A Framework for Minimizing Information Aging in the Exchange of CAV Messages

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***Abstract*—Connected and Autonomous Vehicles (CAVs) are expected to become a reality on roads in the near future bringing significant social, economic, and environmental benefits. Cooperation and coordination among CAVs will be enabled through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) wireless communications. Each vehicle knows its current location and in many cases will have to communicate this information to its associated Roadside Unit (RSU). With the proliferation of CAVs, the RSU is expected to receive and process a large amount of feedback information from its assigned CAVs. Thus, an event-triggered communication scheme is proposed instead of conventional approaches where communication takes place in a periodic manner. Further, the effect of age of information on the resulting accuracy of the vehicle tracking error is taken into account by considering the message queue wait time at the RSU. A family of optimization problems is proposed, used to determine the optimal accuracy threshold for the event-triggered algorithm, so as to minimize the effect of the tracking error caused by the queue wait time.**

***Index Terms*—connected and autonomous vehicles, intelligent transportation systems, age of information, event-triggering**

I. INTRODUCTION

The introduction of connected and autonomous vehicles (CAVs) will revolutionize road transportation and personal mobility in the years to come. According to the independent think tank RethinkX, by 2030 95% of passenger miles in the U.S. will take place utilizing fleets of CAVs, while the mobility model of people will change from individual car ownership to a new business model of Transport as a Service (TaaS) [1].

The emergence of CAVs is expected to bring beneficial changes to our transportation system. Many studies show that the use of CAVs has the potential to improve road safety by significantly reducing traffic accidents [2]. Additionally, CAVs are expected to reduce traffic congestion and travel times, factors with great economic impact on today's society. These factors will further bring environmental benefits by leading to less fuel consumption and gas emission [3]. Finally, CAVs will promote user equity, as persons who are not able to drive a vehicle, e.g., elderly and disabled, will have the ability to go anywhere anytime.

Although features such as self-parking, advanced driver assistance, and autonomous emergency braking systems are already becoming available, full autonomy is still away from the market as several scientific and technological challenges are still open and need to be addressed [4], [5]. The full positive outcomes of CAVs will be realized by developing technologies that enable Vehicle-to-Infrastructure (V2I) communications. The interaction between vehicles and roadside infrastructure will allow the CAVs to know the road conditions ahead of time and enable cooperative traffic management for maximum efficiency. In order to support traffic management functions through V2I communications, e.g., autonomous overtaking and intersection crossing, the CAVs need to send messages to their corresponding RSUs providing information about their state, e.g., location, speed, acceleration, etc. Without loss of generality, the focus of this work is on the vehicle location information sent to an RSU by all vehicles associated to a particular RSU.

When a large number of CAVs are sending periodic messages to an RSU, a very large number of small-sized messages are generated. A vast number of messages received at the RSU creates a bottleneck, as these messages must be processed after waiting in a queue. Too many messages may lead to two potentially undesirable situations. First, if the incoming rate of messages is greater than the speed at which the RSU can process them, the queue will grow infinitely long. Second, even if the processing speed is adequate, the queue wait time will contribute to the tracking error, as the position status of a vehicle is updated only after it is processed by the RSU (while the vehicle continues to travel). Therefore, the time that elapses since the last received update was generated needs to be investigated in terms of its effect on the resulting tracking accuracy.

In the field of networked systems, this concept has recently emerged as a notable topic and is referred to as the *age of information* [6]. It is a novel metric that aims to quantify the freshness of information and it is therefore inherently related to the time a piece of information is queued prior to being processed. The fundamental problem of how often should a system's status be updated with respect to the age of information, taking into account that the status updates will wait in a queue, was initially presented in [7]. Following this seminal work, other related works have been published, e.g., [8], [9]. Further, the authors in [10] investigate several aspects related to the age of information on IoT applications.

