Multi-Agent Deep Reinforcement Learning enabled Computation Resource Allocation in a Vehicular Cloud Network

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Abstract—In this paper, we investigate the computational resource allocation problem in a distributed Ad-Hoc vehicular network with no centralized infrastructure support. To support the ever increasing computational needs in such a vehicular network, the distributed virtual cloud network (VCN) is formed, based on which a computational resource sharing scheme through computation offloading among nearby vehicles is proposed. In view of the time-varying computational resource in VCN, the statistical distribution characteristics for computational resource are analyzed in detail. Thereby, a resource-aware combinatorial optimization objective mechanism is proposed. To alleviate the non-stationary environment caused by the typically multi-agent environment in VCN, we adopt a centralized training and decentralized execution framework. In addition, for the objective optimization problem, we model it as a Markov game and propose a DRL based multi-agent deep deterministic reinforcement learning (MADDPG) algorithm to solve it. Interestingly, to overcome the dilemma of lacking a real central control unit in VCN, the allocation is actually completed on the vehicles in a distributed manner. The simulation results are presented to demonstrate our scheme’s effectiveness.

Index Terms—Vehicular cloud network, vehicular network, computation offloading, deep reinforcement learning, deep deterministic policy gradient.

I. INTRODUCTION

With the development of intelligent transportation systems (ITS), it has been predicted that the number of interconnecting vehicles will increase to around 250 million by 2020 [1]. In the future, the emerging computation-intensive and delay-sensitive vehicular applications such as autonomous driving technologies, location-based Virtual/Augmented Reality (VR/AR) and in-vehicle multimedia service, are widely considered to rely on the wide-coverage and resource-rich mobile edge computing servers (MEC) which are usually installed on the transportation infrastructures such as roadside units (RSUs) or base station (BS). However, due to the asynchronous and unbalanced development of economic budgets and technological levels all over the world, the resource-rich transportation infrastructure is hard or almost impossible to be deployed homogeneously on all the roads. Thereby, the computational resource scarcity issues for vehicles in these areas will cause a series of social problems. For example, vehicles will drive on rural areas or highways where infrastructures are rarely deployed, and unfortunately the base station (BS) based network access to remote cloud (RC) computing center is also either unobtainable due to the limit coverage or infeasible caused by the unacceptable latency [2]. In this way, owing to the highly reliance on external computational resource, the vehicle on these area will face serious hazards for the failure or degraded performance of vehicular service. To address the aforementioned challenges, it is necessary to find an effective scheme to alleviate or eliminate the reliance on the external computational resource provided by MEC or RC.

As we all know, along with the burgeoning progress on computing hardware manufacturing level and the emerging development of wireless communication technology, it can be expected that, in the future, the smart vehicles will be equipped with computation units, multi-communication modules, a comprehensive sensor platform and advanced human-computer interaction devices. In this way, vehicles with onboard computational resource can dynamically build up a vehicular cloud network (VCN). In this way, a resource self-sufficient sharing paradigm rekindles the hope of solving the resource scarcity issue in VCN. Specifically, in VCN, some vehicles with underutilized resource can share their idle resource with other resource demanding vehicles in vicinity. By this reciprocal way, vehicles will not be trapped in some blind areas without external resource supplying. In fact, even if vehicles are within the coverage of infrastructures, the vehicular tasks can be performed with more efficiency as well as higher quality than before.

In VCN, the available resource and resource-demanding requests are dispersed on distinct vehicles driving on the road. To enhance the resource utilization for the current resource and provide the required level of computation capacity for each request, the variability and heterogeneity of resource arising from dynamically-changeable vehicular network environment should be taken into consideration. In reality, the computational resource in VCN, usually demonstrates some implicitly statistic distributional characteristics. From a macro perspective, the computational resource supply and demand can achieve a dynamic balance, and their statistical distribution properties usually demonstrate a similar tendency. The above analysis further illustrates the feasibility of our proposed computation offloading in VCN without other infrastructures. Nevertheless, because of its high complexity, the computation offloading in VCN is still full of challenges.

To the best of our knowledge, so far, there have been numerous works involving the computation offloading in vehicular network which usually comprise MEC or RC, but the ones merely focus on computation offloading in VCN are very limited [3]–[8]. In particular, the concept of VCN is
In recent years, multi-agent RL has progressively become a research hotspot. \cite{13} introduces a multi-agent RL-based approach to enable all V2V agents to perform resource allocation simultaneously. Under multi-agent environment, \cite{17} proposes a centralized training mechanism in the base station. A hyper Q-Learning algorithm is put forward to infer the intent of other agents in \cite{18}. Here, to solve our objective problem in multi-agent environment, we exploit a DRL based multi-agent deep deterministic policy gradient (MADDPG) algorithm to obtain the optimal policy, which is a centralize learning and decentralized execution framework. In this case, the adverse effects brought by the dynamically shifting environment can be mitigated or eliminated by leveraging extra information during the centralized training phase.

In this work, we mainly utilize DRL based MADDPG to address the computation offloading scheduling problem in VCN. Our main contributions are summarized as follows.

- We put forward a novel framework consisting of centralized training and decentralized execution for computation offloading scheduling in VCC network, and which can be implemented on the vehicle in a distributed way.
- The statistic distribution characteristics of the computation tasks in VCN are analyzed, which can provide a prerequisite for the scalability and generality applicability of our scheme from the theoretical perspective.
- Considering the variable resource availability in VCN network, a concise and yet adaptive combinational optimization objective paradigm is presented, in which the optimization objective can be adjusted adaptively on the resource-aware environment.
- Under a elaborately designed Markov game model, the MADDPG algorithm is firstly utilized to solve the computation offloading scheduling issue in VCN, and whose effectiveness is validated with the numerical simulation results.

The rest of this paper can be organized as follows. Section II introduces the system model and problem formulation. The statistical distribution property for computing tasks in VCN is analyzed and an adaptive combinational optimization objective scheme is proposed in Section III. Section IV reshapes our concerned problem as a Markov game and utilize MADDPG algorithm to solve the objective function in Section IV. The numerical simulations results are analyzed in Section V. Section VI draws a conclusion for this work.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Description

Here, we consider a traffic scenario with $K$ vehicles equipped with heterogeneous resource availability or resource requirements, and the vehicle with resource availability will act as volunteers to share their resource with other vehicles with resource requirements. In the following, for the sake of simplicity, the vehicle with underutilized resource and resource requirement is named as service vehicle and task vehicle respectively. The amount of service vehicles and task vehicle...
are defined as $K_s$ and $K_t$ respectively, and which satisfy $K_s + K_t = K$.

