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Assessment of connected vehicle information quality for signalised traffic control

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***Abstract*—Connected vehicles (CVs) present a great opportunity to smooth and improve traffic flows at intersections thanks to their communication capabilities, which may allow a real-time flow of information with the controllers operating traffic signals. Therefore, it is reasonable to envision that, in the near future, CV data may complement or replace spot detector data that is currently used to operate traffic signals. However, CV data may be affected by errors, such as positioning error, which may depend on the technology that is employed. In this paper, we investigate the performances of different control strategies, namely a strategy that employs only aggregated information, such as queue lengths, and a strategy using disaggregated vehicle-based information, when they are operated with CV data, considering various realistic measurement accuracy settings. Our experiments, conducted via microscopic simulations, show that the disaggregated strategy features better performance and robustness in most of the tested scenarios.**

***Index Terms*—traffic control, connected vehicles, signal timing, GPS**

I. Introduction

Current signal control systems have been mainly developed based on the use of data collected by spot detectors, e.g, inductive-loop detectors, magnetometers, radars, and traffic cameras. Thanks to the data provided by spot detectors, various adaptive signal control methods are implemented and are able to adapt signal timing to traffic conditions, such as SCATS [1] and SCOOT [2]. Nevertheless, implementing these systems needs the installation of several detectors on intersections, which also require adequate maintenance, generating a significant cost. Moreover, spot detectors can only transmit data to the controller when a vehicle is in the detection range; therefore, these systems may not be able to predict arriving flows to an intersection from upstream, in particular in the presence of disturbances. On the contrary, in the future, connected vehicles (CVs) will be able to transmit accurate vehicle information in real-time to signal controllers. Thus, it is reasonable to envision that, in a not-so-distant future, controllers will not need anymore spot detectors, while, thanks to CV features, the control devices can receive vehicle data in real-time such as speed, position, and acceleration. Consequently, useful traffic measures can be extracted, e.g, arrival traffic flows, queue length, delays and fuel and energy consumption [3].

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In order to collect accurate and real-time vehicle position information, CVs are usually equipped with Global Positioning Systems (GPS). These are based on a network of satellites emitting microwave signals for location and timing purposes [4]. However, data obtained via GPS is not perfect. In fact, GPS position accuracy depends on five factors: ionospheric errors, tropospheric errors, signal obstruction and multipath errors, geometric configuration of satellite errors, and other minor errors [5]. GPS devices can be categorized into three different types based on the level of accuracy: High Accuracy GPS, Standard GPS with a Receiver Autonomous Integrity Monitoring (RAIM), and mobile GPS. High Accurate GPS are devices that rely on ground stations to obtain very high position accuracy, with a technique used to enhance the precision of position data obtained from the GPS systems called Real-Time Kinematic (RTK) positioning system. It has been demonstrated that RTK GPS networks can reach centimeter-level accuracy. However, the necessity of installing 3 or more fixed stations in the system, makes RTK GPS networks a very expensive solution to determine the position [5]. RAIM is a technology developed to assess the integrity of GPS signals, allowing to evaluating GPS signal data consistency and reducing positioning errors [6]. As a result, it is commonly integrated into safety-critical GPS applications, such as in aviation or marine navigation. Finally, mobile GPS is an inexpensive technology, which is frequently used in many devices, such as smartphones. The standard GPS accuracy is annually collected and published by the US government [7]. It is fairly known that mobile GPS are less accurate than traditional GPS receivers. Nonetheless, they can still represent a great opportunity since it is reasonable to assume that, even nowadays, there is at least a mobile GPS device in every vehicle, resulting in a potentially large availability of data. There exist studies on the usage of different GPS technologies for other applications, such as [4], where the position is simplified to a 2D model since accuracy is not required in the height coordinate [8].

