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Power allocation strategy for NOMA and CR networks based on modern control theory

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Abstract: Non-orthogonal multiple access (NOMA) and cognitive radio (CR) technologies are the two most promising techniques to improve spectral efficiency for the next-generation mobile communication system. For the CR-NOMA network, we propose a new power allocation to maximize the energy efficiency of secondary users (SUs) without deteriorating the quality of service (QoS) of the primary users (PUs). The traditional power control is transformed into the power control problem of NOMA and CR based on the control theory through the linear quadratic optimal regulator (LQR) method. First, we build a CR-NOMA network. Then the modern control theory is based on the state space method, the state space description must be used as a mathematical model in this process. The control theory is used to dynamically adjust the transmission power of SUs, find the optimal transmission power, and compare its energy efficiency with other algorithms. The simulation results show that the system performance of the proposed algorithm is better than the genetic algorithm and FTPC algorithm.

Keywords: Cognitive radio; Non-orthogonal multiple access; Control theory; Power allocation; Energy efficiency.

1. Introduction

As new radio access technologies emerge, and IoT devices become more common, hardware will influence the design of 6G networks. The high cost and power consumption of hardware components will significantly affect the transceiver architecture and algorithm design. This will result in a shortage of hardware devices. However, wireless devices will explode and mobile communication systems face a shortage of spectrum resources . To further improve the spectrum efficiency, it is the most effective and direct way to improve the utilization rate of the spectrum. Among them, NOMA and CR can significantly improve spectrum efficiency, thereby improving the throughput of a mobile communication system [2-3].CR is a promising technique by enabling the SUs to share the licensed spectrum with the PU on the condition that the interference leaked to the PU is acceptable [4,5-6]. Besides CR, NOMA is another promising technique to enhance system spectrum efficiency and achieve massive connectivity of IoT devices in CR networks by employing the under-laying strategy. NOMA usually utilizes the power domain for multiple access, where different users are served at different power levels depending on the radio channel quality and the successive interference cancellation (SIC) which are employed to distinguish the different transmit signals may eliminate the co-channel interference at the receiver . Unlike previous orthogonal multiple access (OMA)approaches, NOMA improves the efficiency of the system by introducing controlled interference to overload the system users at the cost of increasing the complexity of the receiver [8-9].

The interference situation that traditional CR needs to consider is more complex. Traditional CR can avoid mutual interference between sub-users by orthogonal means, but the resources available to each sub-user become less, and the number of sub-users accessed is smaller. Based on this, in order to improve the total system rate, system energy efficiency, and the number of users accessed in the system, a CR-NOMA network was adopted.

To this end, the literature considers the Underlay CR-NOMA scenario, allowing the overlay transmission of information between SUs through NOMA, and selects a suitable target data rate constraint and power allocation factor. Their simulation results show that user terminals with NOMA can obtain better performance compared to Underlay CR-OMA systems. This shows that the combination of NOMA and CR is of research interest. Currently, how to effectively combine NOMA power allocation and CR [11-12] has become a new research hotspot. The literature shows that the adoption of NOMA techniques in cognitive radio networks can significantly improve the system throughput. The literature focuses on increasing the number of accessible SUs in CR-NOMA networks under the constraint of total power.

The combination of existing NOMA power allocation and CR is mainly focused on improving the system throughput and the maximum rate that can be achieved by users in the system, and only a small amount of literature deals with energy efficiency optimization. The current literature on energy efficiency focuses on the primary user's communication quality requirements in CR networks. The energy efficiency of SUs is not fully considered while meeting the demand of PUs, and the traditional optimization methods are mainly static power control, which is not flexible enough. The downlink of CR-NOMA power allocation problem is solved utilizing the modern control theory to maximize the energy efficiency of the SUs under the constraint of the QoS of the PUs and Sus and the total transmit power of the base station. In this paper, the LQR algorithm is used to achieve closed-loop optimization by sensing the environmental conditions and dynamically adjusting the transmit power. In addition, the LQR algorithm has lower time complexity compared to other algorithms.

