Energy Efficiency Optimization for DAS Based on Neural Network

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Absrtact: Aiming at the huge energy consumption problem in the communication industry, this paper proposes an optimization algorithm of geometric topology of base station based on neural network to improve the system energy efficiency. The relative position between the base station and the user affects the path loss of signal propagation and the size of interference signal, thus affecting the spectral efficiency and energy efficiency of the system. In this paper, communication simulation experiments are conducted to obtain some location coordinates of randomly distributed BTS and their corresponding system energy efficiency values, which are put into the neural network for training. Finally, the network model of base station location and system energy efficiency is obtained, and the maximum value of system energy efficiency is solved. The experimental results show that the algorithm can improve the system energy efficiency by 10 times, which has achieved the desired goal.

Keywords: information and communications technology(ICT), system energy efficiency, radio energy efficiency, distributed antenna system(DAS), geometric topology of base station, neural network

I. INTRODUCTION

5G (5th Generation Mobile Communication Technology), as one of the representative technologies in the ICT (Information Communications Technology) industry, has adopted M-MIMO (Massive Multiple-input Multiple-output) technology to improve system capacity. M-MIMO has many RF channels and a large antenna array, so the spectral efficiency and energy efficiency of the 5G system are relatively high, but the absolute value of the system energy consumption will increase significantly with the continuous expansion of the antenna array[1].According to statistics[2], ICT industry has become the fifth largest energy consuming industry in the world, accounting for 6% of global energy consumption.

At present, the academic and industrial circles around the world are both advocating energy conservation for green development, China has also put forward the "double carbon" policy, and plans to achieve "carbon peak" by 2030, so it is urgent to save energy and reduce emissions in the ICT industry. Based on the current growth trend of business traffic, this paper predicts that the energy efficiency of the system will be increased to 10 times by 2030[2].

Figure 1 describes the energy flow model from the base station to the user in the communication system. The power station burns fossil energy and clean energy to provide power resources. The power supply system converts DC/AC power to convert power resources into electrical signals. The base station antenna radiates radio waves outward to transmit information. The user receives the radio waves and performs signal demodulation and filtering to retain useful information bit streams.

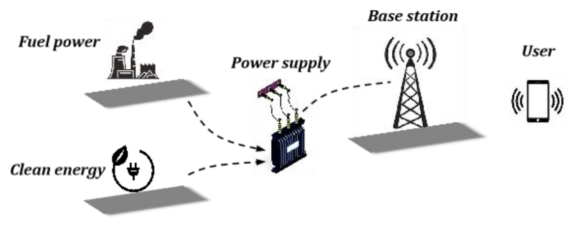

Fig. 1. Energy flow model of communication system

As shown in figure 2. According to the energy flow model of the above communication system, this paper divides the system energy efficiency EE into two parts: carbon energy efficiency E_c and radio energy efficiency E_t,which is corresponding to the efficiency of two intermediate states I_1 and I_2 in the energy flow process. E_c represents the energy utilization rate in the process of energy conversion from raw fuel to electrical signal, E_t represents the energy utilization rate in the process of energy conversion from electrical signal to information bit stream. The total energy efficiency of the whole system EE is the product of two parts of energy efficiency,i.e:

$$EE = E_c \times E_t \tag{1}$$

$$E_c = P_t/carbon\_energy, E_t = DOU/P_t \tag{2}$$

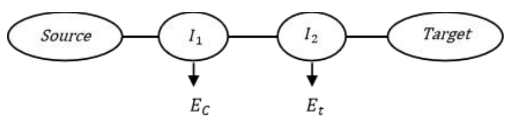

Fig. 2. System energy efficiency breakdown diagram

Based on the research on the open data of the leading enterprises [3] and suppliers[4] in the ICT industry, the technology saturation value of the E_c increase multiple is 2 times, so this paper plans to increase the E_t by at least 5 times [5] to meet the demand of EE by 10 times..

