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Massive MIMO OFDMA Downstream System Energy Efficiency Resource Allocation Algorithm

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Abstract: Aiming at large-scale multiple-input multiple-output (MIMO) orthogonal frequency division multiple access (OFDMA) downlink mobile communication systems, a resource allocation algorithm based on the best energy efficiency is proposed. In the case of zero-forcing (ZF) precoding, the proposed algorithm is based on maximizing the lower bound of system energy efficiency, while considering the minimum rate requirements of each user, and optimizes by adjusting bandwidth allocation, power allocation and base station antenna number allocation Energy efficiency function. First, an iterative algorithm is proposed to determine the bandwidth allocation of each user according to the optimization conditions, and then the nature of the fractional planning is used and the convex optimization method is used to optimize the energy efficiency function by jointly adjusting the number of transmitting antennas at the base station and the transmitting power of the user. The simulation results show that the proposed algorithm can achieve better system energy efficiency performance and throughput performance while reducing the number of iterations.

Keywords: OFDMA, Massive MIMO, Wireless Communication, Downlink, Resource Allocation, Energy Efficiency

I. Introduction

With the rapid increase in energy consumption of wireless communication equipment and the high degree of concern about global warming, green communication has gradually become a trend. Therefore, the research hotspot of resource allocation has gradually shifted from spectrum efficiency resource allocation [1~3] to energy efficiency resource allocation. [4~15]. Literature [5] studied the energy efficiency design of the multi-user OFDMA mobile communication downlink system, and proposed a user scheduling and rate allocation strategy under consideration of the QoS requirements of each user. Literature [6] studied the energy efficiency design of the downlink OFDMA mobile communication system, and given a sub-carrier allocation and power allocation algorithm taking into account the minimum data rate requirements. Literature [7] studied the energy efficiency resource allocation problem of the downlink SISO-OFDM system. First, it proved that the OFDMA strategy can achieve the best energy efficiency, and then transformed the non-convex problem into a convex optimization problem to obtain an effective power allocation algorithm.

Multiple input multiple output (MIMO) technology can transmit and receive through multiple antennas, making full use of space resources to improve channel capacity and system reliability. Therefore, it is recognized as one of the key technologies in the next generation of multi-user broadband wireless communication systems. Literature [12] studied the issue of energy-efficient resource allocation for uplink multi-user MIMO systems, and proposed an energy-efficient multi-user power allocation (EMMPA) algorithm based on water injection algorithm, but this algorithm has a relatively large amount of calculation. Literature [13] derives the lower bounds of the capacity when maximum ratio combining (MRC), zero forcing (ZF) and minimum mean square error (MMSE) are used in the uplink of a massive multiuser MIMO system, and studies energy efficiency and spectrum The relationship between efficiency, but the power consumption of the circuit is not considered in the power consumption of the system. Literature [14] studied the problem of energy efficiency resource allocation in massive MIMO downlink OFDMA system, and gave an iterative algorithm, but this algorithm only considers the system throughput requirements, and does not consider the minimum rate requirements of each user.

Based on the above analysis, this paper studies the energy efficiency resource allocation of multi-user massive MIMO OFDMA downlink systems. First, assume that the transmitter fully knows the channel state information (CSI), and uses zero-forcing (ZF) precoding to obtain the lower bound expression of the system capacity, and then obtain the lower bound expression of energy efficiency. Under the minimum rate requirement of each user, pass appropriate the bandwidth allocation, power allocation and number of base station antennas are allocated to maximize the lower bound of the system's energy efficiency. Since the objective function is non-convex and requires an exhaustive method to obtain the optimal solution, this paper proposes a low-complexity sub-optimal solution. First, the bandwidth allocation of each user is determined according to the user's minimum rate requirement and the objective function, and then Based on the user bandwidth allocation, the user transmit power and the number of base station antennas are jointly optimized. Finally, simulations verify the effectiveness and superiority of the proposed algorithm.

II. System model and problem description

This paper considers a typical single-cell downlink multi-user MIMO-OFDMA wireless communication system, in which the base station is equipped with M transmit antennas to communicate with K geographically dispersed single-antenna mobile users. Assuming that the channel is a block fading model, suppose that there are N subcarriers in the system divided into V frequency blocks (including $\frac{N}{V}$ subcarriers) as the basic unit of resource scheduling. According to the reciprocity of the channel, the uplink channel matrix $G_v = H_v D^{1/2}$(H_v represents the $M \times K$ fast fading matrix from the user to the base station on the frequency block v, $D^{1/2} = diag\left\{\sqrt{\beta}_1, \dots, \sqrt{\beta}_K\right\}$ indicate $K \times K$ diagonal matrix, the diagonal element $\sqrt{\beta}_k$ represents the slow fading coefficient from user k to the base station), and the downlink channel matrix $G_v^T =$

