Traffic Signal Control for Connected and Non-Connected Vehicles

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***Abstract*—Transportation is one of the city's processes to achieve an efficient, livable and sustainable community aiming to improve the citizens' quality of life and the perception of smartness of a city. Each of us experiences unnecessary delays and expects improvement in mobility with the introduction of new technologies, specially in traffic signal control due to its big influence in urban traffic networks. One trend in modern vehicle technologies is that *Connected Vehicles* (CV) will communicate to the traffic infrastructure, so called V2I (*Vehicle-to-Infrastructure*), which may enable cities to provide better services through cooperation under limited infrastructure. Therefore, this paper proposes and evaluates three algorithms for traffic control using connected vehicles instead of stationary detectors: (i) a *Dynamic Maximum Gap* (DMG) between arrivals at stop line (specific for each vehicle), and (ii) the *Throughput Adjusted Delay* (TAD) accounting the relation between intersection throughput and delay, while (iii) the *Throughput Adjusted Stopped Time* (TAST) uses stopped time (waiting time) for such relation instead of delay. We demonstrate that our DMG algorithm at non-peak flows, compared to traditional actuated control, reduces the travel time up to 15%, waiting time (time spent with speed lower than 0.1 m/s) by almost 80%, and delay 50%. The TAD and TAST strategies maintain good performance even at 10% penetration rate of CV. Future research will contribute to the assessment of the environmental and economical benefits of traffic signal control using CVs, implementation on more realistic scenarios, as well as exploration of other information from CVs and application of advices sent from the infrastructure to vehicles.**

***Index Terms*—connected vehicles, intelligent transport systems, smart cities, traffic signal control, V2I**

I. INTRODUCTION

A city can be viewed as a system composed of different subsystems, those subsystems require high level of cooperation between interdisciplinary fields to form an alliance system with the main goal of improving citizens' quality of life [1] [2]. Such complex system can be decomposed into three layers, according to [2]: (i) goals, representing efficient, livable and sustainable community; (ii) city processes to achieve such goals; and (iii) city resources. In respect to the city processes, the application of advanced ICT (*Information and Communication Technology*) to the city's transport process, for instance, should: (a) enhance mobility (decreasing travel times); (b) promote accessibility (easiness for a citizen to pursue its activity), and (c) increase safety (sharing pro-active information to avoid dangerous situations); as long as (d) promote sustainability of the city's resources. The trend on those particular subsystems utilizes all available knowledge about the city to provide best services, through cooperation under limited infrastructure using minimal resources [3].

Within this context, the current development stage of modern vehicle technologies allows the possibility of vehicles communicating with the road infrastructure, known as V2I (*Vehicle-to-Infrastructure*). The potential of this *Connected Vehicle* technology was analyzed in [4] for a real network located in Toronto, Canada. The authors' assessment resulted in 37% reduction in travel time, lower emissions by 30%, and improvement in safety indicators by 45%. The V2I communication enable us to innovate the current traffic control strategies: (i) fixed time, in which pre-programmed signal plans are based on historical traffic data along the day; (ii) traffic-actuated, where real-time traffic conditions either change the length or order of signals phases; (iii) adaptive, which also predicts near future traffic conditions in order to optimize signal timing using an objective function. Although traffic-actuated and adaptive strategies may be desired to provide better usage of intersection capacity, they rely on traffic detectors that only provide little information about all vehicles passing a specific cross-section of the road, and they usually cannot measure vehicle states (e.g position, heading, speed). On the other hand, collecting CV (*Connected Vehicle*) data is significantly cheaper than installing and maintaining traffic detectors. Additionally, a communication failure by a connected vehicle to infrastructure would only reduce the penetration rate, what would lead to little impact to the overall system performance [5].

Several studies have implemented CV technology to tackle uncertain or rapid changing traffic volumes and make "smarter" decisions. Their common principle is that the intersection infrastructure (e.g. traffic controller) gather vehicles' state information, such as positions and speeds, to either predict the time instant each vehicle will reach the stop line, or use CV data to estimate queue length. Extension of this principle varies on the estimation of non-connected vehicles state (using microscopic models or statistical methods), and/or the application of two-way communication for systems like *Green Light Optimal Speed Advisory* (GLOSA), *Local Level Routing*, and *Priority Management and Negotiation*, more information can be found in [6].

