A Real-Time Transit Signal Priority Control Model Considering Stochastic Bus Arrival Time

Xiaosi Zeng, Yunlong Zhang, Kevin N. Balke, and Kai Yin

***Abstract*—Transit signal priority (TSP) strategy gives transit vehicles preferential treatments to move through an intersection with minimum delay. To produce a good TSP timing, advance planning with enough look-ahead time is the key. This, however, means added uncertainty about bus arrival time at stop bar. In this paper, we proposed a stochastic mixed-integer nonlinear program (SMINP) model as the core component of a real-time TSP control system. The model adopts a novel approach to capture the impacts of the priority operation to other traffic by using the deviations of the phase split times from the optimal background split times. In addition, the model explicitly accounts for the randomness of the bus' arrival time by considering the bus stop dwell time and the delay caused by standing vehicle queues. The SMINP is implemented in a simulation evaluation platform developed using a combination of a microscopic traffic simulator and a commercial optimization solver. Comparison analyses were performed to compare the proposed control model with the state-of-the-practice TSP system [i.e., ring-barrier controller (RBC)-TSP]. The results showed the SMINP has yielded as much as 30% improvement of bus delay compared with RBC-TSP in a single-bus case. In a multiple-bus case, SMINP handles the bus priority request much more effectively under congested traffic conditions.**

***Index Terms*—Degree of saturation, mixed-integer nonlinear model, near-side bus stop, rolling horizon, stochastic optimization, transit signal priority (TSP).**

I. Introduction

IN MANY major metropolitan cities, transit vehicles serve as a main public transportation means to move a large number of passengers efficiently. Transit signal priority (TSP) is very a cost-effective preferential treatment for transit vehicles, such as buses, in mixed traffic conditions. A TSP system usually requires minimal infrastructure upgrades and may quickly increase roadway's capacity for buses, improve bus travel time, and improve operation reliability [1].

Different from the signal preemption operations, a priority-capable signal control strategy cannot unconditionally disrupt normal signal operations in favor of the priority vehicles. An effective TSP strategy minimizes the interruptions to other traffic while attempting to provide priority to the transit vehicles. In the literature, mathematical models have been proposed to find optimality for a predefined objective function. Ma *et al.* [2] formulated the objective using bus delays, whereas Li *et al.* [3] added the auto delays in the formulation. Christofa *et al.* [4] multiplied the estimated number of occupants in each type of vehicles in order to minimize the person delay. He *et al.* [5] took a different approach that minimizes bus delays while maximizing the green times on the phases with higher traffic demands. These studies all confirmed the fact that the attempt to reduce bus delay will necessarily increase the delay to other vehicles, particularly those on the conflicting phases. Many of these models give the users the ability to assign weights to the respective traffic flows.

Another key design factor for successful transit priority implementation is the ability to accurately predict the arrival time of the bus at the stop bar [6]. Models have been developed to estimate vehicle arrival times at bus stops or along a corridor [7]–[9]. Inaccurate predictions would generally result in failed treatments for transit vehicles. For this reason, models have been developed to robustly account for the uncertainty of bus arrival time at the stop bar. A mixed-integer linear programming (MILP) formulation developed by He [10] explicitly allows an input of interval arrival time instead of a point arrival time. Stevanovic *et al.* [11] also expressed the importance of modeling randomness in the design of bus priority schemes.

The approaches used in previous studies only allowed the consideration of the uncertainty of bus arrival time within a small interval, but large variations of arrival times render great difficulties in seeking for an optimal solution. Therefore, a stochastic model needs to be developed to truly account for the randomness. Few research have considered the stochastic nature of bus arrival times. Furthermore, the impact of the stochastic nature on the performance of a TSP strategy is largely amplified when a nearside bus stop is present. Current practice typically ignores or circumvents the problem. For example, the user manual of the ring-barrier controller (RBC) in VISSIM [12] recommends that a common practice is to place a detector at the exit of the bus stop to detect the departure of a bus. Such an approach eliminates the need to consider bus dwell time. However, this strategy leaves very little time for any control strategies to implement a good timing plan. Early detection of a transit vehicle is the key to provide more time to adjust the signals to provide priority while minimizing traffic impacts [13]. A need exists not only to be able to capture this impact of this randomness to the prediction accuracy but also to be to use this uncertainty to our advantage to devise an expectedly optimal timing plan.

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In this paper, a stochastic mixed-integer nonlinear programming (SMINP) optimization is developed for real-time TSP control. The optimization model minimizes the deviation of green time from optimal background green time, as a proxy to the impacts of the priority timing on nontransit vehicles. Meanwhile, the arrival time of the bus at both the nearside bus stop and the stop bar is formulated using the deterministic queuing model as a function of dwell time. The formulation allows the mathematical model to explicitly minimize the bus delay due to not only signal timing but also vehicle queues. A rolling optimization scheme for handling of multiple buses is developed to enable the real-time capability of the control system.

II. Methodology

A. Two-Stage Stochastic Programming

A stochastic mathematical program [14], [15] finds an optimal solution to a problem by explicit modeling of the uncertainties of input parameters. This technique has been applied in many areas, including vehicle routing [16], fleet assignment [17], and production planning [18].

In its simplest forms, a stochastic program typically consists of two stages, each of which can be thought of a particular timeline in a decision-making process. Stage one is the "now" stage that corresponds to the time that one has to make a decision on a set of decision variables. Let x denote an n_1-element vector of first-stage decision variables. All parameters associated with x are collected prior to decision making and can be deterministically formulated in the "now" stage. Stage two is the "future" stage that represents processes that would occur after the decision-making process. Because these "future" processes have not been observed yet, these parameters are inherently random and may take a variety of values when the future unfolds.

