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UCAA: User-Centric User Association and Resource Allocation in Fog Computing Networks

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ABSTRACT In recent years, with the eruptive popularity of mobile Internet and the emergence of various new IoT applications, fog computing is proposed to shift the cloud computing services towards the edge, making up for its lack of mobility support and high delay. Fog computing is customized for scenarios with scarce resources and unpredictable environments, but there is no user-centric joint optimization fog computing models designed for such scenarios. In this paper, we aim to maximize the user experience and overall system performance by jointly optimizing user association and resource allocation in the scenarios mentioned above, which can be formulated as a mix-integer non-linear programming problem. To solve the NP-hard problem, we propose a low-complexity two-step interactive optimal algorithm, named UCAA algorithm. For the user association problem, we propose a semi-definite programming based algorithm, and then further propose a Kuhn-Munkres algorithm based user association decision approximation algorithm. For the resource allocation problem, we first prove that it can be decoupled into two sub-problems, ie., transmission power selection problem and computing resource allocation problem, and solve them individually, in addition, we have given a rigorous proof that the optimal solution of the two sub-problems is the optimal solution to the original problem as well. The numerical results show that the proposed UCAA algorithm achieves better performance than conventional algorithms in terms of the value of average user-centric utility, especially in case of more user equipments (UEs), fewer fog nodes, limited computing capacity of fog nodes, lower delay tolerance, lower local computation capacity, etc., which presented to illustrate that the UCAA algorithm can significantly improve user experience and system performance in the considering fog computing scenarios.

INDEX TERMS Fog computing, user-centric, user association, resource allocation, externalities.

I. INTRODUCTION

Due to the tremendous progress in mobile communication technologies and smart devices, Internet of Things (IoT) has become popular, which can make our world smarter. According to Cisco, more than 50 billion devices are expected to be connected to the Internet by 2020, and monthly mobile data traffic will grow from 30 EB (exabyte) in 2012 to 292 EB in 2019 [1], which have resulted in a large amount of redundant and duplicate information in the network. Meanwhile, some new mobile latency-critical and computation-intensive applications, such as virtual reality (VR), augmented reality (AR), high-quality real-time video stream, real-time object recognition, autonomous driving, etc. [2]–[5], have developed rapidly over the years. However, with the increasing demand of users for quality of experience (QoE) and the

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performance of mobile devices, the IoT is facing enormous challenges due to limited battery and computing capacity of mobile terminals. A potential solution is to employ mobile cloud computing (MCC) technology, which can provide IoT devices with powerful computing and storage services. Nevertheless, due to the remote location and limited front-haul capacity, it's still difficult for the traditional centralized cloud center to support some latency-critical services, in addition, the unreliable wireless connections, e.g., deep fading, can lead to data loss.

In response to the above challenges, a feasible solution is to migrate a small amount of communication, computing and storage resources to the edge of the network to serve UEs nearby, it's generally known that fog computing has been proposed as an attractive solution to extend the cloud computing paradigm to the local in the past few years [6], [7], network resources including computing, communication, caching, etc. can be flexibly deployed on each fog nodes with the help of many technologies such as Network Function Virtualization, Software-Defined Networking, Machine Learning, etc. [8]–[10]. In fog networks, the fog nodes with certain computing and storage capacity can provide nearby user equipments (UEs) with low delay, high reliability, location awareness and privacy preservation services [11]. Due to the flexible computing and communication resources sharing from the fog node and remote cloud center in fog computing network, reduce the traffic loads at the back-haul networks significantly, fog computing has great potential to improve system energy efficiency. Moreover, fog computing is very suitable for some special scenarios, where the environment is changeable and resources are severely limited, such as tactical edge, deserted land, etc [12].

However, some characteristics of fog node that are different from centralized cloud center, such as mobility support, geographical restrictions and limited resources capacity, make fog computing face several new challenges. The limited resources of fog nodes can't be able to satisfy the requirements of multiple UEs simultaneously, if the limited resources are not allocated properly, not only will the resources be wasted, but also the system throughput will be reduced. Hence, for a fog computing network, how to share the limited resources efficiently and fairly among multiple UEs with heterogeneous requirements has attracted more research attention in the past several years.

A. RELATED WORK

There have been some works focusing on minimizing the end-to-end delay or energy consumption of the task offloading and computing in fog computing or edge computing systems. In [13], Liu et al. studied a network device model to explore the power dissipation characteristics of CMOS devices and proposed an on-demand energy-efficient resource allocation algorithm, on this basis, the authors proposed a novel resource placement in edge networks. In [14], Zhang et al. proposed a novel energy consumption minimized task offloading algorithm based on fairness scheduling metrics of each fog node, which are determined by the task offloading energy consumption, the historical average energy of fog nodes, and the priority of fog nodes. In [15], Yang et al. studied the tradeoff between performance gains and energy costs of collaborative task offloading in homogeneous fog networks, and developed an efficient task scheduling algorithm for achieving maximum energy efficiency among homogeneous fog nodes. In [16], Zeng et al. studied task placement and scheduling problem to minimize the completion time of maximum task in the considered fog-cloud software-defined network. In [17], Ali et al. studied a cloudlet selection problem to minimize the delay of fog networks which can be converted into a many-to-one matching game, they proposed a distributed and self-organizing resource allocation algorithm to solve it. In [18], Zhang et al. established a general analysis framework in a fog network under voluntary mode and proposed a delay-optimal task scheduling algorithm. In [19], Lee et al. studied joint fog network formulation and task offloading problems in a hybrid fog-cloud network and proposed a novel online optimization framework to minimize the maximum delay of the fog nodes in the considered network.

The delay-energy consumption tradeoff problem has attracted significant attention. In [20], Mao et al. studied the power-delay consumption tradeoff in a multi-user edge computing system and proposed a task offloading algorithm based on Lyapunov optimization. In [21], Liu et al. studied a computation offloading optimization problem in the fog network by designing queuing models for users, fog nodes and cloud centers, respectively, to jointly minimize the system energy consumption, delay, and cost. In [22], Du et al. studied a joint computation offloading and resource allocation optimization problem to minimize the delay and energy consumption among all UEs while ensuring the fairness of users in the considered hybrid fog-cloud collaboration network. In [23], Deng et al. designed a system framework to explore the delay-energy consumption issue in fog-cloud network and decomposed the formulated task allocation problem into three sub-problems that can be solved separately. In [24], Bozorgchenani et al. studied partial offloading by comparing a centralized and a distributed architecture considering the tradeoff between fog nodes delay and energy consumption in edge computing. In [25], Zhang et al. developed a multiple algorithm service model to reduce the energy consumption and delay cost while guaranteeing the quality of the results.

Other research focuses on the application of fog computing in some IoT scenarios, such as the Industrial Internet of Things (IIoT) [26], healthcare [27], smart grid [28], smart traffic [29],etc. In [30], Wan et al. studied the deployment of fog nodes to meet the requirements of real time industrial dynamic order analysis and equipment scheduling in smart factory, and proposed an energy-aware load balancing and scheduling algorithm to enhance the autonomy of the factory. In [31], Han et al. studied a collaborative charging algorithm based on network density clustering in wireless rechargeable sensor networks. In [32], Gu et al. integrated fog computing into medical cyber-physical systems and studied the quality of service (QoS) guaranteed minimum cost resource management problem in the proposed fog computing supported medical cyber-physical system. In [33], Han et al. proposed an uneven cluster-based mobile charging algorithm, an uneven clustering scheme and a novel charging path planning scheme are incorporated in this algorithm.

Besides, a number of researchers have proposed new mathematical models. In [34], Abedin et al. studied an AHP-based matching algorithm to solve distributed user association and resource allocation problems in fog network considering the QoS parameters and their priorities. In [35], Zhang et al. studied a joint resource allocation optimization problem in the proposed three-tier fog network, which is solved by the Stackelberg game and many-to-many matching. In [36], Xu et al. proposed a post-decision state based learning algorithm, which can learn the optimal joint offloading and autoscaling strategy in energy harvesting edge networks in real time. In [37], Yin et al. proposed a novel QoS prediction model with neighbors feature learning, based on convolutional neural network and matrix factorization, to promote the quality in neighbors selection in edge computing environment.

B. MOTIVATION AND CONTRIBUTIONS

As mentioned above, fog computing has received remarkable attention in the world of academia, and has been further applied in the fields of industry and healthcare. In some scenarios where resources are severely limited and the environment is complex, problems such as data loss and collaboration difficulties are prone to occur, it is appropriate to apply fog computing to such scenarios. However, so far there is few related research focusing on investigating the above issues. The motivation and the challenges of this work can be summarized as follows:

1) The joint optimization problem of user association and resource allocation in a fog computing scenario under complex environment has not been well investigated, especially for the problem considering both user experience quality and overall system performance.

2) In general, each UE with different active levels and requirements in the realistic wireless network scenarios. To our knowledge, the joint user association and resource allocation optimization problem considering both user requirements and system performance does not seem to be studied so far in the context of fog computing.

3) It is still challenging to approach the optimal solutions with respect to the joint design of user association and resource allocation in a computation-efficient way. In addition, the stability of solutions will be affected by externalities such as environmental factors, which are ignored by most of the existing research.

Considering the above mentioned challenges, this paper serves as a starting point to address these issues, in which we studied the joint optimization of user association and resource allocation in some specific fog computing scenarios. The primary contribution of this work is briefly summarized as follows:

1) A more realistic user-centric model considering both user association and resource allocation is proposed in fog computing scenarios under complex environment. More specifically, a new concept named user-centric utility (UCU) that takes into account external factors is defined to quantify the subjective feelings of the UEs and the fog nodes. To the best of our knowledge, this is the first work on the above circumstances, which can be served as a cornerstone for future research possibilities.

2) To improve resource utilization, user experience quality and overall system performance, we formulate the joint user association and resource allocation optimization problem as a mixed integer non-linear programming (MINLP) optimization problem where the environmental factors are taken into account. In particular, the objective function is defined as a linear combination of delay, energy consumption, and bit error rate, in addition, the practical constraints on the maximum computation capacity of fog nodes, maximum computing resources of fog nodes, maximum delay tolerance of UEs and maximum transmission power of UEs are taken into account. We propose an optimal algorithm, referred to as user-centric user association and resource allocation (UCAA) algorithm, which solves this challenging optimization problem efficiently.