It should be noted that even though the age of information characterizes the freshness of information in terms of time, it does not take into account the freshness with respect to the information content. For example, in the case of vehicle tracking, it is not only the time since the last received update was generated that affects the tracking accuracy, but rather the combination of this time and the speed of the vehicle (i.e., the distance the vehicle will travel within this interval) and hence its location accuracy will depend on the vehicle's speed. Such meaningful variations of the age of information concept have been recently investigated in [11], [12].

Further, in order to initially reduce the number of messages to be sent to the RSU, instead of a periodic signaling approach, this work proposes the adoption of an event-triggered signaling scheme, where signaling takes place only upon the occurrence of an "event". Within the context of event-triggering systems, an event corresponds to an unexpected situation, i.e., an incident outside the system's expected behavior [13]. Unlike periodic schemes, the idea behind event-triggering approaches is to carry out actions only upon the occurrence of certain events [13]. Over the past years this concept has attracted the interest of the scientific community as it typically decreases the computation and communication burden and thus, exhibits certain advantages over periodic approaches [14], [15]. The topic of event-triggered communications has been also recently addressed in the literature in relation to intelligent transportation systems and IoT, e.g., [16]–[22].

The rest of this paper is structured as follows. The vehicle tracking problem is presented in Section II, while Section II-A describes the event-triggered tracking approach. Section II-B discusses the tracking error caused by the queue wait time and its effect on the tracking accuracy of the event-triggered approach. This is followed by Section III, that presents a family of optimization problems used to derive the optimal tracking accuracy for the event-triggered technique, while also taking into account the tracking error caused by the queue wait time. Finally, Section IV offers some concluding remarks and potential avenues for future research.

II. Vehicle Tracking Problem

A scenario is considered where the CAVs need to inform their associated RSU about their current location. The route that a vehicle will follow is known to the RSU, however, at any given time the RSU needs to know the location of the vehicle along its route. This work is subsequently divided into two parts; initially, the tracking of the vehicle using event-triggering is presented, followed by the determination of the queue-induced tracking error.

A. Event-Triggered Tracking

An event-triggered vehicle tracking approach is presented, in which both the RSU and the vehicle use a predetermined mobility model to estimate the movement of the vehicle with respect to time. Compared to periodic signaling, instead of sending a message to the RSU in every period, a vehicle sends a message in a period only if an event has occurred. An event is triggered if there is a difference between the predicted (based on the mobility model) and actual location of the vehicle that exceeds a predetermined threshold (in meters). When an event occurs, the vehicle and RSU update the vehicle's estimated position and the model parameters used.

The mobility model used to predict the locations of the vehicles is a set of speed values assigned to every possible location and time. Specifically, in this work the model considers a speed value for each road for each hour of the day (the average speed at road r between hours h and $h+1$, $h \in \{0, 1, \cdots, 23\}$, is denoted as $U_{\mathrm{p}}(r, h)$). The model is derived from a real dataset of GPS-based vehicle traces. In particular, the dataset comprises of traces generated by the onboard devices of approximately 1700 state-owned vehicles in Cyprus and contains all the routes traveled by the vehicles from February 2017 till July 2019 island-wide. The GPS-coordinates of the vehicles are recorded every 30 seconds and, additionally, when the vehicle turns or when unexpected driving behavior is detected. Throughout the day, the number of active vehicles ranges from approximately $300 - 350$ (around midnight and early morning hours) to 1700 (during the morning and early afternoon hours).

The route of each vehicle is known a priori and is defined as a sequence of road segments. For the purpose of this work, it suffices to represent a route, R, as a sequence of pairs, $\{(r_n, L_n)\}$, where r_n is the road id and L_n the length of the road segment that is part of the specific route. Without loss of generality, for the following analysis the focus is on a particular route, R.

In addition, time is considered in terms of periods (T is the period length). Considering that a vehicle starts traveling on route R at time instant zero, period k corresponds to the interval between time instants $(k-1)T$ and kT. Given the prediction model utilized, for each period k the pairs of road ids and lengths traveled is denoted as $R_k = \{(r_{k_l}, L_{k_l})\}$, where $(r_{k_l},\, L_{k_l})$ is the l-th pair of road id and road segment length traveled during period k. Specifically, given the time of day, the vehicle's location at the end of each period can be estimated utilizing the model's predicted speeds. It is noted that R_k is not a subset of R, as a segment of the route, (r_n, L_n), is possibly split between two or more time periods.

