1. The probability distribution of (3) is shown in Fig. 1.

If inter-green time is considered, $\lambda > 0.5$ is the usual case. Since $p(s^+ = 1|s) = \lambda$ when $d/\bar{v} = T_h$, it can be shown that $\alpha_1 = \lambda/T_h$ and $\alpha_2 = (1 - \lambda)/T_h$. Thus

$$\bar{r} = \begin{cases} \lambda\mu_r & \text{if } \dfrac{d}{\bar{v}} \geq T_h \\ \dfrac{\lambda d}{\bar{v}T_h}\mu_r & \text{if } \dfrac{d}{\bar{v}} \leq T_h \text{ and } s = 0 \\ \dfrac{\bar{v}T_h - (1-\lambda)d}{\bar{v}T_h}\mu_r & \text{if } \dfrac{d}{\bar{v}} \leq T_h \text{ and } s = 1 \end{cases}$$

$$= \begin{cases} \lambda\mu_r & \text{if } \dfrac{d}{\bar{v}} \geq T_h \\ \left(\dfrac{\bar{v}T_h - d}{\bar{v}T_h}s + \dfrac{\lambda d}{\bar{v}T_h}\right)\mu_r & \text{if } \dfrac{d}{\bar{v}} \leq T_h \end{cases}$$

The algorithm for obtaining $\bar{v}$ and $\bar{r}$ can be summarised as follows (the sampling window is 5 min):

1. 'Input': μ_r, $\bar{v}$ obtained from previous cycles;
2. Obtain $\{v_1, v_2, \ldots, v_n\}$ for the last 5 min, and calculate the average $v' = (1/n)\sum_i v_i$;
3. For $\{r_i/r_i > 0\}$, calculate average r'; and
4. Update μ_r, $\bar{v}$ using

$$\bar{v} = (1-\rho)\bar{v} + \rho v', \quad \mu_r = (1-\rho)\mu_r + \rho r' \tag{4}$$

where learning rate $\rho = 0.1$ in this work.

5 ADP method

In this section, we discuss the formulation of the problem using state-space presentation and the ADP [4] method to solve the problem for real-time control. Using state-space representation, and according to the definitions in Section 3, the state of the system can be expressed as $\boldsymbol{x}_t = \{\boldsymbol{q}_t, \boldsymbol{s}_t\}$, where

$$\boldsymbol{q}_t = \begin{bmatrix} z_t(1) \\ \vdots \\ z_t(N) \end{bmatrix}, \quad \boldsymbol{s}_t = \begin{bmatrix} s_t(1) \\ \vdots \\ s_t(N) \end{bmatrix}$$

and N is the total number of vehicles in the system. The vehicle state, z, can be expressed as

$$z_t(n) = \begin{bmatrix} v_t \\ d_t \end{bmatrix} \text{ for } n = 1, 2, \ldots, N$$

where v is the speed of vehicle and d the distance to stopline.

The controller state, s, is binary, where

$$s(n) = \begin{cases} 0 & \text{if signal is green for vehicle } n \\ 1 & \text{if signal is red for vehicle } n \end{cases}$$

For a control problem thus defined, the DP [32] method decomposes the problem into stages. Each stage corresponds to successive discrete-time epoch on the time series. The time series and stage definition can be shown as Fig. 2.

In each stage, the DP algorithm evaluates decisions $\boldsymbol{u}_t \in U$, and impletes the optimal decision $\boldsymbol{u}_t^*$. With exogenous information process $\{\boldsymbol{w}_0, \boldsymbol{w}_1, \ldots, \boldsymbol{w}_t\}$ and decision $\boldsymbol{u}_t^*$, the system is transferred from state $\boldsymbol{x}_t$ to $\boldsymbol{x}_{t+1}$. This control process can be expressed as

$$\mathfrak{F} = \{\boldsymbol{x}_0, \boldsymbol{u}_0^*, \boldsymbol{w}_0, \boldsymbol{x}_1, \boldsymbol{u}_1^*, \boldsymbol{w}_1, \ldots, \boldsymbol{x}_{m-1}, \boldsymbol{u}_{m-1}^*, \boldsymbol{w}_{m-1}, \boldsymbol{x}_m\}$$

