2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)
Windsor Oceanico Hotel, Rio de Janeiro, Brazil, November 1-4, 2016

Comparing Actuated and Bid-based Control Strategies

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***Abstract*—In this paper we explore some fundamental differences between control strategies modeled based on economic theory principles as opposed to more traditional control theory principles. More specifically, we explored differences between our bid-based control model and various actuated control models. The comparisons include situations where maximum greens are imposed in actuated control, and situations where they are not. To incorporate these ideas, two bid-based (b1, and b2)and four actuated (a1, a2, a3, and a4) control options are considered. Simulation experiments have been conducted to test these ideas for an intersection with two one-way, one-lane approaches, one eastbound and one northbound. Here are some of the inferences that can be drawn: 1) with actuated control, vehicles on the NB approach, with the larger volumes, always experience higher delays than the EB approach, while the differences between the NB and EB approaches are less significant for bid-based control; 2) Actuated control scenarios where maximum green are imposed (a2, a4) produced lower delay distributions than the scenarios where they are not imposed (a1, a3); 3) it is possible to find a combination of max-greens for a given flow condition that allow the actuated controller to match the performance (at least in terms of delays) of bid-based control; 4)bid-based control produced cycle length distributions that are smaller than those produced by various actuated control models; 5)Actuated control scenarios where maximum green are imposed (a2, a4) produced lower cycle length distributions than the scenarios where they are not imposed (a1, a3).**

I. Introduction

Constantly-changing traffic conditions ensure that signalized traffic control is a challenging problem, especially since drivers expect control systems to guarantee minimal delays. Current state-of-the-art control strategies, while very effective, are relatively primitive. They use pre-set control values, and fail to capitalize on the emerging dedicated short-range–communications capabilities authorized by Congress. The advent of connected vehicle technologies (vehicle-to-vehicle(V2V), and vehicle-to-infrastructure(V2I)) makes it possible to give agency to individual drivers and allow them to directly influence control decisions.

This alternative approach has led to application of ideas from competitive markets. Vasirani and Ossowski [1], [2] proposed a computational market for distributed allocation of green time in an urban road network, where drivers purchase reservation slots to cross intersections by trading with infrastructure agents in a virtual market place. Similarly, Carlino et al., [3] proposed a framework in which each driver in a given queue bids for the lead vehicle in that queue to be discharged. Here the auction format in this case is that of a second price, sealed-bid auction, and the winners split the second-price cost proportionally to what they originally bid.

Isukapati [4], and Isukapati and List [5] proposed a multi-tiered market approach, where drivers make payments for service to infrastructure agents responsible for managing specific movements. In turn, these movement managers submit bids to a designated infrastructure agent (the municipality) for control of the intersection.

The model proposed by Isukapati [4] is distinguishable from earlier models in one important respect. It has the ability to enforce the fairness and safety constraints that govern traffic signal operations in practice. For example, every movement must receive a minimum green (g_{min}) time duration and a minimum transition time (the summation of yellow and all-red times, also referred as a clearance interval (c)), when shifting from one movement to the next. The models of Vasirani [1], [2] and Carlino [3] assume scenarios where these constraints can be ignored (e.g., total autonomous driving, pedestrian-free zones). In [6] this market-based approach was shown to outperform an actuated-control strategy, a form of adaptive traffic signal control in wide use today, on a simulated network of simple two-movement intersections. This raises an interesting research question i.e., what are some fundamental differences between control strategies modeled based on economic theory principles as opposed to more traditional control theory principles.

In this paper we explore these additional differences between Isukapati's [4] bid-based control model and actuated control models. We present outputs from a bid-based control model, and compare them with outputs from various actuated control models. Fundamentally, a traffic signal controller makes decisions about when to shift the green from one phase to another. In the context of bid-based control, this is done through the bidding process, whereas gap time aids these decisions in the case of actuated control. This can be problematic because queue length on the approach waiting to be served does not influence decisions about whether or not

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to stop the extension of green on the existing approach. For example, consider an intersection where the flow of traffic on various approaches is significantly different, vehicles on the approaches with lower flows may experience high delays. This is due to lack of opportunities for gap-out on approaches with higher flows. Typically, maximum greens (g_{max}) are employed to address these issues; however, given the highly stochastic nature of traffic systems, values of g_{max} ought to be determined on ex post facto basis. To test this hypothesis, we created actuated control scenarios where maximum green are imposed, and scenarios where they are not. Whether or not these produces results similar to bid-based control is a research issue explored in this paper.

