Modeling Traffic Control Agency Decision Behavior for Multimodal Manual Signal Control Under Event Occurrences

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***Abstract*—Traffic control agencies (TCAs), including police officers, firefighters, or other traffic law enforcement officers, can override automatic traffic signal control and manually control the traffic at an intersection. TCA-based traffic signal control is crucial to mitigate nonrecurrent traffic congestion caused by planned and unplanned events. Understanding and predicting TCA behaviors is significant to optimize event traffic management and operations. In this paper, we propose a pressure-based human behavior model to mimic TCA's decision-making behavior. The model calculates TCA's pressure based on two attributes: vehicle and pedestrian queue dynamics and the red time duration for each phase. When TCA's pressure on each phase meet certain criteria and the minimal green is satisfied, TCA will terminate the current phase and switch to another phase. In order to study TCA behavior systematically, we first build a manual signal control simulator based on a microscopic traffic simulation tool. Supported by the manual control simulator, a series of human subject experiments have been conducted with real-world TCAs. Experiment data are divided into training data and test data. The proposed behavior model is then calibrated by training data, and the model is validated by both offline segment-based phase and duration prediction and online VISSIM-based simulation. Further, we test the model with videotaped TCA behavior data at a real-world intersection. Both validation results support the effectiveness of proposed behavior model.**

***Index Terms*—Human behavior modeling, multimodal event traffic, traffic signal control.**

I. Introduction

TRAFFIC congestions occur frequently, which affect daily life and pose all kinds of problems and challenges. Alleviation of traffic congestions not only improves traffic safety and efficiencies but also reduces environmental pollution.

Traffic congestions easily arise during large planned events (e.g., sporting games, parades, and conferences, etc.), or unplanned events (e.g., traffic incidents, natural disasters, inclement weather, and facility problems, etc.). Such events often result in significant non-recurrent congestion due to unexpected high demand or reduced network capacity [1]. 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 operations. Therefore, properly managing traffic under event occurrence becomes challenging for traffic safety and mobility.

When traffic over-saturates the network, human intervention by traffic control agency (TCA) is believed to be a very effective method to handle multi-modal traffic conditions [2]. TCAs usually consist of police officers, firefighters, parking enforcement agencies, or temporally hired personnel. The primary objective 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. Experienced TCAs can effectively balance queue length, increase network throughput, and prevent pedestrian-vehicle crashes. Therefore, manual traffic control performed by TCAs serves as a common approach to handle severe event traffic congestions. Correctly deploying TCAs in the network to direct traffic movements can significantly help mitigate traffic congestions. There are two typical methods to manually control traffic, either using hand signal or a pigtail manual switch in the signal controller [3]. The method by using hand signal allows TCAs to adjust both phase sequences and phase green time; while the manual switch in the controller can only adjust the green time in each phase but not the phase sequence. Without loss of generality, we focus on modeling hand signal control performed by onsite TCAs.

Large behavioral heterogeneity exists in TCA's control, due to individual differences and lack of systematic training. Understanding and predicting TCAs' behaviors are significant to event traffic management and operations. With a well-calibrated human behavior model, one may be able to simulate the manned intersections with different traffic scenarios and locations. Such human operator based simulation can evaluate the event-based traffic control plans with different TCA deployment strategies. The behavior model could also be applied for TCA training and assisting decision making for TCA deployment in a complicated network.

In this paper, our contributions are: (i) build a manual signal control simulator based on a popular microscopic traffic

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simulation tool-VISSIM, (ii) propose a pressure-based model to mimic TCA's decision making behavior, considering multi-modal traffic dynamics, including passenger cars and pedestrians, and (iii) validate the effectiveness of the proposed model by data collected from both human subject experiments and field experiments.

The following sections are organized as follows. Section II reviews existing related studies. Section III depicts the overall framework of TCA control behavior modeling. Section IV presents the pressure-based human behavior modeling. Human subject experiments for manual traffic control are described in details in Section V. Calibration and validation of proposed model using experiments data are presented in Section VI, respectively. Finally, Section VII provides concluding remarks, discussion and future work.

II. Literature Review

It has long been recognized that non-recurring events can cause at least half of total traffic congestion [4]. In terms of traffic congestion management, among all the solutions, traffic signal control is commonly considered as an important and effective method. Over years, a large amount of effort has already been invested in studying how to alleviate traffic congestion with traffic signal control. The literature on adaptive traffic signal control, multi-modal traffic signal control, traffic signal control with artificial intelligence, manual signal control, and human control behavior modeling, bears relevance to this research.

Nowadays, the most advanced and sophisticated traffic signal control systems are adaptive traffic signal control systems. Representative adaptive traffic signal control systems, including SCOOT [5], SCATS [6], RHODES [7], [8], UTOPIA [9] and PRODYN [10], have been developed in the past few decades. However, various practical limitations have restricted the practicability of adaptive signal control systems. Less than 100 out of 300,000 traffic signals in U.S are implemented with adaptive signal control systems [11], [12]. Further, it is well known that adaptive signal control systems still cannot manage oversaturated traffic, which commonly arises during events.

Recently, due to the advent of advanced communication technologies, multi-modal traffic signal control with Connected Vehicles has received attentions [13], [14]. A multi-modal signal control formulation called PAMSCOD, which relies only on significant level penetration of Vehicle-to-Infrastructure (V2I) communications, is proposed to consider priorities of bus, pedestrian and passenger cars [15]. This formulation is further revised to be more practical by assuming only traffic modes with priority (such as emergency vehicles, buses, and pedestrians) are equipped with V2I communication systems [16]. There also exist other signal priority control strategies [17], [18]. However, the previous work in multi-modal priority signal control did not directly address the specific issues during event occurrences, such as a massive amount of pedestrians, saturated traffic conditions, and so on.

Traffic signal control with artificial intelligence is another emerging research topic. With the rapid development of computer technology, artificial intelligent techniques, such as fuzzy logic [19], [20], neural networks [21], [22], evolutionary algorithms [23], [24], reinforcement learning [25], [26] and multi-agent technology [27], [28] are applied and expected to play important roles in more complicated traffic control systems. The results showed that intelligent control system has better performance and is more cost effective compared to a conventional fixed-time control system [29]. An agent-based approach is suitable to the traffic system because of its geographically distributed nature. It allows distributed subsystems collaborating with each other to perform traffic control and management based on real-time traffic conditions [30]. Several artificial intelligence based models, such as a multi-layer neural network model and a Kohonen Feature Map (KFM) method, were shown to be effective to classify traffic situations and useful to optimize signal timings so as to minimize the total weighted sum of delay time and stop frequencies compared with those by a conventional method [31]. Other studies leverage recent developments in parallel control and management for traffic control, which explicitly incorporates engineering and social complexities for modeling a large-scale system [32]. However, the existing traffic signal control methods with artificial intelligence neither are validated by real-world TCA's control experiences, nor can accommodate unexpected event traffic which contains multiple traffic modes and causes non-recurrent congestions.

