Computer-Aided Civil and Infrastructure Engineering **26** (2011) 270–284

Modeling and Implementation of Adaptive Transit Signal Priority on Actuated Control Systems

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Abstract: *This article describes the development and implementation of adaptive transit signal priority (TSP) on an actuated dual-ring traffic signal control system. After providing an overview of architecture design of the adaptive TSP system, the article presents an adaptive TSP optimization model that optimizes green splits for three consecutive cycles to minimize the weighted sum of transit vehicle delay and other traffic delay, considering the safety and other operational constraints under the dual-ring structure of signal control. The model is illustrated using a numerical example under medium and heavily congested situations. The findings from a field operational test are also reported to validate and demonstrate the developed TSP system. At a congested intersection, it is found that the average bus delay and average traffic delay along the bus movement direction were reduced by approximately 43% and 16%, respectively. Moreover, the average delay of cross-street traffic was increased by about 12%.*

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DOI: 10.1111/j.1467-8667.2010.00677.x

1 INTRODUCTION

Transit signal priority (TSP) is an operational strategy that facilitates in-service transit vehicles passing through signalized intersections. It can reduce transit delay at intersections and improve its on-time performance or schedule adherence, thereby increasing the quality of transit service. TSP has been implemented in Europe and North America since 1968 (Courage and Wallace, 1977; Evans and Skiles, 1970; ITS America, 2004). Early adoptions were not very successful because the negative impact on other traffic was not well considered. In recent years, its deployment has been growing rapidly in the United States with more consideration on balancing the benefits and negative impacts of TSP.

TSP systems may be categorized into three types: passive, active, and adaptive (ITS America, 2004). Passive priority strategies are to develop signal timings to favor transit vehicles along signalized arterials. They are often applied to fixed-time signal control systems and do not require transit vehicle detection. Such strategies only work well when transit operations are predictable and frequent, and traffic demand is low (Vincent et al., 1978). On the other hand, active TSP systems adopt selective vehicle detections to detect approaching transit vehicles and adjust signal timings in a predefined manner to provide, for example, early green, green extension, or special transit phase to them. A majority of the TSP deployments in the United States are active systems (e.g., Fehon et al., 2004; Kimpel et al., 2004). These deployments have demonstrated positive effects on improving transit service quality. In the literature, Link and Shalaby (2003) applied an artificial intelligence method to optimize green phase durations to reduce transit headway deviations. They also conducted a simulation study to demonstrate the model performance on reducing transit headway deviations with limited impact on other traffic. Janos and Furth (2002) proposed a rule-based TSP system for the transit system in San Juan, Puerto Rico that has an extremely high serving frequency. Nichols and Bullock (2004) have discussed the use of global positioning system (GPS) technology for estimating an upper bound on the potential benefits of active TSP systems. However, many active TSP systems result in substantial variability in the impacts to other traffic, because (1) the TSP benefits and negative impacts are not explicitly balanced; (2) a "point" detection is often used in the close proximity of the intersection. This "short notice" only gives the signal control system limited lead time to borrow "seconds" from the remaining phases, which inevitably causes delay to the traffic served by these phases.

In contrast, adaptive TSP systems provide priority to transit vehicles while at the same time trying to minimize negative impacts to other traffic. A typical adaptive TSP system may consist of three important components: (1) a continuous detection that can detect an approaching transit vehicle continuously, so that its arrival time can be predicted and updated in a real-time manner; (2) communication links among transit vehicle, priority request system and signal controllers to share transit vehicle's arrival time, real-time traffic and pedestrian condition, signal status, and real-time signal timing strategy; (3) a signal control algorithm that adjusts the timing to provide priority while explicitly considering the impacts to the rest of the traffic and ensuring traffic and pedestrian safety. The signal control algorithm should gracefully make a trade-off between transit delay and traffic delay and adapt to the movement of the transit vehicle and the prevailing traffic condition.

Most adaptive TSP systems have been coupled with adaptive signal control systems, because the latter possesses the capability of inferring the prevailing "system-wide" traffic condition, forecasting the evolution of the traffic condition, and optimizing signal timing in real time, for example, SCATS (Lowrie, 1982), SCOOT (Hunt et al., 1981), UTOPIA (Turksma, 2001), and RHODES (Mirchandani et al., 2001) among others. However, a big share (according to Gettman et al., 2007, over 90%) of signals in the United States is still closed-loop actuated with the dual-ring structure. At the same time, wide-scale implementation of adaptive control systems may be many years away, partly due to the associated high costs for implementation and maintenance (Smith et al., 2002). Therefore, it may be more cost-effective to implement adaptive TSP on actuated control systems than replacing the existing traffic control system with another adaptive traffic control system. We believe that such adaptive TSP systems would have the potential for large-scale deployment, thereby leading to fairly significant benefits.

Very limited research has been conducted in developing adaptive TSP on actuated systems. Unlike adaptive traffic signal control, actuated signal control relies on actuation from detection but has no quantitative objective. Therefore, implementing adaptive TSP on an actuated system is very different from realizing adaptive TSP on an adaptive traffic control system. For example, Head et al. (2006) proposed a decision model based on the precedence graph for priority control. Such model presents an analytical framework for the analysis of complex controller behavior.

Implementation of adaptive TSP on actuated signal control systems requires additional effort of addressing the incapability, insufficiency, or inflexibility of detection means, communications and signal controllers employed in those systems. This article develops and implements an adaptive TSP system over an actuated control system. The remainder of the article is organized as follows. Section 2 provides an overview of architecture design of the TSP system and Section 3 presents an adaptive TSP optimization model, including general assumptions, model inputs and outputs, formulations, solution procedure, and a numerical example. Section 4 then reports a field operational test of the developed TSP system. Finally, Section 5 offers some concluding remarks and recommendations for further research.

2 SYSTEM ARCHITECTURE

The physical parties directly or indirectly involved in a TSP system include transit vehicles, transit management center, signal control system, traffic management center, transit vehicle detection means, and communications links among them. In terms of functionality, every implementation of a TSP system shall have two primary components: priority request generator (PRG) and priority request server (PRS). The former aims to initiate a priority request while the latter manages and prioritizes one or more priority requests and generates service requests, which are then sent to and executed by

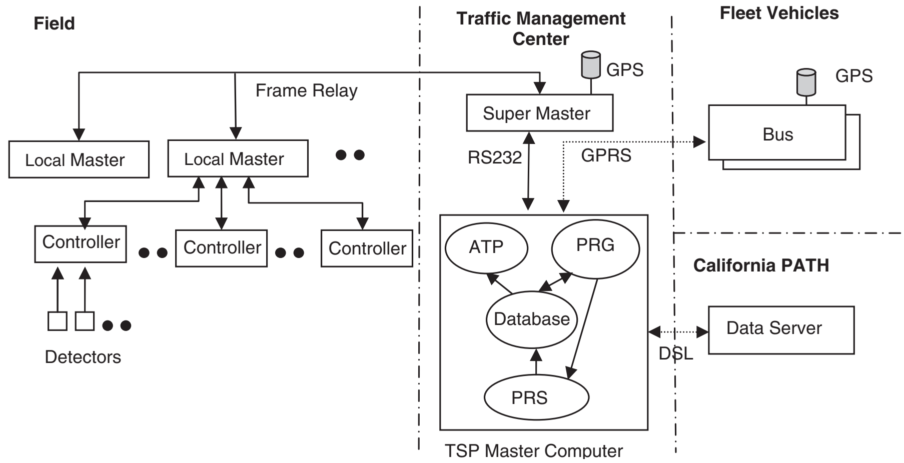

Fig. 1. System architecture for a prototype adaptive TSP system.

signal controllers (AASHTO/ITE/NEMA, 2008). PRG and PRS can be physically placed in different locations and fulfilled by various means, thereby resulting in multiple system architectures available for a TSP implementation.