The rest of the paper is organized as follows: Section 2 presents overview of bid-based and actuated control strategies; Section 3 presents details of experimental design; Section 4 presents results from several simulation experiments. And Section 5 presents conclusions and recommendations.

II. Overview of the control strategies

Since the purpose of this paper is to compare performance of bid-based control strategy with various actuated control models, it is worth presenting high-level overview of these strategies and the subsequent text in this section presents those details.

A. Bid-Based Control

In our previous research [4], [5], [6], we proposed a bid-based control system where intersection space is viewed as a scarce commodity, the use of which is allocated through an interactive bidding process involving vehicle and infrastructure decision agents. Unlike systems grounded in traditional approaches, the application of game theory principles in a market-based system empowers drivers and stakeholders to actively influence the control decision process. Ultimately, the control problem is envisioned as an auction system in which drivers pay to get responsive treatment. Any financial transactions in the game can be figurative or literal.

More specifically, the intersection control problem is formulated as a game involving three classes of players: drivers, movement managers, and a municipality that ensures global fairness.

Drivers arrive at the intersection and pass through it. They want to pass through the intersection in minimum time. Drivers can either be active (i.e., high VOT) or passive (low VOT) players in the game. If they are passive, they pay an initial fee to the movement manager to arrange a time for them to go, and then wait for their appointed crossing time. On the other hand, if they are active players, they constantly evaluate the system, and make additional voluntary monetary contributions to expedite their service.

Movement Managers bid for use of the intersection on behalf of drivers in their queue. They do this once every bidding cycle. When they win, they are given control of the intersection space for a specific period of time. (If the win follows one or more losses, the duration is the ***minimum green*** time constraint (g_{min}). If the win follows a win, the duration is a smaller, fixed green time extension (g_{ext}).) Movement managers use bank accounts to keep track of how much money they presently have, and they track payments received from drivers and amounts paid to the municipality.

The Municipality oversees the bidding process. It determines which movement manager wins. It receives winning bid payments from the movement managers. Implicitly, it determines the rules under which the bidding process takes place.

In any realization of the game, movement managers negotiate for use of the intersection on behalf of drivers making a specific turning movement. Drivers interact with movement managers to receive information about their position in queue and make payments for service. They pay an initial fee upon their arrival and make additional voluntary monetary contributions depending on their value of time (VOT). Drivers with a high VOT are willing to make voluntary contributions to expedite passage. Movement managers interact with the drivers, prepare bids, and communicate with the municipality regarding financial transactions and the bidding process. The municipality receives bids, makes decisions about control assignments, and passes decisions back to the movement managers. The municipality also conducts financial transactions with movement managers. The outcome of the game is a sequence of wins for specific movement managers, which translate into vehicle discharges by movement. In effect, playing the game creates the signal timings.

Drivers and movement managers learn how to play as the game unfolds. They learn what to do, how to interact, the influence of data on how they behave, and how their decisions influence the outcome of the game. Since drivers are transient players, they learn about playing while they are in queue. The movement managers, on the other hand, continue to learn for the games duration, because they are always negotiating on behalf of their arriving drivers. Algorithm 1 presents details of bid-based control logic.

B. Actuated Control

Actuated control uses detector inputs to determine the green time durations. Movement sequences run in parallel, called rings, and they resolve the spatial conflicts. The ring structure ensures that movements end simultaneously to ensure that spatial conflicts do not arise. Green time durations are determined by minimum greens, gap timers, and maximum greens. The resulting phase patterns (movement combinations) and switching times are superior to fixed-time control [7], [8].

Actuated control can further be classified into fully-actuated control and semi-actuated control [9]. We discuss fully-actuated control here. Semi-actuated control pertains to actuated signals in coordinated networks, and this paper does not focus on that domain.

