Research on Green Multitask Offloading Algorithm in Heterogeneous Wireless Architecture

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Abstract: In this paper, a wireless heterogeneous environment system model is constructed. In the process of task offloading, queuing theory is considered to offload it to edge nodes and edge clouds. In addition, solar panels are deployed in roadside units, the use of green energy can reduce system grid energy consumption. Since the optimization objective is a multi-objective non-convex NP-Hard problem, and the application scenario of multiple edge nodes makes it difficult to solve this problem, this paper solves the problem by improving the selection and crossover links of the genetic algorithm, and establishes an external file to speed up the convergence of the population. The simulation results show that the improved genetic algorithm can effectively reduce the system cost and the use of traditional electric energy.

1. Introduction

In recent years, computational offloading and resource allocation based on MEC have attracted much attention from researchers [1-3]. In view of the characteristics of low latency and high bandwidth of 5G communication network, literature [4] divides the tasks generated by vehicles into two categories: emergency and non-emergency, and considers the M/M/1 model of queuing theory to realize task offloading. Reference [5] studies the ME task offloading process based on the queuing model, and the task computing execution process of edge nodes is considered as the M/M/1/∞ model. References [6-7] designed an uncertain task offloading model based on queuing theory. Reference [8] performs multi-objective optimization on the energy consumption, delay and cost of user equipment task offloading based on queuing theory, and uses the interior point method (IPM) to optimize the user offloading rate and transmit power. Reference [9] considers electric energy and green energy in the ultra-dense heterogeneous network model, and provides energy supply for the base station at the same time, and proposes a user association algorithm to solve it.

By summarizing the above work, it is found that there are relatively few researches on task offloading based on queuing theory, and most of them are for a single edge node. In addition, this paper considers the problem of green energy from the perspective of realizing the dual carbon target and the adjustment of power energy structure, and constructs the green task offloading based on queuing theory. The green energy involved in this paper is mainly solar energy.

2. System Architecture

2.1 Network Model

As shown in Fig.1, this paper considers a heterogeneous wireless edge computing system consisting of n user devices, M edge nodes and an edge cloud. The set of edge service nodes is defined as $M = \{1, 2, \cdots, I, I+1, I+2, \cdots, I+J\}$, where I and J are the number of UAVs and RSUs respectively. Each RSU is equipped with an energy harvesting device that uses energy generated by the sun to reduce power consumption. We use $p_n^l \in [0,1]$, $p_n^m \in [0,1]$, and $p_n^{mc} \in [0,1]$ respectively represent user n tasks on the local, edge server (UAV and RSU) and performed by the two edge

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server relay to the edge of the cloud of unloading ratio, and meet $p_n^l + p_n^m + p_n^{mc} = 1$.The transmission model in this paper adopts the transmission mode in reference [10] and ignores the return delay.

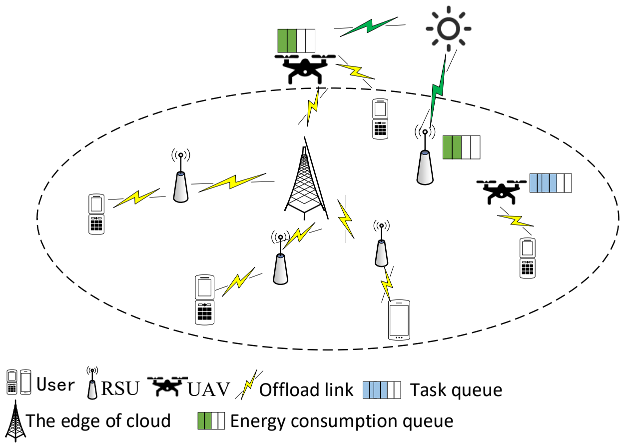


Figure 1 Heterogeneous wireless network model.

