Daily Traffic Control Agency Deployment for Large Scale Planned Special Events

Project Report
SUNY Small Grant Sustainability Fund

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List of Figures

Figure 1: (a) Manual signal control by hand signals when pedestrians crossing at Millersport & Amherst Manor; (b) Queue spillover at Flint & Audubon; (c) Manual signal control by the manual signal control switch in the cabinet

Figure 2: Three major intersections of UB event traffic

Figure 3: 9/19/2012 Game Traffic Counts

Figure 4: Components and simulation interface of MIC-Sim

Figure 5: (a) Layout of the test intersection; (b) TCA in the experiment

Figure 6: Experience and performance index of all subjects

Figure 7: Multi-modal delay. (a) S1-with pedestrians; (b) S2-with pedestrians; (c) S3-without pedestrians; (d) S4-without pedestrian

Figure 8: Flow chart of TCA control behavior modeling

Figure 9: Description of segments through one experiment

Figure 10: e1, rate of incorrectly predicted phased VS PIs

Figure 11: Layout of UB stadium traffic

List of Tables

Table 1: Summary of Data Collections of Five Games

Table 2: Summary of interview results

Table 3: Summary of Control Manners

Table 4: Average multi-modal traffic turning movement counts (per hour) for each scenario

Table 5: Multi-modal average delay for each subject in each scenario

Table 6: Baseline ASC settings

Table 7: Average cycle length and multi-modal weighted delay

Table 8: TCA Decisions in the experiments

Table 9: Main Steps of obtaining parameters with minimal error

Table 10: Results of Press-based behavior modeling

Table 11: Results of TCA deployment model
**Project Summary**

Properly managing traffic under event occurrence is crucial for traffic safety, mobility and energy consumption. Large scale planned events, such as sporting games, concerts, parades and conferences, and unplanned events, such as traffic incidents, disasters, inclement weather, and infrastructure failures, either attracting high volume of multi-modal traffic, or reducing existing network capacity, result in significant non-recurrent traffic congestion.

Human intervention for event traffic, conducted by police or other traffic control agencies (TCA), who overrides traffic lights to direct traffic movements, still serves as the most commonly adopted approach to handle severe event traffic congestion. Different with most of pre-timed traffic signal control systems, experienced TCAs can effectively balance queues, increase network throughput, and prevent pedestrian-vehicle crashes. When event traffic oversaturates the network, there exists much need for understanding the mechanism to efficiently conduct network wide TCA-based manual intersection control. Some questions, such as how to efficiently train TCAs, and where to deploy TCAs, remain without explicit answers. In response to this pressing need, this project aims to help operation center optimize both deployment of TCAs and multi-modal signal control to mitigate traffic congestion caused by large scale planned events.

This project has three closely related objectives and corresponding findings.

1. The first objective is to understand the existing TCA control knowledge by interviews and simulation experiments. We conducted traffic control experiments on eight police officers and firefighters with developed manual traffic control simulator. It was shown that TCA’s manual traffic control outperformed state-of-practice actuated signal control by around 30% under event traffic conditions.

2. The second objective is to model TCA’s behavior by mathematic equations and validate the model by using conducted experiments. We developed a press-based traffic control model to capture the TCA’s real-time traffic control behavior. The proposed behavior model can mimic TCA’s behavior with up to 92% accuracy.

3. Building on the prior experience of field TCA planning, the third objective is to develop a daily TCA deployment optimization model, which is able to predict traffic congestion and queue length by embedding traffic macroscopic models. By implementing the
optimal TCA deployment plan, the total costs, including network delay and TCA deployment costs, can be saved up to 15%, compared with the existing TCA deployment plan.

The project partially funded one PhD student, Nan Ding, from Industrial and Systems Engineering at University at Buffalo. She has three papers produced out of this project,


Moreover, we recently submitted a proposal to NSF to extend the work from this project.


The results delivered by this project are also used to further refine and formalize two recent special topics courses at SUNY Buffalo: CIE/IE515 “Transportation Analytics” and CIE/IE500 “Transportation System Modeling and Control” that were offered by Dr. He in academic year 2012-2013. The major content of the courses will cover specific topics in data fusion of floating and fixed data, incident detection, and multi-modal traffic signal control and simulation.

Also the project deliverables are integrated in SUNY Buffalo’s National Summer Transportation Institute (NSTI), funded by Federal Highway Administration (FHWA). NSTI at Buffalo, led by Dr. He, is designed to introduce secondary school students to all modes of transportation careers and encourage them to pursue transportation-related courses of study at the college/university level. During the most recent NSTI in July 2013, Dr. He successfully recruited 20 high school students and assigned them a multi-modal manual signal control project. We hope that such experiences will be able to generate their interests toward pursuing transportation engineering careers in future.
1. Introduction / Background

Large scale planned special events (PSE), such as sporting games, concerts, parades and conferences, either attracting high volume of multi-modal traffic, or reducing existing network capacity, result in significant non-recurrent traffic congestion as attendees simultaneously attempt to enter or exit the event, overloading the local transportation network. Despite the fact that there exists advanced signal control technology, the additional benefit brought by those technologies is limited during periods of non-recurrent congestion, since most of them are not designed for the event-based operation. To reduce traffic congestion in large events, it is significant to optimize traffic signals in critical intersections. Properly managing traffic under event occurrence is essential for traffic safety and mobility. However, pre-timed traffic signals don’t accommodate surge of traffic demand caused by events.

One effective way for PSE-based intersection control is to correctly deploy traffic control agency (TCA) in the intersection to override traffic signals. TCAs usually consist of police, parking enforcement agency, or temporally hired personnel. The primary function of manual traffic control by TCAs is to move vehicles and pedestrians safely and expeditiously through or around special event sites while protecting on-site personnel and equipment. There are several reasons that TCA is critical for event traffic management.

1) Safety: Large scale PSE usually involves a significant number of pedestrians. Pre-timed traffic signal controllers don’t take the surge of pedestrian crossing demand into account. When more and more people are waiting for “Walk” signal, short “Walk” phase will probably cause jaywalking and potential vehicle-pedestrian crashes. Such issues with high demand pedestrians can be easily tackled by TCA control, shown as Figure 1(a). By stopping the vehicle traffic, TCA will grant priority to large volume of pedestrians, and ensure their safety for intersection crossing.

2) Mobility: Prior-event or post-event traffic, due to the event time constraint, overloads the local transportation network in a short period of time. Lack of proper signal timing for event traffic, the surge of traffic demand usually generates long queues at critical intersections, or even queue spillover, where the downstream queue blocks the upstream intersection since it exceeds the queue storage capacity.
Figure 1(b) shows that the incoming northbound event traffic fully blocked the intersection, resulting in severe traffic gridlock. Such traffic queue spillover can be avoided by assigning a TCA before or after the event. TCA is able to manually balance the queue at each link and efficiently utilize the intersection capacity.

3) Energy consumption: Traffic congestion is a key factor to energy consumption. Road transportation alone is consuming on average 85% of the total energy used by the transport sector in developed countries (Rodrigue, Comtois, and Slack 2009). Vehicle acceleration, road grade, tire rolling resistance and aerodynamic drag contribute to the absolute power (Koupal et al. 2002). The stop-and-go nature of traffic congestion, which involves frequent vehicle acceleration and deceleration, eventually causes large amount of energy consumption. With respect of large variations of event traffic demand, experienced TCAs are able to coordinate by radios and smooth network traffic by creating “green wave” at consecutive intersections. Therefore, the energy consumption of event traffic will dramatically decrease by appropriate TCA planning.

Figure 1: (a) Manual signal control by hand signals when pedestrians crossing at Millersport & Amherst Manor; (b) Queue spillover at Flint & Audubon; (c) Manual signal control by the manual signal control switch in the cabinet

Manual control is believed to be a very efficient method to handle non-recurrent multimodal traffic conditions. Successful spatial-temporal TCA planning will mitigate traffic congestion to its large extent. However, there are very few previous studies systematically addressing the issues of deploying TCA for large scale events. This project aims to optimize both deployment of TCAs and multimodal signal control to mitigate traffic congestion caused by
large scale PSEs. There are four stages of this project. First, collecting field data and conducting simulation experiments to understand the performance of manual signal control conducted by TCAs. Second, model TCAs’ control behavior by mathematical equations with existing TCA control information. Building on the prior knowledge of field TCA behavior, the third stage is to develop a daily TCA deployment optimization model. The fourth stage is to use real-world event traffic data to validate proposed TCA deployment model and demonstrate how the developed control systems can be used to improve existing TCA deployment strategies.

2. Literature Review

It has long been recognized that non-recurring events can cause as least half of total traffic delay. Over years, a large amount of effort has already been invested in studying how to alleviate non-recurrent congestion with automatic signal control methods. Although human-involved manual intersection control still keeps its significance for complicated event management, there are a few studies focusing on manual control operation. Mahalel, Gur, and Shiftan (1991) collected field data at a single intersection to understand the differences between automatic and manual signal control. They concluded that manual signal control was shown to have improved the operation of congested signalized intersections, as measured both by the degree of saturation and total throughput and to bring the capacity above the demand. The handbook of managing special events, emphasizes that traffic control officers have a large role in maximizing intersection operating efficiency. The officer commands a driver’s attention and works to control the speed of vehicles entering and departing the intersection, thus reducing rubbernecking, especially at traffic incident sites. Wojtowicz and Wallace (2010) employed tabletop exercises for traffic management of special events, using traffic microscopic simulation software. In the scenario of event egress, results from their simulation showed when using police control at critical intersections there is more than a 50% reduction in discharge time. Lassacher et al. (2009) examined traffic management strategy for a large football game. They concluded that signal retiming and manual traffic control strategies allowed for dramatic improvements in traffic level of service. Lee et al. (2012) conducted Hardware-in-the-Loop Simulation (HILS) simulation experiments to evaluate manual traffic control performance under oversaturated conditions. They demonstrated the performances of the manual traffic signal control and concluded that manual control showed the best results among the proposed strategies at an oversaturated intersection. However, participants in their experiments are college students, who
have much less field intersection control experiences compared to professional TCAs. Therefore, the performance measured does not totally reflect the TCA’s traffic control results during the real-world events. In addition, only one traffic mode, passenger car, was taken into account in that study. Although manual signal control is crucial to ensure road safety, avoid queue spillover and enforce traffic law under event occurrences, this research topic has not been extensively studied and very limited previous work can be found. Moreover, most of the previous works only summarized empirical observations and experiences. They barely consider either transit vehicles or pedestrians in the event traffic.

