

# Real-Time Traffic Control for Sustainable Urban Living

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**Abstract**—Traffic congestion significantly degrades the quality of life in urban environments. It results in lost time, wasted fuel resources and reduced air quality for urban residents. Recent work in real-time, schedule-driven control of traffic signal networks has introduced new possibilities for reducing congestion in urban environments. However so far, this work has focused mainly on achieving more efficient vehicle flows and on reducing emissions, and the broader mobility of other modes of traffic that are central to sustainable urban living - especially pedestrians - has not been emphasized in an integrated way. In this paper, we extend this decentralized, schedule-driven approach to traffic network control in the direction of this broader mobility objective. We focus specifically on accommodating pedestrians and optimizing the delay tradeoffs between vehicles and pedestrians. Three basic extensions are introduced and evaluated on a real-world road network. Simulation results are first presented which analyze the ability of the extended approach to achieve good delay tradeoffs under different pedestrian traffic conditions. Tests are then performed in the field at selected intersections of the target road network, to demonstrate the effectiveness of the approach in operation.

## I. INTRODUCTION

It is generally recognized that one of the most effective ways to reduce congestion on surface streets is through adaptive traffic signal control. However, the adaptive control problem is challenging, as the combined number of signal control choices and traffic conditions is huge for one intersection [1], and grows exponentially with the network size. Various traffic control techniques have been proposed. At the intersection level, reinforcement learning methods [2] and online planning algorithms [3] have been proposed for local optimization. At the network level, decentralized optimization, and agent-based [4] approaches have been developed to obtain better coordination between intersections.

Recent work in schedule-driven control of traffic signals [5], [6] has demonstrated the strong potential of decentralized, real-time adaptive signal control in urban environments. In an initial urban deployment, improvements of over 26% reductions in travel times, over 40% reductions in idle time, and a projected reduction in emissions of over 21% were achieved [7]. Although these results are quite impressive, they do not fully account for one important reality of urban environments: that traffic flows are multi-modal. In addition to vehicles, pedestrians, bicyclists and transit riders move in urban environments, and sustainable urban living requires

that all traffic modes be appropriately balanced. It has been an increasing shift in policy toward better integration of people and traffic for sustainable mobility [8].

Walking is critical to the overall effectiveness of urban mobility in supporting other transportation modes. Pedestrians, however, are often not favored in existing traffic control systems. Excessive delays at signalized intersections often make pedestrians pursue non-compliant behavior, leading to significant crash risk [9]. In the U.S. alone, an estimated 73,000 pedestrians were killed or injured in traffic accidents in 2011 [10]. Limited efforts have been made to better accommodate pedestrians within existing traffic control systems. Simple methods are to adjust signal timing parameters [11], [12]. Alternative gaps for vehicle-actuated logic are considered in MOVA [13]. In [14], a rule-based control strategy is proposed. Recent work [15] has proposed a priority-based approach to managing multi-modal flows.

One rather extreme perspective is advocated by the current “Complete Streets” movement [16], where vehicles are given lowest priority, and only simple, fixed traffic signal control schemes are permitted. This view assumes that any resulting vehicle congestion will simply be tolerated. But when traffic congestion occurs, overall quality of life degrades due to increased emissions and noise pollution [17], and driver frustration may also increase crash risk [18].

In this paper we investigate the possibility of achieving better pedestrian-vehicle delay tradeoffs through extension of the real-time adaptive signal control techniques mentioned above. To address this question, we propose and evaluate some extensions to the adaptive control approach deployed in [7]. In contrast to other methods, our approach aims to exploit the synergy between competing modes, and by doing so achieving a better overall balance for urban quality of life.

## II. PROBLEM DEFINITION

We focus on an urban road network with signalized intersections. For each intersection, the traffic light cycles through a fixed sequence of phases  $I$ , and each phase  $i \in I$  governs the right of way for a set of compatible movements, which may include both vehicles traveling from entry road segments to exit road segments and pedestrians crossing the intersection in various directions. Each phase has minimum ( $G_i^{min}$ ) and maximum ( $G_i^{max}$ ) constraints on its duration (to ensure fairness), and the yellow light after each phase  $i$  runs for a fixed duration ( $Y_i$ ). It is assumed that approaching vehicle streams can be sensed in real time (via video cameras, radar or other means), and that pedestrians can signal their presence and request phase  $i$  by pressing a pushbutton. When a pedestrian makes such a request, the minimum phase time

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constraint changes from  $G_i^{min}$  to a fixed pedestrian walk time ( $P_i$ ) for safe passage.

