Resource Prediction and Allocation Method for 5G C-RAN Based on Power Internet of Things

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Abstract. The construction of power Internet of things is an important practice of network power strategy, which can greatly improve the coordination and data connectivity between various businesses of power grid. With the continuous maturity of 5G technology, it also can be used as an alternative access network solution. Facing the power Internet of things, this paper discusses the feasibility of C-RAN cloud wireless access network architecture in the power Internet of things access. Furthermore, this paper designs the base station traffic prediction algorithm based on LSTM and the network resource allocation algorithm based on genetic algorithm, which improves the utilization efficiency of network resources, and is of great significance for the future access network in the power industry to save construction costs and energy consumption.

Keywords: Ubiquitous power internet of things · Electric power wireless network · C-RAN · Genetic algorithm

1 Introduction

On May 22, 2020, the third session of the 13th National People's Congress opened in Beijing. Premier Li Keqiang made a government work report. The report pointed out that in the current epidemic situation, we should continue to "promote the reduction of production costs of enterprises". The policy of reducing the electricity price of industry and Commerce by 5% will be extended to the end of this year ". It is estimated that the electricity tariff will be reduced by 92.6 billion yuan in the whole year [1, 2]. While firmly implementing the decision-making and deployment of the Party Central Committee and the State Council, the State Grid actively saves resources and opens up current, increases investment in power grid by 9.9%, reduces costs and continuously improves input-output efficiency [3–5].

Investment in the construction of the power Internet of things can effectively promote the recovery of the upstream and downstream of the industrial chain, and play an important role of power grid investment. After the completion of the power Internet of things, it will greatly improve the connectivity and coordination of data between the various

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services of the power grid, which is conducive to the implementation of the requirements of cost reduction and efficiency improvement. From the concept, the power Internet of things is to use the most cutting-edge mobile Internet communication, artificial intelligence and other modern technologies, aiming at each link and process of the power system, so that the heterogeneous terminal equipment in each link of the power system can be connected with each other, and the working state and communication situation of all terminal equipment in the system and the system itself can be comprehensively monitored and controlled through the perception layer. The efficient use of system information realizes the intelligent driving of the system through data, which greatly improves the utilization efficiency of resources. At present, about 450 million devices of various types are connected to the power grid system, including electricity meters and various types of equipment used for information collection, system protection and equipment control. According to the latest planning of the State Grid, it is estimated that there will be about 2 billion heterogeneous terminal devices in the system by 2030. At that time, the power Internet of things will become the biggest Internet of things with the largest number of terminal devices State circle.

In order to maintain an IoT ecosystem with such a large number of access devices, it is very important to save the construction cost and energy consumption of the power Internet of things, and the access network is the largest part of the construction cost and energy consumption of the system, so the selection of access network solution is very important for the whole system. At present, there are three kinds of access network schemes, which are 2G, 3G, 4G and 5G technologies of mobile public network, 230MHz and 1800MHz technologies of power wireless private network, and lpwa low-power WAN technologies, including Lora and NB-IoT technologies. Different access network schemes have different advantages and disadvantages, which form complementary to each other to a certain extent. With the continuous development of 5G wireless network, C-RAN, as a network architecture that can provide high band and wide access, has the characteristics of wide coverage and high bandwidth, and can be widely used in switching stations, distribution rooms, charging piles, power consumption information collection and other services [6].

The first section of this paper mainly introduces the characteristics of C-RAN access network architecture and the current research focus of the architecture, and expounds the applicability of the architecture for the power Internet of things. In the second section, aiming at the resource allocation problem of the power Internet of things based on C-RAN, this paper first proposes an access site traffic prediction algorithm based on LSTM model, and analyzes the prediction performance of the model through the predicted data. In the third section, based on the predicted traffic results, this paper proposes a network resource allocation algorithm based on genetic algorithm, and makes a comparison with existing algorithms in many aspects. The simulation results show that the performance of the algorithm is better than the existing algorithm. In the fourth section, the two algorithms proposed in this paper are summarized respectively.