The aim of this paper is to develop traffic signal control strategies that use only V2I communication and knowledge of the upstream traffic flow. We evaluate the performance of our proposed strategies using the traffic simulator *Simulation of Urban Mobility* (SUMO) [7], in which we model an isolated intersection and compared it against a traditional actuated strategy that uses one stationary detector on each approach based on the green time extension principle. We measure the results in terms of benefits on mobility (trip duration, delay, waiting time) at peak and non-peak hours flow, while other types of analysis are open for future research. The best achievements (compared to an actuated control) are in non-

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peak flows with reduction of the travel time up to 15%, waiting time by almost 80%, and 50% for delay.

This paper is structured as it follows: section I briefly reviews the state of the art in the field of traffic signal control using connected vehicles, while section II describes our proposed traffic control algorithms. In section III we present our simulation model environment used for the evaluation of our strategies and the traditional one, as well as the simulation results and analysis of these results. Section IV includes conclusions and possible future research.

II. PROPOSED STRATEGIES

Fig. 1 illustrates an example of how we define and divide the real-world scenario, containing the events in which we need to estimate the state of each vehicle (time instant, distance to stop line and speed).

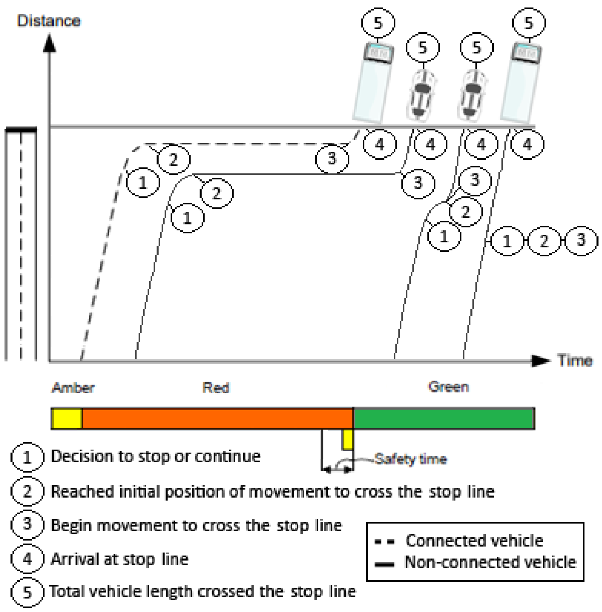

Fig. 1. Key events to estimate vehicle state

A. Trip Generation and Detection

At each time step, we use the information presented on Table I for each vehicle i to be discharged in the communication range. Such data is collected from Connected Vehicles (CV) and estimated for non-Connected Vehicles (non-CV) using standard values.

TABLE I
NEEDED DATA FOR THE PROPOSED TRAFFIC SIGNAL CONTROL

Vehicle Data	Unit	Notation
Vehicle Type	$dimensionless$	$type_i$
Acceleration Capability	m/s^2	acc_i
Perceived Deceleration	m/s^2	$decel_i$
Desired Speed	m/s	$vdes_i$
Vehicle Length	m	len_i
Position	m	$(vehx_i, vehy_i)$
Speed	m/s	v_i
Approach	int	app_i

For Penetration Rates (PR) lower than 100%, we generate Artificial Vehicles (AV) to simulate non-CV according the defined PR and O-D (Origin-Destination) flow volumes. Assuming Exponential Distribution of arrivals (due the setup of an isolated intersection with random arrivals), we calculate the headway x of the next AV as it follows from [8]:

$$x = \mu(-\ln R) \tag{1}$$

where μ is the mean headway of CV and non-CV flow, and R is a random number between 0 and 1. In order to add AV's as close as the real arrivals of all vehicles, we look into the cumulative probability of the CV's headways. The cumulative probability is given by:

$$F(x;\lambda) = 1 - e^{-\lambda x} \tag{2}$$

where $\lambda = \frac{1}{\mu}$ that represents an average number of CV and non-CV arriving during the time aggregation of the O-D flow volume. The adjustment of the mean headway μ for all vehicles on the same flow is:

$$\mu^* = \mu + \mu\left[\frac{F(x_{mean};\lambda) - F(x_{lst\_dct};\lambda)}{F(x_{lst\_dct};\lambda)}\right] \tag{3}$$

in which x_{mean} is the CV's mean headway and x_{last_dct} the last detected headway. In fact we use μ^* in Eq. 1 only when the flow of CV's for the O-D pair is higher than a min_cvph to avoid sampling of sporadic CV arrivals. Additionally, for every time step longer than the last detected headway lst_dct the adjusted mean headway μ^* gradually changes back to its average value μ. To maintain the PR, we calculate the headway of the next AV's at each new generated AV, but only introduce it if there was not a CV detected during the AV headway.