$D^{1/2}H_v^T$ is obtained. Therefore, the expression of the signal received by the k^{th} user on the v^{th} frequency block is

$$y_{v,k} = g_{v,k}^T \sum_{k=1}^{K} \sqrt{p_{v,k}}\, f_{v,k} x_{v,k} + z_{v,k}$$
$$= g_{v,k}^T \sqrt{p_{v,k}} f_{v,k} x_{v,k} + g_{v,k}^T \textstyle\sum_{i=1,i\neq k}^{K} \sqrt{p_{v,i}} f_{v,i} x_{v,i} + z_{v,k} \quad (1)$$

where, $g_{v,k}$ represents the k-th column of matrix $G_v, f_{v,k}$ represents the precoding matrix of user k on frequency block v, and $x_{v,k}$ represents the transmission signal of user k on sub-carrier frequency block v. Obviously, the first and second terms after the second equal sign in equation (1) respectively represent the desired signal of user k and the interference from other users, and the last term is additive white Gaussian noise.

In order to eliminate the mutual interference between different users, this paper uses zero-forcing precoding. Let the precoding matrix $F_y = G_v^*(G_v^T G_v^*)^{-1}$, namely $G_v^T F_v = I_k$. Among them, $F_v = [f_{v,1}, \dots, f_{v,K}]$, therefore, $g_{v,k}^T f_{v,i} = \delta_{ki}$

$$\delta_{ki} = \begin{cases} 1, & k = i \\ 0, & k \neq i \end{cases}$$

Therefore, the traversal achievable rate of user k on frequency block v is expressed as

$$r_{v,k} = E\left\{Wlb\left[1 + \frac{p_{v,k}}{WN_0\left[\left(G_v^T G_v^*\right)^{-1}\right]_{kk}}\right]\right\} \quad (2)$$

From Jensen's inequality, the lower bound of the rate of user k on the frequency block v is

$$r_{v,k} \geq Wlb\left[1 + \frac{p_{v,k}}{WN_0 E\left\{\left[\left(G_v^T G_v^*\right)^{-1}\right]_{kk}\right\}}\right] \quad (3)$$

Where

$$E\{[(G_v^T G_v^*)^{-1}]_{kk}\} = \frac{1}{\beta_k} E\{[(H_v^T H_v^*)^{-1}]_{kk}\}$$
$$= \frac{1}{K\beta_k} E\{tr[(H_v^T H_v^*)^{-1}]\} \quad (4)$$

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

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

$$r_{v,k} = Wlb\left[1 + \frac{p_{v,k}(M-K)\beta_k}{WN_0}\right] \quad (5)$$

Figure 1 shows the system throughput of equations (2) and (5) summing the number of users k and the number of frequency blocks v. Here, assuming the number of users K 12, the theoretical value is the sum of equation (2), the derived value is the sum of formula (5). It can be seen from the figure that the lower bound of the deduced rate expression is very close to the theoretical value, so this article uses this lower bound instead of the theoretical value.

It can be seen from equation (5) that the rate allocated by the user on each frequency block is only related to the large-scale fading of the user. Therefore, the rate allocated by user k can be expressed as

$$r_k = m_k Wlb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right] \tag{6}$$

where, m_k represents the number of frequency blocks allocated to user k, and p_k represents the transmit power of user k. Therefore, the lower bound of the system energy efficiency function can be expressed as

$$U = \frac{\sum_{k=1}^{K} r_k}{\sum_{k=1}^{K} m_k p_k + M p_C} = \frac{\sum_{k=1}^{K} m_k Wlb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right]}{\sum_{k=1}^{K} m_k p_k + M p_c} \tag{7}$$

where, p_c represents the circuit power consumption of each antenna. The circuit power consumption here includes the power consumption of all circuit modules on the signal transmission path, such as A/D conversion, D/A conversion, frequency synthesizer, mixer, power amplifier, etc. [16].

Based on the above analysis, the constraint maximization problem corresponding to the energy efficiency resource allocation in the downlink multi-user massive MIMO OFDMA system can be expressed as follows.

Optimization: $\max\limits_{P,m,M} U(P,m,M)$

Constraints:

$$\begin{cases} r_k \geq R_{min} \\ \sum_{k=1}^{K} m_k = V \end{cases} \text{which} \begin{cases} m_k Wlb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right] \geq R_{min} \\ \sum_{k=1}^{K} m_k = V \end{cases} \tag{8}$$

where, $P = [p_1, .., p_k, \dots, p_k]^T$ represent the transmit power vector, $m = [m_1, \dots, m_k, \dots, m_k]^T$represent the vector of the number of frequency blocks allocated by the user, and R_{min} is the user's lowest rate constraint.

