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Published in:
2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems

DOI:
10.1109/MTITS.2019.8883378

Published: 01/06/2019

Document Version
Peer reviewed version

User throughput optimization for signalized intersection in a connected vehicle environment

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***Abstract*—Development of connected vehicles has provided different opportunities for traffic management based on high-resolution data. However, dominant methods are focused on vehicle-based strategies. The aim of this research is the development of a user-based signal timing (UST) strategy aiming at maximizing user throughput in a connected vehicle environment. The inputs of the proposed optimization algorithm are position, speed, and length of connected vehicles, as well as the number of passengers for each of vehicles, while the output is the optimum green time duration for each phase of signal timing. A microscopic simulation environment is used to collect data and validate the model employed within the algorithm. Then, the proposed optimization problem is solved by genetic algorithm method. The results obtained via UST optimization are compared with a vehicle-based optimization strategy, which is solved by the same algorithm. Results show significant increase in user throughput and share of vehicles with higher number of users on-board when UST is employed. The UST algorithm can be also implemented as transit signal priority strategy and supportive policy for ride-sharing.**

***Index Terms*—connected vehicles, signalized intersection, user-based signal timing, traffic control**

I. Introduction

Intersections are one of the most important components of urban transport networks. Large-scale intersection systems usually depend on traffic signal control for facilitating traffic flow and preventing extensive queuing and delays. From 1868 until now, different management strategies have been used to improve signalized intersection performance relying on a range of detection mechanisms and control objectives [1]–[3]. The main detection mechanism in conventional traffic signal control relied dominantly on discrete point or area detection, using such technologies as inductive loops, video image processing, or floating car data [4]–[6]. These detection mechanisms are capable of providing data on such parameters as vehicular flow and arrival speeds. Further development of detection and communication technologies have relied on the use of GPS, Bluetooth, RFID, and various other devices for special vehicle types and intersections, e.g., for emergency, transit vehicles, ground-level railroad crossings [7]–[10]. These technological advancements have enabled development of control strategies that can accommodate different vehicle types and a wider range of intersection types. Over many decades of technological development, the control objectives have remained vehicle-centered, such as maximizing vehicular throughput, or minimizing vehicular delay, stops, or queue lengths.

Connected vehicle (CV), as one of the emerging mobility technologies, is the new source of reliable data for various application in traffic management [11], [12]. In particular, CVs can share more reliable, higher resolution, and real-time data with the surrounding users, vehicles, and infrastructures [13]. For example, data on flow volumes, travel times, queue lengths, and shockwave boundaries originating from CV applications are available for use in traffic signal control strategies. This improved detection and communication capabilities provides various opportunities for controlling signalized intersections, such as improved signal arterial coordination, transit signal priority, or signal-vehicle coupled control [13]–[17].

Nevertheless, despite the advancement in detection and communication technology, traffic control strategies remain dominantly focused on vehicle-based performance measures. Some recent works have suggested a shift from vehicle- to user-based traffic control strategies. Christofa et al. have developed a person-based signal timing method in order to minimize person delay at signalized intersections while considering average occupancy for private and public vehicles [18]. This framework is implemented in some subsequent studies for flexible cycle lengths [19], for phase rotation [20], and for evaluating transit preferential treatments strategy [21]. Furthermore, a person-capacity-based approach is proposed for an integrated optimization of isolated signalized intersection for transit priority operation [22].

Despite the fact that CVs provide significant capabilities for data collection, in addition to vehicle-related data, CV technology can, for example, provide data on a range of user-related parameters, such as the number of users in each vehicle, which can be obtained through seat-belt activation or seat occupancy sensors. Previously, traditional vehicles occupancy data collection was limited to estimating average vehicle occupancy [23] by using roadside windshield and the carousel method [24]. Currently, the extent of CV data collection and communication capabilities is not being used to its fullest in developing signal control strategies. In fact, development of CV technology is an excellent opportunity to consider implementing user-centered control strategies [25].

This research is partly funded by Henry Ford Foundation Finland (Henry Fordin Säätiö).

Implementing user-based strategies in traffic management can be an effective solution for related challenges of mobility management. For instance, Noeh et al. have presented effectiveness of HOV lanes as a user-based traffic management policy on willingness to carpool [26]. Similarly, there are related concerns of increase in travel distances through vehicle automation [27]. Overall, considering the exact number of users for maximizing user-throughput in signal timing optimization has not been investigated before. In addition, vehicle throughput strategies has been never analyzed based on the effectiveness of serving the exact number of users.

This paper proposes a User-based Signal Timing (UST) optimization algorithm, designed for a CV environment. The UST optimization algorithm is designed to calculate the optimum green time splits to maximize user throughput. Accordingly, UST can distinguish between detected vehicles based on number of users on-board, which has not been implemented previously in literature. This ability could also be exploited to prioritize high occupancy vehicles at intersection as a transit signal priority strategy and a ride-sharing supportive policy. The remainder of this paper is organized as follows. Section II presents analytical UST optimization algorithm. Section III describes an implementation of UST method by a simulation experiment. The results of validation and evaluation are presented in IV. Finally, summary of key findings and conclusion are expressed in Section V.

II. ALGORITHM FORMULATION

This section introduces the methods used within the UST strategy for calculation of stop-bar passage time for each vehicle and on-board users. The objective is to predict which vehicles can pass the intersection in given green times within in assigned approach to each phase in different signal rings. Then, user-throughput is calculated based on number of users for served vehicles in a cycle time. Firstly, initial queue is estimated for each approach. Then, based on whether a vehicle joins the queue (before or while discharging) or not, different mathematical formulations are developed for three distinct cases to cover all possibilities. The algorithm is not dependent on the to flow state and can be implemented in under saturated, saturated and over saturated condition. The details of the developed algorithm are presented as follows.

A. Assumptions

The following assumptions are considered for vehicles and driving behavior in the UST strategy:

- vehicle data include speed, location, length and number of users which are provided in a fully connected environment;
- overtaking and lane changing are not allowed;
- all vehicles in queue move with same speed, constant safety distance (thus also time headway is constant);
- speed of all vehicles in stopped queue is zero;
- desired speed for all vehicles is constant and identical.

B. Queue length estimation

Different queue length estimation methods have been developed based on connected vehicles or probe vehicles data such as [28]–[30]. Proposed methods are usually developed to estimate accurate queue length while the penetration rate of connected vehicles is lower than 100 %.