The system architecture of the developed adaptive TSP system is illustrated by Figure 1 and elaborated as follows:

2.1 Fleet vehicles with location detections

The adaptive TSP system uses global positioning system (GPS) on buses as detection means to continuously monitor bus locations. Bus arrival times to intersections are predicted and updated by an arrival time predictor (ATP). Many previous studies have conducted bus arrival time prediction using regression models (Tan et al., 2007; Zhou et al., 2004), Kalman filtering (Wall and Dailey, 1999), or neural networks (Chien et al., 2002). In this study, we adopted the regression model-based arrival time predictor. This concept allows all buses instrumented with GPS/Automatic vehicle location (AVL) systems to become signal priority capable without additional equipment on buses. Many transit agencies have deployed or planned to deploy GPS/AVL systems to their fleets. In 2006, 56% of fixed route buses in the United States are equipped with such a system (USDOT, 2008).

2.2 Signal control and traffic detection systems in the field

As previously mentioned, the adaptive TSP system is built upon a distributed closed-loop signal control system where controllers receive calls or actuations from inductive loop detectors, indicating that a service is demanded for a particular movement. Arrival and departure traffic counts and occupancies can be made available. In addition, high frequency (e.g., 1HZ or 0.5HZ) signal status information can be archived and retrieved for all phases. Such real-time information is essential for dynamic traffic operation (e.g., Hooshdar and Adeli, 2004).

2.3 Traffic management center with priority request system

The PRG and PRS are hosted by a TSP master computer and physically located in the traffic management center as well as the ATP and a real-time database. The TSP master computer is connected with the super master of the signal control system through a direct serial port connection, allowing traffic data and signal status to be received by the real-time database. And, bus status data are also received by the database via a wireless communication.

An adaptive TSP model, embedded in the PRG, uses information of predicted bus arrival information, estimated queue condition, signal status, and pedestrian presence to optimize TSP strategies. The PRG sends a priority request message to the PRS whenever a bus needs it and a check-out request after the vehicle has passed the signalized intersection. Upon receiving priority requests from multiple buses, the PRS will prioritize all the different priority requests based on the requested priority treatments, requested phase, and desired service time, and then generate a service request and eventually send the service request to signal controllers for execution. It is noted that PRS in the proposed model follows a first-come-first-serve rule and only considers the time when the service is requested to prioritize requests. With additional information of schedule adherence or number of passengers on board, PRS can better prioritize requests.

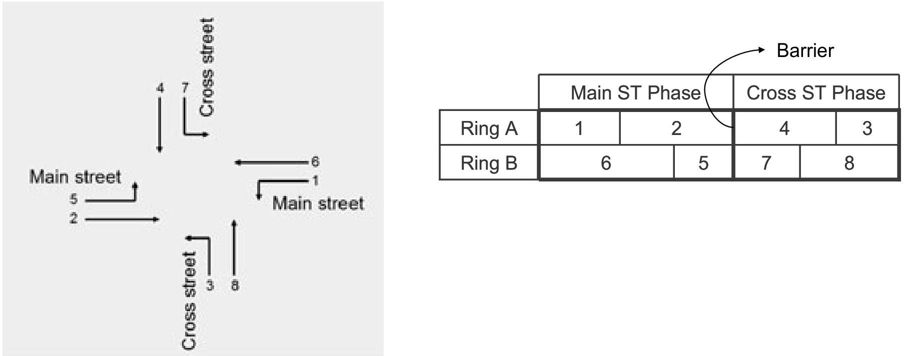

Fig. 2. Definition of standard NEMA phases, rings, and barrier.

On account of fluctuating traffic conditions and various driver behaviors, there are uncertainties in predictions of arrival times at downstream intersections. Thus, the closer buses get to the intersections the higher the predictions' confidence levels will be due to fewer uncertainties. So the later the PRG generates a TSP request, the better data input it is based on. However, the earlier the PRG can send the service request, the more flexibly the signal controller is able to adjust signal timings. There is no optimal location or time to generate a TSP request. PRG keeps listening to the real-time inputs, for example, bus arrival time, signal status, pedestrian button information, and traffic flows. Based on such latest information, PRG will update its request if necessary. PRS will check difference among requests and send the appropriate one to signal controllers.

3 ADAPTIVE TSP OPTIMIZATION MODEL

The core of the adaptive TSP system is a TSP algorithm that manipulates actuated signal controllers to grant priority to buses. This section will introduce the model formulation and solution algorithm, followed by a numerical example. For other developments, such as ATP, readers of interest may refer to Zhou et al. (2004).

3.1 General consideration and assumption

A timing optimization model is developed to minimize a weighted sum of traffic and bus delay at an isolated intersection. To facilitate the model formulation, the following consideration and assumptions are made about intersection geometry, traffic demand, and signal settings:

1. The model considers a single bus request for one particular intersection along a corridor that is coordinated by an actuated system. As defined by National Electrical Manufacturers Association (NEMA) on Figure 2, movements 1, 6, 2, and 5 are on the main corridor streets; movements 4, 7, 3, and 8 are on cross streets. Movement 2 or 6 is the sync movement, which actually represents the coordination direction.
2. A new definition for signal cycle is used to facilitate the formulation. In contrast to the traditional NEMA-defined signal cycle, which references to the on/off of sync movements, we refer a cycle with respect to the onset of cross-street movements. It is noted that the new definition does not impact the model outputs as described below.
3. The adaptive TSP model attempts to change green splits for at most three consecutive cycles.
4. Traffic demand fluctuates across time-of-day (TOD). It is assumed the arrival flow within three consecutive cycles is stationary. Moreover, the intersection capacity (saturation flow) is assumed to be stationary. It is noted that accurate estimation of traffic arrival flows and mixed-flow traffic capacity can be obtained as shown in Dharia and Adeli, 2003; Jiang and Adeli, 2004a, b, 2005; Xie et al., 2007; Vlahogianni et al., 2008; Stathopoulos et al., 2008; and Washburn and Cruz-Casas, 2010. TSP operations should not cause residual queues for any movement after three TSP control cycles. It is noted that the number of cycles for transitions can be readily customized in the proposed model. The intersection with high traffic demand on all approaches might need more cycles in transition than the intersection with low traffic demands.