Compared to automatic signal control, manual signal control is able to improve the management of congested signalized intersections due to its use of long cycle times, which is suggested to be implemented as part of automatic control [2]. The handbook of managing special events [1], emphasizes that traffic control officers have a large role in maximizing intersection operating efficiency. Recently, experiments of Hardware-in-the-Loop Simulation (HILS) were conducted to evaluate manual traffic control performance under oversaturated intersection [33], which drew the conclusion that manual traffic control had the best performance results among the proposed strategies at an oversaturated intersection. This conclusion is further confirmed in authors' prior work [3]. They developed a performance index based on TCAs' performance with both throughputs and delays. It was shown that manual traffic control can significantly (by roughly 30%) improve the control performance compared with state-of-practice actuated signal control.

There have been numerous attempts at modeling human behaviors based on obtained behavior data [34]–[37]. The simulation of human performance for analysis and prediction has taken the form of probabilistic models of cognitive processes in train control system modeling [38] and air traffic management [39]. Intelligent Agent-Based Model for Policy Analysis of Collaborative (IMPACT), which is also a simulation model, was used to capture the behavioral complexity of human decision-making in traffic flow management operations when weather disrupts airline schedules [40].

However, very few of previous studies have focused on modeling manual road traffic control behavior. To better improve event traffic management and operations, it is essential to model TCA traffic control behaviors and understand how they make decisions under different traffic conditions.

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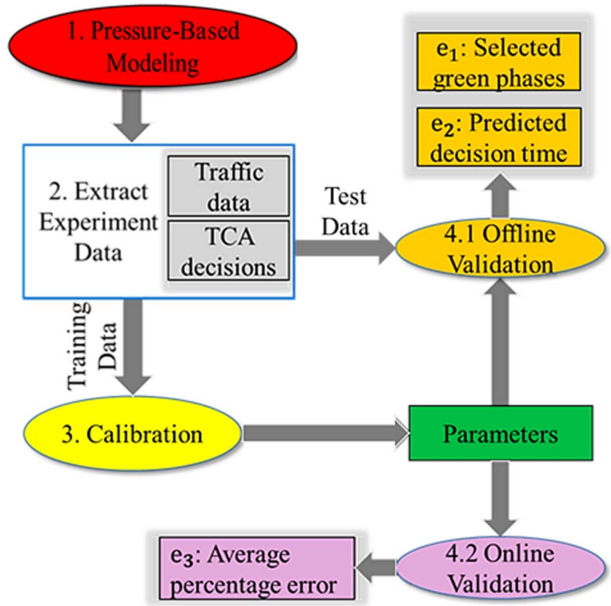

Fig. 1. Overall flowchart of TCA control behavior modeling.

III. Overview of Proposed Methodology

In this paper, TCA control behavior modeling consists of four stages, illustrated in Fig. 1. First, we propose a pressure-based human behavior model. Second, human-based simulation experiments are conducted to record TCAs' manual traffic control behavior. Third, a part of the data will be selected as training data to calibrate model parameters while the other part of the data will be test data applied to offline validation of the model in the fourth stage. The proposed pressure-based model is validated with both offline segment-based phase and duration prediction and online VISSIM-based simulation.

IV. TCA Traffic Control Behavior Modeling

A. *Pressure-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 an intersection. We assume that TCAs are aware of queue length and phase duration for each phase p at the intersection. TCAs carry out intersection control to serve vehicles or people waiting behind stop bar. Therefore, we consider they have a sense of obligation or pressure to provide "green" as a type of service. The pressure received from an approach depends on the total waiting time perceived [41]. Let S^p denote the TCA's pressure associated to the phase p. In this paper, TCA's pressure is associated with two attributes: phase queue information (Q^p), the phase red time (T^p). For timing phases, we set T^p equal to zero. Note that all the variables presented above are human perceived data, not the true data. We assume that TCAs can obtain accurate T^p information (e.g., through stop watch), but not accurate queue information. Therefore, we conduct a series of small human subject experiments to build the regression relationship between human interpreted queue information (*y*) and true queue information (*x*), presented in Appendix.

In order to combine the metrics reflecting both attributes in a single expression, we normalize both attributes using a genetic function, $\gamma(a^p)$, where $a \in \{Q, T\}$. The attribute, a^p, is divided by the maximal attribute across all phases. Thus the attributes can be transformed into range [0, 1] and compared among phases. $\gamma(a^p)$ is defined as follows:

$$\gamma(a^p) = \frac{a^p}{max_{p\in P}\{a^p\}}. \tag{1}$$

If phase p is composed of both pedestrian and vehicle traffic, a weight w_{ped} is assigned to pedestrian traffic. And then the genetic function will be modified as

$$\gamma(a^p) = \frac{a^p}{max_{p_1,p_2\in P}\left\{a^{p1}, w_{ped}a_{ped}^{p_2}\right\}} \tag{2}$$

where p_1, p_2 are vehicle phases and pedestrian phases, respectively. And a_{ped} represents the attributes of pedestrians. In this paper, we do not assign a particular weight for buses because TCAs usually treat buses as long passenger cars in many cases [3]. However, bus length has been taken into account in calculating the total queue length.

For each time step t, for phase $p \in P$, phase queue information is Q_t^p and the phase red time is T_t^p.Given normalized information, the approach defines the pressure score for phase p as a nonlinear combination of $\gamma(Q_t)$ and $\gamma(T_t)$ as shown below:

$$S(p) = w_q * \left[\frac{\gamma\left(Q_n^p\right) + \gamma\left(Q_l^{\boldsymbol{p}}\right) + \gamma\left(Q_r^p\right)}{3}\right]^2 + w_t * [\gamma(T^p)]^2 \tag{3}$$

where w_q and w_t are TCA specific weights for queue length and red time, respectively, which can be calibrated from TCA experiments. The queue information is represented by three variables, number of vehicles/pedestrians in the queue (Q_n^p), queue length in distance (Q_l^p) and queue-to-capacity ratio (Q_r^p). Note that each TCA has its own set of weights.

