This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.2974249, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2019.DOI

Intelligent Mobile Edge Computing with Pricing in Internet of Things

ZICHAO ZHAO[1], WEN ZHOU[2], DENG DAN[3], JUNJUAN XIA[1], and LISENG FAN[1]

[1]School of Computer Science and Cyber Engineering, Guangzhou University, Guangzhou 510006, China
[2]College of Information Science and Technology, Nanjing Forestry University, Nanjing, China
[3]Guangzhou Panyu Polytechnic, Guangzhou, 511483, China.

Corresponding authors: Junjuan Xia and Liseng Fan (e-mail: xiajunjuan@gzhu.edu.cn, lsfan2019@126.com).

This work was supported by the NSFC under Grant 61601275, and in part by the Science and Technology Program of Guangzhou under Grant 201807010103.

ABSTRACT In this paper, we investigate mobile edge computing (MEC) networks for intelligent information services, where there are N users equipped with K antennas and one access point (AP). The users have some computational tasks, and some of them can be decoupled by the AP, at the cost of a fee charged by the AP. For the considered system, we firstly consider two important metrics of interest: latency and fee. Then, we formulate a stochastic game to model the interaction between users and the AP. In this game, the AP sets prices to maximize its profit, while users devise the offloading strategy to reduce both the latency and charge. We further optimize the system by applying the array signal processing schemes on the users, in order to reduce the transmission latency. Simulation results are finally presented to verify the effectiveness of the stochastic game, and it is shown that the array signal processing scheme can help reduce the transmission latency significantly.

INDEX TERMS Intelligent information services, mobile edge computing, intelligent algorithms.

I. INTRODUCTION

In recent years, the research of wireless communications has made a great progress [1]–[3], where the transmission data rate and the reliability have been explosively increasing [4], [5]. For example, the data rate in the fifth-generation (5G) communication systems has increased to about ten or hundred times, compared with the data rate in the fourth-generation (4G) communication systems. To support the explosively increasing data rate, many new techniques have been proposed. In particular, the technique of multiple antennas has been proposed to speed up the data rate by exploiting the spatial and temporal gains among antennas [6]–[8]. As a virtual form of multiple antennas, relaying technique is shown to be effective in improving the data rate by providing transmission diversity gain [9]–[12]. Besides the multiple antennas and relaying, cognitive technique has attracted much attention from researchers [13]–[15], since it can efficiently utilize the spectrum resources and help improve the transmission data rate [16]–[18]. Recently, the intelligent surface reflection technique has been proposed, which has extended the research of wireless communication from the conventional engineering perspective to the perspective of material science [19]–[22].

As an extension and application of 5G communication systems, the intelligent internet of things (IoT) has attracted much attention from the researches, since it can be used in a lot of fields and daily life, such as the intelligent transportation systems and intelligent video surveillance. Many new technologies have been proposed to support the application of the intelligent IoT. One big progress is the wireless caching technique [23]–[25], where the files can be pre-stored at the near-by nodes during the non-peak traffic. In this area, an important research aspect is to devise which files should be cached at the nodes, since in general the storage at the nodes is limited [26], [27]. The conventional most popular content (MPC) and largest content diversity (LCD) can be applied, which can obtain the largest signal cooperation gain and largest caching gain, respectively [28], [29]. Besides the caching technique, some intelligent algorithms can be applied into the intelligent information services. For example, the Q-learning based intelligent algorithms [30]–[34] have been proposed into the wireless transmission systems, in order to guarantee the security for the application systems [35].

An evolution of wireless cache is the mobile edge computing (MEC), which has been widely applied in the intelligent information services in recent years. In MEC networks, nodes can not only cache and communicate, they can also compute or help compute the tasks from the near-by nodes. In this way, the computational tasks can be computed very efficiently, with limited latency and energy consumption. In MEC networks, an important research point is the offloading strategy, which determines while file should be computed by which node. In this areas, some existing works such as [36]–[38] have studied the offloading strategy, and proposed some intelligent algorithms, in order to reduce both the latency and energy consumption.

In this paper, we investigate MEC networks for intelligent information services, where there are N users equipped with K antennas and one access point (AP). The users have some computational tasks, and some of them can be decoupled by the AP, at the cost of a fee charged by the AP. For the considered system, we firstly consider two important metrics of interest: latency and fee. Then, we formulate a stochastic game to model the interaction between users and the AP. In this game, the AP sets prices to maximize its profit, while users devise the offloading strategy to reduce both the latency and charge. We further optimize the system by applying the array signal processing schemes on the users, in order to reduce the transmission latency. Simulation results are finally presented to verify the effectiveness of the stochastic game, and it is shown that the array signal processing scheme can help reduce the transmission latency significantly.

The organization of this paper is given as follows. After the introduction in this section, we will discuss the system model of MEC networks from the perspectives of both users and the AP in Sec. II. Then, we introduce how to intelligently optimize the system performance by using the intelligent algorithms as well as the array signal processing in Sec. III. Sec. IV will present the simulation results and conclusions are finally made in Sec. V.

II. SYSTEM MODEL

Fig. 1 describes the system model of MEC network with multiple users, where there exits one access point (AP) with one MEC server. Each user has a task to be computed within a slot. Due to the limited computational power, these users may not complete the tasks within the prescribed time. Users need to offload partial or full task to the nearly AP with powerful computational capacity. The AP can assist users to complete the offloaded tasks and charge some expenses for users. We assume that there are N users and each user equipped with K antennas has a task of length l_n. Therefore, the set of tasks for all users can be denoted as $\mathcal{L} = \{l_1, l_2, \dots, l_N\}$. The AP with powerful computational capability can provide users with different computational capability based on users' requirement, reasonably, the AP will set a higher price for more powerful computational capability. The set of the computational capability by the AP can be denoted as $\Xi = \{\xi_1, \xi_2, \dots, \xi_M | \xi_1 \leq \xi_2 \leq \dots, \leq \xi_M\}$, and the corresponding price set is denoted as $\mathcal{M} = \{\mu_1, \mu_2, \dots, \mu_M | \mu_1 \leq \mu_2 \leq \dots, \leq \mu_M\}$. The AP