III. Massive MIMO OFDMA downlink system energy efficiency resource allocation

The optimization problem described by equation (8) includes user frequency block number allocation, that is, bandwidth allocation, power allocation, and base station optimal antenna number allocation. The exhaustive method is very complicated to obtain the optimal solution, and it is usually difficult to achieve. . Therefore, this section adopts the sub-optimal resource allocation method. First, determine the bandwidth allocation for each user, and then allocate the power and the number of base station antennas for the users.

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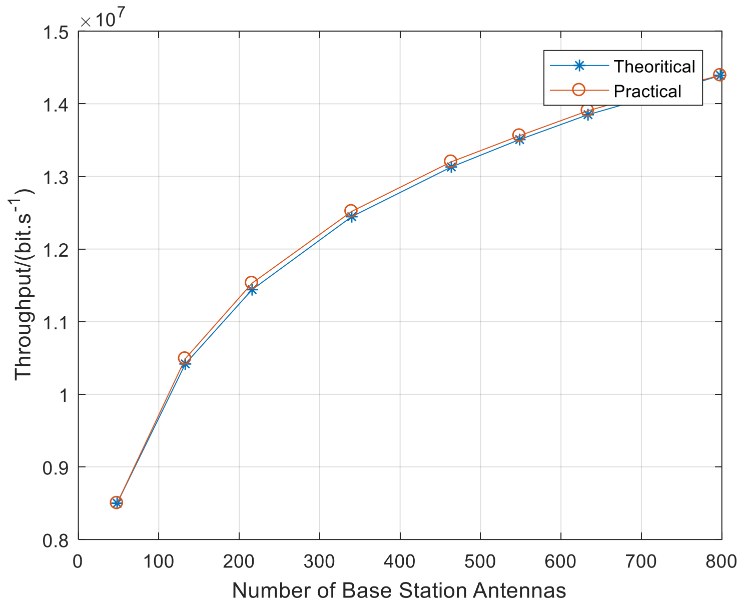

Fig 1. Throughput comparison

3.1.Bandwidth allocation algorithm for maximizing energy efficiency based on minimum rate requirements (BAA)

This paper proposes a bandwidth allocation algorithm (BAA) that maximizes energy efficiency based on the lowest rate requirement. From the optimization objective function, the objective function of bandwidth allocation can be expressed as

$$m_k = \max_{m} \frac{\sum_{k=1}^{K} m_k W lb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right]}{\sum_{k=1}^{K} m_k p_k + M p_c}$$

(9)

The BAA algorithm is described as follows.

Initialize the user transmits power vector P_0 and allocates R_0 at the rate at which P_0 is initialized

$$m_k \leftarrow \left\lceil \frac{R_{min}}{R_0(k)} \right\rceil$$

$$while \ \sum_{k=1}^{K} m_k > V$$

$$do \quad \left\{k^* \leftarrow arg \max_{1\le k\le K} m_k m_{k^*} \leftarrow 0\right\}$$

$$end \ \ While$$

$$While \ \sum_{k=1}^{K} m_k < V$$

$$do \quad \left\{ Q_k = \frac{(m_k+1)Wlb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right]}{(m_k+1)p_k+Mp_C} - \frac{m_k Wlb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right]}{m_k p_k + Mp_C} \quad l \leftarrow arg \max_{1\le k\le K} Q_k \quad m_l = m_l + 1 \right\} \quad end\ While$$

3.2.Resource allocation algorithm for maximizing energy efficiency based on minimum rate requirements (RAA)

Since the energy efficiency function is a fractional form and is non-convex, this paper considers using the nature of fractional planning to transform the fractional form into a subtractive form, and proves that the objective function of the subtractive form is jointly concave with respect to (P, M), and then transformed into the problem of convex optimization.

