Quality-Cost Trade-off on Constructing Logical Views for Vehicular Cyber-Physical Systems: A Deep Reinforcement Learning Approach

Junyuan Wu1, Xincao Xu2, Chuzhao Li3, Hao Zhang4, Ke Xiao5, Kai Liu1,3
1College of Computer Science, Chongqing University, China
2Shenzhen Institute for Advanced Study, University of Electronic Science and Technology of China, China
3National Elite Institute of Engineering, Chongqing University, China
4College of Computer Science and Technology, Chongqing University of Posts and Telecommunications, China
5College of Computer and Information Science, Chongqing Normal University, China
Email: jy.wu@cqu.edu.cn, xc.xu@uestc.edu.cn, lichuzhao@126.com, zhanghao@cqupt.edu.cn, xiaoke@cqnu.edu.cn, liukai0807@cqu.edu.cn

Abstract—With the development of sensing technologies, vehicle-to-everything (V2X) communications, edge computing paradigm, vehicular cyber-physical systems (VCPS) are emerging as the most fundamental platform for realizing future intelligent transportation systems (ITSs). In particular, the construction of logical views at the edge nodes based on heterogeneous information sensing and uploading are critical to the realization of VCPS. However, a higher-quality view in terms of timeliness and accuracy may require higher cost on sensing and uploading. In view of this, this paper is dedicated to striking a balance between the quality and the cost for constructing logical views of VCPS. Specifically, we first derive an information sensing model based on multi-class M/G/1 priority queue and a data uploading model based on reliability-guaranteed vehicle-to-infrastructure (V2I) communications. On this basis, we design two metrics, namely, age of view (AoV) and cost of view (CoV), simultaneously. Then, we formulate a bi-objective problem to minimize the CoV and AoV. Further, we propose a distributed distributional deep deterministic policy gradient (D4PG) solution to determine sensing information, frequency, uploading priority, transmission power, and V2I bandwidth. Finally, we build a simulation model and give a comprehensive performance evaluation, and the simulation results conclusively demonstrate the superiority of the proposed solution.

Index Terms—Vehicular cyber-physical system, vehicular network, vehicle-to-infrastructure communications, resource allocation, bi-objective optimization, deep reinforcement learning

I. INTRODUCTION

Recent advances in sensing, communication, computing drive the development of vehicular cyber-physical systems (VCPS), which is a key enabler of the next generation of intelligent transportation systems (ITSs) [1]. As shown in Fig. 1, vehicles may collaboratively sense via on-board sensors, such as GPS, cameras, and LiDAR. The heterogeneous information, including traffic light status, vehicle locations, and surveillance videos, are uploaded to the nearby roadside units (RSUs) by vehicle-to-infrastructure (V2I) communications.

This work was supported in part by the National Natural Science Foundation of China under Grant 62172064. (Corresponding author: Xincao Xu)
architecture [5] and intent-based network control framework [6]. To improve caching efficiency, some other researchers proposed content caching frameworks in vehicular networks, such as blockchain-empowered distributed content caching framework [7] and dynamic content caching scheme based on the cooperation among RSUs [8]. Some researchers studied task offloading mechanisms, multi-dimensions intent-aware task offloading strategy [9] in vehicular networks and a joint task offloading and resource optimization via V2I communications method was proposed to maximize the service ratio [10]. These studies on data dissemination, information caching, and task offloading formed the basis of modeling VCPS. Further, several studies have been studied on predicting technologies, such as the hybrid velocity-profile prediction method [11], lane-level localization and acceleration prediction [12]. Some researchers developed scheduling schemes, such as physical-ratio-K interference model-based broadcast scheme [13] and path planning scheduling method based on an established map model [14]. In addition, some studies proposed controlling algorithms, such as vehicle acceleration control algorithm [15]. These predicting, scheduling and controlling technologies facilitated the implementation of various upper-layer applications. A few studies have concerned the information quality and transmission cost in VCPS, including timeliness [16] [17], consistency [18] [19], and accuracy [20]. Nevertheless, to the best of our knowledge, none of the prior studies have investigated the trade-off between the quality and cost for constructing logical views of VCPS.

With above motivations, we present a scheduling algorithm to striking a balance between the quality and the cost for constructing logical views of VCPS. The primary contributions are summarized as follows.

