Joint Delay and Energy Optimization for WPT-MEC System Based on Immune Algorithm

Lu Sun[1], Dianju Li[1], Hao Lu[2,3], Liangtian Wan[4(✉)], Jianbo Zheng[3,5(✉)], and Xianpeng Wang[6]

[1] Department of Communication Engineering, Institute of Information Science Technology, Dalian Maritime University, Dalian 116026, China
{sunlu,1120210225li}@dlmu.edu.cn

[2] City University of Macau, Macau, China

[3] Guangdong-Hong Kong-Macao Joint Laboratory for Emotional Intelligence and Pervasive Computing, Shenzhen MSU-BIT University, Shenzhen 518172, Guangdong, China

[4] School of Software, Dalian University of Technology, Dalian 116620, China
wanliangtian@dlut.edu.cn

[5] Artificial Intelligence Research Institute, Shenzhen MSU-BIT University, Shenzhen 518172, Guangdong, China
jianbo.zheng@smbu.edu.cn

[6] School of Information and Communication Engineering, Hainan University, Haikou 570228, China
wxpeng2016@hainanu.edu.cn

Abstract. In some production workshops, because the space is too small to be suitable for the layout of the equipment charging device, the joint application of mobile edge computing (MEC) and wireless power transfer (WPT) can solve such problems. However, this scenario has a double near-far effect that is unfair to terminal devices far away from edge servers and energy transfer stations, so this paper considers relay collaboration among devices when computing offloading. This paper uses the frequency division multiple access (FDMA) technology to enable multiple terminals to perform tasks offloading simultaneously. In this paper, the total communication delay and total energy consumption of the system are optimized through effective computing resources scheduling and reasonable tasks allocation, which is a weighting and minimizing problem of normalized system delay and energy consumption rate, and also a NP-hard problem. This paper improves the immune algorithm (IA) in the scenario of multi-server and multi-terminal to obtain the Q-IADE algorithm. The improved Q-IADE algorithm not only has the characteristics of wide application, but also further improves the global search

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ability, which can better solve the problems we raised. Finally, the simulation results show that the proposed Q-IADE algorithm has strong global search ability and stable convergence effect, and the algorithm performance is superior to the other three comparison algorithms, especially when relay offloading can be performed.

Keywords: WPT-MEC · FDMA · Relay collaboration · IA

1 Introduction

In the context of the era of the Internet of Everything, the data types generated by the devices at the edge of the network are varied, and the data is also generated all the time, but the amount of these data is actually much smaller than the amount of tasks that need to be transmitted to the cloud computing in the era of centralized big data processing, and the real-time requirements of the network edge devices for data processing are very high, so the tasks that originally need to be transmitted to the cloud computing are migrated to the edge cloud near the device terminal for processing, which can improve the data transmission performance to ensure the real-time processing.

Because the batteries of edge devices are limited, how to provide sustainable energy supply for edge devices is a major challenge in the era of the Internet of Things. Of course, we can use wired charging for it, but in many cases, wired charging is unlikely or inconvenient [1–4]. In order to overcome this bottleneck of limited battery of network edge devices, the wireless power transfer (WPT) technology is combined with mobile edge computing (MEC) to form a WPT-MEC system.

However, if the energy station and the edge cloud server are configured together, there is a "double near-far effect" in the multi-node WPT-MEC system [5], under the influence of this effect, the terminals close to the energy station will have better channel conditions, which means that the terminals farther away from the energy station collect less energy but consume more energy from/to the edge cloud.

In summary, the WPT-MEC system has received widespread attention from the academic community both domestically and internationally. However, there is currently very little research on the application of intelligent evolutionary algorithms for resource allocation methods in WPT-MEC systems where multiple user devices can collaborate with each other.

The major contributions of this paper are as follow:

1) We propose a WPT-MEC model that takes into account the double near-far effect.
2) We propose a scheme for multi-terminal relay cooperation to overcome the double near-far effect.
3) We select Immune Algorithm(IA) as a resource allocation algorithm for this model and we propose a improved Q-IADE algorithm to improve the performance of IA. In this algorithm, we improve the local search capability and dynamic programming performance of IA.