B. Estimation of Vehicle State

Following the principle that a leader vehicle will influence the follower, we estimate the attributes for each key event on Fig. 1 from the first vehicle in the order (by distance) on the approach. While the distance to the stop line $dist\_stopline_i$ of CV's is estimated by Euclidean Distance, for AV's we use the Krauss Car-Following Model [9], which is based on the safe speed v^{AV}_{safe} of a vehicle i:

$$v^{AV}_{safe} = v_l + \frac{gap_{l,f} - v_l T}{\frac{v_f + v_l}{2 \times decel_i} + T} \tag{4}$$

where l represents the leader, f the follower and $gap_{l,f}$ the gap (in distance) between them, moreover T is the reaction time of drivers. The algorithm then update the speed v_i and distance to stop line $dist\_stopline_i$ of AV's using Eqs. 5 and 6, respectively, and considering that st represents the time step.

$$v^{AV}_{i,st+1} = \min\ \left\{vdes_i,\ v^{AV}_{i,st} + acc_i \times st,\ v^{AV}_{safe}\right\} \tag{5}$$

$$dist\_stopline^{AV}_{i,st+1} = dist\_stopline^{AV}_{i,st} - v^{AV}_{i,st+1} \times st \tag{6}$$

Assuming that vehicles want to stop at a minimum distance gap ($dist\_gap$ in meters) from the vehicle ahead, they will start slowing down at the distance threshold ($dist\_thres$ in meters) from the target. Based on the simplified Gipps'model presented in [10] we have:

$$dist\_thres_i = -\frac{v_i^2}{2 \times decel_i} + v_i T + dist\_gap \tag{7}$$

This gives us the distance of the key event (1) on Fig. 1:

$$evt^1_{dist,f} = event^2_{dist,l} + len_l + dist\_thres_f \tag{8}$$

where the superscript represents the event number. We will generically denote evt_{dist}, evt_{time} and evt_{speed} for the attributes at any key events, while superscript e for event index.

We derive two different sets of equations from the fundamental equations of constant translational acceleration in a straight line from Physics [11]. One set when vehicle i will be accelerating between key events (Eqs. 9, 10 and 11):

$$evt^e_{speed} = \sqrt{(evt^{e-1}_{speed})^2 + 2 \times acc_i \times \Delta d^e_{acc}} \tag{9}$$

$$evt^e_{time} = \frac{evt^e_{speed} - evt^{e-1}_{speed}}{acc_i} + \frac{\Delta d^e_{const}}{evt^e_{speed}} \tag{10}$$

$$evt^e_{dist} = evt^{e-1}_{dist} - \Delta d^e_{acc} - \Delta d^e_{const} \tag{11}$$

where Δd is the distance of the movement, computed using the maximum possible elapsed times Δt as follows:

$$\Delta t^e_{acc} = \min\left\{\frac{vdes_i - evt^{e-1}_{speed}}{acc_i}, aval\_acc\_t\right\} \tag{12}$$

$$\Delta t^e_{const} = aval\_acc\_t - \frac{evt^e_{speed} - evt^{e-1}_{speed}}{acc_i} \tag{13}$$

$$\Delta d^e_{acc} = \min\left\{\frac{vdes_i^2 - (evt^{e-1}_{speed})^2}{2 \times acc_i}, evt^{e-1}_{dist}, evt^{e-1}_{speed} \times \Delta t^e_{acc} + \frac{1}{2} acc_i \times (\Delta t^e_{acc})^2\right\} \tag{14}$$

$$\Delta d^e_{const} = \min\left\{evt^{e-1}_{dist} - \Delta d^e_{acc}, \Delta t^e_{const} \times vdes_i\right\} \tag{15}$$

