Abstract—Mobile edge computing (MEC) networks are one of the key technologies for ultra-reliability and low-latency communications. The computing resource allocation solution needs to be carefully designed to guarantee the computing resource efficiency of MEC networks. Based on the potential game theory, a computing resource allocation solution is proposed to reduce energy consumption and improve computing resource efficiency in MEC networks. The computing resource allocation solution includes two parts: the first part is the power control scheme based on the potential game theory and the second part is the computing resource allocation scheme based on linear programming. The power control scheme is to find a set of the transmission powers of base stations (BSs) that maximizes the potential function of MEC networks. The computing resource allocation scheme is to maximize the average computing resource allocation coefficient of the MEC networks based on the results of the power control scheme. Compared with traditional solutions, simulation results indicate the computing resource utilization and energy efficiency of the proposed computing resource allocation solution are significantly improved.

Index Terms—mobile edge computing, potential game, power control, computing resource allocation, PSO algorithm

I. INTRODUCTION

The exponential increment of data traffic, the sustained growth of terminals, as well as more and more diverse service scenarios, increase the pressure of the fourth generation (4G) cellular networks, which has led to the advent of the fifth generation (5G) cellular networks [1] [2]. The MEC technology is a promising solution for 5G networks, which can provide the complex computing capability at the radio access network (RAN) [3] [4]. The function of the cloud data center is sunk to the edge of cellular networks by MEC technologies, which provide users with some functions of the core network such as computing, storage and communication resources in base stations (BSs) at the edge of wireless networks. However, the interference among adjacent BSs not only influences wireless traffic transmissions but also affects the resource allocation in MEC networks. It is an important challenge for resource allocation optimization in MEC networks.

In the literature about resource allocation in MEC networks, a joint caching and offloading mechanism was proposed to upload uncached computation results as well as download computation result at BSs [5]. However, this mechanism is not suitable for applications involving with large computational demands and time-critical requirements as well as large-scale computational results, such as augmented reality, interactive online gaming, and multimedia conversions. An energy-efficient resource allocation scheme was presented for a multi-user MEC system with inelastic computation tasks and non-negligible task execution durations [6]. However, this scheme only focuses on reducing energy consumption and neglects resource allocation coefficient in MEC systems. A fair resource-allocation scheme was proposed to maximize the total throughput of a wireless network when each users’ transmission rate is constrained with the minimum transmission rate [7]. Based on the double-sided auction game, an efficient resource allocation scheme with limited resources between suppliers and consumers was proposed in [8]. A new distributed resources block (RB) and power allocation (PA) algorithm based on non-cooperative game theory was presented to improve the energy efficiency of MEC networks [9]. However, the computing resource allocation utilization and energy efficiency of MEC networks have not been simultaneously investigated in existing studies.

This paper focuses on reducing the energy consumption and improving the computing resource allocation utilization in MEC networks. The main contributions of this paper is summarized as follows:

1) To improve the computing resources utilization and energy efficiency of MEC networks, a computing resource allocation solution are proposed in this paper. Simulation results show that the proposed solution can save energy consumption and improve resource utilizations.
2) To reduce the energy consumption of MEC networks, a power control scheme is developed based on the potential game theory.

3) To improve the average computing resource allocation coefficient of MEC networks, a new computing resource allocation scheme is developed based on the linear programming.

The rest of this paper is arranged as follows. Section II gives the system model. Section III describes the proposed computing resource allocation solution. Simulation results and analysis are presented in Section IV. Section V draws the conclusions.

II. SYSTEM MODEL

Without loss of generality, one MEC server and $K$ BSs are configured for a MEC network. $P_k$ denotes the transmission power of the $k$–th BS ($k \in B = \{1, 2, \ldots, K\}$). The maximum transmission power of each BS is denoted as $P_{\text{max}}$. All users are assumed to be governed by a uniformly distribution with the density $\rho$. The coverage of the $k$–th BS is configured as a circle with the radius of $r_k$. The maximum coverage radius is denoted as $r_M$. The distance between the $m$–th BS and the $n$–th BS is denoted by $r_{mn}$. The required computing resources for the $k$–th BS is denoted by $f_k^{BS}$ and the computing resources actually allocated to the $k$–th BS is denoted by $s_k^{BS}$. Assumed that the required computing resources of all users are configured as a constant $f_{UE}$. The total number of actual computing resources for the MEC server is denoted by $S$. The system model of MEC networks is illustrated in Fig. 1.

