Computation Offloading and Resource Allocation in Vehicular Networks Based on Dual-side Cost Minimization

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***Abstract*—The proliferation of smart vehicular terminals (VTs) and their resource hungry applications imposes serious challenges to the processing capabilities of VTs and the delivery of vehicular services. Mobile Edge Computing (MEC) offers a promising paradigm to solve this problem by offloading VT applications to proximal MEC servers, while TV white space (TVWS) bands can be used to supplement the bandwidth for computation offloading. In this paper, we consider a cognitive vehicular network (CVN) that uses the TVWS band, and formulate a dual-side optimization problem, to minimize the cost of VTs and that of the MEC server at the same time. Specifically, the dual-side cost minimization is achieved by jointly optimizing the offloading decision and local CPU frequency on the VT side, and the radio resource allocation and server provisioning on the server side, while guaranteeing network stability. Based on Lyapunov optimization, we design an algorithm called DDORV to tackle the joint optimization problem, where only current system states, such as channel states and traffic arrivals, are needed. The closed-form solution to the VT-side problem is obtained easily by derivation and comparing two values. For MEC server side optimization, we first obtain server provisioning independently, and then devise a continuous relaxation and Lagrangian dual decomposition based iterative algorithm for joint radio resource and power allocation. Simulation results demonstrate that DDORV converges fast, can balance the cost-delay tradeoff flexibly, and can obtain more performance gains in cost reduction as compared with existing schemes.**

***Index Terms*—Computation offloading, mobile edge computing, resource allocation, stochastic optimization, vehicular networks.**

I. Introduction

With the rapid development of Internet of Vehicles (IoV), vehicles become smarter in supporting intelligent applications, such as autonomous driving, video-aided real-time navigation, and interactive gaming [1]–[4]. Many of these applications are computationally-intensive, power-hungry, delay-sensitive, and bandwidth-demanding, which on the one hand, consumes a large amount of energy and imposes great pressures on the processing capabilities of vehicular terminals (VTs) [5], and on the other hand, poses a great burden on radio access networks [6].

To tackle the issues such as poor terminal processing capabilities and high energy consumption, mobile edge computing (MEC) [7]–[18] enabled vehicular networking [20], [21] has been regarded as a promising solution, where the processing of VT applications is pushed to the adjacent radio access networks. By attaching MEC servers to roadside units, i.e., MEC enabled roadside units (MRSU) which are deployed along the roadside offering wireless access to VTs, an MEC based integrated communication and computation platform can be constituted. By offloading computations to MEC servers, many complex VT applications can be enabled, and/or the energy consumption of VTs can be reduced, and/or the response of applications can be accelerated [9]–[14].

Since the input data for computation offloading should be transmitted to MEC servers via radio access networks through vehicular-to-roadside (V2R) communications, the chronic problem of radio spectrum scarcity has to be first considered, otherwise the performance and efficiency of task offloading may be deteriorated even neutralized. Long-term evolution-vehicle (LTE-V) [22] and dedicated short-range communications (DSRC) [23] both have limitations when employed for computation offloading in vehicular networks. The cellular network based LTE-V is facing issues of the explosive growth of mobile data traffic (in contrast to the scarcity of licensed cellular spectrum) and the relatively expensive cost of using the licensed spectrum. More importantly, V2R communications are usually more appealing during long journeys along motorways where cellular 3G/4G/5G coverage and services are typically unsatisfactory [6], [24]. For DSRC, many studies have shown that the bandwidth is insufficient for supporting resource-demanding V2R communications [2], [3], [25]. The short transmission range of WiFi systems have limited their usage in V2R scenarios, where a large number of WiFi APs along the road would be needed for seamless coverage, which is uneconomical, and will result in frequent handovers of high-speed VTs [6], [24].

In the meanwhile, plenty of TV White Spaces (TVWS) bands, which have desirable long-distance propagation char-

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acteristics [6], [24], [25], can be used as a feasible supplement to the limited DSRC bandwidth [3], [6], [24]–[27], and related standards have been put forwarded by relevant organizations such as U.S. Federal Communications Commission (FCC) [28]. Therefore, to solve the related wireless spectrum problems, in this paper we will investigate vehicular computation offloading using TVWS band for wireless data transmission. However, new problem arises: to exploit TVWS band, the basic principle is the protection of primary users (PUs), and the IEEE 802.22 PUs could transmit with a power up to 4 W [29], while the secondary users (SUs), such as VTs performing computation offloading in a cognitive vehicular network (CVN), are only permitted to use a power no more than 100 mW [29]. Consequently, the offloading from VTs may be blocked by 802.22 PUs. Therefore, the power asymmetry problem should be settled when VTs reuse the TVWS spectrum.

In most existing works, computation offloading optimizations are usually performed unilaterally, i.e., only concerning the user-side or the server-side performance. On the user side (e.g., VTs), while offloading tasks to MEC servers to save energy consumption, VTs need to minimize costs including the energy consumption in data transmission and the fees for the computation and communication services [17], by optimizing offloading decisions and the allocation of local CPU frequency. On the server side (e.g., MRSU), while it makes profit from providing VTs with computing services and the corresponding data transmission services in data offloading, it needs to minimize costs including the cost for renting wireless bandwidth, and the electricity bills for running edge servers, by optimizing the allocation of radio resources and edge servers.

Considering that MRSU and VTs have conflict objectives while each trying to minimize its own cost, in this paper, we formulate two intercoupled dual-side cost minimization problems in an integrated IEEE 802.22 based vehicular framework. The dual-side cost minimization involves stochastic optimization problems, which is much more challenging than unilateral user-side or server-side optimization because on the one hand, the two stochastic optimization problems are intercoupled with each other and the optimization in each frame is also intercoupled, and on the other hand, both stochastic optimization problems involve a large amount of state information as well as control variables. With the help of Lyapunov optimization theory, we devise low complexity algorithms to solve the two intertwined problems.

The main contributions are summarized as follows:

- We develop a task offloading framework for an IEEE 802.22-CVN coexisting network, where the IEEE 802.22 channel is reused by the CVN for computational task offloading, with the unique features of the TVWS wireless channels such as temporal and spatial changes in channel availability, and FCC's requirements for the protection of PUs taken into consideration.
- We formulate a dual-side cost minimization in an integrated framework under a competition scenario where VTs and MRSU aim to minimize their own costs. On the VT-side, each VT optimizes its computation offloading decision and local CPU frequency control independently so as to minimize its cost, while on the MRSU-side, the server provisioning, the IEEE 802.22 burst (which will be detailed below) assignment, and the transmit power control are jointly optimized to minimize the cost of MRSU.
- Leveraging Lyapunov optimization, we decouple the two stochastic optimization problems into independent per-frame optimizations, without requiring any knowledge of future task arrivals or network state information. In each frame, the VT-side offloading decision is obtained by comparing the cost of local processing and that of task offloading, and the VT's local CPU frequency is obtained by the derivative of the objective function. For MRSU-side optimization, we first devise simple algorithm for server provisioning, and then we develop a continuous relaxation and Lagrange dual decomposition based low-complexity algorithm to obtain the joint IEEE 802.22 burst allocation and transmit power control policies.
- Simulation results verified the convergence of our proposed iterative radio resource allocation algorithm, the tradeoff between the cost and queue length, and the performance of our proposed joint optimization algorithm compared with other existing algorithms.

The remainder of this paper is organized as follows. Related works are presented in Section II. Section III and Section IV introduce the system model and the dual-side problem formulation, respectively. In Section V, we transform the original formulated problem into per-frame optimization by employing Lyapunov optimization. The VT-side per-frame optimization is solved in Section VI, and the MRSU-side per-frame problem is settled in Section VII. In Section VIII we present the complexity analysis of our proposed algorithms. Simulation results are provided in Section IX. Finally, the paper is concluded in Section X.

II. Related Works

Recent years, MEC-based (or fog computing based) computation offloading has attracted a great deal of attentions and has stimulated extensive researches from distinct perspectives in terms of different metrics. Specifically, task partitioning and offloading policy is jointly optimized to maximize the energy conservation [9] or to minimize the energy consumption [10]. The works in [9], [10] were then extended to multi-user scenarios, where except offloading decision is optimized, the joint optimization of transmit power control and computation resource allocation [11], of radio bandwidth and computation resource allocation [12], of transmit power control, computation and radio bandwidth allocation [13] or resource block (RB) allocation [14] were also studied in different multi-user scenarios.

In the above references [9]–[14], the authors only considered the performance of processing a single task, nevertheless, for applications like multi-media and file backup, etc., the coupling among the random task arrivals should not be neglected, so long-term performance metrics and stochastic task models are more suitable. Reference [15] studied offloading decision optimization to minimize the average execution cost. The authors in [16] considered the joint optimization of offloading policy, the local CPU speed control, and network interface selection to minimize the time-averaged expected total average energy consumption.

However, the formulations in [9]–[16] are unilateral optimizations, which could not reflect the practical situation very well. The authors in [17] designed a practical dual-side optimization framework, where code offloading, computation resource allocation, and network interface selection policies were jointly optimized for mobile users, and service pricing were optimized for the service provider. The formulation with joint radio and computation resource allocation optimization for multi-user MEC systems was proposed in [18] to minimize the long-term averaged total power consumption of the MEC server and all its served mobile devices.

MEC-enabled vehicular networks have also attracted much attention from many researchers in recent years. The authors in [5] proposed an MEC based computation offloading framework for CVNs to minimize the VTs' cost in task offloading, while guaranteeing task processing delay and considering VTs' mobility. In [20], in order to maximize the economical profit of service providers while guaranteeing the delay tolerance of tasks, the authors developed a distributed algorithm to jointly optimize offloading decision making and computation resource allocation. The authors in [21] presented a vehicular fog computing architecture where vehicles acted as the infrastructure nodes to provide communication and computation services.