3) By analyzing structural properties, we first propose a low-complexity two-step interactive optimal algorithm to decompose the challenging optimization problem into two sub-problems and solve them individually. For the non-convex user association problem, we propose a semi-definite programming based algorithm and a Kuhn-Munkres algorithm based user association decision approximation algorithm. For the convex resource allocation problem, we also propose a two-step optimal algorithm by solving two sub-problems, ie., transmission power selection and computing resource allocation, respectively, in addition, relevant rigorous proofs are given. Therefore, optimal solutions can be obtained with polynomial computational complexity.

4) We demonstrated the feasibility and performance of the proposed UCAA algorithm by extensive simulations. In detail, the numerical results confirm that the proposed scheme has a better performance in terms of average user-centric utility, compared with other baseline algorithms, which confirms that the proposed UCAA algorithm can improve both of the user experience and the overall system performance in the fog computing scenarios under complex environments.

The remainder of this paper is organized as follows. In section 2, we present the system model including the formulation of joint optimization problem. We propose a low-complexity two-step interactive optimal algorithm in Section 3. Section 4 verifies the proposed user-centric user association and resource allocation algorithm by experiments and provides analysis of the numerical results. Finally, the conclusion is drawn in Section 5.

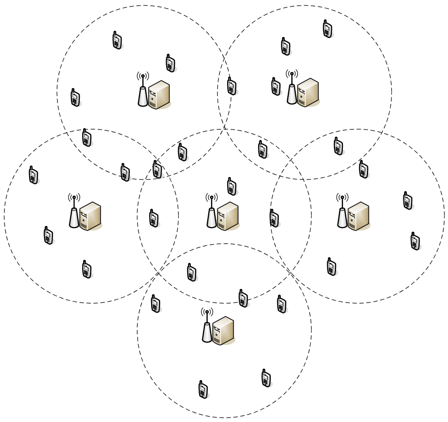

FIGURE 1. Fog network model.

II. SYSTEM MODEL AND PROBLEM FORMULATED

In this section, we first introduce a fog computing system model with multiple UEs and fog nodes, and then we analysis the delay, bit error rate and energy consumption generated in the process of communicating and computing in detail. Afterwards, we propose the minimizing average user-centric optimization problem.

A. DESCRIPTION OF CONSIDERED SCENARIO

As depicted in Fig. 1, we consider a heterogeneous mobile fog computing network consisting of N UEs and K fog nodes, the set of UE is denoted as $U = \{u_1, u_2, \ldots, u_N\}$, the set of fog nodes is denoted as $F = \{f_1, f_2, \ldots, f_K\}$. Considering the privacy of data, we assume that each UE u_n which is equipped with a single-antenna, associates with a unique fog node which is equipped with a large number of antennas via a wireless link, whereas each fog node can be associated with several UEs. In addition, we assume that each UE u_n has only one delay-sensitive task t_n which is atomic and cannot be divided into sub-tasks to be handled offloaded for processing by the nearby fog node through the following procedure within a calculation period. Firstly, each UE sends an offloading request to the nearby fog nodes. Then each fog node performs optimization to decide which UE to serve considering all requests received, and finally, the offloading decisions are delivered to the corresponding UEs.

The task of each UE can be characterized by a tuple of three parameters, $t_n = \{S_n, C_k, \tilde{D}_n\}$, in which S_n (in bit) denotes the size of task t_n, C_k (in cycle/bit) denotes the number of CPU cycle required for computing 1-bit data of task t_n for the fog node f_k, and $\tilde{D}_n$ (in second) denotes maximum tolerable delay. Let $V_k > 0$ denote the local computing capability of fog node f_k in terms of CPU cycle/s, which is fixed and different from each other.

B. USER-CENTRIC PARAMETERS ANALYSIS

We define a binary variable μ_{nk} to indicate whether UE u_n is associated with fog node f_k or not, i.e.,

$$\mu_{nk} = \begin{cases} 1 & \textit{if UE } u_n \textit{ is associated with fog node } f_k \\ 0 & \textit{otherwise} \end{cases} \tag{1}$$

We assume that each UE $u_n \in U$ can only associate with unique fog node $f_k \in F$.

1) COMMUNICATION MODEL

For ease of analysis, we assume that the fog nodes start processing corresponding tasks after receiving all the input data. Each fog node f_k can serve multiple UEs based on the available statistical channel state information (CSI), and each UE is allocated with a sub-channel, the bandwidth of which is W (in Hz). Respectively, we adopt orthogonal frequency-division multiple access (OFDMA) method for channel access. Considering the Shannon capacity formula, the transmission capacity between UE u_n and fog node f_k is given by,

$$r_{nk} = W\log_2(1 + \frac{P_n^t h_{nk}}{|N_0|}) \tag{2}$$

where P_n^t denotes the transmission power of UE u_n, N_0 denotes the noise power spectral density of the Additive White Gaussian Noise (AWGN) for each sub-channel, h_{nk} denotes the channel gain between UE u_n and fog node f_k.

The data transmitted from the UE to the associated fog node may be lost even if the noise N_0 is trivial. The transmission bit error rate can be expressed as,

$$B_{nk} = 0.2 \times \exp(\frac{\frac{-1.6P_n^t}{N_0}}{\log(g) - 1}) \tag{3}$$

2) DELAY MODEL

The total delay for the proposed architecture can be considered as three parts. The transmission delay generated in the network because of traversing the computing requests among the fog nodes. The queuing delay, that is, the time when the UEs wait for the associated fog node to process tasks of other UEs. The computing delay generated in the network for processing tasks by the fog nodes. In particular, we assume that the size of the calculation is usually small so that the receiving delay can be ignored for ease of analysis. Thus, the overall expected delay for the UE u_n is,

$$D_{nk} = d_{nk}^w + d_{nk}^c + d_{nk}^t \tag{4}$$

where d_{nk}^w, d_{nk}^c and d_{nk}^t denote, the queuing delay, transmission delay and computation delay, respectively.

(1) Queuing Delay

We assume the workload of each fog node follows Poisson arrival process, the main arrival rate of the fog node f_k can be denoted as λ_k (in bit/s). The task processing in fog node f_k can be regarded as a M/M/1 queuing system. Thus, the queuing delay can be calculated by Little's law, as given by,

$$d_{nk}^w = \frac{\lambda_k C_k}{V_k(V_k - \lambda_k C_k)} \tag{5}$$

(2) Transmission Delay

The transmission delay is given by,

$$d_{nk}^t = \frac{S_n}{r_{nk}} \tag{6}$$

(3) Computation Delay
The computation delay is given by,

$$d^c_{nk} = \frac{S_n C_k}{a^c_{nk} V_k} \tag{7}$$

where a^c_{nk} denotes the normalized allocation coefficient of computing resources to UE u_n.

3) COST MODEL

In this sub-section, we consider the energy consumption of each UE and fog node.

As is mentioned above, the UE's receive delay has been ignored, each UE may be in one of the following two possible states: transmitting and idle. The transmitting state refers to offload tasks to the associated fog node, similarly, the idle state refers to remaining time. Thus, the overall energy consumption of UE u_n is given by,

$$E_{nk} = P^t_n X \frac{S_n}{r_{nk}} + P^i_n X \left(\frac{\lambda_k C_k}{V_k(V_k - \lambda_k C_k)} + \frac{S_n C_k}{a^c_{nk} V_k}\right) \tag{8}$$

where P^i_n denotes the idle power of UE u_n, X denotes the environmental factor, for easy figures, we assume that the environmental factors have the same impact on UEs and fog nodes.

Each fog node may be in one of the following four possible states: receiving, computing, idle and sleeping. The receiving state refers to the interaction with the associated UEs, the computing state refers to the computation performed in the fog node itself and the idle state refers to the remaining time. Moreover, when the number of UEs in the coverage of each fog node decreases to a certain threshold, the fog node will stop working and transfer the service to the neighboring fog nodes. The overall energy consumption of fog node f_k is given by,

$$E_{kn} = \left(1 - \frac{\lambda_k C_k}{V_k}\right)\left(P^c_k X S_n C_k + P^i_k X \frac{S_n}{r_{nk}}\right) + \frac{\lambda_k C_k}{V_k}\left(P^c_k X S_n C_k\right) \tag{9}$$

where P^i_k (in W)and P^c_k (in J/cycle) represent the idle power and computation energy consumption of fog node f_k, respectively.

In later section we will formulate a joint user association and resource allocation optimization problem.

C. PROBLEM FORMULATION

In this work, the goal is to maximize the quality of experience for each UE while considering the overall system performance in the considering fog computing scenarios. From the UEs' perspective, who have delay sensitive tasks to process, prefer lower delay, better communication quality and lower energy consumption. Similarly, the fog nodes prefer lower energy consumption. Compared to fog nodes, UEs have fewer resources and are more susceptible to external factors than nodes such as environmental factors, in addition, each UE has their own preferences. Thus, we need to determine the utility ratio of the UE to the associated fog node, the user-centric utility function can be formulated as:

$$J_{nk} = X^o\left(\omega_1 \frac{D_{nk}}{\tilde{D}_{nk}} + \omega_2 \frac{B_{nk}}{\tilde{B}_{nk}} + \omega_3 \frac{E_{nk}}{\tilde{E}_{nk}}\right) + \frac{E_{kn}}{\tilde{E}_{kn}} \tag{10}$$

where X^o denotes the user-centric coefficient, ω_1, ω_2 and ω_3 represent the delay weight coefficient, bit error rate weight coefficient and energy consumption weight coefficient of each UE, respectively. In addition, we standardize the relevant parameters of the defined user-centric utility function above, where $\tilde{D}_{nk}$ represents the maximum delay tolerance of u_n, $\tilde{B}_{nk}$, $\tilde{E}_{nk}$ and $\tilde{E}_{kn}$ are, respectively, maximum bit error rate, maximum energy consumption of u_n, maximum energy consumption of f_k. It's obvious that the value of $\tilde{B}_{nk}$ can be obtained by minimizing the transmission power P^t_n of u_n, in addition, the value of $\tilde{E}_{nk}$ and $\tilde{E}_{kn}$ can be obtained by numerical simulation.