B. *Rule-Based TCA Signal Control*

Pressure can be categorized into green pressure and red pressure according to signal status. Pressure under current timing phases is denoted as green pressure. Similarly, pressure for current red phases is identified as red pressure. We assume the pressure for timing phases keeps decreasing since queue is discharging, whereas the pressure for other phases keeps increasing since queue is forming. The process of TCA decision making on phase termination and switch can be depicted as four sub-processes: 1) check if any red pressure is high enough; 2) check if any green pressure is low enough; 3) check if the minimal green is satisfied; 4) check if the maximal green is violated. We can describe these sub-processes using the following four rules:

1) Red-to-Green Rule: Red-to-green rule applies to red phases p at each time step. This rule is to compare the pressure of current red phase s_t^p with its red-to-green threshold s_{r2g}^p.

If $s_t^p \geq s_{r2g}^p$, then current red phase p will be the potential phase that would be changed to green at next time step.

2) Green-to-Red Rule: Green-to-red rule applies to green phases p at each time step. This rule is to compare the pressure of current green phase s_t^p with its green-to-red threshold s_{g2r}^p.

If $s_t^p \le s_{g2r}^p$, then current green phase is allowed to be changed to red at next time step. Note that both $s_{r2g}^p$and s_{g2r}^p are to be determined by training data.

3) MinGreen Rule: MinGreen rule also applies to green phases at each time step. This rule enforces that the green duration of each green phase should reach minimum green time to ensure safety.

4) MaxGreen Rule: Under oversaturated traffic condition, it is difficult to satisfy Green-to-red rule due to a large amount of arrivals. Therefore, MaxGreen rule is utilized to replace Green-to-red rule for green phases. We set a maximal green time for each phase. The MaxGreen rule is satisfied when the total amount of green time exceeds the maximal green time. Selected red phases will then turn green, and queues in corresponding phases will be discharged. It is worth mentioning that maximal green times are usually determined according to the congestion level as well as the event type. We set these values based on (1) TCA's survey and response in the interview, (2) TCA's actual performance in each scenario of the experiment. In this paper, maximal green times are 30∼60 s for left turning movements, 60∼80 s for through traffic on the side road, and 70∼100 s for through traffic on the main road. However, under some occasions (e.g., traffic after a football game), the maximal green time could be set to over 10 minutes due to extreme high volume of pedestrian flow.

To summarize rule-based TCA decision modeling, we define the following conditions under both of which a new traffic control decision, from phase p to phase p', can be made to change the phase status:

- Conditions for terminating timing phase p:
  - Green-to-red rule and MinGreen rule are both satisfied. Or
  - MaxGreen rule is satisfied
- Conditions for switching to phase p':
  - Red-to-green rule is satisfied.

If one considers dual ring structure (e.g., NEMA 8 phase dual ring configuration [42]), we will allow the next chosen phase timing together with its compatible phases.

V. Human Subject Experiments for Manual Traffic Signal Control

In order to better understand TCA's behavior, it is essential to conduct human subject experiments with real-world TCAs. The details of human subject experiments have been reported in our previous work [3]. Each experiment consists of two parts. In the first part, the TCA subjects were asked to take a 15-minutes interview, which covers the basic background (e.g., job title, work experiences, and etc.) and general control rules for manual traffic control under different circumstances, such as oversaturated conditions, traffic accidents, power outage, construction sites and planned special events. TCAs also reported their weights, or levels of priority, for different traffic modes. Given the assumption that ordinary passenger cars have weight equal to 1, and emergency vehicles 10, we found that TCAs tend to assign high weights to pedestrians in groups (average 6.4), and medium weights to buses (average 4.4).

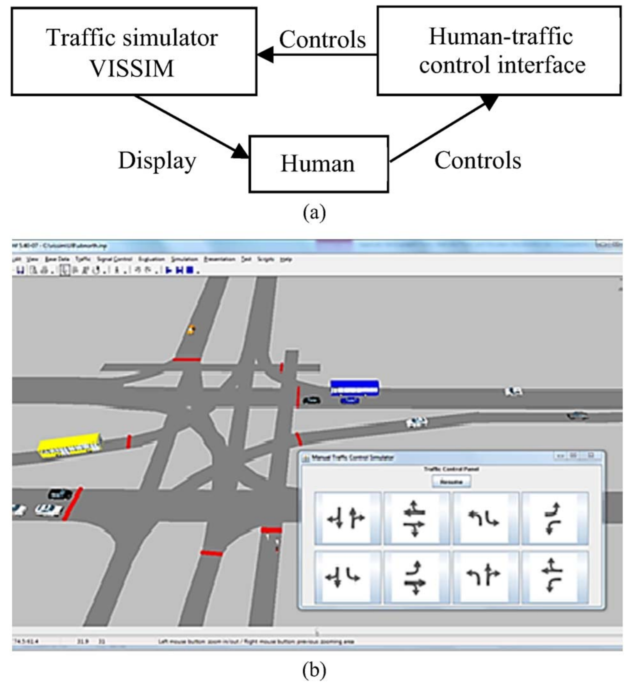

Fig. 2. (a) Components of the MIC-Sim; (b) Simulation interface of the MIC-Sim.

The second part is a simulation-based experiment, which lasts about 1 hour. The experiment was conducted using the Manual Intersection Control Simulator (MIC-Sim) shown as Fig. 2(a). Such human-in-the-loop simulator consists of three components in a loop: human, the human-traffic control interface and a microscopic traffic simulation tool, called VISSIM [43]. The traffic conditions, such as signal status, and number of vehicles in the queue, are displayed on the GUI and will dynamically change by animation. The traffic data used in the experiment was collected from a campus football game at University at Buffalo, scheduled at 7 pm, September 19, 2012. The game traffic, as shown in Fig. 3(a), was monitored two hours before its starting time. The prior game inbound traffic, including buses, pedestrians, and passenger cars were collected.

In the experiment, subjects were asked to apply their own control experiences to manually control traffic at the intersection close to the stadium. Once the subject perceives the traffic condition at the intersection, he or she can manually control the signal in real-time by clicking the corresponding traffic movement phases in the control panel, depicted in Fig. 2(b) Based on the geometry of the intersection, we designed a dual ring and six phase signal control configuration, shown as Fig. 3(b).

There are four scenarios tested in one subject experiment and each scenario will last 30 minutes in simulation (equivalent to 10 minutes in wall clock time). Scenario 1 and 2 simulate the prior-game multi-modal traffic, whereas Scenario 3 and 4 only contains passenger cars and buses. Scenario 3 is equivalent to Scenario 1 with pedestrian demand removed. Scenario 4 contains an artificial saturated traffic condition.

