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Value Matters: A Novel Value of Information-Based Resource Scheduling Method for CAVs

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***Abstract*—The Internet of Vehicles (IoV) can support applications in connected autonomous vehicles (CAVs), the implementation of which can effectively improve traffic efficiency. However, safety-related CAV applications have very strict requirements on the reliability and latency of each packet, which is difficult to achieve due to limited resources and the high dynamics of CAVs. In this paper, we investigate communication resource scheduling for remote autonomous driving (AD) to improve the performance of the remote control system when network resources are constrained. Specifically, we introduce a novel performance metric, i.e., *value of information* (VoI), to capture how sending a packet will affect the performance of CAV driving safety and efficiency, i.e., the value of the packet on the considered CAV system. The formulation of VoI is derived using the Lyapunov optimization method, and the lower-bound for the performance of the AD system with a VoI-based scheduling strategy is analyzed. Then, a communication resource scheduling approach is proposed based on the VoI of each packet. Simulation results demonstrate that the proposed VoI-based resource scheduling approach is capable of accurately assessing the impact of information transfer on system performance, while ensuring the CAV's safety and enhancing traffic efficiency.**

***Index Terms*—Connected autonomous vehicles, Internet of Vehicles, resource scheduling, value of information.**

I. Introduction

THE emergence of the Internet of Vehicles (IoV) and autonomous driving (AD) technologies have transformed modern transportation into a complex system that integrates perception, communication, computing, and control [1]. Due to the limitations of vehicle sensing performance, AD necessitates the support of IoV, particularly in scenarios with multiple vehicles and intricate traffic conditions [2]–[5]. IoV is the technology that empowers vehicles for information exchange and environment perception. Participants cover vehicles, infrastructure, mobile devices carried by pedestrians, and remote cloud servers, supporting communication from vehicle-to-everything (V2X) [6]–[11]. In IoV, vehicles can exchange information with roadside units (RSU) or remote traffic management centers to gain the additional status of other vehicles and road conditions [6], which greatly improves connected and autonomous vehicle (CAV) sensing ability and, therefore, AD performance, becoming a key component in enhancing the safety and efficiency of CAVs.

While the benefits are attractive, AD has stringent network performance requirements, especially for safety-related applications. According to 5G V2X standardization, the requirements of V2X communications to support CAV can be as strict as 99.99999% reliability and 10 ms latency [12]. The loss or timeout of packets containing critical information can severely affect the performance of AD. However, meeting such stringent requirements for each data packet poses a significant challenge to the network, since the amount of required resources increases exponentially when the packet reliability and latency requirements become more stringent [13], [14]. The situation of resource shortage gets worse when massive devices send packets simultaneously in the network. Even with the off-the-shelf 5G networks, it still cannot be guaranteed such stringent transmission requirements in CAV. Therefore, this raises an important research issue which is to guarantee the CAV system requirements, i.e., driving safety and efficiency, under limited wireless resources.

This issue has been extensively studied by many scholars. One solution is to set priority for vehicle packets. ProSe Per-Packet Priority (PPPP) is a concept proposed by the standardization organization 3GPP [15]. PPPP mainly emphasizes the priority ranking in sending packets. Based on this idea, some works have attempted to set priority for vehicle packets [16]–[19], which improve the throughput and spectrum efficiency of CAV. However, such approaches only set priority for differentiating data packets of different task types, such as safety-related packets and non-safety-related packets. Vehicle status information in remote driving, as a type of safety-related information, still has different requirements among different vehicles. There is another way to schedule packets of the same type of task. Kaul *et al.* [20] first introduced a metric called the age of information (AoI). This metric is defined as the time elapsed since the generation time of the last received packet. AoI characterizes the freshness of

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information. Much of the subsequent work inherited the idea of AoI [21]–[29], minimizing AoI to make a balance between maximum average throughput and minimum average latency. However, merely evaluating the long-term average throughput and latency performance is often inadequate for CAV tasks, since the loss of a crucial packet could result in severe safety issues, even if it does not violate the time-average performance [30].

The above approach is more concerned with meeting specific average communication latency or reliability requirements. In addition, the performance of the task should be also considered. Specifically, we guarantee the reliable and low-latency transmission of only those packets that have a high impact on the task performance. In such task-oriented resource scheduling, an extra metric reflecting the impact of packet transmission on task performance is *value of information* (VoI). Differing from AoI which reflects network KPIs, VoI represents a more abstract concept. As described in [31], the evaluation of VoI is highly task-dependent, making it challenging to discuss VoI in isolation from specific tasks. In a broad sense, VoI can be defined as the benefits decision-makers gain through acquiring particular pieces of information. Recent discussions on VoI are mostly anchored in specific systems, such as state update systems, wireless sensor networks (WSN), and others [32]–[42].

Evaluating the VoI of a packet is a challenging task due to the following two reasons. First, the VoI is required to evaluate timely, especially in delay-sensitive tasks. However, the computational capabilities of traditional network nodes are insufficient to calculate the VoI of a flow of data packets in a low latency manner. Second, the evaluation of VoI depends heavily on the task to which the transmitted data is applied, and therefore expert knowledge related to the task scenario is required. Evaluating VoI in connected autonomous driving systems is particularly challenging due to frequent information generation and the strict requirements to ensure safety in AD tasks [4].

In this paper, we aim to devise a strategy for scheduling packets for CAVs to meet the stringent requirements of AD under limited communication resources. To achieve this, the model predictive control (MPC) algorithms are employed to control the vehicle in AD tasks. CAVs communicate with the MPC controller in the RSU to acquire reference paths and report their status by vehicle-to-infrastructure (V2I) communications. The RSU determines which vehicles can transmit packets at a given time. The objective is to minimize the cost of AD, which represents a trade-off between performance and expenditure. To tackle this problem, a novel framework is developed for evaluating the VoI of vehicle packets in AD tasks. In this framework, VoI is defined as the expected benefit of transmitting packets, and to evaluate this benefit, we analyze the relationship between system costs and transmission decisions. Then, the expected transmission benefit (i.e., VoI) is evaluated using the Lyapunov method. With the obtained VoI, we convert the cost minimization problem into a VoI maximization problem and develop a packet-level communication resource scheduling strategy named the VoI strategy, which is implemented in both centralized and distributed networks. The main contributions of this paper are summarized as follows.

1) We present a framework for evaluating VoI. The framework can evaluate the potential impact of vehicle packet content on AD performance. VoI is sensitively responsive to safety hazards associated with AD and is simple to calculate. And then, we analyze the long-term performance of CAV using the Lyapunov optimization method and obtain an approximate expression for the long-term VoI. Adjusting the long-term VoI can trade off between control and communication costs over a long time scale.
2) We design a novel VoI-based communication resource scheduling method, and the communication strategy based on this method is named the VoI strategy for short. Such a method lets those packets whose values are low are not transmitted, and therefore the limited communication resources are more efficiently utilized. Then, we derive an upper bound on the average cost using the proposed method theoretically. For distributed communication systems, an improved Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) strategy is proposed.
3) Extensive simulations are conducted. Simulation results show that the VoI-based communication strategy can better cope with unexpected situations in the AD task. In both the path-tracing task and the more complex intersection scenarios, the VoI-based communication strategy achieves better performance compared to the AoI-based communication strategy, especially when dealing with extreme conditions, and the VoI strategy ensures the safety of AD.

The remainder of this paper is organized as follows. We first discuss related work in Section II. The system model is described in Section III. In Section IV, the VoI in the system is analyzed from a cost perspective. Section V presents centralized and distributed transmission strategies based on VoI. Simulation and analysis are given in Section VI. This paper is concluded in Section VII.

II. Related work

A. Resource Scheduling in IoV

Due to the complexity of AD scenarios, the design of resource allocation algorithms necessitates a holistic consideration of various requirements, including communication, perception, control, computation, and more, to assist in the execution of AD tasks. Recent research efforts have predominantly focused on optimizing communication network metrics to meet the demands of perception, computation, and control tasks. For instance, in [43], the authors investigate how to enhance the safety and platoon accuracy of formation driving by minimizing queue delays. [44] addresses the provision of highly reliable and low-latency transmission for platoon driving, mitigating queue delays resulting from member dynamics during formation travel. [45] introduces artificial intelligence algorithms to design adaptive data transmission and computation optimization schemes, aiming to reduce the long-term energy consumption of autonomous driving systems while ensuring an average queue delay. In [46], the focus

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shifts towards improving V2I communication reliability and throughput to enhance the control performance of formation driving.

The aforementioned works primarily optimize V2X networks from various metrics, such as latency, reliability, and throughput, to meet the requirements of autonomous driving tasks by enhancing network performance. In contrast, our approach diverges in that it does not explore network performance improvement; rather, we focus on the evaluation of data's value of information. This evaluation helps eliminate low-value information to reduce network loads, thereby meeting the demands of AD tasks.

B. Value of Information

The study of VoI begins with the work of analyzing the influence of information content on decision-makers in [32]. Recent work on VoI or similar concepts is generally based on two forms. One is the extension of research based on AoI; the other focuses on the direct or indirect impact of information on specific system efficiency.

Studies based on nonlinear AoI are concentrated in WSN and status update systems. In underwater wireless sensor networks (UWSN), researchers initially set a subjective value for the data packet and then define a decay model, which is defined as the negative exponential form of AoI, and VoI is defined as the product of subjective value and decay. The aim is to describe the change of VoI during the process of information transmission [33], [34]. These studies enhance the efficiency of UWSN. In the status update system, [35] uses the Update Delay Cost (CoUD) metric to describe the cost of using outdated information, CoUD is a nonlinear function of AoI. The Value of Update Information (VoIU) is defined as the proportional function of CoUD, which reflects the decrease in CoUD when the update is received. The work [36] based on similar ideas, studied various queuing rules based on VoI in the status update system. Zhou *et al*. [37] defines a metric called Urgency of Information (UoI), which is defined as the product of status error and AoI nonlinear functions, measuring the nonlinear change of the importance of state information over time, which is related to the non-uniform context dependence of state information.

