Research Article

A Person-Based Adaptive Traffic Signal Control Method with Cooperative Transit Signal Priority

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Real-time traffic signal control has long been a critical way to improve traffic congestion. Transit Signal Priority (TSP) is seen as a cost-effective way to reduce travel time variability. Most of the previous studies develop real-time signal control systems on a vehicle basis, which is unable to efficiently provide preferential treatment on transit vehicles. Person-based signal control systems, which transform traffic delay computation units from vehicle to passenger, have been proposed to try to address this limitation. However, their models, optimizing signal plan cycle-by-cycle, cannot rapidly respond to traffic variations. This study proposes a Person-based Adaptive traffic signal control method with Cooperative Transit signal priority (PACT). In PACT, not only do Road-Side Units (RSUs) perform signal optimization, but also On-Board Units (OBUs) provide in-vehicle speed advisory to reduce delays. The interaction between RSU and OBU is conducted second-by-second, which has high adaptability to traffic variations. Experiments are performed based on real traffic data via traffic simulation platform SUMO. The results indicate that PACT can efficiently reduce delays of both bus passengers and auto passengers at a signalized intersection. Compared to preoptimized signal plans, the results show that each passenger on transit vehicles experiences 33%–70% decreases in delays, and each auto passenger experiences 3%–29% decreases in delays. PACT can reduce 80%–98% in delays when the occupancy weight factor is relatively large, showing the potential of extending PACT on performing signal preemption.

1. Introduction

With the growth of the city, traffic congestion has become a serious problem since it causes high air pollution and fuel consumption. One of the solutions to such a problem is to enhance the mobility of the transportation system. In urban transportation networks, traffic signal control plays a significant role in the efficiency of urban mobility. Adaptive traffic signal control (ATSC) systems can rapidly adjust signal settings in response to dynamic changes in traffic flow. In the past several decades, abundant studies of ATSC, such as SCAT [1], SCOOT [2], OPAC [3], PRODYN [4], and RHODES [5], have been proposed. In order to optimize signal settings, ATSC strategies need to predict traffic conditions based on traffic data collected from vehicle detection techniques. The quality and dimensions of traffic data significantly affect the performance of ATSC systems [6]. Most of the ATSC systems [1–5] are developed based on fixed-point detectors (e.g., loop detectors), which provide limited dimensions of traffic information. The high cost of such detectors on deployment, maintenance, and operation when collecting data on a large scale weakens the signal control accuracy [7].

More recently, the emergence of Connected Vehicle (CV) technology brings new sights of the approaches on traffic signal control. CV technology has shown its great potential for improving signalized intersection efficiency and safety [8–10]. With Vehicle-to-Infrastructure (V2I) communication, real-time states of vehicles such as vehicle type, speed, position, and trajectories can be used to enhance signal control modelling. Conventional loop-detector-based ATSC strategies are unable to deal with such abundant real-time traffic information. Abundant studies have contributed to CV-based real-time signal control [11–14]. However, it is...
expected that the penetration rate of On-Board Unit (OBU) will remain low in the near future due to technological and economic challenges [15]. The requirement of a high penetration rate of OBU limits the applicability of CV-based systems in real life. In recent years, Vision-based Traffic flow Detection (VTD) systems powered by deep learning techniques, such as YOLO [16], can capture all movement (i.e., speed and position) of vehicles with high-resolution cameras [17]. The systems can provide detailed real-time traffic states without requiring a high penetration rate of OBU.

Transit Signal Priority (TSP) is a collection of techniques that provide transit vehicles riding through a signalized intersection smoothly. TSP decreases the travel time variability of buses and enhances operation reliability by adjusting signal settings that favour bus arrivals [18]. However, serving signal priority to buses may deteriorate nonprioritized traffic. To lessen negative impacts, several studies have developed optimization models of TSP under various constraints [19–21]. Though both ATSC and TSP aim to mitigate traffic congestion, there is a conflict between the objectives of ATSC and TSP. The objective of TSP is to minimize bus delays at intersections; however, traditionally, the objective of ATSC is to minimize total vehicle delays. A study has shown that this is a trade-off relationship [22]. In contrast to vehicle-based signal control, which ignores person mobility in the transportation network, a series of studies have proposed a person-based traffic signal control framework [23–28]. The objective of person-based signal control is to minimize total person delays at an isolated intersection or multiple intersections. Person-based systems transform the number of vehicles to persons via a weighted function. With such a system, signal control can decrease delays of vehicles and make transit vehicles naturally get “signal priority” due to high passenger occupancy. Christofa et al. [23] firstly proposed a responsive traffic signal control system that incorporates Transit Signal Priority on the basis of passenger occupancy. Then the person-based signal control model is revised to reduce computation complexity [24]. In addition to adaptive signal control, the person-based approach has also been applied on optimizing lane allocation and passive TSP timing settings [26], signal optimization for center transit lanes with various types of travelers [27], and dynamic exclusive bus lane optimization [28]. Zeng et al. [29] formulated the person-based signal control model under the CV environment, and Yu et al. [30] relaxed the constrained on fixed cycle length and considered uncertain bus arrival time. Li et al. [31] considered the effects of passenger and pedestrian delays at downstream intersections under coordinated green wave control.

