Route-Based Transit Signal Priority Using Connected Vehicle Technology to Promote Bus Schedule Adherence

Xiaosi Zeng, Yunlong Zhang, Jian Jiao, and Kai Yin

***Abstract*— In this paper, we explore the use of enriched bus data enabled by the Connected Vehicle (CV) technologies and propose signal timing optimization models that aim to improve bus service reliabilities via Transit Signal Priorities (TSP). Specifically, a route-based TSP model (R-TSP) and its local version (L-TSP) are formulated. Timing and progression deviations are introduced as a simple and novel way to approximate the TSP impacts on passenger vehicle delays. An online adaptive TSP system is developed to leverage the continuous availability of CV data to monitor bus priority needs, trigger new formulations of the TSP models with newly updated bus running data, and implement new signal timings in real-time. Simulation studies are conducted to evaluate a variety of R-TSP and L-TSP model variants to understand their respective effectiveness to improve bus schedule adherence and their impacts to other traffic. Simulation study on a hypothetical corridor show that an R-TSP model variant with both timing and progression deviation defined can improve a 100% late bus fleet to 98.4% of on-time arrival with only 5.5% increase in passenger car delays. In comparison, none of the L-TSP models could produce comparable benefits for buses and caused too much delay on passenger vehicles. These simulation studies conclude that (1) connected vehicle technologies provide critical data to allow route-based TSP model to be formulated simply and solved continuously, and (2) granting bus priority at route level is much more beneficial than only providing bus priority on a signal by signal basis.**

***Index Terms*— Bus route, mixed-integer linear model, signal coordination, transit signal priority, connected vehicle.**

I. Introduction

A. Transit Signal Priority

REAL-TIME Transit Signal Priority (TSP) is among the most cost-effective preferential treatments for transit buses. A TSP control strategy seeks to modify signal timing in real-time to facilitate the passage of transit vehicles through one or multiple intersections, with the goal of improving public transit service. A wide range of research and implementations can be found in the literature that focused on the effectiveness of a number of TSP control strategies. In earlier studies, research focused on isolated intersections, and optimization objectives normally were the total delays of multiple conflicting buses [1], [2], the total vehicle delays [3], [4], and the total person delays of buses and passenger cars [5]–[10]. In recent years, focuses have been shifted to the developments and evaluations of corridor- or route-level TSP priority strategies using rule-based algorithms [11]–[13] and math model-based approaches. For example, there are models that minimize bus-delay [14] on a route, total vehicular-delay [15] and total person-delay [7], [16], [17] along coordinated signal corridors. In addition to mathematically expressed optimization models, genetic algorithm and artificial neural network modeling approaches have also been explored [18].

In this paper, we explore the model-based approach in a coordinated signal corridor.

B. Bus Performance

All these models focused mainly on minimizing bus corridor delay. Schedule is often used only as a condition to determine whether priority should be implemented. However, bus service reliability is equally critical for the quality of bus services from customers' point of view [19], if not more than bus travel time itself.

For service reliability on a route, there are generally two main objectives: 1) headway regularity, and 2) schedule regularity. Headway regularity is important in high-frequency bus routes where on-time schedule arrival is not important due to very short headway [20]. Researches [8], [20], [21], [22] have attempted to use TSP as a pull-and-push tool to regulate headways. Schedule regularity includes the consideration of schedule lateness and schedule deviation. Schedule lateness refers to the amount of time that bus is late, and schedule deviation is the amount of time a bus is either early or late. Studies on TSP strategies for bus schedule deviations remain very limited. There are studies allowing intentional increase of bus delays [20], using second-order formulation to explicitly minimize schedule deviation [18], aiming to reduce crowding of on-board passengers [23], and resolving conflicting transit signal priority requests while minimizing delay [24]–[27].

C. Connected Vehicle Research

Connected vehicle technologies have shown a lot of promises in recent literatures [28]–[31]. Using vehicle to infrastructure (V2I) communications, detailed vehicle state, trajectory history, vehicle state, routing information can be used to enhance detection and modeling of traffic/vehicular

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dynamics; on the other hand, signal phasing and timing can be used to inform vehicular operators for more efficient driving [31]–[34]. It was demonstrated in recent studies [17], [24], [31] that connected vehicle technologies can be well-suited to provide more enriched information, including schedule, passenger counts to improve the effectiveness of TSP models.

D. Motivation and Contribution

There are few studies about how signal timings across multiple coordinated intersections should be adjusted in real-time to achieve route-level bus service reliability. This is largely due to the complexity of modeling TSP impacts on passenger vehicles and how to properly account for ever evolving traffic conditions.

In this paper we formulate a novel route-based TSP model by introducing two timing deviation concepts to linearly approximate the nonlinear impacts of the TSP operation on cross street and corridor traffic. To account for the ever-changing traffic conditions, we further propose an online adaptive TSP system (instead of trigger based TSP system) that leverages the data available from the connected vehicle technologies, and to take advantage of capabilities of this technology (including advanced vehicle localization, two-way communications, on board compute units, etc.) to coordinate the joint priority of multiple bus routes in real-time. A simulation study using two bus routes on a corridor is conducted and comparisons are made to empirically show the necessity of using route-based TSP algorithms to maximize bus route performance (e.g. route schedule adherence) while minimizing impacts to other arterial traffic.

II. Model Formulations

A. Model Applicability Settings

The common goal of any TSP control schemes in mixed traffic conditions is to seek the best signal timing that benefits buses while keeping the costs to other passenger cars the lowest possible. So it is logical to assume that any TSP algorithms/models are most applicable when the prevailing traffic condition is undersaturated.

Secondly, in any normal well-maintained signalized corridor, it is an expected routine for traffic engineers to optimize signal plans for passenger cars. So we assume the signal timings without any TSP activated is optimal for the prevailing traffic conditions and is available for TSP algorithms. It should also be noted that the interaction between bus control systems like the dispatching units and signal control are not considered in the research scope because the focus of the paper is on optimizing traffic signals to achieve bus's schedule adherence without changing bus dispatching processes and parameters.

Thirdly, and most importantly, we explore a likely future situation where Connected Vehicle data are available [28]. Under the CV data assumption, buses are equipped with V2I Onboard Units (OBU), and real-time data that are transmitted to a Roadside unit (RSU) connected to a traffic signal control system would at least include the following:

- Bus route metadata – bus stop timetable, stop locations, historical average of time spent at each stop
- Bus current operating state – GPS location, speed, number of onboard passengers

B. Simplifying Assumptions

As demonstrated in [27], bus arrival time distribution at an intersection could be used to improve the expected bus delay at that intersection. However, the stochastic optimization model applied to multiple intersections is much more complicated, difficult to solve, and could easily suffer the curse of dimensionality. Therefore, we propose a practical engineering approach later in this paper for adaptively solving TSP models simplified by the following assumptions:

- **Assumption I**: Any deviations of signal timings from the optimal timing would incur linear increase of average vehicular delays for general traffic.
- **Assumption II**: Any deviations of signal timings from the optimal timing for a coordinated corridor would additionally incur linear increase of average vehicular delays for general traffic on this corridor.

C. Model I - Localized Transit Signal Priority (L-TSP)

The first model we present is a localized-TSP model. Different from the Route-based TSP model to be introduced in section II-D, the L-TSP model formulates one signal timings optimization program per intersection and adjust the timing based only on the buses currently approaching the intersection.

Specifically, we formulate a linear mixed-integer program that models the signal phase and timing relationship across multiple cycles, and optimizes the phase durations to improve bus schedule reliability.