The main structure of the paper is as follows: Sect. 2 is related work in this area. Section 3 is the model for multi-device relay cooperation WPT-MEC system model. Section 4 is the description for the promotion of Q-IADE. Section 5 gives the simulation experiments. Section 6 is the conclusion of this paper and the future work.

2 Related Works

The literature [6] proposes a multi-user MEC system, there is also a "double near-far effect", which is clearly unfair to distant devices. The literature [7] proposes a WPT-MEC system with only two mobile devices. And experiments have shown that the offloading of remote mobile devices by relay will have lower total emission energy and better performance than APs without cooperative systems. The literature [8] also takes into account the "double near-far effect", but the authors do not take into account the computing power of the mobile device itself, that is, the data tasks can only be completely offloaded. The literature [9] proposes a pricing mechanism based on dual-user collaboration. However, the authors only studied distant devices in the article, simplifying the task situation of nearby devices.

The system models described in the above literature show that the impact of the "double near-far effect" on remote device nodes in the WPT-MEC system cannot be ignored, and there is a lack of research on the existence of multiple device terminals in the WPT-MEC system of inter-user collaboration.

The authors design an iterative algorithm by using the Lagrange dual method [6]. The literature [7] is to obtain the optimal energy transmission power by the bisecting search algorithm. The literature [5] uses the Dinkelsbach method to transform the studied problem into a convex optimization problem. The authors use the classical Lagrange method, Newtonian iterative method and subgradient algorithm to obtain the optimal solution of the convex optimization problem [8]. The literature [10] cleverly uses mathematical methods to directly solve nonconvex problems. The literature [11] uses variable substitution and semi-definite relaxation to transform the original problem into a convex optimization problem, and then obtains the optimal solution by the Lagrange method. The literature [12] designs an unloading algorithm based on the process of merging and splitting. The paper [13] uses the equivalent substitution method to convert the problem into a convex optimization problem, and then use the Lagrange method to find solution. The literature [14] designs a neural model to learn the offloading and time-division decisions of each time slot. The literature [15] designs a framework to support federated learning in the WPT-MEC system.

From the above literature, it can be seen that most of the algorithms used to solve resource scheduling problems in the WPT-MEC model are traditional optimization algorithms, and the application of scheduling algorithms based on reinforcement learning is still limited. However, traditional optimization algorithms based on mathematical theory, which are based on calculus, make it difficult to get started, and their application scale is small, and the solution results strongly depend on the initial values. However, heuristic algorithms do not require the mathematical properties of solving the target problem.

3 System Model

The system model of this paper is shown in Fig. 1. The system model is mainly composed of a single energy transmitting station, N base stations with integrated mobile edge computing servers and M low-power terminals. The energy station and base stations in the model have stable power supply.

