Economical Profit Maximization in MEC Enabled Vehicular Networks

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***Abstract*—Mobile edge computing enabled vehicular networking has appeared as a promising solution to the emerging resource hungry vehicular applications. In this paper, we study the computation offloading in a cognitive vehicular network that reuses the TV white space (TVWS) bands. We propose to maximize the average economical profit of the service provider by jointly considering communication and computation resource allocation, while guaranteeing network stability and the QoS of TVWS primary users. Based on Lyapunov optimization, we design an per-frame algorithm to tackle the joint optimization problem, where we first derive the closed-form solution for computation resource allocation, and then develop a continuous relaxation and Lagrangian dual decomposition based iterative algorithm for radio resource allocation. Simulation results demonstrate that the proposed algorithm can flexibly balance the profit-delay tradeoff, and can improve the economical profit of the service provider significantly as compared with the existing schemes.**

***Index Terms*—Computation offloading, resource allocation, stochastic optimization, TVWS, vehicular networks.**

I. Introduction

The popularity of vehicle-mounted intelligent applications imposes great pressures on the processing capabilities of vehicular terminals (VTs) [1]–[3]. Mobile edge computing (MEC) [4], [5] enabled vehicular networking has been regarded as a promising solution to relieve this issue. By attaching MEC servers to roadside units (RSUs), an MEC based integrated communication and computation platform can be constituted and can accelerate the response or enable complex tasks [2], [6], [7]. From the standpoint of service providers, it is a good opportunity to make more economical profit through proving computing services.

When tasks are offloaded to MEC servers, general wireless communication technologies have their respective disadvantages in vehicular-to-roadside (V2R) data transmission. The cellular network based Long-term evolution-vehicle (LTE-V) is facing issues of the explosive growth of mobile data traffic and relatively expensive cost. For dedicated short-range communications (DSRC), many studies have shown that the bandwidth is seriously insufficient. WiFi is constrained in V2R scenarios because their short coverage range will result in frequent handovers of high-speed VTs. To solve those issues, TV white spaces (TVWS) band communication has been used as a feasible supplement to the limited DSRC bandwidth owing to their desirable long-distance propagation characteristics [8].

MEC in vehicular networks has attracted much attention in recent years. The authors in [9] proposed an MEC based computation offloading framework for cognitive vehicular network (CVN) [10] to minimize the cost of task offloading while guaranteeing task processing delay and considering VTs' mobility. In [11], 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. In the above existing works [9], [11], only short-term performance, i.e., the performance for processing a single task was considered, without considering the coupling among the randomly arrived tasks or stochastic computation offloading policies.

In this paper, we study computation offloading in a mixed CVN and IEEE 802.22 network from a long-term perspective, by addressing the power asymmetry issues and jointly optimizing the allocation of computation and communication resources, in order to maximize the operator's long-term average economical profit. The joint optimization is formulated as a stochastic mixed integer non-linear programming (MINLP) problem. Employing Lyapunov optimization, we propose an algorithm called **d**ynamic joint task **o**ffloading and **r**esource allocation algorithm in **v**ehicular networks (DORV), to decouple the problem into deterministic per-frame optimizations. In each frame, we first optimize the computation resource allocation using linear programming, and then we develop a continuous relaxation and Lagrange dual decomposition based iterative algorithm to obtain the optimal radio resource allocation policies.

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II. System Model

A. Basic Concepts and Scenario Description

IEEE 802.22 [12] was designed for broadband access employing the TVWS band in low population density regions where the frame length is 10 milliseconds, and each frame is partitioned into an uplink and a downlink sub-frame. The uplink scheduling information of 802.22 primary users (PUs) is incorporated in the downlink messages, which are broadcast by the 802.22 base station (BS) at the beginning of each frame. Through listening to the 802.22 network deployed in the same area, VTs can obtain the uplink scheduling information of 802.22 PUs. By appropriate resource allocation, the low power vehicular network could coexist with the high power 802.22 network, and reuse its TVWS channels. To be consistent with 802.22, we also take frame length $T = 10$ milliseconds [12].