Therefore, given the model as described above, at the end of period m, i.e., at time mT, an event is triggered for a particular vehicle if the difference between the predicted and actual location of the vehicle exceeds a threshold α:

$$\left| \sum_{k=n+1}^{m} \sum_{l=1}^{|R_k|} U_{\mathrm{p}}(r_{k_l}, h_k) t_{k_l} - \int_{nT}^{mT} U(t) \mathrm{d}t \right| > \alpha, \qquad (1)$$

where nT is the time instant the last message was sent from the vehicle, h_k is the time of the day corresponding to time period k, t_{k_l} is the time needed to travel the road length L_{k_l} with the corresponding predicted speed $U_{\mathrm{p}}(r_{k_l}, h_k)$, $|R_k|$ denotes the length of sequence R_k, and $U(t)$ is the actual instantaneous speed of the vehicle.

Since the inequality of Eq. (1) is checked at the end of each period, the instantaneous speed of the vehicle, $U(t)$, can be replaced by the average speed within the specific time interval.

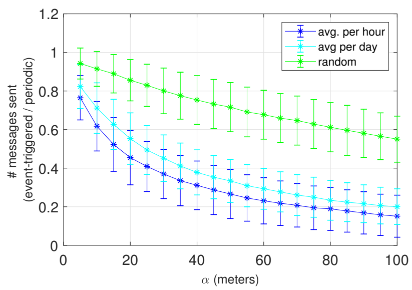


Figure 1. The average number of messages sent with the event-triggered approach normalized against periodic signaling using three different prediction models for the speeds of the vehicles.

For time interval t_{k_l}, i.e., during the l-th road segment of period k, the average speed, U_{k_l}, is calculated by:

$$\int_{(k-1)T+t_{k_{l-1}}}^{(k-1)T+t_{k_l}} U(t)\ \mathrm{d}t = U_{k_l}\ t_{k_l} \tag{2}$$

Then, Eq. (1) becomes:

$$\left| \sum_{k=n+1}^{m} \sum_{l=1}^{|R_k|} \left(U_{\mathrm{p}}(r_{k_l}, h_k) - U_{k_l} \right) t_{k_l} \right| > \alpha, \tag{3}$$

Clearly, the degree to which the number of messages decreases compared to a conventional periodic approach depends on the differences between the actual and predicted speeds, that is, the degree to which the actual vehicle movement matches the behavior model utilized. Moreover, the threshold value α determines the tracking accuracy of the algorithm. Clearly, the smaller the value of α, the higher the required tracking accuracy and the number of messages that will be sent.

Figure 1 illustrates the average number of messages sent when using the described event-triggered approach normalized over the number of messages that would have been sent with periodic signaling. The result is the average obtained by tracking 166 vehicle routes. These routes are randomly selected from the aforementioned dataset and they correspond to different areas and different times of the day. The prediction models for the speeds of the vehicles that were used included the average speed per road per hour of the day as described in this section, the average speed per road (averaged over all hours of the day), and randomly generated speeds within the same range as real average speeds in the dataset.

Figure 1 clearly shows that the event-triggered algorithm decreases the number of messages that need to be sent, compared to periodic signaling. Also, as one would expect, more accurate prediction models yield a higher decrease in the number of communicated messages.

B. Queue-Induced Tracking Error

When an event is triggered, the vehicle sends a message, M, to the RSU. However, the vehicle and the RSU will only resynchronize as soon as the message M is processed by the RSU, after waiting in the queue for some time, t_q. Thus, the resulting accuracy of the event-triggered approach is given by

$$\alpha + Ut_q, \tag{4}$$

where U is the average speed of the vehicle over the duration of t_q. We designate Ut_q as the queue-induced tracking error. Essentially, it is the distance the vehicle will travel while its latest received message waits in the queue at the RSU.