Remark 1: In order to calculate and analyze the relevant parameters of the proposed user-centric function under the same standard, several standardized coefficients are introduced to avoid the value of the relevant parameters have an excessive impact on the user-centric utility. The weight coefficients ω_1, ω_2 and ω_3 are introduced to quantify UEs' preferences, in addition, the environmental factor X and user-centric coefficient X^o are introduced to quantify internalities and externalities, respectively. To our knowledge, this is the first work to propose such a user-centric utility function which considers the above issues comprehensively.

For the sake of improving user experience and overall system performance in the considering fog networks, a joint optimization problem is proposed for minimizing the formulated user-centric utility. Appropriate user association and resource allocation strategies can be regarded as efficient methods to achieve the above goals, hence, the user-centric utility minimization problem can be formulated as follows:

$$\begin{aligned}
\mathcal{P}1: \quad & \min_{\mu_{nk}, a^c_{nk}, P^t_n} \sum_{n \in N} \sum_{k \in K} \mu_{nk}\Big[X^o\Big(\omega_1 \frac{D_{nk}}{\tilde{D}_{nk}} + \omega_2 \frac{B_{nk}}{\tilde{B}_{nk}} + \omega_3 \frac{E_{nk}}{\tilde{E}_{nk}}\Big) + \frac{E_{kn}}{\tilde{E}_{kn}}\Big] \\
s.t. \quad & P^t_{n(min)} \le P^t_n \le P^t_{n(max)} \quad \forall n \in N && (11) \\
& \sum_{k \in K} \mu_{nk} = 1 \quad \forall n \in N && (12) \\
& D_{nk} \le \tilde{D}_{nk} \quad \forall n \in N && (13) \\
& \lambda_k C_k \le V_k \quad \forall k \in K && (14) \\
& \mu_{nk} \in \{0, 1\} \quad \forall n \in N, k \in K && (15) \\
& \omega_1 + \omega_2 + \omega_3 = 1 && (16) \\
& 0 < a^c_{nk} \le 1 \quad \forall n \in N && (17) \\
& \sum_{n \in N} \mu_{nk} a^c_{nk} \le 1 \quad \forall k \in K && (18)
\end{aligned}$$

In the aforementioned optimization problem, the constraint (11) bounds the minimum and maximum transmission power of each UE. In (12), the constraint indicates that each UE can be associated with a unique fog node. The constraint (13) guarantees that the tasks completion time on UE u_n is bounded by the maximum delay tolerable $\tilde{D}_{nk}$. The constraint (14) indicates that the tasks of the associated UEs cannot exceed the maximum computing capacity of the fog node. (15) and (16) are the constraints on the user association decision and corresponding weight of the user-centric parameters. (17) and (18) are the constraints on computing resource allocation for each fog node.

It can be observed that $\mathcal{P}1$ is a mixed-integer non-linear programming problem, which is non-convex and NP-hard to solve in general. Exhaustive search method can be used to solve it, however, the search space of $\mathcal{P}1$ will increase exponentially with the number of UEs in the fog networks, which generally imposes a huge computational burden on the system.

$\mathcal{P}1$ jointly optimize user association, computing resource allocation and transmission power selection in the considering fog networks, the decision variables, ie., continuous variable P_n^t, a_{nk}^c and integer variable μ_{nk}, come from different sub-systems and are tightly coupled with each other, which makes the relationship between the workload offloading and the power consumption-delay-bit of error tradeoff not clear. Additionally, the sub-channel condition of each UE is varied by associating with different fog nodes, therefore, it's difficult to transform the non-convex optimization problem into convex optimization problem. To address these issues, we propose an approximate approach to decompose it into two sub-problems and solve them individually.

1) USER ASSOCIATION DECISION PROBLEM

In this sub-section, the user association sub-problem with certain transmission power and computing resource allocation coefficient is formulated to obtain the stable UE-fog node pairs based on $\mathcal{P}1$, the user association optimization problem can be expressed as follows:

$$\begin{aligned}
\mathcal{P}2: \quad & \min_{\mu_{nk}} \sum_{n\in N}\sum_{k\in K} \mu_{nk}[X^o(\omega_1\frac{D_{nk}}{\tilde{D}_{nk}}+\omega_2\frac{B_{nk}}{\tilde{B}_{nk}}+\omega_3\frac{E_{nk}}{\tilde{E}_{nk}}) \\
& \quad +\frac{E_{kn}}{\tilde{E}_{kn}}] \\
\text{s.t.} \quad & \mu_{nk}\in\{0,1\} \quad \forall n\in N,\ k\in K && (19)\\
& \sum_{k\in K}\mu_{nk}=1 \quad \forall n\in N && (20)\\
& \mu_{nk}D_{nk}\le\tilde{D}_{nk} \quad \forall n\in N && (21)\\
& \sum_{n\in N}\mu_{nk}a_{nk}^c\le 1 \quad \forall k\in K && (22)
\end{aligned}$$

2) RESOURCE ALLOCATION DECISION PROBLEM

In this sub-section, according to the obtained user association decision, the transmission power selection and computing resource allocation coefficient are jointly optimized for minimizing the average user-centric utility.

$$\begin{aligned}
\mathcal{P}3: \quad & \min_{a_{nk}^c, P_n^t} \sum_{n\in N}\sum_{k\in K} \mu_{nk}[X^o(\omega_1\frac{D_{nk}}{\tilde{D}_{nk}}+\omega_2\frac{B_{nk}}{\tilde{B}_{nk}}+\omega_3\frac{E_{nk}}{\tilde{E}_{nk}})+\frac{E_{kn}}{\tilde{E}_{kn}}] \\
\text{s.t.} \quad & 0<a_{nk}^c\le 1 \quad \forall n\in N && (23)\\
& P_{n(min)}^t\le P_n^t\le P_{n(max)}^t \quad \forall n\in N && (24)\\
& \sum_{n\in N}\mu_{nk}a_{nk}^c\le 1 \quad \forall k\in K && (25)\\
& D_{nk}\le\tilde{D}_{nk} \quad \forall n\in N && (26)
\end{aligned}$$

III. USER-CENTRIC USER ASSOCIATION AND RESOURCE ALLOCATION ALGORITHM

In this section, the user-centric user association and resource allocation algorithm is proposed to obtain the optimal user association and resource allocation decisions.

A. USER ASSOCIATION DECISION

In the considering fog computing scenarios, the user's association decision depends not only on the UE's own offloading requirements, but also on the needs of other UEs and fog nodes. Game theory is considered to be one of the effective methods to solve such decision-making problems with internal competition in general, because it uses strict mathematical models to solve conflicts of interest among decision-making bodies in the real world, so as to achieve the best combination of strategies. However, the matching results produced by game theory are vulnerable to external factors such as environmental factors, which exist in the considering fog computing scenarios and cannot be ignored.

In this sub-section, we try to solve the user association problem for given transmission power and computing resource allocation partition. In other words, P_n^t and a_{nk}^c are known to us.

1) EQUIVALENT TRANSFORMATION

It's easy to determine that the problem $\mathcal{P}2$ is not convex due to the decision variable μ_{nk} is a binary variable. In order to reduce the computational complexity, we first define a $K\times 1$ vector $Z_n=[\mu_{n1},\ldots,\mu_{nk},\ldots,\mu_{nK}]^T$ and then transform the problem $\mathcal{P}2$ into a equivalent quadratically constrained quadratic program(QCQP) form as follows:

$$\begin{aligned}
\mathcal{P}4: \quad & \min \sum_{n\in N} Y_n^T Z_n \\
\text{s.t.} \quad & {Z_n}^T diag(e_k) Z_n - {e_k}^T Z_n = 0 \quad \forall n\in N,\ k\in K && (27)\\
& (Y_{nk}^u)^T Z_n = 1 \quad \forall n\in N && (28)\\
& \left(Y_{nk}^d\right)^T Z_n \le \tilde{D}_{nk} \quad \forall n\in N && (29)\\
& \sum_{n\in N}(Y_{nk}^c)^T Z_n\le 1 \quad \forall k\in K && (30)
\end{aligned}$$

where e_K is a standard unit vector with size of $1\times K$, and, respectively

$$\begin{aligned}
Y_n = [&X^o(\omega_1\frac{D_{n1}}{\tilde{D}_{n1}}+\omega_2\frac{B_{n1}}{\tilde{B}_{n1}}+\omega_3\frac{E_{n1}}{\tilde{E}_{n1}}) \\
&+\frac{E_{1n}}{\tilde{E}_{1n}},\ldots,X^o(\omega_1\frac{D_{nk}}{\tilde{D}_{nk}}+\omega_2\frac{B_{nk}}{\tilde{B}_{nk}}+\omega_3\frac{E_{nk}}{\tilde{E}_{nk}}) \\
&+\frac{E_{kn}}{\tilde{E}_{kn}},\ldots,X^o(\omega_1\frac{D_{nK}}{\tilde{D}_{nK}}+\omega_2\frac{B_{nK}}{\tilde{B}_{nK}}+\omega_3\frac{E_{nK}}{\tilde{E}_{nK}})+\frac{E_{Kn}}{\tilde{E}_{Kn}}]^T
\end{aligned}$$

$$Y^u_{nk} = [1_{1\times K}]^T$$
$$Y^d_{nk} = [0_{1\times k}, D_{nk}, 0_{1\times (K-k-1)}]^T$$
$$Y^c_{nk} = [0_{1\times k}, a^c_{nk}, 0_{1\times (K-k-1)}]^T$$

However, the problem $\mathcal{P}4$ is still non-convex and in general NP-hard [38]. We are committed to developing low-complexity algorithms to obtain near-optimal solutions instead of looking for the optimal solutions. In addition, it is difficult to design an efficient algorithm directly applied to the original problem.

2) SEMIDEFINITE RELAXATION

The semidefinite programming (SDP) relaxation technique has been used widely to solve QCQP by polynomially constructing optimal or suboptimal solutions of the rank-one SDP problem [39]. In problem $\mathcal{P}3$, we can note that all the matrices are real symmetric and all the vectors are real, which satisfy the relaxation conditions for SDP.