In addition to CV-based signal control, another emerging CV application is in-vehicle Driving Advisory Systems (DASs). DASs provide driver speed advisories for various objectives (e.g., eco-driving and passengers’ comfort) based on Signal Phase and Timing (SPaT) information. A well-known example of DASs is GLOSA [32], followed by a series of studies on DASs for eco-driving [33, 34]. The Cooperative Intelligent Transportation System (C-ITS) established a two-way communication scheme between signals and vehicles, which allows cooptimizing traffic signal control and vehicle traveling efficiency. Several studies have evaluated C-ITS frameworks, and the results show significant improvement in either fuel consumption or travel time. However, these works either assume a 100% penetration rate of OBUs on all vehicle types [35] or postulating vehicles are homogenous, which does not take different vehicle types (e.g., transit vehicles) and passenger numbers into consideration [36, 37]. Hu et al. [38] and Wu et al. [39] enabled DASs on TSP to coordinate traffic signal plans among multi-intersections. Seredyński et al. [40–43] presented a complete analysis on implementing DASs on TSP. The results demonstrate that DASs can enhance TSP control efficiency without dramatically interfering in nonprioritized traffic. Nonetheless, little attention has been paid to integrate DASs into person-based real-time signal control.

In summary, several studies have contributed to the person-based signal control and cooperation method on a signalized intersection. All the literature on person-based signal control systems optimizes signal settings cycle-by-cycle, which may not be able to respond to traffic variations in real time. Although transit vehicles can get preferential treatment in person-based systems due to higher occupancy, buses may still experience delays at intersections since the interference of other traffic factors, such as the volume of competitive traffic. Inspired by the above points, this study proposed a Person-based Adaptive traffic signal control with Cooperative Transit signal priority (PACT) system. The contribution of the proposed PACT method can be summarized as follows:

1. PACT is an integrated system featuring a signal-vehicle cooperate-control structure. PACT optimizes signal settings in a short period (per second) with the objective of minimizing total person delay. The real-time optimal signal settings are transmitted to OBUs via I2V, and then OBUs can calculate optimal speed advisory with the objective of maximizing passing probability of the intersection.

2. PACT performs both signal optimization and speed advisory calculation for buses. The rolling horizon procedure provides additional reduction in bus delays without dramatically deteriorating the performance of nonprioritized traffic. Therefore, PACT can minimize total person delays and enhance the traveling efficiency of transit vehicles.

The remainder of this paper is organized as follows: Section 2 depicts the structure of the proposed PACT system and model formulation of signal control and speed advisory algorithm. In Section 3, a case study of an isolated intersection is introduced, following the evaluation of the effectiveness and performance of the PACT system. Finally, the findings of this study and future works are discussed in Section 4.

2. Methodology

2.1. System Framework. The concept of PACT is illustrated in Figure 1. At each second, PACT sequentially conducts the
following three stages. In stage I, the RSU retrieved real-time traffic information (i.e., speed and position) using VTD techniques and transformed the vehicle unit into person unit. In stage II, the RSU optimizes signal timing settings with the objective of minimizing total person delay. A Binary Mixed Integer Linear Program (BMILP) model revised by Zeng et al. [29] is constructed and utilized by the signal timing optimization. In stage III, the RSU sends SPaT information to OBUs on transit vehicles via CV communication. OBUs perform driving speed advisory computation with the objective of maximizing intersection passing probability. In the next second, three stages are repeated.

2.2. Model Formulation. For model simplicity, we have the following assumptions in the proposed PACT:

1. All the transit vehicles are equipped with OBUs. OBUs send vehicle information (i.e., speed and position) and receive SPaT via V2I communication such as IEEE 802.11p or C-V2X.

2. Bus stops are far side located. The impacts of bus dwell time are neglected.

3. Bus drivers fully comply with the optimal driving speed advisory as long as safety spacing is maintained.

4. Since the standard CV domain roughly ranges from 150 to 300 m [44], both CV communication range and VTD detection range are set as 300 m.

2.2.1. Objective of Signal Optimization. The signal optimization model of PACT is developed by Zeng et al. [29], in which delays of each vehicle are calculated individually under the CV environment assumption. PACT divides vehicles in the VTD detection range into two groups: queueing vehicles and approaching vehicles. Vehicle’s speed <1 km/hr is defined as queueing; the others are defined as approaching. In each group, every vehicle is labelled an order \( x \) according to relative position to the stop bar. \( J \) is the number of total phases, \( I^Q_j \) refers to the number of queueing vehicles, and \( I_j \) is the total number of vehicles in the VTD detection range. \( W_{x,j} \) represents the person-based weighted parameter of vehicle \( x \) of phase \( j \). The objective of signal optimization is to minimize both delays of queueing vehicles \( d_{x,j}^Q \) and approaching vehicles \( d_{x,j} \). The objective function is formulated as follows:

\[
\text{Min } \sum_{j=1}^{J} \sum_{x=1}^{I^Q_j} W_{x,j} d_{x,j}^Q + \sum_{j=1}^{J} \sum_{x=1}^{I_j} W_{x,j} d_{x,j}.
\]

(1)

Person-based weighted parameter \( (W_{x,j}) \) is obtained through equation (2). \( O_A \) is auto occupancy and \( O_B \) is transit vehicle occupancy. The parameter \( \alpha \) is introduced to increase the priority level on transit vehicles. Real-time auto passenger occupancies data are currently not available. However, occupancies of autos vary slightly from day to day for a specific time of a day. Historical data can provide estimates of average occupancy per auto. Real-time information about bus passenger occupancies can be obtained by smart card automated fare collection systems or auto passenger counter systems. Such systems are widely used in transit systems and can be connected to OBUs to send passenger number data.

\[
W_{x,j} = O_A \text{ if vehicle } x \text{ is Auto},
\]

\[
W_{x,j} = (1 + \alpha)O_B \text{ if vehicle } x \text{ is Bus}.
\]

(2)

2.2.2. Modelling Ring-and-Barrier Signal Control. As shown in Figure 2, an effective model of eight-phase, dual-ring
signal developed by L. Head et al. [44] is adopted. The decision variable is the actual green time $t_{jk}$ (phase $j$ and cycle $k$) at the intersection.

