GENERATION RATE CONTROL WITH AOI UNDER TRAFFIC HOLE PROBLEM IN VEHICULAR NETWORKS

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Abstract – *In 6G mobile networks, vehicular networks will significantly benefit from extremely high network throughput and capacity. For Internet of Things (IoT) within a vehicular network, the sensor data as an update is delivered from each sensor source to a nearby gateway, by Vehicle-to-Vehicle (V2V) and Vehicle to Roadside unit (V2R) communications. The mobility of the vehicles is not only affected by the vehicle itself, but also by external means, such as the signal operations of traffic lights. The red light stops the vehicles at the intersection, which will increase the time it takes for updates carried by the vehicle to be delivered. On the other hand, the red light can also increase the opportunities of vehicles moving behind to catch up with the waiting vehicles in forwarding updates. This is termed as the traffic hole problem by the traffic lights in vehicular networks. In this paper, we investigate the influence of traffic lights in vehicular networks using the metric of Age of Information (AoI). We discuss the optimal generation rate at the source by considering the trade-off between AoI and transmission cost. We propose a Total Average Cost aware generation rate Algorithm (TACA) for the generation interval time at the sensor source. Our intensive simulations verify the proposed algorithm and evaluate the influence of the traffic lights on AoI.*

Keywords – Age of information, generation rate control, traffic hole, vehicular network

1. INTRODUCTION

The deep integration of 6G and vehicular networks spawns future vehicular networks that have the potential to support autonomous driving and other advanced vehicular applications. A wide range of spectrums, such as microwave, millimeter wave, Terahertz (THz) wave, and visible light, is used for transmitting data generated by many types of on-board sensors [1]. Over the past several years, the Department of Transportation (DOT) and its operating administrations have engaged in numerous activities related to connected vehicles, including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Pedestrian (V2P) communications, collectively referred to as "V2X" communications [2]. Vehicle-to-Vehicle (V2V) communication technology can increase the performance of vehicle safety systems and help save lives [3]. Major applications include environment monitoring, safety messages, and multimedia sharing [4]. Due to the increasing demands of various applications on vehicles, both academic researchers and automotive industries are paying a lot of attention to vehicular networks. This is a particular type of mobile sensor network [5], in which the vehicle-mounted sensors send harvesting data to a remote sink via vehicular networks.

In vehicular networks, timely and lossless multi-hop data delivery among vehicles is essential. A new metric called Age of Information (AoI) was introduced in [6] to capture the requirement for timely status updating. To formally model and capture the concept of the freshness of information at the monitor/controller, the instantaneous age at any time is defined as the difference between the current time and the generation time of the last update that has been successfully received [7, 4]. In general, the AoI is the average of the instantaneous age. Ubiquitous smart devices and high-quality wireless networks enable workers to participate in Spatial Crowdsourcing (SC) easily [8], which refers to assigning location-based tasks to moving workers, has drawn increasing attention. Many real-world SC applications (e.g., Uber [9], and Waze [10]) require vehicular networks for task sensing and data delivery, the impact of traffic lights on the quality of SC can be measured by AoI. That is, the traffic lights can affect the vehicular network directly, and affect the quality of SC indirectly.

However, the mobility of vehicles is not only affected by the vehicle itself, but also by external means such as the signal operations of traffic lights. Therefore, traffic lights can affect data delivery in vehicular networks. For example, while a vehicle carries an update to move along a path, it may stop at a red light. We call this situation a *traffic hole* [11]. On the other hand, the vehicles stopped by the red light must wait with the vehicles moving behind, which could increase the opportunities for vehicles moving behind to catch up in data forwarding. As shown in Fig. 1, the sensor source generates the updates with the interval time τ, and the nearby vehicles will deliver them to the next Roadside Unit (RSU) as a gateway for uploading to a server by V2V and V2R communications.

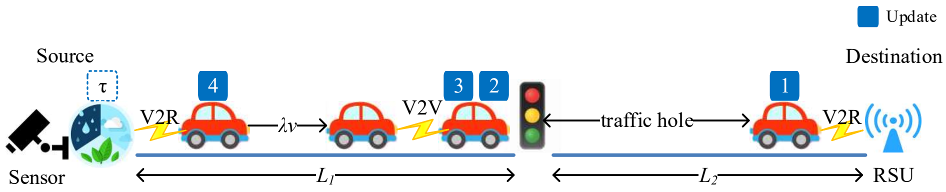


Fig. 1 – Scenario of update delivery under traffic light in vehicular networks

The second vehicle is stopped by the red light and a traffic hole appears between the first and the second vehicle, blocking the V2V data transmissions and increasing the delivery delay of the second update. While the second vehicle carrying the second update is waiting at the red light, the third vehicle catches up and forwards the third update to reduce its delay.

In this paper, we investigate the influence of traffic lights on data delivery in vehicular networks using the metric of Age of Information (AoI). Since traffic lights block V2V data delivery, we discuss the optimal generation rate at the source by considering the trade-off between the AoI and transmission cost. A red light stops the vehicles carrying the updates and increases the updates' delays. Meanwhile, the vehicles moving behind could catch up with the waiting vehicles in forwarding the new updates, and the old updates at the traffic light will lose their contributions on AoI. Increasing the generation rate can reduce the AoI, but also increase the number of such old updates at the red light. We also consider the transmission cost (energy consumed) [7], as increasing the generation rate can also increase the cost. Therefore, generation rate control at the sensor source should consider the influence of traffic lights on the data transmissions. We also propose a Total Average Cost aware generation rate Algorithm (TACA) for deciding the generation interval time at the sensor source. Our intensive simulations verify the proposed algorithm and evaluate the influence of the traffic lights on AoI.

The remainder of this paper is organized as follows: In Section 2, we review the most related work. We discuss the system model and the traffic hole problem in Section 3. We analyze the AoI and transmission cost in Section 4. We evaluate the efficacy of the analysis model and the data delivery with traffic lights in Section 5. The final section concludes the paper.