We introduce a matrix variable $m_n = [{Z_n}^T, 1]^T$ and the equivalent matrix form of the problem $\mathcal{P}3$ can be formulated in terms of M_n:

$$\begin{aligned}
\mathcal{P}5:\ &\min_{M_n} \sum_{n\in N} Tr\left(O_n M_n\right) \\
s.t.\ & Tr\left(O^e_{nk} M_n\right) = 0 \quad \forall n \in N,\ k\in K && (31)\\
& Tr\left(O^u_{n} M_n\right) = 1 \quad \forall n \in N && (32)\\
& Tr\left(O^d_{nk} M_n\right) \le \tilde{D}_{nk} \quad \forall n \in N && (33)\\
& \sum_{n\in N} Tr\left(O^c_{nk} M_n\right) \le 1 \quad \forall k \in K && (34)\\
& rank(M_n) = 1 \quad \forall n \in N && (35)\\
& M_n \ge 0 \quad \forall n \in N && (36)
\end{aligned}$$

where

$$O_n = \begin{bmatrix} 0 & \frac{1}{2}Y_n \\ \frac{1}{2}{Y_n}^T & 0 \end{bmatrix}$$
$$O^e_{nk} = \begin{bmatrix} diag\left(e_k\right) & -\frac{1}{2}e_k \\ -\frac{1}{2}{e_k}^T & 0 \end{bmatrix}$$
$$O^u_{n} = \begin{bmatrix} 0 & \frac{1}{2}Y^u_{nk} \\ \frac{1}{2}(Y^u_{nk})^T & 0 \end{bmatrix}$$
$$O^r_{nk} = \begin{bmatrix} 0 & \frac{1}{2}Y^d_{nk} \\ \frac{1}{2}(Y^d_{nk})^T & 0 \end{bmatrix}$$
$$O^\lambda_{nk} = \begin{bmatrix} 0 & \frac{1}{2}Y^c_{nk} \\ \frac{1}{2}(Y^c_{nk})^T & 0 \end{bmatrix}$$
$$M_n = m_n \cdot {m_n}^T$$

The problem $\mathcal{P}5$ can be relaxed into a SDP problem by removing the nonconvex rank constraint (35):

$$\begin{aligned}
\mathcal{P}6:\ &\min_{M_n} \sum_{n\in N} Tr\left(O_n M_n\right) \\
& s.t.\ (31), (32), (33), (34), (36)
\end{aligned}$$

$\mathcal{P}6$ is a standard convex optimization problem, ${M_n}^*$ denotes the optimal solution of the SDP relaxation of $\mathcal{P}5$, which can be obtained polynomially via a convex optimization toolbox, such as SeDuMi, SDPT3, YALMIP.

By solving $\mathcal{P}6$, a lower bound of the original problem can be achieved in general. Therefore, a fundamental issue is how to convert a globally optimal solution ${M_n}^*$ to $\mathcal{P}6$ into a feasible solution ${Z_n}^*$ to $\mathcal{P}4$. If ${M_n}^*$ is of rank one, a feasible solution of the original problem can be recovered from ${M_n}^*$ by solving ${M_n}^* = {m_n}^* \cdot {m_n}^{T*}$, where ${m_n}^* = [{Z_n}^{T*}, 1]^T$. However, if the rank of ${M_n}^*$ is larger than one, it is a critical issue to extract the optimal solution to the original problem, in fact, it is even nontrivial to transform ${M_n}^*$ into a feasible solution. Noticing that all the diagonal elements in ${M_n}^*$ are 0 or 1, however, only the upper left $K \times K$ sub-matrix $\hat{M}^*_n$ of matrix ${M_n}^*$ is related to the user association decision.

In the following sub-section, we will propose an approximation algorithm to induce a rank-one near-optimal solution of the original QCQP problem $\mathcal{P}5$.

3) EXTRACTING USER ASSOCIATION DECISION

In this sub-section, we propose an approximation algorithm to extract the feasible solution to $\mathcal{P}4$ for u_n from the optimal solution ${M_n}^*$ to $\mathcal{P}6$.

The approximation problem can be equivalently into a standard form of the two-dimensional assignment problem, where each UE can only be associated with a unique fog node. The main idea of the proposed user association decision approximation algorithm are shown in Algorithm 1.

For the constructing weighted bipartite graph $G = (\mathcal{V}, \mathcal{E})$, where $V = V_1 \cup V_2, V_1 \cap V_2 = \emptyset$. $V_1 = \{u_n : n = 1, \ldots, N\}$ and $V_2 = \{f_k : k = 1, \ldots, K\}$ denote the set of UEs and fog nodes distributed in the fog network. $\mathcal{E} = \{e_{nk} : n = 1, \ldots, N.k = 1, \ldots, K\}$ denote the set of the edge of the bipartite graph G with corresponding weight, which will correspond to the UE-fog node pair (n, k) such that $\mu_{nk} > 0$. $A_k = \sum_{n\in N} Ty_{nk}$ denotes the number of UEs associated with the fog node f_k. We apply the Kuhn-Munkres algorithm to find a perfect matching $\mathbb{M}$, which can be denoted as $\{u_n, f_k, e_{nk}\}$.

We can obtain the integer user association decision from the perfect matching $\mathbb{M}$, where each UE could associated with the unique fog node. Therefore, we can find a feasible integer solution in polynomial time.

B. RESOURCE ALLOCATION DECISION

In the previous subsection, we obtain the optimal user association solution to minimize the average user-centric utility for given transmission power and computing resource allocation coefficient, that is, it has been determined that each UE will

Algorithm 1 User Association Decision Approximation Algorithm

Input: V_1, V_2, $M_n{}^*$.
Initialize $\mathbb{M}$, $\mathcal{E}$, Ty_n, A_k.
for $k = 1 : K$ **do**
  for $n = 1 : N$ **do**
    if $Rank(M_n{}^*) = 1$ **then**
      Obtain the optimal user association decision for u_n by solving $M_n{}^* = m_n{}^* \cdot m_n{}^{T*}$.
    end
    else
      Extract the upper left $K \times K$ sub-matrix $\hat{M}_n^*$ from $M_n{}^*$.
      Calculate $Ty_n \triangleq diag(\hat{M}_n^*) = \{Ty_{n1}, ...Ty_{nk}, \ldots, Ty_{nK}\}$, where $Ty_{nk} \in \{0, 1\}$.
    end
  end
  Calculate $A_k = \sum_{n\in N} Ty_{nk}$.
end
Step 1: Construct the weighted binary graph G.
for $k = 1 : K$ **do**
  if $A_k \leq 1$ **then**
    There is only one UE $u_n \in V_1$ associated with the fog node $f_k \in V_2$.
    for $n = 1 : N$ **do**
      if $Rank(M_n{}^*) \neq 1$ **then**
        if $Ty_{nk} = 1$ **then**
          Add (u_n, f_k) into $\mathcal{G}$, and set the weight of this edge as $e_{nk} = Ty_{nk}$.
        end
        else
          Add (u_n, f_k) into $\mathcal{G}$, and set the weight of this edge as $e_{nk} = 0$.
        end
      end
    end
  end
  else if $A_k > 1$ **then**
    for $n = 1 : N$ **do**
      if $Rank(M_n{}^*) \neq 1$ **then**
        if $Ty_{nk} = 1$ **then**
          Add (u_n, f_k) into $\mathcal{G}$, and set the weight of this edge as $e_{nk} = \frac{Ty_{nk}}{A_k}$.
        end
        else
          Add (u_n, f_k) into $\mathcal{G}$, and set the weight of this edge as $e_{nk} = 0$.
        end
      end
    end
  end
end

Algorithm 1 User Association Decision Approximation Algorithm (Continued)

Step 2: Calculate the adjacent matrices of the constructed weighted binary graph $\mathcal{G}$.
Step 3: Find the perfect matching $\mathbb{M}$ by executing Kuhn-Munkres algorithm that exactly matches all UEs in $\mathcal{G}$.
Output: The perfect matching $\mathbb{M}$

offload the task to a certain fog node. In this subsection, we will further investigate the resource allocation optimization problem for given UE-fog nodes pairs, which can be formulated as $\mathcal{P}3$.

Noticing that $\mathcal{P}3$ jointly optimize the transmission power selection and computing resource allocation for the considering fog network. To reduce the computational complexity of solving this problem, we propose to decompose $\mathcal{P}6$ into two sub-problems by analyzing the intrinsic relationship between the objective function and the decision variables, and we have the following theorem.

Theorem 1: $\mathcal{P}3$ can be decoupled into two sub-problems and solve them individually.

Proof: Please see Appendix A.

According to Theorem 1, we can first minimize the bit error rate B_{nk} and the energy consumption E_{kn} for each optimal matching pair μ_{nk}^* to find the optimal transmission power, which can be denoted as $P_n^t{}^*$. Thus, the optimization problem can be mathematical formulated as,

$$\begin{aligned}\mathcal{P}7: \ & \min_{P_n^t{}^*} \sum_{n\in N}\sum_{k\in K} \mu_{nk}(X^o \frac{B_{nk}}{\tilde{B}_{nk}} + \frac{E_{kn}}{\tilde{E}_{kn}}) \\ & s.t. \ \ P^t_{n(min)} \leq P^t_n \leq P^t_{n(max)} \quad \forall n \in N \qquad (37)\end{aligned}$$

After obtaining the optimal transmission power, we can solve $\mathcal{P}8$ for given μ_{nk}^* and $P_n^t{}^*$ to find the optimal computing resource allocation coefficient $a_{nk}^c{}^*$. Therefore, the optimization problem can be expressed as,

$$\begin{aligned}\mathcal{P}8: \ & \min_{a_{nk}^c{}^*} \sum_{n\in N}\sum_{k\in K} \mu_{nk}[X^o(\omega_1 \frac{D_{nk}}{\tilde{D}_{nk}} + \omega_2 \frac{B_{nk}}{\tilde{B}_{nk}} + \omega_3 \frac{E_{nk}}{\tilde{E}_{nk}}) \\ & \quad + \frac{E_{kn}}{\tilde{E}_{kn}}] \\ & s.t. \ \ 0 < a_{nk}^c \leq 1 \quad \forall n \in N \qquad (38) \\ & \quad \sum_{n\in N} \mu_{nk} a_{nk}^c \leq 1 \quad \forall k \in K \qquad (39) \\ & \quad D_{nk} \leq \tilde{D}_{nk} \quad \forall n \in N \qquad (40)\end{aligned}$$

We try to find the optimal solution of $\mathcal{P}7$ and $\mathcal{P}8$.

Lemma 1: $\mathcal{P}7$ and $\mathcal{P}8$ are both convex optimization problems.

Proof: Please see Appendix B.