Zeng et al. [29] assume that signal optimization is conducted per cycle. Once the optimization completes, signal parameters are implemented instantly and remain the same until the next optimization process (i.e., next cycle) begins. However, optimization is conducted per second in PACT. The impacts of elapsed time in a cycle should be considered. Two necessary revisions are summarized as follows.

1) Minimum green constraint relaxation: Figure 3 shows the idea that the minimum green constraint $g_{j}^{\min}$ of phase $j$ gradually relaxes along with time lapses. To clearly describe the phase elapsed time $\tau_{jk}$ at a particular time, the time order is shown in the bracket. At time $t_{1}$, one second has elapsed, and the phase elapsed time $\tau_{jk}$ should be subtracted from minimum green $g_{j}^{\min}$. At time $t_{9}$, since the accumulated time length at time $t_{9}$ has exceeded the minimum green, the model allows assigning zero to feasible green time variable $g_{jk}$. The equations are listed as follows:

\[
g_{jk} \geq g_{j}^{\min} - \tau_{jk} \text{ if } \tau_{jk} < g_{j}^{\min},
\]
\[
g_{jk} \geq 0 \text{ if } \tau_{jk} \geq g_{j}^{\min}.
\]

The if-else statement in equation (3) can be transformed into mathematical formulations in

\[
\tau_{jk} - g_{j}^{\min} < M \cdot \rho_{jk},
\]
\[
\tau_{jk} - g_{j}^{\min} \geq - M \cdot (1 - \rho_{jk}),
\]
\[
g_{jk} \geq g_{j}^{\min} - \tau_{jk} - M \cdot \rho_{jk},
\]
\[
g_{jk} \geq - M \cdot (1 - \rho_{jk}).
\]

A binary variable, $\rho_{jk}$, is introduced to indicate that the elapsed time is less or larger than the minimum green. When the elapsed time is less than minimum green, $\rho_{jk}$ is constrained to be 0. Otherwise, $\rho_{jk}$ is constrained to be 1.

Therefore, the constraints of minimum green time (equations (6) and (7)) can be chosen correctly. $M$ is the big number constraint.

2) Equal constraint of green time: in PACT, once phase $j$ ends, the green time of phase $j$ ($g_{j,k}$) becomes a constant that equals elapsed time $\tau_{jk}$ (shown in Figure 4).

For the example shown in Figure 4, at time $t_{1}$, all actual green time $t_{jk}$ is free to be optimized. At time $t_{9}$, the optimization assigns $g_{1,k}$ and $g_{5,k}$ to be zero, which means terminating phases 1 and 5. At time $t_{26}$, since phase 1 and phase 5 end, $t_{1,k}$ and $t_{5,k}$ are no longer adjustable and should be circumscribed to equal phase elapsed time (i.e., 26 seconds). Moreover, $t_{ijk}$ cannot be larger than maxim green time $g_{j}^{\max}$. These conditions are mathematically expressed as follows:

\[
t_{jk} = g_{jk} \cdot (1 - P_{jk}) + \tau_{jk} \cdot P_{jk},
\]
\[
g_{j}^{\max} \geq t_{jk}.
\]

$P_{jk}$ represents the activation status of phase $j$. If phase $j$ ends, $P_{jk}$ equals 1. Otherwise, $P_{jk}$ equals 0. If the phase $j$ ends, $g_{jk}$ becomes a constant and is replaced with the elapsed time $\tau_{jk}$. Finally, the ring-and-barrier model can be completed through equations (9) to (14). $T_{jk}$ denotes start
time of green of phase $j$ in cycle $k$; yellow interval and all-red interval are $Y$ and $AR$, respectively. The duration of cycle $k$ is $C_k$. Note that PACT allows cycle length to be variable within a user-defined range, and the maximum and minimum cycle length are denoted as $C_{\text{max}}$ and $C_{\text{min}}$, respectively.

\[ T_{1,k} = T_{5,k} = 0, \]
\[ T_{3,k} = T_{7,k}, \]
\[ T_{j,k} = T_{j-1,k} + t_{j-1,k} + Y + AR + \tau_{j-1,k} \cdot \left( 1 - P_{j-1,k} \right) \cdot \forall j \in \{2, 3, 4, 6, 7, 8\}, \]
\[ T_{4,k} + t_{4,k} + Y + AR + \tau_{4,k} \cdot \left( 1 - P_{4,k} \right) - T_{1,k} = C_k, \]
\[ T_{8,k} + t_{8,k} + Y + AR + \tau_{8,k} \cdot \left( 1 - P_{8,k} \right) - T_{5,k} = C_k, \]
\[ C_{\text{max}} \geq C_k \geq C_{\text{min}}. \]  

### 2.2.3. Modelling Vehicle Delays

Since Zeng et al. [29] optimized signal settings per cycle to take into consideration future traffic flows, the planning horizon of Zeng’s model is two-cycle lengths, and the communication range of CV technology is set as 2 km. In this study, one cycle is adopted as PACT’s planning horizon. Delays that are unable to be captured in the planning horizon are estimated with the background signal plan.