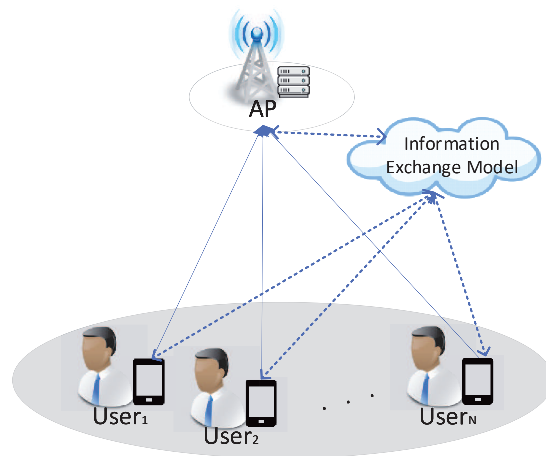


FIGURE 1: **System model of MEC network with multiple users.**

can evaluate proper price parameters, meanwhile users can obtain the price that the AP set by the information exchange model and they design proper offloading strategy. It is worth noting that each user cannot obtain the offloading decision of other users.

A. USER MODEL ANALYSIS

In this system, we focus on the charge which users should pay to complete the computational tasks by the AP, and the latency includes both the latency calculated locally and the latency offloaded to the AP. We use the symbol θ_n to denote the offloading decision for the user n, where θ_n satisfies the constraint of $\theta_n \in [0, 1]$. When $\theta_n = 0$, it means that the whole task will be calculated locally and the computational capability of the user n is denoted by ζ_n. When $\theta_n = 1$, the whole task of user n will be calculated by the MEC server. When $0 < \theta_n < 1$, a partial task with size $\theta_n l_n$ will be offloaded to the AP and the residual task with size $(1-\theta_n)l_n$ will be calculated locally. By analyzing offloading decision, we can obtain the local computing time of user n as

$$T_{local,n} = \frac{(1-\theta_n)l_n}{\zeta_n}. \tag{1}$$

Since user n need not pay the charge when whole task is computed locally, the charge is equal to zero. When a part of task is offloaded to the AP, user n will transmit it to the AP by wireless link and then the AP computes it and returns the result to the user. At the same time, the user will pay for the associated charge to the AP. Therefore, the transmit latency can be given by

$$t_{off,n}^{trans} = \frac{\theta_n l_n}{R_n}, \tag{2}$$

where R_n is transmit rate of user n and it can be denoted by

$$R_n = B_n \log_2 \left(1 + \frac{P_n |h_n|^2}{\sigma^2}\right). \tag{3}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.2974249, IEEE Access

In Eq. (3), the symbol B_n is bandwidth allocated by the system to user n, and P_n is the transmit power of user n. Notation $h_n \sim \mathcal{CN}(0, \epsilon_n)$ is the channel parameter of the wireless link from user n to the AP, and σ^2 is the noise power of the additive white gaussian noise (AWGN) at the AP [39]–[41], where the noise effect on the receiver can be found in the literature [42]–[44]. In addition, for user n, the time that the offloaded task is executed by the AP is given by

$$t_{off,n}^{comp} = \frac{\theta_n l_n}{\xi_m}, \tag{4}$$

when the AP sets the price as μ_m. Since the computational result is very small in general, the time that result is returned is ignored in this system. From the above description, we can write the latency to complete the offloaded task as

$$T_{off,n}(\theta_n) = t_{off,n}^{trans} + t_{off,n}^{comp}. \tag{5}$$

In practice, task offloading and task computing locally can be implemented in parallel for mobile devices. Therefore, the total time for each user n to complete own task is the maximum of the time of computing locally and the time of offloading to the AP. Accordingly, for the user n, the total time T_{total} can be given by

$$T_{total,n}(\theta_n) = \max\{T_{local,n}, T_{off,n}\}. \tag{6}$$

Duo to computational assist, the user n need pay for the charge to the AP. We assume that the charge is proportional to the size of the offloaded task, and hence the charge of user n can be given by

$$\Lambda_n(\theta_n) = \theta_n l_n \mu_m. \tag{7}$$

For the n-th user, it can improve its communication and computational performance by reducing the total latency and the total charge. As wireless mobile communication technology has been developing continually, transmitting a large data is no longer a limitation in wireless networks. So users can reduce the total latency by offloading more tasks to the AP with powerful computational capability. While, by the equation (7), users have to pay more charge to the AP if they offload more tasks to the AP. From above description, the key to improve the user's performance is designing a proper offloading strategy θ_n.

For the users, there are two important metrics of interest for the MEC-based wireless network, and we try to minimize both the latency and charge to reduce each user's cost. By the description, we find that it is a multi-objective optimization problem to improve users performance, which causes much difficulty to solve in practice. In addition, users may face an urgent task or tend to pay less in different scenarios. We use a weighted factor and turn the multi-objective optimization problem into a linearly weighted objective function by the weighted factor λ. The linearly objective function can be given by

$$\Phi_n(\theta_n) = \lambda T_{total,n} + (1-\lambda)\Lambda_{total,n}, \tag{8}$$

where the weighted factor $\lambda \in [0, 1]$, and the Φ_n is the total cost that the n-th user completes the computational task. The usage of weighted factor λ not only simplifies the multi-objective optimization problem into a single-objective optimization problem, but also enables Eq. (8) to apply to more scenarios. In particle, when the value of λ becomes lager, the latency becomes dominant in the optimization problem. Instead, when the value of λ becomes small, the users need to compute task locally as much as possible to reduce the total cost of users.