2. RELATED WORK

6G and vehicular networks: The 6G vehicular network aims to develop a highly dynamic and intelligent system, which enables the networks to change the environment to satisfy various application requirements and service types, such as enhanced Mobile Broadband (eMBB), ultra-Reliable and Low-Latency Communications (uRLLCs), and massive Machine-Type Communications (mMTCs) [12]. 6G network transmission can reach speeds of 1Tbps, allowing for transmission of multimedia data such as vehicle images for use in machine learning-related applications [13, 12]. 6G networks allow for the introduction of the Internet of Things or other real-time application services, such as artificial intelligence and big data computing applications [14]. With speeds up to 1Tbps and packet delays below $100\mu/s$, 6G networks can meet quality of service guarantee requirements [15]. In order to meet high requirements of 6G networks such as high reliability and high security in a dynamic and heterogeneous vehicular network, Zhang et al. [16] propose a novel Weight-Based Ensemble machine Learning Algorithm (WBELA) to identify abnormal messages of vehicular Controller Area Network (CAN) bus network. Employing machine learning into 6G vehicular networks to support vehicular application services is being widely studied and a hot topic for the latest research work in the literature. In vehicular networks, network entities need to make decisions to maximize network performance under uncertainty. Mekrache et al. [14] provide a comprehensive review of research work that integrated reinforcement and deep reinforcement learning algorithms for vehicular networks management with an emphasis on vehicular telecommunications issues.

There are many vehicular applications based on sensing and communications between vehicles. Ahn *et al.* [17] present the Road Information Sharing Architecture (RISA), a distributed approach to road condition detection and dissemination for vehicular networks. SignalGuru [18] relies solely on a collection of mobile phones to detect and predict a traffic signal's schedule. For such an infrastructure-less approach, multiple phones in the vicinity use opportunistic ad-hoc communications to collaboratively learn traffic signals' timing patterns and predict their schedules. Various advanced sensors (e.g., lidar, radar, camera, etc.) equipped on a representative autonomous vehicle. Due to the intrinsic limitations of these sensors, autonomous vehicles are prone to making erroneous decisions and causing serious disasters. Networking and communication technologies can greatly make up for sensor deficiencies, and are more reliable, feasible and efficient to promote the information interaction, thereby improving autonomous vehicles' perception and planning capabilities, realizing better vehicle control, and ultimately greatly improving the security of autonomous vehicles [19].

Table 1 – Description of frequently-used notations

Notation	Description
τ	Generation interval time of updates at source.
λ	The interval time of arrival vehicles.
r_i, L_i	The i^{th} road with the length of L_i.
τ_c	Cycle time of a traffic light.
$\tau_r(\tau_g)$	Duration of a red (green) light.
v	The moving speed of vehicles.
R	Wireless communication range.
Δ_{av}/Δ_{sum}	Average AoI / Sum AoI of each cycle.
t_i/t_i'	Generation / receiving time of i^{th} update.

Age of information: The AoI, a recently proposed metric, has inspired a series of studies on the analysis and optimization of timeliness performance. Saurav et al. in [20] consider a node-monitor pair and propose an updates transmission strategy. They transmit any newly arrived update with a fixed probability or never transmit that update to minimize a linear combination of AoI and average transmission cost. Li et at. in [21] indicate that, by knowing a set of nodes with given AoI deadlines, tolerance rates, and packet loss rates in sources-base station scenarios, can be determined whether it is schedulable. In addition, for different cases, they propose different feasible scheduler algorithms. Farazi et al. in [22] study multi-source multi-hop wireless networks with an explicit channel contention scenario. Lower bounds for peak and average age of information are derived and expressed in terms of fundamental graph properties including the connected domination number.

AoI in vehicular networks: Generation rate control is investigated as a means of reducing the AoI in vehicular networks. The analytical model formulated by Baiocchi et al. in [23] uses the connectivity graph of the network to demonstrate the relationship of average system AoI with vehicle density and broadcast intervals. Llatser et al. [24] consider a convoy of vehicles and analyze the change in AoI with respect to variable broadcast intervals and convoy size. Choudhury et al. in [4] show that minimizing AoI solely does not always improve the safety of V2V networks. They propose a novel metric, termed Trackability-aware Age of Information (TAoI), that in addition to AoI takes into account the self-risk assessment of vehicles.

3. SYSTEM MODEL

To analyze the data delivery with AoI in a vehicular network that is affected by the traffic lights, we investigate a typical scenario with two roads and one traffic light in Fig. 1. Frequently-used notations in this paper are listed in Table 1.

3.1 Assumption

The well-known car-following model [25] states that a vehicle moves at or near the same speed as the vehicle in front of it, while there is a vehicle within a sufficient range of the current vehicle. Thus, we assume that the velocities of the vehicles on a road are all the same. The velocity is denoted by v. Vehicles communicate with each other through short-range wireless channels. Let R denote the communication range of each vehicle node. We assume each vehicle has enough space to buffer the delivered up- dates.

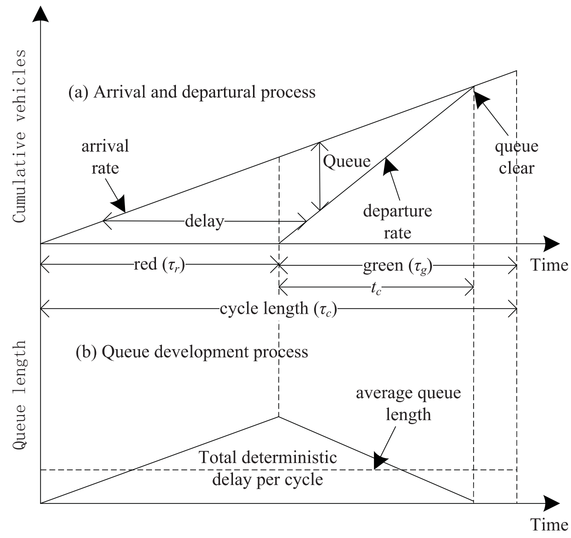


Fig. 2 – Queuing delay under traffic light

In general, the signal operations of the traffic lights are periodic and a cycle in the signal operation is defined as a complete sequence of intervals or phases. Under a simple traffic control system, the traffic flow has two states in a cycle: red and green. The duration of a cycle, red light and green light, is denoted by τ_c, τ_r and τ_g, respectively.