1. Queueing vehicles: equation (7) shows the delay calculation on queueing vehicles, as illustrated in Figure 5. For vehicle $x$ in the queue, its delay depends on the saturation time of the vehicles in front of it. The number of lanes of phase $j$ is $N_j$ and start time of phase $j$ in cycle $k$ at the intersection is $T_{j,k}$. Delays of queueing vehicles $d_{x,j}^Q$ can be derived through (15) with a saturation flow rate $s$.

\[ d_{x,j}^Q \geq T_{j,k} + \frac{\left( x - 1 \right) / N_j}{s}. \]  

To avoid oversaturation, the green time of each phase should not be less than the dissipating time of queueing vehicle $I_j^Q / N_j / s$. The situation is formulated as follows:

\[ g_{x,j} \geq \frac{I_j^Q}{N_j} / s - M \cdot P_{j,k}. \]  

Note that the effectiveness of this constraint depends on the status of the phase. The constraint becomes ineffective if the phase $j$ ends ($P_{j,k} = 1$).

2. Approaching vehicles: the arrival time of each vehicle at the stop bar equals the free-flow travel time to the stop bar $T_{x,j}^p$. Delay of approaching vehicles can be separated into two categories:

**Category 1.** Arrival before the end of green time in the current cycle (cycle $k = 0$).

\[ T_{x,j}^p \leq T_{j,k} + \tau_{j,k} \cdot \left( 1 - P_{j,k} \right) + t_{j,k} - y_{x,j}^k \cdot M, \]

**Category 2.** Arrival after the end of green time in the current cycle (cycle $k = 0$).

\[ T_{x,j}^p \leq T_{j,k} + \tau_{j,k} \cdot \left( 1 - P_{j,k} \right) + t_{j,k} + \left( 1 - y_{x,j}^k \right) \cdot M, \]

The binary variable $y_{x,j}^k$ is used to identify the category, and the binary variable $\theta_{x,j}^k$ is introduced to identify whether

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**Figure 4:** Example of green time equal constraint.
a vehicle can leave the intersection in cycle $k$ or not. Equation (19) indicates that the value of $\theta^k_{x,j}$ is constrained by the category of vehicle $x$. $y^k_{x,j}$ equals 0 means that vehicle $x$ arrives after the end of green time in cycle $k$. Hence, $\theta^k_{x,j}$ must be 0.

According to different queueing statuses, Category 1 includes three types (see Figure 6):

Type I. Vehicles that arrive at the back of the queue before green starts.

Type II. Vehicles that arrive at the back of the queue after green starts and the queue has not been cleared yet.

Type III. Vehicles that arrive at the stop bar after green starts without any queue remaining. $T^A_{x,j}$ denotes actual arrival time at the stop bar of vehicle $x$ for phase $j$. The arrival time includes waiting time in queue and travel time from queueing position to stop bar. The number of vehicles in the queue upon the $x$ th vehicle’s arrival is denoted as $q_{x,j}$. Given the average length of vehicles $L_s$ and free-flow speed $v_f$, the time of $x$ th vehicle that arrives at the back of the queue $T^r_{x,j}$ can be calculated by subtracting the average queue clearance time from $T^p_{x,j}$ (as shown in (20)). For type III, there is no queue when a vehicle arrives at the stop bar; thus, $T^r_{x,j}$ equals $T^p_{x,j}$.

The binary variable $\sigma_{x,j}$ is used to decide whether the arrivals of vehicles belong to Type I or II ($\sigma_{x,j} = 1$ for Type I and $\sigma_{x,j} = 0$ for Type II). The equations are listed as follows:

$$T^r_{x,j} \leq T^p_{x,j} - \frac{q_{x,j} \cdot L_s}{v_f}$$ \hspace{1cm} (20)

The queuing length upon vehicle $x$ arriving behind the queue ($q_{x,j}$) can be estimated through equations (22)–(24), which refer to Types I, II, and III, respectively:

$$q_{x,j} \geq \frac{x - 1}{N_j} \cdot (1 - \sigma_{x,j}) \cdot M$$ \hspace{1cm} (22)

$$q_{x,j} \geq \frac{x - 1}{N_j} - s \cdot (T^r_{x,j} - T_{j,k}) - \sigma_{x,j} \cdot M$$ \hspace{1cm} (23)

$$q_{x,j} \geq 0.$$ \hspace{1cm} (24)

Equations (25) to (28) refer to the calculation of time to clear the queue. If the vehicle fails to leave the intersection in cycle $k$ (i.e., saturation time of the queue is larger than green time), the vehicle needs to wait for the start of green in the next cycle.
As shown in (29), if the vehicles cannot leave the intersection in the cycle \( k \), that is, \((\sigma_{x,j}^k = 0)\), extra waiting time \( d_{x,j}^E \) estimated from the background signal timing plan is calculated in equation (29). \( T_{x,j}^A \) is actual arrival time.

\[
d_{x,j}^E = T_{j,k+1}^b - T_{x,j}^A.
\]  

(29)

According to the arrival type of each vehicle, the calculation of \( T_{x,j}^A \) is formulated as follows:

\[
T_{x,j}^A \geq \frac{q_{x,j}}{s} + T_{j,k} + \frac{q_{x,j}}{v_f} \cdot L_s + \theta_{x,j}^k \cdot M + (1 - \sigma_{x,j}) \cdot M,
\]

\[
T_{x,j}^A \leq T_{x,j}^r + \frac{q_{x,j}}{s} \cdot L_f + \theta_{x,j}^k \cdot M + \sigma_{x,j} \cdot M,
\]