As previously mentioned, the concept of taking into account the time that has elapsed since the last received update was generated is defined as the age of information [6]. By its classical definition the age of information is a measure of time representing the freshness of information in terms of the amount of time that has passed, regardless of how much the information content has changed. The queue-induced tracking error is a quantity strongly linked with the age of information, in the sense that it is the effect of the age of information on the information content, i.e., how much the location of the vehicle has changed as a consequence of the fact that in the meantime the information has aged.

In order to estimate the queue wait time, t_q, known results from queuing theory are employed. Without loss of generality, a single server and arrivals following a Poisson process are considered. Since all messages in the queue are of the same type and size a deterministic service time is also considered. Thus, an $M/D/1$ queue is used, for which it is known that the average wait time in the queue is given by [23]:

$$t_q = \frac{\rho}{2\mu(1-\rho)}, \tag{5}$$

with $\rho = \lambda/\mu$, where μ is the number of messages per second processed by the RSU, and λ is the number of messages per second received at the RSU. The value of μ is determined by the messages' size and the RSU's processing speed.

In the case of a conventional periodic signaling approach, parameter λ would be equal to V/T, where V is the number of vehicles in the network and T the length of the period, whereas for an event-triggered approach, the message arrival rate depends on the value of α. Specifically, the arrival rate is estimated using the empirical result of the event-triggered tracking algorithm, i.e., by estimating an approximate polynomial, $p(\alpha)$, using the results of Fig. 1. For these results the prediction model, when using a speed value for every road for every hour of the day, can be fitted by a 4-th degree polynomial (Fig. 2) that will be used for the rest of this work. Note that, in this case the number of messages sent per second by V vehicles is estimated by $Vp(a)/T$.

Figure 3 demonstrates the effect of the queue-induced tracking error on the accuracy of the event-triggered approach. Specifically, Fig. 3(a) illustrates the average wait time in the queue and Fig. 3(b) illustrates the resulting accuracy of the approach. The figures correspond to a scenario with 1000 vehicles traveling with a constant speed of 30 m/s and a period of 5 s, while all vehicles use the same value for α (see Eq. (3)). It is shown that for very small values of α, the queue (thus the wait time) at the RSU will grow infinitely, as too

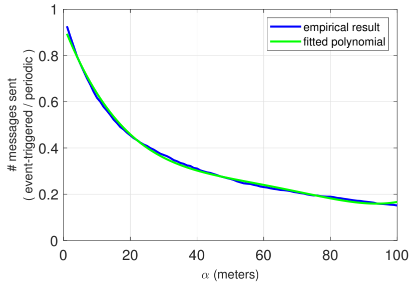
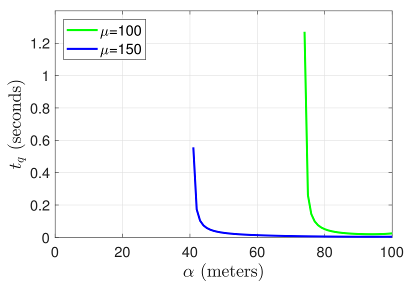
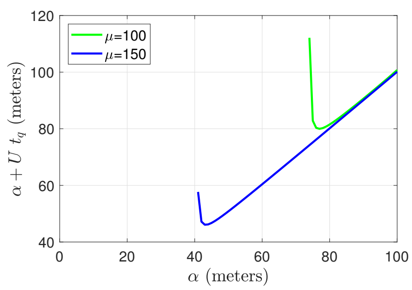


Figure 2. $p(\alpha)$, fitted by a 4-th degree polynomial, for the empirical results of event-triggered signaling presented in Fig. 1.