According to the literature [17], according to the nature of fractional planning, the objective function (7) in fractional form can be converted into a subtractive form

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

Where

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

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

$$F(q) = \max_{\mathrm{M,P}} R(P,M) - q[P_T(P) + P_C(M)]$$

$$= \max_{\mathrm{M,P}} \sum_{k=1}^{K} m_k Wlb\left[1+\frac{p_k(M-K)\beta_k}{WN_0}\right] - q\left(\sum_{k=1}^{K} m_k p_k + Mp_C\right)$$
$$\approx \max_{\mathrm{M,P}} \textstyle\sum_{k=1}^{K} m_k Wlb\left[\frac{p_k(M-K)\beta_k}{WN_0}\right] - q(\sum_{k=1}^{K} m_k p_k + Mp_C)$$

(10)

Constraints:

$$m_k Wlb\left[\frac{p_k(M-K)\beta_k}{WN_0}\right] \ge R_{min}$$

Hypothesis

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

The Hessian matrix of function f is

$$H(f) = \begin{bmatrix} -\frac{m_k W}{p_k^2 ln2} & 0 \\ 0 & -\sum_{k=1}^{K} \frac{m_k W}{(M-K)^2 \ln 2} \end{bmatrix}$$

Obviously, $H(f)$ is a negative definite matrix. At this time, the function f is jointly concave with respect to (P,M), which can be solved by convex optimization. Therefore, the Lagrangian function of the objective function can be expressed as

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

(11)

where, $\lambda_k\geq 0$ is the Lagrangian multiplier corresponding to the constraint formula (10b). Therefore, the dual problem of equation (10) can be expressed as

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

(12)

Given λ, using KKT conditions, the optimal transmit power $P^{\star}$ and the number of base station antennas $M^{\star}$ can be expressed as

$$\frac{\partial L}{\partial p_k}=\frac{m_kW}{ln2.p_k}-qm_k+\frac{\lambda_km_kW}{ln2.p_k}=0\Rightarrow p_k^{\star}=\frac{(1+\lambda_k)W}{ln2.q}$$

(13)

$$\frac{\partial L}{\partial M}=\frac{W\sum_{k=1}^{K}m_k}{ln2(M-K)}-qp_c+\frac{W\sum_{k=1}^{K}\lambda_km_k}{ln2(M-K)}=0\Rightarrow M^{\star}=\left\lceil\frac{(V+\sum_{k=1}^{K}m_k\lambda_k)W}{ln2.qp_c}+K\right\rceil$$

(14)

where, $\lceil\bullet\rceil$ Means rounding up.

The Lagrange multiplier λ is obtained by recursive method

$$\lambda_k(j+1)=\left[\lambda_k(j)-\delta\left[m_kWlb\left(\frac{p_k(M-K)\beta_k}{WN_0}\right)-R_{min}\right]\right]^{+}$$

(15)

where, j represents the number of iterations, and δ represents the iteration step length. Using the Dinkelbach method in the literature [17], an iterative method is proposed. The specific algorithm is described as follows.

1) Initialization $P^{\star}=P_0, M^{\star}=M_0,\ q^{\star}=0,\ \lambda=0,\delta=\delta_0,\varepsilon=0.01$
2) While $R(P^{\star},M^{\star})-q^{\star}[P_T(P^{\star})+P_C(M^{\star})]>\varepsilon$
3) do $q^{\star}\leftarrow\frac{R(P^{\star},M)}{[P_T(P^{\star})+P_C(M^{\star})]}$
4) Use equation (15) to update the Lagrangian multiplier
5) Use equation (13) to get the power distribution
6) Use equation (14) to get the number of base station antennas

$Return\ q^{\star},\ P^{\star},\ M^{\star}$

The proof of the convergence of the algorithm can be found in literature [11].

IV. Simulation results and algorithm complexity analysis

4.1.Simulation results and analysis

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In the simulation, a hexagon with a cell radius of 1000 m is set, and users are randomly assigned to a range 100 m away from the base station. The large-scale fading from the k-th user to the base station is $\beta_k = \frac{z_k}{\left(\frac{r_k}{r_h}\right)^u}$, where z_k is the standard deviation The log-normal random variable of σ_{shadow} is the distance from the user to the base station, and u is the path loss index. The specific system parameters are shown in Table 1.

Parameters	**Values**
Total Bandwidth	2.56MHz
Number of Frequency Blocks	128
Noise Density N_0	-131 dBW/MHz
σ_{shadow}	8dB
u	3.8
Circuit power consumption of each antenna at the base stationP_C	100mW
User initialized transmit power P_0	$[0.1, \ldots, 0.1]^T mW$
Initial value of the number of base station antennas M_0	$K + 1$ (K Represents number of users)
Step size δ	10^{-4}
Rate requirements for each user R_{min}	$\frac{3.0\times10^7}{k}$bits/s (K Represents number of users)

