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Energy-Efficient Task Offloading Based on Differential Evolution in Edge Computing System With Energy Harvesting

YINGYING SUN[1,5], CHUNHE SONG[2,3,4,5], SHIMAO YU[2,3,4,5], YIYANG LIU[2,3,4,5], HAO PAN[1], AND PENG ZENG[2,3,4,5]

[1]College of Information Engineering, Shenyang University of Chemical Technology, Shenyang 110142, China
[2]State Key Laboratory of Robotics, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China
[3]Key Laboratory of Networked Control Systems, Chinese Academy of Sciences, Shenyang 110016, China
[4]Institutes for Robotics and Intelligent Manufacturing, Chinese Academy of Sciences, Shenyang 110169, China
[5]Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China

Corresponding authors: Chunhe Song (songchunhe@sia.cn) and Yiyang Liu (sialiuyiyang@sia.cn)

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ABSTRACT To optimize the energy efficiency of edge computing system with energy harvesting, this paper proposes an energy-efficient task offloading method optimized by differential evolution. First, a wireless edge computing network model is established to analyze the energy harvesting, task offloading and task calculation of the system, as well as the total number of calculated bits and total energy consumption of the system. Second, according to the total number of calculated bits and total energy consumption of the system, an objective function is established to optimize the energy efficiency of system, and a differential evolution based optimization method is proposed, with which the optimal energy efficiency of system calculation, offloading time, calculation time and frequency are obtained. Experimental results show that the proposed method can not only achieve better convergence effect, but also can effectively solve the energy shortage problem of the micro-equipment and extend the service life of the equipment.

INDEX TERMS Edge computing, task offloading, energy harvesting, differential evolutionary algorithm.

I. INTRODUCTION

With the rapid development of mobile communication technology and the continuous popularization of the Internet of Things (IoT), terminal equipment and data are growing explosively. Meanwhile, the IoT industries such as intelligent connected vehicles and autonomous driving, virtual reality, industrial IoT, smart home and smart city are developing rapidly. These emerging industries need to consume a large amount of computing resources to meet their own needs. As an effective solution to improve the energy efficiency of the system, recent years mobile edge computing has attracted great attentions [1]. The main service objects of mobile edge computing are mobile devices, sensors, etc. These devices basically rely on battery power, and when there are a lot of computing tasks to be done in the device, the battery power will be consumed quickly. The miniaturized devices, in particular, generally operate with limited battery power and transmit data over an unlicensed spectrum. The problem of energy shortage limits the service life of the equipment. Owing to some devices are installed in hard-to-reach places, it is difficult for workers to replace the batteries of these devices. Even with sufficient energy supply, data transmission of devices conflicts with other networks that coexist in the unlicensed spectrum band, which creates the spectrum scarcity issue.

There have been many optimization research topics, such as spectrum perception, spectrum access strategy, spectrum management, spectrum decision making, cognitive radio network, etc. [2]–[4]. In the existing cognitive radio models of energy harvesting, the detection rate of spectrum perception is only taken as a fixed parameter, so as to optimize the number of channels, perception time, transmission frequency, etc. To solve the problem of spectrum scarcity, Zhang *et al.* [4]

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proposed the cognitive radio theory to deal with the problem of insufficient spectrum utilization in the way of opportunity access. However, as the number of cognitive wireless devices increases, the demand for power on devices is increasing. The optimization of energy harvesting, storage and distribution of equipment has attracted the attention [5]–[11]. Most of the existing research schemes are based on energy harvesting maximization or computational energy efficiency optimization maximization. To solve these problems, a mainstream method is that, first the objective function to be optimized is designed, and then the non-convex optimization problem is transformed into a convex optimization problem by the generalized fractional programming theory, and then the optimal solution of the objective function can be obtained.

In the model of spectrum sensing and energy harvesting, resource allocation has been one of the focuses of researchers. Reasonable allocation of energy harvesting time, energy transmission time and task offloading can guarantee the communication quality of the whole system. However, with the increase of the number of optimization parameters, the complexity of the solution increases dynamically. Therefore, to overcome this issue, this paper comprehensively considers the limited energy and computing capacity of sensor nodes in wireless communication networks, and proposes an optimization scheme for energy harvesting and task computing based on differential evolution. The main contributions of this paper are as follows:

(1) First, a wireless edge computing network model is established to analyze the energy harvesting, task offloading and task calculation of the system, as well as the total number of calculated bits and total energy consumption of the system.

(2) Second, according to the total number of calculated bits and total energy consumption of the system, an objective function is established to optimize the energy efficiency of system, and a differential evolution based optimization method is proposed, with which the optimal energy efficiency of system calculation, offloading time, calculation time and frequency are obtained.