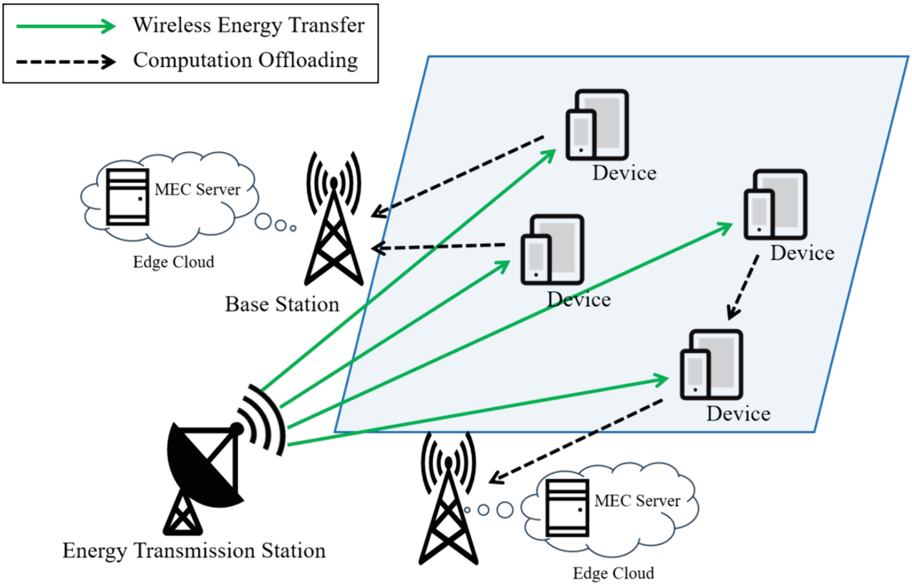

Fig. 1. The overview of system model.

This paper considers the relay collaboration among terminals in the model. This paper applies the Frequency Division Multiple Access (FDMA) technology to the system, that is, the base station can simultaneously receive offloading tasks from M terminals. Figure 2 shows the allocation of time slots. In the first stage, the energy transmitting station wirelessly charges the terminal battery, and this time slot is marked as t_h; In the second stage, the terminal performs task processing. This paper sets the local computation and offloading of the terminal in the model to be possible simultaneously. We mark the time slot for local calculation of terminal i as $t_{loc,i}, i \in \mathbf{M} = 1, 2, ..., M$, and the offloading time slot as t_i. We record the sum of the time between edge server calculations and the return of calculation results as $t_{re} \approx 0$.

This paper assumes that the base station has prior knowledge of channel state information (CSI) between each terminal and the status information of

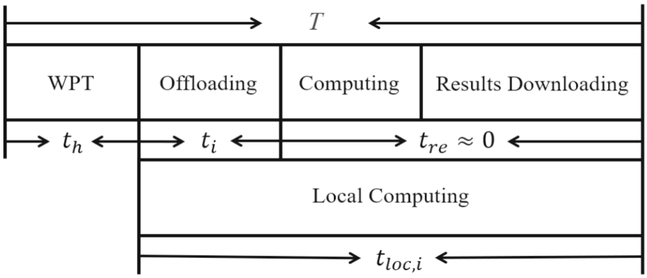

Fig. 2. Time slots allocation within the time block T.

each terminal. This paper adopts a block fading channel model, assuming that the channel state remains unchanged within a time block T, but can change between different time blocks T. In addition, the energy collected by the terminal and the downlink channel gain between the base station and the terminal are both h_i. And the channels have reciprocity. The block fading channel model in the system is $h = 10^{-3}d^{-\alpha}\varphi$, where φ represents short-term fading, where d is the distance, α is the path loss index.

Next, we will continue to introduce the two phases involved in the system model in this paper.

3.1 Energy Harvesting Phase

At the time slot t_h, the energy transmitting station wirelessly charges the terminal. The energy collected by terminal i is

$$E_{har,i} = \eta_i P_0 h_{edo,i} t_h, \forall i \in \mathbf{M}, \tag{1}$$

where η_i represents the energy conversion efficiency of terminal i, and satisfies $0 < \eta_i \leq 1, \forall i \in \mathbf{M}$, P_0 represents the transmission power of the energy transmission station; $h_{edo,i}$ represents the downlink channel gain from the energy transmitting station to terminal i.

Due to the battery capacity $C_{max,i}$ of terminal i is limited, therefore $E_{har,i}$ needs to meet: $E_{har,i} \leq C_{max,i} - E_{res,i}, \forall i \in \mathbf{M}$, where $E_{res,i}$ represents the remaining energy in the terminal i battery before charging.

3.2 Task Data Processing Phase

In this stage, the terminal performs task processing, including two parts: task data offloading and local computing.

3.2.1 Offloading Model

This paper assumes that the task data is bit by bit independent and considers partial offloading. To overcome the dual near far effect, we propose a relay offloading transmission scheme.