3.2 Inputs and outputs

As shown in Figure 3, the optimization model takes five real-time inputs, including bus arrival time and schedule adherence (early, on time, or late) generated and updated by ATP; short-term traffic demand prediction obtained by using a moving average method that analyzes the time-series traffic counts from traffic detectors;

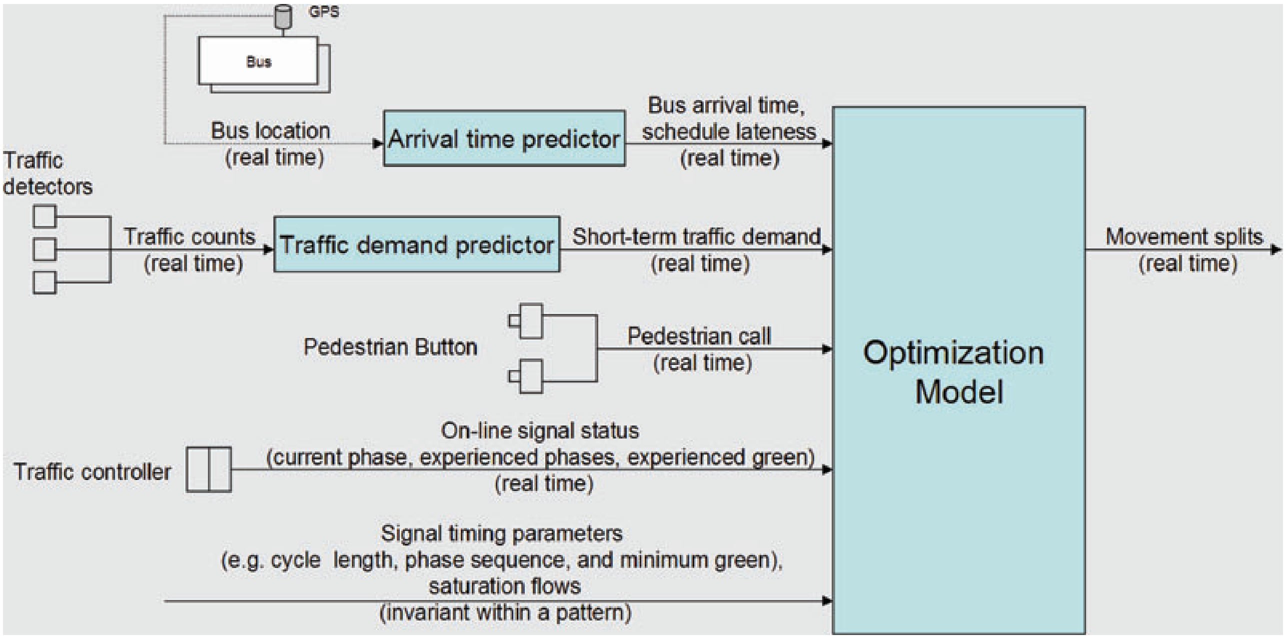

Fig. 3. Input/output control diagram.

pedestrian calls and online signal status received in real time from the signal controller; and other static inputs such as signal timing parameters (e.g., cycle length and minimum green) and saturation flow rates, which are invariant within a pattern typically defined by time of day.

The model outputs are priority requests in the form of movement splits. The movement splits can be converted to any form of controllable parameter, for example, green split, force-off point, or maximum green. Zhou et al. (2004) validated that 170E signal controller, a popular model for actuated systems primarily in California, New York, as well as some other states, is capable of performing more adaptively through online updating timing parameters, such as force-off points, gaps, and maximum green, etc. NEMA-type controller, the other popular model of traffic signal controllers, is also capable of performing such operations. However, an actuated control system may not be able to work the same way as an adaptive system due to two constraints in their control logic: the first one is cycle length constraint, which requires the duration between the end of the sync movement and the end of the next sync movement to be a constant while the other concerns the movement sequence. No movement can be revisited before the cycle ends in many controllers (Some latest version of the control firmware has been modified to allow longer cycles and phase reservice. Such features are not considered in the article.). Essentially, both constraints aim to keep all signals of the corridor in coordination and make the control logic simple and applicable to the field controllers. As neither constraint can be overridden, the proposed model must satisfy them.

3.3 Model formulation

As aforementioned, the optimization model manipulates movement splits in three consecutive cycles for an approaching bus. We denote the cycle that contains the predicted bus arrival time as cycle 1. Correspondingly, the previous and following cycles are labeled cycle 0 and 2, respectively. The TSP model confirms accurate prediction of bus arrival by the end of cycle 0, and provides bus priority in cycle 1, and then uses cycle 2 as a transition cycle to compensate the loss of other traffic due to the priority operation. Note that the signal cycles mentioned here and hereinafter are based on our definition in Section 3.1.

Phase sequence can be defined by lead-lag relationships between the four conflicting movement pairs: 1&2, 3&4, 5&6, and 7&8. Four binary variables are introduced in (1) to uniquely represent a particular phase sequence.

$$L_i = \begin{cases} 1, & \text{if mov}'i \text{ is lead} \\ 0, & \text{if mov}'i \text{ is lag} \end{cases}, \quad \forall i = 1, 3, 5, 7 \quad (1)$$

Figure 4 shows an example phase sequence, which is consistent with Figure 2. The corresponding binary variables are (1, 0, 0, 1). Phase 6 is the sync phase. Although the newly defined cycle starts from the beginning of phase 4 and 7 and ends after phase 2 and 5, the traditional constant cycle length C is between the end of sync phase and its next end, as shown in Figure 4.

3.3.1 Decision variables. As depicted in Figure 5, cycle 1 and cycle 2 are control cycles, during which the TSP

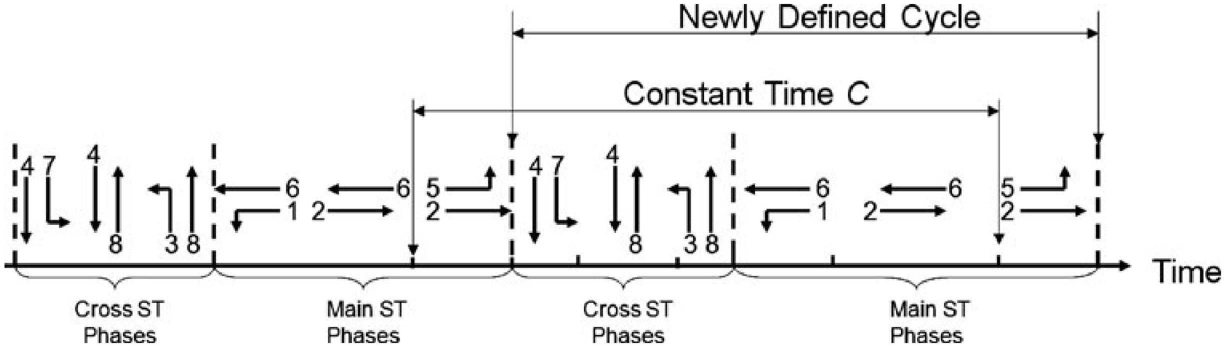

Fig. 4. An example phase sequence.

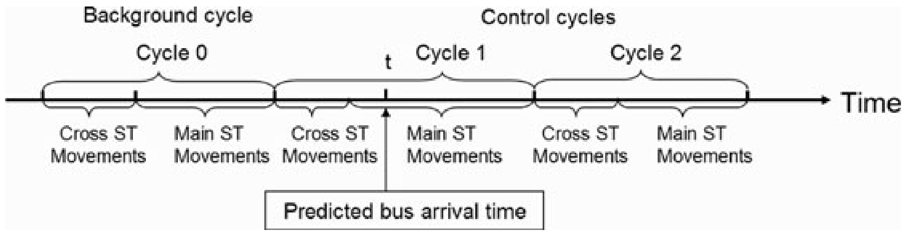

Fig. 5. Background and control cycles.

algorithm manipulates the splits of green time for different movements. All the movement splits within the control cycles are decision variables of the optimization model. In contrast, the green splits in the background cycle are not controlled by the TSP model. The green split for movement i in cycle j is denoted as g_{ji}, while red time as r_{ji}.

3.3.2 Constraints. The optimization model may satisfy six sets of constraints: (1) minimum green; (2) cycle length; (3) barrier; (4) undersaturation; (5) red–green relationship, and (6) real-time updates. All these constraints are elaborated as follows.

