Transportation Planning and Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gtpt20

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To cite this article: Zongyuan Wu, Ben Waterson & Bani Anvari (2022) Developing and evaluating a coordinated person-based signal control paradigm in a corridor network, Transportation Planning and Technology, 45:6, 498-523, DOI: 10.1080/03081060.2022.2134128

To link to this article: https://doi.org/10.1080/03081060.2022.2134128

Published online: 18 Oct 2022.

TRANSPORTATION PLANNING AND TECHNOLOGY
2022, VOL. 45, NO. 6, 498–523
https://doi.org/10.1080/03081060.2022.2134128

Developing and evaluating a coordinated person-based signal control paradigm in a corridor network

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ABSTRACT

Connected Vehicles (CVs) provide both vehicle trajectory data and occupancy information to the junction controller, which make person-based signal controls to be possible by realizing the importance of reducing person delay. This study presents a coordinated person-based signal control algorithm (C-PBC), which has extended a previously developed approach from isolated junctions to multiple junctions. C-PBC incorporates vehicle information that is outside the CV communication range from the adjacent junction. It also updates data inputs for signal optimization algorithms based on formulated different arrival vehicle trajectory situations and coordinated data supplement algorithms. The developed algorithm has been evaluated using simulation with benchmarking signal control methods under a variety of scenarios involving CV penetration rates and predictive horizons. The results indicate that C-PBC is able to significantly improve person delay reduction when compared with fixed time control and vehicle-based control using CV data in 100% CV penetration rate under saturated flow conditions.

ARTICLE HISTORY
Received 19 October 2021
Accepted 3 October 2022

KEYWORDS
Traffic signal control; coordinated control; connected vehicle; person-based control; C-PBC

1. Introduction

Road congestion imposes severe burdens on drivers and the economy worldwide. According to statistics in 2018, road congestion wastes U.S. drivers 97 h, U.K. drivers 178 h and German drivers 120 h on average, which results in massive economic costs (Reed 2019). To mitigate this, traffic signal controls at urban signalized junctions play a crucial role in managing vehicle flows from conflicting directions and their stop-and-go behaviours. The recent development of Connected Vehicle (CV) technology makes vehicles and infrastructures to be informationally connected via wireless communication technologies (e.g. Dedicated Short Range Communications (DSRC)) (Kenney 2011). In such a way, signal controllers have the ability to gather abundant real-time vehicle data involving vehicle IDs, positions and speeds to improve their signal control optimization schemes.

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A large number of researchers proposed adaptive traffic signal control in CV environments (Jing, Huang, and Chen 2017). However, only a few parts of them realized the importance of enhancing person mobility and took into account the exact passenger occupancy of CVs for reducing person delay. In a previous study, an adaptive person-based signal control (PB-ACA) was developed to achieve this goal in the isolated junction (Wu, Waterson, and Anvari 2020). The proposed approach incorporated the occupancy data of all CVs into a three-layered Dynamic Programming (DP) system. PB-ACA aims to minimize total person delay in certain prediction periods. The signal schemes with flexible phase combinations and stage sequences are adopted to explore optimal solutions for reducing person delay from all feasible possibilities. The upper layer uses a forward recursion DP to calculate the optimal solution based on signal plans and vehicle departure times in every stage. The median layer explores all possible signal-timing strategies for the next stage by implementing the signal adjacent algorithm, which also updates vehicle predictive departure time in all lanes for the next stage. In the bottom layer, the algorithm finds the optimal person-based performance measure with maximum value function at the end of the planning horizon.

This study presents a Coordinated Person-based signal Control algorithm (C-PBC) which has extended a previously developed approach on the isolated junction to multiple junctions. This paper aims to explain how adaptive person-based control formulates and implements in multiple junctions and how it affects junction performances in terms of average person delays. By implementing the proposed algorithm, every junction controller will be able to update the vehicle occupancy list and departure predictive list by using information received from adjacent junctions. The developed C-PBC algorithm has been tested under a number of scenarios which use different CV penetration rates, traffic flow demands and prediction horizons. The test results are compared with those benchmarking models, including fixed-time and vehicle-based coordinated control models for multiple junctions under undersaturated and oversaturated flow conditions.

2. Literature review

Plenty of studies have been conducted on how to use CV information to optimize signal control and vehicle trajectory planning, which can be generally categorized into three groups. In the first group, each junction was typically assumed to be managed by a central agent which can constantly receive instantaneous location and speed information from CVs (Feng et al. 2015; Lee, Park, and Yun 2013; Guler, Menendez, and Meier 2014; Sun, Zheng, and Liu 2018). The second group of studies integrated autonomous vehicles (AVs) under vehicular environments with mixtures of CVs and conventional vehicles (Dresner and Stone 2005; Lee and Park 2012; Kamal et al. 2015; Feng, Yu, and Liu 2018). However, all the studies in the above two groups use vehicle-based signal control systems.

In the third group, researchers have also considered person delay by incorporating passenger occupancies of transits and cars into their optimization algorithms and frameworks (Yang, Menendez, and Guler 2018; Yu, Gayah, and Christofa 2017; Mohammadi, Roncoli, and Mladenovic 2019). These studies have transferred signal control from vehicle-based to person-based systems by utilizing CV data. However, only fixed stage sequences and limited phase combinations were presented. Yu et al. (2022) then improved their person-based approach by incorporating phase rotation and flexible signal schemes with a pre-determined six-phase complex signal timing plan in a six-phase isolated junction. In our previous study, we developed a person-based control PB-ACA with a three-layered DP optimization algorithm to figure out more flexible signal plans with complete flexible phase durations, signal stage sequences and combinations in an 8-phase isolated junction (Wu, Waterson, and Anvari 2020). The algorithm we proposed can better react to passenger vehicles with a variety of occupancy levels from different directions and arrival lanes. However, the applicability of this algorithm was still limited to the isolated junction but not to the larger network.

As far as coordinated signal control in the scale of the network was concerned, some researchers have utilized a centralized computer to optimize some signal timing parameters (such as common cycle, phase split and offset) at several adjacent junctions and reduce total delay or stops (Hunt, Robertson, and Winton 1981; Abu-Lebdeh and Benekohal 1997; Chang and Sun 2004). But their computational complexity also increased with the extension of network scales. Other studies using a hierarchical structure broke down the whole optimization problem into several levels to determine the junction cycle, green duration split, offset (at the global level) and more detailed signal timing parameters (at the local level) separately. The local control unit at each junction was capable of switching among different signal phases flexibly, based on real-time demand variation detected by inductive loops or cameras. Examples of such hierarchical signal control systems include SCATS (Sims and Dobinson 1980), OPAC (Gartner, Pooran, and Andrews 2001), UTOPIA (Mauro and Di Taranto 1990) and RHODES (Head, Mirchandani, and Sheppard 1992). With the adoption of Connected and Automated vehicles (CAVs) in road environments, Yu et al. (2019) managed to provide cooperative vehicle trajectories planning along non-signalised corridors under 100% penetration of the CAVs environment by using a mixed-integer linear programming approach. Yang, Feng, and Liu (2021) designed a cooperative driving framework for urban arterials in a hierarchical way with the mixtures of CAVs, CVs and regular vehicles. There are also a few studies on signal controls for multiple junctions by the decomposing whole network into small areas and weakening the coordination among adjacent junctions (Porche and Lafortune 1999; Wongpiromsarn et al. 2014; Al Islam and Hajbabaie 2017).

Studies on coordinated signal control utilizing CV information are mostly vehicle-based to reduce average vehicle delays or vehicle travel times (Vilarinho, Tavares, and Rossetti 2017), without priority given to high-occupancy vehicles. Those coordination approaches treated all vehicles on road without any difference to decide vehicle departure sequences regardless of the number of passengers in each vehicle. The relevant authority has emphasized the importance of improving personal mobility in urban networks in future urban traffic strategies (Department for Transport 2019). Therefore, person-based signal controls in multiple urban signalized junctions should be developed to such end.

One effective way to achieve arterial coordination control at the corridor level is green wave control. By this strategy, traffic signals of adjacent junctions can switch to green light successively for a vehicle platoon travelling on the artery of buses to confer non-stop crossing and reduce travel time and fuel consumption.

Of those studies that adjusted signal stages based on CV data and predictive platoon arrival time, many focused on optimizing maximum green wave bandwidth (Little, Kelson, and Gartner 1981; Wang et al. 2016; Yao, Tan, and Tang 2019). Few studies focused on more detailed arterial green wave control strategies such as dispersing heavy traffic on the congested road (Soon, Lim, and Parthiban 2019), incorporating pedestrian crossing time (Zhang et al. 2020), etc. The green wave control strategy assigned higher priority to a few vehicles with more passengers (platoons on arteries or buses) to reduce delays at multiple junctions. However, it pays less attention to the travel time of vehicles on branch roads or various distributions of occupancy vehicles from all lanes. Occupancy vehicles usually tend to approach junctions from different routes with many types of arrival sequences, resulting in unpredictable and variable vehicle environments. Therefore, we believe it is increasingly important to develop coordinated paradigms for person-based signal control using CV data, considering that currently coordinated controls were mainly proposed for vehicle-based controls or main vehicle platoons.