According to Shannon's formula, the offloading rate of terminal i task is

$$R_i = B_i \log_2\left(1 + \frac{h_{i,j} a P_i}{\sigma_0^2}\right), \forall i \in \mathbf{M}, \tag{2}$$

where B_i represents the bandwidth occupied by terminal i, as we adopt the FDMA scheme, which affects the total bandwidth B_{max} has constraints: $\sum_{i=1}^{M} B_i \leq B_{max}, \forall i \in \mathbf{M}$, $h_{i,j}$ represents the channel gain that terminal i chooses to offload to the server or other terminal j; P_i indicates the transmission power of terminal i chooses to offload; a is a constant used to constrain the unloading power:

$$a = \begin{cases} 1, \forall J \in \mathbf{N} = \{1, 2, ..., N\}, \\ 0.6, \forall J \in \mathbf{M}, \end{cases} \tag{3}$$

σ_0^2 represents the additive white Gaussian noise power near the offloaded data receiver.

Assuming the total task volume of terminal i is $N_i \geq 0$ bits, the task of $N_{off,i}$ bits needs to be offloaded to edge servers or other terminals, so there are $0 \leq N_{off,i} \leq N_i, \forall i \in \mathbf{M}$,

$$N_{off,i} = R_i * t_i, \forall i \in \mathbf{M} \tag{4}$$

The energy consumption of terminal i for offloading task data is

$$E_{off,i} = aP_i * t_i + P_c * t_i, \forall i \in \mathbf{M} \tag{5}$$

wherein P_c is the constant circuit power consumption of the terminal. $E_{off,i}$ is constrained by the actual remaining energy in the terminal i battery at this time: $E_{off,i} \leq E_{res,i} + E_{har,i}, \forall i \in \mathbf{M}$.

This paper uses q_i represents the CPU revolutions required for terminal i to calculate 1 bit of data. To ensure that the delay in result return can be ignored, assuming there are limitations: $\sum_{i=1}^{M} N_{off,i} * q_i \leq Q, \forall i \in \mathbf{M}$, where Q represents the computing power that the CPU of the edge server.

3.2.2 Local Computation Model

After terminal i offloaded $N_{off,i}$ bits, perform local calculations on the remaining bits:

$$N_{loc,i} = N_i - N_{off,i}, \forall i \in \mathbf{M}, \tag{6}$$

where $N_{loc,i}$ represents the amount of task data for local computation.

Thus, we can calculate the time that terminal i is used for local calculation:

$$t_{loc,i} = \frac{N_{off,i} * q_i}{f_i}, \forall i \in \mathbf{M}, \tag{7}$$

where f_i represents the CPU frequency of terminal i, which cannot exceed the maximum frequency limitations on $f_{max,i}$.

The energy consumption when local computing can be calculated by:

$$E_{loc,i} = N_{loc,i} * q_i * e_i, \forall i \in \mathbf{M}, \tag{8}$$

where $e_i = k_i f_i^2$ represents the energy consumption generated by the CPU of terminal i, k_i represents the effective capacitance coefficient of terminal i.

Similarly, the execution of local calculations by terminal i is limited by energy consumption: $E_{loc,i} \leq E_{res,i} + E_{har,i}, \forall i \in \mathbf{M}$.

Based on the above computing offloading and local calculation processes, there are constraints: $E_{off,i} + E_{loc,i} \leq E_{res,i} + E_{har,i}, \forall i \in \mathbf{M}$.

4 Problem Formulation

The problem studied in this paper is to minimize the weighted sum of the normalized system delay and the normalized system energy consumption rate.

Therefore, the problem can be expressed as a formula:

$$\min_{\forall i \in \mathbf{M}} \beta * \frac{t_h + \max(t_i, t_{loc,i})}{T} + (1-\beta) * \frac{\sum(E_{off,i} + E_{loc,i})}{\sum(E_{res,i} + E_{har,i})} \tag{9}$$

s.t.