Since proposed algorithm in this study is based on fully connected environment, a simple queue length estimation is used. The main assumption for queue length estimation in our algorithm is that vehicles with speed equal to zero are in queue. Note that this module is completely separated from the main algorithm and more advanced queue length estimation algorithm can be replaced in case of need, considering, for example, distance and front/rear vehicles status. This consideration allows to more accurate detection in real networks when in-queue vehicles speed is greater than zero but are considerably low. In this paper, we use simplest possible assumption for queue length estimation to reduce complexity of problem and consequently calculation time. Then, based on number of vehicles in queue, their length and safety distance, initial queue length is estimated for each phase separately. The initial estimated length may be updated if more vehicles join the queue before discharging. Mathematical formulation of estimation algorithm is presented as follows:

$$Q_{ij}^1 = \sum_{n=1}^{N_{ij}} q_{ij}^n (l_{ij}^n + S) \tag{1}$$

$$q_{ij}^n = \begin{cases} 1 & \text{if } v_{ij}^n = 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where:
Q_{ij}^1: estimated initial queue length in assigned lane for phase i in ring j (m);
i: signal phase index (i=1,2,..,I);
j: ring index (j=1,2,..,J);
n: vehicle index (n=1,2,..,N_{ij});
l_{ij}^n: length of vehicle n in phase i of ring j (m);
S: safety distance between stopped vehicles (m);
q_{ij}^n: binary parameters indicating the vehicles is in queue or not;

C. Stop-bar passage time prediction

Some previous works suggested classification of arriving vehicles to intersection. The goal of this classification is to cover all possible arrival conditions to intersection. Vehicles have been categorized to queuing region vehicles, slow-down region vehicles, and free-flow region vehicles in [31] in order to use in an adaptive signal control framework. For example, Christofa et al. [18] proposed 6 cases for arriving platoons (for cars and transit) to intersection in order to implement a person-based signalized intersection optimization.

In this paper, all arriving vehicles in a lane are classified in 3 different main cases and 6 sub-cases. Then, based on each case properties, a formulation for stop-bar passage time is proposed. A first criterion for classification is if the vehicles will join the existing queue or not. In order to calculate in-queue vehicles and arriving vehicles , kinematic wave theory principles [32] are used in most cases. On the other hand, minimum time headway is considered in the formulation, in order to satisfy car-following principles. The stop-bar passage time prediction starts from the nearest detected vehicle to stop-bar until the furthest. Fig. 1 shows a graphical representation of developed arrival cases in UST algorithm. The different cases are presented as follows.

1) Case 1: No initial queue $(Q_{ij}^1 = 0)$

There is no initial queue in assigned lane for phase i of ring j. This case is further classified into two sub-cases based on whether the vehicle arrives at the stop-bar before or during green time. At first, travel time with current speed between vehicle position and stop-bar is calculated. Then, comparison between travel time and signal timing determines the arrival condition. Note that this case is only possible for first vehicle (closest to stop-bar) in a lane. The mathematical formulation is presented as:

$$\alpha_{ij}^n = \begin{cases} 1, & \text{if } t_{ij}^n < c_{ij} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$t_{ij}^n = d_{ij}^n / v_{ij}^n \tag{4}$$

$$c_{ij} = \sum_{k=1}^{i-1} g_k + (i-1)Y, \tag{5}$$

where:
α_{ij}^n: binary variable indicating the vehicles arrive to stop-bar before green time or during time;
t_{ij}^n: travel time between initial position of vehicle n to stop-bar in assigned lane for phase i of ring j (s);
d_{ij}^n: initial distance between head of vehicle n and stop-bar in assigned lane for phase i of ring j (m);
c_{ij}: time from starting of cycle to starting of phase i in ring j (s);
g_{ij}: green time of phase i in ring j (s);
Y: amber and all red time duration (s);
Depending on the resulting variable α_{ij}^n, we can further distinguish the following two sub-cases.

- Case 1.1: vehicle arrives to stop-bar before starting green time ($Q_{ij}^1 = 0$ and $\alpha_{ij}^n = 1$)
  In this sub-case, vehicle should stop at safety distance before the stop-bar until starting of green time. In addition to previous phases and amber times, stop-bar passage time in this case also depends on time gap between start of green and start of vehicle movement as well as speed of vehicle. We assume that the speed of vehicles in queue, denoted by v_q, is constant and smaller than the desired speed. In order to calculate the time gap between start of green and start of vehicle movement, backward recovery shock-wave speed, denoted as v_s, is used, assuming a constant headway time. Since vehicle stopping causes queue, queue length should be updated for next vehicles stop-bar passage time analysis. Calculation for this case is expressed as follows:

$$v_s = \left(\frac{H_t}{S} - \frac{1}{v_q} \right)^{-1} \tag{6}$$

$$T_{ij}^n = c_i + S\left(\frac{1}{v_q} + \frac{1}{v_s} \right) \tag{7}$$

$$Q_{ij}^{n+1} = Q_{ij}^n + l_{ij}^n + S \tag{8}$$

where:
v_q: vehicles speed in moving queue (m/s);
v_d: desired speed of vehicles (m/s);
v_s: backward recovery shock-wave speed (m/s);
H_t: time headway between vehicles and time gap between starting of green and stop-bar passage of first vehicle (s);
T_{ij}^n: time between starting of cycle and when vehicle n in phase i of ring j, passes the stop-bar(s).

- Case 1.2 vehicle arrives at the stop-bar during green time ($Q_{ij} = 0$ and $\alpha_{ij}^n = 0$)
  In this case, vehicle arrives to stop-bar during green time and is expected to pass the intersection without stopping. In this case, queue length will not increase and remains zero. Stop-bar passage time for this vehicle is calculated as:

$$T_{ij}^n = t_{ij}^n \tag{9}$$

$$Q_{ij}^{n+1} = Q_{ij}^n. \tag{10}$$

2) Case 2: There is initial queue at the intersection and vehicle is part of queue $(Q_{ij} > 0$ *and* $q_{ij}^n = 1)$

In this situation, vehicle can be served during green time as a part of queue. First car in queue is considered similar to case 1.1. Stop-bar passage time for next vehicle is calculated based on front vehicle passage time, while the queue length does not change in this case. Formulation is described as follows:

$$T_{ij}^n = \begin{cases} c_{ij} + S\left(\frac{1}{v_q} + \frac{1}{v_s}\right), & \text{if } n = 1 \\ T_{ij}^{n-1} + \left(S + L_{i-1j}^n\right)\left(\frac{1}{v_q} + \frac{1}{v_s}\right), & \text{if } n > 1 \end{cases} \tag{11}$$

$$Q_{ij}^{n+1} = Q_{ij}^n. \tag{12}$$

3) Case 3: There is initial queue at the intersection and vehicle approaches to intersection $(Q_{ij} > 0$ *and* $q_{ij}^n = 0)$