There are many researches on improving system energy efficiency in academic circles[6-9].[6]has proved that the energy efficiency of the system can be improved by changing the network configuration and replacing CAS (the centralized antenna system) with DAS (the distributed antenna system).[7]has studied the elastic resource allocation algorithm of DAS, and has established the structure of dynamic adaptation of coverage and service requirements. [8]has studied the base station user cluster management of distributed system, and has derived the maximum energy efficiency of the system.[9]has studied the downlink signal detection algorithm of DAS, and has established a multi-user joint detection model. There are many factors that affect the system energy efficiency, including the number of channels of the base station antenna and the geometric topology of the base station. This paper proposes an optimization algorithm based on neural network to further optimize the system energy efficiency of DAS. The algorithm inputs the measured data in the communication simulation experiment into the BP neural network for training, obtains the network model of base station location system energy efficiency, and then iteratively solves the maximum value of system energy efficiency E_{tmax} and the corresponding geometric topology of the base station.

Figure 3 describes the impact of the distance d between the base station and the user on the system energy efficiency, and explains the principle of the algorithm. In the distributed antenna system, the propagation loss on the antenna increases with the increasing of d, but the interference signal decreases with the increasing of d. For the reason that these two impacts offset each other, a more complex model is needed to describe the relationship between base station location and system energy efficiency, rather than a linear function. So this paper thought of using neural network to train the model.

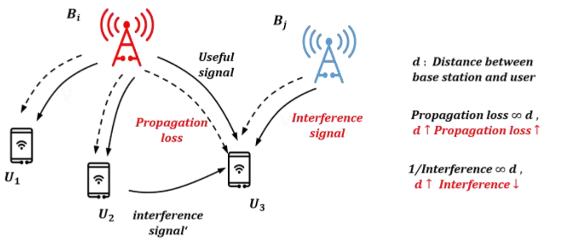

Fig. 3. Influence of base station location on system energy efficiency

Section.I predicted the goal of improving the system total energy efficiency EE by 10 times, and then divided the goal into two parts. The focus of the overall goal was to improve the radio energy efficiency E_t by at least 5 times. Section.II conducts a small-scale experiments and verifies that DAS can improve the radio energy efficiency to a certain extent.Section.II also analyzes the power consumption model of downlink of DAS. Section.III proposes an innovative optimization algorithm based on neural network to continue to optimize the energy efficiency of DAS. Section.IV shows and analyzes the experimental results. Section.V summarizes the data and the full text, proving that the algorithm can achieve the desired effect.

II. SYSTEM MODEL

A. System Models of the DAS

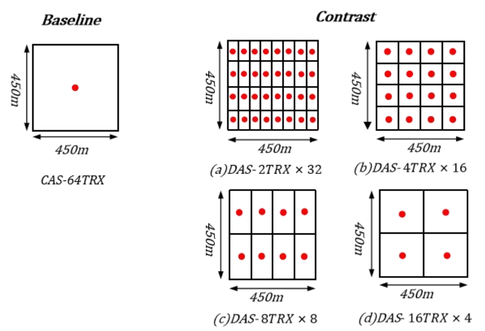

Fig. 4. System Models of the CAS and DAS

Distributed antenna system (DAS) uses multiple distributed base stations to replace a centralized base station of centralized antenna system (CAS). This paper conducts a small-scale simulation to study the energy efficiency of DAS and CAS. As shown in figure 4, each red dot represents a base station, which is geometrically evenly deployed in a fixed size area. The baseline of the experiment is CAS, and the number of antenna channels of the base station is 64. The experimental control group (a) - (d) consists of four DAS. The number of antenna channels of the base station is 2, 4, 8, and 16, respectively. The area of antenna array also decreases in equal proportion with the number of channels. All other channel parameters are the same.

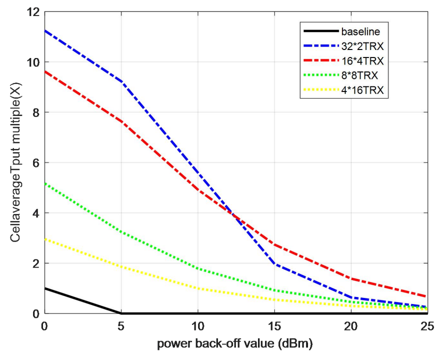

Fig. 5. Throughput-Transmit power curve of different DAS

Figure 5 shows the simulation results. There are five curves in the figure, the solid line represents the baseline of this experiment, and the other four dotted lines represent the control group (a) - (d) of this experiment. The X-axis represents the power back-off value (dBm) of the system's transmission power, and the power back-off value of the baseline is 0dBm (1W). The Y-axis represents the spectral efficiency multiple of the system, and the baseline is 1 time.