Given the initial state $\boldsymbol{x}_0$ and a sequence of decisions $\boldsymbol{u}_t$ at discrete time t, the DP algorithm is to solve

$$\min_{\boldsymbol{u}_t \in U} \underset{W}{E}\left\{\sum_{t=0}^{m-1} \alpha^t g(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}) | \boldsymbol{x}_0 = \boldsymbol{x}\right\} \tag{5}$$

The algorithm then recursively computes the 'Bellman equation'

$$J(\boldsymbol{x}_t) = \min_{\boldsymbol{u}_t = U} \underset{\boldsymbol{w}_t}{E}\{g(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}) + \alpha J(\boldsymbol{x}_{i+1}|\boldsymbol{x}_t)\}$$
$$\text{for } t = m-1, m-2, \ldots, 0 \tag{6}$$

where decision $\boldsymbol{u}_t$ is selected from a finite set of U at each time step, and the expectation operator is taken in respect to the probability in state transition from $\boldsymbol{x}_t$ to $\boldsymbol{x}_{t+1}$ with decision $\boldsymbol{u}_t$. $J(\boldsymbol{x}_t)$ values are stored in a look-up table, where a $J(.)$ value is associated with every state from t_0 to t_m.

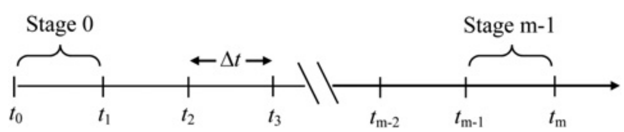

Fig. 2 *Time series and stage definition*

The DP is the only exact solution for the control process described above. However, its application for many real-time control problem is restricted. This is because a problem formulated in the DP usually cannot be solved analytically, and the computational requirement for finding optimal solution numerically is in an exponential order to the size of state space. Additionally, a complete set of information for the whole problem is required. For operations at real time, we usually do not have complete information a priori.

Using approximation techniques can mitigate the difficulties of solving the DP. One of the usual techniques for approximating DP is the function approximation. Using function approximation, we define a continuous function $\tilde{J}(\cdot, \boldsymbol{r}):X \times \mathbb{R}^K \to \mathbb{R}$ to replace the exact $J(\cdot):X \to \mathbb{R}$, where $\boldsymbol{r}$ is a K-dimensional parameter vector of $\tilde{J}$, and X is the state space. By indexing successive states with positive integers, we can view the state space as the set $X = \{1, \ldots, n\}$, where n is possibly infinite. The sequence of states visited by the stochastic process is denoted by $\{\boldsymbol{x}_t | t = 0, 1, \ldots\}$. At each discrete temporal interval t, we calculate

$$\boldsymbol{u}_t^*(\boldsymbol{x}_t) = \arg\min_{u_t \in U} E\{g(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}) + \alpha\tilde{J}(\boldsymbol{x}_{t+1}, \boldsymbol{r}_t)\} \tag{7}$$

and record

$$\hat{J}(\boldsymbol{x}_t) = \min_{u_t \in U} E\{g(\boldsymbol{x}_t, \boldsymbol{x}_{t+1}) + \alpha\tilde{J}(\boldsymbol{x}_{t+1}, \boldsymbol{r}_t)\}$$

In this study, we use (1) as the basis function for constructing $\tilde{J}$, and define the approximation function as

$$\begin{aligned}\tilde{J}(\boldsymbol{x}) &= \sum_{m=1}^{M}\sum_{n=1}^{N} \delta_m(n) \\ &= \sum_{m=1}^{M}\sum_{n=1}^{N} \left(\frac{d_m(n)}{\bar{v}_m} + \bar{r}_m(n)\right)\end{aligned} \tag{8}$$

where m indicates the approach lane and n is the number of vehicles in lane m. The immediate cost function $g(\cdot)$ is defined by

$$g(\boldsymbol{x}, \boldsymbol{u}) = \sum_{m=1}^{M}\sum_{n=1}^{N} \varphi(\boldsymbol{u})\Delta r_m(n) \tag{9}$$

where $\varphi(\boldsymbol{u})$ is a binary variable that takes the value unity if the action is to change signal state and is zero otherwise; $\Delta r_m(n)$ is the additional waiting time induced by the action. In our case, $\Delta r_m(n)$ is the inter-green time enforced during the process of changing signal state.

