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AoI-Oriented Context-Aware Priority Design and Vehicle Scheduling Strategy in Vehicular Networks

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***Abstract*—Real-time status updates are playing a key role in the emergence of autonomous driving. Due to the limited and dynamic environment, the vehicle communications may not guarantee the required quality of service (QoS) on demand. In this paper, we consider the intersection scenario with relatively heavy traffic and slightly higher risk, where the base station (BS) remotely controls multiple vehicles. The vehicles sense their own and surrounding contextual information through sensors and send them to the BS through the uplink. Since the urgency of different status information is distinct, the analytic hierarchy process (AHP) method is used to give each status information a context-aware weight so that emergency vehicles can be scheduled first by the BS. Then, age of information (AoI) is also exploited to describe the time elapsed since the generation of the status information obtained from the perspective of the BS. On this basis, the Lyapunov method is considered to optimize the average weighted AoI subject to the limited throughput constraint. Finally, a scheduling strategy based on dynamic domain value is proposed to update vehicles in real time in the long run, so as to minimize the average weighted AoI. The simulation results show that the context-aware weight proposed in this paper has a significant impact on scheduling, and the average weighted AoI of the whole system is optimized compared with other approaches.**

***Index Terms*—Analytic hierarchy process, context-aware weight, the average weighted AoI, dynamic domain value.**

I. Introduction

According to the statistical research report of the world health organization, the number of people injured in traffic accidents is about 50 million worldwide every year, among which the number of deaths is as high as 1.25 million, and that resulting from road traffic accidents accounts for about 80%. Without practical solutions, the number of traffic accidents will further increase and traffic congestion will worsen, resulting in more casualties and property damage. In order to alleviate the various problems of the current traffic system, the intelligent transportation systems (ITS) are constructed to perfect the intelligent degree of the road, maximize the capacity of the existing traffic infrastructure, improve traffic efficiency, and reduce the incidence of traffic accidents. As a key component of ITS, connected and autonomous vehicles (CAVs) have attracted wide attention. Via information interaction and collaboration between different cars, CAVs can effectively improve vehicle safety and traffic efficiency.

For CAVs, information freshness is very important for the control of vehicles. If the control center receives outdated information or fails to get new status information, it may lead to deviations in the accuracy and reliability of system decision-making, resulting in huge potential safety hazards. In order to measure the freshness of status information, Altman of Avignon University in France has put forward the concept of information aging since 2011, which is used to quantitatively study the problem that internet users obtain information service fees based on small information update costs. In the same year, Kaul of Rutgers University formally put forward the concept of age of information (AoI) [1], which represents the time elapsed since the generation of information. Different from traditional data communications, which pay more attention to the delay of information transmission, real-time update applications such as behavior alarm, cooperative driving and even automatic driving in CAVs put more emphasis on the timeliness of information. After the data is generated, with the passage of time, the obsolescence of data information also increases and continues to "age". To ensure the timely transmission of information and rational use of resources, two main research directions in AoI are being investigated, i.e., the optimization of the queuing model in the media access control (MAC) layer and the optimization of the scheduling strategy of status updates.

Aiming at the optimization of queuing mode in the MAC layer, [2] analyzed the age of the last-come first-service (LCFS) queue under different arrival time and service time distributions. [3] investigated the age of M/M/1, M/D/1, D/M/1, M/G/ 1 and G/G/1 queues under first-come first-service (FCFS) service. [4] analyzed the average AoI of the system model by FCFS and LCFS queues for M/M/1 and D/M/1 Queuing Models. [5] investigated the same problem for the researched M/M/1 queuing model with FCFS and LCFS, but they studied the case with and without packet preemption respectively. Finally, [6] and [7] studied the beacon broadcast transmission mode based on carrier sense multiple access (CSMA) competition mechanism. AoI was significantly reduced in the highly competitive wireless local area network (WLAN) by reducing the packet loss caused by conflict in the uplink transmission process. For the optimization of scheduling strategy, [8] proposed a truncated scheduling strategy in industrial internet of things (IoT), which can achieve the asymptotic optimal average AoI performance of the whole network. [9] developed three low complexity transmission scheduling strategies, namely random strategy, maximum weight strategy and whittle index strategy, trying to minimize AoI under the minimum throughput requirement. [10] proved that a static scheduling strategy is optimal when there is always fresh information in the transmission, and analyzed the peak AoI and average AoI of discrete-time G/Ber/1 queue for the first time.