$$\begin{aligned}
&C1: 0 < \eta_i \leq 1, \forall i \in \mathbf{M}\\
&C2: E_{har,i} \leq C_{max,i} - E_{res,i}, \forall i \in \mathbf{M}\\
&C3: \sum_{i=1}^{M} B_i \leq B_{max}, \forall i \in \mathbf{M}\\
&C4: 0 \leq N_{off,i} \leq N_i, \forall i \in \mathbf{M}\\
&C5: t_h + t_i \leq T, \forall i \in \mathbf{M}\\
&C6: \sum_{i=1}^{M} N_{off,i} * q_i \leq Q, \forall i \in \mathbf{M}\\
&C7: t_h + t_{loc,i} \leq T, \forall i \in \mathbf{M}\\
&C8: f_i \leq f_{max,i}, \forall i \in \mathbf{M}\\
&C9: E_{off,i} + E_{loc,i} \leq E_{res,i} + E_{har,i}, \forall i \in \mathbf{M}
\end{aligned} \tag{10}$$

In (9), the β represents the weight of the normalized system delay, and its value is 1 with the weight of the normalized system energy consumption rate.

Due to the close coupling relationship between the variables involved in the problem studied in this paper, the problem studied in this paper has become a mixed integer nonlinear programming problem. Obviously, the problem being studied involves multivariate combinatorial optimization, which is limited to a certain range of values, making it a NP-hard problem. To solve this problem, the following algorithm has been designed.

5 The Q-IADE-Based Resource Scheduling Algorithm

Immune algorithm(IA) is a heuristic algorithm designed by scholars inspired by the biological immune system. This paper improves and enhances it. The IA combines the concept and theory of immunity with genetic algorithm, and adds antibody concentration evaluation operators and incentive degree calculation operators to maintain the diversity of individual populations, avoiding the "premature" problem in the general optimization process.

5.1 Searching Ability Improvement

It is difficult for IA to achieve a global optimal position, and as the population iterates, the convergence speed of the algorithm and the accuracy of feasible solutions will also decrease.

The differential evolution(DE) algorithm has the characteristics of strong robustness and fast convergence speed. Therefore, this article takes the mutation, crossover, and selection operators in DE as part of the IA iteration process, allowing them to participate in the antibody cloning operator of IA, thereby enhancing the local search ability of the original IA.

5.2 Relay Selection Optimization

The model in this paper has a relay offloading scheme, which corresponds to the selection of the optimal offloading path. The optimal path selection involves dynamic planning, and although heuristic algorithms can be used to solve it, its actual effect is poor.

In fact, reinforcement learning is developed from dynamic programming, and the most important thing is that dynamic programming is best at dealing with dynamic optimization problems. The Q-learning algorithm is a model-independent reinforcement learning algorithm, which is theoretically supported by Markov's decision-making process. Therefore, this paper intends to use Q-learning to deal with the problem of how to select relay objects, and help us choose the optimal offloading strategy in a given environment.

Compared with heuristic algorithms, reinforcement learning can give full play to the role of information in historical samples. Finally, the pseudocode of the Q-IADE algorithm obtained by improving the IA is shown in Algorithm 1.

In Algorithm 1, t represents the allocation of the time, D represents the location coordinates of the terminals and base stations.

6 Numerical Simulation

In this section, simulation experiments are designed to verify the effectiveness of the proposed algorithm in our model.

In this paper, three newly proposed evolutionary algorithms in the past two years are selected, namely Adaptive Weighting PSO (AWPSO) algorithm, Dung

Algorithm 1. The procedure of Q-IADE.

Input: t, D
Output: the value v of the objective function
while the number of training $<N_1+1$
randomly generate state S
for each action A in $A(S)$
Calculate rewards R and generate Q tables
end for
select the offload-object U_i of individual i
end while
return offloading policy U
while iteration $<N_2+1$
randomly generate population P_0 under the condition of U
calculate the fitness and the similarity between the solution and the solution, and order P_0
for each individual j from 0 to $0.25P_0$
variation,cross,select
end for
for each individual j from $0.25P_0$ to $0.5P_0$
immune manipulation
end for
for each individual j from $0.5P_0$ to P_0
flash P_0
end for
calculate the fitness and the similarity between the solution and the solution, and order P_0
end while
return the value v of the objective function

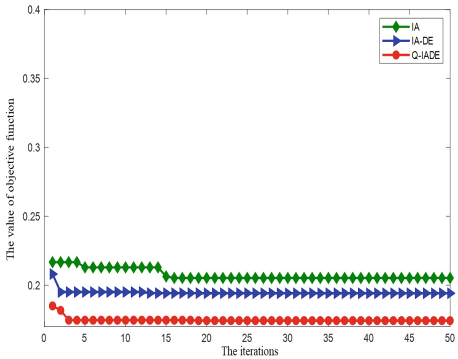

Fig. 3. Comparison of Algorithm Improvement Effects.

