# NOMA-based Joint Allocation and Offloading Strategy of Communication and Computing Resources

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***Abstract*—This paper proposes an offloading strategy for communication resources and computing resources. Based on the communication background of NOMA, this strategy combines D2D communication and cellular mobile communication to consider the use of resources in the communication process. According to the performance of communication resources, the power of cellular network users and D2D users is controlled to make the task unloading decision between users and small MEC server base stations. The purpose is to find the minimum sum of the total cost of the user group within the coverage of the entire base station. The cost is obtained from the task completion time and the base station usage payment. The experimental results show that this method can find the optimal solution of the user group cost, and it also has a good performance in user fairness. In reality, taking D2D communication into consideration for coordinated distribution in a cellular network can greatly reduce the cost of the two.**

***Index Terms*—mobile edge computing (MEC), Non-orthogonal multiple access (NOMA), device-to -device (D2D), game theory**

## I. Introduction

With the development of the Internet of Things technology, the large-scale computing requirements of applications are increasing. However, the computing resources of traditional smart terminals are limited, so they cannot handle heavy tasks in a short time. Cloud computing supports mobile users to send large amounts of data to cloud servers far away from mobile terminals for processing, so that they have higher data storage capabilities. But this causes high latency, which increases network load. Edge computing will offload user data and computing tasks to the edge cloud, and dynamically and optimally allocate appropriate resources to perform these offloading tasks. A reasonable and effective uninstall strategy can better reduce the impact of different factors on its performance. Therefore, this is very valuable work.

### A. Motivation

This article assumes that the user cost comes from uploading and calculation, because the calculation result data volume returned to the user by the task base station is very small and can be ignored. In terms of communication resource allocation, NOMA can better adapt to user network environment changes and feedback processing delays. Therefore, this article considers the NOMA technical solution based on the uplink scenario. The scenario in this article is shown in Fig. 1,

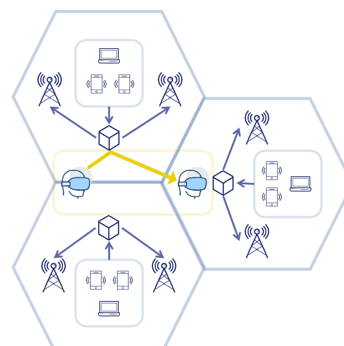

Fig. 1. Example of a figure caption.

where D2D users and cellular network users jointly control the allocation of channel resources. There are several groups of users in the cellular communication network, and the tasks and computing power of the users in the groups are different. The situation of users in different groups is also different. The user needs to coordinate the task through the intermediate task manager and then assign the task to each MEC base station. Since the computing capabilities of each MEC base station are also heterogeneous, a reasonable allocation between users and MEC base stations is particularly important for reducing the cost of user groups. At the same time, there are devices for D2D communication in cellular communication. D2D users need to select MEC base stations and power that can minimize the cost of all users in the scene through the intermediate task manager for transmission.

### B. Our Contribution

We propose a strategy optimization problem based on NOMA communication. This problem arises in a scenario where

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D2D communication and traditional cellular network communication coexist. The purpose of the thesis is to solve the problem of task transmission and offloading decision-making for normal cellular network users and D2D communication network users in small area communication scenarios. We expect to minimize the overall cost of the system in the entire small area while meeting the differentiated requirements of different users such as delay and energy. In terms of restriction conditions, it is necessary to consider different factors such as the needs of individual users, the hardware conditions of the user's own equipment, the heterogeneity of the small MEC server base station, and the communication conditions between each device and the base station. Since its cost is composed of task processing delay and task processing cost, it is necessary to consider the mutual influence between the allocation of user communication resources and the allocation of computing resources. Therefore, the problem is a complex multi-objective optimization problem. Therefore, we describe the problem as a non-cooperative load balancing purely strategic game problem that arises when multiple users share a server. From the rational point of view of maximizing their own interests, they participate in non-cooperative load balancing. The main contributions of this article are as follows:

- We constructed a scene model combining D2D communication with traditional cellular network communication.
- We propose the construction of optimization problems for two conflicting goals, and model the cost optimization problem of various users in complex communication scenarios as a non-cooperative game load balancing problem.
- For this complex non-convex problem, an effective algorithm DGT is proposed to solve it. Based on its effectiveness, the Nash equilibrium solution of the problem is obtained. Experiments show that this method not only guarantees accuracy, but also performs well in fairness and other indicators.

## II. Related Work

This paper reviews the related research status of the unloading strategy.