The proposed control method in this study is a scalable framework, which can be implemented in multiple junctions, imperfect CV situations and mixture fleets with buses. Our previous study proposes an Adaptive Person-based Signal Control Algorithm (PB-ACA) which can minimize person delay by exploring all possible phase combinations and feasible signal plan strategies at the isolated urban junction. This paper extends the previous work further to coordinated paradigms to understand how person-based signal control with flexible phase combinations and stage sequences would be implemented in multiple junctions better. The CV information from both surrounding CVs and adjacent junctions can be acquired to enable the junction controller to understand vehicular situations within further range. The data collected from adjacent junctions can be utilized as supplement information for predictive vehicle arrival time lists according to vehicle trajectory data and signal strategy. This will provide controllers with additional information in order to make adaptive signal timing decisions for all surrounding vehicles with different occupancies. The proposed paradigm differs from the state-of-the-art in the sense that it can reduce total person delay by assigning proper priorities to all vehicles involving cars and buses at the corridor level. Future works on how to improve the proposed approach in more realistic traffic situations will also be discussed in the conclusion section.

3. Methodology

In our previous study, we optimized the signal plan by using PB-ACA in isolated junctions. In this study, we employ C-PBC which extends the PB-ACA optimization to multiple junctions as a decentralized coordination format. Section 3.1 first briefly introduces the general framework of PB-ACA at a local junction. Section 3.2 then explains how the proposed C-PBC works. This is followed by modelling and operating algorithms of C-PBC in Section 3.3 and Section 3.4, respectively.

3.1. General framework of PB-ACA

The purpose of developing PB-ACA was to explore optimal signal plans at an isolated junction in the previous study. In this study, as a decentralized coordination control, C-PBC allows the local controller at every junction (shown in Figure 1) in the road network region to operate PB-ACA independently based on CVs data within its wireless communication range to optimize person-based signal plans. For each junction, the communication range is defined as a circle with a 250 m radius from the junction centre and the planned junction can only receive data within this communication range. The adjacent upstream junction in C-PBC has the ability to receive CV data within its CV communication range but out of the communication range of the optimized junction. C-PBC can receive this part of CV data from the upstream junction and vehicles can cross the

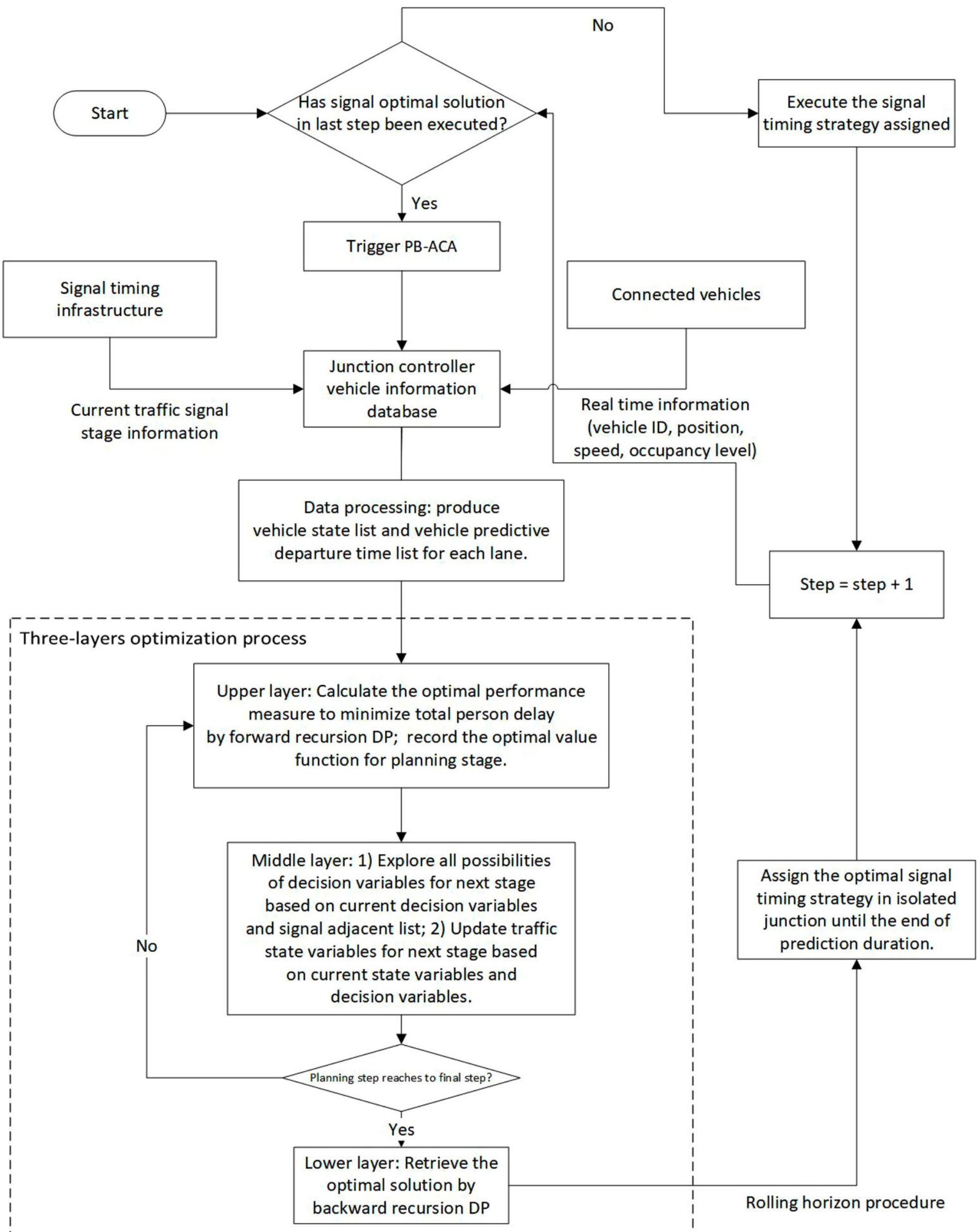

Figure 1. Conceptual framework flowchart of PB-ACA.

junction centre area during the following prediction horizon to the optimized junction to enhance the data inputs of the optimization algorithm. The framework of the PB-ACA is illustrated in Figure 1 which consists of five steps as below. The proposed algorithm figures out signal timing plans for a given horizon period and will be triggered to carry out for the next period when the scheme has been completely executed. The mechanism of PB-ACA is rather complicated. Considering the limited paper length, this paper only describes the general procedure of it to elaborate on how C-PBC can be incorporated into the previous algorithm PB-ACA to achieve coordination. Readers can refer to (Wu, Waterson, and Anvari 2020) for more details.

Step 1: PB-ACA collects information from every CV within the wireless communication range around junction A and arranges it by approaching lanes, location list $S(A) = [S_1, S_2, \ldots, S_n]$, instantaneous speed list $V(A) = [V_1, V_2, \ldots, V_n]$ and occupancy level list $O(A) = O_1, O_2, \ldots, O_n]$ at every lane, assuming there are n vehicles detected. The elements in those lists are ranked by their distances to the cross line from the nearest to the furthest within the detection range.

Step 2: Given the position list and speed list of each lane, we predict the initial departure time list for vehicles $T(A) = [T_1, T_2, \ldots, T_n]$ at the start of optimization by assuming that the next time step for this lane will be equally activated with green lights.

Step 3: The upper layer of the three-layered DP optimization algorithm takes $T(A) = [T_1, T_2, \ldots, T_n]$ from all lanes as inputs at the initial time step. For each stage, the upper layer of DP calculates the performance measure of passenger discharging benefits, determines and records the optimal solution combined with sub value function accumulated until the last stage for each state.

Step 4: In order to calculate performance measures, the middle layer of the three-layer DP optimization algorithm updates the vehicle departure time list in every time step, which also explores all kinds of possible signal plans based on the flexible traffic light state machine.

Step 5: At the final stage, the optimization algorithm compares function values of different states to decide the optimal signal timing plans with the highest objective function value. A series of phase allocations for each stage reaching the optimal state are searched by a backward recursion in the lower layer.

The general framework illustrates that the signal plan optimization at the isolated junction relies on the quality of data inputs processed by Steps 1 and 2. In the isolated junction scale, the controller can receive CV data from all approaching lanes to the junction centre within the CV communication range to find out the optimal signal plan. However, in multiple junction scales, some CVs travelling to the upstream junction on arterials are out of the wireless communication range of the planning junction. The C-PBC proposed method enables adjacent upstream junctions to collect this part of information and deliver them to the planning junction to enhance the quality of its data inputs. In other words, the C-PBC actually augments the data inputs processed by Steps 1 and 2 in PB-ACA to affect the remained optimization process in Steps 3–5 to figure out more intelligent signal controls considering coordinated CV information.

3.2. Benefits of the proposed C-PBC approach

As discussed in Section 2, central architecture and hierarchical structure make it more complex and less flexible for junction controllers to implement real-time signal control under CV environments. This study, therefore, proposed a decentralized structure to enable local controllers to operate their adaptive signal control algorithms. When compared with non-coordinated signal controls in multiple junctions, it can receive more comprehensive real-time vehicular data to realize surrounding environments. Meanwhile, as shown in Steps 1 and 2 in Section 3.1, the benefits of PB-ACA are that it can use vehicle arrival prediction and explicit occupancy level as data inputs. In order to make less interruption to local algorithm operation and provide adjacent junctions with more CV data for decision-making purposes, C-PBC is adopted which incorporates decentralized structure into vehicle trajectories estimation. The occupancy level and trajectory information of those CVs which are out of the communication range of the planning junction can also be acquired from the upstream junction and processed as supplementary trajectories inputs to predict their arrival time for local controllers. Another advantage of using C-PBC is that it can predict queue lengths of connected lanes at any optimizing time steps so that the holding-back phenomenon of high-demand vehicle platoons can be prevented.