(3) Third, experimental results show that the proposed method can not only achieve better convergence effect, but also can effectively solve the energy shortage problem of the micro-equipment and extend the service life of the equipment.

The organization of the rest of this paper is as follows. Section II introduces in detail the work related to system computing energy efficiency maximization, summarizes the contributions made by predecessors and analyzes them. Section III expatiates the scheme in detail, builds the system model, and analyzes the model principle. Section IV gives the experimental results and discussion, and Section V gives the conclusion.

II. RELATED WORK

The optimization of energy harvesting, storage and distribution of equipment has attracted the attention of many researchers. Among them, Xu *et al.* [5] proposed a competitive multi-channel multi-level user energy harvesting cognitive radio network, and modeled the existence of primary users through Poisson distribution instead of using spectrum sensing method, so as to model the competitive energy harvesting among multi-cognitive users to optimize throughput. Chatterjee *et al.* [6] studied the combined spectrum efficiency and energy optimization for spectrum sensing and energy harvesting by two groups of secondary users, resulting in a 19% increase in energy efficiency and a 14% increase in spectrum efficiency. Zareei *et al.* [7] studied the control of transmission power, made dynamic adjustment of transmission power, and used the high energy nodes to transmit more information to reduce the load of energy nodes. The proposed scheme improves the transmission rate by at least 15% by simulation in an energy harvesting cognitive wireless network with better end-to-end connectivity. To achieve energy harvesting, Simultaneous Wireless Information and Power Transfer (SWIPT) technology is used to transmit both user signals and RF energy. SWIPT technology was first discussed in the Single Input Single Output (SISO) communication system designed in [8], which considered flat fading and frequency-selective channels, and showed the tradeoff between information rate and energy transfer for co-addressable information decoding. Wang *et al.* [9] studied a resource allocation method to maximize energy efficiency in orthogonal multi-access wireless networks. A resource allocation scheme is designed based on incomplete channel state information. By presenting the resource allocation problem as a hybrid non-convex optimization problem, user scheduling, data rate adaptation and power allocation are designed under the constraints of maximum transmission power and interruption probability to maximize the energy efficiency of the system. Zlatanov *et al.* [10] proposed a more practical and feasible power distribution scheme by comprehensively considering the performance measurement, interrupt probability and average SNR in the communication theory. Ozel *et al.* [11] proposed the optimization problem of energy harvesting and data transmission in wireless fading channel communication under limited battery capacity for the wireless system composed of rechargeable nodes.

The pursuit of both spectrum efficiency and energy efficiency in the communication neighborhood gives rise to the cognitive radio network based on energy and spectrum harvesting technology. Although it can improve both spectrum efficiency and energy efficiency at the same time, the allocation of resources in the spectrum sensing and energy harvesting model brings certain challenges to researchers. Reasonable allocation of energy harvesting time, energy transmission time and task offloading can guarantee the communication quality of the whole system. However, with the increase of the number of optimization parameters, the complexity of the solution increases sharply. In addition, sensor nodes deployed in wireless networks generally need to meet the requirements of small size, low price and low power consumption. Due to these factors, sensor nodes are bound to face the problems of weak computing capacity and low energy storage. How to use the limited computing resources and storage energy to complete many collaborative tasks has become one of the challenges faced by researchers.

Sensor nodes are small in size and can only carry batteries with limited capacity. However, in the network environment, usually there are many sensor nodes, and the distribution area is wide. Meanwhile, some devices are installed in hard-to-reach places, so it is difficult to replace the batteries of these devices. Therefore, in the case of limited energy, it is particularly important to find a way to reduce system energy consumption and improve energy utilization. In addition, due to cost and volume constraints, sensor nodes have limited memory, resulting in relatively weak computing, storage, and processing capabilities for data. So, how to complete the task computing as fast as possible under the constraint of limited computing power has become a difficult problem for researchers.