Road is divided into several segments and each is covered with an RSU which serves its covered VTs. Suppose the speed of a VT is 20 m/s, and an RSU can cover 500 m, then the VT can move at most 0.2 m each frame. Therefore, the networks can be deemed as static in each frame and may be different in different frames. Each RSU is equipped with an MEC server with certain processing capability, and vehicular applications can be offloaded to MEC servers in RSU for enhanced processing. For notation simplicity, we call the RSUs equipped with MEC server as MEC enabled RSUs (MRSUs) in this paper. Each MRSU performs scheduling independently among its served VTs.

There's a TWVS channel consisting several subchannels in the system. In 802.22 [12], the basic resource element is "burst" [12], which consists some sub-channels in frequency domain and several OFDM symbols in time domain. There are two kinds of uplink bursts: type 1 burst occupies the whole uplink sub-frame in time domain, while a type 2 burst, a.k.a. normal burst, occupies part of the uplink sub-frame. Let $\mathcal{M} = \{1, 2, ..., M\}$ and M be the set and number of bursts, and each is allocated to a PU. According to normal burst, the uplink sub-frame can be partitioned into several "burst intervals" (BIs) [12]. Denote the set and the number of BIs as $\mathcal{L} = \{1, 2, ..., L\}$ and L, respectively, and $L \in \{1, 2, 3, 4\}$ [12]. Let $C_{m,l} \in \{0, 1\}$ denote the burst–BI indicator, where $C_{m,l} = 1$ means burst m locates in BI_l, and $C_{m,l} = 0$ otherwise. In order to guarantee the QoS of PUs, 80222 [12] requires that the total transmit power of all the VTs sharing a TVWS channel should be less than P^{max} in each BI.

Let $\mathcal{N} = \{1, 2, ..., N\}$ and N be the set and the number of VTs, and each VT is running fine-grained tasks [8]: at the beginning of each frame t, $D_n(t)$ bits of computation task arrive at VT n, with a calculation amount of size $C_n(t)$ (in CPU cycles). $D_n(t)$ and $C_n(t)$ are i.i.d. over frames and satisfy $0 \leq D_n(t) \leq D_n^{max}$ and $0 \leq C_n(t) \leq C_n^{max}$, where D_n^{max} and C_n^{max} are the upper limit of $D_n(t)$ and $C_n(t)$. The arrived task of VT n is denoted as $\Lambda_n(t) = \{D_n(t), C_n(t)\}$, which will first be pushed into its data queue $Q_n(t)$, and then be transmitted to MRSU through the shared TVWS wireless links, afterwards $\Lambda_n(t)$ will be processed by MRSU [6], [8]. At the beginning of each frame, each MRSU obtains the downlink messages from 802.22 BS and the task information form all its serving VTs, according to which it performs scheduling, and then it broadcasts the scheduling information to its served VTs [8].

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. Then the maximum transmit rate of vehicle n on burst m in frame t can be given by $r_{nm}(t) = B_m \log_2 \left(1 + \frac{p_{nm}(t)G_{nm}(t)}{p_m^{PU}(t)G_m^{PU}(t)+N_0}\right)$, where N_0 is the power of additive Gaussian white noise.

Define the occupancy of a TVWS channel as a random variable t^{PU}, which indicates the spare time before a PU returns and occupies the 802.22 channel [8]. Suppose the probability density function (PDF) $f(t^{PU})$ and cumulative distribution function (CDF) $F(t^{PU})$ of t^{PU} is known at MRSU [8]. Since PUs transmit with high power, the data transmission of VTs may be interrupted by PUs' return. We consider a VT's data transmitted before PU returns to be successful, and otherwise to be lost. Let t_m represent the time duration between the start time of burst m and the start time of the current uplink sub-frame, 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, i.e., $\bar{T}_m = T_m$. (ii) On the country, if PUs disturb the VT's transmission, then the valid transmission time is $\bar{T}_m = t^{PU} - t_m$. The expected valid transmission time $\bar{T}_m$ of a VT on burst m is given in our previous work [8] and is omitted here for space limitation. Since t_m, T_m and $F(t^{PU})$ are all known at the MRSUs, and thus $\bar{T}_m$ is a constant [8].