The multi-modal traffic signal control problem of interest then is as follows: at a given intersection the problem is to dynamically allocate green time to phases so as to optimize the weighted cumulative delay over time, where weighting can be used to balance the delay trade-offs between vehicles and pedestrians; at the road network level, achieving multi-modal travel efficiency (e.g., minimizing wait times or travel times) and reducing emissions are the primary objectives.

As indicated earlier, our approach to this multi-modal traffic control problem extends recent work in real-time control of urban signal networks. Before describing and evaluating our proposed extensions, we first summarize this underlying schedule-driven traffic control approach.

### III. SCHEDULE-DRIVEN TRAFFIC CONTROL

Schedule-driven traffic control [5], [6] is a recently developed approach to real-time adaptive traffic signal control, designed specifically to accommodate urban road networks. It follows the same decentralized structure of earlier “on-line planning” approaches to signal control [3], but avoids the prohibitive computational expense of earlier approaches through use of a more efficient core problem formulation. In operation, each intersection is controlled independently by a local scheduler, which maintains a phase schedule that minimizes the total delay for vehicles traveling through the intersection and continually makes decisions to update the schedule according to a rolling horizon. The scheduler also communicates outflow information implied by its current schedule to its neighbors, to extend visibility of incoming traffic and achieve network level coordination.

1) *Intersection Level*: At the individual intersection level, the ability to consider real-time variability of traffic flows is made tractable by a novel formulation of online planning as a *single machine scheduling* problem [5]. Key to this formulation is an aggregate representation of traffic flows as *inflows*, i.e.,  $IF = (J_1, \dots, J_{|I|})$ , where  $J_i$  contains those vehicles with the right of way during phase  $i$ . Each  $J_i$  contains a sequence of *jobs*, where a job contains a set of vehicles traveling in close proximity, over a limited prediction horizon ( $H_P$ ). Each job can be represented as a triple, i.e.,  $\langle \text{vehicle count}, \text{arrival time}, \text{departure time} \rangle$ . These job sequences preserve the non-uniform nature of real-time flows while providing a more efficient *scheduling search space* than traditional time-tick based search space formulations. For each *partial schedule* with  $k$  jobs, the corresponding state variables are defined as a tuple,  $(X, s, pd, t, d)_k$ , where  $X$  indicates the jobs that have been serviced across all phases,  $s$  and  $pd$  are the index and duration of the last phase,  $t$  is the finish time of the  $k$ th job, and  $d$  is the cumulative delay for all  $k$  jobs. The scheduling problem is to construct an optimal sequence of all jobs that preserves the ordering of jobs along each inflow. A given sequence dictates the order in which jobs will pass through the intersection and can be associated with an expected phase schedule that fully clears the jobs in the shortest possible time, subject to basic

timing and safety constraints. The optimal schedule is the one that incurs minimal delay for all vehicles.

This scheduling problem is solved using a dynamic programming process. The *greedy* version, which eliminates states in the same  $(X, s)$ , has at most  $|I|^2 \cdot \prod_{i=1}^{|I|} (|J_i| + 1)$  state updates. Its time complexity is tractable in the prediction horizon  $H_P$ , since  $|I|$  is limited for any intersection. The *full* version, which eliminates states in the same  $(X, s, t)$ , is bounded instead by  $H_O$ , the maximum finish time of all schedules. Normally, the *greedy* version is used.

2) *Network Level*: When operating within an urban road network, any local intersection control strategy operating with a limited prediction horizon is susceptible to myopic decisions that look good locally but not globally. To reduce this possibility, neighbor coordination mechanisms are layered over the basic intersection control strategy.

As a basic protocol, each intersection sends its projected *outflows* to its direct neighbors [6]. Given an intersection schedule, projected outflows to all exit roads are derived from models of current inflows and recent turning proportions at the intersection. Intuitively, the outflows of an intersection’s upstream neighbors become its predicted non-local inflows. The joint local and non-local inflows essentially increase the look-ahead horizon of an intersection, and due to a chaining effect, can incorporate non-local impacts from indirect upstream neighbors. The optimistic assumption that is made is that direct and indirect neighbors are trying to follow their schedules. Normally the optimization capability of the base intersection control approach normally results in schedules that are quite stable given sufficient traffic volumes and a sufficiently long prediction horizon. There is also often slack time between successive jobs to absorb minor changes. However, circumstances can cause schedules to change and mis-coordination can occur, especially for intersections that are very close together. To cope with these cases, additional mechanisms are incorporated for handling specific mis-coordination situations, e.g., road spillback.