In this case, vehicle n in assigned lane to phase i of ring j moves toward the intersection when there is an existing queue before the stop-bar. This case is classified into three sub-cases based on whether the vehicle can reach the queue before clearance or not. Firstly, travel time between vehicle position and tail of queue (considering a safety distance) is calculated. Then, comparison between vehicle travel time and queue clearance time illustrates vehicle arriving type. First level of classification shows whether vehicle will join queue before discharging or not, as follows:

$$\beta_{ij}^n = \begin{cases} 1, & \text{if } \gamma_{ij}^n < \theta_{ij}^n \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

$$\gamma_{ij}^n = \frac{d_{ij}^n - (Q_{ij}^n + S)}{v_d} \tag{14}$$

$$\theta_{ij}^n = c_{ij} + \frac{Q_{ij}^n}{v_s} \tag{15}$$

where:
β_{ij}^n: binary parameter indicating the vehicles will join queue before discharging or not;
γ_{ij}^n: travel time between initial position to tail of queue for vehicle n in assigned lane to phase i of ring j (s);
θ_{ij}^n: time interval from starting of cycle to when backward recovery shock-wave arrives to tail of queue (s).

If the first level calculation shows that vehicle n joins the queue, the second level of classification is implemented to determine if the vehicle will join the queue during discharge or pass the stop-bar after queue discharging, as follows:

$$D_{ij}^n = d_{ij}^n - v_{ij}^n \frac{Q_{ij}^n}{v_s} \tag{16}$$

$$\mu_{ij}^n = \frac{D_{ij}^n - Q_{ij}^n}{v_{ij}^n - v_q} \tag{17}$$

$$\delta_{ij}^n = \frac{Q_{ij}^n}{v_q} \tag{18}$$

$$\phi_{ij}^n = \begin{cases} 1, & \text{if } \delta_{ij}^n > \mu_{ij}^n \\ 0, & \text{otherwise,} \end{cases} \tag{19}$$

where:
D_{ij}^n: updated position of vehicle n in assigned lane to phase i in ring j, when backward recovery shock-wave arrives to the tail of queue;
μ_{ij}^n: travel time from updated position of vehicle n to tail of moving queue (s);
δ_{ij}^n: time interval from when the backward recovery shock-wave arrives to tail of queue and when the tail of queue passes the stop-bar (s);
ϕ_{ij}^n: binary variable indicating that the vehicle will join queue while discharging or passes the stop-bar after queue. Depending on the variables β_{ij}^n and ϕ_{ij}^n, we further distinguish into the following sub-cases.

- Case 3.1: vehicle arrives to tail of queue before queue starts to discharge ($Q_{ij} > 0$, $q_{ij}^n = 0$, $\beta_{ij}^n = 1$)
  As the vehicle joins the queue, stop-bar passage time in this condition is calculated based on of front vehicle calculated time, backward recovery shock-wave, and queue discharging speed. Since, vehicle joins the queue, queue length should be updated. The formulation is expressed as follows:

$$T_{ij}^n = T_{ij}^{n-1} + (S + L_{i-1j}^n)\left(\frac{1}{v_q} + \frac{1}{v_s}\right) \tag{20}$$

$$Q_{ij}^{n+1} = Q_{ij}^n + l_{ij}^n + S. \tag{21}$$

- Case 3.2: vehicle arrives to tail of queue during queue discharging ($Q_{ij} > 0$, $q_{ij}^n = 0$, $\beta_{ij}^n = 0$, $\phi_{ij}^n = 1$)
  Similar to Case 3.1, vehicle joins the queue but the difference is that in this condition, queue is moving, thus backward recovery shock-wave speed is not included in calculation:

$$T_{ij}^n = T_{ij}^{n-1} + \frac{S + L_{i-1j}^n}{v_q} \tag{22}$$

$$Q_{ij}^{n+1} = Q_{ij}^n. \tag{23}$$

- Case 3.3: vehicle cannot reach to tail of queue before or during discharge ($Q_{ij} > 0$, $q_{ij}^n = 0$, $\beta_{ij}^n = 0$, $\phi_{ij}^n = 0$)
  In this case, vehicle n does not join the queue and passes the stop-bar after queue is completely discharged. Queue length does not change in this case.

$$T_{ij}^n = \frac{d_{ij}^n}{v_d} \tag{24}$$

$$Q_{ij}^{n+1} = Q_{ij}^n. \tag{25}$$

D. *Comparison of stop-bar passage time and green time*

In this step, the calculated stop-bar passage time for each detected vehicle is compared to the corresponding green time, in order to determine if a vehicle can be served in cycle time or not. The comparison is summarized as follows:

$$G_i = \sum_{i=1}^{i} g_i + (i-1)Y \tag{26}$$

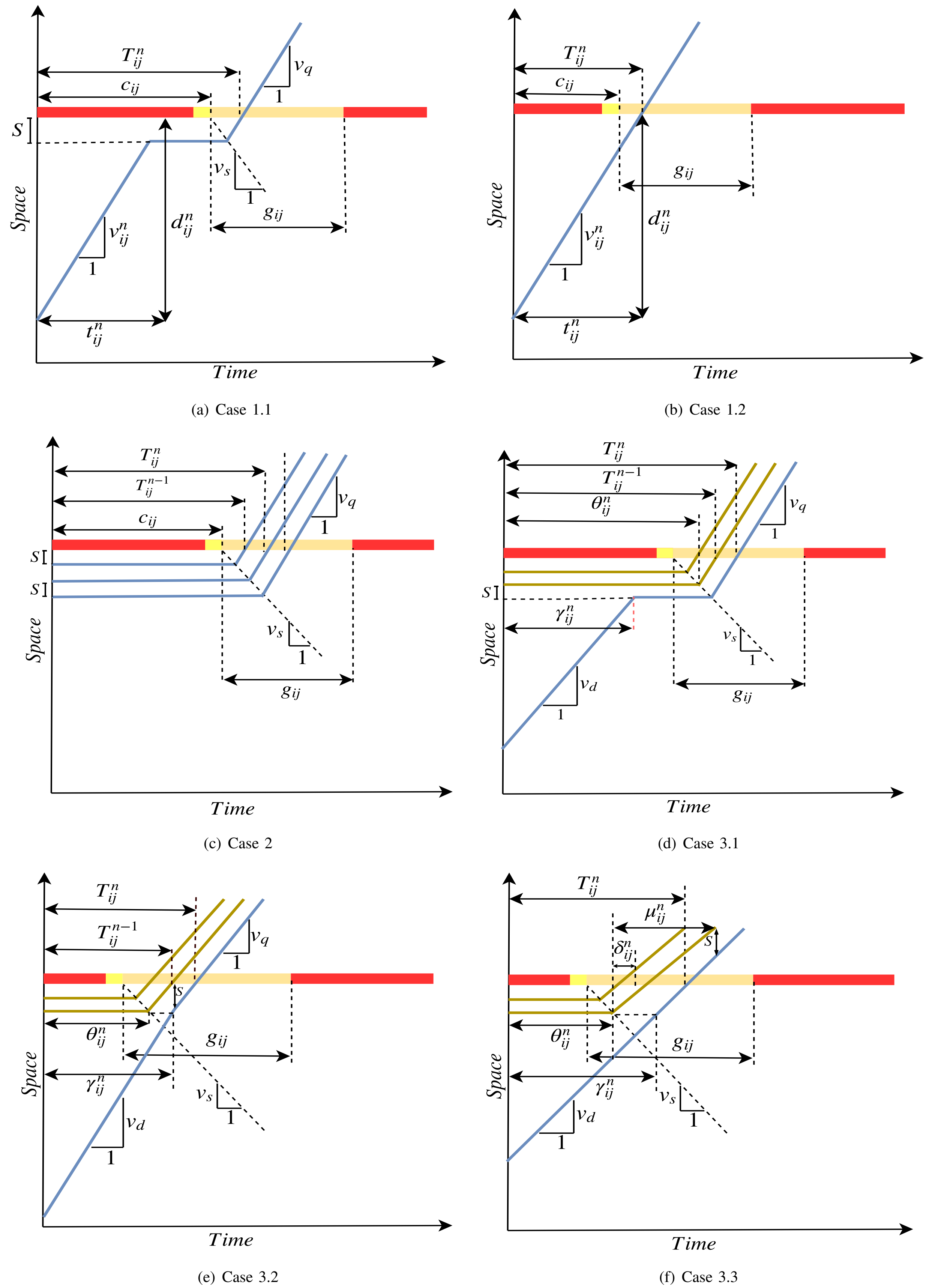
$$p_{ij}^n = \begin{cases} 1, & \text{if } T_{ij}^n < G_i \\ 0, & \text{otherwise,} \end{cases} \tag{27}$$

where:
G_i: end of green time for phase i (s);
p_{ij}^n: binary parameter indicating if vehicle n is served in current cycle or not;

E. *User-based signal optimization*

The objective function of optimization is to maximize users throughput in a fixed cycle and sequence signal timing. According to previous section, UST algorithm considers the prediction of the number of vehicles that are served in a given green time for each phase. Hence, user throughput can be calculated based on number of users in each vehicle. UST optimization algorithm objective function and constraints are expressed as:

$$\max \sum_{j=1}^{J} \sum_{i=1}^{I} \sum_{n=1}^{N_{ij}} p_{ij}^n u_{ij}^n \tag{28}$$



(a) Case 1.1

(b) Case 1.2

(c) Case 2

(d) Case 3.1

(e) Case 3.2

(f) Case 3.3

Fig. 1: Graphical representation of the different cases considered in UST algorithm

subject to:

$$\sum_{i=1}^{I} g_i + (I-1)Y = C \tag{29}$$

$$g_i > g_{i,\min} \quad \forall i \tag{30}$$

$$g_i < g_{i,\max} \quad \forall i \tag{31}$$

where:
C: cycle time (s);
u_{ij}^n: number of users for vehicle n in assigned lane to phase i of ring j;
$g_{i,\min}$: minimum green time of phase i (s);
$g_{i,\max}$: maximum green time of phase i (s).

III. Implementation

To illustrate the efficiency of UST algorithm, a set of simulation-based experiments are designed. An artificial four-leg intersection, as presented in Fig. 2, is considered as test platform. Phase sequence settings are assumed according to NEMA Standard ring-and-barrier [33] (Fig. 3).

Three different traffic flow states are considered to evaluate the algorithm in different traffic conditions. Cycle time is pre-fixed and is calculated based on traffic volumes. Minimum and maximum green times are considered 10 s and 50 s, respectively. Four type of vehicles, based on their number of users, are considered in traffic flow:

- number of users on-board = 1 (U1)
- number of users on-board = 2 (U2)
- number of users on-board = 3 (U3)
- number of users on-board = 4 (U4)

Two scenarios are designed in order to show ability of algorithm to increase user throughput and prioritizing vehicles with more users on-board. The employed scenarios are expressed as follows and summarized in Table I:

- Scenario 1: each vehicle class is assigned to simultaneous phases with balanced traffic input;
- Scenario 2: high traffic flow with low number of users in major streets and low traffic flow with high number of users in minor streets.

The microscopic simulation software VISSIM [34] is used to produce realistic vehicle arrivals and to validate the model presented in Section II. For each scenario and flow state, simulations are run for 50 unique random seeds in order to consider stochasticity of users and vehicles arrival pattern. Data are collected from VISSIM at a pre-determined time after simulation warm-up. The extracted data include speed, position, length, and number of vehicle users. Then, via COM interface, data are imported in MATLAB in order to solve the optimization problem. The developed UST algorithm is a mixed-integer nonlinear program (MINLP), whose feasible solution region is composed by numerous combination of green times, which leads to unacceptable calculation time for real time problems by conventional solution methods. To deal with this issue, a genetic algorithm method is implemented to solve the optimization problem by using a MATLAB library [35]. The optimisation problem is solved for 10 separate random instances for each of the random seeds and then the green time splits with maximum user throughput is selected as the best solution for each random seed. GA parameters to solve optimization problem are considered as follows: population size=40, generation number=50, crossover probability=1, and mutation probability=0.5.