3.3. C-PBC modelling

This section explains how C-PBC augments the data inputs in Steps 1 and 2 in Section 3.1. The distributions of local controllers and surrounding vehicles in multiple junctions are illustrated in Figure 2, where the communication range of junction A cannot completely cover the link road between junction A and B. However, those vehicles that are out of the wireless communication range of junction A on the link road, especially for vehicle platoons with high-occupancy levels, still have chances to cross junction A if adequate green time is given under the person-based delay reduction strategy to save travel time for more passengers. If we assume there is no transmission packet loss and communication delay, junction B is still capable of

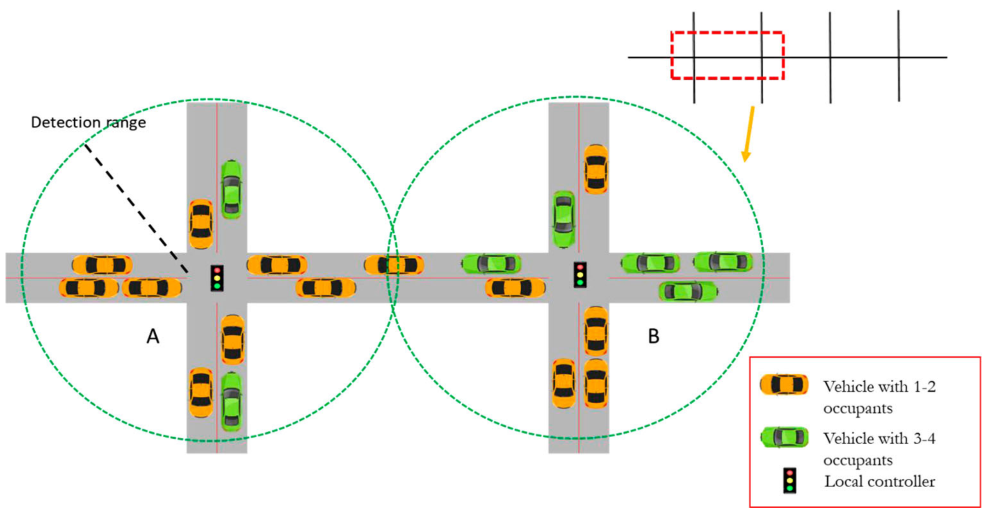

Figure 2. Diagram illustrating coordinated control and vehicle distributions at multiple junctions.

obtaining data from these vehicles and delivering it to junction A. In order to provide a comprehensive vehicular environment for a person-based algorithm and reduce interference to the local signal decision in the C-PBC model, we made changes to the vehicle location, speed, occupancy level and initial prediction time lists as mentioned in Steps 1 and 2 in PB-ACA.

Figure 4 illustrates that on the link road junction A can detect n vehicles and additionally m vehicles that are out of the communication range but potentially cross the junction in the planning horizon. $D(A, B)$ represents the distance between two junctions and P_{n+i} is the distance from the cross line of junction B to $(n+i)$th vehicle. For distance from the cross line of junction A to $(n+i)$th vehicle S_{n+i} on link road, there is:

$$S_{n+i} = D(A, B) - P_{n+i}\,, \quad 1 \leq i \leq m \tag{1}$$

Otherwise if vehicle S_{n+i} is not on link road, it should satisfy:

$$S_{n+i} = D(A, B) + P_{n+i}\,, \quad 1 \leq i \leq m \tag{2}$$

The distance between two junctions ($D(A, B)$) is a constant. Figure 3(a) illustrates four types of relationships between $D(A, B)$ and communication range (R), where

(a) $D(A, B)$ is lower than R.
(b) $D(A, B)$ is higher than R but lower than $2R$.
(c) $D(A, B)$ is higher than $2R$ but lower than the coordination distance recommendation value (0.75 miles).
(d) The distance of junction $D(A, B)$ is higher than 0.75 miles.

Distance from the cross line of junction B to $(n+i)$th vehicle (P_{n+i}) is variable under different cases. When C-PBC is applied to a new location, $D(A, B)$ will be measured first and then the flowchart in Figure 3(b) be used to determine P_{n+i} and S_{n+i} using Equations (1) and (2). The vehicle location can be directly determined by junction A if $D(A, B)$ satisfies the criteria set in case (a), or calculated by junction B in case (b). If $D(A, B)$ satisfies the criteria in case (c), junction B needs to detect the vehicle travelling from junction B to A with several time steps before the optimization. The value of the time step from detection to optimization equals gap distance ($D(A, B){-}2R$) divided by free-flow travelling speed V_d. Then those vehicles in the gap between two communication ranges can be estimated by the distance between them at the detection time step. If $D(A, B)$ exceeds 0.75 mile, there would be no coordination for the link. In such circumstances, vehicle location, speed and occupancy level list can be updated as $S(A) = [S_1, S_2, \ldots, S_n, S_{n+1}, \ldots S_{n+m}]$, $V(A) = [V_1, V_2, \ldots, V_n, V_{n+1}, \ldots V_{n+m}]$, $O(A) = O_1, O_2, \ldots, O_n O_{n+1}, \ldots O_{n+m}]$, respectively.

If a vehicle queue forms at the approaching lane in the junction B (such as case (a) in Figure 4) due to red light, $(n+i)$th vehicle will first try to discharge from junction B with time $C(n+i)$ with a constantly green light. $C(n+i)$ represents the time needed for $(n+i)$th vehicle to be discharged from junction B at the initial time step if it is not on the link road. It will then experience an acceleration process

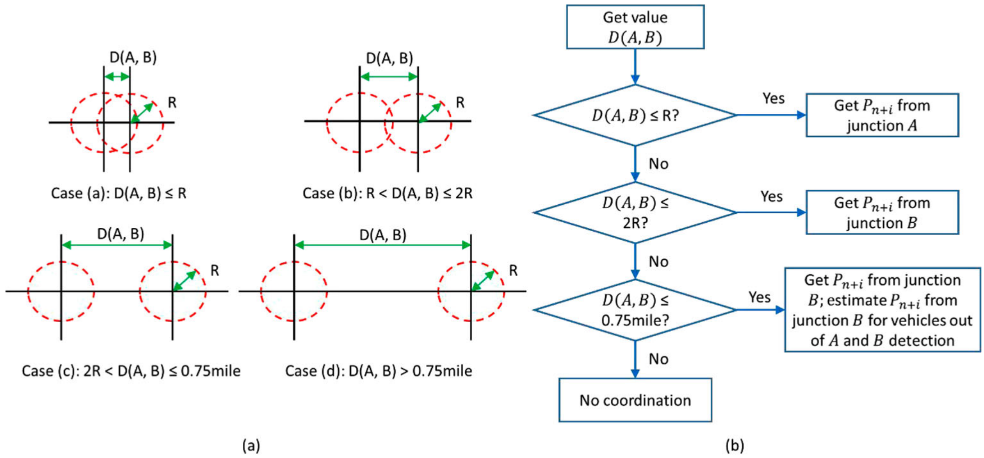

Figure 3. (a) Four cases of relationships of $D(A, B)$ and R; (b) Flowchart of determining P_{n+i} in different relationships of $D(A, B)$ and R.

from the initial discharging velocity at saturated flow (V_0) to free-flow travelling velocity (V_d), with constant acceleration a. The time needed for such an acceleration process (t_a) satisfies:

$$t_a = \frac{V_d - V_0}{a} \tag{3}$$

The distance vehicle travelled throughout the acceleration process (D_a) can be calculated as follows:

$$D_a = \frac{V_d^2 - V_0^2}{2a} \tag{4}$$

The vehicle will then approach to cross junction A with V_d during the green light, or stop at the end of the queue formed on the link road to wait for discharge. Therefore, the initial predictive time of $(n+i)$th vehicle (T_{n+i}) is the highest value of two cases,

$$T_{n+i} = \max\left(T_{n+i-1} + h_s, C(n+i) + D_a + \frac{D(A,B) - D_a}{V_d}\right), \quad 1 \le i \le m \tag{5}$$

Where T_{n+i-1} is the predictive discharging time of the previous vehicle and h_s is saturated headway of discharging queue. In case (b) of Figure 4, the $(n+i)$th vehicle crosses junction B with free-flow travelling velocity (V_d). It will keep crossing junction A at V_d unless the existing vehicle queue on the link road blocks its trajectory. The predictive time of vehicle T_{n+i} is thus calculated as follows:

$$T_{n+i} = \max\left(T_{n+i-1} + h_s, \frac{S_{n+i}}{V_d}\right), \quad 1 \le i \le m \tag{6}$$

To ensure that vehicles under both two cases in Figure 4 can be discharged within the planning horizon T, the time predictions under free-flow travelling status have