1) Modeling Signal Phases and Timings: First, we model a basic ring-barrier signal timing structure using a simple precedence-relations first proposed in [1]. This defines the red, green and yellow time relationships for all phases at the i^{th} intersection:

$$t_{ijk} = 0, \quad k = 1, j \in J_{il}^{first}, \forall i, l \tag{1}$$

$$t_{ij'k} = t_{ijk} + v_{ijk}, \quad \begin{array}{l} j \in J_{il} \backslash J_{il}^{last} \\ j' = J_{il}\{orderof(j) + 1\} \\ \forall i, k, l \end{array} \tag{2}$$

$$t_{ij,k+1} = t_{ij'k} + v_{ij'k}, \quad \begin{array}{l} j \in J_{il}^{first}, j' \in J_{il}^{last} \\ k \in K_i \backslash |K_i|, \forall i, l \end{array} \tag{3}$$

$$t_{ijk} = t_{ij'k}, \quad j \neq j' \in J_{il}^{barrier}, \forall i, k, l \tag{4}$$

$$t_{ijk} + v_{ijk} = kC, \quad k = |K_i|, j \in J_{il}^{last}, \forall i, l \tag{5}$$

where t_{ijk} and v_{ijk} are respectively the start time and phase split (duration) of phase j of cycle k at intersection i. C is the common cycle length given for a coordination signal arterial. J_{il} is the set of phases in ring l. Constraints (1) and (5) define the start and end times of the planning horizon with a fixed length of $|K_i|$ cycles. Constraints (2) and (3) define the precedency among J phases over several K cycles on different L rings. Note that the *orderof*(.) operator returns the order of a phase in its ring. For example, if $J_{il} = \{2, 1, 4, 3\}$ and $j = 2$, then $J_{il}\{\text{orderof}(j)+1\} = 4$. Eq. (4) defines a barrier because it ties together the start times of the barrier phases $J_{il}^{barrier}$ over all rings. For example, if phase 3 and 7 are barrier phases in ring 1 and 2, their start time needs to be the same.

One advantage of this formulation is that the two most widely implemented timing modification strategies – green extension and red truncation [35]–are modeled without adding additional binary variables that increase the model complexity. But the disadvantage is that phase resequencing is not modeled.

In addition to phase start times, green time duration should also be explicitly accounted for while modifying the timings for TSP. Therefore, we write the phase split (v_{ijk}), in Eq. (2) as a function of the green (g_{ijk}), a common yellow (Y) and a common red clearance (R) of the phase j at intersection i for cycle k:

$$v_{ijk} = g_{ijk} + Y + R, \quad \forall i, j, k \tag{6}$$

And we also define the useful lower-bounds for the green times, to ensure min-green ($G_{ijk}^{\min}$) is not violated while priority is activated, inequality(7), and there is enough green time to prevent oversaturation for a phase, inequality(8):

$$g_{ijk} \geq G_{ijk}^{min}, \quad \forall i, j, k \tag{7}$$

$$g_{ijk} \geq \frac{V_{ij}C}{S_{ij}X_C}, \quad \forall i, j, k \tag{8}$$

where X_c is the critical degree of saturation that a phase shouldn't go above. 0.9 or 0.95 is a good number to constrain a green time that would result in higher saturations. The rest of the constants in (8) are estimated/detected prevailing flow V_{ij} and saturation flow S_{ij} for phase j at intersection i.

2) Modeling TSP Impact on Intersection Delay: TSP impact is quantified in different ways in the literature. Christofa and Skabardonis [6] applied a simplified HCM-based second order equation for delay formulation. He *et al.* [36] did not directly quantify it but maximized the slack green time for a phase to indirectly minimize the TSP impact. We rely on the simplifying Assumption I, and define a *timing deviation*, y_{ijk}, to approximate the TSP impact for phase j at cycle k at current intersection i:

$$y_{ijk} \geq G_{ijk}^{opt} - g_{ijk}, \quad j \in J_i \backslash J_i^{coord}, \forall i, k \tag{9}$$

$$y_{ijk} \geq 0, \quad \forall i, j, k \tag{10}$$

Note that the definition of the deviation, y_{ijk}, is one sided, because the delay for the vehicles on this phase would increase only if the new green time g_{ijk} is shorter than the original green time G_{ijk}^{opt} which was optimized for passenger cars.

3) Modeling TSP Impact on Corridor Delay: Modifying signal timing due to TSP operation can impact corridor signal progressions much more heavily. By extending the concept of timing deviation, we rely on the simplifying Assumption II and define *progression deviation* for this purpose. This deviation quantifies the deviations of the start and/or end times of the coordinated phases from their originally scheduled time points as follows:

$$x_{ijk} \geq t_{ijk} - T_{ijk}^{opt}, \quad j \in J_i^{coord}, \forall i, k \tag{11}$$

$$z_{ijk} \geq T_{ijk}^{opt} + G_{ijk}^{opt} - t_{ijk} - g_{ijk}, \quad j \in J_i^{coord}, \forall i, k \tag{12}$$

$$x_{ijk}, z_{ijk} \geq 0, \quad \forall i, j, k \tag{13}$$

where x_{ijk} is the total seconds for starting the coordinated phases later than the optimal start time T_{ijk}^{opt} of the phase without TSP, while z_{ijk} computes the seconds for terminating the coordinated phases early. An important note is that inequalities (9) to (13) represent only one way of quantifying the TSP impacts on both cross-street and main-street traffic. The simulation studies in this paper briefly explored several reasonable definitions in later sections.

4) Modeling Bus Performance:

Bus Intersection Delays

A bus may arrive at (reach the stop line of) an intersection at any time in a cycle, and it may be served (clear the stop line) either in the same or the next cycle under the undersaturated traffic condition assumption. To predict arrival time, the CV data provide current bus speed and location, hence the arrival time R_{in} for bus n at intersection i can be roughly estimated by extrapolating the bus current motion to the intersection stop line. And this estimate is reasonably accurate when bus n is detected within the CV range (<1000ft) of intersection i, and there is no nearside bus stop.

So to determine which cycle bus n is served, it is equivalent to finding which cycle k that R_{in} would fall into:

$$R_{in} > t_{ij,k-1} + g_{ij,k-1} - (1 - \theta_{ijkn})M, \quad i \in I_n, j \in J_{in}, k \in K_i \backslash K_i\{1\}, \forall n \tag{14}$$

$$R_{in} \leq t_{ijk} + g_{ijk} + (1 - \theta_{ijkn})M, \quad i \in I_n, j \in J_{in}, \forall k, n \tag{15}$$

$$\sum\nolimits_{k \epsilon K} \theta_{ijkn} = 1, \quad i \in I_n, j \in J_{in}, \forall n \tag{16}$$

$$\theta_{ijkn} = \{0, 1\}, i \in I_n, j \in J_{in}, \forall k, n \tag{17}$$

where M is a very large constant value that is used with indicator variables in integer programming. The above constraints tie the indicator variable θ_{ijkn} to t_{ijk} and g_{ijk}, to indicate that bus n can only be served by phase j of cycle k at intersection i if R_{in} falls between the end of phase j in cycle k-1 and in cycle k. In addition, these set of constraints tie all the bus's arrival time together. So if bus n arrive at a conflicting phase j at the same cycle k of same intersection i comparing to bus *n-1*, these constraints would find the best timing to try to accommodate both buses.

It naturally follows with the definition of the priority delay of bus n at intersection i given expected discharge time for initial queue Q_{ij}:

$$d_{in} = t_{ijk} + Q_{ij} - R_{in} - (1 - \theta_{ijkn})M, \quad i \in I_n, j \in J_{in}, \forall k, n \tag{18}$$

Note Q_{ij} ensure bus delay accounts for the initial queue discharge time. But since it is a constant so we omit it from distracting the main formulation. Eq. (18) may yield a negative bus delay. In order to maintain non-negativity for d_{in} when the bus is not served in a phase (i.e. $\theta_{ijkn}=0$), a free variable $d^{\pm}_{in}$ is introduced and Eq. (18) is expanded using two inequalities:

$$d^{\pm}_{in} \geq t_{ijk} - R_{in} - (1-\theta_{ijkn})M, \quad i \in I_n, j \in J_{in}, \forall k, n \tag{19}$$

$$d^{\pm}_{in} \leq t_{ijk} - R_{in} + (1-\theta_{ijkn})M, \quad i \in I_n, j \in J_{in}, \forall k, n \tag{20}$$

A positive $d^{\pm}_{in}$ means that the bus would arrive before the start of green, or arrive after the start of green if the value is negative. In addition, we use an indicator variable β_{in} to tie the free variable $d^{\pm}_{in}$ with the non-negative variable d_{in} as:

$$d^{\pm}_{in} \leq (1-\beta_{in})M, \quad i \in I_n, \forall n \tag{21}$$

$$d^{\pm}_{in} \geq -\beta_{in}M, \quad i \in I_n, \forall n \tag{22}$$

$$d^{\pm}_{in} free, \quad i \in I_n, n \tag{23}$$

$$d_{in} \geq d^{\pm}_{in} - \beta_{in}M, \quad i \in I_n, \forall n \tag{24}$$

$$d_{in} \geq 0, \quad i \in I_n, \forall n \tag{25}$$

When $\beta_{in}=0$, the bus delay (d_{in}) is exactly $d^{\pm}_{in}$; otherwise, when $\beta_{in}=1$, d_{in} is zero, and that means bus n has no delay (i.e. clear the stop line as soon as it arrives) at intersection i.