Most of previous studies focus on reducing the delay of data packets in the transmission process, avoiding packet loss, reducing packet conflict, and seeking to achieve a balance between throughput and reduced use of resources. However, these schemes do not take into account the environmental context and dynamics. In order to evaluate the timeliness-related contextual information in remote control system, [11], [12] and [13] proposed a context-aware metric for the information lapse, which is the product of the context-aware weight and the information lapse. The information lapse in these papers identifies how inaccurate the information at the base station (BS) is as compared with the actual status. Although [11] proposed a method to foresee the future context-aware weight for each user, the weight is designed for general IoT applications. In the specific scenario of CAVs, the information context and its priority setting are quite different from the general IoT with fixed locations, which makes the weight designing method in [11] inapplicable.

In this paper, we consider an average weighted AoI minimization problem for CAVs in a complex and changeable intersection scenario, where the long-term vehicle scheduling strategy is optimized. As the schedule priority of each vehicle significantly affects the AoI performance, a CAV-specific context-aware weight design scheme is first proposed, where the analytic hierarchy process (AHP) [14], [15] method is adopted to evaluate the vehicle status information, so as to ensure that vehicles with emergency or outdated information are scheduled first. With the carefully designed weight, the Lyapunov drift and penalty are then applied to optimize the vehicle schedule strategy. Considering the influence of the next time slot instead of selecting the worst vehicle for scheduling, our proposed schedule strategy can reduce the average weighted AoI of the whole system in the long run. In the simulation, we present the impact of average weight on the schedule strategy and compare the performance of our proposed scheme with the greedy algorithm.

II. System Model

In this section, we consider a remote-control vehicle system, which is mainly divided into three parts. The considered network scenario of this paper are described in the network model. Then, the weighted AoI is proposed to represent the current state of the vehicles. Finally, the problem of minimizing the average weighted AoI under the constraint of limited throughput is formulated.

A. Network Model

As shown in Fig. 1, in this paper, we consider a scenario at the intersection with one BS and N vehicles. The BS schedules the vehicles through the ideal downlink, and the scheduled vehicle transmits the perceived status information to the BS through the uplink, including speed, position and surrounding environment information. Let the time be slotted, with slot

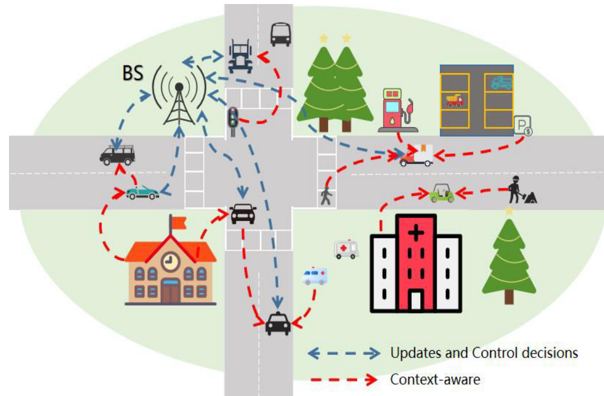

Fig. 1. Road Model of Intersection

index $t \in \{0, 1, 2, ..., T-1\}$, and consider a wireless channel that schedule packets transmission per slot. Let $u_i(t)$ be the indicating function that is equal to 1 when the BS selects vehicle i during slot k, otherwise $u_i(t) = 0$ otherwise. And we assume that once the vehicle is scheduled, the data packets can be successfully transmitted to the BS. A vehicle executes an application that generates a data packet comprising vehicle's status information every T slots.

