A multi-objective optimization MEC task hierarchical offloading system based on SWIPT

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ABSTRACT

As a new framework mode, the Mobile Edge Computing (MEC) can overcome the problems of energy limitation and long delay in the operation of equipment by combining with simultaneous wireless information and power transfer (SWIPT). In this paper, we propose a SWIPT-MEC task hierarchical offloading model based on multi-objective optimization. The purpose is to offload different computing tasks to different MEC offloading levels through multi-objective optimization, so that the equipment can effectively reduce the consumption of energy and time in the face of computing task intensive scenes. Based on this model, a multi-objective MEC hierarchical optimization offloading strategy is proposed by using multi-objective optimization improved strength Pareto evolutionary algorithm 2 (SPEA2). The results of simulation experiments demonstrate that the multi-objective MEC task hierarchical offloading strategy can reduce the energy consumption rate and time consumption rate of the equipment during the offloading process.

Keywords: Mobile edge computing, simultaneous wireless information and power transfer, multi-objective optimization, improved strength Pareto evolutionary algorithm

1. INTRODUCTION

To tackle the computing capability limitations, computation offloading through mobile edge computing (MEC) or the more general concept of fog computing has attracted a lot of attention in recent years[1]. In short, mobile edge computing deploys the server to the edge node near the user to provide services to the user at the network edge (such as wireless access point), avoiding long-distance data transmission and providing users with faster response[2]. The MEC offloading strategy in single-user mode can effectively solve the problem of resource management in the process of computing tasks performed by mobile devices, and can improve the resource utilization efficiency of mobile devices.

In current studies, many scholars have carried out in-depth and extensive research on single-user MEC offloading from two aspects of the computation delay and energy consumption of mobile devices. Reference[3] considers computation offloading strategy optimization with multiple heterogeneous servers in mobile edge computing, the average response time, average energy consumption and cost performance ratio of the system are optimized respectively. The offloading scheduling strategy and power allocation of multiple independent computing tasks in a single-user MEC system are studied, and the optimal task offloading scheduling strategy and the trade-off relationship between system delay and energy consumption are determined[4].

However, the slow development of battery technology, and the manual replacement or charging of battery leads to frequent interruption of wireless equipment[5]. The simultaneous wireless information and power transfer (SWIPT) technology uses the characteristics of radio frequency (RF) signals carrying energy and information at the same time, so that nodes can collect energy while receiving information[6]. Each mobile device has two sets of antennas, which are used to transmit computing tasks and receive energy respectively[7]. And it allows partial offloading, so that local computing and offloading can exist at the same time, which improves the offloading efficiency

The MEC offloading strategy in single-user mode can effectively solve the problem of resource management in the process of computing tasks performed by mobile devices, and can effectively improve the resource utilization efficiency of mobile devices. In this paper, a hierarchical task offloading architecture and optimization algorithm based on multi-

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objective optimization SPEA2 are proposed for SWIPT, which effectively balances the low energy consumption and low time consumption of MEC offloading.

Our paper has the following contributions compared with the other related researches.

- A multi-objective SWIPT-MEC task hierarchical offloading architecture and mathematical model with single-user are constructed to improve the execution efficiency of the equipment in the scenario of intensive computing tasks;
- In order to weigh the conflicting relationship between time consumption and energy consumption, a hierarchical task offloading optimization strategy based on multi-objective optimization SPEA2 is designed.
- Experiments verify the effectiveness of the task hierarchical offloading optimization strategy.

2. SYSTEM MODEL

In this paper, we design a SWIPT-based MEC model, which includes an access point, a mobile device and a MEC server, as shown in Figure 1. In this model, we can divide the task into local computation, normal level offloading computation and optimized level offloading computation based on different task conditions. The AP can transmit relevant signal information and energy to the mobile device. Different channels are selected for energy transmission and information transmission, and more accurate channel states information (CSI) can be estimated at the beginning of transmission.

Figure 1. SWIPT-based MEC system.

The mobile device contains N computing tasks. At the beginning, each task $I \in \{1,2\cdots,N\}$ can be defined, and it contains the following initial instruction U

$$U = \{u_i | u_i \in \{0,1\}, \forall i \in N\} \tag{1}$$

where u_i is generated randomly. $u_i = 1$ represents that the mobile device will offload the computing task to the normal level of MEC offloading computing. $u_i = 0$ represents that the task to local computation. At the beginning of the task, the computation task length can be expressed as Q_i(bit). Compared with the size of the computation task, the size of the computation result can be ignored, so we do not consider the time consumption and energy consumption of the computation result return. For a locally computation task, the CPU calculation ability is written as X_i.