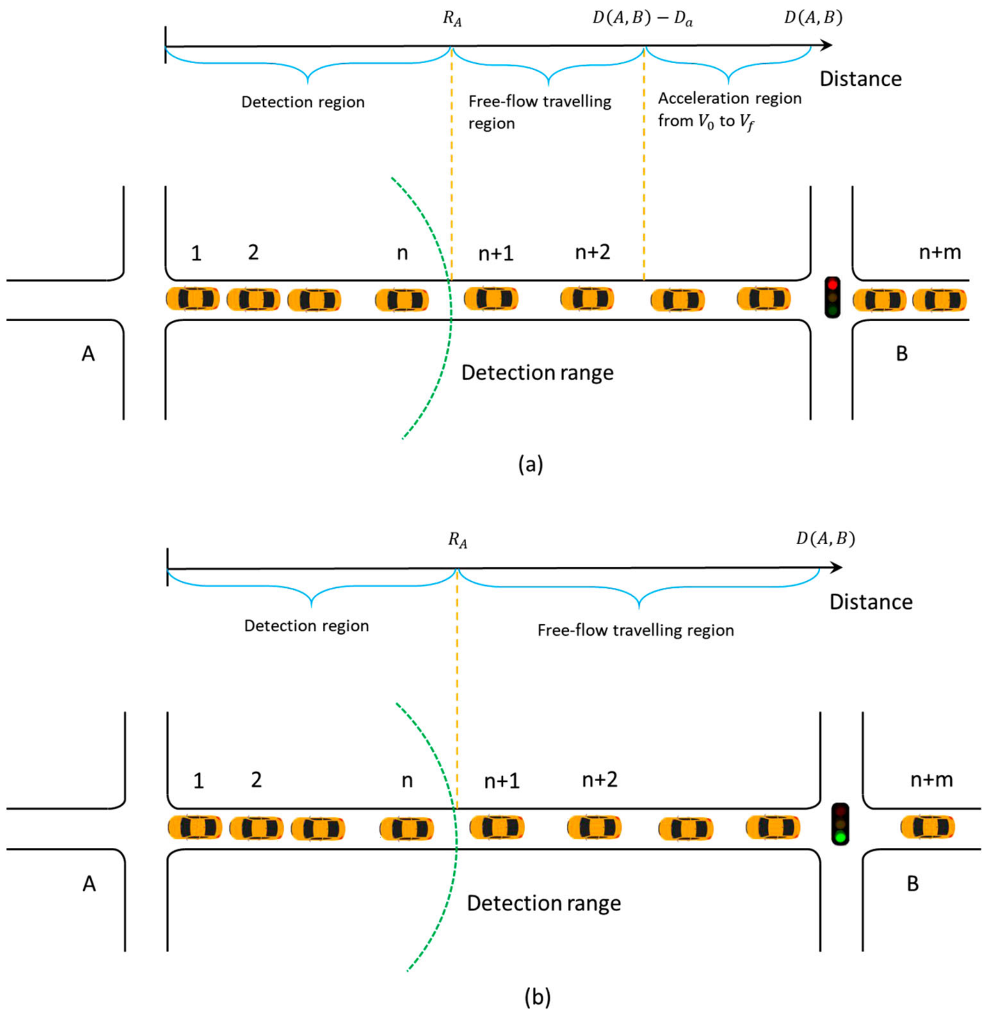

Figure 4. Vehicle situations on link road between junctions *A* and *B* in case (a): red light; and case (b): green light at junction *B*.

constraints as below:

$$0 < \frac{S_{n+i}}{V_d} < C(n+i) + D_a + \frac{D(A,B) - D_a}{V_d} \leq T, \quad 1 \leq i \leq m \tag{7}$$

To avoid possible flow holding back problems (Doan and Ukkusuri 2012) in coordinated junctions, the maximum queue length is defined as $Q_{\max}$ on road link where at any time step (t) in planning horizon (T), queue length $Q(t)$ cannot exceed $Q_{\max}$. Such constraint is expressed as follows:

$$Q(t) < Q_{\max}, \quad 0 \leq t \leq T \tag{8}$$

where $Q(t)$ is determined by:

$$Q(t) = \begin{cases} Q_0, & t = 0 \\ Q(t-1) + f(t) - g(t), & 0 < t \le T \end{cases} \tag{9}$$

where Q_0 is the initial queue length estimated by counting the number of vehicles at the stopped status on the link road. $f(t)$ and $g(t)$ refer to vehicle arrival rate and the discharging rate at time step t, respectively. Assuming that queue length equals to $i-1$, we can estimate $f(t)$ according to whether the ith vehicle will be stopped at the end of the queue or not as below:

$$f(t) = \begin{cases} 1, & T_i = T_{i-1} + h_s \\ 0, & T_i > T_{i-1} + h_s \end{cases} \tag{10}$$

On the other hand, $g(t)$ can be determined by the predictive time of the first vehicle (T_1) and signal plans Sig(t) at junction A. The criterion is expressed as follows:

$$g(t) = \begin{cases} 1, & \text{if } 0 < T_1 \le 1 \text{ and } \mathrm{Sig}(t) = \text{green} \\ 0, & \text{other cases} \end{cases} \tag{11}$$

The threshold of queue length is a signal to remind the junction controller that transfers the optimization mode from a person-based objective to maximum junction throughput. The vehicle can still stop behind the queue length threshold line and the junction will attempt to discharge them with a maximum junction throughput target once this triggers.

3.4. Description of coordinated control algorithm

By applying the above model assumptions to a coordinated level, we expect that PB-ACA will be improved for multiple junctions. As part of a coordinated person-based control algorithm or Algorithm 1, a coordinated data supplement algorithm has been developed to provide the local controller with additional data sources received from the adjacent junction. The lists of location, velocity, occupancy level and time prediction were first generated by steps 1 and 2 in PB-ACA. Locations of those vehicles that are out of communication range were calculated and appended to the location list, by means of information obtained from junction B and Equations (1) and (2). Once velocity and occupancy level lists were completed, initial prediction times of vehicles out of the CV detection range were calculated using Equations (3)–(7) and appended to the prediction time list. Model parameters for predicting vehicle arrival were regressed by simulations. The average Mean Square Error (MSE) was found to be less than 0.5 s per vehicle as validation of the model prediction accuracy. The new lists then replaced the original lists as input data for the local controller to implement the person-based optimization algorithm (Algorithm 2).

Algorithm 1. Coordinated data supplement algorithm

Data collection and processing procedure (ID, location, speed, occupancy, lane ID of CVs):
  For each approaching lane i of junction A:
    Generate location list $S(i, A)$ based on lane ID
    Generate velocity list $V(i, A)$, occupancy level list $O(i, A)$ according to sequence of CV's ID in location list
    Generate initial time prediction list $T(i, A)$ based on $S(i, A)$ and $V(i, A)$
    If lane i is road link between junction A and B:
      Generate location list $T(i, B)$, velocity list $V(i, B)$, occupancy level list $O(i, B)$

```
            Update S(i, A), V(i, A), O(i, A) based on Equation (1)
            For each approaching lane of junction B except link road:
                Update S(i, A), V(i, A), O(i, A) based on Equation (2)
            Update T(i, A) based on S(i, A), V(i, A) and Equation (3), (4), (5) and (6)
            Remove the following elements in T(i, A) if their values exceed planning horizon T based on equation (7)
            Remove relative elements in S(i, A), V(i, A), O(i, A)
        Else:
            Pass
    End procedure
```

C-PBC in Algorithm 2 has taken into account dynamic queue length and flow holding back prevention procedure. The junction controller receives all CV data within the communication range to realize the vehicular environments of all approaching lanes from different directions, including arterial traffic and cross-street traffic. The information from the coordinated junction is processed as a format to update and improve the data inputs of the optimization algorithm from the isolated junction. After receiving the improved vehicle arrival information, the junction controller can make better decisions by considering vehicles and their occupancies from all directions and lanes. Meanwhile, C-PBC keeps calculating queue length on the link road at any time step after assigning the signal plan for the current step. If queue lengths of one or more lanes exceed the maximum value, the junction will terminate the current signal plans and trigger a signal plan optimization process to reach maximum junction throughput. Once the time step arrives at the end of the planning horizon, Algorithm 2 will make a strategy of minimizing person delay and have it ready for implementation. The pseudocode of Algorithm 2 is presented below.

Algorithm 2. Signal optimization algorithm for planning junction

```
    Signal optimization algorithm for planning junction procedure:
        Generate S(i, A), V(i, A), O(i, A), T(i, A) for approaching lane i of junction A based on Algorithm 1, get current
    phase P_0 at time step 0
        For time step t from 1 to T:
            Create possible signal plan set in next step based on signal adjacent list and P_{t−1}
            For each in signal plan set:
                Calculate queue length based on Equation (9), (10) and (11)
                If queue length reaches to maximum constraint based on Equation (8)
                    Switch the objective function value from minimum average person delay to maximum junction
    throughput
                Else:
                    Pass
                Calculate sub-optimal performance value to minimum person delay based on T(i, A) from PB-ACA
                Update time predictive list T(i, A) and O(i, A)
                Record signal plan path to sub-optimal value
        Find out optimal performance value from all possible strategies at time T
        Retrieve signal plans reaching to optimal performance value
    End procedure
```

The upstream junction figures out the signal plan first to realize the vehicles that can transverse the junction during the planning horizon. The data can be delivered to the downstream junction to predict their arrival time of them by the proposed algorithm. The downstream junction optimizes signal plans with CV data it collects and supplements the data delivered by the upstream junction. After the optimization, the vehicle transverses the junction and can be sent to the further downstream junction.

In this way, the vehicles can be considered by downstream junctions to decide whether they can cross the junction in one horizon.