Nevertheless, since successful and efficient task offloading highly depends on the wireless channels, opening source of more available wireless band is more urgent to mitigate the spectrum scarcity of DSRC. The authors in [6], [24], [25] novelly proposed to open source of TVWS for wireless data transmission. The authors in [26], [27] ulteriorly proposed a coexistence framework including a CVN and an 802.22 network, by appropriate radio resource allocation scheme, spare IEEE 802.22 TVWS channels could be reused by CVNs and the spectrum shortage issue in CVNs could be relieved.

III. System Model

A. Basic Concepts and Scenario Description

IEEE 802.22 [29] was designed for broadband access employing the TVWS band in low population density regions. In the standard, the frame length is 10 milliseconds, and each frame is partitioned into an uplink and a downlink subframe. The uplink scheduling information of 802.22 PUs is incorporated in the downlink messages, which are broadcasted by the 802.22 base station (BS) at the beginning of each frame. PUs then access the TVWS channel according to the received uplink scheduling information. Through listening to the 802.22 network deployed in the same area, VTs can obtain the uplink scheduling information of 802.22 network. By implementing appropriate resource allocation schemes, the low power vehicular network could coexist with the high power 802.22 network, and reuse the TVWS channels of 802.22 network. To be in line with 802.22, in this paper, time is also partitioned into discrete frames and each is with a length of $T = 10$ milliseconds [29].

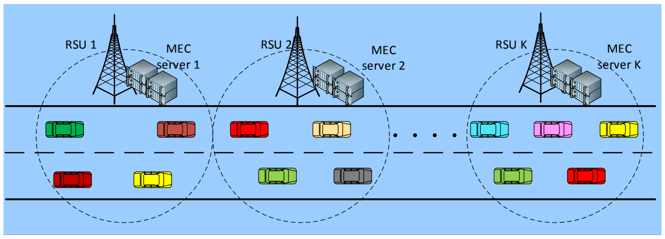

Fig. 1: Architecture of MEC-enabled vehicular networks.

As shown in Fig. 1, the road is partitioned into K segments, and each is covered by an RSU. When a VT moves from a segment to another, it needs to register with the new RSU. Suppose a VT moves at an average speed of 20 m/s, and the average coverage region of an RSU is 500 m, then the vehicle needs to register with a new RSU every 50 seconds, and can move at most 0.2 m during each frame. Consequently, the network can be considered to be quasi-static where VTs and wireless channels keep unchanged in each frame but can vary in different frames. We focus on MEC enabled V2R communication for the emerging intelligent nonsafety applications [3]. Those applications are usually computation-intensive and energy-demanding, however, contribute much to the commercial success of vehicular MEC. In accordance with the 802.22 standard and many existing works on CVN [26], [27], we adopt a centralized periodic model for each segment, i.e., scheduling is performed independently by each RSU among all its covered VTs in each frame, so in the following we will discuss the optimization within a certain RSU as a representative.

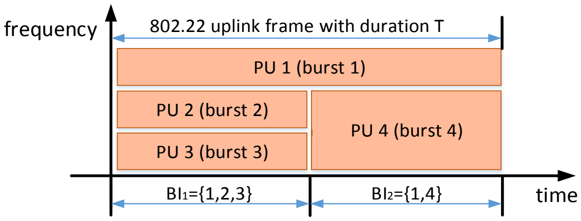

Fig. 2: Structure of 802.22 uplink subframe.

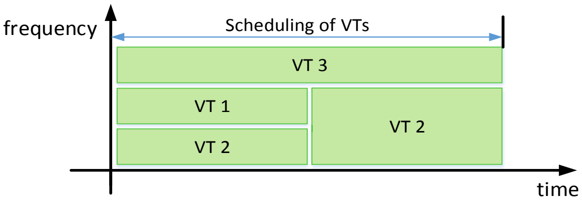

Fig. 3: Scheduling of VTs.

There's a TVWS channel consisting of several sub-channels to be reused by all the VTs. In 802.22, the basic resource element can be scheduled is called a "burst" [29], which is a two-dimensional element, consisting several subchannels in frequency domain and some orthogonal frequency division multiplexing (OFDM) symbols in time domain. There are two different types of uplink bursts in 802.22 standard. Type 1 burst occupies the whole uplink subframe in time domain, while a type 2 burst occupies part of the uplink subframe, which is called normal burst. For instance, burst 1 is a type 1 burst, and bursts 2–4 are type 2 bursts in Fig. 2. The uplink subframe is divided into several "burst intervals" (BIs) [29] on the basis of normal type 2 burst. We denote the set and the number of BIs as $\mathcal{L} = \{1, 2, ..., L\}$ and L, respectively. In IEEE 802.22 standard, $L \in \{1, 2, 3, 4\}$ [29], so there are two BIs in Fig. 2, where bursts 1, 2, 3 are located in BI_1, and bursts 1, 4 belong to BI_2. Let $\mathcal{M} = \{1, 2, ..., M\}$ and M be the set and number of PUs, respectively, and $C_{m,l} \in \{0, 1\}$ be the burst–BI indicator, where $C_{m,l} = 1$ means burst m locates in BI_l, and $C_{m,l} = 0$ otherwise. Each burst has been allocated to a PU in advance. In order to avoid unacceptable interference to PUs, FCC requires that the total transmit power of all the secondary users (SUs, i.e., VTs in our framework) sharing a TVWS channel should be no more than a threshold P^{max} (which is currently defined as 100 mW [28]) in each BI. For instance, both the total transmit power of VTs $1, 3$ in BI_1 and the total transmit power of VTs $2, 3$ in BI_2 should be no more than P^{max} in Fig. 3.

B. Computation Tasks and Data Arrival Models

Let $\mathcal{N} = \{1, 2, ..., N\}$ and N be the set and the number of VTs served by each MRSU, and assume that each VT is running fine-grained tasks [18]: at the beginning of each frame t, $D_n(t)$ bits of computation task arrive at VT n, with a processing density λ_n (in CPU cycles/bit). Without loss of generality, we assume $D_n(t)$ is i.i.d. over frames and may have an arbitrary probability distribution, and is limited by $0 \leq D_n(t) \leq D_n^{max}$. Since our system works in tiny frames and the tasks are fine-grained and arriving at each frame, so we can suppose the tasks do not have instantaneous delay constraints in each frame similar to many existing works [9], [16]–[19]. Then the task of VT n on frame t can be denoted as $\Lambda_n(t) = \{D_n(t), \lambda_n(t)\}$. In our MEC enabled vehicular network, $\Lambda_n(t)$ can be processed locally by VT n or be offloaded and executed remotely by its attached MRSU according to different offloading decisions. Our system works in frames and scheduling is performed in each uplink subframe (which is called frame for short) [26], [27].

C. Local processing Model

Let $x_n(t)$ denote the offloading decision of VT n on slot t, where $x_n(t) = 1$ indicates the application is offloaded to MRSU, and $x_n(t) = 0$ represents the application is processed by VT n locally.

In each frame t, if task $\Lambda_n(t)$ is executed locally, the power consumption of VT n is $p_n^{loc}(t) = k(f_n^{loc}(t))^3$, where k is a constant coefficient related to the CPU chip architecture [18], and $f_n^{loc}(t)$ denotes the local processing capability (in CPU cycles/s) of VT n, which is constrained by $0 \leq f_n^{loc}(t) \leq f^{max}$. Thus, in each frame t, the local execution time and energy consumption of VT n are given by $T_n^{loc}(t) = \frac{D_n(t)\lambda_n}{f_n^{loc}(t)}$ and $E_n^{loc}(t) = kD_n(t)\lambda_n(f_n^{loc}(t))^2$ (in J), respectively.

D. Remote Processing Model

If VT n offloads its task $\Lambda_n(t)$ on slot t, then all its arrival input data of size $D_n(t)$ will be transmitted to MRSU through the shared TVWS wireless links, afterwards $\Lambda_n(t)$ will be processed by MRSU, and finally the processing result is sent back to the VT. Since the processing result is usually very tiny, we neglect the downlink output return process, and only the uplink communication is discussed [12], [13], [18].

1) ***Communication Model:*** As the TVWS channel is shared by all PUs and reused by all VTs, before we perform burst allocation among all the VTs, we should first determine how PUs occupy a TVWS channel in each frame. We define the occupancy of a TVWS channel as a random variable t^{PU}, which refers to the spare time before a PU returns and occupies the 802.22 channel [26], [27]. Suppose the MRSUs know the information of the probability density function (PDF) $f(t^{PU})$ and cumulative distribution function (CDF) $F(t^{PU})$ of t^{PU} [6], [27], [28], [30], while exact behaviors of PUs are not clear.[1] Since PUs transmit with high power, consequently, the data transmission of VTs can be interrupted by PUs' return with non-zero probabilities. We consider the data transmission of a VT to be successful when the data is transmitted before PU returns, while the remaining transmission is blocked by PU and the transmitted data is deemed to be lost. Let t_m represent the time duration between two start times, i.e., the start time of burst m and the start time of the current uplink subframe. Then the valid transmission duration $\bar{T}_m$ of a VT on burst m can be obtained as follows. (i) If PUs return to burst m after the VT have finished the transmission, the whole burst is usable and we have $\bar{T}_m = T_m$. (ii) On the country, if PUs disturb the VT's transmission, then the valid transmission time is $\bar{T}_m = t^{PU} - t_m$. As t^{PU} is a random variable, the expected valid transmission time $\bar{T}_m$ of a VT on burst m can be given by the following Eq. (1). Since t_m, T_m and $F(t^{PU})$ are all known at the MRSUs, and thus $\bar{T}_m$ is a constant for each burst m.