2.2 Energy Consumption Model

Due to the instability of the solar energy supply, energy collection easy to be affected, the arrival rate of solar energy is not only associated with the acquisition speed and area S of solar panels, and is associated with the conversion efficiency ξ of RSU j energy, due to the randomness and intermittency of solar energy resources, definition λ_j^e is the collection rate of solar energy resources of RSU with random distribution satisfying $0 \le \lambda_j^e \le \lambda_j^{\max}$. Then the expression of solar resource generation power on the RSU j side is as follows:

$$P_j^e = \lambda_j^e \times S \times \xi \tag{1}$$

The energy generation rate of the RSU j during the computation task is:

$$E(m_j^e) = P_j^e T_j^{off} \tag{2}$$

Where T_j^{off} represents the time consumed by the user when the task is processed in the roadside unit. The energy integration queue of the RSU j is modeled to simulate the arrival of solar resources.

$$E_j^e = \max\left\{E_j^{off} - E(m_j^e), 0\right\} \tag{3}$$

Equation (3) shows that the energy consumption model of RSU is related to the generation of energy and the energy consumed by the task for calculation in the roadside unit.

2.3 Calculation Model

2.3.1 Local Computing

Use μ_n^l to represent the local service capability of user n. Considering that the client adopts M/M/1 queue, assuming that the CPU occupied ratio of the client is l_n^l, the average response time T_n^l and energy consumption E_n^l of the local computing request are expressed as:

$$T_n^l = \frac{1}{\mu_n^l(1 - l_n^l) - p_n^l \lambda_n} \tag{4}$$

$$E_n^l = e_n^l T_n^l \tag{5}$$

2.3.2 RSU Computing

N users choose to uninstall to RSU j task execution process of obeying Poisson distribution of $p_n^j \lambda_n$, unloading to the edge of the cloud can be part of the task by RSU j relay and obey distribution of $p_n^{jc} \lambda_n$, according to the properties of the Poisson distribution, the total task to reach RSU j request rate expressed as $(p_n^j + p_n^{jc})\lambda_n$, so the task transmission delay and upload energy consumption is expressed as (6) and (7):

$$T_{n,j}^{up} = \frac{(p_n^j + p_n^{jc})\lambda_n b_n}{R_{n,j}} \tag{6}$$

$$E_{n,j}^{up} = P_n^l T_{n,j}^{up} \tag{7}$$

Definition μ^j is the service rate of RSU j .The sum of task request rates of different users in the system also follows the Poisson distribution. Therefore, the average RSU j rate is expressed as follows:

$$\lambda_p^j = \sum_{n=1}^{N} \lambda_n p_n^j \tag{8}$$

Therefore, the corresponding service intensity when RSU performs task calculation as an edge node can be expressed as follows:

$$\rho^j = \frac{\lambda_p^j}{J\mu^j}, i < m < j \tag{9}$$

The average processing time of each task on the RSU includes task waiting time and execution time, which is expressed by the formula:

$$E_{j,c}^c = P_n^c T_{j,c}^c \tag{10}$$

$$T_{n,j}^{wait} = \frac{C}{J\mu^j - \lambda_p^j} + \frac{1}{\mu^j}, i < m < j \tag{11}$$

Where C is the Erlang formula of RSU quantity and service intensity.

The power consumption calculation formula provided by the RSU during task execution is (3), denoted as E_j^e. According to the above formula, the delay T_n^j and energy consumption E_n^j of user n task unloading to RSU j can be obtained as follows:

$$T_n^j = T_{n,j}^{up} + T_{n,j}^{wait} \tag{12}$$

$$E_n^j = E_{n,j}^{up} + E_j^e \tag{13}$$

2.3.3 Edge Cloud Computing

Due to the wired connection between RSU and edge cloud, the fixed transmission rate of some tasks relaying through RSU j is R, and the time delay and energy consumption of roadside unit relaying to edge cloud are:

$$T_{j,c}^{up} = \frac{p_n^{jc}\lambda_n b_n}{R} \tag{14}$$

$$E_{j,c}^{up} = P_n^j T_{j,c}^{up} \tag{15}$$

Assuming that the service rate of the edge cloud is μ^c, the cloud can provide huge computing resources for the task, so the waiting time of the task in the edge cloud can be ignored. Then the service response time and energy consumption of the edge cloud can be calculated as follows:

$$T_{j,c}^{c} = \frac{1}{\mu^c} \tag{16}$$

$$E_n^{c_{RSU}} = E_{j,c}^{up} + E_{j,c}^{c} \tag{17}$$

In view of the low computing power of the UAV and to avoid the heavy workload of the UAV *i,* the queue time will become too long and affect the user experience process, the tasks can be relayed to the edge cloud through the UAV for processing. The UAV offloading process is similar to RSU.