In our model, we assume that the smart vehicles can support the Device to Device (D2D) based Vehicle to Vehicle (V2V) communication, as well as Non-orthogonal Multiple Access (NOMA) technology based Vehicle to multi-Vehicle (V2mV) communication. With V2V or V2mV links, the computation tasks can be offloaded to the service vehicles for each task vehicle. Due to lacking of central control units in VCN, and here, based on Network Function Virtualization (NFV), we introduce a virtual computing center which is composed of the service vehicles in our model. In the virtual computing center, each service vehicle can transmit the required information to other service vehicles with an sequential broadcast communication mechanism. In addition, these service vehicles are assumed to be equipped with high-performance and large-capacity storage device, which can meet the demand for data storing. The key mathematical notations used in our paper are listed in Table I.

B. Communication Model

Due to the instantaneous channel state information (CSI) cannot be acquired accurately in vehicular environment, we mainly take large-scale fading caused by path loss and small-scale fading due to the relative speed into consideration. The large-scale fading can be modeled as $\alpha = PL \cdot (d_{TX-TR})^{-\varphi}$, wherein PL is the path loss constant, $d_{TX-TR}$ is the distance between transmitter and receiver, $\varphi$ is the power decay exponent. The small-scale fading is denoted as $h$, which is assumed as erogdic Rayleigh small-scale fading in our model.

On the basis of the analysis in II-A, we will define the communication model for V2V and V2mV links respectively in the following. As for V2mV, we assume there are $k_i$ ($k_i \leq K_s$) service vehicles have been allocated to task vehicle $i$. For $1 \leq k' \leq k \leq k_i$, if the channel gain $h_{i,k'}$ between $k'$ and $i$ is superior to $h_{i,k}$ between $k$ and $i$, the power allocation $P_{i,k}$ and $P_{i,k'}$ is defined as (1) based on the serial interference cancellation (SIC) technology in NOMA. Then, the total capacity $C_i$ can be obtained with $C_{i,k}$ and $C_{i,k'}$ in (2) and (3) respectively.

$$h_{i,k} < h_{i,k'} \rightarrow P_{i,k} > P_{i,k'}, (P_{i,k} + P_{i,k'} \leq P_{i,sum}) \quad (1)$$

$$C_{i,k} = B_i \left( \log_2 \left( 1 + \frac{P_{i,k} |h_{i,k}|^2}{I_{1}^{\text{intra}} + N_0} \right) \right), \quad (2)$$

$$C_{i,k'} = B_i \left( \log_2 \left( 1 + \frac{P_{i,k'} |h_{i,k'}|^2}{N_0} \right) \right), \quad (3)$$

$$C_i = \sum_{1 \leq k' \leq k \leq k_i} C_{i,k}, \quad (4)$$

where $I_{1}^{\text{intra}} = \sum_{1 \leq k' < k \leq k_i} P_{i,k'} |h_{i,k}|$ is the intra-interference in NOMA enabled V2mV link, $N_0$ is additive white Gaussian noise (AWGN) power variance, $B_i$ is the bandwidth allocated to user $i$. For simplicity, we assume that each task vehicle is allocated a spectrum resource block without sharing with other vehicles. Thereby, there is no interference among task vehicles in our model. Moreover, the capacity for V2V link is similar to (3), and hence we omit here.

C. Problem Formulation

The optimization objective can be formulated as a total utility value maximization problem with multi-constraint, which mainly involve in the computation offloading strategy, spectrum resource allocation and power allocation. As for spectrum resource allocation, we only consider the benefits
is given as is assigned in this paper for simplify. The objective function of NOMA in practical applications, the further research on the number of connection multiplexing caused by the complexity brought by communication process and the constraint in the flow and communication process for task vehicle computing tasks to service vehicle$^j$, wherein$^k$should be no more than its demanding ones. $^m_\text{comp}$ indicates that the allocated computing resource to task vehicle$^i$represents that the allocated computing resource for all the resource, wherein $^L_\text{i,j} = 1$ expresses task vehicle$^i$ will offload its partial or all the computing tasks to service vehicle$^j$. C3 means that the allocated computing resource to task vehicle$^i$ should be no more than its demanding ones. C4 and C5 indicates the maximum offloading links supported by service vehicle$^j$ and task vehicle$^i$ respectively. C6 means that the transmitting rate $C_i$ should be superior to the regulated baseline transmitting rate $R_\text{baseline}$.

III. THE STATISTICAL ANALYSIS FOR COMPUTATIONAL TASKS AND ADAPTIVE OPTIMIZATION OBJECTIVE FUNCTION

In this section, we firstly analyze the statistic distribution characteristics for the overall computing tasks in VCN, and then proposed a resource-aware adaptive combinatorial optimization paradigm for variable resource availability.

A. The Statistical Analysis for Combinational Tasks

In most prior works, Poisson Distribution has been repeatedly characterized as the statistic distribution for depicting the tendency of each vehicle’s computing tasks [2], [9], [22]. This paper will borrow this idea and not reinvent the wheel. Here, we concentrate on the variability of overall computing tasks from a macro perspective, which will lay the foundation for investigating computation offloading scheduling in VCN. The derivation and proving process is given as follows.

For vehicle$^k$, the emergence of its computing task$^k$ obeys Poisson Distribution with probability distribution function (8).

$$P\{X_k < x_k\} = \sum_{m<x_k} \frac{\lambda_k^m e^{-\lambda_k}}{m!}.$$  (7)

The accumulative computing tasks of multiple vehicles is considered in the following. For purposes of easy explainability, we only consider two users’ case, and then generalize to multiple users case. For each vehicle, its computational tasks flow is $X_k (k = 1 \text{ or } 2)$. Their overall computing task flow is $X = X_1 + X_2$, which obeys the Poisson distribution with parameter $\lambda = \lambda_1 + \lambda_2$ with (9). The derivation process is as follows.