Coordinated control optimization is a one-way coordination paradigm to explore the optimal solutions sequential for different pairs of junctions (for instance, the direction of optimization is from the left side to the right side). The optimizations of downstream junctions can only be triggered once the signal plans of upstream junctions are determined. However, the optimizations of downstream junctions determine the number of vehicles and their arrival times crossing the downstream junction centres and in turn influence the approaching vehicles on the arterial link road to the upstream junctions. Searching for the optimal solutions among successive junctions is a recursive problem and is challenging to be solved in real-time optimization as the arrival vehicles of planning junctions are mutually affected by the optimization results of adjacent junctions. To simplify the problem, this paper only considers the crossing possibilities of high-occupancy vehicles (3 occupancy vehicles, 4 occupancy vehicles and buses) from the downstream junction and their influences on the planning junction. Algorithm 3 is presented below as the coordination paradigms with the considerations of downstream junctions by integrating Algorithms 1 and 2.

Algorithm 3. Coordinated control optimization algorithm considering the influences of downstream junctions

Coordinated person-based control optimization algorithm procedure:
  For planning junction n from 1 to $N - 1$:
    Calculate optimal solution of adjacent downstream junction $n + 1$ from time step 1 to $T - t_{adj}$ using Algorithm 2
    If there is at least one 3+ occupancy vehicle or bus can cross the junction $n + 1$ from time step 1 to t_{adj} and it is not on the link road between junctions n and $n + 1$
      Update $S(i, A)$, $V(i, A)$, $O(i, A)$, $T(i, A)$ of junctions n using Algorithm 1 with the supplement of vehicles leaving junction $n + 1$ between time step 1 to t_{adj}
    Else:
      Pass
    If the junction is not the junction 1:
      Fix the signal plan of junction n from time step 1 to $T - t_{adj}$
    Else:
      Pass
    Calculate optimal solution of adjacent downstream junction n from time step 1 to T using Algorithm 2
  Calculate optimal solution of adjacent downstream junction N from time step 1 to T using Algorithm 2
End procedure

The aim of Algorithm 3 is to guarantee high-occupancy vehicles from the contrary of the optimization direction can cross the downstream junction. Algorithm 3 introduces t_{adj} to represent the time left for the vehicles to cross the adjacent downstream junction at the beginning of the signal plan execution time step $[1, t_{adj}]$ so that they have the chance to cross the planning junction at the time step $[T - t_{adj}, T]$. t_{adj} is calculated as:

$$t_{adj} = T - \frac{D(A, B)}{V_d}, \quad 0 < t_{adj} < T \tag{12}$$

For example, t_{adj} equals 6 s supposing T is 30 s, $D(A, B)$ is 500 m and V_d is 16.67 m/s. This represents that the vehicles which cross the adjacent downstream junction in the first 6 s have the chance to cross the planning junction in the last 6 s during the optimization horizon. Before the optimization of the planning junction, the adjacent downstream junction optimizes first in the time step $[1, T - t_{adj}]$ so that the signal plan decisions are not affected by the vehicles that need to be discharged from adjacent junctions. Meanwhile, the optimal signal plan in $[1, t_{adj}]$ executed by the time step $[1, T - t_{adj}]$ is assumed to not be heavily affected by the optimal signal plan in $[1, t_{adj}]$ executed by the time step $[1, T]$. If one or more high-occupancy vehicles can be discharged in the time step $[1, t_{adj}]$, the planning junction updates its data inputs and makes signal decisions on coordinated information from bi-directional adjacent junctions. The signal plan in $[1, t_{adj}]$ for the adjacent downstream junction is fixed. Thanks to the recursive structure of the DP algorithm, all cases of traffic states, signal decisions and objective function values of the adjacent downstream junction in the time step $[1, T - t_{adj}]$ are recorded and it can be directly used for optimizing the signal plans in the time step $[1, T]$ to avoid duplicate calculations. The optimization process repeats until the final pair of junctions.

4. Validation of simulation results

To validate the performances of the proposed coordinated person-based optimization algorithm, we have considered in total 5 junctions and vehicular scenarios. SUMO microsimulation environment was chosen as the testing platform because of its open-source, space-continuous and multi-model features (37). SUMO simulation can be controlled by a Python API, which can interact with SUMO to develop new complicated logistic managements proposed by researchers. The model uses discrete time steps of 1 s. Each junction consists of two-lane links (one dedicated left-turn lane and one straight and right lane) with a saturation flow of 1080 vehicles per lane, two-way roadways from four directions and National Electrical Manufacturing Association (NEMA) phase numbers, as indicated in Figure 5. From the left side to the right side, junctions are named Junctions 1–5. Bus routes and their directions are illustrated in Figure 5 by the yellow lines with arrows. Bi-directional bus routes are arranged across the arterial link road and north–south lines of Junctions 1 and 2. Conflicting bus routes exist in the junction control areas of Junctions 1 and 2.

Krauss microscopic car-following model was chosen to describe the behaviours of vehicles driving in the road network because its parameters can ensure vehicle flows are stable and collision-free (Krauß 1998). The CVs are assumed not superior to typical passenger cars in terms of reaction time, etc. Therefore, Krauss microscopic car-following model is applicable to all passenger vehicles and buses tested in simulations. The parameters of the car-following model are default values adopted in the SUMO simulation. In further research work with the real-world case study, the parameters can be calibrated by the observed data such as the time vehicles spent crossing a certain road segment. The default values of model parameters for passenger cars and buses, as described in Table 1, were adopted during the simulations.

To test the performances of the proposed algorithms under various demands scenarios, we considered two demand scenarios, namely balanced undersaturated and unbalanced oversaturated flow scenarios, where

- Balanced undersaturated demand scenario refers to 300 vehicles per hour per lane in each entry and road link and 10 vehicles per hour crossing the arterial link road;

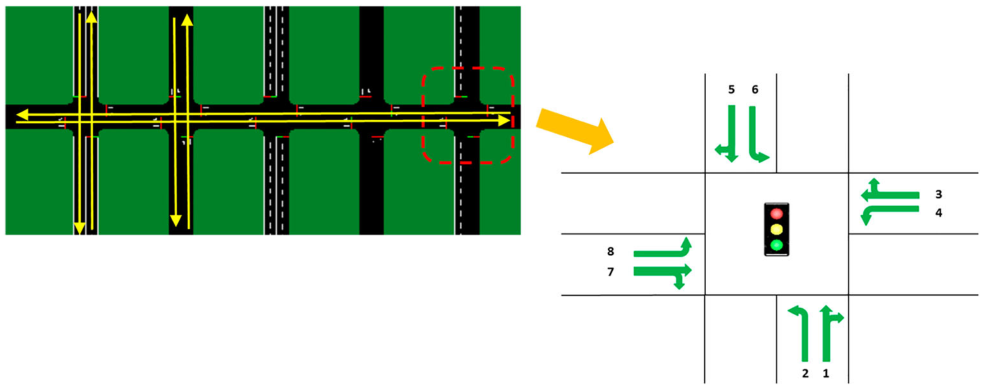

Figure 5. Multiple junction layouts and signal phase diagram of tested experiments (bus routes and their operation directions are represented by the yellow lines with arrows).

- Unbalanced oversaturated demand scenario refers to 300 vehicles per hour per lane in each crossroad entry; 1100 vehicles per hour per lane in each road link and 30 vehicles per hour across the arterial link road.

The prediction of vehicle arrivals is a process result of an optimization algorithm. The sub-performance values corresponding to different signal strategies in the optimization algorithm are calculated from the vehicle arrival prediction. The parameters of vehicle arrivals prediction have been calibrated in simulation experiments by comparing the vehicle arrival results observed from the simulation. The average Mean Squared Error of predicted value and observed results is less than 0.3 s per vehicle, which ensures the prediction accuracy to some extent.

In each simulation, the number of passengers per car was randomly assigned from 1 to 4 and those per bus were assigned to be 30. To identify the benefits brought by PB-ACA in terms of reducing average person delays over vehicle-based methods and person-based methods without coordinated paradigm, we have compared it with the below signal control models:

- Fixed time signal control TRANSYT (FTSC) calibrated by average traffic flow in the case study area.
- Actuated Coordinated Control (ACC): signal control decision parameters for green duration are variable, partly in response to real-time data collected from inductive loops.

Table 1. Parameter values of passenger cars and buses of Krauss car-following model.

Description	Unit	Value	Value
Vehicle type	–	Passenger car	Bus
Maximum acceleration	m/s^2	2.6	1.0
Maximum deceleration	m/s^2	4.5	3.5
Vehicle length	m	5	12.0
Vehicle min gap	m	2.5	2.5
Driver imperfect value	–	0.5	0.5
Driver reaction time	s	1	1.0
Maximum Speed	m/s	50	23.6

- Vehicle-based Signal Control (VBSC): VBSC adopts the same flexible stage sequence and phase combinations theory as our previous study. The difference between VBSC and C-PBC is that the objective of VBSC is to minimize vehicle delay in the certain planning horizons. The coordination paradigms proposed in this study are also adopted in VBSC to allow the junction controllers to receive supplementary CV data from the adjacent junction.
- No Coordination – Person-based Control (NC-PBC): in NC-PBC person-based signal control is used in multiple junctions but without any coordination and each local controller optimizes signal plans PB-ACA using CVs data within its independent communication range.
- Coordination – Person-based Control (C-PBC): In C-PBC proposed by this study, the direction of coordination is from left to right by simulation experiments as shown in Figure 5. The junction on the left optimizes signal plans first at the planning step and delivers data to the next junction downstream to enhance the data inputs. This step repeats itself until all the data has been received by junctions on the right.