Firstly, comparing the system spectral effect at 0dBm, and there is $a > b > c > d$,which means the system of experimental group (a) has the highest energy efficiency. Secondly, comparing the power back-off value at $Y = 1$, and there is $b > a > c > d$,which means experimental group (b) has the highest power back-off value.Compared with the 1W baseline, the 24dBm (250mW) power back-off means the energy efficiency of the distributed antenna system is improved by four times. This is because with the increase of the number of distributed base stations, the distance between the base station and the user is getting closer, the communication quality is improved, and the propagation loss of the line is reduced. Although the deployment of distributed base stations can improve the system energy efficiency to a certain extent, it has not reached the expected goal, so it is necessary to further optimize the energy efficiency of the distributed antenna system.

B. Power consumption model and P_t calculation of DAS

Before studying the E_t details of DAS, it is necessary to determine its power consumption model and P_t *calculation* in advance. [10,11]propose a power consumption model of wireless communication system, including the power consumption of the hardware circuit of the base station and the signal transmission power of the base station. The former requires electronic design to reduce the power consumption. This paper only studies the signal transmission powerP_t.

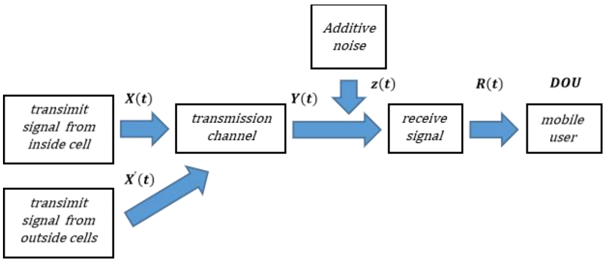

Fig. 6. Signal processing flow diagram of DAS system

Figure 6 is a commonly used downlink power consumption model of DAS. Assume that the user receives the BTS signal of this cell and the BTS signal of the outer macro cell at the same time, $\boldsymbol{X(t)}$ is the signal sent by the BTS transmitter in the cell, $\boldsymbol{X}'(\boldsymbol{t})$ is the signal sent by the transmitter of the outer cell, $\boldsymbol{Y(t)}$ is the channel response signal, $\boldsymbol{z(t)}$ is additive noise of channel, $\boldsymbol{R(t)}$ is Receiving signal of receiver, $\boldsymbol{DOU}$ is demodulated data bit stream. $\boldsymbol{X(t)}$ and $\boldsymbol{X}'(\boldsymbol{t})$ modulate to high-frequency sub-carrier after local D/A, and then transmit to channel after being processed by mixer, filter, RF signal amplifier, etc. After channel convolution and noise adding, the mixed signal forms a response signal $\boldsymbol{Y(t)}$, and then transmit to the receiving end of the mobile user. The receiver performs A/D on the received signal $\boldsymbol{R(t)}$ and modulates the symbol into $\boldsymbol{DOU}$ using QPSK/16QAM/64QAM/256QAM modulation.

$\boldsymbol{R(t)}$ is the signal received by the mobile user receiver. $\boldsymbol{H(d)}$ in the expression (3) is the impulse response function of the channel, which is mainly related to the transmission distance of the signal, and its size indicates the quality of the channel transmission conditions.

$$\boldsymbol{R(t)} = \boldsymbol{X(t)} \otimes \boldsymbol{H(d)} + \boldsymbol{X}'(\boldsymbol{t}) \otimes \boldsymbol{H(d)} + \boldsymbol{z(t)} \tag{3}$$

$\boldsymbol{R(t)}$ is consisted of three parts, which includes useful signal, interference signal from outer macro cell and channel additive noise. Expression (4) is used to describe the signal-to-noise ratio $SINR$ (dBm) of channel transmission,i.e:

$$SINR = 10\log\left(\frac{\boldsymbol{X(t)} \otimes \boldsymbol{H(d)}}{\boldsymbol{X}'(\boldsymbol{t}) \otimes \boldsymbol{H(d)} + \boldsymbol{z(t)}}\right) \tag{4}$$