The minimum green constraint requires a minimum protected green for each movement. Pedestrian crossings are consolidated into this minimum constraint. We introduce a variable to indicate pedestrian presence as Equation (2). When the pedestrian button is pushed, the minimum green for the corresponding movement is elongated to the protected "walk" plus "flash don't walk" time, as described by Equation (3).

$$Ped_{ji} \quad (i = 1, \ldots, 8; j = 1, 2) = \begin{cases} 1, & \text{ped' button pushed for mov' } i \text{ in cycle } j \\ 0, & \text{no ped' info for mov' } i \text{ in cycle } j \end{cases} \tag{2}$$

$$g_{ji} \geq (1 - Ped_{ji}) G_i^{\min} + Ped_{ji} G_i^{\text{ped}} (i = 1, \ldots, 8; j = 1, 2) \tag{3}$$

where $G_i^{\min}$ is the minimum green for movement i and G_i^{ped} is the protected "walk" plus "flash don't walk" time.

The cycle length constraint is formulated as Equation (4). The first expression represents a lead-lead phase sequence while the second one represents the lead-lag or lag–lag sequence. Lead or lag operation suggests whether the left-turn traffic is released before or after the opposing traffic.

$$(j = 1, 2) \quad \begin{cases} L_1 L_5 \left(C - \sum_{i=1}^{4} g_{ji} \right) = L_1 L_5 \left(C - \sum_{i=5}^{8} g_{ji} \right) = 0 \\ (2 - L_1 - L_5)[C - L_5(g_{j-1,1} - g_{j1}) \\ \quad - L_1(g_{j-1,5} - g_{j5}) - (1 - L_1)(1 - L_5)(g_{j-1,i} - g_{ji}) \\ \quad - g_{ji} - g_{j,i+1} - g_{j,i+2} - g_{j,i+3}] = 0 \quad (i = 1, 5) \end{cases} \tag{4}$$

where C is the signal cycle length.

The barrier constraint, as shown in Equation (5), means that ring A and B at the same side of the barrier should have the same duration:

$$\begin{aligned} g_{j1} + g_{j2} &= g_{j5} + g_{j6} \\ g_{j3} + g_{j4} &= g_{j7} + g_{j8} \end{aligned}, \quad j = 1, 2 \tag{5}$$

The undersaturation constraint, in the form of Equation (6), is to guarantee that no residual queue will be present after the two control cycles.

$$\frac{\lambda_i \sum_{k=j}^{2} (g_{ki} + r_{ki})}{\mu_i \sum_{k=j}^{2} g_{ki}} \leq 1, \quad i = 1, \ldots, 8,\ j = 1, 2 \quad (6)$$

where λ_i is traffic arrival rate for movement i and μ_i is saturation flow for movement i.

Except for the predefined all-red period, a traffic signal must show green to one movement while showing red to the conflicting movements. Such red–green relationships form another set of constraints for the optimization model, as described in Equation (7).

$$r_{ji} = \begin{cases} g_{j-1,i+1} + g_{j-1,i+2} + g_{j-1,i+3} \\ \quad - L_i(g_{j-1,i+2} + g_{j-1,i+3} \\ \quad - g_{j,i+2} - g_{j,i+3}) & i = 1, 5, j = 1, 2 \\ g_{j,i-1} + g_{j,i+1} + g_{j,i+2} & i = 2, 6, j = 1, 2 \\ g_{j,i-2} + g_{j-1,i-1} + g_{j,i+1} \\ \quad + L_{i-2}(g_{0,i-2} - g_{1,i-2}) \\ \quad + L_i(g_{0,i+1} - g_{1,i+1}) & i = 3, 7, j = 1, 2 \\ g_{j,i-3} + g_{j-1,i-2} + g_{j,i-1} \\ \quad + L_{i-3}(g_{0,i-3} - g_{1,i-3}) \\ \quad + (1 - L_{i-1})(g_{0,i-1} - g_{1,i-1}) & i = 4, 8, j = 1, 2 \end{cases}$$

To achieve the "adaptive" goal, another real-time updating constraint is needed, as shown in Equation (8). One major advantage of the adaptive TSP system is that the central control module can update timing plans real time based on real-time information, such as bus arrival time. In addition, if the control module is aware of the execution status of a particular movement, whether skipped or ended, it will not consider the length of this movement $g_{ji}^{\exp}$ as a decision variable any more. For other statuses, either ongoing or forthcoming, $g_{ji}^{\exp}$ will be another lower bound of the decision variable g_{ji} other than that in Equation (3).

$$\begin{cases} g_{ji} \geq g_{ji}^{\exp} \\ M_{ji}(M_{ji} - 1)g_{ji} & j = 0, 1, 2; i = 1, \ldots, 8 \quad (8) \\ \quad \leq M_{ji}(M_{ji} - 1)g_{ji}^{\exp} \end{cases}$$

where $g_{ji}^{\exp}$ is the experienced green time for movement i in control cycle j andM_{ji} is the execution status for movement i in control cycle j, defined as follows

$$\begin{matrix} M_{ji} \\ (i = 1, \ldots, 8; j = 0, 1, 2) \end{matrix} = \begin{cases} 0, & \text{mov}' \text{ is not started yet} \\ 1, & \text{mov}' \text{ is ongoing} \\ 2, & \text{mov}' \text{ is ended or skipped} \end{cases}$$

3.3.3 Objective function. The adaptive TSP operation is to grant priority to buses while minimizing the impacts on other vehicular traffic. To make a trade-off between these two objectives, a weighting factor on bus delay is used, which represents the preference between reducing bus delay and reducing traffic delay. Therefore, the objective function of the proposed model is to minimize a weighted sum of bus and other traffic delay. To compute traffic delay, we have two scenarios for each movement to consider:

1. Scenario I: no residual queue at the end of cycle 1
2. Scenario II: residual queues exist in cycle 1 but not in cycle 2.

A classic deterministic queuing model is applied to estimate delays at signalized intersections, assuming uniform traffic arrivals and vertical queues at the intersection stop lines. It is known that the model may not accurately represent the exact number of queued vehicles at a given instant. However, the model does not bias the delay estimation over an entire queue formation and dissipation process and works for both under- and oversaturated traffic conditions (Dion et al., 2004). It is noted that the focus of the model is not on delay calculation model but the optimization and balance of TSP benefits and negative impacts on other traffic. The model can actually relax the assumption of uniform arrival by two approaches. First, a scenario-based stochastic model was developed (Yin, 2008) to address the fluctuating traffic conditions. Second, the data driven model (Li et al., 2009) was proposed to utilize the existing detection system upon closed-loop actuated control system.

According to the deterministic queuing model, traffic delays in cycle 0, 1, and 2 are calculated by Equation (9), which can be consolidated into Equation (10). It is noted that the overall impact on traffic delay by the TSP system should not be limited to the one intersection. On account of the system coordination, the traffic along the coordinated directions may experience additional delay at adjacent intersections due to the timing changes at one intersection. However, this part of delay is not captured by the current model.

$$\begin{cases} \text{Scenario I}: & d_i = \frac{\mu_i}{2}\rho_i r_{0i}^2 + \frac{\mu_i}{2}\rho_i(r_{1i}^2 + r_{2i}^2) \\ \text{Scenario II}: & d_i = \frac{\mu_i}{2}\rho_i r_{0i}^2 + \frac{\mu_i}{2}\rho_i(r_{1i} + r_{2i})^2 - r_{2i}\mu_i g_{1i} \end{cases} \quad (9)$$

$$d_T = \sum_{i=1}^{8} \left[\frac{\mu_i}{2}\rho_i(r_{1i} + r_{2i})^2 - r_{2i}\mu_i \min(g_{1i}, \rho_i r_{1i}) + \frac{\mu_i}{2}\rho_i r_{0i}^2\right] \quad (10)$$

where: $\rho_i = \frac{\lambda_i}{\mu_i - \lambda_i}$.