According to the performance requirements of computing offloading, the common offloading strategies can be divided into three main types: minimizing delay, minimizing energy consumption and maximizing revenue. In recent years, the main researches on the strategy of minimizing delay are as follows: the Stackelberg game theory method proposed in reference [1] is used to solve the problem. The voltage and power control scheme proposed in reference [2] is task dependent. The unloading strategy of minimizing energy consumption is mainly composed of: in reference [3], a deterministic and stochastic offline strategy is proposed for a single mobile device for joint dynamic optimization calculation. In reference [4], an offline precomputing unloading strategy is proposed, which is transformed into a Markov decision process problem to solve. In the unloading strategy to maximize revenue, the authors in reference [5] used dynamic scheduling mechanism, combined with task calculation queue and wireless channel state to make unloading decision. In reference [6], the optimal transmitting power and the unloading strategy under matching are obtained by dichotomy. Reference [7] proposed an optimization problem for the cooperation between queue information and channel state under dynamic coordination mechanism.

From the point of view of resource allocation, resource allocation can be divided into three types: resource allocation, resource allocation and resource allocation. In the calculation only resource allocation, literature [8] proposed the unloading strategy scheme under double auction combining economics and resource allocation. Reference [9] proposed a power summer solstice and linear programming resource allocation unloading strategy based on game theory. In communication resource allocation, reference [10] established a convex optimization resource allocation problem which combines network bandwidth and current channel conditions to solve. In reference [11], the problem model is transformed into a continuous problem and solved by using Nash bargaining game theory. Joint computing and communication resource allocation are comprehensive considerations. At present, the main researches are as follows: literature [12] proposed an optimal resource allocation unloading algorithm based on TDMA (time division multiple access) system. Reference [13] considered the unloading strategy of joint computation and convex optimization of spectrum. In reference [14], an unloading strategy considering the length of task queue and the state of network channel is proposed.

In the actual network scenario, cellular communication network coexists with a large number of D2D communications. The spectrum efficiency can be improved by controlling the cooperation of the two in the channel. The current main research literature [15] proposes a fixed power edge range to adjust the strategy of reducing user interference. Reference [16] proposed a cross-linked game algorithm combined with user history. Under this analysis and investigation, the communication scenario in this paper considers the overlapping of cellular communication network and D2D communication network. The problem is defined as the decision-making problem of splitting tasks for joint communication and computing resources in noma transmission mode.

## III. System Model and Problem Modeling

The thesis scenario is the work of minimizing the cost of the divisible task between a group of users and multiple heterogeneous small MEC base stations, and the coordinated control of the power of D2D users. Suppose there are N users, and each user has a separable computationally intensive task to be processed. $U = \{1, 2, ..., N\}$. O small MEC base stations, each base station has different computing power and unit time usage price. $M = \{1, 2, ..., O\}$. D has a one-to-one matching relationship DS-DR for the DS(Sending device) and DR(Receiving device). $D = \{1, 2, ..., Q\}$. The total computational workload of each user is expressed as $N_k$. The transmission workload of each DS-DR user is expressed as $N_d$

### A. Unloading Delay and Energy Consumption of UE-NOMA

For each user who offloads tasks, the inequality about $h_s$ indicates that the channel gains between users sending K tasks to M servers are as follows:

$$h_1 < h_2 < ... < h_m < h_n < ... < h_M \tag{1}$$

In the paper, we assume that each transmission channel is a quasi-static flat Rayleigh fading channel, which shows that its channel transmission characteristics follow the Rayleigh probability density function. This function is a constant in a transmission block, and multipath propagation will not cause inter-symbol interference. The paper considers that in each resource block (unit time block), users can transmit tasks to K small MEC base stations at the same time. When using the OMA (Orthogonal Multiple Access) traditional method, the user divides the task into K subtasks. Each unit time block has T seconds. When performing unloading tasks, users need to queue the tasks and load them on the MEC base station respectively. We consider that in the NOMA uplink transmission scenario, users can load multiple tasks to multiple servers at the same time. In order to facilitate the discussion of the advantages of NOMA, we assume that the current single user k has two tasks loaded on two small MEC base stations ($MEC_m$; $MEC_n$) and the channel gain is the same as the above expression.