Bus Schedule Lateness

The schedule lateness (δ_{in}) can be expressed as a function of the priority delay. More detailed discussions is provided in R-TSP section. Here, the schedule lateness is defined as:

$$\delta_{in} \geq r_{in} + d_{in} - R^{plan}_{in}, \quad i = I_n\{|I_n|\}, \forall n \tag{26}$$

$$\delta_{in} \geq 0, \quad i = I_n\{|I_n|\}, \forall n \tag{27}$$

That is, the lateness is the difference between actual departure time ($r_{in}+d_{in}$) and planned departure time R^{plan}_{in}. The key here is to compute this value. Different from the R-TSP formulation to be shown later, R^{plan}_{in} in the L-TSP model needs to be constructed from the bus stop time-table, because not every intersection has an upstream bus stop. For any intersections that do not have an upstream bus stop, we used expected saturation levels of all intersections between two consecutive bus stops as factors to construct the planned arrival time table for the corridor.

5) L-TSP Objective Function per Intersection: With the relationships between signal timing and bus performance modeled in the previous constraints, the objective of the L-TSP model is to modify the signal timings to give priority to buses while minimizing the deviations from optimal timing at intersection i:

Minimize:

$$\sum_{j\in J}\sum_{k\in K} c_{ijk}y_{ijk} + \sum_{l\in L}\sum_{j\in Z^2_{il}}\sum_{k\in K} c'_{ijk}(x_{ijk}+z_{ijk}) + \sum_{n\in N} o_n\tau_n \tag{28}$$

The first term, y_{ijk}, and the second term $x_{ijk+}z_{ijk}$, are timing and progression deviations for intersection i, respectively, for approximating the TSP impacts using Assumption I and II. Weights c_{ijk} and c'_{ijk} define the relative importance between the timing and the progression deviations. These values, in this paper, are computed as a function of the degree of saturation for the phase in prevailing traffic conditions, so the optimization would allow less congested phases to deviate more from optimal timing. τ_n denotes bus performance, which could be replaced with bus intersection delay d_{in} or schedule lateness δ_{in}. And o_n is a weighting factor that help tune the relative importance of bus performance to signal timing deviations.

A total of $|\ I\ |$ math programs are needed. One program per intersection for all $|N\ |$ arriving buses. And these programs are optimized independently. Hence the name localized TSP.

D. Model II - Route-Based Transit Signal Priority (R-TSP)

The objective of an R-TSP model is to provide bus priorities on a route level. This is done via connecting all $|\ I\ |$ L-TSP models together via linking constraints: (1) signal coordination, and (2) bus route trajectory. In addition, the bus schedule lateness formulation is slightly different from that of the L-TSP model.

In this section, we only present the linking constraints and the new formulation for schedule related measure to avoid repetition.

1) Signal Coordination Constraints: For a coordinated corridor, a fixed reference point in a signal cycle is necessary to guarantee signal synchronization among all intersections. In an actuated-coordinated control scheme, this time point is normally called *yield point* [37]. Adopting the concept of the actuated-coordinated control operation, the R-TSP model defines two constraints that would allow the coordinated phases to time pass their respective *yield points* in some cycles, as follows:

$$t_{ijk} + v_{ijk} \geq (k-1)C + YP_i, \quad k \in K_i\backslash|K_i|, j \in J^{yield}_i, \forall i \tag{29}$$

$$t_{ijk} + v_{ijk} = (k-1)C + YP_i, \quad k = |K_i|, j \in J^{yield}_i, \forall i \tag{30}$$

where YP_i denotes the yield point and $|K_i|$ is the cardinality of set K_i that contains timing cycle indices for all future optimization horizons for intersection i. The "$\geq$" sense in inequality (29) allows the coordinate phases to end no early than the yield point. This is particularly useful in extending the green time of a priority phase, but it may cause cycles to drift away from the reference point over time. Therefore, hard constraint (30) is enforced for the last cycle in the optimization horizon so as to ensure the signal timing at current intersection would recover back to synchronization after a TSP operation. This formulation would result in the same system level behavior for timing recovery over a few cycles from a conventional rule-based TSP operation [37].

2) Bus Route Trajectory Constraints: Another critical part for the R-TSP formulation is connecting bus arrival times at all intersections along a route of interest together. Note, this is where the name Route-TSP is derived to emphasize the ability of the model to pick any sequence of intersections in the formulation together instead of only those on a coordinated arterial corridor.

The arrival time (r_{in}) of bus n at intersection i is a direct result of the arrival times ($r_{i-1,n}$) and signal delays ($d_{i-1,n}$) at the upstream intersection i-1, the its travel times ($T^{Bus}_{\{i-1,i\},n}$) at road segment i-1 to i, and the time spent at a bus stop ($D_{\{i-1,i\},n}$) at the same road segment, if any. It is not possible to predict travel times and time spent at a bus stop accurately, even with CV technologies. Accurate estimates, however, are not necessary if they can be continuously updated and be used to adjust the TSP timings adaptively. Next section will discuss the adaptive TSP system more in-depth. This relationship of these quantities above can be expressed as:

$$r_{in} = r_{i-1,n} + d_{i-1,n} + D_{\{i-1,i\},n} + T^{Bus}_{\{i-1,i\},n} \quad i \in I_n \backslash I_n\{1\}, \forall n \tag{31}$$

$$r_{in}, r_{i-1,n} \geq 0 \quad i \in I_n \backslash I_n\{1\}, \forall n \tag{32}$$

Note that $d_{i-1,n}$ is not restricted in eq. (31), so it could take on any arbitrary values to satisfy the equality. However, bus n would travel a path that either result in a positive delay when the bus arrives in red or no delay when the bus arrives in green. In order to model the bus traveling trajectory that accounts for delays along the bus route, we replace d_{in} with $d^{\pm}_{i,n}$ and an indicator variable β_{in}, and replace eq. (31) with the following formulations:

$$r_{in} \geq r_{i-1,n} - (1-\beta_{i-1,n})M + D_{\{i-1,i\},n} + T^{Bus}_{\{i-1,i\},n}, \quad i \in I_n \backslash I_n\{1\}, \forall n \tag{33}$$

$$r_{in} \leq r_{i-1,n} + (1-\beta_{i-1,n})M + D_{\{i-1,i\},n} + T^{Bus}_{\{i-1,i\},n}, \quad i \in I_n \backslash I_n\{1\}, \forall n \tag{34}$$

$$r_{in} \geq r_{i-1,n} + d^{\pm}_{i-1,n} - \beta_{i-1,n}M + D_{\{i-1,i\},n} + T^{Bus}_{\{i-1,i\},n}, \quad i \in I_n \backslash I_n\{1\}, \forall n \tag{35}$$

$$r_{in} \leq r_{i-1,n} + d^{\pm}_{i-1,n} + \beta_{i-1,n}M + D_{\{i-1,i\},n} + T^{Bus}_{\{i-1,i\},n}, \quad i \in I_n \backslash I_n\{1\}, \forall n \tag{36}$$

when $\beta_{i-1,n} = 1$, it would indicate bus n arrives in green time at intersection i-1, so the bus would not experience any delay (i.e. $d^{\pm}_{i-1,n} \leq 0$), so constraint (33) and (34) would be active. But, when $\beta_{i-1,n} = 0$, it would indicate the bus arrives at red time with $d^{\pm}_{i-1,n} \geq 0$ amount of delay at intersection i-1, hence increasing the bus's arrival time (r_{in}) at intersection i. and constraint (35) and (36) would be active.