(30)

Finally, delays for an approaching vehicle of each scenario are formulated as

\[
d_{x,j} \geq \frac{q_{x,j}}{s} + T_{j,k} - T_{x,j}^r - \left(1 - \sigma_{x,j}\right) \cdot M - (1 - \theta_{x,j}^k) \cdot M,
\]

\[
d_{x,j} \geq \frac{q_{x,j}}{s} + T_{j,k} - T_{x,j}^r + d_{x,j}^E - \left(1 - \sigma_{x,j}\right) \cdot M - \theta_{x,j}^k \cdot M,
\]

\[
d_{x,j} \geq \frac{q_{x,j}}{s} - \sigma_{x,j} \cdot M - (1 - \theta_{x,j}^k) \cdot M,
\]

\[
d_{x,j} \geq \frac{q_{x,j}}{s} + d_{x,j}^E - \sigma_{x,j} \cdot M - \theta_{x,j}^k \cdot M.
\]

(31)\rightarrow(34)

2.2.4. Driving Speed Advisory Computation. The flowchart of calculating speed advisory is shown in Figure 7. At first, OBU requests SPaT information of the intersection. Next, OBU computes passing probability based on SPaT. A threshold of passing probability is used to determine the activation of speed advisory calculation. If the passing probability is larger than the threshold, there is no need to provide speed advisory since current speed can almost ensure that transit vehicles pass intersections without delays (Case 3). If the passing probability is less than the threshold, computation of speed advisory will be conducted. The OBU may suggest an advisory speed (Case 1) or advise maintaining the vehicles’ current speed (Case 2).

(1) Computation of passing probability at the intersection: in this study, transit vehicles operate under mixed traffic circumstances without exclusive lanes. Results of bus travel time prediction may be biased if a simple calculation (i.e., distance to intersection divided by vehicle’s current speed) is adopted. To consider the uncertain nature of arrival time, we assume that the arrival time of bus \( b \) at the intersection is a random variable \( T_{b}^B \), which follows a normal distribution with a standard error \( e \).

The detail of the passing probability calculation is shown in Figure 8. At time \( t_{bf} \), there is a bus \( b \) with speed \( v_b \) towards the intersection. The expected arrival time \( E(T_{b}^B) \) is calculated from the distance to stop bar \( L \) divided by bus current speed \( v_b \). The standard error \( e \) is a function related to the bus distance to the stop bar. Therefore, we can calculate the passing probability by the cumulative density function of the normal distribution. The integration range is the intersection of green duration \((g_{j,k})\) and arrival time \((T_{b}^B)\). Since bus expected arrival time may cross several cycles, preoptimized signal plans are applied on cycles that are not involved in the planning horizon of ATSC.

The detail of calculating the probability of passing the intersection is listed in Algorithm 1. The input parameters include bus order \( b \), bus speed \( v_b \), signal settings \((T_{j,k})\) and \((g_{j,k})\), and distance to the intersection. The order, speed, and distance to the intersection are retrieved via CV communication. The result of passing probability, PassProb, is the result of passing probability, PassProb, is

\[
e = \frac{1}{3} \cdot \left(2 + \frac{L}{50}\right).
\]

Through lines (4) to (5), three times standard error extended from mean is used to approximate the earliest
arrival time EarliestArrival and latest arrival time LatestArrival. Line (6) shows the intersection of green duration and arrival time (i.e., $F$ to $H$), which is computed by intersecting the arrival time range and green duration. Finally, we can obtain the passing probability by integrating $F$ to $H$ with the cumulative density function of normal distribution.

(2) Finding an optimal driving speed: the objective of speed advisory is to find a speed $v$ that can maximize the probability of passing intersection. Due to the limited space of the feasible solutions, it is possible to get a global optimal solution by the enumeration method. Algorithm 2 shows the process of finding optimal driving speed.

Line (1) is the initialization of variables. Line (2) indicates the algorithm start enumerating a speed $v$ from 0.7 $v_{lim}$ to $v_{lim}$. $v_{lim}$ is speed limit of the road. In line (3), the algorithm calculates the probability of passing the intersection; the result is PassProb. In lines (4) to (6), a comparison between PassProb and MaxPassProb is performed to choose a speed $v$ that can maximize passing probability. Lines (7) to (9) are a stabilization mechanism designed to prevent OBU from frequently providing different speed advisory. PreStepPassProb is the passing probability of the previous time step. An optimal speed is updated only if the difference between MaxPassProb and PreStepPassProb is larger than $\beta$.

For example, at time step $t$, the optimal speed of bus $b$ is 13 m/s, and the bus has an 85% probability of passing the intersection. However, at time step $t-1$, the speed of bus $b$ is 11 m/s, and the probability of passing the intersection is 82%. Here, we assume $\beta$ as 5%. Although the optimal speed at time step $t$ has a higher passing probability (85% > 82%), the difference is less than $\beta$ (85%−82% = 3% < 5%). Thus, the optimal speed at time $t$ is 11 m/s, not 13 m/s. If the difference between MaxPassProb and PreStepPassProb is less than $\beta$, the algorithm advises maintaining current speed $v_b$ (i.e., Case 2).

3. Experimental Evaluation

Traffic simulation is adopted to evaluate the performance of the PACT system. The simulation platform and process are introduced, and then the intersection layout and related traffic settings are depicted.