$$P(X_1 + X_2 = m) = \sum_{y=0}^{m} P(X_1 = y) P(X_2 = m - y)$$

$$= \sum_{y=0}^{m} \frac{\lambda_1^y e^{-\lambda_1}}{y!} \frac{\lambda_2^{m-y} e^{-\lambda_2}}{(m-y)!} \frac{\lambda_1^y e^{-\lambda_1}}{y!} \frac{\lambda_2^{m-y} e^{-\lambda_2}}{(m-y)!}$$  

$$= \sum_{y=0}^{m} \frac{\lambda_1^y \lambda_2^{m-y}}{y!(m-y)!}$$

$$= e^{-(\lambda_1 + \lambda_2)} \sum_{y=0}^{m} \frac{\lambda_1^y \lambda_2^{m-y}}{y!(m-y)!}$$

$$= e^{-(\lambda_1 + \lambda_2)} \left(1 + \frac{\lambda_1}{\lambda_2}\right)^m$$

wherein BT is the abbreviation for Binomial Theorem. Then, assuming that there exists a swarm of vehicles with number $\bar{K}$, their accumulative computing tasks flow is defined as follows:

$$X = \sum_{1\leq k \leq \bar{K}} X_k.$$ (9)

Based on the inductive method, the overall computing tasks flow $X$ obeys the poisson distribution with $\lambda = \sum_{1\leq k \leq \bar{K}} \lambda_k$.

Due to the central limit theorem, $X$ will gradually converge to Normal distribution, and its proof process is given as follows. Firstly, the feature function for Poisson Distribution is (11):

$$\varphi_x = E(e^{itX}) = e^{\lambda(e^{it}-1)},$$ (10)

though power series expansion with variable $t$ [23], we can get:

$$e^{it} = 1 + it - \frac{t^2}{2} - \frac{it^3}{3!} + \cdots,$$ (11)

due to the components from $\frac{t^3}{3!}$ is smaller than the front ones, thus we abandon them for simplicity.

$$e^{it} - 1 = it - \frac{t^2}{2},$$ (12)

correspondingly, (11) can be formulated as (14):

$$e^{\lambda(e^{it}-1)} \approx e^{\lambda i t - \frac{\lambda t^2}{2}}.$$ (13)

Fortunately, (14) is exactly the feature function of the standard Normal distribution as well. Due to the uniqueness theorem for feature function, we can know that the characteristic function is uniquely determined by the distribution function. In consequence, Poisson distribution is approximately equal to
Normal Distribution with a probability distribution function as
\[ F(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\frac{(y-\mu)^2}{2\sigma^2}} dy. \] (14)

In this way, from the macro perspective, the distribution of
overall computing tasks can be assumed to obey Normal dis-
tribution. From another point of view, the underutilized computa-
tional resource is in fact the accumulation of a handful of sam-
pling samples from the Normal Distribution in (15). Based on
the Chebyshev theorem, the available computational resource
will mainly distribute on the domain \([\mu - k\sigma, \mu + k\sigma]\)
with a probability \([1 - 1/k^2]\), where \(\mu\) and \(\sigma\) are the mean
and standard deviation of the specific distribution respectively, \(k\)
is a positive integer. In other words, the available computing
resource will mainly concentrated in the area around the mean.
Simultaneously, the computing tasks arising from VCN will
show a similar statistical property.

Based on the above analysis, we can assert that, if we
sample the resource utilization status from their correspond-
ing Normal distribution uniformly, most of samples will be
distributed around the expected value \(\mu, \mu'\) respectively. Note
that, the condition \(\mu = \mu'\) is corresponding to the perfect
condition that the resource availability is equivalent to the
computing tasks. In this paper, we believe that \(\mu = \mu'\) can be
realized by scientifically evaluate the computing tasks in VCN
and configuring the vehicle hardware level appropriately. To
successfully perform the computing offloading in VCN, the
proposed scheme must be generalized to accommodate the
requirements of diverse scenarios. However, for the scenario
of each time slot in VCN, there are two possible conditions
cannot be neglected due to the variable computational resource
demand and supply, which correspond to the samples distri-
buted on both sides of the mean value in Fig.2. In real
traffic scenario, the two cases signify resource oversupplying
and undersupplying statuses respectively. To address the afore-
mentioned dilemma, we propose an resource-aware adaptive
combinatorial optimization objective paradigm.

B. Resource-Aware Combinatorial Optimization Objective
Paradigm

![Diagram](image)

**Fig. 2.** The overall reward comparisons among different schemes

As we stated earlier, one of major and fatal challenges in
VCN is the unbalanced and time-variant resources supply and
demand, which are easily to happen under the dynamic VCN
environment. In this section, we proposed a resource-aware
combinatorial optimization objective mechanism consisting of
Multiplex Offloading mechanism and Value-Priority mecha-
nism respectively.

1) Multiplex Offloading Mechanism: Oversupplying de-
notes the case that resource provision overweighs the re-
quirement, namely, \(R_{idle} > R_{demand}\) in Fig.2, which will
probably happen in the dense vehicular environment [7]. In
addition, due to the dynamic VCN environment, there is a
risk of failure in the computation offloading in vehicular
network. To fully utilize underutilized resource and enhance
the reliability of computation offloading, we introduce the
concept of multiplex offloading, namely, allocating the redun-
dant computing resources to these task vehicles which have
been allocated computational resource. Here, to reflect the risk
of computation offloading failure in VCN, a novel reliability
metric \(\zeta\) is defined to characterize anti-risk ability pertain-
ing to task vehicles’ computation can be successfully offloading
under a turbulent VCN environment, which can be achieved
with a risk coefficient \(\varepsilon\) and multiplexing factor \(\xi\) as follows.

\[
\max_{1 \leq i \leq \xi} \zeta = 1 - \varepsilon^\xi
\] (15)

s.t. \(\bar{\xi} = \left\lfloor \sum_{1 \leq i \leq K_i} C_i^{comp} / \sum_{1 \leq i \leq K_i} C_i^{comp} \right\rfloor\)

where \(\varepsilon\) denote the average failure probability for each com-
putation offloading in VCN. It is apparent that \(\zeta\) will decrease
exponentially with multiplexing factor \(\xi\) with the maximal
value \(\bar{\xi}\). Compared with the conventional offloading strategy
\(\xi = 1\), our proposed mechanism can enhance the reliability
for computation offloading in VCN by enable \(\xi > 1\).

