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Energy Efficiency Optimization and Resource Allocation of Cross-Layer Broadband Wireless Communication System

ZUOLIN DONG [1], JIAHONG WEI [2], XIAOYU CHEN [1], AND PENGFEI ZHENG [3]

[1]Electronic and Information Engineering College, Henan Institute of Technology, Xinxiang 453000, China
[2]College of Electrical Engineering and Automation, Henan Institute of Technology, Xinxiang 453000, China
[3]College of Electronic and Electrical Engineering, Henan Normal University, Xinxiang 453007, China

Corresponding author: Jiahong Wei (jhwei1213@163.com)

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ABSTRACT Green energy-saving communication is one of the important research topics for the development of 5G technology. Under the premise of widespread distribution of intensive base stations, system resource allocation and energy efficiency optimization are the keys to improving system performance. Therefore, how to effectively control system energy consumption and resource allocation has become the key to whether 5G technology can achieve effective application effects. In order to improve the energy efficiency performance of the cross-layer broadband wireless communication network system, this study combines the analysis of the broadband wireless communication system to optimize the energy efficiency of the cross-layer wireless communication system. Simultaneously, with the help of resource allocation technology, this study optimizes the multi-user underlying transport layer of the FDD-OFDMA system. In addition, this study explores the most reasonable system resource allocation method and achieves reasonable resource allocation through the optimization of energy efficiency resources in massive MIMO-OFDMA downlink systems. Finally, this study sets up a controlled experiment to analyze the algorithm's energy efficiency performance. The research shows that the method proposed in this paper has certain effects and can provide a reference for subsequent related research.

INDEX TERMS Green communication, cross-layer broadband, wireless communication, system energy efficiency, resource optimization.

I. INTRODUCTION

The rising demand of people in the era of big data has led to the continuous development of Internet technology, which has increasingly higher requirements for the speed of information transmission. From the first 1G technology to the GSM network 2G technology, to the TD-SCDMA network 3G technology, and to the 4G technology after 2010, the development of each generation of communication technology means that network data transmission speed requirements are getting higher and higher, and the network speed is getting faster and faster, which puts forward higher requirements for network system performance. At present, people have gradually entered the 5G era, and the speed of the 5G era is far faster than the 4G era. Therefore, the system performance needs to be further improved, especially when the system has resource allocation problems and energy consumption problems during operation [1].

From the actual situation, 4G technology has been unable to meet the current data transmission speed requirements of various software and website systems. Therefore, while continuing to promote the development of 4G technology, communication research institutions around the world have taken the development of 5G technology as the new communication development direction, which has now reached the application level and is gradually promoted [2]. With the large-scale promotion of 5G technology, the problems it faces also need to be resolved. The main issues are system resource allocation and energy efficiency optimization. In particular, under the premise of widespread distribution of dense base stations, how to effectively control system energy consumption and resource allocation has become the key to whether 5G technology can achieve effective application effects.

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5G technology is a high-speed information transmission network technology after 2020, which has great flexibility and has strong support for instant information transmission. In particular, with the rapid development of wireless network control remote object technology and the support of 5G technology, the business needs of different network environments can be met. At present, 5G technology-related standards have been formulated and pilots have been launched in multiple cities. In view of the development law of mobile technology, 5G technology has greatly improved in frequency utilization rate, energy efficiency, resource utilization and data transmission speed, and dense base stations will further increase network coverage and greatly improve user experience. From the perspective of transmission rate, the transmission rate of 5G technology can reach at least 10Gbs, which is equivalent to 10 times of the current 4G network. Moreover, the transmission rate of some specific services can reach at least 100Gbs, and there is a smaller time delay in the data transmission process, which is at least 5-10 times shorter than the 4G network in terms of time delay. 5G networks are dense networks, and base stations are more densely arranged. Therefore, in the 5G era, green energy-saving communication is one of the important research topics for the development of 5G technology.

Aiming at the distribution of network resources, the currently popular method is dynamic resource allocation technology, which mainly allocates system resources based on channel status and interference received by signals, adjusts parameters, and optimizes data transmission schemes. This technology can not only obtain higher spectrum efficiency, but also effectively meet the various needs of customers. It is currently the most advanced and widely used communication free allocation technology [3]. In the 5G network era, the optimization of communication technology is to rationally allocate system resources so as to achieve the rational use of system resources and take the maximum throughput or the minimum system energy consumption as the objective function. For green communications in the 5G era, the most important thing is system energy efficiency. Therefore, constructing an objective function based on maximizing the energy efficiency of the system is the main problem of the resource allocation algorithm [4].

This study combines the analysis of broadband wireless communication systems to optimize the energy efficiency of cross-layer and cross-band wireless communication systems. Moreover, in this study, the resource allocation technology is used to optimize the multi-user lower-level transport layer of the FDD-OFDMA system, and to explore the most reasonable system resource allocation method. In addition, this study achieves reasonable resource allocation by optimizing the energy efficiency resources of the massive MIMO-OFDMA downlink system, thereby promoting the optimal energy efficiency of cross-layer broadband wireless communication systems in the 5G era. This study combines the analysis of broadband wireless communication systems to optimize the energy efficiency of cross-layer and cross-band wireless communication systems. Moreover, with the help of resource allocation technology, the multi-user lower-layer transport layer of the FDD-OFDMA system is optimized. At the same time, this study explores the most reasonable system resource allocation method to achieve reasonable resource allocation by optimizing the energy efficiency resources of the massive MIMO-OFDMA downlink system. In the research, the focus is on energy efficiency optimization and resource allocation for cross-layer wireless communication systems in wireless communication systems, and optimization analysis is performed using multi-user parallel data transmission processes in common network communication systems as an example, and analysis of energy efficiency impact parameters is carried out. In addition, simulation verification of system resource optimization is performed to simulate energy efficiency optimization problems in large-scale network environments.

II. RELATED WORK

Wireless communication devices such as mobile phones have been popularized, which has promoted the further development of wireless mobile communication technology. Moreover, the current 4G technology has been popularized around the world. However, due to special reasons, very few areas cannot deploy base stations and lack 4G network coverage. From a broad perspective, most people's wireless communication speed transmission needs are basically met. However, with the continuous development of science and technology and the increase in data volume, people have higher and higher requirements for data transmission speed, and especially in the 5G era, the data information transmission speed has increased 10 times directly. In this background, wireless communication energy consumption has increased significantly. Therefore, the greenhouse gas generated by energy consumption during the operation of the wireless communication system has caused some impact on the earth's ecology and caused widespread concern in the society. Studies show that the current greenhouse gas pollution caused by mobile communication systems has accounted for 3% of global greenhouse gas pollution. And, with the advent of the 5G era, greenhouse gas emissions from communications systems will further increase. Currently, it is increasing at a rate of about 20% every year [5]. In addition, the slow development of battery technology is also an important cause of energy consumption, so people pay more attention to the study of energy consumption. The green communication section can maximize the improvement of energy efficiency, and in the study, the main price energy consumption is defined as the number of bits consumed per unit energy transmission. In the 5G era, it is necessary to face high-energy data transmission, so the green communication resource allocation technology will be the top priority in the 5G era [6]. Literature proposed that the maximum energy effect was used as the objective function [7]. This algorithm was named BSAA algorithm, and the basic idea of the algorithm was to reasonably allocate the rate vector by dichotomy to achieve the desired result required by the objective function. People have studied the OFDMA communication problem earlier.

In literature, the energy consumption problem in the OFDMA system is modeled, and the model is optimized. On the basis of continuous research on the energy efficiency of communication networks, literature optimizes energy efficiency based on Massive MIMO systems, and provides a reference direction for the development of green communication technologies [8]. In literature, a non-cooperative game method was used to analyze the energy consumption of communication network systems. Literature used the fractional programming method to transform the energy consumption function into a fractional form. Furthermore, model optimization processing is performed on this basis. Literature used Dinkelbach algorithm to study the energy efficiency of communication network systems, and established corresponding models for analysis, and formulated corresponding strategies [9].