3.2 Traffic hole problem

Traffic flow can be divided into two primary types [26]. The first type is called uninterrupted flow, which is regulated by the interactions between vehicles and interactions between vehicles and the roadway, such as the vehicles traveling on an interstate highway. The second type of traffic flow is called interrupted flow, which is regulated by external means, such as a traffic light or pedestrian signal.

The traffic hole problem can be seen everywhere within the transportation environment, even during rush hour, with the highest traffic volume. All the vehicles moving onto the road are blocked at the entrance by the traffic light. When a vehicle stops at the intersection due to the red light, the vehicle ahead moves on, and a gap appears between them. The length of the gap is increasing during the red time. If the length of this gap is larger than the communication range of vehicles (R) , it can block the wireless communication between the vehicles.

At an intersection where the traffic light can stop the vehicles, queueing will inherently occur. Let $Q(t)$ denote the

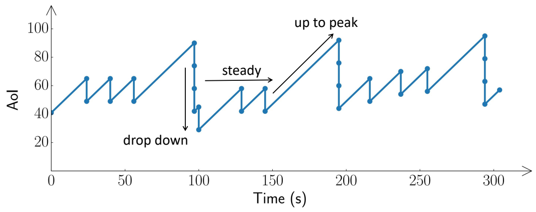


Fig. 3 – Data analysis for AoI by SUMO

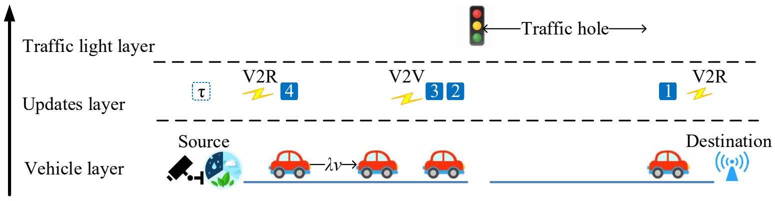


Fig. 4 – Discretization model of update delivery under traffic light

number of queued vehicles at time t. It is assumed that the cycle time τ_c is fixed, and each approach is split in a red phase ($0 < t \leq \tau_r$) and a green phase ($\tau_r < t \leq \tau_c$). If the number of queued vehicles at the start of the red phase is represented by $Q(0)$, the queue during the red phase is given by [27]: $Q(t) = Q(0) + A(t),\ (0 < t \leq \tau_r)$, where $A(t)$ represents the cumulative arrivals of vehicles. In order to illustrate the waiting queue at the signalized intersection, we take an example of $D/D/1$ queueing model [28], which assumes that arrivals and departures are deterministic.

Using the form of queueing with an arrival rate λ, certain useful values regarding the consequences of queues can be computed as shown in Fig. 2. During the red light (τ_r), the arrival vehicles with the rate λ wait at the traffic light, and the queue length increases. Let Q_{max} denote the queue length when the light turns green. Thus, the maximum number of vehicles in a queue can be found as: $Q_{max} = Q(0) + \lambda \cdot \tau_r$. After the time when the light turns green, the vehicles in the queue start to move onto the road with the departure rate s. Let ρ denote the arrival rate divided by departure rate, i.e. $\rho = \lambda/s$. Thus, the clearance time of the waiting queue can be calculated as: $t_c = \rho\tau_r/(1-\rho)$. While the time to queue clearance t_c is equal to or larger than the green time (i.e. $t_c \geq \tau_g$), the input of the traffic flow at the intersection is termed as *saturated* or *over-saturated* flow. While the time to queue clearance at the intersection is less than the green time, (i.e. $t_c < \tau_g$), the input of the traffic flow at the intersection is termed as *under-saturated* flow.

3.3 Data analysis and motivation

We operate SUMO [29] to simulate a scenario with two roads and one traffic light as the same as Fig. 1. The lengths of the two roads (L_1 and L_2) are 800 and 101 meters, respectively. The duration of the red or green light (τ_r/τ_g) is 28 or 70 seconds, respectively. The arrival of the vehicles at the entrance of the road follows a uniform time interval, and the expected interval time denoted by λ is 7 seconds. The average speed of the vehicle moving on the road (v) is 15 m/s. The generation of the updates by the source follows a uniform time interval, and the expected interval time denoted by τ is 16 seconds. The communication range of vehicles (R) is 100 meters.

The simulation result of instantaneous age at any time is shown in Fig. 3. We notice that the instantaneous age in

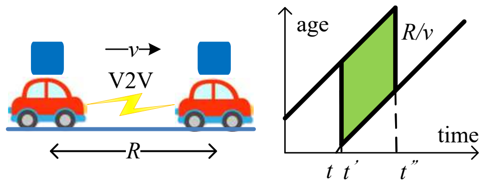


Fig. 5 – Cost model for each V2V hop

this scenario changes periodically, and each period can be divided into three stages as follows: (1) steady stage, while the traffic light is green, the update from the source is delivered by the vehicles via V2V communications and the vehicle carrying this update is moving without stopping; (2) up-to-peak stage, when the traffic light changes to red, the first vehicle carries an update that will stop at the intersection, and the data delivery delay will increase to the age of information; (3) drop-down stage, while the traffic light is still red, the vehicles behind that carry new updates, will catch up with the first vehicle waiting at the traffic light, so they forward the new updates to the first vehicle and all these updates will send to the destination at once.

4. MODEL FOR TOTAL AVERAGE COST

In this section, we give the assumptions and describe the model for analyzing the AoI and transmission cost under the traffic hole problem.

4.1 Discretization model

To analyze the age of information under traffic lights in vehicular networks, we propose a discretization model of uniform distribution with three layers (see Fig. 4) as fol- lows: the first layer is the road traffic, and the expected interval time of the arrival vehicles is denoted by λ. The second layer upon the previous one are the updates gene- rated by the source sensor, and the expected interval time of generation rate is denoted by $\tau = k_0 \cdot \lambda$ where $k_0 \in \{1, 2, \cdots\}$ is an integer value. The third layer is the traffic light. The durations of red light, green light and a cycle, are denoted by $\tau_r = k_r \cdot \tau$, $\tau_g = k_g \cdot \tau$ and $\tau_c = \tau_r + \tau_g$, respectively. Here, k_r and k_g are integer values.