To overcome this issue, Wang *et al.* [12] proposed a distributed task offloading strategy for low-load base stations under mobile edge computing environment. By modeling the communication resources, computing resources and computing tasks of low-load base stations, the energy consumption in the process of task offloading was quantified. Chen *et al.* [13] proposed a method for joint user offloading selection and resource allocation in moving edge computing. The energy efficiency maximization problem was described as a non-linear optimization problem, which was converted into a convex optimization problem by relaxation transformation method, and the optimal solution for user selection and power allocation was given. Wang *et al.* [14] described the problem of energy consumption minimization as an optimization problem considering task relevance, and designed an efficient collaborative task computing offloading strategy to solve this problem. Li *et al.* [15] used execution delay and task success rate as performance indexes to evaluate offloading strategy, and proposed a low-complexity dynamic offloading decision algorithm. You *et al.* [16] first optimized local calculation and calculated offloading according to the known channel state, then selected a more energy-saving mode among the above two modes, and finally extended it to the dynamic channel to realize the optimal allocation scheme of computing tasks. Zhang *et al.* [17] studied the energy saving calculation scheme of offloading under wireless channel, and determined the optimal operation region of local execution and edge execution according to the relationship between data volume and delay tolerance. Wang *et al.* [18] designed a cognitive real-time forwarding condition that protects primary users and mitigates forwarding delay, and proposed a OFBR protocol which can reduce the overhearing and duty cycles of cognitive sensors by short preamble sampling. Wei *et al.* [19] studied the health assessment methods for industrial robots, to address the problems of accuracy degradation and equipment failure. Based on radial basis function (RBF) neural network, Bai *et al.* [20] proposed a method to establish power model of the deep-sea electric manipulator. Song *et al.* [21] proposed a cloud edge collaborative intelligence method of insulator string defect detection for Power IIoT. However, the main issue of current method is that it is difficult to transform a non-convex optimization problem into a convex optimization problem if too many parameters are involved and the calculation is complex. Differential evolutionary algorithm is a highly parallel and random search method for objective optimization, which is very suitable for multivariable and non-convex problems. Therefore, in order to solve the above problems, this paper proposes a scheme of systematic calculation of maximum energy efficiency resource allocation based on differential evolutionary algorithm. Under the constraints of transmitting power of dedicated energy station, computing frequency of server and edge users, this paper analyzes the changes of total energy consumption and the number of calculated bits, and establishes a joint optimization model to maximize the system's computational energy efficiency. By using differential evolution algorithm, the energy efficiency of system calculation is optimized generation by generation, so as to obtain the optimal energy harvesting and task computing scheme and the optimal offloading time, computing time and frequency.

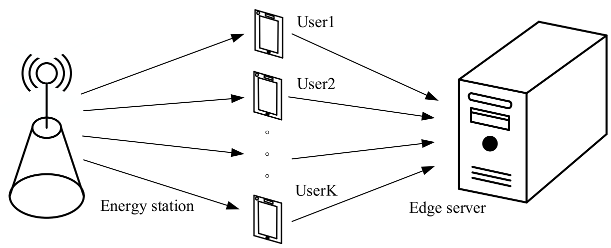

FIGURE 1. Wireless edge computing network model.

III. THE SCHEME OF THIS PAPER

A. SYSTEM MODEL

In this paper, edge computing network for wireless power supply is studied. The system framework model is shown in Figure 1. The system consists of a dedicated power station, K edge users, and an edge server. The power station provides energy for the edge users. The edge users use the received energy to unload part of the tasks that need to be calculated to the edge server, and the other part to calculate locally. The edge server calculates the data delivered by the edge user and feeds back to the edge user after completion. The two interact with each other through a wireless channel.

1) ENERGY HARVESTING PHASE

In the stage of energy harvesting, it is assumed that the transmitting power of the energy station to the edge users is P_0, the transmission time is τ_0, and the energy conversion efficiency is η. Suppose the number of edge users is k ($k = 1, 2, 3 \ldots K$), g_k is the channel gain between the energy station and the *k-th* edge user. In the energy harvesting stage, the total energy collected by each edge user from the energy station is as follows:

$$E_k = \eta P_0 g_k \tau_0 \tag{1}$$

2) TASK OFFLOADING

The computing power of smart mobile devices can be enhanced by wirelessly migrating computing tasks to resource-rich edge servers in an approach known as computing offload or task offload. Through the powerful processing power of the server, the computing speed of tasks can be accelerated, the completion time of tasks can be shortened, and energy can be saved for mobile devices. In this way, computing tasks are performed outside of the device to reduce the burden on the mobile device. Through task offloading, mobile devices do not need to have super computing power and storage capacity. Therefore, in the case of limited computing power and other hardware conditions, edge users can still complete the processing of computing tasks.

After harvesting energy, edge users perform local computation and task offloading. And local computing is to directly calculate and process locally. Task offloading is to unload the computing task to the edge server. The edge server performs the calculation operation and returns the result to the edge user. By offloading the task, the computing task is offloaded to the edge server for execution, which can achieve the purpose of relieving the calculation and storage pressure of the local device, thus extending the service life of the battery. In this paper, it is assumed that all task programs can be partitioned. Suppose that the time of the k-th edge user to unload the task is τ_k, W is the system bandwidth, and h_k is the channel gain between the edge user and the edge server, p_k represents the transmitting power of the k-th edge user, σ^2 represents the noise power. Then the number of bits unloaded from the k-th edge user to the server and the total number of bits unloaded by all users to the edge server are as follows:

$$R_k^o = \tau_k W \log_2\left(1 + \frac{p_k h_k}{\sigma^2}\right) \tag{2}$$

$$R_0 = \sum\nolimits_{k=1}^{K} R_k^o = \sum\nolimits_{k=1}^{K} \tau_k W \log_2\left(1 + \frac{p_k h_k}{\sigma^2}\right) \tag{3}$$

