Accommodating high value-of-time drivers in market-driven traffic signal control

Conference Paper · June 2017

DOI: 10.1109/IVS.2017.7995888

2 authors:

Isaac K. Isukapati
Carnegie Mellon University

Stephen F. Smith
Carnegie Mellon University

Accommodating High Value-of-Time Drivers in Market-Driven Traffic Signal Control

Isaac K Isukapati
The Robotics Institute
Carnegie Mellon University
Pittsburgh, PA 15213
Email: isaack@cs.cmu.edu

Stephen F Smith
The Robotics Institute
Carnegie Mellon University
Pittsburgh, PA 15213
Email: sfs@cmu.edu

Abstract*—In this paper, we propose a market-driven approach to traffic signal control. In contrast to traditional traffic engineering approaches, our approach gives agency and decision-making influence to individual drivers and exploits auction mechanisms to make traffic control decisions. Drivers make payments to their corresponding movement managers (each responsible for a particular directional flow through the intersection), and movement managers then compete for control of the signal. These financial transactions, if treated literally provide an alternate source of funding transportation infrastructure. Previous work with this model has demonstrated the ability to achieve better overall traffic flow performance than actuated control, a simple adaptive traffic signal control strategy based on detection and monitoring of waiting vehicles. Here we consider the design and analysis of bidding strategies capable of factoring in a given driver's value of time (VOT), as indicated by the amount of voluntary contributions that are made on top of the fixed fee that every driver is charged. We analyze the potential for expediting high VOT drivers without undue disruption of overall traffic flows.

I. Introduction

The emergence of connected and autonomous vehicle technologies will enable real-time vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, presenting new opportunities for managing traffic flows at signalized intersections. A typical signalized intersection(see Figure 1) uses a *signal timing plan* to dictate operations. All timing plans (fixed or adaptive) assign and specify durations of green times to compatible vehicle paths known as movement phases (e.g., east-west, north-south, adjacent left turns, etc.). To ensure safe operations, constraints (yellow and all-red periods) are imposed between phases transitions. Traditionally, the generation of signal timing plans has been treated as an offline resource allocation problem where expected flow volumes are used to construct pre-determined phase sequences and corresponding green durations that simply repeat from one cycle to the next. Increasingly, sensors are being used to detect real-time traffic flows and dynamically adapt green time allocation, and the prospects of even more ubiquitous sensing have led to a range of agent-based models for traffic signal control [1] incorporating such concepts as reservation-based intersection management [2], and learning traffic control agents [3], [4]. However, even in these cases, approaches have followed the classic traffic engineering perspective of optimizing overall system performance at the expense of any individual vehicle. With the advent of V2I communication, it becomes possible to consider approaches that give drivers agency and involve them directly in traffic control decision-making.

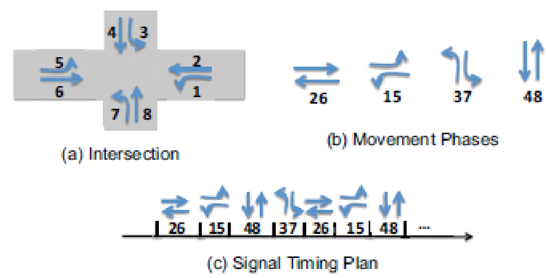


Fig. 1: Overview of signal timing plan (taken from [5])

Such thinking has led to the application of such non-traditional theoretical frameworks as competitive economic markets to traffic signal control [6], [7], [8]. These approaches start with the assumption that drivers will pay a fee to move through signalized intersections, and investigate schemes that provide the right dynamics under this assumption. Although at first glance this assumption may seem unrealistic, this is not necessarily the case. In the US, for example, traffic signal infrastructure is funded largely through the Federal Gas Tax, which has been a shrinking revenue stream and will continue to decline in the future as the electrification of vehicles progresses. Alternative means for maintaining infrastructure will eventually have to be found and the idea of shifting the burden of infrastructure cost to those that create congestion is not that unreasonable. On the other hand, economically-based models of traffic signal control can be interpreted and implemented figuratively, if the main objective is not to collect fee from drivers but understand the economics of signal control operations.