Also note that all these constraints are defined for all intersections I_n except the first intersection $I_n\{1\}$ for bus n. This is because the arrival time of the bus at the first intersection could be estimated via the CV data about the bus's current location and speed given the bus is relatively close to the first intersection in the formulation. So effectively the following:

$$r_{in} = R_{in}, \quad i = I_n\{1\}, \forall n \tag{37}$$

where R_{in} is the estimated arrival time at intersection $I_n\{1\}$, and is used as a known quantity in the formulation.

3) Conversion of Local Time to System Time: In the constraints (33) to (36), r_{in} is in reference to the cycle start time of intersection i. So putting r_{in} and $r_{i-1,n}$ on the same formulation is not exactly correct. It is necessary to put the arrival times all in reference to one system clock for bus trajectory constraint formulations. We introduce an *optimization offset* quantity (notated as Δ^o_i) to do the conversion, see Fig. 1.

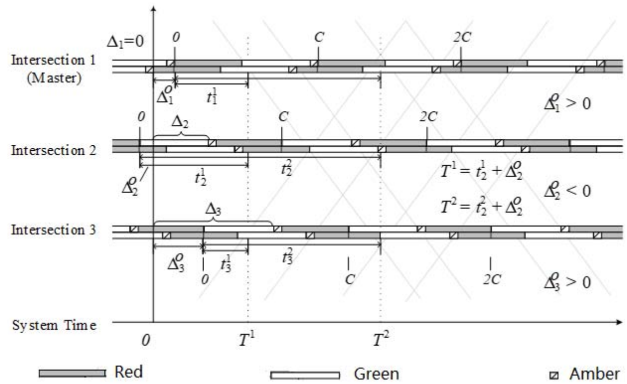


Fig. 1. Conversion between Local (t) and System (T) Times on a coordinated signal corridor with a common cycle length (C).

Each intersection has one and only one Δ^o_i, which is directly computed using the *a priori* information, collected from optimal timing table, such as signal coordination offset Δ_i, the cycle start time at an intersection, and the common cycle length C. Fig. 1 illustrates three different situations the optimization offset could be computed in relation to the coordination offset.

As a result, any local time can be easily converted to the system time using simply $T_i = t_i + \Delta^o_i$. And the bus trajectory constraints (33) to (36) and the following formulations should be rewritten to convert r_{in} into system times. To avoid cluttered math, we leave out the offset conversion without loss of critical information.

4) Bus Performance Measures:

Bus Route Delays

Minimizing bus delay along its route over I intersections is an important objective to achieve for travelers already on the bus. For the route delay of bus n, it is the summation of its delays at all intersections as follows:

$$d_n = \sum\nolimits_{i \in I} d_{in}, \quad \forall n \tag{38}$$

Bus Route Schedule Lateness

Another important objective for a bus operation is to adhere to a bus schedule. Many models use schedule lateness or deviation as weight coefficients to prioritize among different buses [38], [39] or as a condition to determine if the priority is needed at all [17]. Any such algorithms or models consider schedule-based metrics merely as parameter inputs instead of decision variables for the model to optimize.

To really achieve optimal bus route performance, we formulate the bus schedule lateness (δ_{in}) as the following:

$$\delta_{in} \geq r_{in} + d^{\pm}_{in} - R^{plan}_{in} - \beta_{in}M, \quad i \in I^{main}_n, \forall n \tag{39}$$

$$\delta_{in} \geq r_{in} - R^{plan}_{in} - (1-\beta_{in})M, \quad i \in I^{main}_n, \forall n \tag{40}$$

$$\delta_{in} \geq 0, \quad i \in I^{main}_n, \forall n \tag{41}$$

where I^{main}_n is a subset of intersections which situated directly downstream of the main bus stops for bus n. Since the arrival times of a bus stop is available in the bus stop time-stable, so R^{plan}_{in} can be trivially computed based on that information.

Bus Route Schedule Deviation

The formulation for schedule deviation is similar to that for schedule lateness except that the lateness variable, δ_{in}, needs to be replaced by the absolute value $|\delta_{in}|$. However, this makes the formulation nonlinear. A typical formulation trick to linearize the absolute value is to replace $|\delta_{in}|$ with $\delta_{in}^{+}+\delta_{in}^{-}$ in the objective function and $\delta_{in}^{+}-\delta_{in}^{-}$ in the constraints:

$$\delta_{in}^{+}-\delta_{in}^{-} \geq r_{in}+d_{in}^{\pm}-R_{in}^{plan}-\beta_{in}M, \quad i=I_{n}^{main}, \forall n \tag{42}$$

$$\delta_{in}^{+}-\delta_{in}^{-} \leq r_{in}+d_{in}^{\pm}-R_{in}^{plan}+\beta_{in}M, \quad i=I_{n}^{main}, \forall n \tag{43}$$

$$\delta_{in}^{+}-\delta_{in}^{-} \geq r_{in}-R_{in}^{plan}-(1-\beta_{in})M, \quad i=I_{n}^{main}, \forall n \tag{44}$$

$$\delta_{in}^{+}-\delta_{in}^{-} \leq r_{in}-R_{in}^{plan}+(1-\beta_{in})M \quad i=I_{n}^{main}, \forall n \tag{45}$$

$$\delta_{in}^{+}, \delta_{in}^{-} \geq 0 \quad i=I_{n}^{main}, \forall n \tag{46}$$

5) R-TSP Objective Function: Different from L-TSP where one math program needs to be formulated and solved independently per intersection, the R-TSP objective function ties together all buses route performance on the same signal corridor. And the formulation is essentially the same.

Minimize:

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk}y_{ijk}+\sum_{i\in I}\sum_{l\in L}\sum_{j\in Z_{il}^{2}}\sum_{k\in K} c'_{ijk}(x_{ijk}+z_{ijk}) + \sum_{n\in N} o_n\tau_n \tag{47}$$

where c_{ijk}, c''_{ijk} and o_n are weighting factors for each term for designers to tune their relative importance. τ_n denotes bus performance, which could be replaced with bus route delay, schedule lateness or schedule deviations as defined above.

Minimizing for all intersections at the same time yields the system optimal solution, which means using the least amount of signal deviations to achieve highest amount of bus route performance for all considered buses. Due to the weights c_{ijk} and c'_{ijk} are related to the degree of saturations, the objective function then effectively distributes the TSP impacts (i.e., deviations) intelligently to all phases on the corridor. That is, the TSP operation will cause relatively less deviations to more congested phases.

III. Adaptive TSP System

Both L-TSP and R-TSP models are formulated as deterministic linear models, which do not explicitly model uncertainty. However, bus route running conditions (e.g. travel time, time spent at a stop) are inherently uncertain and unpredictable. Any models with long planning horizons (e.g. R-TSP model), cannot ignore this uncertainty along the route. Therefore, an adaptive TSP system is proposed to address this issue. Using the classifications defined in Diakaki's paper [40], this TSP system would be a hybrid between Public-Transit-weighted and Public-Transit-triggered strategies.

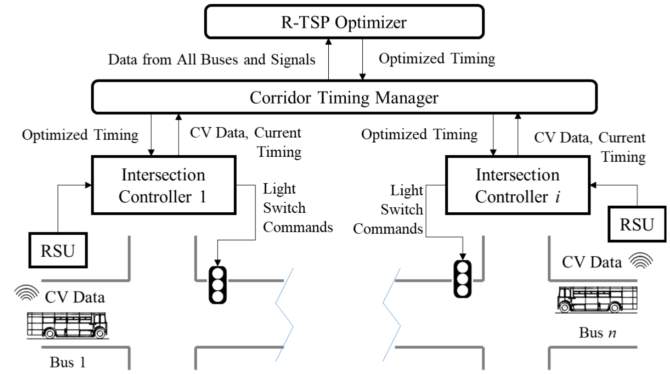


Fig. 2. General architecture of the online route-based adaptive TSP system.

A. Adaptive R-TSP System

An adaptive system is the one that adapt to changes in the system inputs. For the L-TSP and R-TSP models, this include R_{in}, $D_{\{i-1,i\}n}$, $T_{\{i-1,i\}n}$. As shown in Fig. 2, this is a system that heavily leverage connected vehicle technologies to collect CV data and transmit them to the closest *RSU* on a continuous basis. The data is then relayed to the *intersection controller* for preprocessing before sending to the *corridor timing manager*. The corridor manager collects the data from all intersection controllers and determines if a new optimization would be necessary for the entire corridor based on a triggering mechanism to be discussed in the next subsection. Interested readers can refer to [41] for more details of system architecture.