2 Introduction of C-RAN Access Network Architecture

The C-RAN architecture is an improvement on the distributed base station architecture proposed by China Mobile Research Institute in 2010. The core idea is to divide the

BBU and RRH which need to be fixed into two independent parts and place them separately [7]. The two are connected through optical fiber. All baseband processing units (BBBs) are uniformly placed in the BBU pool [8], sharing baseband processing resources and corresponding supporting facilities, such as air conditioning and other refrigeration equipment, reduce the construction cost and energy consumption of supporting facilities. The architecture has four main advantages, namely, reducing energy consumption, saving cost, easy to upgrade and expand, and greatly improving the utilization efficiency of baseband processing resources (Fig. 1).

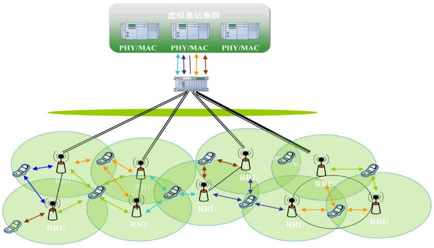

Fig. 1. C-RAN network architecture diagram.

C-RAN architecture has great advantages in network adaptability, energy saving and base station construction cost saving. In order to give full play to the advantages of the architecture, there are some problems to be solved, the most important of which is to achieve the prediction of base station traffic and the reasonable allocation of network resources. At present, the research work on C-RAN energy saving mainly focuses on the energy saving of RRH and transmission network. The energy-saving research of BBU is still in its infancy. How to intelligently allocate network resources to save energy consumption of BBU pool while maintaining good network performance has high research value.

The network resource allocation model discussed in this paper adopts 5G access network solution, and specifically uses C-RAN as access network architecture. The focus of the research is to allocate network resources intelligently through algorithm. In the power Internet of things, C-RAN network structure can be used to carry high-definition video monitoring, mobile operation and other large bandwidth services, as well as remote control business, feeder automation and other control services, and online power assets physical ID and other large connection services.

3 Traffic Prediction Algorithm of Access Station Based on LSTM Model

3.1 The Change Law of Node Station Flow

In the area covered by power 5G C-RAN, the location and communication status of some dynamic equipment such as intelligent inspection equipment are generally in continuous change, which also leads to a relatively regular, temporal or spatial change of base station load. There are two kinds of changes in time: large span oscillation and small span oscillation. The large span oscillation is often caused by the mobile changes of dynamic equipment, which can lead to a regular change of the base station load, and the change range is also relatively large, which is usually in hours. However, the small span oscillation is often caused by the access and disconnection of the service terminal equipment or the change of the communication status of the equipment. This kind of vibration is random and difficult to predict, and the change range is small. The time span is usually in minutes [9]. Large span oscillation and small span oscillation constitute the change curve of base station service load.

Taking the data of public network communication network as an example, as shown in Fig. 2, the load change of a station for several consecutive days is shown. It is obvious that the traffic shows regular fluctuations, and each traffic waveform is similar. Figure 3 shows the daily flow fluctuation of the station, with two obvious peaks. At the same time, due to the existence of small span oscillation, the curve has strong suddenness.

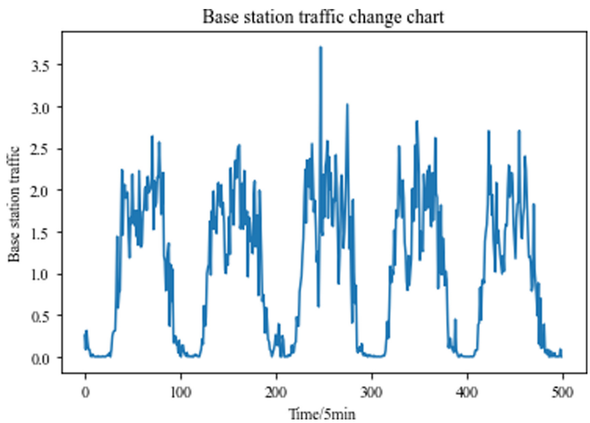

Fig. 2. Multi day load changes of base stations.