Average person delay is selected as the parameter in this study to measure the delay suffered by passengers in vehicles. Delay is described as the excess time one vehicle takes to complete its travelling routes compared to the free-flow travel time. The delay of one vehicle equals actual travel time minus free-flow travel time. Delays of all passengers inside one vehicle are the same for each passenger in this vehicle. Therefore, the total delay of passengers in a vehicle equals the total number of passengers multiply vehicle delay. For valuation purposes, various other control algorithms have also been used to estimate vehicle delay, in addition to the proposed person-based algorithm in this study.

During simulations, 30 runs were performed for each signal control by different random seeds to avoid the influences of randomness on generated traffic demands and occupancy sequences. Average person delay and vehicle delay were then recorded and calculated. The optimization direction from left to right and from right to left are simulated respectively for 30 experiments to decide which optimization direction should be adopted for coordinated control. The average results of two optimization directions indicated that there is no significant difference in average person delay in the two flow demand scenarios. The optimization direction from left to right is selected for coordinated paradigms as it achieves slightly fewer average person delays in summation experiments.

All the simulations were carried out on a laptop equipped with Windows 10 system and Intel Core i7 CPU (2.9 GHz) and the computational cost was also recorded. Average computation time for each time step (which consists of 1 s of decision stage and 29 s of execution stage) and each decision point was all less than 1 s, or 0.168 and 0.472 s, respectively under balanced saturated flow conditions, and 0.203 and 0.575 s, respectively under unbalanced saturated flow condition. During the whole simulation, the number of times when the max queue is reached and the algorithm triggers the alternative scheme account for 8.4% and 37.9% of the total optimization process under balanced saturated flow conditions and unbalanced saturated flow conditions respectively.

CV penetration rate and planning duration are two factors that probably affect the prediction accuracy of arrival vehicles and optimization results. To understand their impacts, we evaluated a number of scenarios under two demand levels. The penetration rate of CVs was set between 10% and 100% with a step of 10%. Under such penetration rates, only CVs can deliver their information to the junction controller including ID, location, speed and occupancy. Moreover, for those controls relying on the planning horizon, we varied the planning duration from 10 to 60 s with a step of 10 s to study their impacts under VBSC, NC-PBC and C-PBC.

5. Results and discussion

5.1. Results

Tables 2 and 3 provide a summary of average person delay by cars and buses at different occupancy levels using different control strategies under two flow scenarios: balanced undersaturated flow and unbalanced oversaturated flow scenario, respectively. The last two columns in Tables 2 and 3 represent the collected output data of average person/vehicle delay over the simulation. All values are collected under a 100% CV penetration rate. The hypothesis tests are also carried out to identify the result differences between C-PBC and benchmarking models. As the actual average delays of vehicles in different signal controls are unknown but evaluation experiments can measure the sample values of average delay, two sample *t*-test is adopted to evaluate the effectiveness of C-PBC. Two sample *t*-test requires two independent samples from two groups, which can be acquired from the delay performances of C-PBC and a reference model over 30 experiments. The average delay significances of C-PBC and benchmarking models for different occupancy vehicles and summation values are indicated in Tables 2 and 3.

Figures 6 and 7 are box plots of delay value distributions for passengers in different vehicle occupancy levels under the two flow scenarios. The statistics of those passengers across four approaches under the same vehicle occupancy level are arranged into the same plot, as they are identical vehicles with the same routes and departure time, which makes their performances to be comparable in different approaches. Each plot consists of four subplots, or subplot (a), (b), (c) and (d), which corresponds to the vehicle occupancy level of 1, 2, 3 and 4, respectively. The upper and lower band represent the 95th and 5th percentiles of the data, respectively. The upper box line, orange colour line and lower box line refer to the 75th, 50th and 25th percentiles of the data, respectively.

The results are discussed concerning the two flow scenarios in the followings.

Under the balanced undersaturated flow scenario, Table 2 indicates that the average person delay under ACC, VBSC, NC-PBC and C-PBC can be reduced by 32%, 62%,

Table 2. Comparison of different average person delay (s/per) and vehicle delay (s/veh) values with different signal controls in balanced undersaturated flow condition under 100% penetration rate.

	Average delay						
Signal controls	Cars with 4 people	Cars with 3 people	Cars with 2 people	Cars with 1 person	Buses with 30 people	Summation person delay	Summation vehicle delay
FTCC	120.29(Sig)	119.38(Sig)	121.04(Sig)	120.82(Sig)	119.85(Sig)	120.20(Sig)	120.45(Sig)
ACC	81.28(Sig)	83.51(Sig)	81.59(Sig)	82.48(Sig)	82.70(Sig)	82.15(Sig)	82.31(Sig)
VBSC	44.86(Sig)	45.81(Sig)	46.06(Sig)	44.71(Sig)	45.62(Sig)	45.40(Sig)	45.36
NC-PBC	36.42(Sig)	40.49(Sig)	53.11	59.86	29.84(Sig)	42.89(Sig)	47.49
C-PBC	30.29	33.37	55.39	62.72	15.79	39.31	45.71

Note: Abbreviation 'Sig' behind the numeric value means the average delay of the benchmarking modes is significantly different from C-PBC in 95% confidence degree hypothesis tests.

Table 3. Comparison of different average person delay (s/per) and vehicle delay (s/veh) values with different signal controls in unbalanced oversaturated flow condition under 100% penetration rate.

	Average delay						
Signal controls	Cars with 4 people	Cars with 3 people	Cars with 2 people	Cars with 1 person	Buses with 30 people	Summation person delay	Summation vehicle delay
FTCC	177.71(Sig)	175.92(Sig)	177.18(Sig)	176.39(Sig)	176.75(Sig)	176.95(Sig)	176.81(Sig)
ACC	143.46(Sig)	144.81(Sig)	143.09(Sig)	142.69(Sig)	144.27(Sig)	143.72(Sig)	143.46(Sig)
VBSC	112.58(Sig)	113.86	112.56	113.49(Sig)	113.17(Sig)	113.14	112.85
NC-PBC	110.36(Sig)	113.29	116.82	122.61(Sig)	68.23(Sig)	112.91	115.50
C-PBC	106.17	110.04	116.65	120.72	53.59	110.91	114.18

Note: Abbreviation 'Sig' behind the numeric value means the average delay of the benchmarking modes is significantly different from C-PBC in 95% confidence degree hypothesis tests.

64% and 67%, respectively, from that under FTCC, with C-PBC having the largest reduction effect. The signal control methods using CV data achieve fewer average person delays because vehicular data from CVs provide more accurate estimations of vehicle crossing time than infrastructure sensors such as inductive loops or pre-determined off-line signal optimization. The optimization process of FTCC or ACC cannot or only partially react to the real-time traffic dynamics, which heavily degrades the performance of TRANSYT-Network. C-PBC also achieves better person delay reduction effects (14% less) than VBSC with the coordinated paradigm under the premise of not degrading the performances of average vehicle delay. The hypothesis results also indicate the significant improvement of average person delay reduction against C-PBC and VBSC in a 95% confidence degree. Moreover, person and vehicle delay reductions by C-PBC are 8.3% and 3.8% higher than those by NC-PBC, respectively. This is because the coordinated model provides the junction controller with more vehicle information to react to dynamic flow demand and arrival platoon for optimization.

In addition to person delay reduction, adaptive CV signal control (VBSC and C-PBC) also reduces the delay variability experienced by vehicle users and passengers at all

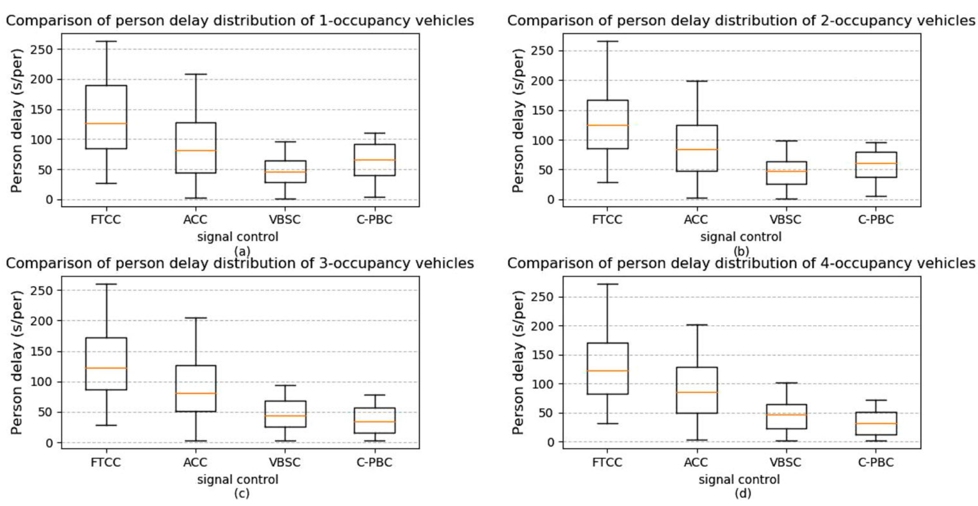

Figure 6. Box plots of person delay distributions categorized by different vehicle occupancy levels with different signal controls in balanced undersaturated flow condition under 100% penetration rate.

