IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 27, 2017, accepted June 12, 2017, date of publication July 4, 2017, date of current version August 8, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2721957

Combinational Auction-Based Service Provider Selection in Mobile Edge Computing Networks

HELI ZHANG[1], FENGXIAN GUO[1], HONG JI[1], (Senior Member, IEEE), AND CHUNSHENG ZHU[2], (Member, IEEE)

[1]Key Laboratory of Universal Wireless Communication, Ministry of Education, Beijing University of Posts and Telecommunications, Beijing 100876, China
[2]Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, BC V6T 1Z4, Canada

Corresponding author: Heli Zhang (zhangheli@bupt.edu.cn)

This work was supported in part by the National Natural Science Foundation of China for the Youth under Grant 61501047, in part by the Fundamental Research Funds for the Central Universities of China under Grant 2017RC04, and in part by the National Science and Technology Major Project of the Ministry of Science and Technology of China under Grant 2016ZX03001017.

ABSTRACT Via processing the computation intensive applications (apps) at the network edge, mobile edge computing (MEC) becomes a promising technology to enhance the ability of the user equipments (UEs). Most existing works usually focus on whether to offload or where to offload the apps under the premise that sufficient resources are owned by the network edge. However, the demand heterogeneity of UEs and the limitation of resources are usually failed to be considered. Since the limited resources may constrain the number of accessed UEs, how the MEC service providers (SPs) choose the UEs to serve while ensuring UEs' Quality of Service (QoS) is a key issue. Under this context, in this paper, we study the matching problem between the MEC SPs and the UEs in a multi-MEC and multi-UE scenario. Within this scenario, MEC SPs are equipped with limited wireless and computational resources. Auction theory is utilized to model the matching relationship between MEC SPs and UEs as the commodity trading. With this trading, UEs can obtain MEC service from SPs, when they successfully purchase the combinational resources (including computational and wireless resources) from SPs. To complete the auction process, a multi-round-sealed sequential combinatorial auction mechanism is proposed. The properties of the auction are proved and various simulation results are done to show that the proposed approach has better system performance compared with the existing algorithms.

INDEX TERMS Mobile edge computing, computation offloading, MEC SP and UE matching, combinational auction, demand heterogeneity.

I. INTRODUCTION

A. MOTIVATION

More and more resource-hungry applications like interactive gaming, augmented reality and face recognition are running on user equipments (UEs) [1]–[3]. Due to the physical size constraint, the UEs are usually resource-constrained, having limited computation capacity and battery life. As a result, it is hard to implement these resource-hungry apps at the UEs smoothly. To solve this problem, offloading the computation tasks to the cloud via wireless access is considered as a promising approach.

Mobile Cloud Computing (MCC) can augment the capacities of the UEs by offloading the computation tasks to a centrally controlled cloud infrastructure. However, the public clouds usually locate in remote location and higher transmission latency maybe generated, and thus resulting in the poor quality of experience (QoE). To tackle this problem, the cloudlet based MCC is proposed, in which the UEs offload the computation tasks to the cloud server via an one-hope WiFi wireless access. In this way, the delay can be shorten, however, the ubiquitous service and the QoS of the large number of UEs cannot be guaranteed. To provide UEs with more reliable service and conquer the disadvantage of MCC and Cloudlet, MEC is proposed [4]–[6], which enables computation offloading to the cloud server deployed at the edge of the radio access networks (e.g. 3G/4G base station, named as MEC SPs in this paper).

In recent year, studying the performance of computation offloading in the MEC networks has attracted much attention from researchers. However, in these works, the limitation of resources is largely failed to be considered. Besides, demand heterogeneity of the UEs is also ignored. Demand heterogeneity is defined as the demand differences between UEs. For example, some of the UEs need a short latency for

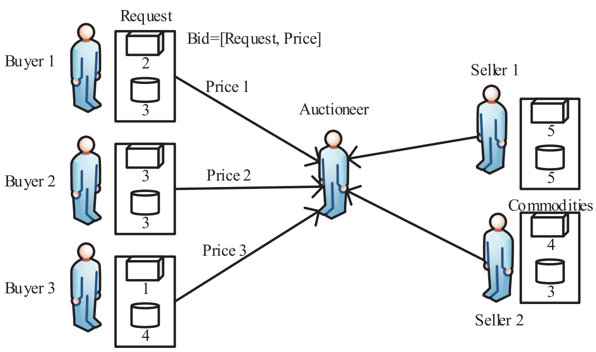

FIGURE 1. **Combinatorial auction.**

higher QoE (e.g. interactive gaming), some other UEs with long latency tolerance may require more energy saving. Under this context, to provide better computational capacity to UEs, we should consider how to match MEC SPs with limited resources to UEs.

B. CONTRIBUTION

In this paper, we consider a network scenario with multiple MEC SPs and multiple UEs, where the MEC SPs are equipped with limited wireless and computational resources. Since MEC SPs are equipped with limited resources and UEs have heterogeneous demands, the MEC network is analogue to the real markets, where various participants transact commodities under certain regulations and try to gain profit. Among the best-known market-based allocation mechanisms, auctions are outstanding on both perceived fairness and allocation efficiency [7]. Therefore, in our work, it is appropriate to apply the auction method to solve the matching relationship between MEC SPs and UEs .

As shown in Fig. 1, four elements are indispensable in one auction, which are seller, buyer, auctioneer and commodity. A seller is the one who possess some commodities. A buyer is the one who want to purchase the commodities to complete their own tasks (we may use bidder as the synonyms for "buyer" in this paper). Auctioneer acts as the executer to perform the auction and decides the winners and the payment to the seller. Commodity is the object traded between a buyer and a seller, each commodity has a valuation, based on which the buyer/seller agrees to buy/sell specified commodities. In general, valuation is a monetary evaluation of assets, which is an private information of the buyer/seller. In addition, a buyer's bid includes two parts: the requirements and the bidding price for the resources.

When applying the auction to model the matching relationship between MEC SPs and UEs, the MEC SPs take the role of the sellers and auctioneers, UEs act as the buyers. The wireless and computational resources are regarded as the commodities. To ensure UEs' heterogeneous demands, we adopt the combinatorial auction, in which one trading can be successfully agreed when a bundle of resources are allocated simultaneously to UEs. The bundle of resources includes both wireless and computational resources, and different resource combinations can cover different requirements of UEs. When employing the combinatorial auction mechanism, the following challenges emerges:

1) How to determine UEs' valuation on the bundle of resources;
2) How to choose the winners (the UEs that one SP will serve) for the MEC SPs;
3) How to decide the final payment of UEs submitted to the MEC SPs.

