Joint C-V2X Based Offloading and Resource Allocation in Multi-Tier Vehicular Edge Computing System

Weiyang Feng, *Graduate Student Member, IEEE*, Siyu Lin, *Member, IEEE*, Ning Zhang, *Senior Member, IEEE*, Gongpu Wang, *Member, IEEE*, Bo Ai, *Fellow, IEEE*, and Lin Cai, *Fellow, IEEE*

***Abstract*— Emerging intelligent transportation services are latency-sensitive with heavy demand for computing resources, which can be supported by a multi-tier computing system composed of vehicular edge computing (VEC) servers along the roads and micro servers on vehicles. In this work, we investigate the dual Uu/PC5 interface offloading and resource allocation strategy in Cellular Vehicle-to-Everything (C-V2X) enabled multi-tier VEC system. The successful transmission probability is characterized to obtain the normalized transmission rate of PC5 interface. We aim to minimize the system latency of task processing while satisfying the resource requirements of Uu and PC5 interfaces. Due to the non-convex and variables coupling, we decompose the original problem into two subproblems, i.e., resource allocation and offloading strategy subproblems. Specifically, we derive the closed-form expressions of packet transmit frequency of PC5 interface, transmission power of Uu interface, and CPU computation frequency in the resource allocation subproblem. Moreover, for the offloading strategy subproblem, the offloading ratio matrix is obtained by proposing the PC5 interface based greedy offloading (PC5-GO) algorithm, which concludes offloading decision and ratio. Simulation results are provided that the proposed PC5-GO algorithm can significantly improve the system performance compared with other baseline schemes by 13.7% at least.**

***Index Terms*— Multi-tier vehicular edge computing, C-V2X, Uu/PC5 interface, partial offloading, resource allocation.**

I. Introduction

INTERNET of Vehicles (IoV) [1], [2], [3] is emerging in support of providing network connections for intelligent transportation services. In addition to network connection, computation resources are needed to meet the latency requirement for intelligent transportation services [4], [5]. With increasing number of vehicles and high computation requirements of services, the computing power of traditional edge computing can no longer meet the demand of transportation services [6], [7], [8]. The edge computing and vehicular computing can be integrated to form a multi-tier vehicular edge computing (VEC) system [9], [10], [11], [12] to better support the decision-making of intelligent services [13]. Specifically, by exploiting the computing capacities at the road side unit (RSU) or other vehicles, multi-tier VEC system can help satisfy the demands from IoVs [14], [15]. In a multi-tier VEC system, the vehicle can offload tasks to VEC servers or other vehicles to reduce the computing service latency and ensure the safety of intelligent transportation system [16].

Offloading strategy of vehicular edge computing has attracted a lot of attention. However, offloading and resource allocation strategies are designed without considering the characteristics of C-V2X link. In fact, the vehicle sensing under the C-V2X architecture is not stable enough because of rapid change of the topology. Compared with the traditional offloading strategy, it is a big challenge to model successful transmission probability of C-V2X to reflect the Vehicle-to-vehicle (V2V) link quality. Besides, different link characteristics of PC5 and Uu interfaces make it difficult to jointly optimize the offloading strategy and resource allocation.

In this work, we study the influence of successful transmission probability of V2V on the offloading strategy, communication and computation resource allocation in C-V2X based VEC system. The vehicle generates a series of tasks, and the

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Weiyang Feng and Siyu Lin are with the Collaborative Innovation Center of Railway Traffic Safety, School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing 100044, China (e-mail: wyfeng@bjtu.edu.cn; sylin@bjtu.edu.cn).

Ning Zhang is with the Department of Electrical and Computer Engineering, University of Windsor, Windsor, ON N9B 3P4, Canada (e-mail: ning.zhang@uwindsor.ca).

Gongpu Wang is with the Beijing Key Laboratory of Transportation Data Analysis and Mining, School of Computer and Information Technology, Beijing Jiaotong University, Beijing 100044, China (e-mail: gpwang@bjtu.edu.cn).

Bo Ai is with the Frontiers Science Center for Smart High-Speed Railway System, School of Electronic and Information Engineering, State Key Laboratory of Rail Traffic Control, Beijing Jiaotong University, Beijing 100044, China (e-mail: boai@bjtu.edu.cn).

Lin Cai is with the Department of Electrical and Computer Engineering, University of Victoria, Victoria, BC V8P 5C2, Canada (e-mail: cai@ece.uvic.ca).

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part of each task is partially offloaded to the VEC server by the Uu interface, and the other part is offloaded to nearby couldlet vehicles by PC5 interfaces. Then we formulate the latency minimization problem to optimize offloading matrix, and communication and computation resource allocation. The original problem is then transformed into the equivalent problem to deal with the variable coupling. We decompose the equivalent problem into resource allocation subproblem and offloading strategy subproblem and solve them separately. The closed expression of packet transmit frequency of PC5 interface, transmission power of Uu interface, and computation frequency of VEC server and cloudlet vehicles can be derived by KKT condition in resource allocation subproblem. In the offloading strategy subproblem, we derive the optimal offloading ratio and propose the PC5 Interface based greedy offloading (PC5-GO) algorithm to obtain the offloading decision. The main contributions of this paper are summarized as follows.

- To characterize the performance of vehicle sensing, we formulate the *successful transmission probability* by considering half-duplex effect, packet sensing ratio, and successful sensing probability. Then we can obtain the normalized V2V transmission rate to reflect influence of C-V2X, i.e., PC5 interface on offloading.
- The latency minimization problem of task processing is formulated by joint optimizing the communication resource of Uu and PC5 interfaces, computation resource of VEC server and cloudlet vehicles, and offloading matrix. Due to the variables coupling of offloading matrix and resource allocation variables, we decouple the problem into two subproblems, i.e., resource allocation subproblem and offloading strategy subproblem.
- The closed expressions of transmission power at the Uu interface, packet transmit frequency at the PC5 interface, and computation frequency of VEC server and cloudlet vehicles are derived by KKT condition in the resource allocation subproblem. Moreover, the optimal offloading ratio is obtained and a low complexity PC5-GO algorithm is proposed to obtain the offloading matrix.
- The simulation results are provided that demonstrate the performance of packet transmit frequency at the PC5 interface of the proposed PC5-GO algorithm. Besides, we also show the latency performance benefits of the proposed PC5-GO algorithm and analyze the practicability of PC5-GO algorithm and other schemes without C-V2X in different situations.

The remainder of the paper is organized as follows. In Section II, we review the related works for offloading strategy and resource allocation in the VEC system. In Section III, the system model is presented, including the task, communication and computation model. In Section IV, we formulate the latency minimization problem of task processing. In Section V, the optimal expressions are derived and PC5-GO algorithm is proposed. Simulation results are provided in Section VI, followed by the conclusions in Section VII.

II. Related Work

In this section, we discuss the related work on offloading strategy and transmission and computing resource allocation in VEC system. Besides, we also present the works on resource allocation of VEC system based on C-V2X.

A. *Offloading Strategy in VEC System*

In the literature, many works on task offloading in VEC system have been reported. For latency minimization, Dai et al. [17] formulated a cooperative computation offloading problem to minimize the expected system service latency. The reverse offloading framework was proposed to minimize the system latency and relieve the burden of the VEC server [18], and the offloading and resource allocation algorithms were proposed for binary offloading and partial offloading schemes. The network-based vehicular latency-tolerant scheme for data management was proposed in [19], where computation and communications issues were studied to analyze the impact on message transmission latency, response time, and throughput. For other system metrics, Wang et al. [20] proposed a multiuser noncooperative computation offloading game to maximize the system utility, and a distributed best response algorithm was designed to adjust offloading probability of each vehicle. A Deep Reinforcement Learning (DRL) based task-offloading approach was proposed to minimize energy consumption by considering the dynamics of mobile vehicular networks [21]. A distributed Software Defined Network (SDN) controlled VEC network architecture was proposed [22] to optimize offloading and migration decisions. The joint federated learning and computation offloading problem was investigated to minimize overall latency and energy cost, where an evolutionary search-based genetic algorithm was proposed to obtain the offloaded portions for vehicular users [23]. Zheng et al. proposed an infinite horizon semi-Markov decision process (SMDP) to obtain the optimal decision-making scheme in the VEC system [24]. Yuan et al. investigated a joint service migration and mobility optimization approach for VEC system based on a multi-agent deep reinforcement learning algorithm [25]. Dai et al. optimized the allocation of edge computing and caching resources to maximize the system utility in the proposed AI-empowered vehicular network architecture [26]. Xie et al. studied the dynamic computation offloading strategy by considering fast time-varying wireless channel [27] and Tang et al. proposed the distributed task scheduling in serverless edge computing networks [28]. In addition, on allocation of communication and computation, Yu et al. considered a hierarchical architecture for cloud-based vehicular networks, and proposed the virtual resource migration for resource reservation scheme [29]. The allocation of networking, caching and computing was optimized to enhance the performance in the integrated framework of vehicular networks in [30], and He et al. proposed a novel deep reinforcement learning approach to obtain the resource allocation policy. To enhance the computational capabilities in dynamic vehicular environments, the autonomous vehicular edge framework was proposed [31], which provides computation services in a decentralized manner. Besides, an ant colony optimization based scheduling algorithm was proposed to solve the formulated job assignment problem.

However, some of the above studies only focus on the orthogonal resources allocation at Uu interface, which requires a large coverage of infrastructure, i,e., base stations (BS). In fact, it is difficult to guarantee that vehicles are always covered by BS due to the high mobility and uncertainty of the IoV, and thus the communication between vehicles is mainly realized through PC5 interface.

B. Resource Allocation Scheme of C-V2X Based VEC System

The system based on Cellular Vehicle-to-Everything (C-V2X) can better cope with the changing network topology, where vehicles communicate with other vehicles through the LTE or NR PC5 interfaces while using the LTE or NR Uu interface to communicate with BSs. For the development of C-V2X in [32], a semi-persistent scheduling (SPS) algorithm is proposed in LTE V2X mode 4 of 3GPP Release 14, and 3GPP Release 16 further supplements it in mode 2 in NR V2X [33]. Specifically, each vehicle senses the channel in a given duration interval, identifies those resources with the least interference, randomly selects a channel for transmission, and continuously occupies the channel resources with a given probability. The SPS algorithm of C-V2X can improve the defects of offloading and resource allocation in the frequently changing network topology. Compared with Uu interface, the PC5 interface does not need reliable coverage. Therefore, the offloading between vehicles in the actual scene is mostly transmitted through PC5 interface. Jointly exploiting PC5 interface and Uu interface of C-V2X system can better support task offloading and computation of services in the multi-tier VEC system.