With the increasing emphasis on the natural environment, energy efficiency issues have received widespread attention from experts at home and abroad, and most experts and scholars have also started to apply the Dinkelbach algorithm in system models and have achieved certain results [10]. For a communication system, there are many users in the system with hierarchical characteristics, that is, all users are not in the same fading state, so each subcarrier can be allocated to the corresponding channel according to the actual situation, and data transmission is performed according to the condition [11]. This method is currently the more common OFDMA access method. OFDMA access method mainly aims at allocating parameter resources such as subcarriers, transmit power, and rate to users when optimizing targets. By optimizing these parameter resources, higher power utilization and first-level spectrum utilization can be obtained. In actual research, the dynamic resources in OFDMA access methods can be summarized according to the optimization target differences [12], mainly including the following three: The first type is an algorithm that takes the maximum throughput of the system as the objective function, which is named the RA algorithm [13]. Aiming at the research of this algorithm, the literature studies the allocation of subcarriers in the United States and stipulated that each subcarrier was allocated to the user with the highest channel gain, and the water injection algorithm was used to allocate the subcarrier power so that it can reach the maximum throughput. On this basis, it can provide relevant basis for the allocation of subcarriers. Moreover, the traversing capacity of the model built on this basis only considers the number of bits sent by the transmitting end per second, but the packet error rate in this process is ignored [14]. From the actual situation, it can be seen that the packet error rate can be ignored only when the transmitting end has fully understood the status information. Similarly, in literature, the laboratory of the incomplete information of the transmitting end is known as the research channel, and the maximum effective output of the system is used as the objective function of the model [15]. Under the assumption that the information at the transmitting end is completely unknown, literature proposed a resource allocation algorithm that maximizes as the objective function [16]. Literature researched and analyzed the problem of minimum system function energy consumption of the system model and combined the Lagrange function to solve the model optimal solution. From the actual situation, the algorithm needs to search for two Lagrangian functions at the same time, so the system is difficult to run, and it is limited to the theoretical research process and cannot be applied to practice. From a practical point of view, the optimization analysis of the system scheme by the suboptimal solution is a simpler solution, and the algorithm is less difficult to run. It can be subdivided into distributed algorithms, heuristic algorithms, and convex optimization algorithms. Among them, distributed algorithms mainly allocate joint problems such as power and number of bits [17]. During the system operation, the degree of freedom of resource allocation is reduced, the complexity of the system operation is abnormally reduced, and the system operation efficiency is improved [18]. Literature proposed a distributed resource allocation algorithm with minimum system power consumption as the objective function [19]. First, the number of subcarriers is determined according to the system user rate renewal and the average signal-to-noise ratio, and then the specific subcarriers are allocated power according to the algorithm. With the continuous development of technologies for network system energy efficiency optimization and resource allocation, experts and scholars take complexity as one of the important parameters for model research. Moreover, more heuristic optimization algorithms appear on this basis. The common algorithms include simulated annealing algorithm, genetic algorithm, particle swarm algorithm, etc [20].

The convex optimization algorithm is also an effective algorithm to reduce the complexity in the energy efficiency model of the communication system [21]. This algorithm mainly combines the convex optimization theory to downgrade the complex problem, so that the complex problem becomes several independent sub-problems. As long as the results of the sub-questions are solved and synthesized, the final answer of the original question can be obtained. Compared with the above algorithms, the convex optimization algorithm has good performance, and is higher than the above algorithms in speed and effect [22]. Literature researched the maximum and minimum criterion resource allocation of the system, constructed an optimization model, achieved the system's proportional fairness at the minimum transmission rate, and increased system capacity as the optimization goal [23]. Through this algorithm, each user can basically obtain the same rate, thereby ensuring absolute fairness among users in the system. However, this system cannot effectively increase the system capacity, so there are still some problems. In order to balance the absolute fairness of system users, the literature studied the resource allocation algorithm based on proportional fairness in downlink OFDMA system [24]. Through simulation analysis, multiple parameters of the system are studied and analyzed, and it is proved that the algorithm has good performance with a slight reduction in throughput and can effectively maintain system fairness [25]. Literature carried out research and analysis on weight and rate maximization. Through this algorithm, a weight coefficient can be introduced for each user, and resources are allocated according to their respective weights. Based on this, the actual needs of different users can be met, and the system can be diversified [26].

III. PROBLEM DESCRIPTION AND ALGORITHM CONSTRUCTION

A. PROBLEM DESCRIPTION

This study takes a typical multi-line user MIMO-OFDMA wireless communication system as an example. It is set that the base stations in the network system are configured with a total of M antennas for signal transmission. Furthermore, there are K locations that are communicatively connected to the base station through a single antenna. We assume that a total of N subcarriers are divided into V frequency blocks (including N/V subcarriers) in this system. These frequency blocks are the smallest unit of resource scheduling in the communication system. Combining the channel reciprocity of the network system, we can know the uplink channel matrix $G_\upsilon = H_\upsilon D^{1/2}$, Where H_υ represents the user-to-base station $M \times K$ fast fading matrix on the frequency block, $D^{1/2} = diag\left\{\sqrt{\beta_1}, \cdots, \sqrt{\beta_k}\right\}$ represents the $K \times K$ angular matrix, and the diagonal element $\sqrt{\beta_k}$ is the slow fading coefficient from the base station to obtain the downlink channel matrix $G_\upsilon^T = D^{1/2} H_\upsilon^T$,Then, the signal matrix of the V-th frequency space received by the user can be expressed as follows:

$$\begin{aligned} y_{\upsilon,k} &= g_{\upsilon,k}^T \sum_{k=1}^{K} \sqrt{p_{\upsilon,k}} f_{\upsilon,k} x_{\upsilon,k} + z_{\upsilon,k} \\ &= g_{\upsilon,k}^T \sqrt{p_{\upsilon,k}} f_{\upsilon,k} x_{\upsilon,k} + g_{\upsilon,k}^T \sum_{i=1, i\neq k}^{K} \sqrt{p_{\upsilon,i}} f_{\upsilon,i} x_{\upsilon,i} + z_{\upsilon,k} \end{aligned} \tag{1}$$

In the formula, $g_{\upsilon,k}$ represents the kth column of the matrix g_υ, $f_{\upsilon,k}$ represents the precoding matrix of user k on frequency block V, and $x_{\upsilon,k}$ represents the transmission signal of user k on frequency block V.. There are two equal signs in the above formula, and the second equal sign part indicates the user's desired signal in the system and the interference and other Gaussian white noise that the user receives in the system.

Based on the above analysis, it can be known that the signals received by users will be subject to multiple interferences, and the signals between multiple users may interfere with each other. Therefore, these mutual interferences need to be eliminatePrecoding matrix $F_\upsilon = G_\upsilon^* \left(G_\upsilon^T G_\upsilon^*\right)^{-1}$ by zero-forcing precoding.In the formula, $F_\upsilon = \left[F_{\upsilon,1}, \cdots, F_{\upsilon,\mathrm{K}}\right]$. Therefore, $g_{\upsilon,k}^T F_{\upsilon,i} = \delta_{ki}, \delta_{ki} = \begin{cases} 1, & k = i \\ 0, & k \neq i \end{cases}$.

Then, the signal matrix that has received the Vth frequency space can be expressed as follows:

$$r_{\upsilon,k} = \mathrm{E}\left\{ W \log_2 \left[1 + \frac{p_{\upsilon,k}}{WN_0 \left[\left(G_\upsilon^T G_\upsilon *\right)^{-1}\right]_{kk}} \right] \right\} \tag{2}$$

According to the above formula, the lower bound of the frequency of the signal received by the user in the Vth frequency space is:

$$r_{\upsilon,k} \geq W \log_2 \left[1 + \frac{p_{\upsilon,k}}{WN_0 \mathrm{E}\left\{ \left[\left(G_\upsilon^T G_\upsilon *\right)^{-1}\right]_{kk} \right\}} \right] \tag{3}$$

In the formula,

$$\begin{aligned} E\left\{ \left[\left(G_\upsilon^T G_\upsilon *\right)^{-1}\right]_{kk} \right\} &= \frac{1}{\beta_k} \mathrm{E}\left\{ \left[\left(H_\upsilon^T H_\upsilon *\right)^{-1}\right]_{kk} \right\} \\ &= \frac{1}{K\beta_k} \mathrm{E}\left\{ tr\left[\left(H_\upsilon^T H_\upsilon *\right)^{-1}\right] \right\} \end{aligned} \tag{4}$$

Since $\mathrm{E}\left\{tr\left[\left(W^{-1}\right)\right]\right\} = \frac{m}{t-m}$, where $W - W_m(t, I_t)$ is the central complex Wishart matrix with degrees of freedom $t\ (t > m)$, $\mathrm{E}\left\{ tr\left[\left(H_\upsilon^T H_\upsilon *\right)^{-1}\right] \right\} = \frac{K}{M-K}$.

In summary, the lower bound of the rate of user k on the frequency block u can be expressed as:

$$r_{\upsilon,k} = W \log_2 \left[1 + \frac{p_{\upsilon,k} (M-K) \beta_k}{WN_0} \right] \tag{5}$$

Parametric simulation analysis through experiments, Figure 1 shows the system throughput of summing the number of users and the number of frequency blocks in the cases shown in equations (2) and (5). In this figure, $K = 12$ is set, and then the theoretical value of the number of users is summed, and the formula (5) is summed by the derived value. It is not difficult to derive from Figure 1 that the lower bound of the theoretical value is very close to the rate value derived by the formula, which can be assumed to be equal by default. Therefore, in this study, this value is used instead of the theoretical value.