In the OMA transmission mode, the user's transmission depends on the system to allocate a certain period of time to offload tasks to the MEC base station. Assuming that the tasks assigned by users to m and n are of the same size, the offload rate is:

$$R_m = Blog(1 + \frac{P_k h_m}{N_0})$$

Then the user first transmits the task from the channel to the small MEC base station m, and the time it takes is $T_m$

$$T_m \triangleq \frac{\frac{N}{2}}{R_m} = \frac{N}{2Blog(1 + \frac{P_k h_m}{N_0})} \tag{2}$$

Similarly, the transmission time transmitted by the user to the small MEC base station n is:

$$T_n \triangleq \frac{\frac{N}{2}}{R_n} = \frac{N}{2Blog(1 + \frac{P_k h_n}{N_0})} \tag{3}$$

Therefore, the time required for the user to complete the uplink transmission of the small MEC base station m and the small MEC base station n is expressed as $T_{OMA} = T_m + T_n$.

In the NOMA transmission mode, due to the characteristics of NOMA transmission, the user can perform offloading and transmission of tasks to the MEC server m during the time $T_n$ when the MEC server n alone occupies the channel. Therefore, the transmission time of the small MEC base station m is expressed as:

$$T_m \triangleq \frac{\frac{N}{2}}{R_m} = \frac{N}{2Blog_2(1 + \frac{P_k h_m}{P_k h_n + N_0})} \tag{4}$$

The transmission time of small MEC base station n is expressed as:

$$T_n \triangleq \frac{\frac{N}{2}}{R_n} = \frac{N}{2Blog_2(1 + \frac{P_k h_n}{N_0})} \tag{5}$$

In the above formula, $P_k$ represents the offload transmission power of user k. $N_0$ represents the spectral power density of background noise power, when $T = T_n$.

If all the transmissions cannot be completed within the time block of $T_n$, the remaining transmission tasks can be completed within a part of the time period of $T_m$. $(0 \leq \theta < 1)$: $T_{NOMA} = max(T_m, T_n) = (1 + \theta)T_n$

Therefore, in the scenario of one user with two small MEC base stations, the delay difference between traditional OMA and NOMA is:

$$\begin{aligned} T_{OMA} - T_{NOMA} &= (T_m + T_n) - max(T_m, T_n) \\ &= \frac{N}{2Blog_2(1 + \frac{P_k h_m}{N_0})} + \frac{N}{2Blog_2(1 + \frac{P_k h_n}{N_0})} \\ &-max(\frac{N}{2Blog_2(1 + \frac{P_k h_m}{P_k h_n + N_0})}, \frac{N}{2Blog_2(1 + \frac{P_k h_n}{N_0})}) \end{aligned} \tag{6}$$

The result shows $T_{OMA} - T_{NOMA} \geq 0$, which shows that $T_{NOMA}$ is always better than $T_{OMA}$ in terms of latency. It should be clear that, under the limitation of the channel gain situation above, adding the user's transmission to MEC base station m to the user's transmission time block $T_n$ to MEC base station n will not affect the user's original transmission to MEC base station n.

The channel gain between the user and the MEC base station meets the above preconditions. In this case, the signal transmitted by the user to the MEC server n will be decoded before the user transmits the signal to the MEC base station m. In summary, the NOMA transmission mode has better performance than the traditional OMA transmission mode in terms of delay.

From the time delay consumption, the energy consumption of traditional OMA to complete the task is expressed as $E_{OMA} = 2TP_k$. The energy consumed by NOMA to complete the task is expressed as $E_{NOMA} = (1 + \beta)TP_k$. $E_{OMA} - E_{NOMA} = (1 - \beta)TP_k \geq 0$ shows that under the condition of completing the same amount of tasks, NOMA performs better than traditional OMA in terms of energy consumption.

### B. UE-NOMA Scene Model

Users divide their own intensive tasks and send them to multiple small MEC base stations. It should be noted that not all base stations will choose to unload tasks. Therefore, this article uses $\omega_{k,m}$ to represent the connection relationship between user k and base station m, which is defined as:

$$\omega_{k,m} = \begin{cases} 1 & USER\ k\ collected\ with\ MEC\ m \\ 0 & USER\ k\ not\ collected\ with\ MEC\ m \end{cases} \tag{7}$$

Define the set $W_k = \{k|\omega_{k,m} = 1\}$ to indicate whether a connection is established between user k and the small MEC base station.