Our particular interest in this paper is the work of Isukapati [8]. This work is unique in considering an economic decision-making model that incorporates the basic safety and fairness constraints that govern traffic signal control decisions in practice. It proposes a multi-tiered framework where drivers make basic payments to traverse intersections and also have the option of making additional voluntary contributions to reduce their wait time. Variants of this approach [9], [10], [11] have been shown to outperform actuated control, a basic form of adaptive traffic signal control that is in wide use today. However, the ability to expedite high value of time (VOT) drivers without causing arbitrary delay to passive drivers that are just interested in paying the toll has remained elusive.

In this paper, we specify and analyze a more basic variant of this multi-tiered market model to better understand the circumstances under which demands of high VOT drivers can be accommodated with bounded effect on overall traffic flows. As in previous work, we assume a model with two classes of drivers, low VOT drivers who pay only a nominal fee to cross the intersection and high VOT drivers who are willing to make additional contributions in hopes of minimizing delay. Since the problem formulation is as a non-cooperative game, the establishment of bidding strategies that achieve the desired control behavior is difficult, and any attempt to bias auction results toward high VOT drivers runs the risk of causing behavior to degenerate. We present a set of bidding strategies that effectively expedites high VOT drivers without undue disruption to overall system performance, and analyze its performance impact on both classes of drivers under various traffic flow volume assumptions. In some circumstances, we observe that low VOT drivers also benefit from riding on the coattails of high VOT drivers.

The rest of the paper is organized as follows: Section 2 presents details of the proposed model, Section 3 describes the results of simulation experiments carried out on an isolated intersection, Section 4 discusses the performance characteristics of the model, and Section 5 provides conclusions and points out future lines of work.

II. Market Based Traffic Signal Control Model

We assume that traffic signal control is realized as a result of economic exchanges between three types of agents:

- *Drivers*, who are intent on moving through the intersection,
- *Movement Managers*, who bid to promote green time for the particular movement phase through the intersection that they represent, and
- *The Municipality*, a designated agent that arbitrates the bids of competing movement managers.

Drivers (active or passive) pay to move through the intersection. Movement managers collect a mandatory fees from all drivers (active, passive, and whether they arrive on green or red) and voluntary contributions (if any) from the drivers (vehicles) waiting in their queues, who are interested in expediting their service time. Movement Managers use these collected funds to bid for control of the intersection from the Municipality. From the bids issued on any given decision cycle, the Municipality determines whether to extend the current green phrase or to initiate safety clearance events (yellow and all red transition sequences) and allocate green time to the next movement phase.

More precisely, we assume that each vehicle communicates its expected arrival time to the intersection upon approach, and from communicated location and speed information, the corresponding movement manager can determine the vehicle's queue entry time. For simplicity we assume a single lane in each direction approaching the intersection and hence a first come, first served service policy, but the ideas to be presented can be straightforwardly generalized to multiple approach lanes. Each vehicle pays its obligatory fee and as it joins the queue at the intersection it is free to contemplate making additional contributions. The intersection control decision is revisited every g_{ext} seconds if the last control decision was to extend the current phase; any time that a control decision shifts the green to the next movement phase then the new phase will get the green for at least the specified minimum green time for the phase, g_{min}, and assuming that the intersection clearance time is c, the control decision will be revisited after $c + g_{min}$ seconds. g_{min} is a basic fairness constraint set by municipality traffic engineers and typically $c + g_{min} >> g_{ext}$.

A. Movement Managers

Movement managers are unaware of the vehicle arrival patterns or state of other intersection movement phases, and base their bid decisions on local information. To formulate a bid at any given control decision point, each movement manager considers three parameters: (1) the average bid ($\bar{b_i}$) based on the last n bid-cycles ($n = 50$ for the experiments reported in this paper), (2) the probability (Pr_i) of submitting a losing bid during the last n bid-cycles, and (3) the percentage of high VOT drivers'(η_i) in the movement manager's queue. Algorithm 1, describes the formula used to compute the bid. The rationale behind the formula is to submit a higher bid when either there are high VOT drivers in the queue, or there is an increase or decrease in the bid depending on success in submitting a winning bid. Before submitting bid (b_i) the movement manager confirms that there are sufficient funds to accommodate at least the nominal fee to discharge the rest of the vehicles in the queue. To meet this budget constraint, bid (b_i) is adjusted downward as necessary to ensure movement manager's solvency.