3) TASK COMPUTING

After receiving the tasks unloaded by the edge users, the edge server starts to calculate the received tasks. In order to make the system built in this paper closer to the actual situation, it is assumed that the edge server has limited computing capacity, and its working frequency is f_m and working time is τ_c. C_{cpu} is the clock period for calculating a bit. Then the maximum number of task bits of the edge server is:

$$R_m = \frac{\tau_c f_m}{C_{\text{cpu}}} \tag{4}$$

The final number of computing bits calculated by the edge server is:

$$R_m^e = \min\left(R_m, R_o\right) \tag{5}$$

Assuming ε_m is the effective capacitance of the edge server, the energy consumption of the edge server in the task calculation phase is as follows:

$$E_m^e = \varepsilon_m f_m^3 \tau_c \tag{6}$$

Assume that t_k and f_k respectively represent the time and frequency of the local calculation of the k-th edge user, and ε_k is the effective capacitance coefficient of the k-th edge user. Then the number of bits and energy consumption of the k-th edge user for local computing are as follows:

$$R_k^e = \frac{t_k f_k}{C_{\text{cpu}}} \tag{7}$$

$$E_k^e = \varepsilon_k f_k^3 t_k \tag{8}$$

When considering energy consumption, most researchers only consider edge users, but ignore the energy consumption of power station and edge server. In this paper, the energy consumption of dedicated energy station, edge server, sensor and edge users are taken into account in the design of experiments. The energy consumption of the dedicated energy station, edge server, sensor and edge user are E1, E2 and E3 respectively, which are as follows:

$$E1 = \left(P_0 + P_{\text{sc}}\right)\tau_0 - \sum\nolimits_{k=1}^{K} E_k \tag{9}$$

$$E2 = E_m^e \tag{10}$$

$$E3 = \sum\nolimits_{k=1}^{K} \left(p_k + p_{c,k}\right)\tau_k + \sum\nolimits_{k=1}^{K} E_k^e \tag{11}$$

The total energy consumption of the system is:

$$E_{\text{total}} = \xi_1 E1 + \xi_2 E2 + \xi_3 \text{E3} \tag{12}$$

where, P_{sc} is the circuit loss of the dedicated energy station, and $p_{c,k}$ is the circuit loss of the k-th edge user. The weighted factors of dedicated energy station, edge server, sensor and edge user's energy consumption are respectively represented by ξ_1, ξ_2 and ξ_3. By setting different weights for them, the weighted sum is taken as the total energy consumption of the system. The total number of computing bits in the system consists of two parts: the number of bits calculated locally by edge users and the number of tasks unloaded by edge users calculated by edge servers. The calculation Eq. is as follows:

$$R_{\text{total}} = R_m^e + \sum\nolimits_{k=1}^{K} R_k^e \tag{13}$$

Then the calculated energy efficiency of the whole wireless functional computing network system is as follows:

$$f_x = \frac{R_{\text{total}}}{E_{\text{total}}} \tag{14}$$

That is, the ratio of the total number of calculated bits and the total energy consumption of the whole system is also the objective function to be optimized for the whole joint optimization system.

B. ESTABLISH MATHEMATICAL MODEL

In this paper, the cooperative relationship among dedicated power station, edge user and edge server are comprehensively considered. The transmission power, transmission time, offloading time of edge users, local computing time and frequency, and computing time and frequency of edge server are optimized by differential evolution algorithm to optimize the computing energy efficiency of the whole network system f_x.

There are many parameters to be considered in the whole system. If the objective function is transformed into a standard convex function by the theory of generalized fractional programming, and then the optimal solution is obtained by iteration, the process will be very complicated. However, due to its high parallel and random search characteristics, differential evolution algorithm is very suitable for the optimization system with more parameters. Subsequent simulation experiments also prove the efficiency and feasibility of this scheme. According to the whole process above, the mathematical model of the system is built as follows:

$$\max_{\tau_k, t_k, p_k, f_k, P_0, \tau_0, \tau_c, f_m} f_x \tag{15}$$

$$\tau_0 + \sum_{k=1}^{K} \tau_k + \tau_c \leq T \tag{16}$$

$$R_{\text{total}} \geq L_{min} \tag{17}$$

$$\left(p_k + p_{c,k}\right) \tau_k + \varepsilon_k f_k^3 t_k \leq E_k, \quad \forall k \tag{18}$$