There are D D2D pairs (DS-DR) in the scene. Each USER-MEC cluster group contains a variable number of DS-DR task-intensive D2D communication users. We use $\theta_{d,f}$ to represent the connection relationship between $DS - DR_d$ and each USER-MEC cluster group, which is defined as:

$$\theta_{d,f} = \begin{cases} 1 & DS - DR_d \ collected \ with \ group \ f \\ 0 & DS - DE_d \ not \ collected \ with \ group \ f \end{cases} \tag{8}$$

We define the set $Q_d = \{d|\theta_{d,f} = 1\}$ as the set of $DS - DR_d$ who have established a connection with the USER-MEC group f.

During the transmission of DS-DR to the USER-MEC cluster group, $DS_d$ will transmit the task to $DR_d$ with a transmission power of $P_d$. The noise received by the user transmission also includes the signal power of the DS-DR sender $DS_d$ in the USER-MEC group. We use $O_d$ to represent it: $O_d \triangleq \sum_{d=1}^{D} P_d h_d \theta_{d,f}$. User k signal power $S_k$is expressed as $S_{k,m} \triangleq P_k h_m \omega_{k,m}$, Where $P_k$ represents the unloading power of the task sent by user k. The noise power $I_{k,m}$ caused by other users in the USER-MEC cluster group to user $k$ is expressed as: $I_{k,m} \triangleq \sum_{n=k+1}^{K} P_n h_n \omega_{n,m}$. $N_0$ is the spectral power density of the background noise. According to Shannon's formula, the M-channel transmission rate of user K to MEC base station is:

$$\begin{aligned} H_{k,m} &\triangleq Blog_2(1 + \frac{S_{k,m}}{I_{k,m} + O_d + N_0}) \\ &= Blog_2(1 + \frac{P_k h_m \omega_{k,m}}{\sum_{n=k+1}^{K} P_n h_n \omega_{n,m} + \sum_{d=1}^{D} P_d h_d \theta_{d,f} + N_0}) \end{aligned} \tag{9}$$

In the upload phase, the total transmission time of user k is as follows:

$$T_k^{upp} = max\{\frac{N_{k,m}}{H_{k,m}}|m \in MEC\} \tag{10}$$

According to the energy consumption formula, the energy consumption of user k in the upload phase is as follows:

$$E^{upp} = T_k^{upp} P_k \tag{11}$$

### C. DS-DR-NOMA Scene Model

D2D communication reuses uplink resources. Therefore, the base station can control the transmission power of D2D and coordinate its multiplexed resources to adjust the interference caused by D2D communication to users in cellular communication. We assumes that the channel gain of DS-DR users in the scene is expressed as $h_1 < h_2 < ... < h_D$.

The signal power of $DS - DR_d$ is expressed as: $S_d \triangleq P_d h_d$. The noise power $O_d$ of other DS-DR in the USER-MEC cluster group received by $DS - DR_d$ is expressed as: $O_d \triangleq \sum_{n=d+1}^{D} P_d h_d \theta_{d,f}$. Therefore, the transmission rate is expressed as::

$$\begin{aligned} H_d &\triangleq Blog_2(1 + \frac{S_d}{O_d + N_0}) \\ &= Blog_2(1 + \frac{P_d h_d}{\sum_{n=d+1}^{D} P_d h_d \theta_{d,f} + N_0}) \end{aligned} \tag{12}$$

Suppose that the transfer task size of $DS - DR_d$ is $N_d$. The total time to complete the transmission task is as follows:

$$T_d = \frac{N_d}{H_d} = \frac{N_d}{Blog_2(1 + \frac{P_d h_d}{\sum_{n=d+1}^{D} P_d h_d \theta_{d,f} + N_0})} \tag{13}$$

### D. Computing Rsesource model

Small MEC base stations are heterogeneous, so they have different computing capabilities, denoted as $\gamma_m$.

The entire communication process of cellular network users is divided into uploading, remote MEC calculation processing, and downloading. Theoretically, compared to the amount of data uploaded, the amount of data downloaded in the three stages is less, and in general, there is not much time cost difference. Therefore, in the calculations in this article, only the time cost of uploading and remote MEC calculation processing is considered. The processing time is expressed as $T^{pro}$:

$$T^{pro}\{m \in MEC\} = max\{\frac{N_{k,m}}{\gamma_m}\} \tag{14}$$

The user has certain local computing capabilities, which is expressed as $\gamma^{loc}$. This means that tasks that have not been unloaded are processed locally. We define local processing time as:

$$T^{loc} = \frac{N_k - \sum_{m=1}^{m=M} N_{k,m}}{\gamma^{loc}} \tag{15}$$

The monetary cost of this article uses the Amazon Web Services server pricing model. Under this pricing model, the price function $\rho_m$ of each small MEC base station is positively related to its computing power.