For the C-V2X VEC system, Raza et al. [34] proposed a mobility-aware computational efficiency based task offloading and resource allocation scheme to maximize the computation efficiency, which achieves a tradeoff between computation time and energy consumption by considering the 5G NR V2X communication model. An intelligent software defined C-V2X network framework was proposed in [35], where a deep learning based approach was proposed to improve the traffic offloading efficiency. Qiu et al. studied the security provisioning of C-V2X computation-offloading network with imperfect channel state information, and optimized the access threshold to maximize the security throughput and balance the security and reliability of the offloading link [36]. In the VEC assisted cellular-V2X networks, the authors proposed a joint computation and URLLC resource allocation strategy to maximize the average energy consumption, where communication and computation resource allocation were obtained by the Lyapunov optimization method [37]. Li et al. proposed the offloading problem and equate the offloading process as a dynamic multi-step decision process in the mobile edge computing and C-V2X collaborative scenario, and design a mobility-aware dynamic offloading algorithm to minimize the impact of vehicular mobility on offloading [38].

In the aforementioned works, offloading and resource allocation strategies based on the characteristics of C-V2X link was not considered in previous works. In this work, we model successful transmission probability of C-V2X to reflect the transmission rate of V2V link. Besides, joint offloading strategy and resource allocation of PC5 and Uu interfaces in C-V2X based VEC system is considered.

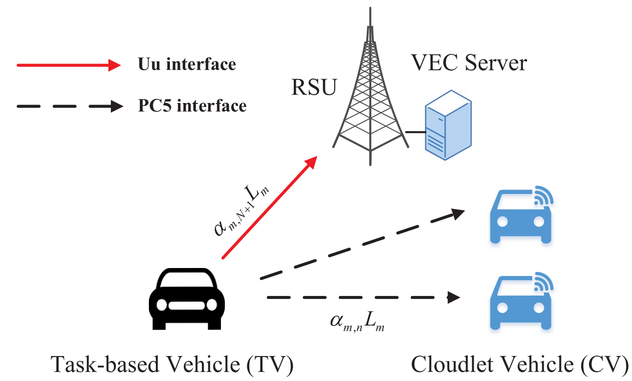


Fig. 1. System model.

III. System Model

We consider a C-V2X aided multi-tier VEC system with multiple vehicles and a single RSU connected with VEC servers, which is shown in Fig.1. These vehicles can be divided into two types. The first type is the task-based vehicle (TV), which generates tasks to support the service of vehicular network. The second type is called cloudlet vehicles (CV), denoted by the $\mathcal{N} = \{1, 2, \ldots, N\}$, which generally provide transportation services, such as buses and taxis. During the peak hours, the number of buses and taxis is also large, which can deploy micro-computing servers to provide computing resources for TVs. The multi-tier VEC system is composed of MEC and CVs, in which the TV exchanges data with the RSU and CVs through Uu interface and PC5 interface, respectively. With partial offloading, TV offloads a part of each task to the VEC server through the Uu interface, and the other part to the CV through the PC5 interface. After computation, the VEC server and CV will return the results to the TV.

A. Task Model

The TV generates M periodic tasks, denoted by $\mathcal{M} = \{1, 2, \ldots, M\}$, and the size of task is denoted by $L_m, m \in M$. There is a serial relationship between tasks at the TV, that is, after the computation of the m-th task is completed, the $(m+1)$-th task starts to be processed. For each task L_m at TV, the partial offloading is adopted, where one part is offloaded to RSU (VEC server) for computation, and the other part is offloaded to a CV within the communication range of TV. The VEC server is indexed as the $(N+1)$-th CV.

We define offloading matrix as $\boldsymbol{\alpha}$, where the entry is $\alpha_{m,n} \in [0, 1], m \in \mathcal{M}, n \in \mathcal{N} \cup \{N+1\}$. For computing at VEC server, i.e., $n = N+1$, $\alpha_{m,N+1} > 0$ means that the TV offloads a part of m-th task $\alpha_{m,N+1}L_m$ to the VEC server; otherwise, $\alpha_{m,N+1} = 0$ means that the TV does not offload any part of m-th task to the VEC server. For computing at CVs, i.e., $n \in \mathcal{N}$, $\alpha_{m,n} > 0$ means that the TV offloads a part of m-th task $\alpha_{m,n}L_m$ to the n-th CV; otherwise, $\alpha_{m,n} = 0$ means that the TV does not offload any part of m-th task to the n-th CV. Since one CV is assigned to compute one part of a task, thus from the first column to the n-th column of each row of the matrix $\boldsymbol{\alpha}$, one element is greater than 0, and all other elements are equal to 0. According to the partial offloading mechanism, when $\alpha_{m,n} > 0$, we have $\alpha_{m,N+1} + \sum_{n=1}^{N} \alpha_{m,n} = 1$.

B. Communication Model

There are two types of communication links for offloading, i.e., Uu and PC5 interfaces.

- Uu interface: communication interface between vehicle and RSU, which supports reliable communication in a long distance.
- PC5 interface: communication interface between vehicles. The PC5 interface can be used for V2V communication no matter whether there is cellular network coverage or not.

The TV exchanges data and/or control information with the RSU using the Uu interface and other CVs through the PC5 interfaces, so that the TV can obtain the channel state information and computing resource information of VEC server and CVs.

1) Uu Interface: The Uu interface is the communication interface between TV and RSU. The orthogonal frequency division multiple access (OFDMA) technique is adopted for the channel access. It is assumed that the perfect channel state information (CSI) between the RSU and vehicles can be estimated. The channel gain between the TV and RSU is denoted by g_{N+1}^{Uu}. The transmission rate of m-th task between the TV and RSU is given by

$$r_{m,N+1}^{\text{Uu}} = B_{m,N+1} \log_2 \left(1 + \frac{p_{m,N+1}^{Uu} g_{m,N+1}^{Uu}}{\sigma^2} \right) \tag{1}$$

where $B_{m,N+1}$ denotes the available bandwidth, σ^2 denotes the noise power, and $p_{m,N+1}^{Uu}$ denotes the transmission power of Uu interface of TV. The offloading latency of part of m-th task from TV to the VEC server can be expressed as

$$T_m^{ser-o} = \frac{\alpha_{m,N+1} L_m}{r_{m,N+1}^{\text{Uu}}} \tag{2}$$

2) PC5 Interface: The 5G V2X standard is first defined in Release 16, including 5G NR PC5 interface. The PC5 interface is the communication interface between TV and other CVs. The packet transmit frequency of PC5 interface is denoted by λ, which indicates the number of packets transmitted per second of TV. The λ can be adjusted adaptively. The practical transmit frequency of the local transmitter at TV is less than the perfect shannon channel capacity [39], which is denoted as $C_{v2v}^{\max}$.

In the C-V2X aided multi-tier VEC system, vehicles occupy resource blocks semi-persistently by the SPS algorithm [33], i.e., vehicles use the selected sub-channels for the transmission and occupies the same resource periodically till its Reselection Counter is counted down to zero [40], [41]. Here we consider that other vehicles do not change their occupied resources within the perception range of the TV. In C-V2X, the transmission error between TV and CV can affect the V2V transmission rate. Next, we focus on formulation of the normalized V2V transmission rate based on the influence of C-V2X characteristics.

First, the half-duplex(HD) error is that the vehicle can not receive the data packet when it transmits its own data packet in the same sub-frame, since the wireless transmission mode of C-V2X is half duplex. The HD error can be given as [42] $\delta_{HD} = \frac{\lambda}{N_{frame}}$.

The traffic density is denoted by β in vehicles per meter. Then the successful sensing probability (SSP) can be given as

$$\mathcal{P}_{SEN} = e^{-\lambda \frac{K\beta \cdot 2d_{sen}}{N_{sub-f} N_{sub-c}}} \tag{3}$$

where K is the conversion coefficient considering multiple lanes, d_{sen} is the sensing distance of TV, and N_{sub-f} and N_{sub-c} denote the number of sub-frames and sub-channels in the Selection Window (SW), respectively.

When the received signal power is higher than the perceived power threshold P_{Sen}^{th}, the receiver at the CV can decode data. Thus the Packet Sensing Ratio(PSR) can be given by [42]

$$PSR(d_n) = \frac{1}{2} \left(1 + erf \left(\frac{P^{PC5} - PL(d_n) - P_{Sen}^{th}}{\sigma\sqrt{2}} \right) \right) \tag{4}$$

where d_n and $PL(d_n)$ denote the distance and pathloss between TV and n-th CV, respectively. Here P^{PC5} is the transmission power at the PC5 interface of the TV, which satisfies $P^{PC5} = \sum_{m=1}^{M} \sum_{n=1}^{N} p_{m,n}^{v2v}$.

Hence, the successful transmission probability (STP) can be given as

$$\mathcal{P}_{STP}(d_n) = (1 - \delta_{HD}) \cdot \mathcal{P}_{SEN} \cdot PSR(d_n) \tag{5}$$

Considering the influence of STP, the normalized transmission rate of m-th task between the TV and CVs n is given by

$$r_{m,n}^{\text{PC5}} = \mathcal{P}_{STP}(d_n) L_m \lambda \tag{6}$$

The offloading latency of offloaded part of m-th task from TV to the n-th CV can be given by

$$T_{m,n}^{veh-o} = \frac{\alpha_{m,n} L_m}{r_{m,n}^{\text{PC5}}} \tag{7}$$

C. Computation Model

The computation burden of the m-th task of TV is denoted by C_m in cycle/bit, which means the number of CPU cycles for computing one-bit task datum.

We define the computation frequency of VEC server assigned to the m-th task part as f_m^{ser} in cycles per second. The computation latency for the m-task at the VEC server can be expressed as

$$T_m^{ser-c} = \frac{\alpha_{m,N+1} L_m C_m}{f_m^{ser}} \tag{8}$$

Besides, we define the computation frequency of n-th CV assigned to the m-th task part as $f_{m,n}^{veh}$ in cycles per second.

The computation latency for the m-task at n-th CV can be given by

$$T_{m,n}^{veh-c} = \frac{\alpha_{m,n} L_m C_m}{f_{m,n}^{veh}} \quad (9)$$

Here we ignore the download transmission latency of results due to the small data size.