Every "now" decision x has consequences on the future processes. For every "now" decision that is incompatible with the "future" process, one pays a "cost." This cost is generally termed as the recourse cost, quantified by the second-stage decision variables. Let z denote an n_2-element vector of second-stage decision variables. If we can summarize the recourse costs as a function of the "now" decision and the "future" processes [which is called a recourse function, denoted as $f(x,\tilde{\omega})$], then we can find the best "now" decision that minimizes the recourse costs under all "future" scenarios. Here, we present a generic mathematical description for a two-stage stochastic program model as in the following:

$$\begin{aligned} & & \text{Min} \quad & c^T x + \mathbb{E}\left[f(x,\tilde{\omega})\right] \\ \text{Stage 1 :} & & \text{s.t.} \quad & Ax \geq b \\ & & & x \geq 0 \end{aligned} \tag{1}$$

where c, A, and b are parameters with known values at the timing of decision making, whereas $\tilde{\omega}$ is a random parameter defined on a probability space (Ω, F, P). $f(\cdot)$ is the recourse function that gives the penalty of a selection of a second-stage decision variable on the first-stage objective function. $\mathbb{E}[\cdot]$ denotes the expectation function. For a given x and an outcome $\omega \in \Omega$, the recourse function can be written as

$$\begin{aligned} & & & f(x,\tilde{\omega}) = \text{Min} \quad q^T z \\ \text{Stage 2 :} & & \text{s.t.} \quad & Wz \geq r(\omega) - Tx \\ & & & z \geq 0 \end{aligned} \tag{2}$$

where q, W, and T are parameter matrices that do not vary according to the realization of scenario ω, whereas r is the parameter matrix that does vary for scenario ω. For interested readers, Birge and Louveaux [19] provided an excellent introduction to the fundamentals of stochastic programming.

B. Formulations for TSP

In a TSP control system, advance planning is the key to any successful strategies. Once detected upstream, the signal control system may need to decide if timing adjustments will be needed to prepare for the arrival of a priority vehicle. However, the arrival time of the bus is not certain, and the decision for a certain timing to be implemented "now" may or may not be consistent with the actual bus arrival time in the "future." It is easy to compute the extra bus delay that would occur if we choose a timing that is inconsistent with the actual bus arrival time. Therefore, the bus delay can be thought of the recourse cost, which is a function of the "now" decisions of signal timing and the "future" bus arrival time. Following this logic, we can build a stochastic two-stage SMINP for a typical TSP problem. We define all the variables first.

1) Variable Definitions

Sets

J	set of all phases;
K	set of cycles within the planning horizon;

Decision variables

t_{jk}	start time for phase j of cycle k;
g_{jk}	green time for phase j of cycle k;
v_{jk}	split for phase j of cycle k;
y_{jk}	deviation of green time on phase j of cycle k from optimal green time;
d_j	priority delay of a bus requesting for phase j;
d_{jk}	queue delay for the bus requesting phase j of cycle k;
θ_{jk}	priority service decision for a bus at phase j of cycle k;

Parameters

C	cycle length;
c_{jk}	weight for green deviation of phase j of cycle k;
Y, R	yellow time and red clearance time;
V_{jk}	average flow rate for phase j in cycle k;
S_j	saturation flow rate on phase j;
X_{jk}	degree of saturation for phase j;
g'_{jk}	background green time for phase j of cycle k;
$g_{jk,min}$	minimum green time for phase j of cycle k;
D_{dwell}	dwell time at the bus stop;
BR_j	time within a cycle that a bus arrives on phase j;
$\overline{BR}_j$	projected bus arrival time on phase j excluding possible delays;
$\underline{BR}_{jk}$	latest time to start green on phase j of cycle k without causing queue delay to the bus on cycle k.

2) First-Stage Objective Function: The first-stage objective function is the overall objective function that considers the expected recourse cost computed from the second-stage objective function. Let $\boldsymbol{t}$ and $\boldsymbol{v}$ be the vectors of start times and splits of all phases respectively, and $\widetilde{BR}$ be the vector of unknown bus arrival times. The overall objective function can be formulated as follows:

$$\text{Minimize}: \quad \sum_{k\in K}\sum_{j\in J} c_{jk}y_{jk}^2 + \mathbb{E}\left[Q(\mathbf{t},\mathbf{v},\widetilde{BR})\right]. \tag{3}$$

The first term is the sum of the nonexpanding changes in green times. Given a fixed cycle length, the green time of a phase has a monotonical inverse relationship with the average delay on that phase, and reducing the green time necessarily implies nondecreasing vehicular delay. Hence, the deviation can be used as a proxy to the phase delay. One immediate benefit is to eliminate the need of explicitly writing out a second-order delay formulation. Additionally, even if a quadratic function is imposed on, i.e., y_{jk}, to penalize higher deviation values, the objective function will remain positive semidefinite as long as the coefficients are nonnegative. This results in a convex program that can be easily solved by any standard commercialized solvers. The second term is the expected delay of the priority request, which is a piecewise linear function of the signal timing. In sum, the optimality of the overall objective is found at *the signal timing that cuts down the most bus delays* while *deviates the least from the timing that is optimal for the general traffic*.

Each weight on the first term c_{jk} determines how much one phase should be penalized when compared with another phase. In effect, the weight parameter controls the distributions of priority needs in terms of seconds among all the conflicting phases. The weight parameter can be formulated as a function of the congestion level on each phase. The idea is that phases that are more congested shall deviate less from the optimal green time compared with those less congested phases.

3) First-Stage Constraints: The formulation in this stage shall realistically model the behavior and the characteristics of the signal controller in question. Head *et al.* [20] proposed a precedence relationship to model the standard ring-barrier signal timing structure. Later, He *et al.* [5] applied the framework to develop a deterministic priority model that minimizes the delay of priority requests. We applied this precedence framework in the formulations of the first-stage constraints.

Constraints in the first stage are mostly defined for the precedence relationships of all phases of all look-ahead cycles within the planning horizon. The validity and illustration of the precedency are clearly documented in [5] and [20]. The phase relationships are formulated as follows:

$$t_{1,k} = 0; \quad \forall k \tag{4}$$

$$\begin{aligned} &t_{2,k} = t_{1,k} + v_{1,k}; t_{3,k} = t_{2,k} + v_{2,k}; t_{4,k} = t_{3,k} + v_{3,k} \\ &t_{6,k} = t_{5,k} + v_{5,k}; t_{7,k} = t_{6,k} + v_{6,k}; t_{8,k} = t_{7,k} + v_{7,k} \qquad \forall k \end{aligned} \tag{5}$$

$$t_{1,k} = t_{5,k}; t_{7,k} = t_{3,k}; t_{6,k} = t_{2,k} \qquad \forall k \tag{6}$$

$$t_{4,k} + v_{4,k} = kC \qquad k = |K| \tag{7}$$

$$v_{jk} = g_{jk} + Y + R \qquad \forall j, \forall k \tag{8}$$

$$g_{jk} \geq g_{jk,\min} \qquad \forall j, \forall k \tag{9}$$

$$t_{jk}, g_{jk}, v_{jk} \geq 0 \qquad \forall j, \forall k. \tag{10}$$

This formulation explicitly models the ring-barrier control structure [21], which is widely used in North America. Constraint (5) defines the timelines and sequences of all the phases in both rings. Constraint (6) indicates which phases are serving as barriers. Constraint (7) defines the end time of the planning horizon as a multiple of cycle length. This would allow the optimization get back to the normal cycle start time if the intersection is a part of a coordinated corridor. The minimum green requirement is defined in constraint (9).