Therefore, the cost of user K on MEC server m is as $G_{k,m} = \frac{N_{k,m}}{\gamma_m} \rho_m$. When user k establishes a connection with multiple MEC servers, the total cost of task offloading for user k is:

$$G^{tot} = \sum_{m=1}^{m=M} \frac{N_{k,m}}{\gamma_m} \rho_m \tag{16}$$

### E. Problem Modeling

Due to the limitations of user local equipment performance and MEC server performance, the mathematical modeling of the problem considers the following constraints.

The total amount of tasks of a cellular network user includes the amount of tasks that users offload to the small MEC base station and the amount of tasks processed locally. Constraint 1: the sum of the tasks should be equal to the sum of the tasks that the user needs to process:

$$\sum_{m=1}^{m=M} N_{k,m} + N_{loc} = N_k \tag{17}$$

Constraint 2: the sum of transmission power and local calculated power of all users must be less than the maximum power of local intelligent device:

$$P_k + P_{loc} \leq P_k^{max} \tag{18}$$

The local energy consumption of users is as $E^{loc} = T^{loc} * P_{loc}$. Constraint 3: the total energy consumption of the user's equipment shall not exceed the energy value of the equipment itself:

$$E_k = E^{upp} + E^{loc} \leq E_{max} \tag{19}$$

The time cost of user is the sum of upload time and unload processing time, and the maximum value of local calculation processing time. Constraint 4: The user's time cost should be less than the expected maximum delay of the user's task.

$$T^{tot} = max\{T^{upp} + T^{pro}, T^{loc}\} \leq T_{max} \tag{20}$$

The user's monetary cost is only due to the money paid to the service provider for the tasks that are offloaded to the MEC server for processing. Constraint 5: the monetary cost of user should be less than the maximum expected value of user task

$$G^{tot} = \sum_{m=1}^{m=M} \frac{N_{k,m}}{\gamma_m} \rho_m \leq G_{max} \tag{21}$$

Constraint 6 and constraint 7: the transmission power of DS-DR users is within the scope of equipment realization:

$$P_d^{min} \leq P_d \leq P_d^{max} \tag{22}$$

We assumes that each user has a certain preference for delay and money cost. $\alpha$ is used to control the delay preference, and $\beta$ is used to control the preference for money cost. Therefore, the total user cost is expressed as $C_k = \alpha T^{tot} + \beta G^{tot}$ $(\alpha + \beta = 1)$. Since D2D users do not use computing resources on MEC server, the cost of D2D users is only related to their time cost: $C_d = T_d = \frac{N_d}{H_d}$. The goal of this paper is to find a strategy to minimize the total cost of users and D2D devices in the system while meeting the needs of users. Different service providers attach different importance to the D2D equipment in the system, so $\eta$ is used to indicate their importance. Therefore, the objective function of this paper is as follows:

$$Subject: \quad Min \quad \sum_{k=1}^{N} C_k + \eta \sum_{m=1}^{M} C_d$$

$$Constraint: \quad (17), (18), (19), (20), (21), (22)$$

$$Variables: \quad \omega_{k,m}, \ \theta_{d,f}, \ P_k, \ P_d$$

$$\{k, m, d | k \in U \quad m \in M \quad d \in D\}$$

## IV. Solution algorithm

This section mainly solves the problems raised in the previous section. In order to reduce the complexity and time cost of the algorithm, we decoupled functions in the allocation of computing resources and communication resources. The DGT algorithm is composed of three parts: Algorithm 1: PA (Power Adjustment) 2: CalCost 3: GA(Game Adjustment). Because we have listed communication-related formulas in the previous chapters, we will not repeat them in the algorithm in this section. The transmission time of the user and the transmission time of the D2D device are directly calculated.