To conquer the above problems and select appropriate MEC SPs for the UEs, we propose a MSSCA mechanism. The mechanism is composed of three factors: the bid strategy, winner determination and payment rule. With the bid strategy, the UEs sequentially submit their bids and valuations on the wireless and computational resources to the MEC SPs based on their QoS requirements. A multi-round auction mode is employed in case that the UEs misrepresent their bids. In the winner determination process, a two-dimensional Knapsack algorithm is used to determine whether the MEC SPs serve the accessed UEs. And then based on the payment rule, the final payments of UEs who win in the auction are determined.

The main contributions of this paper are summarized as the follows:

- To achieve efficient computation offloading, we study the matching relationship in a network scenario with multiple MEC SPs and UEs, where the MEC SPs are equipped with limited wireless and computation resources.
- Considering UEs' demand heterogeneity, we select the MEC SP that can satisfy both the wireless and computational resource requirements of UEs as the serving SP. In addition, we model the matching relationship between MEC SPs and UEs as the commodity trading process.
- We propose a multi-round sealed sequential combinatorial auction (MSSCA) mechanism to match the MEC SPs to UEs. This mechanism is composed of three important parts: the bid strategy, winner determination and payment rule.

The rest of this paper is organized as follows: In Section II, some related works are shown about computation offloading in MEC. In Section III the system model is described. In Section IV, the problem is formulated and In Section V, auction mechanism is designed. In Section VI some properties of the auction are proved. Various simulation results are given in Section VII. In Section VIII, we conclude this paper.

II. RELATED WORK

In the MEC networks, computation offloading is a key technology which enables the mobile devices to execute resource-intensive Apps on the MEC SPs. Much previous approaches have been done in this area. In [8], authors present a survey about MEC, revealing the open research challenges and future directions. In [9], authors study the computation offloading

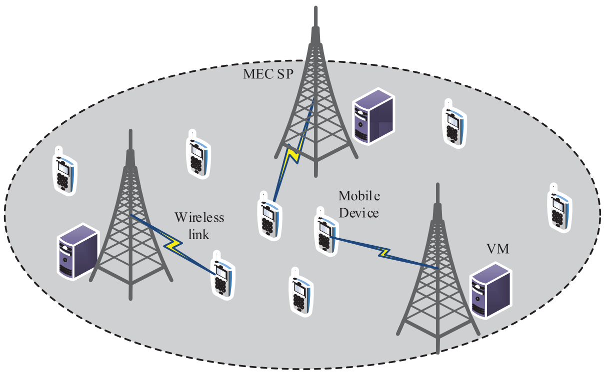

FIGURE 2. The MEC network scenario with multi-SPs and UEs.

optimization schemes from a 5G perspective. The authors in [10], [11] study whether to offload the tasks according to the network cost consumption. The authors in [12], [13] propose an optimization scheme considering the joint wireless and computational resources allocation. In [14], network interference is regarded as an important in the computation offloading scheme design. Considering saving the network energy cost , an energy efficient resource allocation scheme is studied for mobile edge computation offloading in [15]. The authors in [16] develop an online computation offloading algorithm for a MEC system with energy harvesting technology. In the works of [17]–[19], the tradeoff between the energy and latency spent for task transmission and computation is studied.

Game theory is useful tool for the computation offloading scheme design. The authors of [20] formulate the offloading decision problem as a game problem, and an algorithm is design to achieve the Nash equilibrium. Manuscript [21] studies the computation offloading decision problem for multi-UEs under a multi-channel interference environment, and adopts a game theoretic approach to maximize the number of UEs who offloaded computation tasks to the MEC.

III. SYSTEM MODEL

A. NETWORK MODEL

As illustrated in Fig. 2, we consider a MEC scenario with K MEC SPs and N UEs, in which there is no centralized control entity. Each of the MEC SPs is equipped with limited wireless resources and computational resources. The wireless resources are quantified by the subchannels while the computational resources are described in terms of CPU cycles. We assume the resource status of MEC SP i be the 4-tuple (B_i, b_i, C_i, c_i), where B_i and C_i are the total number of channels and CPU cycles owned by a MEC SP i, b_i means the bandwidth of one single channel, and c_i represents the time duration of one CPU cycle. The SPs broadcast their resource status periodically. After receiving SPs' status information, UEs can master the resource capacity of SPs.

Each UE has a different computation task to be offloaded to the MEC SPs. The computation task of UE j can be expressed by (f_j, s_j), where f_j is the total number of CPU cycles required to accomplish the computation task, s_j denotes the size of the task, which is related to the program codes and the input parameters. To finish one computation task smoothly, both the wireless and computational resources are required, where the wireless resources is used for task transmission while the computational resource is responsible for task computation. Based on this description, the matching of MEC SP and UE is equalized to the allocation of wireless and computational resources to UEs.

B. COMPUTATION OFFLOADING COST MODEL

In this section, we will introduce the computation offloading cost model in detail.

We assume that UEs intend to offload the computation tasks to the MEC SPs when the function of (1) and (2) are satisfied. The two functions mean that the cost generated by the local task computation at the UE is larger than the cost consumed by offloading the task to the network edge. Denote t_j and e_j be the overall delay and energy consumption when the task is executed remotely at the MEC SP, then we have:

$$t_j \leq \overline{t_j} \tag{1}$$
$$e_j \leq \overline{e_j} \tag{2}$$

where $\overline{t_j}$ and $\overline{e_j}$ mean the cost of delay and energy consumption when the task is computed locally at the UE.

For t_j and e_j, we have

$$\begin{aligned} t_j &= t_j^t + t_j^e \\ &= \frac{f_j}{c_i} + \frac{s_j}{r_j} \end{aligned} \tag{3}$$
$$e_j = P_j t_j^t \tag{4}$$

where P_j is the transmission power of UE j. t_j^t and t_j^e denote the transmission and execution delay of the task, respectively. f_j is the number of CPU cycles required by UE j. $r_j = b_{ij} log_2(1 + \frac{P_j h_{ij}}{N_0})$ denotes the transmission rate of UE j. b_{ij} represents the channel bandwith allocated to the UE. h_{ij} denotes the channel gain between UE j and MEC SP i, N_0 denotes the background noise power.