2) Value-Priority Mechanism: Apart from oversupplying,
undersupplying should not be ignored as well, where the
available resource is not sufficient to satisfy the requirements
of task vehicles, namely \(R_{idle} < R_{demand}\) in Fig.2. This
plight is an undesirable but inevitable situation, and which may
happen when there are a low vehicle density or complicated
road conditions as well as some traffic urgency. Facing the grim
reality for shortage of computational resource, as well as
considering the dilemma in VCN without any external resource
provision, we must make reluctant trade-offs among numerous
resource-demanding requests at this pivotal time, and some
relatively important or urgent requests must be guaranteed first,
especially these safety-related vehicular applications or some
computing tasks with high-quality of service (QoS). Here,
we propose a Value-Priority mechanism to perform the com-
putation offloading in VCN. More specifically, according to
distinctive QoS requirements, the resource demanding requests
will be divided into different levels with the corresponding
values. For example, security-related requests will be arrange
with a higher value, while the entertainment-like requests
will be defined a lower value. Then, we can redefine the
optimization objective function (5) as (16).

\[
\max_{1 \leq i \leq \bar{K}_i} \sum_{1 \leq i \leq \bar{K}_i} U_i
\] (16)
requests set are eventually fulfilled, \(C\) displays the task vehicles’ request with high value will be fulfilled preferentially, \(C8\) states the worst and most optimistic situation corresponding to the lower and upper bounds of \(\tilde{K}_t\) respectively, \(C9\) indicates that the allocated computational resource cannot exceed the maximal overall available computing resource in our model. Different from the optimization objective function (5), there are much more constraints in (17) to guarantee the priority of resource demanding requests with higher QoS requirements.

3) The Feasibility and Scalability Analysis for Adaptive Combinatorial Optimization Objective Scheme: In this part, we will analyze the feasibility and scalability of our proposed computation offloading scheme from the practical perspective. In terms of the multiplex offloading for over-supplying situations, each task vehicle needs to offload its computing tasks to multiple service vehicles, which can be completed by the collaboration of computing task upload in a multicast way and computation results sending back with a polling method. In addition, the multiplex offloading scheme can be friendly scalable to and being generically applicable to the computation offloading scenarios under vehicular network environment with MEC or RC, where the computational resource can be assumed to be abundant in most cases.

As for the value-priority mechanism, it is a promising scheme in keeping with the practical vehicular network. As we all know that, at the present stage, most of safety-related vehicular applications, like self-driving technology, which are usually completed by the vehicles themselves with their own on-board computational resource, rather than depending on external computational resources. In a similar vein, we assume that, in our model, each vehicle will preferentially allocate its own existing computing resource to these aforementioned safety-related computing tasks with high priorities. Then, the remaining ones will be distributed to non-safety-related vehicular request. In this way, it is reasonable to consider that, even in the case of undersupplying, the performance of safety-related vehicular applications or computing tasks with high QoS will not be degraded or jeopardized at all. Furthermore, the priority-value mechanism can scale well to the resource-sufficient situation, where the computing tasks with higher-value will have more opportunities to choose these service vehicles with better transmission channel quality or superior computational performance, which can be found through the numerical simulation results later.

In short, our proposed resource-aware combinatorial optimization objective paradigm shows a better applicability and scalability performance in reality, the whole process for our proposed scheme is summarized in Algorithm 1. In the following, the focus of our work will shift to propose an effective algorithm to solve the objective function.

**Algorithm 1** The Adaptive Combinatorial Optimization Objective for Computation Offloading Scheduling in VCN

**Input:** The underutilized resource set \(R_{idle}\) and the requirement for computational resource \(R_{demand}\)

**Output:** The computational resource allocation scheme

1. If \(R_{idle} > R_{demand}\)
2. Compute the Multiplex factor \(\xi\)
3. Perform Multiplex Offloading Mechanism
4. While \(R_{idle} > 0\)
5. Implementing computational resource allocation algorithm
6. \(R_{idle} = R_{idle} - R_{demand}\)
7. End While
8. Else
9. Perform Value-Priority Mechanism
10. End If

IV. MADDPG FOR COMPUTATION OFFLOADING IN VEHICULAR CLOUD COMPUTING NETWORK

The objective optimization problem in (5) is NP-Complete which has been proved in Lemma 1 as follows.

**Lemma 1:** Computation Offloading problem in VCN is a NP-Complete combinatorial optimization problem with multiple knapsack constraints.

Proof: In the conventional Knapsack optimization problem \([24]\), there exists a set \(N\) with \(|N|\) items. For each item \(n \in N\) is assigned with a weight \(w_n\), a volume \(o_n\) and a profit \(\rho_n\). In addition, there are a set \(M\) with \(|M|\) knapsacks. For each knapsack \(m \in M\), it is associated with a maximum weight capacity \(w_m\) and volume capacity \(o_m\). The optimization objective is maximizing the overall profit of the whole system with (17).

\[
\rho_{sum} = \max \sum_{n \in N} \sum_{m \in M} \rho_n \cdot \chi_{n,m} \quad \text{subject to} \quad \sum_{m \in M} \chi_{n,m} = 1.
\]

In what follows, we come back to our objective optimization problem (5), in which each computation task \(i \in \Omega_t\) can be regarded as an item \(n \in N\) and each service vehicle’s underutilized resource \(j \in \Omega_s\) is equivalent to a knapsack \(m \in M\). Moreover, the communication and computation constraints, i.e., \(C3\) and \(C6\) in (5) is corresponding to the weight and volume \(w_n, o_n \in R\) of each item. The profit of task \(V\) which will be defined later is equal to the profit of items \(\rho_n \in [0, 1]\). The allocation \(L_{i,j} \in \{0, 1\}\) is equal to the allocation result \(\chi_{n,m} \in \{0, 1\}\). Thus, our optimization objective is to maximize the overall utility value, which is also equivalent to the optimization objective in (17). In consequence, the computation offloading problem in VCN is equal to the multiply-constrained multiple Knapsack problem which has been proven to be NP-Complete.

In our work, apart from the NP-complete property in our objective problem, the computation offloading environment in VCN is a typically fully cooperative, partially observable, parallel multi-agent decision making problem, in which the multi-agent environment dramatically exacerbate challenges,
we adopt a decentralized framework based MDDPG algorithm and analyze the algorithm’s performance in many metrics.