**Algorithm 1** PA

**Input:** parameters, U, M, D
**Output:** Pair

1: Initialization: $T_{min} = T = 10$, $T_{max} = 1$, $l = 1$
2: Put all $DS$ into the first group of USER-MEC $Pair$.
3: $Pair[0] = [U[1], M[1], D]$, $Pair[f] = [U[f], M[f], []]$
4: **while** $T > T_{min}$ **do**
5: Using formula and Scipy to solve multi-objective minimum value problem, and get the minimum transmission time $Time_a$ of USER and DS.
6: Randomly select a $DS$ from m group and put it into another random n group.
7: $DS_d \notin Tmp\_Pair[m] = [U[m], M[m], D[m]]$
8: $\rightarrow DS_d \in Tmp\_Pair[n] = [U[n], M[n], D[n]]$
9: Do the same calculation as step 5 to get $Time_b$.
10: $Pro = Exp(\frac{Time_a - Time_b}{T})$, $a = random(0, 1)$
11: **if** $Time_a - Time_b > 0$ or $a < Pro$ **then**
12: Update $Pair = Tmp\_Pair$
13: **end if**
14: $l+ = 1$, $T = \frac{T_{max}}{log(l)}$
15: **end while**
16: **return**

The function of algorithm 1 is: 1. Matching the DS-DR user and the cellular network USER-MEC group. 2. Find the best power for both cellular network users and DS-DR users.

First, match the DS set into the first USER-MEC cluster. By default, the DS set matched by other USER-MEC cluster is empty. The US and MEC in the matching here respectively represent a group of cellular users and a group of MEC small base stations. The cycle condition is that when the current temperature of the algorithm is greater than the initial algorithm minimum temperature $T_{min}$, the exchange operation must be performed on the matching. By using the communication resource calculation formula described earlier in the paper and the Scipy multi-objective optimization algorithm to find the minimum transmission time $Time_a$ under the current match, and record the current user and DS-DR transmission power. Then randomly select two DSs in the MEC cluster group with non-duplicate users for temporary exchange. If $Time_a - Time_b > 0$, the overall transmission time can be made smaller after the exchange. Or when the random exchange probability is reached, the exchange is considered valid in both cases.(U[1] represents a group of multiple users, and so does M[1])

The function of Algorithm 2 is to obtain the minimum cost value of each user in the allocation scenario through all known USER-MEC matching pairs and the respective task upload time of each user. First, set the initial time $t$ and the search $step$ size of the initialization algorithm, and assign the user's acceptable delay upper limit to $T^{upp}$. Determine whether the MEC and the user's local equipment can fulfill the user's task requirements at the current cost. When the user's task can be completed under the cost value, the lower limit of the cost is adjusted to the current cost, otherwise the upper limit of the current cost is adjusted to the current cost. The condition for stopping adjusting the current cost of the user is that the difference between the upper and lower cost limits of the user is less than the preset cost accuracy threshold. Finally, the algorithm returns the minimum cost value group corresponding to the user group under the current match.

**Algorithm 2** CalCost

**Input:** Pair,$T^{upp}$,k
**Output:** $C^{best}$

**for** $k \in U$ **do**
  $step = n^{min}$, $t = step$, $T^{upp} = T_k^{Max}$, $T^{low} = 0$, $C^{upp} = n^{max}$, $C^{low} = 0$
  **while** $t < T_k^{Max}$ and $t < T_k^{Loc}$ **do**
    $C^{upp} = \alpha * T^{upp} + \beta * G^{upp}$
    $C^{low} = \alpha * T^{upp}$
    **while** $(C^{upp} - C^{low}) > \epsilon$ **do**
      $C^{cur} = \frac{(C^{upp} + C^{low})}{2}$
      Use an algorithm to find out whether the task can be completed by $C^{cur}$
      **if** Can complete the task **then**
        $C^{upp} = C^{cur}$
      **else**
        $C^{low} = C^{cur}$
      **end if**
      **if** $C^{cur} < C^{best}$ **then**
        $C^{best} = C^{cur}$
      **end if**
      t+=step
    **end while**
  **end while**
**end for**
**return**

Algorithm 3 first initializes the matching situation of user-MEC pairs, and puts all MECs into the matching set of the first user. This means that the first user will select and use resources on all MECs, while the remaining users can only perform task calculation processing locally. In this initial matching case, algorithm 1 is used to calculate the minimum cost.The main idea of the entire exchange process is that each user will exchange the mec currently owned by him to other users through polling. After the exchange, calculate the sum of the two benefits brought by the process. When the income is positive, it means that the total cost of this exchange can be reduced, and it is recorded in the current user's meaningful exchange set $EC$. On the contrary, when the income is negative, no record is made. If the current change set $EC$ is not empty, it means that there is exchange behavior that can reduce its overall cost. Then perform an exchange operation that maximizes cost reduction. Then poll all users again. If the number of stable users recorded is equal to all users, it means that all users have reached the Nash equilibrium stable state, and the algorithm stops at this time.