For $\overline{t_j}$ and $\overline{e_j}$, we have:

$$\overline{t_j} = t_j^l \tag{5}$$
$$\overline{e_j} = e_j^l \tag{6}$$

where t_j^l and e_j^l denote the task computation delay and energy consumption when the task is performed locally.

$$t_j^l = \frac{f_j}{F_j^l} \tag{7}$$
$$e_j^l = P_j^l f_j \tag{8}$$

where F_j^l is the local computational rate of UE j, and $P_j^l = 10^{-11} F_j^l$ is the energy consumed per CPU cycle [22].

The number of required channels bandwidth b_{ij} can be figured out from the expression of $b_{ij} = \frac{r_j}{log_2(1+\frac{P_j h_{ij}}{N_0})}$. And then the number of the requested subchannels m_{ij} can be expressed by:

$$m_{ij} = \lceil \frac{b_{ij}}{b_i} \rceil \tag{9}$$

where '⌈⌉' is the ceiling function.

C. VALUATION AND BIDDING PRICE

We will discuss the valuation and bidding prices for the heterogeneous resources in this section. In an auction, the valuation is the maximum price that one UE is willing to pay for the commodities, which also means UEs' preference to the resources. This parameter is privately to the UE.

It is more reasonable to value the resources according to UEs' performance improvement when utilizing these resources. Let $v_j^b(q)$ be the valuation of $q(1 \leq q \leq B)$ contiguous subchannels of UE j. Since the maximum throughput function is a concave non-decreasing function to the channel width, we define the valuation function of channels similarly to work in paper [23]:

$$\frac{v_j^b(x)}{x} \geq \frac{v_j^b(y)}{y}, \quad \forall j \in N, \quad 1 \leq x \leq y \leq B \tag{10}$$

where $v_j^b(x)$ and $v_j^b(y)$ denote the valuation of UE j on x contiguous and y contiguous channels.

Define the valuation function of computation resources as a linear function to the number of CPU cycles, the function can be denoted as:

$$\frac{v_j^c(x)}{x} = \frac{v_j^c(y)}{y}, \quad \forall j \in N, \ \forall x, y \in \{1, 2, \ldots, C_i\} \tag{11}$$

where $v_j^c(x)$ and $v_j^c(y)$ denote the valuation of UE j on computational resources with x and y CPU cycles.

The bidding price of UE j on wireless and computation resources can be defined as the following:

$$\frac{p_j^b(x)}{x} \geq \frac{p_j^b(y)}{y}, \quad \forall j \in N, \ \forall x, y, \quad s.t. \ 1 \leq x \leq y \leq B \tag{12}$$

$$\frac{p_j^c(x)}{x} = \frac{p_j^c(y)}{y}, \quad \forall j \in N, \quad \forall x, y \in \{1, 2, \ldots, C_i\} \tag{13}$$

where $p_j^b(x)$ and $p_j^b(y)$ denote the bidding price of UE j when x and y contiguous channels are required, and $p_j^c(x)$ and $p_j^c(y)$ denote the bidding price for computational resources of x and y CPU cycles.

IV. PROBLEM FORMULATION

In this section, we address the following problem: how to select the appropriate MEC SPs for UEs while achieving the maximum utility under the restriction of the limited resources.

Define the SP-UE matching matrix as $X = \{x_{ij}\}_{K \times N}$, where $x_{ij} \in \{0, 1\}$ is the indicator revealing whether MEC SP i can serve the UE j with a bundle of resources. If the resource requirement of UE j can be satisfied by MEC SP i, then we have $x_{ij} = 1$, otherwise, $x_{ij} = 0$. The matching matrix must satisfy the following constraint:

$$\sum_{i=1}^{K} x_{ij} \leq 1, \quad \forall 1 \leq j \leq N \tag{14}$$

which ensures that one UE can only be served by at most one MEC SP.

If UE j is allowed to be served by MEC SP i, then the UE should pay $p_{ij}^b + p_{ij}^c$ to MEC SP i. Thus the utility of MEC SP i, gained from selling resources to UE j can be given by:

$$U_{ij} = x_{ij}(p_{ij}^b + p_{ij}^c) \tag{15}$$

The overall utility of MEC SP i can be denoted as the follows:

$$U_i = \sum_{j=1}^{N} U_{ij} \tag{16}$$

According to the analysis above, our SP-UE matching problem can be formulated as the following:

$$\max \ U_i, \quad \forall i \in K \tag{17}$$

Considering the limitation of resources on each MEC SP, we have the following constraints:

$$\sum_{j=1}^{N} x_{ij} m_{ij} \leq B_i, \quad \forall i \in K \tag{18}$$

$$\sum_{j=1}^{N} x_{ij} f_i \leq C_i, \quad \forall i \in K \tag{19}$$

The optimization problem (16) is actually a 2-dimensional 0-1 knapsack problem that can be solved using dynamic programming [24].

V. THE MULTI-ROUND SEALED SEQUENTIAL COMBINATORIAL AUCTION

In this section, we design a multi-round sealed sequential combinatorial auction (MSSCA) mechanism to solve the proposed problem.

A. AUCTION DESIGN

The auction is an efficient method for the resource allocation problem, in which the allocation efficiency can be achieved by the market competition. When applying the auction theory to solve our matching problem, the MEC SPs act as the sellers and auctioneers while the UEs act as the buyers. MEC SPs who own the wireless and computation resources want to lease out these resources to UEs. The UEs intend to buy the resources from the MEC SPs and complete the task computation. When a commodity trading is agreed between one MEC SP and one UE, the UE should pay monetary payment to the SP. The payment is decided by the auctioneer. To guarantee the utility for UEs, the final payment should not exceed the valuation of the UE. For the SPs, they have the responsibility for providing smooth computation offloading service to the UE via allocating channels and CPU cycles.

Considering the characteristics of the matching problem, our auction design should follow the rules below:

1) This auction is a combinational auction.
2) This auction is a multi-round auction.

In the MEC networks, computation offloading includes a communication procedure to transmit the computation task to the network edge and a computation process to execute the task. And thus, to complete the computation task, the UEs need both the wireless and computation resources. One trading in the auction can be agreed successfully between MEC SPs and UEs when both the two kinds of resources required by UEs are satisfied. Under this circumstance, our auction falls into the scope of combinatorial auction.