A. Modeling of Multi-Agent Environments

To solve the combinatorial optimization problem with RL, the policy search process is usually model as a Markov Decision Process (MDP), for which the conventional RL algorithms, such as Q-Learning, Deep Q-network (DQN), etc. are sufficient to obtain the solutions. However, the applicability of MDP is usually limited to the stationary vehicular environment. In our model, with the assumption that each task vehicle is defined as an agent, there are multiple agents co-evolving together, which directly results in a turbulent environment for each agent. In this fashion, MDP based RL algorithms are no longer applicable for our environment. In our work, we employ the partially observable Markov game to model the multi-agent environment, and which is an extension of MDP. Here, the Markov game is defined as a tuple \((S, A, R, T, \gamma)\) standing for discrete state space, discrete action space, reward function and state transition probability as well as discount factor respectively. In the following, the components of Markov game will be introduced separately.

1) State Space: For each agent \(i\), its state space usually embraces all factors related to our concerned problems. Here, it mainly comprises the channel gains, computational resource requirement and availability with \(H_i, C_{i,comp}, C_{i,comp}^{\Omega} \).

2) Action Space: In contrast to the identical and fixed action dimension in traditional RL algorithms, due to the heterogeneity of resource demanding and availability in our work, the action dimension may be distinct and time-varying. Here, the action space of agent \(i\) can be defined with (18).

\[
A_i = \{ A_{i,1}^1, \ldots, A_{i,m}^m, \ldots, A_{i,M}^M \}, \tag{18}
\]

where \(A_i\) comprises a group of action subset \(A_{i,m}\), \(1 \leq m \leq M\) with a maximal dimension \(M\) defined in (19), action set \(A_{i,m}\) is extended in (20), in which \(a_{i,j}^{m}, 1 \leq j \leq K_s - m + 1\) is an m-dimensional action vector in action subset \(A_{i}^m\), where \(K_s\) is the number of service vehicles and \(C_{i,comp}\) is the number of required computational resource respectively. In addition, the overall number of action space \(|A_i|\) and action subset \(|A_{i,m}|\) is given with (21), where \(C_{km}\) denotes the total number of possible combinations choosing \(m\) elements from all service vehicles.

\[
|A_i| = \sum_{1 \leq m \leq C_{km}} |A_{i,m}|, |A_{i,m}| = C_{km} \tag{21}
\]

3) Reward Function: In this work, our optimization objective is to maximize the overall utility of all the agents. Correspondingly, the reward is defined the total reward from all the agents, which mainly arise from communication \(R_{comp}\) and computing process \(R_{comp}\) in (23).

\[
R = R_{comp} + R_{comp}, \tag{22}
\]

\[
\begin{align*}
R_{comp} &= \frac{1}{1+\gamma} \sum_{1 \leq i \leq K_t} L_i^t \left(1 + T_i^t\right), \\
R_{comp} &= \frac{1}{1+\gamma} \sum_{1 \leq i \leq K_t} \sum_{1 \leq j \leq N_1} \left(\frac{l_{ij}}{t_{ij}}\right), \tag{23}
\end{align*}
\]

Fig. 3. The framework for MDDPG based Computation Offloading in VCC Network
wherein, $T^i_j$ is the signal-to-interference and noise ratio (SINR) for the communication links between task vehicle $i$ and service vehicle $j$, $L_i = \sum_{1 \leq j \leq K_i} L_{i,j}$ and $L_j = \sum_{1 \leq i \leq K_j} L_{i,j}$ denote the amount of service vehicles allocated to task vehicle $i$ and the amount of task vehicles allocated to service vehicle $j$, respectively. Motivate by the fact that the computational complexity caused by the modulation and demodulation in NOMA will increase greatly with the multiplexing users' amount, thus the idea that less service vehicles for each task vehicle, the great benefit, is adopt here.

4) Policy: The policy can be regraded as a mapping from state space to action space as $\pi (a, s) : S \rightarrow A$. In general, it can be stochastic or deterministic which correspond to choosing multiple actions with probability $p(a|s) < 1$ or only selecting one specific action with probability $p(a|s) = 1$.

5) Value function: Value function $Q^\pi (s, a)$ in (25) is generally utilized to evaluate the long term cumulative reward in (24), which can drive the policy iterative to update towards the direction of the optimal policy.

\[
R = \sum_{t=0}^{\infty} \gamma^t r_e (s_t, a_t) \tag{24}
\]

\[
Q^\pi (s, a) = E \{ R | s_0 = s, a_0 = a, \pi \} \tag{25}
\]

where $\gamma$ is a discounted factor satisfying $0 \leq \gamma < 1$, $r_e$ is the reward obtained in $t$th step condition on the state $s_t$ and action $a_t$. Through simple derivation, $Q^\pi (s, a)$ can also be achieved with a recursive relationship as (26), which is the well-known Bellman equation [25].

\[
Q^\pi (s, a) = E \{ r_e (s_e, a_e) + \gamma Q^\pi (s_{e+1}, a_{e+1}) \} \tag{26}
\]

In this work, the optimization objective is to find the optimal policy with the maximal overall rewards, which can be defined as an optimal trace $J(\pi)$ with the maximal cumulative discounted reward.

\[
J(\pi) = \int_S \gamma^T (s_e | s_0, \pi) \int_A \pi_0 (a_e | s_e) Q^{\pi_0} (s, a) \, da \, ds
\]

where $T (s_e | s_0, \pi)$ is the state transition probability from $s_0$ to $s_e$, which is unknown in our model, thus an alternative approach with model-free strategy estimation is adopted here. With the model-free policy, it is usually considered that the optimal policy can be eventually obtained after infinite iterations [26]. In the following, a MADDPG algorithm is introduced to solve our objective problem.

B. MADDPG Scheme Design

In this part, we firstly present some essential background knowledge and related works about RL algorithms, and then progressively elaborate on MADDPG algorithm adopted in this work.

1) Related Work: In general, RL algorithms mainly can be divided into value-based and policy-based two types. The conventional Q-Learning [21, 25] and DQN [27, 28] algorithms as well as their variants are value-based RL algorithms. As for DQN [27, 28], it combines the Q-Learning and deep neural network to compute the value function. Replay memory and target network frozen mechanisms are introduced to decouple the selection of greedy action from action evaluation, and decrease the overestimation of state-action value in the training process. In contrast, policy gradient (PG) [29] and deep policy gradient (DPG) [30] along with their variants are policy-based RL algorithms. With the development of RL domain, some high-performance hybrid RL algorithms have been proposed which splice value-based and policy-based RL algorithms together, such as actor-critic (AC) [26] algorithm and deep deterministic policy (DDPG) [31] algorithm. In terms of AC [26], it is a collaboration of a value function estimation network (critic) and a policy network (actor). As an extension of AC and DRL, MADDPG algorithm has been envisioned as a promising approach for solving decision-making problem under multi-agent environment.