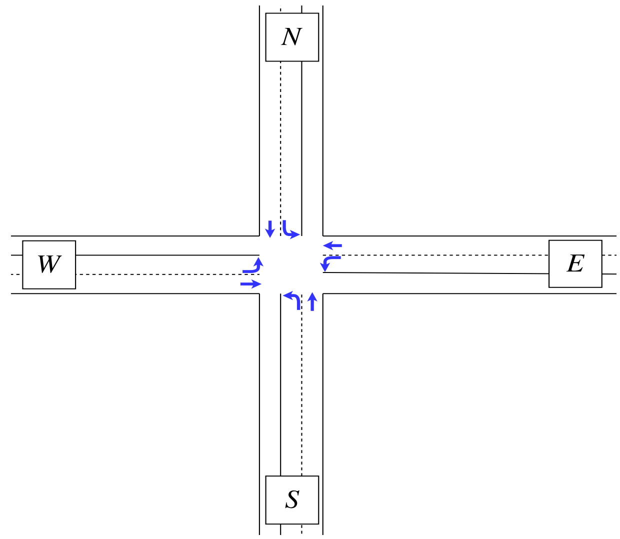


Fig. 2: Test intersection

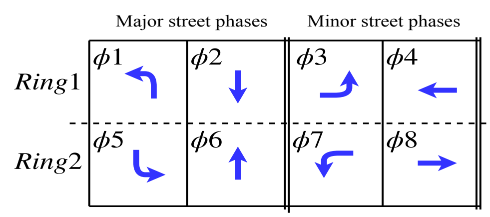


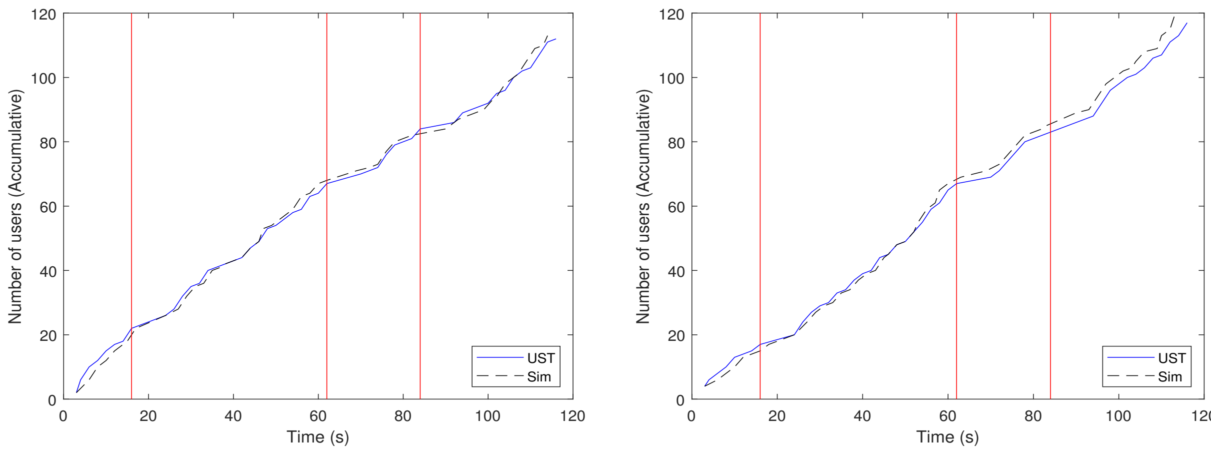
Fig. 3: Phases settings

UST optimization results are compared to vehicle-based signal timing (VST) optimization to measure effectiveness of the proposed strategy. VST strategy follows the same formulation proposed for UST, with the difference that all vehicles are assumed to carry only one user on-board ($u_{ij}^n = 1$, $\forall n$). The signal timing optimization is implemented and green times for maximum user throughput and maximum vehicle throughput are respectively selected as solution of UST and VST optimization. In VST optimization, user throughput is also calculated for best solution in order to use in comparison. Furthermore, throughput of each defined vehicle types are recorded for both algorithm. Finally, results are compared to evaluate efficiency of UST algorithm. The parameters for the UST and VST algorithms are set as follows. The desired speed v_d and queue discharging speed v_q are set to 60 km/h and 30 km/h, respectively. Minimum safety distance between vehicles is set to 2 m and minimum time headway is considered 2 s.

TABLE I: Scenarios summary

Phase	Scenario 1					Scenario 2				
	Flow state (veh/h/l)			Vehicles composition		Flow state (veh/h/l)			Vehicles composition	
	1	2	3	Vehicle type	Share (percent(%))	1	2	3	Vehicle type	Share (percent(%))
1	240	480	960	1	100	480	960	1920	1, 2	50, 50
2	240	480	960	2	100	480	960	1920	1, 2	50, 50
3	240	480	960	3	100	240	480	960	3, 4	50, 50
4	240	480	960	4	100	240	480	960	3, 4	50, 50
5	240	480	960	1	100	480	960	1920	1, 2	50, 50
6	240	480	960	2	100	480	960	1920	1, 2	50, 50
7	240	480	960	3	100	240	480	960	3, 4	50, 50
8	240	480	960	4	100	240	480	960	3, 4	50, 50

Cycle times are set 90 s, 120 s and 150 s respectively for flow state 1, 2 and 3 in both scenarios.



(a) Ring 1

(b) Ring 2

Fig. 4: UST algorithm validation test

Note that calculation time to run one iteration of GA for this problem is approximately 6 sec by a laptop computer with a i5-7300, 2.6-GHz central processing unit. Since GA iterations can be run in a parallel fashion, total calculation time is not affected by running multiple iterations.

IV. Validation and Evaluation

A validation test is designed in order to illustrate the accuracy of the model. In this regard, accumulated user-throughput in a cycle in UST algorithm and VISSIM simulation are compared for Scenario 1, flow state 2. The comparison is done for two rings separately. Fig. 4 shows result of algorithm validation. The comparison proves high accuracy of UST algorithm in prediction of vehicles and users stop-bar passage time.