Using (7), we circumvent the difficulty associated with the high dimensionality in state space. This is because (6) requires a look-up table of $J(\cdot)$ for all $\boldsymbol{x} \in X$. Consequently, the size of the look-up table and the computational demand required to update the look-up table make solving the problem at real-time impossible. Using (7), we reduce the size of the look-up table to a degree linear to the number of approaching lanes, as we only record $\bar{v}$ and $\bar{r}$ for each approaching lane. The general approach of using an approximation function to replace the exact function in DP is referred to as ADP.

The control algorithm for the VICAC can be summarised as

Step 0: Initialisation
0.1. Choose an initial system state $\boldsymbol{x}_0$;
0.2. Initialise $\bar{v}$ and $\bar{r}$; and
0.3. Set time index $t = 0$.
Step 1: Receiving new information
1.1. Set time index $t = t + 1$ and
1.2. Receive V2I information $\boldsymbol{z}_t$.
Step 2: Evaluate control action
2.1. If changing traffic signal is not permissible, that is, within minimum green interval or all red interval, set $\boldsymbol{u}_t^* = 0$ and
2.2. If changing traffic signal is permissible, obtain $\boldsymbol{u}_t^*$ using (5).
Step 3: Update $\bar{v}$ and $\bar{r}$, if applicable
3.1 Update $\bar{v}$ and $\bar{r}$ using (4) at the end of a 5-min interval;
Step 4: Implement the optimal control action $\boldsymbol{u}_t^*$.
Step 5: Stopping criteria.
5.1 If $t < T$, go back to Step 1; otherwise, terminate the programme.

6 Numerical experiment

The numerical experiments in this study consists of two parts. The first part sets a single intersection with straightforward movement, whereas the second part builds on a two-intersection traffic network with turn movements and vehicle platooning.

6.1 Single intersection

6.1.1 Experiment design: Numerical experiments are carried out using a single traffic intersection modelled in Commuter 2.0 [©2010 Azalient, http://www.azalient.com/]. Commuter™ is a microscopic traffic simulation tool. The simulator incorporates Gipps [33], Fritzsche [34] and Wiedemann [35] models as optional methods for the underlying behavioural principle. On top of this, the simulator adds further behavioural terms including the rate of compliance, lane gap, visibility etc. Vehicle behaviour is bonded by the physical limits, including engine specifications, brakes, dimensions etc. This allows us to explore vehicular information that would be available with V2I communication. The important parameter settings for the simulation are presented in Appendix.

A specific controller plug-in was developed for Commuter™ 2.0 in order to control traffic signals. The geometric layout of the intersection is shown in Fig. 3. We assume that the V2I facilities are able to send and receive data from any vehicle within a 500-m radius of the centre of the junction. This communication range is justified based on the notional 1 km range touted for 802.11p [36] at 5.9 GHz. Assuming vehicles in average occupy 5 m of linear road-space on a single lane, we have an upper limit of approximately 80 vehicles per lane. Vehicular data include speed, position, accumulated travel time and accumulated waiting time.

At this preliminary stage, we only model straight movements at the intersection. Consequently, the controller has two signal phases: Phase *A* for westbound and eastbound traffic and Phase *B* for northbound and southbound traffics. Each lane approaching the intersection is 380 m long and 3 m wide with an enforced speed limit of 50 km/h. The saturation departure rate per lane is 1440 v/h. Vehicle information is assumed to be available from the entrance of each approaching lane.

Vehicles introduced into the simulation are of a single type defined as a car of dimension 4.0 × 2.0 × 1.5 (length/width/