2) MADDPG enabled Computation Resource Allocation: In our multi-agent environment, based on their own local observations, all the agents make decisions independently and simultaneously according to their individual policies, which directly result in an extremely turbulent environment [32]. As a result, the convergence performance in model training will become one major and fatal bottleneck in our work. To address the above problems, we adopt a centralized training and decentralized execution framework to perform MADDPG algorithm.

MADDPG algorithm comprises critic network and actor network, as well as their corresponding target network. Critic network is in fact a parameterized state-action value function, while actor network is utilized to select a suitable action based on the observed state and transfer to critic network for evaluation. In the centralized training stage, all agents’ state and action information are leveraged to train our model, by which each agent can get a relatively global perception of the environment and implicitly learn other agents’ strategies, where the multi-agent environment can be assumed to be stationary no matter whether or not the strategy changes [33]. In this way, by virtue of the benefits brought by reward sharing and exchangeability, the convergence performance can be enhanced significantly. In contrast, to reduce the signaling overhead, in decentralized execution stage, each agent will make decision merely depending on its own locally-observed information. In the following, we will introduce critic and actor network respectively.

For critic network, to reduce the gap between the predictive value and actual value in each episode, its network parameter is updated based on the loss function with Temporal-Difference (TD) in (28), where $Q^0_i (s, a_1, \cdots, a_{K_i})$ is the state-action value achieved in critic network and $y_i$ is the target state-action value obtained in target critic network with (29).

\[
Loss (\theta_i) = E_{s, a, r, s'} \left[ (Q^0_i (s, a_1, \cdots, a_{K_i}) - y_i)^2 \right], \tag{28}
\]

\[
y_i = r_i + \gamma Q^\pi_i (s, a_1, \cdots, a_{K_i}). \tag{29}
\]

For actor network, its objective is to choose optimal action with maximal reward. Without loss of generality, we update the actor network parameters along with the direction of increasing the state action value function with the loss function (30), which can be completed by the gradient transmitting
from critic network to actor network. Under the stochastic strategy, the loss gradient for actor network is defined as (31).

\[ L(w) = -E[Q(s, a, w)] \]  
\[ \nabla_{\theta_i} J_{\theta} = E_{s,a,T^\nu} \left[ \nabla_{\theta_i} \log \mu_{\theta_i}(a_i|s_i) \cdot Q^\mu(s, a) \right] \]  

where \( a = (a_1, \cdots, a_N) \). Owing to the deterministic strategy adopted in MADDPG, and the policy gradient are directly updated by calculating Q value’s semi-gradient with (32). With a softmax function, the actor network will converge to the optimal strategy after continuously parameters updating \([26]\).

\[ \nabla_{\theta_i} J_{\theta} = E_{s,a \sim D} \left[ \nabla_{\theta_i} \log \mu \left( s_i | \theta_i^\mu \right) \cdot \nabla_{a_i} Q^\mu(s, a | a_j = \mu_i(s_i)) \right] \]  

Note that, to encourage exploration and avoid converging to non-optimal deterministic policies, we add Ornstein-Uhlenbeck process based noise \( N_e \) to the output of actor network with (33).

\[ a_e = \mu(s_e | \theta^\mu) + N_e, \]  
\[ dX(t) = \kappa(\mu - X(t))dt + \sigma_y Y(t), Y(t) \sim N(0, dt), \]  
\[ \sum_{1 \leq k \leq K} C_{\text{comp}}^k \geq C_{\text{comp}}^{K-1} \geq p_k, \hat{K} \leq K. \]  

For \( N_e \), which mainly comprise mean reversion and diffusion two parts as (34), where \( \kappa \) and \( \sigma \) denote the weights for mean reversion and diffusion respectively, \( X(t) \) is a variable with mean \( \mu \) and \( Y(t) \) is a variable obeying to Gaussian distribution with mean 0 and variance \( dt \).

Then, to satisfy each task vehicle’s computation resource requirement, we can choose \( N \) actions in descending order of probability distribution \( p = (p_1, p_2, \cdots, p_K) \) given by actor network’ output layer with (35). In this fashion, we can formulate a tuple \( \{S_e, A_e, R_e, S_{e+1}\} \) to store in the replay buffer \( D \).

3) Training and Execution: The centralized training stage is implemented on the virtual computing center in VCN, which is intrinsically a group of dispersed service vehicles driving on the road. Owing to the shorter transmission distances and the smaller relative speeds between service vehicles and their neighboring task vehicles, we can obtain the more stable transmission channels and a labor-saving state information from the task vehicles in vicinity. Thus, service vehicles can be regarded as a samples collector to some degree. After that, the information transmission among service vehicles will be performed with a round-robin manner, and each service vehicle will eventually obtain the global samples information required for centralized training. Then, the training stage will be performed with Algorithm 2.

After the training stage in each episode, the parameters update for critic network and actor network have been completed, and every task vehicle will download its policy network parameters from its belonging service vehicle. The target network parameters for critic \( \theta^{Q^\prime} \) and actor \( \theta^{\mu^\prime} \) can be update with (36) and (37) respectively, where \( \tau \) is a weight for updating step and which is usually defined as positive real number far less than 1.

\[ \theta^{Q^\prime} \leftarrow \tau \theta^{Q^\prime} + (1 - \tau) \theta^{Q} \]  
\[ \theta^{\mu^\prime} \leftarrow \tau \theta^{\mu^\prime} + (1 - \tau) \theta^{\mu} \]  

As a matter of fact, the conventional centralized training framework relying on the central control unit, is not suitable to solve our proposed problem in VCN. Not to mention that there is no infrastructure empowered by central control unit in our scenario, the high-mobility of vehicles enables the fixed-location based center control unit ashamed for its limited coverage. Moreover, the timeless requirement constrain the generating samples must be uploaded in time, the terrible signaling overhead from all the vehicles will bring extremely heavy burden to the control center, and the unstable channel quality as well as the serious multi-interference can cause serious hazards. Last but not least, once the control center units is invaded or interrupted for some reasons, the entire system will fall into a paralyzed state completely.

C. Performance Analysis

In this part, we will analyze our proposed algorithm’s performance from the following aspects.