### IV. ACCOMMODATING PEDESTRIAN TRAFFIC

As is the case with most existing traffic control methods, the schedule-driven approach just discussed is designed in a vehicle-centric way, and as a consequence pedestrians can experience excessive delay in the system. This lack of attention also has safety implications. As pedestrians become impatient and resort to non-compliant behavior, the risk of accidents increases significantly. For both of these reasons we consider extensions that enable real-time adaptive control of multi-modal traffic flows. While our particular interest is in optimizing delay-tradeoffs between vehicle and pedestrian traffic, we do so with an eye toward accommodating additional modes (e.g., bicycles, transit).

#### A. Multi-Modal Formulation

One simplifying assumption made in the work of [5], given its vehicle centric focus, is that all moving traffic entities are equivalent. Hence in computing cumulative delay, the number of vehicles specified in each job is all that

matters. The situation becomes more complex in multi-modal traffic settings. Different traffic modes imply different moving entities (e.g., a pedestrian, a passenger vehicle, a bus), and job size must be translated to some normalized common denominator (e.g., the number of people per moving entity). Different traffic modes may also have different relative importance and this could vary in different locations according to local policy. Finally, traffic flow patterns may be quite different for different modes and have varying impact on network level coordination. For example, vehicles move from intersection to intersection, while pedestrians generally have destinations other than intersections.

Taking these factors into account, we define a multi-modal generalization of the intersection control problem. Let  $M$  designate the set of traffic modes (e.g.,  $M = \{Ped, Veh\}$ ). Drawing on the work of [11], we associate with each mode  $m \in M$ , its relative value of time ( $V$ ), indicative of the mode's relative importance, and its average occupancy ( $O$ ).  $O$  refers to a normalized common denominator as mentioned above. We also associate a binary *coordination flag* ( $L$ ) with each  $m \in M$  to indicate whether traffic mode  $m$  requires coordination across intersections. For our purposes in this paper,  $L_{Ped} = 0$  and  $L_{Veh} = 1$ .

Equipped with this extended model, we can now specify the notion of a multi-modal job. For pedestrians, only waiting users are considered, and they are assumed to depart at the start of the phase that they have requested. We also assume  $P_i$  (the minimum green time constraint to be enforced when a pedestrian is waiting) is sufficiently long to clear all waiting pedestrians. Thus, for each phase with pedestrian waiting, there is only a single pedestrian job, with arrival time and departure time set to 0. In the event that there are also vehicles waiting for this phase, then this pedestrian job is merged with the first vehicle job sharing the phase.

To compute cumulative delay for a given schedule in this multi-modal setting, it is necessary to assign a normalized weight to each job. To this end, we define a job  $j$ 's normalized cost as  $nc = \sum_{m \in M} n_m^j V_m O_m$ , where  $n_m^j$  is the number of entities of this mode contained in job  $j$  (e.g., number of vehicles, number of pedestrians).

A separate weight is required for proper communication of planned outflows to neighbors. We define a job  $j$ 's normalized coordination cost to be  $ncc = \sum_{m \in M} n_m^j V_m O_m L_m$ . Thus the generalized formulation of a job becomes a four tuple  $\langle nc, ncc, arrival\ time, departure\ time \rangle$ .

### B. Maximal Wait Time Constraint

Another simple policy for accommodating pedestrians is to set a maximum wait time limit ( $MWT$ ), after the first pedestrian is detected (e.g., the pushbutton is activated). This limit provides a guaranteed level of service in the worst case. When constructing an intersection schedule, this policy can be realized by replacing the phase maximum  $C_i^{max}$  for the current phase with this tighter  $MWT$  constraint when appropriate. However, due to the fact that jobs are treated as indivisible (or non-preemptable) during the core scheduling process, tighter phase maximum constraints become increas-

ingly difficulty for the scheduler to enforce. In fact, the enforcement of any phase maximum constraint could require that an input job be split. In practice, however, violation of the maximum time constraint is really only a concern for the current phase, since some of the green time has already expired. Maximum time constraints for subsequent phases less important given the limited prediction horizon.