Moreover, we design our auction as a multi-round auction. According to the difference of the bidding behaviors, auctions can be divided into two categories: one-round and multi-round auction [7]. In one-round auction, all the bidders submit their bids simultaneously, and the auctioneer determine the winners and match the appropriate buyers to the sellers. The one-round auction is not suitable for our multiple MEC-SP network scenario [25]. On one hand, in the one-round auction, the bidder can't decide from which seller the commodities can be bought. On the other hand, the one-round auction requires a central controller or coordination among the sellers, which is not practical for our network with multiple MEC SPs and UEs without a centralized controller. Thus, the multi-round auction is applied to our auction design.

B. AUCTION MECHANISM

According to the analysis above, the process of the MSSCA mechanism is shown in algorithm 1.

We define the maximum rounds of the auction be R. At each round, UEs perform **Bid Submission** firstly. They submit their resource requirements and bid vectors to all neighboring MEC SPs. After receiving the vector information from UEs, the MEC SPs perform the step of **Winner Determination**, checking their local wireless and computational resources and calculating the utilities. In this step, the UEs allowed to be served by the MEC SP are determined. In each round of auction, some UEs with lower bids will fall into the loser vector Θ, where no UEs are served by the current MEC SPs. To make itself more competitive for other MEC SPs, the UE failed to be served in the last round of auction will improve the bidding price in the next round. The auction algorithm stops when the difference between the utilities of the current round and last round is below the threshold Δ or the algorithm implementation rounds has achieved to the maximum number.

From the algorithm, it is obvious that three sub-processes plays an important role: the bidding strategy, winner determination and payment rule. The users' bidding strategy is designed as a multi-round mode. The winner determination is to determine which of the UEs can be served by the MEC SPs. As to the payment rule, it intends to calculate the final price of UEs payed to the MEC SPs, while guaranteeing the properties of the auction. In the following, we will describe them in detail.

Algorithm 1 Multi-Round Sealed Sequential Combinatorial Auction Algorithm

Input:
UEs' resource requirement and bid vector $\{m_{ij}, n_{ij}, p_{ij}^b, p_{ij}^c\}$;
$i \in \{1, \ldots, K\}, j \in \{1, \ldots, N\}$;
SPs' Status $\{B_i, C_i\}, i \in \{1, \ldots, K\}$;
$\Theta = 1, \ldots, N$;
$U_{temp} = 0$;
for $r = 1, \cdots, R$ **do**
  Bid Submission
  UEs submit their resource requirement and bid vector to their preferred MEC SPs according to Bidding Strategy.
  $U_{temp} = \sum_{i=1}^{K} U(i)$
  Winner Determination
  for $j = 1 : N$ **do**
    for $i = 1 : K$ **do**
      $x = o_{ji}$;
      $(U(x), X, \Theta) = Knapsack(x)$;
      if $x_{ij} = 1$ **then**
        $U_{ij} = x_{ij}(\overline{p_{ij}^b} + \overline{p_{ij}^c})$;
        $U = \sum_{i=1}^{K} U(ij)$;
        $\Theta = \Theta - \{j\}$;
      end if
    end for
  end for
  if $U_{temp} - U < \Delta$ **then**
    Auction complete ;
    Break;
  end if
  Bid Improvement based on Algorithm2 (int $j + 1$);
end for
Output: Matching matrix X, payment P, utility U

1) BIDDING STRATEGY

Each UE sorts the MEC SPs according to the distance between the UE and MEC SPs. Denote the MEC SP priority vector for UE j be $O_j = (o_{j1}, o_{j2}, \ldots, o_{jK})$, where $\forall o_{jk} \in \{1, 2, \ldots, K\}$ shows that MEC SP k is the k^{th} SP that preferred by UE j. In each round of the auction, the UEs sequentially submit their bids to the MEC SPs in the priority vector. When one MEC SP agrees to serve the UE, the bid submission process will stop.

In MSSCA, since a multi-round auction mode is employed, i.e. the UEs can adjust their current bidding price according to the results of the last round. In the next round of the auction, the UEs that are not served in the last round will submit higher bids to win the SP, the bid improvement will stop until the bid

Algorithm 2 Bid Improvement

```
Input: user j's current bidding price p^b_ij, p^c_ij, the rising degree α
Output: user j's next bidding price p^b_ij, p^c_ij
Bid Improvement for wireless resources
if p^b_ij ≤ v^b_j then
    p^b_ij = p^b_ij + α * p^b_ij
    if p^b_ij ≥ v^b_j then
        p^b_ij = p^b_ij
    end if
else
    p^b_ij = p^b_ij
end if
Bid Improvement for computational resources
if p^c_ij ≤ v^c_j then
    p^c_ij = p^c_ij + α * p^c_ij
    if p^c_ij ≥ v^c_j then
        p^c_ij = p^c_ij
    end if
else
    p^c_ij = p^c_ij
end if
```

achieves UE's valuation on the resources. The bid improvement process is shown in algorithm 2. Within this algorithm, the bid will update by function $p^b_{ij} = p^b_{ij} + \alpha * p^b_{ij}$, where α denotes the step length of each improvement. This parameter is related to the convergence speed of the algorithm.

2) WINNER DETERMINATION

The goal of the winner determination algorithm is to decide whether one MEC SP intends to serve the UE.

When UE j bids to MEC SP i, the SP figures out its own utility according to step 5 in Algorithm 3. As noted, we compare the utility of UE j with that of UE $j-1$. If the former is no higher than the latter, i.e. $U(i,j,b,c) \le U(i,j-1,b,c)$, then we have $x_{ij} = 0$ and UE j is moved to the loser vector Θ (Θ denotes the vector of the losers who failed to obtain service from the SP), otherwise, $x_{ij} = 1$, UE $j-1$ is moved to the loser vector α. In the next auction round, the UEs in Θ will bid iteratively to the next SP for computation service.

3) PAYMENT RULE

The final price paid by the winners is determined by the payment scheme. The design of this part directly determines the properties of the auction mechanism. A carefully designed payment scheme can guarantee the truthfulness of the auction. An auction should be constructed while the price paid by the player is independent of his own bids (William Vickrey, 1961) [26]. Considering this, we adopt the sealed second price auction, in which the winner chooses the second high bidding price as the payment.