Regarding the bus intersection delay, if a transit vehicle is expected to arrive before its normal green in control cycle 1, the optimization model would make the decision before control cycle 1 to reduce green times of phases prior to the bus phase. Such a strategy is called "early green." "Green extension," another popular TSP strategy, will be executed instead if the transit vehicle is expected to barely miss its original green. As green extension may disrupt existing coordination for main street phases, traffic engineers often impose some restrictions on this strategy. For example, the extended green cannot be longer than 10% of the cycle length.

The bus that requests signal priority can arrive at any phase in the proposed model. The most complicated scenario is that the phase of bus arrival is the last phase of a cycle because the green extension strategy under this scenario would break the cycle length constraint for two consecutive cycles. The case with bus arrival on nonsync phase is easier to solve. In addition, most rapid transit services that need TSP run along major corridors. Therefore, we assume that buses are running on movements 2 and 6 in the delay calculation. The model can be readily adapted by changing the phase number in Equations (11)–(13) when a bus is actually not on movement 2 or 6. Here we introduce a binary variable as in Equation (11) to indicate buses' running directions

$$B = \begin{cases} 1, & \text{if bus is on movement 2} \\ 0, & \text{otherwise bus is on movement 6} \end{cases} \tag{11}$$

The predicted bus arrival time t_{bus} is referenced to the end of a sync movement or a real clock (Zhou et al., 2004). To compute bus delay, we convert t_{bus} into T_{bus}, which is referenced to the end of green of the bus phase

$$T_{bus} = t_{bus} + B(1 - L_1)g_{01} + (1 - B)(1 - L_5)g_{05} \tag{12}$$

For early green, the model will shrink the red time for the bus phase, from R' to R, as shown in Figure 6. At T_{bus}, the bus is expected to arrive at the intersection to join a standing queue. The number of queued vehicles ahead of the bus is N_T, and the corresponding queue discharging time is bus delay d_{bus} because the bus leaves the intersection at $T_{bus} + d_{bus}$. The queue disappears at t_q, which can be computed as follows:

$$t_q = R + B\rho_2 r_{12} + (1 - B)\rho_6 r_{16} \tag{13}$$

where R is the red time for the bus movement, $R = Br_{12} + (1 - B)r_{16}$.

From the geometry of Figure 6, bus delay can be obtained as follows:

$$\frac{d_{bus}}{R} = \frac{\max(t_q - T_{bus}, 0)}{t_q} \tag{14}$$

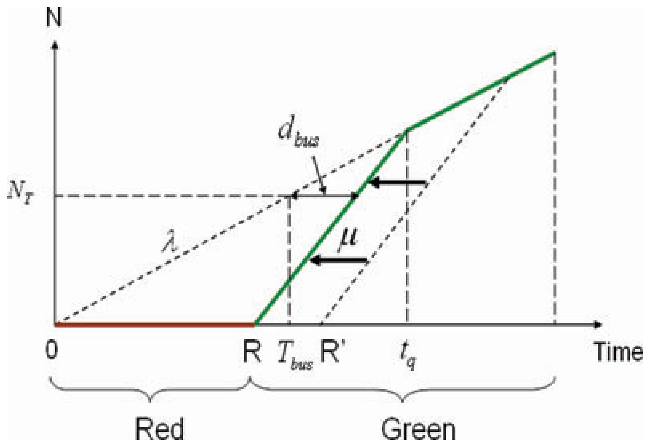

Fig. 6. Flow-time diagram for bus movement with TSP.

$$d_{bus} = \frac{R}{t_q}\max(t_q - T_{bus}, 0) \tag{15}$$

Therefore, the objective function for early green strategy is

$$\min d = \sum_{i=1}^{8}\left[\frac{\mu_i}{2}\rho_i(r_{1i} + r_{2i})^2 - r_{2i}\mu_i \min(g_{1i}, \rho_i r_{1i}) + \frac{\mu_i}{2}\rho_i r_{0i}^2\right] + w_b\frac{R}{t_q}\max(t_q - T_{bus}, 0) \tag{16}$$

where w_b is the weighting factor for buses.

For green extension, the green of the bus phase in cycle 0 is extended until the approaching bus leaves the intersection. Therefore bus delay will be zero. So the objective function for green extension is simply to minimize Equation (10). Changes are also needed on the signal timing constraints for the green extension strategy. As the bus arrived at the beginning of a cycle, the sync phase in the cycle before the bus arrival is extended by G_{ext}. As a result, the cycle length of the previous cycle is elongated and that of the bus arrival cycle is shrunken by as much as G_{ext}.

In summary, the TSP optimization models are to minimize (16) or (10). Given specific setting of the signal and real-time traffic information, all the constraints are linear. By introducing additional auxiliary variables, the objective function (16) or (10) can be easily transformed into quadratic functions. Moreover, we treat all decision variables as continuous as signal controller works at 10 hertz and their working frequency is 10 times per second. Therefore, the formulated models are standard quadratic programming models, which can be easily solved by commercial solvers.

3.4 Computation procedure

Given a set of traffic signal information and transit movement data, an optimization solver for convex

Table 1
General information and parameters for the example

Movement	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Minimum green (sec)	4	6	4	6	4	6	4	6
Demand (veh/h)	200	1,200	200	800	200	1,200	200	800
Saturation flow (veh/h)	1,200	5,400	1,200	3,600	1,200	5,400	1,200	3,600
Green split (sec)	20	53	20	27	20	53	20	27
Delay (sec/veh)	50	23.8	50	46.7	50	23.8	50	46.7

Table 2
Performance of the adaptive TSP algorithm (medium-congested scenario)

	Average vehicle delay (sec/veh)							
	Bus		*Traffic at bus movement*		*Traffic at other movements*		*Total vehicle delay*	
Weighting factor	*(sec)*	*Diff′*	*(sec)*	*Diff′*	*(sec)*	*Diff′*	*(sec)*	*Diff′*
1 (Ref′)	10.24	0.00%	19.05	0.00%	37.46	0.00%	15,782.41	0.00%
50	4.98	−51.34%	19.27	1.13%	37.65	0.52%	15,877.40	0.60%
100	3.12	−69.54%	19.37	1.67%	38.02	1.50%	16,018.45	1.50%
150	1.1	−89.24%	19.48	2.24%	38.68	3.25%	16,263.63	3.05%
200	0.2	−98.04%	19.60	2.88%	39.07	4.29%	16,416.62	4.02%
250	0.14	−98.61%	19.64	3.06%	39.09	4.35%	16,428.58	4.09%
300	0.02	−99.85%	19.66	3.19%	39.18	4.60%	16,464.55	4.32%
350	0.00	−100%	19.70	3.38%	39.18	4.60%	16,469.16	4.35%
400	0.00	−100%	19.70	3.38%	39.18	4.60%	16,469.16	4.35%

quadratic objective with linear constraints, may output two sets of phase splits for early green and green extension strategy, respectively. By comparing the values of the two objective functions, the optimal strategy is determined for the coming bus. The final priority request, which is the output to PRS, consists of the phase splits in the form of force-off or green splits together with other information consistent with the NTCIP 1211 specification.

3.5 Numerical case study

We present a numerical example here to demonstrate the proposed models. We also conducted the sensitivity analysis on weighting factor in the objective. Although the selection of weighting factor can be political, policy and circumstance dependent, the results presented in the sensitivity analysis can provide some guidance to decision makers on the benefits and cost comparison resulted from different weighting factors.