In fully-actuated control, detectors are placed on all of the movements, upstream of the stop-bar. The detectors identify the passage or presence of vehicles. The detector inputs

enable the signal controller to create phase sequences (movement combinations) and switching times that are response to the traffic streams. Typically, once the intersection control is allocated to a specific approach, vehicles on that approach are serviced for a duration equivalent to minimum green (g_{min}). During g_{min} vehicles on the subject approach are discharged at saturation headway.

Starting at the end of g_{min}, decisions are made concerning extending green on the subject approach; display of green on subject approach can be terminated in one of the two possible ways: 1) gap-out; 2) max-out.

1) gap-out: In the case of a gap-out termination, a gap-timer reaches zero (from some specified initial value) before the next vehicle is detected. The purpose of setting a gap-timer is to measure the time interval between successive vehicle arrivals (vehicle headways). Green extensions on the subject approach continue until the vehicle headways are greater than the pre-specified passage times on the stop-bar detector (or until maximum green is reached). If a gap out occurs and there is a non-zero queue on other conflicting approach, then display of green is terminated on the subject approach and a clearance interval of 4 seconds is imposed before shifting control to the approach with non-zero queue.

2) max-out: In the case of a max-out, the duration of green reaches a maximum allowable value. For this to happen, the stop-bar detector on the subject approach never gaps-out (meaning the passage time is always less than or equal to gap-timer). If this scenario persists even at the end of maximum green and if there is a non-zero service queue on the other approach, then display of green is terminated on the subject approach and a clearance interval of 4 seconds is imposed before shifting control to the approach with non-zero queue.

III. Experimental Design

As mentioned earlier, the objective of this paper is to compare and contrast the differences between bid-based control and actuated control strategies; these comparisons include situations where maximum greens are imposed in actuated control and conditions where they are not. Two bid-based and four actuated control options are considered to achieve this objective.

Two bid-based control options are:

b1) Gaps, minimum greens, and change intervals;

b2) Gaps, no minimum greens, and no change intervals, to reflect a more automated control condition. The purpose for creating this option is to explore maximum throughput issues, not to suggest practical options. Traffic engineers often overlook the fact that the minimum greens and clearance intervals consume what would otherwise be available vehicle processing time. There are good safety reasons for doing so, but these times interfere with intersection productivity. Hence, it is useful to see what the productivity of the intersection might be if it is controlled by an automated procedure.

Four actuated control options are:

a1) Gaps, minimum greens, and clearance intervals, but no maximum greens. This allows explorations of how actuated control performs if no maximums are imposed; this parallels bid-based option-1.

a2) Gaps, minimum greens, clearance intervals, and maximum greens. This allows an analysis of the impact of including maximum greens. It is effectively a simple realization of standard practice today.

a3) Gaps, no minimum greens, no clearance intervals, and no maximum greens. This parallels the bid-based option-2.

a4) Gaps, no minimum greens, no clearance intervals, but maximum greens. This again allows an examination of the impacts of maximum greens in an option akin to bid-based control option-2.

A. Simulation Experiments

Simulation experiments have been conducted for an intersection with two one-way, one-lane approaches, one eastbound and one northbound. Readers that are interested in the simulation details can find them described in [4].

Three traffic scenarios have been explored involving a total of 1500 vehicles per hour between the two approaches. Since the processing capacity of a signalized intersection is around 1700-1800 vehicles per hour, this loading places the intersection at about 80-90% of capacity.

The three scenarios involve different combinations of volumes on the northbound and eastbound approaches:

1) Scenario 1: Equal volumes ($v_N = 750, v_E = 750$)
2) Scenario 2: Slight imbalance ($v_N = 900, v_E = 600$)
3) Scenario 3: Significant imbalance ($v_N = 1200, v_E = 300$)

An agent-based simulation model of the bid-based control was developed in Python consistent with the game rules previously presented. A Python-based model of actuated control as also developed, consistent with the description presented. These two simulation models exist within the same analysis program.