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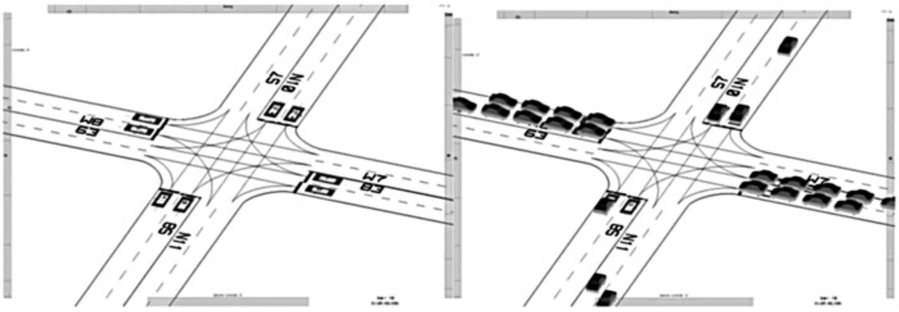

a b

Fig. 3 *Layout of the test-bed intersection in Commuter 2.0 (colour inverted)*
a Without traffic
b With traffic

height in metres) and a mass of 1000 kg. Two scenarios of traffic demand, one at moderate level and one at high level, are generated to facilitate investigation of control performance. The traffic demand scenarios are summarised in Table 1.

6.1.2 Benchmarking control methods: The benchmarking control methods are the optimised fixed-time method and the basis policy. The optimised fixed-time traffic signal timings computed using the Webster's [37] method are presented in Table 2.

The basis policy is derived from exploiting the apparent optimality of the saturation flow algorithm [38], in which the signals change only when the favoured queue is exhausted. In the further study [39], DP was used to show that there were domains in the state space where the basis policy was optimal in controlling traffic signals. Recent studies in adaptive traffic signal control using ADP suggest that using information derived from the arriving traffic as an extra dimension of state space improves the performance of the basis policy. In this study, the detected vehicle headway is used as an indicator of the arriving traffic. The control policy can be summarised as follows:

Decision (a): signals are switched if all the following conditions are satisfied: (i) the favoured queues are exhausted, (ii) vehicle headways of the concerned approaches exceed a critical value and (iii) the minimum green is exhausted. Decision (a) is overridden if decision (b) is applicable.

Decision (b): signals are switched if the maximum red is exhausted or if the maximum cycle time is exhausted.

The critical values for vehicle headway are set at 3.0 s for the 'moderate' demand and 5.0 s for the 'high' demand. The principal assumption regarding the basis policy is that the queue length is known at any time during the control process, which is usually not realistic at real time. Including this policy in the study is to provide a comparison with the VICAC control process that is near optimal in the domain where the state-space representation is queue-based.

6.1.3 Results: For each traffic demand scenario, we provide two vehicle arrival profiles: one profile with uniform arrival rate, and the other with varying arrival rate. The arrival profile for the varying arrival rate is shown in Table 3. Vehicles in simulation are released from origin following the Poisson distribution. Each run simulates the morning peak from 07:59 to 09:29, with the first trip taking place at 08:00 and the last at 09:00. This allows all trips to complete at the end of each simulation run. After each run, we record the total travel time and the total number of stops incurred.

For better understanding result comparison, it is important to note that the percentage reduction in travel time cannot be interpreted directly as reductions in delays of the same magnitude. This is because the denominators in the two cases are different (total travel time and total delay, respectively), and total delay is only part of the total travel

Table 1 Traffic demand scenarios moderate (high), in v/h

	Origins of traffic				Sum
	West	East	South	North	
west		600(600)			600(600)
east	600(600)				600(600)
south				200(600)	200(600)
north			300(600)		300(600)
sum	600(600)	600(600)	300(600)	200(600)	1700(2400)

Table 3 Profile of varying arrival rate in 1-h traffic simulation

Time interval, mm–mm	00–15	15–30	30–45	45–60
% Of total demand, %	17.2	39.9	17.2	25.6

Table 2 Optimised fixed-time signal timings for respective demand traffic scenarios, using Webster's in method

Scenario	Phase	Demand, v/h	Intensity	Lost time, s	Cycle time, s	Green ratio	Green time, s	Saturation
moderate	*A*	600	0.416667	4	46	0.54902	25	0.758929
	B	300	0.208333	4		0.27451	13	0.758929
high	*A*	600	0.416667	4	102	0.460784	47	0.904255
	B	600	0.416667	4		0.460784	47	0.904255

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time. The percentage reduction in travel time should be equivalent to a much larger percentage reduction in delay.