B. AP MODEL ANALYSIS

The AP with MEC server earns revenue by assisting users to compute tasks. We assume that the AP's profit can be expressed as a function with the sum of offloaded tasks, and we set the AP's price μ_m to independent variable of profit function. According, the AP's profit can be formulated as

$$U_{total}(\boldsymbol{\theta}, \boldsymbol{l}, \mu_m) = \sum_{n=1}^{N} \theta_n l_n \mu_m - C_{total}(\boldsymbol{\theta}, \boldsymbol{l}), \tag{9}$$

where the vector $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_N)$ and $\boldsymbol{l} = (l_1, l_2, \ldots, l_N)$ are offloading decision list and task size list for all users, respectively. $C_{total}(\boldsymbol{\theta}, \boldsymbol{l})$ is the total cost that the AP computes all offloaded tasks. From (9), we find that the AP's profit is related to the price and the total offloaded tasks, and hence the AP pricing will directly affect the AP's profit. If the price is too low, the AP's profit will decrease; while users tend to compute task in local if the price is too high. Therefore, a dynamic price scheme should be applied to adjust to a variety of scenarios and make more profit for the AP.

III. PROBLEM OPTIMIZATION

In this section, we firstly analyze the objective functions of users and the AP, from which we formulate the system optimization into a stochastic game problem. The method Win or Learning Fast Policy Hill Climbing (WoLF-PHC) is proposed to solve the stochastic game problem. Moreover, we apply some array signal processing schemes to further enhance the system performance of MEC networks.

A. STOCHASTIC GAME FORMULATION

In this system, each user wants to minimize the total cost of completing its computational task by designing the offloading decision θ_n based on the computational capability and the AP's price. Meanwhile, the AP wants to increase its profit by changing prices. Therefore, the system model can be described as two optimization problem: the AP wants to maximize its profit by selling the computational capability to users, and the optimization problem can be expressed as

$$\boldsymbol{P1}: \quad \max_{\mu_m \in \mathcal{M}} \quad U_{total}(\boldsymbol{\theta}, \boldsymbol{l}, \mu_m). \tag{10}$$

The objective of each user is to minimize its own cost by choosing the optimal offloading decision for a given price μ_m

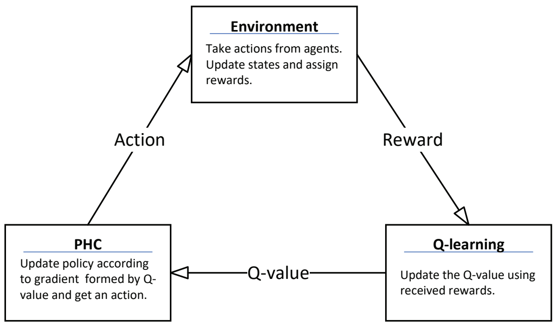


FIGURE 2: Information passing in the WoLF-PHC algorithm.

by the AP, and the optimization problem can be expressed as

$$\boldsymbol{P2:} \quad \min_{\theta_n} \quad \Phi_n(\theta_n, \mu_m) \qquad (11)$$
$$\text{s.t.} \quad 0 \le \theta_n \le 1.$$

Note that the problem $\boldsymbol{P1}$ and the problem $\boldsymbol{P2}$ are coupled in a complicated way: the AP's price strategies affect the offloading decision of each user and each user's offloading decision θ_n also has an influence on the AP's profit in turn. Hence, $\boldsymbol{P1}$ and $\boldsymbol{P2}$ can be described as a stochastic game problem.

A stochastic game problem can be described as a multi-agent reinforcement learning problem with a known reward matrix. However, it is very difficult to do "moving target" in the multi-agent problem. In the multi-agent problem, the agents' environment will be affected when each player changes the offloading decision. Each player is not able to control the other players or even know their next state, i.e., each user can only obtain the price of the AP, but it cannot obtain the offloading decision of other users.

To solve the multi-agent optimization problem, we apply the Win or Learn Fast Policy Hill Climbing (WoLF-PHC), which extends PHC with the "Win or Learn Fast" and Policy Hill Climbing (PHC) is a reinforcement learning algorithm that extends Q-learning to increase the selection probability of the maximum expected action. As the name implies, each agent has to determine whether it is currently wining or losing, and each agent will choose a low learning rate when it is wining currently, instead, it will learning quickly.

In the following, we will introduce the detail of WoLF-PHC in multi-agent MEC networks. WoLF-PHC can be applied to multi-agent stochastic game scenarios because it combines the algorithm Q-learning and PHC. As shown in Fig. 2, for each agent, there are mainly three parts in WoLF-PHC: environment, Q-learning and PHC. Each agent gets an action according to choosing selection probability of the maximum expected action in PHC model. Then, each agent obtains the reward value and next state by the selected action in environment model. Finally, each agent updates the Q-table by action, reward and next state in Q-learning model. The detailed description of the WoLF-PHC is given by the algorithm 1.

Algorithm 1 Win or Learn Fast Policy Hill-Climbing

Let α, $\delta_l > \delta_w$ be learning rates. Initialize,
$Q(s,a) \leftarrow 0, \quad \pi(s,a) \leftarrow \frac{1}{|\mathcal{A}_i|}, \quad C(s) \leftarrow 0.$

for each agent i in all agents **do**

(a) From state s, select action a with probability $\pi_i(s,a)$ with some exploration.

(b) Observing reward r and next state s',
Update the Q-table by

$$Q_i(s,a) \leftarrow (1-\alpha)Q_i(s,a) + \alpha(r + \gamma \max_{a' \in \mathcal{A}_i} Q_i(s',a')). \qquad (12)$$

Update estimate of average policy $\overline{\pi}$
$C_i(s) \leftarrow C_i(s) + 1$

$$\forall a' \in \mathcal{A}_i \quad \overline{\pi}(s,a') \leftarrow \overline{\pi}(s,a') + \frac{1}{C(s)}(\pi_i(s,a') - \overline{\pi}_i(s,a'))). \qquad (13)$$