Next we discuss burst allocation among VTs. Define $s_{nm}(t)$ as burst allocation indicator, where $s_{nm}(t) = 1$ represents burst m is allocated to VT n in frame t, and $s_{nm}(t) = 0$ otherwise. Let T_m and B_m denote the time duration and bandwidth of burst m, $p_m^{PU}(t)$ and $G_m^{PU}(t)$ represent the transmit power and channel gain of PU m on burst m in frame t, and $p_{nm}(t)$ and $G_{nm}(t)$ denote the transmit power and channel gain of VT n on burst m, respectively. In order to enable tractable analysis, we neglect the interference between MRSUs. Then the maximum transmit (in bps) rate of VT n on burst m in frame t can be given by

$$r_{nm}(t) = B_m \log_2 \left(1 + \frac{p_{nm}(t) G_{nm}(t)}{p_m^{PU}(t) G_m^{PU}(t) + \sigma^2} \right), \qquad (2)$$

where σ^2 is the power of additive Gaussian white noise. Thus,

[1] According to FCC standards [28], SUs obtain the information of the TVWS channels from a geotagged database [6], [27], [28], [30]. The information stored in the database is updated according to the information provided by PUs.

$$
\begin{aligned}
\bar{T}_m &= \int_0^\infty \Big[T_m \cdot \mathbf{1}_{t^{PU} \geq t_m + T_m} + (t^{PU} - t_m) \cdot \mathbf{1}_{t_m \leq t^{PU} \leq t_m + T_m}\Big] f(t^{PU}) dt^{PU} \\
&= \int_{t_m+T_m}^\infty T_m \cdot f(t^{PU}) dt^{PU} + \int_{t_m}^{t_m+T_m} (t^{PU} - t_m) f(t^{PU}) dt^{PU} \\
&= T_m[1 - F(t_m + T_m)] + \int_{t_m}^{t_m+T_m} (t^{PU} - t_m) dF(t^{PU}) \\
&= T_m[1 - F(t_m + T_m)] + T_m F(t_m + T_m) - \int_{t_m}^{t_m+T_m} F(t^{PU}) dt^{PU} \\
&= T_m - \int_{t_m}^{t_m+T_m} F(t^{PU}) dt^{PU}. \qquad (1)
\end{aligned}
$$

the maximum transmit rate of VT n in frame t is given by

$$r_n(t) = \sum_{m \in \mathcal{M}} s_{n,m}(t) r_{n,m}(t) \frac{\bar{T}_m}{T}. \qquad (3)$$

Denote the transmit power of VT n in task offloading as $p_n(t) = \sum\limits_{m \in \mathcal{M}} p_{nm}(t)$, and thus, the energy consumption (in J) in task offloading is given by

$$E_n^{off}(t) = p_n(t) T. \qquad (4)$$

*2) **Server Provisioning Model**:* Suppose there are q^{max} edge servers in each MRSU, and each is with a processing capability s_c (in CPU cycles/s). When VT n offloads it task to MRSU, MRSU should determine the number of edge servers $q_n(t)$ allocated to the task of VT n. The process is called server provisioning [17], and the total number of allocated servers is constrained by $\sum_{n \in \mathcal{N}} q_n(t) \leq q^{max}$.

E. Queueing Model and Related Concepts

In our system, two data queues are formulated for the computation tasks of each VT n, i.e., the user-side queue $Q_n(t)$ (in bits), and the MRSU-side queue $Z_n(t)$ (in bits). The queues $Q_n(t)$ and $Z_n(t)$ stand for the unfinished tasks of each VT n, and they evolve according to

$$
\begin{aligned}
Q_n(t+1) = max\big[&Q_n(t) - T r_n(t) x_n(t) \\
&- (1 - x_n(t)) \frac{f_n^{loc}(t)}{\lambda_n} T, 0\big] + D_n(t), \quad (5)
\end{aligned}
$$

$$Z_n(t+1) = max\big[Z_n(t) - q_n(t) \frac{s_c}{\lambda_n} T x_n(t), 0\big] + r_n(t) T x_n(t). \qquad (6)$$

Definition 1: *A discrete time queue $Q(t), t \in \{0, 1, ..\}$ is strongly stable if satisfies: $\bar{Q} = \lim\limits_{t \to \infty} \sup \frac{1}{t} \sum\limits_{\tau=0}^{t-1} \mathbb{E}\{Q(\tau)\} < \infty$ [31], [32].*

Definition 2: *If all the individual queues are stable, the network is stable [31], [32].*

Remark 1: *According to the Little's Theorem [31], [32], under given traffic arrival rate, the average delay is in direct proportion to the average queue length. Therefore, Definitions 1 and 2 indicate that, if the system is ensured to be stable, the average delay can be guaranteed to be finite.*

F. Cost Model

Next we discuss the monetary cost of VTs and MRSU, respectively.

*1) **Cost of VTs**:* In local processing, the monetary cost of VT n can be given by $U_n^{loc}(t) = \alpha_n E_n^{loc}(t) = \alpha_n k D_n(t) \lambda_n (f_n^{loc}(t))^2$, where α_n (in \$/J) is a human-determined weight coefficient, which is used to convert energy consumption into money and depends on the human-sensitiveness on money and and energy consumption [17].

When VT n offloads its task for remote processing, it will consume different costs and need to pay different fees: (i) The energy consumption of VT n in data transmission (in J). (ii) The TVWS channel service fee $\theta r_n(t)$ that VT n has to pay to MRSU, where θ (in \$/bit) is the price of transmitting per bit data. (iii) Task processing fee $\eta \lambda_n r_n(t)$ that VT n needs to pay to MRSU, where η (in \$/cycle) is the price for processing each unit CPU cycle task. So the monetary cost of VT n in task offloading is $U_n^{off}(t) = [\alpha_n p_n(t) + \theta r_n(t) + \eta \lambda_n r_n(t)]$T.

Thus, the cost (in \$) of each VT n in frame t is given by

$$
\begin{aligned}
U_n(t) = &(1 - x_n(t)) \alpha_n k D_n(t) \lambda_n (f_n^{loc}(t))^2 \\
&+ x_n(t) \big[\alpha_n p_n(t) + \theta r_n(t) + \eta \lambda_n r_n(t)\big] T, \quad (7)
\end{aligned}
$$

and the total cost of all UEs can be given by $U(t) = \sum_{n=1}^N U_n(t)$.

*2) **Cost of MRSU**:* MRSU possesses and operates the MEC servers, and leases radio bandwidth (in bps) from wireless network operator. By providing computation offloading services, MRSU earns the same amount of money paid by VTs for wireless data transmission and task processing. The price it charge from VTs for data transmission is θ (in \$/bit), and for task processing is η (in \$/cycle). On the other hand, it has to pay electricity bills to grid operator for operating edge servers, and pay to wireless network operator for renting radio bandwidth. Denoting $e(t)$ as the electricity bills (in \$) for running an edge server, and the price for renting radio bandwidth (in bps) from wireless network operator as δ (in \$/bit), the cost of each MRSU in frame t is given by

$$
\begin{aligned}
&U_{MRSU}(t) \\
&= \sum_{n \in \mathcal{N}} \Big[q_n(t) e(t) + \delta r_n(t) T - \theta r_n(t) T - \eta \lambda_n r_n(t) T\Big] x_n(t) \\
&= \sum_{n \in \mathcal{N}} \Big[q_n(t) e(t) - (\theta + \eta \lambda_n - \delta) r_n(t) T\Big] x_n(t). \qquad (8)
\end{aligned}
$$

A summary of the mainly used notations are presented in TABLE I.

IV. Dual Side Problem Formulation

In this section, we construct two optimization problems under a competition scenario. One is the VT-side problem $(\mathcal{P}_{\mathbf{V}})$, while the other one is the MRSU-side problem $(\mathcal{P}_{\mathbf{M}})$, respectively.

A. VT-side Optimization Problem

The objective of VT-side optimization problem $(\mathcal{P}_{\mathbf{V}})$ is to minimize the average total cost of all the VTs subjecting to the queue stability of both VT-side and MRSU-side, so as to guarantee all the computation tasks be executed within a finite time. We need to optimize the offloading decision $\mathbf{x}(t) = \{x_1(t), ..., x_N(t)\}$ and the local CPU frequency $\mathbf{f}^{loc}(t) = \left\{f_1^{loc}(t), ..., f_N^{loc}(t)\right\}$ under given MRSU's policy. Problem $(\mathcal{P}_{\mathbf{V}})$ is given by

$$
\begin{aligned}
(\mathcal{P}_{\mathbf{V}}):\ & \min_{\mathbf{x}(t),\mathbf{f}^{loc}(t)} \bar{U} = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{U(t)\}\\
\text{s.t. } & (\mathrm{C_V}1):\ \bar{Q}_n < \infty,\ \bar{Z}_n < \infty,\ \forall n \in \mathcal{N},\\
& (\mathrm{C_V}2):\ x_n(t) \in \{0,1\}, \quad \forall n \in \mathcal{N},\\
& (\mathrm{C_V}3):\ 0 \le f_n^{loc}(t) \le f^{max}, \quad \forall n \in \mathcal{N}, \qquad (9)
\end{aligned}
$$

where (C_V1) ensures the network is stable; (C_V2) is the binary constraints on computation offloading decisions; and (C_V3) is the CPU-cycle frequency constraint for each VT.