- We formulate the problem with the objectives of maximizing the quality and minimizing the cost of VCPS. Specifically, we derive an information sensing model and a data uploading model based on the multi-class M/G/1 priority queue and reliability-guaranteed V2I communications. Then, two metrics named age of view (AoV) and cost of view (CoV) are defined to quantify the quality and cost of logical views, respectively.
- We propose a distributed distributional deep deterministic policy gradient (D4PG) solution. Specifically, the D4PG is implemented in the RSU with the action space of determining the sensing information, sensing frequencies, uploading priorities, transmission power, and V2I bandwidth allocation. The reward function is defined as the sum of the complement of achieved average AoV and average CoV in vehicular networks.
- We give comprehensive performance evaluation. First, we build the simulation model based on real-world vehicular trajectories extracted from Didi GAIA Initiative [21]. We implement the proposed solution, and two competitive algorithms, including random allocation (RA) and multi-agent deep deterministic policy gradient (MADDPG) [22]. The simulation results conclusively demonstrate the superiority of the proposed solution. In particular, D4PG outperforms RA and MADDPG by around 20.79% and 13.88%, respectively, in terms of maximizing the cumulative reward.

The remainder of this paper is organized as follows. Section II presents the system model. Section III proposes the D4PG solution. Section IV presents the numerical results. Finally, Section V concludes this paper.

II. SYSTEM MODEL

A. Information Sensing Model

We consider the vehicular networks with E RSUs and S vehicles. We denote the set of discrete time slots as T and the set of heterogeneous information as D. Each information d ∈ D is characterized by a three-tuple d = (type_d, u_d, |d|), where type_d, u_d, and |d| are the type, state update interval, and size, respectively. Each RSU e ∈ E is characterized by a three-tuple e = (l_e, r_e, b_e), where l_e, r_e, and b_e are the location, communication range, and bandwidth, respectively. Each vehicle s ∈ S is characterized by a three-tuple s = (l_s, D_s, π_s), where l_s, D_s, and π_s are the location, sensed information set, and transmission power, respectively. For each information d ∈ D_s, the sensing cost in vehicle s is denoted by φ_d,s. The distance between vehicle s and RSU e is denoted by dis_{s,e}. The sensing information indicator indicating whether information d is sensed by vehicle s at time t, is denoted by

\[ c^t_{d,s} \in \{0,1\}, \forall d \in D_s, \forall s \in S, \forall t \in T \] (1)

Thus, the set of information sensed by vehicle s at time t can be denoted by \( D^t_s = \{d | c^t_{d,s} = 1, \forall d \in D_s\} \), where the sensing frequency and uploading priority are denoted by \( \lambda^t_{d,s} \) and \( \pi^t_{d,s} \), respectively. Due to the limited sensing ability, we have the following constraints on information sensing.

\[ \lambda^t_{d,s} \in [\lambda^t_{d,s}^{\min}, \lambda^t_{d,s}^{\max}], \forall d \in D^t_s, \forall s \in S, \forall t \in T \] (2)

\[ \pi^t_{d,s} \neq \pi^t_{d,s}^*, \forall d \in D^t_s \setminus \{d\}, \forall d \in D^t_s, \forall s \in S, \forall t \in T \] (3)

where \( \lambda^t_{d,s}^{\min} \) and \( \lambda^t_{d,s}^{\max} \) are the minimum and maximum of sensing frequency for information with type_d in vehicle s, respectively.

The queuing time of information sensed by vehicles is modeled by multi-class M/G/1 priority queue [23]. The transmission time \( t^t_{d,s,c} \) of information with type_d follows a class of General distribution with mean \( \alpha_{d,s}^t \) and variance \( \beta_{d,s}^t \). Therefore, the uploading workload \( \rho^t_s \) in vehicle s is represented by \( \rho^t_s = \sum_{d \in D^t_s} \lambda^t_{d,s} \alpha_{d,s}^t \). According to the principle of the multi-class M/G/1 priority queue, it requires \( \rho^t_s < 1 \) to guarantee the existence of the queue steady-state. The inter-arrival time \( i^t_{d,s} \) is the duration between the arrival of two adjacent information with type_d in vehicle s, i.e., \( i^t_{d,s} = 1/\alpha_{d,s}^t \). Therefore, the arrival moment and updating moment of the freshest information with type_d before time t are denoted by \( u^t_{d,s} \) and \( u^t_{d,s}^* \), respectively, which can be obtained by \( u^t_{d,s} = \lfloor t \alpha_{d,s}^t \rfloor i^t_{d,s} \) and \( u^t_{d,s}^* = \lfloor t \alpha_{d,s}^t / u_d \rfloor u_d \), where \( u_d \) is the updating interval. The set of information
with a higher uploading priority than information $d$ is denoted by $D^t_{s,e} = \{d^* | \lambda_{d^*,s} > \lambda_{d^*,e}, \forall d^* \in D^t_s\}$. Thus, the uploading workload ahead of information $d$ in vehicle $s$ at time $t$ is denoted by $\rho^t_{d,s} = \sum_{d \in D^t_s} \lambda_{d,s}^t \alpha_{d,s}^t$. According to the Pollaczek-Khintchine formula [24], the queuing time of information $d$ in vehicle $s$ is calculated by

$$q^t_{d,s} = \frac{1}{1 - \rho^t_{d,s}} \left[ \lambda_{d,s}^t \beta_{d,s}^t + \sum_{d \in D^t_s} \lambda_{d,s}^t \alpha_{d,s}^t \right] - \alpha_{d,s}^t$$