According Lemma 1, $\mathcal{P}7$ is a convex optimization problem, so the optimal solution can be efficiently obtained by standard convex optimization solvers such as CVX.

Similarly, $\mathcal{P}8$ has a unique optimal solution according Lemma 1, which can be solved by the Lagrangian duality method and Karush-Kuhn-Tucker (KKT) conditions. We denote the decision variables as $\Gamma = \{a_{nk}^c\}$, and define the dual variable $\Theta = \{\alpha, \beta\}$, where α, β represent Lagrange multipliers related to the constrains (38) and (39), respectively. Moreover, the other constrains will be satisfied in the KKT conditions. Thus, the Lagrangian function of the original problem can be expressed as:

$$\begin{aligned} L(\Gamma,\Theta) = &\sum_{n\in N}\sum_{k\in K}\mu_{nk}[X^o(\omega_1\frac{\frac{\lambda_k C_k}{V_k(V_k-\lambda_k C_k)}+\frac{S_n C_k}{a_{nk}^c V_k}+\frac{S_n}{r_{nk}}}{\tilde{D}_{nk}} \\ &+\omega_2\frac{0.2\times\exp(\frac{\frac{-1.6P_n^t}{N_0}}{\log(g)-1})}{\tilde{B}_{nk}} \\ &+\omega_3\frac{\frac{P_n^t S_n}{r_{nk}}+P_n^i X(\frac{\lambda_k C_k}{V_k(V_k-\lambda_k C_k)}+\frac{S_n C_k}{a_{nk}^c V_k})}{\tilde{E}_{nk}}) \\ &+\frac{(1-\frac{\lambda_k C_k}{V_k})(P_k^c S_n C_k+P_k^i\frac{S_n}{r_{nk}})+\frac{\lambda_k C_k}{V_k}(P_k^c S_n C_k)}{\tilde{E}_{kn}}] \\ &+\sum_{k\in K}\alpha(\sum_{n\in N}\mu_{nk}a_{nk}^c-1)+\sum_{n\in N}\beta(\frac{\lambda_k C_k}{V_k(V_k-\lambda_k C_k)} \\ &+\frac{S_n C_k}{a_{nk}^c V_k}+\frac{S_n}{r_{nk}}-\tilde{D}_{nk}) \end{aligned} \tag{41}$$

The corresponding dual function can be expressed as followsčž

$$\mathcal{D}(\Theta) = \min_{\Gamma}\mathcal{L}(\Gamma,\Theta) \tag{42}$$

The dual problem is

$$\begin{aligned} &\max_{\Theta}\mathcal{L}(\Gamma,\Theta) \\ &s.t.\ \ \Theta\geq 0 \end{aligned} \tag{43}$$

Since $\mathcal{P}6$ has strong duality, the optimal solution of $\mathcal{P}6$ and its dual problem (43) can be obtained by KKT conditions. The optimal solution of $\mathcal{P}6$ is set to be $a_{nk}^{c\ *}$, the optimal solution of (43) is set to be α^*, β^*. The KKT conditions applied to $\mathcal{L}(\Gamma,\Theta)$ can be expressed as follows:

$$\begin{aligned} \frac{\partial\mathcal{L}(\Gamma,\Theta)}{\partial a_{nk}^{c\ *}} &= \alpha^*\mu_{nk}-\frac{C_k\,S_n\,\beta^*}{a_{nk}^{c\ *2}\,V_k}-\frac{C_k\,S_n\,X_0\,\omega_1\,\mu_{nk}}{a_{nk}^{c\ *2}\,\tilde{D}_{nk}\,V_k} \\ &\quad\times\begin{cases}=0,\ 0<a_{nk}^{c\ *}<1\\ \leq 0,\ a_{nk}^{c\ *}=1\end{cases} \end{aligned} \tag{44}$$

$$\sum_{n\in N}\mu_{nk}a_{nk}^{c\ *}=1 \tag{45}$$

$$\beta^*(\frac{\lambda_k C_k}{V_k(V_k-\lambda_k C_k)}+\frac{S_n C_k}{a_{nk}^{c\ *}V_k}+\frac{S_n}{r_{nk}}-\tilde{D}_{nk})=0 \tag{46}$$

$$\alpha^*,\beta^*\geq 0 \tag{47}$$

By sorting out the KKT conditions (44), it can be concluded that β^* can take any value that satisfies the condition (47) and $\alpha^*\neq 0$ to satisfy $\sum_{n\in N}\mu_{nk}a_{nk}^{c\ *}=1$. Then we can discuss the solutions based on the value of the dual variables α^* and β^*, therefore, we have following two cases on optimum α^* and β^*.

Case 1: $\alpha^*>0$ and $\beta^*=0$.

$$\frac{\partial L(\Gamma,\Theta)}{\partial a_{nk}^{c\ *}}=\alpha^*\mu_{nk}-\frac{C_k\,S_n\,X_0\,\omega_1\,\mu_{nk}}{a_{nk}^{c\ *2}\,\tilde{D}_{nk}\,V_k}=0$$

We can obtain $a_{nk}^{c\ *}=\sqrt{\frac{C_k\,S_n\,X_0\,\omega_1}{\alpha^*\,\tilde{D}_{nk}\,V_k}}$, where the Lagrange multiplier α^* can be obtained by solving the following optimization problem,

$$\begin{aligned} \mathcal{P}9:\ &\min_{\alpha^*}\sum_{n\in N}\mu_{nk}a_{nk}^{c\ *}-1 \\ &s.t.\ \ \alpha^*>0 \qquad (48)\\ &\sum_{n\in N}\mu_{nk}a_{nk}^{c\ *}-1\geq 0 \qquad (49) \end{aligned}$$

Lemma 2: $\mathcal{P}9$ is a convex optimization problem.

Proof: Please see Appendix C.

The optimal solution to $\mathcal{P}9$ can be determined by the popular interior point method.

Case 2: $\alpha^*>0$ and $\beta^*>0$.

$$\begin{cases}\frac{\partial L(\Gamma,\Theta)}{\partial a_{nk}^{c\ *}}=0\\ \frac{\lambda_k C_k}{V_k(V_k-\lambda_k C_k)}+\frac{S_n C_k}{a_{nk}^{c\ *}V_k}+\frac{S_n}{r_{nk}}-\tilde{D}_{nk}=0\end{cases}$$

We can obtain $a_{nk}^{c\ *}=\frac{S_n C}{(\tilde{D}_{nk}-\frac{S_n}{r_{nk}}-\frac{\lambda_k C}{V_k(V_k-\lambda_k C)})V_k}$.

Theorem 2: the optimal solutions obtained by solving $\mathcal{P}7$ and $\mathcal{P}8$ can make up the feasible solution of $\mathcal{P}3$.

Proof: Please see Appendix D.

The presented joint optimization algorithm of transmission power selection and computing resource allocation is summarized in Algorithm 2. At each iteration, we first decouple $\mathcal{P}3$ into two sub-problems and then solve them individually. For the transmission power selection sub-problem, the Lagrangian dual decomposition method and interior point method are adopted to solve it. For the computing resource allocation sub-problem, the optimal solution can be obtained by convex optimization algorithms.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, the performance of proposed user association and resource allocation algorithm is evaluated by the presented simulation results. All simulations are conducted with Matlab R2017a on a X64-based laptop. The laptop is equipped with a 2-core Intel(R) Core(TM) i5-4200H CPU of speed 2.80 GHz and a memory of 8 GB.

For simplicity but without loss of generality, we consider a fog network, where multiple UEs, ranging from 5 to 30, and 4 fog nodes are uniformly distributed within circular area of radius 500m, the locations of the UEs and fog nodes are assumed to be fixed unless specified otherwise. The CPU processing rate V_k for each fog node is uniformly distributed within $[2, 4]*10^7$ cycle/s to account for the heterogeneous

Algorithm 2 Joint Optimization Iterative Algorithm to Solve $\mathcal{P}3$

Input: User association decision μ_{nk}.

Initialize the maximum error tolerance $\chi > 0$, iteration index $i = 1$, the maximum number of iterations $i_{\max}$, the objective value $J^{(i)}$ of $\mathcal{P}3$ under a feasible solution $(p_n^{t\,(i)}, a_{nk}^{c\,(i)})$, and $J^{(0)} = 0$.

repeat

Step 1: Decouple $\mathcal{P}3$ into two sub-problems, ie., $\mathcal{P}7$ and $\mathcal{P}8$.

Step 2: Obtain the optimal transmission power $p_n^{t\,(i)}$ to $\mathcal{P}7$.

Solve $\mathcal{P}7$ to obtain the optimal transmission power $p_n^{t\,(i)}$ with the given μ_{nk}.

Step 3: Obtain the optimal computing resource allocation coefficient $a_{nk}^{c\,(i)}$ to $\mathcal{P}8$.

Solve $\mathcal{P}8$ to obtain the optimal resource allocation $a_{nk}^{c\,(i)}$ with the given μ_{nk} and the obtained $p_n^{t\,(i)}$.

Obtain the objective value $J^{(i)}$ of $\mathcal{P}3$ with the given μ_{nk} and the obtained $p_n^{t\,(i)}$, $a_{nk}^{c\,(i)}$.

Update $i = i + 1$.

until $\frac{|J^{(i)} - J^{(i-1)}|}{J^{(i-1)}} \le \chi$ or $i \ge i_{\max}$

Output: The optimal transmission power $P_n^{t\,(i)}$ and computing resource allocation coefficient $a_{nk}^{c\,(i)}$.

computing capability of FNs, and the computation energy consumption of fog nodes is uniformly distributed within $[1, 6] * 10^{-7}$ J/cycle. The average arrival rate λ_k for each fog node is uniformly distributed within $[1, 2] * 10^3$ bit/s. The bandwidth of each sub-channel is 10kHz, the noise power spectral density N_0 is -174dBm/Hz, the maximum transmission power $P^t_{n(max)}$ and idle power of each UE is 0.2 W and 0.01 W, respectively, the idle power of each fog node is 0.04 W. The wireless channel is assumed to experience Rayleigh fading with mean 1, we presume that the path loss model is determined as $46.5 + 34 * \log_{10}(x)$, where x (in meters) denotes the distance between fog nodes and UEs. The environmental factor X_0 and X is uniformly distributed within [2,3] and [1,2], respectively. The required number of CPU cycles per bit follows the uniform distribution with $C \in [500, 1000]$ cycle/bit. The size of UEs' tasks and maximum delay tolerance of each UE are uniformly distributed within [2,4] Mb and [6,15] s, respectively.