Considering the input type of the signal controllers, in this work, we distinguish two main categories: aggregated input controllers (AICs) and disaggregated input controllers (DICs). Most of the current and conventional signal controllers are AIC, where the controllers require aggregated data about the intersection approaches, such as queue lengths and vehicle flows, since only the aggregated information can be obtained from spot detector data. Various AICs are currently being implemented on signalized intersections such as fully actuated controllers, semi-actuated controllers and Max-Pressure (MP) or back-pressure controllers [9], [10]. In fully actuated and semi-actuated signal timing, the controller extends or truncates a phase based on the presence of a vehicle or pedestrian on the detectors. In this study, we choose MP as a state of the art AIC. MP requires as input the queue length on all approaches of the intersection and produces as output the time for each phase, by assigning more green time to a higher queue length approach, considering cycle time, minimum and maximum green time. MP controller has been widely studied as an effective adaptive signal control due to its simple implementation, the lower communication requirements, and computational burdens [10]–[12]. In MP, at the beginning of each cycle, which has a fixed length, the green times are allocated for each phase based on queue measurements [13]. On the other hand, a DIC is assumed to operate with information on individual vehicles as input. CV capabilities are functional to deploy DICs since real-time and accurate data of vehicles are transmitted via V2I (vehicle-to-infrastructure) communication systems. Improved detection and communication capabilities offered by CVs provide various opportunities for controlling signalized intersections, such as improved signal arterial coordination, transit signal priority or signal-vehicle coupled control [3], [14]–[16]. The aim of these controllers is usually to minimize vehicle delay or maximize vehicle throughput by using CV accurate and real-time data to estimate the arrival time of each vehicle to the intersection. However, it is reasonable to assume that the performance of these controllers is highly dependent on the accuracy of the available data. GPS error in collecting vehicle position data could lead to inaccurate vehicle arrival time estimation or inaccurate queue length estimation. However, such a decrease in signal performance efficiency as a function of CV data quality has not been widely studied. Existing relevant work includes, for example, the influence of the loss of information in communications [17].

The aim of this paper is to study the effect of CV data quality on adaptive signal controller performance. We consider two types of adaptive controllers in a CV environment namely an AIC and a DIC. The first one is MP, which has been developed originally as an adaptive control strategy using spot detectors data, which has been modified to operate with CV data. The second one is a vehicle-based signal controller (VST) [18], which has been developed originally to operate solely with CV data. In order to consider data inaccuracy, we consider the above mentioned three different types of GPS devices, namely high accurate GPS, standard GPS with RAIM and mobile GPS.

The remainder of this paper is organized as follows. Section II describes the various components of the methodology of the paper. Section III describes the simulation experiments. Numerical results, in terms of control strategies evaluation, are presented in Section IV. Finally, Section V summarises and discusses the key findings and outlines further research directions.

II. Methodology

In this section, we elaborate on the overall methodology implemented here to measure the effect of CV data quality on signal control performance. The proposed framework, illustrated in Figure 1, consists of a set of interconnected components. CV data is assumed to be collected from the traffic process by means of different technologies. As we employ microscopic simulations, we retrieve exact information on the vehicles; therefore, we include a module that perturbates the measurements depending on the GPS technology. These data are then processed in a form that can be used as input by the controllers. Controller results are then fed-back to the traffic system via traffic signals. In the following sections, we describe in detail the different components.

A. GPS data error

Conventionally, GPS errors are defined as the difference between the actual position of the GPS receiver and the position that is measured by the GPS receiver. The amount of such error depends on the GPS accuracy, which can vary from a radius of 2 cm for high accuracy GPS devices to about 13 m with mobile phone GPS [8], [19]. This error can also affect secondary data, such as speed and acceleration. In this section, we describe how we model the GPS error effect on the CV data before it is transmitted to the controller.

As we deal with road traffic, we assume that CVs are always located within the lanes of an intersection approach, which, in practice, can be achieved, e.g., via some map-matching algorithm [20]. Here, we consider the problem of projecting the reported GPS location in the (known) road lane. First, we introduce a polar coordinate system to project the GPS error onto the road (see Fig. 2). By assuming the simplification that each approach is represented as a two-dimension coordinate system, the projection is obtained by multiplying the value of the distance by the cosine of the angle formed with the axis of the street, according to

$$\epsilon_t = r_t \cos(\theta_t), \tag{1}$$

where t is the time index, ϵ_t is the error projection on the street axis, r_t is the radius error of GPS, and θ_t is the angle of radius error with the street axis. Accordingly, the projected position of a vehicle at time step t can be obtained as

$$p_t = d_t + \epsilon_t, \tag{2}$$

where p_t is the projected position of vehicle and d_t is actual position of vehicle.

We assume that GPS error can be described by a Gaussian (normal) distribution of mean μ and covariance σ^2. Also, θ_t is a uniformly distributed random angle between 0 and π.