2.1. Local computing

When $u_i = 0$ represents that the task to local computation. The time consumed by the mobile device to perform local computation can be expressed as

$$T_i^{LC} = \frac{Q_i \times X_i}{f_i} \tag{2}$$

where f_i represents the CPU clock frequency when the mobile device processes a computing task.

$$f_i \in [f_{min}, f_{max}] \forall i \in N \tag{3}$$

In the process of executing local computation, and according to reference[8], the energy consumption per CPU cycle can be written as

$$e^{LC} = k \times (f_i)^2 \tag{4}$$

where $\mathrm{k} = 1 \times 10^{-24}$ represents the relationship constant between the energy consumption per CPU cycle and the CPU execution frequency. Therefore, the mobile device's energy consumption can be expressed as

$$E_i^{LC} = e^{LC} \times Q_i \times X_i \tag{5}$$

We assume that there are two constants t^b and h^b, which represent the maximum allowable delay and standard energy value of each computing task respectively. When T_i^{LC} and E_i^{LC} meet the determination conditions for the two constants, the computing task executed locally is offloaded to the MEC optimization level for computation.

2.2. Computation offloading

When u_i = 1 (or when performing optimized level offloading computation) represents that the task to computation offloading. We assume the channel bandwidth as ω.R_i represents the transmission rate of the channel. According to reference[9], it is denoted as

$$R_i = \omega\, log_2\left(1 + \frac{h_i \times p_i}{\sigma^2}\right) \tag{6}$$

where h_i represents the channel gain of the transmission channel, σ^2 represents the noise power of the receiver, p_i represents the transmission power of the computing task during offloading

$$p_i \in [p_{min}, p_{max}] \forall i \in N \tag{7}$$

The time when the mobile device sends a task to the MEC server can be written as

$$T_i^{CO} = \frac{Q_i}{R_i} \tag{8}$$

Sending information process energy consumption can be expressed as

$$E_i^{CO} = p_i \times T_i^{CO} \tag{9}$$

2.3. MEC server computation

In order to efficiently process a certain number of tasks, the MEC server processing mechanism is divided into two processing levels: optimization level and normal level. Depending on the processing level of offloading, different offloading instructions X are assigned to tasks

$$X = \{x_i | x_i \in \{0,1\}, \forall i \in N\} \tag{10}$$

where $x_i = 0$ represents that the task is offloaded to the normal level. $x_i = 1$ represents that the task is offloaded to the optimization level

When the computing task is executed locally, if $T_i^{LC} > t^b$ or $E_i^{LC} > h^b$ is satisfied, the mobile device offloads the computing task to the MEC server optimization level for operation, and assigns the task offloading instruction x_i =1. The time of the MEC computing task is

$$T_i^{MC} = \frac{Q_i \times X_i}{F_i} \tag{11}$$

where F_i represents the CPU clock frequency of the MEC server processes the calculation task

$$F_i \in [F_{min}, F_{max}] \forall i \in N \tag{12}$$

The normal level is for computing tasks that process the initial instruction u_i = 1. In order to simplify the model, the total time consumed by the process is the maximum allowable execution time t^b of the current computing task.

2.4. Energy harvesting

In this paper, we use the SWIPT scheme to harvest energy, which is collected before each computing task. We use the downlink to transmit energy for mobile devices. According to reference[10], the energy received by the mobile device can be defined as

$$E_i^H = v \times \left(p_i^{DL} \times t_i^b \times h_i^{EH} + \sigma^2\right) \tag{13}$$

where ν denotes the energy absorption rate of mobile device, p_i^{DL} represents the maximum downlink power, h_i^{EH} represents the channel gain of energy collected by the mobile device. We assume that the channel is fixed and the channel gain remains unchanged for a period of time. We use B_i to represent the current battery power. Assuming that there is no upper limit on the battery power, the current power is

$$B_i = B_i + E_i^H \tag{14}$$

2.5. Problem formulation

In order to maximize the balance between the energy consumption and time consumption of mobile devices in the computation process, a multi-objective MEC task hierarchical offloading mathematical model is constructed for the local computing frequency, task transmission power and MEC server computing frequency according to the MEC task hierarchical offloading architecture shown in Figure 1, the objective functions can be expressed as P1 and P2,

$$\textbf{P1}\text{: } \min_{f_i, p_i, F_i} \sum\nolimits_{i \in N} \frac{(1-u_i)\times T_i^{LC} + u_i \times \left(x_i \times \left(T_i^{CO} + T_i^{MC}\right) + (1-x_i) t^b\right)_i}{t^b}$$

s.t. (1), (3), (7), (12)

$$T_i^{LC} \le t^b \tag{15}$$

$$T_i^{CO} + T_i^{MC} \le t^b \tag{16}$$

where P1 represents the problem of minimizing time consumption. The constraints (15) and (16) represent the local computation and offload computation time are less than the maximum tolerable time of the task.