B. MRSU-side Optimization Problem

The MRSU-side optimization $(\mathcal{P}_{\mathbf{M}})$ aims at minimizing the average cost of MRSU, by jointly optimizing the burst allocation $\mathbf{S}(t) = \{s_{nm}(t)\}$, $\forall n \in \mathcal{N}$, $\forall m \in \mathcal{M}$, the transmit power control $\mathbf{P}(t) = \{p_{nm}(t)\}$, $\forall n \in \mathcal{N}$, $\forall m \in \mathcal{M}$, and the server provisioning $\mathbf{q}(t) = \{q_1(t), ..., q_N(t)\}$, and the problem is formulated as

$$
\begin{aligned}
(\mathcal{P}_{\mathbf{M}}):\ & \min_{\mathbf{q}(t),\mathbf{S}(t),\mathbf{P}(t)} \bar{U}_{MRSU} = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}\mathbb{E}\{U_{MRSU}(t)\}\\
\text{s.t. } & (\mathrm{C_M}1):\ \bar{Z}_n < \infty,\ \forall n \in \mathcal{N},\\
& (\mathrm{C_M}2):\ \sum_{n\in\mathcal{N}} s_{nm}(t)p_{nm}(t)G_{nm}(t) \le \beta_m,\ \forall m \in \mathcal{M},\\
& (\mathrm{C_M}3):\ \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} C_{ml}s_{nm}(t)p_{nm}(t) \le P^{max}, \forall l \in \mathcal{L},\\
& (\mathrm{C_M}4):\ \sum_{n\in\mathcal{N}} s_{nm}(t) \le 1,\ \forall m \in \mathcal{M},\\
& (\mathrm{C_M}5):\ s_{nm}(t) \in \{0,1\},\ \forall n \in \mathcal{N}, \forall m \in \mathcal{M},\\
& (\mathrm{C_M}6):\ p_{nm}(t) \ge 0,\ \forall n \in \mathcal{N}, \forall m \in \mathcal{M},\\
& (\mathrm{C_M}7):\ \sum_{n\in\mathcal{N}} q_n(t) \le q^{max}, \qquad (10)
\end{aligned}
$$

where (C_M2) means that the interference caused by burst reuse for VT's uplink transmission should be no more than a threshold β_m to ensure the QoS of PU m; (C_M3) is used to satisfy FCC's requirement that the total transmit power of SUs on a TVWS channel should be no more than a threshold. (C_M4) and (C_M5) represent a burst can be allocated to at most one VT to avoid interference within the MRSU; (C_M6) indicates the transmit power should be non-negative; (C_M7) constraints the number of allocated edge servers cannot exceed that MRSU possesses.

Remark 2: *Problems $(\mathcal{P}_{\mathbf{V}})$ and $(\mathcal{P}_{\mathbf{M}})$ are difficult to solve, since they are stochastic optimization problems where optimization should be performed at each time slot, and a great deal of the channel and task buffer state information need to be handled, and large amounts of optimization variables should be determined. Moreover, the optimal decisions are temporally correlated due to the random arrivals of tasks [18].*

V. Problem Transformation

In the following, we propose online algorithms to tackle problems $(\mathcal{P}_{\mathbf{V}})$ and $(\mathcal{P}_{\mathbf{M}})$ based on Lyapunov optimization theory, leveraging which we can resolve the formulated stochastic optimization problems efficiently by solving deterministic problems at each frame [18], without requiring any future information about task arrivals, network status, etc., and only the current state information is required [31], [33].

Let $\mathbf{Q}(t) = \{Q_1(t), ..., Q_N(t)\}$, $\mathbf{Z}(t) = \{Z_1(t), ..., Z_N(t)\}$, and $\mathbf{\Theta}(t) = \{\mathbf{Q}(t), \mathbf{Z}(t)\}$, basing on which the Lyapunov functions for $(\mathcal{P}_{\mathbf{V}})$ and $(\mathcal{P}_{\mathbf{M}})$ are given by

$$
L(\mathbf{\Theta}(t)) \triangleq \frac{1}{2}\sum_{n\in\mathcal{N}} Q_n^2(t) + \frac{1}{2}\sum_{n\in\mathcal{N}} Z_n^2(t), \qquad (11)
$$

$$
L(\mathbf{Z}(t)) \triangleq \frac{1}{2}\sum_{n\in\mathcal{N}} Z_n^2(t). \qquad (12)
$$

Then the Lyapunov drift functions $\Delta(\mathbf{\Theta}(t))$ and $\Delta(\mathbf{Q}(t))$ are given by

$$
\begin{aligned}
\Delta(\mathbf{\Theta}(t)) &\triangleq \mathbb{E}\{L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t))|\mathbf{\Theta}(t)\}, \quad (13)\\
\Delta(\mathbf{Z}(t)) &\triangleq \mathbb{E}\{L(\mathbf{Z}(t+1)) - L(\mathbf{Z}(t))|\mathbf{Z}(t)\}, \quad (14)
\end{aligned}
$$

where $L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t))$ satisfies

$$
\begin{aligned}
& L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t))\\
& \le \sum_{n\in\mathcal{N}}\left\{Q_n(t)\left[D_n(t) - r_n(t)Tx_n(t) - (1-x_n(t))\frac{f_n^{loc}(t)}{\lambda_n}T\right]\right.\\
& \left. + Z_n(t)\left[r_n(t)T - q_n(t)\frac{s_c}{\lambda_n}T\right]x_n(t)\right\} + B_1 + B_2, \quad (15)
\end{aligned}
$$

and $L(\mathbf{Z}(t+1)) - L(\mathbf{Z}(t))$ satisfies

$$
\begin{aligned}
& L(\mathbf{Z}(t+1)) - L(\mathbf{Z}(t))\\
& \le \sum_{n\in\mathcal{N}} Z_n(t)\left[r_n(t)T - q_n(t)\frac{s_c}{\lambda_n}T\right]x_n(t) + B_2. (16)
\end{aligned}
$$

The constants B_1 and B_2 in Eq. (11) are given by

$$
\begin{aligned}
B_1 &= \frac{1}{2}\sum_{n\in\mathcal{N}}\left[(D_n^{max})^2 + \left(r_n^{max}T + \frac{f^{max}}{\lambda_n}T\right)^2\right],\\
B_2 &= \frac{1}{2}\sum_{n\in\mathcal{N}}\left[(r_n^{max}T)^2 + \left(q^{max}\frac{s_c}{\lambda_n}T\right)^2\right]. \qquad (17)
\end{aligned}
$$

TABLE I: Notation Definitions

Symbol	Definition
$D_n(t)$	The size of the arrived task of VT n at frame t (in bits)
λ_n	Processing density of the arrived tasks of VT n (in CPU cycles/bit)
f^{max}	Maximum local processing capability of each VT (in CPU cycles/s)
q^{max}	The total number of edge servers each MRSU possess
P^{max}	The threshold of the total transmit power of all SUs on a TVWS channel
β_m	The threshold of interference caused by burst reuse in VTs' uplink transmission
$Q_n(t)$, $Z_n(t)$	VT-side and MRSU-side queue backlog of the task of VT n in frame t
T_m,B_m	The time duration and bandwidth of burst m
$\bar{T}_m$	The valid transmission duration of a VT on burst m
$p_m^{PU}(t)$	The transmit power of PU m on burst m in frame t
$G_m^{PU}(t)$	The channel gain between PU m and the BS
$p_{nm}(t)$, $G_{nm}(t)$, $r_{nm}(t)$	The transmit power, channel gain and transmit rate of VT n on burst m in frame t
$\mathbf{x}(t)$, $x_n(t)$	Offloading decision vector and offloading decision of VT n in frame t
$\mathbf{f}^{loc}(t)$, $f_n^{loc}(t)$	Local CPU clock frequency vector of all VTs and of VT n in frame t
$\mathbf{S}(t)$	Matrix of all VTs' burst allocation in frame t
s_{nm}(t)	Indicator of whether burst m is allocated to VT n in frame t
$\mathbf{P}(t)$	Matrix of all VTs' transmit power control in frame t
$\mathbf{q}(t)$	Vector of server provisioning in frame t
$q_n(t)$	The number of edge servers allocated to the task of VT n in frame t
$\mathcal{N}$,N	The set and number of all VTs
$\mathcal{N}_1$,N_1	The set and number of remote processing VTs
$\mathcal{L}$, L	The set and number of burst intervals (BIs)
$\mathcal{M}$,M	The set and number of primary users (PUs)
θ	The price of transmitting per bit data via wireless channels (in \$/bit)
δ	The price MRSU rents radio bandwidth form operator for data transmission (in \$/bit)
η	The price for processing each unit CPU cycle task (in \$/cycle)
s_c	The CPU clock frequency of an edge server (in cycles/s)
$e(t)$	The price of electricity (in \$) for running an edge server
α_n	Coefficient used to convert energy consumption into money(in \$/J)
k	Coefficient used to model local processing energy consumption depending on chip architecture
$U_n(t)$, $U_{MRSU}(t)$	The cost of VT n and MRSU in frame t
U,U_{MRSU}	The time averaged expected cost of all VTs' and of MRSU

For notation simplicity, we denote $B = B_1 + B_2$.

In the above derivation procedure, we have adopted the following inequality

$$(max[Q-b,0]+A)^2 \leq Q^2 + A^2 + b^2 + 2Q(A-b), \quad \forall Q \geq 0, \forall b \geq 0, \forall A \geq 0. \tag{18}$$