The performance of the proposed user-centric user association and resource allocation algorithm (UCAA) is compared with the following three baseline schemes. The first one is full random scheme (FR), where each UE will be randomly associated with a unique fog node, in addition, the transmitting power is randomly selected by the UEs, and the computing resources of fog nodes are randomly allocated to the associated UEs. The second one is random association scheme (RA), the user association strategy of which is same

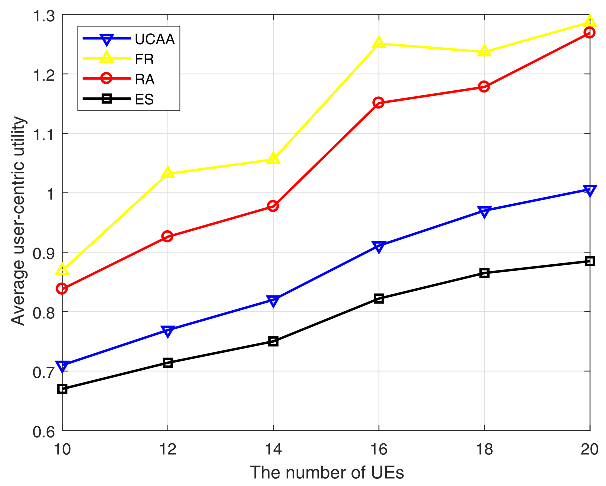

FIGURE 2. The average user-centric utility of UCAA, FR, RA and ES versus the number of UEs with 4 fog nodes.

as that of FR, however, the transmission power and computing resource allocation coefficient are determined by applying the proposed algorithm. Exhaustive search based scheme (ES) considers all the possibilities with the objective of minimizing the average user-centric utility for all the UEs, the solution to the ES algorithm is regard as the global optimal at the sacrifice of high computation complexity.

The value of average user-centric utility in different schemes varying with the number of UEs is shown in Figure 2. It can be observed that the average user-centric utility of all schemes is monotonically increasing as the number of UEs increasing. This is reasonable because when the network is small, that is, when the number of fog nodes is fixed, the number of UEs is small, from the UEs' point of view, the UEs which apply the proposed UCAA algorithm can pick the one that is best for them from the distributed fog nodes to associate with, the UEs which apply the random association strategy are more likely to associate with the appropriate fog nodes, in addition, the UEs are seemly to be possible to be allocated sufficient computing resources in this case, from the fog nodes' point of view, the CPU of which does not need to run at full speed due to the smaller work load, as a result, the corresponding energy consumption will be lower. Moreover, the growth rate of the average user-centric utility of each considering scheme will decrease to varying degrees as the number of UEs increase due to the limited computing resources of fog nodes, note that the average user-centric utility for the ES scheme is basically unchanged as the number of UEs exceed 18, which means the system is almost fully loaded, ie., both serviceable UEs and allocable computing resources have reached the limit. The proposed transmission power selection and computing resource allocation strategy can reasonably utilize the computing resources, this is the reason why the RA scheme performs better than the FR scheme especially when the number of UEs is small. In addition, the numerical results show that the solution to proposed UCAA algorithm approaches the globally optimal

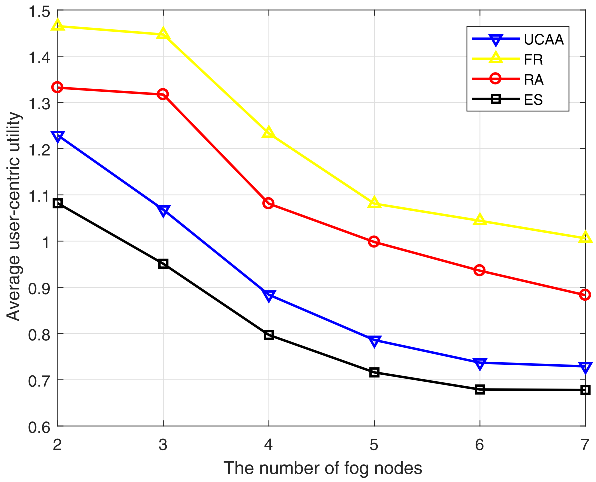

FIGURE 3. The average user-centric utility of UCAA, FR, RA and ES versus the number of fog nodes with 20 UEs.

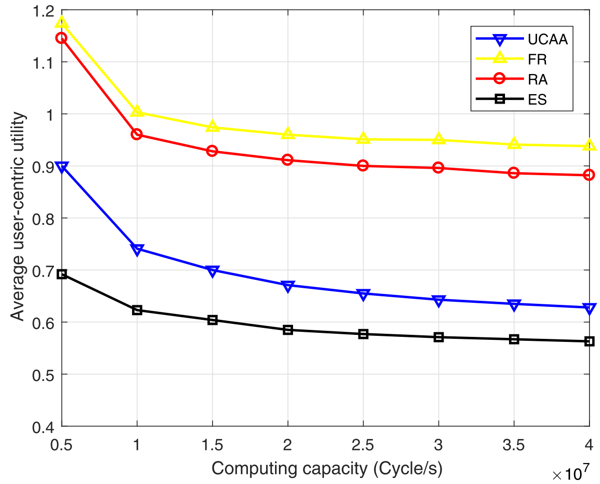

FIGURE 4. The average user-centric utility of UCAA, FR, RA and ES versus different local maximum computing capacity with 4 fog nodes and 10 UEs.

solution when the number of UE is small. Furthermore, the performance of the RA scheme is obviously better than the FR scheme except for the number of UEs is 10 and 20. This is because the computing resources are sufficient when the number of UES is 10. On the contrary, when the number of UEs is 20, the computing resources are insufficient. In the above two cases, using only the proposed resource allocation algorithm without the proposed user association algorithm has limited impact on the value of the average user-centric utility.

The value of average user-centric utility in different schemes varying with the number of fog nodes is shown in Figure 3. It can be seen that the value of average user-centric utility of all schemes decreases with the number of fog nodes increases, there is only some UEs can be served due to the limited computing capability of fog nodes, therefore, more UEs can be served and they can offload tasks to more appropriate fog nodes which can provide higher quality services with more fog nodes distributed nearby. Note that when the number of fog nodes exceeds 4 the decreasing speeds of average user-centric utility of all schemes are getting significant slow, this is because the computing resources of these fog nodes are sufficient to provide UEs with good enough services. However, the average user-centric utility for the UCAA scheme and the ES scheme does not change substantially when the number of fog nodes reaches 6, because the number of UEs is fixed, and they have been well served when the number of fog nodes is sufficient, the increasing number of fog nodes won't make much difference any longer. In addition, it can be seen that the performance of the UCAA scheme and the ES scheme is comparable, especially when the number of fog nodes exceeds 6, which indicates that the proposed UCAA algorithm approaches the globally optimal solution.

The value of average user-centric utility in different schemes varying with the different local maximum computing capability of the fog nodes is shown in Figure 4. It is observed that the average user-centric utility significant decreases as the local maximum computing capability of the fog nodes increases from 0.5 to 1. Note that the performance gap between the RA scheme and the FR scheme is small when the maximum computing capacity is small, indicating that the proposed resource allocation strategy plays a very limited role due to the lack of computing resources, conversely, as the maximum computing capability increases, the resource allocation strategy gradually takes effect, and the corresponding average utility increases accordingly. Besides, the performance gap between the UCAA scheme and the ES scheme is small when the maximum computing capability is big, indicating that the proposed UCCA algorithm has good performance even close to the optimal solution. Furthermore, the proposed UCAA scheme always outperforms than the FR scheme and the RA scheme, indicating that the proposed UCAA algorithm can make better use of limited computing resources.

The value of average user-centric utility in different schemes varying with the maximum tolerable deadline is shown in Figure 5. From this figure, we can find that the average user-centric utility monotonically decreases with the increase of the maximum delay tolerance of the UEs. The reasons can be summarized as follows, in terms of the UEs, larger delay tolerance means lower transmission power and corresponding lower transmission energy consumption, in terms of the fog nodes, which means lower computing resource allocation coefficient and corresponding lower computation energy consumption, so that the average value of user-centric utility will also be decreased. Furthermore, the proposed UCAA algorithm also yields better performance than the RA algorithm with the same resource allocation strategy, which shows the superiority of the optimization of user association.

The value of average user-centric utility in different schemes varying with the task size is shown in Figure 6. We can see that the value of average user-centric utility

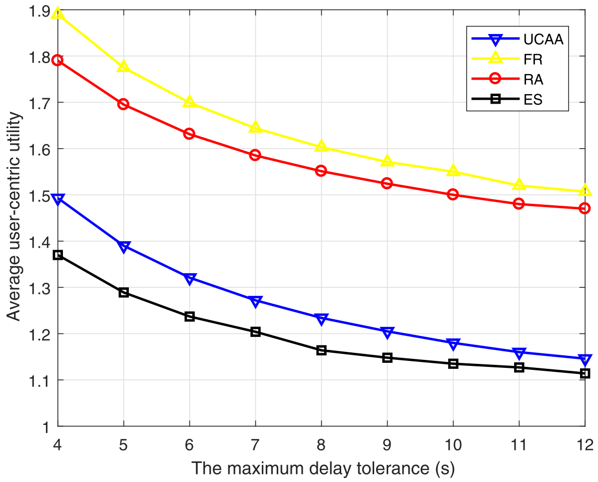

FIGURE 5. **The average user-centric utility of UCAA, FR, RA and ES versus different maximum delay tolerance with 4 fog nodes and 10 UEs.**

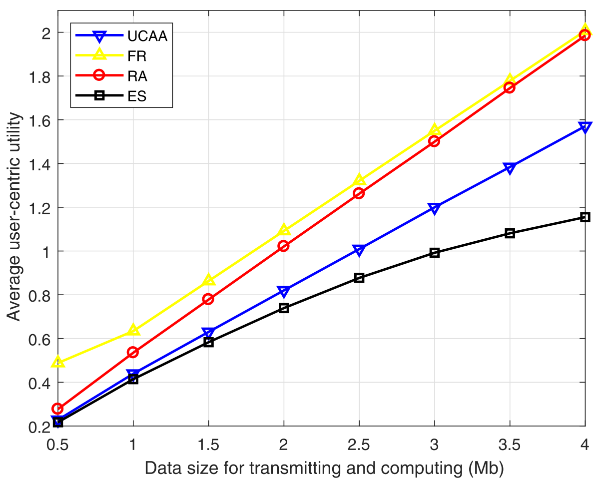

FIGURE 6. **The average user-centric utility of UCAA, FR, RA and ES versus different data size with 4 fog nodes and 10 UEs.**

increases with the task size for all schemes, this is because more tasks need to be transmitted and computed in order to satisfy the delay tolerance constraints of all UEs. In addition, it can be seen that the average user-centric utility of the RA schemes which utilize the proposed resource allocation approaches that of the UCAA schemes when the data size is small, however, the value of the average user-centric utility of the proposed UCAA scheme grows much faster than the RA scheme, indicating the superiority of the proposed user association strategy, especially when the data size is large.