Research focusing on the impact of information on system efficiency is relatively scattered. Chen *et al*. [38] proposed a method based on information entropy to determine VoI in the 6G massive Internet of Things. This method helps to decide whether to transmit data and reduce network burden, which is particularly important for the Internet of Things because it also faces the challenge of limited network resources. In the network control system, the VoI of the data packet transmitted to the controller can be evaluated by measuring the error of the sensor, which can correspondingly balance the control cost and the average transmission rate [39]. In WSN, the analytic hierarchy process (AHP) is used to extract the characteristics of sensor information and evaluate the VoI of sensing information to determine the transmission priority of sensor data [40]. In the IoV, researchers also use AHP to evaluate the information value of vehicle data, considering the three main information features: timeliness, proximity, and information quality [41]. In theoretical research, the VoI in Hidden Markov Process is defined as the mutual information between the observed state sequence and the source state sequence, and sampling based on VoI can reduce uncertainty when observing the system [42].

VoI has received extensive attention, but its application in IoV is limited. It is not appropriate to directly apply the evaluation method of VoI in WSN to IoV, as most update cycles in WSN or status update networks are at the time scale in the level of seconds and most applications are irrelevant to safety. The recent work on applying the concept of VoI to IoV is [41]. The difference between our work and [41] is that we consider more specific AD applications, and there are differences in the evaluation of VoI.

III. System Model and Problem Formulation

A. Communication Model

Considering the vehicle network shown in Fig. 1, with multiple CAVs in an RSU coverage area, the RSU needs to collect status information of the CAVs in the area by V2I links to assist the CAVs in their AD tasks. All vehicles share limited spectrum resources. The length of each time step is t_p. At each time step, vehicles transmit status information x_t to the RSU through the uplink, while the RSU conveys feedback control u_t to vehicles through the downlink. To simplify the system, we only focus on the scheduling of uplink communication resources, and assume that the downlink is perfect, i.e., the control feedback of all vehicles can be transmitted within the current time step. The uplink bandwidth is divided into N_t subcarriers, which are orthogonal. Each subcarrier has the same bandwidth W_s. At the beginning of each time step, the RSU should decide how to allocate subcarriers to CAVs, and each CAV can only be allocated one subcarrier, where the CAV has a constant transmit power S.

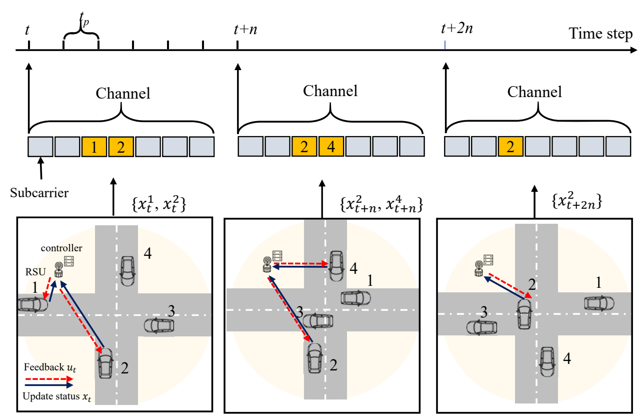

Fig. 1. Vehicles need to report their velocity and position status to the RSU and get feedback suggestions. The communication resources are divided into N_t subcarriers, and at each interval t_p, the RSU allocates a subcarrier to the CAV.

1) V2I Communication Cost: We consider the scenario with constrained resources, i.e., the number of subcarriers is less than the number of vehicles. Thus only a portion of vehicles

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can communicate in each time step t_p. The communication cost at each time step t_p can be formulated as

$$J_{com}(t) = \frac{1}{M}\sum_{i=1}^{M} R_{i,t}, \tag{1}$$

where M denotes the total number of vehicles and $R_{i,t} \in \{0,1\}$ indicates the subcarrier allocation decision of vehicle i at time t. $R_{i,t} = 1$ means that vehicle i is assigned subcarrier at time t, and $R_{i,t} = 0$ otherwise.

2) V2I Channel Model: According to Shannon's theorem, the channel capacity $C_{i,t}$ between CAV i and RSU at t-th time step can be formulated as

$$C_{i,t} = W_s \log_2[1 + \frac{S g_{i,t}(d_{i,t})}{\sigma^2_{noise}}], \tag{2}$$

where σ^2_{noise} is the noise power, and $g_{i,t}(d_{i,t})$ is the V2I channel gain. Considering the coverage area of the RSU and the fast movement of the CAV, we assume that the V2I channel obeys Rayleigh fading, i.e., the channel gain $g_{i,t}(d_{i,t})$ obeys an exponential distribution with parameter $d_{i,t}$, where $d_{i,t}$ denotes the distance between the CAV i transmitting antenna and the RSU receiving antenna at time t. According to [46], when CAV i is assigned a subcarrier, the probability that the RSU successfully receives its state information data can be formulated as

$$\begin{aligned} p_{i,t} &= \text{Prob}\left\{C_{i,t} \geq \frac{D_x}{t_p}\right\} \\ &= \exp\left(-\frac{2^{\frac{D_x}{W_s}} - 1}{S}\sigma^2_{noise} d^2_{i,t}\right), \end{aligned} \tag{3}$$

where D_x represents the data size that the CAV needs to send to the RSU within the time step t_p. We define $P_{i,t}$ as the indicator variable that the RSU has successfully accepted the CAV i status information at time t when CAV i is assigned a subcarrier, i.e., $P_{i,t} = 1$ when $C_{i,t} \geq \frac{D_x}{t_p}$; and vice versa $P_{i,t} = 0$.

B. Vehicle Control Models for Autonomous Driving

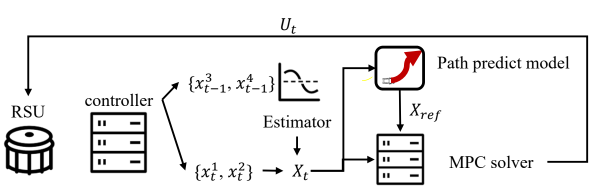

Fig. 2. AD system uses the actual and estimated states to plan the reference path and feedback control.

We use the point mass model as the vehicle dynamics model to facilitate path planning, which is similar to [47]. The vehicle control model is MPC, which is widely used in AD systems [48]. Specifically, MPC controller and path gauge are arranged on the RSU to provide suggested reference paths and control feedback to all CAV vehicles, and actuators are placed on the CAV vehicles. The state of the vehicle consists of its coordinates and velocity, and the control variable u is the acceleration of the vehicle, where both velocity and acceleration have horizontal and vertical components. The dynamic equations of the vehicle model can be established as

$$\dot{x} = \dot{\boldsymbol{A}}x + \dot{\boldsymbol{B}}u + \dot{\omega}_t, \tag{4}$$

where $\dot{\boldsymbol{A}}$ and $\dot{\boldsymbol{B}}$ are coefficient matrices obtained by dynamics model calculations, $\dot{\omega}_t$ is a disturbance vector. After discretizing (4), we can get status update equation

$$x_{t+1} = \boldsymbol{A}x_t + \boldsymbol{B}u_t + \omega_t, \tag{5}$$

where $\boldsymbol{A} = \boldsymbol{I} + \dot{\boldsymbol{A}}_t t_p$, $\boldsymbol{B} = \dot{\boldsymbol{B}}_t t_p$, $\omega_t = \dot{\omega}_t t_p$. As shown in Fig. 2, in each time step, the RSU uses the collected vehicle state to plan the path for the vehicle. The MPC controller in the RSU solves the control feedback u_t concerning the planned reference path and estimated state of the vehicle. When the vehicle communicates with the RSU, the MPC solver uses the actual state of the vehicle x_t to solve the control feedback u_t, and when the RSU fails to receive the vehicle state, the controller estimates its x'_t according to the status transition equation, with the estimation error expressed as $e = x'_t - x_t$. This estimation error will accumulate until the next time vehicle communicates with the RSU successfully. The RSU sends the solved control $u_{i,t}$ and a horizon reference path (reference path for future N_p time steps) to vehicles. According to [49], the average cost function of the vehicle in time t can be modeled as

$$\begin{aligned} J_{veh}(t) = \frac{1}{M}\sum_{i=1}^{M} \Big\{ &(x_{i,t} - x^{ref}_{i,t})^T \boldsymbol{Q_1} (x_{i,t} - x^{ref}_{i,t}) \\ &+ u^T_{i,t} \boldsymbol{Q_2} u_{i,t} \Big\}, \end{aligned} \tag{6}$$

where i represents the vehicle number, M represents the total number of vehicles at time t, $x^{ref}_{i,t}$ is the reference status of vehicle i in t-th time step of the reference path, $u_{i,t}$ is the control decision variable for vehicle i at the t-th time step, $\boldsymbol{Q_1}$ and $\boldsymbol{Q_2}$ are weight parameter matrices that reflect the trade-off between the control performance and the cost of control. The vehicle's overall cost contains two aspects. The first aspect is the error between the vehicle's actual status and the reference status, which can be considered as the cost of performance loss; the second aspect is the cost of control according to $u_{i,t}$. We define the vehicle control problem as the minimization of the vehicle cost for N_t future time steps

$$\begin{aligned} \mathcal{P}1: \min_{\boldsymbol{U}} \sum_{i=1}^{M}\sum_{t=1}^{N_p} \Big\{ &(x_{i,t} - x^{ref}_{i,t})^T \boldsymbol{Q_1} (x_{i,t} - x^{ref}_{i,t}) \\ &+ u^T_{i,t} \boldsymbol{Q_2} u_{i,t} \Big\}, \end{aligned} \tag{7}$$

$$s.t. \quad -U_{max} \leq u_{i,t} \leq U_{max}, \tag{7a}$$

$$x_{i,t} \in X_{pm}, \tag{7b}$$

where N_P is the time step path planning model prediction, and $\boldsymbol{U}$ represents the set of all vehicle control decision variables. Constraint (7a) represents the vehicle's dynamics limitation of acceleration. Constraint (7b) represents $x_{i,t}$ must be in an allowed status that is safe for the vehicle i. The pure control problem can be solved by a quadratic programming solver, which is not detailed for the sake of brevity.