Given the average saturation flow rate for a phase S_j, the average flow rate V_{jk} for the phase in cycle k, and the effective green time g_{jk} and cycle length C_k for each cycle, one can ensure the degree of saturation for the phase X_j over the planning period to be less than the maximum allowable value, i.e., X_c, as follows:

$$X_j = \frac{\sum_{k\in K} V_{jk}C_k}{\sum_{k\in K} S_j g_{jk}} \leq X_C \qquad \forall j. \tag{11}$$

Note that inequality (11) only restricts the overall degree of saturation of a phase X_j but not X_{jk}. This implies that, if the green of phase j in one cycle k is too short (e.g., rendering oversaturation), then the green for the same phase in the other cycles within the planning cycles has to be long enough to clear the excessive queue from cycle k. This formulation renders additional flexibility in adjusting the timing in favor of the transit bus, but the resulting temporary oversaturation may have an undefined behavior. One of the most infamous consequences is left spill back or blockage [22]. To avoid undefined behaviors, additional constraints can be imposed to ensure that the minimum green time for a phase has to meet the maximum degree of saturation at every cycle. All the above inequalities jointly define the limits for timing adjustment.

It is equally important to characterize how the control system behaves. Constraint (12) defines the deviations of new green times g_{jk} from optimal background green times g'_{jk}

$$\begin{cases} y_{jk} \geq g'_{jk} - g_{jk} \\ y_{jk} \geq 0 \end{cases} \qquad \forall j, \forall k. \tag{12}$$

The two inequalities effectively dictate that only the positive deviations are penalized, and any increase in g_{jk} from g'_{jk} has no direct costs to the objective function. However, it should be noted that, given a fixed planning horizon and the precedence relationship, the expansion of a phase necessarily leads to the compression of the conflicting phases given a fixed length of planning period. Therefore, the expansion of a phase is possible only to the degree that it does not compress other phases beyond acceptable ranges.

4) Second-Stage Objective Function: For given $\boldsymbol{t}$, $\boldsymbol{v}$, and a number of random events $\omega \in \Omega$, recourse function $Q(\cdot)$ is deterministically computable. With a well-defined discrete probability space $(\Omega, \mathcal{F}, P)$, the expectation can be evaluated by $E(Q) = \sum_{\omega\in\Omega} p(\omega)Q(\omega)$. For a given discrete random event ω, the second-stage recourse function of a classical two-stage stochastic program can be formulated as follows:

$$Q(\mathbf{t}, \mathbf{v}, BR_j(\omega)) := \min \sum_{j \in J} o_j d_j. \tag{13}$$

$BR_j(\omega)$ represents a realized bus arrival time out of all the possible arrival scenarios in Ω. For notational convenience, ω is omitted from further discussions. d_j denotes the delay to the priority request placed on phase j, which is a function of the bus arrival time and current signal timings. The weight o_{jn} of the priority delay determines the level of priority for a bus. This priority can be formulated based on need, for example, as a function of the bus passenger loads or bus schedule lateness.

5) Second-Stage Constraints: The constraints in the second stage mostly involve in the computations of bus priority delay

$$BR_j \geq t_{j,k-1} + g_{j,k-1} - (1 - \theta_{jk})M \qquad \forall k \in K \setminus \{1\}, \forall j \tag{14}$$

$$BR_j \leq t_{jk} + g_{jk} + (1 - \theta_{jk})M \qquad \forall k, \forall j \tag{15}$$

$$\sum_{k \in K} \theta_{jk} = 1 \qquad \forall j \tag{16}$$

$$\theta_{jk} = \{0, 1\} \qquad \forall j, \forall k \tag{17}$$

where θ_{jk} is a binary variable that indicates in which phase and cycle the bus will be served. If a bus arrives after the end of phase j of cycle $k-1$ [i.e., inequality (14)] and before the end of phase j of cycle k [i.e., inequality (15)], θ_{jk} is one for phase j of cycle k. For all other cycles, θ_{jk} are zeros. M is a large constant that can be set as the end time of the planning horizon (i.e., $|K|C$).

Assuming no delays caused by vehicle queues dissipating before the bus, the delay to the bus is simply $d_j = \max\{t_{jk} - BR_j, 0\}$. If the bus is to be served at phase j of cycle k, then $\theta_{jk} = 1$. This can be expressed as

$$d_j \geq t_{jk} - BR_j - (1 - \theta_{jk})M \qquad \forall j, \forall k \tag{18}$$

$$d_j \geq 0 \qquad \forall j. \tag{19}$$

The formulation to compute priority delay via constraints (14)–(19) is for a single bus. Extension to multiple buses can be easily done by adding a separate set of these constraints for each additional bus to be considered.

C. Computation of Queue Delay

A critical issue arises when it comes to determining the arrival time of the bus BR_j at the stop bar. Current practice generally assumes a constant travel time from the detection time of the bus. However, when a nearside bus stop is present, buses may interact with standing queues, which complicate the estimates of precise bus arrival times.