Algorithm 1: Movement Manager i's bid computation

1: $\bar{b_i}$ = average bid over the last n bid-cycles
2: Pr_i = probability of losing a bid over the last n bid-cycles
3: η_i = percentage of high VOT drivers in queue
4: $b_i = \bar{b_i} \times [0.5 + \mathrm{Pr}_i] \times [1 + \eta_i]$
5: lower b_i in case of impending insolvency

B. Drivers

High VOT drivers make voluntary monetary contributions to expedite their movement, as their perception of expected delay increases. Upon entering the queue at the intersection, a high VOT driver computes an initial estimate of expected delay, and this expected delay is updated at each successive bid cycle. When increases in expected delay are observed, the driver attempts to compensate by making additional contributions to its movement manager.

To compute an initial estimate of expected delay, let x_j^0 be driver j's initial position in the queue and $\overline{h_s}$ be the saturation headway (i.e., the amount of time it takes two successive vehicles moving in a platoon to cross the same point on the road, head to head). Then driver j's initial delay estimate, $\hat{d}_j$, is given by:

$$\hat{d}_j = x_j^0 \times \rho_j \times \overline{h_s} \tag{1}$$

where ρ_j is a bid win factor that reflects how frequently driver j's movement manager is expected to win the bid. For this paper, high VOT drivers assume that their movement manager will win every other bid, which will result in doubling the time it takes for the driver to pass through the intersection (i.e., $\rho_j = 2$).

Algorithm 2: high VOT driver's decision process

1: Let c_j = cost of delay per second
2: compute initial estimate of delay upon arrival (eq. 1)
3: update belief about estimated delay (eq. 2)
4: compute $\delta_d = d_j^{k+1} - \hat{d}_j$
5: **if** $\delta_d > 0$ **then**
    $\epsilon_j = \delta_d \times c_j$;
    compute $p(cont)$ (eq.3) ;
    $p = U(0,1)$ sample from uniform distribution
  end
6: **if** $p \leq p(cont)$ **then**
    make a contribution ϵ_j
  end

During each successive bidding cycle $k = 1, 2, 3, ...$ after joining the queue, driver j updates its delay estimate, based on the movement manager's actual win ratio and its current position in the queue. The estimate is adjusted upward if the movement manager loses (more likely to lose in the future), and downward if the movement manager wins (increased chances of winning). More precisely, d_j^{k+1} is computed as follows:

$$d_j^{k+1} = d_j^k + x_j^k \times (1 + p_j^{k+1}(l|D_j^k)) \times \overline{h_s}, \tag{2}$$

where:

- d_j^{k+1} = estimated delay of queued vehicle j in $(k+1)^{st}$ bidding cycle
- d_j^k = actual delay of queued vehicle j at the end of k^{th} bidding cycle
- x_j^k = position of vehicle j in queue at the end of k^{th} bidding cycle
- D_j^k = bidding outcome data that driver 'j' collected since the time he/she joined the queue until the end of k^{th} turn
- $p_j^{k+1}(l|D_j^k)$ = probability that the movement manager loses in $(k+1)^{th}$ turn

Drivers estimate $p^{k+1}(l)$ based on bidding outcome data since the time they joined until the end of the k^{th} turn (D_j^k). The rationale underlying the update procedure described in equation (1) is that as $p_j^{k+1}(l) \rightarrow 1$ the estimate of anticipated delay increases, and as $p_j^{k+1}(l) \rightarrow 0$ the estimate of d_j^{k+1} goes down.

Every bid-cycle, drivers compute the difference between the updated and initial estimates of their expected delay. If this difference in delay (δ_d) is positive, there is a likelihood that the driver will make a voluntary monetary contribution and that likelihood function is given by:

$$p(cont) = \frac{1}{1 + e^{10 \times (p(w) - 0.5)}} \tag{3}$$

If the drivers anticipate expected delay to increase, they make a voluntary contribution (ϵ_j) equivalent to the product of (δ_d)and c_j (cost of delay per second) to expedite their service.