It can be known from formula (5) that the user's allocation rate on a single frequency is closely related to the user's large-scale fading. Then, the rate obtained by user k allocation can be expressed as:

$$\begin{aligned} r_k &= m_k W \log_2 \left[1 + \frac{p_{\upsilon,k} (M-K) \beta_k}{WN_0} \right] \\ &\approx m_k W \log_2 \left[\frac{p_k (M-K) \beta_k}{WN_0} \right] \end{aligned} \tag{6}$$

In the above formula, m_k represents the number of frequency blocks allocated by user k, and p_k represents the power allocated by user K in any one of m_k frequency blocks. Then, the lower bound of the energy efficiency function in

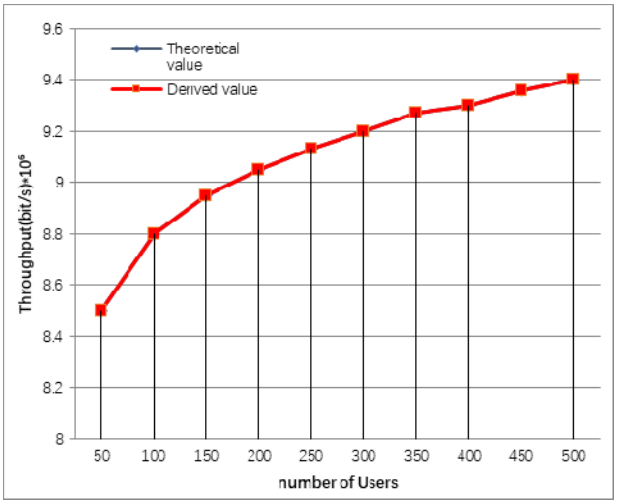


FIGURE 1. Throughput comparison chart.

this system can be expressed as:

$$U = \frac{\sum_{k=1}^{K} T_k}{\sum_{k=1}^{K} m_k p_k + M p_c} = \frac{\sum_{k=1}^{K} m_k W \log_2 \left[\frac{p_k (M-K) \beta_k}{W N_0}\right]}{\sum_{k=1}^{K} m_k p_k + M p_c} \tag{7}$$

According to the analysis, it can be known that the corresponding maximization problem in the energy efficiency resource allocation of the massive MIMO-OFDMA system existing in the downlink users can be expressed as follows:

Optimization problem $\max_{P,m,M} U(P, m, M)$

Restrictions:

$$\begin{cases} T_k \geq R_{\min} \\ \sum_{k=1}^{K} m_k = V \end{cases}$$
$$\begin{cases} m_k W \log_2 \left[\frac{p_k (M-K) \beta_k}{W N_0}\right] \geq R_{\min} \\ \sum_{k=1}^{K} m_k = V \end{cases} \tag{8}$$

In the formula, $p = [p_1, \cdots, p_k, \cdots, p_K]^T$ represents the transmission power vector, $m = [m_1, \cdots, m_k, \cdots, m_K]^T$ represents the vector of frequency block numbers allocated to the user, and $R_{\min}$ is the minimum rate constraint of the user.

B. ENERGY-EFFICIENT RESOURCE ALLOCATION FOR MASSIVE MIMO OFDMA DOWNLINK SYSTEMS

From the problem described by equation (8), it can be known that the allocation of the number of user frequency blocks is mainly required in the system resource allocation. Therefore, the traditional exhaustive mode will lead to a huge amount of system operation data and high complexity, which is difficult to implement in a computer. Therefore, the resource allocation algorithm needs to be optimized and its optimization process is performed step by step. First, the bandwidth of each user is determined, and then the power allocation and the number of base station antennas are allocated.

Firstly, a bandwidth allocation algorithm (BABEE) based on maximizing energy efficiency under the minimum rate requirement is proposed. Based on the signal-to-noise ratio bandwidth allocation algorithm (BABS), the algorithm mainly uses the average signal-to-noise ratio and bit rate received by the user as parameters to calculate the number of subcarriers obtained by the user. The optimization process of the bandwidth allocation objective function can be expressed as follows:

$$m_k = \max_{m} \frac{\sum_{k=1}^{K} m_k W \log_2 \left[\frac{p_k (M-K) \beta_k}{W N_0}\right]}{\sum_{k=1}^{K} m_k p_k + M p_c} \tag{9}$$

In order to meet the minimum user rate requirements during system operation, it may not be possible to achieve effective bandwidth matching based on the above formula. Therefore, the bandwidth needs to be allocated and processed first. The algorithm can be described as follows:

The user transmit power vector P_0 is initialized, and the initialized rate allocation R_0 is obtained according to P_0.

1) $m_k \leftarrow \left\lceil \frac{R_{\min}}{R_0(k)} \right\rceil$
2) *while* $\sum_{k=1}^{K} m_k > V$
3) $\left\{ k^* \leftarrow \arg\max_{1 \leq k \leq K} m_k, m_k. \leftarrow 0 \right\}$
4) *end while*
5) *while* $\sum_{k=1}^{K} m_k < V$
6) *do* $$Q_k = \frac{(m_k+1) W \log_2 \left[\frac{p_k (M-K) \beta_k}{W N_0}\right]}{(m_k+1) p_k + M p_c} - \frac{m_k W \log_2 \left[\frac{p_k (M-K) \beta_k}{W N_0}\right]}{m_k p_k + M p_c}$$ $$l \leftarrow \arg\max_{1 \leq k \leq K} Q_k$$ $$m_l = m_l + 1$$
7) *end while*

Based on the above research, a new energy efficiency maximization resource allocation algorithm (RABEE) based on the minimum rate requirement is proposed, that is, after the bandwidth is reasonably allocated, the power and the number of antennas are allocated to promote the optimal energy efficiency of the system. From a formal point of view, the energy efficiency function is a fractional form, so the energy efficiency function needs to be processed first to make it into a subtractive form, and then it is turned into a solution to a convex optimization problem. Combining the properties of fractional form, the objective function can be expressed as:

$$R(P, M) - q * [P_T(P) + P_C(M)]$$

In the formula,

$$q* = \frac{R(P^*, M^*)}{P_T(P^*) + P_C(M^*)} = \max_{M,P} \frac{R(P, M)}{P_T(P) + P_C(M)}$$

Therefore, the objective function can be transformed into an optimization problem as follows:

$$F(q) = \max_{M,P} R(P,M) - q[P_T(P) + P_C(M)]$$
$$= \max_{M,P} \sum_{k=1}^{K} m_k W \log_2\left[\frac{p_k(M-K)\beta_k}{WN_0}\right]$$
$$-q\left(\sum_{k=1}^{K} m_k p_k + Mp_c\right) \tag{10}$$

Restrictions $m_k W \log_2\left[\frac{p_k(M-K)\beta_k}{WN_0}\right] \geq R_{\min}$

We assume that

$$f = R(P,M) - q[P_T(P) + P_C(M)]$$
$$= \sum_{k=1}^{K} m_k W \log_2\left[\frac{p_k(M-K)\beta_k}{WN_0}\right]$$
$$-q\left(\sum_{k=1}^{K} m_k p_k + Mp_c\right) \tag{11}$$

The Hessian matrix of function f is

$$H(f) = \begin{bmatrix} -\frac{m_k W}{p_k^2 In2} & 0 \\ 0 & -\sum_{k=1}^{K} \frac{m_k W}{(M-K)In2} \end{bmatrix} \tag{12}$$

From the above, we know that $H(f)$ is a negative definite matrix. In this case, the function f is concave for (P, M), and the objective function can be converted into a convex optimization problem. Lagrange function can be expressed as:

$$L(\lambda, P, M)$$
$$= \sum_{k=1}^{K} m_k W \log_2\left[\frac{p_k(M-K)\beta_k}{WN_0}\right] - q\left(\sum_{k=1}^{K} m_k p_k + Mp_c\right)$$
$$+ \sum_{k=1}^{K} \lambda_k \left\{m_k W \log_2\left[\frac{p_k(M-K)\beta_k}{WN_0}\right] - R_{\min}\right\} \tag{13}$$

In the formula, $\lambda_k \geq 0$ is the Lagrangian multiplier corresponding to the constraint in formula (10). The dual problem of equation (10) can be expressed as:

$$\min_{\lambda \geq 0} \max_{P,M} L(\lambda, P, M) \tag{14}$$

When λ is given and the KKT condition is adopted, the optimal transmission power P^* and the number of base station antennas M* can be expressed as:

$$\frac{\partial L}{\partial p_k} = \frac{m_k W}{In2 \times p_k} - qm_k + \frac{\lambda_k m_k W}{In2 \times p_k} = 0 \Rightarrow p_k{}^*$$
$$= \frac{(1+\lambda_k) W}{In2 \times q} \tag{15}$$

$$\frac{\partial L}{\partial M} = \frac{W\sum_{k=1}^{K} m_k}{In2 \times (M-K)} - qp_c + \frac{W\sum_{k=1}^{K} \lambda_k m_k}{In2 \times (M-K)}$$
$$= 0 \Rightarrow M* = \frac{\left(V + \sum_{k=1}^{K} m_k \lambda_k\right) W}{In2 \times qp_c} + K \tag{16}$$

The Lagrange multiplier λ is obtained by recursion:

$$\lambda_k(j+1) = \left[\lambda_k(j) - \delta \times \left[m_k W \log_2\left(\frac{p_k(M-K)\beta_k}{WN_0}\right)\right.\right.$$
$$\left.\left. - R_{\min}\right]\right]^+ \tag{17}$$

In the above formula, δ represents the number of iterations, and m represents the iteration step size. Based on this, an iterative algorithm for energy efficiency maximization resource allocation (RABEE) based on the minimum rate requirement is proposed. The specific algorithm is described as follows:

1) Initialization $P^* = P_0, M^* = M_0, q^* = 0, \lambda = 0.\delta = \delta_0, \varepsilon = 0.01$
2) $while R(P^*, M^*) - q^*\left[P_T(P\hat{a}st) + P_C(M^*)\right] > \varepsilon$
3) $\left\{doq^* \leftarrow \frac{R(P^*,M^*)}{[P_T(P^*)+P_C(M^*)]}\right\}$
4) The Lagrangian multiplier is updated.
5) The power allocation is calculated.
6) The number of base station antennas is calculated.
7) *Return* q^*, P^*, M^*

Based on the above analysis, an energy-efficient multi-user power allocation based on the water injection algorithm is proposed. The water injection algorithm is used to allocate resources to the multi-user MIMO energy efficiency system. By formula

$$\frac{\partial U(P, \mathrm{m}, \mathrm{M})}{\partial p_k} |p = p^* = 0 \tag{18}$$