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. Thus, the maximum transmit rate of VT n in frame t is given by $r_n(t) = \sum_{m \in \mathcal{M}} s_{n,m}(t) r_{n,m}(t) \frac{\bar{T}_m}{T}$, and $Q_n(t)$ evolves according to

$$Q_n(t+1) = max\big[Q_n(t) - r_n(t), 0\big] + D_n(t). \tag{1}$$

Suppose there is a logical operator *mobile network operator* (MNO) which owns and manages the communication resource and physical facilities of the system [8], and each MRSU rents radio resources (in bps) from MNO and provides communication and computation services to and charges fees from the served VTs. We intend to maximize the economical profit of all the MRSUs through the involved optimization.

B. Utility Function

Suppose the price that MRSU rents radio bandwidth from MNO is δ per bps, and the charged price form VTs for uplink data transmission is θ per bps. Thus the net economical profit charged from VT n for communication is $l_n(t) = (\theta - \delta) r_n(t)$.

For the profit gained from computation resource allocation, we suppose MRSU will charge each VT only from the extra portion of computing resource $f_n(t)$ more than the local processing capability f_n^{loc} [8], and the price of each unit extra computation task (UECT) is λ. Then the profit gained from VT n in computation resource allocation is $\Omega_n(t) = \lambda\left(\frac{f_n(t)}{C_n(t)} - \frac{f_n^{loc}}{C_n(t)}\right)$.

The total benefited economical profit of MRSU is given by $U(t) = \sum_{n\in\mathcal{N}}(\theta-\delta)r_n(t)+\lambda\left(\frac{f_n(t)}{C_n(t)} - \frac{f_n^{loc}}{C_n(t)}\right)$, and our utility function is defined as the time averaged expected total profit of each MRSU, which is given by

$$\bar{U} = \lim_{t\to\infty}\frac{1}{t}\sum_{\tau=0}^{t-1}\mathbb{E}\{U(\tau)\}. \tag{2}$$

C. Problem Formulation

We adopt the utility function in (2) as the objective function of our optimization problem, and intend to maximize the utility value $\bar{U}$ of each 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 computing resource assignment $\mathbf{f}(t) = \{f_1(t), ..., f_N(t)\}$. The optimization is formulated as

$$\begin{aligned}
(\mathcal{P}_1):\ & \max_{\mathbf{f}(t),\mathbf{S}(t),\mathbf{P}(t)} \bar{U} = \lim_{T\to\infty}\frac{1}{t}\sum_{t=0}^{T-1}\mathbb{E}\{U(t)\}\\
\text{s.t. } & (\text{C1}): \lim_{T\to\infty}\frac{\mathbb{E}\{Q_n(t)\}}{T} = 0,\ \forall n\in\mathcal{N},\\
& (\text{C2}): \sum_{n\in\mathcal{N}} s_{nm}(t)p_{nm}(t)G_{nm}(t) \le \beta_m,\ \forall m\in\mathcal{M},\\
& (\text{C3}): \sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} C_{ml}s_{nm}(t)p_{nm}(t) \le P^{max},\ \forall l\in\mathcal{L},\\
& (\text{C4}): \sum_{n\in\mathcal{N}} s_{nm}(t) \le 1,\ \forall m\in\mathcal{M},\\
& (\text{C5}): s_{nm}(t)\in\{0,1\},\ \forall n\in\mathcal{N},\forall m\in\mathcal{M},\\
& (\text{C6}): p_{nm}(t)\ge 0,\ \forall n\in\mathcal{N},\forall m\in\mathcal{M},\\
& (\text{C7}): \sum_{n\in\mathcal{N}} f_n(t)\le F,\\
& (\text{C8}): (f_n(t)-f_n^{loc})\ge 0,\ \forall n\in\mathcal{N},
\end{aligned} \tag{3}$$

where (C1) ensures the network is stable [8], [13]; (C2) constraints the interference caused by VT's uplink transmission no more than a threshold β_m to ensure the QoS of PUs; (C3) restraints the total transmit power of SUs on a TVWS channel. (C4) and (C5) represent a burst can be allocated to at most one VT; (C6) indicates the transmit power should be non-negative; (C7) shows the total allocated computation resources should be less than the total computation resource F of MRSU; (C8) ensures the computation resource allocated to each VT n should be greater than that of itself.