in which $aval\_acc\_t$ is the available time for the acceleration. The other set is for deceleration, which we have Eqs. 16, 17, and 18:

$$evt^e_{speed} = evt^{e-1}_{speed} + decel_i \times evt^e_{time} \tag{16}$$

$$evt^e_{time} = \min\left\{aval\_decel\_t, -\frac{evt^{e-1}_{speed}}{decel_i}\right\} \tag{17}$$

$$evt^e_{dist} = evt^{e-1}_{dist} - \frac{(evt^e_{speed})^2 - (evt^{e-1}_{speed})^2}{2 \times decel_i} \tag{18}$$

where $aval\_decel\_t$ is the available time for the deceleration.

From Eq. 9 to 18, the vehicle's states are dependent on the expected traffic signal timings. When vehicles need to yield to an preferential traffic, we calculate the capacity of discharge (saturation flow) of the approach that must yield cap_{app} assuming exponential arrivals of the opposite preferential traffic, otherwise we use standard values. Eq. 19 is the same of the capacity for non-signalized intersections [12], due the fact that vehicles also yield to others in order to cross.

$$cap_{app} = \frac{q_{opp} e^{-q_{opp} T_{cr}}}{1 - e^{-q_{opp} T_0}} \tag{19}$$

where q_{opp} is the flow on the opposite traffic (the number of scheduled vehicles to pass the stop line over the green period), T_{cr} is the critical gap time and T_0 is the follow-up time. After that, we estimate a possible waiting time $wait\_time$ (to be summed to the evt^4_{time}) if left-turning vehicles need to yield to opposite preferential traffic.

$$wait\_time_p = \begin{cases} 1/cap_{app} & \text{if } q_{opp} > 0 \\ 0 & otherwise \end{cases} \tag{20}$$

C. Traffic Signal Control Strategies

Fig. 2 presents the basic flow with all of our proposed strategies together.

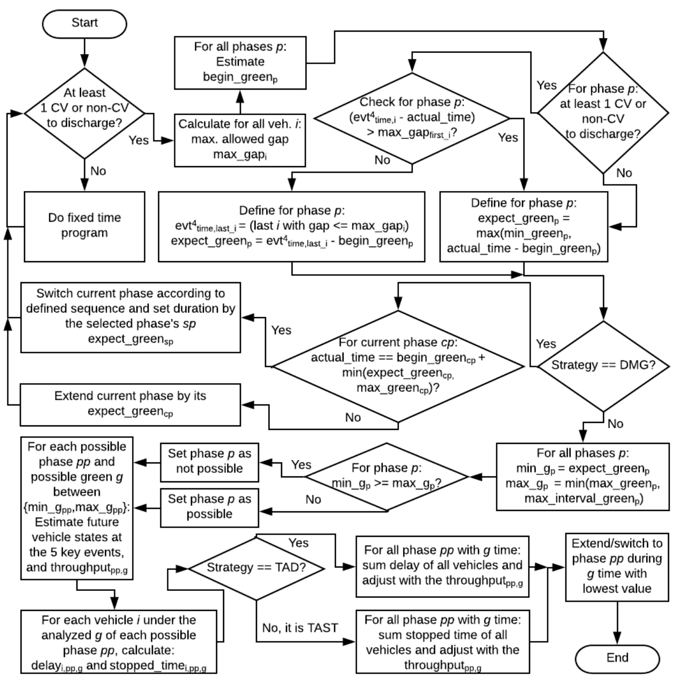

Fig. 2. Proposed traffic signal control strategies

The common attribute among our proposed strategies is the $expect\_green_p$ for each phase p, which represents the green time to ensure the last vehicle, with difference of $evt^4_{time,i}$ with a leader vehicle (or stop line) shorter than a maximum allowed gap max_gap_i, will cross the stop line:

$$max\_gap_i = \min\left\{ref\_gap\left(\frac{vdes_i}{v_i}\right), max\_dyn\_gap\right\} \tag{21}$$

where ref_gap is a reference of maximum time gap and max_dyn_gap an absolute maximum time gap. Eq. 21 deals to situations that could lead to gaps higher than the ref_gap, and ensure that CVs will be able to cross the stop line if they are slow or stopped under low penetration rates. Additionally, the determination when a phase p gets green $begin\_green_p$ is based on the sequence of phases in the cycle.