**Algorithm 3** GA

**Input:** $T^{upp}$
**Output:** $LastCost$

Initialization: $stable\_user = 0$
put all mec in first user group
$Pair[0] = [U[0], M, D[0]]$, $Pair[f] = [U[f], [], D[f]]$
Use Algorithm 2 to obtain $C^{ini}$
**while** $stable\_user < len(U)$ **do**
  $stable\_user = 0$
  **for** all $k_a \in U$ and $k_b \in U$ and $(k_a \neq k_b) m \in M$ **do**
    Randomly select a $mec_a$ from m group and put it into another random n group.
    $mec_a \notin Tmp\_Pair[m] = [U[m], M[m], D[m]]$
    $\rightarrow mec_a \in Tmp\_Pair[n] = [U[n], M[n], D[n]]$
    Use Algorithm 2 to obtain $C^{tmp}$
    change=$C^{ini} - C^{tmp}$
    **if** $change > 0$ **then**
      record it in $\{EC\}$
    **end if**
  **end for**
  **if** $\{EC\} \neq \emptyset$ **then**
    find $change^{max}$ and update it in Pair
  **else**
    $stable\_user$+=1
  **end if**
**end while**
Use Algorithm 2 to obtain $LastCost$
**return**

## V. Experimental Result

In order to verify the effectiveness and various indicators of the algorithm in this paper, this section presents and analyzes the experimental numerical results.

In terms of performance evaluation, we conducted separate experiments on the cost and user fairness of different user scales, and the cost and user fairness of different mec scales. The final results of the experiment are the average of multiple groups of experimental results to reduce randomness. The main indicators are defined as:

$$Cost = Group\_Cost + \xi D2D\_Cost$$

$$Fair = (\sum_{i=1}^{m} C_k)^2 / m \sum_{i=1}^{m}$$

Fig. 2 shows the overall user cost performance of each algorithm under a certain DS-DR communication scenario. Macroscopically, as the number of DS-DR users increases, the total user demand will increase, so the total user cost will also show an upward trend.

The blue square line shows the cost change when only DS-DR communication matching is performed without power control, and the green triangle line shows the cost change when only DS-DR power control is performed without communication matching. It can be seen that the cost values of the two are generally between the simulated reality algorithm and the DGT

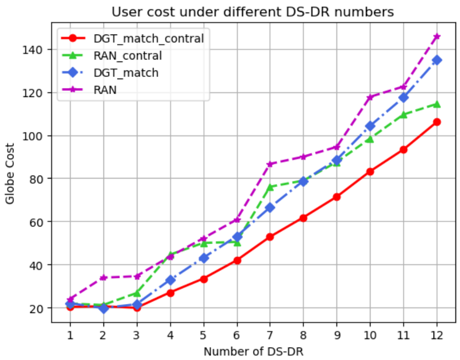
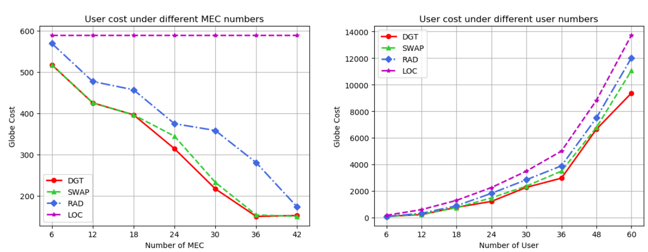



Fig. 2. Example of a figure caption.

algorithm. The cost of the two shows that the algorithm that only performs communication matching and the algorithm that only performs power control can effectively reduce the cost. At the same time, reasonable adjustment and control of the two can achieve mutual gain effects. The cost in the scenario of no communication matching and no power control is represented by the purple line. It can be seen that the cost will cause a high cost value for users under all user scales. Under different DS-DR scales, the DGT algorithm can achieve a cost reduction of nearly 30% compared with the simulated reality algorithm through communication matching and power control.




(a) (b)

Fig. 3. ChangeMECUSER

As shown in Fig. 3(a), with the increase in the number of MECs, the total cost of users has shown a downward trend. On the scale of 24 and 30 mec, the optimal solution of game theory algorithm is slightly better than exchange algorithm.

As shown in Fig. 3(b), the increase in the number of users will increase the cost of the entire user group. As the competition between users for MEC becomes more and more fierce, the cost difference is very obvious when the number of users reaches 60. The cost value of game theory algorithm saves 3000 cost compared with random algorithm, and nearly 2000 cost compared with exchange algorithm. . It can be seen that the DGT algorithm can maintain a very good optimal cost accuracy rate when the calculation is small and accuracy is required. The DGT algorithm can also minimize user costs and adapt to the needs of different user scales.