IV. Problem Formulation

For partial offloading, the processing latency of each task includes two parts: i) one is the sum of the offloading and computation latency from TV to the VEC server and ii) the other is the sum of the offloading and computation latency from TV to CV. Thus, the processing latency of m-th task is the larger one between the two parts, which is given by

$$T_m^{tot} = \max\{T_m^{ser-o} + T_m^{ser-c}, T_{m,n}^{veh-o} + T_{m,n}^{veh-c}\} \quad (10)$$

We aim to minimize the total processing latency of all tasks, by jointly optimizing transmission power of Uu interface $\boldsymbol{p^{Uu}}$, packet transmit frequency of PC5 interface $\boldsymbol{\lambda}$, VEC server CPU frequency $\boldsymbol{f^{ser}}$, CPU frequency $\boldsymbol{f^{veh}}$ of the CV, and offloading matrix $\boldsymbol{\alpha}$. The total latency is the sum of latency of all tasks for TV since tasks of TV are processed in serial. The system latency minimization problem is formulated as follows.

$$\min_{\boldsymbol{p^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}},\boldsymbol{\alpha}} \sum_{m=1}^{M} T_m^{tot} \quad (11)$$

$$\text{s.t.} \sum_{m=1}^{M} p_{m,N+1}^{Uu} + P^{PC5} \le P^{max} \quad (11a)$$

$$L_m \lambda \le C_{v2v}^{\max} \quad (11b)$$

$$\lambda \in (0, \lambda^{max}] \quad (11c)$$

$$\sum_{m=1}^{M} f_m^{ser} \le f_{ser}^{max} \quad (11d)$$

$$\sum_{m=1}^{M} \mathcal{I}(\alpha_{m,n}) f_{m,n}^{veh} \le f_n^{veh,max}, \quad \forall n \in \mathcal{N} \quad (11e)$$

$$\alpha_{m,n}, \alpha_{m,N+1} \in [0,1], \quad \forall n \in \mathcal{N} \quad (11f)$$

$$\alpha_{m,N+1} + \sum_{n=1}^{N} \alpha_{m,n} = 1, \quad \forall n \in \mathcal{N} \quad (11g)$$

$$\sum_{n=1}^{N} \mathcal{I}(\alpha_{m,n}) = 1 \quad (11h)$$

$$f_m^{ser}, f_{m,n}^{veh}, p_{m,N+1}^{Uu} \ge 0 \quad (11i)$$

where P^{max} is the power constraint of the TV, $\lambda^{max} = N_{frame}$ is the maximum packet transmit frequency of PC5 interface, f_{ser}^{max} and $f_n^{veh,max}$ are maximum computation frequency of VEC server and n-th CV, respectively.

Constraint (11a) guarantees the total power constraints of the TV. Constraints (11b) and (11c) correspond to the packet transmit frequency constraints by perfect channel capacity and maximum transmission frequency, respectively. Constraints (11d) and (11e) ensure the maximum frequency constraints of VEC server and n-th CV, respectively. Constraint (11f) indicates the ratio of m-th task offloaded to the n-th CV or VEC server in the range of 0-1. Constraint (11g) indicates the sum of the ratios of the m-th task offloaded to the CV or VEC server is equal to one. Constraint (11h) ensures a part of m-th task is only offloaded to a CV for computation.

This problem is challenging to solve due to the following reasons. First, the form of the objective function includes the sum of multiple max functions due to the serial nature of tasks. Second, the optimization variable $\boldsymbol{\alpha}$ is coupled with other variables, i.e., $\boldsymbol{p^{Uu}}$, $\boldsymbol{\lambda}$, $\boldsymbol{f^{ser}}$, $\boldsymbol{f^{veh}}$ in the objective function and constraint (11e). Finally, problem (11) introduces the characteristics of C-V2X, i.e., STP (successful transmission probability), which poses challenges to the design of offloading strategy. Different from traditional offloading of VEC network, the joint optimization of communication resources between Uu and PC5 interfaces makes the problem non-convex and difficult to solve.

V. Joint Offloading and Resource Allocation Strategy

In this section, since problem (11) is non-convex, we transform the formulated problem (11) into an equivalent problem by transforming the objective function. Then the problem is further decomposed into two sub-problems, i.e., resource allocation subproblem and offloading strategy subproblem. For resource allocation sub-problem, we derive the optimal transmission resource allocation of Uu and PC5 interfaces, and computation resource allocation. For offloading strategy sub-problem, the optimal offloading ratio between Uu interface and PC5 interface is derived. Therefore, a PC5-GO algorithm is proposed for the latency minimization problem (11).

A. Problem Transformation

Since the objective is non-convex, it is difficult to solve, we transform the objective function by following Proposition.

Proposition 1: When $T_m^{ser-o} + T_m^{ser-c} = T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$, the optimal solution $\boldsymbol{p^{Uu,*}}, \boldsymbol{\lambda^*}, \boldsymbol{f^{ser,*}}, \boldsymbol{f^{veh,*}}, \boldsymbol{\alpha^*}$ can be obtained. The objective function of (11) can be transformed into

$$\sum_{m=1}^{M} \frac{\alpha_{m,n} L_m}{\mathcal{P}_{STP}(d_n) L_m \lambda} + \frac{\alpha_{m,n} L_m C_m}{f_{m,n}^{veh}} \quad (12)$$

while satisifies

$$\frac{\alpha_{m,N+1} L_m}{B_{m,N+1} \log_2\left(1 + \frac{p_{m,N+1}^{Uu} g_{m,N+1}^{Uu}}{\sigma^2}\right)} + \frac{\alpha_{m,N+1} L_m C_m}{f_m^{ser}} = \frac{\alpha_{m,n} L_m}{\mathcal{P}_{STP}(d_n) L_m \lambda} + \frac{\alpha_{m,n} L_m C_m}{f_{m,n}^{veh}} \quad (13)$$

Proof: Please refer to the Appendix A. □

Besides, we introduce auxiliary variables $\gamma_m = \frac{g_{m,N+1}^{Uu}}{\sigma^2}$, $s_m^{Uu} = \frac{1}{\log_2\left(1+\gamma_m p_{m,N+1}^{Uu}\right)}$ to facilitate the solution $p_{m,N+1}^{Uu}$. According to the transmission power P^{max}, we have $s_m^{Uu,min} = \frac{1}{\log_2(1+\gamma_m(P^{\max} - P^{PC5}))}$. Based on Proposition 1 and auxiliary variables, problem (11) can be equivalently transformed as

$$\min_{\boldsymbol{s_m^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}},\boldsymbol{\alpha}} \sum_{m=1}^{M} \frac{\alpha_{m,n}L_m}{\mathcal{P}_{STP}(d_n)L_m\lambda}+\frac{\alpha_{m,n}L_mC_m}{f_{m,n}^{veh}} \tag{14}$$

$$\text{s.t.} \sum_{m=1}^{M}\frac{1}{\gamma_m}\left(2^{\frac{1}{s_m^{Uu}}}-1\right)+P^{PC5}\le P^{max} \tag{14a}$$

$$(11b),(11c),(11d),(11e),(11f),(11g)$$
$$(11h),(11i)$$

Since variable coupling still exists, problem (14) is nonconvex. Thus we decouple the problem into resource allocation subproblem and offloading strategy subproblem, which decouple the resource allocation variables $\boldsymbol{s_m^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}}$ and offloading matrix $\boldsymbol{\alpha}$. In the resource allocation subproblem, we optimize the variables $(\boldsymbol{s_m^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}})$ to obtain the optimal resource allocation of communication and computation. In the offloading strategy subproblem, we derived the optimal ratio of offloading matrix and obtain the decision of offloading matrix $\boldsymbol{\alpha}$.

B. Resource Allocation Subproblem

The resource allocation subproblem can be expressed as

$$\min_{\boldsymbol{s_m^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}}} \sum_{m=1}^{M} \frac{\alpha_{m,n}L_m}{\mathcal{P}_{STP}(d_n)L_m\lambda}+\frac{\alpha_{m,n}L_mC_m}{f_{m,n}^{veh}} \tag{15}$$
$$\text{s.t. } (11b),(11c),(11d),(11e),(11i),(14a)$$

Proposition 2: Problem (15) is convex with respect to $(\boldsymbol{s_m^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}})$.

Proof: Please refer to the Appendix B. □

According to Proposition 2, problem (15) is a convex problem, and thus it can be solved by the KKT condition [43]. The partial Lagrangian of problem (15) can be given as

$$\begin{aligned}
&\mathcal{L}(\boldsymbol{s_m^{Uu}},\boldsymbol{\lambda},\boldsymbol{f^{ser}},\boldsymbol{f^{veh}},\boldsymbol{\eta_1},\boldsymbol{\eta_2},\boldsymbol{\eta_3},\boldsymbol{\psi})\\
&=\sum_{m=1}^{M}\frac{\alpha_{m,n}L_m}{\mathcal{P}_{STP}(d_n)L_m\lambda}+\frac{\alpha_{m,n}L_mC_m}{f_{m,n}^{veh}}\\
&\quad+\eta_1\left(\sum_{m=1}^{M}\frac{1}{\gamma_m}\left(2^{\frac{1}{s_m^{Uu}}}-1\right)+P^{PC5}-P^{max}\right)\\
&\quad+\eta_2\left(L_m\lambda-C_{v2v}^{\max}\right)+\eta_3\left(\sum_{m=1}^{M}f_m^{ser}-f_{ser}^{max}\right)\\
&\quad+\sum_{n=1}^{N}\psi_n\left(\sum_{m=1}^{M}\mathcal{I}(\alpha_{m,n})f_{m,n}^{veh}-f_n^{veh,max}\right)
\end{aligned} \tag{16}$$

where $\boldsymbol{\psi}=\{\psi_n\}$. By using the KKT conditions, the optimal computation resource allocation of VEC server is derived in the following theorem.

Theorem 1: The optimal CPU computation frequency of the VEC server is given by

$$f_m^{ser,*}=\begin{cases}\min\left\{\sqrt{\dfrac{\alpha_{m,N+1}L_mC_m}{\eta_3}},f_{ser}^{max}\right\}, & \alpha_{m,N+1}>0\\ 0, & \alpha_{m,N+1}=0\end{cases} \tag{17}$$

where $\forall n\in\mathcal{N}$.