B. Optimization Triggering Mechanism

The proposed R-TSP model formulates the bus route trajectory constraints based upon estimated travel times $T_{\{i-1,i\}n}$ and time spent at a stop $D_{\{i-1,i\}n}$. As a bus travels down the corridor, the actual values are most likely different from the ones that were used in the initial formulation. This means the signal timings that were optimized using those initial values are stale, and a new optimization based on the latest estimates is necessary. This adaptive scheme is similar to other adaptive signal control system, which adjust when prevailing traffic condition changes [42].

In this study, we keep prevailing traffic conditions stable, but only adapt to bus travel and time spent at bus stops. So an evaluation between the planned bus trajectory and observed bus trajectory is sufficient to capture changes in both quantities. Therefore the triggering condition can be formalized as:

> *The observed time of the bus at one location along its route is $\pm q$ seconds from the planned time of the same location resulted from the last optimization.*

Because of this, a new optimization can be triggered at any points in a cycle, not just the start of the cycle. Thus, the formulation needs to be adjusted to fix the timings for the phases have already timed in the current cycle. Therefore, the following constraints are added to the TSP models:

$$g_{ijk} \geq G_{ijk}^{curr}, \quad j \in J_{i}^{cur}, \forall i, k \tag{48}$$

$$g_{ijk} = G_{ijk}^{past}, \quad j \in J_{i}^{past}, \forall i, k \tag{49}$$

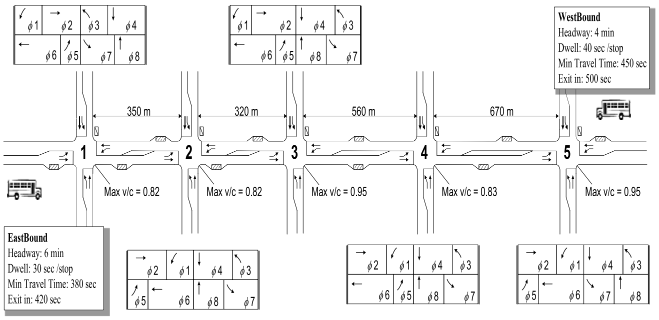


Fig. 3. Hypothetical test corridor with five coordinated intersections.

TABLE I
TRAFFIC VOLUME AND SIGNAL TIMING SETUPS FOR SIMULATION EVALUATION

Intersection 1 (offset = 0)								
Phase	$\phi 1$	$\phi 2$	$\phi 3$	$\phi 4$	$\phi 6$	$\phi 5$	$\phi 7$	$\phi 8$
# of Lanes	1	2	1	2	2	1	1	2
Volume (vph)	156	858	125	530	1092	109	140	390
Optimal Splits (s)	19	40	16	25	44	15	19	22
Intersection 2 (offset = 59)								
Phase	$\phi 2$	$\phi 1$	$\phi 4$	$\phi 3$	$\phi 5$	$\phi 6$	$\phi 8$	$\phi 7$
# of Lanes	2	1	2	1	1	2	2	1
Volume (vph)	942	100	550	70	50	1220	450	150
Optimal Splits (s)	44	16	29	11	11	49	22	18
Intersection 3 (offset = 56)								
Phase	$\phi 1$	$\phi 2$	$\phi 4$	$\phi 3$	$\phi 6$	$\phi 5$	$\phi 8$	$\phi 7$
# of Lanes	1	2	2	1	2	1	2	1
Volume (vph)	130	982	400	140	1470	180	250	100
Optimal Splits (s)	19	48	20	13	51	16	20	13
Intersection 4 (offset = 16)								
Phase	$\phi 2$	$\phi 1$	$\phi 4$	$\phi 3$	$\phi 6$	$\phi 5$	$\phi 8$	$\phi 7$
# of Lanes	2	1	2	2	2	1	2	1
Volume (vph)	882	180	340	300	1210	130	500	20
Optimal Splits (s)	42	22	20	16	48	16	26	10
Intersection 5 (offset = 61)								
Phase	$\phi 2$	$\phi 1$	$\phi 4$	$\phi 3$	$\phi 5$	$\phi 6$	$\phi 7$	$\phi 8$
# of Lanes	2	1	2	1	1	2	2	2
Volume (vph)	592	150	720	80	160	1270	240	250
Optimal Splits (s)	42	21	27	10	15	48	16	21
Common Cycle Length = 100 sec								
Veh Clearance = 4 sec								

where G_{ijk}^{curr} is the green time that has already elapsed for the current phase j of cycle k at intersection i, and G_{ijk}^{past} is that for a previous phase of the current timing cycle.

IV. SIMULATION SETUPS

A. Test Corridor Setup

In this paper, we set up a test corridor with five closely spaced and naturally coordinated signal intersections, as shown in Fig. 3, for comparing the effectiveness of L-TSP and R-TSP models.

All intersection approaches have two through lanes and one exclusive left-turn lane. General traffic volume is at a medium congestion level with intersection 3 and 5 closer to saturation. Aggregately, the westbound direction has heavier vehicular traffic. The lane configurations and prevailing traffic conditions for each approach are summarized in Table I. The popular signal optimization software, SYNCHRO [43], is used to optimize the corridor signal timing offline based on the prevailing traffic conditions, and the optimal timings that correspond to the optimal phasing sequence shown in Fig. 3 are also listed in Table I.

TABLE II
BASIC STATISTICS FOR BUS ROUTES

Direction	Free Flow Travel Time (sec)	Headway (min)	Min Observed TT w/o TSP (sec)	Max Observed TT w/o TSP (sec)	On-Time Travel Time (Sec)	% Late Bus w/o TSP by x Seconds				
						0	10	20	30	40
EB	380	6	420	640	450	89	84	75	67	63
WB	450	4	578	678	540	100	100	100	100	87.3
Overall	-	-	-	-	-	95.6	93.6	90	86.8	77.58

* 4, 6 min headways are selected to inject more buses priority conflicts to stress test the algorithm's ability to handle high-frequency bus headways. It is important to recognize that schedule adherence are typically more important for low-frequency bus routes [19].

B. Bus Route Setups

Two bus routes are set up on the test corridor, one going eastward, another going westward. In simulation, all buses are set up to have a maximum speed of 50 kph (31 mph), about 10 kph (6.2 mph) slower than passenger cars. The first and the last stops for both bus routes are considered as main stops, whose scheduled departure times are known and important to adhere to for good bus rider experiences. Table II shows some basic stats.

Buses on the EB route enter the network every 6 minutes, and they traverse from intersection 1 to 5 and dwell at each bus stop for roughly 30 seconds (i.e. uniformly randomly distributed between 20-40 seconds). These buses are scheduled to exit this group of 5 intersections at exactly 420 seconds after their entry. The travel times without TSP range from 420 to 640 seconds, so about 89% of all buses are late if no TSP, 84% are late by at least 10 seconds, and 75% are late by at least 20 seconds and so on. The minimum possible travel time, accounting for only the travel time and the time spent at bus stops, is 380 seconds.

The WB bus route is a little busier, with a 4-minute headway. Buses on this route dwell roughly 40 seconds per stop (i.e. uniformly randomly distributed between 30-50 seconds), and have a scheduled exit time of 500 seconds after entry. The minimum possible travel time without any signal delays on westbound is about 450 seconds. The travel times without TSP range from 578 to 678 seconds, so all WB buses would be late by at least 30 seconds.

V. SIMULATION STUDIES

A. Model Formulation Analyses

The L-TSP and R-TSP models presented earlier lay out a modeling framework for providing transit signal priorities on a corridor. But there are many factors in the formulation could potentially affect model performances. To understand which constraints and/or definitions could be potentially influential to the model performances, we set up a few variants for both L-TSP and R-TSP models based on (1) whether it allows variable cycle lengths, and (2) how to define progression deviations.