$$0 \leq P_0 \leq P_{max}, \quad p_k \geq 0, \ \forall k \tag{19}$$

$$0 \leq f_m \leq f_{\max},$$

$$0 \leq f_k \leq f_k^{\max}, \ \forall k \tag{20}$$

$$0 \leq t_k \leq T, \quad \forall k \tag{21}$$

$$\tau_0 > 0, \quad \tau_k \geq 0, \ \tau_c \geq 0, \ \forall k \tag{22}$$

where Eq. (16) indicates that the energy transmission of the whole system, task offloading and task calculation of the server should be completed within the specified time T, where T is equivalent to setting a maximum delay. Eq. (17) gives the minimum number of bits ($L_{\min}$) required by the system. Eq. (18) indicates that the energy consumed by edge users cannot exceed the energy they receive from the energy station. Eq. (19) defines that the maximum transmitting power of the energy station cannot exceed $P_{\max}$. Eq. (20) defines that the maximum working frequency of edge server and the maximum local computing frequency of edge users should not exceed $f_{\max}$ and $f_k^{\max}$ respectively. Eq. (21) is the time constraint of local calculation for edge users, and the local calculation time cannot exceed T. Eq. (22) is the time constraint of energy transfer time, edge user offloading task time and edge server for calculation.

C. DIFFERENTIAL EVOLUTION ALGORITHM

Differential evolution algorithm is a global optimization algorithm based on population adaptability [22]. Its advantages are high parallelism and randomness, and it has good global optimization ability. In addition, differential evolution algorithm is also robust, simple, practical and efficient, and has been widely used in artificial intelligence, big data and other fields. Differential evolution algorithm has fast convergence and global optimization ability, which can solve the energy efficiency optimization problem of system computing proposed in this paper. In addition, a large number of experiments have proved that differential evolutionary algorithm is the fastest evolutionary algorithm.

The basic idea of differential evolutionary algorithm is as follows: using the difference component of two individual vectors randomly selected from the population as the disturbance quantity of the third random reference vector, the variation vector is obtained. Then the variation vector and the reference vector are hybridized to generate the test vector. Then compare the baseline vector with the experimental vector, and the better ones are kept in the next generation. This cycle is repeated several times to improve the population quality generation by generation and guide the population to focus to the optimal solution position.

The algorithm consists of five basic steps: population initialization, fitness function definition, variation operation, crossover operation and selection operation. Its key link lies in: variation, crossover, selection. Reasonable setting of fitness function can effectively evaluate the environmental adaptability of individuals in the population. Meanwhile, the value of fitness function corresponds to the evaluation of the performance of task assignment scheme, and ultimately determines whether the task assignment scheme solved is close to the optimal solution.

The fitness function of this scheme, namely the objective function f_x mentioned above, is optimized by differential evolution algorithm generation by generation to make the value of f_x reach the maximum. By observing the fitness function value, we can judge the quality of distribution scheme of differential evolution algorithm to the whole system. When the fitness function value reaches the maximum, that is, the whole allocation scheme reaches the best. The fitness function of this scheme is as follows:

$$F(x) = f_x \tag{23}$$

Selection, crossover and mutation are the three key steps of differential evolution algorithm. Selection, that is, according to the fitness function value, select the excellent genes that make the fitness function value larger, and save them. Crossover, or recombination of genes, to create new individuals. In the process of gene recombination, differential evolution algorithm will judge whether a gene is an excellent gene or not according to the fitness function value of the gene at the corresponding position on chromosome. Therefore, the individuals generated after crossover all inherit the excellent genes from their male and female parent, so they can better adapt to the environmental requirements than the previous generation. Mutation, that is, the mutation of one or some genes on chromosomes increases the diversity of genes. Crossover cannot produce new genes, but mutation can. The existence of variation increases the probability of generating more and better feasible solutions.

The differential evolutionary algorithm includes three main parameters: Population size NP, scaling factor F, and hybridization probability Cr. The increase of population size can increase the diversity of the population and improve the quality of the optimal solution. However, with the increase of population size, the computation will increase and the convergence speed will slow down. A small population size can accelerate the convergence of the whole optimization process, but it is easy to cause the algorithm to be premature and fall into local optimization. In this system model, the value of population size is set as 100. The scale factor represents the degree of disturbance to the basis vector. If the scale factor is large, the disturbance amount will be large, leading to the value of the search step size within a large range, which will improve the diversity of the population, but weaken the local search ability of the algorithm. If the scaling factor is small, the disturbance amount will be small, so that the new individual and the reference individual will not change much, and the local search ability is strong. The algorithm will search in the neighborhood of the reference individual, and the convergence speed will be improved, but it will cause the local optimal problem. In the simulation experiment of this paper, take the value of scaling factor as 0.5. The hybridization probability is equivalent to a weight used to adjust the historical information and current information. The higher the hybridization probability, the more information comes from the variation vector, which makes the hybridization vector and the reference vector have a big difference, and then improves the population diversity. If the hybridization probability is small, the population diversity is relatively low, which is not conducive to finding the global optimal solution. In this experiment, the hybridization probability is 0.7, and the maximum evolutionary algebra is 2000.