$$\textbf{P2}\text{: } \boldsymbol{\min_{f_i, p_i, F_i} \sum\nolimits_{i \in N} 1 - \frac{B_i - (1-u_i)\times E_i^{LC} + u_i \times E_i^{CO}}{B_i}}$$

s.t. (1), (3), (7), (10), (12)

$$E_i^{LC} \le B_i + E_i^H \tag{17}$$

$$E_i^{CO} \le B_i + E_i^H \tag{18}$$

where P2 represents the problem of minimizing energy consumption. The constraints (17) and (18) represent the of energy are less than the current battery power. B_{i+1} represents battery power at the beginning of the next task

$$B_{i+1} = B_i - (1-u_i) \times E_i^{LC} + u_i \times E_i^{CO} \tag{19}$$

3. A MULTI-OBJECTIVE OPTIMIZATION ALGORITHM FOR TASK OFFLOADING IN MEC

To solve the task offloading described in task intensive scenarios， we propose a multi-objective task hierarchical offloading mode. By effectively dividing the offloading level and selecting a reasonable optimization algorithm, the relationship between energy consumption and time consumption is weighed to improve the execution efficiency of the system. The offloading strategy can be described as follows:

STEP1: initialising i = 0;

STEP2: Performing equipment computation tasks;

STEP3: Determining the variable u_i, selecting local computation or offloading to normal level computation;

STEP4: By SPEA2 algorithm to optimize the local computing frequency and task transmission power;

STEP5: Determining the time and energy consumption of local computation, selecting local computation or offloading to optimization level computation;

STEP6: By SPEA2 algorithm to optimize the computation frequency and task transmission power of server.

In order to solve the conflict between the P1 and the P2, we use a multi-objective optimization SPEA2 algorithm[11] to optimize the objective function. The algorithm of SPEA2 is described in Algorithm 1.

In this paper, the two objective functions P1 and P2 are combined into a matrix of 1×2, and the number of rows of the matrix is determined as the size of the initial population P_0, i.e., $N = 1$. At the same time, a zero matrix with size 1×1 is constructed as the Pareto optimal set $\overline{P}_0$ of the external file, and the intensity value assigned in combination with the number of individuals in the set is $S(i)$:

$$S(i) = |\{j | j \in P_t + \overline{P_t} \wedge j < i\}| \tag{20}$$

According to the value of S, the individual's original fitness R(i) is updated and the individual's original fitness $R(i)$ is calculated

$$R(i) = \sum_{j \in P_t + \overline{P_t}, j > j} S(i) \tag{21}$$

The density $D(i)$ of each individual is calculated

$$D(i) = \frac{1}{\sigma_i^k + 2},\ k = \sqrt{N + \overline{N}} \tag{22}$$

where $\overline{N}$ and N are determined by the number of objective functions, and the final individual fitness value $F(i)$ is got

$$F(i) = R(i) + D(i) \tag{23}$$

According to the calculated fitness value, environmental selection is carried out. The individuals who meet the selection conditions are put into the mating pool to perform crossover and mutation operations. After completing the relevant steps, the above steps are iterated to complete the relevant iterations, and the optimal solution of the function that satisfies the application conditions is obtained.

Algorithm 1. SPEA2 algorithm

1. Initialization: Generate an initial population *P0*, set $\overline{P_0} = 0$, $t = 0$;
2. Update the external Pareto optimal set
   a. Find non-dominated individuals in the population and copy them to the external Pareto set
   b. Find the external Pareto set of non-dominated individuals.
   c. If $(\overline{P_{t+1}}) < \overline{N}$ (already specified external pareto set size). Then, $|\overline{P_{t+1}}| = \overline{N}$.
   d. If $(\overline{P_{t+1}}) > \overline{N}$,Then delete the individual in $(\overline{P_{t+1}})$ until $|\overline{P_{t+1}}| = \overline{N}$.
3. Compute the fitness values of P_t and $\overline{P_t}$;
4. Select the better one and copy it to the mating pool.
5. Perform crossover and mutation operations in the mating pool.
6. Determine the end standard and end the operation when the standard is met.