4.2 Total Average Cost (TAC)

Inspired by [7], since the network has the trade-off between AoI and transmission cost, we set the total average cost (TAC) of each cycle to be our objective as follows:

$$TAC(\tau_c) = C_{av}(\tau_c) + \Delta_{av}(\tau_c) \quad (1)$$

where $C_{av}(t)$ denotes the average transmission cost, and $\Delta_{av}(t)$ denotes average AoI.

In the model of transmission cost, the cost is the energy consumed by the V2V communications. As shown in Fig. 5, the cost of each hop can be modeled as the reduction of AoI. For the road with length of R, the delay of carrying by the vehicle is $t'' - t = \frac{R}{v}$, and the delay of V2V communication is $t' - t \approx 0$ which is too short to be neglected. Thus, the cost of each hop is calculated as follows:

$$c_h = \frac{R}{v} \cdot (t'' - t') \approx (\frac{R}{v})^2 \quad (2)$$

During the time of the green light, there will be $\frac{T_g}{\tau}$ cars carrying updates passing by the traffic light without stopping. As can be seen from the previous assumptions, the distance between a vehicle and the vehicles in front of and behind it is greater than the communication radius. Therefore, an update will pass from the source to a vehicle by 1 hop, and from the vehicle to the destination by 1 hop. Since the number of updates driving through during a green light is $\frac{T_g}{\tau}$, the number of hops at a green light in a cycle is $\frac{2T_g}{\tau}$. During the time of the red light, there are $\frac{T_r}{\tau}$ vehicles with updates queuing at the intersection, and $\frac{T_r}{\tau} - 1$ vehicles will transmit an update to the first vehicle before the red light through V2V. Similarly, it takes 2 hops for a vehicle after receiving an update from the sensor and transmitting it from the vehicle to the RSU. Therefore, in one cycle, the number of hops at red light is $\frac{2T_r}{\tau} + \frac{T_r}{\tau} - 1$.

From the above explanation, the number of hops during each green light is $h_g = \frac{2\tau_g}{\tau}$, and the number of hops during each red light is $h_r = \frac{3\tau_r}{\tau} - 1$. Thus the number of hops in each cycle is $h = h_g + h_r$. Thus, the average transmission cost of each cycle is calculated as follows:

$$C_{av}(\tau_c) = (\frac{2\tau_g + 3\tau_r}{\tau} - 1) \cdot \frac{c_h}{\tau_c} \quad (3)$$

4.3 AoI in each cycle

The AoI in each cycle of traffic light includes three stages: up-to-peak, drop-down and steady stages, as shown in Fig. 6. In the steady stage of each cycle, the traffic light is green and the vehicle carrying this update is moving without stopping. The update from the source is delivered by the vehicles via V2V communications. For simplicity, we assume that the distance between two moving vehicles is larger than their transmission range, i.e. $v \cdot \lambda > R$. Thus, the delivery delay of each update in the steady stage denoted by d_S is calculated by:

$$d_S = \frac{L_1 + L_2 - R}{v} \quad (4)$$

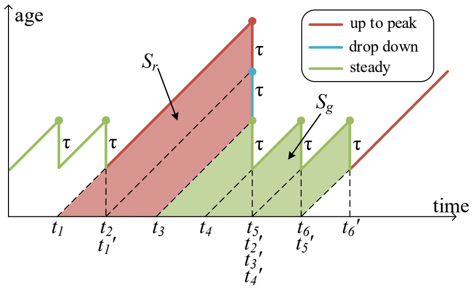


Fig. 6 – Age of information with traffic hole problem

As shown in Fig. 6, the first update is generated at t_1 and is received at t_1' in a steady stage, where its delay is equal to $t_1' - t_1$. According to our discretization model, the number of the update in steady stage is $k_g = \lfloor \frac{T_g}{\tau} \rfloor$.

In the up-to-peak stage of each cycle, the traffic light changes to red, and the first vehicle that carries an update will stop at the intersection. The update delivery delay will increase so as to the age of information. Thus, the delay of the update carried by the first vehicle waiting for the traffic light (denoted by d_U) is calculated as follows:

$$d_U = \frac{L_1}{v} + \tau_r + \frac{L_2 - R}{v} \quad (5)$$

In the drop-down stage of each cycle, while the traffic light is still red, the vehicles behind that carry new updates will catch up with the first vehicle waiting at the traffic light. Thus, they forward the new updates to the first vehicle, and all these updates will send to the destination at once. According to our discretization decentralization model, the amount of the updates in drop-down stage of each cycle is $k_r = \lfloor \frac{\tau_r}{\tau} \rfloor - 1$, and the i^{th} update of them has the delivery delay as follows:

$$d_D^i = \frac{L_1}{v} + (\tau_r - i \cdot \tau) + \frac{L_2 - R}{v}, i \in [1, k_r] \quad (6)$$

Therefore, to calculate the sum AoI, we divide the sum AoI in each cycle into two areas: S_r and S_g as shown in Fig. 6, which denote the sum AoI of the updates meet red light and green light, respectively. The sum AoI of S_r is calculated as follows:

$$\begin{aligned} S_r &= \frac{1}{2}[(\tau + d_U)^2 - {d_D^{k_r}}^2] \\ &= \frac{1}{2} \cdot {\tau_r}^2 + \tau_r \cdot (\frac{L_1 + L_2 - R}{v} + \tau) \end{aligned} \quad (7)$$

The sum AoI of S_g is calculated as follows:

$$\begin{aligned} S_g &= \frac{\tau_g}{\tau} \cdot [\frac{1}{2}(\tau + d_S)^2 - \frac{1}{2}{d_S}^2] \\ &= \tau_g \cdot (\frac{1}{2}\tau + \frac{L_1 + L_2 - R}{v}) \end{aligned} \quad (8)$$