In terms of traffic operation control, previous research has primarily focused on purely automatic traffic control models to achieve real-time adaptive, traffic-responsive control in order to reduce the stops and delay incurred by vehicles at signalized intersections (Yu & Recker 2006; Meneguzzer 1997; Wey 2000; Zheng et al. 2010). Compare to automatic operation, manual operation is able to improve the operation of congested signalized intersection due to its use of long cycle times, which is suggested to be implemented as part of the automatic control (Mahalel et al. 1991).

Since previous studies already addressed the large promising advantage by deploying TCAs for event traffic management. However, little formal work has been accomplished or disseminated in theoretically modeling and improving existing manual intersection control. Therefore, there is a pressing need to pursue a systematic study on this topic.

The outline of this report is as following: Section 3 observes and collects field traffic information during special planned events. In Section 4, human based simulation experiments are conducted to evaluate the performance of TCA manual signal control given multi-model event traffic. Section 5 develops a mathematical model to mimic TCAs’ control behavior pattern which will be served as input of Section 6. In Section 6, a daily TCA deployment optimization model is proposed to provide total number of TCAs needed and the spatial-temporal TCA deployment plan. Finally, Section 7 provides concluding remarks, discussions and future work.

3. Field Data Collection

PSEs usually attract huge number of vehicular and pedestrian traffic before and after the event which affects the transportation network in the vicinity of the place where the event is held.
The simultaneous entry and exit of the attendees also causes an imperative non-recurrent congestion. This part of field data collection renders an analysis of the pre and post event traffic for football games held at SUNY Buffalo North Campus in Buffalo, NY. It captures pedestrian and vehicular traffic flow, and also filling rate of parking lot during the five Buffalo Bulls home games. Three important intersections near the stadium that were affected the most during the game were identified which are Augspurgur-Amherst Manor Intersection, Millersport-Amherst Manor Intersection and Flint-Audubon Intersection. These intersections are as shown in Figure 2.

![Figure 2: Three major intersections for UB football event traffic](image)

Table 1 represents the summary of five data collections, including game information, data collection spots and analysis type. It is clearly shown in the table that weather conditions and final scores were different from game to game. The observations for the first two games were made two hours before their start time, game 1 was at 6pm Sep. 8 and game 2 was at 7pm Sep. 19. The observations for game 3, 4 and 5 were made one and a quarter hours prior to the end of the game. Weather was rainy and UB lost for game 4, weather was cold while UB won for game 4, and weather was pleasant while UB won for game 5. Traffic during the first two games was analyzed from the perspective of solving the traffic ingress issues and during the last 3 games from the perspective of solving the traffic egress issues.

Traffic counts were recorded for these five games at observed intersection. Figure 3 shows traffic counts for game 2 at 7pm, Sep. 19, 2012, which is further analyzed in later section. As observed, most of parking lots were fulfilled 60 minutes before the game started. The attendants started coming in 2 hours prior to game start. The rate of arrivals kept rising till 60
minutes prior to game start when it reached its peak rate. Node 5 and 7 were observed as two bottleneck intersections, also long spillover queues were observed on node 7 westbound 60 minutes prior to the game. For game 1, traffic flow reached its peak approximately 30 minutes prior to the game and parking lots were not filled. There was a large difference between peak value of traffic counts which could be caused by bad weather during game 1 but pleasant weather during game 2. For game 3 the number of pedestrians coming from north end at Millersport-Amherst Manor intersection was significantly high at 6pm which indicated that people were leaving in middle of the game. For game 4 and 5, both pedestrian and vehicle flow were low during the game but shot up slightly at the end of the game. Large number of pedestrians and vehicles were observed during first 15 minutes after the game ended. From the observation, people seemed to stay longer for game 4 and 5, which could be due to both better weather and satisfying game score. Overall, for all games, weather and game score were observed to be significant factors affecting the time at which people would leave the stadium. The time period for maximum traffic flow was 60 minutes before game start and 15 minutes windows before and after the game ended.
Figure 3: 9/19/2012 Game Traffic Counts
<table>
<thead>
<tr>
<th>Game No.</th>
<th>Date and time (start/end)*</th>
<th>Teams</th>
<th>Analysis Type</th>
<th>Weather</th>
<th>Game Result</th>
<th>Data Collection Spots</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6pm, 9/8/2012 (Saturday)</td>
<td>Buffalo Bulls v/s Morgan State Bears</td>
<td>Pre-Game (16:00-18:30)</td>
<td>Cold and Chilly with slight showers</td>
<td>Won (56-34)</td>
<td>Intersections : Millersport-Amherst Manor, Flint-Audobon Observation of the traffic pattern on the roads on a bike.</td>
</tr>
<tr>
<td>2</td>
<td>7pm, 9/19/2012 (Wednesday)</td>
<td>Buffalo Bulls v/s Kent State Golden Flashes</td>
<td>Pre-Game (17:00-19:30)</td>
<td>Pleasant with slight showers</td>
<td>Lost (23-7)</td>
<td>Intersections : Millersport-Amherst Manor, Flint-Audobon Observation of the traffic patterns on the roads on a bike.</td>
</tr>
<tr>
<td>3</td>
<td>7pm, 10/20/2012 (Saturday)</td>
<td>Buffalo Bulls v/s Pittsburgh Panthers</td>
<td>Post-Game (17:45-19:30)</td>
<td>Cold and Chilly with slight showers</td>
<td>Lost (20-6)</td>
<td>Intersections : Millersport-Amherst Manor, Flint-Audobon Observation of the attendees’ pattern in the stadium.</td>
</tr>
<tr>
<td>4</td>
<td>3pm, 11/03/2012 (Saturday)</td>
<td>Buffalo Bulls v/s Miami (OH) Redhawks</td>
<td>Post-Game (13:45-15:45)</td>
<td>Cold and Chilly</td>
<td>Won (27-24)</td>
<td>Intersections : Millersport-Amherst Manor, Flint-Audobon, Augspurger-Amherst Manor Observation of the attendees’ pattern in the stadium.</td>
</tr>
<tr>
<td>5</td>
<td>7pm, 11/10/2012 (Saturday)</td>
<td>Buffalo Bulls v/s Western Michigan Broncos</td>
<td>Post-Game (17:45-19:30)</td>
<td>Pleasant</td>
<td>Won (29-24)</td>
<td>Intersections : Millersport-Amherst Manor, Flint-Audobon, Augspurger-Amherst Manor Observation of the attendees’ pattern in the stadium.</td>
</tr>
</tbody>
</table>
4. Human Subjects Experiments

In order to understand the performance of manual signal control, human operator based interviews and experiments are conducted in this Section. This study explicitly assesses the TCA’s performance based on the Manual Intersection Control Simulator (MIC-Sim), developed on a commercial traffic simulation platform. Therefore, the goal of this paper is to evaluate the performance of TCAs compared to automatic control and optimal control of an isolated intersection. The results of manual operation are expected to benefit national wide transportation authorities who are responsible for event traffic planning and management.

4.1 Interview

4.1.1 Procedure

In the beginning, the TCA participants were asked to take a 15-minute interview, which is composed of three Sections. The first Section obtains the basic background of participants in manual traffic control, including job title and working experience, sources to learn skills, circumstances and frequency that they perform manual traffic signal control. In the second Section, they report the general rules when they conduct manual signal control in the field. The third one requires them to explain their detailed manners to control traffic under different circumstances, including oversaturated intersections, traffic accidents, power outages, construction sites and special events.

4.1.2 Participants

The experiments recruited eight participants, in which seven are police officers and one is a firefighter. Table 2 summarizes the information collected during the interviews, including general information of subjects and their control behavior. In order to keep sample diversity, the participated subjects are with different genders, different job titles and different number of years in traffic control. On average, TCA participants have 14 years of experiences, ranging from 2.5 years to 27 years. All TCA participants learned the traffic control skills through police academy, on-site practice, and paired training by seniors. All of the police officers reported that they would perform manual traffic control due to car accidents, power outage and special events, while some of them also mentioned other reasons as extreme weather conditions. Firefighters are mostly involved in emergency events or regular events with hazardous materials. For example, the
firefighters usually conduct annually two-day manual traffic control during the household hazard disposal event. The frequency of manual traffic control generally varies from 10 to 30 times per year, while it could be less than 5 times or more than 40 times per year, with a small chance.