3.2 LSTM Traffic Prediction Model and Training Result Analysis

After preprocessing the original data, the preprocessed data is used to train the LSTM traffic prediction model. The MAE is used as the loss function. The function is shown in Eq. (1), which can better reflect the actual situation of the predicted value error.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{1}$$

Figure 4 shows the learning curve of the LSTM traffic prediction model. When the model is trained to 20 epochs, the loss function MAE of the training set and the verification set is about 0.1, and the model tends to converge. After training, the loss

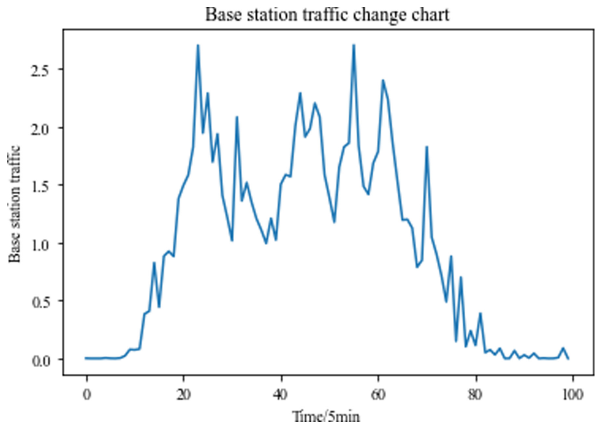

Fig. 3. Single day load change of base station.

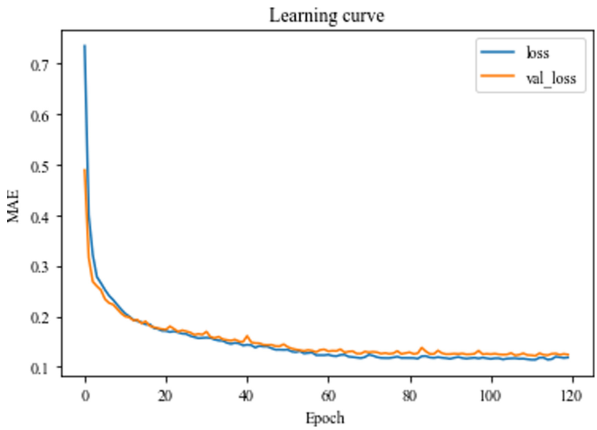

Fig. 4. Learning curve of LSTM model.

function value of the verification set is about 0.06, and the training situation of the model is good.

Figure 5 shows the comparison chart of the prediction results of LSTM traffic prediction model. By using the LSTM traffic prediction model after training, the traffic prediction data within a certain period of time can be obtained. By comparing the traffic prediction data obtained with the actual data, it can be found that the fitting degree of the two curves is good, and the prediction curve can better reflect the change of the flow. At the same time, it also can be found that the traffic prediction data in a certain period of time can be obtained. Although the prediction curve can also reflect the actual situation of traffic to a certain extent, there is still a certain deviation between the two curves, which also shows that the short-term irregular small span oscillation of network traffic is difficult to learn through the model. To sum up, the model has a strong learning ability for the regular large-span oscillation, but it is difficult to predict the irregular

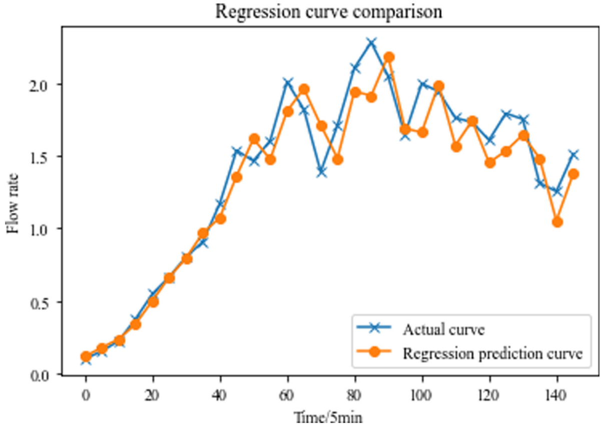

Fig. 5. Comparison chart of LSTM model prediction data.

small span oscillation, but it can also better reflect the flow changes, and the model has a high accuracy of flow prediction.

4 Network Resource Allocation Algorithm Based on Genetic Algorithm

4.1 Optimization Objective of C-RAN Model

After obtaining the characteristics of different types of traffic in the network, considering the diversity of Internet of things equipment terminals, it provides different power IoT terminals with network quality services, which can maintain network QoS and reduce energy consumption to the greatest extent.