III. Problem Transformation

In the following, we propose an online algorithm based on Lyapunov optimization theory to tackle the intractable problem $(\mathcal{P}_1)$, which is transformed into a deterministic problem at each frame, without any prior information about the traffic arrivals [8], [13].

The Lyapunov function can be defined by $L(\mathbf{Q}(t)) \triangleq \frac{1}{2}\sum_{n\in\mathcal{N}}Q_n^2(t)$. The conditional Lyapunov drift $\Delta(\mathbf{\Theta}(t))$ is given as $\Delta(\mathbf{Q}(t)) \triangleq \mathbb{E}\{L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t))|\mathbf{Q}(t)\}$, where $L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t))$ satisfies $L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t)) \le B+\sum_{n\in\mathcal{N}}Q_n(t)(D_n(t)-r_n(t))$, and the constant B is given by $B = \frac{1}{2}\sum_{n\in\mathcal{N}}[(D_n^{max})^2 + (r_n^{max})^2]$, where r_n^{max} is an upper limit of $r_n(t)$.

According to Lyapunov optimization theory, in order to maximize $\bar{U}$ in $(\mathcal{P}_1)$, the drift-plus-penalty function $\Delta(\mathbf{Q}(t)) - V\mathbb{E}\{U(t)|\mathbf{Q}(t)\}$ should be considered, which is bounded by

$$\begin{aligned}
&\Delta(\mathbf{Q}(t)) - V\mathbb{E}\{U(t)|\mathbf{Q}(t)\} \\
&\le B + \sum_{n\in\mathcal{N}}\mathbb{E}\{(D_n(t)-r_n(t))Q_n(t)|\mathbf{Q}(t)\} - V\mathbb{E}\{U(t)|\mathbf{Q}(t)\}\\
&= B + \sum_{n\in\mathcal{N}}\mathbb{E}\Bigg\{\big(D_n(t)-r_n(t)\big)Q_n(t) - V(\theta-\delta)r_n(t)\\
&\qquad - \lambda V\left(\frac{f_n(t)}{C_n(t)} - \frac{f_n^{loc}}{C_n(t)}\right)\Bigg|\mathbf{Q}(t)\Bigg\},
\end{aligned} \tag{4}$$

where V is a non-negative constant used to make a tradeoff between queue length and the profit of MRSU. Then the dynamic joint computation resource allocation, transmit power control, and burst assignment problem at each frame t can be obtained by minimizing the upper bound of the drift-plus-penalty function in (4) as follows

$$\begin{aligned}
&(\mathcal{P}_2):\\
&\max_{\mathbf{f}(t),\mathbf{S}(t),\mathbf{P}(t)} \sum_{n\in\mathcal{N}}[Q_n(t)+V(\theta-\delta)]r_n(t) + \frac{\lambda V}{C_n(t)}f_n(t) + c_1\\
&\text{s.t. } (\text{C2}) - (\text{C8}),
\end{aligned} \tag{5}$$

where $c_1 = Q_n(t)D_n(t) + \frac{\lambda V f_n^{loc}}{C_n(t)}$ is a constant and will not affect our optimization, so it is ignored in the following.

IV. Computation resource allocation

$(\mathcal{P}_2)$ can be further separated into two independent subproblems, i.e., the computation resource allocation subproblem in $(\mathcal{P}_3)$ and the radio resource allocation subproblem in $(\mathcal{P}_4)$, and the former is given by

$$\begin{aligned}
(\mathcal{P}_3):\ & \max_{\mathbf{f}(t)} \sum_{n\in\mathcal{N}}\frac{\lambda V}{C_n(t)}f_n(t)\\
\text{s.t. } & (\text{C7}): \sum_{n\in\mathcal{N}} f_n(t)\le F,\\
& (\text{C8}): f_n(t)-f_n^{loc}\ge 0, \forall n\in\mathcal{N},
\end{aligned} \tag{6}$$

from which the computing resource allocation could be obtained as

$$f_n(t) = \begin{cases} (F - \sum\limits_{\substack{n\in\mathcal{N}\\ n\neq\arg\max\{\frac{\lambda V}{C_n(t)}\}}} f_n^{loc}), & if\ n = \arg\max\{\frac{\lambda V}{C_n(t)}\},\\ f_n^{loc}, & otherwise. \end{cases} \tag{7}$$