For a given input volume on the facility, the program creates a sequence of arrival headways for each scenario for both approaches. A shifted negative exponential headway distribution is employed with a minimum headway of 1.5 seconds and an average headway consistent with the arrival flow rate. These arrival patterns are used both by the bid-based control model and the actuated control model. Simulations are 9,000 seconds long. The saturation headway is set to be uniform between 1.5 to 2.6 seconds with an average of 2.1 seconds (1,714 vehicles/hour) see below. The other simulation parameters are a nominal fee = \$1, an initial fee = \$1, and 50% high VOT drivers.

B. Setting the maximum greens

Inasmuch as maximum greens are employed in two of the actuated control options, a procedure was needed to determine what values to employ. It seemed most appropriate to identify combinations of maximum greens that would ensure that the actuated control delays matched those from the bid-based control. Exhaustive searches were conducted

to find these values. For each approach, a range of possible maximum greens was identified, and then all combinations of these values were examined to find the best combination. An illustration of the results from this search process is provided in Table 1 for the Scenario-2 flow conditions (NB = 900 vph; EB = 600 vph). The table shows that the maximum green combinations that come closest to matching the bid-based delays. The first two columns present the average delay in seconds produced by bid-based control on the NB and EB approaches, respectively (a single value for each approach). The other columns present results for the maximum green combinations. The values in the third and fourth columns are the maximum greens on the NB and EB approaches. Columns five and six are the average delay in seconds on the NB and EB approaches when only both minimum and maximum greens are employed. It can be seen that for this situation the maximum green combination of (55, 40) produces average delays that closely match those of bid-based control. A conclusion from this analysis is that it is possible to find a combination of max-greens for a given flow condition that allow the actuated controller to match the performance (at least in terms of delays) of bid-based control.

Bid Based Control (Option # 1)		Actuated Control			
delay in Sec (NB)	delay in Sec (EB)	Maxgreen (NB)	Maxgreen (EB)	delay in Sec (NB)	delay in Sec (EB)
22	28	50	40	27	27
22	28	50	45	33	26
22	28	50	50	35	27
22	28	55	30	18	64
22	28	55	35	20	41
22	28	55	40	**23**	**30**
22	28	55	45	27	27
22	28	55	50	29	28
22	28	55	55	29	27
22	28	60	30	18	66
22	28	60	35	20	44
22	28	60	40	21	31

Fig. 1. Average delay (sec) for different combinations of maxgreen for Scenario-2 flow condition

For the three scenarios considered, the combinations of maximum greens employed were as follows:

- Scenario-1: (750-750) 45 seconds northbound, 45 seconds eastbound
- Scenario2: (900,600) 55 seconds northbound, 40 seconds eastbound
- Scenario3: (1200,300) 80 seconds northbound, 30 seconds eastbound

IV. Evaluation and Analysis

Two metrics are employed to compare and contrast the results from the various scenarios and signal control options: 1) Individual vehicle delays; 2) Cycle lengths;

A. CDFs of individual vehicle delays

Figures 2 presents the cumulative distribution functions (CDFs) for individual vehicle delays for the bid-based control options (dashed lines) and the actuated control options (solid lines). It contains six subplots; the three subplots to the left (three graphs in first column) represent results for the NB approach for each flow combination; three subplots to the right (three graphs in the second column) represent similar results, but for the EB approach.

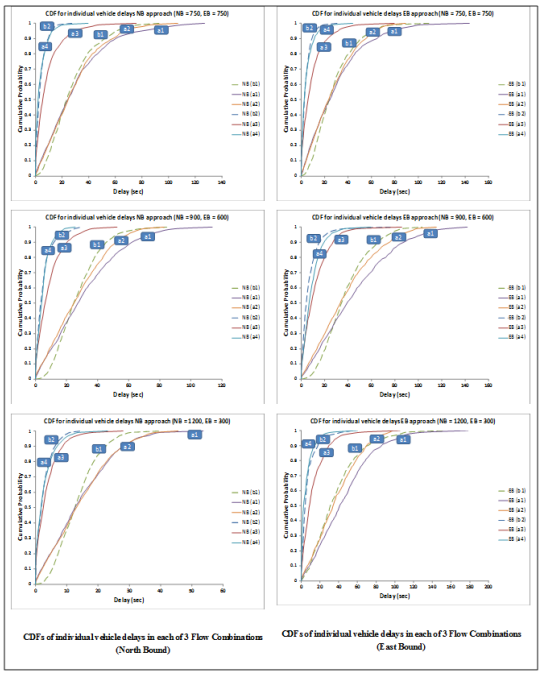


Fig. 2. Results (delays) for six simulation scenarios (NB)