1) Computational Complexity and Communication Overhead Analysis: In our algorithm, the computational complexity mainly arises from the training stage and execution stage. The training stage is a long-term and on-going process based on the continuously generating samples from VCN environment, which will be performed in each service vehicle for a small
number task vehicles and the computational capacity in service vehicle is sufficient to do this job.

In execution stage, we assume that policy network is a $Z$ layers neural network structure. For each layer $z$, $(1 \leq z \leq Z)$ in policy network, there are $F_z$ neurons. In this way, the computation expense between $z$th layer and $z-1$ layer is $F_z F_{z-1} + F_z$, and the overall computational complexity in actor network is $O \left( K_1 \left( \sum_{2 \leq z \leq Z} F_z F_{z-1} + \sum_{2 \leq z \leq Z} F_z \right) \right)$. To further lessen the computational complexity, it is feasible to perform the algorithm over a small number of vehicles.

In our model, since the local samples information is only a few kilobytes in size, the communication overhead for samples collection and information interchangeability is relatively small, which is acceptable for each vehicle. After the centralized training stage, on account of the short-distance transmission and a small data quantity of neural network parameters with about $200K bit$ in size, the policy network parameters download for each task vehicle is cheap as well.

2) Memory Space Analysis: In this work, the memory space requirements mainly arises from the storage of samples and network parameters. In training stage, the data quantity of network parameters is very small, and thus we mainly focus on the required memory space for these samples stored in the memory replay buffer.

For each sample, with the conventional one-hot encoding mechanism, its state or action dimension can be defined as $1 \times (K_s K_t)$ with the assumption of $K (K = K_s + K_t)$ vehicles driving on the road. In this case, the total memory space is defined in (38), where $K_{\text{max}}$ is the maximal vehicles capacity on the unit road segment. However, due to the time-varying amount of service vehicles and task vehicles, there are so many possible cases for one-hot coding schemes and it unrealistic and expensive to consider each situation separately.

To solve this problem, we adopt a multi-hot encoding scheme proposed in our earlier work, by which the dimension of each state and action will reduce to $1 \times K_{\text{max}}$, the overall memory space is given in (39). Next, we calculate the memory space requirements based on a realistic traffic scenario. Assuming that the unit road segment is defined as $500m$ and a safety distance $90m$ between two vehicles, there are $K_{\text{max}} = 18$ vehicles at most. Here, with the binary data storing format, each decimal value can be represented by 4 bits binary number and each sample can be present with 220 bits. On the assumption that we store $N = 30000$ samples, the overall data quantity is $6.6 \text{ MBit}$ with (39), which is supportable for most of vehicles.

$$
|D| = N \cdot \sum_{1 \leq K \leq K_{\text{max}}} \sum_{1 \leq K_t \leq K} [3 (K_t \cdot (K - K_t)) + 1] \quad (38)
$$

$$
|D| = N \cdot [3K_{\text{max}} + 1] \quad (39)
$$

Last but not least, owing to the role-switching between service vehicles and task vehicles caused by the resource variability, it is necessitating that all of vehicles in our model to maintain a replay buffer to store samples.

3) Scalability and Safety Analysis: In terms of scalability, our proposed scheme can better adapt to the dynamic changeable vehicular network environment by flexibly adjust the network size. In addition, our proposed scheme can be easily scalable to the VCN with the resource-rich infrastructures which can be regarded as the static service vehicles to some degree. As for the concerned safety, our proposed algorithm is more robust than the conventional centralized computation offloading scheduling scheme. When some risks and intrusion occur, unlike the dilemma that the centralized resource scheduling strategy will fall into paralyzed overall, our propose scheme will only have some local performance deterioration at most and the self-organized network mechanism can enhance the robustness by blocking the affected vehicles to protect the safe and sound vehicles.

V. SIMULATION RESULT AND ANALYSIS

In this section, to more comprehensively validate our proposed algorithm’s (MADDPG) performance, we introduce some baseline algorithms for comparisons, which are Q-learning in [21]. Greedy algorithm and Random algorithm respectively.

Under the traffic scenario with unidirectional road segment of three lanes, a bunch of numerical simulations are performed. To better reflect the impact of different vehicle composition ratios on system performance, we assume that the amount on different kinds vehicles can be adjusted artificially, and the generating vehicles will be randomly dispersed on the road. To demonstrate the heterogeneity, we allocate one or two RUs as resource requirement or available computational resource to vehicle. As for the network framework, the actor network is a four-layer network fully connected neural network with two hidden layers, and whose dimensions are $d_1 = K_{\text{max}}$, $4d_1$, $2d_1$ respectively. Each critic network is a five-layer network with three hidden layers, and their dimensions are $d_2 = (K_{\text{max}})^2$, $d_2$, $8d_2$, $4d_2$ respectively. At the beginning, all of the parameters are initialized by the method of random normal. The size of replay memory is 30000. Without other special statement, the learning rates for actor network and critic network is defined as 0.0001 and 0.001 separately. These simulations are conducted in Matlab based R2016 on a server platform with hardware and software conditions: Window Server 2019, Intel(R) Xeon(R) 2.6GHz Processor, 16GB RAM. The other related parameters is formulated in TABLE II.

| Parameter                        | Value       |
|----------------------------------|-------------|
| Cellular transmission power      | 0.2 W       |
| Baseline power for 2mV link      | 0.1 W       |
| Noise power                      | -174 dBm/Hz |
| Pathloss index                   | 2           |
| Number of Lanes                  | 5           |
| Velocity of Each Lane            | [120 km/h, 90 km/h, 60 km/h] |
| Safety Distance of Each lane     | [120 m, 90 m, 60 m]   |
| Lane width                       | 4 m         |
| Bandwidth of Each Vehicle        | 20 MHz      |
| Power allocation index           | 0.8, 0.2    |
| Learning rate $\alpha$           | 0.0         |
A. Simulation Result

In Fig. 4, under the vehicular scenario with three task vehicles and six service vehicles, the convergency performance of MADDPG and Q-Learning algorithm are demonstrated. In comparison with Q-Learning algorithm, it is apparent that our proposed algorithm shows a superior convergency performance. A contributing factor is that, by virtue of the centralized training mechanism, MADDPG algorithm can achieve a faster convergency speed. On the contrary, Q-learning is a tabular based RL algorithm and its state and action space will grow explosively with the increase of agents. In contrast, due to action exploring strategy $\varepsilon$-greedy in which the agent will select the maximal value with a probability of $1-\varepsilon$ or acts randomly with a probability of $\varepsilon$, some state and action will never be visited at all. As a consequence, Q-Learning will inevitably yielding degraded performance on both convergency speed and convergency quality.