From the interview, most of the participants gave more control attention to the number of vehicles in the queue over the queue length; while two other aspects, queue spillover and pedestrians, were proposed to be considered. The weights assigned to each control attention are shown in Table 2. Participants were also asked to assign weights to prioritize three traffic modes, including bus, pedestrians, and emergency vehicles (EV). Assuming the weight for passenger vehicle is always 1, three traffic modes were weighted by a score from 1 to 10 from TCAs. The average assigned weights are depicted in Table 2. Some weights are “N/A” because corresponding TCAs didn’t report the values. Among all reported weights, as one can see, EV always has the highest score of 10, and most of the TCA didn’t grant high weight for buses (4.4). They intended to allocate high weights for pedestrians in groups (6.4) due to their high vulnerability. The normalized average weights for passenger car, bus and pedestrian, are 0.08, 0.37 and 0.54 respectively.

Table 3 shows TCAs’ control manner under five different scenarios, including oversaturated intersection, traffic accident, power outage, construction site and planned events. Police always perform manual traffic under all proposed scenarios, while firefighters usually get involved in emergency or hazardous events. When performing manual control at a congested, even oversaturated intersection, most of the TCAs will do it in a similar manner to flow as many cars as possible and avoid queue spillover if it is a large intersection. Sometimes, TCAs will first stop traffic of all directions to let the direction with the longest queue go, then make decisions whether or not to shut down the left turning lanes to only let the through traffic go. If it is a small intersection, TCAs will let one approach go for 30 seconds (reported by 2 TCAs), and one by one like rotation. In addition, some of them mentioned that one quarter mile of queue length is a priority. If pedestrians are waiting at the intersection, TCAs will allow them pass through as a group.
### Table 2: Summary of interview results

<table>
<thead>
<tr>
<th>TCA NO.</th>
<th>TCA job title</th>
<th>Gender</th>
<th>Years of experience</th>
<th>Sources where traffic control skills were learned</th>
<th>Reasons for manual control</th>
<th>Manual control frequency (/year)</th>
<th>Control attention</th>
<th>Priority weights of traffic modes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Num. of vehicles in queue</td>
</tr>
<tr>
<td>A</td>
<td>Police supervisor</td>
<td>M</td>
<td>15</td>
<td></td>
<td>Events; Car accidents; Power outage; Extreme weather conditions; Firefighters on-duty</td>
<td>20~30</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>B</td>
<td>Police supervisor</td>
<td>M</td>
<td>25</td>
<td></td>
<td></td>
<td>10~12</td>
<td>0.67</td>
<td>0.33</td>
</tr>
<tr>
<td>C</td>
<td>Police supervisor</td>
<td>F</td>
<td>18</td>
<td></td>
<td></td>
<td>1~5</td>
<td>0.67</td>
<td>0.33</td>
</tr>
<tr>
<td>D</td>
<td>Police supervisor</td>
<td>M</td>
<td>8.5</td>
<td></td>
<td></td>
<td>10~12</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>E</td>
<td>Police officer</td>
<td>M</td>
<td>4.5</td>
<td></td>
<td></td>
<td>&gt;40</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>F</td>
<td>Police officer</td>
<td>M</td>
<td>2.5</td>
<td></td>
<td></td>
<td>20~30</td>
<td>0.2</td>
<td>0.3</td>
</tr>
<tr>
<td>G</td>
<td>Fire fighter</td>
<td>M</td>
<td>27</td>
<td></td>
<td></td>
<td>10~12</td>
<td>0.67</td>
<td>0.33</td>
</tr>
<tr>
<td>H</td>
<td>Police officer</td>
<td>M</td>
<td>10</td>
<td></td>
<td></td>
<td>5~6</td>
<td>0.5</td>
<td>0.25</td>
</tr>
</tbody>
</table>
Table 3: Summary of Control Manners

<table>
<thead>
<tr>
<th>TCA NO.</th>
<th>Oversaturated Intersection</th>
<th>Traffic Accident</th>
<th>Power Outage</th>
<th>Construction Site</th>
<th>Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Manually control and cooperate with other officer</td>
<td>Protect the scene, may block roads</td>
<td>Close the road or reduce the travel; block lanes or convert to 4-way stop</td>
<td>Different from traffic accident, construction site is always pre-planned; use signs to direct the traffic around. Police are only involved if a large congestion occurs.</td>
<td>Have the traffic plan before event, including the route and officers’ assignments; Group the pedestrians.</td>
</tr>
<tr>
<td>B</td>
<td>Rotate the direction and have as many cars proceed through the intersection as possible; group the pedestrians</td>
<td>Safety comes first; reroute the traffic</td>
<td>Manually control the intersection</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>4-way stop, let each direction proceed for 30s</td>
<td>Direct the traffic around or shut down the road if necessary</td>
<td>Convert to a 4-way stop</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>Keep the queue even and rotate the direction one by one</td>
<td>Safety comes first and move the car involved in the accident to allow traffic through</td>
<td>Manually control the intersection</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>Keep the flow as long as possible</td>
<td>If people are badly injured, block the intersection to the accident site and protect the scene; if there are no injuries, move the car and allow the traffic through</td>
<td>Manually control the intersection</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>Allocate time to the approaches according to the congestion based on queue length</td>
<td>Protect the scene, avoid a secondary accident</td>
<td>Consistently flow traffic on an approach until the other side backs up</td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>Let the direction with the longest queue go first</td>
<td>Direct the traffic around the scene; or shut down and reroute the traffic</td>
<td>Manually control the intersection</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
When a traffic incident occurs, safety issue comes first. TCAs will first make sure people are safe, then protect the incident scene, block the roads and detour the traffic if necessary. Also they will direct the traffic to avoid secondary accident and start to recover the traffic from the incident once investigators take pictures of the scene. For the scenario of a power outage which could be caused by natural disasters, most likely the signalized intersection will be either changed to a 4-way stop intersection or manually controlled by TCAs. TCAs may also close the road or block lanes to reduce the traffic if it is a minor intersection. Normally 2 or 3 TCAs will be assigned to the intersection for manual control. As for the case of construction sites which are planned ahead of time, the control strategy is different with traffic accidents. Most of the construction sites are pre-deployed with barricades and signs to direct traffic, thus TCAs won’t be assigned unless the safety on the construction site is a concern. Similarly, special events are always fully pre-planned with traffic route and officers’ assignments. Under occurrences of special events, assigned TCAs will manually control the traffic according to planned event traffic route. Since large numbers of pedestrians will show up for the event, they will get the highest priority and be arranged as a group to pass through.

4.2 Simulation-based Experiments

4.2.1 Experimental Platform and Tasks

The experiment was conducted using the Manual Intersection Control Simulator (MIC-Sim), depicted in Figure 1. MIC-Sim consists of three components in a loop: human, human-traffic control interface and a commercial traffic simulator, shown as Figure 4(a). It builds the human-traffic control interface on a microscopic simulator, VISSIM, with Java and COM [image description].
(Component Object Model) technology. The participant will be provided a 3D view of traffic condition at a simulated intersection. The traffic condition, such as number of vehicles in the queue, is displayed on the screen and will dynamically change by animation. Once the participant perceives the traffic condition at intersections, he/she can manually control the traffic signals in real-time by clicking the corresponding traffic movement phases in the control panel, illustrated in Figure 4(b). Usually TCA starts to manually control traffic in the first minute. Once TCA starts to take over, intersection traffic will continue to be manually controlled through the simulation horizon. The control actions and traffic data are recorded in the achieved files for further analysis.

In the experiment, subjects were asked to apply their own control experiences to manually control traffic at the intersection of Millersport Highway and Amherst Manor Drive at North Campus of SUNY Buffalo, shown as Figure 5(a).

![Diagram of the test intersection and TCA in the experiment](image-url)

Figure 5: (a) Layout of the test intersection; (b) TCA in the experiment

The traffic data in the experiment was collected from a campus football game, scheduled at 7pm, September 19, 2012. The attendance of this game was 9,764, counted from the ticket scanner in the stadium. The game traffic was monitored two hours before its starting time. Many people parked in the south of Amherst Manor Dr., thus a large amount of northbound pedestrians was observed before the game starts. The prior game inbound traffic, including both passenger cars and pedestrians, are as shown in Figure 3.
4.2.2 Subjects and Experimental Procedure

Eight TCAs participated in the experiment, depicted in Figure 5(b). One experiment comprised a 5-minute training, which consisted of demonstrations and suggestions by the experimenter, combined with practice trials. In this warm-up Section, participants were asked to properly adjust the simulation view to minimize the discrepancies between real-world and simulation. After a warm-up training Section, each subject conducted manual traffic signal control under four different scenarios, which last 30 minute each. The first two scenarios simulate the real multi-modal traffic demand from a busy weekday PM peak football game, including three traffic modes, passenger cars, buses and pedestrians, while the last two scenarios only have two traffic modes, passenger cars and buses. Detailed multi-modal traffic demand data for 12 turning movements and one pedestrian movement are also provided in Table 4. All scenarios contain two bus lines, which have the same bus demand, 8 buses per hour per line. Scenarios 1 and 3 have the same traffic demand in buses and passenger cars while scenario 3 doesn’t generate pedestrian traffic. Scenario 4 contains an artificial saturated traffic condition. The traffic conditions are determined by critical intersection volume-to-capacity ratio in Chapter 18 of Highway Capacity Manual.

The critical volume-to-capacity ratio for this intersection is

\[ \frac{C}{c_{-c}} \sum_{t\in c} y_{c,t} \]

with

\[ \sum_{t\in c} l_{t,i} \cdot y_{c,t} = \frac{v_i}{N_{S_i}} \]

where C is cycle length, L is cycle lost time, ci is set of critical phases on the critical path, \( l_{t,i} \) is phase i lost time, and \( v_i \) is demand flow rate, \( N_{S_i} \) is saturation flow for phase i. Therefore, the critical volume-to-capacity ratios for four scenarios are shown in Table 4 as 0.775, 0.801, 0.775 and 1.208, respectively.