The following formula can be obtained

$$p_k^* = \frac{W}{U * \ln 2} - \frac{WN_o}{(M-K)\beta_k} \tag{19}$$

Then, the optimal energy efficiency allocation process can be expressed as follows:

$$p_k{}^* = \begin{cases} \frac{W}{U * \ln 2} - \frac{WN_o}{(M-K)\beta_k} & when\ U^* < \frac{(M-K)\beta_k}{N_o \ln 2} \\ 0 & otherwise \end{cases} \tag{20}$$

Definition

$$f(\mu) = U(P(\mu)) \tag{21}$$

The specific algorithm is described as follows:

1) $\mu_1 = \min \frac{WN_0}{(M-K)}\beta_k$
2) $\mu_2 = \mu_1{}^*\alpha, \alpha > 1$
3) $while\ f'(\mu_2) > 0$
4) $do\ \mu_1 \leftarrow \mu_2, \mu_2 \leftarrow \mu_2^*\alpha$
5) *While no convergence*
6) $do\ \mu = \frac{\mu_1+\mu_2}{2}$

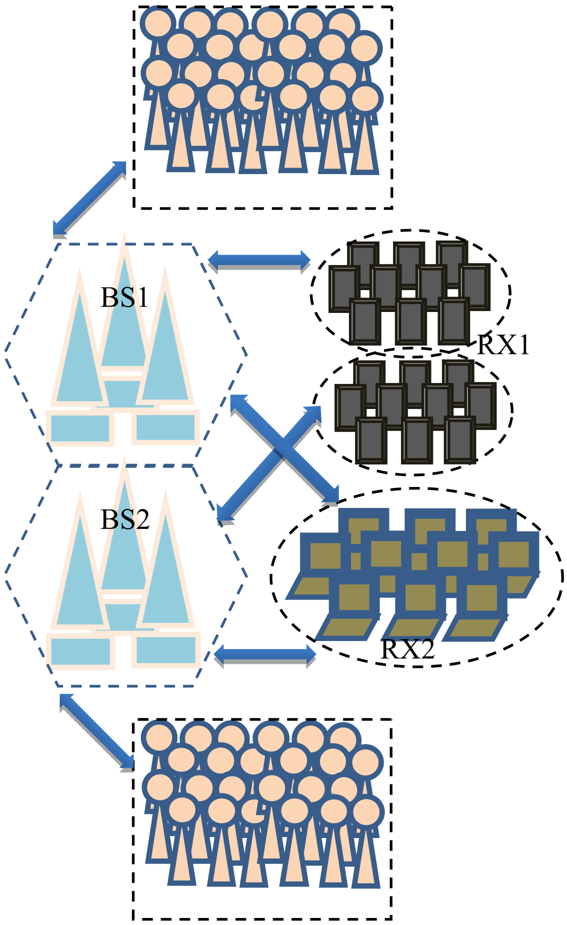


FIGURE 2. System model.

7) *if* $f'(\mu) > 0$
8) *then* $\mu_1 \leftarrow \mu$
9) *else* $\mu_2 \leftarrow \mu$
10) *return* μ *and* $p_k^* = \left[\mu - \frac{MN_0}{(M-K)\beta_k}\right]^+$

IV. SYSTEM MODEL

In this study, a typical wireless communication network that is relatively common is taken as an example for analysis, and the network system is set to cover L cells. Moreover, each cell is equipped with a corresponding base station, which has N antennas and K single-antenna users. The structure diagram is shown in Figure 2.

The signal strength received by user k can be expressed as follows:

$$y_k = \sum_{l=1}^{L} h_{kl} x_l + n_k \tag{22}$$

In the formula, $h_{kl} \in \mathbb{C}^{1\times N}$ represents the channel matrix from the first base station to the k-th user, and the elements obey $CN\,(0, 1)$; $x_l \in \mathbb{C}^{N\times 1}$ represents the transmitted signal of the first base station, and n_k represents observing $CN \sim \left(0, \sigma^2\right)_n$-additive white noise.

It is assumed that there is a cooperative operation for all base stations in the cell. Therefore, the signal sent by the system to the user K can be expressed as s_k. $\|s_k\| = 1$, w_{kl} represents the transmit power from the first base station to the k-th user in the system, $\|w_{kl}\| = 1$.The transmission signal x_l can be expressed as follows:

$$x_l = \sum_{k=1}^{K} w_{kl} \sqrt{p_{kl} s_k} \tag{23}$$

In the above formula, p_{kl} represents the transmission power from the first base station to the k-th user in the system. Based on the above analysis, the signal received by user k can be expressed as follows:

$$y_k = \sum_{l=1}^{L} h_{kl} x_l \sqrt{p_{kl} s_k} + \sum_{k'=1,k'\neq k}^{K} \sum_{l=1}^{L} h_{kl} w_{k'l} \sqrt{p_{k'l} s_{k'}} + n_k \tag{24}$$

In the above formula, the front part of the plus sign indicates the expected signal of user k in the system, and the back part of the plus sign indicates the interference of other users received by user k in the system. The signal-to-noise ratio received by user k at work can be expressed as follows:

$$SINR_k = \frac{\left\| \sum_{l=1}^{L} h_{kl} w_{kl} \sqrt{p_{kl}} \right\|^2}{\left\| \sum_{k'=1,k'\neq k}^{K} \sum_{l=1}^{L} h_{kl} w_{k'l} \sqrt{p_{k'l}} \right\|^2 + \sigma_n^2} \tag{25}$$

Encoding is performed by zero-forcing (zF) precoding. The precoding matrix $F_l = [f_{1l}, \cdots, f_{kl}]$ transmitted by the first base station in the system can be expressed as:

$$F_l = H_l^H \left(H_l H_l^H\right)^{-1} \tag{26}$$

In the above formula, $H_l \in \mathbb{C}^{K\times N}$ represents the channel matrix from the first base station to all users in the system. The precoding matrix w_{kl} of the channel matrix from the first base station to the k users in the system can be expressed as follows:

$$w_{kl} = \frac{f_{kl}}{\|f_{kl}\|} \tag{27}$$

The signal received by user k can be described as:

$$y_k = \sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\|} s_k + n_k \tag{28}$$

The reachable rate of user k is expressed as follows:

$$\begin{aligned} r_k &= \log_2 \left(1 + \left\| \sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0} \right\|^2\right) \\ &\approx \log_2 \left(\left\| \sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0} \right\|^2\right) \end{aligned} \tag{29}$$

In the above formula, N_0 represents the noise density. It is not difficult to see from the above formula that the relationship between the user's reachable rate and the number of base station antennas is not explicit, so it is difficult to draw a practical relationship between the two. Assuming that the fixed value of power consumption can be expressed as P_C, the transmission power matrix can be expressed as:

$$P = \begin{bmatrix} p_{1,1} & \cdots & h_{1,L} \\ \vdots & \ddots & \vdots \\ p_{K,1} & \ddots & P_{K,L} \end{bmatrix} \tag{30}$$

Based on the above analysis, the system energy efficiency can be expressed as:

$$U(P) = \frac{\sum_{k=1}^{K} r_k}{\sum_{l=1}^{L}\sum_{k=1}^{K} p_{kl} + P_C} = \frac{\sum_{k=1}^{K} \log_2\left(\left\|\sum_{k=1}^{K} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right\|^2\right)}{\sum_{l=1}^{L}\sum_{k=1}^{K} p_{kl} + P_C} \tag{31}$$

Considering maximizing system energy efficiency as an optimization goal, it can be expressed as:

$$\underbrace{\max}_{p} U(P) \tag{32}$$

V. ENERGY EFFICIENCY RESOURCE ALLOCATION

A. OPTIMIZED ALGORITHM

According to the nature of score planning, the original score optimization problem can be transformed into a subtractive form. Based on this, an iterative algorithm can be obtained. In the study, multiple cells can be regarded as an extension of two cells. In the same way, the system base station cooperation problem can be regarded as the cooperation problem between two base stations, and the objective function can be expressed as

$$F(q) = \underbrace{\max}_{p} \sum_{k=1}^{K} \log_2\left(\left\|\sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right\|^2\right) - q\left(\sum_{l=1}^{L}\sum_{k=1}^{K} p_{kl} + P_C\right) \tag{33}$$

If

$$f = \sum_{k=1}^{K} \log_2\left(\left\|\sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right\|^2\right) - q\left(\sum_{l=1}^{L}\sum_{k=1}^{K} p_{kl} + P_C\right) \tag{34}$$

then,

$$\frac{\partial^2 f}{\partial p_{kl}^2} = -\frac{\left(\sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right)^2 \frac{p_{kl}^{-1}}{\|f_{kl}\| N_0} + p_{kl}^{-\frac{3}{2}} \left(\sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right) \left\|\sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right\|^2}{2\left\|\sum_{l=1}^{L} \frac{\sqrt{p_{kl}}}{\|f_{kl}\| N_0}\right\|^2 \|f_{kl}\| N_0 \ln 2} \tag{35}$$

From the above analysis, it can be known that the function f is concave with respect to P, and can be solved by the standard optimization problem solving method, and the optimal transmission power is expressed as follows:

$$p_{kl} = \frac{1}{q \ln 2} \frac{1}{\frac{\|f_{kl}\|^2}{\sum_{l'=1, l' \neq l}^{L} \|f_{kl'}\|^2 + 1}} \tag{36}$$

Based on the above analysis, a most energy-efficient method is proposed, that is, optimizing P^* and q^*. The algorithm process can be described as follows:

1) initialization $P^* = P_{0,} q^* = 0, \varepsilon = 0.01$
2) *while* $\sum_{k=1}^{K} \log_2\left(\left\|\sum_{l=1}^{L} \frac{\sqrt{p_{kl}^*}}{\|f_{kl}\| N_0}\right\|^2\right) - q^*\left(\sum_{l=1}^{L}\sum_{k=1}^{K} p_{kl}^* + P_C\right) > \varepsilon$
3) $do q^* \leftarrow \frac{\sum_{k=1}^{K} \log_2\left(\left\|\sum_{k=1}^{K} \frac{\sqrt{p_{kl}^*}}{\|f_{kl}\| N_0}\right\|^2\right)}{\sum_{l=1}^{L}\sum_{k=1}^{K} p_{kl}^* + P_C}$
4) Equation (36) is used to get the power distribution
5) $Return q^*.P^*$

B. MINIMUM POWER ALGORITHM DESCRIPTION

Aiming at the user's signal-to-noise ratio constraint, an algorithm for minimizing the transmission power of the system is proposed. Assuming the noise density can be expressed as 1, the power allocation algorithm can be expressed as:

Optimization issues: $\min_{p \succ -0} \sum_{k=1}^{K}\sum_{l=1}^{L} p_{kl}$

Restrictions $\left\|\sum_{l=1}^{2} \frac{\sqrt{p_{kl}}}{\|f_{kl}\|}\right\| \geq \gamma_k$

The resulting power allocation is:

$$p_{kl} = \left(\frac{\sum_{l'=1, l' \neq l}^{2} \|f_{kl}\|^2 \|f_{kl}\|}{\sum_{l=1}^{2} \|f_{kl}\|^2}\right)^2 \gamma_k \tag{37}$$

This study mainly analyzes two layers of heterogeneous networks. The study area is set as the central macro cell, and there are S $(S \geq 0)$ small cell access points, and the access point can be expressed as SCA_s. The macro base station is equipped with N_{BS} transmitting antennas to communicate with K geographically dispersed single-antenna mobile users, and each configuration point is configured with $N_{SCA}((1 \leq N_{SCA} \leq 4))$ antennas to communicate with K_s geographically dispersed single-antenna mobile users$((SK_s = K))$. Then, the signal received by the user k ofthe s-th SCA_s can be expressed as:

$$
\begin{aligned}
y_k = & \sqrt{p_{k,0}} g_k w_{k,0} x_{k,0} + \sum_{i=1, i \neq k}^{K} \sqrt{p_{i,0}} g_k w_{i,0} x_{i,0} \\
& + \sqrt{p_{k,s}} h_{k,s} w_{k,s} x_{k,s} + \sum_{m=1, m \neq k}^{Ks} \sqrt{p_{m,s}} g_{k,s} w_{m,s} x_{m,s} \\
& + \sum_{j=1, j \neq s}^{S} \sum_{l=1}^{Ks} \sqrt{\alpha} \sqrt{p_{l,j}} h_{l,j} w_{l,j} x_{l,j} + n_k \qquad (38)
\end{aligned}
$$

Among them, $p_{k,0}$, o represents the transmitting power m of the macro base station to the user $g_k = \sqrt{\beta_k} h_{k,0}$, β_k represents the large-scale fading factor of the user k, and $h_{k,0} \in C^{1 \times N_{BS}}$BS represents the small-scale fading factor of the macro base station to the user k, and its elements obey $CN\ (0, 1)$. $w_{k,0} \in C^{N_{BS} \times 1}$ represents the precoding matrix used by the macro base station for user k, $\left\| w_{k,0} \right\|_F^2 = 1$. $x_{k,0}$ represents the signal transmitted by the macro base station to user k. $p_{k,s}$ represents the transmission power of the S-th s to the user k. $h_{k,s} \in C^{1 \times N_{SCA}}$CA represents the small-scale fading factor from the s-th SCA_s to the user k, and its elements obey $CN\ (0, 1)$. $w_{k,s} \in C^{N_{SCA} \times 1}$ represents the s-th precoding matrix used for user k,, $\left\| w_{k,s} \right\|_F^2 = 1$. $x_{k,s}$ represents the transmission signal SCA_s to user k. α $(\alpha < 1)$ represents the long-term average power from other small cell access points to the user's k-channel. $n_k \sim CN\left(0, \sigma^2\right)$ is additive white Gaussian noise.

Based on the above analysis, assuming that the macro cell and g mainly eliminate mutual interference between users through zero-forcing precoding, the following formula can be obtained.

$$
\begin{aligned}
\overline{G} &= \left[g_1^H, g_2^H, \cdots, g_{k-1}^H, g_{k+1}^H, \cdots, g_K^H \right]^H \\
\overline{H} &= \left[h_{1,s}^H, h_{2,s}^H, \cdots, h_{k-1,s}^H, h_{k+1,s}^H, \cdots, h_{Ks,s}^H \right]^H
\end{aligned}
$$

Then,

$$
\begin{aligned}
w_{k,0} &= \left[I - \overline{G}^H \left(\overline{G}\overline{G}^H \right)^{-1} \overline{G} \right] G_{k,0}^H \\
w_{k,s} &= \left[I - \overline{H}^H \left(\overline{H}\overline{H}^H \right)^{-1} \overline{H} \right] H_{k,s}^H
\end{aligned}
$$

Therefore, the formula (38) can be expressed as follows:

$$
\begin{aligned}
y_k = & \sqrt{p_{k,0}} g_k w_{k,0} x_{k,0} + \sqrt{p_{k,s}} h_{k,s} w_{k,s} x_{k,s} \\
& + \sum_{j=1, j \neq s}^{S} \sum_{l=1}^{Ks} \sqrt{\alpha} \sqrt{p_{l,j}} h_{k,j} w_{l,j} x_{l,j} + n_k \qquad (39)
\end{aligned}
$$

From the actual situation, the transmission power of other cells is very small compared to the macro cell, so it can be ignored. When only the interference from the macro cell to other cells is considered, the data rate obtained by the user k from the macro base station is expressed as follows:

$$
r_k^B = E\left\{ \log_2 \left[1 + \frac{p_{k,0} \left\| g_k w_{k,0} \right\|^2}{\sigma^2} \right] \right\} \qquad (40)
$$

The data power obtained by user K from other cells can be expressed (41), as shown at the bottom of this page.

Based on this, the energy efficiency and resource allocation problems in a MIMO heterogeneous network can be described as follows:

The optimization goals are:

$$
\begin{aligned}
& \max_{P, \overline{p}, N_{BS}} U\left(P, \overline{p}, N_{BS}\right) \\
& = \frac{\sum_{k=1}^{K} \left\{ r_k^B + r_k^S \right\}}{\sum_{k=1}^{K} p_{k,0} + N_{BS} p_C^{BS} + \sum_{k=1}^{K} \sum_{s=1}^{S} p_{k,s} + \rho S N_{SCA} p_C^{SCA}}
\end{aligned}
$$

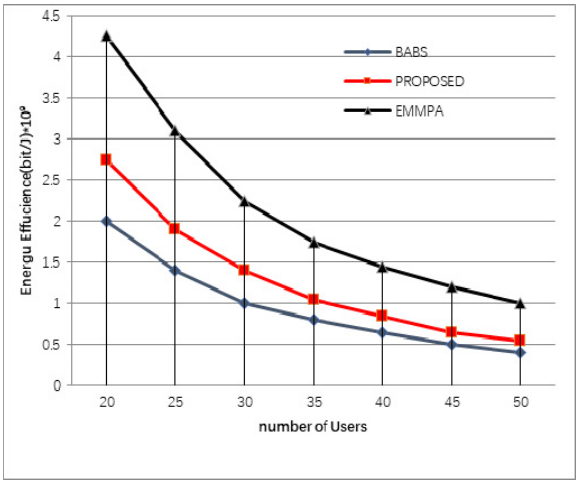
VI. SIMULATION RESULTS AND ALGORITHM COMPLEXITY ANALYSIS

In this simulation, the cell radius is set to a hexagon with a circumscribed circle of 1000m. A certain number of base stations are arranged in this area, and users are randomly distributed within a range of 100m with the base station as the center. The large-scale fading from the kth user to the base station can be expressed as. In the formula, is a log-normal random variable with a standard deviation of, is the distance of the user from the base station, and u is the path loss in the transmission process.

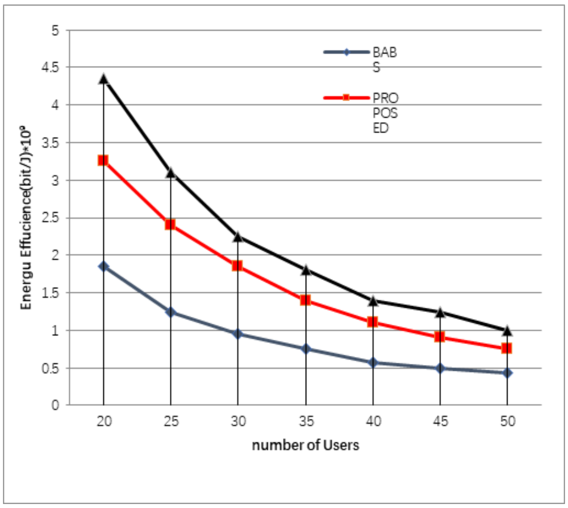
In order to facilitate the comparison of algorithm performance in the experiment, this study defines that the BABS algorithm mainly performs loan allocation, while the RABEE algorithm mainly performs power allocation and base station antenna allocation and uses the average allocation method to process the bandwidth in the EMPMA algorithm. The allocation of power and the number of base station antennas is performed by the EMMPA algorithm because the algorithm is not affected by any constraints when performing energy efficiency calculations.