Proof: According to Proposition (1), the objective function of Problem (15) can be equivalently transformed into $\sum_{m=1}^{M}\frac{\alpha_{m,N+1}L_m}{B_{m,N+1}\log_2\left(1+\gamma_m p_{m,N+1}^{Uu}\right)}+\frac{\alpha_{m,N+1}L_mC_m}{f_m^{ser}}$. When $\alpha_{m,N+1}>0$, based on the first-order condition $\frac{\partial\mathcal{L}}{\partial f_m^{ser}}=0$, we have $-\frac{\alpha_{m,N+1}L_mC_m}{(f_m^{ser})^2}+\eta_3=0$. With some manipulation, the optimal CPU frequency of VEC server $f_m^{ser,*}$ is given by (17).

This completes the proof. □

Similarly, the optimal computation resource allocation of CVs is derived in the following theorem.

Theorem 2: The optimal CPU computation frequency of CVs is given by

$$f_{m,n}^{veh,*}=\begin{cases}\min\left\{\sqrt{\dfrac{\alpha_{m,n}L_mC_m}{\psi_n}},f_n^{veh,max}\right\}, & \mathcal{I}(\alpha_{m,n})=1\\ 0, & \mathcal{I}(\alpha_{m,n})=0\end{cases} \tag{18}$$

where $\forall n\in\mathcal{N}$.

Proof: The proof is similar to Theorem 1. Due to space limitations, we omit it. □

The optimal transmission power of Uu interface can be derived in the following theorem.

Theorem 3: The optimal transmission power of Uu interface is given by

$$p_{m,N+1}^{Uu,*}=\begin{cases}\dfrac{1}{\gamma_m}\left(2^{\frac{\mathcal{W}\left(\frac{\ln 2\Delta^{\frac{1}{2}}}{2}\right)}{\frac{\ln 2}{2}}}-1\right), & k_m\le 0\\ P^{\max}-P^{PC5}, & k_m>0\end{cases} \tag{19}$$

where $\Delta=\frac{\gamma_m\alpha_{m,N+1}L_m}{\eta_1\cdot\ln 2\cdot B_{m,N+1}}$, $k_m=\frac{\partial\mathcal{L}}{\partial s_m^{Uu}}\big|_{s_m^{Uu}=s_m^{Uu,min}}$ and $\mathcal{W}(x)$ denotes the Lambert-W function, which is the inverse function of $f(z)=z\exp(z)=x$, i.e., $z=\mathcal{W}(x)$.

Proof: Please refer to the Appendix C. □

We iteratively update the dual variables $(\boldsymbol{\eta_1},\boldsymbol{\eta_2},\boldsymbol{\eta_3},\boldsymbol{\psi})$ with the optimal solution $(\boldsymbol{p^{Uu,*}},\boldsymbol{\lambda^*},\boldsymbol{f^{ser,*}},\boldsymbol{f^{veh,*}},\boldsymbol{\alpha^*})$. Given the previous iterate $\eta_1^{(k)}$, $\eta_2^{(k)}$, $\eta_3^{(k)}$, $\psi_n^{(k)}$, the current iterate $\eta_1^{(k+1)}$, $\eta_2^{(k+1)}$, $\eta_3^{(k+1)}$, $\psi_n^{(k+1)}$ is updated as

$$\begin{aligned}
\eta_i^{(k+1)}&=\left[\eta_i^{(k)}+s_i^{(k)}\frac{\partial\mathcal{L}}{\partial\eta_i^{(k)}}\right]^+, \quad i\in\{1,2,3\}\\
\psi_n^{(k+1)}&=\left[\psi_n^{(k)}+s_n^{\psi_n,(k)}\frac{\partial\mathcal{L}}{\partial\psi_n^{(k)}}\right]^+, \quad n\in\mathcal{N}
\end{aligned} \tag{20}$$

where $s_i^{(k)}$ and $s_n^{\psi_n,(k)}$ are positive step size of $\boldsymbol{\eta_i}$ and $\boldsymbol{\psi}$, respectively.

The optimization of packet transmit frequency of PC5 interface can be decoupled from Problem (15), since $\boldsymbol{\lambda}$ is independent when $\boldsymbol{\alpha}$ is fixed. The following problem is formulated to obtain the optimal packet transmit frequency of PC5 interface.

$$\min_{\boldsymbol{\lambda}} \sum_{m=1}^{M}\frac{\alpha_{m,n}L_m}{\mathcal{P}_{STP}(d_n)L_m\lambda}$$
$$\text{s.t. } (11b),(11c) \tag{21}$$

The range of λ can be determined to be $\lambda \in (0, \lambda^{cons}]$, where $\lambda^{cons} = \min\{\lambda^{max}, \frac{C_{v2v}^{\max}}{L_m}\}$. For convenience, we define the objective function of (21) as $y(\lambda)$, i.e., $y(\lambda) = \sum_{m=1}^{M} \frac{\alpha_{m,n} L_m}{\mathcal{P}_{STP}(d_n) L_m \lambda}$. The second derivative of the function $y(\lambda)$ satisfies $\frac{\partial^2 y(\lambda)}{\partial \lambda^2} > 0$. Since constraints (11b), (11c) are all linear constraints, according to the Second-order condition, the Problem (21) is a convex problem.

By calculating $\frac{\partial y(\lambda)}{\partial \lambda} = 0$, we have $\lambda^* = \frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2}$ where $\Pi = \frac{N_{sub-f} N_{sub-c}}{K\beta(2d_{sen})}$. Considering the constraints of λ, i.e., $\lambda \in (0, \lambda^{cons}]$, the λ^* can be obtain when $\frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2} \leq \lambda^{cons}$. On the other hand, when $\frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2} > \lambda^{cons}$, $\lambda^* = \frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2}$ can not be reached. We have $\frac{\partial y(\lambda)}{\partial \lambda} < 0$, thus the objective function (21) is monotonically decreasing in the $(0, \lambda^{cons}]$. In this case, the optimal λ^* can be given by $\lambda^* = \lambda^{cons}$. Therefore, the optimal λ^* can be derived as following theorem.

Theorem 4: The optimal packet transmit frequency of PC5 interface is given by

$$\lambda^* = \begin{cases} \frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2}, \\ \frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2} \leq \lambda^{cons} \\ \lambda^{cons}, \\ \frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2} > \lambda^{cons} \end{cases} \tag{22}$$

where $\Pi = \frac{N_{sub-f} N_{sub-c}}{K\beta(2d_{sen})}$.

Remark 1: Considering HD error, SSP (successful sensing probability), and PSR (Packet Sensing Ratio), the optimal packet transmit frequency of PC5 interface can be derived as (22). When $\frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2} \leq \lambda^{cons}$, increasing of transmission frequency beyond $\frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2}$ will not increase the transmission rate, but will damage it. It is because that increasing packet transmit frequency will reduce the successful transmission probability, which will reduce the transmission rate and further increase the latency of PC5 interface. When $\frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2} > \lambda^{cons}$, the optimal solution $\frac{N_{\text{frame}}}{2} + \Pi - \sqrt{\frac{N_{\text{frame}}{}^2}{4} + \Pi^2}$ can not be reached. Therefore, the packet transmit frequency should be increased as much as possible within a certain range to increase the successful transmission probability and reduce the latency of PC5 interface.

C. Uu/PC5 Interface Based Offloading Strategy Subproblem

In this subsection, with the given $(\boldsymbol{s_m^{Uu}}, \boldsymbol{\lambda}, \boldsymbol{f^{ser}}, \boldsymbol{f^{veh}})$, the optimal offloading ratio is derived in the offloading strategy subproblem. Besides, we propose a PC5 interface based greedy offloading algorithm to obtain the offloading matrix $\boldsymbol{\alpha}$.

According to the given $(\boldsymbol{s_m^{Uu}}, \boldsymbol{\lambda}, \boldsymbol{f^{ser}}, \boldsymbol{f^{veh}})$, the offloading strategy subproblem can be expressed as

$$\begin{aligned} \min_{\boldsymbol{\alpha}} \ & \sum_{m=1}^{M} \frac{\alpha_{m,n} L_m}{\mathcal{P}_{STP}(d_n) L_m \lambda} + \frac{\alpha_{m,n} L_m C_m}{f_{m,n}^{veh}} \\ \text{s.t.} \ & (11f), (11g), (11h) \end{aligned} \tag{23}$$

By Proposition 1, when $T_m^{ser-o} + T_m^{ser-c} = T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$, the optimal $\boldsymbol{\alpha^*}$ can be obtained. Through manipulation, we can obtain the relational value of the offloading matrix as follows.

Theorem 5: The optimal relational value of offloading matrix is given by

$$\begin{aligned} \alpha_{m,n} &= \frac{1}{\Gamma + 1} \\ \alpha_{m,N+1} &= \frac{\Gamma}{\Gamma + 1} \end{aligned} \tag{24}$$

where $\Gamma = \frac{\frac{1}{\mathcal{P}_{STP}(d_n) L_m \lambda^*} + \frac{C_m}{f_{m,n}^{veh,*}}}{\frac{1}{B_{m,N+1} \log_2\left(1 + \frac{p_{m,N+1}^{Uu,*} g_{m,N+1}^{Uu}}{\sigma^2}\right)} + \frac{C_m}{f_m^{ser,*}}}$.

For the offloading decision in the offloading matrix of TV, we propose a low complexity greedy based algorithm to obtain the offloading decision $\boldsymbol{\alpha}$ instead of the exhaustive method with high complexity $\mathcal{O}(2^N)$.

The detailed description and parameter are introduced as follows. Firstly, the resource allocation subproblem is solved and the optimal resource allocation of communication and computation, i.e., $\boldsymbol{p^{Uu,*}}, \boldsymbol{\lambda^*}, \boldsymbol{f^{ser,*}}, \boldsymbol{f^{veh,*}}$, can be obtained. Then, considering the influence of V2V link of PC5 interface, we use the evaluation criteria set $\boldsymbol{\Omega}$ to determine the offloading decision, which is defined as the product of STP and maximum computation frequency of the CV, i.e., $\boldsymbol{\Omega} = \mathcal{P}_{STP}(d_n) \cdot f_n^{veh,max}$. In accordance with the criteria, CVs are sorted from large to small in the criteria set. The algorithm is divided into two cases, one is $M \leq N$, i.e., the number of tasks is less than the number of CVs, that is, each CV has sufficient computation resources for tasks, the other is $M > N$,i.e., the computation resources of CVs may be insufficient when the number of tasks is too large.