2.4 Problem Formulation

For multiple users in the system, it is necessary to consider the offloading strategy of all users during task calculation. Then, the average delay and average energy consumption of the system in edge computing are expressed as:

$$T(p_n^l, p_n^j, p_n^{jc}, p_n^{ic}) = \frac{1}{N}\sum_n^N p_n^l T_n^l + p_n^j T_n^j + p_n^{jc} T_n^{c_{RSU}} + p_n^{ic} T_n^{c_{UAV}} \tag{18}$$

$$E(p_n^l, p_n^j, p_n^{jc}, p_n^{ic}) = \frac{1}{N}\sum_n^N p_n^l E_n^l + p_n^j E_n^j + p_n^{jc} E_n^{c_{RSU}} + p_n^{ic} E_n^{c_{UAV}} \tag{19}$$

Therefore, the cost function and constraints of the system are expressed as follows: α is the delay weight of the system, and （1−α) is the energy consumption weight of the system

$$\min[\alpha \frac{T}{T_{\max}} + (1-\alpha)\frac{E}{E_{\max}}] \tag{20}$$

$$\begin{aligned} s.t.\ &(\mathrm{C1})\ p_n^l + p_n^j + p_n^{jc} + p_n^{ic} = 1, (n \in N) \\ &(\mathrm{C2})\ p_n^l, p_n^j, p_n^{jc}, p_n^{ic} \in [0,1], (n \in N, j \in J, i \in I) \\ &(\mathrm{C3})\ p_n^l \lambda_n - \mu_n^l (1 - l_n^l) < 0, (n \in N) \\ &(\mathrm{C4})\ \lambda_p^j - J\mu^j < 0, (j \in J) \end{aligned}$$

Where $T_{\max}$ and $E_{\max}$ represent the maximum tolerated delay and energy consumption of the system. Constraints (C1) and (C2) represent the offloading ratio constraints, and constraints (C3) and (C4) represent the service rate constraints of different servers.

3. Optimization Algorithm for Task Uninstallation Ratio

Equation (20) is a multi-objective non-convex NP-hard problem. Therefore, this paper adopts an improved genetic algorithm (IGA) to solve the unloading proportion optimization problem.

3.1 Parameter Encoding and Initialization Population

Assumes that population size is S, the discharge ratio of N users scheme is encoded as a population of GA matrix, then the population matrix for a S line $4N$ columns of the matrix, in which each user can be regarded as an individual, The offloading ratio of each part of the user is the individual gene. In order to describe the offloading strategy of the user intuitively, the real number coding method is adopted.

3.2 Fitness Function

Formula (21) represents the fitness function of the unloading scheme, where the denominator is the system cost of the objective function in this paper. The larger the fitness value is, the smaller the system cost is, indicating that the unloading scheme is better.

$$f(n)=\frac{1}{\min[\alpha\frac{T}{T_{\max}}+(1-\alpha)\frac{E}{E_{\max}}]} \tag{21}$$

Upon completion of fitness value calculation, the roulette and elite reserved mix strategy to select high fitness value of individual operation, after each iteration to descending order of fitness value, according to the algorithm of setting elite reserve ratio choose individuals to keep high fitness value, the rest of the individual as a new species for subsequent crossover and mutation operation.

3.3 Crossover and Mutation Process

Preferred choice in individual species, according to the crossover probability to choose from two individuals as the parent generation to carry on the cross, because of the same user of the constraint condition of unloading proportion as the sum of 1, therefore in the process of cross from cross method was improved, adopt the way of alleles cross gene exchange as a whole in the same user and generate new individuals, In addition, an external file is established to store individuals with excellent fitness values. In order to avoid the "premature" phenomenon of the algorithm in the iterative process, the mutation process adopts a method similar to crossover.

If the number of current iterations has reached the previously set threshold or the optimal fitness value is no longer improved after several iterations, the termination condition of the algorithm is met and the optimal solution is obtained. On the contrary, continue to iterate the algorithm until the termination condition is met.

4. Analysis of Simulation Results

4.1 Parameter Settings

Table 1 Simulation parameter Settings.