The best performance is reflected by the curves furthest to the left. Those distributions have the smallest delay values. It is easy to see that the CDFs for **b2** and **a4** have the best distribution of delays. **a3** is the next best, followed by **b1**, **a1**, and **a2**. In addition, with actuated control, vehicles on the NB approach, with the larger volumes, always experience higher delays than the EB approach, while the differences between the NB and EB approaches are less significant for bid-based control.

Please recall that **a3** and **a4** are actuated control realizations that parallel bid-based option **b2**, whereas **a1** and **a2** are realizations that parallel bid-based option **b1**. Kolmogorov-Smirnov tests were conducted to check the statistical differences between actuated and bid-based control options. Table 4 and Table 5 contain a summary of test results for NB and EB approaches, respectively. Results suggest a statistically significant difference in delay distributions for the three flow combinations and both the NB and EB approaches.

Figure 2 allows a comparison of the delays for bid-based control and actuated control. And while average delay is the main focus, the outcomes do have an economic interpretation. Smaller delays result in smaller delay costs for the drivers. Especially when minimum greens, and clearance intervals are imposed the bid-based control strategy produces driver costs that are smaller than or equal to those produced by actuated control and the results presented in Figure 2 also corroborate that inference. Secondly, the further left the delay

Metric	b1	a1	a2	b2	a3	a4
Mean delay (sec)	26.9	29.5	27.9	3.9	8.8	3.8
Stdev delay (sec)	17	24.1	20.3	4	10.5	4.7
15th perc delay (sec)	10.3	6.4	7.1	0.2	0.6	0.1
50th perc delay (sec)	23.4	24.3	24.5	2.7	5.5	2
75th perc delay (sec)	35.8	41	38.4	5.5	11.5	5.4
95th perc delay (sec)	60.8	80.2	67.3	12.2	28.5	12.8

(a) NB Scenario - 1

Metric	b1	a1	a2	b2	a3	a4
Mean delay (sec)	27.2	29.2	26.6	4	9.1	4.6
Stdev delay (sec)	17.1	24	19	4.1	10.6	5.6
15th perc delay (sec)	10.9	6	6.3	0.2	0.5	0.4
50th perc delay (sec)	23.9	24.6	23.5	2.7	5.8	2.6
75th perc delay (sec)	36.4	41.5	38.8	5.7	12.4	6
95th perc delay (sec)	61.6	77	62.9	11.9	31.6	15.3

(b) EB Scenario – 1

Metric	b1	a1	a2	b2	a3	a4
Mean delay (sec)	26.9	30.9	26.7	5	8.6	4.8
Stdev delay (sec)	14.1	22.2	17.9	5.4	8.7	4.3
15th perc delay (sec)	12.7	7.1	7.2	0.4	0.7	0.6
50th perc delay (sec)	24.6	27.3	24.8	3.3	6.2	4
75th perc delay (sec)	35.6	44.8	39.5	6.4	12.1	6.6
95th perc delay (sec)	52.2	73.6	59.4	16.8	26.7	13.7

(c) NB Scenario - 2

Metric	b1	a1	a2	b2	a3	a4
Mean delay (sec)	37.3	44.2	37.2	6.8	11.7	8.9
Stdev delay (sec)	19.3	30.7	25.4	8.2	11.7	8.3
15th perc delay (sec)	17.7	11.7	9.5	0.8	1.1	1.4
50th perc delay (sec)	34.3	39.1	33.4	4.4	8.7	6.8
75th perc delay (sec)	48.7	63.7	54.2	9.3	17.2	12.6
95th perc delay (sec)	74.3	103	85.3	21	32.9	25.1