B. Information Freshness

In this paper, information freshness is defined by AoI, which describes the time elapsed since the status information was generated from the perspective of the BS. $h_i(t)$ set as a positive integer, indicating the AoI of the status information sent by vehicle i to the BS at the beginning of time slot t. If the BS does not receive the packet from vehicle i in the next slot, $h_i(t+1) = h_i(t)+1$. If the BS receives a packet from vehicle i, $h_i(t+1) = 1$because we assume that the transmission of data packets does not exceed one slot. Thus, the iteration of $h_i(t)$ is shown below

$$h_i(t+1) = \begin{cases} 1, & \text{if } u_i(t) = 1; \\ h_i(t)+1, & \text{otherwise.} \end{cases} \tag{1}$$

Due to the dynamic complexity of the vehicle network, the types of status information are ever-changing. If AoI is solely judged by a criteria that changes linearly over time, that is, all packets are "fair". This will lead to that limited resources will be wasted on relatively trivial information, and emergency vehicles will be unable to be updated in time, posing security problems. Therefore, we use context-aware weight $\alpha_i(t)$ to the importance of the status information from vehicle i at t slot. The more urgent the vehicle's status information, the greater the context-aware weight. Finally, we use the weighted AoI $D_i(t)$ to represent the freshness of status information as

$$D_i(t) = \alpha_i(t) h_i(t). \tag{2}$$

Therefore, the average weighted AoI of vehicle i in T time slots can be expressed by $E[\sum_{t=0}^{T-1} \frac{\alpha_i(t) h_i(t)}{T}]$. Finally, we use the average weighted AoI to measure the freshness of the

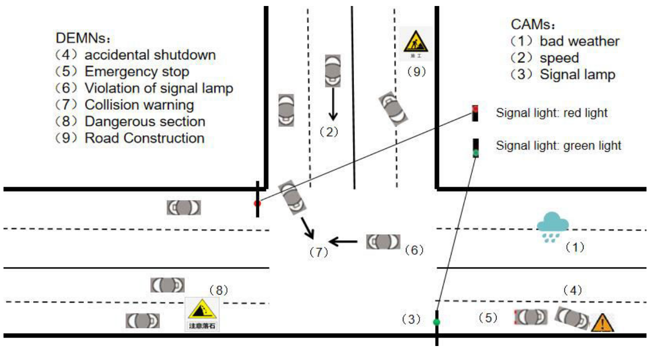

Fig. 2. Information Classification by ITS

entire vehicle network information, and the result under the scheduling policy π can be expressed as

$$E[J_T^{\pi}] = \frac{1}{TN}E[\sum_{t=0}^{T-1}\sum_{i=1}^{N}\alpha_i(t)h_i(t)]. \tag{3}$$

C. Problem Formulation

Due to the limitation of channel resources in the uplink, it is impossible for each vehicle in each time slot to be scheduled. We assume that a single vehicle's average throughput in a single time slot does not exceed ρ, which is a strict positive real value not greater than 1. Thus, we can define the average throughput of vehicle i when using scheduling strategy π, which is expressed as

$$q_i^{\pi} = \lim_{T\to\infty}\lim_{N\to\infty}\frac{1}{TN}\sum_{t=0}^{T-1}\sum_{i=1}^{N}u_i(t). \tag{4}$$

Then, the throughput constraint for vehicle i is expressed as

$$q_i^{\pi} \leq \rho \leq 1, \forall i \in \{1,2,3,...,N\}. \tag{5}$$

With the definition of weighted AoI and throughput limits, the average weighted AoI minimization problem in vehicle networks is formulated as

$$\mathcal{P}1: \min_{u_i(t)} \quad \lim_{T\to\infty}\frac{1}{TN}E[\sum_{t=0}^{T-1}\sum_{i=1}^{N}\alpha_i(t)h_i(t)], \tag{6a}$$

$$\text{s. t.} \quad q_i^{\pi} \leq \rho, \forall i \in \{1,2,3,...,N\}. \tag{6b}$$

III. Scheduling Strategy

In the section, the weight of status information for different vehicles is determined by AHP. Then, in order to minimize the average AoI, we use the Lyapunov method to optimize the problem of (6) and obtain a new objective equation. Finally, this paper proposes a strategy based on dynamic domain value to schedule vehicles to send status updates according to the new objective equation.