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C. Problem formulation

For the connected autonomous driving system, we aim to minimize the long-term average joint cost of the system where joint cost defines as a weighted sum of communication and vehicle costs, where the weight parameter is λ. The optimization variables include the control decision $\boldsymbol{U}$ and the communication decision $\boldsymbol{R}$, where $\boldsymbol{R}$ represents the set of all vehicle communication decision variables. Different from solving the control problems independently, the communication decision also influences vehicle cost. Specifically, the communication decision plays a role in the accumulation and elimination of the estimation error $e_{i,t}$. When CAV successfully communicates with the RSU, estimation error is eliminated. Taking into account the estimation error and the communication constraint, the problem can be formulated as

$$\begin{aligned}
\mathcal{P}2: \quad & \min_{\boldsymbol{U},\boldsymbol{R}} \lim_{T\to\infty} \frac{1}{MT}\sum_{i=1}^{M}\sum_{t=1}^{T}(x_{i,t}-x_{i,t}^{ref})^T\boldsymbol{Q_1}(x_{i,t}-x_{i,t}^{ref}) \\
& + u_{i,t}^T\boldsymbol{Q_2}u_{i,t} + \lambda R_{i,t}, && (8)\\
s.t. \quad & -U_{max} \le u_{i,t} \le U_{max}, && (8a)\\
& x_{i,t} \in X_{pm}, && (8b)\\
& x_{i,t+1} = \begin{cases} Ax_{i,t}+Bu_{i,t}+e_{i,t}, & \text{if } R_{i,t}P_{i,t}=1; \\ Ax_{i,t}+Bu_{i,t}, & \text{otherwise,} \end{cases} && (8c)\\
& \sum_{i=1}^{M} R_{i,t} \le N_t, && (8d)\\
& \lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[R_{i,t}] \le \rho, && (8e)\\
& R_{i,t}\in\{0,1\}. && (8f)
\end{aligned}$$

Constraints (8a) and (8b) are equivalent to constraints (7a) and (7b), respectively. Constraint (8c) represents the status update equations and reflects the interplay between communication and control. Constraint (8d) limits the number of subcarriers. Constraint (8e) ensures fairness by limiting the average communication frequency of each vehicle. Constraint (8f) represents the range of transmission decision.

D. Definition of VoI

The optimization objective of problem $\mathcal{P}2$ aims to minimize the long-term cost, which is a challenging task to solve directly. As a solution, we simplify the problem by defining and evaluating VoI. Specifically, we consider VoI as a reflection of the future gain of the cost that can be obtained by transmitting packets. To define VoI, we consider the state information at time t and assume that the total cost at time t is J_t. The expected system cost under the transmission decision R_t is denoted as $\mathbb{E}[G_t|R_t]$, where $\mathbb{E}[\cdot]$ represents the expectation. Here, $G_t = \lim_{T\to\infty}\sum_{t'=t}^{T} J_{t'}$ denotes the future long-term cost. VoI is defined as:

$$VoI_t = \mathbb{E}[G_t|R_t=0] - \mathbb{E}[G_t|R_t=1]. \quad (9)$$

VoI represents the long-term benefit of the current transmission decision in cost deduction. The system can achieve optimal long-term cost by choosing the packet with the largest VoI at the current moment.

IV. Evaluating Value of Information

In this section, we begin by identifying the system characteristics that influence costs and proceed to derive short-term costs to compute short-term VoI. Subsequently, we estimate long-term costs under communication frequency constraints based on the short-term costs, employing Lyapunov optimization techniques to minimize long-term costs and establish their upper bounds. Utilizing this upper bound, we introduce a VoI assessment mechanism based on a queue drift penalty function. This approach yields an extended VoI expression derived from the short-term VoI. The final VoI comprehensively reflects the benefits of transmission decisions in terms of long-term cost reduction.

A. Short-term Cost Evaluation

Based on the system model, the transmission decision influences the controller's perception of the vehicle state and thus leads to variations in the control variables derived by the controller. We first derive expressions for the optimal control and the optimal vehicle cost based on (5), where the variables solely comprise the vehicle states observed by the controller. Thus, the short-term cost is easily obtained, and we refer to the VoI evaluated based on the short-term cost as the short-term VoI.

The predicted status update equation can then be defined as

$$\begin{aligned}
& x(t+1|t) = \boldsymbol{A}x(t) + \boldsymbol{B}u(t|t), \\
& x(t+2|t) = \boldsymbol{A}^2x(t) + \boldsymbol{AB}u(t|t) + \boldsymbol{B}u(t+1|t), \\
& \vdots \\
& x(t+N_p) = \boldsymbol{A}^{N_p}x(t) + \sum_{i=0}^{N_p-1}\boldsymbol{A}^{N_p-1-i}\boldsymbol{B}u(t+i|t), \quad (10)
\end{aligned}$$

where $x(t+n|t)$ denotes the state at time $t+n$ estimated from the state at time t, and it can be converted to matrix form as

$$\begin{bmatrix} x(t+1|t) \\ x(t+2|t) \\ \vdots \\ x(t+N_p|t) \end{bmatrix} = \begin{bmatrix} \boldsymbol{A} \\ \boldsymbol{A}^2 \\ \vdots \\ \boldsymbol{A}^{N_p} \end{bmatrix} \times x(t)$$
$$+ \begin{bmatrix} \boldsymbol{A}^0\boldsymbol{B} & \cdots & 0 & 0 \\ \boldsymbol{A}^1\boldsymbol{B} & \boldsymbol{B} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A}^{N_p-1}\boldsymbol{B} & \boldsymbol{A}^{N_p-2}\boldsymbol{B} & \cdots & \boldsymbol{B} \end{bmatrix} \times \begin{bmatrix} u(t|t) \\ u(t+1|t) \\ \vdots \\ u(t+N_p-1|t) \end{bmatrix}. \quad (11)$$

Here, the coefficient matrix is denoted by $\boldsymbol{C}$ and $\boldsymbol{D}$, with the resulting equation being $X_t = \boldsymbol{C}x(t) + \boldsymbol{D}U_t$. The control vector that needs to be solved is denoted by U_t, and X_t denotes the status vector for the next N_p time steps derived from $x(t)$. The following lemma can reformulate the control problem (7).

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Lemma 1. *The MPC problem (7) can be transformed as*

$$\begin{aligned}\min J =&(X_t - X_{ref})^T \mathbb{Q}_1 (X_t - X_{ref}) + U_t^T \mathbb{Q}_2 U_t \\ =&x(t)^T \boldsymbol{\mathcal{G}} x(t) + U_t^T \boldsymbol{\mathcal{E}} U_t + 2x(t)^T \boldsymbol{\mathcal{H}} U_t,\end{aligned} \tag{12}$$

where the matrix $\boldsymbol{\mathcal{G}}, \boldsymbol{\mathcal{E}}, \boldsymbol{\mathcal{H}}$ are positive definite, while $\mathbb{Q}_1$ and $\mathbb{Q}_2$ are the quasi-diagonal matrix generated by $\boldsymbol{Q_1}$ and $\boldsymbol{Q_2}$. The specific form of the above matrix is detailed in the Appendix.

Proof. See Appendix A. □

Without considering constraint (7a), the optimal solution of problem (7) can be given as

$$U_t^* = -\boldsymbol{\mathcal{E}}^{-1} \boldsymbol{\mathcal{H}} x(t). \tag{13}$$

U_t^* is optimal when any element u_t^* within U_t^* satisfies $-u_{max} \le u_t^* \le u_{max}$, and $u_t^* = \frac{u_t^*}{|u_t^*|} \times u_{max}$ otherwise. Accordingly, the system estimates $x(t)'$ to calculate u_t if the vehicle does not transmit the status $x(t)$ to the controller. Let $x(t)' = x(t) + e(t)$, where $e(t)$ is the estimation error. The transmission benefit of the vehicle cost can be estimated as

$$\begin{aligned}\Delta J(t) &= J(x(t), U_t(x(t)')) - J(x(t), U_t(x(t))) \\ &= \frac{1}{2} U_t(x(t)')^T \boldsymbol{\mathcal{E}} U_t(x(t)') + x(t)^T \boldsymbol{\mathcal{H}}(x(t)) U_t(x(t)') \\ &- \frac{1}{2} U_t(x(t))^T \boldsymbol{\mathcal{E}} U_t(x(t)) - x(t)^T \boldsymbol{\mathcal{H}}(x(t)) U_t(x(t)) \\ &= \frac{1}{2} e(t)^T \boldsymbol{\mathcal{H}} \boldsymbol{\mathcal{E}}^{-1} \boldsymbol{\mathcal{H}} e(t) \\ &= \frac{1}{2} e(t)^T \boldsymbol{\mathcal{W}} e(t) \ge 0.\end{aligned} \tag{14}$$

ΔJ represents the benefits of the transmission decision in short-term vehicle cost reduction, and $J(\cdot)$ corresponds to the vehicle cost function in (12), while $U(\cdot)$ refers to the optimal control based on (13). As (14), the transmission benefit depends on the error in the controller's estimation of the vehicle state at the current time, and is always greater than zero. The short-term VoI can be determined by evaluating the expression as

$$VoI_s(t) = \frac{1}{2} e(t)^T \boldsymbol{\mathcal{W}} e(t) - \lambda, \tag{15}$$

$e(t)$ refers to the estimation error at time t, $\boldsymbol{\mathcal{W}}$ is the weight matrix, and λ represents the weight of the communication cost. Notably, the calculation of weight matrix $\boldsymbol{\mathcal{W}}$ in the expression needs multiple matrix operations and varies with the time step.

B. Long-term Cost Evaluation

We have evaluated the short-term VoI of packets based on the transmission benefit in the immediate future. However, the impact of transmission decisions on long-term costs is still unknown. In this part, we first simplify the problem by restricting our analysis to a single vehicle and instead the vehicle cost by using its approximation. This decouples the transmission decision from the control decision, allowing us to evaluate the long-term benefits that can be obtained from the transmission decision. Next, we represent the cumulative change in state error using a queue backlog vector and introduce a virtual queue to represent the communication frequency constraint. We then transform the single-vehicle problem into a problem of minimizing the queue drift-penalty at each time step by the Lyapunov optimization method and solve the single-vehicle problem. The drift-penalty function of the vehicle represents a trade-off between queue stability and cost function expectations, and based on the drift penalty function, we evaluate the long-term VoI of the vehicle. Then, we can apply the long-term VoI to the solution of the original problem.