(d) EB Scenario – 2

Metric	b1	a1	a2	b2	a3	a4
Mean delay (sec)	13.3	14.3	14.3	2.6	3.6	2.7
Stdev delay (sec)	6.6	10	9.7	2.6	4	3.1
15th perc delay (sec)	6.3	3.3	3.5	0.2	0.1	0.1
50th perc delay (sec)	12.7	12.6	13.1	1.9	2.5	1.8
75th perc delay (sec)	17.3	21.4	20.7	3.7	5.2	4
95th perc delay (sec)	25.5	32.2	32.6	8.1	11	9.2

(e) NB Scenario - 3

Metric	b1	a1	a2	b2	a3	a4
Mean delay (sec)	35.1	44.9	36.3	6.8	12.6	5.6
Stdev delay (sec)	23.2	30.5	23.7	8.1	12.9	7.7
15th perc delay (sec)	11.8	13.5	10.9	1	1.4	0.4
50th perc delay (sec)	30.7	41	33.7	4.1	8.7	2.5
75th perc delay (sec)	48.4	62.3	52.8	8	17.6	7.5
95th perc delay (sec)	80.6	104	79.9	23.3	37	19.6

(f) EB Scenario – 3

Fig. 3. Various delay statistics for six simulation options

distribution, the closer it is to the efficient frontier. That is, the combinations of average delay between the two approaches are non-dominated. There is no other control option that produces less delay. (This is an observation that will hold true among all of the volume combinations.)

Lastly, Figure 3 presents various delay statistics for six simulation options. In a way these results summarize some of the statistical properties of each of the distributions presented in Figure 2; even though the differences between bid-based control and four actuated control options seem not significant at first, KS test results presented in Figure 4 suggest the distributions are statistically significantly different.

Scenario	KS	KSa	D=max|F1-F2|	Prob > D	D+=max(F1-F2)	Prob > D+	D-=max(F2-F1)	Prob > D-
(b2, a3)	0.1638253	10.037556	0.3276505	<.0001*	0.0586042	0.0016*	0.3276505	<.0001*
(b2, a4)	0.0501871	3.0753707	0.1003743	<.0001*	0.057491	0.0020*	0.1003743	<.0001*
(b1, a1)	0.0564731	3.4601006	0.1129462	<.0001*	0.1129462	<.0001*	0.0980288	<.0001*
(b1, a2)	0.0636654	3.9007738	0.1273308	<.0001*	0.1273308	<.0001*	0.0554076	0.0031*

(a) Scenario – 1 (NB)

Scenario	KS	KSa	D=max|F1-F2|	Prob > D	D+=max(F1-F2)	Prob > D+	D-=max(F2-F1)	Prob > D-
(b2, a3)	0.1573536	10.525062	0.3147072	<.0001*	0.0585606	0.0005*	0.3147072	<.0001*
(b2, a4)	0.0853822	5.7110422	0.1707644	<.0001*	0.0621368	0.0002*	0.1707644	<.0001*
(b1, a1)	0.0621368	4.1562035	0.1242736	<.0001*	0.1198033	<.0001*	0.1242736	<.0001*
(b1, a2)	0.0567725	3.7973946	0.1135449	<.0001*	0.0862763	<.0001*	0.1135449	<.0001*

(b) Scenario – 2 (NB)

Scenario	KS	KSa	D=max|F1-F2|	Prob > D	D+=max(F1-F2)	Prob > D+	D-=max(F2-F1)	Prob > D-
(b2, a3)	0.1242555	9.660013	0.2485109	<.0001*	0.1211118	<.0001*	0.2485109	<.0001*
(b2, a4)	0.1130046	8.785338	0.2260093	<.0001*	0.2260093	<.0001*	0.010589	0.7126
(b1, a1)	0.0727995	5.6596614	0.1455989	<.0001*	0.1455989	<.0001*	0.1207809	<.0001*
(b1, a2)	0.0746195	5.8011529	0.1492389	<.0001*	0.1141628	<.0001*	0.1492389	<.0001*

(c) Scenario – 3 (NB)