A. Determination of Weight

As we all know, road safety is closely related to people's lives and property. The BS must accurately and fully identify all kinds of dynamic and static targets on the road according to the status information of vehicles, so as to make corresponding

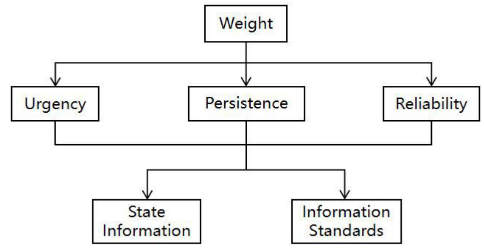

Fig. 3. Hierarchy of AHP

TABLE I. Nine Scale Method

Verbal judgment	Numeric value
Extremely important	9
	8
Very strongly more important	7
	6
Strongly more important	5
	4
Moderately more important	3
	2
Equally important	1

decisions. However, if all status information is treated equally, it will inevitably lead to improper resource allocation. For example, according to the ITS, the information is divided into cooperative awareness messages (CAMs) (such as weather, vehicle speed, location, etc.) and decentralized environmental notification messages (DENMs) (such as emergency braking of vehicles ahead, road construction warning, etc.). And according to the information content, DENMs has a higher priority than CAMs (as shown in Fig. 2). Therefore, We use AHP to give each status information a weight α_i to measure the importance of the status information in this situation.

AHP has three main steps. The first step in AHP is to build a hierarchy, also known as decision modeling, which simply consists of building a hierarchy to analyze decisions. This paper constructs the problem into a hierarchy as shown in Fig. 3, in which the meanings of three attribute criteria are defined as follows.

- Urgency: The urgency of information. Such as emergency stop, etc.
- Persistence: Whether a message is valid over a long period of time. Such as weather information, dangerous roads and so on.
- Reliability: The intrinsic quality of the information source, for example, the distance between the information source and the vehicle, etc.

The second step in the AHP process is to derive the weight α_i of the criteria. Obviously, the importance or weight of each standard is different. Therefore, we first need to determine the relative priority of each standard relative to other standards through pairwise comparison. The digital comparison scale developed by Saaty is used, as shown in Table I. By filling

TABLE II. Comparison Matrices

Attribute	Urgency	Persistence	Reliability
Urgency	1	α	β
Persistence	$\frac{1}{\alpha}$	1	γ
Reliability	$\frac{1}{\beta}$	$\frac{1}{\gamma}$	1

the pairwise comparison matrix (as shown in Table II) with comparison scores (i.e., α, β, γ), the relative priority between vehicle attributes, i.e., urgency, persistence, and reliability, is obtained. Comparison scores (ranging from 1/9 to 9) are assigned according to the Satty scale method, and the importance of attributes in the row is assessed relative to those in the column.

The third step of the AHP is to obtain an average value of the weight of each attribute obtained in the second step, which is the required characteristic value λ_{max}. The priority weight represents the value of each attribute compared with the other attributes. Obviously, the AHP method determines relative (rather than absolute) priority weights based on empirical evaluation criteria and is therefore somewhat arbitrary. In order to make the weight vector able to represent the relative importance of attributes, matrix should be consistent. Therefore, we need to request the consistency index of $C_I = (\lambda_{max} - n)/(n-1)$. Finally, we calculated the consistency ratio:

$$C_R = C_I/R_I(n) < 0.1, \tag{7}$$

where R_I is the average of C_I obtained by randomly generating reciprocal matrices of size n (for n=3, we get $R_I = 0.58$). Because C_R is less than 0.10, we can assume that our judgment matrix is reasonably consistent. Thus, we can continue to use AHP for decision-making.