IV. ANALYSIS OF SIMULATION EXPERIMENT

This chapter will verify the feasibility and effectiveness of the proposed method through computer simulation experiment. Firstly, the mathematical model of the edge computing network for wireless power supply is built through Python language. Then the corresponding differential evolutionary algorithm is designed according to the established mathematical model. The optimal offloading scheme and the optimal energy efficiency of the system were found by differential evolutionary algorithm. The optimization process of the whole system can be controlled within 1.6 seconds. This chapter also analyzes the actual performance of the proposed method for system energy efficiency optimization, and compares the experimental results with other methods. The simulation scenario includes a dedicated power station, four edge users and one edge service. The relevant parameters in the simulation experiment are shown in Table 1.

In order to measure the superiority of the proposed scheme and the influence of relevant parameters on the energy efficiency of system calculation, the scheme is compared with other allocation schemes, and the influence of some indicators on the computational energy efficiency of the system is analyzed. As shown in Figure 2, the horizontal axis represents the population genetic algebra, and the vertical axis represents the system's computational energy efficiency. The orange curve in the figure represents the change of the optimal individual objective function value of the population with the population algebra. The blue curve represents the variation of the average objective function value of all individuals in the population, and the recombination of the two curves tends to a certain value, indicating that the proposed method can achieve a good convergence state. It is not difficult to see from the figure that when the population evolution algebra reaches 750 generations, the calculated energy efficiency of the system has reached a stable convergence state. The proposed scheme can achieve good convergence in finite evolutionary algebra, which means that the proposed scheme is feasible and correct.

In Figure 3, the horizontal axis is the number of edge users, and the vertical axis is the computational energy efficiency of the system. It is not difficult to see from the figure that with the increase of the number of edge users, the calculation energy efficiency of the system is continuously improved. This is because with the increase of K, the growth rate of system computing bits is higher than the total energy consumption of the system. With the increase of the minimum number of calculated bits in the system, the energy efficiency of the system calculation presents a downward trend. It can be seen that with the increase of the minimum number of calculated bits in the system, the total energy consumption of the system also keeps increasing, and the increase of energy

TABLE 1. Simulation parameters.

System Parameter	Numerical Value
Number of edge users(K)	4
P_{max}	3W
T	1s
W	1MHz
η	0.6
P_{sc}	10mW
C_{cpu}	1000Cycles/bit
ε_m	10^{-28}
ε_k	10^{-26}
f_{max}	10GHz
f_{kmax}	500MHz
L_{min}	6×10^4
$\xi1,\xi2,\xi3$	1, 1, 1
$p_{c,k}$	1mW

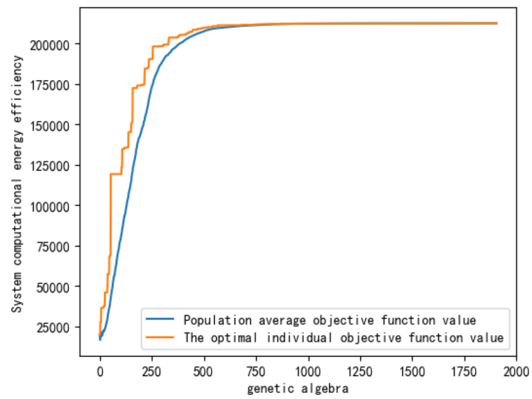

FIGURE 2. Convergence of computational energy efficiency.

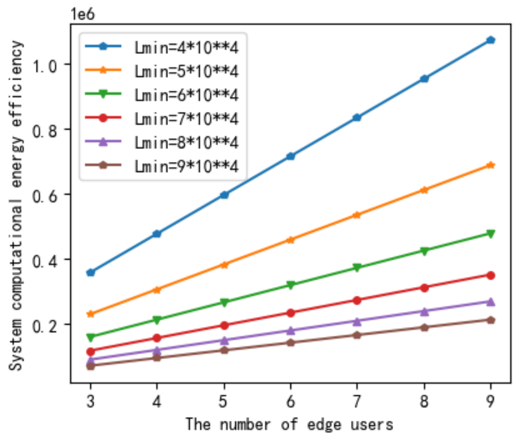

FIGURE 3. **Edge users and minimum task bits.**

consumption is faster than that of the number of calculated bits in the system.