Update $\pi_i(s,a)$ and constrain it to a legal probability distribution,

$$\pi_i(s,a) \leftarrow \pi_i(s,a) + \begin{cases} \delta, & \text{If } a = \arg\max_{a' \in \mathcal{A}_i} Q(s,a) \\ \frac{-\delta}{|\mathcal{A}_i|-1}, & \text{Otherwise} \end{cases}. \qquad (14)$$

with

$$\delta = \begin{cases} \delta_w, & \text{If } \sum_{a \in \mathcal{A}_i} \pi(s,a)Q(s,a) > \sum_{a \in \mathcal{A}_i} \overline{\pi}(s,a)Q(s,a) \\ \delta_l & \text{Otherwise} \end{cases}. \qquad (15)$$

end for

In this algorithm, the Q-values are stored and updated in the same manner as the Q-learning, which can be described by Eq. (12). Instead of using the action with the highest Q-value as the response for a given state, a probabilistic policy π is used which follows a selection probability function. The selection probability function consists of one probability per action. As the agent takes action, the selection probability function is modified by Eq. (14), and $\mathcal{A}_i$ is the action set of agent i. In WoLF-PHC, the learning rates δ_w and δ_l are designed to change the algorithm's learning rate δ, and the rule for selecting the learning rate δ is given by Eq. (15). The estimate of average policy $\overline{\pi}(s,a)$ is used to estimate whether the agent i wins or not currently. Meanwhile, it is related to the times $C(s)$ that current state s is visited and updated by Eq. (13). In addition, the WoLF-PHC is rational, since only the rate of the learning process is altered. This modification provides additional time for the other players to adapt the agent's changes in the same environment.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.2974249, IEEE Access

B. ARRAY SIGNAL PROCESSING

In this system, all users have multiple antennas, and hence the channel gain can be exploited by the array signal processing. Users need to offload a partial task to the AP to reduce the total cost of users by the wireless communication. Users are able to choose different antenna selection schemes to improve the channel gain from users to the AP. The K antennas are equipped at each user, and a simple method to exploit the multiple antennas is the random antenna selection (RAS) scheme, which means that each user may choose only one antenna randomly among K ones. Accordingly, the transmit rate that the offloaded task is transmitted from user n to the AP can be given by

$$R_n = B_n \log_2\left(1 + \frac{P_n|h_{n,k}|^2}{\sigma^2}\right), \tag{16}$$

where the $h_{n,k} \sim \mathcal{CN}(0, \epsilon_k)$ is the channel gain when user n select the antenna k to communicate with the AP.

In addition, other antenna selection schemes are exploited at users in this subsection. Generally, the selection combining (SC) method can improve the equivalent channel gain, thereby increasing the transmit rate. SC can maximize the transmit rate of wireless communication when some antennas are used in MEC network. Using the SC selection antenna scheme, the transmit rate for user n can be given by

$$R_n = B_n \log_2\left(1 + \frac{P_n \max\limits_{1\le k\le K} |h_{n,k}|^2}{\sigma^2}\right). \tag{17}$$

The maximum ratio transmission (MRT) is another antenna selection scheme to improve the data transmit rate of the users. MRT scheme means that multiple antennas are used to assist users when users offload tasks to the AP. This method can significantly improve the users's transmit rate at the cost of increasing RF chains. And the transmit rate is written by

$$R_n = B_n \log_2\left(1 + \frac{P_n \sum\limits_{k=1}^{K} |h_{n,k}|^2}{\sigma^2}\right). \tag{18}$$

IV. SIMULATION RESULTS

In the simulations, we explore the proposed multi-agent game algorithm with different antenna selection schemes. There are 3 users in this system and their computational capabilities are set to 0.7×10^9 cycle/sec, 0.6×10^9 cycle/sec and 0.7×10^9 cycle/sec, respectively. Moreover, each user is equipped with two antennas, and the size of computed task l_n is in the range of [2, 3] Mega Bytes. Different pricing schemes are used and there are three prices corresponding to three computational capabilities. The three prices are set to 0.1, 0.2 and 0.5, respectively, and the three computational capabilities are set to 1×10^9 cycle/sec, 2×10^9 cycle/sec and 4×10^9 cycle/sec, respectively. This means that users need to pay more charge when they choose more powerful computational capability. In not specified, we use the equal bandwidth with 20 Mhz for

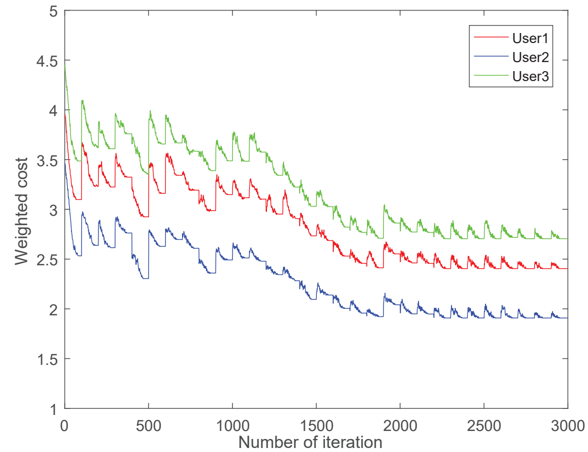


FIGURE 3: Convergence of the WoLF-PHC algorithm versus iteration for all users, where the weighted factor is equal to 0.5.