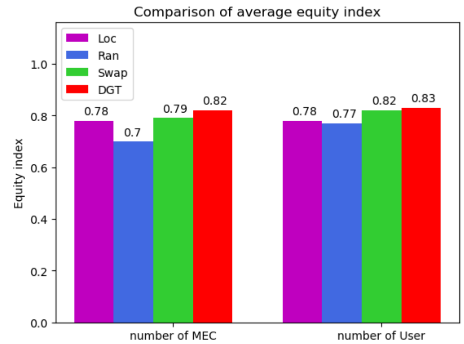
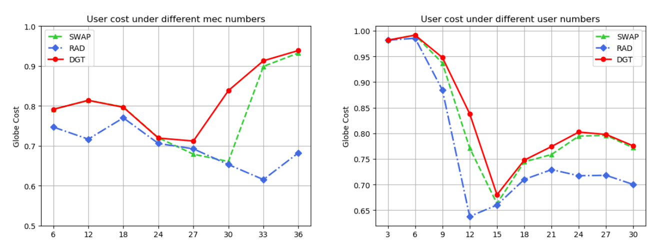



Fig. 4. Example of a figure caption.

Fig. 4 shows the performance of the cost average fairness index for different scales of MEC and different scales of users. It can be seen from the figure that the fairness index of the random algorithm is the worst, followed by the local algorithm. When the MEC scales are different, DGT performs well on the user fairness index, reaching a fairness index of more than 80%, followed by exchange algorithms. When the user scale is different, the local algorithm and the random algorithm perform similarly, while the exchange algorithm performs similarly to the DGT algorithm. Therefore, it shows that an effective distribution algorithm will have a positive effect on the user's perception of fairness.




(a) (b)

Fig. 5. FairChangeMECUSER

Fig. 5(a) shows the change in the average fairness index of users when the number of MECs changes. It can be seen that the fairness index of the random algorithm is very unstable and low. When there are a large number of MEC base stations, the average fairness of the DGT algorithm under each user scale is better than the switching algorithm. It can be seen that the DGT algorithm takes into account the needs of users for fairness while ensuring that the overall user cost is as small as possible, and has a good performance.

Fig. 5(b) shows the change in the average fairness index of users when the number of users changes. When the number of users is very small, user demand exceeds the amount of services MEC can provide. With the increase in the number of users, user competition for MEC has gradually increased. Generally, at the stage where the number of users is 12-15, the fairness index will reach the lowest value due to inconsistent distribution. However, it can be seen that even when the number of users is at a relatively high level of competition, the DGT algorithm can maintain a fairness index that is better than other algorithms. The whole line graph shows that the DGT algorithm can adapt to the optimized environment of various resource imbalance scenarios. It can reduce the cost value of the user community while taking into account the fairness needs of users from the perspective of community.

## VI. Conclusion

This article discusses the group optimization problem of DS-DR users and cellular network users considering communication resources, computing resources and power allocation. This problem has two conflicting goals: 1. User money cost and time delay cost. 2. Cellular network user cost and DS-DR user cost. In addition to user equipment capabilities and MEC hardware attributes, the factors that affect the final cost mainly depend on the transmission power of DS-DR users and cellular network users, and the offloading and matching strategy of cellular network users and MEC small base station equipment. In the communication resource allocation process, we reasoned about the superiority of the NOMA communication mode in terms of transmission speed and energy consumption compared with the traditional communication mode, and used it. In the process of computing resource allocation, we have reasonably considered the user's money cost and delay cost. We have separately considered and balanced the impact of cellular network users and DS-DR users on the total cost. In order to solve this complex multi-objective optimization problem, we carried out reasonable mathematical modeling and task decoupling. In the process of communication resource allocation, algorithm 1 is proposed to solve the problem under the exchange mode based on the flame retardation theory. In the process of computing resource allocation, the problem is described as a Nash equilibrium problem under non-cooperative game based on game theory, and it is solved by algorithm 2 and 3. On this basis, we conducted experiments on different types of system configuration scenarios. For example, different DS-DR scales, different user scales, and different MEC scales. The experimental results show that the reasonable allocation of power for DS-DR users and cellular network users can save nearly $30\%$ of the cost compared to simulated real-life allocation. In the allocation strategy, the DGT algorithm can ensure that the cost is minimized after the user is matched with the MEC server, and it also has a good performance in the consideration of fairness between users.

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