(4)

B. Data Uploading Model

We model the data uploading via reliability-guaranteed V2I communications based on the Shannon theory. The transmission power of vehicle $s$ at time $t$ is denoted by $\pi^t_s$. The set of vehicles within the radio coverage of RSU $e$ at time $t$ is denoted by $S^t_e = \{s | d_{s,e}^t \leq r, \forall s \in S, S^t_e \subseteq S\}$. The V2I bandwidth allocated by RSU $e$ for vehicle $s$ at time $t$ is denoted by $b^t_{s,e}$, and we have the following constraints on data uploading:

$$\pi^t_s \in [0, \pi_s], \forall s \in S, \forall t \in T$$

(5)

$$b^t_{s,e} \in [0, b_e], \forall s \in S^t_e, \forall e \in E, \forall t \in T$$

(6)

The signal to noise ratio (SNR) [25] of V2I communications between vehicle $s$ and RSU $e$ at time $t$ is denoted by $\text{SNR}^t_{s,e} = \frac{1}{N_0} |h_{s,e}|^2 \tau d_{s,e}^{-\alpha} \pi^t_s$, where $N_0$ is the additive white Gaussian noise (AWGN); $h_{s,e}$ is the channel fading gain; $\tau$ is a constant that depends on the antennas design; $\varphi$ is the path loss exponent, and $\pi^t_s$ is the transmission power of vehicle $s$ at time $t$. According to the Shannon theory, the achievable transmission rate of V2I communications between vehicle $s$ and RSU $e$ at time $t$ is denoted by $R^t_{s,e} = b^t_{s,e} \log_2 (1 + \text{SNR}^t_{s,e})$, where $b^t_{s,e}$ is the bandwidth allocated by RSU $e$ at time $t$. Thus, the transmission time of information $d$ from vehicle $s$ to RSU $e$, denoted by $g^t_{d,s,e}$, is computed by

$$g^t_{d,s,e} = \inf_{j \in \mathbb{R}^+} \left\{ \left\lfloor \frac{k^t_{d,s} + j}{k^t_{d,s}} \right\rfloor \pi^t_s \right\} - k^t_{d,s}$$

(7)

where $k^t_{d,s}$ is the moment when vehicle $s$ starts to transmit information $d$, and $k^t_{d,s} = t + q^t_{d,s}$.

We assume that the channel fading $|h_{s,e}|^2$ follows a class of distribution with the mean $\mu_{s,e}$ and variance $\sigma_{s,e}^2$. The distribution set is represented by $\tilde{p} = \{P \in \mathbb{P} | \mathbb{E}[|h_{s,e}|^2] = \mu_{s,e}, \mathbb{E}[(|h_{s,e}|^2)^2] = \mu_{s,e}^2 + \sigma_{s,e}^2\}$. The transmission reliability is meared by the possibility that a successful transmission probability is beyond a reliability threshold, i.e., $\inf_{\tilde{p} \in \tilde{P}} \Pr(p) (\text{SNR}^t_{s,e} \geq \text{SNR}^t_{s,e} \tilde{p}) \geq \delta$, where $\text{SNR}^t_{s,e}$ and $\delta$ are the target SNR threshold and reliability threshold, respectively. The set of information uploaded by vehicle $s$ and received by RSU $e$ is denoted by $D^t_{s,e} = \bigcup_{s \in S^t_e} D^t_s$.

C. Age/Cost of View Formulation

Denote the set of views in the system as $V$, and the set of information required by view $v \in V$ is denoted by $D_v = \{d | y_{d,v} = 1, \forall d \in D\}$, $\forall v \in V$, where $y_{d,v}$ is a binary indicating whether information $d$ is required by view $v$. The number of required information in view $v$ is denoted by $|D_v|$. Each view may require multiple pieces of information, i.e., $|D_v| = \sum_{d \in D_v} y_{d,v} \geq 1, \forall v \in V$. The set of views required by RSU $e$ at time $t$ is denoted by $V^t_e$. Therefore, the set of information received by RSU $e$ and required by view $v$ can be represented by $D^t_{v,e} = \bigcup_{v \in V^t_e} \{d | y_{d,v} = 1, \forall d \in D_v\}$, $\forall v \in V^t_e, \forall e \in E$, and $|D^t_{v,e}|$ is the number of information that received by RSU $e$ and required by view $v$, which is computed by $|D^t_{v,e}| = \sum_{s \in S^t_e} \sum_{d \in D^t_s} y_{d,v} d_{s,e}$. Then, we define the view’s five characteristics of heterogeneous information fusion, including timeliness, consistency, redundancy, sensing cost, and transmission cost.