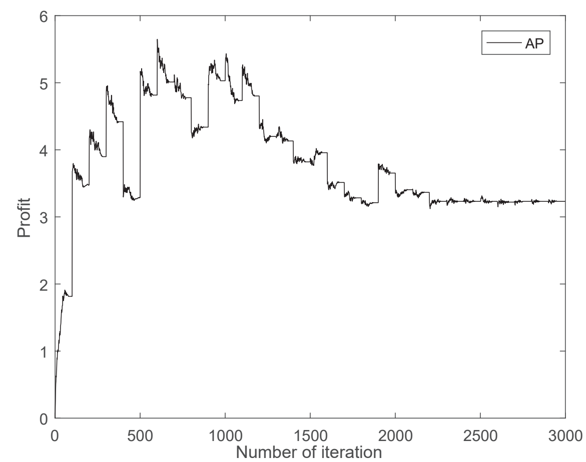


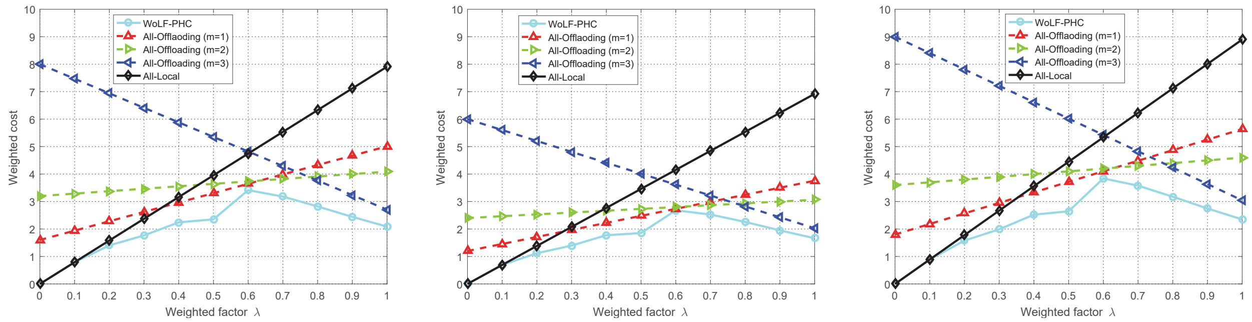
FIGURE 4: Convergence of the WoLF-PHC algorithm versus iteration for AP, where the weighted factor is equal to 0.5.

each price. In algorithm WoLF-PHC, the α is equal to 0.8, and the symbols δ_w and δ_l are set to 0.1 and 0.5, respectively.

In Fig. 3 and Fig. 4, the convergence of the algorithm is shown. We present how the weighted cost of each user and the AP's profit vary with the number of iterations in the WoLF-PHC algorithm, where we set the weighted factor λ to 0.5. From Fig. 3, we can find that the overall trend of the weighted cost is falling, while the profit of the AP is rising in volatility as shown in Fig. 4. All lines are convergent when iterating to more than 2500 times. From these results, we can see that WoLF-PHC can be used to solve the multi-agent game problem efficiently.

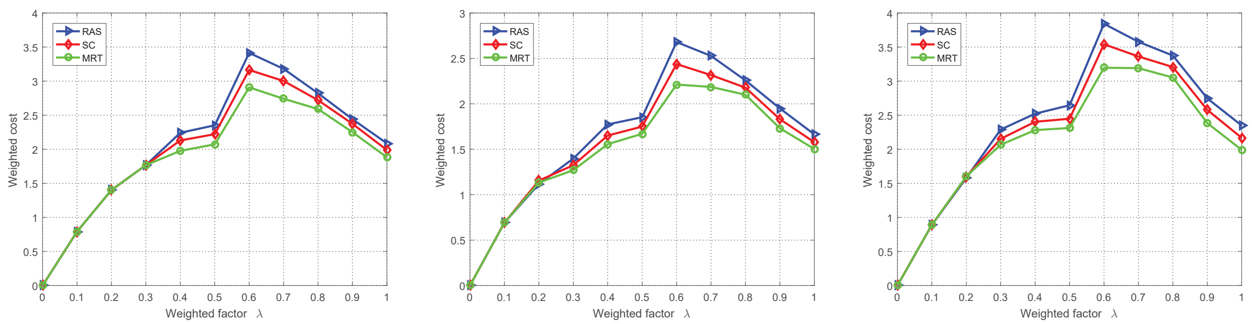
In Fig. 5, the weighted cost of each user is exploited with respect to the weighted factor λ, which varies from 0 to 1. Some other offloading schemes are used to compare with the proposed WoLF-PHC. There, "All-Offloading (m=1)", "All-Offloading (m=2)" and "All-Offloading (m=3)" mean that user 1, 2 and 3 offload the whole task to the AP with $\theta_n = 1$, where the AP prices are set to μ_1, μ_2 and μ_3, respectively. In addition, we consider the offloading scheme

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.2974249, IEEE Access



(a) User 1 (b) User 2 (c) User 3

FIGURE 5: Comparison of the different task offloading decisions for each user versus the weighted factor λ.



(a) User 1 (b) User 2 (c) User 3

FIGURE 6: Comparison of the different antenna selection schemes for each user versus the weighted factor λ.

where each user computes the whole locally, denoted by "All-Local". From these figures, we find that the offloading decision "WoLF-PHC" has smaller weighted cost than other offloading decisions when the weighted factor $\lambda \in [0.2, 1]$. On the contrary, the weighted cost of "WoLF-PHC" is almost the same as "All-Local" when $\lambda \in [0, 0.1]$ and $n \in [1, N]$. The reason of this phenomenon is that the computed task is a non-urgent task. Meanwhile, each user wants to pay the AP as little as possible and tends to execute the whole task locally. As λ increases, the latency will dominate in the weighted cost of users, and accordingly, users prefer offloading task to the AP to reduce latency. The value of Λ_n is larger than $T_{total,n}$ when the decision "All-Offloading (m=3)" is used, therefore line "All-Offloading (m=3)" is a downward trend with the increase of λ. In addition, the line "WoLF-PHC" increases with the increase of λ when $\lambda \in [0, 0.6]$. This indicates that the latency dominates in the weighted cost.

In practical scenarios, the task may be urgent, and it should be completed within a prescribed time in MEC networks. So we exploit whether the task of each user can be completed within a time limit or not, and meanwhile, we observe the influence of different time limits on users' weighted cost and the AP's profit. In order to exploit the problem globally, we add the fourth pricing and computational capability for the AP, which can be expressed as $\mu_4 = 0.8$ and $\xi_4 = 8 \times 10^9$, respectively. The simulation results are shown in Fig. 7. From the results, we can see that users' weighted cost increases

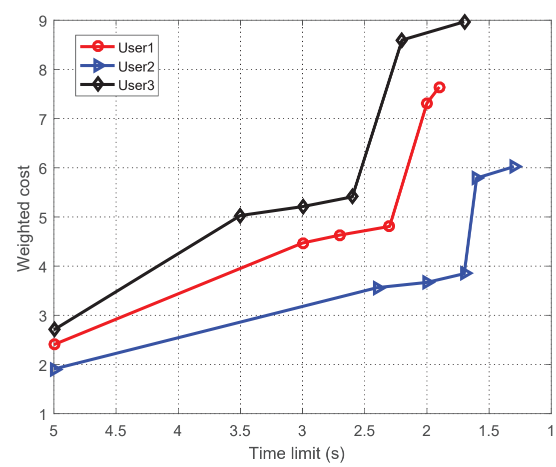


FIGURE 7: Impact of the time limit on the weighted cost for each user , where λ is equal to 0.5.

when the time limit decreases. This phenomenon implies that each user needs to increase θ_n, in order to complete his own task within the time limit. Accordingly, users' total cost and the AP's profit increase.

