Multi-leader Multi-follower Stackelberg Game based Resource Allocation in Multi-access Edge Computing

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***Abstract*—In this paper, we propose a multi-leader multi-follower Stackelberg game model for the resource allocation problem between edge nodes and terminal users in the multi-access edge computing system. In the proposed model, the edge nodes can set the price of edge computing resources according to the strategies of other nodes and predict users' behaviors. Subsequently, the terminal users can choose their optimal strategies based on the price strategies of edge nodes. A game theory based algorithm is proposed to find the optimal pricing strategies and optimal resource allocation solutions by solving the Nash equilibriums, so that the benefits of both edge nodes and terminal users are optimally satisfied. Simulation results show that the proposed approach yields a high utility at the equilibrium.**

***Index Terms*—Stackelberg game, multi-leader multi-follower, resource allocation, multi-access edge computing**

I. Introduction

With the technology development of Internet of Things (IoT) and mobile Internet, there is an increasing demand in computing resources, which brings more pressure in the cloud centers, and higher latency requirement in the communication networks [1]. To cope with the diverse computation requirements, multi-access edge computing (MEC) based computing services [2] are proposed for IoT. Using computation offloading and resource allocation, the MEC service providers integrated with various computing resources can provide users with satisfied services and can improve the quality of experience. However, how to achieve the maximum benefits for all MEC service providers is still a challenge faced by the researchers. The resources of edge computing nodes need to be allocated optimally.

To cope with above mentioned challenge, game theory can be used to solve the resource allocation problem in various computing and communication systems [6]. Lots of works have been done in the computation offloading and resource allocation of MEC systems based on game theory. For the edge user assignment problem, He et al. [3] proposed an user assignment game model and designed a new decentralized algorithm for solving the Nash equilibrium of the game. Xu et al. [4] proposed a Stackelberg dynamic game based resource pricing and trading scheme to achieve optimal allocation of edge computing resources between edge computing base stations and UAVs. Kim et al. [5] considered the computation offloading problem in a single-cloud multi-user network, researched the resource requirements of each mobile user, and proposed an optimal pricing scheme.

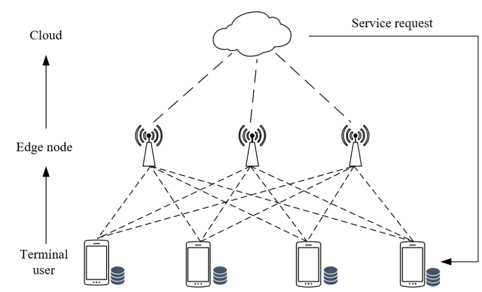

Fig. 1. System model

In this paper, we model the relationships between edge computing nodes and terminal users as a multi-leader multi-follower Stackelberg game. In the proposed game model, the edge nodes act as the leaders and the terminal users act as the followers. Firstly, each leader predicts the behaviors of the followers, and the strategies of other edge nodes. Then, the leaders can give their optimal strategies on the computing resource price for the followers. The terminal users, as the followers, can choose their strategies based on the price announced by the edge nodes. The behaviors of other terminal users are also considered. By solving the proposed multi-leader multi-follower game problem, we can obtain the equilibrium solutions for both the edge nodes and the terminal users.

The remainder of this paper is organized as follows. In Section II, we present the system model. In Section III and IV, we formulate the related problem and propose the optimal algorithm , respectively. In Section V, simulation results and discussions are given. We conclude the paper in Section VI.

II. System Model

In this section, we firstly introduce the network mode in Section II-A. Then the utility model of edge nodes and terminal users are given in Section II-B and Section II-C, respectively.