To address this constraint, we augment the online scheduling process with a *phase switching analysis*. As shown in Fig. 1(a), a maximum time constraint  $t_{max}$  is applied for the current phase  $i$  at the current time  $t_c$ . Each job  $[i, j]$  is the  $j$ th job in the  $i$ th inflow. Then, prior to initiating the online scheduling process, the jobs in  $IF_i$  are preprocessed and if a job is found that violates the time constraint, it is split into two jobs (Fig. 1(b)). Let  $l$  be the index of the last job before  $t_{max}$  ( $l = 3$  in the example). During generation of candidate schedules, the current phase might be terminated (switched) either at  $t_c$  or at the departure time of any job  $j$  for  $j \leq l$ , and the projected switch-back process (i.e., to competing phase  $\bar{i}$  and back again to phase  $i$ ) removes the time constraint at  $t_{max}$ . Fig. 1(c) gives two possibilities, where *schedule 2* has a lower delay than *schedule 1*. However, in this case, *schedule 2* will be found only if all partial schedules up to the  $(l+2)$ th job can be guaranteed to survive state elimination.

We first consider a simple case, where all competing inflows ( $\bar{i}$ ) are empty. In this case, all partial schedules before the  $j$ th job ( $j \leq l$ ) might not survive across phase switches, since both the delay  $d$  and the finish time  $t$  will be higher if the switch process causes any delay. In the example, *schedule 2* will be eliminated when  $[i, 2]$  is added. This problem is avoided by extending the above pre-processing step to insert an dummy job  $[\bar{i}, 1]$  into the non- $i$  inflow. For example, now  $[i, 1][\bar{i}, 1][i, 2]$  and  $[i, 1][i, 2][\bar{i}, 1]$  cannot eliminate each other since they stay in  $(X, s)$  groups with different  $s$ .

There is still a problem when adding the  $(l+1)$ th job into a partial schedule for the *greedy* intersection scheduler. Compared to the partial schedule switched at the  $l$ th job (e.g.,  $[i, 1][i, 2][i, 3][\bar{i}, 1][i, 4]$  in *schedule 1*), the partial schedule that switched at an earlier job (e.g.,  $[i, 1][\bar{i}, 1][i, 2][i, 3][i, 4]$  in *schedule 2*) can have a higher delay  $d$  and be eliminated. To avoid this mistake when adding the  $(l+1)$ th job, the state elimination check is extended to consider the potential delay that might be incurred on remaining jobs in inflow  $i$  (e.g.,  $[i, 5][i, 6]$ ) if the partial schedule contains only one switch. The added computation time for this check is negligible.

### C. Coordination Protocol

When a pedestrian button is pressed, the minimal green time of the corresponding phase will be replaced by the significantly longer minimal service time. From a vehicle-centric focus, this can lead to disturbances in the coordination of heavy vehicle flows between intersections, particularly when links are short and one end leads to a major intersection. From the viewpoint of pedestrians and emerging multi-modal urban policy, pedestrian wait times should be bounded to be reasonably short [16].



TABLE I: Pedestrian, vehicular, and weighted wait time under different control strategies, at intersection **E**.

	$\lambda = 1/(2.5 \text{ seconds})$			$\lambda = 1/(10 \text{ seconds})$			$\lambda = 1/(40 \text{ seconds})$		
	$pw$	$vw$	$ww$	$pw$	$vw$	$ww$	$pw$	$vw$	$ww$
Fixed-Time	46.18	36.20	38.85	47.85	36.20	37.12	43.69	36.20	36.36
Vehicle-Actuated	52.83	49.81	50.61	53.02	49.81	50.06	40.63	38.36	38.40
$MTC(0, max)$	57.52	22.04	31.46	59.23	21.58	24.57	56.94	21.66	22.38
$MTC(0, 60s)$	21.74	22.74	22.47	24.16	22.20	22.36	28.31	21.83	21.97
$MTC(3, 60s)$	17.14	22.76	21.27	16.26	22.73	22.22	14.80	22.44	22.28
$MTC(actual, 60s)$	12.50	23.49	20.57	16.07	22.76	22.23	21.36	22.33	22.31

 TABLE II: Pedestrian, vehicular, and weighted wait time under different control strategies, at intersection **I**.