In addition, the weighted cost is presented in Fig. 6 with different antenna selection schemes versus the weighted factor λ. In Sec. III, RAS, SC and MRT are employed and antenna selection schemes mainly effect the transmit latency. There, we set the number of antennas to 2 and set the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.2974249, IEEE Access

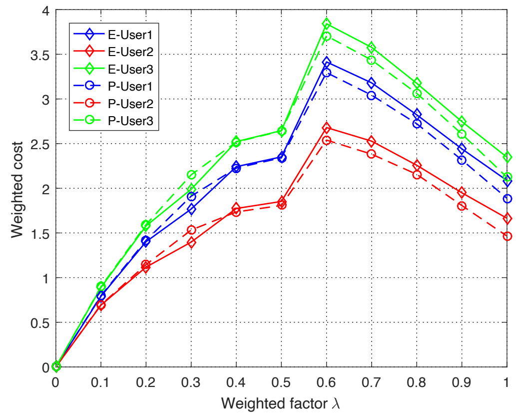


FIGURE 8: Comparison of the two bandwidth allocation scheme for each user versus the weighted factor λ.

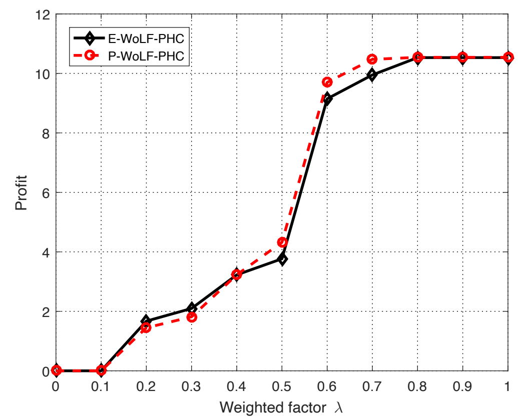


FIGURE 9: Comparison of the two bandwidth allocation scheme for AP versus the weighted factor λ.

weighted factor to 0.5. From Fig. 6, we can find that the MRT has the smallest weighted cost, and the SC outperforms the RAS in the total cost for all users when the weighted factor λ varies in $[0.3, 1.0]$. On the contrary, the three antenna selection schemes show the similar performance when $\lambda \in [0.0, 0.2]$. This is because that the charge Λ_n is dominant and the task tends to be computed locally instead of by the AP. In Eq. (6), the total time required to complete the task l_n is the maximum between the $T_{local,n}$ and $T_{off,n}$ for each user, while antenna selection schemes can only help reduce transmission latency. Therefore, the antenna selection schemes cannot affect the system performance when $T_{local,n} > T_{off,n}$.

Finally, we exploit the impact of bandwidth for MEC networks. We set different bandwidth schemes for different prices of the AP. A simple bandwidth allocation scheme is to allocate the bandwidth equally for different prices, where, the bandwidth corresponding to prices $[\mu_1, \mu_2, \mu_3]$ is $[20, 20, 20]$ MHz. Another scheme is to allocate the bandwidth based on the different prices, where, the bandwidth corresponding to prices $[\mu_1, \mu_2, \mu_3]$ is $[10, 20, 30]$ MHz. For simplicity, we denote these two schemes by "E-WoLF-PHC" and "P-WoLF-PHC", respectively. From Fig. 8 and 9, we find that the scheme "P-WoLF-PHC" has a better performance when the tasks are urgent. This is because that users need more powerful computational capability and the AP sets higher prices for users when the weighted factor λ increases. Meanwhile, users tend to offload the whole task to the AP when the weighted factor λ is equal to 0.8 in Fig. 9. Hence, the AP's profit will not increase when the value of λ varies from 0.8 to 1.0.

V. CONCLUSIONS

In this paper, we investigated MEC networks for intelligent information services, where there are N users equipped with K antennas and one AP. The users had some computational tasks, and some of them could be decoupled by the AP, at the cost of a fee charged by the AP. For the considered system, we firstly considered two important metrics of interest: latency and fee. Then, we formulated a stochastic game to model the interaction between users and the AP. In this game, the AP set prices to maximize its profit, while users devised the offloading strategy to reduce both the latency and charge. We further optimized the system by applying the array signal processing schemes on the users, in order to reduce the transmission latency. Simulation results were finally presented to verify the effectiveness of the stochastic game, and it was shown that the array signal processing scheme could help reduce the transmission latency significantly. In further works, we will apply the considered MEC networks into the application of IoT based systems such as the works in [45]–[47]. Moreover, we will consider to use some other intelligent algorithms [48]–[54] to the considered system, in order to further enhance the system performance by reducing the latency and energy consumption.