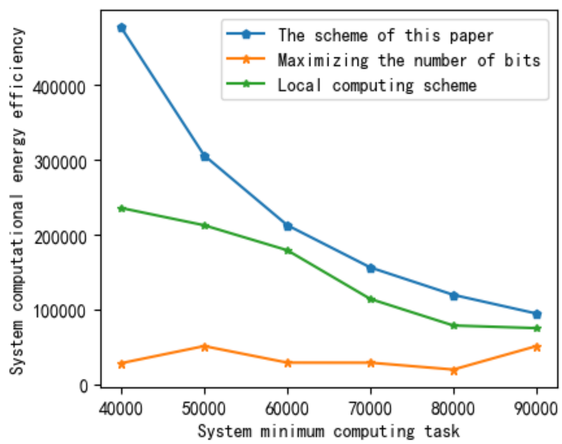

FIGURE 4. **Comparison Test of different schemes.**

In Figure 4, a comparison experiment is conducted between the proposed scheme and the scheme for calculating the maximum number of bits and the local scheme. The horizontal axis is the minimum number of task bits for system calculation, and the vertical axis is the energy efficiency for system calculation. It is not difficult to see from the figure that with the increase of the minimum number of calculated bits in the system, the energy efficiency of the proposed scheme, the scheme to maximize the number of calculated bits and the local computing scheme presents a downward trend. And the scheme proposed in this paper is superior to the scheme of calculating the maximum number of bits and the local computing scheme. This is because the calculation of bit number maximization scheme is optimized with the calculation of bit number as the objective function of the system, without considering the energy consumption of the system. The scheme proposed in this paper is aimed at maximizing the computational energy efficiency of the system, taking into account both the calculated bit number and the energy consumption of the system. The local computing solution is to complete all the computing tasks locally at the mobile end user, instead of offloading them to the edge server for computing. The scheme proposed in this paper is to screen out the best offloading scheme through differential evolutionary algorithm, including local computing and all offloading schemes. Therefore, this scheme is only a special case in the scheme proposed in this paper, and its effect will not be better than that of this scheme. It can be seen that the scheme proposed in this paper can comprehensively consider various situations and cover all parts of the whole system.

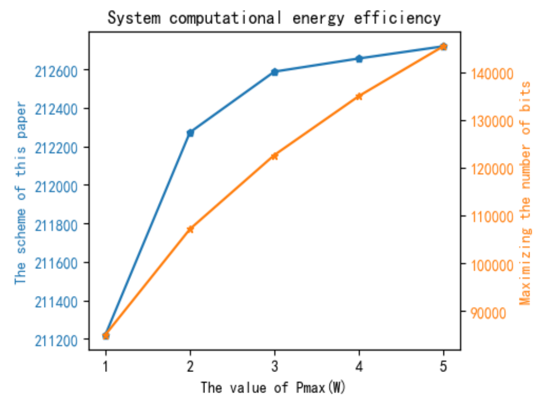

FIGURE 5. **Maximum transmitting power of energy station.**

Figure 5 describes the influence of the maximum transmitting power of the energy station on the computational efficiency of the system under the two scenarios of the proposed scheme and the scheme with the maximum number of bits. The figure is drawn with a double vertical axis, the horizontal axis represents the maximum transmitting power of the energy station, the left vertical axis represents the calculation energy efficiency of the scheme in this paper, and the right vertical axis represents the calculation energy efficiency of the scheme with the maximum number of bits. As can be seen from the figure, with the increase of the maximum transmitting power of the energy station, the computational energy efficiency of the two schemes also increases, but the increase range of the computational energy efficiency is not large. It can be seen from the figure that the scheme proposed in this paper is obviously superior to the scheme of maximizing the number of bits.

Figure 6 shows the change of energy efficiency of system calculation under different weighting factor ratios. Suppose that the weighted factor of energy consumption of energy station (ζ_1) is equal to 1, and that of edge server (ζ_2) is equal to 1. Taking the abscissa of ζ_3 as the abscissa and taking the system energy efficiency as the ordinate, we get the corresponding graph of the weighting factor and the system energy efficiency as shown below. With the increase of weighted factor (ζ_3), power station and edge server proportion relatively reduced, but the energy consumption of the edge users in proportion of the total energy consumption of the whole