C. Municipality

The municipality coordinates the bid cycle process carried out by movement managers and makes decisions about how to assign control of the traffic signal among movement managers. For the traffic control model considered in this paper, we restrict attention to intersections with just two movement phases: an east-west movement and a north-south movement. (We briefly discuss extensions to more complex intersections at the end of the paper). In this context, the municipality is partitioning control of the intersection to two movement managers and at any point in time we can distinguish the *enfranchised* manager (which currently has the green) and the *disenfranchised* manager (which is waiting for the green). As mentioned earlier, the municipality enforces standard safety and fairness constraints; the former referring to the clearance interval c from one phase to the next, and the latter corresponding to a minimum green time g_{min} for each phase. These constraints dictate when the next bid-cycle is scheduled by the municipality whenever a control decision is made, i.e., after $c + g_{min}$ seconds if shifting from one phase to the other; after g_{ext} seconds or until the next vehicle arrives (whichever comes first) otherwise.

During a given bidding event, if only one movement manager has a queue to be serviced then that manager is an automatic winner; upon paying the nominal fee to the municipality, movement manager is allocated the intersection for the next period (as determined above). During this time, the movement manager discharges vehicles in it's queue consistent with a pre-specified discharge distribution.

Algorithm 3 describes the procedure for bid-cycle assignment for scenarios in which both movement managers have service queues. As one might notice the municipality collects three pieces of information from each movement manager: 1) bid (b_i); 2) average delay of vehicles in queue ($\hat{d}_i$); and 3) the percent difference between the average delay of each

Algorithm 3: Bid-cycle assignment in case of competing queues

1: $\hat{d}_i$ = average delay for movement manager i's queue
2: $d_{i,j}^{max}$ = max delay of high VOT driver j on queue i
3: b_i = bid submitted by movement manger i
4: ξ_i = % diff between $\hat{d}_i$ and $d_{i,j}^{max}$
5: **if** $\xi_e \leq 0$ *and* $\xi_d \leq 0$ **then**
    $MC = [(\hat{d}_e + g_{min} + 2c) - (\hat{d}_f + g_{ext} + c)] \times c_{soc}$;
    $b_d^{min} = b_e + MC$
  end
6: **if** $\xi_e > 0$ *or* $\xi_d > 0$ **then**
    declare manager with higher ξ_i as winner
  end
7: $_e$ refers to enfranchised manager
8: $_d$ refers to disenfranchised manager

queue and the maximum delay among high VOT drivers in each queue (ξ_i).

The main idea here is to expedite service for high VOT drivers when their delay is growing; the sign of the indicator variables ξ_i reflect delay experienced by high VOT driver. For example, $\xi_i \leq 0$ implies that service times experienced by high VOT drivers are better or on-par with average service times for that approach, and positive ξ_i values indicate otherwise. In that sense, during every bid-cycle either there is a need to serve the approach with high VOT drivers (because their delay is increasing) or there is not. In the former, municipality declares the approach with higher ξ_i as winner. In the latter, municipality sets the minimum bid (b_d^{min}) that the disenfranchised manager must submit to take over the control of the intersection as sum of enfranchised manager's bid and marginal cost (MC) of delay. Let c_{soc} be the unit cost of delay. If the enfranchised manager loses the bid, then the next earliest time that manager is able to compete for intersection control is $g_{min} + c$, so each vehicle on that managers approach incurs an additional delay equivalent to $g_{min} + 2c$. On the other hand, if the disenfranchised manager loses the bid, then the next earliest time that manager can compete for the intersection control is equal to g_{ext} , so each vehicle on that managers approach incurs an additional delay equivalent to $g_{ext} + c$.

Incorporating average delay estimates from the bid information, once the winning bidder is selected by the municipality, the winner is allocated use the intersection space for this bid-cycle; the winning movement manager pays the municipality the amount that was bid (first-price bidding); and discharges vehicles at saturation headway for the duration of bidding cycle. Movement managers and high VOT drivers update their belief about the system.