(a)



(b)

Figure 3. Effect of the queue-induced tracking error: (a) The average queue wait time (b) Resulting tracking accuracy of the event-triggered approach.

many messages are generated by the vehicles. Further, as the α value becomes larger, it is shown that there is a region where the queue-induced tracking error is high enough so that the resulting accuracy of the event-triggered tracking is larger than the value of α that has been set as a threshold.

III. Minimizing Information Aging

As previously discussed, for optimal performance, the accuracy threshold (α) of the event-triggered vehicle tracking algorithm must be at least sufficiently large so that the queue at the RSU does not grow infinitely. In addition, it is desirable that α is large enough so that the actual accuracy of the tracking algorithm does not end up being larger than the set threshold (α) due to the queue-induced tracking error.

Thus, a family of optimization problems is defined below in order to determine the optimal accuracy threshold (α) for the event-triggered approach. According to the specifics of the application considered, different optimization problem variations can be defined (in this work three different formulations are presented accounting for roads, vehicles, and routes). This optimization problem is solved at the RSU and the result is communicated to the vehicles. Since the optimization problems can be solved quickly, this allows for frequent updates of the optimal accuracy values.

The first variation of the optimization problem considers a different value of α for every road. The rationale behind this approach is that depending on the road type, e.g., highway, local street or arterial street, a different tracking accuracy is desired. Thus, the following problem ($P1$) is defined:

$$(P1) \quad \min_{\alpha_i} \quad \sum_{i=1}^{N} \alpha_i + U_p(r_i, h_n)\ t_q(\mu, \alpha_i, V_i) \tag{6a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} \frac{p(\alpha_i)\ V_i}{T} < \mu, \tag{6b}$$

$$\alpha_i \leq \alpha_{i,\max}, \quad \forall i \in \{1, 2, \cdots, N\}, \tag{6c}$$

where N is the number of roads in the network under consideration, $U_p(r_i, h_n)$ is the average speed at road r_i at the current time of the day h_n, V_i is the current number of vehicles traveling on road r_i, and α_i the accuracy threshold for road r_i. The optimization function(6a) corresponds to the minimization of the sum of the queue-induced tracking errors (Eq. (4)) of all roads. Following the discussion of Section II-B, constraint (6b) rejects solutions for which the queue grows infinitely, while constraint (6c) sets the maximum acceptable value for the accuracy threshold for each road.

Moreover, it is of practical interest to assign priorities to different roads. High priority means that a higher tracking accuracy is desired for that particular road compared to roads with lower priorities. In this case, the specific thresholds imposed by the inequalities of Eq. (6c) can be replaced by more relaxed constraints. Specifically, the set of N roads can be divided into subsets according to their priorities. For example, defining Q priority classes and subset $P_q \subset \{1, 2, \cdots, N\}$ as the set of road indexes assigned a priority q (with sets $P_1, P_2, \cdots, P_Q$ disjoint and priorities descending from P_1 to P_Q), constraint (6c) can be replaced with $\alpha_i < \alpha_u$, $\forall i \in P_q, u \in P_{q'} : q < q'$, so that roads in classes with higher priority will be assigned lower values of α.

Another alternative is to determine a different value of accuracy per vehicle and per route. That is, to assign an α_j to each vehicle j so that a maximum expected number of messages corresponds to the current route of the vehicle from source to destination. Thus, problem $P2$ is defined:

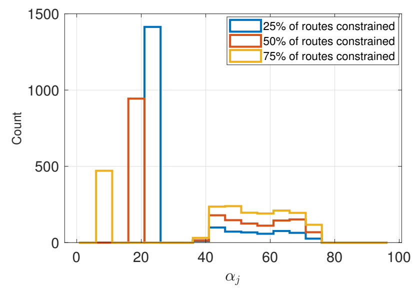


Figure 4. Histogram of the solutions obtained by $P2$ when 25%, 50%, and 75% of the routes are constrained by the inequalities of 7d.