When $M \leq N$, based on the criteria set $\boldsymbol{\Omega}$, the task offloaded to the CV for computation is given a priority to be offloaded to the CV with high criteria value, i.e., line 7-11. Specifically, the CV with the high probability of successful transmission and strong computation ability is prioritized for task computation, since the V2V transmission and computation communication of CV with the high value of criteria set is sufficient and further the latency can be reduced. Then the relational value of offloading matrix can be obtained. When m exceeds the integer multiple of N, the criteria set needs to be updated. Moreover, when $M > N$, the judgment condition about the limitation of the computation resources of CV needs to be verified. If the computation resources allocated by the m-th CV to multiple tasks exceed its computation resource limitation, then the task is designed to the current task is allocated to the next CV in the criteria set.

Based on the above explanation and analysis, the PC5-GO algorithm is shown in Algorithm 1.

Algorithm 1 PC5 Interface Based Greedy Offloading Algorithm

Require: initial value $\boldsymbol{\alpha}^{(0)}$, $\eta_1^{(0)}$, $\eta_2^{(0)}$, $\eta_3^{(0)}$ and $\psi_n^{(0)}$ and candidate set $\mathcal{S} = \emptyset$.
1: **repeat**
2: Update $p^{Uu,(k)}$, $\lambda^{(k)}$, $f^{ser,(k)}$ and $f^{veh,(k)}$ by calculating (19), (22), (17) and (18).
3: Update $\eta_1^{(k)}$, $\eta_2^{(k)}$, $\eta_3^{(k)}$, $\psi_n^{(k)}$ by calculating (20).
4: Define the criteria $\boldsymbol{\Omega} = \mathcal{P}_{STP}(d_n) \cdot f_n^{veh,max}$.
5: **if** $M \leq N$ **then**
6: **for** $m = 1$ to $\mathcal{M}$ **do**
7: The i-th CV selected to compute the m-th task is $\omega_i = \arg\max_{i\in\mathcal{N}} \boldsymbol{\Omega}$.
8: Assign the index i to candidate set $\mathcal{S}$.
9: Update the $\boldsymbol{\Omega} \leftarrow \boldsymbol{\Omega} \setminus \boldsymbol{\Omega_{i\in\mathcal{S}}}$.
10: Update $\alpha_{m,i\in\mathcal{S}}^{(k)} \Leftarrow 1$,
11: Update $\alpha_{m,n\in\{\mathcal{N}\setminus i\}}^{(k)} \Leftarrow 0$.
12: Update relational value of offloading matrix by calculating (24).
13: **end for**
14: **else**
15: **for** $m = 1$ to $\mathcal{M}$ **do**
16: **while** $M = X \times N$, $X \in N^*$, i.e., the set of positive integers **do**
17: Update the criteria $\boldsymbol{\Omega}$.
18: **end while**
19: **if** $\sum_{m\in\mathcal{M}} f_{m,i\in\mathcal{S}}^{veh} \leq f_{i\in\mathcal{S}}^{veh,max}$ **then**
20: Line 7-12.
21: **else**
22: $i \Leftarrow i + 1$.
23: **end if**
24: **end for**
25: **end if**
26: Update $k + 1 \leftarrow k$.
27: **until** $|T^{(k)} - T^{(k-1)}| \leq \epsilon$
28: **return** T and $\mathcal{S}$

D. Algorithm Complexity Analysis

In this section, we analyze the computational complexity of the proposed PC5-GO algorithm. In the PC5-GO algorithm, lines 2-4 are executed in sequence to obtain the optimal communication and computation resource allocation, values of dual variables and criteria. The number of loop iterations of line 6-13 is M. We assume the iteration number of line 19-24 is K_1, where K_1 satisfies $K_1 < M$ obviously. The execution times of the algorithm are $3 + M + MK_1$, thus the computational complexity of PC5-GO algorithm is $\mathcal{O}(MK_1)$.

VI. Performance Evaluation

A. Simulation Setup

We consider a multi-tier VEC system with a single RSU with VEC server and multiple vehicles, which includes a TV and N CVs. The path loss model [44] is $PL = 38.77 + 16.7\log_{10}(d) + 18.2\log_{10}(f_c)$ for NR V2X Sindelink (PC5 interface), where f_c denotes the carrier frequency in GHz and

TABLE I
Simulation Parameters

Parameters	Values
Number of tasks of TV M	20
Number of CVs in multi-tier VEC N	5
Mumber of lanes	4
Maximum vehicle density per lane β	0.8×84^{-1}
Conversion coefficient of multiple lanes K	1.2
Number of RBs between RSU and TV	20
Number of sub-frames in 1 second N_{frame}	1000
Number of sub-frames in the SW N_{sub-f}	100
Number of sub-channels in the SW N_{sub-c}	4
Number of RBs per sub-channel	12
Sensing distance of TV d	1 km
Maximum transmission power of TV P^{max}	23 dBm
The data size of m-th task L_m	$U(1,2) \times 10^4$ bits
Computation load of m-th task C_m	$U(500, 1000)$ cycle/bit
Maximal frequency of VEC server f_{ser}^{max}	2×10^9 cycle/s
Maximal frequency of CV $f_n^{veh,max}$	$U(1,2) \times 10^9$ cycle/s

d denotes the Euclidean distance between a TX and a RX in 3D space in meters. For the NR V2X Uplink (Uu interface), the channel model is based on the Rayleigh fading model and the path loss exponent is set as 3. The background noise power is set as -70 dBm. The other simulation parameters are summarized in Table I [33]. For comparison, the benchmark schemes are set as follows.

- VEC server computing (SC) scheme: All tasks are offloaded to the VEC server by Uu interface for computation.
- CVs computing (VC) scheme: All tasks are offloaded to CVs for computation, and the link is C-V2X link, i.e., PC5 interface.
- NR-based offloading (NRO) scheme [45]: considering the traditional orthogonal channel allocation, one part of each task is offloaded to the VEC server and the other part is offloaded to the CV for computation.

B. Simulation Results

In this chapter, we describe the performance about packet transmit frequency of PC5 interface and system latency under the different indicators, which including vehicle density, number of CVs, task size, transmission power of PC5 interface, CPU computation frequency and wireless resource.

1) Packet Transmit Frequency of PC5 Interface: Fig. 2 depicts the packet transmit frequency of PC5 interface versus the vehicle density β. It shows that the packet transmit frequency of different $p_{m,n}^{v2v}$ decreases with β and converge to the same trend, which implies the λ will also be reduced to reduce transmission errors at PC5 interface when the vehicle density is high, thus achieving the compromise between transmission rate and reliability. Moreover, we note that the packet transmit frequency decays rapidly for the case with large $p_{m,n}^{v2v}$, which demonstrates that the impact of packet transmit frequency of large $p_{m,n}^{v2v}$ is more significant when β increases.

Fig. 3 depicts the packet transmit frequency of PC5 interface versus the task size L_m, where RB $= 2/4/6$ indicates the number of RB in subchannel configurations. The TV can occupy all RBS in subchannels for offloading. When the data

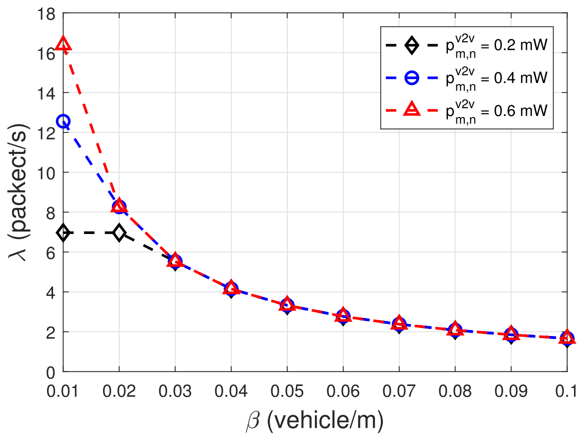


Fig. 2. Packet transmit frequency of PC5 interface versus the vehicle density.

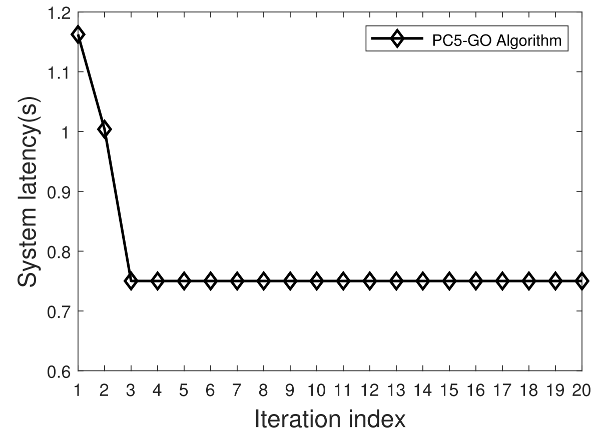


Fig. 4. Convergence of PC5-GO algorithm.

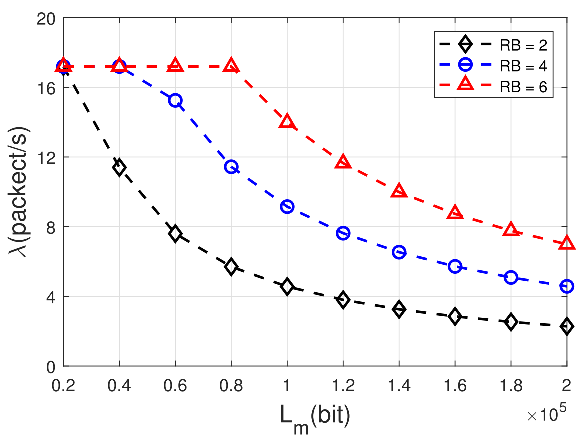


Fig. 3. Packet transmit frequency of PC5 interface versus the task size.

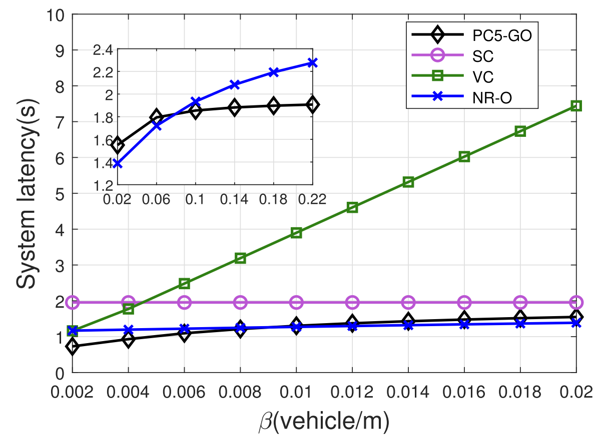


Fig. 5. System latency versus the vehicle density.

size of TV increases, the packet transmit frequency decreases, as the λ is limited by constraint (11b), i.e., the product of λ and L_m is less than the Shannon channel capacity $C_{v2v}^{\max}$.