First, heterogeneous information is time-varying, and information freshness is essential for modeling the quality of views. The timeliness $\Theta_v \in \mathbb{Q}^+$ of view $v$ is defined as the sum of the maximum timeliness of information sensed by each vehicle, i.e., $\Theta_v = \sum_{s \in S^t_e} \max_{d \in D^t_s} \pi^t_s + \pi^t_e + \sigma^t_{s,e} - \phi^t_{d,s}$. Since different types of information have their sensing frequencies and uploading priorities, keeping the versions of different kinds of information as close as possible when constructing a view is essential. The consistency $\Psi_v \in \mathbb{Q}^+$ of view $v$ is defined as the maximum of the difference between information updating time, i.e., $\Psi_v = \max_{s \in S^t_e} \min_{d \in D^t_s} \pi^t_s - \phi^t_{d,s}$. Then, we give the formal definition of age of view, synthesizing the timeliness and consistency to measure view quality.

Definition 1 (Age of View, AoV). The age of view $\text{AoV}_v \in (0, 1)$ is defined as a weighted average of normalized timeliness and normalized consistency of view $v$.

$$\text{AoV}_v = w_1 \Theta_v + w_2 \Psi_v, \forall v \in V^t_e, \forall e \in E$$

(8)

where $\Theta_v \in (0, 1)$ and $\Psi_v \in (0, 1)$ denote the normalized timeliness and normalized consistency of view $v$, respectively, which can be obtained by rescaling the range of the timeliness and consistency of view $v$ in $(0, 1)$ via the min-max scaling. The weighting factors for $\Theta_v$ and $\Psi_v$ are denoted by $w_1$ and $w_2$, respectively, and we have $w_1 + w_2 = 1$. These weighting factors can be tuned accordingly based on the different requirements of upper-layer applications.

Second, vehicles may sense the same information redundantly when the view requires it, which wastes the sensing and transmission resources of the vehicles. The redundancy $\Xi_v \in \mathbb{N}$ of view $v$ is defined as the sum of redundant information in view $v$, i.e., $\Xi_v = \sum_{d \in D_v} |D^t_{d,v,e}| - 1$, where $D^t_{d,v,e}$ is the set of the information that received by RSU $e$, required by view $v$, and has the same type with information $d$, which is represented by $D^t_{d,v,e} = \{d^* | \text{type}_{d^*} = \text{type}_d, \forall d^* \in D^t_v\}$, $\forall d \in D^t_v$. On the other hand, sensing more information also brings more cost to vehicles. The sensing cost $\Phi_v \in \mathbb{Q}^+$ of view $v$ is defined as the sum of information sensing cost of information required by view $v$, i.e., $\Phi_v = \sum_{s \in S^t_e} \sum_{d \in D^t_s \cap D^t_v} \theta_{d,s}$. Meanwhile, information transmission requires energy consumption of vehicles, i.e., the transmission power consu-
The transmission cost $\Omega_e \in \mathbb{Q}^+$ of view $v$ is defined as the sum of consumed transmission power during the data uploading in view $v$, i.e., $\Omega_e = \sum_{t \in T} \sum_{s \in S_t^e} \sum_{d \in D_s^e} \lambda_{d,s} \pi_{d,s} |d| + \sum_{t \in T} \sum_{s \in S_t^e} \sum_{d \in D_s^e} p_{d,s} |d|$. Then, we give the formal definitions of cost of view, which synthesizes the redundancy, sensing cost, and transmission cost to evaluate the cost of view.

**Definition 2** (Cost of View, CoV). The cost of view $\text{CoV}_v = (0, 1)$ is defined as a weighted average of normalized redundancy, normalized sensing cost, and normalized transmission cost of view $v$.

$$\text{CoV}_v = w_3\Xi_v + w_4\Phi_v + w_5\Omega_v, \forall v \in V^t, \forall t \in T$$

where $\Xi_v \in (0, 1)$, $\Phi_v \in (0, 1)$, and $\Omega_v \in (0, 1)$ denote the normalized redundancy, normalized sensing cost, and normalized transmission cost of view $v$, respectively. The weighting factors for $\Xi_v$, $\Phi_v$, and $\Omega_v$ are denoted by $w_3$, $w_4$, and $w_5$, respectively, and we have $w_3 + w_4 + w_5 = 1$.