B. Problem Reformulation

We first define a virtual queue H_t that satisfies the throughput constraint:

$$H_{t+1} = [H_t - \rho + u_t]^+, \tag{8}$$

then define a Lyapunov function $L_t = \sum_{i=1}^{N} \theta_i h_i(t), \theta_i > 0$, and at the same time, Lyapunov drift is defined as

$$\Delta_t = E[L_{t+1} - L_t | h_t, \omega_{t+1}]. \tag{9}$$

Let the penalty at the t slot be the weighted AoI at the $t+1$ slot, i.e $f_t = \sum_{i=1}^{N} \omega_i(t+1)h_i(t+1)$, given h_t and ω_{t+1}, drift plus penalty is written as

$$\begin{aligned}\Delta_t + E[f_t|h_t,\omega_{t+1}] =& E[\sum_{i=1}^{N}\theta_i[h_i(t+1)-h_i(t)]+ \\ & \omega_i(t+1)h_i(t+1)|h_t,\omega_{t+1}].\end{aligned} \tag{10}$$

Substituting $h_i(t+1) = (1-u_i(t))h_i(t)+1$ into (10), and get

$$\begin{aligned}\Delta_t + E[f_t|h_t,\omega_{t+1}] =& \sum_{i=1}^{N}[\theta_i + \omega_i(t+1)] - \sum_{i=1}^{N}\theta_i u_i(t) h_i(t) \\ & + \sum_{i=1}^{N}\omega_i(t+1)(1-u_i(t))h_i(t).\end{aligned} \tag{11}$$

To minimize the above equation, a new scheduling policy can be obtained

$$\mathcal{P}2: \max_{u_i(t)} \quad \sum_{i=1}^{N}[\theta_i + \omega_i(t+1)]u_i(t)h_i(t), \tag{12a}$$

$$\text{s. t.} \quad q_i^\pi \leq \rho, \forall i \in \{1,2,3,...,N\}. \tag{12b}$$

Let $\pi = (\pi_1, \pi_2, ..., \pi_N)$ be a stationary scheme of the formula for the average AoI minimization problem. Since ω_{t+1} is independent of h_t, expect from both sides of $\Delta_t + E[f_t|h_t, \omega_{t+1}]$, we have

$$\begin{aligned}E[L_{t+1} - L_t + f_t|h_t] =& \sum_{i=1}^{N}(\theta_i + \bar{\omega}_i) \\ & + \sum_{i=1}^{N}[\bar{\omega}_i(1-\pi_i) - \theta_i\pi_i]h_i(t).\end{aligned} \tag{13}$$

If $\theta_i \geq \frac{\bar{\omega}_i(1-\pi_i)}{\pi_i}$, the last term of the above equation is not greater than 0. To minimize the first term, let $\theta_i = \frac{\bar{\omega}_i(1-\pi_i)}{\pi_i}$ take the expectation again, we have

$$E[L_{t+1} - L_t + f_t] \leq \frac{1}{N}\sum_{i=1}^{N}\frac{\bar{\omega}_i}{\pi_i}. \tag{14}$$

Take the limit of the sum of $t \in \{0,1,2,...,T-1\}$, then $L_0 < \infty$ and $L_t > 0$, we have $\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}E[f_t] \leq \sum_{i=1}^{N}\frac{\bar{\omega}_i}{\pi_i}$. Because f_t is weighted AoI in $t+1$ slot, so

$$\lim_{T\to\infty}\frac{1}{TN}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\alpha_i(t)h_i(t) \leq \frac{1}{N}\sum_{i=1}^{N}\frac{\bar{\omega}_i}{\pi_i}. \tag{15}$$

Substituting $\theta_i = \frac{\bar{\omega}_i(1-\pi_i)}{\pi_i}$ into the (12) schedule strategy to obtain the new objective equation

$$\mathcal{P}3: \max_{u_i(t)} \quad \sum_{i=1}^{N}[\frac{\bar{\omega}_i(1-\pi_i)}{\pi_i} + \omega_i(t+1)]u_i(t)h_i(t), \tag{16a}$$

$$\text{s. t.} \quad q_i^\pi \leq \rho, \forall i \in \{1,2,3,...,N\}. \tag{16b}$$