V. Communication Resource Assignment

In this section, we will tackle the radio resource allocation subproblem embedded in $(\mathcal{P}_2)$, which includes a joint optimization of burst assignment $\mathbf{S}(t)$ and transmit power control $\mathbf{P}(t)$ among all the VTs in $\mathcal{N}$, and can be given by

$$(\mathcal{P}_4): \max_{\mathbf{S}(t),\mathbf{P}(t)} \sum_{n\in\mathcal{N}_1} [Q_n(t)+V(\theta-\delta)]r_n(t) \tag{8}$$
$$\text{s.t.}\ \ \text{(C2)} - \text{(C6)},$$

where $r_n(t) = \sum_{m\in\mathcal{M}} s_{nm}(t)\frac{\bar{T}_m}{T}B_m \log_2\Big(1 + \frac{p_{nm}(t)G_{nm}(t)}{p_m^{PU}G_m^{PU}(t)+N_0}\Big)$. However, $(\mathcal{P}_4)$ is still a MINLP problem and can be generally NP-hard [19]. Observing $(\mathcal{P}_4)$, it can be known that 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.

A. Convert $(\mathcal{P}_4)$ to a Convex Program

First we relax the integer constraint into $s_{nm}(t) \in [0,1]$, and then replace $p_{nm}(t)$ with $y_{nm}(t) = s_{nm}(t)p_{nm}(t),\ \forall n \in \mathcal{N}_1, \forall m \in \mathcal{M}$, we have

$$\begin{aligned}
(\mathcal{P}_5): \max_{\mathbf{S}(t),\mathbf{Y}(t)} &\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} [Q_n(t)+V(\theta-\delta)]B_m\frac{\bar{T}_m}{T}s_{nm}(t) \\
&\log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{s_{nm}(t)\big(p_m^{PU}G_m^{PU}(t)+N_0\big)}\right)\\
\text{s.t. (C2)}: &\sum_{n\in\mathcal{N}_1} y_{nm}(t)G_{nm}(t) \le \beta_m,\ \forall m\in\mathcal{M},\\
\text{(C3)}: &\sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}} y_{nm}(t)C_{ml} \le P^{max},\ \forall l\in\mathcal{L},\\
\text{(C4)}: &\sum_{n\in\mathcal{N}_1} s_{nm}(t)\le 1,\ \forall m\in\mathcal{M},\\
\text{(C5)}: &\ s_{nm}(t)\in[0,1],\ \forall n\in\mathcal{N}_1,\forall m\in\mathcal{M},\\
\text{(C6)}: &\ y_{nm}(t)\ge 0,\ \forall n\in\mathcal{N}_1,\forall m\in\mathcal{M}.
\end{aligned} \tag{9}$$

Problem $(\mathcal{P}_5)$ is jointly convex in $\mathbf{S}(t)$ and $\mathbf{Y}(t)$, which can be proved similar to the Appendix B of [6] and is omitted due to space limitation.

Next we use Lagrangian dual decomposition technique to solve it. The partial Lagrangian function of $(\mathcal{P}_5)$ is given in (10), 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 (C2) and (C3) in $(\mathcal{P}_5)$, respectively.

As $(\mathcal{P}_5)$ is convex, zero duality gap can be guaranteed and we can solve the following dual problem to obtain the optimal radio resource allocation

$$\min_{\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)}\ \max_{\mathbf{S}(t),\mathbf{Y}(t)} L(\mathbf{S}(t),\mathbf{Y}(t),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)). \tag{11}$$

B. Obtain Power Allocation

According to (11), given dual variables $\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)$ and burst allocation $\mathbf{S}(t)$, we can first obtain the optimal transmit power by solving $\mathbf{Y}(t)$. Using KKT conditions [6] by letting $\frac{\partial L(\mathbf{S}(t),\mathbf{Y}(\mathbf{t}),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t))}{\partial y_{nm}(t)} = 0$, $y_{nm}^*(t)$ can be given by

$$y_{nm}^*(t) = \Big[\frac{\bar{T}_mB_m\big(Q_n(t)-V(\theta-\delta)\big)}{T\ln 2\big(\mu_m(t)G_{nm}(t)+\sum_{l\in\mathcal{L}}\omega_lC_{ml}\big)} - \frac{p_m^{PU}G_m^{PU}(t)+N_0}{G_{nm}(t)}\Big]s_{nm}(t). \tag{12}$$