	$\lambda = 1/(2.5 \text{ seconds})$			$\lambda = 1/(10 \text{ seconds})$			$\lambda = 1/(40 \text{ seconds})$		
	$pw$	$vw$	$ww$	$pw$	$vw$	$ww$	$pw$	$vw$	$ww$
Fixed-Time	34.75	36.20	35.83	36.92	36.20	36.26	32.05	36.20	36.11
Vehicle-Actuated	12.00	37.25	30.66	12.66	37.29	35.30	13.01	36.58	36.06
$MTC(0, max)$	55.55	20.63	29.75	57.24	20.59	23.56	53.84	20.62	21.35
$MTC(0, 60s)$	23.76	20.88	21.63	27.22	20.88	21.39	29.37	20.94	21.13
$MTC(3, 60s)$	13.40	20.97	19.00	14.84	20.72	20.24	17.79	20.65	20.58
$MTC(actual, 60s)$	9.07	21.60	18.32	14.91	21.32	20.80	26.27	20.77	20.89

$MTC(nPed, MWT)$  strategies are the adaptive multi-modal traffic control strategies considered in this paper. As the original schedule-driven traffic control algorithm without any consideration on pedestrians,  $MTC(0, max)$  returns the longest  $pw$  values, and thus is not favorable to pedestrians. This also significantly increase its  $mw$ , as the pedestrian flow is heavy. All other  $MTC$  strategies can produces low  $pw$  and  $vw$  times. The phase switching analysis keeps  $vw$  low by seeking the best switch time after setting  $MWT$  as 60 seconds. Using  $nPed$  can further drive  $pw$  down. When the number of pedestrians is high, using the actual  $nPed$  produces lower  $pw$  and  $mw$  than using a fixed  $nPed$ , though when  $\lambda$  is low, using a fixed  $nPed$  produces lower  $pw$ .

### B. Field Pedestrian Information Extraction

As shown in Fig. 3, phase and pushbutton activation data are used for measuring pedestrian wait time ( $\widehat{pw}$ ) and arrival time ( $\widehat{pa}$ ). For phases,  $i$  and non- $i$  ( $\bar{i}$ ) phases interleave along with time. For pedestrians to be serviced in an  $i$ -phase, let  $ped_i^n$  be the  $n$ th pushbutton activation time. Then  $\widehat{pw}_i^n$  is the duration to the start of the next  $i$ -phase, and  $\widehat{pa}_i^n$  is the duration starting from the end of the  $i$ -phase that serviced for  $ped_i^{n-1}$ . Note that  $\widehat{pa}$  might span multiple phases.

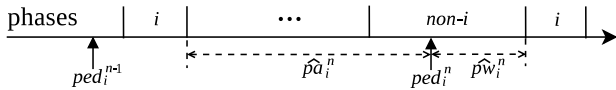

 Fig. 3: Measuring pedestrian wait time ( $\widehat{pw}$ ) and arrival time ( $\widehat{pa}$ ) based on phase and pushbutton activation data.

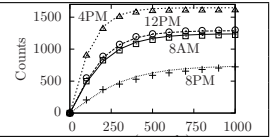
Table III show statistic information about pedestrian arrivals for four time-of-day periods (two hours each) collected in an eight-week time window starting in August, 2013, for intersections **E** and **I**. The cumulative counts in different arrival times can be well fitted using Gamma distribution  $\Gamma(k, \theta)$ , where  $k$  and  $\theta$  are respectively the *shape* and *scale* parameters. The mean arrival time is  $\mathbb{E}[\widehat{pa}] = k\theta$ . For **E**,

bootstrapping with 1000 resamples verifies the mean statistic with low biases (-0.02%–0.01%) and standard errors (2.57%–3.71%). The square errors of distribution fit to field data is higher for **I** than for **E**, which might due to that the fact that the former has lower sample sizes (lower pedestrian activity). If assuming the arrival rate is fixed for each time-of-day period, the  $\Gamma(k, \theta)$  function might be interpreted as the time until the  $k$  arrivals ( $k > 1$  means some pedestrians do not press the pushbutton), for a Poisson process with the rate  $\lambda = 1/\theta$ . This implies that a higher rate of pedestrians fail to press the buttons at intersection **I** than at **E**, and a higher pedestrian arrival rate at intersection **E** than at **I**.

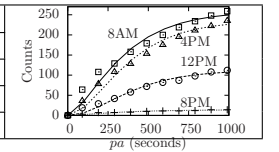
 TABLE III: Time-of-day pedestrian arrival statistics at intersections **E** and **I**, and the fitting in  $\Gamma(k, \theta)$  distribution (dots are actual data and lines are fitted, as shown in the figure).

 (a) Pedestrian arrival statistics at intersection **E**

	$\theta$	$k$	sq. err
8AM	159.3	1.17	1.5E-4
12PM	135.5	1.30	9.2E-5
4PM	96.7	1.24	1.2E-4
8PM	216.7	1.29	5.8E-4


 (b) Pedestrian arrival statistics at intersection **I**

	$\theta$	$k$	sq. err
8AM	218.1	1.67	3.3E-3
12PM	176.2	2.42	2.4E-3
4PM	188.2	2.12	2.8E-3
8PM	232.1	1.54	6.1E-3



The estimation of the number of pedestrians might still be lower than the actual number, since people sometimes arrive in groups. Nevertheless, it provides a sense of the pedestrian flows and their relative volume during different periods of the day, and is useful for algorithm parameter selection.