Expression (5) is rewritten by expression (4), assuming that the variance of channel additive noise is σ^2. Then combining expression (6) and Shannon Formula, so as to get the expression of $\boldsymbol{DOU}$ (bps),i.e:

$$SINR = 10\log\left(\frac{\boldsymbol{X(t)} \otimes \boldsymbol{H(d)}}{\boldsymbol{X}'(\boldsymbol{t}) \otimes \boldsymbol{H(d)} + 10^{\frac{\sigma^2}{10}}}\right) \tag{5}$$

$$\boldsymbol{DOU} = B \times \log\left(1 + 10\log\left(\frac{\boldsymbol{X(t)} \otimes \boldsymbol{H(d)}}{\boldsymbol{X}'(\boldsymbol{t}) \otimes \boldsymbol{H(d)} + 10^{\frac{\sigma^2}{10}}}\right)\right) \tag{6}$$

The specific expression of E_t(bps/dBm) can be obtained by combining the definition of radio energy efficiency in expression (2) and expression (6),i.e:

$$E_t = \frac{B \times \log\left(1 + 10\log\left(\frac{\boldsymbol{X(t)} \otimes \boldsymbol{H(d)}}{\boldsymbol{X}'(\boldsymbol{t}) \otimes \boldsymbol{H(d)} + 10^{\frac{\sigma^2}{10}}}\right)\right)}{P_t} \tag{7}$$

There is a key variable d in expression (7), which means distance between base station and user.So in the following content, this paper uses machine learning method and neural network to train the $d - E_t$ model and solve the E_{tmax}.

III. OPTIMIZATION ALGORITHM

A. Principle of optimization algorithm

At present, the geometric topology of BTS in DAS are distributed regularly [12,13], including typical hexagonal cell structures [12] and circular structures[13]. In the communication simulation experiment, it is very difficult to directly seek all the base station positions, because there are many possibilities to randomly change the base station positions, resulting in a huge amount of computation. Take 7 base stations as an example. Within the area of $100 \times 100\text{m}^2$, assume that the base stations appear every 1m, there are 10000^7 possibilities of BTS locations. In a small area, the computational complexity of the experiment has reached the trillion level. Obviously, we can not traverse the solution, but we can use limited data to build a model.

As shown in figure 7, this paper solves the above model based on BP neural network. Firstly, randomly generating the position coordinates (x_i, y_i) of n groups of base stations, and recording the system energy efficiency value E_{ti} of the communication simulation experiment. Then they are input to the neural network as the samples for training, and the (x_i, y_i) - E_{ti} neural network model is obtained. Finally, the experiment randomly generates the location coordinates of some base stations, and predicts the maximum energy efficiency of the system according to the above model.

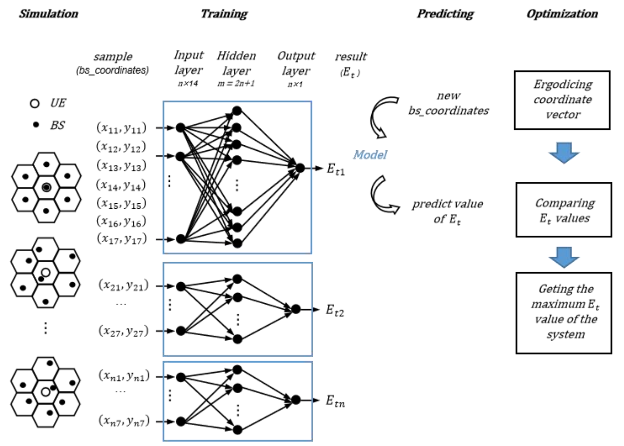

Fig. 7. System energy efficiency optimization algorithm

B. Flow chart of optimization algorithm

The design of the algorithm is divided into two parts. One is the neural network model for training neural network model of (x_i, y_i)- E_{ti}, the other part is to use the model to predict the maximum energy efficiency of the system.First of all, this paper conducts a large number of communication simulation experiments randomly and repeatedly to build a data set of neural network. Then, dividing the data set and starting to training the neural network, iterates over multiple epochs, and outputs them as ". m" files. Finally, this paper sets constraints, and solves the maximum system energy efficiency and the corresponding time base station location coordinates according to the model. The algorithm proposed in this paper follows the following steps:

- Step1: Setting the coordinate of the initial base stations (x_i, y_i) and distributing it randomly.