3.1. Simulation Settings. The simulation tool, Simulation of Urban Mobility (SUMO), is selected as the simulation
platform [45]. A well-known optimizer GUROBI [46] is employed for optimizing the signal control model. As shown in Figure 9, the Python programs can control and retrieve results from SUMO via Traffic Control Interface (TraCI).

For signal parameters, $C_{\text{min}}$ is set as 50 seconds and $C_{\text{max}}$ is $(1 + \gamma) \cdot \text{Original Cycle Length}$. The parameter $\gamma$ stands for an adjustable range of cycle length, a number in $[0, 1]$. For example, the cycle length is 100 seconds, $\gamma$ is 0.2, and PACT allows generating an optimal signal plan that has a maximum cycle $C_{\text{max}} = 100 \cdot (1 + 0.2) = 120$. A fixed-time signal plan optimized by PASSER-V [47] serves as the background plan. For OBUs, the threshold of passing probability is set at 50%. Parameter $\beta$ is set as 5% to avoid OBUs providing unstable speed advisory. The occupancy of each auto is set as 1.5 passengers, and bus is 30 passengers. The speed limit of each approach is 60 km/hr. $V_f$ is set as 15 m/s (i.e., about 54 km/hr) for both autos and buses.

A real four-leg with a left-turn bay intersection, Xiao-Dong Road and Chungwha Road, in Tainan, Taiwan, was established in a simulation environment. As shown in Figure 10. The length of each leg is 500 m. The detection range of VTD and CV communication ranges are set as 300 m. Seven bus lines pass through this intersection: Bus 20, Bus 15, Bus 2, Bus 19, Bus G17, Bus O12, and Bus H62. The headway of each bus line is 30, 20, 15, 20, 30, 60, and 25 minutes, respectively.

Detailed signal settings and historical traffic volume are shown in Figure 11. Historical traffic volumes are surveyed in morning peak hours (8:00 to 9:00 am), and the corresponding V/C ratio is 0.9. The preoptimized signal plan is adopted as the baseline in the following experiments.

Simulation environment parameters are listed in Table 1. The saturation flow rate is 0.5 veh/sec, and the maximum acceleration and deceleration rate is 4 m/s$^2$ and 5 m/s$^2$, respectively. The safety spacing between two vehicles is 2 m. The average vehicle length $L_s$ is set as 4 m.

### 3.2. Results Evaluation

Three types of evaluation modes are evaluated: PASSER-V optimization plan (PASSER-V), PACT without Optimal Speed advisory (PACT-No OS), and PACT with Optimal Speed advisory (PACT-OS). The simulation time of each experiment scenario is 2 hours of 5 runs with 8 random seeds, excluding 5-minute warm-up time. The CPU is Intel i5-9600K, and the average computation time in the most complex case (i.e., $\gamma = 0.9$ and $V/C = 0.9$ case) is 0.15 seconds. All experimental results are statistically significant at a $p$-value $< 0.05$.

#### 3.2.1. Various V/C Ratios (without Buses)

This experiment aims to evaluate the performance of PACT under four levels of V/C ratios where transit vehicles are not included. As listed in Table 2, four V/C ratios are tested: 0.3, 0.5, 0.7, and 0.9. The results show that $V/C = 0.9$ case has the greatest significant delay reduction (i.e., $-29.69\%$ in vehicle-based and $-29.67\%$ person-based) compared to other V/C ratio cases. As the V/C ratio becomes lower, the amount of delay reduction decreases as well. There is only about a $2.7\%$ delay reduction in $V/C = 0.3$ case. The minimum cycle length setting causes the result of insignificant delay reduction in lower V/C ratio cases. The minimum cycle length is 50 s in simulation settings, limiting the improvement of bus delay in a lower V/C ratio.

#### 3.2.2. Various V/C Ratios (with Buses)

Figures 12 and 13, respectively, illustrate the person-based delay and vehicle-based delay changes among various control types. In Figure 12, bus passenger delay reduces by 68% in PACT-No OS and 81% in PACT-OS compared with the PASSER-V plan in 0.9 V/C ratio case. It is evident that PACT-OS outperforms PACT-No OS in reducing bus passenger delays. The additional benefit is 17% (V/C = 0.5 case) and 13% (V/C = 0.7 case). For light traffic volume (V/C ratio $< 0.5$), the amount of delay reduction is minor since traffic variations are lighter. A significant reduction in auto passenger delay is presented in high traffic volume (V/C ratio $> 0.5$). Auto passenger delay reduces by 10%–15% in 0.7 V/C ratio case and 25%–30% in 0.9 V/C ratio case, showing that PACT can favour transit vehicles without dramatically interfering with non-prioritized traffic. For vehicle-based results (Figure 13), bus delay is 23.12 s, and auto delay is 23.72 s in V/C = 0.9 case. PACT-No OS decreases bus delay to 7.47 s, and PACT-OS further decreases to 4.58 s. For auto delay, PACT-No OS is 17.97 s, and PACT-OS is 17.66 s. Since speed advisory is only applied on transit vehicles, the results of PACT-No OS are nearly the same as PACT-OS. The results show that PACT can reduce auto delays even if they are not equipped with OBUs (OBUs are only equipped on transit vehicles).