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

$$p_{nm}^*(t) = \left[\frac{\bar{T}_mB_m\big(Q_n(t)-V(\theta-\delta)\big)}{T\ln 2\big(\mu_m(t)G_{nm}(t)+\sum_{l\in\mathcal{L}}\omega_l(t)C_{ml}\big)} - \frac{p_m^{PU}G_m^{PU}(t)+N_0}{G_{nm}(t)}\right]^+, \tag{13}$$

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

C. Obtain Burst Assignment

Next we obtain the optimal burst assignment by plugging $p_{nm}^*(t)$ back to Lagrangian function. For notation simplicity, we define $d_{nm}(t)$ and $E(t)$ as

$$\begin{aligned}
d_{nm}(t) = &\\
&\frac{\bar{T}_m}{T}[Q_n(t)+V(\theta-\delta)]B_m\log_2\left(1+\frac{p_{nm}^*(t)G_{nm}(t)}{p_m^{PU}G_m^{PU}(t)+N_0}\right)\\
&-\left(\mu_m(t)G_{nm}(t)+\sum_{l\in\mathcal{L}}\omega_l(t)C_{ml}\right)p_{nm}^*(t),\\
E(t) = &\sum_{m\in\mathcal{M}}\mu_m(t)\beta_m+\sum_{l\in\mathcal{L}}\omega_lP^{max},
\end{aligned} \tag{14}$$

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

$$\begin{aligned}
(\mathcal{P}_6): \max_{\mathbf{S}(t)} &\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} d_{nm}(t)s_{nm}(t) - E(t)\\
\text{s.t. (C4)}: &\sum_{n\in\mathcal{N}_1} s_{nm}(t)\le 1,\ \forall m\in\mathcal{M},\\
\text{(C5)}: &\ s_{nm}(t)\in[0,1],\ \forall n\in\mathcal{N}_1,\forall m\in\mathcal{M}.
\end{aligned} \tag{15}$$

Problem $(\mathcal{P}_6)$ is the sum of a set of linear functions w.r.t $s_{nm}(t)$, therefore burst allocation $s_{nm}(t)$ must be binary, since the optimal value of a linear function is obtained at the endpoints. Therefore, we have

$$s_{nm}^*(t) = \begin{cases} 1, & if\ n = \arg\max_{\hat{n}} d_{nm}(t)\ \&\ d_{nm}(t)\ge 0,\\ 0, & otherwise. \end{cases} \tag{16}$$

$$L(\mathbf{S}(t),\mathbf{Y}(t),\boldsymbol{\mu}(t),\boldsymbol{\omega}(t)) = \sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}}[Q_n(t)+V(\theta-\delta)]B_m\frac{\bar{T}_m}{T}s_{nm}(t)\log_2\left(1+\frac{y_{nm}(t)G_{nm}(t)}{s_{nm}(t)\big(p_m^{PU}G_m^{PU}(t)+N_0\big)}\right) - \sum_{m\in\mathcal{M}}\mu_m(t)\Big(\sum_{n\in\mathcal{N}_1}y_{nm}(t)G_{nm}(t)-\beta_m\Big)-\sum_{l\in\mathcal{L}}\omega_l(t)\Big(\sum_{n\in\mathcal{N}_1}\sum_{m\in\mathcal{M}}y_{nm}(t)C_{ml}-P^{max}\Big). \quad (10)$$

D. Dual Variables Update

To solve the outer minimization problem in (11), a subgradient method [6] can be used to update the dual variables as follows

$$\mu_m^{i+1}(t)=\left[\mu_m^i(t)-h_m^i(t)\left(\beta_m-\sum_{n\in\mathcal{N}_1}y_{nm}(t)G_{nm}(t)\right)\right]^+, \quad \forall m\in\mathcal{M}, \quad (17)$$

$$\omega_l^{i+1}(t)=\left[\omega_l^i(t)-k_l^i(t)\left(P^{max}-\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}}y_{nm}(t)C_{ml}\right)\right]^+, \quad \forall l\in\mathcal{L}, \quad (18)$$

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 [6]. The Lagrangian dual variables are updated iteratively until the required precision is satisfied.