According to Lyapunov optimization theory, in order to minimize $\bar{U}$ in $(\mathcal{P}_{\mathbf{V}})$ and $\bar{U}_{MRSU}$ in $(\mathcal{P}_{\mathbf{M}})$, the drift-plus-penalty functions $\Delta(\boldsymbol{\Theta}(t)) + V\mathbb{E}\{U(t)|\boldsymbol{\Theta}(t)\}$ and $\Delta(\mathbf{Z}(t)) + V\mathbb{E}\{U_{MRSU}(t)|\mathbf{Z}(t)\}$ should be considered, which are bounded by

$$\begin{aligned}
&\Delta(\boldsymbol{\Theta}(t)) + V\mathbb{E}\{U(t)|\boldsymbol{\Theta}(t)\} \\
&\leq \sum_{n\in\mathcal{N}} \mathbb{E}\Bigg\{ Q_n(t)\left[D_n(t) - r_n(t)Tx_n(t) - (1-x_n(t))\frac{f_n^{loc}(t)}{\lambda_n}T\right] \\
&\quad + Z_n(t)T\left[r_n(t) - q_n(t)\frac{s_c}{\lambda_n}\right]x_n(t) \\
&\quad + Vx_n(t)\Big[\alpha_n p_n(t) + \theta r_n(t) + \eta\lambda_n r_n(t)\Big]T \\
&\quad + V(1-x_n(t))\alpha_n k D_n(t)\lambda_n(f_n^{loc}(t))^2 \Bigg| \boldsymbol{\Theta}(t)\Bigg\} + B,
\end{aligned} \tag{19}$$

and

$$\begin{aligned}
&\Delta(\mathbf{Z}(t)) + V\mathbb{E}\{U_{MRSU}(t)|\mathbf{Z}(t)\} \\
&\leq B_2 + \sum_{n\in\mathcal{N}} \mathbb{E}\Big\{ Z_n(t)T\Big(r_n(t) - q_n(t)\frac{s_c}{\lambda_n}\Big)x_n(t)\Big|\mathbf{Z}(t)\Big\} \\
&\quad + V\sum_{n\in\mathcal{N}} \mathbb{E}\Big\{\Big(q_n(t)e(t) - (\theta + \eta\lambda_n - \delta)r_n(t)T\Big)x_n(t)\Big|\mathbf{Z}(t)\Big\} \\
&= B_2 + \sum_{n\in\mathcal{N}_1} \mathbb{E}\Big\{ Z_n(t)T\Big(r_n(t) - q_n(t)\frac{s_c}{\lambda_n}\Big) \\
&\qquad + Vq_n(t)e(t) - V(\theta + \eta\lambda_n - \delta)r_n(t)T\Big\},
\end{aligned} \tag{20}$$

where $V \in (0, \infty)$ (in $bit^2/\$$) is a non-negative control parameter used to strick a balance between the cost and delay, i.e., how much we put our emphasis on cost reduction or processing delay reduction. The notations N_1 and $\mathcal{N}_1 = \{1, 2, ..., N_1\}$ denote the number and the set of VTs who offload their tasks for remote processing. Then, the original long-term minimization problems $(\mathcal{P}_{\mathbf{V}})$ and $(\mathcal{P}_{\mathbf{M}})$ can be transformed into the following optimization problems $(\mathcal{P}_{\mathbf{V}}^{\mathbf{1}})$ and $(\mathcal{P}_{\mathbf{M}}^{\mathbf{1}})$, which minimize the upper bound of the drift-plus-penalty functions is (19)-(20) in each frame t, respectively.

$$
\begin{aligned}
(\mathcal{P}_{\mathbf{V}}^{\mathbf{1}}):\ & \min_{\mathbf{x}(t),\mathbf{f}^{loc}(t)} \sum_{n\in\mathcal{N}} \\
& \Big\{(1-x_n(t))\Big[V\alpha_n k D_n(t)\lambda_n(f_n^{loc}(t))^2-\frac{Q_n(t)}{\lambda_n}f_n^{loc}(t)T\Big] \\
& \quad + x_n(t)T\Big[V\Big(\alpha_n p_n(t)+\theta r_n(t)+\eta\lambda_n r_n(t)\Big) \\
& \qquad + Z_n(t)\Big(r_n(t)-q_n(t)\frac{s_c}{\lambda_n}\Big)-Q_n(t)r_n(t)\Big]\Big\} \\
& \text{s.t. } (\mathrm{C_V}2),(\mathrm{C_V}3)\ in\ (\mathcal{P}_{\mathbf{V}}),
\end{aligned}
\tag{21}
$$

and

$$
\begin{aligned}
(\mathcal{P}_{\mathbf{M}}^{\mathbf{1}}):\ & \min_{\mathbf{q}(t),\mathbf{S}(t),\mathbf{P}(t)} \sum_{n\in\mathcal{N}} \Big[\Big(Z_n(t)-V(\theta+\eta\lambda_n-\delta)\Big)r_n(t)T \\
& \qquad + \Big(Ve(t)-\frac{s_cT}{\lambda_n}Z_n(t)\Big)q_n(t)\Big] \\
& \text{s.t. } (\mathrm{C_M}2)-(\mathrm{C_M}7)\ in\ (\mathcal{P}_{\mathbf{M}}).
\end{aligned}
\tag{22}
$$

By Little's law [31], the average delay is proportional to the average queue backlogs under given average data arrival rate, so in the following, we will use the two terms, i.e., average delay and average queue backlog interchangeably.

VI. Solve the VT-side per Frame Optimization Problem ($\mathcal{P}_{\mathbf{V}}^{\mathbf{1}}$)

Each VT considers the VT-side and the MRSU-side queue backlogs, the networks status, and then it needs to determine the offloading decision and the corresponding CPU cycle frequency optimization in local processing model, where the following two cases should be taken into consideration:

1) : If VT n selects local processing model ($x_n(t)=0$), it needs to further obtain the optimum local CPU clock frequency $f_n^{loc}(t)$ as follows

$$
\begin{aligned}
\Omega_n^{loc}(t)^* = & \min_{f_n^{loc}(t)} V\alpha_n k D_n(t)\lambda_n(f_n^{loc}(t))^2-\frac{Q_n(t)}{\lambda_n}f_n^{loc}(t)T \\
& s.t.\ \ (\mathrm{C_V}3):\ 0\le f_n^{loc}(t)\le f^{max},
\end{aligned}
\tag{23}
$$

the closed form solution to which can be easily obtained as

$$
f_n^{loc}(t)^* = \min\Big\{\frac{Q_n(t)T}{2V\alpha_n k D_n(t)\lambda_n^2}, f^{max}\Big\},
\tag{24}
$$

and we can obtain $\Omega_n^{loc}(t)^* = V\alpha_n k D_n(t)\lambda_n(f_n^{loc}(t)^*)^2 - \frac{Q_n(t)}{\lambda_n}f_n^{loc}(t)^*T$, consequently.

2) : If $x_n(t)=1$, we can directly obtain

$$
\begin{aligned}
\Omega_n^{off}(t)^* = & V\Big(\alpha_n p_n(t)+\theta r_n(t)+\eta\lambda_n r_n(t)\Big)T \\
& + Z_n(t)\Big(r_n(t)-q_n(t)\frac{s_c}{\lambda_n}\Big)T - Q_n(t)r_n(t)T.
\end{aligned}
\tag{25}
$$

By comparing the values of $\Omega_n^{loc}(t)^*$ and $\Omega_n^{off}(t)^*$, the offloading decision of each VT n can be given by

$$
x_n^*(t) = \begin{cases} 1, & if\ \Omega_n^{loc}(t)^* > \Omega_n^{off}(t)^* \\ 0, & otherwise \end{cases}.
\tag{26}
$$

Remark 3: *In order to obtain offloading decision in (26), each VT n needs to compare which decision, i.e., local processing or task offloading, is more beneficial in the aspects of cost reduction and queue stability. It can be observed that, when the VT-side queue $Q_n(t)$ is much longer than the MRSU-side queue $Z_n(t)$, and the wireless networks are in good conditions, task offloading ($x_n(t)=1$) is much preferred.*

Remark 4: *The VT-side optimization algorithm is low in computational complexity, since each variable can be determined by comparing two values, and the two values can be obtained in closed form.*

VII. Solve the MRSU-side per Frame Optimization Problem ($\mathcal{P}_{\mathbf{M}}^{\mathbf{1}}$)

Next we solve the MRSU-side problem ($\mathcal{P}_{\mathbf{M}}^{\mathbf{1}}$). It can be decomposed into two sub-problems, i.e., the server provisioning subproblem and the radio resource allocation subproblem. Since there's no coupling between the two subproblems, we can solve them independently.

A. Server Provisioning Subproblem

The server provisioning subproblem is given by

$$
\begin{aligned}
& \min_{\mathbf{q}(t)} \sum_{n\in\mathcal{N}_1}\Big[Ve(t)-\frac{s_cT}{\lambda_n}Z_n(t)\Big]q_n(t) \\
& \text{s.t. } (\mathrm{C_M}7): \sum_{n\in\mathcal{N}_1} q_n(t)\le q^{max}.
\end{aligned}
\tag{27}
$$

Observe problem (27) we can know that for a certain VT n, if $Ve(t)\ge\frac{s_cT}{\lambda_n}Z_n(t)$, it will be allocated with no edge server. Denote the set of the VTs who may be allocated with edge servers as $\mathcal{J}$, and we have $\mathcal{J}=\Big\{n\in\mathcal{N}_1\Big|Ve(t)<\frac{s_cT}{\lambda_n}Z_n(t)\Big\}$. From the objective of problem (27) we can further know that among the VTs in $\mathcal{J}$, MRSU prefers to assign edge servers to the VT whose MRSU-side queue backlog $Z_n(t)$ is large. The larger $Z_n(t)$ is, the more unfinished tasks are queued, and MRSU will allocate the more edge servers to VT n for delay reduction. The proposed server provisioning algorithm is summarized in Algorithm 1.

B. Radio Resource Allocation Subproblem

In this section, we will tackle the radio resource allocation subproblem embedded in ($\mathcal{P}_{\mathbf{4}}$), where transmit power control $\mathbf{P}(t)$ and burst assignment $\mathbf{S}(t)$ among all the offloading VTs in $\mathcal{N}_1$ should be determined as follows

$$
\begin{aligned}
& \max_{\mathbf{S}(t),\mathbf{P}(t)} \sum_{n\in\mathcal{N}_1}\Big[V(\theta+\eta\lambda_n-\delta)-Z_n(t)\Big]r_n(t)T \\
& \text{s.t. } \ (\mathrm{C_M}2)-(\mathrm{C_M}6),
\end{aligned}
\tag{28}
$$

where $r_n(t) = \sum_{m\in\mathcal{M}} s_{nm}(t)\frac{\bar{T}_m}{T}B_m\log_2\Big(1+\frac{p_{nm}(t)G_{nm}(t)}{p_m^{PU}(t)G_m^{PU}(t)+\sigma^2}\Big)$. However, (28) is still an MINLP problem and can be generally NP-hard [19]. Observing (28), the difficulty comes from two aspects, i.e., the integer constraints and the non-convex objective function. Under this observation, the proposed continuous relaxation and Lagrangian dual decomposition based method works as follows.