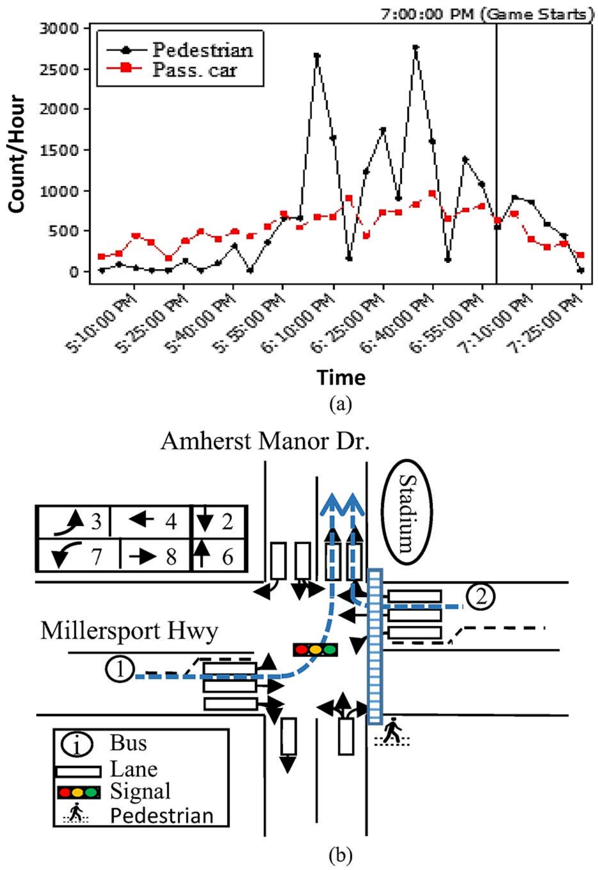

Fig. 3. (a) Prior-game inbound traffic counts at the intersection of Millersport & Amherst Manor on 9/19/2012(bus arrives every 15 minutes); (b) Layout of the test intersection.

8 experienced TCAs participated in the experiment, and their control decisions were recorded and presented in Table I. The number of decisions represents the number of times TCA switch timing phases. These eight subjects were of different genders, different job titles and had different years of experience in traffic control. Out of eight subjects, one was female while the rest were males. The age of TCA participants varied from 26 to 57 years old, with average age of 41 years old and standard deviation of 10 years. On average, TCA participants had 14 years of related experience, whereas the experiences in number of years ranged from 2.5 years to 27 years with standard deviation of 8.5 years. The frequency of TCAs' manual traffic control generally varied from 10 to 30 times per year.

Table I summarizes the TCA's decisions, which are defined as phase changes. The results include the number of decisions, mean and standard deviation of the 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. As one can see, more decisions (shorter phase duration) were made to control scenarios without pedestrians, which are Scenario 3 and Scenario 4.

VI. Calibration and Validation of Proposed TCA Behavior Modeling

In order to better calibrate the model, we divide the entire simulation horizon into N decision segments, where N denotes the total number of decisions. A decision segment is defined between two decision points, shown as Fig. 4. As depicted in Fig. 4. t_i^{dec} is the decision time point of the ith decision at which TCA changes the timing phase from one pair to the other. For example, during segment 1, the green phases are phase 2 and 6. At t_1^{dec}, TCA decides to change green phases to phase 3 and 7, which means the segment 1 is defined from $= 0$ to t_1^{dec}. Thus segments are divided by TCA's decision time points. For each decision segment, the starting time, the ending time, current

TABLE I
TCA Decisions in the Experiments

	Scenario 1							**Scenario 2**						
	N*	Mean green time (s) for phase p per cycle						N	Mean green time (s) for phase p per cycle					
TCA		2	3	4	6	7	8		2	3	4	6	7	8
A	45	21	12	25	21	13	19	47	26	13	21	28	19	14
B	42	28	14	25	28	17	18	31	37	18	37	37	22	28
C	36	26	21	26	26	24	22	43	23	16	21	23	20	16
D	30	33	22	37	35	27	28	37	30	18	28	33	21	23
E	37	21	20	22	21	20	22	43	21	20	20	21	20	20
F	47	20	13	27	18	14	22	51	20	14	22	20	15	19
G	49	36	17	18	23	17	18	58	18	15	14	18	15	14
H	32	33	24	31	33	24	31	35	39	20	28	31	19	31
	Scenario 3							**Scenario 4**						
	N	Mean green time (s) for phase p per cycle						N	Mean green time (s) for phase p per cycle					
TCA		2	3	4	6	7	8		2	3	4	6	7	8
A	60	14	7	15	14	10	9	69	14	11	17	13	14	12
B	37	30	15	33	30	20	22	39	22	20	28	22	22	24
C	--**	--	--	--	--	--	--	45	18	17	20	18	19	18
D	59	19	10	21	19	12	15	52	19	12	32	19	15	23
E	75	12	12	12	12	12	12	58	15	16	15	15	16	15
F	44	16	10	17	16	10	16	45	21	15	24	21	16	22
G	92	42	9	9	11	9	9	62	15	15	15	13	15	15
H	58	20	11	19	20	12	16	45	25	13	15	25	26	21

*: N is the number of decisions made in an experiment;
6 phases are illustrated as shown in Fig.3(b).
**: The TCA's data was not collected due to wrong simulator operations.

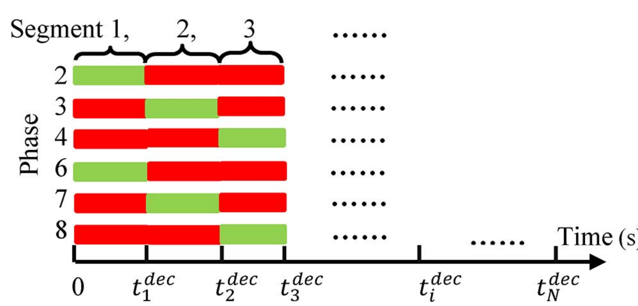

Fig. 4. Description of segments through one experiment.

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green phases and current red phases are recorded to further analyze their manual control behavior.