4.2.3 Evaluation Criteria

The purpose of this research is to evaluate the manual multi-modal signal control performance of TCAs. There are several challenges in multi-modal signal control. First, it is crucial to set weights for different traffic modes. Due to lack of previous work, we simply set multi-modal weights according to TCA’s interview results. The second one is how to select different evaluation criteria. According to the previous interview, safety is the first priority
considered by TCA. We leave this criterion for future study. Network throughput and average delay are also top criteria but sometimes they conflict with each other. For example, lower cycle length usually results in lower pedestrian delay, though it increases total lost time and lead to lower total throughput.

In this paper, we take two criteria for the evaluation of signal control: delay and throughput. In addition, each criterion is evaluated in three aspects due to multi-modal traffic: passenger car, bus, and pedestrian. In order to compare with state-of-practice automatic control method, fully actuated-signal control (ASC), is served as the baseline of traffic control performance. Moreover, we assume optimal control results can be obtained from a control algorithm called PAMSCOD (Platoon-based Arterial Multimodal Signal Control with Online Data) [4], which aims to reduce multi-modal traffic delay. PAMSCOD assumes Vehicle-to-Infrastructure (V2I) communication is available with 100% penetration rate in this study, and every vehicle or pedestrian will send controller a request with its phase and arrival time when approaching the intersection. To fit this study, we trimmed the constraints of PAMSCOD for an isolated intersection and added special delay evaluation constraints for pedestrians. Table 5 shows the simulation results of all subjects, fully actuated-signal control (ASC) and optimal signal control for four scenarios, with respect to three considered traffic modes. Table 6 shows detailed ASC settings used in the experiments. All scenarios have the same settings for minimum green time, vehicle extension, yellow time and all-red time for all six phases. Scenarios which have pedestrians, i.e. S1 and S2, also have the same settings for pedestrian walk and clearance time. Maximum green durations for different scenarios are different as shown in Table 6. In order to compare the performance of different operations in a uniform approach, next section shows the method to calculate performance index.
### Table 4: Average multi-modal traffic turning movement counts (per hour) for each scenario

<table>
<thead>
<tr>
<th></th>
<th>NBL*</th>
<th>NBT</th>
<th>NBR</th>
<th>NB-Ped</th>
<th>SBL</th>
<th>SBT</th>
<th>SBR</th>
<th>WBL</th>
<th>WBT</th>
<th>WBR</th>
<th>WBR-Bus</th>
<th>EBL</th>
<th>EBL-Bus</th>
<th>EBT</th>
<th>EBR</th>
<th>Volume-Capacity Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>25.0</td>
<td>120.0</td>
<td>41.1</td>
<td>1458</td>
<td>72.1</td>
<td>39.8</td>
<td>136.0</td>
<td>167.2</td>
<td>651.0</td>
<td>227.8</td>
<td>8</td>
<td>365.5</td>
<td>8</td>
<td>888.9</td>
<td>151.6</td>
<td>0.78</td>
</tr>
<tr>
<td>S2</td>
<td>22.5</td>
<td>108.4</td>
<td>37.1</td>
<td>1338</td>
<td>76.2</td>
<td>42.1</td>
<td>143.7</td>
<td>176.4</td>
<td>687.1</td>
<td>240.5</td>
<td>8</td>
<td>374.9</td>
<td>8</td>
<td>911.7</td>
<td>155.5</td>
<td>0.80</td>
</tr>
<tr>
<td>S3</td>
<td>25.0</td>
<td>120.0</td>
<td>41.1</td>
<td>0</td>
<td>72.1</td>
<td>39.8</td>
<td>136.0</td>
<td>167.2</td>
<td>651.0</td>
<td>227.8</td>
<td>8</td>
<td>365.5</td>
<td>8</td>
<td>888.9</td>
<td>151.6</td>
<td>0.78</td>
</tr>
<tr>
<td>S4</td>
<td>96.5</td>
<td>464.0</td>
<td>158.8</td>
<td>0</td>
<td>346.7</td>
<td>191.4</td>
<td>653.6</td>
<td>193.7</td>
<td>754.2</td>
<td>263.9</td>
<td>8</td>
<td>392.7</td>
<td>8</td>
<td>955.1</td>
<td>162.9</td>
<td>1.21</td>
</tr>
</tbody>
</table>

*: NB, SB, WB and EB represent northbound, southbound, westbound and eastbound traffic, respectively. L, T and R represent left-turn, through and right-turn traffic, respectively.

### Table 5: Multi-modal average delay for each subject in each scenario

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject</td>
<td></td>
<td>Car</td>
<td>Bus</td>
<td>Ped</td>
<td>Car</td>
<td>Bus</td>
<td>Ped</td>
</tr>
<tr>
<td></td>
<td>Delay (s)</td>
<td>Delay (s)</td>
<td>Delay (s)</td>
<td>Delay (s)</td>
<td>Delay (s)</td>
<td>Delay (s)</td>
<td>Delay (s)</td>
</tr>
<tr>
<td>A</td>
<td>26.53</td>
<td>41.90</td>
<td>33.34</td>
<td>28.15</td>
<td>14.45</td>
<td>54.04</td>
<td>15.65</td>
</tr>
<tr>
<td>B</td>
<td>34.79</td>
<td>36.89</td>
<td>35.04</td>
<td>53.66</td>
<td>57.40</td>
<td>54.04</td>
<td>25.02</td>
</tr>
<tr>
<td>C</td>
<td>33.21</td>
<td>33.90</td>
<td>45.14</td>
<td>33.31</td>
<td>22.95</td>
<td>44.24</td>
<td>26.62</td>
</tr>
<tr>
<td>D</td>
<td>37.25</td>
<td>26.40</td>
<td>51.74</td>
<td>38.53</td>
<td>32.81</td>
<td>53.54</td>
<td>16.85</td>
</tr>
<tr>
<td>E</td>
<td>31.39</td>
<td>28.71</td>
<td>23.64</td>
<td>37.93</td>
<td>37.47</td>
<td>27.34</td>
<td>14.22</td>
</tr>
<tr>
<td>F</td>
<td>32.57</td>
<td>45.85</td>
<td>18.04</td>
<td>26.99</td>
<td>28.80</td>
<td>23.84</td>
<td>18.55</td>
</tr>
<tr>
<td>G</td>
<td>33.26</td>
<td>17.85</td>
<td>37.94</td>
<td>29.77</td>
<td>22.80</td>
<td>33.04</td>
<td>11.95</td>
</tr>
<tr>
<td>H</td>
<td>45.92</td>
<td>46.09</td>
<td>27.74</td>
<td>60.11</td>
<td>58.69</td>
<td>38.34</td>
<td>19.43</td>
</tr>
<tr>
<td>ASC</td>
<td>34.10</td>
<td>38.94</td>
<td>47.00</td>
<td>35.79</td>
<td>60.84</td>
<td>59.20</td>
<td>17.80</td>
</tr>
<tr>
<td>Optimal</td>
<td>22.43</td>
<td>4.70</td>
<td>12.80</td>
<td>21.25</td>
<td>11.35</td>
<td>14.90</td>
<td>14.66</td>
</tr>
</tbody>
</table>

*: NB, SB, WB and EB represent northbound, southbound, westbound and eastbound traffic, respectively. L, T and R represent left-turn, through and right-turn traffic, respectively.
Table 6: Baseline ASC settings

<table>
<thead>
<tr>
<th>Phase No.</th>
<th>2,4,8</th>
<th>6</th>
<th>3,7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min. Green (s)</td>
<td>7</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Veh. Extension (s)</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Ped. Walk (s)</td>
<td>N/A</td>
<td>10</td>
<td>N/A</td>
</tr>
<tr>
<td>Ped. Clearance (s)</td>
<td>N/A</td>
<td>45*</td>
<td>N/A</td>
</tr>
<tr>
<td>Yellow (s)</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>All Red (s)</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Max. Green (s)</td>
<td>80</td>
<td>80</td>
<td>35</td>
</tr>
</tbody>
</table>

*: The pedestrian clearance time is calculated by assuming a pedestrian speed of 3.5 ft/s.

4.3. Performance Index

We use utility functions to measure the TCA’s performance. Two attributes, weighted average delay \( d \) and total throughput \( h \), are considered in the utility function:

\[
U_{ij}(d, h) = \ln\left(\frac{h_{ij}}{d_{ij}}\right), \tag{Eq 2}
\]

\[
d_{ij} = w_c * d^c_{ij} + w_b * d^b_{ij} + w_p * d^p_{ij}, \tag{Eq 3}
\]

and

\[
h_{ij} = O_c * h^c_{ij} + O_b * h^b_{ij} + O_p * h^p_{ij}, \tag{Eq 4}
\]

where \( U_{ij}(d, h) \) is a natural logarithm utility function. \( i \) represents the \( i \)th TCA from A to H and \( j \) represents the \( j \)th scenario from 1 to 4. The weights for the three modes, \( w_c \) for a passenger car, \( w_b \) for a bus, and \( w_p \) for pedestrians, were obtained and normalized from interview results (\( w_c = 0.085, w_b = 0.373, w_p = 0.542 \), respectively). \( O_c, O_b \) and \( O_p \) represent the average occupancy of a car, a bus and a pedestrian, respectively. Based on our empirical studies, the value for \( O_c \) was set at 1.75, and values for \( O_b \) and \( O_p \) were set at 40 and 1, respectively. Correspondingly, the delays for a car, bus and pedestrians are \( d^c, d^b \) and \( d^p \), where the throughputs for these three modes are \( h^c, h^b \) and \( h^p \), respectively.