To reduce the energy consumption of access network, we need to rely on the scheduling algorithm of BBU pool to realize the effective utilization of BBU, so as to reduce the overall energy consumption of BBU pool. The energy consumption of BBU pool mainly considers two parts, the operation energy consumption of BBU and the migration energy consumption of tasks in RRH in BBU. The operation energy consumption includes the energy consumption of calculation resources and the energy consumption of supporting facilities. Because the energy consumption of BBU in sleep state is far lower than that in operation, the overall energy consumption of BBU pool can be greatly reduced by shutting down the BBU with low load and constraining the remaining BBU load in a reasonable range [10]. In order to achieve the above purpose, it is necessary to migrate the services in the BBU, and the task migration will also generate a certain amount of energy consumption, that is, task migration energy consumption [11]. The task here can be regarded as one-to-one correspondence with the Internet of things services on the wireless side. Generally, the energy consumption of task migration is directly proportional to the amount of tasks. Now assume that all BBUs in the BBU pool are the same, and there is no difference in baseband processing capacity, downlink network rate and rated power.

The mathematical model of the system is as follows (2)−(10):

Objective function:

$$Min\,P_{total}(t) = \alpha_{total}(t) + \beta_{total}(t) + P_{static}(t) \tag{2}$$

Cost function:

$$\alpha_{total}(t) = \sum\nolimits_{i=1}^{n} Pb_i(t) \tag{3}$$

$$Pb_i(t) = \gamma \cdot \sum\nolimits_{z=1}^{h} G_i^z(t) \cdot S_z(t) + Pb_{basic}(t) \tag{4}$$

$$\beta_{total}(t) = \delta \cdot \sum\nolimits_{z=1}^{h} G_{i,j}^{'z}(t) \cdot S_z^{'}(t) \tag{5}$$

$$\varphi(\mu_i^m) = \alpha \cdot \mu_i^m \tag{6}$$

Environmental constraints:

$$\gamma, \delta, \alpha > 0 \tag{7}$$

$$\sum\nolimits_{m=1}^{M} \varphi(\mu_i^m) \le P_{\max} \tag{8}$$

$$\sum\nolimits_{m=1}^{M} c_i^m \le \mathrm{C}_{Max} \tag{9}$$

$$\mu_i^m = c_i^m \tag{10}$$

Equation (2) is the expression of the objective function, $P_{total}(t)$ is the sum of the energy consumption of the system. All we have to do is to reduce the value of the objective function as much as possible while maintaining QoS. $\alpha_{total}(t)$ is the total energy consumption of BBU operation, mainly the baseband data processing energy consumption; $\beta_{total}(t)$ is the total energy consumption of data migration; $P_{static}(t)$ is the total static energy consumption of the system, such as air conditioning refrigeration energy consumption and forward link energy consumption.

Equation (3) is the expression of the total energy consumption of BBU operation, n is the total number of BBUs in the BBU pool, and $Pb_i(t)$ is the energy consumption of the ith BBU in time t.

Equation (4) is the calculation formula of $Pb_i(t)$, h is the total number of tasks, $G_i^z(t) = 1$ is a boolean variable, indicating that at time t, the z-th task is assigned to the i-th BBU, $S_z(t)$ is the task amount of the z-th task, γ is the correction weight of the running energy consumption, $Pb_{basic}(t)$ is the basic energy consumption when the BBU is turned on. This part of energy consumption is fixed, and this part of energy consumption will not be generated until the BBU is closed.

Equation (5) is the expression of the total energy consumption of data migration. $G_{i,j}^{'z}(t)$ is a boolean variable, $G_{i,j}^{'z}(t) = 1$ indicates that the z-th task migrates from the i-th BBU to the j-th BBU at time t, $S_z^{'}(t)$ represents the data volume of the task during data migration, and δ is the correction weight of the task energy consumption.

Equation (6) is the power expression of the corresponding task, μ_i^m is the processing rate of the m-th task in the i-th BBU. According to the relevant references, the instantaneous power of the task has a linear relationship with the corresponding processing rate, α is the correction weight of the power.

Equation (7) indicates that γ, δ and α are all greater than 0.