REFERENCES

[1] N. Zhao and X. Liu, "Communications, caching, and computing oriented small cell networks with interference alignment," IEEE Communications Magazine, vol. 54, no. 9, pp. 29–35, 2016.
[2] Z. Na, Y. Wang, and X. Li, "Subcarrier allocation based simultaneous wireless information and power transfer algorithm in 5g cooperative OFDM communication systems," Physical Communication, vol. 29, pp. 164–170, 2018.
[3] S. Wang, D. You, and M. Zhou, "A necessary and sufficient condition for a resource subset to generate a strict minimal siphon in S 4pr," IEEE Trans. Automat. Contr., vol. 62, no. 8, pp. 4173–4179, 2017.
[4] N. Zhao and Y. Cao, "Artificial noise assisted secure interference networks with wireless power transfer," IEEE Trans. Vehicular Technology, vol. 67, no. 2, pp. 1087–1098, 2018.
[5] Z. Na, J. Lv, M. Zhang, and M. Xiong, "GFDM based wiereless powered communication for cooperative relay system," IEEE Access, vol. 7, pp. 50 971–50 979, 2019.
[6] X. Hu, C. Zhong, X. Chen, W. Xu, and Z. Zhang, "Cluster grouping and power control for angle-domain mmwave mimo noma systems," IEEE Journal of Selected Topics in Signal Processing, vol. 13, no. 5, pp. 1167–1180, 2019.
[7] W. Xu, J. Liu, S. Jin, and X. Dong, "Spectral and energy efficiency of multi-pair massive MIMO relay network with hybrid processing," IEEE Trans. Communications, vol. 65, no. 9, pp. 3794–3809, 2017.
[8] C. Lu, W. Xu, S. Jin, and K. Wang, "Bit-level optimized neural network for multiantenna channel quantization," IEEE Wirel. Commun. Lett., vol. PP, no. 99, pp. 1–4, 2020.

[9] L. Fan, N. Zhao, X. Lei, Q. Chen, N. Yang, and G. K. Karagiannidis, "Outage probability and optimal cache placement for multiple amplify-and-forward relay networks," IEEE Trans. Veh. Technol., vol. 67, no. 12, pp. 12 373–12 378, 2018.

[10] X. Lai, "Distributed secure switch-and-stay combining over correlated fading channels," IEEE Trans. Information Forensics and Security, vol. 14, no. 8, pp. 2088–2101, August 2019.

[11] X. Lai and W. Zou, "DF relaying networks with randomly distributed interferers," IEEE Access, vol. 5, pp. 18 909–18 917, 2017.

[12] J. Xia, "When distributed switch-and-stay combining meets buffer in iot relaying networks," Physical Communication, vol. 38, pp. 1–10.

[13] J. Zhao, "Power control algorithm of cognitive radio based on non-cooperative game theory," China Commun., vol. 10, no. 11, pp. 143–154, 2013.

[14] J. Zhao and Q. Li, "Computation offloading and resource allocation for cloud assisted mobile edge computing in vehicular networks," IEEE Trans. Vehicular Technology, vol. 68, no. 8, pp. 7944–7956, 2019.

[15] S. Ni, "Enhancing downlink transmission in MIMO hetnet with wireless backhaul," IEEE Trans. Vehicular Technology, vol. 68, no. 7, pp. 6817–6832, 2019.

[16] J. Zhao, "Power allocation based on genetic simulated annealing algorithm in cognitive radio networks," Chinese Journal of Electronics, vol. 22, no. 1, pp. 177–180, 2013.

[17] X. Wang, "Joint resource allocation for cognitive OFDM-NOMA systems with energy harvesting in green IoT," IEEE Access, vol. PP, no. 99, pp. 1–8, 2020.

[18] J. Zhao and N. Shanjin, "Multiband cooperation for 5G HetNets: A promising network paradigm," IEEE Vehicular Technology Mag., vol. PP, no. 99, pp. 1–10, 2019.

[19] S. Pan, "Synthesis of naked plasmonic/magnetic au/fe3o4 nanostructures by plasmon-driven anti-replacement reaction," NANOTECHNOLOGY, vol. 30, 2019.

[20] ——, "Plasmon-engineered anti-replacement synthesis of naked cu nanoclusters with ultrahigh electrocatalytic activity," JOURNAL OF MATERIALS CHEMISTRY A, vol. 6, pp. 18 687–18 693, 2018.

[21] Y. K. Wang, "The superior thermal stability and tensile properties of hot rolled w-hfc alloys," International Journal of Refractory Metals and Hard Materials, vol. 81, pp. 42–48, 2019.

[22] M. M. Wang, "Grain size effects of tungsten powder on the micro-structure and mechanical properties of tungsten-based alloys," Materials Science and Engineering A, vol. 754, pp. 216–223, 2019.

[23] F. Shi, "Secure probabilistic caching in random multi-user multi-uav relay networks," Physical Communication, vol. 32, pp. 31–40, 2019.

[24] X. Lin, "Probabilistic caching placement in uav-assisted heterogeneous wireless networks," Physical Communication, vol. 33, pp. 54–61, 2019.

[25] ——, "MARL-based distributed cache placement for wireless networks," IEEE Access, vol. 7, pp. 62 606–62 615, 2019.

[26] J. Xia, "Secure cache-aided multi-relay networks in the presence of multiple eavesdroppers," IEEE Trans. Commun., vol. 67, no. 11, pp. 7672–7685, Nov. 2019.

[27] ——, "Cache-aided mobile edge computing for b5g wireless communication networks," EURASIP Journal on Wireless Communications and Networking, vol. PP, no. 99, pp. 1–5, 2019.

[28] B. Lu, "Interference suppression by exploiting wireless cache in relaying networks for b5g communications," Physical Communication, vol. PP, pp. 1–10, 2020.

[29] W. Huang, "Multi-antenna processing based cache-aided relaying networks for b5g communications," Physical Communication, vol. PP, pp. 1–10, 2020.

[30] C. Li and Y. Xu, "Protecting secure communication under UAV smart attack with imperfect channel estimation," IEEE Access, vol. 6, no. 1, pp. 76 395–76 401, 2018.

[31] Y. Xu, "Q-learning based physical-layer secure game against multi-agent attacks," IEEE Access, vol. 7, pp. 49 212–49 222, 2019.

[32] C. Li, "Cache-enabled physical-layer secure game against smart uav-assisted attacks in b5g noma networks," EURASIP Journal on Wireless Communications and Networking, vol. PP, no. 99, pp. 1–5, 2019.

[33] C. Li and W. Zhou, "Enhanced secure transmission against intelligent attacks," IEEE Access, vol. 7, pp. 53 596–53 602, 2019.

[34] J. Xia, "Intelligent secure communication for internet of things with statistical channel state information of attacker," IEEE Access, vol. 7, no. 1, pp. 144 481–144 488, 2019.