Original problem (8) can be simplified to single-vehicle problem as

$$\begin{aligned}\mathcal{P}3: \quad & \lim_{T\to\infty} \min_{R,U} \frac{1}{T} \sum_{t=1}^{T} (J_{veh}(t) + \lambda J_{com}(t)) \\ & s.t. \quad (8a), (8b), (8c), (8e), (8f).\end{aligned} \tag{16}$$

To decouple the transmission decision from the control decision, we can approximate the cost $J_{vel}(t)$ using

$$J_{veh}(t) \cong J_{veh}(t|R_t = 1) + \Delta J(t)(1 - R_t P_t), \tag{17}$$

where $\Delta J(t)$ denotes the transmission benefits at time t according to (14) and $J_{veh}(t|R_t = 1)$ denotes the vehicle cost when transmission decision $R_t = 1$. The transmission decision variable R_t does not affect $J_{veh}(t|R_t = 1)$. Therefore, problem (16) can be transformed into the following form

$$\begin{aligned}\mathcal{P}4: \quad & \lim_{T\to\infty} \min_{R} \frac{1}{T} \sum_{t=1}^{T} (\Delta J(t)(1 - R_t P_t) + \lambda J_{com}(t)) \\ & s.t. \quad (8e), (8f).\end{aligned} \tag{18}$$

To solve problem (18), we build queue backlog vector $\boldsymbol{\Theta}(t) = (\Theta_1(t), \dots, \Theta_{N_e}(t))$ and virtual queue $H(t)$. The queue update functions are given as

$$\Theta_n(t+1) = \Theta_n(t) + a_n(t) - P_t R_t \Theta_n(t), \tag{19}$$

$$H(t+1) = [H(t) + R_t - \rho]^+. \tag{20}$$

The vehicle's error is represented by the queue backlog vector $\boldsymbol{\Theta}(t)$, where $\Theta_n(t)$ represents the queue of the n-th element in the status x. The increment of the error component with expectation μ_n and variance δ_n^2 is represented by $a_n(t)$. The virtual queue H_t indicates the update frequency, where $[H]^+ = \max(H, 0)$. The update frequency constraint (8e) is maintained by $H(t)$ as lemma 2 which was proven in [37]. The queue symbol $H_t, \boldsymbol{\Theta}_t$ have the same meaning as $H(t), \boldsymbol{\Theta}(t)$ for the sake of symbol simplicity. Then, we used Lyapunov optimization to solve problem (18).

Lemma 2. *If queues H are mean rate stable, H_t satisfy with*

$$\lim_{T\to\infty} \frac{\mathbb{E}[H_t]}{T} = 0. \tag{21}$$

Then,

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} R_t \le \rho. \tag{22}$$

We define Lyapunov function as $L_t = \frac{1}{2}H^2(t) + \sum_{n=1}^{N_e}\theta_n\Theta_n^2(t)$, where θ_n is weight parameter. The drift of the Lyapunov function is

$$\Delta_t = \mathbb{E}[L_{t+1} - L_t|\mathbf{\Theta}_t, H_t]. \tag{23}$$

According to update function (19) and (20), we can derive the drift of Θ_t and H_t as

$$\begin{aligned}
\Theta_{t+1}^2 - \Theta_t^2 &= (\Theta_t + a_t - \Theta_t R_t P_t)^2 - \Theta_t^2 \\
&= \Theta_t^2 P_t^2 R_t^2 - 2\Theta_t a_t P_t R_t - 2\Theta_t^2 R_t P_t + 2\Theta_t a_t + a_t^2 \\
&= a_t^2 + 2\Theta_t a_t(1 - R_t P_t) - \Theta_t^2 R_t P_t, \qquad (24)\\
H_{t+1}^2 - H_t^2 & \\
&= \{\max\{H_t - \rho + R_t, 0\}\}^2 - H_t^2 \\
&= 2H_t R_t - 2H_t\rho + (R_t - \rho)^2 \le 2H_t(R_t - \rho) + 1, \qquad (25)
\end{aligned}$$

then, we can derive the upbound of Δ_t as

$$\begin{aligned}
&\mathbb{E}[L_{t+1} - L_t|\mathbf{\Theta}_t, H_t] \\
&\le \{H_t - \sum_{n=1}^{N_e}\theta_n p(2\mu_n\Theta_n(t) + \Theta_n^2(t))\}\mathbb{E}[R_t|\mathbf{\Theta}_t, H_t] \\
&\quad + \frac{1}{2}(1 - 2\rho H_t) + \sum_{n=1}^{N_e}\theta_n\delta_n^2 + 2\sum_{n=1}^{N_e}\theta_n\mu_n\Theta_n(t).
\end{aligned} \tag{26}$$

The penalty f_t is defined as $f_t = \lambda R_t + \sum_{n=1}^{N_e}(1-R_t)\xi_t\Theta_n^2(t)$ which represents the value of the objective function at time t. $\mathbb{E}[f_t|\mathbf{\Theta}_t, H_t]$ has the expression as

$$\begin{aligned}
\mathbb{E}[f_t|\mathbf{\Theta}_t, H_t] =& \mathbb{E}[R_t|\mathbf{\Theta}_t, H_t](\lambda - \sum_{n=1}^{N_e}\xi_n\Theta_n^2(t)) \\
&+ \sum_{n=1}^{N_e}\xi_n\Theta_n^2(t).
\end{aligned} \tag{27}$$

Therefore, the drift-plus-penalty $\mathbb{E}[L_{t+1} - L_t + Vf_t|\mathbf{\Theta}_t, H_t]$ have the upbound as

$$\begin{aligned}
&\mathbb{E}[L_{t+1} - L_t + Vf_t|\mathbf{\Theta}_t, H_t] \\
&\le \{H_t + V\lambda - 2p\sum_{n=1}^{N_e}\theta_n\mu_n\Theta_n(t)\}\mathbb{E}[R_t|\mathbf{\Theta}_t, H_t] \\
&- \sum_{n=1}^{N_e}(p\theta_n + V\xi_n)\Theta_n^2(t)\mathbb{E}[R_t|\mathbf{\Theta}_t, H_t] \\
&+ \frac{1}{2}(1 - 2\rho H_t) + \sum_{n=1}^{N_e}\theta_n(\delta_n^2 + \frac{V\xi_n}{\theta_n}\Theta_n^2(t) + 2\mu_n\Theta_n(t)) \\
&= U(R_t, H_t, \mathbf{\Theta}_t) + Res.
\end{aligned} \tag{28}$$

In (28), $U(R_t, H_t, \mathbf{\Theta}_t)$ is calculated as

$$\begin{aligned}
U(R_t, H_t, \mathbf{\Theta}_t) = \{&H_t + V\lambda - 2p\sum_{n=1}^{N_e}\theta_n\mu_n\Theta_n(t) \\
&- \sum_{n=1}^{N_e}(p\theta_n + V\xi_n)\Theta_n^2(t)\}\mathbb{E}[R_t|\mathbf{\Theta}_t, H_t],
\end{aligned} \tag{29}$$

the term Res is not related to $\mathbb{E}[R_t|\mathbf{\Theta}_t, H_t]$ and is defined by

$$Res = \frac{1}{2}(1 - 2\rho H_t) + \sum_{n=1}^{N_e}\theta_n(\delta_n^2 + \frac{V\xi_n}{\theta_n}\Theta_n^2(t) + 2\mu_n\Theta_n(t)). \tag{30}$$

According to Lyapunov optimization theorem in [50], the upper bound on the expectation of f_t can be guaranteed by minimizing drift-plus-penalty.

Theorem 1. *The penalty function can obtain an upper bound by minimizing drift-plus-penalty in each time step as*

$$\min_{R_t}(\Delta_t + f_t) \tag{31}$$

$$s.t. \quad R_t \in \{0, 1\}. \tag{31a}$$

Then,

$$\lim_{T->\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[f_t] \le f^* + \frac{\gamma}{V}, \tag{32}$$

where $f^* = \lambda\rho$, $\theta_i = \frac{V\xi_i(1-\rho)}{\rho p}$, $\gamma = \frac{1}{2} + \sum_{i=1}^{n}\theta_i\delta_i^2$.

Proof. See Appendix B. □

Since Res does not contribute to minimizing drift-plus-penalty, the value of drift-plus-penalty depends only on the preceding term $U(R_t, H_t, \mathbf{\Theta}_t)$. Therefore, problem (18) can be transformed to

$$\mathcal{P}5: \quad \min_{R_t} U(R_t, H_t, \mathbf{\Theta}_t) \tag{33}$$

$$s.t. \quad R_t \in \{0, 1\}, \tag{33a}$$

The solution of problem $\mathcal{P}5$ at each time step demands only the identification of whether $U(R_t, H_t, \mathbf{\Theta}_t)$ is greater than 0. This effective approach to minimizing the drift-plus-penalty function is referred to as strategy π. The upper bound on the average cost of the single-vehicle problem, which is desirable under strategy π, can be established using Theorem 1. Therefore, for any vehicle that adheres to strategy π, the long-term cost under transmission decision R_t can be evaluated as

$$\begin{aligned}
\mathbb{E}_\pi[G_t|R_t] &= \lim_{T\to\infty}\sum_{t'=t}^{T}\mathbb{E}[J_{t'}] \\
&= \lim_{T\to\infty}\sum_{t'=t}^{T}\mathbb{E}[f_{t'} + J_{vel}(t'|R_t' = 1)] \\
&= \lim_{T\to\infty} f_t + \sum_{t'=t+1}^{T}\mathbb{E}[f_{t'}] + \sum_{t'=t}^{T}\mathbb{E}[J_{vel}(t'|R_t' = 1)] \\
&\le \frac{U(R_t, H_t, \mathbf{\Theta}_t)}{V} + Res_f,
\end{aligned} \tag{34}$$

where Res_f is not related to R_t and is defined by

$$\begin{aligned}
Res_f = &\lim_{T\to\infty}(T - t - 1)(f^* + \frac{\gamma}{V}) + (T - t)\overline{J}_{vel} \\
&+ \frac{Res - \Delta_t}{V},
\end{aligned} \tag{35}$$

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where $\overline{J}_{vel}$ is the average vehicle cost which is not associated with the transmission decision. Then, the long-term VoI can be expressed as the drift-plus-penalty benefit after transmission

$$\begin{aligned} VoI(t) &= \mathbb{E}_{\pi}[G_t|R_t=0] - \mathbb{E}_{\pi}[G_t|R_t=1] \\ &\leq \frac{U(0,H_t,\boldsymbol{\Theta}_t)}{V} - \frac{U(1,H_t,\boldsymbol{\Theta}_t)}{V} \\ &= \frac{1}{V}\{\sum_{n=1}^{N_e}(p\theta_n + V\xi_n)\Theta_n^2(t) - V\lambda - H_t\} \\ &= \{\sum_{n=1}^{N_e}\xi_n\Theta_n^2(t) - \lambda\} + \frac{1}{V}\sum_{n=1}^{N_e}p\theta_n\Theta_n^2(t) - \frac{H_t}{V}. \end{aligned} \tag{36}$$

Based on the above analysis, selecting a value function to measure the benefits of successful transmission needs to consider three crucial factors: status estimation error (which corresponds to short-term VoI), queue drift estimation, and virtual queue backlog. Queue drift measures the implications of the decision on future status, while virtual queue reflects the frequency of transfers over time. Long-term VoI will henceforth be referred to as VoI in the subsequent sections unless otherwise specified.