A. Network Model

The researched system is illustrated in Figure 1. We consider an IoT environment containing multiple IoT devices, multiple edge nodes and a cloud server. The IoT devices belong to various users and are deployed in the distributed scenarios. These IoT devices are able to collect data to assist in certain sensing tasks. Assuming there is a set of $N = \{1, ..., N\}$ IoT devices working as the terminal users for sensing data from the environments, which computation abilities are limited. In our proposed system, we assume that the terminal users are willing to help the cloud server with certain sensing tasks, but they do not upload the related sensing data directly to the cloud server due to the higher transmission latency. The terminal users transmit the relevant data to the edge nodes for data processing. The terminal users need to buy the computing resources from the edge nodes. Once the edge nodes complete the relevant computation tasks based on the data from the terminal users, they will upload the results to the cloud server. The number of edge nodes is denoted by M, with $M = \{1, ..., M\}$. The edge nodes can provide computing resources to the terminal users. It is assumed that different edge nodes have different trust levels among all the terminal users, which will also affect the resource strategies of terminal users. Since the computation resources on the edge servers are also limited, the terminal users need to compete the resources among each other in advance based on the resources price announced by the edge nodes. Therefore, the edge nodes can control their own revenue by adjusting the resource price, and the terminal nodes can control the required resources to decrease the cost. The cloud server acts as a service center that can assign relevant tasks to the terminal users according to the business requirements, which means the cloud server sends the tasks requirements to the terminal users when the cloud server receive the relevant business applications. After receiving the tasks, the terminal users perform the relevant operations, such as data sensing and collection. For example, in environmental monitoring, terminal user devices collect environmental data delivered to edge nodes for processing, and finally the edge nodes upload the results to the cloud.

To analyze the interaction process between edge nodes and terminal users in the proposed system, we consider the relationships as a Stackelberg game, where the edge nodes are the leaders and the terminal users are the followers. Firstly, the edge nodes announce the price and load quantities of computing resources. Then, the terminal users decide their purchase levels in different edge nodes based on the resource price and edge nodes' trust level. In the following two subsection, we will describe the objective models of edge nodes and terminal users, respectively.

B. Utility Model of Edge Node

Based on the tasks sent from the cloud server, the terminal users perform the related data sensing and collection operations. Since the terminal users are computationally limited, they need to complete the tasks using the computing resources of edge nodes. Using the computing resources of edge nodes, the terminal users need to pay the corresponding payments. Then the main revenue of edge nodes will come from providing the computing resources to terminals. In addition, the edge nodes also need to pay for the service cost in operation and maintenance, which is denoted as E^{en}. Meanwhile, the edge nodes need to upload the computing results to the cloud server, which will also bring corresponding cost denoted as e_t. Therefore, the profit maximization problem of each edge node can be denoted as follows,

$$U^{en}(p) = Pr^{en} - E^{en} - e_t, \tag{1}$$

where Pr^{en} denotes the profit earned by the edge node. The service cost in operation and maintenance E^{en} mainly includes the energy consumption and the hardware costs, which is related to the users' purchase. Then, the service cost can be defined as $E^{en} = ex$ for the convenience of analysis, where e denotes the cost coefficient and x denotes the size of data. Based on the above analysis, the final profit of edge node j is equal to,

$$U_j^{en}(p_j) = \sum_{i=1}^{N} p_j x_{ij} - e_j \sum_{i=1}^{N} x_{ij} - e_t, \tag{2}$$

where x_{ij} is the data offloaded from terminal user i to edge node j.

C. Utility Model of Terminal User

It is assumed that the terminal users are selfish. The cloud server can offer some rewards based on the contribution of terminal users to incentive the terminal users to assist in the sensing tasks. Generally, the contribution of an terminal user mainly depends on the amount of uploaded data. Inspired by [7] and [8], the profit function of terminal user is defined as follows,

$$Pr^{user}(x) = u_k \log(1 + x), \tag{3}$$

where $\log(1 + x)$ reflects the rewards offered by the cloud server for the uploaded data of terminal users. The reason for using the $\log$ function to represent the rewards is that the demand for terminals' data decreases gradually in the cloud server as the data results provided by the edge nodes increase. Thus, the total amount of rewards received by the terminal users decreases with it. Term u_k denotes the reward index.