For the moderate demand scenario, the results with uniform arrival rate are shown in Table 4, and the results with varying arrival rate are in Table 5. The results show that with moderate demand, the benefits from using the VICAC controller comes primarily from reduced vehicle stops, as compared against the benchmarking methods. The reductions in vehicle stops are about 21 and 18% as compared with the optimised fixed-time method and the basis policy, respectively, given uniform arrival rate. In the case of varying arrival rate, the corresponding margins reduce to about 16 and 12%, respectively. The differences in total travel time are broadly insignificant with moderate demand. The reduction in vehicle stops and the indifference in total travel time indicate that the VICAC controller generates smoother vehicle trajectories than the benchmarking methods, resulting in better trip quality and fuel efficiency.

Results for the high demand scenario are shown in Table 6. In this case, we only considered the varying traffic demand profile. The results show that in addition to the significant reduction in vehicle stops (14.48 and 10.79% as compared against the optimised fixed time and the basis policy, respectively), the reduction in total travel time is substantial. The VICAC controller saves about 11% total travel time from the optimised fixed-time method and 9% from the

Table 4 Performance comparisons between VICAC and the benchmark methods, moderate traffic with uniform arrivals, average results from batch samples (ten independent runs each batch)

Demand phase *A*/*B* (vehicle/h)	Control methods	Average total travel time, min			Stops		
		Mean	Std.	Margin % by VICAC	Mean	Std.	Margin % by VICAC
moderate 600/300	fixed-time	2087.90	6.87	– 1.44	947.30	17.95	– 21.14
	basis policy	2072.70	17.22	– 0.71	913.70	27.56	– 18.25
	VICAC	2057.90	10.26	0.00	747.00	14.76	0.00

Table 5 Performance comparisons between VICAC and the benchmark methods, moderate traffic demand with varying arrivals, average result from batch samples (ten independent runs each batch)

Demand phase *A*/*B* (vehicle/h)	Control methods	Average total travel time, min			Stops		
		Mean	Std.	Margin % by VICAC	Mean	Std.	Margin % by VICAC
moderate 600/300	fixed-time	2188.60	8.92	– 0.40	992	33.53	– 16.64
	basis policy	2091.00	9.35	0.91	945.30	15.38	– 12.53
	VICAC	2110.10	24.23	0.00	826.90	35.44	0.00

Table 6 Performance comparisons between VICAC and the benchmark methods, high traffic demand with varying arrivals, average result from batch samples (ten independent runs each batch)

Demand [hase *A*/*B* (vehicle/h)	Control methods	Average total travel time, min			Stops		
		Mean	Std.	Margin % by VICAC	Mean	Std.	Margin % by VICAC
high 600/600	fixed-time	3504.00	23.88	– 11.13	1575	23.01	– 14.48
	basis policy	3421.70	19.23	– 9.00	1510	29.45	– 10.79
	VICAC	3114.00	28.83	0.00	1347	49.39	– 0.00

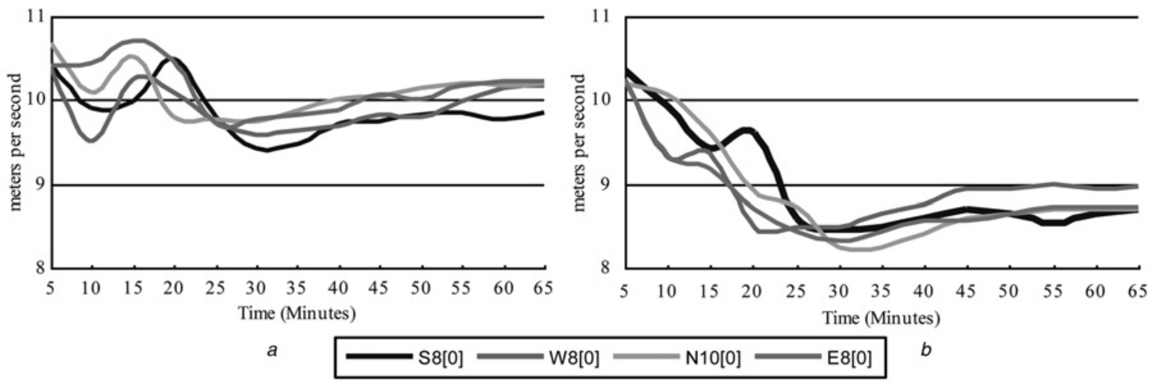

Fig. 4 *Average speed on selected approaching lanes in 1-h traffic simulation, varying arrival rate, demand at 600/600 (high)*
a ADP
b Fixed-time.