Algorithm 1 Server Provisioning Algorithm

```
Initialization:
Initialize $\mathcal{J} = \emptyset$.
Iteration:
for $n = 1 : N_1$ do
    Calculate the value of $Ve(t) - \frac{s_c T}{\lambda_n} Z_n(t)$.
    if $Ve(t) - \frac{s_c T}{\lambda_n} Z_n(t) < 0$ then
        $\mathcal{J} = \mathcal{J} \bigcup n$.
    end if
end for
Sort all the VTs in $\mathcal{J}$ in ascending order according to the value of $|Ve(t) - \frac{s_c T}{\lambda_n} Z_n(t)|$.
for $j = 1 : |\mathcal{J}|$ do
    $q_j(t) = \min\left\{ \left\lceil \frac{Z_j(t)\lambda_j}{s_c T} \right\rceil, q^{max} \right\}$.
    $q^{max} = q^{max} - \left\lceil \frac{Z_j(t)\lambda_j}{s_c T} \right\rceil$.
    if $q^{max} \le 0$ then
        break.
    end if
end for
Output: $\mathbf{q}(t) = \{q_n(t)\},\ n \in \mathcal{N}_1$.
```

1) Convert Problem (28) *to a Convex Programming Problem:* First, by relaxing the integer constraint into $s_{nm}(t) \in [0,1]$, and replacing $p_{nm}(t)$ with $y_{nm}(t) = s_{nm}(t)p_{nm}(t),\ \forall n \in \mathcal{N}_1, \forall m \in \mathcal{M}$, we can obtain

$$\begin{aligned}
\max_{\mathbf{S}(t),\mathbf{Y}(t)} & \sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}} \Big[V(\theta+\eta\lambda_n-\delta)-Z_n(t)\Big] B_m \bar{T}_m s_{nm}(t) \\
& \qquad \log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{s_{nm}(t)\big(p_m^{PU}(t)G_m^{PU}(t)+\sigma^2\big)}\right) \\
\text{s.t. } (\mathrm{C_M}2'):\ & \sum_{n\in\mathcal{N}_1} y_{nm}(t)G_{nm}(t) \le \beta_m,\ \forall m\in\mathcal{M}, \\
(\mathrm{C_M}3'):\ & \sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}} y_{nm}(t)C_{ml} \le P^{max},\ \forall l\in\mathcal{L}, \\
(\mathrm{C_M}4'):\ & \sum_{n\in\mathcal{N}_1} s_{nm}(t) \le 1,\ \forall m\in\mathcal{M}, \\
(\mathrm{C_M}5'):\ & s_{nm}(t)\in[0,1],\ \forall n\in\mathcal{N}_1, \forall m\in\mathcal{M}, \\
(\mathrm{C_M}6'):\ & y_{nm}(t)\ge 0,\ \forall n\in\mathcal{N}_1, \forall m\in\mathcal{M}. \qquad (29)
\end{aligned}$$

Proposition 1: Problem (29) is jointly convex in $\mathbf{S}(t)$ and $\mathbf{Y}(t)$.

Proof: See Appendix A. ■

Although the convex problem (29) could be settled by general algorithms such as Interior Point Method, which however suffers from high time complexity. Next we use Lagrangian dual decomposition technique to design a low-complexity algorithm. The partial Lagrangian function of (29) is given in (30), where $\boldsymbol{\mu}(t) = \{\mu_m(t)\} \succeq 0, m \in \mathcal{M}$ and $\boldsymbol{\omega}(t) = \{\omega_l(t)\} \succeq 0, l \in \mathcal{L}$ are dual variables corresponding to constraints $(\mathrm{C_M}2')$ and $(\mathrm{C_M}3')$ in (29), respectively.

As problem (29) is convex, zero duality gap can be guaranteed. Thus, we can solve the following dual problem to obtain the optimal radio resource allocation.

$$\begin{aligned}
&\min_{\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)} \max_{\mathbf{S}(t),\mathbf{Y}(t)} L(\mathbf{S}(t),\mathbf{Y}(t),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)) \\
&= \min_{\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)} \max_{\mathbf{S}(t)} \max_{\mathbf{Y}(t)} L(\mathbf{S}(t),\mathbf{Y}(t),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)). \qquad (31)
\end{aligned}$$

2) Obtain Power Allocation: According to (31), assuming dual variables $\boldsymbol{\mu}(t)$ and $\boldsymbol{\omega}(t)$ and burst allocation $\mathbf{S}(t)$ are given, we can first obtain the optimal transmit power through solving $\mathbf{Y}(t)$. Using KKT conditions [34] and by letting $\frac{\partial L(\mathbf{S}(t),\mathbf{Y}(\mathbf{t}),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t))}{\partial y_{nm}(t)} = 0$, the optimal $y_{nm}^*(t)$ can be given by

$$\begin{aligned}
y_{nm}^*(t) = \Bigg[& \frac{\bar{T}_m B_m \big[V(\theta+\eta\lambda_n-\delta)-Z_n(t)\big]}{\ln 2\big(\mu_m(t)G_{nm}(t)+\sum\limits_{l\in\mathcal{L}}\omega_l C_{ml}\big)} \\
& - \frac{p_m^{PU}(t)G_m^{PU}(t)+\sigma^2}{G_{nm}(t)}\Bigg] s_{nm}(t). \qquad (32)
\end{aligned}$$

Since $y_{nm}^*(t) = s_{nm}(t)p_{nm}^*(t)$, we can obtain the optimal transmit power control policy as

$$\begin{aligned}
p_{nm}^*(t) = \Bigg[& \frac{\bar{T}_m B_m \big[V(\theta+\eta\lambda_n-\delta)-Z_n(t)\big]}{\ln 2\big(\mu_m(t)G_{nm}(t)+\sum\limits_{l\in\mathcal{L}}\omega_l(t) C_{ml}\big)} \\
& - \frac{p_m^{PU}(t)G_m^{PU}(t)+\sigma^2}{G_{nm}(t)}\Bigg]^+, \qquad (33)
\end{aligned}$$

where $x^+ = \max\{x, 0\}$.

3) Obtain Burst Assignment: In this step, by plugging the obtained optimal transmit power allocation back to Lagrangian function, we solve the optimal burst assignment. For notation simplicity, we define $d_{nm}(t)$ and $E(t)$ as follows

$$\begin{aligned}
d_{nm}(t) = & \Big[V(\theta+\eta\lambda_n-\delta)-Z_n(t)\Big] \\
& \bar{T}_m B_m \log_2\left(1+\frac{p_{nm}^*(t)G_{nm}(t)}{p_m^{PU}(t)G_m^{PU}(t)+\sigma^2}\right) \\
& - \left(\mu_m(t)G_{nm}(t)+\sum_{l\in\mathcal{L}}\omega_l(t)C_{ml}\right)p_{nm}^*(t), \\
E(t) = & \sum_{m\in\mathcal{M}}\mu_m(t)\beta_m + \sum_{l\in\mathcal{L}}\omega_l P^{max}, \qquad (34)
\end{aligned}$$

where $d_{nm}(t)$ is the weight coefficient and $E(t)$ is a constant. Then the optimal burst assignment can be obtained by solving

$$\begin{aligned}
\max_{\mathbf{S}(t)} & \sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}} d_{nm}(t)s_{nm}(t) - E(t) \\
\text{s.t. } (\mathrm{C_M}4''):\ & \sum_{n\in\mathcal{N}_1} s_{nm}(t) \le 1,\ \forall m\in\mathcal{M}, \\
(\mathrm{C_M}5''):\ & s_{nm}(t)\in[0,1],\ \forall n\in\mathcal{N}_1, \forall m\in\mathcal{M}. \qquad (35)
\end{aligned}$$

It is not difficult to know, problem (35) is the sum of a set of linear functions w.r.t $s_{nm}(t)$. Consequently, burst allocation $s_{nm}(t)$ must be binary, since the optimal value of a linear function is obtained at the endpoints. Therefore, the optimal burst assignment $s_{nm}(t)$ can be given by

$$s_{nm}^*(t) = \begin{cases} 1, & if\ n = \arg\max\limits_{\hat{n}} d_{nm}(t)\ \&\ d_{nm}(t) > 0, \\ 0, & otherwise. \end{cases} \qquad (36)$$

$$\begin{aligned} L(\mathbf{S}(t),\mathbf{Y}(t),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)) \ &= \sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}}\Big[V(\theta+\eta\lambda_n-\delta)-Z_n(t)\Big]B_m\bar{T}_m s_{nm}(t)\log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{s_{nm}(t)\big(p_m^{PU}(t)G_m^{PU}(t)+\sigma^2\big)}\right) \\ &\quad -\sum_{m\in\mathcal{M}}\mu_m(t)\Big(\sum_{n\in\mathcal{N}_1}y_{nm}(t)G_{nm}(t)-\beta_m\Big)-\sum_{l\in\mathcal{L}}\omega_l(t)\Big(\sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}}y_{nm}(t)C_{ml}-P^{max}\Big). \end{aligned} \tag{30}$$

Remark 5: *Equation (36) manifests that a burst should be allocated to the VT with the maximum positive weight upon it. If all VTs are in deep fading and with negative weights, this burst should not be allocated to any VT, since using it will lead to more waste but less profit.*

4) Dual Variables Update: To solve the outer minimization problem in (31) (also called master dual problem), a subgradient method [35] can be used to update the dual variables. More specifically, the update can be performed as

$$\mu_m^{i+1}(t)=\left[\mu_m^i(t)-h_m^i(t)\left(\beta_m-\sum_{n\in\mathcal{N}_1}y_{nm}(t)G_{nm}(t)\right)\right]^+, \quad \forall m\in\mathcal{M}, \tag{37}$$

$$\omega_l^{i+1}(t)=\left[\omega_l^i(t)-k_l^i(t)\left(P^{max}-\sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}}y_{nm}(t)C_{ml}\right)\right]^+, \quad \forall l\in\mathcal{L}, \tag{38}$$

where i is the iteration index; $h_m^i(t)$ and $k_l^i(t)$ are the sequences of scalar step sizes of the ith iteration. In this paper we adopt square summable but not absolute summable step sizes [35]. The Lagrangian dual variables are updated iteratively until the required precision is satisfied.