Our first strategy is a traffic actuated control named *Dynamic Maximum Gap* (DMG), which monitors the $expect\_green_p$ at every time step and (from its minimum green time min_green_p) keeps extending the current phase. If the current phase cp reaches its maximum green time or no vehicle has gap shorter than its max_gap_i, then it changes the phase following a predefined sequence of phases.

The second and third strategies correspond to adaptive traffic control. Their only difference are the decision variables, the *Throughput Adjusted Delay* (TAD) uses the estimated total delay of choosing a phase with certain green duration, while the *Throughput Adjusted Stopped Time* (TAST) is based on the total time stopped (waiting time). For those strategies we created a maximum interval without green for each phase that limits the green time of a conflicting phase, allowing to skip phases but maintain minimum green time. All phases p in which their max. time max_g_p is bigger than their min. time min_g_p (set as the $expect\_green_p$) are analyzed to be possible next phases pp.

Using the procedure and equations of section II-B, the TAD and TAST strategies look ahead in a horizon of two "cycles" to estimate vehicle's states at all key events if it is applied each possible phase pp with each green time duration g. This means a first analyzed green time g (ending at time instant end_green_{pp}), and the next green time (e.g. in the second "cycle") that starts after end_green_{pp} plus the estimation of green time for the other conflict phases. Moreover, it is assumed the application of same green time g on the second "cycle" for phase pp, what yields to the end of this next green time at $end\_next\_green_{pp}$. These time instants are used to apply a penalty $pnty_{i,pp}$ for vehicles not crossing until $end\_next\_green_{pp}$:

$$lateness = evt^4_{time,i,pp,g} - end\_next\_green_{pp}$$
$$pnty_{i,pp} = \begin{cases} lateness & \text{if } lateness > 0 \\ 1 & otherwise \end{cases} \quad (22)$$

Then the delay and stopped time (waiting time) for each vehicle i under possible phase pp with duration g are:

$$delay_{i,pp,g} = \left(evt^4_{time,i,pp,g} - evt^4_{time,i,last}\right) pnty_{i,pp} \quad (23)$$

$$stops_{i,pp,g} = \left(evt^3_{time,i,pp,g} - evt^2_{time,i,pp,g}\right) pnty_{i,pp} \quad (24)$$

where $evt^4_{time,i,last}$ represents the last estimation of stop line time-of-arrival for vehicle i without getting any delay from the traffic signal, while $stops_{i,pp,g}$ also accounts waiting time at previous "cycles". Another metric is $throughput_{pp,g}$ (in veh/s), which represents the amount of vehicles that will cross the stop line under possible phase pp with duration g from the decision time of the next phase until $end\_next\_green_{pp}$. Finally, the selected phase and duration time will be the one with the lowest decision variable $dec\_var_{pp,g}$:

$$dec\_var_{pp,g} = \begin{cases} \frac{\sum_i delay_{i,pp,g}}{throughput_{pp,g}} & \text{if TAD} \\ \frac{\sum_i stops_{i,pp,g}}{throughput_{pp,g}} & \text{if TAST} \end{cases} \quad (25)$$

III. SIMULATION AND RESULTS

We wrote our connected vehicle traffic signal control algorithms in Python [13], and simulated it using *Simulation of Urban Mobility* (SUMO) [7] via TraCI (the interface between SUMO and Python) [14]. Fig. 3 shows the flow volumes and the intersection model. The speed limit is 70 km/h and each approach is around 560 meters long (though the communication range for connected vehicles is 400 meters), while the left-turn bays have 100 meters.

From [15] we define the amber time of 4 s, and safety time as 3 s (1 for red clearance and 2 of red + amber time), as well as the number of phases with their necessary green times (seen on Table. II). The minimum green time for non-peak flows is based on the driver expectancy, while for peak flows we use the Webster's optimal cycle length model and the maximum degree of saturation of the approaches for each phase. Moreover, the saturation flow is 1800 veh/h for cases without yield, otherwise Eq. 19.