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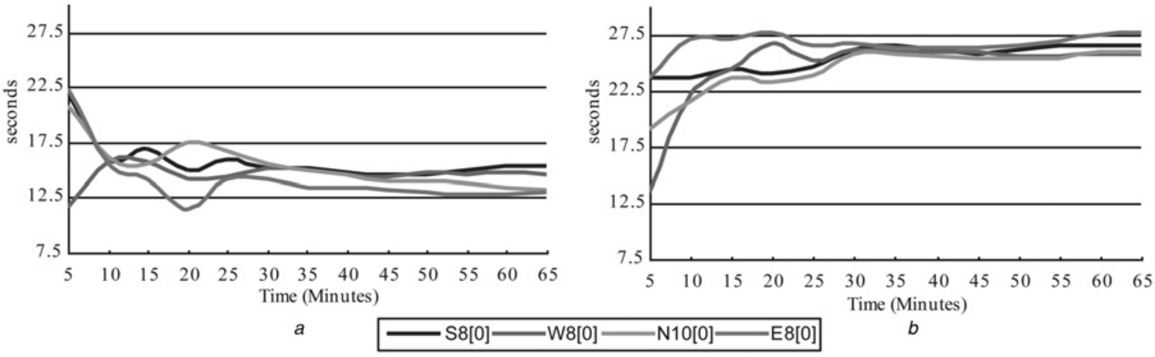

Fig. 5 *Average waiting time on selected approaching lanes in 1-h traffic simulation, varying arrival rate, demand at 600/600 (high)*
a ADP.
b Fixed-time

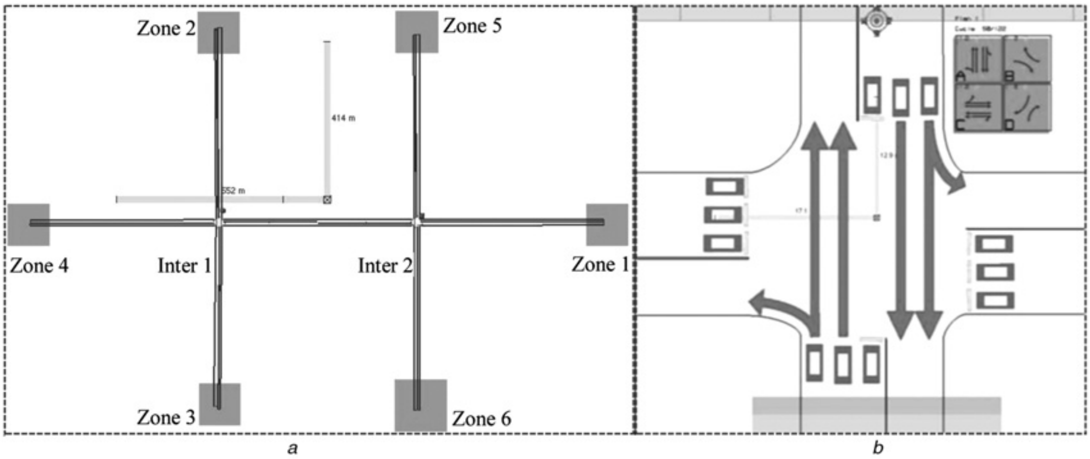

Fig. 6 *Traffic network layout and intersection configuration*
a Two-intersection traffic network
b Intersection with four phases

basis policy. The improved observability on the traffic state powered by the V2I communication is key to this achievement.

To further analyse control performance, we plot the moving average of vehicle speed on the selected approaching lanes in Fig. 4 and the moving average of waiting time in Fig. 5. Vehicle waiting time is defined as the accumulated time in which a vehicle in the system is stopped. Since the simulation is empty at the start and demand is being increased until the 30th minute, the average speed under the optimised fixed-time controller decreased until the end of the high demand period. On the other hand, the average speed under VICAC saw a managed fluctuation in the same period, and established a margin of 1 m/s against the fixed-time method. A similar trend in vehicle waiting time can be seen in Fig. 5.