III. Simulation Experiments

To analyze the behavior of the above traffic control model, a number of experiments were performed with a microscopic traffic simulator. Specifically, we considered an intersection with two one-way, one-lane approaches - one eastbound (EB) and one northbound (NB) - and explored three basic traffic scenarios. Each scenario involved a total of 1200 vehicles per hour. The three scenarios vary the relative numbers of vehicles moving along the northbound and eastbound approaches:

1) Scenario 1: Equal volumes ($v_N = 600, v_E = 600$)
2) Scenario 2: Slight imbalance ($v_N = 750, v_E = 450$)
3) Scenario 3: Large imbalance ($v_N = 900, v_E = 300$)

As mentioned earlier, our objective is to accommodate high VOT drivers who are willing to pay more to expedite their passage without significantly disrupting overall system performance. To quantify this tradeoff, we conduct simulation runs with varying percentages of high VOT drivers along each approach and contrast them with the "system optimal" baseline case where there are no high VOT drivers.

For each of the three scenarios, the percentage of high VOT drivers on NB was varied between [0, 80] in increments of 5% from one case to the next, whereas % of high VOT on EB was held constant. Therefore, for a given % of high VOT drivers on EB, there are a total of 17 cases with varying % of high VOT drivers on NB. Furthermore, the fixed % of high VOT drivers on EB was varied between [10, 90] in increments of 10%. Hence, there are 153 sub-cases for each of the three scenarios.

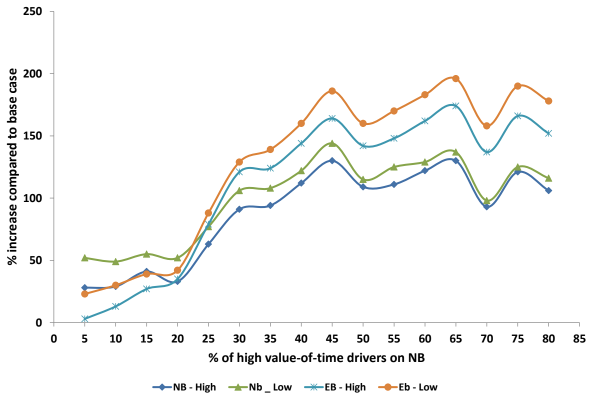
A microscopic simulation model of the bid-based control was developed in Python consistent with the experimental design objectives and traffic theory principles. The other simulation parameters are a nominal fee = $1 and an initial fee = $1. The results presented in this paper are based on the data obtained from 10 Monte Carlo simulations each 3,600 seconds long.

IV. Analysis of Results

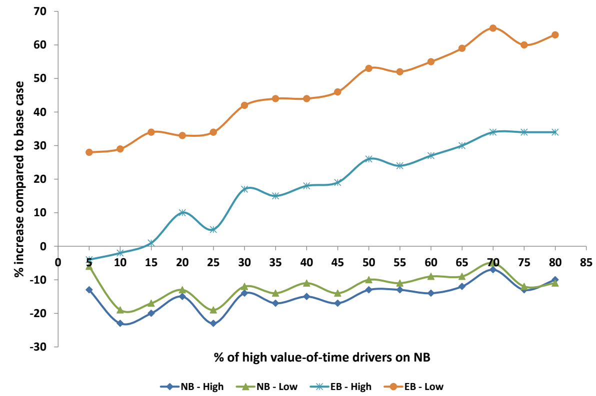
Simulation output data for a given scenario and case was further processed to compute % improvement or degradation in average delays for high and low VOT drivers compared to the base-case (a scenario in which no high VOT drivers are present). Three basic questions are considered: 1) Under what circumstances can service times for high VOT drivers on both NB and EB be reduced? 2) What impact do the reduced service times of high VOT drivers have (if any) on low VOT drivers' service times? Are there circumstances where low VOT drivers are able to ride on the coattails of High VOT drivers?; and 3) What is the impact of high VOT drivers on overall system performance. The analysis presented below will addresses each of these questions.