4. SIMULATION AND RESULT ANALYSIS

We present the numerical results obtained by our MATLAB simulations, which combined with PlatEMO optimization platform[12]. The simulation parameters have been shown in Table 1. In order to facilitate data comparison, all experimental results are normalized.

In order to prove the superiority of the model we designed, we analyzed the system from two aspects: the number of computing tasks (Figure 2) and the length of computing tasks (Figure 3). Figure 2 shows the relationship between the number of tasks and the rate of time and energy consumption. In Figure 2a, we can see that the time consumption rate decreases with the increase of the number of tasks, because the number of tasks involved in optimization increases with the increase of the number of tasks. At the same time, the time consumption rate of MEC hierarchical optimization offloading model is lower than the model of without optimization level.

Table 1. Simulation parameters.

Parameter	Value	Parameter	Value
Number of tasks (N)	40-140	Minimum CPU frequency of mobile device (f_{min})	1 (Hz)
Channel bandwidth (ω)	1.25×10^5 (Hz)	Maximum CPU frequency of mobile device (f_{max})	2×10^8 (Hz)
Noise (σ^2)	10^{-13} (W)	Minimum CPU frequency of MEC (F_{min})	1 (Hz)
Bit length of the task (Q_i)	1000-1500 (bit)	Maximum CPU frequency of MEC (F_{max})	5×10^8 (Hz)
Operational capability (X_i)	1000 cycles/bit	Channel gain (h_i)	0.01
Downlink power (p_i^{DL})	2.5 (W)	Battery initialization charge (B)	10 (J)
Minimum transmission power (p_{min})	0.5 (W)	Energy absorption rate (ν)	100
Maximum transmission power (p_{max})	0.6 (W)	Tolerance time (t^b)	0.01 (s)

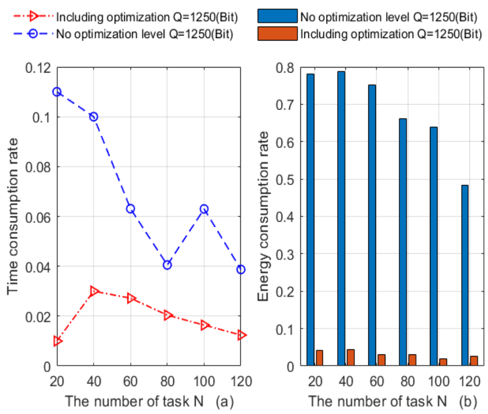

Figure 2. Impact of varying task quantities on the model.

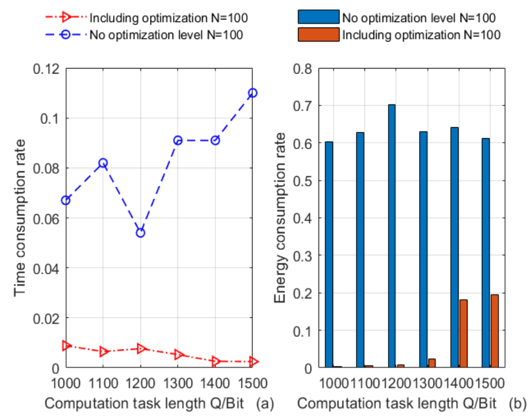

Figure 3. Impact of different task lengths on the model.

In Figure 2b, we can find that the energy consumption rate of the system decreases as the number of tasks increases. It is proved that the proposed algorithm can reduce the energy consumption rate of the equipment while reducing the time consumption rate of the equipment. In particular, the energy consumption rate of MEC hierarchical optimization offloading model is lower than the model of without optimization level.

Figure 3 shows the relationship between the SWIPT-based MEC mode time consumption rate and energy consumption rate and the task lengths. Figure 3a shows that the time consumption rate of MEC hierarchical optimization offloading model under different task lengths is lower than that of the offloading model without optimization level. At the same time, the time consumption rate of MEC hierarchical offloading model decreases with the increase of task length, which verifies the superiority of the system. In Figure 3b, we can see that the offloading model without optimization level has stable energy consumption rate in different task lengths. However, the energy consumption rate of MEC hierarchical optimization offloading model is too low when dealing with tasks with small task length, which can prove the rationality of the proposed model.

5. CONCLUSION

In this work, we have developed a SWIPT-MEC task hierarchical offloading architecture based on multi-objective optimization. In particular, we combined with SPEA2 algorithm, which can achieve multi-objective optimization with minimum energy consumption and time consumption of MEC system. The simulation results shows that the proposed model and the optimization algorithm can effectively solve the trade-off between energy consumption and time consumption when there are many computing tasks.

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