TABLE III
MODEL SETUP PARAMETERS AND EVALUATION TEST RESULTS

Model Variants	Strategy	Deviation	Max Cycles	Variable Length	Bus		All PC		Bus	Main St. PC	Cross St. PC	All PC
					Stops (/veh)	Delay (s/veh)	Stops (/veh)	Delay (s/veh)	Delay Change (%)			
TSP_0	No TSP	-	-	-	0.86	34.4	0.51	24.4	-	-	-	-
TSP_L1	L-TSP	SG	-	0	0.73	26.6	0.52	24.7	-23	1.5	1.0	1.2
TSP_R1	R-TSP	SG	-	0	0.67	25.1	0.53	25.7	-27	3.0	6.6	4.9
TSP_L2	L-TSP	SG	10	1	0.67	21.8	0.53	25.8	-37	8.4	3.3	5.6
TSP_R2	R-TSP	SG	10	1	0.49	17.6	0.54	26.5	-49	7.0	9.3	8.2
TSP_L3	L-TSP	LG	-	1	0.69	22.9	0.54	26.2	-33	12.0	3.1	7.1
TSP_R3	R-TSP	LG	-	1	0.27	8.0	0.59	28.6	-77	23.1	11.9	16.9
TSP_L4	L-TSP	LG+ER	-	1	0.66	21.5	0.52	25.1	-37	-2.6	7.4	2.8
TSP_R4	R-TSP	LG+ER	-	1	0.26	8.0	0.56	27.4	-77	12.2	12.3	12.2
TSP_L5	L-TSP	GD+ER	-	1	0.65	21.4	0.52	25.2	-38	-2.9	7.7	2.9
TSP_R5	R-TSP	GD+ER	-	1	0.40	12.0	0.53	25.9	-65	3.8	8.0	6.1

* SG – Short Green; LG – Late Green; ER – Early Red; GD – Green Start Deviation.

In total, five model variants were developed in the formulation analysis. Table III reports the main differences in the model formulations. These differences include priority provisional strategy (i.e., strategy), definition of progression deviations (i.e. p. deviation), maximum number of cycles allowed for continuous implementation (i.e. max cycles), and whether variable cycle lengths (i.e. variable length) are allowed. The corridor delays per vehicle for both bus and passenger cars (PC) and the percent changes of delays are reported at the end of Table III. All model variants are compared against the baseline TSP_0, which was running the optimal fixed-time timing plan without bus signal priority.

1) Fixed and Variable Cycle Lengths: The first set of model variants (TSP_L1, TSP_R1) are not to allow changeable cycle length. This is to ensure signals along the test corridor stay in sync over time. Both models only allow changing green durations and penalize green times that are shorter than optimal green times (Short Green). When a bus requires a priority, either model can only push the green times of the phases conflicting to the priority phase to minimum greens. As a result, both model variants provide some limited benefits to the buses needing priority, yielding about 23-27% bus delay reduction. The up side is that there is no more than 5% delay increase to all passenger cars (PC).

Fixed cycle length is too restrictive in terms of reducing bus corridor delay. To allow more flexibility, TSP_L2 and TSP_R2 allow the coordinated phases to time past the yield points, effectively allowing the cycle length to change. This is an operation that resembles the actuated-coordinated signal control. However, to prevent the corridor from losing synchronization over time, it is also implemented with a max number of consecutive cycles with TSPs allowed. When the max number is reached, any further priority requests are ignored until signal timing recovers to normal. As a result, more reduction of bus corridor delay is observed for TSP_L2 (i.e. 37%) than TSP_L1. However, variable cycle length induced much more delays onto vehicles on the main streets. It is not surprising since variable cycle lengths may break up main street traffic progression. On the other hand, TSP_R2 was able to yield even more bus delay reduction (i.e. 49%). It is because the R-TSP model can project bus arrival time downstream, and recognize the needs of a few extra seconds at current intersection may help significantly reduce downstream delays. However, the added reduction of bus delay is not without a price – 8% of delay increase was resulted for other traffic to provide the few extra seconds.

2) Penalizing Progression Deviations: The first two model variants are set up to keep the coordinated cycles not going out of sync, which has some limited success. To not restrict cycle times, TSP_L3 and TSP_R3 both penalize the late start of coordinated greens (Late Green). Essentially, only constraint (11) is enforced. In this way, any timing that would result in late start of the phases is discouraged. However, this penalization option alone does not work too well and it seems to keep shifting the progression band to the right on a time-space diagram. And it has led to increases of the overall vehicle delays, especially impactful for traffic on the main street. Delays of main street traffic surged to 12% and 23% for TSP_L3 and TSP_R3 respectively.

To keep coordinated phases of an intersection on the corridor traffic progression band, constraint (12) is also needed to penalize early terminations of coordinated phases. TSP_L4 and TSP_R4 are formulated exactly like that. As a result, the bus delay decreases for TSP_L4 is maintained at the highest level for localized strategy (i.e. 37%), while the increase in overall traffic delay has dropped to 3% from 6%. For TSP_R4, bus delay reduction is maintained at 77% as in TSP_R3, while the increase of main-street traffic delay is dropped from 23% to 12 %.

However, giving green to coordinated phases sometimes is detrimental to corridor signal progression. Therefore, the third option of penalizing progression deviations is to penalize the deviations of new start times of the coordinated phases from the scheduled start times. x^+ and x^- are introduced to linearize the nonlinear deviation function (i.e. $|x|$). In the objective function, x_{ijk} is replaced with $x^+_{ijk} + x^-_{ijk}$, and the following equality is added to the constraint set:

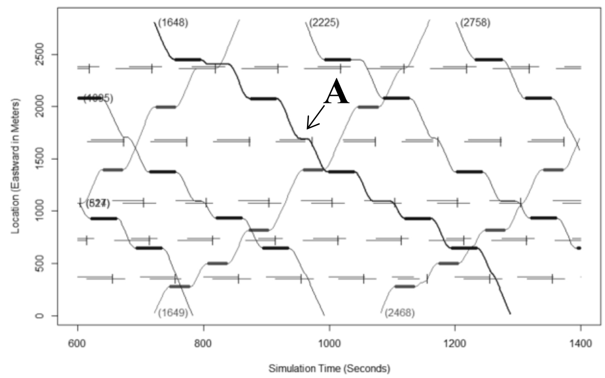
$$x^+_{ijk} - x^-_{ijk} = t_{ijk} - T^{opt}_{ijk}, \quad j \in J^{coord}_i, \forall i, k \tag{50}$$

This formulation variation is implemented in TSP_L5 and TSP_R5. Clearly, this helps minimize the TSP impacts on other traffic in the R-TSP model but does not have much positive effects on the L-TSP model. As a result, the TSP impact on other traffic for TSP_R5 is only about 6.1%. This TSP impact is similar to that in the TSP_L2 model, while its reduction in bus delay is far greater (i.e. 65% vs 37%), indicating a much efficient use of signal timing to provide priority.

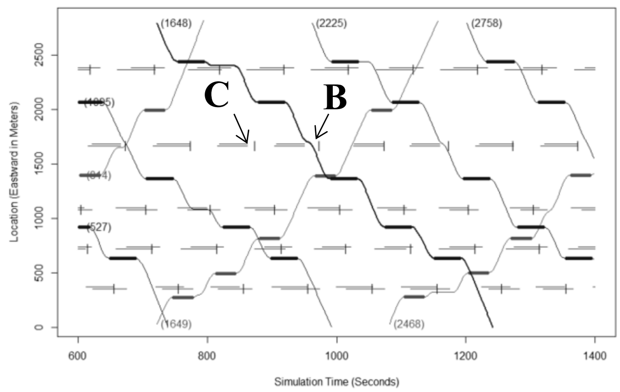
B. Trajectory Analysis

The formulation analyses on the TSP models point to an important realization that a localized approach could not achieve high level bus delay reduction as the route-based approach (i.e. 38% vs 77%). To understand how L-TSP and R-TSP models modify the corridor signal timings differently, we conduct a trajectory analysis to look for cases they differ the most. Fig. 4 shows a set of bus trajectories in a space-time

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.



(a) Localized TSP (TSP_L4)



(b) Route-based TSP (TSP_R4)

Fig. 4. Time-Space plots of bus trajectories along the corridor.

diagram at the test corridor. We select one bus (ID: 1648) for this trajectory analysis.