Denote the winners served by MEC SP i in the k^{th} round of auction be $\mathcal{N}_k = \{1, 2, \ldots, N_k\}$, where $N_k \le N$ denotes

Algorithm 3 Knapsack Algorithm

```
1:  Input: user j's bid (m_ij, n_ij, p^b_ij, p^c_ij), U(i, j, B_i, C_i)
2:  Output: Selection matrix X, Utility U, Losers group Θ
3:  for b = 1, ··· , B_i do
4:      for c = 1, ··· , C_i do
5:          U(i, j, b, c) = max{U(i, j−1, b, c), U(i, j−1, b−m_ij, c−n_ij) + p_ij}
6:          if U(i, j, b, c) ≤ U(i, j−1, b, c) then
7:              x(i, j) = 0
8:              Θ = Θ ∪ {j−1}
9:          else
10:             x(i, j) = 1
11:             Θ = Θ ∪ {j}
12:         end if
13:     end for
14: end for
15: return U(i, j, B_i, C_i), X, Θ
```

the number of the winners. We calculate the payment for channels and CPU cycles, respectively. For the channels, we group the winners by vector $G^b = \{g^b_1, g^b_2, \ldots, g^b_m\}$, where $m < B_i$ is the number of the winner groups and $|g^b_x|$ denotes the number of winners in the x^{th} group. The winner groups in G^b should satisfy the following relationship:

$$\bigcup_{1 \le x \le m} g^b_x = N_k, \tag{20}$$

which means that all the winners are involved.

$$g^b_x \cap g^b_y = \emptyset, \quad \forall g^b_x, g^b_y \in G^b \wedge x \neq y, \tag{21}$$

Which means that no winner can emerge in multiple groups.

The bidding price of g^b_x can be defined as:

$$p^b_x = (p^b_{x1}, p^b_{x2}, \ldots, p^b_{x|g_x|}), \tag{22}$$

where p^b_{xi} denotes UE's bidding price for the channels. Assume that the bidding price of the winners for the channels in each group are sorted in a descending order:

$$p^b_{x1} \ge p^b_{x_2} \ge \ldots \ge p_{x|g_x|^b} \tag{23}$$

According to the sealed second-price design, the payment of UE i for the channels in group g^b_x is given by:

$$\overline{p^b_{xi}} = p^b_{x(i+1)}. \tag{24}$$

For the CPU cycles, it has the similar payment determination process to the payment of channels.

VI. PROOF OF PROPERTIES

In this section, we prove the properties of the proposed auction, which are given in the following definitions and lemmas.

Definition 1: **Individual rationality**, the utility of the sellers and buyers should be no less than zero.

Definition 2: **Budget balance**, the gain of the auctioneer should be no less than zero, i.e., the overall charges from the buyers can't exceed total payments to the sellers.

Lemma 1: The multi-round sealed sequential combinatorial auction is individual rational.

Proof: As described in expression (16), the utility of the MEC SP is the total payments from the winning UEs. For the UEs, who are not served by MEC SPs, their utilities are 0. When the UE participates in the auction and wins, this UE pays for the channels and CPU cycles with the second higher bidding price, and thus the utility of UE should be not less than 0. Since the utilities of all the participants and MEC in the auction are non-negative, the proposed auction is individual rational.

Lemma 2: The multi-round sealed sequential combinatorial auction is budget balance.

Proof: As said before, the seller takes the role of the auctioneer. As shown in expression (15), the overall payments to the seller are equal to the total charges from the buyers. Hence, the proposed auction is budget balance.

VII. SIMULATIONS

In this section, we evaluate the performance of the proposed auction mechanism by numerical simulation results.

A. SIMULATION SETUP

We consider the scenario where the MEC SPs and UEs are randomly deployed in the area. The number of channels and CPU cycles are randomly chosen from $\{20, 30, 40\}$, the minimum separable unit of channel bandwidth and CPU cycles are 15kHz and 5GHz respectively. The transmission power is $P_j = 1.5W$ and the background noise is $N_0 = -60$ dBm [27]. And we set the channel gain be $h_{ij} = l_{ij}^{-\alpha}$, where l_{ij} denotes the distance between MEC SP i and UE j. $\alpha = 4$ denotes the pass-loss exponent [28].

For the computation task, the data size is randomly chosen from [100, 1000]KB, and the total number of CPU cycles f_j of the computation task is randomly chosen from [200, 1000] megacycle. The local computation capacity F_j^l of a UE is randomly assigned from the set of $\{1, 1.5, 2\}$ GHz. For UE j' valuation, we first generate a unit valuation within [5, 10], and then give the valuations of the set of channels and the bundle of CPU cycles separately according to the expression (10) and (11). The initial bidding price is a half of the task valuation.

B. SIMULATION RESULTS

In simulation, we first study the convergence of the proposed algorithm MSSCA and then compare the performance of MSSCA to the candidate algorithms: One-shot Sealed Sequential Combinatorial Auction (OSSCA) and Random Sealed Combinatorial Auction (RSCA). OSSCA is an one-round auction, and within RSCA, MEC SPs randomly choose the winners under the condition that limited resources are owned by the MEC SPs. The simulation results are presented from Fig. 3 to Fig. 10.

Fig. 3 and Fig. 4 show the utility and the number of winners for MSSCA when the number of UEs are different, where

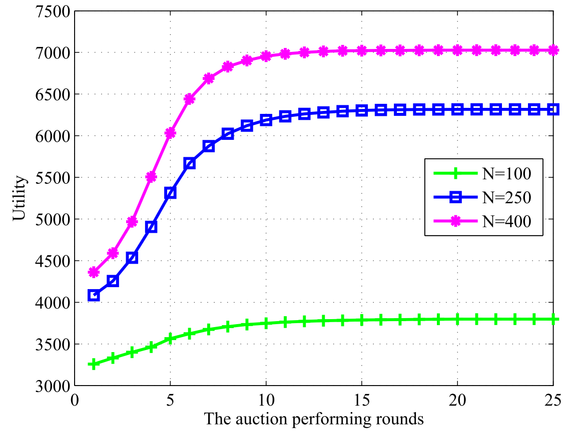

FIGURE 3. The utility of MSSCA.

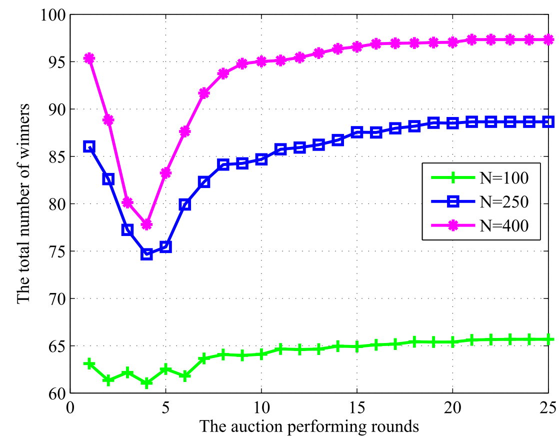

FIGURE 4. The winner number of MSSCA.