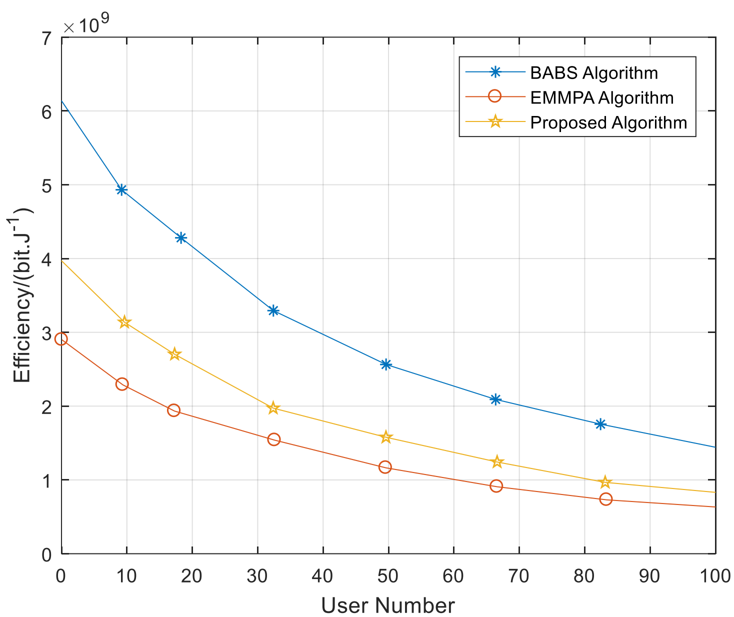

Fig 2. Performance Comparison of Energy efficiency over variable user number

In order to better compare the performance of the algorithm, the bandwidth allocation in the BABS algorithm uses the signal-to-noise ratio-based bandwidth allocation algorithm (BABS) proposed in the literature [18], and the power allocation and the number of base station antenna allocations use the RAA algorithm proposed in this paper; EMMPA The bandwidth allocation in the algorithm first adopts the method of equal allocation. The remaining frequency blocks are allocated to users with better channel conditions, that is, users with the largest large-scale fading factor. Power allocation and base station antenna number allocation use the EMMPA algorithm proposed in [12]. This algorithm maximizes the energy efficiency of the system by adjusting the user transmit power without any constraints. In the simulation, it is assumed that the number of base station antennas of the algorithm is $(K+1)$, and the power allocation is $p_k = \left[\mu - \frac{WN_0}{(M-K)\beta_k}\right]^+$.

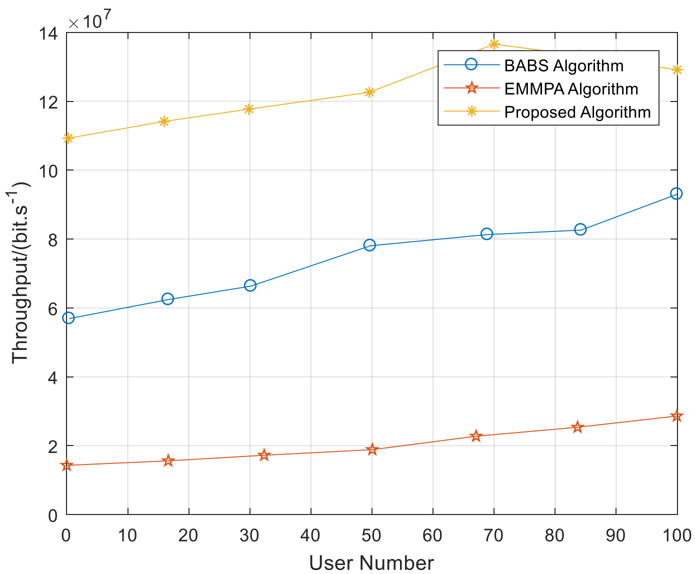

Fig 3. Performance comparison of proposed algorithm with literature with variable user numbers

Figure 2 shows the energy efficiency performance of each algorithm under different number of users. It can be seen from the figure that the performance of the algorithm in this paper is between the EMMPA algorithm and the BABS algorithm. This is because the EMMPA algorithm maximizes the energy efficiency of the system without any constraints, so the algorithm has the best energy efficiency performance, while the BABS algorithm is Bandwidth allocation algorithm based on signal-to-noise ratio, so the energy efficiency performance of this algorithm is worse than that of the algorithm in this paper. It can also be seen from the figure that as the number of users increases, the energy efficiency performance of the system gradually decreases. This is because as the number of users increases, the bandwidth that each user can allocate gradually decreases and the transmission power needs to be increased to meet the requirements. The user's minimum rate requirement for the EMMPA algorithm, although there is no rate requirement, the average bandwidth allocation will cause the bandwidth allocated to users with better channel conditions to gradually decrease, thereby reducing system energy efficiency. At the same time, as the number of user's increases, the bandwidth allocated by the minimum user rate requirement $m_k \leftarrow \left\lceil \frac{R_{min}}{R_0(k)} \right\rceil$ will occupy the dominant position of the two bandwidth allocation algorithms of this paper and the BABS algorithm. , Leading to their energy efficiency performance gap is getting smaller and smaller.