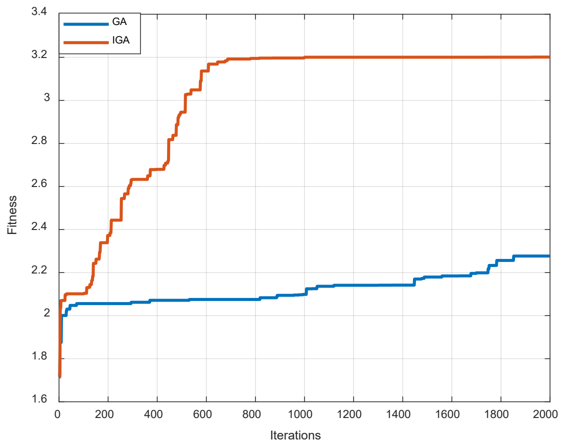
Name	Value
b_n/KB	400~1000
B/MHz	20
λ_n/MIPS	1.5
μ_n^l/MIPS	4.5
μ^j/MIPS	10
μ^c/MIPS	20
P_n^i/dBm	30
P_n^j/dBm	46
S/m^2	0.75
ξ	0.46
α	0.5

In this paper, a multi-edge node task offloading scheme in wireless heterogeneous environment is studied. Users are densely and randomly deployed within 500 meters, and sparsely deployed within 500-1000 meters. Edge clouds are deployed in the scene center, and edge nodes are randomly distributed according to user deployment characteristics. The population size was set as 40, the iteration number was 2000, the individual crossover probability was 0.95, and the mutation probability was 0.05. Table 1 lists other parameters.

4.2 Result Analysis

In this paper, GA algorithm is used to solve the unloading problem and improve the algorithm. Figure 2 reflects the performance of GA algorithm. It can be seen from the figure that with the increase of the number of iterations, the fitness value of GA algorithm gradually increases and finally converges to a certain value. This is because in the selection process, the elite retention strategy is adopted to replicate the individuals with good fitness value. In order to avoid the algorithm falling into the local optimum, in the process of population renewal, the old and new populations are merged and the population size is selected to select the optimal individuals as the new population, so the convergence of the algorithm is better.

Figure 3 shows the relationship between the number of users and the system overhead. From the overall trend, the system overhead increases with the increase of users. When the number of users is the same, compared with the cost of basic GA, the improved algorithm is better than other algorithms.



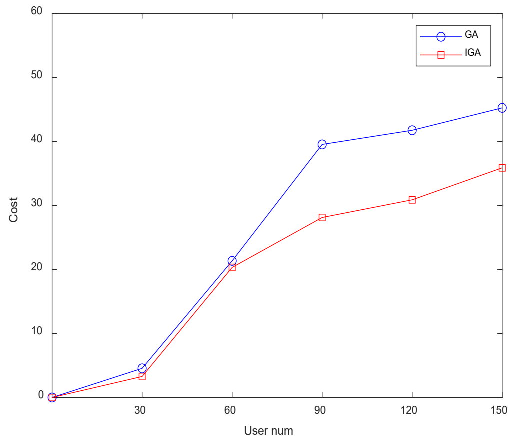
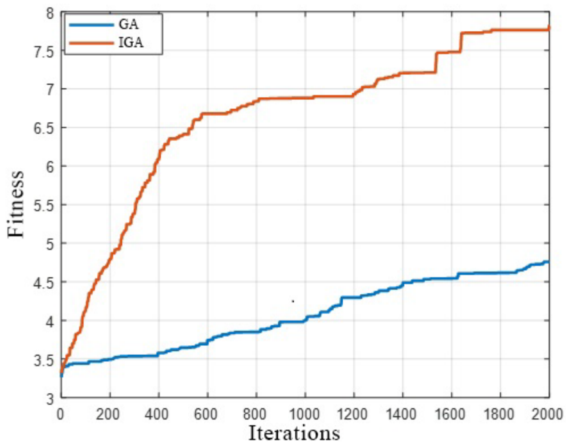


Figure 2 GA optimization iteration diagram.   Figure 3 User num VS the system overhead.