V. VoI Scheduling Strategy for Multi-Vehicle Connected Autonomous Driving Problem

In this section, we propose two VoI-based packet-level communication resource scheduling strategies in multi-vehicle scenarios: one for centralized networks where the RSU senses the VoI of all CAVs and allocates sub-carriers accordingly, and another for distributed networks where CAVs evaluate the VoI of their own packets to determine the appropriate time to transmit. Moreover, the expected system average cost upper bound of the VoI strategy in a centralized network is analyzed.

A. VoI Strategy in Centralized Networks

The multi-vehicle scenario requires the RSU to make scheduling decisions at each time step. Then, the multi-vehicle cost problem at time t can be formulated as minimizing the future cumulative cost of all vehicles. The future cumulative cost of vehicles can be expressed as

$$\begin{aligned} &\sum_{i=1}^{M}\sum_{t'=t}^{T} J_{i,t'} = \sum_{i=1}^{M}\mathbb{E}[G_{i,t}|R_{i,t}] \\ &= \sum_{i=1}^{M} R_{i,t}\mathbb{E}[G_{i,t}|R_{i,t}=1] + (1-R_{i,t})\mathbb{E}[G_{i,t}|R_{i,t}=0] \\ &= \sum_{i=1}^{M}\mathbb{E}[G_{i,t}|R_{i,t}=0] - VoI(i,t)R_{i,t}, \end{aligned} \tag{37}$$

where $J_{i,t}$ denotes the total cost of vehicle i at time t, and $\mathbb{E}[G_{i,t}|R_{i,t}]$ denotes the expected future cumulative cost under decision $R_{i,t}$. Then, the problem of minimizing the future cumulative cost can be transformed into the VoI maximization problem. In centralized networks, maximizing VoI is simple; RSU senses the VoI evaluated by CAVs and schedules N packets with the highest VoI at the current time. This problem of maximizing VoI is formulated as

$$\mathcal{P}6: \max_{R}\sum_{i=0}^{M} VoI(i,t)R_{i,t}, \tag{38}$$

$$s.t. \sum_{i=1}^{M} R_{i,t} \leq N, \tag{38a}$$

which can be solved using a simple sorting algorithm, and the subcarriers can be allocated to the vehicle in accordance with the sorted VoI values.

To show the system performance achieved by the VoI scheduling strategy, we analyze the average cost of the system when using the VoI strategy (π_V). As in section IV, we use a similar approach, where let $f_t = \mathbb{E}[\sum_{i=1}^{M}\lambda R_{i,t} + \sum_{i=1}^{M}\sum_{n=1}^{N_e}(1-R_{i,t})\xi_{i,t}\Theta_{i,n}^2(t)\}]$ and $L_t = \frac{1}{2}\sum_{i=1}^{M}H_{i,t} + \sum_{i=1}^{M}\sum_{n=1}^{N_e}\theta_{i,n}\Theta_{i,n}(t)$. We have drift-plus-penalty as

$$\mathbb{E}[L_{t+1} - L_t - Vf_t] \leq \sum_{i=1}^{M} U(R_{i,t}, H_{i,t}, \boldsymbol{\Theta}_{i,t}) + Res_M, \tag{39}$$

$$\begin{aligned} Res_M &= \frac{1}{2}\sum_{i=1}^{M}(1-2\rho H_{i,t}) \\ &+ \sum_{i=1}^{M}\sum_{n=1}^{N_e}\theta_n(\delta_{i,n}^2 + \frac{V\xi_{i,n}}{\theta_{i,n}}\Theta_{i,n}^2(t) + 2\mu_{i,n}\Theta_{i,n}(t)). \end{aligned} \tag{40}$$

According to Theorem 1, the average cost can be estimated as

$$\begin{aligned} &\pi_V = \min\sum_{i=1}^{M} U(R_{i,t}, H_{i,t}, \boldsymbol{\Theta}_{i,t}), \\ &\lim_{T\to\infty}\frac{1}{T}\sum_{i=0}^{M}\sum_{t=0}^{T}\mathbb{E}_{\pi_V}[f_t] \\ &\qquad \leq (\lambda\rho + \frac{1}{2V} + \sum_{n=1}^{N_n}\frac{\xi_{i,n}(1-\rho)}{\rho p}\delta_i^2 + \hat{J_{veh}})M, \end{aligned} \tag{41}$$

where $\hat{J_{veh}}$ denotes average vehicle cost at full transmission in (17). The VoI-based communication strategy for CAVs has an upper bound on the average cost, which depends on the error increment variance a_t and maximum communication frequency ρ. This boundary ensures that the performance of the CAVs does not fall below a threshold. The convergence of the average cost is not guaranteed without the boundary, which may lead to the actual path deviating substantially from the reference path and compromising safety in the AD system.

B. VoI Strategy in Distributed Networks

The challenge of incorporating the VoI concept into distributed network architectures is that no single node has the ability to sense the global VoI and assign transmission priority to vehicles. To overcome this challenge, we propose an improved CSMA/CA protocol that applies VoI to distributed network architectures. CSMA/CA is a well-known distributed

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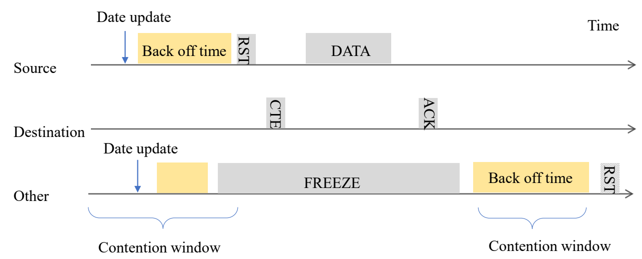

Fig. 3. CSMA/CA sets the back-off timer to avoid contention between nodes. Use the binary exponential back-off algorithm to adjust the contention window for retransmission and double the range of the contention window for each retransmission to avoid channel congestion.

network access protocol commonly used in wireless networks to regulate access to a shared medium. As depicted in Fig. 3, when a node receives data packets, it first senses the channel state. If the channel remains idle for a Distributed Inter-frame Spacing (DIFS), the node initiates the backoff process. During the backoff process, the node randomly selects a backoff time within the contention window (typically set to a default initial value of 31 in the 802.11 standards). The node periodically senses the channel during each slot time, decrementing its random backoff counter if the channel is idle. If the channel is busy due to ongoing transmission by another node, the backoff timer is frozen until the channel becomes idle again. Once the backoff timer reaches zero, the node is permitted to transmit its data. If the packet is not successfully sent (no ack is received) then the contention window length is expanded, and vice versa the contention window length is reset.

Algorithm 1 Distributed Scheduling based on VoI

Input: Vehicle status $x_{i,t}$, reference status $x_{i,t}^{ref}$, time step t, vehicle v_i, queues $H_{i,t}, \mathbf{\Theta}_{i,t}$.

1: $x_{est} = estimate(x_{i,t}, x_{i,t}^{ref})$
2: $a_t = (x_{est} - x_{i,t})^T \mathcal{W}(x_{est} - x_{i,t})$
3: Calculate VoI by (34)
4: Update index $\mathcal{C}_t$ according to (40)
5: Set T_{back} according to (41)
6: Waiting for contention result $R_{i,t}$
7: Update queues $H_{i,t}, \mathbf{\Theta}_{i,t}$ according to (17) and (18)

Output: Index $\mathcal{C}_t$

The CSMA/CA protocol is employed to mitigate channel conflicts by employing a binary exponential backoff timer. One crucial aspect of this protocol is the determination of the contention window length. The objective of our modified protocol is to adapt the length of the contention window based on the VoI in order to prioritize packets. Specifically, we introduce a binary index parameter at time t, denoted as $\mathcal{C}_t$, for each CAV. As the CAV periodically transmits state information packets to the RSU, any previously untransmitted packet from the same vehicle is discarded when a new state information packet needs to be transmitted. Subsequently, the binary index parameter $\mathcal{C}_t$ is updated according to the VoI of the newly arrived packet, and the CAV determines the initial contention window length based on the updated index $\mathcal{C}_t$. The initial contention window length is set as $2^{\mathcal{C}_t}$. Additionally, the backoff timer is reset based on the contention window. The subsequent backoff process aligns with the original CSMA/CA protocol. The CAV awaits a successful transmission signal before generating the next packet, and the queue required to evaluate the VoI is updated based on the transmission's success or failure. Finally, we get the distributed VoI scheduling strategy as algorithm 1.

$$\mathcal{C}_t = \begin{cases} \max\{\mathcal{C}_{t-1} - 1, 0\}, & \text{if} \quad VoI_t \leq 0; \\ \min\{\mathcal{C}_{t-1} + 1, 5\}, & \text{otherwise}, \end{cases} \tag{42}$$

$$T_{back} = \; 2^{\mathcal{C}_t} + random(0, \alpha), \tag{43}$$

where α is a parameter for reducing the probability of collision, and the best setting of α can be obtained empirically. When a CAV generates a new packet at time t in the system model, Algorithm 1 is executed. The first step is to evaluate the VoI of the packet. If the VoI is greater than 0, indicating that the information is more valuable than the transmission cost, the contention window length is shortened. Conversely, if the VoI is lower or equal to 0, the contention window length is increased. The index $\mathcal{C}_t$ is updated according to (42), with the constraint that it remains within the range of 0 to 5, corresponding to CW lengths of 1 to 32. Unlike the original CSMA/CA protocol, our improved protocol sets the backoff timer differently. The backoff timer T_{back} is determined by adding a random time to the contention window length as (43). This setup retains the random nature of the backoff timer to reduce the probability of collisions. Additionally, the improved protocol introduces relative priority for packets with different VoI, ensuring that packets with higher VoI have shorter contention window lengths and then have a higher probability of being transmitted first. Finally, the CAV waits for the contention result R_t, when $R_t = 1$ is an indication that the packet was successfully transmitted within the specified time and $R_t = 0$ vice versa. R_t is used to update the queue needed to evaluate the VoI.