As shown in Figure 3, the results of a system's energy efficiency analysis when users have different low-rate requirements in the system are shown. It can be seen from the figure that compared to the EMMPA algorithm, and BABS algorithm, the performance of the proposed algorithm is not high or low. The reason is that the EMMPA algorithm is

$$
r_k^S = E\left\{ \log_2 \left[1 + \frac{p_{k,s} \left\| h_{k,s} w_{k,s} \right\|^2}{p_{k,0} \left\| g_k w_{k,0} \right\|^2 + \sigma \sum_{j=1, j \neq s}^{S} \sum_{l=1}^{Ks} p_{l,j} \left\| h_{k,j} w_{l,j} \right\|^2 + \sigma^2} \right] \right\} \qquad (41)
$$



(a) $R_{\min} = \dfrac{3\times10^{7}}{K} bit/s$



(b) $R_{\min} = \dfrac{1\times10^{7}}{K} bit/s$

FIGURE 3. **Energy efficiency performance of each algorithm for different numbers of users.**

not affected by any constraints when performing energy efficiency calculations. Therefore, the performance of EMMPA algorithm is the best among the three algorithms. The BABS algorithm is a bandwidth allocation algorithm based on the signal-to-noise ratio, and the algorithm needs to pass the average signal-to-noise ratio and bit rate of the system users. Therefore, a certain constraint is received during the operation. Once all users have obtained sufficient carriers during operation, the algorithm first ensures that their own needs are met. After that, the remaining subcarriers are allocated to effectively reduce the total power sent by the system. Through analysis, it can be seen that this algorithm has certain disadvantages in improving energy efficiency compared to the proposed algorithm. As can be seen from the figure, when the number of users continues to increase, the energy efficiency performance of the two algorithms is gradually

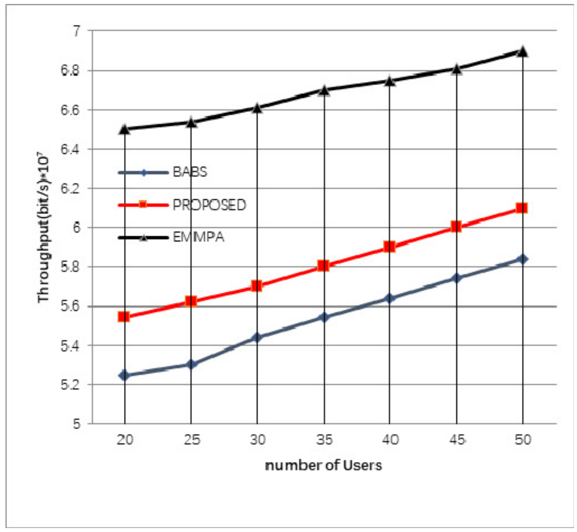


FIGURE 4. **Throughput performance of each algorithm for different numbers of users.**

approaching, and the bandwidth that can be allocated to each user also gradually decreases as the number of users increases. For the EMPPA algorithm, the rate requirements are not high, but the average allocation of bandwidth will cause the bandwidth allocated by users with better channels in the system to show a downward trend, thereby reducing system energy efficiency. When the value of $R_{\min}$ is different, the performance of EMMPA algorithm in energy efficiency performance has a certain stable correlation. The reason for this result is that the bandwidth and energy efficiency optimization of the algorithm are related to the value of $R_{\min}$. However, the energy efficiency performance of the BABS algorithm has a positive correlation with $R_{\min}$, because the bandwidth allocation process of the algorithm first needs to be initialized by $m_k \leftarrow \frac{R_{\min}}{R_0(k)}$, and then the remaining bandwidth is allocated by the minimum transmit power. Therefore, when $R_{\min}$ becomes smaller, the initial bandwidth allocation will become smaller, and most of the remaining bandwidth is mainly used for the allocation process of minimizing the transmission power, thereby reducing the energy efficiency performance.

Figure 4 shows the change in throughput performance for different numbers of users. As can be seen from Figure 4, the proposed algorithm has good performance and throughput. This result is due to the fact that the EMPPA algorithm does not place any requirements on the user rate during the operation, and only requires maximizing the energy efficiency of the system, which results in a lower system throughput. The BABS algorithm allocates bandwidth by minimizing transmit power, so compared to the proposed algorithm, the BABS algorithm has lower energy efficiency performance. It can also be seen from Figure 4 that when the number of users continues to increase, the system throughput shows an upward trend, that is, as the number of users increases, the system's multi-user diversity characteristics become more obvious. It can be seen that the proposed

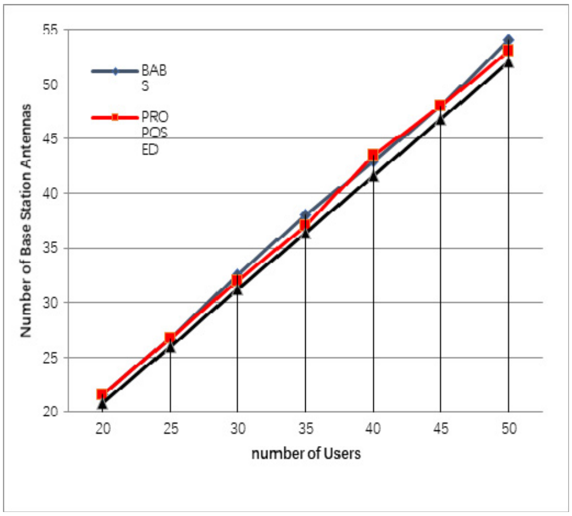


FIGURE 5. Optimal base station antenna number performance of each algorithm for different numbers of users.

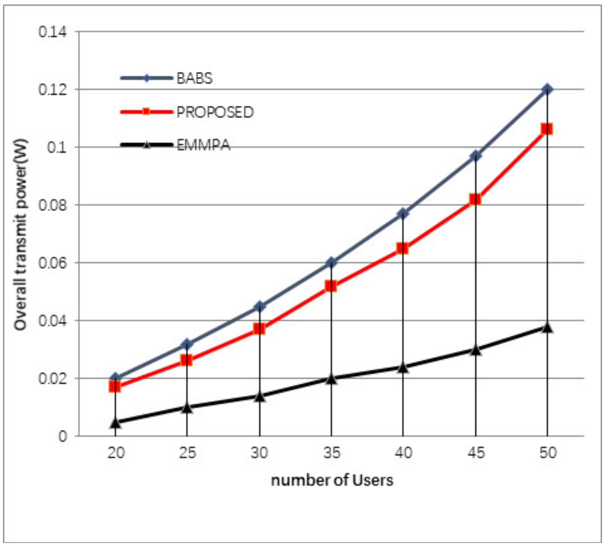


FIGURE 6. Transmit power performance of each algorithm in different number of users.

algorithm is not close to have good system energy efficiency performance, and also has certain advantages in terms of throughput performance.

Figure 5 is the performance analysis chart of the optimal base station antenna number of each algorithm under the condition of different number of users. It can be seen from Figure 5 that when the number of users shows an upward trend, the optimal base station antenna number of the system also shows an increasing trend. The EMMPA algorithm lacks an optimal number of antennas, so it can only be optimized for optimal energy efficiency by changing the transmit power.

Figure 6 shows the relationship between the transmission power performance and the number of users. It can be known from Fig. 6 that when the number of users shows an increasing trend, the transmission power required by the BABS algorithm and the proposed algorithm itself will increase as

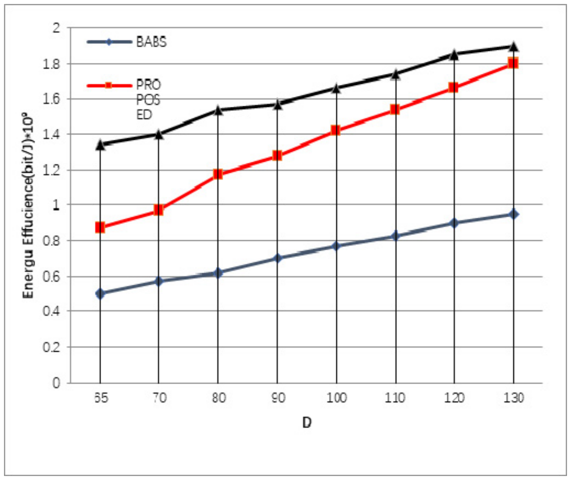


FIGURE 7. Energy efficiency performance of each algorithm under different frequency block numbers.

the number of users increases. The reason for this is that the BABS algorithm and the proposed algorithm are based on the minimum user rate requirements in the system. Compared to these two algorithms, the EMPPA algorithm is not subject to any conditions.

Figure 7 shows the comparison of the energy efficiency performance of the algorithm in on different frequency blocks. As can be seen from Fig. 7, the energy efficiency performance of the proposed algorithm increases with the number of frequency blocks during operation. Compared with the proposed algorithm, the energy efficiency performance of the BABS algorithm and the EMMPA algorithm does not show a rapid increase with the increase in the number of frequency blocks during operation. The reason for this is that the proposed algorithm uses the BABEE bandwidth allocation algorithm, which can effectively use the system's frequency diversity, thereby directly increasing the speed at which the energy efficiency increases with frequency. However, this situation does not occur with the BABS algorithm and the EMPPA algorithm.