Besides the data rewards, the terminal users need to consider the computational cost associated with the data charged by the edge nodes. Thus, the final utility of user i is as follows,

$$U_i^{user}(x_{ij}) = u_k \log\left(1 + \sum_{j=1}^{M} x_{ij}\right) - \sum_{j=1}^{M} p_j x_{ij}. \tag{4}$$

III. Problem Formulation

In this paper, we model the interaction between edge nodes and terminal users as a multi-leader multi-follower (MLMF) Stackelberg game with complete information, which is a two-stage game problem. Specifically, the edge nodes act as leaders selling their computation resources. The terminal users act as followers and accomplish the tasks from the cloud server by purchasing computing resources from the edge nodes. In the first stage, by setting the appropriate price, the edge nodes can maximize their profit by selling the edge computing resources.

In the second stage, each terminal user chooses the amount of computing resources purchased from the edge nodes to maximize its utility. The problems for the terminal users and edge nodes are given in Sections III-A and III-B, respectively.

A. Problem of Terminal User

Knowing the resource price of all the edge nodes, the terminal users can determine their computing service requirements by solving the following maximization problem:

$$\begin{aligned} \mathrm{P\,1} : \max_{x_{ij}} & \left\{ u_k \log(1+\sum_{j=1}^{M} x_{ij}) - \sum_{j=1}^{M} p_j x_{ij} \right\}, \\ \text{s.t. } & C1 : \sum_{j=1}^{M} x_{ij} \le X_i, \\ & C2 : \sum_{j=1}^{M} p_j x_{ij} \le B_i^{max}, \\ & C3 : x_{ij} \ge 0, \\ & C4 : x_{ij} \le c_{ij}, \end{aligned} \tag{5}$$

where $C1$ denotes the task data offload quantity constraint, i.e., X_i denotes the maximum quantity of task data. $C2$ denotes the maximum budget constraint for the terminal user, i.e., B_i^{max} denotes maximum budget of user i. $C3$ denotes that the resource purchased by the terminal user is not less than 0. $C4$ denotes the maximum amount of resources that a user can purchase based on the trust level of edge nodes. In order to ensure the security of their data, the terminal users consider the trust level of edge nodes during the purchase of computing resources and decide the final amount of resources to be purchased.

B. Problem of Edge Node

Taking into account the pricing strategies of other edge nodes and the resource demands of terminal users, each edge node determines its pricing strategy p with the objective of maximizing the desired profit. Then, the expression of the profit maximization problem for the edge node is shown as follows:

$$\begin{aligned} \mathrm{P\,2} : \max_{p_j} & \left\{ \sum_{i=1}^{N} p_j x_{ij} - e_j \sum_{i=1}^{N} x_{ij} - e_t \right\}, \\ \text{s.t. } & C1 : p_j > 0, \\ & C2 : p_j \le P_j^{max}, \\ & C3 : \sum_{i=1}^{N} x_{ij} \le C_j^{max}, \end{aligned} \tag{6}$$

where $C1$ and $C2$ denote the pricing bounds of the edge nodes, and P_j^{max} denotes the maximum pricing of edge node j. Since the computational resources of edge nodes are limited, i.e., C_j^{max} denotes the maximum capacity of edge node j, $C3$ denotes the computational resource bound of the edge nodes. It is worth noting that all edge nodes are selfish and in a non-cooperative state.

IV. Game Analysis

In this section, we employ the backward induction method to study the Stackelberg equilibriums. To facilitate the analysis, the definition of the Stackelberg equilibrium (SE) is given firstly.

Definition 1 *The SE of a Stackelberg game is the NE between the leaders and followers. The Nash equilibrium solutions of a game is a point. At this point, no participant has an incentive to unilaterally change its strategy to obtain better utility and not to the detriment of the utility of other participants. It is assumed that the NE point (p_j^*, x_i^*) and the following conditions are satisfied:*

For edge node j in the first stage, there exists,

$$U^{en}(p_j^*, p_{-j}^*, x_i^*) \le U^{en}(p_j, p_{-j}^*, x_i^*), j \in M. \tag{7}$$

For terminal user i in the second stage, there exists,

$$U^{user}(p_j^*, p_{-j}^*, x_i^*) \le U^{user}(p_j, p_{-j}^*, x_i), i \in N, \tag{8}$$

where, (7) is the Nash equilibrium solution condition of leaders, and (8) is the Nash equilibrium solution condition of followers.