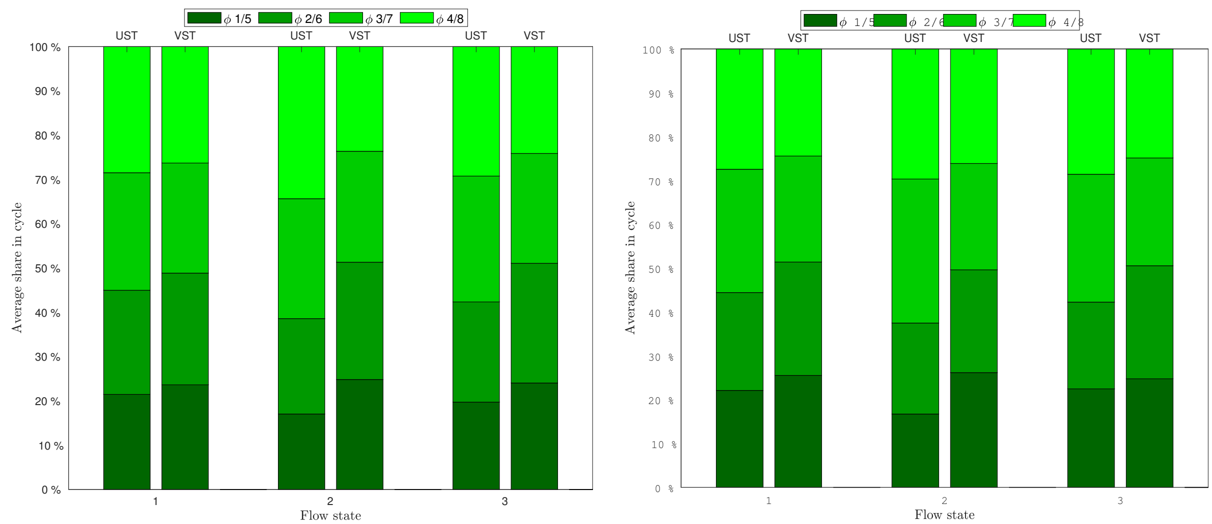
Fig. 5 presents average green time split for each simultaneous pair of phases in all random seeds. In both scenarios, phases which are assigned to vehicles with higher number of users have appropriated more green times in UST while, in VST the shares are approximately equal with tendency to phases with lower number of users. For example, in second flow state of Scenario 2, more than 60% of cycle time is assigned to phases with vehicle types 3 and 4 (ϕ 3,7 and ϕ 4,8) by UST optimization.

In order to evaluate the performance of the developed algorithm, UST optimization results are compared to VST ones, considering two metrics. The first is User throughput Increase percentage (UI) in UST relative to VST. This index shows the effectiveness of the algorithm in increasing user throughput relative to vehicle-based optimization. Mathematical formulation of UI index is expressed as:

$$\mathrm{UI} = 100 \times \frac{U_{\mathrm{UST}} - U_{\mathrm{VST}}}{U_{\mathrm{VST}}} \tag{32}$$

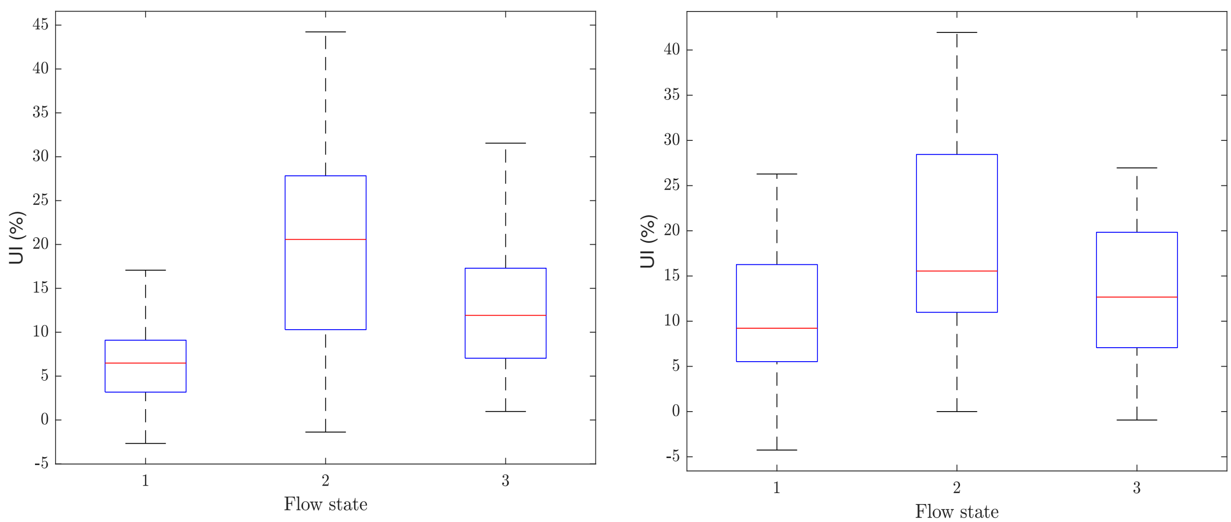
where:
U_{UST}: User throughput of UST algorithm;
U_{VST}: User throughput of VST algorithm.

UI index is calculated for each random seed of simulation. Fig. 6 presents UI index statistical analysis results for two scenarios in different traffic flows states and cycle times. Since, in scenario 1 vehicle types with high number of users can be exclusively served in assigned green time, increase percentage is considerably high (i.e. for flow=960 veh/h/l, UI is increased up to 40%). In addition, UI index is risen by increasing flow because more vehicles with high number of users can be accommodated. On the other hand, results of Scenario 2 show significant UI percentage in three flow states. Since traffic flow