VI. Performance Evaluation

This section evaluates the performance of two primary tasks in the AD scenario: path tracking and intersection passing. Path tracking is essential for AD systems as it involves the safety of CAVs and any deviations from this path are considered performance degradation. The path-tracking task evaluation includes single-vehicle and multi-vehicle scenarios to analyze path-tracking performance, trajectory distribution, cost performance and show the advantages of the proposed strategy. In contrast, crossing intersections is a complex task. The intersection has a high impact on traffic efficiency, considering factors such as high traffic flow and accident-proneness. The ideal communication strategy should enable vehicles to coordinate and safely navigate intersections without reliance on traffic lights. Thus, we compare the performance of different communication strategies in intersection simulations, mainly in terms of safety and passing efficiency. All simulation parameters are summarized in Table I.

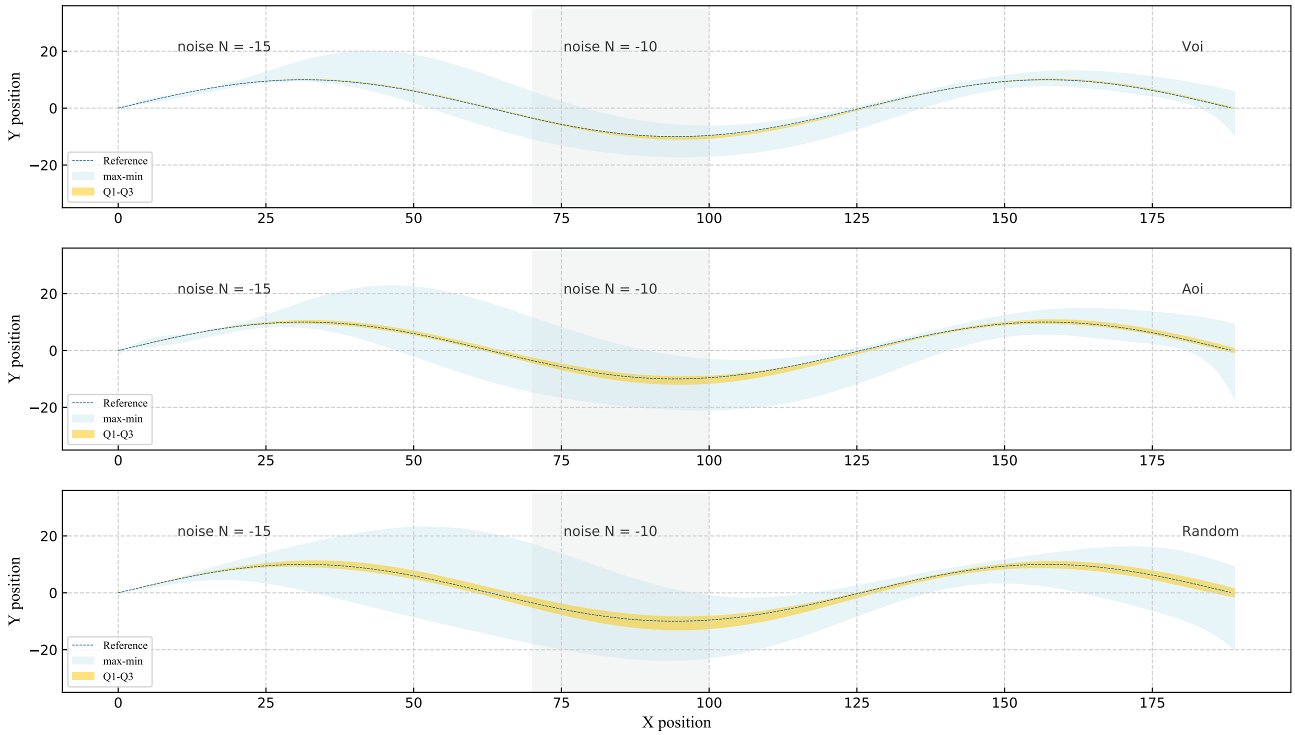

Fig. 4. The trajectory distribution with different strategies in path tracking, VoI represents the VoI strategy discussed in Section IV. The gray area adds the noise N of the control system from -15 to -10 and aims to visually demonstrate the guarantees of VoI on AD performance. Parameter $\rho = 0.1$ represents the maximum average communication frequency.

TABLE I
SIMULATION PARAMETERS

Parameter	**Value**
Vehicle speed	$5 \sim 15m/s$
Vehicle acceleration	$-5 \sim 5m/s^2$
Sample period	50 ms
Number of sub-channel	20
Transmit power	20 dBm
Subcarrier bandwidth	1 MHz
Noise power	-174 dBm
Weight parameter λ	10
Weight parameter V	10
Weight parameter ξ	[2,2,5,5]
Weight parameter δ^2	[0.00002, 0.00002, 0.03, 0.03]
Intersection type	4
Intersection width	3.5m
Number of lanes	4

A. Single-Vehicle Path Tracking Performance

To derive the impact of wireless communication resource limitation on the performance of the AD task, we use the mean square error (MSE) of the actual state path versus the reference state path to reflect the performance of a single path tracking task. The mean μ and standard deviation σ of the path MSE over multiple experiments are used to reflect the distribution of performance. The tracking effect is shown intuitively in Fig. 4 by selecting the sine curve $y = 10 \sin 0.05x$ as the reference path. We performed 500 independent simulations of the path tracking based on each of the three communication strategies. The VoI strategy is as described in Section V using the VoI evaluation function (36). The AoI strategy is defined as the RSU scheduling the priority between packets based on the AoI of the vehicle. The calculation of AoI is similar to that in [20]. The random strategy chooses communication timing randomly, and all three strategies maintain an equal average communication frequency.

We counted the deviation of all the actual paths from the reference paths under the three strategies. The paths are divided into two regions according to the deviation size, where the light blue region represents the actual paths whose deviations lie from the upper bound to the upper quartile and the lower bound to the lower quartile, while the orange region represents the paths whose deviations lie between the upper and lower quartile. The dark blue dotted line represents the reference path. The entire experiment process is divided into two noise regions. The gray area marked as the time step $150 - 200$ has higher control noise, indicating that more attention should be paid to the change of the vehicle state. As shown in Fig. 4, the strategy based on VoI scheduling has the best boundary performance which represents the case where the statistical trajectory deviates the most from the reference path, especially in the high-noise region. Although the scheduling strategy based on AoI achieves similar results in the upper and lower quartiles as the VoI strategy, the boundary performance is significantly worse.

The status (X position, Y position, X velocity, Y velocity) MSE and standard deviation of the three scheduling strategies are shown in Fig. 5. Although the advantages of the VoI strategy in average MSE are not significant, the

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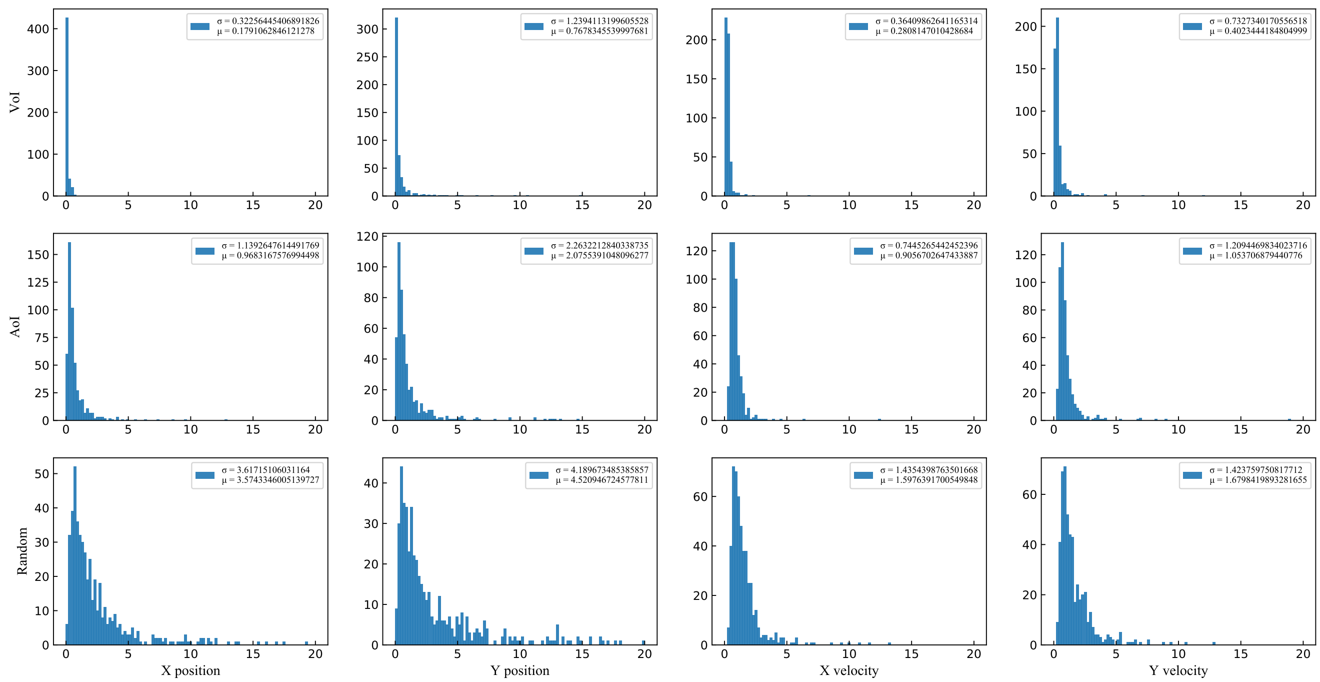

Fig. 5. Setting parameters $N = -15, \rho = 0.1$, the histogram of position and velocity MSE distribution of vehicles with different strategies in path tracking, where X represents the horizontal direction and Y represents the vertical direction.

improvement in standard deviation compared with the AoI strategy is evident. The lower standard deviation advantage of VoI strategies shown in Fig. 4 and Fig. 5 play an essential role in the performance of AD tasks, the proposed strategy ensures that the system performance is affected as little as possible in extreme cases. For AoI strategies, although the average performance is also good, it lacks the ability to deal with extreme environments, making its safety impossible to guarantee.