When the number of RBs available for V2V link of each task is sufficient, it is observed that λ decreases slowly and maintains a high value when the task size L_m is small, e.g., $L_m < 0.8 \times 10^5$ for $RB = 6$. It is because Shannon channel capacity $C_{v2v}^{\max}$ according to (11b), when the number of RBs is large, $C_{v2v}^{\max}$ is also high, and λ can be kept at a relatively high value.

2) System Latency: To investigate the convergence, Fig. 4 indicates the convergence of the PC5-GO algorithm. The convergence curve fluctuates and reaches the stationary value within 3 steps, which shows the high convergence speed of the PC5-GO algorithm.

Fig. 5 shows the system latency versus the vehicle density β. It can be observed that VC increases dramatically with the increase of vehicle density, while SC remains unchanged. This is because SC is only related to the radio resource of Uu interface between the TV and the VEC server, but not to the vehicle density. When the vehicle density ranges from 0.002 to 0.009, the latency performance of PC5-GO is better than that of NR-O. This is because that the STP of task data packet at PC5 interface is high when the vehicle density is low. Then, with the vehicle density increasing to 0.02, the growth rate of latency of PC5-GO is greater than that of NR-O. This is because, from the mathematical expression, SSP decreases exponentially with the increase of vehicle density. When the vehicle density increases to above 0.08, the latency of PC5-GO tends to be stable, while the latency of NR-O still increases. Therefore, the optimal offloading scheme under different vehicle densities can be concluded, that is, PC5-GO should be adopted when the density is below or above certain thresholds, and NR-O is adopted otherwise. On the other hand, in the middle range, as the performance gain of NR-O over PC5-GO is quite small, so it is also practical to use PC5-GO to reduce system complexity.

Fig. 6 shows the comparison of system latency with different number of tasks M. Note that the system latency of PC5-GO algorithm is lower than all other schemes, i.e., SC, VC, and NR-O. With the increase of M, the latency increases of SC faster than other schemes, which indicates that the increase of number of tasks brings a heavy burden to VEC server for its centralized computation.

Fig. 7 depicts the comparison of system latency versus the number of CVs N. It is seen that the PC5-GO algorithm always realizes lower system latency than SC, VC, and NR-O. The system latency of SC remains unchanged as N changes,

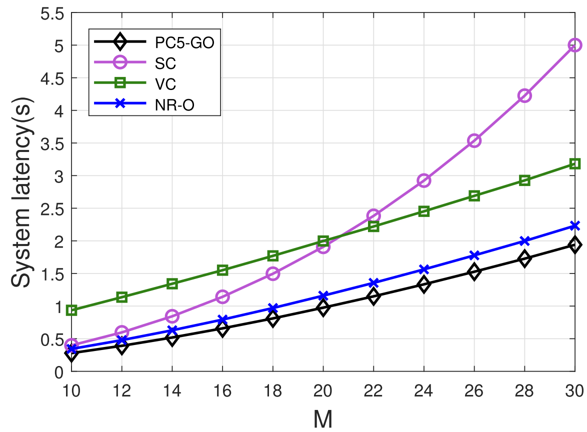


Fig. 6. System latency versus the number of tasks.

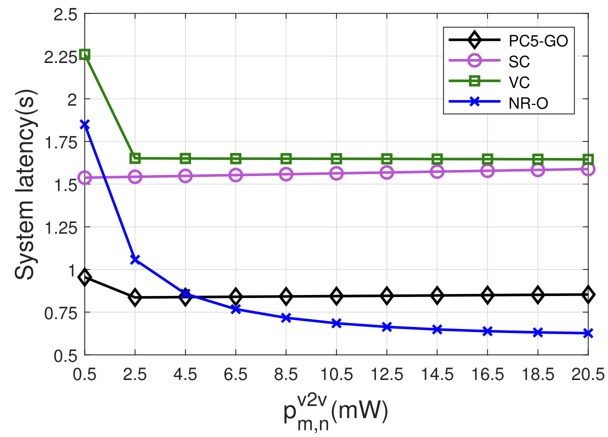


Fig. 8. System latency versus the V2V transmission power.

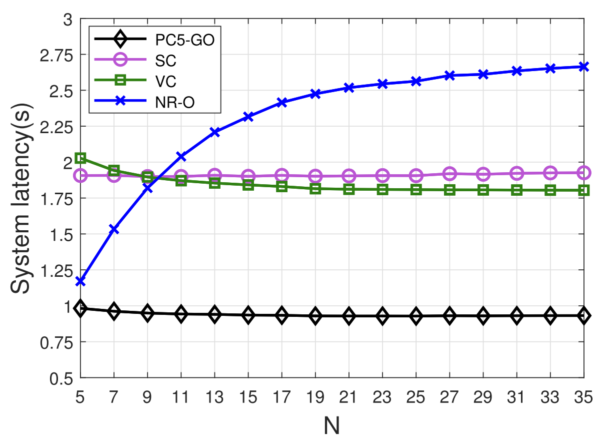


Fig. 7. System latency versus the number of CVs.

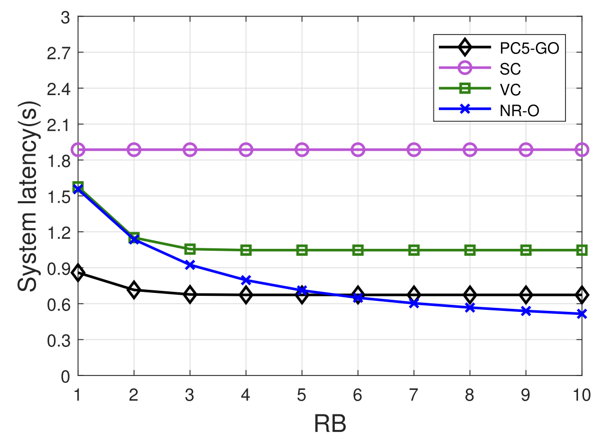
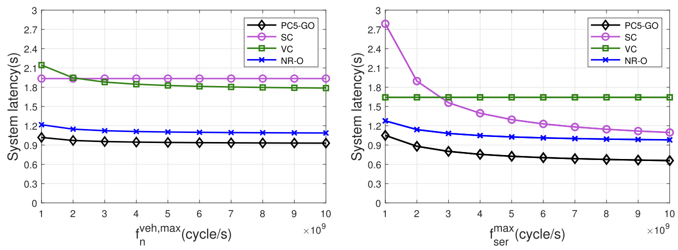


Fig. 9. System latency versus the V2V bandwidth.

since SC only utilizes the computation resources of the VEC server. Besides, with the increase of N, the latency of the PC5-GO and VC algorithms decrease at first, and then it becomes stable. It is because that the increasing number of CVs can increase the vehicular computation capability, but when the computation capability are far greater than the computing demand of tasks, increasing the number of vehicles will not reduce the latency. Moreover, the latency of NR-O increases with the increasing of N, as the increase of the number of CVs will increase mutual interference and further reduces the transmission rate.

Fig. 8 shows the system latency versus the V2V transmission power $p^{v2v}_{m,n}$ at the PC5 interface. With the V2V transmission power increases, the system latency of PC5-GO, VC, NR-O schemes decreases, while the latency of SC increases slightly. It is because that the increase of V2V transmission power will increase the transmission rate of PC5 interface and further reduce the latency. Besides, for the SC scheme, when the total power constraint remains unchanged, the increase of V2V transmission power will reduce the transmission rate of Uu interface, which will further lead to the increase of latency. Moreover, when the $p^{v2v}_{m,n}$ is greater than 4.5 mW, the latency of NR-O is less than that of PC5-GO, which reason is that the packet transmit frequency λ is limited by the Shannon channel capacity. Hence, when the transmission power limit of V2V link is small, PC5-GO is preferred, otherwise NR-O is preferred.

Fig. 9 shows the system latency versus the V2V bandwidth, i.e., the number of resource blocks (RB). The system latency of SC does not change with the change of number of RB. When the number of RBs is small, i.e, $RB \leq 6$, the latency performance of PC5-GO is better than that of NR-O, and the number of RBs is large, i.e., $RB > 6$, the latency performance of NR-O is better. It is because that C-V2X transmits data packets on a fixed set of subchannels, i.e., RBs, while NR-O is based on orthogonal allocation of all RBs to each data packet, and then transmits data packets to each CV. Thus, when the number of RBs increases, the transmission rate of PC5 interface of PC5-GO will increases first, but when the number of RBs exceeds the number of subchannel configurations, it will not increase the transmission rate. Besides, when the wireless resources, i.e., RB, are sufficient, the latency of NR-O is limited by the computation resources. Therefore, it can be concluded that when the number of RBs occupied by the TV is less than the number of RBs in the subchannel configuration, it is preferred to PC5-GO algorithm, otherwise, the NR-O algorithm is preferred. In most cases, it is difficult for users to occupy many RBs due to the large number of users applying



(a) Vehicular frequency (b) VEC frequency

Fig. 10. Impact of (a) computation frequency of cloudlet vehicles and (b) VEC server computation frequency on system latency.

for RBs at the same time, thus the performance of PC5-GO is better than that of NR-O in general.

Fig. 10(a) shows the comparison of system latency with different computation frequency of CVs, i.e., $f_n^{veh,max}$. Here the computation frequency of all CVs is set as same value. It is seen that the system latency of PC5-GO algorithm achieves the best performance than SC, VC, and NR-O schemes, and the system latency of SC remains unchanged as $f_n^{veh,max}$ changes. Moreover, the latency of the PC5-GO, NR-O, and VC decreases with the increasing of computation frequency of CVs, because the increase of computation resources of CVs will reduce the computation latency.

Fig. 10(b) shows the system latency versus the VEC server computation frequency among the PC5-GO and baseline schemes. We can observe that the system latency of PC5-GO algorithm significantly outperforms SC, VC, and NR-O schemes. When VEC server computation frequency increases, the system latency of the PC5-GO, NR-O, and SC are reduced accordingly except VC scheme, which reason is that VC scheme only utilizes the computation resources of CVs. Moreover, as f_{ser}^{max} increases, the latency of PC5-GO, NR-O, and SC tends to be stable for the limitation of wireless resources.