Next, we present the derivation of the Nash equilibrium solution of the proposed Stackelberg game using the backward induction method. Specifically, we firstly derive the optimal resource demands of terminal users. With the pricing strategies, the terminal users is analyzed and the Nash equilibrium (NE) solution of each user is found in Section IV-A. Then, we use these strategies to substitute into the game of edge nodes to solve the Nash equilibrium solution for the edge nodes. The Nash equilibrium solutions of each edge node is discussed in Section IV-B.

A. Optimal Resource Demands of Terminal User

Firstly, we analyze the optimal resources demands of terminal users and give the following theorem.

Theorem 1 *With the information of resource price announced by the edge nodes, the maximum cost that each terminal user can afford, and the terminal users' trust in the edge nodes, the optimal amount of resources to be purchased by the terminal user i by solving Problem P1 is as follow,*

$$\begin{aligned} x_{ij}^* &= \min \left(c_{ij}, \left[\frac{B_i^{max} + \sum_{j=1}^{M} p_j}{M p_j} - 1 \right]^+ \right) \\ &= \min \left(c_{ij}, \left[\frac{B_i^{max} + \sum_{j'=1, j' \ne j}^{M} p_{j'}}{M p_j} + \frac{1}{M} - 1 \right]^+ \right), \end{aligned} \tag{9}$$

where,

$$[x]^+ = \max(0, x), \tag{10}$$

and j denotes the number of edge nodes.

proof: The optimal solution of Problem $P1$ can be solved by the Karush-Kuhn-Tucker (KKT) optimality condition, which are given as follows,

$$
\begin{aligned}
&\mathrm{P\,3}: \max_{x_{ij}} u_k \log(1+\sum_{j=1}^{M} x_{ij}) - \sum_{j=1}^{M} p_j x_{ij} + \\
&\lambda_1 \left(X_i - \sum_{j=1}^{M} x_{ij} \right) + \lambda_2 \left(B_i^{max} - \sum_{j=1}^{M} p_j x_{ij} \right), \\
&\text{s.t.} \begin{cases} \sum_{j=1}^{M} x_{ij} \le X_i, \\ \sum_{j=1}^{M} p_j x_{ij} \le B_i^{max}, \\ \lambda_1 \left(X_i - \sum_{j=1}^{M} x_{ij} \right) = 0, \\ \lambda_2 \left(B_i^{max} - \sum_{j=1}^{M} p_j x_{ij} \right) = 0, \\ \lambda_1 \ge 0, \\ \lambda_2 \ge 0, \\ X_i - \sum_{j=1}^{M} x_{ij} \ge 0, \\ B_i^{max} - \sum_{j=1}^{M} p_j x_{ij} \ge 0, \end{cases}
\end{aligned} \tag{11}
$$

where λ_1 and λ_2 are Lagrangian multipliers. Now, we use the KKT optimality condition to solve the problem $P3$ to obtain the optimal solution as,

$$
x_{ij}^* = \frac{u_k}{p_j + \lambda_1 + \lambda_2 p_j} - 1. \tag{12}
$$

In our model, only partial offloading is considered, i.e., the terminal user offloads only part of data to the edge nodes. So $X_i - \sum_{j=1}^{M} x_{ij} > 0$, i.e., $\lambda_1 = 0$. Then, because $x_{ij} \ge 0$, we must have $\lambda_2 > 0$. Then we can obtain,