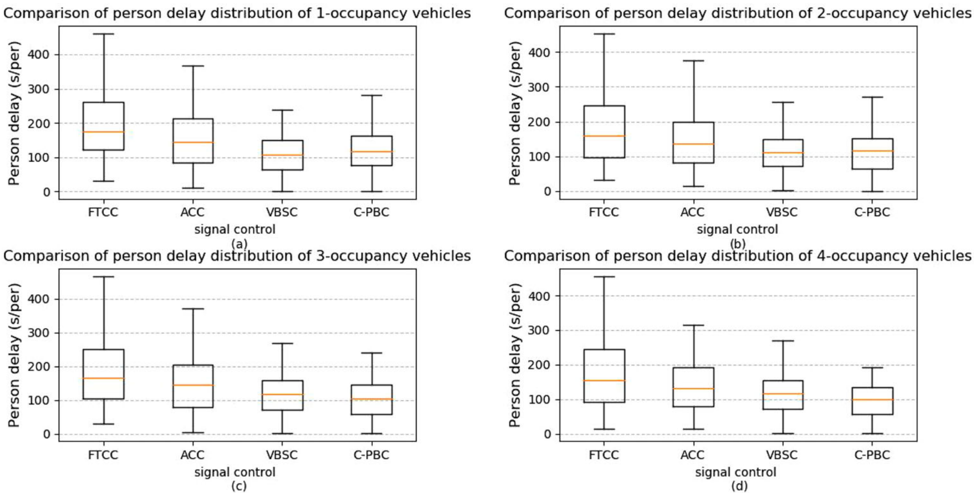

Figure 7. Box plots of person delay distributions categorized by different vehicle occupancy levels with different signal controls in unbalanced oversaturated flow condition under 100% penetration rate.

occupancy levels in the box plots in Figure 6. The variants under ACC slightly outperform those under FTCC but are significantly less stable than those under VBSC and C-PBC. The discrepancy in average person delay and delay variability between ACC and VBSC/C-PBC should be attributed to a rough estimation of road conditions, queue length discharging time, stage switching and green extension by inductive loop sensors. The results indicate that the application of CV technology is more advantageous than inductive loops with respect to signal control in road networks under a 100% penetration rate situation.

Table 2 and simulation results indicate that under different vehicle-based control strategies (FTCC, ACC and VBSC), there is no major difference in terms of reducing average delay for any type of occupancy vehicle. However, under person-based control strategies (NC-PBC/C-PBC), average person delays of 3 and 4-occupancy vehicles are statistically lower than those of 1 and 2-occupancy vehicles. As expected, the proposed algorithm provides more crossing opportunities for high-occupancy vehicles and scarifies the travel time of 1-occupancy vehicles through more flexible signal timing plans in 8-phase junction to reduce the average delay of all drivers and passengers. Therefore, the vehicles with high-occupancy levels cross the junction at the earliest chance and they suffer fewer vehicle delays and stops. The summation person delay in C-PBC can be reduced as the delays of more passengers in high-occupancy levels are decreased.

The comparisons of VBSC and C-PBC in different occupancy levels in Table 2 show that the average person delay of the proposed C-PBC and VBSC are significantly different regardless of the vehicle occupancy based on the hypothesis test results. C-PBC can reduce the average delay of buses, 4 and 3 occupancy vehicles by 65%, 32% and 27% respectively against VBSC. Contrarily, the average delays of passengers in 2 and 1 occupancy vehicles in C-PBC are apparently higher than those in VBSC. Figure 6(c,d) indicates that the variants and majority distributions of person delay in C-PBC outperform those in VBSC in the cases of 3 and 4-occupancy vehicles. Meanwhile, the box plots in Figure 6(a,b) indicate that the variability of person delay in 1 and 2 occupancy vehicles follow similar patterns as those in VBSC, but in slightly worse situations. The above results suggest that the C-PBC is more suitable to be implemented in multiple than non-coordinated person-based controls and vehicle-based controls.

Under the unbalanced oversaturated scenario, the results from Table 3 and hypothesis test results demonstrate that there is no statistically significant difference in reducing average person delay by VBSC, NC-PBC and C-PBC. This is probably because person-based controls shift optimization objectives from minimizing person delay to maximizing throughput when the threshold of queue length triggers. In addition, there is not enough space to implement flexible signal plans due to oversaturated traffic conditions. However, C-PBC can still achieve a 5.7% and 52.6% reduction in person delay for cars with 4 occupancy and buses, respectively, than VBSC. The differences between these two vehicle occupancy types are statistically significant under hypothesis tests. Meanwhile, under a 100% penetration rate CV situation and for all cars and buses with different occupancies, VBSC and NC-PBC/C-PBC can reduce people delay reduction more than FTCC and ACC, as illustrated in Figure 7. The variations of average person delay in FTCA/ACC are higher than in VBSC/C-PBC. This should be attributed to a pre-determined signal-timing plan or inductive loop traffic responsive plan, which cannot completely or partially respond to real-time traffic demand. C-PBC demonstrates similar distribution patterns with VBSC in terms of person delay for different occupancy vehicles. But the median values under 3- or 4-occupancy vehicles are lower than those under 1- or 2-occupancy vehicles. This indicates that even for high-occupancy vehicles person delay can be further reduced by the proposed C-PBC under oversaturated traffic conditions. This is consistent with lower average delay values in Table 3.

5.2. Sensitivity to CV penetration rate

In order to understand how the proposed C-PBC performs under a variety of mixture vehicle environments of conventional vehicles and CVs, the sensitivity analysis has also been conducted for different approaches. Figures 8 and 9 illustrate the average delay of different control strategies under two traffic conditions when the CV penetration rate increases from 10% to 100% at 10% each time.

NC-PBC, C-PBC and VBSC display very similar tendencies, as indicated in Figure 7. But when the CV penetration rate is equal to or less than 80%, the person delays achieved by C-PBC have no statistically significant difference from those by NC-PBC or VBSC. This is because, with fewer CVs, signal optimization algorithms relying on CV data can hardly understand entire vehicle situations in multiple junctions. There is no change in average person delay by FTCC or ACC under different CV penetration rates, as they do not rely on information obtained from CVs. In general, when the CV penetration rate is higher than 50%, NC-PBC or C-PBC or VBSC can achieve significant improvements in reducing person delay against FTCC/ACC.

Figure 9 indicates that when the CV penetration rate ranges from 60% to 100%, the average delays by NC-PBC, C-PBC and VBSC are all lower than ACC. At a 50% penetration rate, average delays by NC-PBC, C-PBC and VBSC are still similar to ACC. When the penetration rate is further decreased to below 50%, NC-PBC, C-PBC or VBSC cannot achieve better person delay reduction than ACC. When the CV penetration rate is less than 20%, their performance is inferior to FTCC. In conclusion, when the CV penetration rate is less than 40%, no improvement is expected by using NC-PBC or C-PBC. As for VBSC, it can only achieve better improvement than ACC in reducing person delay when the CV penetration rate is above 60%.

Control strategies relying on CV data under the unbalanced oversaturated flow scenario display a similar tendency with the balanced undersaturated flow, as indicated by Figures 8 and 9. There is no statistically significantly different among NC-PBC, C-PBC and VBSC when CV penetration rate ranges from 10% to 100%. They all can achieve better person delay reductions than ACC and FTCC when the CV penetration rate is 70% and 40% or higher, respectively. The reason for the similar phenomenon under two flow demand scenarios is that the gradual absence of CVs reduces the data sources of signal optimization algorithms using CV data, making them cannot realize the entire vehicle situation at multiple junctions. As the CV penetration rate decreases, C-PBC/VBSC can only acquire part of vehicular information. The optimization outputs of their algorithms cannot reach the perfect objective function targets of minimizing person/vehicle delay. The performance of FTCA and ACC keep the same in different CV penetration rates as their data inputs do not rely on the data from CVs.

5.3. Sensitivity to planning horizon

As explained above, the suitable planning horizon for the proposed C-PBC is uncertain. Therefore, it is essential to make performance sensitivity analyses under various horizons. Figures 10 and 11 have summarized the sensitivity of average person delay to DP prediction horizons (10 s, 20 s, 30 s, 40 s, 50 s, 60 s) by NC-PBC and C-PBC under two traffic conditions.

Figures 10 and 11 indicate that person delays display a similar tendency under two different flow scenarios. A trough can be found in the NC-PBC and C-PBC when the planning duration is 30 s. Average person delay first rapidly decreases when horizon increases from 10 to 30 s, and then slowly increases when horizon increases from 30 to 60 s. This

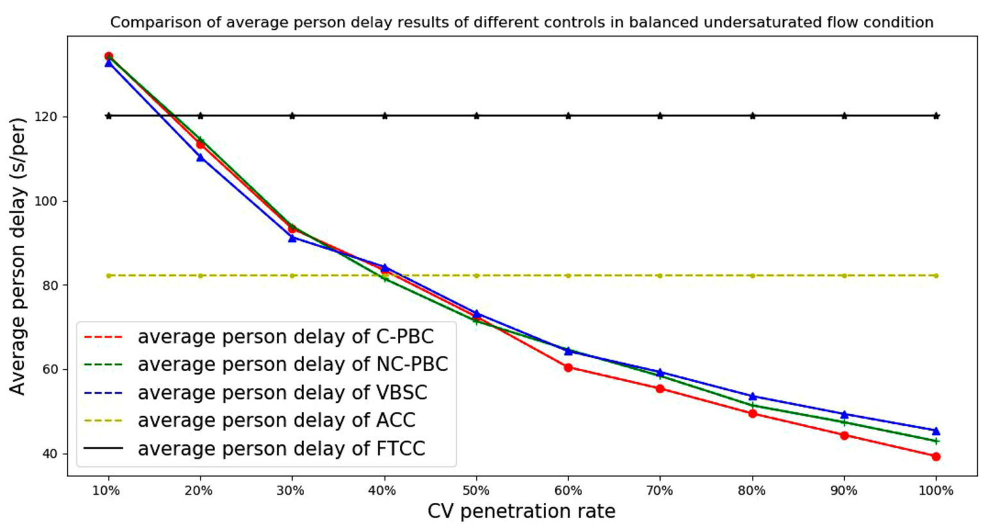

Figure 8. Average person delay under balanced undersaturated flow scenario at different CV penetration rates.