The value of average user-centric utility in different schemes varying with the different sub-channel bandwidth is shown in Figure 7. It can be observed form the figure that the proposed UCAA scheme always performs better than the other baseline schemes considered in this paper except for the ES scheme in different sub-channel bandwidth, because there is a certain relationship between the transmission capacity r_{nk} and the sub-channel bandwidth, ie., the transmission capacity increases as the available sub-channel bandwidth increases, however, the transmission delay and the energy consumption

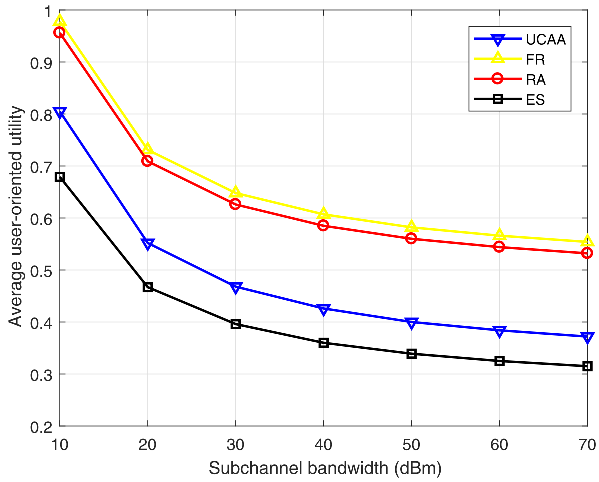

FIGURE 7. **The average user-centric utility of UCAA, FR, RA and ES versus different sub-channel bandwidth with 4 fog nodes and 10 UEs.**

of UEs and fog nodes will decrease, hence, the corresponding average user-centric utility will decrease accordingly.

V. CONCLUSION

In this paper, we present a user-centric user association and resource allocation problem in the considering fog computing scenarios. To solve this mixed-integer non-linear programming problem, we propose a low-complexity two-step interactive optimal algorithm. For the user association decision problem, we transfer it into a QCQP problem, and a semi-definite programming based algorithm is proposed to solve it. In addition, in order to obtain a feasible solution to the original problem from the solution of rank not one, we propose a Kuhn-Munkres algorithm based user association decision approximation algorithm. When considering the resource allocation decision problem, we propose to divide it into two sub-problems and solve them individually, and the relevant rigorous proof is given. Numerical results demonstrate the superior performance of the proposed UCAA algorithm.

APPENDIXES

APPENDIX A

Since our goal is to find the reasonable resource allocation scheme, we obtain the optimal matching pairs between the UEs and fog nodes under the given a^c_{nk} and P^t_n by analyzing the optimal solution of $\mathcal{P}2$, in other words, the UE u_n will offload the task to a certain fog node f_k, we first split the objective of $\mathcal{P}3$ into following four parts:

$$\min_{a^c_{nk},P^t_n} \sum_{n\in N}\sum_{k\in K} \mu_{nk} X^o(\omega_1 \frac{D_{nk}}{\tilde{D}_{nk}}) \tag{50}$$

$$\min_{a^c_{nk},P^t_n} \sum_{n\in N}\sum_{k\in K} \mu_{nk} X^o(\omega_3 \frac{E_{nk}}{\tilde{E}_{nk}}) \tag{51}$$

$$\min_{a^c_{nk},P^t_n} \sum_{n\in N}\sum_{k\in K} \mu_{nk} \frac{E_{kn}}{\tilde{E}_{kn}} \tag{52}$$

$$\min_{a^c_{nk},P^t_n} \sum_{n\in N}\sum_{k\in K} \mu_{nk} X^o(\omega_2 \frac{B_{nk}}{\tilde{B}_{nk}}) \tag{53}$$

It can be observed from (50-53) that the energy cost E_{kn} of fog node and the bit of error rate B_{nk} of UE are only affected by the transmission power P_n^t of the UEs, and the other user-centric utility parameters E_{nk} and D_{nk} are affected by both transmission power P_n^t and computing resource allocation coefficient A_{nk}^c. Thus, $\mathcal{P}3$ can be decoupled into two sub-problems and solve them individually.

APPENDIX B

It's obvious that constraints (23)-(25) are convex. Therefore, we should prove that the objective function and constraints (26) are convex.

For the sub-problems (50)-(51) and constraint (26), we define a new function as follows,

$$f(x,y) = \frac{t_1}{x} + \frac{t_2}{\ln(1+y)} \tag{54}$$

where $x, y, t_1, t_2 > 0$.

The hessian matrix of (54) is,

$$H_{f(x,y)} = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial y \partial x} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{55}$$

The leading principal minors of hessian matrix $H_{f(x,y)}$ are,

$$\Delta_1 = \frac{2t_1}{x^3} \tag{56}$$

$$\Delta_2 = \frac{2t_1 t_2 (ln(1+y)+2)}{x^3 \ln(1+y)^3 (1+y)^2} \tag{57}$$

It's obvious that $\Delta_1, \Delta_2 > 0$. Therefore, the function (54) is convex, so as the sub-problems (50)-(51) and constraint (26).

For the sub-problems (52), we define a new function as follows,

$$f(z) = t_3 + \frac{t_4}{\ln(1+z)} \tag{58}$$

where $z, t_3, t_4 > 0$.

The hessian matrix of (58) is

$$H_{f(z)} = \begin{bmatrix} \frac{\partial^2 f}{\partial z^2} \end{bmatrix} \tag{59}$$

The leading principal minor of hessian matrix $H_{f(z)}$ is,

$$\frac{t_4(\log(1+z)+2)}{\log(1+z)^3(1+z)^2} > 0 \tag{60}$$

Similarly, for the sub-problem (53), the hessian matrix can be defined as,

$$H_{B_{nk}(P_n^t)} = \begin{bmatrix} \frac{\partial^2 B_{nk}}{\partial {P_n^t}^2} \end{bmatrix} \tag{61}$$

The leading principal minor of hessian matrix $H_{B_{nk}}$ is,

$$\Delta_1 = \frac{64 e^{\frac{-(8P_n^t + 5N_0 log(g))}{5N_0 log(g)}}}{125 {N_0}^2 \log(g)^2} > 0 \tag{62}$$

Therefore, the sub-problem (52-53) is convex. According to the properties of convex functions, we can determine that $\mathcal{P}7$ and $\mathcal{P}8$ can be convex optimization problem.

APPENDIX C

It's obvious that constraints (48) is convex. Therefore, we should prove that the objective function and constraint (49) of $\mathcal{P}9$ are convex.

Because the sum of one convex function and another convex function is still a convex function. For the objective function and constraint (49) of $\mathcal{P}9$, we can define a new function as follows,

$$f(q) = t_5 \sqrt{\frac{t_6}{q}} - 1 \tag{63}$$

where $q, t_5, t_6 > 0$.

The hessian matrix of (63) is,

$$H_{f(q)} = \begin{bmatrix} \frac{\partial^2 f}{\partial q^2} \end{bmatrix} \tag{64}$$

The leading principal minor of hessian matrix $H_{f(q)}$ is,

$$\Delta_1 = \frac{3 t_5 {t_6}^2}{4 q^4 (\frac{t_6}{q})^{\frac{3}{2}}} > 0 \tag{65}$$

According to the properties of convex functions, we can determine that $\mathcal{P}9$ is a convex optimization problem.

APPENDIX D

To prove the optimal solutions obtained by solving $\mathcal{P}7$ and $\mathcal{P}8$ can make up the optimal solution to $\mathcal{P}3$. We first define the optimal solution of $\mathcal{P}7$ as ${P_n^t}^{*(7)}$, which satisfy the constraint (24) of $\mathcal{P}3$. Similarly, we define the optimal solution of $\mathcal{P}8$ as ${A_{nk}^c}^{*(8)}$, which satisfy the constraint (23), (25) and (26) of $\mathcal{P}3$.

It's obvious that $\mathcal{P}3$ and $\mathcal{P}8$ have the same objective function. We can prove that they have the same optimal solution by proving the optimal solution of $\mathcal{P}3$ is feasible to $\mathcal{P}8$. To prove the optimal solution to $\mathcal{P}3$ is feasible to $\mathcal{P}8$, we need to verify whether all the optimal solution to $\mathcal{P}8$ satisfies all the constraints of $\mathcal{P}3$. We first define the values of the objective functions of $\mathcal{P}3$ and $\mathcal{P}8$ as $J_k^{*(3)}$ and $J_k^{*(8)}$, respectively. In addition, let ${P_n^t}^{*(3)}, {A_{nk}^c}^{*(3)}$ denote the optimal solution to $\mathcal{P}3$. The detail proof is given as follows.

Since the value of the objective function of $\mathcal{P}7$ is only related to ${P_n}^t$, and ${P_n^t}^{*(7)}$ satisfies constraint (24) of $\mathcal{P}3$. Furthermore, ${P_n^t}^{*(7)}, {A_{nk}^c}^{*(8)}$ satisfies constraint (26) and ${A_{nk}^c}^{*(8)}$ satisfies the other constraints of $\mathcal{P}3$. Therefore, ${P_n^t}^{*(7)}, {A_{nk}^c}^{*(8)}$ is a feasible solution to $\mathcal{P}3$, we have $J_k^{*(8)} \leq J_k^{*(3)}$.