Thus, the sum AoI of each cycle is calculated as follows:

$$\begin{aligned} \Delta_{sum} &= S_r + S_g \\ &= \tau(\frac{1}{2}\tau_g + \tau_r) + \frac{1}{2}{\tau_r}^2 + \frac{L_1 + L_2 - R}{v} \cdot \tau_c \end{aligned} \quad (9)$$

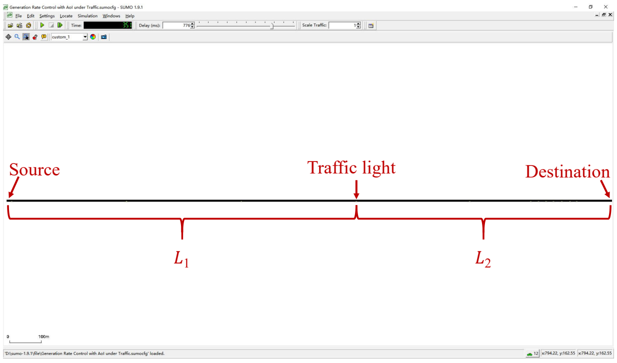


Fig. 7 – Simulation setup by SUMO

4.4 TAC-aware generation rate algorithm

This section introduces a TAC-aware generation rate Algorithm (TACA) to select the generation interval time of the source. The objective function for the Total Average Cost (TAC) of each cycle is as follows:

$$\begin{aligned} TAC(\tau) &= E[\frac{\Delta_{sum} + c_h \cdot h}{\tau_c}] \\ &= \frac{\tau \cdot (\tau_g + 2\tau_r)}{2 \cdot \tau_c} + \frac{(2\tau_g + 3\tau_r) \cdot R^2}{\tau \cdot \tau_c \cdot v^2} \\ &+ \frac{v^2 \cdot {\tau_r}^2 - 2R^2}{2 \cdot v^2 \cdot \tau_c} + \frac{L_1 + L_2 - R}{v} \end{aligned} \quad (10)$$

Since $\tau = k_0 \cdot \lambda$ where k_0 is an integer value, τ is a discrete variable. To calculate the approximate optimal solution of the objective function, we relax k_0 to be fractional, and τ changes to be a continuous variable.

We aim to $min\ TAC(\tau)$. To achieve this goal, we first present the objective function is a convex function, and then we calculate the minimum value of $min\ TAC(\tau)$.

The objective function with the second derivative is calculated as follows:

$$\frac{\partial TAC^2(\tau)}{\partial \tau^2} = \frac{2R(2\tau_g + 3\tau_r)}{v^2 \tau_c} \cdot \frac{1}{\tau^3} > 0 \quad (11)$$

Therefore, the objective function with a convex function about τ.

When the first derivative of function $TAC(\tau)$ is set as 0, that is $\frac{\partial TAC(\tau)}{\partial \tau} = 0$, we obtain $\tau_{OPT} = \sqrt{\frac{4\tau_g + 6\tau_r}{\tau_g + 2\tau_r}} \cdot \frac{R}{v}$. Then the minimal value of $TAC(\tau)$ is calculated as follows:

$$\begin{aligned} TAC_{min} &= R \cdot \frac{\sqrt{\tau_g + 2\tau_r} \cdot \sqrt{4\tau_g + 6\tau_r}}{v \cdot \tau_c} \\ &+ \frac{v^2 \cdot {\tau_r}^2 - 2R^2}{2v^2 \tau_c} + \frac{L_1 + L_2 - R}{v} \end{aligned} \quad (12)$$

Since the original τ is a discrete variable, we set $\tau = \lfloor \frac{\tau_{OPT}}{\lambda} \rfloor \cdot \lambda$. Therefore, to achieve the minimal total average cost, the sensor source generates the updates with this interval time.

5. SIMULATION RESULTS

In this section, we present the simulation setup and verify our proposed analysis model with simulations to ensure the correctness. We will give more results for investigating the influence of traffic lights on the data delivery.

5.1 Simulation setup

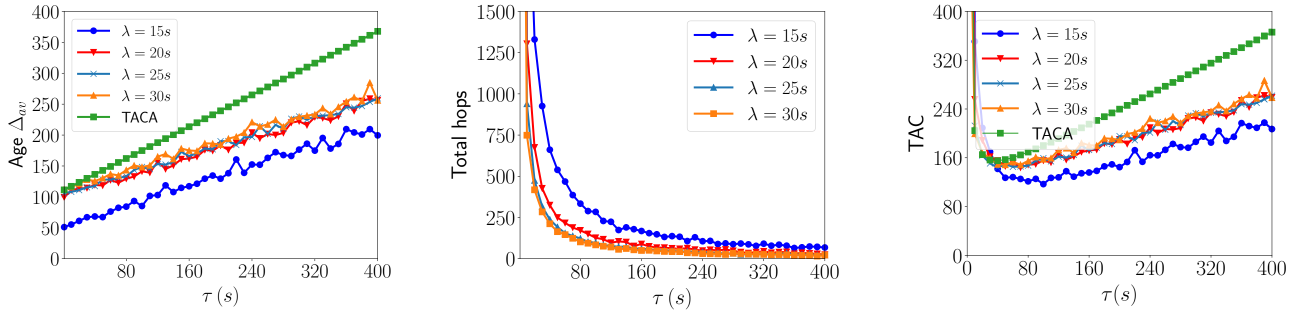
In our simulations, the traces of vehicles are generated by SUMO [29]. As shown in Fig. 7, two one-way roads divided by a traffic light have the length of $L_1 = 1100m$ and $L_2 = 800m$. The default durations of red and green lights are 28 and 70 seconds, respectively. The average speed v with which vehicles move on the path is 15 m/s, and its communication range R is 300m. The simulation time is 1 hour.

5.2 Verification of analysis model

We compare our analytical model with the simulations by SUMO, and the results are shown in Fig. 8. In Fig. 8(a), under the four conditions of vehicle arrival time intervals of 15, 20, 25, and 30s; when τ increases, AoI also increases. Although AoI increases with the increase of τ, when τ is larger, AoI still grows at a small growth rate. The AoI when the vehicle arrival time interval is 15s is significantly smaller than the AoI when the vehicle arrival time interval is 20 or 25s. This is because we set the initial distance between the two vehicles to be greater than the communication range R. When the vehicle arrival time interval is 15s, the distance between the two vehicles is within the communication range, and the update can be transmitted immediately by V2V communications.