Beetle Optimizer (DBO) algorithm and Fire Hawk Optimizer (FHO) algorithm, and compare and simulate to prove the superiority of the proposed algorithm. All emulators are written in the MATLAB programming language.

Figure 3 shows the comparison of the effectiveness of each improvement of IA when the number of base stations is $N = 1$ and the number of terminals is $M = 10$. From the graph, it can be seen that the first improved IA can search for higher quality feasible solutions. After our second improvement on IA, the objective function values further converge and become better.

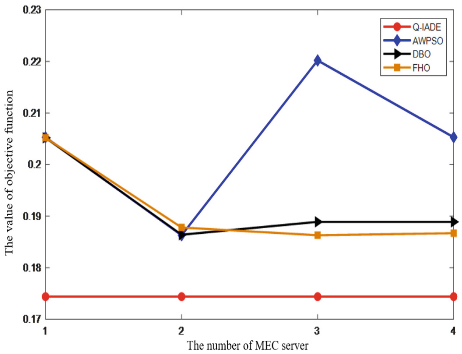

Fig. 4. M=10, the objective function value changes with the number of servers.

Figure 4 shows the comparison of the objective function value and the optimization effect of the number of base stations for four algorithms when the number of terminals is M=10. From the figure, it can be seen that the performance of the Q-IADE algorithm is very stable, which is largely due to the fixed configuration of the terminals in our experiment. It can also be seen that the AWPSO algorithm is the most unstable and prone to falling into local optima.

Figure 5 shows the comparison of the optimization effects of four algorithms on the objective function value and the number of terminals when the number of base stations is $N = 4$. From the graph, it can be seen that our proposed Q-IADE algorithm has the most stable output and better performance compared

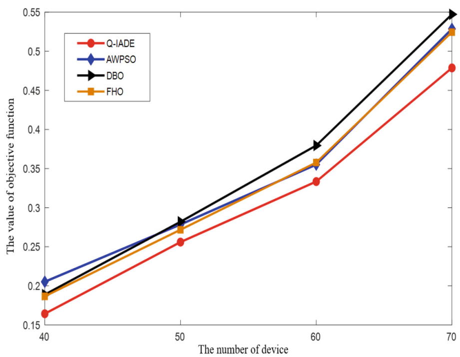

Fig. 5. $M = 10$, the objective function value changes with the number of servers.

to the other three algorithms. In addition, as the number of terminals in the system increases, the performance of the DBO algorithm becomes increasingly weak. Although the performance of the AWPSO algorithm has caught up with the increase in the number of terminals, overall it is still not as good as the FHO algorithm, and the performance of the FHO algorithm is only second to the Q-IADE algorithm.

7 Conclusion

In this paper, we design a WPT-MEC system model with multiple base stations and terminals. In this model, terminals collect energy for task computation, and we use the FDMA technology to achieve simultaneous task offloading for multiple terminals [16,17]. We propose a relay collaborative offloading scheme to overcome the double near-far effect. Our goal is to minimize the weighted sum of normalized system delay and normalized energy consumption rate by jointly optimizing variables such as wireless energy transmission time, offloading time, computing offloading and local computing task allocation, and offloading target selection. In order to improve the solving efficiency, we have improved the immune algorithm and proposed the Q-IADE algorithm. The simulation results show that the performance of our proposed Q-IADE algorithm is superior to other algorithms, and the convergence effect is also more stable. In the future, we will use existing wireless charging devices in actual scenarios to verify the feasibility of our proposed solution and the effectiveness of the Q-IADE algorithm.

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