Given a solution $(C, \Lambda, P, \Pi, B)$, where $C$ denotes the determined sensing information, $\Lambda$ denotes the determined sensing frequencies, $P$ denotes the determined uploading priorities, $\Pi$ denotes the determined transmission power, and $B$ denotes the determined V2I bandwidth allocation, we formulate the problem aiming at maximizing the average view quality and minimizing the average transmission cost simultaneously, which is expressed as follows:

$$\max_{C, \Lambda, P, \Pi, B} \left\{ \frac{\sum_{t \in T} \sum_{s \in S_t^e} \sum_{d \in D_s^e} (1 - \text{AoV}_v) |d|}{\sum_{t \in T} \sum_{s \in S_t^e} \sum_{d \in D_s^e} |d|} + \frac{\sum_{t \in T} \sum_{s \in S_t^e} \sum_{d \in D_s^e} (1 - \text{CoV}_v) |d|}{\sum_{t \in T} \sum_{s \in S_t^e} \sum_{d \in D_s^e} |d|} \right\}$$

subject to (1), (3), (5), (6)

$$\sum_{v \in V^t} \sum_{s \in S_t^e} \lambda_{d,s} p_d < 1, \forall s \in S, \forall t \in T$$

$$\inf_{P \in \mathcal{P}} \Pr_{\mathcal{P} \in \mathcal{P}} \left( \text{SNR}_{s,e}^t \geq \text{SNR}_{s,e}^{\text{tar}} \right) \geq \delta, \forall s \in S, \forall t \in T$$

$$\sum_{v \in V^t} b_s \leq b_e, \forall t \in T$$

where (10a) guarantees the queue steady-state; (10b) guarantees transmission reliability, and (10c) requires that the sum of V2I bandwidth allocated by the RSU $e$ cannot exceed its capacity $b_e$. AoV and CoV are inversely proportional to these averages leads to an enhancement in view quality and a decrease in cost. So the crux of the discussed problem lies in maximizing the cumulative sum of the average AoV and CoV complements.

### III. PROPOSED SOLUTION

In this section, we propose the D4PG model as shown in Fig. 2, implemented in each RSU to jointly determine the sensing information, sensing frequency, uploading priority, transmission power, and V2I bandwidth. The D4PG of RSU $e$ consists of four networks, namely, the local policy network, local critic network, target policy network, and target critic network. The parameter of the local policy and critic networks in RSU $e$ denoted by $\theta_e$ and $\theta_e^\pi$, respectively, are randomly initialized. Then, the parameters of target policy and critic networks are initialized as the same as the corresponding local network, which are denoted by $\theta_e^{\pi}$ and $\theta_e^{\pi}$, respectively. And the replay buffer $B$ is initialized to store replay experiences.

The initialized system state of each iteration is denoted by $o^0$. The local observation of the system state in the RSU $e$ at time $t$ is denoted by

$$o^t_e = \{ t, e, \text{Dis}_{S_t^e}^t, D_1, \cdots, D_{|S^t_e|}, D^t_e, V_t \}$$

where $t$ is the time slot index; $e$ is the RSU index; $\text{Dis}_{S_t^e}^t$ represents the set of distances between vehicles and RSU $e$; $D_s$ represents the set of information that can be sensed by vehicle $s$; $D^t_e$ represents the set of cached information in RSU $e$ at time $t$, and $V_t$ represents the set of views required by RSU $e$ at time $t$. Thus, the system state at time $t$ can be denoted by $o^t = \{ o^t_1, \cdots, o^t_E \}$. The action of RSU $e$ at time $t$ is obtained based on the local observation of the system state:

$$a^t_e = \mu o^t_e + \epsilon N_t$$

where $N_t$ is an exploration noise to increase the diversity of RSU actions, and $\epsilon$ is an exploration constant.

Then, the action space of RSU $e$ consists of the offloading decision of tasks requested by vehicle $s \in S_t^e$, which is denoted by

$$a^t_e = \{ \{ C^t_s, \{ \lambda_{d,s}^t, p_{d,s}^t | \forall d \in D_s^t \}, \pi_{d,s}^t \}, b_{s,e}^t | \forall s \in S_t^e \}$$

where $C^t_s$ is the sensing information decision; $\lambda_{d,s}^t$ and $p_{d,s}^t$ are the sensing frequency and uploading priority of information $d \in D_s^t$, respectively. $\pi_{d,s}^t$ is the transmission power of vehicle $s$ at time $t$, and $b_{s,e}^t$ is the V2I bandwidth allocated by RSU $e$ for vehicle $s$ at time $t$. The set of RSU actions is denoted by $a^t = \{ a^t_e | \forall e \in E \}$. The actions of RSUs $a^t$ are executed in vehicular network environment. The objective of each RSU is to maximize its view quality and minimize the cost. Therefore,
the reward function of the RSU $e$ is defined as the sum of the complement of achieved average AoV and CoV of RSU $e$ at time $t$, which is represented by

$$ r^t_e = \sum_{v \in V_e} \frac{(2 - \text{AoV}_v - \text{CoV}_v)}{|V_e|} $$

The set of rewards of RSUs is denoted by $r^t = \{r^t_1, \ldots, r^t_e, \ldots, r^t_E\}$.