C. Scheduling Policy

According to the target equation (16), since it is a linear combination of scheduling policies $u_i(t)$, the update index is set as

$$I_i(t) = [\frac{\bar{\omega}_i(1-\pi_i)}{\pi_i} + \omega_i(t+1)]h_i(t). \tag{17}$$

According to the above update index, the BS calculates the freshness of the current status information of each vehicle, and then we act according to the dynamic domain which is formed by the virtual queue value comparison. Exceeding this domain value means that the status information of the current vehicle is too old or the current vehicle is in an emergency, which needs to be updated in time to ensure that the BS can accurately grasp the dynamics of the vehicle so as to make timely scheduling and control. Finally, we describe the detailed strategy as Algorithm 1.

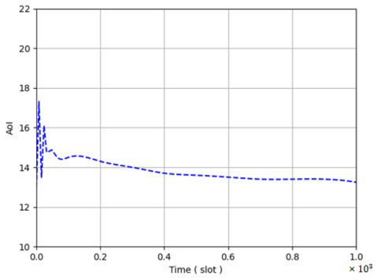

Fig. 4. The variation curve of average weighted AoI

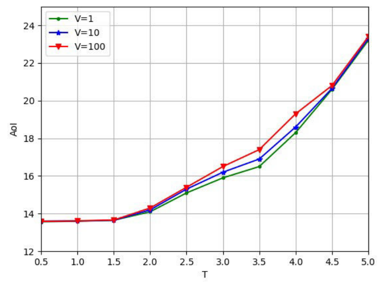

Fig. 5. Average AoI curve with different domain coefficient V

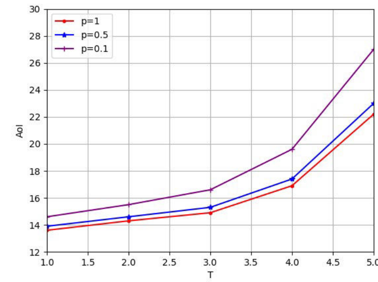

Fig. 6. Average AoI curve with different throughput limit ρ

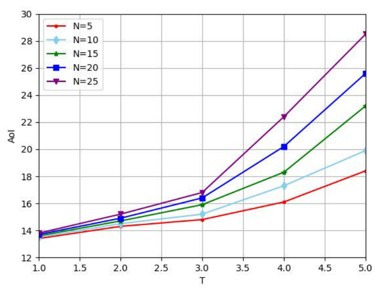

Fig. 7. Average AoI curve with different number of vehicles

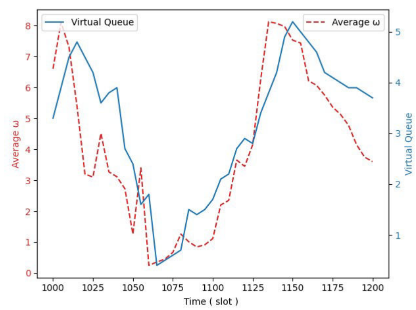

Fig. 8. Curve of weight and virtual queue size over time

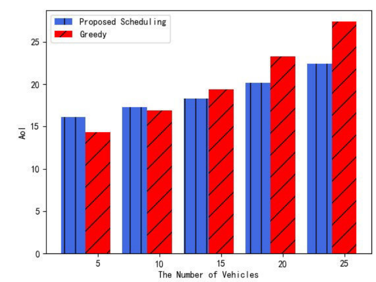

Fig. 9. Policy comparison performance

Algorithm 1 Scheduling Policies Based on Dynamic Domain Values

Input: $\rho, V, H_0, \theta, \pi_i, \bar{\omega}_i$

$t \leftarrow 0$;
$H_t \leftarrow H_0$;
repeat
  $I_i(t) = [\frac{\bar{\omega}_i(1-\pi_i)}{\pi_i} + \omega_i(t+1)]h_i(t)$;
  $U_t = 0$;
  if $I_t > VH_t$ **then**
    $U_t = 1$;
  else
    $U_t = 0$;
  end if
  $H_t = (H_t - \rho + U_t)^+$;
  $t \leftarrow t + 1$;
until end