To further exemplify how VoI and AoI strategies affect AD task performance, we show the variation of some parameters with time steps in a path-tracking task. Fig. 6(a) and Fig. 6(b) show the difference between the actual vehicle velocity and the expected velocity. Fig. 6(c) and Fig. 6(d) illustrate the change in the lateral and longitudinal accelerations of the control variables. Fig. 6(e) presents the variation of square error between actual status and reference status over time. Fig. 6(f) shows the communication opportunities decided by the two scheduling strategies. The above experimental results show the on-demand nature of the VoI strategy, which is sensitive to emergent conditions. Specifically, the presence of higher control noise during the 150-200 time step region increases the likelihood of trajectory deviation compared to other time periods. To mitigate this effect, the VoI strategy identifies variations in packet importance and increases the frequency of packet transmissions during this interval. By doing so, the controller can promptly adapt the control variables, resulting in a timely response that reduces the deviation between the actual and reference paths. Compared with the AoI strategy, which focuses more on the freshness of information, the VoI indicator reflects the impact of information on the system.

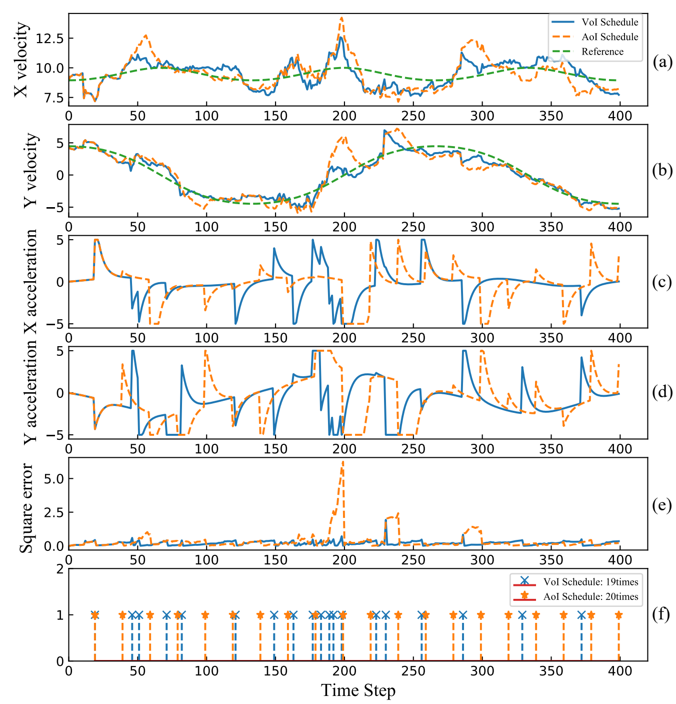

Fig. 6. Vehicle velocity, acceleration, square error, and transmission timing under VoI and AoI strategy.

B. Multi-Vehicle Path Tracking Performance

The simulation experiments conducted in this section aim to evaluate the performance of path tracking in a multi-vehicle scenario, where each vehicle follows its own reference path, and collisions between vehicles are not considered. The network architecture is divided into two scenarios: centralized and distributed. In the centralized network scenario, the RSU allocates sub-carriers to the vehicles at each time step. In contrast, the distributed network scenario involves all vehicles sharing the channel resources without centralized allocation. Fig. 7 shows the relationship between average communication cost and average vehicle cost, where the horizontal coordinate is the vehicle number. Setting the number of subcarriers $N_t = 1$ and noise level at -15, as the number of vehicles increases, the limited communication resources lead to a gradual decrease in the average communication cost and an increase in the vehicle cost, representing a decrease in performance. The remaining four curves represent the vehicle cost using different strategies, and the VoI strategy is advantageous in terms of reducing vehicle cost.

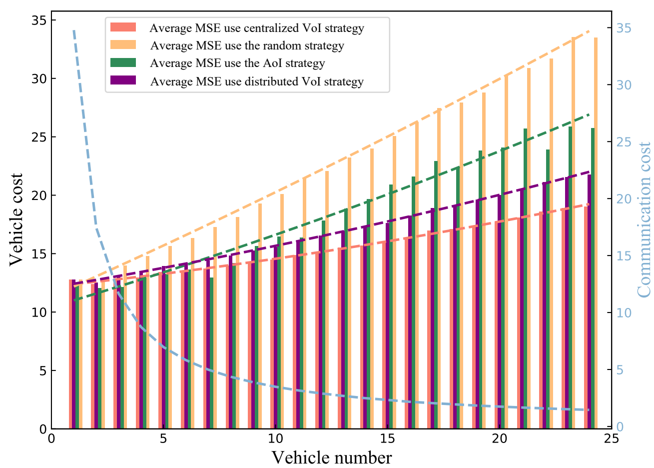

Fig. 7. Average vehicle cost and communication cost of vehicles under different strategies

As shown in Fig. 8, we present the variation of the average total cost for CAVs as vehicle density increases. In addition to the previously mentioned four strategies, we have included two additional special curves for comparison. These two curves represent the full transmission cost and the theoretically upper bound cost obtained using the VoI strategy as estimated in (41), with the parameters involved in calculating the cost bound detailed in Table I. The full transmission strategy does not adhere to subcarrier resource constraints, meaning that all CAVs can successfully communicate with the RSU within each time step. Consequently, its average total cost remains largely constant. The total costs of the remaining four strategies exhibit a trend of decreasing followed by an increase. This is due to the fact that when vehicle density is low, communication costs constitute the majority of the total cost. As vehicle density increases, the average communication frequency, and hence communication costs, decrease. During this period, the degradation in control performance (vehicle cost) is relatively small, resulting in a declining total cost. However, as vehicle density further increases, the degradation in control performance becomes more severe, leading to an increase in total cost. Among these four strategies, the VoI strategy effectively manages the increase in average total cost. Furthermore, it is worth noting that our proposed theoretical upper bound is effective and closely aligns with the cost curve achieved by the actual VoI strategy.

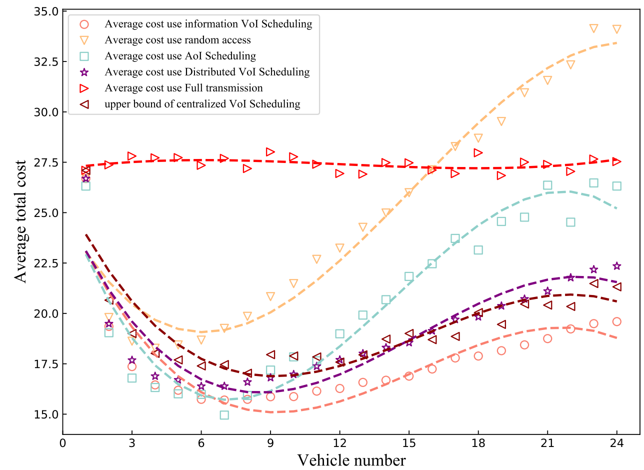

Fig. 8. Average total cost under different strategies and the upper bound of centralized VoI strategy.

Fig. 7 and Fig. 8 also show the performance of the distributed VoI strategy, setting parameter $\alpha = 7$. As in Algorithm 1, CAVs adjust the contention window size based on VoI to obtain the performance between the centralized VoI strategy and the AoI strategy. We show the transmission timing diagram for the case of 10 CAVs in 15-time steps as shown in Fig. 9(a). Fig. 9(b) and Fig. 9(c) show the contention window and VoI variation of CAVs in the corresponding time. The CAV nodes with a higher VoI are given a smaller contention window, and they are prioritized for scheduling within a maximum of 5-time steps.

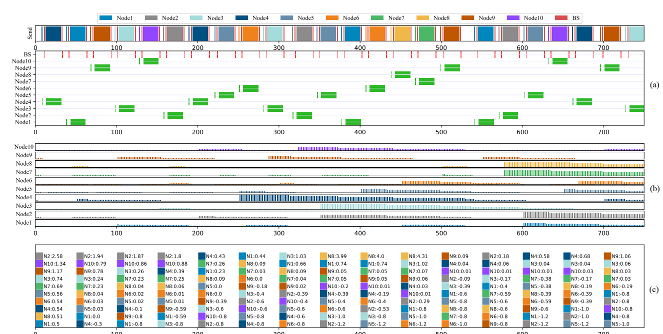

Fig. 9. (a) Transmission time under distributed VoI strategy in 15-time step; (b) contention window of each vehicle node in 15-time step; (c) VoI of each vehicle node in 15-time step.

The simulation results on trajectory tracking cost analysis are shown in Fig. 10. The simulation includes 20 CAVs and limits the number of subcarriers to 2 for both VoI and AoI strategies, while the full-transmission strategy boasts 20 subcarriers. A total of 500 Monte Carlo experiments are conducted to investigate the matter further. As the level of the noise parameter, the performance of the VoI strategy and the AoI strategy undergoes a gradual decrease as shown in Fig. 10(a). This loss in performance can be attributed to the heightened interference posed by the noise. A comparison with a full-transmission strategy is made to evaluate the overall efficacy of the VoI and AoI strategies. The performance of the VoI strategy undergoes a relatively lower degradation as compared to the AoI strategy, especially when subjected to higher noise levels. This is due to the attention of the VoI strategy for the estimation error i.e., taking into account the impact of higher noise levels and adapting accordingly, thereby exhibiting a more robust performance. Fig. 10(b) shows the mean control cost for various scheduling strategies. We can observe that as the noise escalates, the control cost experiences a proportional increase. In comparison to the all-transmission strategy, which is heavily dependent on communication frequency, both VoI and AoI tactics carry a heavier control cost burden. Hence, we found that VoI scheduling does not come without a price and that there is a cost associated with its implementation. Notably, we also find that the utility of VoI strategy is confined within the feasible region of the control variable u_t. The reason for this is obvious since there is a limit to the control cost that the vehicle can pay.

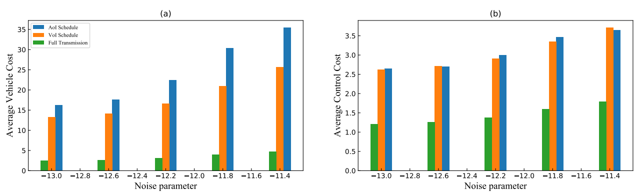

Fig. 10. (a) Average vehicle cost in different strategies. (b) Average control cost in different strategies.