Scenario	KS	KSa	D=max|F1-F2|	Prob > D	D+=max(F1-F2)	Prob > D+	D-=max(F2-F1)	Prob > D-
(b2, a3)	0.1527996	9.4464255	0.3055992	<.0001*	0.0570382	0.0020*	0.3055992	<.0001*
(b2, a4)	0.0720976	4.4156488	0.1442211	<.0001*	0.0370205	0.0766	0.1442211	<.0001*
(b1, a1)	0.0693354	4.2864773	0.1386709	<.0001*	0.0900052	<.0001*	0.1386709	<.0001*
(b1, a2)	0.0570382	3.5262342	0.1140764	<.0001*	0.0884354	<.0001*	0.1140764	<.0001*

(a) Scenario – 1 (EB)

Scenario	KS	KSa	D=max|F1-F2|	Prob > D	D+=max(F1-F2)	Prob > D+	D-=max(F2-F1)	Prob > D-
(b2, a3)	0.183149	10.154451	0.366298	<.0001*	0.0559532	0.0081*	0.366298	<.0001*
(b2, a4)	0.0304803	1.6852626	0.0609616	0.0068*	0.0609616	0.0034*	0.0497971	0.0226*
(b1, a1)	0.0764476	4.2385365	0.1528953	<.0001*	0.102147	<.0001*	0.1528953	<.0001*
(b1, a2)	0.0614834	3.4088656	0.1229668	<.0001*	0.0897853	<.0001*	0.1229668	<.0001*

(b) Scenario – 2 (EB)

Scenario	KS	KSa	D=max|F1-F2|	Prob > D	D+=max(F1-F2)	Prob > D+	D-=max(F2-F1)	Prob > D-
(b2, a3)	0.2270233	8.6686054	0.4540466	<.0001*	0.0205761	0.7344	0.4540466	<.0001*
(b2, a4)	0.1014992	3.8139935	0.2031062	<.0001*	0.2031062	<.0001*	0.0518832	0.1498
(b1, a1)	0.0912209	3.4831556	0.1824417	<.0001*	0.0288066	0.5461	0.1824417	<.0001*
(b1, a2)	0.058299	2.2260769	0.1165981	<.0001*	0.0466392	0.2048	0.1165981	<.0001*

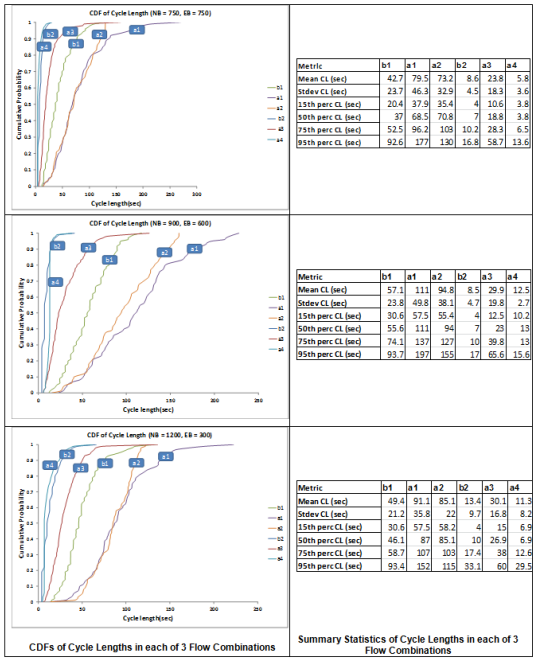
(c) Scenario – 3 (EB)

Fig. 4. KS Test results for delay distributions for NB and EB

B. CDFs of cycle lengths

Figure 5 presents CDFs for cycle lengths and summary statistics associated of those CDFs in the three combinations of flows. Each subplot in the left column contains CDFs for the cycle lengths of both the bid-based control and actuated control options. As was the case for average delays, the best performance is reflected by the curve furthest to the left. When the constraints on minimum greens and clearance intervals are imposed the CDFs produced by bid-based control have distributions with the lowest cycle lengths (**b1**). When maximum greens are imposed with actuated control, the distributions of cycle lengths can be made comparable to those produced by bid-based control (**a2**, and **a4**). For example, the 90th percentile cycle length produced by bid-based control for option-1 is around 75-85 seconds, whereas it is around 150-180 seconds for **a1**.

Also, when maximum greens are imposed, actuated control and bid based control have very similar performance especially when constraints on minimum greens, and clearance interval are removed. Three tables in the right column present various statistics associated with cycle length for six simulation options. In a way these results summarize some of the statistical properties of each of the distributions presented in graphs in the left column.