- Step2: Solving user throughput of distributed system and calculating spectral efficiency E_{ti}.
- Step3: Repeating steps 1 and 2 a hundred times.
- Step4: Inputting vector $[\boldsymbol{X},\boldsymbol{Y}]$ and vector E_t and neural network parameters into the neural network.
- Step5: Dynamically adjusting the network weight.If the number of iterations $\geq$ set epoch, or the error function$\leq$the set accuracy, stopping training.
- Step6: Outputting model as ". m" script file.
- Step7: Generating the location coordinates of two adjacent initial base stations in the upper left corner of the area, then comparing the corresponding E_t, and retaining the location coordinates with higher E_t.
- Step8: Continuing to compare the larger E_t reserved in Step7 with the E_t corresponding to the other adjacent location coordinates, and repeating the judgment principle of Step7.
- Step0: Repeating Step 8 to solve the maximum system energy efficiency E_{tmax} of DAS and its corresponding base station coordinate (x_{max}, y_{max}).

IV. EXPERIMENTAL RESULTS

A. Design of experiment scheme

This part includes scene analysis of communication simulation experiment, channel parameters and the training parameters of neural network.

1) Simulation of DAS

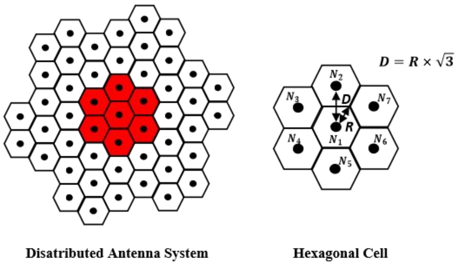

Fig. 8. Simulation of DAS

As shown in Figure 8, the DAS model used in the simulation is folded by seven macro cells. Each macro cell also contains seven hexagonal cells, and one cell contains one base station. Each macro cell has N_t base stations, and the configuration of N_t base stations in each cell in the same macro cell is the same, where N_t is set to 7. D is the distance from the geometric center of the adjacent hexagon, and R is the radius of the circular area covered by the hexagon. They have corresponding geometric relationships. The macro cell with background color in the figure is the central cell, and the users are distributed in the geometric center of the central cell. This paper assumes that the number of mobile users N_r is 7. The mobile user receives the signal from the central cell as a useful signal. The signals from other external cells interfere with the signal from the central cell user. This paper assumes that the mobile user receiver can perfectly estimate the channel state information from the base station transmitter.There is a direct path signal between the signal of the central cell and the mobile user. The channel is a Rice channel with a parameter $\mathrm{K} = 10$. Rayleigh fading exists between other external cells and mobile users, with 6 Rayleigh channels.The propagation model of the channel uses the distance related path loss with an attenuation factor of 36.7 and the logarithmic normal shadow with a standard deviation of 8 dB. The shadow correlation between antennas is set to 0.5. In this experiment, the downlink resource blocks are used to calculate the transmission bit stream of the system. The number of downlink resource blocks is 24, the number of sub-carriers in each resource block is 12, and the system bandwidth is set to 4.32 MHz. Simulation conditions are presented in Table I.