The coverage probability of BSs is expressed as [10]

$$p_c(T, \alpha) = \mathbb{P}[\text{SINR} > T],$$

where $T$ is the threshold of the signal-to-interference-and-noise ratio (SINR), $\alpha$ is the path loss exponent.

Based on the results in [11–13], the SINR of the $k$–th BS is expressed as

$$\text{SINR}_k = \frac{h_k^{\alpha} P_k}{\sigma^2 + I_k},$$

where $h$ is the channel fading assumed to be an exponentially distributed random variable with parameter $\mu (\mu > 0)$ [14], $\sigma^2$ is the noise power in wireless channels.

As a consequence, the coverage radius $r_k$ is derived as

$$\text{SINR}_k = \frac{h_k^{\alpha} P_k}{\sigma^2 + I_k} = T \Rightarrow r_k = \left(\frac{h_k P_k}{T (\sigma^2 + I_k)}\right)^{\frac{1}{\alpha}}. \quad (3)$$

Furthermore, the cumulative distribution function (CDF) of the coverage radius $r_k$ is expressed as

$$F_{r_k}(r) = \mathbb{P}(r_k < r) = \mathbb{P}(h < \frac{T (\sigma^2 + I_k) r^\alpha}{P_k}) = 1 - e^{-\frac{\mu T (\sigma^2 + I_k) r^\alpha}{P_k}}. \quad (4)$$

Moreover, the probability density function (PDF) of the coverage radius $r_k$ is expressed as

$$f_{r_k}(r) = \frac{dF_{r_k}(r)}{dr} = \alpha \mu T (\sigma^2 + I_k) r^{\alpha-1} e^{-\frac{\mu T (\sigma^2 + I_k) r^\alpha}{P_k}}. \quad (5)$$

In the end, the required computing resources of the $k$–th BS is derived as

$$f_k^{BS} = \int_0^{r_M} f_{UE} f_{r_k}(r) 2 \pi r dr = 2 f_{UE} \rho e^{\alpha \mu T (\sigma^2 + I_k)} \int_0^{r_M} r^{\alpha-1} e^{-\frac{\mu T (\sigma^2 + I_k) r^\alpha}{P_k}} dr. \quad (6)$$

III. ALLOCATION SOLUTION OF COMPUTING RESOURCE

Based on the potential game theory, a computing resource allocation solution is proposed in this section to reduce energy consumption and improve computing resource efficiency in MEC networks. The computing resource allocation solution includes two parts: the first part is the power control scheme based on the potential game theory and the second part is the computing resource allocation scheme based on linear programming.

A. Power Control Scheme Based on Potential Game

1) Game Formulation: In this paper the power control problem is modeled as an exact potential game model. In this exact potential game model, related utility function of BSs and potential function of the MEC networks are shown below.

The proposed game model is denoted as $\Gamma = \{B, P = \{P_k\}_{k \in B}, \{u_k\}_{k \in B}\}$, where $B$ is the set of players, $P$ is the strategy vector of which the element $P_k$ denotes the transmit power of the player $k$. For the MEC networks, the power control problem can be described as

$$P^* = \arg \max_P (\Phi(P)), \quad (7)$$

where $\Phi(P)$ is the potential function of the MEC networks, which represents the attainable maximum required computing resources considering interfering BSs.
Potential game is a common game in communication networks. A game can be regarded as the potential game if the influence on the global utility caused by the change in players’ strategy is modeled as a single global function. Such single global function is regarded as the potential function.

The expression of an exact potential game in [15] is given as

\[ \Phi(t_i^t, t_{-i}^t) - \Phi(t_i^t, t_{-i}^t) = u(t_i^t, t_{-i}^t) - u(t_i^t, t_{-i}^t), \]  \hspace{1cm} (8)

where \( t_i \) is the strategy of player \( i \), \( t_{-i} \) is the strategy of all players except \( i \). \( \Phi(t_i^t, t_{-i}^t) \) is the potential function of MEC networks, which denotes the overall benefit of the MEC networks. As the player’s individual utility function, \( u(t_i^t, t_{-i}^t) \) denotes individual benefit of each BS. According to (8), the increment of the potential function of the MEC networks is equal to the increment of the individual utility function of one player, caused by the change in the strategy of the player.

Based on [16], the individual utility function represents the difference between the potential function and cost of the MEC networks.