Similar to the previous research, when conducting complexity research, the cell radius is set to a hexagon with a circumscribed circle of 1000m. A certain number of base stations are arranged in this area, and users are randomly distributed within a range of 100m with the base station as the center. The large-scale fading from the kth user to the base station can be expressed as. In the formula, is a log-normal random variable with a standard deviation of, is the distance of the user from the base station, and u is the path loss in the transmission process.

The BABS algorithm is a bandwidth allocation algorithm based on the signal-to-noise ratio. When the bandwidth is allocated to k users and the number of iterations is V, the computational complexity of the bandwidth allocation can be expressed as $O(KV)$. The computational complexity of bandwidth allocation can be expressed as $O\left[1+K\left(V-\sum_{k=1}^{K}\left\lceil\frac{R_{\min}}{R_0(k)}\right\rceil\right)\right]$. We set the computational complexity of updating the Lagrangian factor in the proposed algorithm to $O(I_\lambda)$, and the computational complexity of the number of base station antennas and power allocation to $O(I_{AP})$. Therefore, the complexity of the proposed algorithm is $O(KI_{AP}, I_\lambda)$. The computational complexity of bandwidth allocation in the EMMPA algorithm is $O\left[1+K\left[\mathrm{mod}\left(\frac{V}{K}\right)\right]\right]$, where mod represents division and remainder. In power allocation, the step size factor is assumed to be α. To get the globally optimal μ^*, it needs at least $\left\lceil \log_2\left[\frac{(\alpha-1)\mu^*}{\varepsilon}-1\right]\right\rceil$ iterations, where $|\mu-\mu^*|<\varepsilon$. Therefore, the computational complexity of this power allocation is $O\left\{K\left\lceil \log_2\left[\frac{(\alpha-1)\mu^*}{\varepsilon}-1\right]\right\rceil\right\}$. In summary, the computational complexity of the BABS algorithm is $O(KV+KI_{AP}\cdot I_\lambda)$, the computational complexity of the algorithm in this paper is

$$O\left\{1+K\left(V-\sum_{k=1}^{K}\left\lceil\frac{R_{\min}}{R_0(k)}\right\rceil\right)+KI_{AP}\cdot I_\lambda\right\},$$

and the computational complexity of the EMMPA algorithm is

$$O\left\{1+K\left[\mathrm{mod}\left(\frac{V}{K}\right)\right]+K\left\lceil\log_2\left[\frac{(\alpha-1)\mu^*}{\varepsilon}-1\right]\right\rceil\right\}.$$

Assuming that the circuit power in the system can be expressed as $P_C=1W$, the user-initialized emission vector can be expressed as

$$P_0=\begin{bmatrix}0.01 & \cdots & 0.01\\ 0.01 & \cdots & 0.01\end{bmatrix}.$$

For reliable performance comparison analysis in the experiment, the "minimum power algorithm" is used to set the user's signal-to-noise ratio constraints equal. In $\gamma_k=\gamma g$ simulation, the highest signal-to-noise ratio that users can obtain is 30dB.

As shown in Figure 8, the relationship between the number of users and the energy efficiency performance of the communication system can be seen when the number of antennas and the signal-to-noise ratio are different. It can be seen from the observation chart that when the number of users is increasing, the energy efficiency of the system is also increasing. When the number of antennas is 100, the energy efficiency performance of the maximum EE algorithm is significantly higher. When the number of antennas is 50 and the Gamma value is 20, the energy efficiency performance of the maximum EE algorithm is significantly higher. In addition, when the number of antennas is 50Gamma and the value is 30, the energy efficiency performance of the maximum EE algorithm is significantly higher. In addition, as the number of antennas continues to increase, the energy efficiency performance of the maximum EE algorithm and the minimum power algorithm has a positive correlation with the number of antennas, and the energy efficiency performance of the minimum power algorithm has increased significantly. By analyzing the reasons for this situation, it can be known that when the number of antennas increases, the system diversity gain will increase, and at this time, the energy efficiency performance will also increase. In addition, the minimum power algorithm's power allocation is proportional to the value of Gamma, so there is a positive correlation between the two.

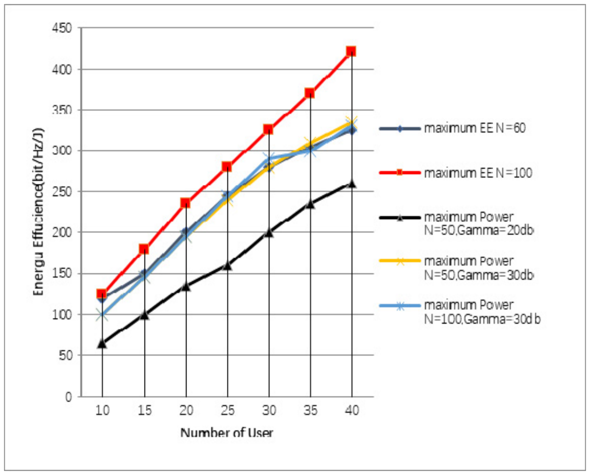


FIGURE 8. Energy efficiency performance of each algorithm for different numbers of user.

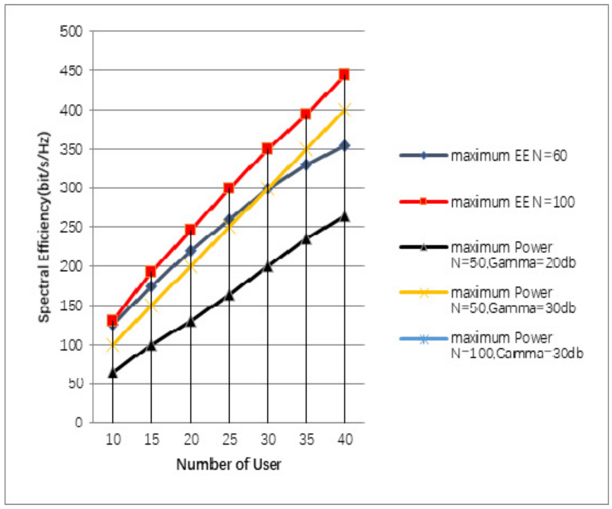


FIGURE 9. Spectral efficiency performance of each algorithm for different number of users.

Figure 9 shows the difference between the number of users and the performance of the spectral efficiency when the number of antennas and the drying ratio constraint are inserted at a certain difference. It can be known from Fig. 9 that when the number of users shows an increasing trend, there is a positive correlation between the spectral efficiency and them. Moreover, it can also be seen from the figure that when the number of antennas is 100, the energy efficiency performance of the maximum EE algorithm is significantly higher. When the number of antennas is 50 and the Gamma value is 20db, the energy efficiency performance of the maximum EE algorithm is significantly higher. When the number of antennas is 50 and the Gamma value is 30, the energy efficiency performance of the maximum EE algorithm is significantly higher. In addition, as the number of antennas

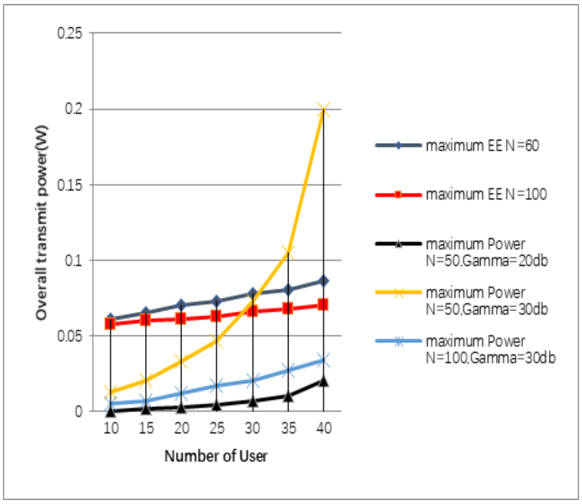


FIGURE 10. Transmit power performance of each algorithm for different numbers of users.

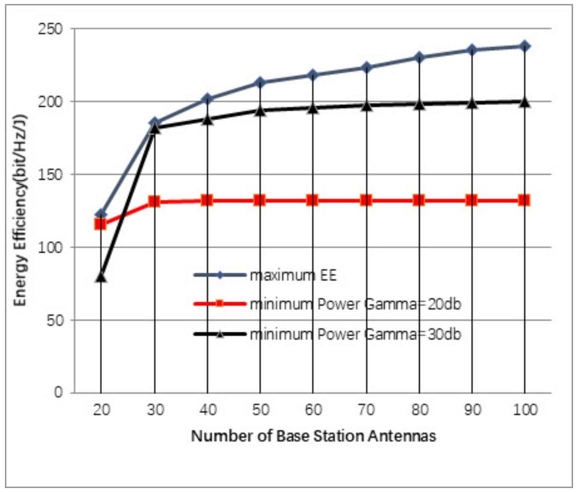


FIGURE 11. Energy efficiency performance of each algorithm under different antenna numbers.

continues to increase, the energy efficiency performance of the maximum EE algorithm and the minimum power algorithm has a positive correlation with the number of antennas, and the energy efficiency performance of the minimum power algorithm has nothing to do with the increase in the drying ratio, and the signal-to-interference and noise ratio Gamma increases significantly. The algorithm power allocation is proportional to the value of Gamma, so there is a positive correlation between the two.