TABLE I. SIMULATION PARAMETERS

Parameters	**Value**
Spacing distance of BTS D	25,50,100,150,200,250m
Number of BTS N_t	
Number of MTS N_r	
Height of BTS	10m
Height of MTS	1.5m
Propagation loss	140.7+36.7log (d)dB, d: distance between BTS and MTS
Shadowing deviation	8dB
Shadowing correlation	0.5
Channel model	One-path Rician channel$(K = 10)$ Six-path Rayleigh channel
Noise power σ^2	-104dBm
System bandwidth	4.32MHz
Transmit power P_t	30dBm
Number of resource blocks	24
Number of symbols per trial	100

2) Neural network training parameters

In this experiment, the deep BP neural network is used to simulate the base station location system energy efficiency model. As shown in Figure 9, input lawyer is the two-dimensional vector with the size of 14×100, 14 represents the abscissa and ordinate of the seven base stations, and 100 represents the input of 100 groups of data to train the neural network model. Output lawyer is the two-dimensional vector with the size of 1×100, 1 represents the system spectral effect output by each group of experiments. There are 100 groups of data in total. The data set is divided into 70%, 15% and 15% of training set, verification set and test set respectively. The neural network has a total of 29 hidden layers, which can avoid over fitting of data and control the rationality of training time as much as possible. The neural network uses the Levenberg Marquardt algorithm, namely the damped least squares method, which can provide a numerical solution of nonlinear minimization. The experiment uses the loss function in the form of the sum of squares of errors to conduct network training, and uses the error function MSE to measure the accuracy of network training, i.e:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2 \quad (8)$$

Where Y_i and $\widehat{Y}_i$ represent the true value of spectral efficiency and the predicted value of network respectively.

The smaller the MSE value, the better the training effect of the network model. In addition, the system uses the correlation function R to show the fitness of the training results. The closer the R value is to 1, the closer the predictive value of the model is to its true value.

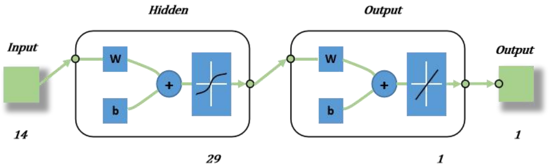

Fig. 9. Neural network model

B. Simulation results

The communication simulation sets up two groups of control experiments (a) and (b), which are respectively the distributed system of the base station in the geometric regular deployment and irregular deployment. The energy efficiency values of the two systems are compared through experiments, and the similarities and differences of the effects of different station spacing on the energy efficiency of the two systems are analyzed.

Figure 10 is the curve of system energy efficiency versus station spacing in simulation (a). It can be seen from the curve that when D = 25~100, the system energy efficiency will increase significantly with the increase of station spacing. However, the increase of system energy efficiency is very small after D reaches 100m, basically stable at about 5.709bps/Hz/mW.

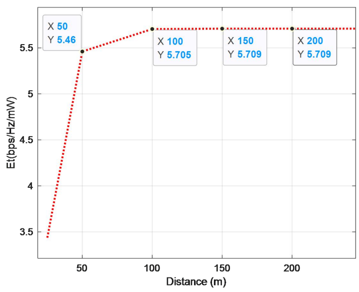

Fig. 10. Impact of station spacing on system energy efficiency

(simulation.(a).DAS with geometrically uniform BTS)

Figure 11 is the curve of system energy efficiency versus station spacing in simulation (b) ,which is similar to curve in figure 10, but the trend is more tortuous. When D = 25~100m , the increase of system energy efficiency is obvious, but the increase of system energy efficiency is very small after D reaches 100m, and even starts to decline when D = 250m. The maximum system energy efficiency is about 6.5bps/Hz/mW. The comparison of it in experiment (a) can infer this scheme can improve the system energy efficiency by 14%.

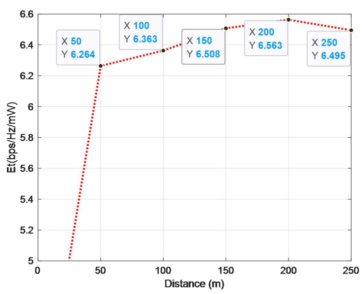

Fig. 11. Impact of station spacing on system energy efficiency

(simulation.(b).DAS with geometrically nonuniform BTS)

In addition, comparing Fig. 10 with Fig 11. It can be found that the influence of station spacing on the system energy efficiency of experiments(a) and (b) is that the small spacing changes obviously, while the large spacing changes slowly, and the change trend of system energy efficiency is different in the case of large spacing. This is because with the increase of the station spacing, the propagation loss of the system increases but the interference decreases relatively. The offset between this two factors will restrict the system's energy efficiency to continue to increase. In addition, the path loss and interference functions of the distributed system with the geometric nonuniform deployment of the base station are more complex and more sensitive to the change of the station spacing.