6.2 Two-intersection traffic network

This traffic network is built on the same simulation environment as the single intersection. The network layout and intersection configuration are shown in Figs. 6*a* and *b*, respectively. Each traffic link in the network is 500 m long, and vehicles are in communication range as they enter into the link. There are six origins/destinations, and the traffic demand matrix between origin and destinations is shown in Table 7. This presents a heavy traffic demand at both intersections. In such a case, dynamic coordination that accommodates vehicle platoons is essential to reduce vehicle delays and stops. Regarding this, we compare performance from VICAC controller against optimised traffic signal plans from TRANSYT 12.0 [40], which optimises cycle time, green splits and offsets. The TRANSYT signal plans are shown in Table 8.

Performance results from VICAC and TRANSYT are compared in Table 9. Each result is obtained from a 2-h simulation with stochastic arrival at entry links. Once again the VICAC controller attained significant advantage against

Table 7 Traffic demand between origin and destination for the two-intersection traffic network

O/D zones	1	2	3	4	5	6	Sum
1	0	50.00	0	1000	50.00	50	1150
2	50	0	1000	50	0	0	1100
3	50	1000	0	50	0	0	1100
4	1000	50.00	50	0	0.00	50	1150
5	50	0.00	0	50	0.00	1000	1100
6	50	0.00	0	50	1000.00	0	1100
sum	1200	1100	1050	1200	1050	1100	

Table 8 Optimised coordinated fixed-time signal timings from TRANSYT 12.0, inter-green times are included in the lost time

Intersection	Phase	Demand, v/h	Green time, s	Lost time, s	Offset, s	Cycle time, s
1	*A*	525	51	4		122
	B	50	2	4		
	C	525	51	4		
	D	50	2	4		
2	*A*	525	51	4	– 50, (1 A)	122
	B	50	2	4		
	C	525	51	4		
	D	50	2	4		

Table 9 Performance comparisons between VICAC and TRANSYT plan, 2-h simulation, averaged result from batch samples (ten independent runs each batch)

Control methods	Mean travel time, s			Stops		
	Average	Std.	Margin % by VICAC	Average	Std.	Margin % by VICAC
TRANSYT 12.0	127.40	0.52	– 11.69	5428	36.38	– 10.08
VICAC	112.50	0.53	0.00	4842	34.09	0.00

its counterpart, with 11.69% reduction in mean travel time and 10.08% reduction in stops. This experiment demonstrates the ability of VICAC to operate under decentralised network control framework.

7 Conclusions

In this paper, we presented an investigation of using V2I communication technologies to develop an adaptive traffic signal controller, the VICAC. The aim of this study is to combine online travel-time estimation with adaptive control process. The former provides performance measures, and the latter optimises performance. The proposed method is evaluated in an idealistic environment where vehicle behaviour is well defined in the micro-simulation, and errors in sampling vehicle localisation data are not considered. We show in numerical experiments that the proposed VICAC method yields significant gains in travel speed and reduction in vehicle stops from the benchmarking methods, which include optimised fixed-time method and queue-length-based heuristic.

This study, in general, presents an early stage investigation on using V2I communication for active traffic management. The travel-time estimation model is relatively simple and time-invariant as it does not depend on elapsed phase time at intersection. The control algorithm can be further developed to explore and exploit available data, which in return offers a larger action space. This work does not include comparisons with existing adaptive control systems, for reasons that controller personality is difficulty to replicate with published sources and that the scope of this work is to demonstrate the potentials of using V2I for advanced control method. Further investigations, especially field trials, are important to evaluate the proposed method.

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10 Appendix

10.1 Parameters for traffic simulation

The following parameters are used in Commuter™ 2.0 for traffic simulation that produced the results presented in Section 6.

10.1.1 Vehicle dimensions: The dimensions of the standard vehicle are shown in Table 10, which is used in the traffic simulation reported in this study.

10.1.2 Vehicle acceleration profile: Accelerations values are in m/s^2. Typically, the vehicle has its highest acceleration in the lower middle range of its speed. The maximum possible acceleration is higher on downward slope (negative gradient) and slower on upward slope (positive gradient) (see Table 11).

10.1.3 Vehicle braking profile: Braking values are specified in the same way as acceleration, in a matrix of speed by gradient (see Table 12).