(a) Scenario 1 (b) Scenario 2

Fig. 5: Average share of green time for each phase group

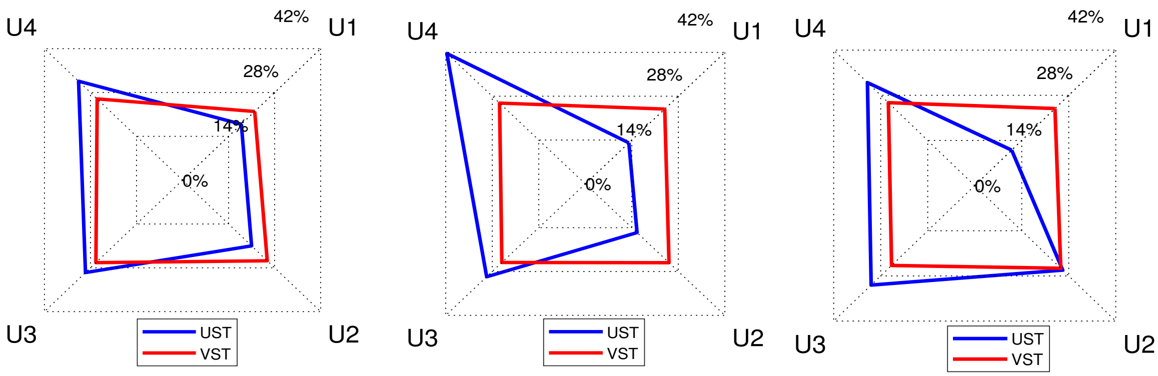


(a) Scenario 1 (b) Scenario 2

Fig. 6: UST algorithm validation test

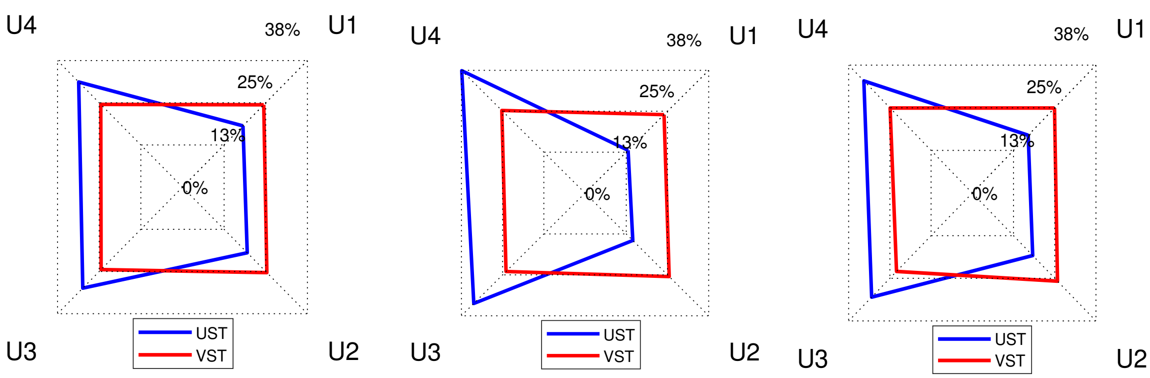
is unbalanced and composed by different vehicles types for major and minor streets, increase percentage is not as much as Scenario 1 in most states. However, UST has accommodate more users in average rather than VST.

In addition, share of each vehicle types from intersection throughput is compared between results of UST and VST algorithms. Average of all random seeds results is considered to calculate shares. This index shows UST algorithm efficiency in serving high occupancy vehicles than vehicles with low number of users. Fig. 7 and Fig. 8 present average share of each vehicle types from intersection throughput for two scenarios separately. According to obtained results, UST prioritizes vehicle types with high number of users (U3 and U4) to low occupancy vehicles (U1 and U2) in relation to VST in both scenarios. In Scenario 1, U4 vehicles share is absolutely most than other vehicle types. Moreover, in all three flow states vehicles with more users on-board have more share than vehicles with lower occupancy (U4>U3>U2>U1). On the other hand, in VST optimization the share of all vehicles are approximately equal due to equivalent flow for all approach. In scenario 2, VST optimization has generally led to more share of throughput for low occupancy vehicles as they are in high flow approaches (major streets). Conversely, UST optimization has prioritized vehicles with higher number of users even though they are assigned to low flow approaches (minor streets).



(a) Flow state 1 (b) Flow state 2 (c) Flow state 3

Fig. 7: Share of each vehicle type in intersection throughput- Scenario 1



(a) Flow state 1 (b) Flow state 2 (c) Flow state 3

Fig. 8: Share of each vehicle type in intersection throughput- Scenario 2

V. Discussion and Conclusion

Previous development of urban traffic signal control strategies, based on conventional detection technologies or connected vehicles, have utilized a range of input parameters. Despite their range from flow volume to queue lengths and arrival velocities, most of these input parameters have remained vehicle-centered. Furthermore, different control strategies have aimed to account for different vehicle types, for example, by giving priority to transit or emergency vehicles. However, despite distinguishing between vehicle types in traffic control strategies, users of vehicles were not taken directly into account. Recently, development of control strategies based on CVs has aimed for accounting for estimated number of users among different vehicle types. Overall, considering the exact number of users in signal timing optimization has not been investigated before. In this paper, we presented UST optimization algorithm in order to maximize user-throughput for signalized intersection in a connected vehicle environment.

First, the developed algorithm predicts vehicles arrival time to intersection. Then, based on exact number of user of each vehicle, user throughput for set of green times is calculated for intersection. To achieve this, a GA is used to find the optimum set of green times. The optimization performance is tested by micro-simulation of two scenarios with three sets of traffic volume distributions. The results illustrates two main abilities of UST signal timing optimization. First, this algorithm increases user-throughput in a signalized intersection relative to vehicle-based strategies optimization. Second, this algorithm prioritizes significantly high occupancy vehicles to low occupancy vehicles in various flow states by assigning more share from cycle. The mentioned abilities can be used as a transit signal priority strategy as well as ride-sharing motivation in the presence of connected and self-driving vehicles. Limitation of conventional data collection tools might be the main reason of inadequate attention to users in signal timing strategies in the past, but novel technologies such as CV can provide sufficient data to implement user-based signal timing. User-based strategies would not only prioritize vehicles based on their number of users, such as transit vehicles, but could also can motivate ride-sharing in urban transportation networks. Consequently, user-based strategies could be a proper approach to improve social side of sustainability as well as environmental and economical aspects.

In some cases, some unexpected results have appeared. UI index statistical analysis shows that, in some cases, UST was not able to increase user-throughput relative to VST.

This contradiction is due to the heuristic way of solving optimization problem where GA can be trapped in local optimum. Nevertheless, the proposed UST method shows clear potential to increase user throughput, as well as prioritizing high occupancy vehicles, as opposed to conventional vehicle-based strategies. In future development, the UST algorithm can be implemented on networks with additional transportation modes, such as buses, pedestrians, and bicycles. Furthermore, other performance measures, such as users delay and emission can be considered, in order to illustrate algorithm performance, and to further refine performance metrics at intersection and network-level.

REFERENCES

[1] A. Hamilton, B. Waterson, T. Cherrett, A. Robinson, and I. Snell, "The evolution of urban traffic control: changing policy and technology," *Transportation planning and technology*, vol. 36, no. 1, pp. 24–43, 2013.

[2] M. Papageorgiou, C. Diakaki, V. Dinopoulou, A. Kotsialos, and Y. Wang, "Review of road traffic control strategies," *Proceedings of the IEEE*, vol. 91, no. 12, pp. 2043–2067, 2003.

[3] M. Mladenovic, "Large scale analysis of traffic control systems," *Traffic Engineering & Control*, vol. 53, no. 1, 2012.

[4] J. A. Bonneson and M. Abbas, "Intersection video detection field handbook," Texas Transportation Institute, Texas A & M University System, Tech. Rep., 2002.

[5] L. A. Klein, M. K. Mills, D. Gibson, and L. A. Klein, "Traffic detector handbook: Volume i," United States. Federal Highway Administration, Tech. Rep., 2006.