A. Model Calibration

TCA's profile data, traffic conditions (e.g., multi-modal traffic demand, and event characteristics) and performance data were obtained in previous manual traffic control experiment. A portion, 60%, of this experimental data will be randomly selected as training data set, $M_{training}$ and then utilized to calibrate the parameters in the model. The rest 40% of the data will be used to validate the model as test data set, M_{test}. The performance of the pressure-based decision model is given by two kinds of errors, e_1 and e_2. e_1 (in percentage) measures the portion of incorrectly predicted next timing phases, whereas e_2 (in seconds) measures the mean absolute deviation (MAD) between predicted and actual phase duration. Therefore, the smaller e_1 and e_2, the more accurate the proposed model will be. e_1 is defined as follows:

$$e_1 = \frac{n_e}{n_{total}} \tag{4}$$

where n_e is the number of incorrectly predicted timing phases, and n_{total} is the total number of selected timing phases in each experiment horizon. e_2 is corresponding to the time points when the decisions are made, defined as follows:

$$e_2 = \frac{\sum_{i \in M} |t_i^p - t_i^a|}{|M|} \tag{5}$$

where M is the set of decisions made by a TCA in the corresponding experiment, $t_i^p$is the predicted phase duration by the model and t_i^a is the actual phase duration of ith decision segment.

Due to a small number of unknown parameters, we develop an exhaustive search algorithm to calibrate proposed pressure-based model. The search algorithm aims to find minimal errors by adjusting parameters w_q, w_t and w_{ped}.

Let N_q be the number of possible choices for w_q, N_t for w_t, and N_{ped} for w_{ped}, respectively. K stands for the total number of possible combinations of w_q, w_t and w_{ped}. Thus K is equal to $N_q * N_t * N_{ped}$. The main steps of the search algorithm are presented in Fig. 5. The time step for the experiment is set to be 1 second.

Parameters for each subject are aggregated by scenarios. Scenarios 1 and 2, which include pedestrians, cars and buses, have the same parameters for each subject. Meanwhile, scenarios 3 and 4 have the same parameters since both of them include only cars and buses. The calibrated parameters for experiments are shown in the following Table II.

B. Offline Model Validation

We develop two validation methods: offline validation and online validation. The major differences between offline validation and online validation are listed as follows:

- Validation levels: Offline validation focuses on each decision segment, whereas online validation considers the entire simulation horizon.

1. Initialize a search vector W_k=[w_q^k, w_t^k, w_{ped}^k] , k = 1,...,K, where K represents the total number of combinations of weights. Let k = 1.
2. For each iteration $\{k \le K\}$, w_q=w_q^k, $w_t = w_t^k$ and $w_{ped} = w_{ped}^k$.
3. For each $\{i \in M_{training}\}$ decision segment, t_i^{dec} is the decision time point. Using (1) to calculate red-to-green press for current red phase as $\{ s_{i,r2g}^{p_r}, p_r \in P_{red} \}$; calculate green-to-red press for current green phase as $\{s_{i,g2r}^{p_g}, p_g \in P_{green} \}$.
4. Do exhausted search for thresholds within [-θ%, +θ%] fluctuation range of $avg(s_{i,r2g}^p)$ and $avg(s_{i,g2r}^p)$. Let set $\{\Phi\}$ present all possible searching combinations of thresholds.
5. For all $\{\phi \in \Phi\}$, predict control decisions for all decision segments. Each decision segment j starts from t_j^{start}. Use (1) to calculate s_t^p for each phase $p \in P$, at time step $t \in [t_j^{start}, t_j^{end}]$with parameters in step 2. Use (4) and (5) to calculate e_1 and e_2. Save the thresholds with the smallest e_1.
6. Set $k = k + 1$. Go to step 2.
7. Stop while $k > K$. Return the smallest weighted error $\alpha e_1 + \beta e_2$, with corresponding parameter set and thresholds.

Fig. 5. Search algorithm for calibrating parameters.

TABLE II
CALIBRATED PARAMETERS AND OFFLINE VALIDATION RESULTS

	Parameters			**Scenario 1**			**Scenario 2**		
TCA	w_q	w_t	w_{ped}	PI*	e_1	e_2	PI	e_1	e_2
A	2	10	5	0.20	0.15	18.64	0.41	0.14	8.53
B	2	5	3	0.18	0.16	12.75	0.06	0.21	13.59
C	2	5	2	0.10	0.04	10.10	0.45	0.03	18.23
D	2	10	2	0.03	0.05	11.48	0.23	0.07	11.88
E	6	10	3	0.49	0.07	13.13	0.52	0.06	8.68
F	6	5	2	0.39	0.08	10.54	0.71	0.14	5.67
G	6	5	2	0.38	0.11	13.52	0.62	0.04	7.48
H	4	5	2	0.18	0.08	10.36	0.17	0.12	8.99
	Parameters			**Scenario 3**			**Scenario 4**		
TCA	w_q	w_t	w_{ped}	PI	e_1	e_2	PI	e_1	e_2
A	6	10	0	0.46	0.13	3.69	0.24	0.15	5.43
B	4	10	0	-0.20	0.11	5.87	0.09	0.07	6.70
C	2	10	0	0.08	N/A	N/A	0.32	0.03	5.03
D	2	10	0	0.21	0.11	4.57	0.18	0.13	23.77
E	10	15	0	0.35	0.03	6.58	0.35	0.04	5.63
F	2	15	0	0.19	0.09	6.33	0.13	0.06	3.94
G	2	10	0	0.48	0.03	2.65	0.77	0.04	3.50
H	4	5	0	0.31	0.13	7.64	0.12	0.12	10.35

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

- Validation measures: Offline validation examines only by the number and duration of next timing phases. However, online validation explores not only the phase decisions but also the simulation outcomes (e.g., delay, number of stops, etc.).

- Validation methods: Offline validation is conducted by offline calculation, whereas online validation is conducted with VISSIM online simulation.

In the stage of offline validation, the calibrated models are fed with test data to obtain e_1 and e_2. Table II reports the prediction errors for eight subjects who participated in the previous simulation experiments of four different scenarios with corresponding performance index (PI), which is positively related to TCA's control performance [3].

Some values are "N/A" because the corresponding TCA did not correctly operate the simulator during the experiment. One can see from the table that most of e_1, which is the rate of incorrectly predicted phases, are below 0.2, and the smallest value is 0.03 which means the accuracy of choosing next timing phases can be up to 97%. And the average accuracy of choosing next time phases is 91%. In general, e_2 gives an acceptable result with average deviation 9.2 seconds among different cases. e_2 in non-pedestrian scenarios (Scenario 3 and Scenario 4 with average error 11.45 seconds) is much higher than multi-modal scenarios (Scenario 1 and Scenario 2 with average error 6.78 seconds). This could be explained by the fact that TCA's control behavior with pedestrian involved traffic varies more and is more difficult to be predicted.