$N = 100, N = 250, N = 400$. The number of MEC SPs is set to be 3.

In Fig. 3, it shows that the lines increase with the increment of the number of UEs. When the number of UE becomes larger, the increment rate becomes slower. Finally, the rise is very small and the lines approach stable, which also means our proposed algorithm can achieve convergence. When the number of UEs is higher, MEC SPs can gain higher utility. This is because the utility of MEC SPs is the overall payments of UEs. More UEs exist in the network, a larger number of UEs can be served, which further leads to higher utility of MEC SPs.

In Fig. 4, the lines reveal how the number of winners varies as the number of auction rounds increases. Firstly the lines decrease with a higher gradient, after reaching the bottom, the lines increase and finally achieve to a stable value. The variation of lines shows that the auction rounds should be set big enough to make the proposed algorithm achieve convergence.

Fig. 5 and Fig. 6 describe the utility and the number of winners under three different algorithms, the MSSCA, RSSCS and OSCA. As we can observe that the MSSCA and OSSCA perform better than RSCA, that is because the RSCA choses the winners in a random way.

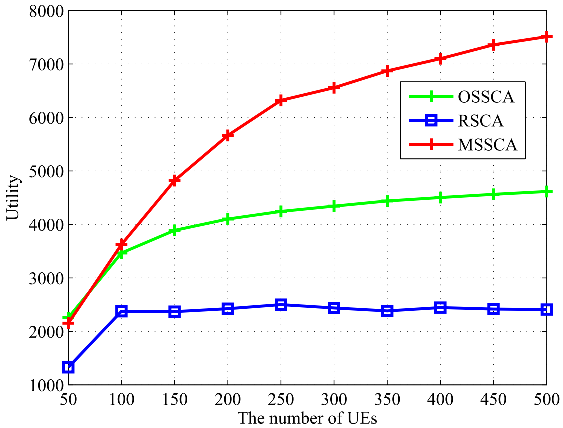

FIGURE 5. The utility variation under the algorithm of MSSCA, OSSCA and RSCA.

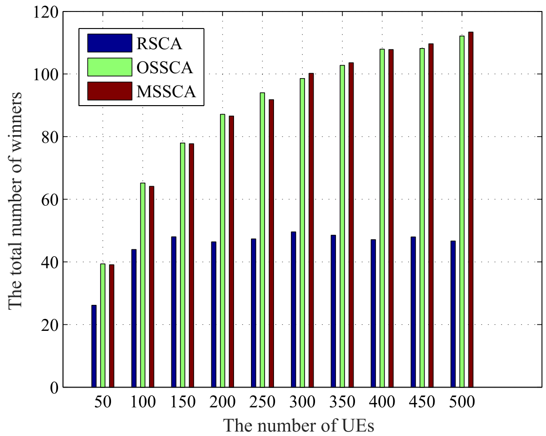

FIGURE 6. The winner number variation under the algorithm of MSSCA, OSSCA and RSCA.

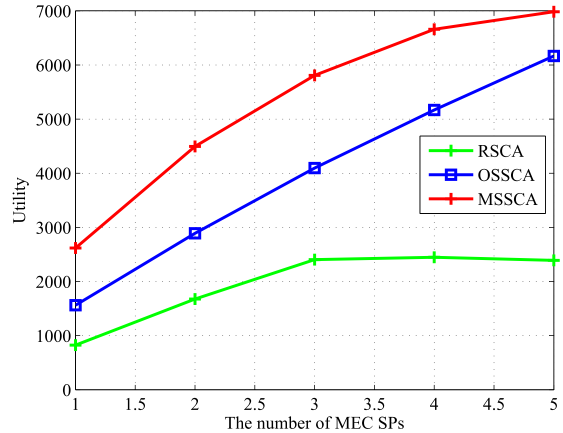

FIGURE 7. The utility variation versus the number of MEC SPs under the algorithms of MSSCA, OSSCA and RSCA.

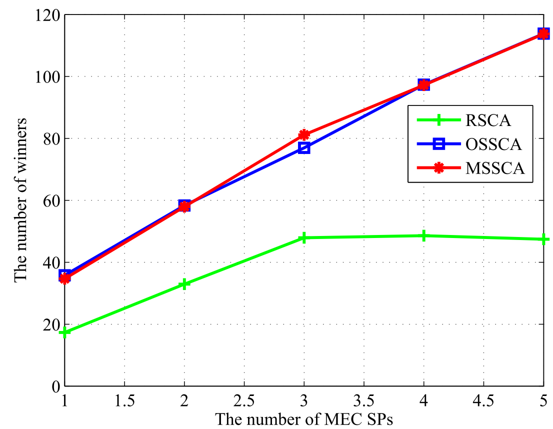

FIGURE 8. The winner number versus the number of MEC SPs under the algorithms of MSSCA, OSSCA and RSCA.

In Fig. 6, the number of winners obtained by MSSCA and OSSCA are almost the same. The proposed MSSCA algorithm obtains a higher utility than OSSCA when the number of UEs is big enough. When the number of UEs is big, UEs should compete for the limited resources for the task computation. The MSSCA is able to select UEs that provide higher utiltiy. When the number of UEs is small, the utility obtained by MSSCA is almost the same as that obtained by OSSCA. That is because all the UEs can be served by the MEC SPs and there is little difference between the line depicted by the MSSCA and the one depicted by the OSSCA.

Fig. 7 and Fig. 8 compare the utility and the number of winners generated by three different algorithms, which are MSSCA, OSSCA and RSCA, respectively. The number of UEs is set to be $N = 200$. As we can see, MSSCA and OSSCA perform better than RSCA in the terms of the number of winners and the utility.

In addition, the utility lines of the three algorithms increase as the number of MEC SPs becomes larger. The increasing rate becomes slower and the lines become stable when the number of MEC SPs is larger. This happens due to the limitation of network resources. When the number of MEC SPs is small, the resources are limited and only part of the UEs can be served. The resources become sufficient when more MEC SPs are deployed. And meanwhile, more UEs can be served and the utility is improved. When the number of MEC SPs is big, enough resources are provided to all the UEs and the utility can be no more improved.