The procedure for joint transmit power control and burst assignment is summarized in Algorithm 1 as follows.

Algorithm 2 Lagrangian Dual Decomposition Based Burst Assignment and Power Allocation Algorithm

```
Initialization:
 1: Initialize $\boldsymbol{\mu}^0(t), \boldsymbol{\omega}^0(t), i^{max}$ and the precision $\epsilon$. Set $i=0$.
Iteration:
 2: while $i \le i^{max}$ do
 3:     Perform transmit power allocation $p_{nm}^i(t), \forall n,m$ according to (33).
 4:     Perform burst assignment $s_{nm}^i(t), \forall n,m$ based on (36).
 5:     Update Lagrangian dual variables $\boldsymbol{\mu}(t), \boldsymbol{\omega}(t)$ according to (37) and (38), respectively.
 6:     if $|\boldsymbol{\mu}^{i+1}(t)-\boldsymbol{\mu}^i(t)|<\epsilon$ & $|\boldsymbol{\omega}^{i+1}(t)-\boldsymbol{\omega}^i(t)|<\epsilon$ then
 7:         $s_{nm}^*(t)=s_{nm}^i(t)$, $p_{nm}^*(t)=p_{nm}^i(t)$.
 8:         break.
 9:     else
10:         $i=i+1$.
11:     end if
12: end while
13: Output: $\mathbf{S}^*(t)=\{s_{nm}^*(t)\}$, $\mathbf{P}^*(t)=\{p_{nm}^*(t)\}$.
```

Till now, our dual-side optimization in a competition scenario is solved, and the joint optimization of offloading decision making and local CPU frequency control is obtained for VT-side, and the joint optimization of transmit power allocation, burst assignment and server provisioning is obtained for MURS-side. Detailed procedure is summarized in Algorithm 2, which is referred to as **d**ual-side **d**ynamic joint task **o**ffloading and **r**esource allocation algorithm in **v**ehicular networks (DDORV).

Algorithm 3 **D**ual-side **D**ynamic Joint Task **O**ffloading and **R**esource Allocation Algorithm in **V**ehicular Networks (D-DORV)

```
 1: At each frame $t$:
 2: MRSU-side optimization
 3: Observe the current MRSU-side queues $Z_n(t)$ and channel states in each frame $t$.
 4: Obtain server provisioning $\mathbf{q}(t)$ according to Algorithm 1.
 5: Perform transmit power control $\mathbf{P}(t)$ and burst assignment $\mathbf{S}(t)$ according to Algorithm 2.
 6: VT-side optimization
 7: Observe the current queues $Q_n(t)$ and $Z_n(t)$ and channel states in each frame $t$.
 8: for $n\in\mathcal{N}$ do
 9:     Obtain the values of $\Omega_n^{loc}(t)^*$ and $\Omega_n^{off}(t)^*$.
10:     if $\Omega_n^{loc}(t)^* > \Omega_n^{off}(t)^*$ then
11:         Set $x_n(t)=0$;
12:         Obtain $f_n^{loc}(t)$ based on (24);
13:     else
14:         Set $x_n(t)=1$;
15:     end if
16: end for
17: Base on the above obtained VT-side optimization results $\{\mathbf{x}(t),\mathbf{f^{loc}}(t)\}$ and MRSU-side results $\{\mathbf{S}(t),\mathbf{P}(t),\mathbf{q}(t)\}$, update queues $Q_n(t)$ and $Z_n(t)$ according to Eqs. (5) and (6).
```

VIII. Complexity Analysis

The computational complexity of our joint dual-side optimization algorithm DDORV in Algorithm 3 comes from two aspects, i.e., the MRSU-side and the VT-side optimization.

The complexity of the MRSU-side complexity mainly determined by Steps 4 and 5. In Step 4, the complexity comes form server provisioning, i.e., Algorithm 1. In Algorithm 1, the complexity of Steps 2-7 is $O(N)$, the complexity of sorting in Step 8 is $O(N^2)$, and the complexity of Steps 9-15 is $O(N)$. Therefore, the total complexity of Algorithm 1 is $O(N)+O(N^2)+O(N)=O(N^2)$. The complexity of Step 5 comes from Algorithm 2. In Algorithm 2, the complexity of power allocation and burst allocation in Steps 3 and 4 are $O(NM)$, the complexity of dual-variable-update in Step 5 is $O(M) + O(L)$. The subgradients need $O(\frac{1}{\epsilon^2})$ iterations to converge. So the complexity of Algorithm 2 is $\frac{1}{\epsilon^2}\Big(O(NM) + O(NM) + O(M) + O(L)\Big) = O\Big(\frac{NM}{\epsilon^2}\Big)$. The complexity of VT-side optimization is $O(N)$. Therefore, the complexity of DDORV in Algorithm 3 is $O(N^2)+O\Big(\frac{NM}{\epsilon^2}\Big)+O(N) = O\Big(\frac{NM}{\epsilon^2}\Big)$.

IX. Simulation Results

In this section, we provide simulations to verify the performance of our proposed algorithms. Our simulations are conducted on a Matlab-based simulator. We simulate an MEC enabled mixed CVN and 802.22 network in a $5km \times 5km$ square area, where an MRSU locates at the center of the region, PUs are scattered uniformly through the region, and VTs are distributed in an $1km \times 10m$ road [27]. A TVWS channel with 6 MHz is reused by all the VTs, which is equally divided into 20 subchannels in frequency domain. The channel occupance t^{PU} of PUs follows Gamma distribution, and the CDF of t^{PU} is $F(t^{PU}) = 1 - e^{-5t^{PU}} - 5t^{PU}e^{-5t^{PU}}$ [27]. For simplicity, the wireless channel gain including the channel gain $G_{nm}(t)$ of VT n on burst m takes values randomly in [1, 5], and the channel gain $G_m^{PU}(t)$ between PU m and the BS is supposed to take values randomly in [5, 10], and be i.i.d. over frames [36]. Time is divided into frames, suppose the length of each uplink frame is $T = 9$ ms, and each frame contains $L = 4$ BIs. There are $M = 44$ bursts, each of which occupies one subchannel in frequency domain. Bursts 1 to 12 are type 1 burst, which covers the whole uplink subframe in time domain, while the rest 32 bursts are type 2 bursts with a length $T/4$ in time domain [27]. The PU interference limit at the BS for PU m (i.e., β_m) is chosen based on the criterion that SINR at the BS is no less than 10 dB, i.e., $SINR_m = \frac{p_m^{PU}(t)G_m^{PU}(t)}{\beta_m+\sigma^2} \geq 10$. Detailed parameters are summarized in Table II.

TABLE II: Simulation Parameters

Parameter	Value
Number of VTs N	20
Length T of uplink frame	9 (ms) [27]
Number of bursts M	44 [27]
Number of BIs L in each frame	4 [27]
Interference limit β_m for PU m	10 dB [27]
Power of Gaussian white noise σ^2	-100 dBm [27]
Transmit power $p_m^{PU}(t)$ of PU m	$0 \sim 4$ W [28]
VT transmit power threshold P^{max}	$100mW$ [29]
Bandwidth B_m of burst m	$\frac{6}{20}$ (MHz) [27]
Number of Types 1 and 2 bursts	12, 32 [27]
Arrived input data size $D_n(t)$	$0.1 \sim 1$ Mbit
Processing density λ_n (cycles/bit)	$10 \sim 1000$
Max. local processing capability f^{max}	1.4 (G cycles/s) [17]
Coefficient k for modeling local processing energy consumption	10^{-27} [18]
Number of edge servers q^{max}	$N + 10$
Processing capability of each edge server s_c	3 (G cycles/s) [17]
Electricity price per edge server $e(t)$	$1 * 10^{-8}$
Energy-money weight parameter α_n	$2.44 * 10^{-4}(\$/J)$ [17]
Price δ for MRSU renting radio bandwidth from operator	$0.5 * 10^{-10}$ ($/bit)
Price θ that MRSU charges from VTs for wireless data trans.	$1.16 * 10^{-10}$ ($/bit)
Price η MRSU charges from VTs for task processing	$3 * 10^{-10}$ (in $/cycle)

In the following, we will first evaluate the convergence of the proposed iterative radio resource allocation algorithm, i.e., Algorithm 2. Then we verify how parameter V affects the tradeoff between the cost of VTs and the length of queues. Finally, we assess the performance of DDORV form the VT-side and MRSU-side, respectively.

A. Convergence of Algorithm 2

In Fig. 4, we show the convergence of Algorithm 2 by plotting the two sets of dual variables $\boldsymbol{\omega} = [\omega_l], l \in \mathcal{L}$ and $\boldsymbol{\mu} = [\mu_m]$, $m \in \mathcal{M}$ versus the number of iterations in the lhs and rhs subfigure, and there are $|\mathcal{L}| = 4$ curves of $\boldsymbol{\omega} = [\omega_l]$, $l \in \mathcal{L}$ and 44 curves of $\boldsymbol{\mu} = [\mu_m]$, $m \in \mathcal{M}$, respectively. Fig. 3 demonstrates that both the two sets of dual variables converge at the $5th$ iteration, demonstrating our Lagrangian dual decomposition based Algorithm 2 converges considerably fast.