Equation (8) is the constraint on the instantaneous power of the BBU, which means that in the i-th BBU, the total power consumed by all tasks shall not be greater than the rated maximum power of the BBU, M is the total number of tasks at this time of the BBU, and $P_{\max}$ is the rated maximum power of the BBU.

Equation (9) is the constraint on the downlink rate of the BBU, which means that the sum of the downlink rates of all tasks in the i-th BBU is not greater than the rated maximum downlink rate of the BBU, c_i^m is the downlink network rate of the M task in the i-th BBU, and C_{Max} is the rated maximum value of the downlink network rate of the BBU.

Equation (10) is the constraint on the processing speed and downlink network speed of the m-th task in the i-th BBU. These two values should be roughly equal, that is $\mu_i^m = c_i^m$, to meet the user's quality of service when receiving downlink data [12].

The above problem is a typical NP hard problem. In this paper, the genetic algorithm of intelligent optimization algorithm is selected to solve the problem.

4.2 Design of Network Resource Allocation Algorithm Based on Genetic Algorithms

Genetic algorithm (GA) is a method of searching for the optimal solution by simulating the process of biological evolution, which makes the population continuously select, cross and mutate. It is often used to optimize and solve NP hard problems [13].

Coding: RRH can be continuously migrated in different BBUs in the C-RAN architecture, so that the load of the BBU is always in a reasonable range, and the overall energy consumption of the BBU pool can be saved by turning off some of the lower load BBUs. The first step of the genetic algorithm is to code the chromosomes. Assuming the number of RRH is m and the number of BBU is n in the access network system, there are M genes in the chromosome. Each gene has n different choices. Genes at different locations represent different RRH. The number of genes indicates the BBU to which the RRH will migrate. Each chromosome is a RRH migration scheme. After coding, a certain number of chromosomes are generated, and the genes in the chromosomes are randomly generated. These chromosomes will begin to evolve as the first generation population.

Selection: By calculating the energy consumption of baseband processing and task migration, the total energy consumption required for each chromosome, is the fitness of the model, can be obtained. The higher the total energy consumption, the lower the environmental adaptability. Using the championship selection method as the selection strategy, two chromosomes were randomly selected from the population at a time to compare the total energy consumption of the two chromosomes [14]. The chromosome with lower total energy consumption was selected to enter the offspring population, while the chromosome with higher total energy consumption was eliminated and repeated until each individual in the population was selected.

Crossing: Chromosome crossing is the exchange of genes between two chromosomes, in which a more adaptable chromosome may be obtained and the crossed chromosome will be added to the offspring population.

Mutation: After chromosome crossover, there is a certain probability that a gene mutation will occur. At this time, two numbers are randomly generated to determine the specific location of the mutation and the value of the mutation. The mutation operation can avoid the population convergence to the local optimal solution, maintain the diversity of population genes to a certain extent, and ensure the algorithm to fully search for the optimal solution.

The flow chart of the algorithm is shown in Fig. 6 below.

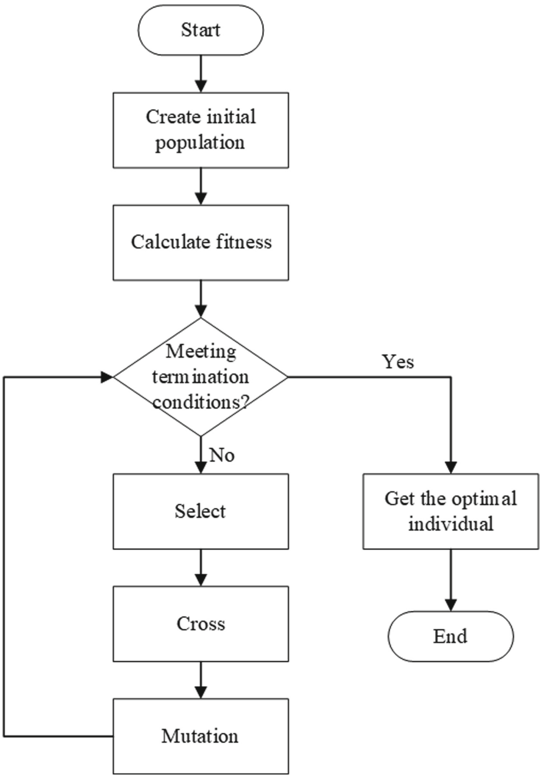

Fig. 6. Flow chart of genetic algorithm.