Figure 3 shows the throughput performance of each algorithm under different number of users. It can be seen from the figure that the throughput performance of the algorithm in this paper is better. This is because the EMMPA algorithm has no rate requirements for users, but only maximizes the energy efficiency of the system, so the throughput of the system is low; while the broadband allocation method used by the BABS algorithm is Minimize the transmission power, so the throughput performance of the system is lower than the algorithm in this paper. It can also be seen from the figure that as the number of users increases, the system throughput performance gradually increases. This is because as the number of users increases, the system's multi-user diversity characteristics become more obvious. Therefore, the algorithm in this paper has both better system energy efficiency performance and better system throughput performance.

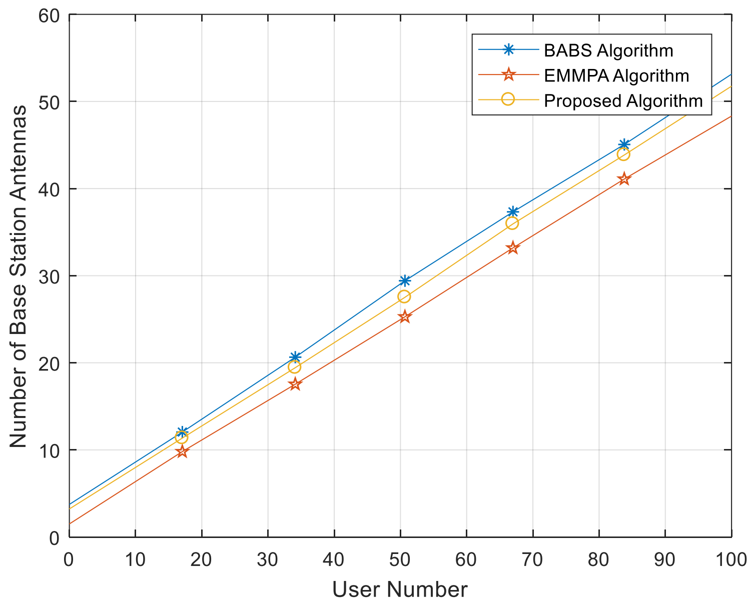

Fig 4. Performance comparison of optimal base station antenna with variable user numbers

Figure 4 shows the optimal base station antenna number performance of each algorithm under different user numbers. It can be seen from the figure that as the number of users increases, the number of optimal base station antennas required by the system gradually increases. The EMMPA algorithm does not optimize the number of antennas. It only optimizes energy efficiency by changing the transmit power. Therefore, the number of base station antennas is always equal to $K + 1$, and the BABS algorithm is very close to the optimal number of base station antennas in this algorithm.

Figure 5 shows the transmit power performance of each algorithm under different number of users. It can be seen from the figure that as the number of users increases, the transmission power required by the BABS algorithm and the algorithm in this paper increases rapidly with the number of users. This is because the BABS algorithm and the algorithm in this paper consider the user's minimum rate requirements, while the EMMPA algorithm does not have any constraints.

Figure 6 shows the energy efficiency performance of each algorithm under different number of frequency blocks. It can be seen from the figure that the energy efficiency performance of the algorithm in this paper increases rapidly with the increase of the number of frequency blocks, while the energy efficiency performance of the BABS algorithm and the EMMPA algorithm increases slowly with the increase of the number of frequency blocks. This is because the BAA bandwidth allocation algorithm is used in the algorithm in this paper. This algorithm enables the energy efficiency performance to increase greatly with the increase of the number of frequency blocks, while the performance of the bandwidth allocation algorithm in the BABS algorithm and the EMMPA algorithm does not change significantly with the increase of the number of frequency blocks. It can also be seen from the figure that as the number of frequency blocks increases, the performance of the algorithm in this paper is closer to that of the EMMPA algorithm. This is because the BAA bandwidth allocation algorithm used in the algorithm in this paper can better realize the multi-user diversity gain of the system.