Figure 10 shows the relationship between the number of users and the power performance when the number of antennas and the signal-to-drying ratio are purely different. By observing Fig. 10, it can be seen that there is a positive correlation between the system transmit power and the number of users, and a negative correlation between the system's transmit power and the number of antennas. In addition, the following information can be obtained from the figure: when the number of antennas is 50 and the gamma value is 20db, the energy efficiency performance of the maximum EE algorithm is significantly higher. When the number of antennas is 50, the minimum power algorithm has a significantly higher transmission power. When the number of antennas is 50 and the gamma value is 20db, the energy efficiency performance of the minimum powe algorithm is significantly higher. When the value of Gamma exceeds 30db, the performance of the maximum EE algorithm exceeds the minimum power algorithm. The reason for this is that when the minimum power algorithm is constructed, the minimum system transmit power is used as the objective function of the model operation, so its own transmit power is smaller than other algorithms. It can also be seen from the figure that the transmission power of the maximum EE algorithm and the minimum power algorithm are negatively related to the number of antennas, and the transmission power of the minimum power algorithm has a positive correlation with Gamma.

As shown in Figure 11, when the number of users is fixed at 20, the function relationship between the number of antennas and different algorithms is not difficult to see from the figure. When the number of antennas shows an increasing trend, the energy efficiency performance of the maximum EE algorithm increases. In addition, the comparison between the maximum EE algorithm and the minimum power algorithm shows that the maximum EE algorithm has better energy efficiency performance. The reason for analysis is that increasing the number of antennas will directly increase the diversity gain of the system, and the optimization objective function of the maximum EE algorithm is set to the system energy efficiency, so its energy efficiency is significantly higher. In addition, when the number of antennas is less than 30, the energy efficiency performance of the minimum power algorithm has a positive correlation with the number of antennas, and when the number of antennas exceeds 30, the energy efficiency of the algorithm shows a stable state. When the number of antennas is set to 20 and the Gamma value is 20dB, the performance of the minimum power algorithm is significantly higher and exceeds the energy efficiency performance when the Gamma value is 30dB. The reason is that when the number of antennas is 20, to increase the value of Gamma to 30db requires more transmit power, which results in a decrease in system energy efficiency. When the number of antennas exceeds 20, the increase of Gamma will directly cause the energy efficiency of the power algorithm to increase.

Figure 12 shows the relationship between the number of antennas and the spectral efficiency performance when the number of users is 20. It can be seen from FIG. 12 that when the number of antennas shows an increasing trend, the spectral efficiency of the maximum EE algorithm has the same increasing trend. Moreover, the minimum power algorithm also requires total power allocation as the user's signal-to-noise ratio dries, so the performance of the algorithm will also show the same trend as the gamma increases. In addition, it can be seen from the figure that when the Gamma value is 20dB, compared with the energy efficiency

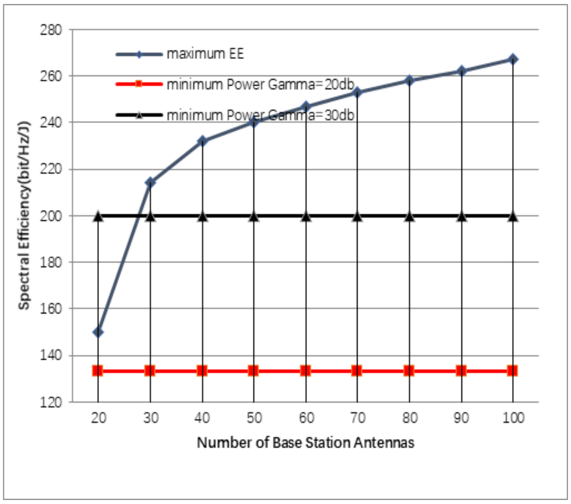


FIGURE 12. Spectral efficiency performance of each algorithm under different number of antennas.

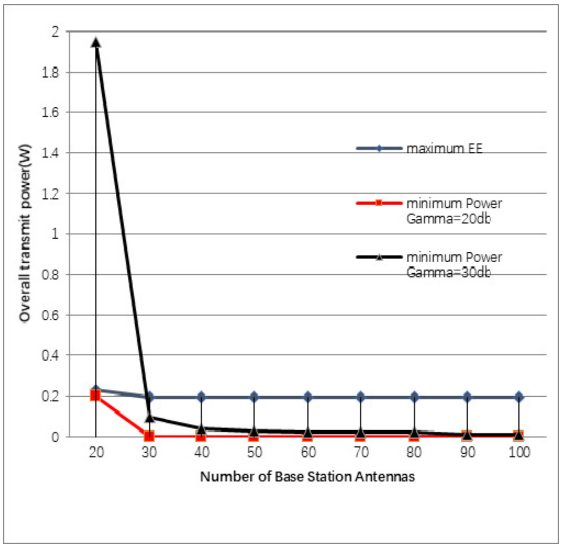


FIGURE 13. Transmit power performance of each algorithm under different antenna numbers.

performance of the maximum EE algorithm and the minimum power algorithm, the maximum EE algorithm is obviously more advantageous. When the Gamma value is 30dB, the number of users can be divided into two cases: excess 30 and less than 30. When the number of users is less than 30, the performance of the minimum power algorithm is higher than the maximum EE algorithm. When the number of users exceeds 30, the performance of the maximum EE algorithm is higher than the minimum power algorithm.

Figure 13 shows the relationship between the number of antennas and the transmission power when the number of users is 20. As can be seen from Figure 13, there is a clear negative correlation between the transmission power of the communication system and the number of antennas. The reason is that an increase in the number of antennas will directly increase the diversity gain of the system, which will directly result in a decrease in transmit power. In addition, it can be seen from the figure that when the Gamma value is 20dB, compared with the energy efficiency performance of the maximum EE algorithm and the minimum power algorithm, the minimum power algorithm has obvious advantages. When the Gamma value is 30dB, the number of users can be divided into two cases: excess 30 and less than 30. When the number of users is less than 30, the performance of the maximum EE algorithm is higher than the minimum power algorithm. However, when the number of users exceeds 30, the performance of the minimum power algorithm is higher than the maximum EE algorithm.

VII. CONCLUSION

This study combines the analysis of broadband wireless communication systems to optimize the energy efficiency of cross-layer and cross-band wireless communication systems. Moreover, with the help of resource allocation technology, the multi-user lower-layer transport layer of the FDD-OFDMA system is optimized. At the same time, this study explores the most reasonable system resource allocation method to achieve reasonable resource allocation by optimizing the energy efficiency resources of the massive MIMO-OFDMA downlink system. In the research, the focus is on energy efficiency optimization and resource allocation for cross-layer wireless communication systems in wireless communication systems, and optimization analysis is performed using multi-user parallel data transmission processes in common network communication systems as an example, and analysis of energy efficiency impact parameters is carried out. In addition, simulation verification of system resource optimization is performed to simulate energy efficiency optimization problems in large-scale network environments. Finally, a comparative experiment is set up to verify the energy efficiency performance. The research results show that the method proposed in this paper has certain effects and can provide a reference direction for subsequent energy efficiency optimization research. This article studies the energy efficiency resource allocation of multi-cell cooperative massive MIMO systems. Assuming that the base stations in the multi-cell cooperative wireless communication system cooperate fully and adopt ZF precoding, a resource allocation method is proposed based on maximizing the energy efficiency of the system. The energy efficiency function is optimized by jointly adjusting the number of antennas of the macro base station, the transmit power of the macro base station, and the transmit power of the small cell access point. The main factors affecting the communication resources between cells are the mutual influence of cell base stations and the operation of invalid base stations caused by dense base stations. This study minimizes these influencing factors, and simulations show that the method proposed in this paper has certain effects.

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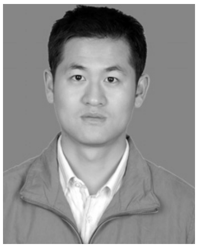
ZUOLIN DONG was born in Nanyang, Henan, in February 1970. He received the bachelor's degree in engineering from the Beijing University of Technology and the master's degree in engineering from Xi'an Jiaotong University. He is currently an Associate Professor and the Deputy Director of the Instruction Center of Innovation and staring a business in Henan Institute of Technology. He is an Outstanding Young Expert in science and technology in Xinxiang and a Senior Assessor of national vocational skills appraisal. He has presided over and participated in three provincial and ministerial level projects, four prefecture-level projects, and seven school level projects, and published seven teaching materials and more than ten academic articles in journals at all levels. He is a member of the Communist Party of China.

JIAHONG WEI was born in Jinzhou, Liaoning, in December 1983. She received the Ph.D. degree from the Dalian University of Technology. She is currently a Lecturer with the Henan Institute of Technology. She has participated in three national level projects, two provincial level projects, and one school level project, and published seven articles in important journals at home and abroad including two articles cited by SCI and EI, and five articles belonging to Chinese core journal. She is a member of the Communist Party of China.



XIAOYU CHEN was born in Xinxiang, Henan, in December 1983. He received the bachelor's degree in engineering from the PLA University of Information Engineering and the master's degree in engineering from the Wuhan University of Technology. He is currently a Teacher with the Henan Institute of Technology. He has presided over one prefecture-level project, participated in five provincial and ministerial level projects and two school level projects, and published two teaching materials and more than ten academic articles in journals at all levels. He is a member of the Communist Party of China.

PENGFEI ZHENG was born in Sanmenxia, Henan, China, in November 1994. He received the bachelor's degree from Henan Normal University, where he is currently pursuing the master's degree with the College of Electronic and Electrical Engineering. He participates in five fund projects.