At the second intersection, where point A is pointing at in Fig. 4(a), the bus 1648 arrived at red time, so it stopped for a while longer than it would at point B in Fig. 4(b). And because of this delay, the bus was not able to clear the next three intersection in Fig. 4(a) without a stop or significant adjustment of the signal timing.

The reason why the bus would not need to stop in the second intersection in Fig. 4(b) was because the R-TSP model planned for the bus's arrival at point B when the bus was still at the first intersection. This advance planning allowed the priority timing to be activated one cycle earlier than the bus's arrival at point C, which effectively distribute the impacts of the bus's priority need over multiple cycles to minimize the overall signal timing deviations.

C. Schedule Analysis

Schedule adherence is a critical performance measure for public transportation vehicles. In this paper, we investigate two schedule adherence metrics: schedule lateness and deviations. To gauge the efficiency of a TSP model, an Improvement per Impact (IPI) index is defined as follows:

$$\mathrm{IPI} = \left| \frac{\text{Bus Improvement}}{\text{PC Delay Increase}} \right| \tag{51}$$

The IPI index normalizes the improvements of bus corridor performance by the TSP impacts on other traffic. The higher

TABLE IV

COMPARISONS OF R-TSP AND L-TSP MODELS FOR BUS CORRIDOR PERFORMANCE

Model Variations	Objective Bus	Bus Stops (/veh)	Bus Delay (s/veh)	All PC Stops (/veh)	All PC Delay (s/veh)	% Bus Delay Reduction	% Late Bus	Schedule Deviation (Sec) Average	Schedule Deviation (Sec) Std Dev.	% All PC Delay Increase	Improve. per Impact *
TSP_0	-	0.86	34.4	0.51	24.4	-	95.6	79.5	43.5	-	-
TSP_L6_L	Lateness	0.67	21.4	0.52	25.3	-37.9	**63.2**	33.9	25.7	3.3	10.2
TSP_L6_V	Deviation	0.72	23.2	0.54	26.0	-32.6	72.8	**33.7**	28.6	6.4	9.0
TSP_R6_L	Lateness	0.43	13.2	0.53	25.8	-61.7	**1.6**	27.6	17.6	5.5	18.0
TSP_R6_V	Deviation	0.59	19.7	0.54	26.0	-42.7	46	**5.6**	9.6	6.4	14.4

* Bus IPI index is computed using the percent change in bus performance of interest divided by the percentage of all PC delay increase. Performances of interest are the ones in bold.

the index value, the more benefits per vehicle delay increase can be produced by a model.

For each of the TSP model families (i.e. R-TSP and L-TSP), two model variants are formulated that differ only in objective function. One model variant optimizes for schedule lateness, while the other optimizes for schedule deviations. So a total of four model variants. TSP_L6_L and TSP_L6_V are the two L-TSP model variants that optimize for lateness and deviation respectively, while TSP_R6_L and TSP_R6_V are formulated as R-TSP models. Table IV listed the results of simulation results for each of the four variants.

First, we look at the bus schedule lateness metric and compare between the L-TSP and R-TSP model variants. TSP_L6_L provides improvements to the average lateness of the bus fleet, dropping from 95.6% late buses to only 63.2% late buses. In comparison, TSP_R6_L helped 98.4% of all buses on both directions of the corridor to arrive either on-time or early. And the IPI value of TSP_R6_L is much higher than that of the TSP_L6_L, indicating highly efficient use of signal timings on improving bus schedule lateness. This clearly suggests that the R-TSP models are superior to the L-TSP models when optimizing for bus schedule lateness.

Similar observations can be made for schedule deviations as well. The TSP_L6_V model virtually made no observable improvements in schedule deviation comparing to the TSP_L6_L variant even though it explicitly optimizes for it. On the other hand, the TSP_R6_V model significantly minimizes the schedule deviation of the all simulated buses so that their on-time arrivals are within 5.6 seconds from scheduled arrival time. Furthermore, the IPI value of TSP_R6_V is clearly higher than that of the TSP_L6_V model.

One reason for such a big difference in performance between TSP_L6_V and TSP_R6_V models is the following. TSP_L6_V treats early and late releases of a bus from current intersection exactly the same if the amount of deviations from the schedule is the same, because its ultimate target is meeting the schedule at the current intersection. However, at a corridor level, early and late releases are not the same for downstream intersections. The locally optimization models (i.e. L-TSP model family) have no way to know how early or late release at this intersection would affect the schedule deviations at downstream intersections. The R-TSP models, however, explicitly account for this relationship of schedule deviations along multiple bus stops; so they are able to quantify how much early release differ from late release and choose the ones that benefit the entire corridor the most.

VI. Conclusion and Future Research

In this paper, a localized TSP (L-TSP) model and a route-based TSP (R-TSP) model are formulated under the assumptions of the availability of bus running data enabled by the Connected Vehicle technologies. Both models are formulated as mixed-integer linear models that optimize the signal timings to provide priority passages for buses while keeping the impacts of timing adjustments minimal. Timing and progression deviations from optimal timing plans are introduced for the first time to approximate the impacts of timing adjustments on passenger vehicle delays. Uncertainties on bus travel time and time spent at bus stops are not formulated into either model, so as to preserve the simplicity and tractability of the models. Instead, an adaptive TSP system is proposed to leverage the availability of CV data to continuously reformulate and re-solve the TSP models to account for the uncertainties of bus travel time and time spent at bus stops.

A test corridor is set up, on which several simulation analyses are carried out to investigate one main question: *if bus priorities should be given on a route level instead of at individual intersections*. Five different formulation variants of both the L-TSP and R-TSP models are analyzed and discussed, followed by a trajectory analysis and a schedule analysis using the best variant. It is found that penalizing start time deviations of the coordinated phases can help greatly limit the TSP impacts on the main street traffic progression. Secondly, the R-TSP models can yield as much as 78% of bus delay reduction, while the best L-TSP model caps out at around 38%. However, great reduction in bus delay comes with high impacts on other traffic. An Improvement per Impact index is defined and is used to suggest that R-TSP model variants are very efficient in improving bus schedule adherence. For example, an R-TSP model variant has improved on-time performance by as much as 98% with as little as 5.5% delay increase on other traffic. Furthermore, it is also found that the L-TSP model is not at all effective in minimizing bus schedule deviations.

The implication of these conclusions is that the state-of-the-practice approach of providing priorities to buses locally cannot realize the full potentials of the pull and push ability of TSP operations on bus performances, especially in terms of schedule adherence. A non-passive TSP strategy using either mathematical programming or other decision-making techniques should consider providing coordinated priority instead of isolated priorities to transit vehicles for superior benefits and lower impacts.

One important future research is the robustness of the R-TSP models or, in another word, the susceptibility of the R-TSP models to the stochastic nature of the traffic system. For example, would larger randomness in time spent at bus stops change the conclusion to favor L-TSP more? Either theoretically or empirically characterization on the impacts of uncertainty for R-TSP effectiveness would help better define boundary conditions to which R-TSP strategies are better than their L-TSP counterparts.

Some other future research direction is to understand how the R-TSP model performs when higher degrees of conflict exist among bus routes running in the same signal corridor, weighing the routes differently, and transferring offline TSP concepts [44] to online systems

References

[1] L. Head, D. Gettman, and Z. Wei, "Decision model for priority control of traffic signals," *Transp. Res. Rec.*, vol. 1978, no. 1, pp. 169–177, Jan. 2006.

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

[3] M. Li, Y. Yin, W.-B. Zhang, K. Zhou, and H. Nakamura, "Modeling and implementation of adaptive transit signal priority on actuated control systems," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 26, no. 4, pp. 270–284, May 2011.

[4] P. Mirchandani, A. Knyazyan, L. Head, and W. Wu, "An approach towards the integration of bus priority, traffic adaptive signal control, and bus information/scheduling systems," in *Computer-Aided Scheduling of Public Transport*. Berlin, Germany: Springer, 2001, pp. 319–334.

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

[6] E. Christofa and A. Skabardonis, "Traffic signal optimization with application of transit signal priority to an isolated intersection," *Transp. Res. Rec.*, vol. 2259, no. 1, pp. 192–201, Jan. 2011.