Errors in the vehicle position due to GPS inaccuracy lead also to errors in terms of speed information. In order to estimate the speed error, we consider that speed is calculated as the first-order derivative of the traveled distance, as follows

$$v_t = \frac{(d_{t+\Delta t} + \epsilon_{t+\Delta t}) - (d_t + \epsilon_t)}{\Delta t}, \tag{3}$$

where v_t is the speed of the vehicle at time t and Δt is the time interval between two data collection points.

B. Signal control

Here, we introduce the two signal control strategies employed in order to assess the effect of GPS data error on signal performance, i.e., MP and VST. A main difference between the two considered controllers is the type of input, i.e., MP needs queue length on each approach of the intersection, while VST utilizes the position and speed of each vehicle approaching the intersection within a given distance. We assume that the penetration rate of CVs is 100%. Furthermore, position, speed, and vehicle length are provided by CVs without any delay or missing data. The two controllers are briefly described in the following sections.

1) Max-Pressure control

The objective of MP is to stabilize the queue length on all legs of an intersection, by measuring the queue length on each approach as input. Then, green times for each phase are calculated by providing priority to approaches with higher queue lengths. At the beginning of each cycle, we calculate the green time of each phase by taking into account cycle length and minimum green time, according to

$$g_k = (C - I g_{\min}) \frac{Q_k}{\sum_{j=1}^{J} \sum_{i=1}^{I} Q_{ij}} + g_{\min}, \tag{4}$$

where:

k: simultaneous signal phases index ($k = 1, 2, \ldots, K$);
g_k: green time of phase k;
Q_k: total queue length of all assigned approaches for phase k (m);
C: cycle length (s);
$g_{\min}$: minimum green time (s).

As the MP strategy has not been originally developed for a CV environment, we adapt the algorithm to use CV data as input instead of spot detectors. In particular, we assume that a vehicle with a speed lower than a given threshold (in the order of, e.g., 3.6 km/h - 1 m/s) is considered as a queuing vehicle. Then, by considering vehicle length and safety distance of stopping vehicles, we estimate the queue on each leg of the intersection. The formulation of this estimation algorithm is presented as follows

$$Q_{ij} = \sum_{n=1}^{N_{ij}} q_{ij}^n (l_{ij}^n + S) \tag{5}$$

$$q_{ij}^n = \begin{cases} 1 & \text{if } v_{ij}^n < 1 \text{ m/s} \\ 0 & \text{otherwise,} \end{cases} \tag{6}$$

where:

i: signal phase index ($i = 1, 2, \ldots, I$);
j: ring index ($j = 1, 2, \ldots, J$);
Q_{ij}: estimated queue length in assigned lane for phase i in ring j (m);
n: vehicle index ($n = 1, 2, \ldots, N_{ij}$);
q_{ij}^n: binary parameters indicating if vehicle n is in queue or not;
l_{ij}^n: length of vehicle n in phase i of ring j (m);
S: safety distance between stopped vehicles (m);
v_{ij}^n: speed of vehicle n in phase i of ring j (m/s);
$\bar{v}$: speed threshold for queuing vehicles (m/s).

2) Vehicle-based Signal Traffic control

We present here the general concept of VST, while interested readers can refer to [18]. In contrast with MP, the VST strategy calculates the stop-bar passage time for each individual vehicle approaching the intersection. Based on this information, the controller maximizes vehicle throughput

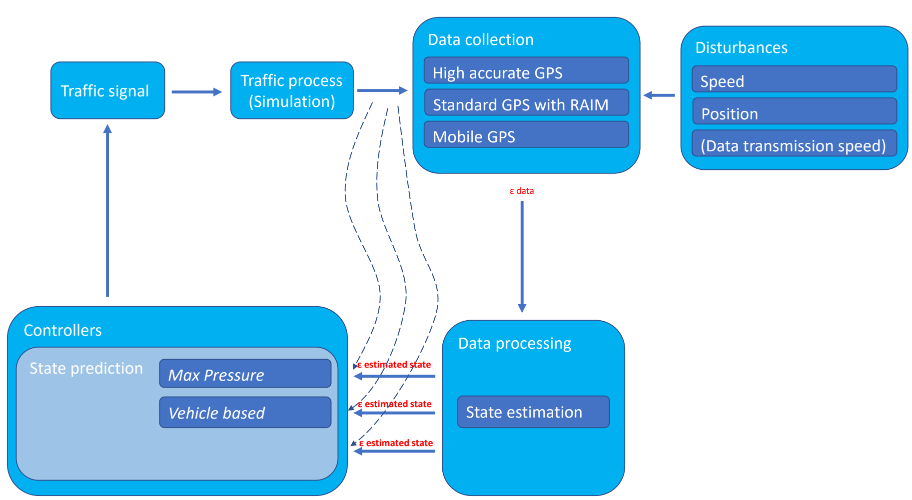


Fig. 1: Process framework for assessing the impact of GPS error on traffic signal control