[6] ——, "Traffic detector handbook: Volume ii," United States. Federal Highway Administration, Tech. Rep., 2006.

[7] R. J. Baker, J. Collura, J. J. Dale, L. Head, B. Hemily, M. Ivanovic, J. Jarzab, D. McCormick, J. Obenberger, L. Smith, and S. GR, "An overview of transit signal priority," Tech. Rep., 2002.

[8] F. Dion, H. Rakha, and Y. Zhang, "Evaluation of potential transit signal priority benefits along a fixed-time signalized arterial," *Journal of transportation engineering*, vol. 130, no. 3, pp. 294–303, 2004.

[9] S. P. Venglar, M. S. Jacobson, S. R. Sunkari, R. J. Engelbrecht, I. Urbanik *et al.*, "Guide for traffic signal preemption near railroad grade crossing," Tech. Rep., 2000.

[10] H. R. Smith, B. Hemily, and M. Ivanovic, "Transit signal priority (tsp): A planning and implementation handbook," 2005.

[11] H. S. Mahmassani, "50th anniversary invited article—autonomous vehicles and connected vehicle systems: Flow and operations considerations," *Transportation Science*, vol. 50, no. 4, pp. 1140–1162, 2016.

[12] A. Olia, H. Abdelgawad, B. Abdulhai, and S. N. Razavi, "Assessing the potential impacts of connected vehicles: mobility, environmental, and safety perspectives," *Journal of Intelligent Transportation Systems*, vol. 20, no. 3, pp. 229–243, 2016.

[13] Q. Guo, L. Li, and X. Jeff, "Urban traffic signal control with connected and automated vehicles : A survey," no. August 2018, 2019.

[14] L. Li, D. Wen, and D. Yao, "A survey of traffic control with vehicular communications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 1, pp. 425–432, 2014.

[15] M. Li, X. Chen, X. Lin, D. Xu, and Y. Wang, "Connected vehicle-based red-light running prediction for adaptive signalized intersections," *Journal of Intelligent Transportation Systems*, vol. 22, no. 3, pp. 229–243, 2018.

[16] B. Xu, X. J. Ban, Y. Bian, W. Li, J. Wang, S. E. Li, and K. Li, "Cooperative method of traffic signal optimization and speed control of connected vehicles at isolated intersections," *IEEE Transactions on Intelligent Transportation Systems*, no. 99, pp. 1–14, 2018.

[17] Y. Guo, J. Ma, C. Xiong, X. Li, F. Zhou, and W. Hao, "Joint optimization of vehicle trajectories and intersection controllers with connected automated vehicles: Combined dynamic programming and shooting heuristic approach," *Transportation Research Part C: Emerging Technologies*, vol. 98, pp. 54–72, 2019.

[18] E. Christofa, K. Ampountolas, and A. Skabardonis, "Arterial traffic signal optimization: A person-based approach," *Transportation Research Part C: Emerging Technologies*, vol. 66, pp. 27–47, 2016.

[19] Z. Yu, V. V. Gayah, and E. Christofa, "Person-based optimization of signal timing: Accounting for flexible cycle lengths and uncertain transit vehicle arrival times," *Transportation Research Record: Journal of the Transportation Research Board*, no. 2620, pp. 31–42, 2017.

[20] ——, "Implementing phase rotation in a person-based signal timing optimization framework," *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pp. 20–25, 2014.

[21] Y. Z. Farid, E. Christofa, and J. Collura, "An analytical model to conduct a person-based evaluation of transit preferential treatments on signalized arterials," *Transportation Research Part C: Emerging Technologies*, vol. 90, pp. 411–432, 2018.

[22] W. Ma, K. L. Head, and Y. Feng, "Integrated optimization of transit priority operation at isolated intersections: A person-capacity-based approach," *Transportation Research Part C: Emerging Technologies*, vol. 40, pp. 49–62, 2014.

[23] R. Jung and A. Gan, "Sampling and analysis methods for estimation of average vehicle occupancies," *Journal of transportation engineering*, vol. 137, no. 8, pp. 537–546, 2010.

[24] R. Jung, A. Gan, K. Liu, X. Li, and D. Sandoval, "Vehicle occupancy data collection methods," *Technical report No.:BD-015-9, Florida International University, Miami, FL. State of Florida Department of Transportation,*, 2005.

[25] M. N. Mladenović, M. Abbas, and T. McPherson, "Development of socially sustainable traffic-control principles for self-driving vehicles: The ethics of anthropocentric design," in *Proceedings of the IEEE 2014 International Symposium on Ethics in Engineering, Science, and Technology*, 2014, p. 77.

[26] J. G. Neoh, M. Chipulu, and A. Marshall, "What encourages people to carpool? an evaluation of factors with meta-analysis," *Transportation*, vol. 44, no. 2, pp. 423–447, 2017.

[27] A. Soteropoulos, M. Berger, and F. Ciari, "Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies," *Transport Reviews*, vol. 39, no. 1, pp. 29–49, 2019.

[28] K. Tiaprasert, Y. Zhang, X. B. Wang, and X. Zeng, "Queue length estimation using connected vehicle technology for adaptive signal control," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 2129–2140, 2015.

[29] J. Zheng and H. X. Liu, "Estimating traffic volumes for signalized intersections using connected vehicle data," *Transportation Research Part C: Emerging Technologies*, vol. 79, pp. 347–362, 2017.

[30] M. R. Shahrbabaki, A. A. Safavi, M. Papageorgiou, and I. Papamichail, "A data fusion approach for real-time traffic state estimation in urban signalized links," *Transportation Research Part C: Emerging Technologies*, vol. 92, pp. 525–548, 2018.

[31] Y. Feng, K. L. Head, S. Khoshmagham, and M. Zamanipour, "A real-time adaptive signal control in a connected vehicle environment," *Transportation Research Part C: Emerging Technologies*, vol. 55, pp. 460–473, 2015.

[32] M. J. Lighthill and G. B. Whitham, "On kinematic waves ii. a theory of traffic flow on long crowded roads," *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, vol. 229, no. 1178, pp. 317–345, 1955.

[33] P. Koonce and L. Rodegerdts, "Traffic signal timing manual." United States. Federal Highway Administration, Tech. Rep., 2008.

[34] "Vissim 11.00-03 user manual," 2018.

[35] K. Deb, "An efficient constraint handling method for genetic algorithms," *Computer methods in applied mechanics and engineering*, vol. 186, no. 2-4, pp. 311–338, 2000.