In this example, the intersection has four lanes on each main street approach, one of which is the left-turn lane. On the cross streets, there are one left-turn lane and two through lanes. Table 1 reports basic settings for the example under a medium-congested scenario whose saturation degree is 0.67. For a simplification of the calculation, traffic arrivals were assumed to be uniformly distributed in the numerical case study. The phase sequence is shown in Figure 4 and the cycle length is 120 seconds. Suppose that a bus is coming along movement 6 and pedestrian buttons will not be pushed in the example.

Assuming that bus can arrive at any second of the local clock, we used the optimization toolbox provided in MATLAB to solve the optimization models. The constraint nonlinear programming problem is solved by computing a quasi-Newton approximation to the Hessian, the second derivatives of the Lagrangian. The interior-point algorithm is applied to the solver. The interior-point algorithm is applied to the solver.

Table 2 presents the performance of the TSP algorithm under the medium-congested scenario. Both the average and total vehicle delays are computed by considering cycle 0, 1, and 2 and averaging across different bus arrival times. When the weighting factor is 1, the bus is treated as important as any other vehicle. Therefore, the objective of this case is to minimize total vehicle delay, including bus delay, which is essentially the adaptive signal control logic. As the weighting factor increases, the approaching bus has relatively higher priority over the other traffic. Accordingly, bus delay will be reduced at the cost of the other traffic. For active

Table 3
Performance of the adaptive TSP algorithm (heavily congested scenario)

	Average vehicle delay (sec/veh)							
	Bus		*Traffic at bus movement*		*Traffic at other movements*		*Total vehicle delay*	
Weighting factor	*(sec)*	*Diff′*	*(sec)*	*Diff′*	*(sec)*	*Diff′*	*(sec)*	*Diff′*
1 (Ref′)	25.09	0.00%	28.60	0.00%	42.44	0.00%	22,475.62	0.00%
100	10.95	−56.38%	29.50	3.15%	43.80	3.20%	23,190.88	3.18%
200	5.45	−78.29%	30.47	6.53%	45.22	6.55%	23,932.43	6.48%
300	1.69	−93.27%	31.49	10.10%	46.98	10.71%	24,834.72	10.50%
400	0.96	−96.19%	31.82	11.26%	47.50	11.92%	25,102.70	11.69%
500	0.31	−98.75%	31.97	11.78%	48.19	13.55%	25,421.80	13.11%
600	0.27	−98.92%	31.96	11.75%	48.24	13.68%	25,444.25	13.21%

rule-based TSP systems, the priority treatment also favors the traffic moving along the bus traveling direction (Zhou et al., 2004). However, it is not necessarily true with adaptive TSP, because the model optimally allocates the disturbance of bus priority treatment to all other traffic. The longer bus phase in cycle 1 may incur a shortened green for the same phase in cycle 2, because other movements need to be compensated in the transition cycle. Consequently, it can be seen in Table 2 that average vehicle delays at the bus and other directions rise up to by 3.38% and 4.6%, respectively as the weighting factor increases.

On the other hand, bus delays are more sensitive to changes in the weighting factor than other traffic delays. When the weighting factor is 50, the average bus delay under different predicted arrival times is reduced by 51.34% while delays to traffic at the bus and nonbus movement only increases by 1.13% and 0.52%, respectively. When the weighting factor increases to 350, buses experience no delay no matter when they arrive at the signal, while average vehicle delay for other traffic rises 0.65 seconds and 1.72 seconds only. We conclude that the proposed adaptive TSP model works well in the medium-congested scenario because it can significantly reduce bus intersection delay without incurring much extra delay for the other traffic.

Rakha (2004) recommends active TSP for medium- or low-congested conditions, because such systems always incur significant delay to nonbus movements in highly congested scenarios. The proposed adaptive TSP system, however, can use the weighting factor to make an explicit trade-off in heavily congested traffic. Table 3 presents the performance of the adaptive TSP algorithm in a scenario with a saturation degree of 0.89. Similar to the results in Table 2, the average bus delay decreases dramatically as the weighting factor increases, while the average delay for other traffic shows a much slower trend of increase. However, the delays experienced by other traffic are more significant than those in medium-congested conditions, because time resource available to conflicting traffic is scarcer when it is highly congested.

Figures 7 and 8 show average bus and other traffic delays versus weighting factor and bus arrival time at the local clock for the heavily congested scenario. If the bus arrives at the beginning of the signal cycle when the bus phase is red, the bus experiences more delay. Note that neither surface is smooth due to the fact that the optimized values are not differentiable with bus arrival time. The surfaces break when the system decides to switch its strategy from green extension to early green.

According to the trends of the surfaces, we can see bus delays decrease as the weighting factor grows and the arrival time increases, while other traffic delays rise as the weighting factor grows. When bus arrival time falls at either end of a cycle, the TSP algorithm can easily extend green or do nothing to manipulate TSP requests. When bus arrival time falls in the middle of a cycle, the TSP algorithm has to provide priority, which would incur greater delay for other traffic. Therefore, other traffic delays peak when arrival time is in the middle of a cycle. Moreover, the peak value increases with the increase of the weighting factor.

4 FIELD OPERATIONAL TEST

The developed adaptive TSP system has been tested in a field environment. The testing site is a stretch of El Camion Real corridor that is a major connector between San Francisco and Silicon Valley, California. The testing site is 2 miles long and consists of seven signalized intersections: from 9th Avenue to 28th Avenue. All the traffic signals are under coordinated

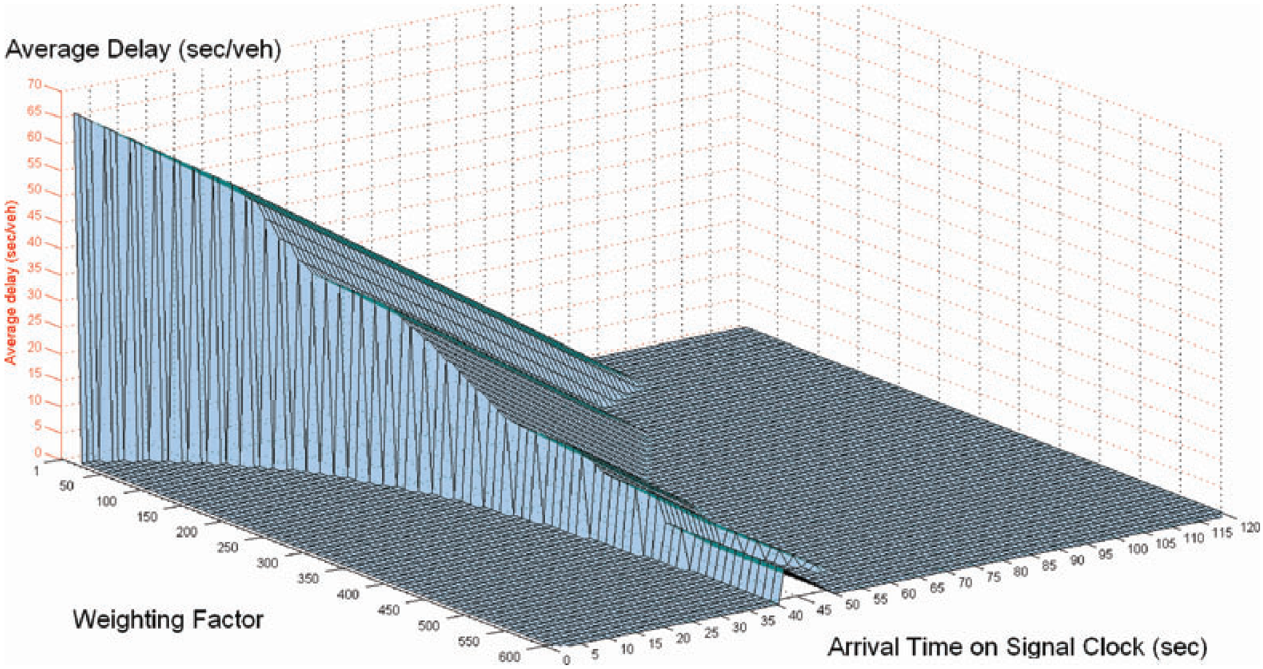

Fig. 7. Average bus delays in the heavily congested scenario.