Metric	b1	a1	a2	b2	a3	a4
Mean CL (sec)	42.7	79.5	73.2	8.6	23.8	5.8
Stdev CL (sec)	23.7	46.3	32.9	4.5	18.3	3.6
15th perc CL (sec)	20.4	37.9	35.4	4	10.6	3.8
50th perc CL (sec)	37	68.5	70.8	7	18.8	3.8
75th perc CL (sec)	52.5	96.2	103	10.2	28.3	6.5
95th perc CL (sec)	92.6	177	130	16.8	58.7	13.6

Metric	b1	a1	a2	b2	a3	a4
Mean CL (sec)	57.1	111	94.8	8.5	29.9	12.5
Stdev CL (sec)	23.8	49.8	38.1	4.7	19.8	2.7
15th perc CL (sec)	30.6	57.5	55.4	4	12.5	10.2
50th perc CL (sec)	55.6	111	94	7	23	13
75th perc CL (sec)	74.1	137	127	10	39.8	13
95th perc CL (sec)	93.7	197	155	17	65.6	15.6

Metric	b1	a1	a2	b2	a3	a4
Mean CL (sec)	49.4	91.1	85.1	13.4	30.1	11.3
Stdev CL (sec)	21.2	35.8	22	9.7	16.8	8.2
15th perc CL (sec)	30.6	57.5	58.2	4	15	6.9
50th perc CL (sec)	46.1	87	85.1	10	26.9	6.9
75th perc CL (sec)	58.7	107	103	17.4	38	12.6
95th perc CL (sec)	93.4	152	115	33.1	60	29.5

Fig. 5. Results (cycle lengths) for six simulation scenarios

V. Conclusion

In this paper we presented differences between bid-based control model and various actuated control models. The comparisons include situations where maximum greens are imposed in actuated control, and situations where they are not. To incorporate these ideas, two bid-based (**b1**, and **b2**)and four actuated (**a1**, **a2**, **a3**, and **a4**) control options are considered. Simulation experiments have been conducted to test these ideas for an intersection with two one-way, one-lane approaches, one eastbound and one northbound. Here are some of the inferences that can be drawn: 1) with actuated control, vehicles on the NB approach, with the larger volumes, always experience higher delays than the EB approach, while the differences between the NB and EB approaches are less significant for bid-based control; 2) Actuated control scenarios where maximum green are imposed (**a2**, **a4**) produced lower delay and cycle length distributions than the scenarios where they are not imposed (**a1**, **a3**); 3) it is possible to find a combination of max-greens for a given flow condition that allow the actuated controller

to match the performance (at least in terms of delays) of bid-based control; 4)bid-based control produced cycle length distributions that are smaller than those produced by various actuated control models.

Algorithm 1: Bid-based Control Logic

```
δ_t = 0.1 (initialize time step);
t = 0 (initiate simulation time);
h_d = saturation headway;
g_min = minimum green;
c = clearance interval;
while t ≤ T do
    t += δ_t;
    if new arrivals = True then
        collect f_min;
        add new arrivals to service queue;
        new drivers in queue will compute d_j
    end
    if only one agent has a service queue then
        declare that agent as a winner for t = t + g_min;
        agent pays municipality an amount p_min;
        discharge vehicles in queue at h_s;
        Movement manager updates win/loss PDF;
        drivers in queue update their belief of the
          system;
        make voluntary contributions (if any);
    end
    if more than one agent has a service queue then
        movement managers submit bids for control;
        highest bidder wins and given control for
          t = t + g_min;
        winning agent pays municipality an amount he
          bid;
        discharge vehicles in queue at h_s;
        Movement manager updates win/loss PDF;
        drivers in queue update their belief of the
          system;
        make voluntary contributions (if any);
    end
    if t > t + g_min then
        movement managers resubmit bids for control;
        Municipality computes marginal social cost;
        Municipality declares winning agent;
        if current winner = previous winner then
            extend green by 3 seconds
        end
        else
            Impose clearance interval;
            allocate intersection control to new winner
              for t = t + g_min
        end
    end
end
```

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