[7] R. Li and P. J. Jin, "Transit signal priority optimization for urban traffic network considering arterial coordinated signal control," *Adv. Mech. Eng.*, vol. 9, no. 8, Aug. 2017, Art. no. 168781401770059.

[8] Y. Lin, X. Yang, G.-L. Chang, and N. Zou, "Transit priority strategies for multiple routes under headway–based operations," *Transp. Res. Rec.*, vol. 2366, no. 1, pp. 34–43, Jan. 2013.

[9] K. Yang, M. Menendez, and S. I. Guler, "Implementing transit signal priority in a connected vehicle environment with and without bus stops," *Transportmetrica B, Transp. Dyn.*, vol. 7, no. 1, pp. 423–445, Dec. 2019, doi: 10.1080/21680566.2018.1434019.

[10] X. Zeng, X. Sun, Y. Zhang, and L. Quadrifoglio, "Person–based adaptive priority signal control with connected–vehicle information," *Transp. Res. Rec.*, vol. 2487, no. 1, pp. 78–87, Jan. 2015.

[11] W. Ma, X. Yang, and Y. Liu, "Development and evaluation of a coordinated and conditional bus priority approach," *Transp. Res. Rec.*, vol. 2145, no. 1, pp. 49–58, Jan. 2010.

[12] E. Albright and M. Figliozzi, "Factors influencing effectiveness of transit signal priority and late–bus recovery at signalized–intersection level," *Transp. Res. Rec.*, vol. 2311, no. 1, pp. 186–194, Jan. 2012.

[13] P. G. Furth and T. H. J. Muller, "Conditional bus priority at signalized intersections: Better service with less traffic disruption," *Transp. Res. Rec.*, vol. 1731, no. 1, pp. 23–30, Jan. 2000.

[14] W. Ma, W. Ni, L. Head, and J. Zhao, "Effective coordinated optimization model for transit priority control under arterial progression," *Transp. Res. Rec.*, vol. 2366, no. 1, pp. 71–83, Jan. 2013.

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

[16] E. Christofa, K. Aboudolas, and A. Skabardonis, "Arterial traffic signal optimization: A person-based approach," in *Proc. 92nd Transp. Res. Board Annu. Meeting*, Washington, DC, USA, 2013, p. 20.

[17] J. Hu, B. B. Park, and Y.-J. Lee, "Coordinated transit signal priority supporting transit progression under connected vehicle technology," *Transp. Res. C, Emerg. Technol.*, vol. 55, pp. 393–408, Jun. 2015.

[18] M. S. Ghanim and G. Abu-Lebdeh, "Real–time dynamic transit signal priority optimization for coordinated traffic networks using genetic algorithms and artificial neural networks," *J. Intell. Transp. Syst.*, vol. 19, no. 4, pp. 327–338, Oct. 2015.

[19] Kittleson & Associate, KFH Group Inc, Parsons Brinckhoff Quade & Douglass, K. H. Zaworski, *Transit Capacity and Quality of Service Manual*, 2nd ed. Washington, DC, USA: Transportation Research Board, 2003.

[20] N. Hounsell and B. Shrestha, "A new approach for co–operative bus priority at traffic signals," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 1, pp. 6–14, Mar. 2012.

[21] N. Hounsell, B. Shrestha, J. Head, S. Palmer, and T. Bowen, "The way ahead for London's bus priority at traffic signals," *IET Intell. Transp. Syst.*, vol. 2, no. 3, pp. 193–200, 2008.

[22] K. Ling and A. Shalaby, "Automated transit headway control via adaptive signal priority," *J. Adv. Transp.*, vol. 38, no. 1, pp. 45–67, 2003.

[23] Y. Wadjas and P. G. Furth, "Transit signal priority along arterials using advanced detection," *Transp. Res. Rec.*, vol. 1856, no. 1, pp. 220–230, Jan. 2003.

[24] J. Hu, B. B. Park, and Y.-J. Lee, "Transit signal priority accommodating conflicting requests under Connected Vehicles technology," *Transp. Res. C, Emerg. Technol.*, vol. 69, pp. 173–192, Aug. 2016.

[25] R. Li, P. J. Jin, and B. Ran, "Biobjective optimization and evaluation for transit signal priority strategies at bus stop-to-stop segment," *Math. Problems Eng.*, vol. 2016, Apr. 2016, Art. no. 1054570, doi: 10.1155/2016/1054570.

[26] Z. Ye and M. Xu, "Decision model for resolving conflicting transit signal priority requests," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 1, pp. 59–68, Jan. 2017.

[27] X. Zeng, Y. Zhang, K. N. Balke, and K. Yin, "A real–time transit signal priority control model considering stochastic bus arrival time," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 4, pp. 1657–1666, Aug. 2014.

[28] X. B. Zeng and K. Songchitruksa, "Potential connected vehicle applications to enhance mobility, safety, and environmental security," Texas Transp. Inst.. College Station, Texas, TX, USA Tech. Rep. SWUTC/12/161103-1, 2012.

[29] Y. Wang, D. Tian, Z. Sheng, and W. Jian, *Connected Vehicle Systems: Communication, Data, and Control*. Boca Raton, FL, USA: CRC Press. 2017.

[30] M. Steadman and B. Huntsman, "Connected vehicle infrastructure: Deployment and funding overview," Tech. Rep. PRC 17-77 F. Texas A&M Transp. Inst., Texas, TX, USA, 2018.

[31] K. F. Turnbull *et al.*, "Automated and connected vehicle (AV/CV) test bed to improve transit, bicycle, and pedestrian safety," Texas, Dept. Transp. Res. Technol. Implement. Office, Texas, TX, USA, Tech. Rep. FHWA/TX-17/0-6875-1, 2017.

[32] X. Liang, S. I. Guler, and V. V. Gayah, "A scalable and computationally efficient connected vehicle–based signal control algorithm," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 66–71.

[33] X. Liang and S. I. V. V. Guler Gayah, "Signal timing optimization with Connected Vehicle technology: Platooning to improve computational efficiency," *Transp. Res. Rec.*, vol. 2672, no. 18, pp. 81–82, 2018.

[34] B. Beak, K. L. Head, and Y. Feng, "Adaptive coordination based on connected vehicle technology," *Transp. Res. Rec.*, vol. 2619, no. 1, pp. 1–12, Jan. 2017.

[35] K. Balke, "Development and laboratory testing of an intelligent approach for providing priority to buses at traffic signalized intersections doctor of philosophy," Texas A&M Univ., Transp. Res. Rec., College Station, TX, USA, Res. Paper, 2017, vol. 2619, doi: 10.3141/2619-01.

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

[37] P. Koonce *et al.*, "Traffic signal timing manual," Federal Highway Admin., Washington, DC, USA, Tech. Rep. FHWA-HOP-08-024, 2008. [Online]. Available: http://ops.fhwa.dot.gov/arterial_mgmt/tstmanual.htm

[38] C.-F. Liao, G. A. Davis, and R. Atherley, "Simulation study of a bus signal priority strategy based on GPS/AVL and wireless communications," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2034, pp. 82–91, Jan. 2007.

[39] A. Skabardonis, "Control strategies for transit priority," *Transp. Res. Rec.*, vol. 1727, no. 1, pp. 20–26, Jan. 2000.

[40] C. Diakaki, M. Papageorgiou, V. Dinopoulou, and I. G. M. Papamichail, "State-of-the-art and-practice review of public transport priority strategies," *IET Intell. Transp. Syst.*, vol. 9, no. 4, pp. 391–406, 2014.

[41] X. Zeng, "Development and evaluation of an adaptive transit signal priority system using connected vehicle technology," Ph.D. dissertation, Dept. Civil Eng., TAMU, College Station, TX, USA, 2014.

[42] M. Conrad, F. Dion, and S. Yagar, "Real–time traffic signal optimization with transit priority: Recent advances in the signal priority procedure for optimization in real–time model," *Transp. Res. Rec.*, vol. 1634, no. 1, pp. 100–109, Jan. 1998.

[43] *SYNCHRO 6 User Guide*. Trafficware. Sugar Land, TX, USA, 2004.

[44] B. Barabino, M. Di Francesco, and S. Mozzoni, "An offline framework for the diagnosis of time reliability by automatic vehicle location data," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 3, pp. 583–594, Mar. 2017.

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