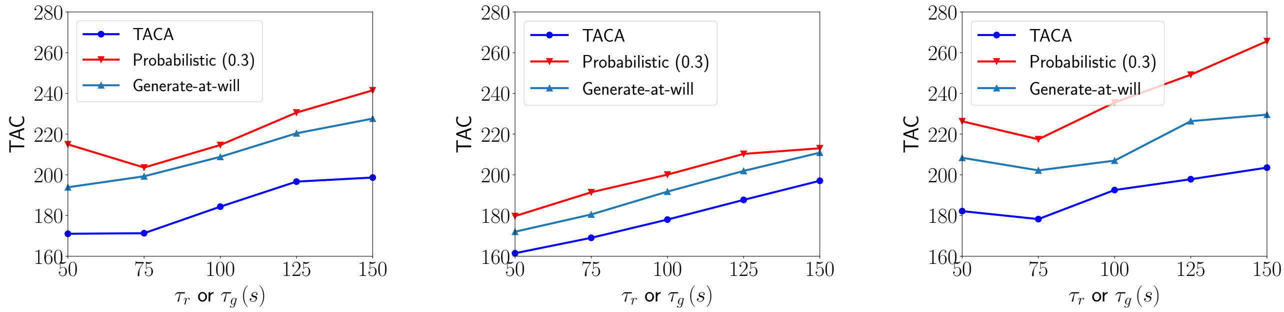
With the increase of τ, the total number of hops shows a decreasing trend in Fig. 8(b). Within one hour of simulation time, as the update generation interval τ increases, the number of transmitted updates decreases. When τ takes different values, the standard deviation of the average number of hops under the four conditions is very small; the average number of hops from generation to reception of each update does not change much. Since the total number of hops is equal to the number of transmitted updates multiplied by the average number of hops per update, as τ increases, the total number of hops will decrease.

As shown in Fig. 8(c), the objective function first decreases with the increase of τ, and then increases. When τ=38s, the objective function achieves the theoretical minimum value, which is 155.07. When the vehicle arrival time interval is 20, 25, 30s, the objective function obtains the minimum value at $\tau = 47, 46, 46s$, respectively, which are 141.56, 141.92, and 148.43. Except for the case where the vehicle arrival time interval is 15s, the simulation results is consistent with the theoretical analysis. This is because the vehicle arrival time interval of 15s does not meet our assumption ($\lambda > 20s$).



(a) Average AoI (b) Total transmissions (c) Total average cost

Fig. 8 – Analytical model compared with simulations



(a) Uniform time interval (b) Poisson time interval (c) Deviation of speed

Fig. 9 – Performance comparisons under different durations of red/green light ($\tau_g = \tau_r$)

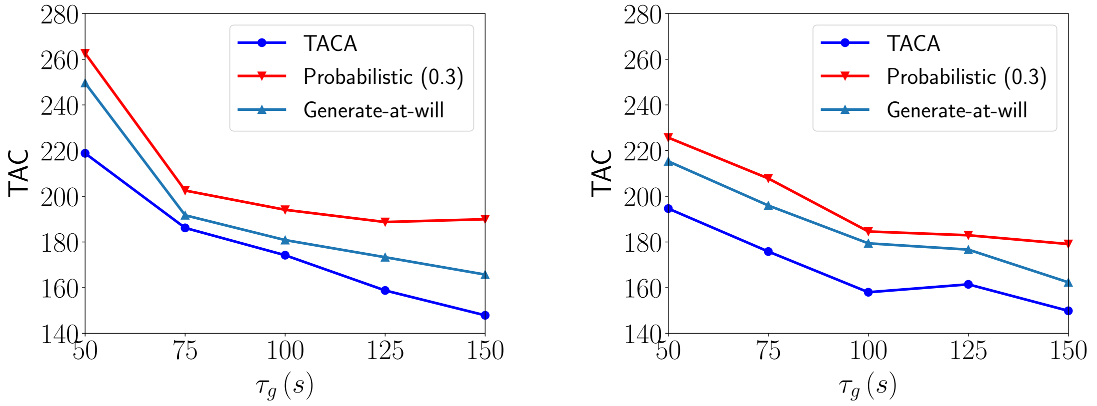
We explain the reason that the value of TAC is the lowest when the vehicle arrival time interval is 15s in Fig. 8(c). The communication range of a vehicle is 300m, so when the vehicle travels at a speed of 15m/s and the vehicle arrival interval follows a Poisson distribution with a parameter of 15, the vehicle interval for every two vehicles is approximately equal to 225m, which is less than 300m. So the V2V transmission delay is almost zero, there is almost no delay in the fast multi-hop transmission be- tween vehicles after an update is transmitted to the first vehicle. Compared with the case of other λ values, when $\lambda = 15$, the delay from the generation of an update to be- ing received by an RSU is greatly reduced, which leads to a greatly decreased average AoI. From $\lambda = 30, 25, 20$ to $\lambda = 15$, the average number of hops transmitted per up- date increases, and the average transmission cost of an update from being generated to being received by the RSU increases. Note that TAC is composed of average AoI and average transmission cost, so TAC is less than that in other cases when $\lambda = 15$.

5.3 Impact of traffic light on performance

We compare the proposed algorithm TACA with two algorithms: (1) Generate-at-will: when a vehicle arrives, the sensor source always generates an update and transmits to it. (2) Probabilistic (0.3): when a vehicle arrives, the sensor source generates an update in a probability 0.3.

Fig. 9 shows the simulation results when we set $\tau_r = \tau_g$. When τ_r and τ_g increases, the total average cost shows an increasing trend. This is because the red light time increases, and the delay of the update waiting for the red light may increase, resulting in an increase in sum AoI and an increase in total average cost. Compared with probabilistic (0.3) and generate-at-will, TACA has the smallest total average cost under each experimental setting. It shows that the TACA method is effective. When the vehicle arrival time interval changes from a fixed value to a Poisson distribution, it can be seen that the total average cost decreases. This is because if the vehicle arrives early and the distance between the vehicle and the previous vehicle is within the communication range, the update can be transmitted in multiple hops, resulting in a decrease in delay, and a decrease in sum AoI and the total average cost. When the deviation of the speed factor changes from 0 to 0.1, it can be seen that under TACA and generate-at- will, the value of the total average cost does not change significantly, and the total average cost by probabilistic (0.3) has been reduced due to its random probability.