Fig. 1 illustrates a possible bus trajectory when the bus is approaching the intersection with a nearside bus stop. It is not unlikely that a bus needs to stop as many as three times at an approach with a nearside bus stop, even under unsaturated traffic conditions. To develop a robust optimization scheme,

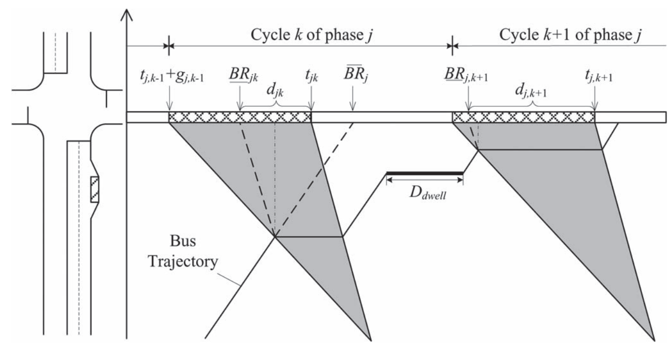

Fig. 1. Projected and actual bus trajectories for nearside bus stop configuration. A bus first encounters a queue before it stops for service at a bus stop, and then it dwells for a time long enough only to catch the backward forming queue again after it exits the bus stop.

the computation of priority delay needs to consider the bus interactions with vehicle queues and the bus stop. For all practical purposes, it is assumed that vehicle arrival rates are constant, acceleration and deceleration for bus are negligible, and the bus dwell time is known.

First of all, recognize that the summation of all stopping time minus the dwell time is the queue delay time, which is controllable through the start and end times of phase j. Let the projected arrival time of the bus under free-flow conditions be $\overline{BR}_j$, which can be calculated with the location of the bus and its running speed. Denote d_{jk} as the queue delay on cycle k for the bus requesting phase j. In addition, let D_{dwell} be the dwell at the bus stop. The actual bus arrival time $BR_j = \overline{BR}_j + D_{dwell} + \sum_{i=1}^{|K|} d_{ji}$. Replacing the arrival time of the original formulation [see inequalities (14) and (15)], we get

$$\overline{BR}_j + D_{dwell} + \sum_{i=1}^{|K|} d_{ji} \leq t_{jk} + g_{jk} + (1 - \theta_{jk})M \qquad \forall k, \forall j \tag{20}$$

$$\overline{BR}_j + D_{dwell} + \sum_{i=1}^{|K|} d_{ji} > t_{j,k-1} + g_{j,k-1} - (1 - \theta_{jk})M \qquad \forall k \setminus \{1\}, \forall j. \tag{21}$$

Further let $\underline{BR}_{jk}$ be the latest time to start phase j green of cycle k so that there would be no queue delay on cycle k for the bus. To compute $\underline{BR}_{jk}$, one needs to find the bus trajectory and the end of queue trajectory in the time–space diagram. Then, one can easily compute $\underline{BR}_{jk}$ from the intersection of two trajectories and the assumed saturation flow rate. The priority delay with consideration of queue delay is then computed as

$$d_{j,k-r} \geq t_{j,k-r} - \underline{BR}_{j,k-r} - (1 - \theta_{j,k-r})M \qquad \forall j, \forall k \setminus \{1, \ldots, r\}, \forall r \in \{0, \ldots, |K| - 1\} \tag{22}$$

$$d_{j,k-r} \geq 0 \qquad \forall j, \forall k \setminus \{1, \ldots, r\}, \forall r \in \{0, \ldots, |K| - 1\} \tag{23}$$

$$d_j = \sum_{k=1}^{K} d_{jk} \qquad \forall j. \tag{24}$$

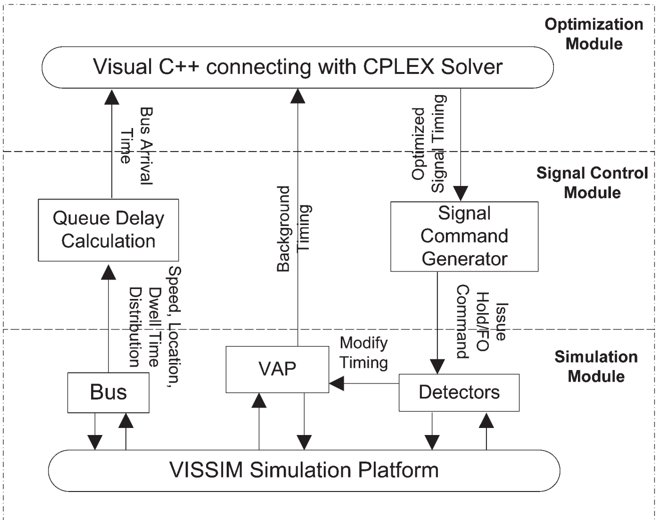

Fig. 2. General architecture of the simulation evaluation platform.

Minimizing the overall bus delay due to queue d_j will result in minimal queue delays in all cycles. In addition, this means that, except $k = 1$, all $\underline{BR}_{jk}$ will be dependent on all d_{jk} from previous cycles. This implies that if $|K|$ is large, the number of constraints will increase exponentially. Fortunately, $|K|$ is generally small.

III. Real-Time Evaluation Platform

A. System Architecture

A simulation platform is developed to implement the proposed SMINP model and to evaluate its performance against current state-of-the-practice TSP-enabled signal control system. The platform is coded and complied using the Microsoft Visual Studio C++ compiler. Fig. 2 illustrates the general architecture of the simulation platform, which consists of the following three main modules:

- simulation: the PTV VISSIM [23] traffic simulator and a fixed-time vehicle actuated programming signal controller.
- optimization: the IBM CPLEX [24] solver through the CPLEX Callable Library.
- signal control: self-developed C++ functions to implement the optimized timing splits.

The signal control module serves as the primary link between the simulation and the optimization modules. The control module extracts vehicle information from the simulation model to feed to the optimization module. After an optimization session is completed, the control module implements the optimized timing splits by placing force-off and hold commands to the signal controller in VISSIM. The use of the force-off and the hold commands allows the system to be easily extendable to any other types of signal controllers.

Optimization is the core module where the model for a TSP strategy is designed. Upon receiving the bus data and the signal timing data from the controller, the optimization module first formulates an initial SMINP model with only one stochastic scenario. The module then reformulates the SMINP model into its deterministic equivalent program (DEP) by enumerating all possible combinations of stochastic scenarios. In this paper, the number of buses arriving at a given short-term period (i.e., two cycles) is small, i.e., no more than three. With a small number of discretized outcomes for each bus, the size of the DEP is still manageable and it can be solved quickly.