$$
\begin{aligned}
(P2) \quad \min_{\alpha_j} \quad & \sum_{j=1}^{V} \alpha_j + U_p(h_n)\ t_q(\mu, \alpha_j) && \text{(7a)}\\
\text{s.t.} \quad & \sum_{i=j}^{V} \frac{p(\alpha_j)}{T} < \mu, && \text{(7b)}\\
& \alpha_j \leq \alpha_{j,\max}, \quad \forall j \in \{1, 2, \cdots, V\}, && \text{(7c)}\\
& \frac{m_{R_j}}{t_R} \leq \frac{p(\alpha_j)}{T}, \quad \forall j \in \{1, 2, \cdots, V\}, && \text{(7d)}
\end{aligned}
$$

where $U_p(h_n)$ is the prediction speed at the current location of the vehicle at current time of the day h_n. Constraint (7d) now sets a maximum expected number of messages, m_{R_j}, for the route R of vehicle j, where t_R denotes the estimated time to traverse route R based on the mobility model in use.

Figure 4 shows the results obtained when solving $P2$, aiming to highlight the effect of constraint (7d) (by considering three scenarios where 25%, 50%, and 75% of the routes are constrained by the inequalities of constraint (7d)). From the figure, it is observed that the α_j's for the routes that are constrained by (7d) take small values, whereas the rest are forced to larger values in order to satisfy the constraint (7b) (so that the queue does not grow infinitely). Note that for all three scenarios the values of the parameters used were: $V = 1886$, $T = 5$ s, $\mu = 150$, $\alpha_i \leq 100$ m, and m_{R_j} values are drawn randomly so that they correspond to a percentage of messages ranging from 20% to 30% of the messages that would have been sent via periodic signaling. Further, the values used for the prediction speeds on each road, $U_p(h_n)$, throughout this work, were drawn from the mobility model of Subsection II-B, which is based on real data.

In practice, depending on the application domain, the number of vehicles on each road might fluctuate continuously. Therefore, the derived values of α_i, $\forall i \in \{1, 2, \cdots, N\}$, will not be the most suitable most of the time. Naturally, the more often the optimization process is performed, the closer to the optimal the utilized values of α_i's will be. Nevertheless, in practice, these values cannot be updated overly often. Thus, it is of practical interest to consider solving the optimization problem taking into account the potential variation on the number of vehicles until the next execution of the optimization algorithm. In this case, two questions must be investigated. First, what modifications need to be made so that the solution can accommodate the expected vehicle fluctuations sufficiently well. Second, by how much the results worsen when the modified formulation is solved for the initial number of vehicles, as compared to the solution to the same problem when the original formulation ($P1$) is used.

Clearly, this optimization problem is a variation of $P1$:

$$
\begin{aligned}
(P3) \quad \min_{\alpha_i} \quad & \sum_{i=1}^{N} \alpha_i + U_p(r_i, h_n)\ t_q(\mu, \alpha_i, V_i) && \text{(8a)}\\
\text{s.t.} \quad & \sum_{i=1}^{N} \frac{p(\alpha_i)\ V_i^+}{T} < \mu F, && \text{(8b)}\\
& \alpha_i \leq \alpha_{i,\max}, \quad \forall i \in \{1, 2, \cdots, N\} && \text{(8c)}
\end{aligned}
$$

The objective function (8a) remains the same, therefore the solution is optimized for the current number of vehicles at a specific time instant. Constraint (8b) now accounts for an increased number of vehicles, with V_i^+ representing the number of vehicles on road i, such that $V_i^+ > V_i$, $\forall i \in \{1, 2, \cdots, N\}$. That is, the constraint guarantees that the increased number of vehicles, V_i^+, $\forall i \in \{1, 2, \cdots, N\}$, can be accommodated without the queue length growing infinitely. The addition of parameter $F < 1$ at the right side of the inequality ensures that not only the queue length remains finite, but the queue wait time for the increased number of vehicles remains within an acceptable limit. Due to the fact that the wait time for the utilized queue model grows exponentially with α, the wait time quickly becomes prohibitively large as the ratio of the mean arrival rate over the mean service rate nears the value 1. Therefore, the value of parameter F must be close to, but smaller than 1. Note that in $P1$ parameter F is not necessary, since both the objective function and constraint (6b) consider the same numbers of vehicles. As a consequence, the same value of wait time affects both the objective function and constraint (6b), thus a large wait time increases the value of the objective function and does not yield an optimal solution.