A. Attending high value-of-time drivers

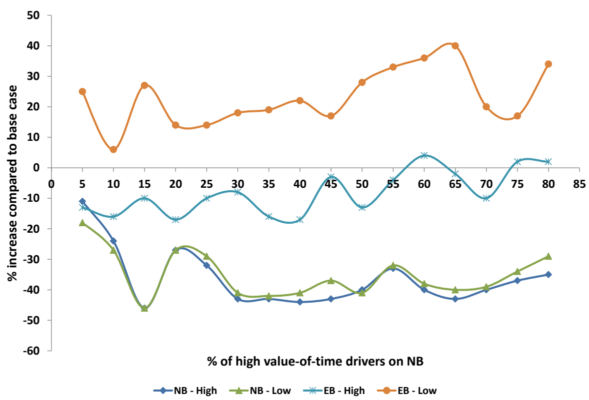
Contrasts in % difference in average service times for high and low VOT drivers on NB and EB are presented in Figure 2. This figure contains three subplots: each subplot presents results for a specific flow combination and 30% high VOT drivers on EB approach. In each subplot, values on x-axis represent % high VOT drivers on NB, whereas values



(a) % high VOT on EB = 30 (600+600)



(b) % high VOT on EB = 30 (750+450)



(c) % high VOT on EB = 30 (900+300)

Fig. 2: % increase in average service times for different classes of vehicles

on y-axis represent the % improvement or deterioration in delay compared to base-case. Therefore, values below x-axis should represent cases in which service times were improved, whereas values above x-axis reflect cases in which service times have deteriorated. Lastly, in each subplot, the trend line in dark blue and light green represent % difference in average service times for high and low VOT drivers on NB respectively. Whereas trend lines in light blue and orange represent similar results but for EB. Several observations can be made from these graphs:

Observation-1: *There is no incentive to have high VOT drivers in the traffic stream, when both NB and EB approaches have equal traffic flows*

Discussion: As evident from Figure 2(a), the scenario in which NB and EB have equal flows ($v_N = 600, v_E = 600$), average service times exacerbates for all drivers in the system. This is because, in most instances high VOT drivers were present on both approaches, and the competing nature of their objectives causes increase in average service times for all drivers in the system.

Observation-2: *With equivalent % of high VOT drivers on both approaches but unequal volumes, the approach with higher flow will dominate and high VOT drivers on this approach will be expedited*

Discussion: Recall that NB has the dominant flow in scenarios 2, & 3. Subplots b & c in Figure 2 show results for these two scenarios respectively. As evident from these graphs, average service times for high VOT drivers on NB are significantly better than those experienced by drivers on EB.

Observation-3: *For low penetration levels of high VOT drivers on both NB and EB, high VOT drivers on both approaches can be serviced expeditiously without causing significant disruption to overall delay*

Discussion: Again subplots 2(b) & 2(c) provide evidence to this claim. It is clear from these graphs, that average service time for high VOT drivers on both approaches improved at low penetration rates of high VOT drivers (15% in scenario-2, and 35-40% in scenario-3).

B. Low VOT driver service times

This subsection highlights the impact of high VOT drivers reduced service times on their counterparts.

Observation-4: *Low VOT drivers are able to ride on the cotails of high VOT drivers on the approach with higher flow*

Discussion: Subplots b, & c in Figure 2 do support this observation. It is evident from these plots that service times of low VOT drivers on NB are almost similar to those experienced by high VOT drivers on that approach; this is not the case for drivers on EB approach. We're aware that the ability to accommodate high VOT drivers comes at the expense of increased delay for low VOT drivers on minor flow approach. However, as noted earlier, market-driven signal control model demonstrated the ability to outperform actuated control by a margin of 20-30 % (95th percentile delay)[11]. So, one could argue that low VOT drivers on the minor approach are still getting service times close to what they would experience today.