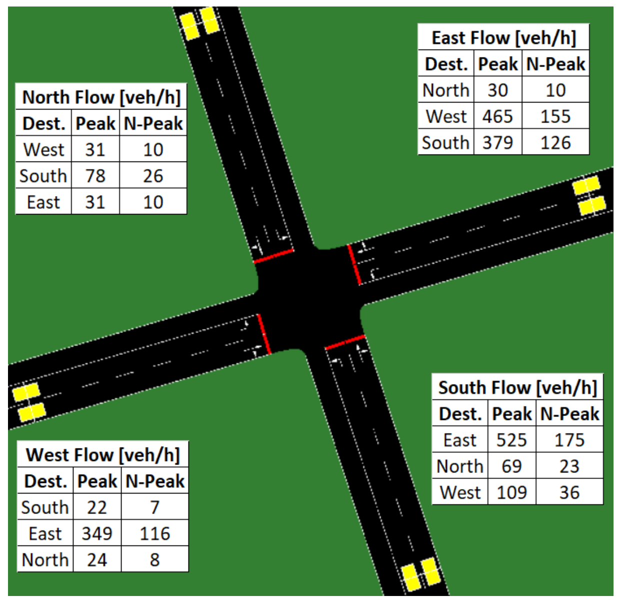

Fig. 3. SUMO intersection model and flow volumes

TABLE II
GREEN TIMINGS FOR PHASES

Phase/Flow	Min. [s]	Max. [s]	Max. Int. [s]	Fixed [s]
Peak Main W-E	5	60	90	11
Peak Main N-S	5	60	90	15
Peak Ext. W-E	5	20	180	3
N-Peak Main W-E	18	60	90	33
N-Peak Main N-S	21	60	90	45
N-Peak Ext. W-E	7	20	180	9

The setup of the traditional actuated signal control works by prolonging traffic phases, and it switches to the next phase after detecting a time gap between vehicles longer than 3 s. The detectors on each approach are positioned 38.88 m in front of the stop line (2 s times the speed limit of 19.44 m/s).

For our proposed strategies, we use SUMO's standard values [16] for the data (Table I) of AV's, including the distance gap

$dist\_gap$ of 2.5 m. The critical time gap for left-turn vehicles T_{cr} is 5.5 s for cars and 7 s for trucks, while the follow-up time T_0 is 60% [17]. We conducted several simulations and 4 s was the best performing value for the reference maximum gap ref_gap, while 10 s for max_dyn_gap. In addition, as we use (unrealistic) static accelerations and deceleration (what overestimate them), we use 85% of their values. The minimum number of CV's per hour to sample the O-D pair flow min_cvph was set to 40.

The experiment comprises several scenarios, for peak and non-peak flows, as well as for 10%, 25%, 50%, 75%, and 100% penetration rate (PR) of connected vehicles. We carried out 115 replications to guarantee at least 95% confidence level of the results, based on the formula for the number of replications found on [18]. The simulation time is 1 hour. The confidence intervals of waiting time and delay aggregated for all vehicles can be seen on Table III, while Figs. 4 and 5 show the Box-plot of trip duration.

TABLE III
CONFIDENCE INTERVALS OF WAITING TIME AND DELAY

Control and PR	Waiting Time [s]		Delay [s]	
	Non-Peak	Peak	Non-Peak	Peak
TAST 10%	11.2 ± 0.2	29.7 ± 0.5	21.2 ± 0.3	51.6 ± 0.9
TAD 10%	12.3 ± 0.2	30.1 ± 0.6	22.2 ± 0.3	51.8 ± 1.0
DMG 10%	21.7 ± 0.4	61.0 ± 2.1	37.0 ± 0.6	106 ± 3.7
TAST 25%	9.2 ± 0.1	28.8 ± 0.4	18.7 ± 0.2	50.2 ± 0.7
TAD 25%	10.5 ± 0.2	29.3 ± 0.6	19.9 ± 0.2	50.5 ± 1.1
DMG 25%	12.2 ± 0.2	26.4 ± 0.6	23.9 ± 0.2	46.7 ± 0.9
TAST 50%	7.5 ± 0.1	27.8 ± 0.7	16.3 ± 0.1	48.5 ± 1.1
TAD 50%	8.3 ± 0.1	28.7 ± 0.6	17.1 ± 0.2	49.6 ± 1.0
DMG 50%	7.8 ± 0.1	21.4 ± 0.3	18.1 ± 0.1	39.2 ± 0.4
TAST 75%	5.6 ± 0.1	26.1 ± 0.5	13.8 ± 0.1	45.9 ± 0.9
TAD 75%	6.3 ± 0.1	27.0 ± 0.6	14.5 ± 0.1	47.4 ± 1.1
DMG 75%	5.9 ± 0.1	21.4 ± 0.2	15.7 ± 0.1	38.8 ± 0.3
TAST 100%	3.4 ± 0.0	22.8 ± 0.4	11.0 ± 0.1	41.9 ± 0.7
TAD 100%	4.0 ± 0.1	22.9 ± 0.4	11.6 ± 0.1	41.9 ± 0.6
DMG 100%	2.7 ± 0.0	19.2 ± 0.3	11.1 ± 0.1	36.2 ± 0.4
Actuated	12.8 ± 0.1	22.7 ± 0.3	24.0 ± 0.2	40.9 ± 0.4