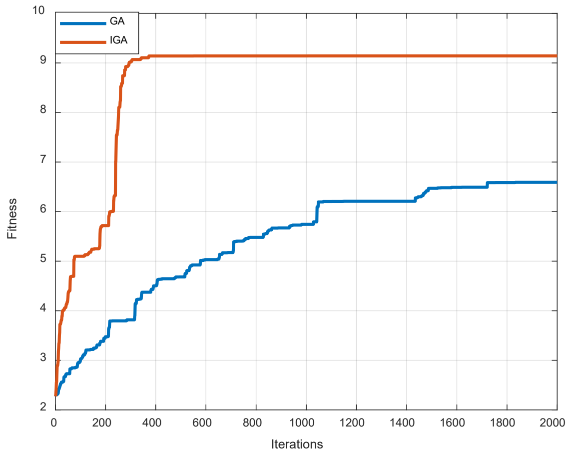


Figure 4 Fitness evolution curve when *N*=90.   Figure 5 Fitness evolution curve when *N*=150.

By mapping network model, with the algorithm of task unloading ratio is optimized to obtain the minimum system energy consumption, figures 4 and 5 respectively, the number of users is equal to 90 and 150 when the fitness of the graph, it can be seen from the picture the improved GA compared with basic GA advantages more apparent, fitness value can be increased with the increase of the number of iterations to achieve convergence condition, And its convergence speed is faster, which proves that the improved genetic algorithm is more suitable for wireless heterogeneous network model with multi-edge nodes.

Figure 6 shows the relationship between solar resource arrival rate and system cost when the number of users is 150 on a sunny day and the task arrival rate is 1.5. As can be seen from Figure 6.1, the system cost gradually decreases over time and eventually tends to a fixed value. This is because the roadside units are powered by a mix of electric and green energy, which does not consume energy from the grid in the presence of light, and the system overhead is gradually reduced. After 11am, the system overhead remains the same, but not zero, as local processing and edge cloud processing still consume energy. As can be seen from Figure 6.2, with the continuous increase of solar energy resources, the system energy consumption gradually decreases and tends to a fixed value. It can be seen that the research of this paper has achieved the purpose of giving priority to the use of green energy to a certain extent.

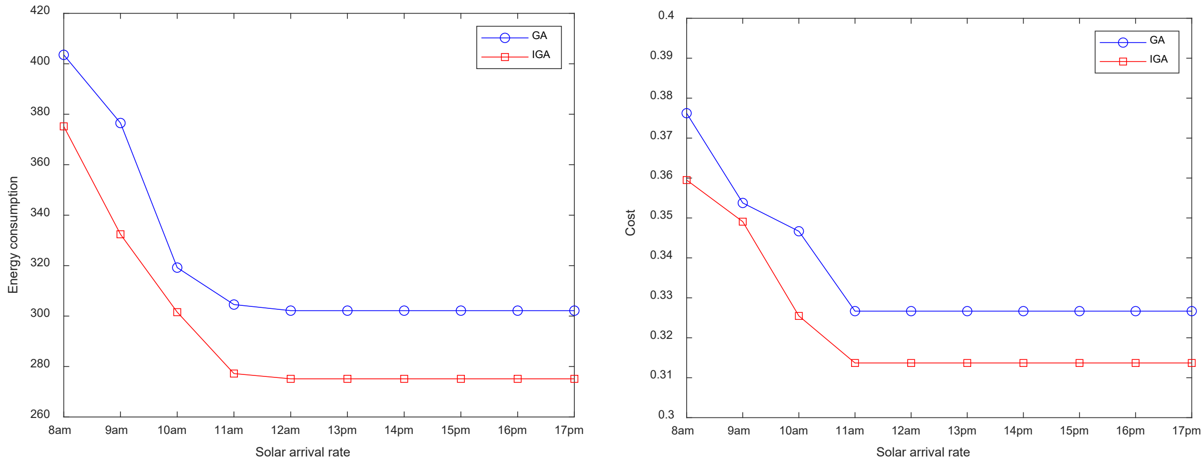


Figure 6 Correspondence map (6.1) system energy consumption;(6.2) system overhead.

5. Conclusion

In this paper, task offloading based on green energy consumption in wireless heterogeneous environment is studied, and improved GA is used to minimize system overhead. In the realization of green energy consumption of roadside units, the scheme of using solar energy on demand is adopted, which will lead to the waste of solar resources in the actual environment. In the future research, we will devote ourselves to applying batteries to roadside units to better make rational use of resources.

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