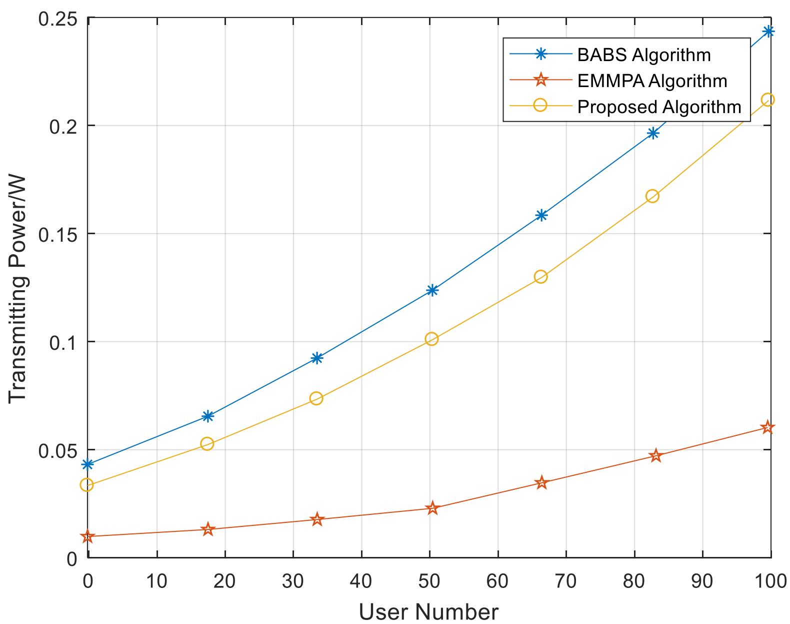

Fig 5. Performance comparison of Transmit power under variable User Number

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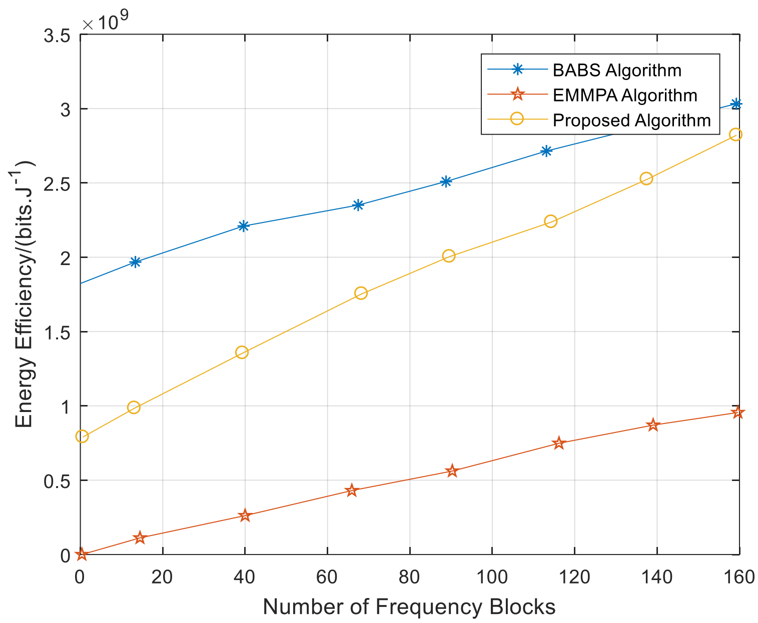

Fig 6. Performance comparison of Energy efficiency performance under variable number of frequency blocks

4.2.Complexity Analysis

The BABS algorithm is a bandwidth allocation algorithm based on the signal-to-noise ratio. During bandwidth allocation, K users iterate V times, so the bandwidth allocation calculation complexity is $O(KV)$. The calculation complexity of bandwidth allocation in the algorithm in this paper is $O\left(1+K\left(V-\sum_{k=1}^{K}\left\lceil\frac{R_{min}}{R_0(k)}\right\rceil\right)\right)$, the computational complexity of the number of base station antennas and power allocation is $O(I_\lambda)$, so the complexity of the RAA algorithm is $O(KI_{AP}I_\lambda)$. The computational complexity of bandwidth allocation in the EMMPA algorithm is $O\left(1+K\left(mod\left(\frac{V}{K}\right)\right)\right)$, where the factor is divided by the power factor α, and the remainder is the power distribution formula. To get the global optimal $\mu^\star$, at least $\left\lceil lb\left(\frac{(\alpha-1)\mu^\star}{\varepsilon}-1\right)\right\rceil$ iterations, where $|\mu-\mu^\star|<\varepsilon$, the computational complexity of this power allocation is $O\left(K\left\lceil lb\left(\frac{(\alpha-1)\mu^\star}{\varepsilon}-1\right)\right\rceil\right)$. In summary, the computational complexity of the BABS algorithm is $O(KV+KI_{AP}I_\lambda)$, and the computational complexity of the algorithm in this paper is $O\left(1+K\left(V-\sum_{k=1}^{K}\left\lceil\frac{R_{min}}{R_0(k)}\right\rceil\right)+KI_{AP}I_\lambda\right)$, the computational complexity of the EMMPA algorithm is $O\left(1+K\left(mod(V/K)\right)+K\left\lceil lb\left(\frac{(\alpha-1)\mu^\star}{\varepsilon}-1\right)\right\rceil\right)$.