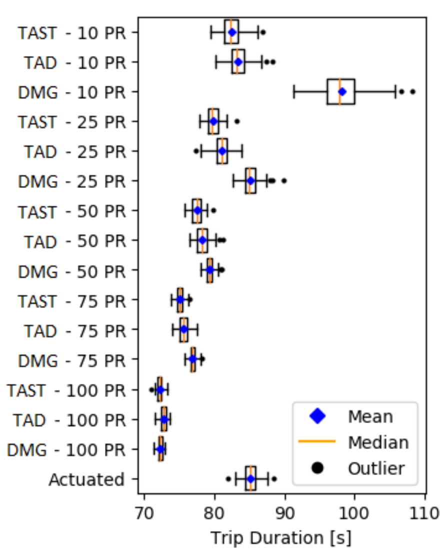

Fig. 4. Trip duration results for non-peak flows

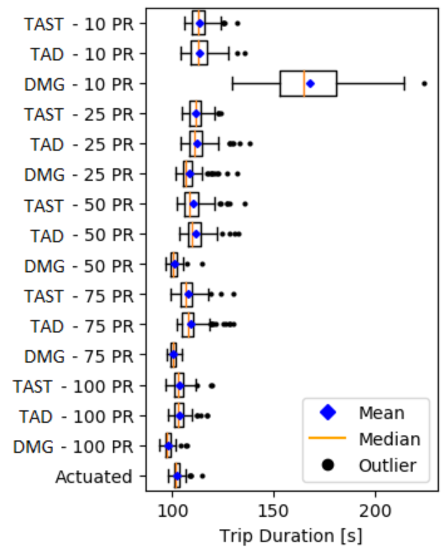

Fig. 5. Trip duration results for peak flows

The most positive gains were on non-peak flows, but as long as the flows increases and the penetration rate decreases the improvements of the proposed algorithms become less expressive. As our DMG algorithm updates every time step, it is more reliant on the PR and flow volumes because switches phases right after the last vehicle with short gap crosses the stop line (compared to the actuated that waits for 3 seconds), therefore many non-CV and less phase changes means less savings (e.g. peak flows). The TAD and TAST algorithms update at the end of the current phase (because if phases would have similar decision variable values it would change too much), thus they depend mainly upon the future prediction within 2 cycles, what can waste few seconds due to inaccuracy.

IV. CONCLUSIONS AND FUTURE RESEARCH

In this paper we investigate contributions of modern vehicle technologies to the Smart Cities initiative, focusing on the benefits related to mobility and sustainability of resources through sharing information from vehicles to the city infrastructure. We proposed three strategies for traffic signal control that use only information from connected vehicles (CV), and compared them against a traditional actuated signal control variating traffic flows and the Penetration Rate (PR) of connected vehicles. Our Dynamic Maximum Gap (DMG) algorithm is the fastest one to adjust to the real-time traffic conditions, though influenced by the precision of non-CV modeling. While the Throughput Adjusted Delay (TAD) and Throughput Adjusted Stopped Time (TAST) tolerate low PR but their performance is undermined by estimation of each vehicle future state and the stochasticity of arrivals during the analyzed horizon.