$$
B_i^{max} - \sum_{j=1}^{M} p_j x_{ij} = 0. \tag{13}
$$

Finally, by substituting (12) into (13) for solving λ_2, we get,

$$
\lambda_2 = \frac{M u_k}{B_i^{max} + \sum_{j=1}^{M} p_j} - 1. \tag{14}
$$

By substituting (14) into (12), we can obtain,

$$
x_{ij} = \frac{B_i^{max} + \sum_{j=1}^{M} p_j}{M p_j} - 1. \tag{15}
$$

Considering the value range of x_{ij}, (15) is able to obtain (9). ■

B. Optimal Pricing Strategies of Edge Node

Assuming that the terminal users trust the edge nodes completely and the edge nodes do not collaborate with each other. On the basis of predicting the behaviors of terminal users, each edge node needs to consider the behavior of other edge nodes and determine its own optimal strategy. Therefore, we need to transform Problem $P2$. We firstly consider the utility of edge nodes based on the amount of terminal users' computational resource demand. By substituting the users' computational computing demand in (9) into (2), the utility function of edge node j is expressed as,

$$
\begin{aligned}
&U_j^{en}(p_j, p_{-j}, x_{ij}) \\
&= \sum_{i=1}^{N} p_j \left[\frac{B_i^{max} + \sum_{j'=1, j' \ne j}^{M} p_{j'}}{M p_j} + \frac{1}{M} - 1 \right] \\
&- e_j \sum_{i=1}^{N} \left[\frac{B_i^{max} + \sum_{j'=1, j' \ne j}^{M} p_{j'}}{M p_j} + \frac{1}{M} - 1 \right] - e_t,
\end{aligned} \tag{16}
$$

where we use $U_j^{en}(p_j, p_{-j}, x_{ij})$ to denote the effect of other edge nodes' strategies p_{-j} on the utility of edge node j, i.e., the effect of pricing decisions of other edge nodes on the pricing decisions of edge node j. For simplicity of representation, we define,

$$
a(p_{-j}) \triangleq \sum_{i=1}^{N} \left[\frac{B_i^{max} + \sum_{j'=1, j' \ne j}^{M} p_{j'}}{M} \right], \tag{17}
$$

$$
b \triangleq \sum_{i=1}^{N} \left[\frac{1}{M} - 1 \right]. \tag{18}
$$

Then, (12) can be transformed into,

$$
U_j^{en}(p_j, p_{-j}, x_{ij}) = a(p_{-j}) + b p_j - e_j \frac{a(p_{-j})}{p_j} - e_j b - e_t. \tag{19}
$$

We translate the constraint $C3$ of Problem $P2$ by substituting (9) as follows,

$$
\sum_{i=1}^{N} \left[\frac{B_i^{max} + \sum_{j=1}^{M} p_j}{M p_j} - 1 \right] \le C_j^{max}, \tag{20}
$$

$$
\Rightarrow \left(C_j^{max} - b \right) p_j - a(p_{-j}) \ge 0. \tag{21}
$$

Given the pricing strategies p_{-j} of other edge nodes, the pricing problem for the first stage edge nodes is,

$$
\begin{aligned}
&\mathrm{P\,4}: \max_{p_j} \{ U_j(p_j, p_{-j}, x_{ij}) \}, \\
&\text{s.t. } C1: p_j > 0, \\
&\quad\quad C2: p_j \le P_j^{max}, \\
&\quad\quad C3: (21).
\end{aligned} \tag{22}
$$

The optimal solution to Problem $P4$ is the optimal pricing strategy for edge node j. To analyze the optimal strategy for edge nodes, we give the following theorem.

Theorem 2 *Given the computing resource price p_{-j} of other edge nodes, the resource demand of users and the load of edge node j, the optimal pricing of edge node j is obtained by solving Problem $P4$ in the following two cases.*

Case 1: Edge node j reaches its maximum load. The optimal pricing strategy is equal to,

$$
p_j^* = \frac{a(p_{-j})}{C_j^{max} + \sum_{i=1}^{N} \left[1 - \frac{1}{M} \right]}. \tag{23}
$$