Finally, the interaction experiences including the system state $o^t$, RSU actions $a^t$, rewards of RSUs $r^t$, and next system state $o^{t+1}$ are stored into the replay buffer $B$. A minibatch of $M$ transitions of length $N$ is sampled from replay buffer $B$ to train the policy and critic networks. The transition of the $M$ minibatch is denoted by $(o^{i:N}, a^{i:N-1}, r^{i:N-1})$. The target distribution of RSU $e$ is denoted by $Y_e^t$, which is computed by

$$ Y_e^t = \sum_{n=0}^{N-1} (\gamma^n r_e^{t+n}) + \gamma^N Q\left(o_e^{t+N}, a_e^{t+N} \mid \theta_e^Q]\right) $$

where $a_e^{t+N}$ is obtained via the target policy network, i.e., $a_e^{t+N} = \mu_t(o_e^{t+N} \mid \theta_e\mu\). The loss function of the critic network is represented by the following:

$$ L(\theta_e^Q) = \frac{1}{M} \sum_i (Y_e^t - Q(o_e^t, a_e^t \mid \theta_e^Q))^2 $$

The parameters of the policy network are updated via policy gradient.

$$ \nabla_{\theta_e^\mu} J = \frac{1}{M} \sum_i \nabla_{a_e^t} Q(o_e^t, a_e^t \mid \theta_e^Q) \nabla_{\theta_e^\mu} \mu(o_e^t \mid \theta_e\mu) $$

The local policy and critic network parameters are updated with the learning rate $\alpha$ and $\beta$. Finally, the RSUs update the parameters of target networks if $t \mod t_{tgt} = 0$.

$$ \theta_e^{\mu'} = n \theta_e^{\mu} + (1-n)\theta_e^{\mu'} $$

$$ \theta_e^{Q'} = n \theta_e^{Q} + (1-n)\theta_e^{Q'} $$

where $t_{tgt}$ is the target network parameter updating period, and with $n \ll 1$.

IV. NUMERICAL RESULTS

In this section, we validate the proposed solution to evaluate the performance. In our system, we consider $E = 9$ RSUs are uniformly distributed in a $3 \times 3$ km$^2$ square area, where the realistic vehicular trajectories are collected from Didi GAIA open data set [21] by extracting from Qingyang District, Chengdu, China, on 16 Nov. 2016. The information sizes are uniformly distributed in $|d| \sim [100 B, 1 MB]$, and we set the transmission power as $\pi_s = 100$ mW. We consider the additive white Gaussian noise, path loss exponent, and channel fading gain as $N_0 = -90$ dBm, $\varphi = 3$, and $h_{s,e} \sim [2-$mean, 0.4- variance] distributions [25], and the communication bandwidth of RSU is set to $b_e = 20$ MHz. The weighting factors for $\Theta_v$ and $\Psi_v$ are set as $w_1 = 0.6$ and $w_2 = 0.4$, compared to the consistency of information arrival, we believe timeliness is more important for the system. The overall system cost is primarily related to sensing and transmission costs. So the weighting factors for $\Xi_w, \Phi_v$, and $\Omega_v$ are set as $w_3 = 0.2$, $w_4 = 0.4$, and $w_5 = 0.4$.

For the implementation of the D4PG, the architectures of the policy and critic networks are described as follows. Both the target policy network and local policy network are five-layer fully connected neural networks with three hidden layers, where the number of neurons is 256, 256, and 256, respectively. The target critic network and local critic network are five-layer fully connected neural networks with three hidden layers, where the numbers of neurons are 512, 512, and 256, respectively.

For performance comparison, we implement two comparative algorithms, i.e., RA, which randomly selects one action to determine the sensing information, sensing frequencies, uploading priorities, transmission power, and V2I bandwidth allocation, and MADDPG [22], which is implemented in vehicles to decide the sensing information, sensing frequencies, uploading priorities, and transmission power based on local observation of the physical environment, and the RSU to determine the V2I bandwidth allocation.