The benefit of the \( k-th \) BS in the MEC networks is denoted as the attainable maximum required computing resources with no interference, which is expressed as

\[ f_{k, max}^{BS} = 2f_{UE}P_k \frac{\alpha \mu T \sigma^2}{P_k} \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_k} r^\alpha} dr. \]  \hspace{1cm} (9)

The cost of the \( k-th \) BS consists of two parts. One is the reduction of the required computing resources caused by the existence of the \( m-th \) BS \((m \neq k)\), denoted as \( I_{k,m} \). The other part is the reduction of the required computing resources considering the interference received by the \( m-th \) BS from the \( k-th \) BS, denoted as \( I_{m,k} \). Based on (6), \( I_{k,m} \) is expressed as

\[ I_{k,m} = 2f_{UE}P_k \frac{\alpha \mu T \sigma^2}{P_k} \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_k} r^\alpha} dr - \left( \alpha^2 + P_m R_{mk}^{\alpha} \right) \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_k} r^\alpha} dr, \]  \hspace{1cm} (10)

where \( P_m \) is the transmit power of the \( m-th \) BS, and \( R_{mk} \) is the distance between the \( m-th \) BS with the \( k-th \) BS. And the estimated reduction of the required computing resources of the \( m-th \) BS caused by the \( k-th \) BS is expressed as

\[ I_{m,k} = 2f_{UE}P_k \frac{\alpha \mu T \sigma^2}{P_m} \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_m} r^\alpha} dr - \left( \alpha^2 + P_k R_{km}^{\alpha} \right) \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_k} r^\alpha} dr, \]  \hspace{1cm} (11)

where \( R_{km} \) is the distance between the \( k-th \) BS and the \( m-th \) BS. And \( R_{km} = R_{mk} \).

Furthermore, the utility function of the \( k-th \) BS can be expressed as

\[ u(t_k, t_{-k}) = 2f_{UE}P_k \frac{\alpha \mu T \sigma^2}{P_k} \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_k} r^\alpha} dr + \frac{\varepsilon}{K-1} \sum_{m \in B, m \neq k} (I_{k,m} + I_{m,k}), \]  \hspace{1cm} (12)

where \( \varepsilon \) is a constant for balancing required computing resources with interference.

The potential function (i.e. overall benefit of the MEC networks) weighted sum of individual utility functions of all BSs, expressed as

\[ \Phi(P) = \sum_{k \in B} \left( 2f_{UE}P_k \frac{\alpha \mu T \sigma^2}{P_k} \int_0^{\tau_M} r^\alpha e^{-\frac{\alpha \mu T \sigma^2}{P_k} r^\alpha} dr - \frac{\varepsilon}{K-1} \sum_{m \in B, m \neq k} (I_{k,m} + I_{m,k}) \right), \]  \hspace{1cm} (13)

where \( b \) is a constant for building exact potential game.

Based on (12) and (13), the game is proved to be an exact potential game in the appendix. Monderer and Shapley demonstrated the theorem that each finite potential game has at least one pure strategy NE [17]. The theorem guarantee the existence of NE for the exact potential games [18].

2) PSO Based Potential Game: The particle swarm optimization (PSO) algorithm is proposed to solve the potential game in Algorithm 1.

Each particle in PSO algorithm represents a solution to a specific problem. In other words, a particle is a point in a multi-dimensional search space in which we are attempting to find an optimal location with respect to a fitness function [19]. Parameters of PSO algorithm include group number \( N \), maximum iteration number \( Ger \), inertia weight \( \omega \), self-learning factor \( c1 \), group learning factor \( c2 \) and search dimension \( d \) which is equal to the total number of BSs. The notations in the PSO algorithm are shown in Table I [19].

| Symbols | Meanings |
|---------|----------|
| \( x \) | A set of positions (states) of N particles |
| \( x_i \) | The position of particle \( i \), which is a set of BSs’s transmit power |
| \( U_i \) | The current fitness of particle \( i \) |
| \( ppm \) | The historical optimal position of particle \( i \) |
| \( Upm \) | The historical optimal fitness of particle \( i \) |
| \( gpm \) | The historical optimal position of group |
| \( Ugpm \) | The historical optimal fitness of group |

B. Computing Resource Allocation Scheme Based on Linear Programming

In this section, we discuss the classification of the results obtained in the proposed PSO algorithm. The actually allocated computing resources at the \( k-th \) BS is denoted as \( s_k \). The computing resources required by the \( k-th \) BS \( f_k \) can be calculated based on (6) and the optimal power control scheme. \( S \) indicates the total number of computing resources owned by the MEC server. The classification is discussed as follows.

1) \( \sum_B f_{BS} \leq S \), indicates that the total number of computing resources required by all BSs is less than or equal to the total number of actual computing resources. Then \( s_k^{BS} = f_k^{BS}, \forall k \in B \), the required computing resources of each BS can be satisfied.