IV. Simulation Results

In this section, simulations are provided to evaluate the performance of our proposed scheme. we consider the timeliness of vehicle's status information transmission at the intersection under the control of a BS (as shown in Fig. 1), where the area coverage R is $35m \times 35m$. Except that Fig. 7 shows the influence of different vehicles on the average weighted AoI, the remaining simulations are displayed to observe the performance of other aspects on the basis of $N = 15$ vehicles. The arrival of vehicles $Vborn$ obeys poisson distribution with a parameter of 5 vehicles per second and generates new status information through its own sensor according to the period T. In addition, the system capacity in the vehicle's cache has the size of only one packet, and the new packet always replaces the old one. The number of lanes L, road width $Rwidth$, speed range Vel, acceleration range Acc, and other parameters are shown in Table III. In order to verify the effectiveness of the proposed scheme, we evaluate the average weighted AoI under different parameters and observe the role of context-aware weight in the system. Then, we compare the proposed scheduling strategy with another strategy.

TABLE III. Simulation Parameters

Parameter	Value
L	2
$Rwidth$	$3.5\ m$
Vel	[5,10]
Acc	[0,2.5]
BS	$[2,8] \times Rwidth$
R	$35\ m \times 35\ m$
$Vborn$	$poisson$

In the simulation, Fig. 4 shows the variation curve of average AoI with fixed domain coefficient V and throughput limitation. It can be seen that average AoI gradually tends to be stable after short-term fluctuation in the early slots, which shows that the proposed scheduling strategy can control the balance of the entire vehicle system.

Fig. 5, 6, 7 show the curve of average AoI under different domain value coefficient V, throughput limit ρ and the number of vehicles, respectively. Fig. 5 shows the results under different domain value coefficients V. It can be seen that the average weighted AoI with different domain value coefficients V is very close after stabilization, but the time consumed in the simulation process varies greatly, and it takes a long time to converge when V is very small or large. Similarly, Fig. 6 and Fig. 7 show that the average weighted AoI keeps increasing with the increase in throughput and the decrease in the number of vehicles, respectively. That is because, under the same throughput, the more vehicles, the fewer resources each vehicle has, and the information can not be transmitted better. Similarly, for the same vehicle, the greater the throughput, the lower the total average weighted AoI. This points out the effect of the parameters we set on the system, and the result is consistent with our expectation.

Fig. 8 shows the curve of the context-aware weight size and the virtual queue size over time, and it can be seen that the virtual queue always changes with the context-aware weight. Therefore, it can be concluded that context-aware weight has a pivotal role in the setting of the system model. The nonlinear performance parameters can effectively measure the degree of urgency of information and better match the reality of the current context than just using AoI as a performance parameter.

Fig. 9 shows the average AoI of the proposed scheduling strategy under different numbers of vehicles compared with a greedy strategy. The results show that the performance of the greedy strategy is better than the proposed strategy with a small number of vehicles. Because the entire vehicle network is relatively simple, the greedy algorithm tendency of the regional optimal is already close to the global optimal. However, with the increase in the number of vehicles and the influence of weight loading, the optimization at this time is not enough to offset the penalty brought by the next time slot. Therefore, the proposed strategy, taking the influence of the next time slot when the vehicle network is relatively complex into account, is more comprehensive. As we can see from Fig. 9, our algorithm can decrease the average weighted AoI by 20% with a large number of vehicles, so it has better performance.

V. Conclusions

In this paper, we have minimized the average weighted AoI of multiple vehicle terminals at the intersection of remote control by the BS in the CAVs system, in which the vehicle's status information is generated by the vehicle sensor from the surrounding environment and successfully transmitted by the BS after scheduling. The Lyapunov optimization have been used to describe the average weighted AoI as a drift plus penalty minimization problem, and we have used a virtual queue method to provide a dynamic domain for orderly scheduling of multiple vehicles on the road. In addition, simulation results have showed that this scheduling strategy has good performance in optimizing the average weighted AoI under certain conditions.

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