In this paper, \( U_{b,j} \) is the performance utility of the ASC in scenario \( j \); \( U_{o,j} \) is the performance utility of optimal control and \( U_{i,j} \) is the \( j \)th trial of \( i \)th subject. Each subject only performs single simulation for each scenario.

The final performance index for the \( j \)th trial of the \( i \)th subject is
A zero index demonstrates that the TCA achieves the same performance as the ASC, whereas a negative index indicates a worse performance than that using the ASC method. The closer the index is to 1, the closer the performance is to the optimal solution.

Figure 6: Experience and performance index of all subjects.

Figure 6 shows the PI of all subjects with the corresponding work experience index (years of experience/30). More experience does not guarantee a higher PI from the study. As shown in Figure 6, when comparing the performance of subject B and F, it is clear that B had a worse performance than that of F, even though B had more experience than F. It is also interesting to observe that subject G, the TCA with the most experience, always achieved high PIs in all scenarios. One noticeable result is that the PI from subject G in S4 is close to 1, which indicates the necessity of manual operation for oversaturated traffic conditions. Moreover, the performances of the same subject from scenario to scenario varied. Most of the subjects were more capable of handling S3 than S1, which has the same traffic condition in passenger cars and buses but with additional pedestrian traffic when compared with that of S3. This result can be explained by the fact that it is easier to handle the condition when pedestrians are not involved. Most likely, subjects will have a better performance in S2 compared with S1 because S2 contains more congested multi-modal traffic than S1. Additionally, it was observed that the PI of subject
2 in S3 is negative because he did not interrupt the predefined fixed time signal plan in this simulation. In such a case, the performance will be worse than that of ASC.

Overall, in Figure 6, there are large performance variations throughout all scenarios. The standard deviations of the PIs were 0.27 across all experiments. Such large discrepancies among the TCAs’ performance could be caused by various human factors, such as age, education background, professional training, work experiences, and so on. However, it is clear that a TCA’s manual signal control outperforms ASC in most of the scenarios. This result can be explained by the fact that ASC does not work well in a congested multi-modal traffic condition, which is always the case for event traffic. Therefore, manual intersection control is indispensable for such cases, particularly when the advanced adaptive signal control system is not properly equipped.

![Figure 6](image)

Figure 6: Schematic view of the intersection with traffic signals and各类 traffic delays.

Figure 7 demonstrates the multi-modal delay of four scenarios compared with that of the corresponding ASC and optimal signal timing, where (a), (b), (c), and (d) in Figure 4 represents 1,
2, 3, and 4, respectively. Both scenario 1 and 2 have three traffic modes, including passenger cars, buses and pedestrians, whereas scenarios 3 and 4 only have two traffic modes, passenger cars and buses. As shown in the figure, the delay of either a bus or pedestrian can be always improved by manual signal control. Compared with ASC, manual control can significantly decrease the bus delay and pedestrian delay in scenarios 1 and 2. It can also be seen that a greater delay deduction of both buses and pedestrians is achieved in scenario 2, which has a larger traffic demand compared with that of scenario 1. This result is similar when comparing scenario 3 with scenario 4, whereas scenario 4 has a larger traffic demand and has more car and bus delay deductions. Moreover, the car delay in S1, S2 and S4 is shown to be improved by manual control, whereas it is worse in S3. This result confirms that manual control is a more effective way to handle congested multi-modal traffic conditions. Figure 7(c) and 4(d) also show the standard deviation of car delay and bus delay. As seen, neither of these standard deviations is small, whereas the standard deviation for the bus delay is larger than that for the car delay.

Comparing manual control with optimal control, one can certainly see that there is a large gap between these two control operations. However, optimal control requires expensive detection technology to receive the rich real-time information at the intersection, and currently, it is infeasible in most real-world intersections, particularly in rural areas. In this case, manual signal control can significantly improve traffic conditions at a low cost.

As previously mentioned, scenarios 1 and 3 have the same traffic demand with respect to passenger cars and buses; pedestrians are not considered in scenario 3. The average delay in scenario 3 is reduced by 41% compared with that in scenario 1. This result can also be validated from Figure 3, which shows the performance in S3 has a higher index value than that in S1 for most of the simulations. This result can be explained by the fact that once a pedestrian is involved, the delay at the intersection increases, and it becomes more difficult to control the traffic.

Table 7 shows the different cycle lengths and delay reductions for each scenario between the two control methods, manual and ASC operation. It can be easily seen from the data that the cycle length during manual operation is longer than during ASC operation for S1, S2 and S3 but not S4. Additionally, in S1 and S2, manual control has a longer cycle length than ASC because manual control has longer pedestrian clearance time and walk time, whereas ASC has fixed
settings. Due to high traffic volume under oversaturated conditions, ASC simply extends the green time until the phase terminates due to reaching the designated maximum green time for the phase (maximum out). In contrast, during manual operation smart decisions are made regarding green time allocation by considering more important factors than traffic demand, including queue spillover, left turn waiting time, coordination between signals, and so on. Thus, it is more flexible to adjust cycle length according to the congested traffic condition by manual operation. Additionally, one can observe that delay is always less in manual operation compared with that of ASC, and the average delay is reduced by 29.2%. Regarding manual control between S1 and S3, the cycle length in S1 with pedestrians is 34.6 seconds longer than that in S3 without pedestrians. In other words, the cycle length in S3 is only 74% of that in S1. This result can be explained by the fact that cycle length should be long enough to accommodate the pedestrian clearance time needed to cross the street.

Table 7: Average cycle length and multi-modal weighted delay

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cycle length (s)</td>
<td>Delay (s)</td>
<td>Cycle length (s)</td>
<td>Delay (s)</td>
</tr>
<tr>
<td>ASC</td>
<td>96.92</td>
<td>42.90</td>
<td>106.62</td>
<td>57.83</td>
</tr>
<tr>
<td>Manual-Avg.</td>
<td>132.84</td>
<td>34.33</td>
<td>144.20</td>
<td>38.37</td>
</tr>
<tr>
<td>Manual-Std.</td>
<td>29.92</td>
<td>4.89</td>
<td>42.52</td>
<td>9.39</td>
</tr>
<tr>
<td>Changes from ASC to Manual (%)</td>
<td>37.07</td>
<td>-19.97</td>
<td>35.25</td>
<td>-33.65</td>
</tr>
</tbody>
</table>

5. TCA Traffic Control Behavior Modeling

With prior observation and understanding of field TCA control behavior, in this section, we propose a press-based model to mimic the TCA decision making behavior. Both the queues of vehicle and pedestrian are taken into account in this model. The effectiveness of the proposed model is validated by comparisons with human subject experiments from Section 4.

5.1 TCA Traffic Control Behavior

In Section 4, human based simulation experiments were conducted to record the manual traffic control behavior of TCAs, including their control actions and traffic data. The stages to simulate TCAs’ decision making behavior are depicted in Figure 8.
2.8 First stage is to extract simulation experiment data from Section 4. Data of traffic demand, traffic volume, queue information and TCAs’ manual control decisions are obtained in stage 1, which will be used as input to in the next stage. Table 8 shows decisions of TCAs during the experiments, including the number of decisions which a TCA made in each experiment, mean and standard deviation of green time under manual control for each phase. It can be seen from the table that the number of decisions varies not only among different TCAs but also among different scenarios. More decisions were made to control scenarios with pedestrian, which are S3 and S4. In each experiment, the whole entire time period horizon is divided into separate segments according to the corresponding decision time points made by the TCA, as depicted in Figure 9. $t_i^{\text{decision}}$ is the decision time point of the $i$th decision at which TCA changes the green phase. For example, during segment 1, the green phases were phase 2 and phase 6. At $t_1^{\text{decision}}$, TCA decided to change green phases to phase 3 and phase 8, which means the segment 1 is from

Figure 8: Flow chart of TCA control behavior modeling.
time=0 to time=$t^\text{decision}_1$. Thus segments are divided by TCA’s decision time points. For each decision segment, the starting time, the ending time and green phases are recorded for analyzing their manual control behavior.

At second stage which is human decision modeling, a press-based human behavior model is implemented to analyze and mimic TCA’s manual control behavior. This proposed press-based human is applied on each decision segment. There are three sub-steps in this stage.

1) Calibrate the press-based model in order to find the best parameters for each experiment.

2) Analyze extracted experiment data by using press-based model to generalize TCA’s traffic control patterns. This step records the time when the TCA changes green phases. And Initial threshold for each phase is obtained at the decision point.

3) Recalculate the press for each phase to compare with the initial threshold obtained in the second sub-step by every time step which is equal to a second. Once the phase press value exceeds its initial threshold, a decision will be made as predicted traffic control action, including both time point and phases changed to be green. After prediction, the final stage is to compare predicted decisions to corresponding actual decisions and get model accuracy.