Future research could contribute by exploring the simplifications and assumptions of our strategies. For instance, the Exponential Distribution is generally used only for isolated intersections with random low flow arrivals, and Eq. 19 works only for such type of distribution. Our model to estimate vehicle states (presented in Section II-B) assumes constant acceleration/deceleration and it is does not deal with multi-lane approaches. Therefore, extend the control considering multiple intersections and realistic driver/vehicle behaviour, as well as assessment of environmental and economical benefits are the next logical steps. We also believe other information (e.g. CV measurements of distance to other vehicles) could help modeling non-CV, while estimating future arrivals within 2 "cycles" may improve the performance. Finally, infrastructure advice regarding speed could create platoons of vehicles to maximize the throughput and minimize waiting time.

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REFERENCES

[1] T. Zelinka, O. Pribyl, and M. Lom, “Smart" as a key component of the sustainable city development,” pp. 317–322, 2016.

[2] O. Pribyl, “Transportation, intelligent or smart? on the usage of entropy as an objective function,” *2015 Smart Cities Symposium Prague, SCSP 2015*, 2015.

[3] O. Pribyl and M. Svitek, “System-oriented Approach to Smart Cities,” *2015 Photonics North*, pp. 1–8, 2015.

[4] A. Olia, H. Abdelgawad, B. Abdulhai, and S. N. Razavi, “Assessing the Potential Impacts of Connected Vehicles: Mobility, Environmental, and Safety Perspectives,” *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, vol. 20, no. 3, pp. 229–243, 2016.

[5] Y. Feng, K. L. Head, S. Khoshmagham, and M. Zamanipour, “A real-time adaptive signal control in a connected vehicle environment,” *Transportation Research Part C: Emerging Technologies*, vol. 55, pp. 460–473, 2014.

[6] A. M. Pereira, H. Anany, O. Pribyl, and J. Prikryl, “Automated vehicles in smart urban environment: A review,” *2017 Smart City Symposium Prague (SCSP)*, vol. 690727, no. 690727, pp. 1–8, 2017.

[7] D. Krajzewicz, *Traffic Simulation with SUMO – Simulation of Urban Mobility*. New York, NY: Springer New York, 2010, pp. 269–293.

[8] T. V. Mathew, “Lecture Notes in Transportation Systems Engineering. Vehicle Arrival Models: Headway,” pp. 1–20, 2017. [Online]. Available: https://www.civil.iitb.ac.in/tvm/nptel/tselnw33.pdf

[9] V. Kanagaraj, G. Asaithambi, C. N. Kumar, K. K. Srinivasan, and R. Sivanandan, “Evaluation of Different Vehicle Following Models Under Mixed Traffic Conditions,” *Procedia - Social and Behavioral Sciences*, vol. 104, pp. 390–401, 2013.

[10] M. Treiber and A. Kesting, *Traffic Flow Dynamics*, 2013, vol. 2013.

[11] K. Johnson, *Physics for You*. Nelson Thornes, 2001.

[12] FHWA, “Traffic Flow Theory Revised. A State-of-the-Art Report (2001 revision),” *TRB Special Report 165 - Revised Monograph on Traffic Flow Theory*, 2001.

[13] P. S. Foundation, “The official home of the Python Programming Language.” [Online]. Available: https://www.python.org/

[14] A. Wegener, M. Raya, S. Fischer, and J. pierre Hubaux, “Traci: An interface for coupling road traffic and network simulators,” in *In Proceedings of the 11th Communications and Networking Simulation Symposium*, 2008.

[15] T. Urbanik, A. Tanaka, B. Lozner, E. Lindstrom, K. Lee, S. Quayle, S. Beaird, S. Tsoi, P. Ryus, D. Gettman *et al.*, *Signal Timing Manual*. Transportation Research Board, 2015.

[16] “Vehicle type parameter defaults.” [Online]. Available: http://sumo.dlr.de/wiki/Vehicle_Type_Parameter_Defaults

[17] K. Fitzpatrick, “Gaps accepted at stop-controlled intersections,” *Transportation Research Record*, vol. 1303, no. 11, pp. 103–112, 1991.

[18] W. Burghout, “A note on the number of replication runs in stochastic traffic simulation models,” no. September, pp. 1–6, 2004.