Fig. 5 demonstrates the overall rewards comparisons between MADDPG algorithm and these baseline algorithms. In our simulations, the sum number of vehicles is installed as 12, and the task vehicles increase progressively from 3 to 9 while the service vehicle will reduce from 9 to 3 synchronously. It is obvious that the performance of MADDPG algorithm is better than other algorithms, and its superiority mainly arising from the additional information in centralized training process of critic network. Moreover, with a growing number of task vehicles, there is a seemingly increasing performance gap between MADDPG and Q-learning algorithms, which can inherently explain why our proposed algorithm is more effective in the competitive environment.

During the process, with the growth of task vehicles, a surging number of computational resource will be utilized to perform computation offloading and thus the overall reward will rise gradually. When there are 6 task vehicles in our model, the overall reward reaches the peak, which corresponds to the balance status between supply and demand. In this case, all the available computational resource have been fully exploited. Then, as service vehicles continue to decrease while task vehicles keep increasing, it is naturally that there are not sufficiently available computational resource to satisfy the resource demanding requirements, and the overall reward will decline gradually.

Fig. 6. The account of task vehicles allocated resource comparisons among different schemes

Under the identical traffic scenario with Fig. 5, Fig. 6 presents the statistic results in terms of vehicles with allocated resource. It is clear that a trend similar to Poisson distribution is presented. Specifically, in the first half period, there are less task vehicles than service vehicles, and thus each algorithm can easily accommodate the resource demanding requirements for all the task vehicles. However, as the increase of task vehicles, the tension between supply and demand creates a bottleneck gradually appear, and oversupplying status will transfer to undersupplying one. In this way, there exists an inherently competitive relationship among all the task vehicles. As a result, in the second half period, some task vehicles’ resource requests cannot be fulfilled. In this case, different algorithms show distinctive users coordination and resource scheduling ability. From the simulation results, it is clearly that MADDPG algorithm is better than other algorithms. In the case of limited available resource, MADDPG algorithm can satisfy the requirements of more vehicles.

In Fig. 7, the parameters sensitivity of MADDPG algorithm is tested. Here, the convergence performance is our focus, and hence only learning rate is considered. It is intuitively known
that the learning rate in both critic network $\gamma_{\text{critic}}$ and actor network $\gamma_{\text{actor}}$ can affect convergence performance. Firstly, we define $\gamma_{\text{actor}} = 0.0001$, and change $\gamma_{\text{critic}}$ from 0.001 to 0.00001, it is apparent that the greater learning rate in critic network, its convergence speed will be faster. When we fixed $\gamma_{\text{critic}} = 0.0001$ and change $\gamma_{\text{actor}}$ from 0.001 to 0.00001, a similar tendency can be obtained. By comparison, we can conclude that the learning rate $\gamma_{\text{actor}}$ has greater impact on the final convergence value than $\gamma_{\text{critic}}$, while $\gamma_{\text{critic}}$ usually has more significant impact on the convergence rate.

In Fig. 8 and Fig. 9, the performance of Multiplex-Offloading mechanism is validated. Fig.8 shows the reliability enhancement brought by our proposed mechanism. For the baseline, where these task vehicles will be allocated just for once no matter how much available resource in VCN with a risk factor $\varepsilon = 0.8$. In contrast, in other schemes with $\varepsilon = 0.7$, $\varepsilon = 0.8$ and $\varepsilon = 0.9$, the computational resource will be repeated allocated to these task vehicles until all the available resource have been allocated. It is clear that reliability can be promoted significantly. In addition, from Fig. 8, we can know Multiplex-Offloading mechanism can enhance the resource utility than the scheme without it.

In Fig. 10 the performance of Value-Priority mechanism is verified by comparisons with the scheme without it. Under a resource-constrained scenario with a variable task vehicles, Fig. 10a shows that the sum reward performance of Value-Priority mechanism is better than the scheme without it. Under a resource-sufficient scenario with a variable service vehicles, our proposed mechanism expresses its superiority in Fig. 10b. In consequence, the Value-Priority scheme is effective to both resource-constrained and resource-sufficient cases. Furthermore, by careful comparison, the resource-constrained condition can achieve a seemingly greater gain than resource-sufficient case. The reason is that, under the sufficient resource supply, the resource requirement of all task vehicles can be accommodated, and there is not much room for further improving performance. However, in resource-constrained case, Value-Priority mechanism will give priority to urgent computing tasks with higher value, so its potential abilities can be fully released to some regard.

B. Discussion

In this work, our proposed computational resource allocation scheme can achieve better performance in many aspects, and it is more scalable when applied to the situation with
multi-agent, such as vehicle platoon in highway, content sharing among vehicles, inter-vehicle communication, etc. Nevertheless, due to our research limitations, there still be some open problems worth future research efforts. In particular, apart from without consideration of the relationship between vehicles driving modes and resource utilization status, a more comprehensive and in-depth statistical distribution model base on real data set for computing tasks and available resource is also necessary. Our proposed framework is still relatively complex, and further optimization is necessitating to obtain a more efficient algorithm. In addition, the computation offloading strategy in different vehicular scenarios should be taken into consideration, like the dense vehicle flows in urban areas and the sparse traffic in rural areas. Furthermore, the investigation on jointly computational resource allocation and communication resource allocation is essential to provide a comprehensive computation offloading scheme in VCN.

VI. CONCLUSION

In this paper, we investigate the computational resource allocation problem in VCN. The objective optimization issue is in fact a combinatorial optimization problem with multiple knapsack constraints, which has been proved to be NP-Complete in our work. Considering the variability of on-board computational resource in VCN, a concise and yet effective resource-aware combinational optimization objective mechanism is put forward to accommodate the resource-demanding in VCN. In addition, to solve this nontrivial problem, we firstly analyze the involved multi-agent environment and reshape the computation offloading problem as a Markov game model. After that, we propose a centralized training and distributed execution framework for the dynamic changeable multi-agent environment and adopt a DRL based MADDPG algorithm to solve it. The simulation results show that our proposed algorithm can achieve superior performance against other baseline algorithms.

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