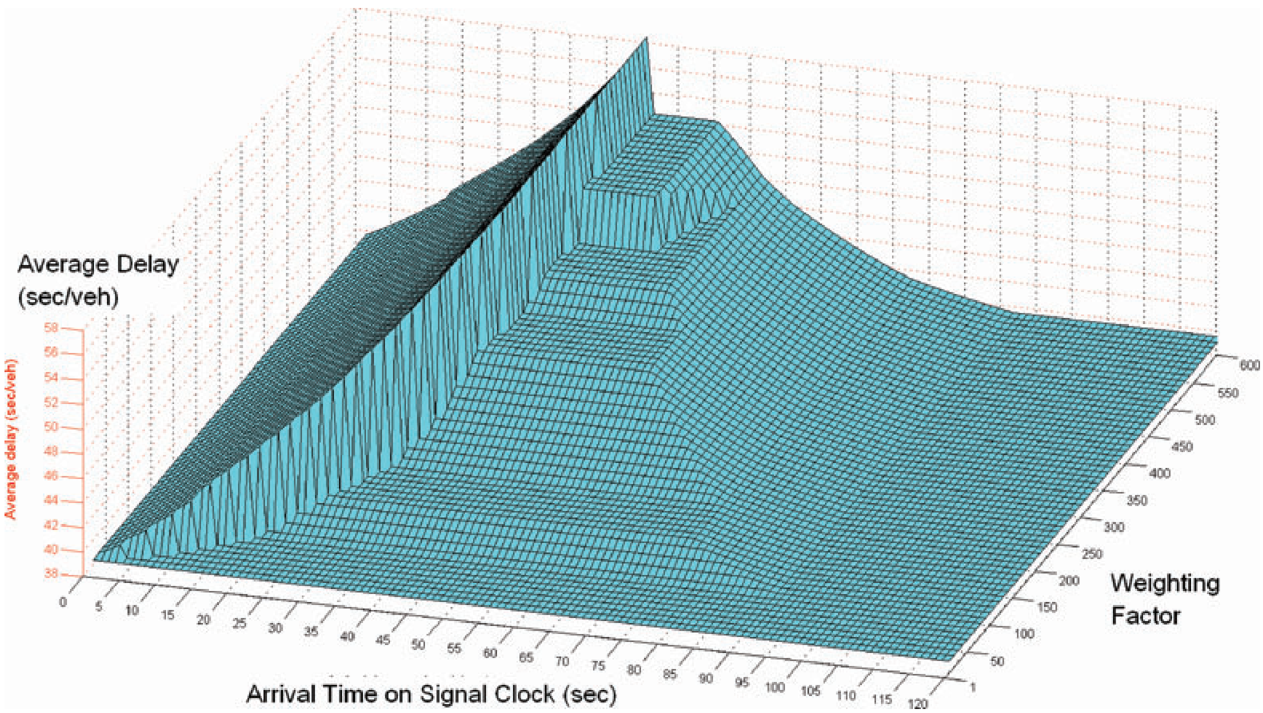

Fig. 8. Intersection delays for other traffic in the heavily congested scenario.

semiactuated control and are installed with 170E signal controller together with California Department of Transportation (Caltrans) C-8 firmware. A quadratic programming solver COPL_QP was selected to solve the problem with convex quadratic objective and linear constraints. The solver used an interior-point algorithm and outputted movement splits, which were then covered into force-off points. The TSP requests were sent to 170E controllers running C-8 firmware. The system operational latency, including data collection, data processing, optimization, and request transmission, was within 5 seconds, which is adequate for real-time operation.

A not-in-service bus from San Mateo County Transit District (SamTrans) was equipped with the GPS and wireless communication-based data acquisition system for the field test. During the 2-week-long testing period, the assigned bus driver drove the testing bus back and forth along the testing site within three designed time windows: morning peak, mid-day, and afternoon peak. The bus arrival time at intersection was predicted using the recursive least-squares method based on both historical data and real-time bus movement data. The prediction error was within 5 seconds when buses were within the range of 300 meters (984 feet). A traffic flow prediction model, based on an adaptive RLS method and real-time loop detector data, has been developed to provide an estimation of traffic arrival flow for every 5 minutes.

Traffic delay was calculated based on the field data from loop detectors. As shown in Figure 1, traffic signal data such as running phase and local cycle timer with high frequency (0.5 to 1 HZ) together with traffic volume data from each loop detector were collected. For most of the coordinated actuated systems particularly in California, there is frame-relay communication in place for coordination. Meanwhile, all controllers are compliant with NTCIP standard or AB3418 in California. Such communication system and protocol are capable of transmitting data frequently to the field master. For actuated control system, advance loops, and four $6' \times 6'$ presence loops, if any, are placed. Arrival and departure traffic counts and occupancies can be made available. In addition, second-by-second signal status information can be archived and retrieved for all phases. The traffic delays shown below were calculated based on the signal arrival and departure curves given the historical right-turn turning ratio. When the presence loops were not placed, a uniform departure curve was built once the signal phase changed its color. For the oversaturation case when the advanced loop is always occupied by the waiting queue, a uniform arrival curve was built for the delay calculation.

Table 4 compares intersection delays for the "before" and "after" scenarios. It is noted that the "before" scenario here is not real "before" scenario due to the limit samples for each time of day period. Instead, an emulation program was developed to mimic the original semi-actuated signal control logic under Caltrans C-8 control firmware. The emulation program generated green splits based on the loop detector data and pedestrian button information we collected from the field and created the "before" case without the TSP request for each of the "after" sample cases. Such a derived "before" scenario is more comparable with the "after" scenario with TSP.

With those derived "before" scenarios, it is shown in Table 4 that traffic delays for both major phases and minor phases were slightly increased after executing TSP. When calculating the average passenger delay at intersections, the average number of passengers on regular vehicles is assumed to be 1.2 persons. For SamTrans buses, the average number of passengers onboard is assumed to be 15 persons per bus. For example, at 9th Avenue, TSP reduced the average bus delay significantly by 95% to 1.98 seconds per bus; the average major-phase traffic delay was reduced by 81% to 2.70 seconds per vehicle; the minor-phase delay increased by 6% to 15.35 seconds per vehicle. The statistic *t*-test results show that the delay reductions for buses and major-phase traffic are significant, while the incurred-delay for minor-phase traffic is negligible. Overall, the average passenger delay for all approaches including buses was reduced by 55%, which is also statistically significant.

Two busiest intersections along the testing corridor are 17th and 25th Avenue. In the field test, a constant weighting factor was applied for all seven intersections. As the weighting factor is the key to balance the level of priority and incurred additional delay to other phases, at those busy intersections the TSP optimization models may reduce the level of priority given to buses. At 17th Avenue, average bus and major-phase delay was reduced by 53% and 14%, respectively. Meanwhile, TSP caused additional minor-phase traffic delay of 1.49 seconds per vehicle. The average passenger delay at 17th Avenue was reduced by 14%, which is statistically significant. Similarly, at 25th Avenue, TSP saved 43% of bus delay and 16% of major-phase traffic delay with costing extra 1.39 seconds per vehicle for minor-phase traffic. The average passenger delay saving is 12%, which is also statistically significant.