VI. Simulation Results

In this section, we verify the performance of our proposed algorithms. 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 [8]. The wireless channel gain takes values randomly in [5, 14] each frames. 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 $F(t^{PU})=1-e^{-5t^{PU}}-5t^{PU}e^{-5t^{PU}}$ [8]. Time is divided into frames, suppose the length of each uplink frame is $T=9$ ms [8], 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 occupying the whole uplink sub-frame, while the rest 32 bursts are type 2 bursts with a length $T/4$ in time domain [8].

The PU interference limit at the BS for PU m (i.e., β_m) is no less than 10 dB, i.e., $SINR_m=\frac{p_m^{PU}G_m^{PU}(t)}{\beta_m+N_0}\geq 0$. N_0 is -100 dBm [8]. $p_m^{PU}(t)$ is set in $0-4$ W uniformly [12]. The threshold of total transmit power P^{max} of all the VTs sharing a TVWS channel is $100mW$ [12]. $N=30$. The total computation resource F of MRSU is 5 G CPU cycles/s. f_n^{loc} distributes uniformly in $10-50$ M CPU cycles/s. The arrived input data $D_n(t)$ is distributed within $1-8$ Kbit uniformly. The calculation amount $C_n(t)$ distributes uniformly in $50*(1-8)$ K CPU cycles. The price that MRSU rents radio resource form MNO is set as $\theta=3*10^{-5}$ units/bps, the price charged from VTs for radio resource allocation is $\delta=1*10^{-5}$ units/bps, and the price charged from VTs for task processing is $\lambda=2*10^{-5}$ units/UECT.

We assess the performance of DORV by comparing it with: i) only computation resource allocation is optimized (Com-Only), and ii) only radio resource allocation (including burst and power allocation) is optimized (Radio-Only) [8].

1) Profit delay tradeoff: In the LHS subfigure of Fig. 1, we show the comparison on the obtained average economical profit of MRSU and the average length of all VTs' data queues, versus the number of VTs N, respectively. As can be seen, with N increases, the obtained profit keeps increasing for all algorithms. Meanwhile, the available bursts and computational resource allocated to each VT decrease, leading to a decrease in the length of data queue (consequently delay), as shown in the RHS subfigure of Fig. 1. Therefore, the two subfigures demonstrate the tradeoff between the obtained profit and the length of data queue. However, thanks to a multi-dimensional optimization, DORV can always outperforms other algorithms which perform only a certain dimensional optimization.

Moreover, as the profit obtained from VT n for computation resource allocation $f_n(t)$ can only be obtained form the extra computation resource more than f_n^{loc}, i.e., the part $f_n(t)-f_n^{loc}$, consequently, the profitable part of computation resource is $F-\sum_{n\in\mathcal{N}_1}f_n^{loc}$, not all the computation resource in MRSU, and therefore, the profit gained from computation resource allocation play a minimal role, and Com-Only is always the worst. DORV always performs the best as a result of joint optimization. This is a same case for all the following figures and will not be repeated again in the following.

2) Impact of resources: In Figures 2 and 3, we demonstrate how the total resources, i.e., the computation resource F of MRSU, and the total radio TVWS channel bandwidth, affect the average profit $\bar{U}$ of MRSU. As can be seen, with the total available radio or computation resource increase, the average profit $\bar{U}$ of all algorithms increase, which is in line with our intuition that more provided resources, more profit will be obtained. Besides, since DORV can obtain benefits from various aspects, it can always obtain more profit than other algorithms.

3) Impact of task parameter: Fig. 4 demonstrates the averaged economical profit decreases exponentially with the calculation amount $C_n(t)$ increase, which is the same for all the algorithms. This is because, the profit benefited form computation resource allocation is defined as the extra portion of computing resource, thus when $C_n(t)$ increases, more computation resource will be necessary to complete the task, and consequently, less extra computing resource will be

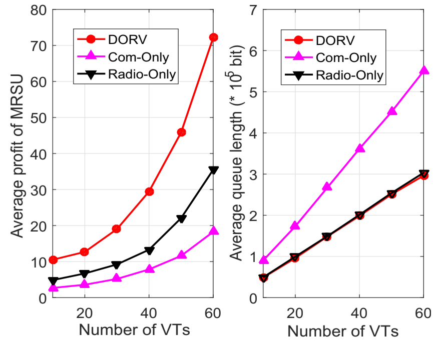

Fig. 1: Profit and queue length versus N.