#### 3.2.3. Various Signal Adjustable Parameters $\gamma$

In comparison with the PASSER-V plan, both PACT-No OS and PACT-OS decrease bus passenger delays for all $\gamma$ cases. As shown in Figure 14, for PACT-OS, bus passenger delay is 0.58 s in $\gamma = 0.1$ case and 0.19 s in $\gamma = 0.9$ case; total passenger delay is 12.56 s in $\gamma = 0.1$ case and 10.04 s in $\gamma = 0.9$ case. PACT generates high benefits in delay reduction with large $\gamma$ in either bus or system perspective. However, the benefit difference of bus passenger delays between PACT-No OS and PACT-OS becomes smaller when $\gamma$ increases. The difference is 10% in $\gamma = 0.9$ case but increases to 21% in $\gamma = 0.1$ case. The difference manifests that speed advisory can considerably improve delays when a strong limitation on the signal adjustable range ($\gamma$) was applied. There is an interesting finding in the results of bus passenger delays. The amount of delay reduction dramatically increases as $\gamma$ gets higher, but the pattern remains near the same when $\gamma$ is above 0.5. The maximum delay improvement of PACT occurs when $\gamma = 0.5$, which is $-67\%$ in bus passenger delays and $-24\%$ in auto. The result is coincident with the traditional traffic view of the relationship between cycle length and intersection capacity: as cycle length increases, the capacity initially increases but eventually remains constant. Due to the limitation of intersection capacity, the maximum improvement of the PACT system occurs when $\gamma = 0.5$. 


3.2.4. Sensitivity Test of Bus Occupancy. The results of the bus passenger sensitivity test are shown in Figure 15 (person-based delay changes) and Figure 16 (vehicle-based delay changes). Based on various passenger occupancy, the experiment suggests the extent of preferential treatment that PACT can generate for buses. In Figure 15, it is evident that PACT provides favourable bus delays in all passenger occupancy cases, even if passenger occupancy is low. In the 2-passenger case, PACT-No OS decreases bus passenger delays by 3.69 s, and PACT-OS decreases bus passenger delays by 5.42 s. As the bus passenger occupancy gets higher, the delay benefits get higher as well. However, if bus passenger occupancy is greater than 20, the improvement on bus delays gets smaller. The benefits maintain about 65% and 77% reduction in PACT-No OS and PACT-OS cases, respectively. In Figure 16, since PASSER-V optimized signal plans on a vehicle basis, the delay results are unaffected by bus passenger occupancy. In the 2-passenger case, the average bus delay under the PASSER-V plan is 23.72 s. PACT-No OS decreases bus delay to 15.75 s, and PACT-OS further decreases bus delay to 12.27 s.

3.2.5. Traffic Signal Preemption. Priority level factor α is used to increase the priority level of a vehicle. This experiment aims to demonstrate the maximum preferential treatment that PACT can provide for vehicles with extreme large α. In Figure 17, the results manifest that PACT can provide above 80% benefits on vehicle delays as long as α ≥ 100 and γ ≥ 0.5. In α = 1000 and γ = 0.7 scenario, the amount adds up to 98% when optimal speed guidance is implemented. Since traffic signals provide near unconditional “signal preemption” for special vehicles, the advantage of speed guidance becomes minor when α ≥ 100. The benefit of delays is near 95% to 97% in both PACT-No OS and PACT-OS. Even signal adjustable range (γ) is small, PACT can reduce considerable delays in special vehicles as long as α is large enough. For γ = 0.3 case, the benefit of the delay is

```
Input: bus order (b), bus speed (v_b), distance to intersection (L), T_{i,j}, and g_{j,k}
Output: probability of passing intersection (passProb).
(1) Initialization: set passProb = 0.
(2) E(T_b^0) = L/v_b.
(3) e = f (L).
(4) Latest_Arrival = E(T_b^0) + 3e.
(5) Earliest_Arrival = E(T_b^0) − 3e.
(6) [F, H] = [Earliest_Arrival, Latest_Arrival] ∩ [T_{j,k}, T_{j,k} + g_{j,k}].
(7) passProb = \frac{\int_{F}^{H} P(F \leq T_b^0 \leq H)dT_{i,b} = \Phi (F + H − E(T_b^0)/e) − \Phi (F − E(T_b^0)/e).}{\int_{F}^{H} dT_{i,b}}
(8) return passProb.

Algorithm 1: Calculation of passing probability at an intersection.
```

```
Input: bus order (b), bus speed (v_b), distance to intersection (L), T_{i,j}, and g_{j,k} passing probability of previous time step (PreStepPassProb)
Output: speed advisory (OptimalSpeed or v_b)
(1) Initialization: passProb = 0, MaxPassProb = 0, PreStepPassProb = 0
(2) For v ∈ [0.7v_{lim}, v_{lim}]: do
(3) PassProb = Algorithm 1 (input: b, v, L, T_{i,j}, g_{j,k})
(4) If PassProb > MaxPassProb then:
(5) MaxPassProb = PassProb
(6) OptimalSpeed = v
(7) If (MaxPassProb - PreStepPassProb) > β then:
(8) PreStepPassProb = MaxPassProb
(9) Return OptimalSpeed
(10) Else:
(11) Return v_b.

Algorithm 2: Finding an optimal speed.

```

Figure 9: Integration of signal optimization and traffic simulation by TraCI.
Figure 10: Layout and bus routes for the intersection of XiaoDong and ZhongHua Road.