Similarly, the optimal solution to $\mathcal{P}3$, ${P_n^t}^{*(3)}, {A_{nk}^c}^{*(3)}$ satisfies all the constraints of $\mathcal{P}8$. Thus, it's a feasible solution to $\mathcal{P}8$, we have $J_k^{*(3)} \leq J_k^{*(8)}$. Hence, $J_k^{*(3)} = J_k^{*(8)}$, which means that the optimal value of $\mathcal{P}8$ equal to that of $\mathcal{P}3$.

REFERENCES

[1] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, ''Fog computing and its role in the Internet of Things,'' in *Proc. 1st Ed. MCC Workshop Mobile Cloud Comput.*, 2012, pp. 13–16.

[2] J. Yu, C. Zhu, J. Zhang, Q. Huang, and D. Tao, ''Spatial pyramid-enhanced NetVLAD with weighted triplet loss for place recognition,'' *IEEE Trans. Neural Netw. Learn. Syst.*, to be published.

[3] W. Zhang, Z. Zhang, and H.-C. Chao, ''Cooperative fog computing for dealing with big data in the Internet of vehicles: Architecture and hierarchical resource management,'' *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 60–67, Dec. 2017.

[4] M. Chiang and T. Zhang, ''Fog and IoT: An overview of research opportunities,'' *IEEE Internet Things J.*, vol. 3, no. 6, pp. 854–864, Dec. 2016.

[5] J. Yu, M. Tan, H. Zhang, D. Tao, and Y. Rui, ''Hierarchical deep click feature prediction for fine-grained image recognition,'' *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published.

[6] M. Peng, S. Yan, K. Zhang, and C. Wang, ''Fog-computing-based radio access networks: Issues and challenges,'' *IEEE Netw.*, vol. 30, no. 4, pp. 46–53, Jul. 2016.

[7] J. Ni, K. Zhang, X. Lin, and X. S. Shen, ''Securing fog computing for Internet of Things applications: Challenges and solutions,'' *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 601–628, 1st Quart., 2018.

[8] K. Liang, L. Zhao, X. Chu, and H.-H. Chen, ''An integrated architecture for software defined and virtualized radio access networks with fog computing,'' *IEEE Netw.*, vol. 31, no. 1, pp. 80–87, Jan. 2017.

[9] A. C. Baktir, A. Ozgovde, and C. Ersoy, ''How can edge computing benefit from software-defined networking: A survey, use cases, and future directions,'' *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2359–2391, 4th Quart., 2017.

[10] Y. Yin, W. Zhang, Y. Xu, H. Zhang, Z. Mai, and L. Yu, ''QoS prediction for mobile edge service recommendation with auto-encoder,'' *IEEE Access*, vol. 7, pp. 62312–62324, 2019.

[11] Z. Zhang, W. Zhang, and F.-H. Tseng, ''Satellite mobile edge computing: Improving QoS of high-speed satellite-terrestrial networks using edge computing techniques,'' *IEEE Netw.*, vol. 33, no. 1, pp. 70–76, Jan. 2019.

[12] H. Gao, W. Huang, Y. Duan, X. Yang, and Q. Zou, ''Research on cost-driven services composition in an uncertain environment,'' *J. Internet Technol.*, vol. 20, no. 3, pp. 755–769, 2019.

[13] P. Liu, S. R. Chaudhry, T. Huang, X. Wang, and M. Collier, ''Multi-factorial energy aware resource management in edge networks,'' *IEEE Trans. Green Commun. Netw.*, vol. 3, no. 1, pp. 45–56, Mar. 2019.

[14] G. Zhang, F. Shen, Z. Liu, Y. Yang, K. Wang, and M.-T. Zhou, ''FEMTO: Fair and energy-minimized task offloading for fog-enabled IoT networks,'' *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4388–4400, Jun. 2019.

[15] Y. Yang, K. Wang, G. Zhang, X. Chen, X. Luo, and M.-T. Zhou, ''MEETS: Maximal energy efficient task scheduling in homogeneous fog networks,'' *IEEE Internet Things J.*, vol. 5, no. 5, pp. 4076–4087, Oct. 2018.

[16] D. Zeng, L. Gu, S. Guo, Z. Cheng, and S. Yu, ''Joint optimization of task scheduling and image placement in fog computing supported software-defined embedded system,'' *IEEE Trans. Comput.*, vol. 65, no. 12, pp. 3702–3712, Dec. 2016.

[17] M. Ali, N. Riaz, M. I. Ashraf, S. Qaisar, and M. Naeem, ''Joint cloudlet selection and latency minimization in fog networks,'' *IEEE Trans. Ind. Informat.*, vol. 14, no. 9, pp. 4055–4063, Sep. 2018.

[18] G. Zhang, F. Shen, N. Chen, P. Zhu, X. Dai, and Y. Yang, ''DOTS: Delay-optimal task scheduling among voluntary nodes in fog networks,'' *IEEE Internet Things J.*, vol. 6, no. 2, pp. 3533–3544, Apr. 2019.

[19] G. Lee, W. Saad, and M. Bennis, ''An online optimization framework for distributed fog network formation with minimal latency,'' *IEEE Trans. Wireless Commun.*, vol. 18, no. 4, pp. 2244–2258, Apr. 2019.

[20] Y. Mao, J. Zhang, S. H. Song, and K. B. Letaief, ''Power-delay tradeoff in multi-user mobile-edge computing systems,'' in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2016, pp. 1–6.

[21] L. Liu, Z. Chang, X. Guo, S. Mao, and T. Ristaniemi, ''Multiobjective optimization for computation offloading in fog computing,'' *IEEE Internet Things J.*, vol. 5, no. 1, pp. 283–294, Feb. 2018.

[22] J. Du, L. Zhao, J. Feng, and X. Chu, ''Computation offloading and resource allocation in mixed fog/cloud computing systems with min-max fairness guarantee,'' *IEEE Trans. Commun.*, vol. 66, no. 4, pp. 1594–1608, Apr. 2018.

[23] R. Deng, R. Lu, C. Lai, T. H. Luan, and H. Liang, ''Optimal workload allocation in fog-cloud computing towards balanced delay and power consumption,'' *IEEE Internet Things J.*, to be published.

[24] A. Bozorgchenani, D. Tarchi, and G. E. Corazza, ''Centralized and distributed architectures for energy and delay efficient fog network-based edge computing services,'' *IEEE Trans. Green Commun. Netw.*, vol. 3, no. 1, pp. 250–263, Mar. 2019.

[25] W. Zhang, Z. Zhang, S. Zeadally, H.-C. Chao, and V. C. M. Leung, ''MASM: A multiple-algorithm service model for energy-delay optimization in edge artificial intelligence,'' *IEEE Trans. Ind. Informat.*, vol. 15, no. 7, pp. 4216–4224, Jul. 2019.

[26] L. Liu, G. Han, Y. He, and J. Jiang, ''Fault-tolerant event region detection on trajectory pattern extraction for industrial wireless sensor networks,'' *IEEE Trans. Ind. Informat.*, to be published.

[27] S. Tong, Y. Liu, H.-H. Cho, H.-P. Chiang, and Z. Zhang, ''Joint radio resource allocation in fog radio access network for healthcare,'' *Peer-Peer Netw. Appl.*, vol. 12, no. 5, pp. 1277–1288, Sep. 2019.

[28] F. Y. Okay and S. Ozdemir, ''A fog computing based smart grid model,'' in *Proc. Int. Symp. Netw., Comput. Commun. (ISNCC)*, May 2016, pp. 1–6.

[29] H. Gao, W. Huang, and X. Yang, ''Applying probabili stic model checking to path planning in an intelligent transportation system using mobility trajectories and their statistical data,'' *Intell. Automat. Soft Comput.*, vol. 25, no. 3, pp. 547–559, 2019.

[30] J. Wan, B. Chen, S. Wang, M. Xia, D. Li, and C. Liu, ''Fog computing for energy-aware load balancing and scheduling in smart factory,'' *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4548–4556, Oct. 2018.

[31] G. Han, J. Wu, H. Wang, M. Guizani, J. A. Ansere, and W. Zhang, ''A multicharger cooperative energy provision algorithm based on density clustering in the industrial Internet of Things,'' *IEEE Internet Things J.*, vol. 6, no. 5, pp. 9165–9174, Oct. 2019.

[32] L. Gu, D. Zeng, S. Guo, A. Barnawi, and Y. Xiang, ''Cost efficient resource management in fog computing supported medical cyber-physical system,'' *IEEE Trans. Emerg. Topics Comput.*, vol. 5, no. 1, pp. 108–119, Jan. 2017.

[33] G. Han, H. Guan, J. Wu, S. Chan, L. Shu, and W. Zhang, ''An uneven cluster-based mobile charging algorithm for wireless rechargeable sensor networks,'' *IEEE Syst. J.*, vol. 13, no. 4, pp. 3747–3758, Dec. 2019.

[34] S. F. Abedin, M. G. R. Alam, S. M. A. Kazmi, N. H. Tran, D. Niyato, and C. S. Hong, ''Resource allocation for ultra-reliable and enhanced mobile broadband IoT applications in fog network,'' *IEEE Trans. Commun.*, vol. 67, no. 1, pp. 489–502, Jan. 2019.

[35] H. Zhang, Y. Xiao, S. Bu, D. Niyato, F. R. Yu, and Z. Han, ''Computing resource allocation in three-tier IoT fog networks: A joint optimization approach combining Stackelberg game and matching,'' *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1204–1215, Oct. 2017.

[36] J. Xu, L. Chen, and S. Ren, ''Online learning for offloading and autoscaling in energy harvesting mobile edge computing,'' *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 3, pp. 361–373, Sep. 2017.

[37] Y. Yin, L. Chen, Y. Xu, J. Wan, H. Zhang, and Z. Mai, ''QoS prediction for service recommendation with deep feature learning in edge computing environment,'' *Mobile Netw. Appl.*, to be published.

[38] A. Nemirovski, C. Roos, and T. Terlaky, ''On maximization of quadratic form over intersection of ellipsoids with common center,'' *Math. Program.*, vol. 86, no. 3, pp. 463–473, Dec. 1999.

[39] C. Chen, A. Atamtürk, and S. S. Oren, ''A spatial branch-and-cut method for nonconvex QCQP with bounded complex variables,'' *Math. Program.*, vol. 165, no. 2, pp. 549–577, Oct. 2017.

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