Table 8: TCA Decisions in the experiments

<table>
<thead>
<tr>
<th>TCA NO.</th>
<th>S1 NO. of Decisions</th>
<th>Mean Green Time (s) for Phase p* per Cycle</th>
<th>S2 NO. of Decisions</th>
<th>Mean Green Time (s) for Phase p per Cycle</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>2 3 4 6 7 8</td>
<td></td>
<td>2 3 4 6 7 8</td>
</tr>
<tr>
<td>A</td>
<td>45</td>
<td>21 12 25 21 13 19</td>
<td>47</td>
<td>26 13 21 28 19 14</td>
</tr>
<tr>
<td>B</td>
<td>42</td>
<td>28 14 25 28 17 18</td>
<td>31</td>
<td>37 18 37 37 22 28</td>
</tr>
<tr>
<td>C</td>
<td>36</td>
<td>26 21 26 26 24 22</td>
<td>43</td>
<td>23 16 21 23 20 16</td>
</tr>
</tbody>
</table>
5.2 Press-Based Human Behavior Modeling

Consider a possible phase $p \in P$, where $P$ denotes the set of all possible phases including vehicle and pedestrian phases in the intersection as shown in Figure 4(a). The decision operator, i.e. TCA, knows the whole vehicle distribution at the intersection. It is thus able to associate the press $S^P$ to the phase $p$. This press depends on two attributes, one is queue information of the phase ($Q^P$), another is the time since the phase was last selected ($T^P$). The queue information included three components, number of vehicles in queue ($Q^P_n$), queue length ($Q^P_l$) and volume-to-capacity ratio ($Q^P_v$).

In order to combine the metrics reflecting both attributes in a single expression to define this press, we normalize both attributes using a genetic function, $\gamma(a^p)$, where $a \in \{Q, T\}$. Thus the attribute can be transformed in the range $[0, 1]$ and be compared easily since it is dimension-free. $\gamma(a^p)$ is defined as follows:

$$\gamma(a^p) = \frac{a^p}{\max_{k \in P} \{a^k\}}$$  \hspace{1cm} \text{Eq 6}

If there is a pedestrian phase along with a vehicle phase, a weight $w_{ped}$ is assigned to pedestrians according to the interviews conduction in section 4 as shown in Table_. And then the genetic function will be modified as:

<table>
<thead>
<tr>
<th>TCA NO.</th>
<th>S3</th>
<th></th>
<th>S4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NO. of Decisions</td>
<td>Mean Green Time (s) for Phase p* per Cycle</td>
<td>NO. of Decisions</td>
<td>Mean Green Time (s) for Phase p* per Cycle</td>
</tr>
<tr>
<td>A</td>
<td>60</td>
<td>14</td>
<td>7</td>
<td>15</td>
</tr>
<tr>
<td>B</td>
<td>37</td>
<td>30</td>
<td>15</td>
<td>33</td>
</tr>
<tr>
<td>C</td>
<td>N/A</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>D</td>
<td>59</td>
<td>19</td>
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<td>E</td>
<td>75</td>
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<td>12</td>
</tr>
<tr>
<td>F</td>
<td>44</td>
<td>16</td>
<td>10</td>
<td>17</td>
</tr>
<tr>
<td>G</td>
<td>92</td>
<td>42</td>
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<td>11</td>
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<tr>
<td>H</td>
<td>58</td>
<td>20</td>
<td>11</td>
<td>19</td>
</tr>
</tbody>
</table>

*: 6 phases are illustrated as shown in Fig.5(a)

$$\text{Eq 6}$$

If there is a pedestrian phase along with a vehicle phase, a weight $w_{ped}$ is assigned to pedestrians according to the interviews conduction in section 4 as shown in Table_. And then the genetic function will be modified as:
\[ \gamma(a^p) = \frac{a^p}{\max_{k_1, k_2 \in P} (a^{k_1}_{\text{w ped}} a^{k_2}_{\text{ped}})} \quad \text{Eq 7} \]

where \( k_1, k_2 \) are vehicle phases and pedestrian phases, respectively. And \( a_{\text{ped}} \) represents the attributes of pedestrians.

Once normalization is realized, the approach would be to define the score as a linear combination of \( \gamma(Q^{(s,d)}) \) and \( (T^{(s,d)}) \) as shown below:

\[ S(p) = w_q \ast \left[ \frac{\gamma(Q^p_w) + \gamma(Q^p_{Q}) + \gamma(Q^p_{w})}{3} \right]^2 + w_t \ast [\gamma(T^p)]^2 \quad \text{Eq 8} \]

where \( w_q \) and \( w_t \) are user-defined weights, which can be defined and changed by user experience.

### 5.3 Behavior Model Accuracy

Since two elements are predicted in the model, decision time point and phases selected to be green, there are two kinds of errors considered in order to show the accuracy of the prediction model. The first kind of error is related to phases selected to be green in the decisions. It gives the ratio of number of incorrectly selected phases over the total number of all actually decided phases, and is defined as follows:

\[ e_1 = \frac{n_e}{n_{\text{total}}} \quad \text{Eq 9} \]

where \( n_e \) is the number of incorrectly predicted phases, and \( n_{\text{total}} \) is the total number of actually decided phases in each experiment.

The second kind of error is corresponding to the time points when making the decisions. It is given by the average difference of predicted decision duration to actual decision duration which is:

\[ e_2 = \frac{\sum_{t \in M}(t^p_t - t^a_t)}{M} \quad \text{Eq 10} \]

where \( M \) is the set of decisions made by a TCA in the corresponding experiment, \( t^p_t \) is the predicted decision time of \( t \)th decision by the model and \( t^a_t \) is the actual decision time of \( t \)th decision.

Therefore, the accuracy of the proposed human decision model is represented by \( e_1 \) and \( e_2 \). The smaller \( e_1 \) and \( e_2 \), the more accurate the proposed model will be.
5.4 Model Calibration and Validation

TCA’s profile data (e.g. work experience), traffic conditions (e.g. multi-modal traffic demand, and event characteristics) and performance data were obtained in Section 4. A portion of these experimental data will then be utilized to calibrate the parameters in the model while other data will be used to verify the model. The performance of the press-based decision model is given by two kinds of errors, $e_1$ and $e_2$. When implementing the press-based model, minimal error can be searched by adjusting parameters $w_q$ and $w_t$. The main steps of searching for minimal error is presented in Table 9.

Table 9: Main Steps of obtaining parameters with minimal error

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Initialization, set up ranges for $w_q$ and $w_t$ as $[1, r_1]$ and $[1, r_2]$, respectively;</td>
</tr>
<tr>
<td>1</td>
<td>for $w_q = w^k_q$ and $w_t = w^k_t$, calculate initial thresholds for all phases as ${s^k_{ini}, k \in P}$;</td>
</tr>
<tr>
<td>2</td>
<td>with the same parameter, during each segment $i$ from $t^{start}<em>i$ to $t^{start}</em>{i+1}$, calculate the press for each phase at each time step as ${s^k_t, k \in P, t^{start}<em>i \leq t \leq t^{start}</em>{i+1}, i \in N}$, and compare with ${s^k_{ini}}$;</td>
</tr>
<tr>
<td></td>
<td>if $s^k_t &gt; s^k_{ini}$, then a decision is made at time $t$ and phase $k$ is selected to be green while another compatible phase $k'$ will be selected as second phase to be green;</td>
</tr>
<tr>
<td>3</td>
<td>Continue step 2 till decisions for all segments are predicted, calculate $e_1$ and $e_2$;</td>
</tr>
<tr>
<td></td>
<td>Set $w_q = w^{k+1}_q$ and $w_t = w^{k+1}_t$, then go back to step 1;</td>
</tr>
<tr>
<td>4</td>
<td>Stop after testing for all combinations for $w_q$ and $w_t$; return error information with corresponding values of $w_q$ and $w_t$.</td>
</tr>
</tbody>
</table>

5.5 Behavior Model Results

Table 10 shows the decision prediction errors for eight subjects who participated in the previous simulation experiments of four different scenarios with corresponding PI. Some values are “N/A” because corresponding TCA did not manually control the traffic under that scenario in the simulation experiment. Thus the model cannot be implemented to predict his manual control behavior. It is seen from the table that most of $e_1$, which is the rate of incorrectly predicted phases, are below 0.35, and the smallest value is 0.07 which means the model accuracy of choosing next timing phases can be up to 93%. $e_2$ can be positive or negative. Positive $e_2$ means the predicted duration is longer than the actual duration, while negative $e_2$ indicates that the predicted duration is shorter than the actual duration. As seen in the table, most of the values of $e_2$ are positive which indicate that the press-based model underestimates the green phase.
duration. This can be caused by that when performing manual traffic control, TCAs underestimated the traffic condition at the decision points to change green phases.

Table 10: Results of Press-based behavior modeling

<table>
<thead>
<tr>
<th>Scenario</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PI*</td>
<td>e1</td>
<td>e2</td>
<td>PI</td>
</tr>
<tr>
<td>A</td>
<td>0.20</td>
<td>0.34</td>
<td>-23.28</td>
<td>0.41</td>
</tr>
<tr>
<td>B</td>
<td>0.18</td>
<td>0.37</td>
<td>-27.47</td>
<td>0.06</td>
</tr>
<tr>
<td>C</td>
<td>0.10</td>
<td>0.14</td>
<td>-34.32</td>
<td>0.45</td>
</tr>
<tr>
<td>D</td>
<td>0.03</td>
<td>0.26</td>
<td>-49.13</td>
<td>0.23</td>
</tr>
<tr>
<td>E</td>
<td>0.49</td>
<td>0.17</td>
<td>-24.28</td>
<td>0.52</td>
</tr>
<tr>
<td>F</td>
<td>0.39</td>
<td>0.40</td>
<td>-20.19</td>
<td>0.71</td>
</tr>
<tr>
<td>G</td>
<td>0.38</td>
<td>0.35</td>
<td>-25.29</td>
<td>0.62</td>
</tr>
<tr>
<td>H</td>
<td>0.18</td>
<td>0.32</td>
<td>-45.96</td>
<td>0.17</td>
</tr>
</tbody>
</table>

*: PI represents the performance index of each TCA in each scenario.