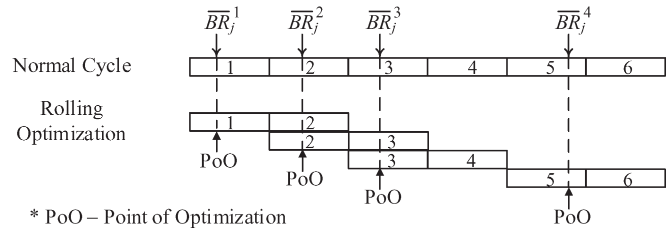

Fig. 3. Rolling optimization scheme. The arrival information $\overline{BR}_j^n$ for bus n is available only after its detection before the point of optimization. The point of optimization is the time instance the SMINP optimization will be conducted.

B. Rolling Optimization for Real-Time Control

Real-time capability is an important design factor for any online signal control system with TSP. In order to achieve this capability, the system needs to be able to continuously optimize and implement new timings at any point on a time horizon for multiple bus arrivals.

In our research, the rolling optimization scheme is implemented in the control system, as illustrated in Fig. 3. When bus one arrives, an optimization is done based on the optimal background timing. The new timing will have to be used as the background timing for the second bus arrival. The process continues until no more bus arrival before the end of the affected period, i.e., the timing reverts to normal.

IV. Simulation Evaluation

A. Test Intersection and Test Scenarios

The SMINP with optimized background timing was then applied to a hypothetical four-leg intersection, as shown in Fig. 4. Three routes were setup for different testing scenarios. Route 1 enters from the eastbound approach, encountering a nearside bus stop at about 60 m (196 ft) from the stop bar. Route 2 enters from the northbound approach and a bus stop located roughly 80 m (261 ft) from the stop bar. Route 3 travels northbound and exits westward without any bus stops. It is assumed that the intersection is equipped with wireless communication equipment that can detect the presence of the approaching bus and obtain information related to the bus speed, current location, and possibly most updated dwell-time data maintained by the transit agency.

Table I shows the setup of three congestion levels represented by the volume-to-capacity (V/C) ratios. All splits are optimized in SYNCHRO [25] with the respective volume levels. The dwell time is assumed to be discretely uniformly distributed with possible outcomes of 20, 30, and 40 s.

B. Calculating Weight for Deviations

The first-stage objective function controls the balance between the phase green time deviations and the bus delay. The

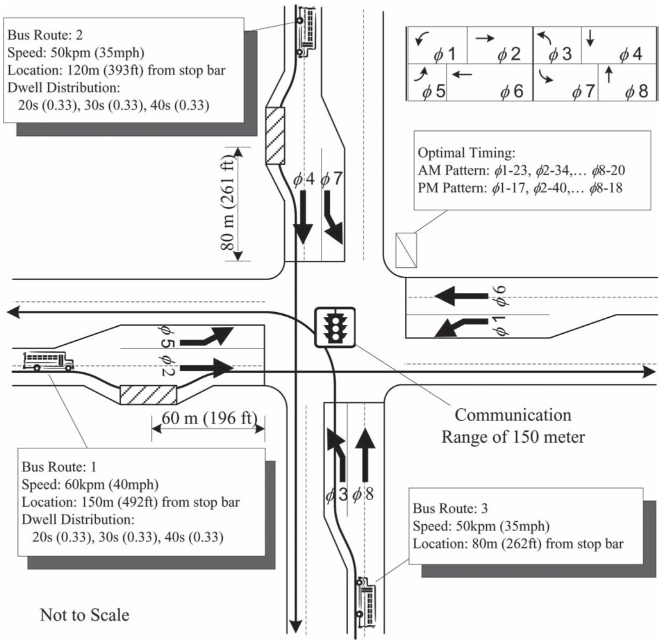

Fig. 4. Hypothetical intersection with nearside bus stops for model testing. The dwell distributions for buses 1 and 2 are discretized uniformly among 20, 30, and 40 s, each of which has a probability of occurrence of 0.33. Other probability distribution is possible if information available.

TABLE I
PARAMETER SETUP FOR SIMULATION EVALUATIONS

Background Timing: Cycle Length = 110 sec								
Dwell Time Distribution: 20 sec (0.333), 30 sec (0.333), 40 sec (0.333)								
Phase	$\phi1$	$\phi2$	$\phi3$	$\phi4$	$\phi5$	$\phi6$	$\phi7$	$\phi8$
# of lanes	1	2	1	2	1	2	1	2
V/C = 0.5								
Volume (vph)	112	616	90	381	78	784	101	280
Opt. splits (s)	23	40	20	27	19	44	21	26
V/C = 0.7								
Volume (vph)	156	858	125	530	109	1092	140	390
Opt. splits (s)	22	44	17	27	16	50	19	25
V/C = 0.9								
Volume (vph)	200	1100	160	680	140	1400	180	500
Opt. splits (s)	21	46	15	28	14	53	17	26

weighting factor of a phase determines the relative importance of this phase compared with others. It is reasonable to penalize more on the phase that is more congested, which can be quantified using a function of the degree of saturation. In this paper, we compared four different such functions as follows:

$$\text{Weight 1}: \quad c_{jk} = \frac{X_{jk}}{\sum_{j\in J} X_{jk}} \tag{25}$$

$$\text{Weight 2}: \quad c_{jk} = \frac{X_{jk}^p}{\sum_{j\in J} X_{jk}^P}, \quad \text{where } p = |J| \tag{26}$$

$$\text{Weight 3}: \quad c_{jk} = \frac{1/(1-X_{jk})}{\sum_{j\in J}\sum_{k\in K} 1/(1-X_{jk})} \tag{27}$$

$$\text{Weight 4}: \quad c_{j} = \frac{1/(1-X_{j})}{\sum_{j\in J} 1/(1-X_{j})}$$

$$\text{where } X_j = \frac{V_j \sum_{k\in K} C_k}{S_j \sum_{k\in K} g_{jk}}. \tag{28}$$

First of all, one shall notice that each weight is normalized by the sum of all weights. Normalization ensures that the weights only dictate the relative importance among different phases but not affecting the relative importance between the total phase deviations and the bus delay.