Case 2: Edge node j does not reach the maximum load. The optimal pricing strategy is equal to,

$$p_j^* = \sqrt{\frac{e_j a\left(p_{-j}\right)}{\sum_{i=1}^{N}\left[1-\frac{1}{M}\right]}}. \tag{24}$$

proof: The optimal solution of Problem $P4$ can be solved by using the KKT optimality condition, where Problem $P4$ can be written as follows,

$$\mathrm{P}\,5: \max_{p_j} U_j\left(p_j, p_{-j}, x_{ij}\right) + \lambda_3\left[\left(C_j^{max}-b\right)p_j - a(p_{-j})\right],$$
$$\text{s.t.} \begin{cases} \left(C_j^{max}-b\right)p_j - a(p_{-j}) \geq 0, \\ \lambda_3\left[\left(C_j^{max}-b\right)p_j - a(p_{-j})\right] = 0, \\ \lambda_3 \geq 0, \\ \left(C_j^{max}-b\right)p_j - a(p_{-j}) \geq 0, \end{cases} \tag{25}$$

where λ_3 is the Lagrange multiplier. By solving the Problem $P5$, we can obtain the optimal solution p_j,

$$p_j^* = \sqrt{\frac{e_j a\left(p_{-j}\right)}{-b-\lambda_3\left(C_j^{max}-b\right)}}. \tag{26}$$

Moreover, according to the complementary slackness condition, there are two cases: the equality condition of (21) holds or not hold. Therefore, we should study these two cases.

Case A - When the edge node receives less tasks offloaded by the users than the maximum number of tasks, (21) does not satisfy the equation, i.e., $\lambda_3 = 0$. Therefore, the final pricing strategy can be obtained as,

$$\begin{aligned} p_j^* &= \sqrt{\frac{e_j a\left(p_{-j}\right)}{-b}} \\ &= \sqrt{\frac{e_j a\left(p_{-j}\right)}{\sum_{i=1}^{N}\left[1-\frac{1}{M}\right]}}. \end{aligned} \tag{27}$$

Case B - When the edge node receives offload data from the user's task equal to the maximum number of loads, (21) satisfies the equation, i.e.,

$$\left(C_j^{max}-b\right)p_j - a(p_{-j}) = 0. \tag{28}$$

By substituting (26) into (28), we obtain,

$$\lambda_3 = -\frac{b}{C_j^{max}-b} - \frac{e_j\left(c_j^{max}-b\right)}{a\left(p_{-j}\right)}. \tag{29}$$

Also considering that the divisor in p_j^* is larger than 0, i.e.,

$$-b-\lambda_3\left(C_j^{max}-b\right) > 0, \tag{30}$$

$$\Rightarrow \lambda_3 < -\frac{b}{C_j^{max}-b}. \tag{31}$$

It can be observed that (29) clearly satisfies condition in (31). Since λ_3 is bounded, i.e., $\lambda_3 > 0$. We can obtain,

$$-\frac{b}{C_j^{max}-b} - \frac{e_j\left(C_j^{max}-b\right)}{a\left(p_{-j}\right)} > 0 \tag{32}$$

$$\Rightarrow e_j < -\frac{ba\left(p_{-j}\right)}{\left(C_j^{max}-b\right)^2}. \tag{33}$$

We substitute (29) into (27) to calculate p, and we obtain,

$$p_j^* = \frac{a\left(p_{-j}\right)}{C_j^{max}-b}. \tag{34}$$

In summary, when e_j satisfies condition (33), the edge node j reaches its own maximal load in order to maximize its profit. ■

C. Algorithm

Based on the above analysis, we design a multi-leader multi-follower game decision-making algorithm, as shown in Algorithm 1.

Algorithm 1: Strategy Of Edge Node In Multi-leader Multi-follower Game

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Initialize $t = 0$ and precision ξ;
Each edge node sets the initial price $p_j = p_j(0)$;
Repeat
  Oberserve other edge node pricing p_{-j};
  for $j = 1$ to M:
    if condition (33) is satisfied:
      Use (23) updated pricing strategies;
    else :
      Use (24) updated pricing strategies;
    End if
  End for
  $t \leftarrow t + 1$
until $||p_j^t - p_j^{t-1}|| \leq \xi$:

V. Numerical Simulations

We evaluate the performance of the proposed algorithm using MATLAB. We consider a scenario containing one cloud, five edge nodes, and fifteen terminal users. We set the initial price and the maximum number of loads for the edge nodes to $[3.5Cent/MB, 3.5Cent/MB, 3.75Cent/MB, 5Cent/MB, 5.5Cent/MB]$ and $[2,000MB, 1,800MB, 1,500MB, 1,000MB, 1,200MB]$, respectively. Each end-user has 1000MB task data. The maximum load of terminal users is uniformly distributed in $[500MB, 2,000MB]$. Each terminal user trusts all edge nodes with 90%, i.e., $c_{ij} = 0.9X_i, j \in M$.