Signal Parameters and Traffic Volume

| Phase order | φ1 | φ2 | φ3 | φ4 |
|-------------|----|----|----|----|
| Number of lanes | 2  | 1  | 2  | 1  |
| Volume (veh/hr) | 617 | 149 | 738 | 235 |
| Signal Parameters (sec) | Green | 24 | 8  | 20 | 13 |
| | Yellow | 3  | | | |
| | All-red | 2  | | | |
| | Cycle | 85 | | | |

| Phase order | φ5 | φ6 | φ7 | φ8 |
|-------------|----|----|----|----|
| Number of Lanes | 2  | 1  | 2  | 1  |
| Volume (veh/hr) | 872 | 116 | 685 | 251 |
| Signal Parameters (sec) | Green | 24 | 8  | 20 | 13 |
| | Yellow | 3  | | | |
| | All-red | 2  | | | |
| | Cycle | 85 | | | |

Figure 11: Detailed signal parameters and traffic volume settings.
Table 1: Details of simulation parameters.

| Parameters                        | Value  |
|-----------------------------------|--------|
| Saturation flow rate (s)          | 0.5 veh/s |
| Maximum acceleration rate         | 4 m/s² |
| Maximum deceleration rate         | 5 m/s² |
| Safety spacing                    | 2 m    |
| Vehicle length (L_v)              | 4 m    |

Table 2: Person-based and vehicle-based delay results without buses under various V/C ratios.

| V/C  | Type  | Measures          | PASSER-V | PACT-No OS | Percentage changes |
|------|-------|-------------------|----------|------------|--------------------|
| 0.9  | Auto  | Vehicle delay (D-AV) | 23.61 (23.44–23.78) | 16.6 (16.48–16.72) | −29.69% |
|      |       | Person delay (D-AP)  | 15.74 (15.62–15.86)  | 11.07 (10.99–11.15) | −29.67% |
| 0.7  | Auto  | Vehicle delay (D-AV) | 17.3 (17.24–17.36)   | 14.13 (14.04–14.22) | −18.32% |
|      |       | Person delay (D-AP)  | 11.53 (11.49–11.57)  | 9.42 (9.36–9.48)    | −18.30% |
| 0.5  | Auto  | Vehicle delay (D-AV) | 14.37 (14.22–14.52)  | 13.28 (13.22–13.34) | −7.59%  |
|      |       | Person delay (D-AP)  | 9.58 (9.48–9.68)     | 8.85 (8.81–8.89)    | −8.14%  |
| 0.3  | Auto  | Vehicle delay (D-AV) | 13.16 (13.07–13.25)  | 12.81 (12.72–12.9)  | −2.66%  |
|      |       | Person delay (D-AP)  | 8.78 (8.72–8.84)     | 8.53 (8.47–8.59)    | −2.85%  |

Note. The numbers in the bracket show 95% confidence intervals.

Figure 12: Delay changes in (a) auto passenger, (b) bus passenger, and (c) total passenger under various V/C ratios.
Figure 13: Delay changes in (a) auto, (b) bus, and (c) total vehicle under various V/C ratios.

Figure 14: Continued.
Figure 14: Delay changes in (a) auto passenger, (b) bus passenger, and (c) total passenger under various signal adjustable parameters.

Figure 15: Delay changes in bus passenger under various bus occupancy.

Figure 16: Delay changes in bus under various bus occupancy.
83% in PACT-No OS and 86% in PACT-OS when $\alpha = 100$. In summary, one can make PACT provide near signal preemption by enlarging weight factor $\alpha$ and enabling speed guidance.

4. Conclusion

This study proposed a person-based cooperative adaptive traffic signal control system named PACT. PACT operates in a rolling horizon procedure, which includes two parts: second-basis adaptive traffic signal control (performed by RSU) and second-basis optimal driving speed guidance (performed by OBU). The signal control model optimizes signal parameters to minimize total person delays. Once optimization completes, the SPaT information is sent to OBUs to calculate optimal speed advisory. Optimal speed advisory algorithms provide an advisory speed that can maximize intersection passing probability. The algorithms consider the stochastic nature of bus arrival time with the normal distribution assumption. After transit vehicles apply recommended speed, RSUs optimize signal parameters based on the latest traffic status, and then the process repeats. PACT’s signal-vehicle cooperate-control structure can enhance the travel efficiency of both transit vehicles and autos.

The experiment results show that PACT has a strong ability to handle real-time traffic variation, reducing total person delays up to about 28% and bus person delays to 60%. Moreover, PACT-OS can generate additional benefits up to 20% compared to PACT-No OS, which implies that optimal speed advisory can further strengthen the benefits of delay reduction. In the sensitivity test of bus occupancy, each bus passenger experiences about a 65% reduction in delay when average bus occupancy is above 20. Furthermore, the maximum benefit of delay reduction of high priority level (i.e., high $\alpha$ value) can be 99%, showing that PACT has high adaptability to manage various priority level demands and can be further extended to emergency vehicle signal preemption.

A promising research direction is to extend the signal control model of PACT to multiple intersections. The effect of arterial traffic flow (e.g., platoon dispersion) must be considered in the multi-intersections model. Future studies can design an experiment to explore the value of $\alpha$ on maintaining the stability of bus operation, such as bus headway and bus bunching problems. This study assumes that bus drivers fully comply with the speed guidance, which is hard to implement in the real world. More experiments on the degree of compliance with OBU’s guidance should be conducted. In the near future, Connected Vehicle technology will advance to virtual-signal (or nonsignal) intersection control. The authority of driving through intersections depend on the direct cooperation between vehicles and virtual signals via V2I communication. The cooperative concept proposed in PACT shows a possible scheme of interaction between vehicles and traffic signals. Future research can apply this concept to virtual-signal control.

Data Availability

The data are generated by a simulation program, and part of the program files included in this study are available by sending a request to the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.
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