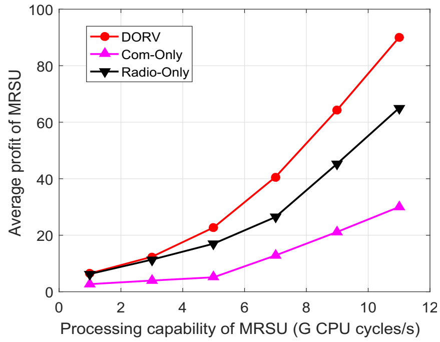

Fig. 2: Profit versus F of MRSU.

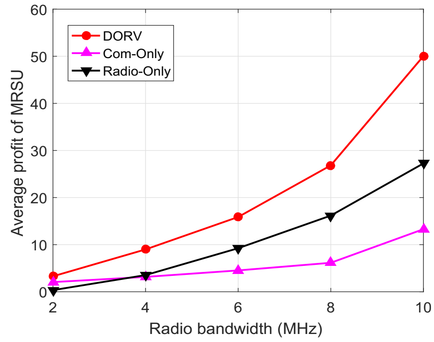

Fig. 3: Profit versus radio bandwidth.

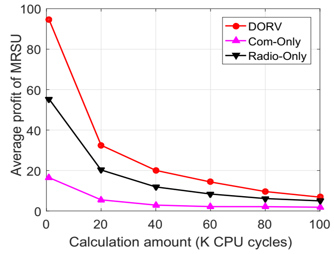

Fig. 4: Profit versus $C_n(t)$.

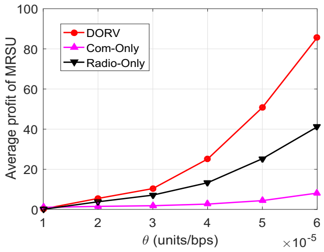

Fig. 5: Profit versus θ.

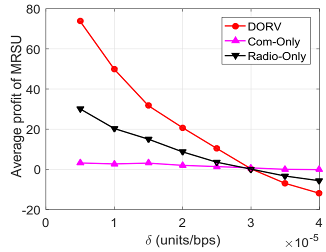

Fig. 6: Profit versus δ.

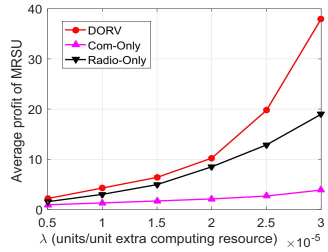

Fig. 7: Profit versus λ.

left, and less profit can be obtained. Moreover, as a joint multidimensional optimization, DORV performs always the best.

4) Impact of prices: The pricing policy has an important effect on the economical profit of MRSU as shown in Figures 5, 6, and 7. As can be seen from Figures 5 and 7, the obtained profit grows with the increase of the sale price of radio and computation resources, i.e., θ and λ, and decrease with the price δ when purchasing radio resource from MNO. Specifically, it can be further observed in Fig. 6 that when $\delta > 3$, i.e., the purchasing price δ of radio resource is greater than the sale price θ, the profit of all the algorithms is less than 0. As was mentioned, radio resource allocation plays a bigger role than computation resource allocation, and a joint minimization further plays a bigger role than radio resource allocation. Therefore, the average profit curves of DORV grows (in Fig. 6) or decreases (in Figures 5 and 7) the most sharply, followed by Radio-Only, and Com-Only.

VII. Conclusions

In this paper, we have studied resource allocation issues in an MEC enabled IEEE 802.22-CVN coexistence system to maximize the economical profit of MRSU. We have proposed a low-complexity online algorithm DORV where only a deterministic optimization needs to be settled in each frame. We have obtained closed-form solutions to computation resource allocation and have solved the radio resource allocation subproblem using continuous relaxation and Lagrange dual theory. Simulation results have demonstrated DORV performs well in terms of average profit of MRSU.

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