V. Conclusion

In this paper the energy efficiency resource allocation problem in the multi-user massive MIMO OFDMA downlink system is studied. In meeting the minimum rate requirement of each user, a corresponding optimization mathematical model was established with the goal of maximizing the lower bound of system energy efficiency. Since the global optimal solution needs to be obtained through exhaustive exhaustion and the complexity is high, the whole optimization process is divided into 2 steps to complete. First, determine the bandwidth allocation of each user according to the minimum rate requirement of each user and the objective function of maximizing system energy efficiency, and then jointly optimize the user's transmit power and the number of base station antennas based on the user's bandwidth allocation. The proposed algorithm achieves better energy efficiency performance and throughput performance on the premise of meeting user QoS requirements.

References:

1. Zhong, Chongxian, Luxi Yang, and Mingli You. "Dynamic resource allocation for downlink multiuser MIMO-OFDMA/SDMA systems." Circuits, Systems and Signal Processing 29.6 (2010): 1061-1074.
2. Huang, Yongming, et al. "Distributed multicell beamforming design approaching pareto boundary with max-min fairness." IEEE Transactions on Wireless Communications 11.8 (2012): 2921-2933.
3. Tervo, Oskari, et al. "Distributed optimization for coordinated beamforming in multicell multigroup multicast systems: Power minimization and SINR balancing." IEEE Transactions on Signal Processing 66.1 (2017): 171-185.
4. Ho, Chieh Yuan, and Ching-Yao Huang. "Single-and multi-user uplink energy-efficient resource allocation algorithms with users' power and minimum rate constraint in OFDMA cellular networks." Wireless networks 19.5 (2013): 673-688.
5. Ho, Chieh Yuan, and Ching-Yao Huang. "Single-and multi-user uplink energy-efficient resource allocation algorithms with users' power and minimum rate constraint in OFDMA cellular networks." Wireless networks 19, no. 5 (2013): 673-688.
6. Yang, Ting, Fabien Héliot, and Chuan Heng Foh. "A survey of green scheduling schemes for homogeneous and heterogeneous cellular networks." IEEE Communications Magazine 53.11 (2015): 175-181.
7. Gao, Yulan, et al. "Dynamic social-aware peer selection for cooperative relay management with D2D communications." IEEE Transactions on Communications 67.5 (2019): 3124-3139.
8. Chen, Xing, and Guizhong Liu. "Joint optimization of task offloading and resource allocation via deep reinforcement learning for augmented reality in mobile edge network." 2020 IEEE International Conference on Edge Computing (EDGE). IEEE, 2020.
9. Wei, Zhiqiang, et al. "Energy-Efficient Radio Resource Management." Wiley 5G Ref: The Essential 5G Reference Online (2019): 1-23.
10. Lv, Hengwei, et al. "Energy-efficient multi-cell resource allocation in cognitive radio-enabled 5G systems." EURASIP Journal on Advances in Signal Processing 2019.1 (2019): 1-17.

11. Wan, Xiao-yu, et al. "Energy efficient resource allocation algorithm for massive MIMO systems based on wireless power transfer." IEICE Transactions on Communications (2018).
12. Shen, Cong, Pengkai Zhao, and Xiliang Luo. "On energy efficient uplink multi-user mimo with shared lna control." ICC 2021-IEEE International Conference on Communications. IEEE, 2021.
13. Chawla, Apoorva, and Aditya K. Jagannatham. "Spectral efficiency of very large multiuser MIMO systems for time-selective fading." 2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring). IEEE, 2019.
14. Uddin, M. B., et al. "Performance analysis of Nakagami-m fading massive MIMO channels with linear receivers." 2014 17th International Conference on Computer and Information Technology (ICCIT). IEEE, 2014.
15. Cai, Yuanxin, et al. "Energy-efficient resource allocation for secure UAV communication systems." 2019 IEEE Wireless Communications and Networking Conference (WCNC). IEEE, 2019.
16. Peng, Yuyang, et al. "Enhancing energy efficiency via cooperative MIMO in wireless sensor networks: State of the art and future research directions." IEEE Communications Magazine 55.11 (2017): 47-53.
17. Nayak, Suvasis, and Akshay Ojha. "An approach of fuzzy and TOPSIS to bi-level multi-objective nonlinear fractional programming problem." Soft Computing 23.14 (2019): 5605-5618.
18. Khalili, Ata, et al. "Antenna selection strategy for energy efficiency maximization in uplink OFDMA networks: A multi-objective approach." IEEE Transactions on Wireless Communications 19.1 (2019): 595-609.