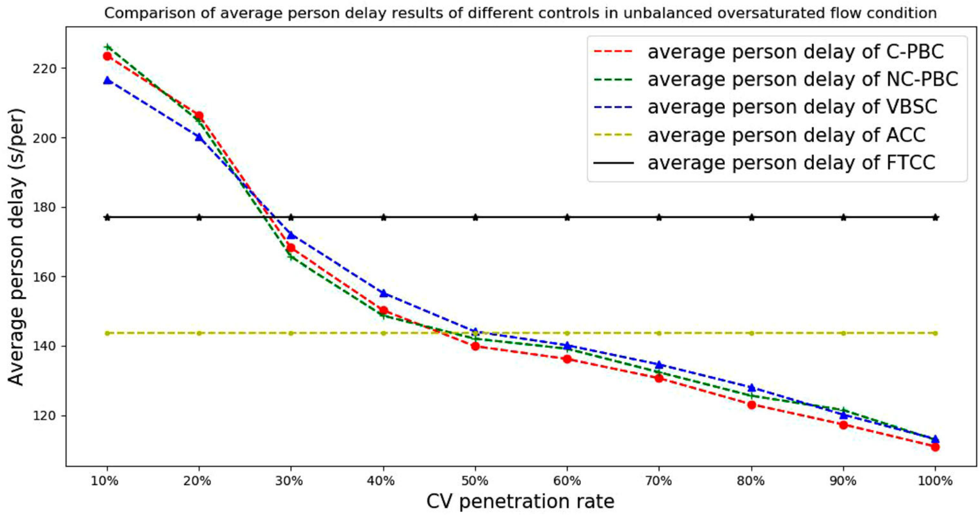

Figure 9. Average person delay under unbalanced oversaturated flow scenario at different CV penetration rates.

indicates that, if we set a too short planning horizon, NC-PBC or C-PBC cannot reduce person delay significantly due to limited signal plan choices and biased function values. The blanking periods of intergreen interval and start-up loss time occupying a considerable part of too short a planning horizon leads to no benefits to people discharging. This will not bring any benefits to people discharging. The results are heavily biased when determining the traffic signal executions as signal schemes are generated based on the highest value function with rarely vehicles can be discharged, regardless of effects on signal phase switching for following flows. The effects on cumulative deviation in long-time vehicle discharging prediction (40 s, 50 s, 60 s) are comparable to less negative influences on the performances

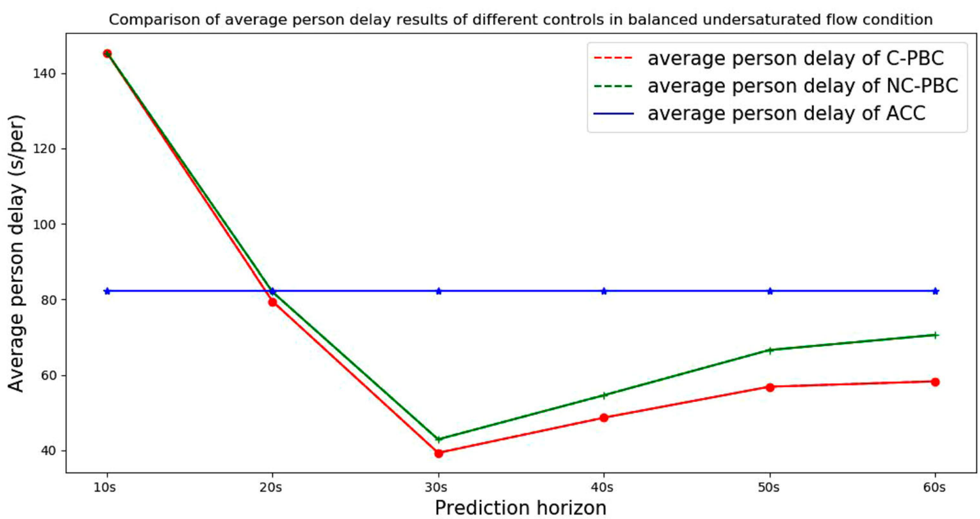

Figure 10. Average person delay (s/per) of NC-PBC and C-PBC at different prediction horizons, balanced undersaturated flow condition.

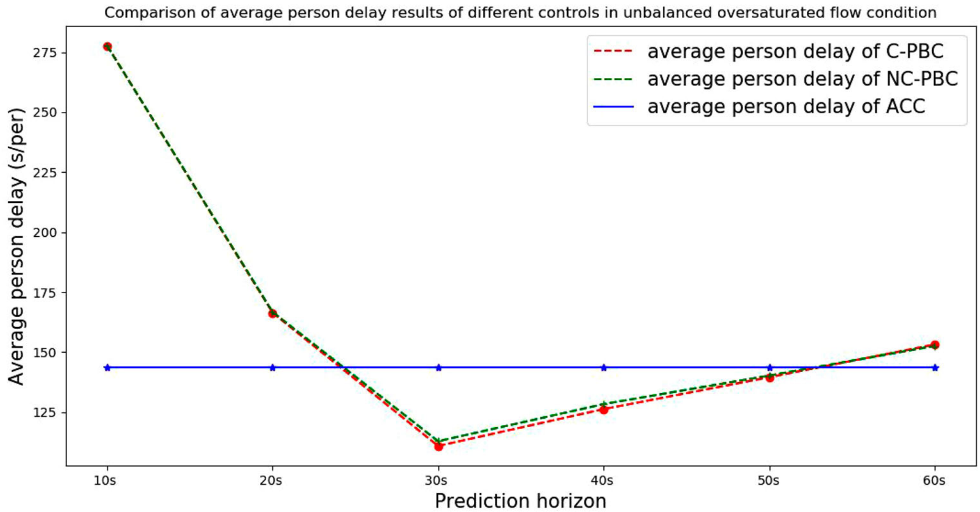

Figure 11. Average person delay (s/per) of NC-PBC and C-PBC at different prediction horizons, unbalanced oversaturated flow condition.

of ACC. C-PBC significantly outperforms NC-PBC when the prediction horizon is above or equal to 30 s under saturated flow. But there is no significant difference between these two strategies for other cases based on simulation results.

One interesting phenomenon we have found is that the performances of NC-PBC and C-PBC are the same at 10 s of the predictive horizon. This is probably because vehicles out of the scope of NC-PBC detection cannot cross the junction within 10 s. In other words, the data inputs of both NC-PBC and C-PBC are completely the same under such a planning horizon. Therefore, the signal plans optimized by NC-PBC and C-PBC lead to the same optimal values. As the predictive horizon increases, C-PBC outperforms NC-PBC by obtaining more arrival vehicle flow data. Generally, 30 s is suggested to be the optimal planning horizon and signal scheme operation cycles for both oversaturated and undersaturated flow conditions.

5.4. Summary

The proposed person-based coordinated control or C-PBC can more significantly reduce person delay when compared with other benchmarking models at 100% CV penetration rate under saturated flow conditions. When arterial traffic is oversaturated, although there is no overall statistically significant difference between C-PBC and NC-PBC/VBSC, the delay reductions of 4 occupancy cars and buses still significantly outperform other strategies. From sensitivity analysis we recommend 40% or above as the CV penetration rates and 30 s as the prediction horizon in both oversaturated and undersaturated flow conditions.

6. Conclusion

This study has developed a coordinated person-based signal control algorithm to understand how person-based control can be applied to multiple junctions. As the extension of the three-layered DP optimization algorithm proposed in the previous study in an isolated junction, this coordinated person-based algorithm aims to reduce person delay in the corridor level and achieve coordination by augmenting initial data inputs for optimization. Local controllers are capable of receiving vehicle information out of wireless communication range from adjacent junctions. The study formulates different arrival statuses and trajectories for undetected vehicles from link roads in different situations. The vehicle location, velocity, occupancy level and initial predictive time list are then updated for each junction controller by the proposed algorithm to achieve coordination.

To understand how the proposed algorithm performs in multiple junctions, we have conducted a number of simulations using the C-PBC and other benchmark signal control strategies under two flow conditions, a variety of CV penetration rates and predictive horizons. The results indicate that C-PBC generally outperforms other signal controls. The coordinated paradigm C-PBC also outperforms significantly other vehicle-based control strategies using CV data with coordinated paradigm VBSC, and person-based control without coordinated paradigm NC-PBC under saturated flow conditions. Thirty seconds of the predictive horizon is recommended to be adopted in C-PBC after sensitivity analysis.

One limitation of the proposed C-PBC is that its performance deteriorates when the CV penetration rate is less than 40%. Therefore, in our future work, we will focus on how to improve performance at low CV penetration rates. The junction controller cannot acquire vehicle trajectories or occupancy information from conventional vehicles, which is a challenge to algorithm improvements. Another aspect of our future work is to take into account other vehicle modes and pedestrians with different occupancy levels for person delay reduction.

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