C. Impact of high value-of-time drivers

Observation-5: *If the approach with lower flow rate has a sufficiently higher % of high VOT drivers in the traffic stream, it will dominate the approach with higher flow rate and the high VOT drivers along this approach will be expedited.*

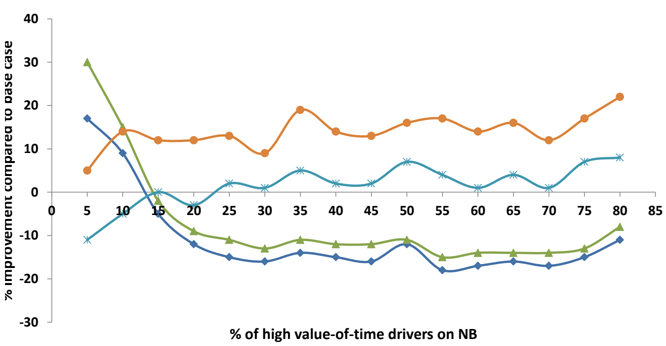


Fig. 3: % improvement in service times for Scenario - 3 (% high VOT drivers on EB = 70)

Discussion: Figure 3 backs this observation. Trends presented in this figure are similar to those in Figure 2, but for a higher % (70) of high VOT drivers on EB approach. As evident from the graph, at low penetration of high VOT drivers on NB approach, Service times experienced by low VOT drivers on EB are better than those experienced by both classes of drivers on NB.

Observation-6: *The distance between the % change in average service times for two classes of drivers on any given approach is a function of relative queue lengths of both approaches; the approach with longer queues will tend to pull low VOT drivers along more effectively.*

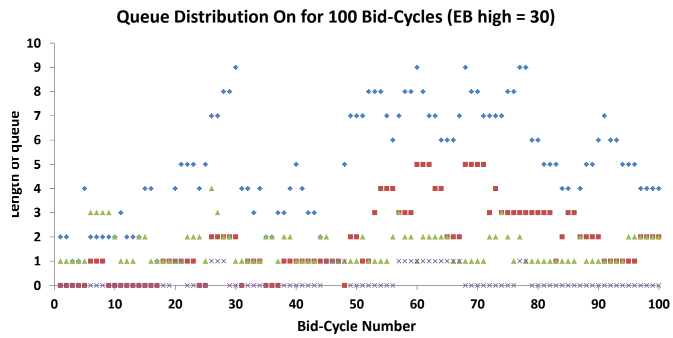


Fig. 4: Scatterplot of queue distribution for Scenario - 3

Discussion: As evident in Figure 4, queues build faster and quicker on the approach with relatively higher flow rate thereby increasing the likelihood of presence of high VOT drivers in the traffic mix at any point in time creating opportunities for low VOT drivers to ride on the coattails of high VOT drivers.

Observation-7: *Overall system performance deteriorates with increased penetration of high VOT drivers in the system*

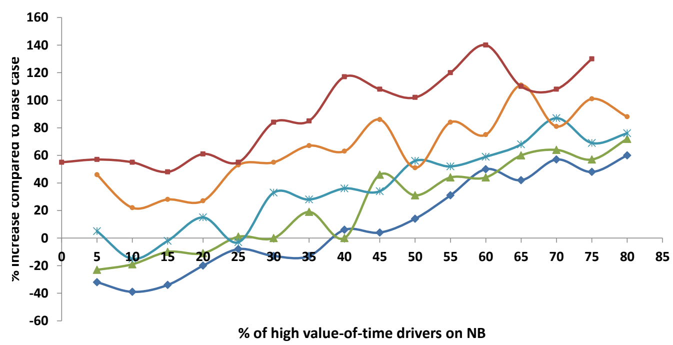


Fig. 5: Impact of high VOT drivers on overall system performance for Scenario - 1

Discussion: Figure 5 presents trends portraying the impact of high VOT drivers on overall system performance for scenario - 2. Values on x-axis represent the % of high VOT of drivers on NB, whereas the values on Y-axis represent % change in overall delay for a given case when compared to base-case. The trend line in dark blue represents a case in which fixed percent of high VOT drivers on EB is 10%. Similarly, trend lines light green, light blue, orange, and red represent similar results but for twenty, thirty, forty, and fifty percent of high VOT drivers on EB respectively. As is evident from these trends, overall system performance deteriorates with increased penetration of high VOT drivers in the system.