For scenario 1 and 2, it is shown in the table that the calibrated pedestrian weights, w_{ped}, display only small fluctuations, which indicates TCAs gave similar priority to the pedestrians. Moreover, those TCAs who gave more weights to queue information, w_q, turn out to be the ones with high PI values, including E, F and G. This indicates that TCAs who paid more attention to queue information performed manual traffic control better. In other words, they were more responsive to the traffic conditions. Since scenario 3 and 4 contain either light or heavy traffic, the weights assigned for phase red time w_t are typically higher than that of queue information w_q. Therefore, TCAs manual traffic control manner for these two scenarios is less responsive to queue information.

Fig. 6 represents the relevance between PI and phase accuracy of each experiment. There is no strong relationship between model accuracy and PI. It is shown in the figure that the next timing phases can be predicted with 80% accuracy for different TCAs. That means the proposed model can adapt to mimic the behavior of both "good" TCAs and "bad" TCAs.

C. Online Model Validation

Besides offline validation, it is essential to conduct online manual traffic control to validate proposed model. Since TCA intersection control is a rare event, and there are no duplicate experiments in the same location with the same traffic demand. Therefore, it is very challenging to use field control data to systematically model TCAs' behavior. Moreover, one may hardly get entire intersection queue information, including number of vehicles in the queue and queue length, from videotaping TCAs' control behavior, especially under oversaturated event traffic conditions.

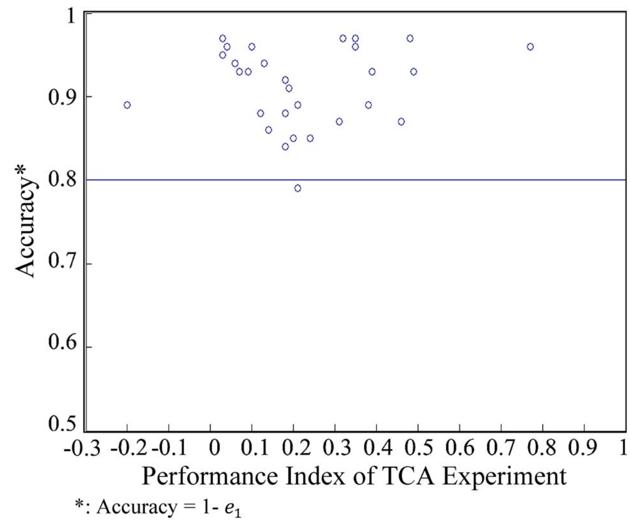

Fig. 6. Accuracy versus PI of offline model validation.

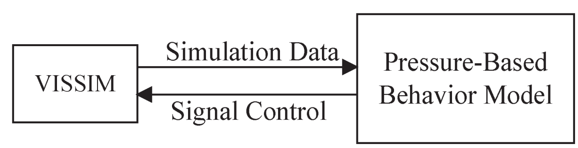

Fig. 7. Java-VISSIM simulation flowchart.

Therefore, validation with microscopic simulation is considered to be an effective way to validate the model. The simulation-based validation is also built on VISSIM with COM (Component Object Model) technologies and Java, shown as Fig. 7. The major difference between simulation-based validation and MIC-Sim is that, the pressure-based model, instead of a real TCA, will make decisions by taking advantage of all captured traffic information in the simulation. Calibrated parameters and thresholds, shown in Table II, will be further applied in the simulation scenarios, which are identical with the scenarios defined in TCA experiments.

Simulation-based validation is conducted for each experiment with corresponding parameters. The result of the simulations is presented by the following two types of attributes. One type is traffic performance-related attributes, which include average delay time per vehicle, average number of stops per vehicle, average speed, network throughput, and total travel time. The other type is phase related attributes, which include green time allocation percentages of different phases.

The performance of online validation is evaluated by average percentage error (APE) of each attribute, e_3^i

$$e_3^i = \frac{(v_i^p - v_i^a)}{v_i^a} \times 100\% \tag{6}$$

where v_i^a is the value of ith attribute in the TCA experiment, and v_i^p is the value of the same attribute predicted by proposed model in online simulation.

The fluctuation of phase pressure is illustrated as shown in following Fig. 8.

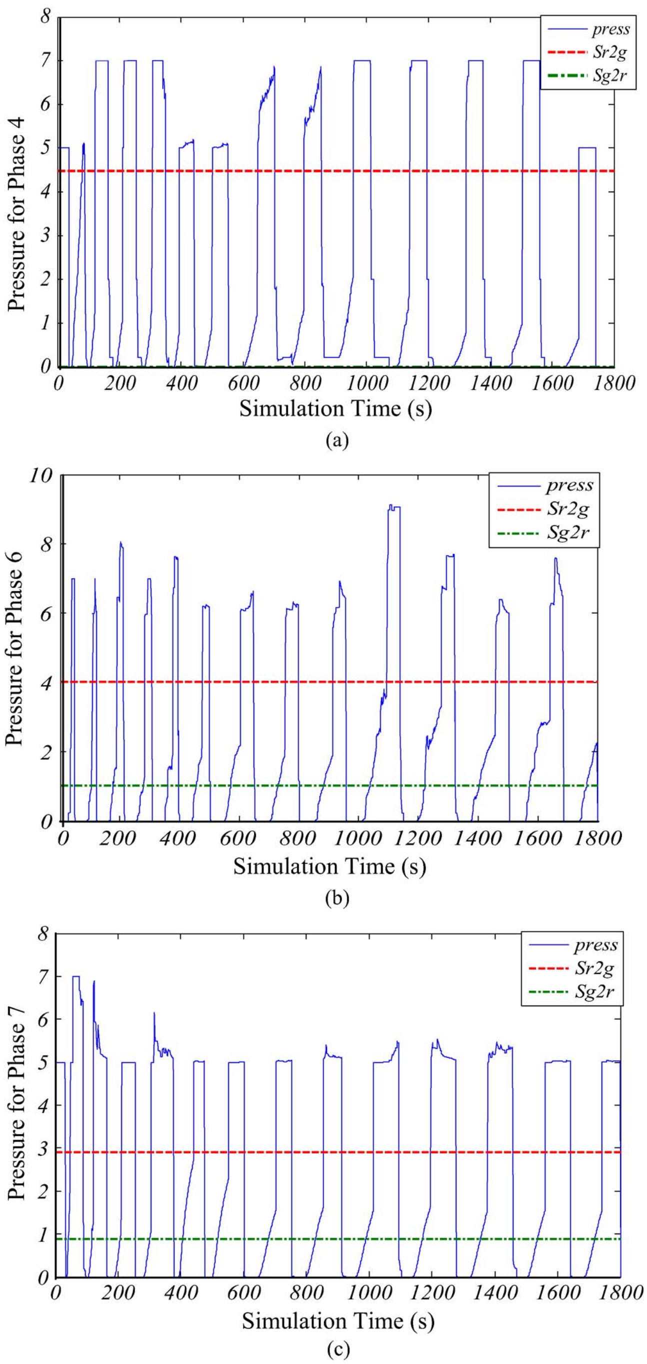

Fig. 8. (a), (b), (c) Pressure for Phase 4, Phase 6 and Phase 7 during the online simulation of Scenario 2, respectively.