To compare the algorithm convergence, Fig. 3 compares the cumulative reward (CR) of the three algorithms. As noted, D4PG converges the fastest (around 300 iterations) and achieves the highest CR (around 517). In comparison, RA and MADDPG achieve a CR of around 428 and 454, respectively. Figure 4 compares the performance of the three algorithms under different V2I bandwidths. A larger bandwidth represents that the allocated bandwidth for each vehicles can be enlarged, which results in a shorter uploading time. As the bandwidth increases, the CR of RA increases accordingly. It is noted that the CR of MADDPG increases when the bandwidth increases from 1 MHz to 2 MHz and decreases when the bandwidth increases from 2 MHz to 3 MHz. The reason is that the system reward consists of two conflicting objectives, i.e., the AoV and CoV, which can be verified in Fig. 4(b) compared the average AoV (AAoV) and average CoV (ACoV) of views. Figs. 4(a) and 4(b) show that D4PG can achieve the best performance across all cases. Figure 5 compares the performance of the three algorithms under different average information numbers of view requirements. The larger average

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number of required information for the views indicates that the vehicles have a higher workload in information sensing and uploading, which leads to a poorer quality of views. With the increasing average required information number, the CR for all algorithms decreases accordingly.

In this paper, an information sensing model was modeled based on multi-class M/G/1 priority queue, and a data uploading model was modeled based on reliability-guaranteed V2I communications. On this basis, two new metrics AoV and CoV were designed to evaluate the quality and cost for the logical views of VCPS. Then, the bi-objective problem was formulated to maximize the quality and minimize the cost of VCPS modeling. Further, the D4PG solution was proposed to jointly determine the sensing information, sensing frequencies, and uploading priorities, transmission power, and V2I bandwidth allocation. Finally, the comprehensive performance evaluation demonstrated the superiority of the proposed solution.

V. CONCLUSION

In this paper, an information sensing model was modeled based on multi-class M/G/1 priority queue, and a data uploading model was modeled based on reliability-guaranteed V2I communications. On this basis, two new metrics AoV and CoV were designed to evaluate the quality and cost for the logical views of VCPS. Then, the bi-objective problem was formulated to maximize the quality and minimize the cost of VCPS modeling. Further, the D4PG solution was proposed to jointly determine the sensing information, sensing frequencies, and uploading priorities, transmission power, and V2I bandwidth allocation. Finally, the comprehensive performance evaluation demonstrated the superiority of the proposed solution.

REFERENCES

[1] X. Xu, K. Liu, Q. Zhang, H. Jiang, K. Xiao, and J. Luo, “Age of view: A new metric for evaluating heterogeneous information fusion in vehicular cyber-physical systems,” in Proc. IEEE Conf. Intell. Transport. Syst. (ITSC). IEEE, 2022, pp. 3762–3767.

[2] D. D. Yoon, B. Ayalew, and G. G. M. N. Ali, “Performance of decentralized cooperative perception in v2v connected traffic,” IEEE Trans. Intell. Transp. Syst., pp. 1–14, 2021.

[3] Y. Cao, O. Kawaiartya, N. Aslam, C. Han, X. Zhang, Y. Zhuang, and M. Dianati, “A trajectory-driven opportunistic routing protocol for vcps,” IEEE Trans. Aeros. Electron. Syst., vol. 54, no. 6, pp. 2628–2642, 2018.

[4] R. Kasana, S. Kumar, O. Kawaiartya, R. Kharel, J. Lloret, N. Aslam, and T. Wang, “Fuzzy-based channel selection for location oriented services in multichannel vcps environments,” IEEE Internet Things J., vol. 5, no. 6, pp. 4642–4651, 2018.

[5] K. Liu, K. Xiao, P. Dai, V. C. Lee, S. Guo, and J. Cao, “Fog computing empowered data dissemination in software defined heterogeneous vaeans,” IEEE Trans. Mob. Comput., vol. 20, no. 11, pp. 3181–3193, 2021.

[6] A. Singh, G. S. Aujila, and R. S. Bali, “Intent-based network for data dissemination in software-defined vehicular edge computing,” IEEE Trans. Intell. Transp. Syst., vol. 22, no. 8, pp. 3530–3538, 2020.

[7] Y. Dai, D. Xu, K. Zhang, S. Mahurjan, and Y. Zhang, “Deep reinforcement learning and permissioned blockchain for content caching in vehicular edge computing and networks,” IEEE Trans. Veh. Technol., vol. 69, no. 4, pp. 4312–4324, 2020.

[8] Z. Su, Y. Hui, Q. Xu, T. Yang, J. Liu, and Y. Jia, “An edge caching scheme to distribute content in vehicular networks,” IEEE Trans. Veh. Technol., vol. 67, no. 6, pp. 5346–5356, 2018.