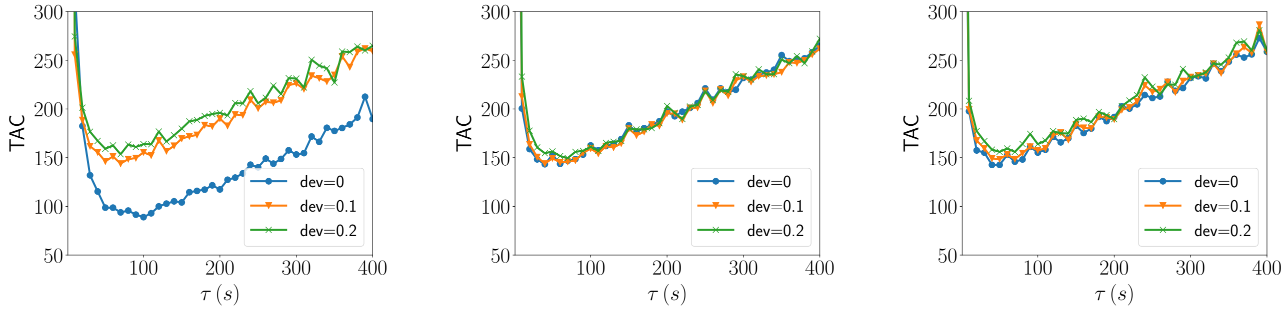
Fig. 10 shows the simulation results when we set $\tau_g + \tau_r = 200$. A day can be divided into many cycles. In a single cycle, parameters are the duration of the red light and green light. We investigate performance that when the duration of the red light and green light are dynamic in different



(a) Uniform time interval

(b) Poisson time interval

Fig. 10 – Performance comparisons under dynamic durations of red/green light ($\tau_g + \tau_r = 200$)



(a) $\lambda = 20$

(b) $\lambda = 25$

(c) $\lambda = 30$

Fig. 11 – Performance comparisons under different speed deviations and vehicle inter-arrival time

cycles. Fig. 10(a) and Fig. 10(b) show our algorithm TACA is effective when the vehicle arrival time intervals obey uniformly distribution (mean=25) and Poisson distribution ($\lambda = 25$) . As the proportion of green light duration increases, TAC shows a decreasing trend. Moreover, no matter what the proportion of green light and red light duration is, our algorithm TACA always obtains the smallest TAC, which is better than the other two update generation policies. Furthermore, due to its random probability and the vehicle arrival interval has the randomness of Poisson distribution, the value of TAC under probabilistic (0.3) is larger than that of generate-at-will.

5.4 Impact of speed deviation

Fig. 11 shows the impact of the speed deviation on TAC under the three conditions vehicle arrival time intervals of 20, 25, and 30s. The speed of a vehicle is sampled from a normal distribution with parameters of a mean speed and a speed deviation, so the speed of a vehicle is not a constant; it may be larger or less than the mean speed. Thus, besides the start and stop phase, a vehicle's speed can be viewed as a speed with dynamic accelerations while it is running. Therefore, we investigate the impact of the speed deviation on TAC. Fig. 11(a) shows the performance when the vehicle arrival time intervals is 20s and the deviation of the speed factor are set as different values. TAC first decreases with the increase of τ, and then increases. When the deviation is set as 0, the value of TAC is significantly smaller than that of the deviation that is set as 0.1 and 0.2. Because the vehicles keep a uniform speed when the deviation is set as 0, the distance between two adjacent vehicles is equal to the communication range, the update can be transmitted in multiple hops, resulting in a decrease in delay, and a decrease in sum AoI and total average cost. As shown in Fig. 11(b) and Fig. 11(c), when the vehicle arrival time intervals is 25, and 30s and τ is at different values, the values of TAC under the deviation is set as 0, 0.1, 0.2 are almost equal. That is to say, when the vehicle arrival time intervals is larger than 20s, the value of TAC is almost unaffected even if there is acceleration and deceleration within a certain range of vehicles.

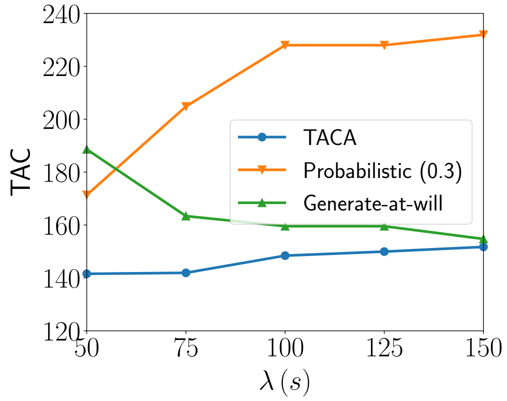


Fig. 12 – Performance comparisons under different update generation policy

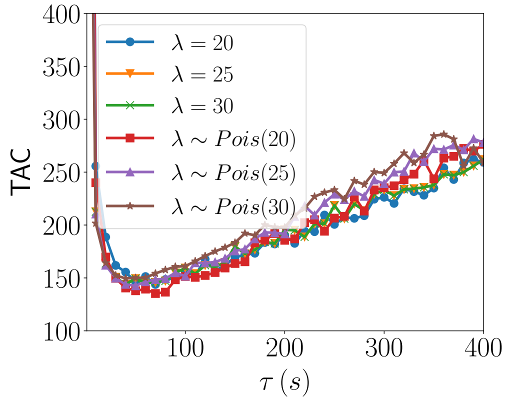


Fig. 13 – Performance comparisons under different distributions of vehicle inter-arrival time