[35] J. Yang, D. Ruan, J. Huang, X. Kang, and Y.-Q. Shi, "An embedding cost learning framework using gan," IEEE Trans. Information Forensics and Security, vol. 15, pp. 839–851, 2020.

[36] Y. Guo, "Intelligent offloading strategy design for relaying mobile edge computing networks," IEEE Access, vol. PP, no. 99, pp. 1–7, 2020.

[37] R. Zhao, "Deep reinforcement learning based mobile edge computing for intelligent internet of things," IEEE Access, vol. PP, no. 99, pp. 1–8, 2020.

[38] Z. Zhao, "A novel framework of three-hierarchical offloading optimization for MEC in industrial IoT networks," IEEE Transactions on Industrial Informatics, vol. PP, no. 99, pp. 1–12, 2019.

[39] J. Ma and S. Zhang, "Interference-alignment and soft-space-reuse based cooperative transmission for multi-cell massive MIMO networks," IEEE Trans. Wireless Communications, vol. 17, no. 3, pp. 1907–1922, 2018.

[40] B. Wang, F. Gao, S. Jin, H. Lin, and G. Y. Li, "Spatial- and frequency-wideband effects in millimeter-wave massive MIMO systems," IEEE Trans. Signal Processing, vol. 66, no. 13, pp. 3393–3406, 2018.

[41] D. Deng, "Link selection in buffer-aided cooperative networks for green IoT," IEEE Access, vol. PP, no. 99, pp. 1–8, 2020.

[42] ——, "A note on implementation methodologies of deep learning-based signal detection for conventional MIMO transmitters," IEEE Transactions on Broadcasting, vol. PP, pp. 1–2, 2020.

[43] Y. Cao, N. Zhao, and F. R. Yu, "Optimization or alignment: Secure primary transmission assisted by secondary networks," IEEE Journal on Selected Areas in Communications, vol. 36, no. 4, pp. 905–917, 2018.

[44] H. Xie, F. Gao, S. Zhang, and S. Jin, "A unified transmission strategy for TDD/FDD massive MIMO systems with spatial basis expansion model," IEEE Trans. Vehicular Technology, vol. 66, no. 4, pp. 3170–3184, 2017.

[45] J. Yang, "Inverse optimization of building thermal resistance and capacitance for minimizing air conditioning loads," Renewable Energy, vol. PP, pp. 1–10, 2020.

[46] J. Yang and H. Wu, "Numerical and experimental study on the thermal performance of aerogel insulating panels for building energy efficiency," Renewable Energy, vol. 138, pp. 445–457, 2019.

[47] H. Huang, "Optimum insulation thicknesses and energy conservation of building thermal insulation materials in chinese zone of humid subtropical climate," Sustainable Cities and Society, vol. 52, p. 101840, 2020.

[48] K. He, "Ultra-Reliable MU-MIMO Detector Based on Deep Learning for 5G/B5G-enabled IoT," EURASIP Journal on Wireless Communications and Networking, vol. PP, no. 99, pp. 1–8, 2020.

[49] ——, "Generic deep learning based linear detectors for MIMO systems over correlated noise environments," IEEE Access, vol. PP, no. 99, pp. 1–9, 2020.

[50] C. Fan, "Cooling load prediction and optimal operation of HVAC systems using a multiple nonlinear regression model," Energy and Buildings, vol. 197, pp. 7–17, 2019.

[51] G. Liu, "Deep learning based channel prediction for edge computing networks towards intelligent connected vehicles," IEEE Access, vol. 7, pp. 114 487–114 495, 2019.

[52] S. Lai, "Intelligent secure communication for cognitive networks with multiple primary transmit power," IEEE Access, vol. PP, no. 99, pp. 1–7, 2020.

[53] C. Fan and Y. Ding, "Analysis of hourly cooling load prediction accuracy with data-mining approaches on different training time scales," Sustainable Cities and Society, vol. 51, p. 101717, 2019.

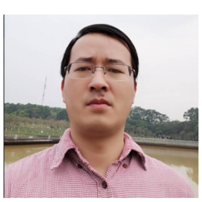
[54] J. Xia, "A MIMO detector with deep learning in the presence of correlated interference," IEEE Trans. Veh. Technol., vol. PP, no. 99, pp. 1–5, 2019.

ZICHAO ZHAO received the B.E. degree from the Yantai University, Yantai, China, in 2018. He is currently pursuing the M.E. degree at the Guangzhou university, Guangzhou, China. His current research interests include Mobile Edge Computing resource scheduling and machine learning.

WEN ZHOU received the Ph.D. degree in engineering from Hong Kong University in 2010. From 2011 to 2016, he was with the Department of Electronic Engineering, Shantou University, China. Currently, he is an associate professor at the College of Information Science and Technology, Nanjing Forestry University, China. The research interests include the internet of things for Forest, MIMO signal processing, and information geometry.

DAN DENG received his Bachelor and Ph.D. degrees from University of Science and Technology of China, in 2003 and 2008, respectively, both from Department of Electronic Engineering and Information Science. From 2008 to 2014, he was with Comba Telecom Ltd. in Guangzhou China, as a Director. Since 2014, he has joined Guangzhou Panyu Polytechnic, where he is currently an Associate Professor. His research interests include MIMO communication and physical-layer security in next-generation wireless communication systems. He has published 45 papers in international journals and conferences. Also, he holds 19 patents, and has served as a member of Technical Program Committees for several conferences.

JUNJUAN XIA received the bachelor degree from the department of computer science from Tianjin University in 2003, and obtained the master degree from the department of electronic engineering from Shantou University in 2015. Now she works for the School of Computer Science and Cyber Engineering, Guangzhou University as a laboratory assistant. Her current research interests include wireless caching, physical-layer security, cooperative relaying and interference modeling.



LISENG FAN obtained the doctoral degree from Tokyo Institute of Technology, Tokyo, in the year of 2008. He is now a Professor at the School of Computer Science and Cyber Engineering of Guangzhou University. He has published more than 40 papers on the IEEE journal and IEEE conferences. His main research interests include the information security, wireless networks, and the artificial intelligence. His recent research interest is the application of artificial intelligence into the wireless networks.