4.3 Simulation Results

Business types and corresponding security requirements and single-point bandwidth in the power Internet of Things are shown in Table 1 below [15]:

Table 1. Power business scenarios

Business category	Safety requirements	Single point bandwidth
Protection	Extremely high	2000 Kbit/s
Control	Extremely high	20 Kbit/s
Information detection	Relatively high	10 Kbit/s
Video	Relatively high	2000 Kbit/s
Marketing	High	1000 Kbit/s

The system parameters used in the simulation experiment are shown in Table 2:

Table 2. C-RAN system parameter setting table

Parameter name	Numerical value
Number of BBU pools	1
Number of BBUs	30
Number of RRHs	60
BBU running power	50 w
Maximum rated power of BBU	500 w
Maximum rated downlink rate of BBU	50 Mb/s

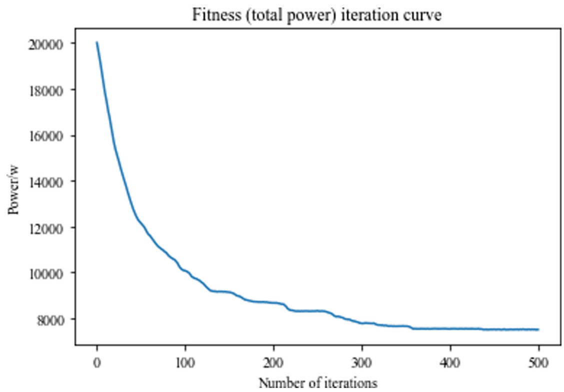

Fig. 7. Genetic algorithm fitness iteration graph.

As shown in Fig. 7, for the fitness iteration diagram of the genetic algorithm, it can be seen that the average fitness of the population has converged and the algorithm has a better effect on the total energy consumption when iterating to 400 generations.

As shown in Fig. 8, the genetic algorithm-based network resource allocation algorithm and the existing algorithm proposed for this paper have the same trend in the number of active BBUs in the system under the same network environment. However, the number of active BBUs in the genetic algorithm is slightly more than the existing algorithm.

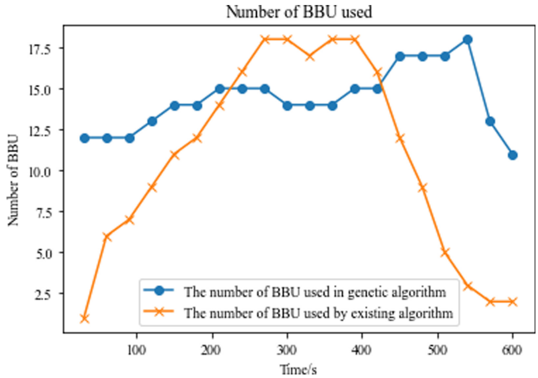

Fig. 8. BBU active number comparison diagram.

As shown in Fig. 9, the task migration times of the two algorithms are compared. The task migration times of the genetic algorithm are always less and the curve is more stable, which will not cause large network fluctuations. The task migration times of existing algorithms are more and the curve changes more.

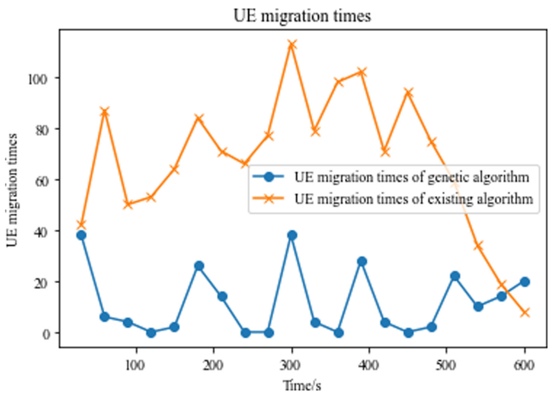

Fig. 9. Comparison diagram of UE migration times.