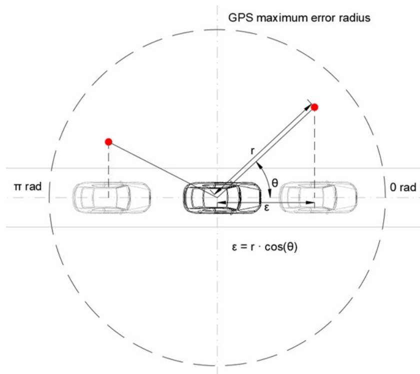


Fig. 2: GPS errors in polar and Cartesian coordinate systems

within a cycle of the signal, by solving the following optimization problem:

$$\max_{g} \sum_{j=1}^{J} \sum_{i=1}^{I} \sum_{n=1}^{N_{ij}} p_{ij}^{n}(\underline{g}) \tag{7}$$

subject to:

$$\sum_{i=1}^{I} g_i + (I-1)Y \leq C \tag{8}$$

$$g_i \geqslant g_{i,\min} \quad \forall i \tag{9}$$

$$g_i \leqslant g_{i,\max} \quad \forall i, \tag{10}$$

where

$$p_{ij}^{n} = \begin{cases} 1, & \text{if } T_{ij}^{n} < G_i \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

Binary variable p_{ij} indicates if vehicle n in phase i of ring j can pass the stop bar during the next cycle or not; T_{ij} is the estimated arrival time of vehicle n to the stop bar and G_i is end of green time for phase i. T_{ij} is calculated for each CV according to 6 different cases that have been proposed in [18].

III. Simulation Setup

We employ a four-leg intersection with two lanes on each approach, as shown in Figure 3, where each approach measures 1 km and each exit 0.5 km. Left lanes are dedicated to left-turn traffic, whereas the right lanes are assigned to straight traffic. The mean desired speed of vehicles is set 60 km/h, while the remaining simulation parameters are set as for standard urban traffic. For both controllers, a minimum green time of 10 s is considered for each phase, while yellow changes and red clearances times are 6 for each cycle. The remaining settings for VST are selected as in [18].

We consider a total of 9 scenarios for each controller, by considering 3 traffic volumes, i.e., undersaturated, saturated, and oversaturated, and 3 GPS settings, i.e., high-accuracy GPS, standard GPS with RAIM, and mobile GPS. For each scenario, we run 20 simulations considering unique random seeds, which allows considering the vehicles' parameters and arrival pattern as stochastic. For each simulation, we set a warm-up time of 600 s and a total simulation time of 3600 s, so that in total 40, 30 or 24 cycles were carried out depending on the cycle length. Since the controllers assume a fixed cycle length, this is determined a priori according to the maximum theoretical capacity according to conventional methods of the Signal Timing Manual [21], and set to 90, 120 and 150 seconds, for undersaturated, saturated, and oversaturated conditions, respectively, as shown in Table II. However, these values may be conservative since they consider a headway of 2.5 s per vehicle, which is slightly high for an urban environment.

TABLE I: GPS errors utilised in simulation experiments

Errors (m)					
High Accurate GPS		**Standard GPS with RAIM**		**Mobile GPS**	
Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
0	0	1.35	0.43	3.49	3.67

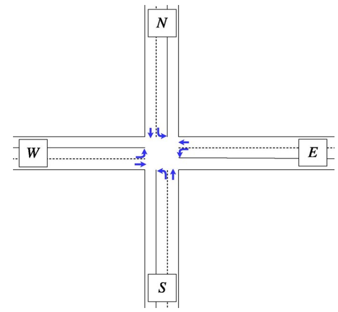


Fig. 3: The intersection considered in simulations

The final errors implemented in each simulation are presented in Table I, in terms of the mean and standard deviation of the normal distribution of the sample for each GPS type.

Concerning traffic distribution, we consider the North and South bounds as the major roads and East and West bounds as the minor roads. Flows are assigned so that traffic flow turning left from the major road and going through in minor road is, on average, half of the one in the major road, while flow turning left in the minor road is a quarter of the main flow in the major road.