Figure 10 represents the relevance between PI and $e_1$ of each experiment. As shown in lower right part of the figure, most of the experiments which have PI value greater than 0.3, the corresponding $e_1$ are at most 0.3. It indicates that manual control behavior of TCAs who have high PI values can be predicted by press-based model within small error.
Based on prior understanding and modeling of TCAs’ manual traffic control behavior, assuming each TCA has perfect information of the network flow, an optimization model is proposed to minimize the total costs including traffic associated cost and TCA deployment cost.

The objective function is expressed as:

$$\text{Minimize } \alpha \sum_{t} \sum_{i} x_{it} + \beta \sum_{t} \sum_{m} y_{mt} + C_{init} B_{max} + \sum_{n} \sum_{t} C_{hr} B_{n} \omega_{nt}$$

where $x_{it}$ and $y_{mt}$ are queue length for vehicles and pedestrians at time $t$, respectively. $\alpha$ and $\beta$ are the coefficients to convert time (e.g., traffic delay) into United States (U.S.) dollars. $\alpha$ can be applied to determine the cost of a vehicle waiting and $\beta$ can be applied to determine the cost of a pedestrian waiting. To translate travel delays into monetary values, the U.S. Department of Transportation (DOT) has used the following travel time values for evaluating transportation projects (1997 U.S. dollars): in-vehicle time at $8.90/\text{person-hour}$; out-of-vehicle time (e.g., waiting for a bus at $17.00/\text{person-hour}$; and commercial truck at $16.50/\text{person-hour}$. $C_{init}$ and $B_{max}$ represent the initial cost of deploying one TCA and the maximal number of TCA deployed. $C_{hr}$, $B_{n}$, and $\omega_{nt}$ stand for hourly rates of TCA, number of TCA needed for

Figure 10: $e_1$, rate of incorrectly predicted phased VS PIs

6. TCA Deployment

Based on prior understanding and modeling of TCAs’ manual traffic control behavior, assuming each TCA has perfect information of the network flow, an optimization model is proposed to minimize the total costs including traffic associated cost and TCA deployment cost.
intersection n, and binary variables if there is a TCA assigned for intersection n at time t, respectively.

### 6.1 Notations of Optimization Model

#### 6.1.1 Decision Variables

- $x_{it}$ $\forall i \in I, t \in T$, queue on link i (e.g., the number of vehicles at road segment x), at time step t;

- $u_{it}$ $\forall i \in I, t \in T$, outflow on link i, at time step t, this represents the number of vehicles that leave the link;

- $y_{mt}$ $\forall m \in M, t \in T$, queue on link m (e.g., the number of pedestrians at sidewalk segment y), at time step t;

- $s_{mt}$ $\forall m \in M, t \in T$, pedestrian outflow on link m, at time step t, this represents the number of pedestrians that leave the link;

- $g_{ntz}$ $\forall n \in N_c, z \in Z, t \in T$, optimized green time at node n, vehicle stage z and time step t, where optimized green time refers to best green time obtained which serves the objective best;

- $g_{npt}$ $\forall n \in N_c, p \in P, t \in T$, optimized green time at node n, pedestrian phase p and time step t;

- $gw_{npt}$ $\forall n \in N_c, p \in P, t \in T$, the green-walking time for pedestrians at node n, phase p and time step t;

- $\omega_{nt}$ $\forall n \in N, t \in T$, a binary decision variable, $\omega_{nt} = 1$ when a TCA should be assigned to work at intersection n at time step t, otherwise $\omega_{nt} = 0$;

- $B_{max}$ is a decision variable that represents the maximum (or total) number of TCAs that are needed in the network.

#### 6.1.2 Sets Inputs

- $n \in N$, the set of all nodes, where the road network is represented as a directed graph with links “i” and intersections “n”;

- $n \in N_c \subseteq N$, the set of nodes needed for signal optimization;
∀i ∈ I, the set of all vehicle links;

m ∈ M, the set of all pedestrian links;

t ∈ T, the set of all time steps;

(i, n, j) ∈ K ≡ I × N × I, the set of all turns, from link i, via node n, to link j;

(i, n, j) ∈ K_c ≡ I × N × I, the set of turns, located in the nodes needed for signal optimization;

z ∈ Z, the set of vehicle signal stages, the signal control plan of an intersection n (or node n) may be based on a fixed number of vehicle stages;

z ∈ Z_{inj}, the set of vehicle signal stages at node n, serving turn (i, n, j); and

p ∈ P, the set of pedestrian signal phases.

6.1.2 Data Inputs

d_{it} ∀i ∈ I, t ∈ T, traffic demand (vehicles/hour) on link i, at time step t;

a_{it} ∀i ∈ I, t ∈ T, turning ratios from link j to link i, a_{ij} is zero if there is no connection between links i and j.

Q_{it} ∀i ∈ I, t ∈ T, flow capacity (vehicles/hour) on link i, at time step t (obtained for example by link width, number of lanes and shoulder width);

x_{oi} ∀i ∈ I, initial queue (vehicle) on link i;

x_{maxi} ∀i ∈ I, storage capacity (vehicle) on link i;

P_{mt} ∀m ∈ M, t ∈ T, pedestrian capacity (pedestrians/hour) on link m, at time step t;

λ_{mt} ∀m ∈ M, t ∈ T, pedestrian arrival rate (pedestrians/hour) on link m, at time step t;

y_{om} ∀m ∈ M, initial pedestrian queue (pedestrian) on link m;

y_{maxm} ∀m ∈ M, pedestrian storage capacity (pedestrian) on link m;

Δ, time step interval (e.g., hour, minute);

Ω_{inj} (i, n, j) ∈ K\K_c, turning capacity (vehicles/hour) at turn (i, n, j);
$S_{inj}(i,n,j) \in K_e$, saturation flow rate (vehicles/hour) on turn (i,n,j), where saturation flow rate is the maximal allowable flow rate in a link;

$R_m \forall m \in M$, saturation flow rate (pedestrians/hour) on pedestrian link m;

$G_{nz} \forall n \in N, z \in Z$, background green time at node n and vehicle stage s, where background green time is offline pre-optimized green time and a vehicle stage s is a certain period of time in which the signal of one or several traffic movement is green (a stage could contain multiple compatible phases);

$G_{np} \forall n \in N, p \in P$, background green time at node n and pedestrian phase p, where pedestrian phase p is a certain period of time in which the signal of one pedestrian movement is green;

$G_{walk_{np}} \forall n \in N, p \in P$, the background green time for pedestrians to walk at node n and pedestrian phase p;

$D_{np} \forall n \in N, p \in P$, don’t walk green time for pedestrians at node n and pedestrian phase p;

$g_{nzt}^{\min} \forall n \in N, z \in Z, t \in T$, the minimal green time (seconds) at node n and vehicle stage s;

$g_{nzt}^{\max} \forall n \in N, z \in Z, t \in T$, the maximal green time (seconds) at node n and vehicle stage s;

$C_n \forall n \in N$, cycle length (seconds) at node n;

$T2S_{turn}$, vehicle green stages matrix which represents a mapping from vehicle links to stages;

$P2S_{turn}$, pedestrian green phase matrix which represents a mapping from pedestrian links to stages;

$L$, lost time in a cycle which represents unused green time which no vehicles are able to pass through an intersection despite the traffic signal displaying a green (go) signal;

$A_{xp} \forall z \in Z, p \in P$, relationship between vehicle stage z and pedestrian phase p, for example a given intersection may have west/east (WE) traffic signals and north/south (NS)
traffic signals, the vehicle traffic signal can have four stages (turn WE, WE, turn NS, NS) and the pedestrian traffic signal can have two phases (walk WE, walk NS), the matrix $A_{zp}$ can be generated to reflect the relationships, for example, $A_{11} = 0$ can reflect that when the vehicle stage is turn WE, pedestrian phase walk WE is not green, and $A_{21} = 1$ can reflect that when the vehicle stage is WE, pedestrian phase walk WE is green;

$$B_n \quad \forall n \in N_c, p \in P,$$ the number of TCAs needed at node $n$;

$\tau_{min}$, the minimal number of time steps that a TCA needs to be working at an intersection;

$C_{init}$, initial cost for a TCA which can includes overhead costs such as vehicles, health insurance, ;

$C_{hr}$, hourly cost for a working TCA; and

$W$, is an integer that is used for constraint selections.

### 6.2 Constraints for Optimization modeling

In this optimization model, the objective function is subject to several constraints including flow conservation constraints (vehicle and pedestrian), turning flow constraints (vehicle and pedestrian), signal plan constraints, and TCA planning constraints. Detailed explanation of these constraints are as follows.

#### 6.2.1 Flow Conservation Constraints

Vehicle flow conservation constraints. These constraints reflect vehicle queue dynamics from one vehicle link to another. For example, the dynamics of a given vehicle link $i$ may be expressed as the conservation equation below:

$$x_{i,t+1} = x_{it} + \left( \sum_j a_{ij} u_{jt} + d_{it} - u_{it} \right) \Delta \quad \forall i \in I, t \in T$$

$$x_{i1} = x_{0i} \quad \forall i \in I$$

$$0 \leq x_{it} \leq x_{maxi} \quad \forall i \in I, t \in T$$

Pedestrian flow conservation constraints. These constraints reflect pedestrian queue dynamics from one pedestrian link to another. For example, the dynamics of a given pedestrian link $m$ may be expressed as the conservation equation below:
6.2.2 Turning Flow Constraints

(1) Vehicle turning flow constraints.