2) \( \sum_B f_{BS} > S \), indicates that the total number of computing resources required by all BSs is more than the total number of actual computing resources.
To solve this problem, the resource allocation coefficient is proposed in this paper, which denotes the ratio of the actually allocated computing resources to the required computing resources. The resource allocation coefficient is denoted as \( Sat = \frac{1}{K} \sum_{k \in B} \frac{s_k^{BS}}{f_k^{BS}} \). In order to maximize the average computing resource allocation coefficient, a specific linear programming problem is formulated as

\[
\text{max } Sat = \frac{1}{K} \sum_{k \in B} \frac{s_k^{BS}}{f_k^{BS}} \text{ s.t. } \begin{cases} \sum_{k \in B} s_k^{BS} \leq S \\ 0 \leq s_k^{BS} \leq f_k^{BS}, \forall k \in B \end{cases}.
\]

### Algorithm 1 PSO algorithm based on potential game

1. **Input:** Total number of base stations \( K \); maximum transmit power of BSs \( P_{max} \); users density \( \rho \); unit user required computing resources \( f_{UE} \); maximum coverage radius of BSs \( r_M \); total number of computing resources \( S \).
2. Initialize the swarm randomly
3. for each particle \( i \) in the search space do
4. 1) Initialize feasible position and velocity
5. 2) Set position information \( ppm, Uppm, gpm \) and \( Ugpm \)
6. 3) Set the lower bound and upper bound of each parameter
7. end for
8. while maximum iterations is not attained do
9. for each particle \( i \) do
10. 1) Calculate fitness value \( U_i \)
11. 2) Update \( Uppm, ppm, Ugpmp \) and \( Ugpm \)
12. if \( U_i > Uppm \) then
13. \( Uppm = U_i \)
14. if \( U_i > Ugpm \) then
15. \( Ugpm = U_i \)
16. \( gpm = x_i \)
17. end if
18. end if
19. end for
20. for each particle \( i \) do
21. 1) Calculate particle velocity: \( v = \omega \cdot v + c_1 \cdot \text{rand()} \cdot (ppm - x) + c_2 \cdot \text{rand()} \cdot (gpm - x) \)
22. 2) Update particle position: \( x = x + v \)
23. end for
24. end while
25. **Output:** \( gpm \) and \( Ugpm \)

### IV. Simulations And Result Analysis

In this section, the proposed computing resource allocation solution is simulated in a grid-based system. The simulation results of the proposed solution are analyzed and compared with the reference solution. Reference solution 1 is the classical equal allocation solution \([20]\), reference solution 2 is \( s_k^{BS} = \min(f_k^{BS}, S/K) \).

The 100m \( \times \) 100m square zone as the simulation scenario. And the main simulation parameters are shown in Table II \([21] [22] [23] [24]\).

![Fig. 2. Average utility function with respect to the BS density considering different path loss exponent.](image1)

![Fig. 3. Average computing resource efficiency with respect to the BS density considering different path loss exponent.](image2)
A computing resource allocation solution for MEC networks is proposed in this paper. The optimization model is constructed, and the potential game theory is explored to guarantee the convergence of utility function. This solution includes the power control scheme based on potential game theory and the resource allocation scheme based on linear programming. Finally, the proposed computing resource allocation solution is evaluated by using a grid-based system. Simulation results show that compared with traditional solutions, the computing resource utilization and energy efficiency of the proposed computing resource allocation solution are significantly improved. So the proposed computing resource allocation solution is applicable under energy saving scene. We hope that the computing resource allocation solution proposed in this paper can promote the development of saving energy and computing resource allocation in MEC networks in the future.
= 2f^{UE} \rho \pi \alpha T \frac{\sigma^2}{P_k} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
+ \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} P_k \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
+ \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
- \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
- \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
= u(t_k', t_k) - u(t_k, t_k)

Since the items other than the first four items are not related to \( k \), we can ignore them in the next calculation.

\[
\Phi(t_k', t_k) - \Phi(t_k, t_k) = 2f^{UE} \rho \pi \alpha T \frac{\sigma^2}{P_k} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
+ \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} P_k \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
+ \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
- \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
- \epsilon \frac{1}{K-1} \sum_{m \in B, m \neq k} \sigma^2 + P_m R_m^{-\alpha} \int_0^T r_\alpha e^{-\frac{\mu T^2 r_\alpha^2}{\sigma^2}} dr \\
= u(t_k', t_k) - u(t_k, t_k)
\]

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