[9] H. Liao, Z. Zhou, W. Kong, Y. Chen, X. Wang, Z. Wang, and S. Al Ouabibi, “Learning-based intent-aware task offloading for air-ground integrated vehicular edge computing,” IEEE Trans. Intell. Transp. Syst., vol. 22, no. 5, pp. 2139–2151, 2021.

[10] X. Xu, K. Liu, P. Dai, F. Jin, H. Ren, C. Zhan, and S. Guo, “Joint task offloading and resource optimization in noma-based vehicular edge computing: A game-theoretic drl approach,” J. Syst. Archit., vol. 134, p. 102780, 2023.

[11] Y. Zhang, L. Chu, Y. Ou, C. Guo, Y. Liu, and X. Tang, “A cyber-physical system-based velocity-profile prediction method and case study of application in plug-in hybrid electric vehicle,” IEEE T. Cybern., vol. 51, no. 1, pp. 40–51, 2019.

[12] T. Zhang, Y. Zou, X. Zhang, N. Guo, and W. Wang, “Data-driven based cruise control of connected and automated vehicles under cyber-physical system framework,” IEEE Trans. Intell. Transp. Syst., vol. 22, no. 10, pp. 6307–6319, 2020.

[13] C. Li, H. Zhang, T. Zhang, J. Rao, L. Y. Wang, and G. Yin, “Cyber-physical scheduling for predictable reliability of inter-vehicle communications,” IEEE Trans. Veh. Technol., vol. 69, no. 4, pp. 4192–4206, 2020.

[14] Y. Lian, Q. Yang, W. Xie, and L. Zhang, “Cyber-physical system-based heuristic planning and scheduling method for multiple automatic guided vehicles in logistics systems,” IEEE Trans. Ind. Inform., vol. 17, no. 11, pp. 7982–7993, 2021.

[15] C. Lv, X. Hu, A. Sangiovanni-Vincentelli, Y. Li, C. M. Martinez, and D. Cao, “Driving-style-based codesign optimization of an automated electric vehicle: A cyber-physical system approach,” IEEE Trans. Ind. Electron., vol. 66, no. 4, pp. 2965–2975, 2018.

[16] A. Alsarhan, Y. Kilani, A. Al-Dubai, A. Y. Zomaya, and A. Hussain, “Novel fuzzy and game theory based clustering and decision making for vanets,” IEEE Trans. Veh. Technol., vol. 69, no. 2, pp. 1568–1581, 2019.

[17] H. Ye, G. Y. Li, and B.-H. F. Jiang, “Deep reinforcement learning based resource allocation for v2v communications,” IEEE Trans. Veh. Technol., vol. 68, no. 4, pp. 3163–3173, 2019.

[18] K. Liu, V. C. S. Lee, J. K. Y. Ng, S. H. Son, and E. H.-M. Sha, “Scheduling temporal data with dynamic snapshot consistency requirement in vehicular cyber-physical systems,” ACM Trans. Embed. Comput. Syst., vol. 13, no. 5s, 2014.

[19] H. Zhao, H. Yue, T. Gu, C. Li, and D. Zhou, “Low delay and seamless connectivity-based message propagation mechanism for vanets of vcps,” Wirel. Pers. Commun., vol. 118, pp. 3385–3402, 2021.

[20] S. T. Rager, E. N. Ciftcioglu, R. Ramanathan, T. F. La Porta, and V. F. D. N. Ali, “A trajectory-driven opportunistic routing protocol for vcps,” IEEE Trans. Aeros. Electron. Syst., vol. 54, no. 6, pp. 2628–2642, 2018.

[21] R. Kasana, S. Kumar, O. Kawaiartya, R. Kharel, J. Lloret, N. Aslam, and T. Wang, “Fuzzy-based channel selection for location oriented services in multichannel vcps environments,” IEEE Internet Things J., vol. 5, no. 6, pp. 4642–4651, 2018.

[22] Y. Zhang, J. Cao, and Y. Zhang, “Adaptive digital twin and multiagent deep reinforcement learning for vehicular edge computing and networks,” IEEE Trans. Indus. Inform., vol. 18, no. 2, pp. 1405–1413, 2021.

[23] M. Moltafet, M. Leinonen, and M. Codreanu, “On the age of information in multi-source queueing models,” IEEE Trans. Commun., vol. 68, no. 8, pp. 5003–5017, 2020.

[24] T. Takine, “Queue length distribution in a fifo single-server queue with multiple arrival streams having different service time distributions,” Queueing Syst., vol. 39, no. 4, pp. 349–375, 2001.

[25] J. Wang, K. Liu, B. Li, T. Liu, R. Li, and Z. Han, “Delay-sensitive multi-period computation offloading with reliability guarantees in fog networks,” IEEE. Trans. Mob. Comput., vol. 19, no. 9, pp. 2062–2075, 2020.