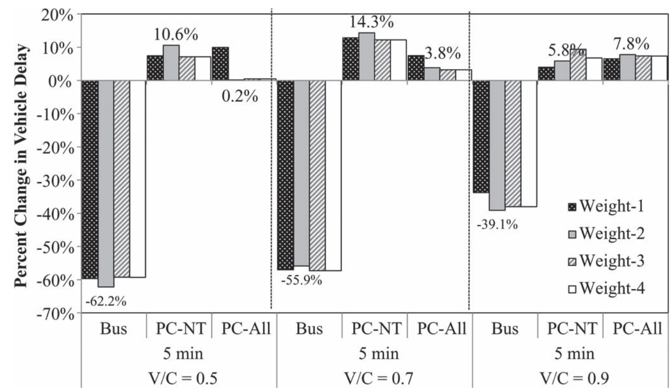

Fig. 5. Comparisons of weight formulations. PC-NT denotes the delays averaged over only the vehicles on phases conflicting with the priority phase. PC-All denotes the delay averaged over all vehicles excluding buses.

Weight 1 and Weight 2 base the importance of each phase directly on the values of the degree of saturation. However, they do not recognize the boundary conditions when traffic conditions significantly degrade from under- to oversaturation. Weight 3 and Weight 4, alternatively, use the reciprocal of the slack in congestion before reaching the boundary condition. Weight 3 may become nonpositive if the degree of saturation is equal to or larger than 1. Weight 4 rectifies the problem by computing the degree of saturation over the entire planning horizon. This also ensures that any oversaturation (i.e., $X_{jk} > 1$) is only temporary and will be recovered before the end of the planning horizon. Weight 4 requires minor modifications on the original objective function as the first term is changed from y_{jk} to y_j

$$\text{Minimize}: \quad \sum_{j\in J} c_j y_j^2 + E\left[Q(\mathbf{t}, \mathbf{v}, \widetilde{BR})\right] \tag{29}$$

and it subjects to one additional constraint for each phase

$$y_j = \sum_{k\in K} y_{jk}. \tag{30}$$

Fig. 5 shows a comparison of the performance of all four weight formulation options under the same network and traffic condition setups. In general, their ability to give priority to buses under various traffic conditions is very comparable. However, Weight 3 and Weight 4 seem to give the lowest impact on general traffic under low to medium degree of saturation levels, while Weight 1 and Weight 4 are less disruptive to general traffic on the high degree of saturation level. Weight 4 appears to be the most robust because it consistently performs above average to the best over all traffic conditions.

C. Level of Bus Priority

The weight of the priority delay o_{jn} is a crucial factor that allows the user to define the level of importance for a priority bus request. Different values of this weight (i.e., *priority coefficient*) may change the outcome of signal timing. For all three congestion levels, we varied the ratio of the priority coefficients $\sum_{j,k} o_{jk}/\sum_{j,k} c_{jk}$ from 0.1 to 10 at an increment of 1. Only bus

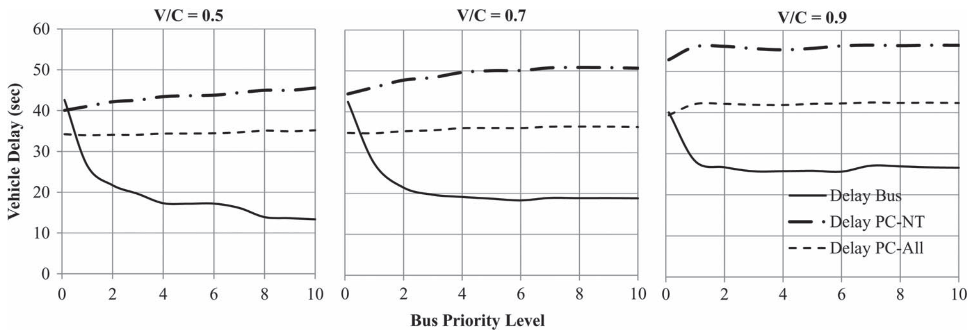

Fig. 6. Impact of priority setting on bus and PC delays. PC-NT denotes the delays averaged over only the vehicles on phases conflicting with the priority phase. PC-All denotes the delay averaged over all vehicles excluding buses.

route 1 is active, and the bus arrival headway is set to 5 min. Five random simulation seeds are used across all priority scenarios.

Fig. 6 illustrates the general trend of the bus delays and the passenger car delays with respect to different levels of priority. As expected, the increase in the priority weights for the bus decreases its delay and increases the delay for traffic on conflicting phases. The decrease in bus delay is particularly notable when V/C is at 0.5; the decrease is most significant from 0.1 to 1, and then delay continues to decrease slowly as the priority coefficient increases. At this congestion level, the signal timing can be significantly adjusted to accommodate the bus priority without considerably impacting other traffic. However, as the intersection gets more congested, the impact of adjusting signal timing on the general traffic becomes more significant. This is manifested by the jump of nontransit passenger car (PC) delay from 52 to 56 when the level of priority increases from 0.1 to 1 at the highest V/C level. Another remarkable feature of the program is the ability to recognize the level of congestion automatically by restricting the amount of changes of the signal timing. For example, when V/C $= 0.7$, the decrease in bus delay levels out at about 4 or 5; when V/C $= 0.9$, the valley of bus delay comes much earlier at around 1. These indicate that the program will automatically cap out the maximum priority allowed to a bus priority request depending dynamically on the prevailing traffic conditions.

D. Control Systems in Comparison

Using the RBC feature in VISSIM [12], we compared the proposed model with traditional TSP operations in a standard traffic signal controller. The RBC uses a pair of check-in and check-out detectors to enable its TSP feature. Upon the detection of a bus at the check-in detector, a constant travel time with a constant slack time is applied to estimate its arrival time interval at the stop bar and performs either green extension or red truncation. With a nearside bus stop, the check-in detector is placed at the bus stop [12] to avoid accounting for the randomness in dwell time.

The RBC-TSP and the SMINP are compared with the baseline fix-time–do-nothing control strategy. To compare these three control types on fair ground, fixed cycle splits are implemented in the RBC controller as well. Five random seeds are simulated for each of the volume and arrival frequency combination. A fixed priority coefficient (i.e., 5) for the SMINP was used for all cases.