The lines of Fig. 7 And Fig. 8 have the same increment tendency. In Fig. 8, the number of winners obtained by MSSCA and OSSCA are almost the same, and both the two lines increase when the number of MEC SPs improves. The improvement of lines is also influenced by the resource limitation.

Fig. 9 and Fig. 10 show the number of winners in each MEC SP under the algorithm of OSSCA and MSSCA. In Fig. 9, utilizing OSSCA, we can see that MEC SP 1 serves more UEs than MEC SP 2 and 3. In Fig. 10, after performing MSSCA, the number of winners in the three MEC SPs are almost the same. From comparing the two figures, it is obvious that our proposed MSSCA is able to provide better fairness to MEC SPs than that of OSSCA, which also means that the proposed MSSCA can highly utilize the network resource and avoid load imbalance.

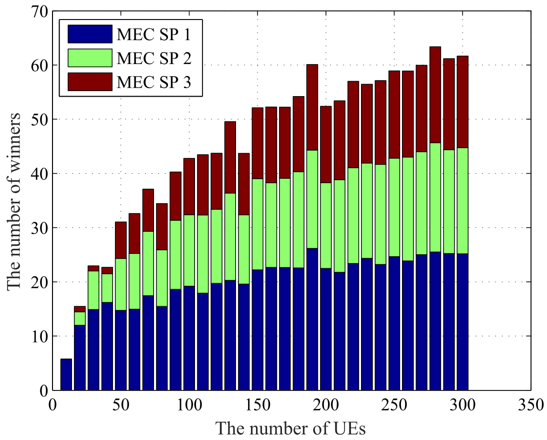

FIGURE 9. The number of winners of three different MEC SPs under OSCCA.

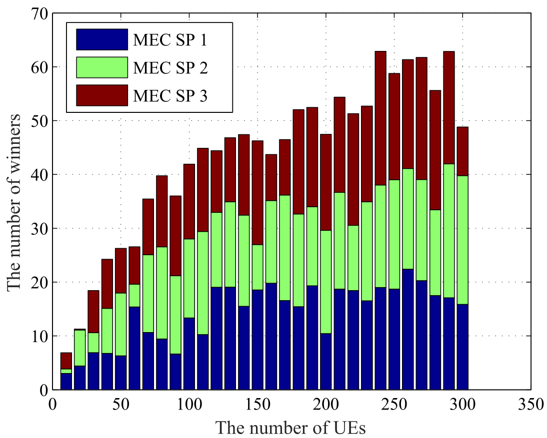

FIGURE 10. The number of winners of three different MEC SPs under MSCCA.

VIII. CONCLUSION

In this paper, we study the computation offloading in a multi-MEC and multi-UE scenario, where MEC service providers (SPs) are equipped with limited wireless and computation resources. We utilize auction model to describe the serving relationship between MEC SPs and UEs, where SPs and UEs are regarded as sellers and buyers, the resources of SPs are deemed as commodities. UEs can obtain service from SPs when SPs have sufficient resources while UEs can successfully purchase resources from SPs. To describe this process, we propose a multi-round sealed sequential combinatorial auction (MSSCA) mechanism. This mechanism is composed of three important parts: users' bid strategy, winners determination and the pricing process. The users' bid strategy is designed based on a multi-round priority rule, the winner determination process is formulated as a two-dimensional Knapsack problem while the pricing process is modeled according to UEs' resource requirements. We also prove the properties of the auction and utilize various simulation results to show that the proposed approach has better performance compared to the existing algorithms.

REFERENCES

[1] G. Han, X. Yang, L. Liu, W. Zhang, and M. Guizani, "A disaster management-oriented path planning for mobile anchor-based localization in wireless sensor networks," *IEEE Trans. Emerg. Topics Comput.*, to be published.

[2] R. Xie, F. R. Yu, H. Ji, and Y. Li, "Energy-efficient resource allocation for heterogeneous cognitive radio networks with femtocells," *IEEE Trans. Wireless Commun.*, vol. 11, no. 11, pp. 3910–3920, Nov. 2012.

[3] C. Zhu, V. C. M. Leung, X. Hu, L. Shu, and L. T. Yang, "A review of key issues that concern the feasibility of mobile cloud computing," in *Proc. IEEE Int. Conf. Cyber, Phys. Social Comput. (CPSCom)*, Sep. 2013, pp. 769–776.

[4] "Mobile-edge computing introductory technical white paper," E. T. S. Institute, White Paper, 2014.

[5] G. Han, L. Liu, S. Chan, R. Yu, and Y. Yang, "Hysense: A hybrid mobile crowdsensing framework for sensing opportunities compensation under dynamic coverage constraint," *IEEE Commun. Mag.*, vol. 55, no. 3, pp. 93–99, Mar. 2017.

[6] C. Zhu, Z. Sheng, V. C. M. Leung, L. Shu, and L. T. Yang, "Toward offering more useful data reliably to mobile cloud from wireless sensor network," *IEEE Trans. Emerg. Topics Comput.*, vol. 3, no. 1, pp. 84–94, Mar. 2015.

[7] V. Krishna, *Auction Theory*. San Diego, CA, USA: Academic, 2002.

[8] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, "A survey on mobile edge networks: Convergence of computing, caching and communications," *IEEE Access*, vol. 5, pp. 6757–6779, 2017.

[9] S. Barbarossa, S. Sardellitti, and P. Di Lorenzo, "Joint allocation of computation and communication resources in multiuser mobile cloud computing," in *Proc. IEEE 14th Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Jun. 2013, pp. 26–30.

[10] M. H. Chen, B. Liang, and M. Dong, "Joint offloading decision and resource allocation for multi-user multi-task mobile cloud," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2016, pp. 1–6.

[11] K. Zhang, Y. Mao, S. Leng, A. Vinel, and Y. Zhang, "Delay constrained offloading for mobile edge computing in cloud-enabled vehicular networks," in *Proc. 8th Int. Workshop Resilient Netw. Design Modeling (RNDM)*, Sep. 2016, pp. 288–294.

[12] S. Sardellitti, G. Scutari, and S. Barbarossa, "Joint optimization of radio and computational resources for multicell mobile-edge computing," *IEEE Trans. Signal Inf. Process. Over Netw.*, vol. 1, no. 2, pp. 89–103, Jun. 2015.