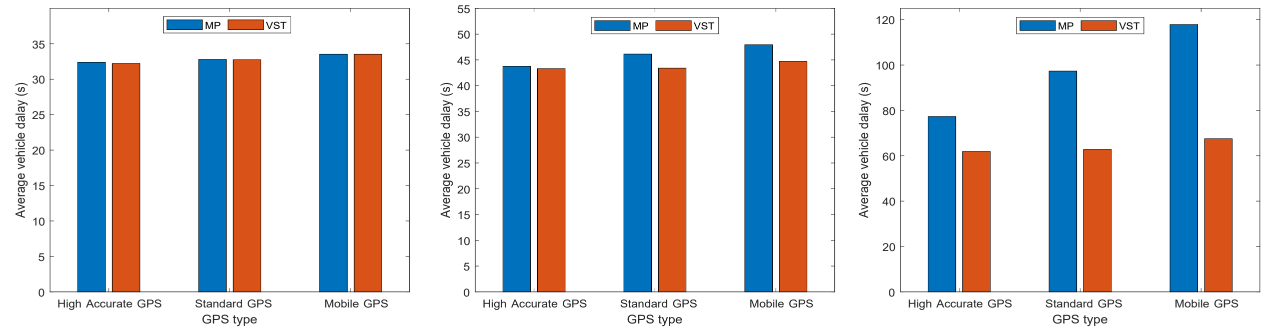
IV. Results

We present here three performance measures to assess the efficiency of the control strategies, which are a) average vehicle delay, b) number of stops per vehicle, and c) vehicle throughput.

Fig. 4 illustrates the average vehicle delay in three traffic conditions. In undersaturated conditions, both controllers have virtually identical performance, while we can observe that using mobile GPS produces higher delays for both controllers

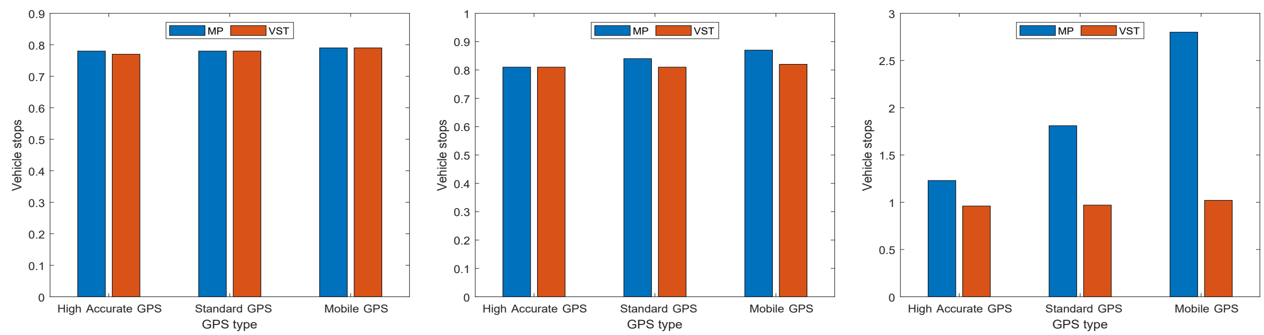
TABLE II: Cycle lengths and maximum intersection capacities

Scenarios	1	2	3
Cycle length (s)	90	120	150
Max conventional capacity (veh/h/lane)	1089	1167	1900



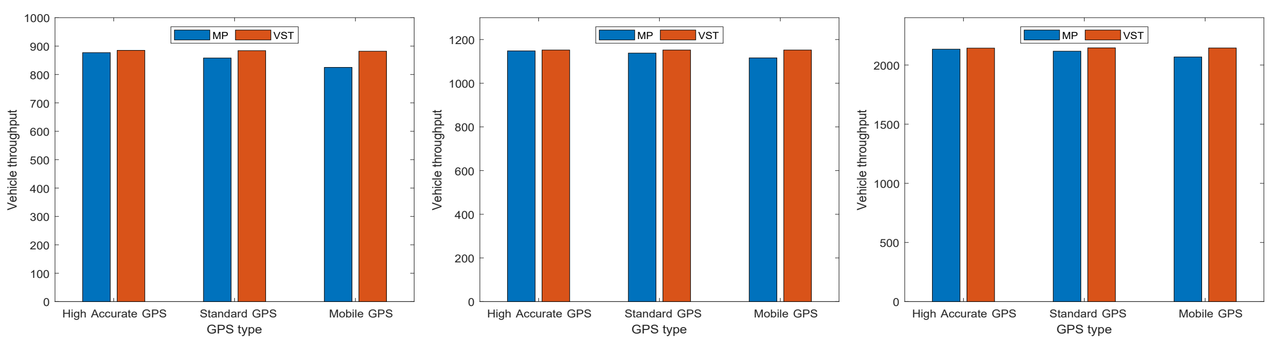
(a) Average vehicle delay (s) - undersaturated
(b) Average vehicle delay (s) - saturated
(c) Average vehicle delay (s) - oversaturated