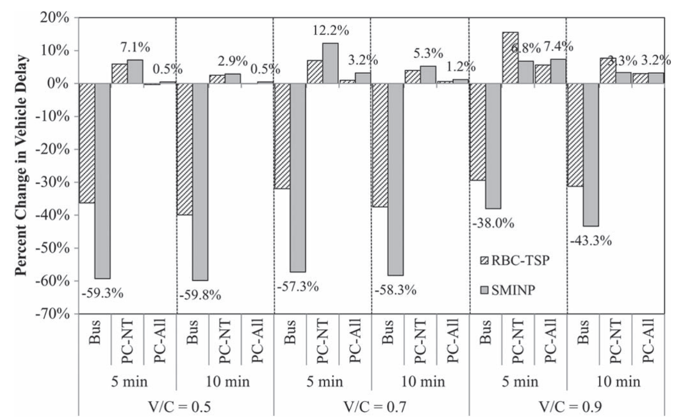

Fig. 7. Percent change in vehicle delays for RBC and SMINP versus fix time control under single bus arrival scenario.

E. Simulation Evaluation for Single Bus Line

Assuming that only bus route 1 in Fig. 4 has regular arrival at the intersection, we tested two arrival frequencies under all three congestion levels shown in Table I. The bus headways for both frequency scenarios are larger than the planning horizon (i.e., two cycles of 110 s). This implies that there will be no overlapping period between two consecutive optimization sessions. Therefore, the impacts of priority services are independent from one another.

Fig. 7 illustrates the changes of vehicle delays compared with the baseline fix-time control for each combination of volumes and arrival frequencies. It is shown that both RBC-TSP and SMINP give signal priority to the bus, resulting in much lower bus delay across all scenarios. The SMINP generally renders lower bus delay compared with the RBC-TSP at all scenarios. In some scenario, the difference is as large as 30% improvement from the RBC-TSP and 60% improvement from the baseline do-nothing scenario. This means that the proposed model was able to better capture the bus arrival time and adjust the timing to favor the bus more. Another reason for the significant improvement is due to the ability of the proposed model to plan ahead. The optimization was done at the time the bus was detected before the bus stops, whereas the RBC-TSP only performs adjustment of signal timings for the bus at the time it is leaving the bus stop. There are about 30–50 s more time for SMINP to adjust the timing. The benefits of this are that not only the bus delay has reduced significantly but also the disturbances to other traffic are comparable or smaller.

TABLE II
VEHICLE DELAYS BY CONTROL TYPES FOR SINGLE BUS ARRIVAL SCENARIO

Deg. of Sat.	Arrival Freq.	Vehicle Delay Type	Control Model		
			Fixed	RBC -TSP	SMINP
V/C = 0.5	5 min	Bus	40.3	25.7	16.4
		PC (Overall)	34.2	34.1	34.3
		PC (Non-Transit)	40.1	42.4	42.9
		PC (Transit)	30.3	28.6	28.7
	10 min	Bus	42.9	25.8	17.2
		PC (Overall)	34.1	34.1	34.3
		PC (Non-Transit)	40.1	41.1	41.2
		PC (Transit)	30.2	29.5	29.7
V/C = 0.7	5 min	Bus	39.6	27.0	16.9
		PC (Overall)	34.9	35.3	36.1
		PC (Non-Transit)	43.6	46.6	48.9
		PC (Transit)	29.2	27.8	27.6
	10 min	Bus	42.6	26.6	17.8
		PC (Overall)	34.9	35.1	35.3
		PC (Non-Transit)	43.5	45.2	45.8
		PC (Transit)	29.2	28.5	28.4
V/C = 0.9	5 min	Bus	42.3	29.8	26.2
		PC (Overall)	39.2	41.4	42.0
		PC (Non-Transit)	51.3	59.3	54.8
		PC (Transit)	31.2	29.7	33.7
	10 min	Bus	44.3	30.5	25.1
		PC (Overall)	39.0	40.2	40.2
		PC (Non-Transit)	51.3	55.3	53.0
		PC (Transit)	30.9	30.3	31.9

Note: PC (Overall) – All passenger cars on all approaches
PC (Non-Transit) – Passenger cars on phases conflicting with the bus requested phase
PC (Transit) – Passenger cars on phases concurrent with the bus requested phase

On the other hand, the SMINP is much more responsive to the expected traffic conditions than the RBC-TSP. This is especially evident at high-volume conditions (i.e., V/C $= 0.9$). At this volume level, when the bus arriving less frequently, the delays of traffic on nontransit phases are about 8% better than the RBC-TSP. When a bus arrives at about 5-min interval, the delays to nontransit vehicles have increased to about 18% more than the baseline fix time control, whereas the SMINP maintains only about 7% increase from the baseline. The ability to be responsive to the traffic condition is because the mathematical model uses the normalized degree of saturation for each phase to spread out the total number of seconds across all phases in the planning horizon to satisfy the bus priority needs. In this way, the start time of the phases may significantly change, but the duration of the phase tends to be kept at their optimal values. The result is a much improved bus delay with a much less cost to the traffic on its conflicting phases. The delay values of all the compared scenarios are shown in Table II.

F. Simulation Evaluation for Multiple Bus Line

Assuming that more than one bus route runs through the intersection regularly, we varied the number of conflicting bus routes (i.e., two and three) under all three degrees of saturation levels, as shown in Table I. The headways for bus routes 1, 2, and 3, as shown in Fig. 4, are set to 5, 6, and 8 min, respectively. Consequently, in any one scenario, the timing optimization process for one priority service is inevitably affected by the timing changes for another priority service request. Therefore, the impacts of priority services are dependent from one another. In these complicated cases, the rolling optimization scheme has to be deployed to ensure that the priority signal control can be performed continuously.

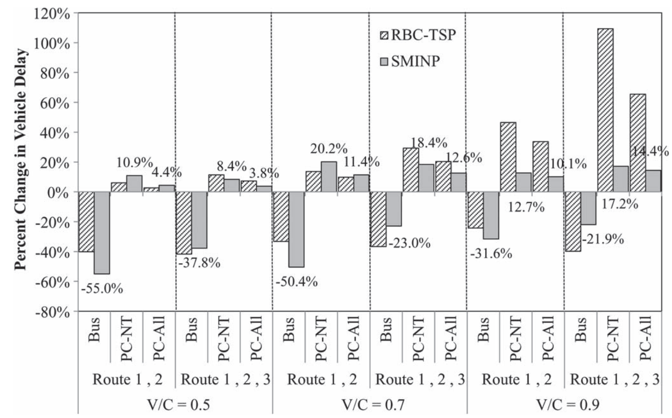

Fig. 8. Percent change in vehicle delays for RBC and SMINP versus fix time control under multiple bus arrival scenarios.