Fig. 8 illustrates the change of pressure in Phase 4, Phase 6 and Phase 7 during the simulation of Scenario 2. It is clearly shown that the pressure increases when the phase is currently red and then drops sharply after the phase turns green. The top reference line represents s_{r2g}, and the lower reference line s_{g2r}. One may notice that s^4_{g2r} is equal to 0, whereas s^6_{g2r} and s^7_{g2r} are positive. Such phenomenon indicates that TCA tends to clear the queue on the main street (Phase 4) before terminating the current green. However, under the same situation, they may keep some residual queue for the minor street (Phase 6) and left turns (Phase 7). Moreover, left turn phases usually has low red-to-green pressure threshold (s^7_{r2g}), compared with the ones in through phases (s^4_{r2g} and s^6_{r2g}).

TABLE III
COMPARISONS OF ONLINE VISSIM PERFORMANCE INDICES IN APE BETWEEN PRESSURE-BASED MODELS AND TCA EXPERIMENTS

Listed attributes	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average delay time per vehicle	0.162	0.239	-0.169	-0.121
Average number of stops per vehicles	0.132	0.129	0.048	0.003
Average speed	-0.035	-0.068	0.058	0.074
Network throughput	0.006	-0.008	-0.001	-0.007
Total travel time	0.055	0.082	-0.051	-0.066
Green time in phase 2	0.291	0.240	0.301	-0.096
Green time in phase 3	-0.013	-0.050	0.238	0.229
Green time in phase 4	-0.202	-0.107	-0.215	-0.004
Green time in phase 6	0.271	0.249	0.301	-0.096
Green time in phase 7	0.184	0.172	0.318	0.306
Green time in phase 8	-0.235	-0.175	-0.190	0.014

Table III summarizes the detailed comparisons in e^i_3 between the pressure-based model and TCA experiments in different attributes collected in VISSIM.

The positive values in the table indicate that the overestimated value of the corresponding attribute in the simulation compared to that in the experiment. Similarly, the negative values indicate underestimation. Overall, the results from online simulations are close to those of TCA experiments. It is observed again that TCA's behavior under vehicle-pedestrian mixed traffic is more difficult to predict than under only vehicular traffic. For Scenario 1 and 2 (with pedestrian traffic), average delay time per vehicle is observed to clearly increase in the online simulation whereas other traffic attributes change slightly. For scenarios 3 and 4 (without pedestrian traffic), average delay time per vehicle, total travel time, and the rest of traffic attributes turn out to remain almost the same, within 10% difference, as those in the TCA experiments.

Moreover, the percentage errors of green time allocation vary from one scenario to the other and also from one phase to the other. In Scenarios 1 and 2, more green time is allocated to phase 2 and 6, which has a large number of pedestrians involved. It may be suggested by the reason that proposed offline calibration model overestimates both red-to-green threshold s_{r2g} and green-to-red thresholds, s_{g2r}. In Scenarios 3 and 4, more green time is allocated to left turning phase 3 and 7. This may be because the red-to-green thresholds, s_{r2g}, as well as the green-to-red thresholds, s_{g2r}, for left turning phases are underestimated than those of other phases, which makes phase 3 and 7 easier to switch from red to green but more difficult to change from green to red.

VII. FIELD EXPERIMENTS

To further validate proposed model, TCA's control behavior has been videotaped by two cameras simultaneously at a real-world intersection Abott Rd. and Southwestern Blvd. at

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

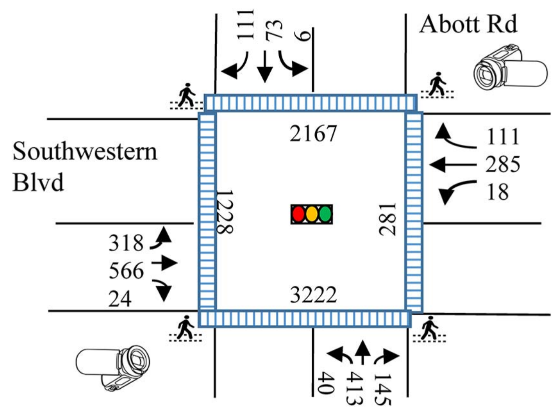

Fig. 9. Multi-modal post-game traffic during peak hour in Bills game on October 13, 2013.

Buffalo, NY, U.S. during Buffalo Bills Football Game on October 13, 2013. The total number of attendees for that game is around 68,000. This study focuses on post-game traffic, which consists of a huge volume of mixed pedestrian and vehicular traffic. The peak hour traffic diagram at Abott and Southwestern is presented in Fig. 9. As one can see, the pedestrian demand is much higher than vehicular demand. Therefore, in addition to vehicular phases 1–8, we defined separate phases 9–12, exclusively for pedestrians.

Total 1.5 hour video data has been collected. We treated first-hour data as training data and the last half hour as test data. In order to obtain high-resolution decision segments, we discretized time horizon into 10 second intervals, during which queue length, red times and timing phases have been recorded for each phase, respectively. The model aims to predict the next interval's timing phases based on the queue length, red time, and four different rules during the current interval. Due to defined high-resolution decision segments, we only examine the performance results for e_1. Out of 180 decision intervals, the model correctly predicts the timing phases for 140 intervals, with e_1 equal to 0.22. Therefore, the results indicate that the model can produce good accuracy in prediction of TCA's decision making. Note that the shortcoming of field experiment is that the traffic scenario is not repeatable. It is difficult to compare different TCAs' behavior during the same traffic conditions.

VIII. Discussion and Concluding Remarks

When event traffic over-saturates the network, there exists much need for understanding the mechanism to efficiently conduct network-wide TCA-based manual intersection control, as well as answering the questions of how to efficiently train TCAs and where to deploy TCAs. This paper proposes a pressure-based human behavior model to predict the decision behavior of manual intersection control for multi-modal traffic given various traffic conditions. The model is calibrated and validated by the data from manual traffic control experiments based on a human-in-the-loop simulator. And it is further validated by online microscopic traffic simulations with VISSIM and field videotaped TCA control data. Both validation results show that the proposed pressure-based human behavior model can predict the TCAs' traffic control behavior within acceptable errors. This proposed model explicitly considers human factors in the manual intersection control, which has not received adequate attention.