In Figure 2, we can observe that the prices tend to stabilize as the number of iterations increases. The algorithm can be found to be convergent by the change in the pricing of the edge nodes. We set the precision of pricing to 0.0001, and we can find that the algorithm has fast convergence. After three iterations, the prices of the edge nodes reach the precision requirement and tend to converge. It can be found that when

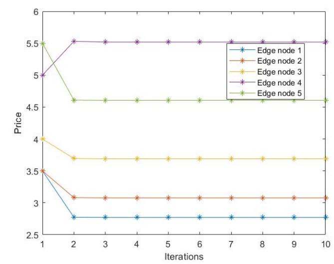

Fig. 2. Pricing strategy of edge nodes.

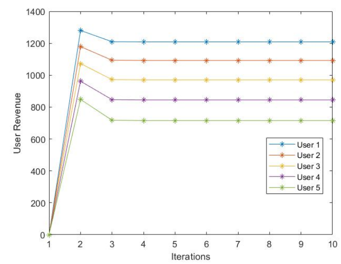

Fig. 4. Utility of terminal users

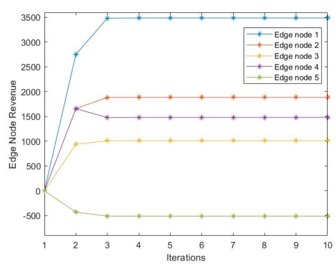

Fig. 3. Utility of edge nodes

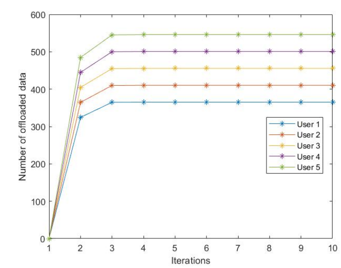

Fig. 5. Number of offloaded data in terminal users

an edge node observes the pricing of other edge nodes, it will adjust the pricing according to the strategies of other edge nodes.

We can observe that the revenue of the edge nodes varies with the pricing, as shown in Figure 3. The edge nodes control the revenue by adjusting the price. When the price tends to be stable, the revenue of the edge nodes converges. When the price of edge nodes is high, it causes users to reduce the amount of offloaded data, and leads to a decrease in their own revenue. By observing the pricing strategies of other edge nodes for adjustment, it makes its own revenue increase.

In order to observe the change of users' status, we randomly selected five terminal users for analysis. Terminal users gain revenue by offloading task data to the edge nodes to provide data services for cloud's tasks, and the trend is shown in Figure 4. The user's revenue varies with the pricing strategy of edge node. The user offload the data when it reaches a certain amount, and the trend of revenue increment decreases.

The pricing strategy of edge nodes affects the number of offloaded data, as shown in Figure 5. When the resource price of edge node is high, users will reduce the corresponding purchase quantity. On the contrary, when the resource price of edge node becomes low, users increase the number of purchased resources. Thereby, users can get more revenue. As the price of edge nodes gradually converges, the resource demand of users converges as well.

VI. Conclusion

In this paper, we consider a network scenario with multiple edge nodes and multiple terminal users, and propose a resource allocation method based on a multi-leader multi-follower game. The edge nodes act as leaders and the terminal users act as followers. In the environment of multiple edge nodes, each edge node is selfish and tries to get the maximum benefit. The edge nodes control the benefits by adjusting the pricing. Users decide the amount of resources to be used based on the pricing and trust of the edge nodes' resources. The Nash equilibrium solution of the game is solved by inverse induction method such that the terminal users and the edge nodes each have the optimal utility. Finally, we verify the effectiveness of the algorithm through relevant simulations.

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