10.1.4 Driving behaviours (see Table 13):

• Compliance: A multiplier. This is used for vehicles to specify the 'perceived' speed limit on any road. Multiply the signed speed limit by this parameter to obtain the perceive speed limit that will be used as the maximum speed a vehicle will attain if unconstrained by other vehicles or lane geometry.
• Minimum gap: A time, in seconds. This is used in the vehicle-following algorithms
• Headway: a distance, in metres, used to specify the minimum spacing between stationary vehicles in congestion.
• Reaction time: A time, in seconds, used in the vehicle-following algorithms.
• Safety margin: Used to calculate stopping distance: the absolute minimum stopping distance derived from current

Table 10 Vehicle dimensions

Length, m	Width, m	Height, m	Weight, kg	Size variation	Displacement, l
4.00	2.00	1.50	1000.00	0.00	1.4–2.0

Table 11 Vehicle acceleration values (m/s^2)

Gradients/speed, %	0	10	20	30	40	50	60	70	80	90	100	110	120	130
– 20	2.21	2.68	3.09	3.44	3.74	3.99	4.18	4.31	4.40	4.42	4.38	4.26	4.06	3.77
– 15	1.98	2.39	2.76	3.08	3.34	3.56	3.74	3.86	3.93	3.96	3.92	3.81	3.63	3.37
– 10	1.74	2.10	2.42	2.70	2.94	3.13	3.28	3.39	3.45	3.48	3.44	3.35	3.19	2.96
– 5	1.49	1.81	2.09	2.33	2.53	2.69	2.82	2.92	2.97	2.99	2.96	2.88	2.74	2.55
0	1.25	1.51	1.74	1.94	2.11	2.25	2.36	2.44	2.48	2.50	2.48	2.41	2.29	2.13
5	1.01	1.22	1.40	1.56	1.70	1.81	1.90	1.96	2.00	2.01	1.99	1.94	1.84	1.71
10	0.76	0.92	1.06	1.19	1.29	1.37	1.44	1.49	1.51	1.52	1.51	1.47	1.40	1.30
15	0.52	0.63	0.73	0.81	0.88	0.94	0.99	1.02	1.04	1.04	1.04	1.01	0.96	0.89
20	0.29	0.35	0.40	0.45	0.49	0.52	0.54	0.56	0.57	0.58	0.57	0.55	0.53	0.49

Table 12 Vehicle braking values (m/s^2)

Gradients/speed, %	0	10	20	30	40	50	60	70	80	90	100	110	120	130
− 20	2.57	2.57	2.56	2.54	2.53	2.50	2.48	2.45	2.42	2.38	2.34	2.29	2.24	2.58
− 15	3.04	3.04	3.02	3.01	2.99	2.96	2.93	2.89	2.85	2.81	2.76	2.71	2.65	3.04
− 10	3.52	3.51	3.50	3.48	3.46	3.43	3.39	3.35	3.30	3.25	3.19	3.13	3.06	3.52
− 5	4.01	4.00	3.98	3.96	3.93	3.90	3.86	3.81	3.76	3.70	3.64	3.56	3.49	4.01
0	4.50	4.49	4.47	4.44	4.41	4.38	4.33	4.28	4.22	4.15	4.08	4.00	3.91	4.50
5	4.99	4.97	4.96	4.93	4.89	4.85	4.80	4.74	4.68	4.60	4.52	4.44	4.34	4.99
10	5.47	5.46	5.44	5.41	5.37	5.32	5.27	5.21	5.13	5.05	4.96	4.87	4.76	5.48
15	5.95	5.94	5.91	5.88	5.84	5.79	5.73	5.66	5.58	5.50	5.40	5.29	5.18	5.96
20	6.42	6.40	6.38	6.34	6.30	6.25	6.18	6.11	6.02	5.93	5.82	5.71	5.59	6.42

Table 13 Driving behaviours

Compliance	Minimum gap, s	Headway, m	Reaction time, s	Safety margin	Lane gap, s
1.00	1.00	0.90	1.10	1.50	2.00

speed and (constant) maximum deceleration is multiplied by this safety margin.

- Lane gap: A time, in seconds, used for the lane-changing algorithm.

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