Then, we demonstrate the impact of the weight parameter V of the Lyapunov penalty function on the VoI strategy. The experiment is configured with 20 CAVs and a long-term average communication frequency constraint is set as $\lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[R_{i,t}] \leq 0.02$. Six different strategies are considered, among which the VoI strategy with V set to 0 represents the short-term VoI strategy without considering the long-term average communication frequency constraint. When V is set to $[1, 5, 10, 100]$, it represents long-term VoI strategies. The last one is the AoI strategy. As shown in Fig. 11, although the short-term VoI strategy has a very low average cost, it fails to maintain the long-term average communication frequency constraint. The AoI strategy is at the other extreme, completely disregarding cost while strictly ensuring the communication frequency constraint. The long-term VoI strategy can be considered as a compromise between the short-term VoI strategy and the AoI strategy, controlled by the parameter V (i.e., the larger the value of V, the more emphasis is placed on whether the short-term communication frequency violates the constraint), seeking a balance between cost and constraints.

C. Intersection Performance

The simulation experiment is conducted in a typical two-lane, four-direction intersection scenario. Vehicles in the scenario are restricted to travel straight ahead. The RSU issues commands to vehicles based on their status to ensure smooth passage through the intersection. CAVs are required to follow the reference path provided by the RSU to avoid collisions with other vehicles. The assumption is made that when vehicles precisely follow the reference path, the system achieves optimal traffic efficiency. The simulation duration is set to 40000-time steps, with each time step lasting 50 ms. The average traffic flow into the intersection follows a Poisson distribution with a rate of 50 vehicles per minute. The number of subcarriers is set to 2. The experiment primarily compares the effects of two communication scheduling strategies: the VoI strategy and the AoI strategy. Additionally, a full transmission strategy without considering communication constraints is employed as a benchmark for optimal performance, where all CAVs can communicate with the RSU at each time step.

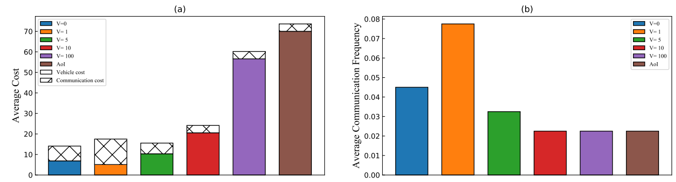

Fig. 11. (a) Average cost with different parameter V. (b) Average communication frequency with different parameter V.

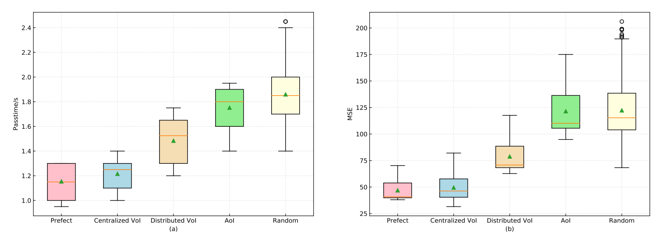

Fig. 12. (a) Pass time in intersection with different strategies, prefect means each vehicle can communicate with equipment at any time. (b) MSE in intersection with different strategies, prefect means each vehicle can communicate with equipment at any time

The distribution of pass times for different strategies are depicted in Fig. 12(a). Pass time refers to the duration between a vehicle entering the intersection and successfully crossing it. Pass time serves as a measure of traffic efficiency. The results demonstrate that both the centralized and distributed VoI strategies yield a lower average pass time and exhibit a denser distribution of pass times. Furthermore, Fig. 12(b) illustrates the distribution of MSE between the actual vehicle paths and the expected paths for different strategies. The VoI strategies outperform the other strategies, demonstrating a smaller average MSE. In terms of performance loss, the centralized VoI strategy exhibits approximately a 20% difference compared to the optimal strategy. Moreover, the centralized VoI strategy demonstrates an improvement of approximately 25% in traffic efficiency compared to the AoI strategy.

VII. Conclusion

In this paper, a novel communication resource scheduling strategy based on VoI has been proposed to measure the impact of information delivery on system performance. The aim is to ensure that the system's performance is partially guaranteed, even when faced with tight communication resources.

This approach has considered both central and distributed communication architectures and meets the driving tasks and communication constraints in connected autonomous driving. The numerical simulation results have shown that our scheme outperforms other strategies in terms of control effect and system cost. Moreover, the intersection simulation experiments have demonstrated that the proposed scheme can still achieve results in complex multi-vehicle scenarios. In future work, we plan to extend the application of VoI to other networks, and some AI methods may be employed to simplify the VoI acquisition process, given its close association with the scene.

APPENDIX A
PROOF FOR LEMMA 1

Let X_t be the status vector derived from $x(t)$, and U_t be the decision column vector. Therefore, the coefficient matrix is derived as

$$X_t = \boldsymbol{C}x_t + \boldsymbol{D}U_t, \tag{44}$$

$$X_{ref} = \frac{X_{ref}}{x_t} \cdot x_t = \boldsymbol{C}_{ref}x_t, \tag{45}$$

$$\begin{aligned} X_t - X_{ref} &= \boldsymbol{C}x_t - X_{ref} + \boldsymbol{D}U_k \\ &= (\boldsymbol{C} - \boldsymbol{C}_{ref})x_t + \boldsymbol{D}U_k = \overline{\boldsymbol{C}}x_t + \boldsymbol{D}U_k. \end{aligned} \tag{46}$$

The original problem can be transformed as

$$\begin{aligned} J =&(X_t - X_{ref})^T \mathbb{Q}_1 (X_t - X_{ref}) + U_t^T \mathbb{Q}_2 U_t \\ =&x_t^T \overline{\boldsymbol{C}}^T \mathbb{Q}_1 \overline{\boldsymbol{C}} x_t + U_t^T (\boldsymbol{D}^T \mathbb{Q}_1 \boldsymbol{D} + \mathbb{Q}_2) U_t + 2x_t^T \overline{\boldsymbol{C}}^T \mathbb{Q}_1 \boldsymbol{D} U_t \\ =&x_t^T \boldsymbol{\mathcal{G}} x_t + U_t^T \boldsymbol{\mathcal{E}} U_t + 2U_t^T \boldsymbol{\mathcal{H}} x_t. \end{aligned} \tag{47}$$

Without considering constraints, the problem can obtain the optimal value of U by derivation. We have

$$U_t^* = -\boldsymbol{\mathcal{E}}^{-1} \boldsymbol{\mathcal{H}} x_t. \tag{48}$$

APPENDIX B
PROOF FOR THEOREM 1

Form (20) we know

$$\begin{aligned} &L_{t+1} - L_t + Vf_t \\ &\leq \{H_t + V\lambda - 2p\sum_{i=1}^{n} \theta_i \mu_i \Theta_i(t) - \sum_{i=1}^{n} (p\theta_i + V\xi_i)\Theta_i^2(t)\}R_t \\ &+ \frac{1}{2}(1 - 2\rho H_t) + \sum_{i=1}^{n} \theta_i (\delta_i^2 + \frac{V\xi_i}{\theta_i}\Theta_i^2(t) + 2\mu_i \Theta_i(t)). \end{aligned} \tag{49}$$

The sum of drift-plus-penalty in T time slot is

$$\begin{aligned} &\sum_{t=0}^{T} \{L_{t+1} - L_t + Vf_t\} = L_{T+1} - L_0 + V\sum_{t=0}^{T} f_t \\ &\leq \sum_{t=0}^{T} \{H_t + V\lambda - 2p\sum_{i=1}^{n} \theta_i \mu_i \Theta_i(t) - \sum_{i=1}^{n} (p\theta_i + V\xi_i)\Theta_i^2(t)\}R_t \\ &+ \frac{1}{2}\sum_{t=0}^{T}(1 - 2\rho H_t) + \sum_{t=0}^{T}\sum_{i=1}^{n} \theta_i (\delta_i^2 + \frac{V\xi_i}{\theta_i}\Theta_i^2(t) + 2\mu_i \Theta_i(t)). \end{aligned} \tag{50}$$

For ease of calculation, set the mean μ to 0. We can simplify the upper bound of $V\sum_{t=0}^{T} f_t$ as

$$\begin{aligned} V\sum_{t=0}^{T} f_t \leq& \sum_{t=0}^{T} \{H_t + V\lambda - \sum_{i=1}^{n} (p\theta_i + V\xi_i)\Theta_i^2(t)\}R_t \\ &+ \frac{1}{2}\sum_{t=0}^{T}(1 - 2\rho H_t) + \sum_{t=0}^{T}\sum_{i=1}^{n} \theta_i (\delta_i^2 + \frac{V\xi_i}{\theta_i}\Theta_i^2(t)) \\ &+ L_0 - L_{T+1}. \end{aligned} \tag{51}$$

The expectation of f_t can be obtained as

$$\begin{aligned} V\sum_{t=0}^{T} \mathbb{E}[f_t] \leq& \rho\sum_{t=0}^{T} \{H_t + V\lambda - \sum_{i=1}^{n} (p\theta_i + V\xi_i)\Theta_i^2(t)\} \\ &+ \frac{1}{2}\sum_{t=0}^{T}(1 - 2\rho H_t) + \sum_{t=0}^{T}\sum_{i=1}^{n} (\theta_i \delta_i^2 + V\xi_i \Theta_i^2(t)) \\ &+ L_0 - L_{T+1} \\ &\leq \frac{T}{2} + TV\lambda\rho + T\sum_{i=1}^{n} \theta_i \delta_i^2 + L_0 \\ &+ \sum_{t=0}^{T}\sum_{i=1}^{n} (V\xi_i(1-\rho) - \rho p \theta_i)\Theta_i^2(t). \end{aligned} \tag{52}$$

Let $\theta_i = \frac{V\xi_i(1-\rho)}{\rho p}$ and $L_0 < \infty$, and the series (52) can be eliminated. Thus, we can get

$$\lim_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T} \mathbb{E}[f_t] \leq \lambda\rho + \frac{\frac{1}{2} + \sum_{i=1}^{n} \theta_i \delta_i^2}{V}. \tag{53}$$

Theorem 1 can be proved.

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