VII. Conclusion

In this paper, a novel offloading strategy based C-V2X has been proposed in the multi-tier vehicular edge computing system. We have formulated the successful transmission probability, which reflects the influence of vehicle sensing characteristics on the transmission rate of V2V link, i,e., PC5 interface. The vehicle offloads the part of each task to the VEC server by PC5 interface and other part to CVs by PC5 interface. The optimization problem has been formulated to minimize the task processing latency by optimizing offloading matrix, communication resource of Uu/PC5 interface, and the computation frequency of CVs and VEC server. To deal with the coupling of communication resource of Uu and PC5 interfaces, we have transformed the objective function and decomposes the transformed problem into two subproblems, i.e., resource allocation and offloading strategy subproblems. By alternative optimization, the PC5-GO algorithm has been proposed to obtain the optimal communication and computation resource allocation, and offloading strategy of task partial offloading. The simulation results demonstrated that proposed PC5-GO algorithm can reduce the task processing latency compared with the other baseline schemes by 13.7% at least. To sum up, the PC5-GO can outperform NR-O in general or PC5-GO can achieve comparable performance as centralized NR-O, while it is a distributed solution and can work in more general settings no matter whether there is BS coverage or not.

For future work, we will consider the offloading strategy and resource allocation of multiple task vehicles in C-V2X based VEC system. In addition, the influence of task characteristics on the offloading strategy needs to be further discussed. The key challenge that affects the C-V2X aided VEC system is how to build a multi-tier computing ecosystem, among which the challenges to be solved include the promotion of C-V2X terminals, incentive mechanism of computing power trading, and privacy security.

Appendix A
Proof of Proposition 1

The proposition can be proofed by contradiction. The optimal latency is defined as T^*. When $T_m^{ser-o} + T_m^{ser-c} = T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$, the optimal λ^*, $f^{ser,*}$, $f^{veh,*}$, α^* is achieved.

Case 1: Assuming λ^*, $f^{ser,*}$, $f^{veh,*}$, α^* is obtained when $T_m^{ser-o} + T_m^{ser-c} > T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$. When $\alpha_{m,n}$ increases, i.e., $\alpha_{m,N+1}$ decreases, the $T_m^{ser-o} + T_m^{ser-c}$ decreases and $T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$ increases. Thus there exist a point $\widetilde{\alpha}_{m,n}$, where $\alpha_{m,n}^*$ increases to $\widetilde{\alpha}_{m,n}$, satisfying that $T_m^{ser-o}(\alpha_{m,n}^*) + T_m^{ser-c}(\alpha_{m,n}^*) > T_m^{ser-o}(\widetilde{\alpha}_{m,n}) + T_m^{ser-c}(\widetilde{\alpha}_{m,n}) = T_{m,n}^{veh-o}(\widetilde{\alpha}_{m,n}) + T_{m,n}^{veh-c}(\widetilde{\alpha}_{m,n}) > T_{m,n}^{veh-o}(\alpha_{m,n}^*) + T_{m,n}^{veh-c}(\alpha_{m,n}^*)$. It is seen that the minimum latency is $T_m^{ser-o}(\widetilde{\alpha}_{m,n}) + T_m^{ser-c}(\widetilde{\alpha}_{m,n}) = T_{m,n}^{veh-o}(\widetilde{\alpha}_{m,n}) + T_{m,n}^{veh-c}(\widetilde{\alpha}_{m,n})$, which is lower than $T_m^{ser-o}(\alpha_{m,n}^*) + T_m^{ser-c}(\alpha_{m,n}^*)$. Therefore, the result contradicts the previous assumption.

Case 2: Assuming λ^*, $f^{ser,*}$, $f^{veh,*}$, α^* is obtained when $T_m^{ser-o} + T_m^{ser-c} < T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$. When $\alpha_{m,n}$ decreases, i.e., $\alpha_{m,N+1}$ increases, the $T_m^{ser-o} + T_m^{ser-c}$ increases and $T_{m,n}^{veh-o} + T_{m,n}^{veh-c}$ decreases. Thus there exist a point $\widetilde{\alpha}_{m,n}$, where $\alpha_{m,n}^*$ decreases to $\widetilde{\alpha}_{m,n}$, satisfying that $T_m^{ser-o}(\alpha_{m,n}^*) + T_m^{ser-c}(\alpha_{m,n}^*) < T_m^{ser-o}(\widetilde{\alpha}_{m,n}) + T_m^{ser-c}(\widetilde{\alpha}_{m,n}) = T_{m,n}^{veh-o}(\widetilde{\alpha}_{m,n}) + T_{m,n}^{veh-c}(\widetilde{\alpha}_{m,n}) < T_{m,n}^{veh-o}(\alpha_{m,n}^*) + T_{m,n}^{veh-c}(\alpha_{m,n}^*)$. It is seen that the minimum latency is $T_m^{ser-o}(\widetilde{\alpha}_{m,n}) + T_m^{ser-c}(\widetilde{\alpha}_{m,n}) = T_{m,n}^{veh-o}(\widetilde{\alpha}_{m,n}) + T_{m,n}^{veh-c}(\widetilde{\alpha}_{m,n})$, which is lower than $T_{m,n}^{veh-o}(\alpha_{m,n}^*) + T_{m,n}^{veh-c}(\alpha_{m,n}^*)$. Therefore, the result contradicts the previous assumption.

Based on the above analysis, the optimal solution λ^*, $f^{ser,*}$, $f^{veh,*}$, α^* can be obtained when $T_m^{ser-o}+T_m^{ser-c} = T_{m,n}^{veh-o}+T_{m,n}^{veh-c}$.

This completes the proof.

Appendix B
Proof of Proposition 2

The constraint (11b), (11c), (11d), (11e), (11i), (14a) are all convex constraints, we only focus on the convexity of objective function as follows.

$$\sum_{m=1}^{M} T_{m,n}^{veh-o} + T_{m,n}^{veh-c} = \sum_{m=1}^{M} \frac{\alpha_{m,n}}{((1-\frac{\lambda}{N_{frame}})\cdot \mathcal{P}_{SEN}\cdot PSR(d_n))\lambda} + \frac{\alpha_{m,n} L_m C_m}{f_{m,n}^{veh}} \tag{25}$$

Next we will prove Hessian matrix of objective function of Problem (15) is positive definite matrix to further verify its convexity [46]. The Hessian of objective function of Problem (15) with respect to $\boldsymbol{\lambda}$ and $\boldsymbol{f^{veh}}$ is given by

$$\boldsymbol{H} = \begin{bmatrix} \frac{\partial^2 f}{\partial\lambda\partial\lambda} & \frac{\partial^2 f}{\partial\lambda\partial f_{m,n}^{veh}} \\ \frac{\partial^2 f}{\partial f_{m,n}^{veh}\partial\lambda} & \frac{\partial^2 f_{m,n}^{veh}}{\partial f_{m,n}^{veh}\partial f_{m,n}^{veh}} \end{bmatrix} = \begin{bmatrix} \frac{\partial^2 f}{\partial\lambda\partial\lambda} & 0 \\ 0 & \frac{\partial^2 f_{m,n}^{veh}}{\partial f_{m,n}^{veh}\partial f_{m,n}^{veh}} \end{bmatrix} \tag{26}$$

Then the first-order principal minor is given by

$$\frac{\partial^2 f}{\partial\lambda\partial\lambda} = \sum_{i=1}^{M}\sum_{j=1}^{N} \frac{\alpha_{m,n}\lambda\left[\zeta(\lambda)e_1^2\lambda + 2e_1\left(-s\lambda e_1+e_2\right)^2\right]}{e^{-s\lambda}PSR(d)\left[\left(1-\delta_{HD}\right)\lambda\right]^4} \tag{27}$$

where $s = \frac{K\beta(2d_{sen})}{N_{sub-f}N_{sub-c}}$, $e_1 = 1-\delta_{HD}$, $e_2 = 1-2\delta_{HD}$, and $\xi(\lambda) = s\left(-s\lambda e_1 + 2e_2\right) + \frac{2(s+1)}{N_{\text{frame}}}$.

Next, we focus on the positive and negative of $\frac{\partial^2 f}{\partial\lambda\partial\lambda}$. For convenience of description, we define the $g(\lambda) = \frac{\partial^2 f}{\partial\lambda\partial\lambda}$. We can obtain that $\frac{\partial^2 g(\lambda)}{\partial\lambda\partial\lambda} < 0$ by calculation, thus the $\frac{\partial g(\lambda)}{\partial\lambda}$ is monotonically decreasing. Besides, we can derive that the $\frac{\partial g(\lambda)}{\partial\lambda}|_{\lambda=0} > 0$ and $\frac{\partial g(\lambda)}{\partial\lambda}|_{\lambda=N_{frame}} < 0$. Thus we can conclude that $g(\lambda)$ increases first and then decreases. Since the $g(\lambda)_{\lambda=0} > 0$ and $g(\lambda)_{\lambda=N_{frame}} > 0$, we can obtain that $g(\lambda) > 0$, i.e., $\frac{\partial^2 f}{\partial\lambda\partial\lambda} > 0$. Moreover, we can obtain

$$\frac{\partial^2 f_{m,n}^{veh}}{\partial f_{m,n}^{veh}\partial f_{m,n}^{veh}} = \frac{2\alpha_{m,n}L_m C_m}{\left(f_{m,n}^{veh}\right)^3} > 0 \tag{28}$$

The second-order principal minor is given by

$$H_{11}H_{22} - H_{12}H_{21} = \frac{\partial^2 f}{\partial\lambda\partial\lambda}\frac{\partial^2 f}{\partial f_{m,n}^{veh}\partial f_{m,n}^{veh}} - 0 > 0 \tag{29}$$

Thus the Hessian matrix of objective function of Problem (15) is positive definite matrix. Therefore Problem (15) is convex.

This completes the proof.