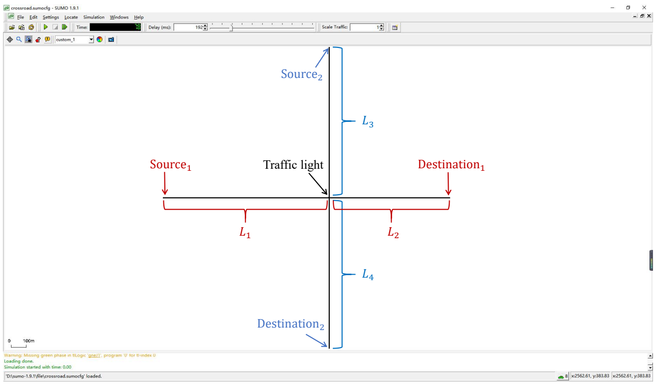


Fig. 14 – Simulation setup by SUMO of crossroads

5.5 Impact of probability of update generation

Fig. 12 shows the results of our model TACA under the optimal τ, and impact on performance when the probability that the sensor source generates an update is different. Under the vehicle arrival time intervals, the value of TAC of our model TACA is lower than that of other two methods due to their random probability (Note that TAC is the lower the better). The reason is that τ is not optimal when the sensor source generates an update at the probabilities, indicates our model TACA performs better than the methods that generate an update randomly.

5.6 Impact of the distribution of λ

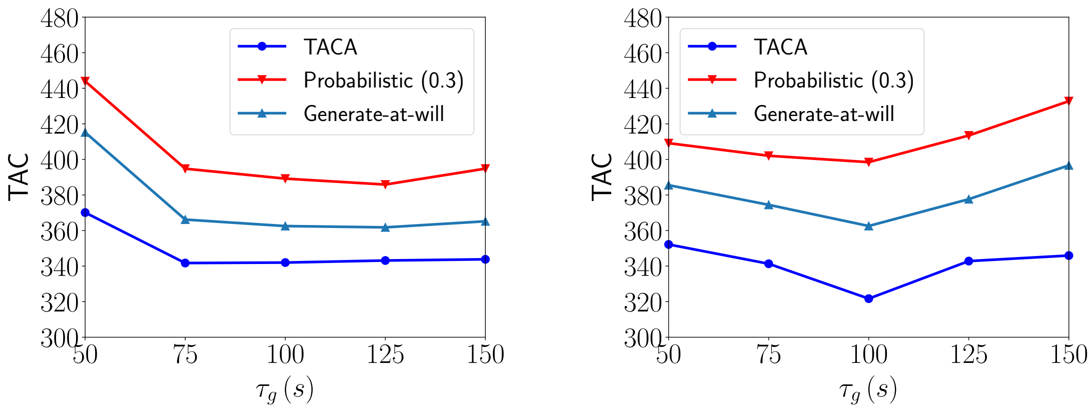
As shown in Fig. 13, when τ is less than 100 seconds, the values of TAC are relatively similar regardless of whether the vehicle arrives at a uniform time interval (λ is a constant) or the vehicle arrives at a time interval that obeys different Poisson distributions. The optimal τ value obtained by our simulation result is about 46s, which is smaller than 100s. In other words, even if the vehicle arrival time interval follows a Poisson distribution, our model still performs better.

5.7 Extension

We consider the following scenario as shown in Fig. 14, a crossroads where the east-west road and north-south road are both straight one-way roads, and the vehicles are stopped by traffic lights. Suppose there is one source in the west and one in the north; there is one RSU in the east and one in the south. Assuming that there are obstacles near the traffic lights. The updates from the east-west direction cannot be transmitted to the north-south direction, and the updates from the north-south direction cannot be transmitted to the east-west direction. That is to say, the update is only transmitted in a straight line and will not be transmitted in a crisscross pattern. We assume that the same application manages the two sources so that the two sources are controlled by the same variable τ, which controls the generation of updates. The east-west direction is open to traffic when a red light is in the north-south direction. The north-south direction is open to traffic when a red light is in the east-west direction. The two directions complement each other. The goal is to optimize the sum of overall average AoI and average transmission cost.

Simulation setting: In this simulation, the traces of vehicles are generated by SUMO [29]. As shown in Fig. 14, crossroads divided by a traffic light have the length of $L_1 = 1100m$, $L_2 = 800m$, $L_3 = 1000m$, $L_4 = 1000m$. The average speed v with which vehicles move on the path is 15 m/s, and its communication range R is 300m. The simulation time is 1 hour.

Fig. 15 shows the simulation results when we set $\tau_g + \tau_r = 200$. In Fig. 15(a) and Fig. 15(b), the vehicle arrival time intervals obey uniformly distribution (mean=25) and Poisson distribution ($\lambda = 25$), respectively. As the proportion of green light duration in the east-west direction increases, the value of TAC decreases first and then increases. The value of TAC is the smallest when the duration of the traffic lights is roughly equal. Because the proportion of the green light duration in the east-west



(a) Uniform time interval

(b) Poisson time interval

Fig. 15 – Performance comparisons under dynamic duration of red/green light ($\tau_g + \tau_r = 200$) in crossroads

direction is too small or too large, it will always lead to a large proportion of the red light duration in one direction at the intersection. To optimize the overall AoI, the overall transmission time will increase, resulting in the increase of TAC. The TAC when the green light duration is 50s and 75s is different from that when the green light duration is 125s and 150s, which will affect the transmission time of updates and which affects the TAC. In addition, no matter the proportion of green light and red light duration, the TAC obtained by our method TACA is always the smallest, which is superior to the other two update generation poli- cies.

6. CONCLUSION

In vehicular networks, the mobility of the vehicles is affected by traffic lights. We investigate the influence of the traffic lights on data delivery in vehicular networks with the metric of AoI. The AoI and transmission cost is modeled as the Total Average Cost (TAC), which is affected by the generation rate at the source. Moreover, TAC is also affected by the traffic light, since the traffic hole problem blocks the old updates and the new updates will catch up. By considering the trade-off between AoI and trans- mission cost, we propose a TAC-aware generation rate Algorithm (TACA) for the generation interval time at the source. Our intensive simulations verify the proposed algorithm, and evaluate the influence of the traffic lights on AoI. In the future, we will extend the V2V scenario to a straight road or mesh road with more traffic lights.

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