Fig. 4: Average vehicle delay for MP and VST while using different GPS type for different traffic congestion scenarios



(a) Vehicle stops - undersaturated
(b) Vehicle stops - saturated
(c) Vehicle stops - oversaturated

Fig. 5: Average number of stops for MP and VST while using different GPS type for different traffic congestion scenarios



(a) Vehicle throughput - undersaturated
(b) Vehicle throughput - saturated
(c) Vehicle throughput - oversaturated

Fig. 6: Vehicle throughput for MP and VST while using different GPS type for different traffic congestion scenarios

compared to other GPS types. In saturated and oversaturated conditions, VST outperforms MP for all the GPS types. We see a clear performance deterioration for MP while considering larger GPS errors, whereas VST appears less sensitive. The difference is clearly more pronounced for oversaturated conditions. In the most extreme case, namely oversaturated conditions for mobile GPS, the average vehicle delay using MP is approximately 60 s higher than the average vehicle delay using VST.

Investigating results in terms of the average number of stops for each vehicle reveals a similar trend as for the average vehicle delay, as can be seen from Fig. 5. The results show that the number of stops using MP is highly sensitive to GPS accuracy, especially in saturated and oversaturated traffic conditions. For instance, the average number of stops using mobile GPS is higher than 2.5 stops per vehicle in oversaturated traffic conditions, whereas, using high accurate GPS, the average number of stops is around 1 stop per vehicle.

Finally, we investigate total vehicle throughput for the different scenarios, which is shown in Fig. 6. For this metric,

TABLE III: Simulated scenarios

Scenarios		1	2	3
Traffic condition		*undersaturated*	*saturated*	*oversaturated*
Approach	**Phase**	**Traffic flow (veh/h/lane)**		
S-W	1	100	130	240
N-S	2	200	260	480
W-N	3	50	65	120
E-W	4	100	130	240
N-E	5	100	130	240
S-N	6	200	260	480
E-S	7	50	65	120
W-E	8	100	130	240
TOTAL		900	1170	2160

we see that VST is never outperformed by MP for any of the tested scenarios; however, the performance appears to be less sensitive to different GPS errors than for the other metrics.

Overall, we observe that VST is considerably less sensitive to measurement errors than MP. A possible explanation is that position and speed errors affect the controller input in a different way. In fact, for MP, errors in vehicle speed may cause to consider or not a vehicle being part of the queue, resulting in a possible overestimation or underestimation of the queue length. As queue length is the only input of MP, this may, in turn, produce an erroneous assignment of the green times. On the other hand, since VST uses each individual vehicle arrival time to the intersection, the errors in position and speed of each vehicle may lead to inaccuracy in the arrival time prediction, but still, all vehicles are taken into account by the controller.

V. Conclusions

In this paper, we tested the effect of CV data quality on signal controller performance. For this purpose, we measured intersection performance using two controllers, MP (in a modified version adapted to operate in a CV environment) and VST, as representative of AIC and DIC, respectively. An isolated four-approach intersection has been simulated considering three traffic conditions and by applying three error distributions associated with different GPS technologies. The simulation results show that VST is less sensitive to data error compared to MP. Our finding shows that errors in CV data may lead to larger performance degradation in aggregated adaptive controllers. In other words, the quality of CVs data affects signal performance particularly, if the controller is an AIC. Although high accurate GPS may solve the problem of inaccurate data, equipping all the vehicles with this type of device may be considerably expensive and unfeasible. Moreover, GPS is already embedded in most of the cellphones which, at least one, is found in every vehicle. Accordingly, mobile GPS data can be used as input of the controller pretty soon. However, DICs can outperform AICs using such data according to our study. This paper can be extended in future works by considering the disruptions of communications in an environment with lower CV penetration rates. Moreover, the effect of the CVs data error applied to coordinated intersections may be investigated. Ongoing efforts can be made not only in the cooperation between the vehicles and the intersections but also among intersections.

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