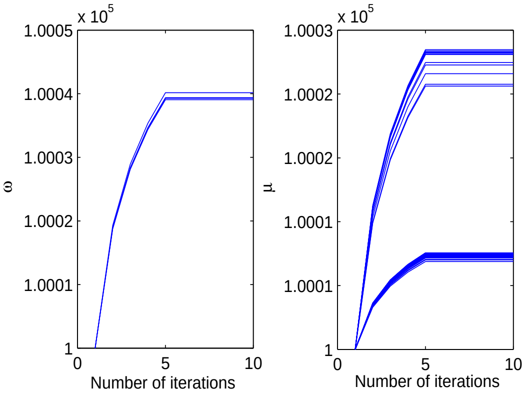

Fig. 4: Convergence of Algorithm 2.

B. Performance of DDORV Versus Control Parameter V

Fig. 5 depicts how the control factor V make a trade off between the cost $\bar{U}$ and the average delay. When V gets larger, the cost $\bar{U}$ decrease, however, the length of queue $\mathbf{Q} + \mathbf{Z}$ will

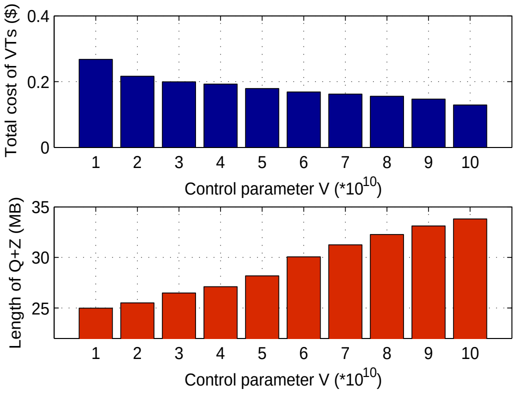

Fig. 5: Tradeoff between cost and queue backlog.

grow, which will lead to more delay in task processing. Thus, it can be known that the control parameter V can make a good balance between the cost and the length of data queues.

C. Performance Comparison for VT-side

Next, we show the performance for VT-side optimization of DDORV, by comparing it with local processing (denoted as Local-pro) and MRSU processing (denoted as MRSU-pro). In Local-pro, all VTs process their tasks locally using the maximum local CPU frequency. In MRSU-pro, all VTs offload their tasks to MRSU, and MRSU-side resource allocation optimization is performed among them.

1) Impact of the number of VTs N: In Fig. 6, we show the comparison on the cost and the queue backlog of all VTs' versus the number of VTs, respectively. As can be seen form Fig. 6 (a), with the number of VTs N increases, the user cost keeps increasing, which is the same for all algorithms. On the other hand, with the number of VTs increase, the available bursts and edge servers allocated to each VT decrease, as a result, the length of data queue increase, which is shown in Fig. 6 (b). Therefore, the two sub-figures indicate a tradeoff between the cost and the length of data queue. However, thanks to a multi-dimensional optimization, DDORV can always outperforms other algorithms, which perform only a certain dimensional optimization and consequently, more cost will be spend.

2) Impact of task parameter: In Figs. 7 and 8, we show how the task parameters affect the cost of VTs, including the input data arrival $D_n(t)$ and the processing density λ_n, respectively. Observing the two figures, it can be known that the cost of VTs grows linearly with respect to the two parameters, which is in accordance with the VT-side cost model in Eq. (7), where the cost of each VT n is proportional to both $D_n(t)$ and λ_n.

From the two figures it can also be known that the performance of MRSU-pro is a little worst than DDORV in performance, which indicates that the MRSU-side optimization plays a bigger role in the dual-side optimization framework.

D. Performance Comparison for MRSU-side

Then we show the performance for MRSU-side optimization of DDORV, by comparing it with Ser-pro-only and Radio-only algorithms. In Ser-pro-only, only server provisioning is optimized, and in Radio-only, only radio resource allocation (including IEEE 802.22 burst and power allocation) is optimized [26], [27], among all the VTs who choose task offloading. According to (8), it can be known that the profit of MRSU equals to the minus cost of MRSU, and the problem in (10) to minimize the cost of MRSU equals to maximizing the profit of MRSU. Therefore, we consider the profit of MRSU instead of discussing the cost for easy observation.

Since the pricing policy (i.e., θ, δ, η, and $e(t)$) plays an important role on the economical profit of MRSU, we show the performance comparison between the algorithms under different pricing policies in Figures 9, 10, 11, and 12.

As can be seen from Figs 8 and 10, the profit of MRSU grows with the increase of the price that it rents radio and computation resources to VTs, i.e., θ and η. Figs. 9 and 11 show that the profit of MRSU decrease with the price δ it rents radio resource from wireless network operators, and the electricity bill $e(t)$ to active per edge server.

X. Conclusions

In this paper, we have studied a dual-side stochastic optimization framework in an MEC enabled IEEE 802.22-CVN coexistence system. Then two problems, i.e., the VT-side and the MRSU-side optimization problems, were formulated, in order to minimize the averaged cost of VTs and the MRSU, respectively. Employing Lyapunov optimization theory, we have proposed a low-complexity online algorithm DDORV, where the two problems are solved in a integrated framework in each frame. Simulation results have verified the convergence of the iterative radio resource allocation algorithm, the tradeoff between the average cost of VTs and the average queue length, and have shown DDORV can performs well compared with other schemes.

Appendix

Appendix A. Proof of Proposition 1

Proof: For notation simplicity, denote constant $[V(\theta+\eta\lambda_n-\delta)-Z_n(t)]B_m\bar{T}_m$ as A. According to convex optimization [34], when $f(x)$ is concave, then the perspective function $g(x,t)=tf(x/t)$ is concave, too. Since $As_{nm}(t)\log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{s_{nm}(t)\left(p_m^{PU}(t)G_m^{PU}(t)+\sigma^2\right)}\right)$ is the perspective function of concave function $A\log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{p_m^{PU}(t)G_m^{PU}(t)+\sigma^2}\right)$, it preserves concavity, too. As the sum of several concave functions is still concave, $\sum\limits_{n\in\mathcal{N}_1}\sum\limits_{m\in\mathcal{M}}As_{nm}(t)\log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{s_{nm}(t)\left(p_m^{PU}(t)G_m^{PU}(t)+\sigma^2\right)}\right)$ is also concave. On the other hand, $(\mathrm{C2})-(\mathrm{C6})$ are all linear constraints. Thus, (28) is a convex optimization programming that maximize a concave function over a convex set. ■

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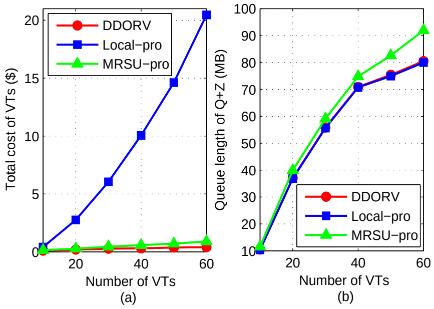

Fig. 6: (a) Total cost of all VTs vs. the number of VTs N, (b) queue backlog vs. the number of VTs N.

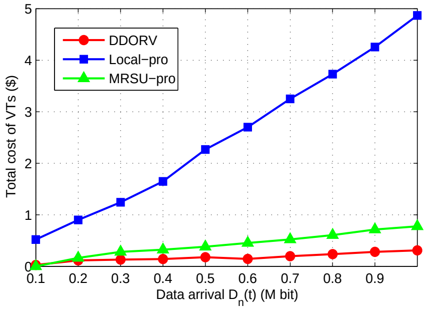

Fig. 7: Total cost of all VTs vs. the data arrival $D_n(t)$.

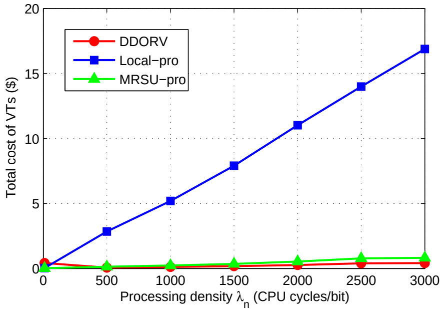

Fig. 8: Total cost of all VTs vs. processing density λ_n.

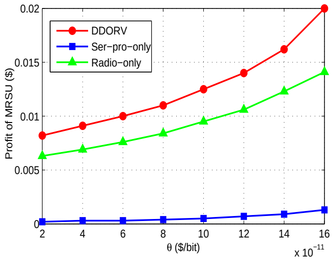

Fig. 9: Profit of MRSU versus the wireless data transmission price θ charged form VTs.

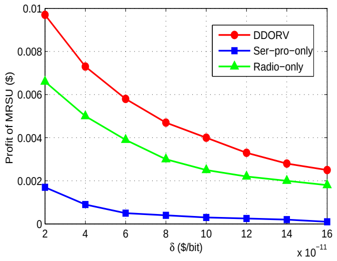

Fig. 10: Profit of MRSU versus the price δ that it rents radio bandwidth from wireless network operator.

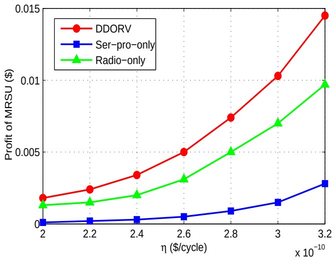

Fig. 11: Profit of MRSU versus the price η that it charges for task processing form VTs.

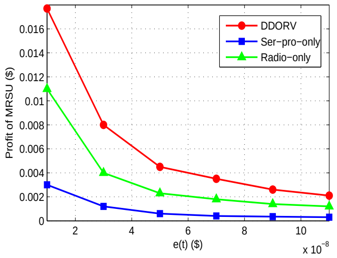

Fig. 12: Profit of MRSU versus the electricity bills $e(t)$ that it pays to grid operator for running an edge server.

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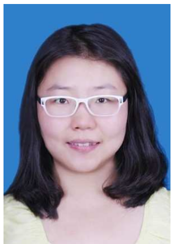

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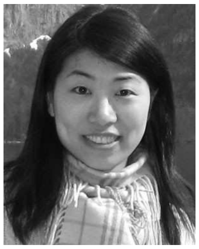

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