The data used in BP neural network training model is the base station location information and system energy efficiency obtained under the condition that the station spacing is 100 $(D = 100m)$ in the experiment (b).

Fig. 12 and Fig 13 is the result of model training, in which the value of MSE in training set, verification set and test set is 0.003, 0.02 and 0.03 respectively, which shows that the accuracy of the model is considerable. The values of the correlation function R on the training set, verification set and test set are 0.98, 0.2 and 0.3. The correlation function R of the training set is very close to 1, and the correlation function of the verification set and test set is also positively correlated, which indicates that the model has obtained a good training effect.

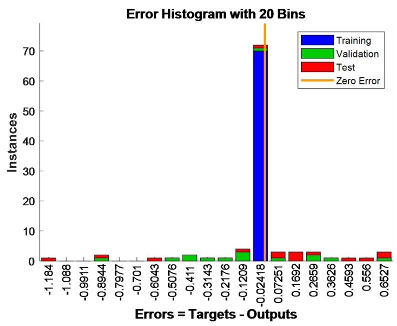

Fig. 12. Error function of neural network

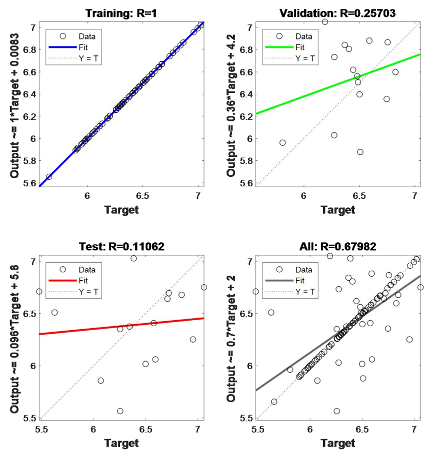

Fig. 13. Correlation function of neural network

Using this model to predict, it can be found that the maximum system energy efficiency is 7.108bps/Hz/mW, which can further improve the system energy efficiency by 10%. The corresponding location coordinates of the seven BTSs are (40,37), (- 40,80), (- 58,21), (- 68. - 60), (- 30, - 62), (48, - 40), and (30,60) respectively.

V. CONCLUSION

The realization process of the total goal can be described in Table.II:

TABLE II. IMPLEMENTATION OF TASKS

<table>
<tr><th rowspan="2">Parameter</th><th colspan="3">Implement</th></tr>
<tr><th>Demand</th><th>Method</th><th>Results</th></tr>
<tr><td>System energy efficiency EE</td><td>10X[2]</td><td colspan="2">$EE = E_c \times E_t$</td></tr>
<tr><td>Carbon energy efficiency E_c</td><td>2X[3]</td><td colspan="2">$E_c = P_t/carbon\_energy$</td></tr>
<tr><td rowspan="2">Radio energy efficiency E_t</td><td rowspan="2">5X</td><td>Replacing centralized antenna system(CAS) with distributed antenna system(DAS)</td><td>4X</td></tr>
<tr><td>Distributing geometrically nonuniform BTS and using energy efficiency optimized algorithm based on neural network</td><td>1.25X</td></tr>
</table>

The experimental results of this study show that using a distributed system and a reasonable geometric topology of the base station can improve the energy efficiency of the system. This is because the closer the distance between the base station and the user is, the smaller the transmission loss on the antenna is, but the stronger the interference signal is, so it is necessary to find a balance between the two cases. Different from previous single communication simulation experiments, this paper combines neural network to train the base station location-system energy efficiency model, and finds the balance point mentioned above. This algorithm can reduce the complexity of communication simulation experiments, and can also be applied in actual scenarios to improve system energy efficiency and achieve "carbon peak" in the wireless communication field. However, the current communication simulation is carried out when the distance between the base stations is 100m, and the corresponding input data of the neural network is less and single. In the future, we will continue to design multiple groups of communication experiments to enrich the data set of the neural network to improve the generalization of the algorithm.

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