V. Conclusions and Future Work

In this paper we have formulated a variant of a previously developed market-based traffic control model that is capable of distinguishing and expediting high value of time (VOT) drivers, and have analyzed the circumstances under which this behavior can be achieved without significantly compromising overall system behavior. Like the previous work that has motivated this study [8], our model assumes two classes of drivers: passive drivers that just pay the required toll and wait for service, and high VOT drivers, who offer up additional voluntary contributions in return for expedited service. A simulation analysis of a single intersection with two one-way, single-lane traffic flows was carried out over a set of scenarios where the percentage of high VOT time drivers was systematically varied along both approaches, and conditions where high VOT drivers were expedited without significant system level degradation as well as conditions where passive drivers were also found to benefit from high VOT driver contributions were identified.

Our analysis has focused on controlling a single intersection to simplify the establishment of bidding strategies that achieve the desired control behavior. Since the traffic signal control problem is formulated as a non-cooperative game, achieving prescribed behavior of any form is difficult and any attempt to bias auction results toward high VOT drivers runs the risk of causing behavior to degenerate. At the same time, we believe that the market-driven control strategy that has been presented in this paper can extend naturally to more complex signalized intersections and to interconnected signal networks. This is the focus of our current research.

Extension to more complex intersections with multidirectional flows and turning phases introduces the issue of compatible movements that can be serviced simultaneously, and consequently requires the introduction of coordinated bid-control mechanisms that are capable of determining multiple winners on a given bidding cycle. Both single stage and two stage bidding mechanisms offer possibilities for realizing such bid-control and investigation of the effectiveness of these is a reasonable next step.

Extension of the framework to control multiple interconnected intersections raises further issues of communication and coordination. Some preliminary work in this area [9] has relied strictly on localized bid-based intersection control, where no information is communicated between neighboring intersections and no attempt is made to synchronize the actions of downstream movement manager. We believe that performance can be enhanced significantly through the communication of relevant flow information to downstream intersections, and this is our initial focus. The basic market-based framework decomposes naturally into a decentralized network control system and hence is inherently scalable.

References

[1] A. L. Bazzan and F. Klügl, "A review on agent-based technology for traffic and transportation," *The Knowledge Engineering Review*, vol. 29, no. 03, pp. 375–403, 2014.

[2] T.-C. Au, S. Zhang, and P. Stone, "Semi-autonomous intersection management," in *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2014, pp. 1451–1452.

[3] K. Tumer, A. Agogino, Z. Welch, A. Bazzan, and F. Kluegl, "Traffic congestion management as a learning agent coordination problem," *Multiagent Architectures for Traffic and Transportation Engineering*, pp. 261–279, 2009.

[4] H. Prothmann, J. Branke, H. Schmeck, S. Tomforde, F. Rochner, J. Hahner, and C. Muller-Schloer, "Organic traffic light control for urban road networks," *International Journal of Autonomous and Adaptive Communications Systems*, vol. 2, no. 3, pp. 203–225, 2009.

[5] S. Sen and K. L. Head, "Controlled optimization of phases at an intersection," *Transportation science*, vol. 31, no. 1, pp. 5–17, 1997.

[6] M. Vasirani and S. Ossowski, "A market-inspired approach to reservation-based urban road traffic management," in *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*. International Foundation for Autonomous Agents and Multiagent Systems, 2009, pp. 617–624.

[7] D. Carlino, S. D. Boyles, and P. Stone, "Auction-based autonomous intersection management," in *Proceedings of the 16th IEEE Intelligent Transportation Systems Conference (ITSC)*, 2013.

[8] I. K. Isukapati, *Intersection Control as a Shared Decision Process*. North Carolina State University, 2014.

[9] I. K. Isukapati and S. F. Smith, "Viewing traffic signal control as a market-driven economy," in *Workshops at the Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.

[10] I. K. Isukapati, G. F. List, and M. S. Kamlet, "Bid-based signal control with all passive players," in *Intelligent Transportation Systems (ITSC), 2016 IEEE 19th International Conference on*. IEEE, 2016, pp. 602–607.

[11] I. K. Isukapati and G. F. List, "Comparing actuated and bid-based control strategies," in *Intelligent Transportation Systems (ITSC), 2016 IEEE 19th International Conference on*. IEEE, 2016, pp. 1516–1521.