[13] S. Barbarossa, S. Sardellitti, and P. D. Lorenzo, "Computation offloading for mobile cloud computing based on wide cross-layer optimization," in *Proc. Future Netw. Mobile Summit (FutureNetworkSummit)*, Jul. 2013, pp. 1–10.

[14] C. Wang, F. R. Yu, C. Liang, Q. Chen, and L. Tang, "Joint computation offloading and interference management in wireless cellular networks with mobile edge computing," *IEEE Trans. Veh. Technol.*, to be published.

[15] C. You, K. Huang, H. Chae, and B. H. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1397–1411, Mar. 2017.

[16] Y. Mao, J. Zhang, and K. B. Letaief, "Dynamic computation offloading for mobile-edge computing with energy harvesting devices," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3590–3605, Dec. 2016.

[17] K. Kumar and Y.-H. Lu, "Cloud computing for mobile users: Can offloading computation save energy?" *Computer*, vol. 43, no. 4, pp. 51–56, Apr. 2010.

[18] Y. Cui, X. Ma, H. Wang, I. Stojmenovic, and J. Liu, "A survey of energy efficient wireless transmission and modeling in mobile cloud computing," *Mobile Netw. Appl.*, vol. 18, no. 1, pp. 148–155, Feb. 2013.

[19] G. Jia, G. Han, J. Jiang, and L. Liu, "Dynamic adaptive replacement policy in shared last-level cache of DRAM/PCM hybrid memory for big data storage," *IEEE Trans. Ind. Informat.*, to be published.

[20] X. Chen, "Decentralized computation offloading game for mobile cloud computing," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 4, pp. 974–983, Apr. 2015.

[21] X. Chen, L. Jiao, W. Li, and X. Fu, "Efficient multi-user computation offloading for mobile-edge cloud computing," *IEEE/ACM Trans. Netw.*, vol. 24, no. 5, pp. 2795–2808, Oct. 2016.

[22] F. Wu, T. Zhang, C. Qiao, and G. Chen, "A strategy-proof auction mechanism for adaptive-width channel allocation in wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 10, pp. 2678–2689, Oct. 2016.

[23] L. M. Ausubel, "An efficient ascending-bid auction for multiple objects," *Amer. Econ. Rev.*, vol. 94, no. 5, pp. 1452–1475, 2004.

[24] K. W. Ross and D. H. K. Tsang, "The stochastic knapsack problem," *IEEE Trans. Commun.*, vol. 37, no. 7, pp. 740–747, Jul. 1989.

[25] L. Gao, Y. Xu, and X. Wang, "Map: Multiauctioneer progressive auction for dynamic spectrum access," *IEEE Trans. Mobile Comput.*, vol. 10, no. 8, pp. 1144–1161, Aug. 2011.
[26] M. Deng, H. Tian, and X. Lyu, "Adaptive sequential offloading game for multi-cell mobile edge computing," in *Proc. 23rd Int. Conf. Telecommun. (ICT)*, May 2016, pp. 1–5.
[27] L. Tang, X. Chen, and S. He, "When social network meets mobile cloud: A social group utility approach for optimizing computation offloading in cloudlet," *IEEE Access*, vol. 4, pp. 5868–5879, 2016.
[28] S. H. Chae, J. Y. Ryu, T. Q. S. Quek, and W. Choi, "Cooperative transmission via caching helpers," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2015, pp. 1–6.

HELI ZHANG received the B.S. degree in communication engineering from Central South University in 2009, and the Ph.D. degree in communication and information system from the Beijing University of Posts and Telecommunications (BUPT) in 2014. She has been the Lecturer with the School of Information and Communication Engineering since 2014. She has been the Reviewer for Journals of IEEE Wireless Communications, IEEE Communication Magazine, IEEE Transactions on Vehicular Technology, IEEE Communication Letters, and IEEE Transactions on Networking. She participated in many National projects funded by National Science and Technology Major Project, National 863 High-tech and National Natural Science Foundation of China, and cooperated with many Corporations in research. Her research interests include heterogeneous networks, long-term evolution/fifth generation, and Internet of Things.

FENGXIAN GUO received the B.E. degree in communication major from Zhengzhou University, China, in 2015. Since 2015, she has been pursuing the Ph.D. degree with the School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing. Her current research interests include small cell networks, resource management, and network optimization.

HONG JI (SM'09) received the B.S. degree in communications engineering and the M.S., and Ph.D. degrees in information and communications engineering from the Beijing University of Posts and Telecommunications (BUPT), Beijing, China, in 1989, 1992, and 2002, respectively. In 2006, she was a Visiting Scholar with The University of British Columbia, Vancouver, BC, Canada. She is currently a Professor with BUPT. She has authored over 200 journal/conference papers. Her research interests include wireless networks and mobile systems, including ICT applications, system architectures, cloud computing, green communications, software defined networks, radio access, management algorithms and performance evaluations. Several papers had been selected for Best Paper. She is serving on the Editorial Boards of the IEEE Transaction on Green Communications and Networking, *Wiley International Journal of Communication Systems*. She has Guest-Editor of the *Wiley International Journal of Communication Systems*, *Special Issue on Mobile Internet: Content, Security and Terminal*. She has served as the Co-Chair of Chinacom'11, and a member of the Technical Program Committee of ISCIT'17, GC'17 Workshops, Globecom'16/15/14/13/12/11, the ICC'13/12/11, the IEEE VTC'12S, and the WCNC'15/12.

CHUNSHENG ZHU (S'12–M'16) received the B.E. degree in network engineering from the Dalian University of Technology, China, in 2010, the M.Sc. degree in computer science from St. Francis Xavier University, Canada, in 2012, and the Ph.D. degree in electrical and computer engineering from the University of British Columbia, Canada, in 2016. He is currently a Post-Doctoral Research Fellow with the Department of Electrical and Computer Engineering, The University of British Columbia, Canada. He has authored over 100 papers published or accepted by refereed international journals/magazines (e.g., the IEEE Transactions on Industrial Electronics, the IEEE Transactions on Computers, the IEEE Transactions on Information Forensics and Security, the IEEE Transactions on Emerging Topics in Computing, the IEEE Transactions on Cloud Computing, the IEEE Systems Journal, the IEEE Access, and the IEEE Communications Magazine) and Conferences (e.g., the IEEE Globecom and the IEEE ICC). His current research interests mainly include wireless sensor networks, cloud computing, Internet of Things, social networks, and security.