In particular, the SMINP model in this experiment used the rolling optimization method. The priority level for each route is set to 5, 3, and 2, respectively, such that route 1 has the highest priority and route 3 has the lowest because it is a cross-street left-turn phase. Routes 1 and 2 have to come to a stop at their respective bus stops before arriving at the stop bar, whereas route 3 does not need to stop at any bus stops. The dwell time for both routes 1 and 2 follows the same discrete uniform distribution with equiprobable outcomes of 20, 30, and 40 s. A rule was applied in the system to prevent the rolling optimization from continuing indefinitely. The rule ignores all the priority requests after the dynamic planning horizon being extended to 10 cycles or more. After the timing recovered back to the background optimal timing at the end of the 11th cycle, new priority requests will be considered.

Fig. 8 illustrates the changes in vehicle delays in terms of percentage when comparing the RBC-TSP and SMINP controls with the fixed-time control, and Table III shows the absolute delay values. From the figure, several interesting observations can be drawn immediately. First of all, the RBC-TSP is slightly better than SMINP in terms of nontransit phase delay and overall PC delay in low to medium degree of saturation levels when only routes 1 and 2 are running. In all the other cases, the RBC-TSP underperforms the SMINP. In particular, when V/C $= 0.9$, the RBC-TSP has failed to maintain the impacts of the priority service to an acceptable level, yielding 50%–110% increase in terms of overall PC delay and 40%–70% increase in terms of nontransit phase delay. This is because, in high V/C cases, the RBC-TSP has no mechanism to capture the intensity of traffic therefore to dynamically underplay the importance bus priority requests in real time. It is possible, in an offline setting, to fine-tune some of the RBC-TSP settings [12] such as the priority min green and recovery min green. However, even by doing this, numerous settings need to be refined in order to adjust the RBC-TSP setting in response to the changing traffic conditions. On the contrary, the SMINP can intelligently recognize the

TABLE III
VEHICLE DELAYS BY CONTROL TYPES FOR MULTIPLE BUS ARRIVAL SCENARIOS

Deg. of Sat.	Running Bus Routes	Vehicle Delay Type	Control Model		
			Fixed	RBC -TSP	SMINP
V/C = 0.5	Route 1, 2	Bus	47.3	28.3	21.3
		PC (Overall)	34.5	36.6	38.3
		PC (Non-Transit)	34.3	35.2	35.8
		PC (Transit)	33.9	33.2	32.3
	Route 1, 2, 3	Bus	46.8	27.3	29.1
		PC (Overall)	33.8	37.7	36.6
		PC (Non-Transit)	34.3	36.8	35.6
		PC (Transit)	34.8	35.8	34.3
V/C = 0.7	Route 1, 2	Bus	46.4	31.0	23.0
		PC (Overall)	35.4	40.3	42.6
		PC (Non-Transit)	35.0	38.4	39.0
		PC (Transit)	34.3	35.8	33.9
	Route 1, 2, 3	Bus	48.0	30.4	37.0
		PC (Overall)	34.3	44.4	40.7
		PC (Non-Transit)	35.0	42.2	39.4
		PC (Transit)	35.8	39.4	37.9
V/C = 0.9	Route 1, 2	Bus	48.9	37.0	33.4
		PC (Overall)	40.8	59.8	46.0
		PC (Non-Transit)	39.2	52.4	43.2
		PC (Transit)	37.0	41.9	39.3
	Route 1, 2, 3	Bus	64.3	38.7	50.2
		PC (Overall)	38.1	79.7	44.6
		PC (Non-Transit)	40.1	66.3	45.8
		PC (Transit)	42.6	49.8	47.4

Note: PC (Overall) – All passenger cars on all approaches
PC (Non-Transit) – Passenger cars on phases conflicting with the bus requested phase
PC (Transit) – Passenger cars on phases concurrent with the bus requested phase

degree of saturation for each phase, and it automatically finds the balance between the general traffic and the buses in real time for multiple bus routes.

V. CONCLUSION AND FUTURE DIRECTIONS

In this paper, we have proposed an SMINP model for the development of a real-time TSP control system. The model proposed a novel approach to capture the impacts of the priority operation on other traffic by using the deviations of phase split times from optimal background split time. In addition, the stochastic formulation explicitly models the randomness of a bus' arrival time to the stop bar, which is most evident when a nearside bus stop is present. The proposed model not only captures the random dwell time of the bus at the bus stop but also accounts for the interactions of the bus with the passenger car queue and is able to minimize the delay to the bus caused by signal timing and the vehicle queue.

The SMINP is implemented in a simulation evaluation platform developed using a combination of a microscopic traffic simulator and a commercially available optimization solver. A numerical experiment to evaluate the effects of priority weighting factor was conducted on a hypothetical intersection with eight phases and running on a fixed cycle. The results indicated that the user could adjust the priority to the bus by solely changing the priority weighting factor from 0.1 to 10. It also showed that the model has the ability to prevent the user from using a priority level that is too high to cause oversaturation to the intersection.

Comparison analyses were then performed to compare the proposed control model SMINP with a standard TSP technique. Both control models are compared with the fixed-time–do-nothing approach using the same hypothetical intersection in a simulation environment. In the case of no competing bus routes, the SMINP resulted inasmuch as 30% improvement of bus delay in low to medium congestion conditions. The comparison also indicated that the SMINP model can recognize the level of congestion of the intersection and automatically give less priority to the bus to minimize impact to the traffic on conflicting phases. In the case when there are three competing bus routes, SMINP handles multiple bus priority much better. The SMINP automatically adjusts the relative importance of bus priority without the need to manually change the priority weighting factor, and it provides more balanced timings for both bus and the general traffic.

An interesting future direction is to extend the stochastic formulation to multiple intersections. Corridor-level priority is more useful than single intersection level. A branch-and-cut algorithm based on a disjunctive decomposition technique [26] may be needed to provide optimal solutions.

Another possible extension is to integrate the model with an adaptive signal control system where additional information about the development of vehicle queues at an approach can be estimated in real time. The additional information relaxes the assumption about constant vehicle arrival and further improves the ability of the SMINP to predict the arrival time distribution of the bus to the stop bar.

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