Figure 5 shows the values of α_i, $\forall i \in \{1, 2, \cdots, N\}$, resulting from the optimization problems $P1$ and $P3$. The total number of vehicles is 1886 and the values of V_i^+ are 10% higher than the corresponding V_i's. The values of the rest of the parameters are $N = 20$, $\mu = 200$, $\alpha_i < 50, \forall i \in \{1, 2, \cdots, N\}$, and $F = 0.995$. This figure shows that, as expected, in order to satisfy the constraint (8b) in $P3$, instead of the constraint (6b) in $P1$, larger values need to be assigned to the values of the α_i's. Further, Fig. 6 illustrates the values of the objective function when the α_i's are provided by the solutions of $P1$ and $P3$, with the values of V_i^+ ranging from -10% to $+10\%$ compared to the corresponding V_i's. The figure shows that the solution of $P3$ can handle a 10% increase in the number of vehicles, whereas for the actual current values of vehicles V_i, $\forall i \in \{1, 2, \cdots, N\}$ (or even for lower values), the solution is not considerably worse than the one given by $P1$. The reader should also note that for the same scenario,

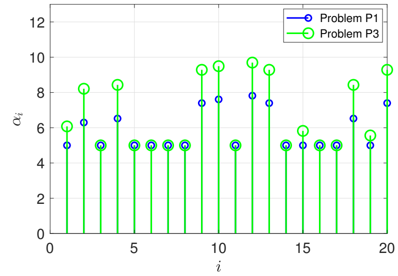


Figure 5. The solutions obtained by $P1$ (blue) and $P3$ (green) when the values of V_i^+'s are increased by 10% compared to the corresponding V_i's.

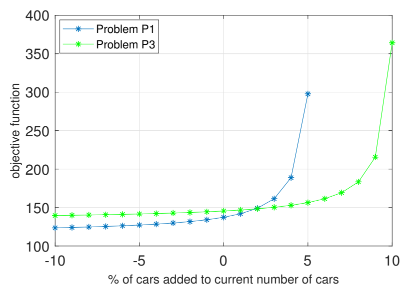


Figure 6. The values of the objective function when the α_i's are provided by the solutions of $P1$ (blue) and $P3$ (green), for the values of V_i^+ ranging from -10% to $+10\%$ compared to the corresponding V_i's.

$P1$ cannot handle more than a 5% increase in the number of vehicles, making $P3$ a more effective approach to the problem when the number of vehicles fluctuate.

IV. CONCLUSIONS

This work proposed the usage of an event-triggered algorithm for vehicle position tracking and showed that, compared to conventional periodic signaling, this approach can significantly decrease the communication overhead. This is an important advantage, especially taking into consideration the expected scale of emerging CAVs.

Furthermore, the concept of the age of information was considered with respect to the proposed event-triggered tracking scheme. It was demonstrated that for large numbers of vehicles, the queue wait time for the messages at the RSU is not negligible and can potentially lead to an additional tracking error. This is a direct consequence of the fact that the position of a vehicle is not updated as soon as the corresponding message is generated, but rather after it is processed by the RSU, while the vehicle continues to travel. Within this context, the actual resulting accuracy of the event-triggered tracking algorithm is defined. Subsequently, a family of optimization problems were formulated (accounting for roads, vehicles, and routes) that can be used to derive the optimal value for the accuracy threshold of the event-triggered tracking algorithm. That is, the optimal value above which an event should be triggered, so that the resulting tracking accuracy of the algorithm, taking into consideration the queue-induced tracking error, is maximized.

Future work involves extending the methodology for a distributed infrastructure, where local controllers process the communication messages only for vehicles in their vicinity.

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