Appendix C
Proof of Theorem 3

The partial derivative of Lagrangian function $\mathcal{L}$ w.r.t. s_m^{Uu} is given as

$$\frac{\partial\mathcal{L}}{\partial s_m^{Uu}} = \frac{\alpha_{m,N+1}L_m}{B_{m,N+1}} + \frac{\eta_1}{\gamma_m}\left(\frac{-\ln 2\cdot 2^{\frac{1}{s_m^{Uu}}}}{(s_m^{Uu})^2}\right) \tag{30}$$

Then the second-order derivative of Lagrangian function $\mathcal{L}$ w.r.t. s_m^{Uu} is $\frac{\partial^2\mathcal{L}}{\partial(s_m^{Uu})^2} = \frac{\eta_1 2^{\frac{1}{s_m^{Uu}}}}{\gamma_m(s_m^{Uu})^3}\left(\frac{(\ln 2)^2}{s_m^{Uu}} + 2\ln 2\right) > 0$. Thus the function $\mathcal{L}$ is monotonously increasing with $s_m^{Uu} \in [s_m^{Uu,min}, +\infty)$, where $s_m^{Uu,min} = \frac{1}{\log_2(1+\gamma_m(P^{\max}-P^{PC5}))}$. According to (30), we have $\lim_{s_m^{Uu}\to+\infty}\frac{\partial\mathcal{L}}{\partial s_m^{Uu}} = \frac{\alpha_{m,N+1}L_m}{B_{m,N+1}}$. We set the parameter $k_m = \frac{\partial\mathcal{L}}{\partial s_m^{Uu}}|_{s_m^{Uu}=s_m^{Uu,min}}$, we have $\frac{\partial\mathcal{L}}{\partial s_m^{Uu}} \in [k_m, \frac{\alpha_{m,N+1}L_m}{B_{m,N+1}}]$. Due to the positive and negative uncertainty of k_m, we discuss the two cases about k_m as follows.

Case 1: When $k_m > 0$, we have $\frac{\partial\mathcal{L}}{\partial s_m^{Uu}} > 0$. Based on the (30), we can obtain that $h_i < h_i^{th} = \frac{\sigma^2}{p_i^{max}}\left(\frac{Q}{\mathcal{W}(Q)\ln 2} - 1\right)$, where $Q = \ln(\ln 2) + \left(\frac{\alpha_i}{\lambda_i^*} + p_i^{\max}\right)\ln 2$.

Thus $\mathcal{L}$ is a monotonously increasing function with s_m^{Uu}. Then we can obtain $s_m^{Uu,*} = s_m^{Uu,min} = \frac{1}{\log_2(1+\gamma_m(P^{\max}-P^{PC5}))}$, i.e., optimal transmission power of vehicle i satisfies $p_{m,N+1}^{Uu,*} = P^{\max} - P^{PC5}$, which means that the offloading from TV to VEC server adopts the maximum transmission power of Uu interface.

Case 2: $k_m \le 0$, which indicates there exists a stationary point satisfies $\frac{\partial\mathcal{L}}{\partial s_m^{Uu}} = 0$. Thus we have

$$\frac{\alpha_{m,N+1}L_m}{B_{m,N+1}} + \frac{\eta_1}{\gamma_m}\left(\frac{-\ln 2\cdot 2^{\frac{1}{s_m^{Uu}}}}{(s_m^{Uu})^2}\right) = 0 \tag{31}$$

With some operations, (31) can be transformed into

$$\left(s_m^{Uu}\Delta^{\frac{1}{2}}\right)^{s_m^{Uu}\Delta^{\frac{1}{2}}} = 2^{2\Delta^{\frac{1}{2}}} \tag{32}$$

where $\Delta = \frac{\gamma_m\alpha_{m,N+1}L_m}{\eta_1\cdot\ln 2\cdot B_{m,N+1}}$, which is defined in Theorem 3. Then, we introduce the Lambert $\mathcal{W}$ function to deal with (32), which is the inverse function of $z\exp(z) = x$, i.e.,$z = \mathcal{W}(x)$. Hence the optimal $s_m^{Uu,*}$ can be given by

$$s_m^{Uu,*} = \frac{\frac{\ln 2}{2}}{W\left(\frac{\ln 2\Delta^{\frac{1}{2}}}{2}\right)} \tag{33}$$

By $s_m^{Uu} = \frac{1}{\log_2\left(1+\gamma_m p_{m,N+1}^{Uu}\right)}$, we can obtain the optimal transmission power of PC5 interface as follows.

$$p_{m,N+1}^{Uu,*} = \frac{1}{\gamma_m}\left(2^{\frac{\mathcal{W}(\frac{\ln 2\Delta^{\frac{1}{2}}}{2})}{\frac{\ln 2}{2}}} - 1\right) \tag{34}$$

This completes the proof.

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Weiyang Feng (Graduate Student Member, IEEE) received the B.S. degree from Northeast Forestry University, Harbin, China, in 2018. He is currently pursuing the Ph.D. degree with Beijing Jiaotong University, Beijing, China. His current research interests include edge/fog computing, vehicular networks, wireless resource allocation, and NOMA.

Siyu Lin (Member, IEEE) received the B.E. and Ph.D. degrees in electronic engineering from Beijing Jiaotong University, Beijing, China, in 2007 and 2013, respectively. From 2009 to 2010, he was an Exchange Student with the Universidad Politecnica de Madrid, Madrid, Spain. From 2011 to 2012, he was a Visiting Student with the University of Victoria, Victoria, BC, Canada. He is currently a Professor with Beijing Jiaotong University. His main research interests include wireless communication networks and railway mobile communications. He has served as the Track Co-Chair for IEEE VTC2020-Fall and VTC2021-Fall. He received the First and Second Class Award of Science and Technology in Railway in 2017 and 2021, respectively.

Ning Zhang (Senior Member, IEEE) received the Ph.D. degree in electrical and computer engineering from the University of Waterloo, Canada, in 2015. After that, he was a Post-Doctoral Research Fellow with the University of Waterloo and the University of Toronto, respectively. Since 2020, he has been an Associate Professor and the Canada Research Chair with the Department of Electrical and Computer Engineering, University of Windsor, Canada. His research interests include connected vehicles, mobile edge computing, wireless networking, and security. He received nine best paper awards from conferences and journals, such as IEEE GLOBECOM, IEEE ICC, IEEE ICCC, IEEE WCSP, and *Journal of Communications and Information Networks*. He also received the IEEE TCSVC Rising Star Award and the IEEE ComSoc Young Professionals Outstanding Nominee Award. He also serves/served as the TPC Chair for IEEE VTC 2021 and IEEE SAGC 2020, a General Chair for IEEE SAGC 2021, a Track/Workshop Chair for several international conferences and workshops, including IEEE ICC, VTC, and INFOCOM and MOBICOM Workshops. He serves/served as an Associate Editor for IEEE TRANSACTIONS ON MOBILE COMPUTING, IEEE COMMUNICATIONS SURVEYS AND TUTORIALS, IEEE INTERNET OF THINGS JOURNAL, and IEEE TRANSACTIONS ON COGNITIVE COMMUNICATIONS AND NETWORKING. He is a Highly Cited Researcher (Web of Science).

Gongpu Wang (Member, IEEE) received the B.Eng. degree in communication engineering from Anhui University, Hefei, Anhui, China, in 2001, the M.Sc. degree from the Beijing University of Posts and Telecommunications, Beijing, China, in 2004, and the Ph.D. degree from the University of Alberta, Edmonton, AB, Canada, in 2011. From 2004 to 2007, he was an Assistant Professor with the School of Network Education, Beijing University of Posts and Telecommunications. He is currently a Full Professor with the School of Computer and Information Technology, Beijing Jiaotong University, China. His research interests include wireless communications, signal processing, and the Internet of Things.

Bo Ai (Fellow, IEEE) received the M.S. and Ph.D. degrees from Xidian University, Xi'an, China, in 2002 and 2004, respectively, and the degree from Tsinghua University, Beijing, China, in 2007.

He was a Visiting Professor with the Department of Electrical Engineering (EE), Stanford University, Stanford, CA, USA, in 2015. He is currently working as a Full Professor and a Ph.D. Advisor with Beijing Jiaotong University, Beijing, where he is also the Deputy Director of the State Key Laboratory of Rail Traffic Control and Safety and the International Joint Research Center. He is one of the main responsible people for Beijing (urban rail operation control system) International Science and Technology Cooperation Base, and the Backbone Member of the Innovative Engineering-Based jointly granted by the Chinese Ministry of Education and the State Administration of Foreign Experts Affairs. He has authored or coauthored eight books and published over 300 academic research articles in his research area. He holds 26 invention patents. He has been the research team leader for 26 national projects and has won some important scientific research prizes. Five of his articles have been the ESI highly cited articles. He has been notified by the Council of Canadian Academies (CCA) that, based on Scopus database, he has been listed as one of the top 1% authors in his field all over the world. He has also been feature interviewed by *IET Electronics Letters*. His research interests include research and applications of channel measurement and channel modeling and dedicated mobile communications for rail traffic systems.

Prof. Ai is a fellow of IET. He has received many awards, such as the Distinguished Youth Foundation and the Excellent Youth Foundation Award by the National Natural Science Foundation of China, the Qiushi Outstanding Youth Award by the Hong Kong Qiushi Foundation, the New Century Talents by the Chinese Ministry of Education, the Zhan Tianyou Railway Science and Technology Award by the Chinese Ministry of Railways, and the Science and Technology New Star Award by the Beijing Municipal Science and Technology Commission. He received the Honor of Excellent Post-Doctoral Research Fellow from Tsinghua University. He is the Vice Chair of the IEEE VTS Beijing Chapter and the Chair of the IEEE BTS Xi'an Chapter. He was the co-chair or the session/track chair for many international conferences. He is also an Editorial Committee Member of *Wireless Personal Communications* journal. He is also an Associate Editor of the IEEE ANTENNAS AND WIRELESS PROPAGATION LETTERS and the IEEE TRANSACTIONS ON CONSUMER ELECTRONICS. He is the Lead Guest Editor of Special Issues on the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, the IEEE ANTENNAS AND PROPAGATION LETTERS, and the *International Journal on Antennas and Propagation*. He is also a Distinguished Lecturer of the IEEE Vehicular Technology Society.

Lin Cai (Fellow, IEEE) received the M.A.Sc. and Ph.D. degrees in electrical and computer engineering from the University of Waterloo, Waterloo, ON, Canada, in 2002 and 2005, respectively. Since 2005, she has been with the Department of Electrical and Computer Engineering, University of Victoria, where she is currently a Professor. Her research interests include communications and networking, with a focus on network protocol and architecture design supporting emerging multimedia traffic, and the Internet of Things. She is a Steacie Memorial Fellow of NSERC E. W. R. and a fellow of Engineering Institute of Canada (EIC). In 2020, she was elected as a member of the Royal Society of Canada's College of New Scholars, Artists and Scientists, and a 2020 "Star in Computer Networking and Communications" by N2Women. She is a Distinguished Lecturer of the IEEE Vehicular Technology Society and the IEEE Communications Society.