One of the primary incentives for TSP is that transit vehicles carry more passengers than other vehicles, so that giving priority to transit vehicles may reduce overall passenger delay. Table 5 presents results of a sensitivity analysis to see how the number of passengers on buses affects overall passenger delay at intersections. Intuitively, more passengers on buses will lead to more significant reduction of overall passenger intersection delay. According to Table 5, Barneson Avenue has higher sensitivity than other intersections due to its relatively smaller traffic volumes. TSP would reduce the average passenger intersection delay if there are more than six passengers onboard. For the other six intersections, TSP operations would always reduce average passenger delay, largely due to the fact that existing semiactuated signal control is less optimal and adaptive optimization of signal timing is always beneficial.

Table 4
Adaptive TSP impacts on intersection delays (sec/veh or sec/passenger)

	Delay (sec/veh or sec/pax)	*Derived "before" scenario*				*"After" scenario*			
		Bus	*Major*	*Minor*	*Pax**	*Bus*	*Major*	*Minor*	*Pax**
9th Ave.	Mean	41.58	14.16	14.42	15.57	1.98	2.70	15.35	6.98
	Standard deviation	19.15	8.50	6.36	5.36	6.86	1.36	4.83	1.88
	Chg								
	sec/veh	N/A	N/A	N/A	N/A	−39.60	−11.46	0.93	−8.59
	%	N/A	N/A	N/A	N/A	−95%	−81%	6%	−55%
	t-test	N/A	N/A	N/A	N/A	sig't	sig't	insig't	sig't
17th Ave.	Mean	61.38	33.20	9.61	25.93	28.56	28.48	11.11	22.19
	Standard deviation	19.49	10.71	3.09	7.34	29.64	12.29	3.33	7.60
	Chg								
	sec/veh	N/A	N/A	N/A	N/A	−32.82	−4.72	1.49	−3.74
	%	N/A	N/A	N/A	N/A	−53%	−14%	16%	−14%
	t-test	N/A	N/A	N/A	N/A	sig't	insig't	sig't	sig't
25th Ave.	Mean	51.30	36.67	13.72	27.42	29.09	30.88	15.11	24.19
	Standard deviation	27.65	10.39	2.76	6.54	28.34	8.07	2.37	5.40
	Chg								
	sec/veh	N/A	N/A	N/A	N/A	−22.21	−5.79	1.39	−3.23
	%	N/A	N/A	N/A	N/A	−43%	−16%	10%	−12%
	t-test	N/A	N/A	N/A	N/A	sig't	sig't	sig't	sig't
27th Ave.	Mean	45.35	18.26	16.94	19.13	17.93	11.63	17.15	12.36
	Standard deviation	17.49	8.58	7.00	7.52	21.74	5.29	3.31	4.30
	Chg								
	sec/veh	N/A	N/A	N/A	N/A	−27.42	−6.62	0.21	−6.76
	%	N/A	N/A	N/A	N/A	−60%	−36%	1%	−35%
	t-test	N/A	N/A	N/A	N/A	sig't	sig't	insig't	sig't
28th Ave.	Mean	45.58	18.83	13.24	18.76	14.07	4.95	16.77	7.20
	Standard deviation	15.06	5.94	2.50	4.40	18.81	2.54	4.23	2.73
	Chg								
	sec/veh	N/A	N/A	N/A	N/A	−31.50	−13.89	3.53	−11.56
	%	N/A	N/A	N/A	N/A	−69%	−74%	27%	−62%
	t-test	N/A	N/A	N/A	N/A	sig't	sig't	insig't	sig't

Notes: Pax*: Delay for passengers on buses and other vehicles; Chg: Change comparing "before" and "after" scenario; *t*-test: *t*-test to check the delay change is statistically significant or insignificant; sig't: Delay change is statistically significant; insig't: Delay change is statistically insignificant.

5 CONCLUSIONS AND FUTURE WORK

The findings of the study may provide the transportation authorities with a cost-efficient way to achieve adaptive TSP in the state-of-the-practice traffic control systems. It provides quantitative models to explicitly balance the benefits and impacts of TSP. Given a specific traffic situation, a cost-benefit analysis could be conducted to determine a weighting factor for the optimization models. Such weighting factor would be able to provide appropriate priority to the transit vehicles, meanwhile with limited negative impacts on other general traffic. A field operational test was conducted upon a 2-mile-long arterial that consists of seven signalized intersections. The results are very promising: the average reductions on the bus delay and traffic delay along the major phases are 64% and 44%, respectively. The negative impact on increasing average traffic delay for minor phases is 12%. Overall, the average passenger delay

Table 5
Sensitivity analysis of passenger intersection delay (sec/pax)

Scenario	*Number of pax*	*9th Ave.*	*12th Ave.*	*Barneson*	*17th Ave.*	*25th Ave.*	*27th Ave.*	*28th Ave.*
Before	1	14.35	6.49	16.40	24.37	26.78	18.20	17.94
	5	14.71	6.72	16.62	24.83	26.96	18.47	18.18
	10	15.14	7.00	16.89	25.39	27.19	18.80	18.47
	15	15.57	7.27	17.15	25.93	27.42	19.13	18.76
	20	15.98	7.52	17.41	26.46	27.64	19.44	19.04
After	1	7.21	5.44	16.86	21.99	24.06	12.17	6.99
	5	7.14	5.35	16.70	21.99	24.10	12.22	7.05
	10	7.06	5.25	16.51	22.09	24.14	12.29	7.12
	15	6.98	5.15	16.32	22.19	24.19	12.36	7.20
	20	6.90	5.05	16.14	22.29	24.24	12.43	7.27
Change	−49.69%	−16.18%	2.80%	−9.77%	−10.16%	−33.19%	−61.04%	−49.69%
	−51.39%	−20.39%	0.48%	−11.44%	−10.65%	−33.84%	−61.22%	−51.39%
	−53.43%	−25.00%	−2.25%	−13.00%	−11.22%	−34.63%	−61.45%	−53.43%
	−55.17%	−29.16%	−4.84%	−14.42%	−11.78%	−35.34%	−61.62%	−55.17%
	−56.82%	−32.85%	−7.29%	−15.76%	−12.34%	−36.06%	−61.82%	−56.82%

considering both transit vehicles and general traffic is reduced by 36%.

In future studies, the weighting factor could be a function of factors such as maximum allowed traffic delay, longest queues, number of transition cycles, transit headways, or schedule lateness. In other words, the TSP algorithm can work with these factors instead of ambiguous weighting factors. Moreover, the assumption of deterministic traffic arrival pattern in traffic delay calculation can be relaxed using scenario-based stochastic modeling approach (Yin, 2008) or using the data-driven model (Li et al., 2009) based on the detections system upon closed-loop actuated control system. Finally, the sensitivity analysis on how the accuracy of the model inputs, for example, bus arrival time and short-term traffic flow, and the communication latency would impact on the final system performance will be conducted.

ACKNOWLEDGMENTS

This research was partly funded by Caltrans. The contents of this article reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the State of California.

The authors wish to thank Kai Leung, Paul Chiu, James Lau, and Lindy Cabugao of Caltrans and Alexander Skabardonis, Mike Cassidy, and Scott Johnston at University of California, Berkeley for their continuing cooperation and support during the study.

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