Vehicle flow capacity is represented as:
\[ 0 \leq u_{it} \leq Q_{it} \quad \forall i \in I, t \in T \]

Vehicle turning capacity is represented as:
\[ a_{ji}u_{it} \leq \Omega_{inj} \quad \forall (i,n,j) \in K \setminus K_c, t \in T \]

In an embodiment, the vehicle saturation flow rate constraint is represented as two mutual exclusive constraints, when \( \omega_{nt} \) is equal to 1, the first constraint is active to ensure vehicle flow rate is less than the maximal allowable flow limited by assigned green times. When \( \omega_{nt} \) is equal to zero, the second constraint is active to ensure vehicle flow rate is less than the maximal allowable flow limited by offline pre-defined green times.

\[
a_{ji}u_{it} \leq S_{inj} \frac{\sum g_{net} * T^{2}S_{turn}}{c_n} + (1 - \omega_{nt}) * W \quad \forall (i,n,j) \in K_c, t \in T
\]

\[
a_{ji}u_{it} \leq S_{inj} \frac{\sum c_{net} * T^{2}S_{turn}}{c_n} + \omega_{nt} * W \quad \forall (i,n,j) \in K_c, t \in T
\]

(2) Pedestrian flow constraints.

Pedestrian flow capacity is represented as:
\[ 0 \leq s_{mt} \leq p_{mt} \quad \forall m \in M, t \in T \]

Pedestrian saturation flow rate constraint is represented as two mutual exclusive constraints. When \( \omega_{nt} \) is equal to 1, the first constraint is active to ensure pedestrian flow rate is less than the maximal allowable flow limited by assigned green times. When \( \omega_{nt} \) is equal to zero, the second constraint is active to ensure pedestrian flow rate is less than the maximal allowable flow limited by offline pre-defined green times.

\[
s_{mt} \leq R_{m} \frac{\sum g_{walk} * R_{p} * S_{turn}}{c_n} + (1 - \omega_{nt}) * W \quad \forall (i,n,j) \in K_c, t \in T
\]
6.2.3 Signal Plan Constraints

An embodiment of modeling traffic signals for an optimized signal includes, by definition, that the constraint:

\[ \sum_{z} g_{nzt} + L = C_{n} \quad \forall n \in N_{c}, t \in T \]

holds at each intersection n, where \( g_{nzt} \) is the optimized green time of stage z at node n at time step t; and \( C_{n} \) is the cycle length at node n.

In addition:

\[ g_{nz}^{\text{min}} \leq g_{nzt} \leq g_{nz}^{\text{max}} \quad \forall n \in N_{c}, z \in Z, t \in T \]

where \( g_{nz}^{\text{min}} \) and \( g_{nz}^{\text{max}} \) are the minimum and maximum permissible green time for stage z at node n, respectively.

Further:

\[ G_{np} = G_{nz} \cdot A_{zp} \quad \forall n \in N_{c}, z \in Z, p \in P \]

\[ G_{walk_{np}} = G_{np} - D_{np} \quad \forall n \in N_{c}, p \in P \]

\[ g_{npt} = g_{nzt} \cdot A_{zp} \quad \forall n \in N_{c}, z \in Z, p \in P, t \in T \]

\[ g_{walk_{npt}} = g_{npt} - D_{np} \quad \forall n \in N_{c}, p \in P, t \in T \]

6.2.4 TCA Planning Constraints

TCA planning constraints can be relaxed in the first stage, which you can understand the best number of TCA needed and how should you assign them in each location and time slots without considering logistics or other constraints of TCAs.

Satisfy minimum working time:

\[ \sum_{k = t}^{t + \tau_{\text{min}}} |\omega_{nk} - \omega_{n,k-1}| \leq 1 \quad \forall t, n \in N \]

Maximal TCA needed at each time step:
\[
\sum_n B_n \omega_{nt} \leq B_{max} \forall t \in T
\]

6.3 Preliminary Results of Optimization Model

The layout of event traffic network, including major intersections and parking lots, is as shown in Figure 11. There are 7 major intersections, of which intersections 1, 6 and 7 are signal controlled while the rest of intersections 2, 3, 4 and 5 are four-way stop intersections. The traffic data to verify this proposed optimization model of TCA deployment was collected from two campus football games. Game 1 was scheduled at 6pm, September 8, 2012 and the other game 2 was at 7pm, September 19, 2012. Traffic of both games was monitored two hours before its starting time. Table 11 shows the TCA deployment plan and compares cost of optimal TCA deployment plan with that of original TCA plan and no-TCA involved plan. From Table 11, for both games, it is observed that under event traffic conditions, TCA can manage traffic with at least 35% reduction in maximum queue and save at least 45% of total cost of traffic network compared to ASC. Furthermore, it also can also be also from the table that the total delay and TCA deployment costs are further reduced by implementing optimized TCA deployment instead of original TCA plan. The total cost is reduce from $16,373 to $6117 in game 1 which is 62.6% reduction, and from $31,953 to 27,333 in game 2 which is 14.5% reduction. And in game 1, the number of TCAs is two which indicates that optimal TCA deployment can improve plan efficiency. In addition, node 5 and 6 are recognized as hot spots for event traffic on UB campus, which is also consistent with our observation in field data collection.

![Figure 11: Layout of UB North Campus and UB stadium traffic](image-url)
Table 11: Results of TCA deployment model

<table>
<thead>
<tr>
<th>Date</th>
<th>Scenarios</th>
<th>Total Cost ($)</th>
<th>Max Queue (s)</th>
<th>Number of TCAs</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>9/8/2012</td>
<td>Optimized TCA Deployment</td>
<td>6117</td>
<td>53.645</td>
<td>2</td>
<td>Node 5,6</td>
</tr>
<tr>
<td></td>
<td>Original TCA Deployment</td>
<td>16,373</td>
<td>45.686</td>
<td>6</td>
<td>Node 4,5,6</td>
</tr>
<tr>
<td></td>
<td>ASC</td>
<td>36,287</td>
<td>134.11</td>
<td>0</td>
<td>NA</td>
</tr>
<tr>
<td>9/19/2012</td>
<td>Optimized TCA Deployment</td>
<td>27,333</td>
<td>102.98</td>
<td>7</td>
<td>Node 2,4,5,6</td>
</tr>
<tr>
<td></td>
<td>Original TCA Deployment</td>
<td>31,953</td>
<td>133.48</td>
<td>6</td>
<td>Node 4,5,6</td>
</tr>
<tr>
<td></td>
<td>ASC</td>
<td>57,853</td>
<td>206.68</td>
<td>0</td>
<td>NA</td>
</tr>
</tbody>
</table>

7. Conclusion and Future Work

Human intervention for event traffic, conducted TCAs, who overrides traffic lights to direct traffic movements, still serves as the most commonly adopted approach to handle severe event traffic congestion. Different with most of pre-timed traffic signal control systems, experienced TCAs can effectively balance queues, increase network throughput, and prevent pedestrian-vehicle crashes. There exists much need for understanding the mechanism to efficiently conduct network wide TCA-based manual intersection control. In response to this pressing need, this project assesses existing TCA’s traffic control skills, models TCA traffic control behavior, and develop a daily TCA deployment optimization model for large scale planned special events.

The project takes a multi-disciplinary approach that combines transportation engineering, operations research and human factors. It explicitly considers human factors in the design and validate of a distributed network manual intersection control simulator, which has not received adequate attention. The project first designed an interview and a simulation-based experiment to mimic the manual multi-modal traffic signal control behavior of TCAs, which included on-duty police officers and firefighters with field data collection. The project then proposed a press-based
model to capture TCA’s traffic control behavior. The proposed press-based model is used to quantify and predict how experienced TCAs make decisions when they control traffic manually. Based on field traffic data and simulation experiments, TCA’s performance is measured by a utility function of two attributes including weighted average delay and total throughput, which shows that manual traffic control not only significantly improve the utility compared to ASC (30% higher) at an oversaturated intersection in event traffic condition, but also could also be very close to the performance of optimized timing plan. The press-based behavior model can mimic TCA’s traffic decision making behavior with an average of 0.3 for $e_1$ and an average of 50 seconds for $e_2$. The accuracy of this behavior model can be up to 92%. Moreover, the proposed optimization model of TCA’s deployment, which is implemented to campus football games, is shown to reduce the total costs including traffic delay and TCA deployment costs by up to 14.5% compared to original TCA plan. The last part of this project developed a framework to optimize TCA deployment for manned intersections under large scale event occurrences which can minimize total delay and TCA deployment costs, assuming that each TCA had perfect information of the network flow. Numeric examples show that optimal TCA placement and planning can save up to 15% of total costs, including both network delay cost and the TCA deployment costs.

In the future, this project can be extended in different perspectives. First, different control elements of event planning will be fully incorporated into the decision model and then implemented as an operational prototype system to more efficiently manage event traffic flow. Also TCA deployment will not only consider intersection control and TCA deployment, but also take all other event control elements into account, such as event parking signs, detours. What’s more, the entire framework of TCA planning study will include offline planning, online planning and event plan assessment, whereas current project only accounts for offline TCA planning.

This project will benefit national wide transportation authorities who are responsible for event traffic planning and management. The proposed network manual intersection control simulator will be used as an effective tool for TCA training and online TCA deployment under event occurrence. It will further advance knowledge in human-involved transportation control systems. On a broader level, this project will enrich the methodological toolbox of transportation operations under events, especially for natural disasters such as Hurricane Sandy that devastated portions of the Caribbean and the Mid-Atlantic and Northeastern United States during late
October 2012. Moreover, this project will improve event resilience, reduce fuel consumption and emission, and contribute to a sustainable society.

Reference