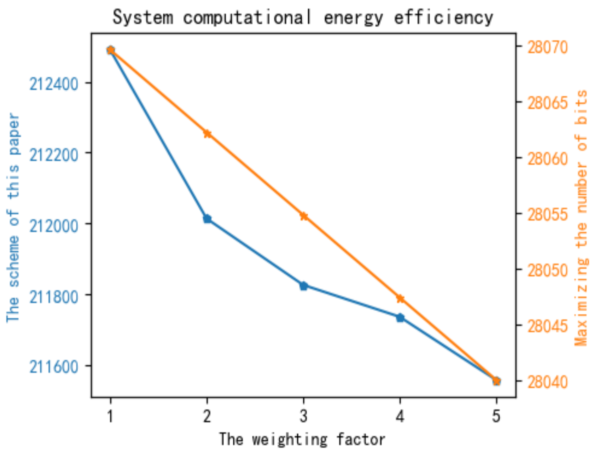

FIGURE 6. Sensor energy consumption weighting factor.

system is more and more big, leading to decrease computing efficiency.

V. CONCLUSION

In order to solve the problem of resource scarcity in energy and spectrum, an optimization scheme for energy harvesting and task computing based on differential evolutionary algorithm is proposed. Considering the constraints such as the transmitting power of the energy station and the computing capacity of the edge server, this scheme builds an edge computing network model for wireless energy supply. This paper also proposes a differential evolution algorithm to optimize the computational energy efficiency of the system model generation by generation, and get the optimal allocation scheme of transmission power and transmission time of dedicated energy station, offloading time and frequency of edge users, local computing time and frequency of edge server. Experimental simulation results verify the effectiveness of the proposed optimization method. Compared with the non-convex function converted into a convex optimization method, this method can not only optimize more efficiently, realize low energy consumption and high computation bit number, but also can effectively alleviate the energy shortage problem of micro-equipment and extend the service life of the equipment. However, there is still some room for improvement in this scheme. For example, every optimization of differential evolution has a certain randomness, so the output results of each time will have slight fluctuations. Future research work will be aimed at this problem.

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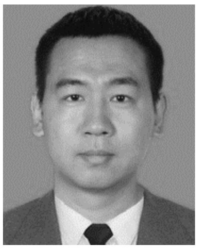
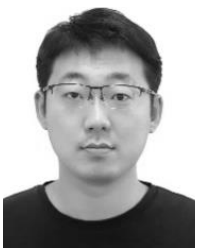
YINGYING SUN was born in Xuchang, Henan, China, in 1995. She received the bachelor's degree from the College of Electrical Engineering, Henan University of Technology, Henan, in 2019. She is currently a jointly trained Graduate Student with the Shenyang University of Chemical Technology and the Shenyang Institute of Automation, Chinese Academy of Sciences. Her main research interests include edge computing and cyber security.



CHUNHE SONG received the Ph.D. degree in computer science from Northeastern University, Shenyang, China, in 2012. He is currently a Professor with the Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang, China. His research interests include artificial intelligence and edge computing.



SHIMAO YU received the master's degree in computer science from the Dalian University of Technology, Dalian, China, in 2017. He is currently an Assistant Professor with the Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang, China. His research interests include image processing, wireless sensor networks, and industrial communication technologies.

YIYANG LIU was born in Shenyang, Liaoning, China, in 1980. He received the B.S. and M.A. degrees in automation, control theory and control engineering from Northeast University, in 2003 and 2006, respectively, and the Ph.D. degree in pattern recognition and intelligent system from the Shenyang Institute of automation, Chinese Academy of Sciences, in 2010.

As a Project Leader, he has presided over a number of National Natural Science Foundation projects, Ministry of Industry and Information Technology's Intelligent Manufacturing special projects, and Industrial Internet special projects. He is currently a Professor and a Principle Investigator with the Shenyang Institute of automation, Chinese Academy of Sciences. His main research interests include cyber-physical systems, complex system modeling and simulation, intelligent optimization, and intelligent control. He is a member of the Edge Computing Committee in the Chinese Association of Automation, an expert in the field of advanced manufacturing technology of "National Technology Prediction" of the Ministry of Science and Technology. He is a peer-reviewed expert of the National Natural Science Foundation of China.

HAO PAN was born in Alax, Inner Mongolia, China, in 1986. He received the Ph.D. degree in automation, control theory and control engineering from the Shenyang Institute of automation, Chinese Academy of Sciences, in 2016. His research interests include artificial intelligence and machine learning.

PENG ZENG received the Ph.D. degree in mechatronic engineering from the Graduate School of the Chinese Academy of Sciences, Beijing, China, in 2005. He is currently the Director of the Industrial Control Network and System Department, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang, China. He is also the Vice Director of the Network Control System Key Laboratory, Chinese Academy of Sciences. He has authored or coauthored more than 100 conference papers, journal articles, and book chapters related to his research area and five pending/filed U.S. patents. His research interests include image processing, wireless sensor networks, and industrial communication technologies.