This study has produced several findings of TCA's control behavior:

1) TCAs who show a better traffic control performance are more responsive to queue information than phase red time.
2) When traffic demand is either light or heavy, TCAs pay more attention to total waiting time in red phases than queue information.
3) If pedestrians are involved, more green time, as well as cycle length, are allocated by TCAs, in order to discharge people and ensure safety.
4) Under oversaturated traffic conditions, TCAs tend to assign more green time on major roads to reduce overall traffic delay.
5) TCAs' tolerance in red-to-green for left turn movements is lower than through traffic movements.
6) TCAs usually clear the queue on the main approach before terminating the green phase, whereas they may keep some residual queues for the side approach or left turns.

With proposed pressure-based human behavior model, one may be able to develop a human-operator based network traffic simulator. Such simulator can evaluate the event-based traffic control plans with different TCA deployment strategies. It could be a potential useful tool for TCA training and online TCA deployment under event occurrence to increase the efficiency of proactive event traffic operation.

TCA deployment strategies can be implemented to human-involved transportation control systems to manage traffic under unexpected events and allocate resources in an effective approach. The traffic control systems will not only consider intersection control and TCA deployment, but also take all other event control elements, such as event parking, road closures, emergency access, and trip planning. Further, this control system can be extended to decision support systems for urgent events, such as traffic incidents, inclement weather and natural disasters, under which prompt TCA deployment and traffic control response are needed. More real-time traffic information and coordination will be required to such responsive conditions, which leads to more challenges and research problems to be addressed.

Appendix
Subjective Perception Experiments for Traffic Conditions

In this experiment, human subjects were asked to report the queue conditions on the pictures. The pictures were taken under different traffic conditions, including uncongested, congested and nearly saturated conditions. Sample pictures are as shown in Fig. 10. Three types of queue information, number of vehicles in the queue, queue length (in meters) and queue-to-capacity ratio, were taken into consideration in the experiment. The data collected from the subjects' experiments was used to

Fig. 10. Sample pictures used to conduct the experiment.

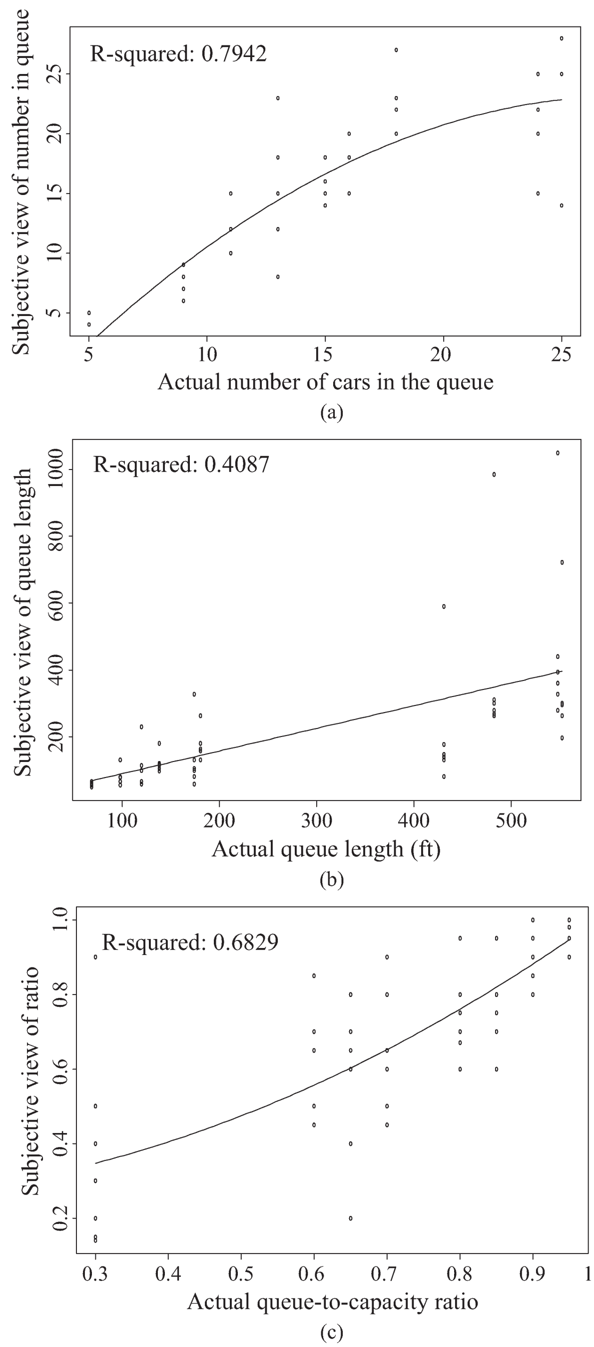

Fig. 11. (a) Regression plot of subjective perception of number of cars in the queue; (b) Regression plot of subjective perception of queue length; (c) Regression plot of subjective perception of queue-to-capacity ratio.

fit the regression model to describe the relationship between human perceived queue information and true queue information.

Ten subjects participated in the experiment. After presented by each picture for 3 seconds, they were asked to report their perceived queue information for each picture. Such data was aggregated to analyze subjective perception of traffic conditions.

Regression function for number of cars in the queue is shown as below

$$\boldsymbol{y_n = -7.686 + 2.219 \cdot x_n - 0.040 \cdot x_n^2}. \tag{a1}$$

Where x_n is the actual number of cars in the queue, y_n is the subjective perception of number of cars in the queue.

Regression function for queue length in distance is presented as follows:

$$\boldsymbol{y_l = 22.158 + 0.677 \cdot x_l}. \tag{a2}$$

Where x_l is the actual queue length, y_l is the subjective perception of queue length.

Regression function for queue-to-capacity ratio is listed as below

$$\boldsymbol{y_r = 0.253 + 0.123 \cdot x_r + 0.639 \cdot x_r^2}. \tag{a3}$$

Where x_r is the actual queue-to-capacity ratio, y_r is the subjective perception of queue-to-capacity ratio.

As one can see from Fig. 11, people tend to underestimate all the queue information, especially under long queues. In addition, there still exist large variations of people's subjective perception. We found people showed much more consistent perception in estimating number of cars in the queue ($R^2 = 0.79$) and queue-to-capacity ratios ($R^2 = 0.69$) than queue length in distance ($R^2 = 0.41$).

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