The number of active BBUs of the genetic algorithm is slightly more than that of the existing algorithms, so the genetic algorithm consumes slightly more energy in the

BBU baseband processing than the existing algorithms, but the number of task migration is much lower than that of the existing algorithms, so the energy consumption of task migration is much lower than that of the existing algorithms. As shown in Fig. 10, the total power consumption of the two algorithms is compared. The total power consumption of the genetic algorithm is lower than that of the existing algorithms, and the curve of the total power consumption is more stable. This shows that the genetic algorithm is better than the existing algorithms in the comprehensive performance.

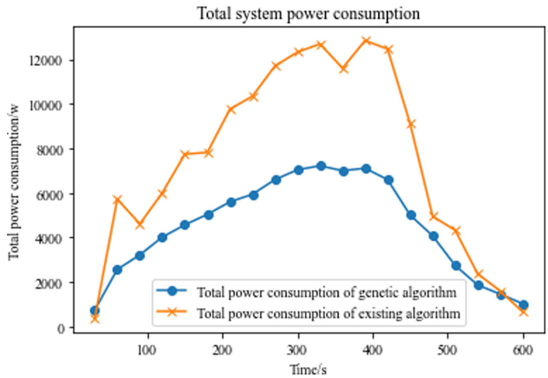

Fig. 10. Comparison of total power consumption of system.

5 Conclusion

For the access network construction of the power Internet of Things, this paper analyses the feasibility of 5G C-RAN network hosting, and proposes LSTM-based traffic prediction algorithm and genetic algorithm-based network resource allocation algorithm respectively. LSTM-based traffic prediction algorithm has good prediction accuracy and can accurately reflect the trend of traffic change. Compared with the existing algorithms, the genetic algorithm-based network resource allocation algorithm has fewer task migrations and lower overall system energy consumption. It can better balance the energy consumption of BBU baseband processing and task migration, and allocate network resources reasonably. This framework and method can provide theoretical basis for the construction and resource allocation of the power Internet of Things. Next, we need to propose a more intelligent and self-adapting dynamic resource adjustment method for different business QoS needs in order to further improve the flexibility of the network and ensure the quality of service of the power Internet of Things.

References

1. https://www.sgcc.com.cn/html/sgcc_main/col2017021449/2020-05/21/20200521171055162880954_1.shtml

2. https://www.sgcc.com.cn/html/sgcc_main/col2017021449/2020-05/23/20200523180427945966122_1.shtml
3. https://www.sgcc.com.cn/html/sgcc_main/col2017021449/2020-05/20/20200520102056702377177_1.shtml
4. https://www.sgcc.com.cn/html/sgcc_main/col2017021449/2020-05/22/20200522093431607370914_1.shtml
5. https://www.sgcc.com.cn/html/sgcc_main/col2017021449/2020-05/18/20200518192952903559108_1.shtml
6. He, E., Geng, P., Zhang, H.: Networking scheme of the power wireless private network based on edge computing. Telecommun. Sci. (Z2), 248–255 (2019)
7. Chunli, Y.E.: BBU-RRH Efficient Load Balancing Analysis for C-RAN. Beijing University of Posts and Telecommunications, Beijing (2016)
8. Weng, B., Wang, J., Liu, L.: The analysis of C-RAN network application. Design. Tech. Posts Telecommun. (11), 57–60 (2012)
9. Chen, W.: Research on load forecasting method and migration scheduing strategy for carrier migration in C-RAN. Xidian University, Xi'an (2017)
10. Guo, H.: Research on Energy Saving Algorithm in C-RAN Architecture. Beijing University of Posts and Telecommunications, Beijing (2017)
11. Chien, W.C., Lai, C.F., Chao, H.C.: Dynamic resource prediction and allocation in C-RAN with edge artificial intelligence. IEEE Trans. Ind. Inform. **15**, 4306–4314 (2019)
12. K, W.: Research on C-RAN based Energy-Efficient Resource Allocation Problems. University of Science and Technology of China, Hefei (2017)
13. H, Z.: Research on Robust Scheduling of Manufacturing Enterprice under MTO Mode. Chongqing University of Technology, Chongqing (2015)
14. Huang, Z.: Comparing for Algorithms on Researching of Active Power Optimization in the Power Systems. Nanchang University, Nanchang (2013)
15. Chen, B., Wu, Q., Lai, M.: Applied research of TD-LTE power wireless broadband private network. Power Syst. Commun. (11), 82–87 (2012)