### C. Field Tests

Running in the field is more complex than in simulation, mainly due to dynamic vehicle and pedestrian flows and real-



world uncertainties. There is also a limit on testing inferior strategies due to negative impacts on real people.

$MTC(3,60s)$  was chosen to be tested on the actual intersections **E** and **I**. The maximal wait time of 60s was chosen to satisfy the Complete Streets policy. Although we cannot automatically detect actual pedestrian numbers at present, the arrival rates do not appear to be very high at these intersections, based on arrival time statistics.

Figure 4 gives the measured results at intersections **E** and **I**, averaged over a four-week period. For vehicles, the queue clearance times ( $\widehat{vqc}$ ) are obtained using the gap in the occupancy data on stop-bar video detectors. For pedestrians, each  $\widehat{pw}$  records the wait time of the first person that pressed the button, thus can be seen as maximum pedestrian wait time information. The actual average wait time might be much lower than the measured maximum, since many pedestrians could arrive after the button is actuated. On intersections **I** and **E**, the baseline strategies are respectively  $MTC(0, max)$  and  $MTC\text{-CoP}$ . On **I**,  $MTC(0, max)$  performed quite unfavorably to pedestrians. On **E**,  $MTC\text{-CoP}$  is installed to coordinate with the bottleneck intersection **D**. It works on the vehicle-pedestrian mixed coordination protocol if the vehicle flow rate on the coordination phase is higher than 15% of the saturation flow rate, otherwise it falls to  $MTC(0, max)$ . The coordination protocol works during most of the day and serves pedestrians more effectively than  $MTC(0, max)$ . On both intersections,  $MTC(3,60s)$  achieved lower  $\widehat{pw}$  with similar  $\widehat{vqc}$ , i.e., reduced the pedestrian delay significantly without interrupted the vehicle flow.

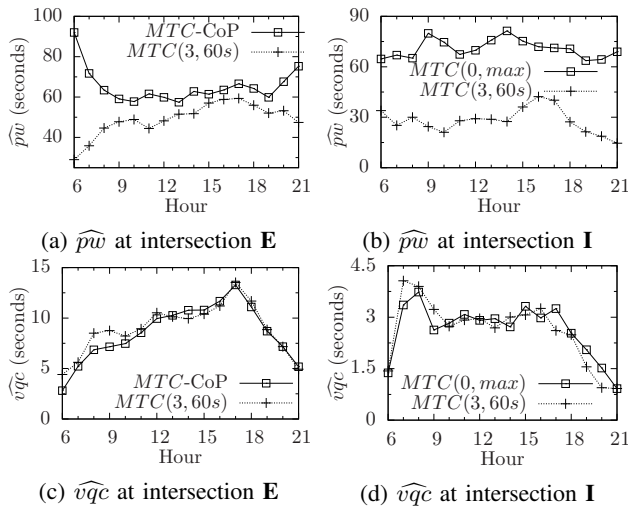


Fig. 4: Measured pedestrian wait time ( $\widehat{pw}$ ) and vehicle queue clearance time ( $\widehat{vqc}$ ) at intersections **E** and **I**.

## VI. CONCLUSIONS

In this paper, we have presented techniques to extend a schedule-driven traffic control approach for optimizing the delay of vehicles and pedestrians in urban environments. We generalized the original formulation of the intersection scheduling problem in a multi-modal setting so that vehicle and pedestrian traffic are considered in a unified way. Next,

the core intersection scheduling procedure was modified to incorporate a maximal pedestrian wait time limit while retaining effectiveness. A pedestrian-aware protocol between neighboring intersections was defined to allow intersections to work in a coordinated manner. Simulation results and field tests were then performed on a real-world road network, to demonstrate the effectiveness of the approach in operation.

There are several aspects of this work that warrant further study. First, it may be possible to better service pedestrians if the scheduling procedure is provided with real-time information about actual pedestrian flow, e.g., using pedestrian cameras. Other interesting techniques might allow pedestrians to request phases before their actual arrival at the intersection using smartphone apps. A final direction of our current research aims to broaden the multi-modal traffic control system to other transportation modes like bus transit.

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