2. System Model

In the downlink CR-NOMA network, as shown in Fig.1. The CR-NOMA network uses the underlay model, that is, PUs and SUs can share the frequency band resources. SUs use NOMA to access the network between them. The SU base station transmits the signals of N SUs through the sub-channels of M authorized PUs as a single antenna. We denote m as an index for the subchannel according to the corresponding PU where $m \in \{1, 2, ..., M\}$ and i as the index for the ith SU where $i \in \{1, 2, \cdots, N\}$. It is assumed that L SUs multiplex the mth PU sub-channel adopting NOMA technology, where $L \le L_{\max} \le N$, $L_{\max}$ is the maximum allowed number of multiplexed SUs on a PU sub-channel. The total signal transmitted by the SU base station on the PU sub-channel m is:

$$x_m = \sum_{i=1}^{L} \sqrt{\beta_{i,m} P_{\mathrm{m}}}\, x_i \tag{1}$$

where x_i is the signal of SU i ; $\beta_{i,m}$ is the power allocation factor assigned to SU i by the base station on sub-channel m. P_m is the power allocated by the base station to the sub-channel, then the actual power transmitted by all SU base stations on sub-channel m and P_t is expressed as:

$$P_t = P_m \sum_{i=1}^{L} \beta_{i,m} \tag{2}$$

On the authorized PU subchannel, the signal received by the SU can be expressed as:

$$y_{i,m} = h_i \sqrt{\beta_{i,m} P_m}\, x_{i,m} + h_i \sum_{j=1, j\ne i}^{L} \sqrt{\beta_{j,m} P_m}\, x_{j,m} + \mathrm{g}_i \sqrt{p_p}\, x_p + n_i \tag{3}$$

(3) where: h_i is the channel gain on sub-channel m from SU i to the secondary base station, g_i is the channel gain from the PU base station to the SU; p_p is the transmit power of PU m ; x_p is the signal from the PU base station to the PU m ; n_i is the additive Gaussian white noise with zero mean and variance σ^2 . For the sake of simplicity, the Gaussian white noise at the receiving end and the interference coming from the PUs can be expressed together as $N_i = \sigma^2 + |g_i|^2 p_p, \forall i \in L$. The generalized background noise power N_i includes the interference power emitted from the PU base station and background noise power at the i SU receiver, which is a reasonable assumption. It is specified in IEEE802.22WRAN that a SU can use a quiescent period (the time when only the PU is communicating) to measure this generalized background noise.

Before the serial interference cancellation SIC is performed at the receiver, the SINR of SU i on subchannel m is:

$$\gamma_i^{before}(k) = \frac{h_i(k) p_i(k)}{h_i(k) \sum_{j=1, j\ne i}^{L} p_j(k) + N_i} \tag{4}$$

Among them, $p_i = \beta_{i,m} P_m$, $p_j = \beta_{j,m} P_m$, $h_i(k) \sum_{j=1, j\ne i}^{L} p_j(k)$ is the interference power of other multiplexed users in the sub-channel. At the receiving end, all SUs performs SIC, i.e., a SU receives a mixed signal from the base station, and then starts detecting the user signal with the worst channel condition in that mixed signal, and removes it from the mixed signal when it is successfully detected. Then the same operation is performed for the user signal with the second worst channel condition. And so on, until the signal of all users whose channels are worse than that user is eliminated. In the ideal state, the SINR of SU ith after SIC is expressed as:

$$\gamma_i(k) = \frac{h_i(k) p_i(k)}{h_i(k) \sum_{j=1}^{i-1} p_j(k) + N_i} \tag{5}$$

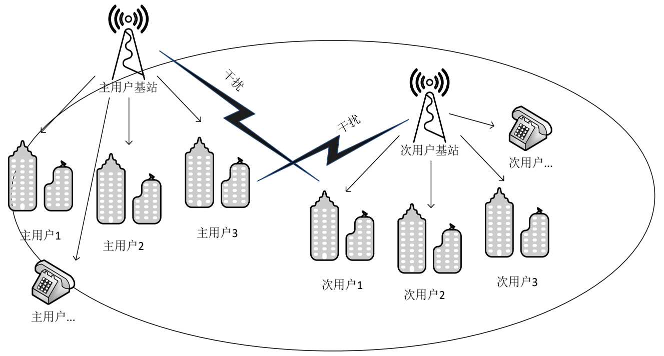

Fig.1 System model

The denominator in the defined equation (5) is the noise-containing interference at the i SU receiver. Then the mathematical description of $I_i^s(k)$ is reduced to $I_i^s(k) = h_i \sum_{j=1}^{i-1} p_j(k) + N_i$ Further, we use $\mu_i(k) = h_i(k) / I_i^s(k)$ to represent the effective channel gain of the ith SU; then (5) becomes $\gamma_i(k) = \mu_i(k) p_i(k)$. In this paper, the decibel scale form of each variable is used, i.e., $\overline{x} = 10\lg x$ is the decibel value of variable x . In turn, the decibel scale form is obtained as:

$$\overline{\gamma}_i(k) = \overline{\mu}_i(k) + \overline{p}_i(k) \tag{6}$$

In the CR-NOMA network, the transmissions of the SUs need not affect the normal communication of the PUs. This criterion is generally ensured by the interference temperature constraint of the PU. The sum of interference power $I(k)$ received by the PU receiver from all SUs at the kth time slot is below a given threshold I_{th} , which is mathematically described as:

$$I(k) = \sum\nolimits_{i\in L} h_i(k) p_i(k) \le I_{\mathrm{th}} \tag{7}$$

As can be seen from the above equation, I_{th} is the interference threshold. It is obvious that the total interference to PU is the sum of that from each SU, which makes the distributed power control more difficult to realize. Considering data transmission of SU in the CR-NOMA on the basis of no communication interrupt for PU, we use an average interference temperature constraint to replace the original one with conservativeness. Then (7) can be transformed as:

$$I_i(k) = h_i(k) p_i(k) \le I_{avg} \tag{8}$$

where $I_{avg} \le I_{th} / M$ is the average interference power threshold which can decentralize the original center control problem. Our purpose is to design a distributed power control strategy only using local information to allocate power to each SU. Substituting the variables of (8) with the decibel values, we can get:

$$\bar{I}(k) = \bar{h}_i(k) + \bar{p}_i(k) \le \bar{I}_{avg} \tag{9}$$

On the other hand, the signal-to-noise ratio (SINR) can be used as a communication quality measure. Assuming that the minimum SINR of SU i multiplexed on sub-channel m is $\gamma_{\min}$, the SINR of SU i is required to be greater than or equal to the minimum SINR in order to guarantee the communication quality of all SUs.

$$\gamma_i \ge \gamma_{\min}, \forall i \in L \tag{10}$$

According to Shannon's formula, the total throughput of a CR-NOMA network over subchannel m is:

$$R_{\mathrm{m}} = \sum_{i=1}^{L} R_{i,m} = \sum_{i=1}^{L} B_m \mathrm{1b}(1+\gamma_i) \tag{11}$$

(11) where B_m is the bandwidth of sub-channel m.

3. Problem Description

In this section, we model the energy efficiency optimization problem of CR-NOMA network. Assuming equal power allocation among sub-channels and the total power of SU base stations is P_{tot}, the power allocated to sub-channels by SU base stations is $P_m = P_{tot} / M$. The energy efficiency on sub-channel m can be derived as $EE = R_m / (P_t + P_c)$, and the energy efficiency of the whole system is defined as $EE = \sum_{m=1}^{M} EE_m$. P_c is the fixed power consumption of the circuit. In order to obtain effective energy efficiency, the following conditions need to be met:

$$\begin{aligned} &\max \ EE \\ &s.t. \\ &C1: \gamma_i \ge \gamma_{\min} \\ &C2: \bar{I}_i(k) \le I_{avg} \\ &C3: P_t \le P_m \end{aligned} \tag{12}$$

The SUs must satisfy the above constraints when accessing the system, i.e., the interference caused to the PUs must be below a given threshold I_{th}, and the quality of service requirements of their users must be satisfied. By combining the above conditions with the algorithm proposed in this paper, the power of the SUs is optimally allocated, and then the energy efficiency of the system is obtained by $EE_m = R_m / (P_t + P_c)$.

4. Energy Efficiency Optimized Power Control Algorithm

4.1. Modeling the State Space

First, the closed-loop power control is a fast power regulation method with the following standard power control law:

$$p_i(k+1) = p_i(k) \left(\frac{\gamma_i^*(k)}{\gamma_i(k)}\right)^{\alpha_i}, 0 < \alpha_i < 1 \tag{13}$$

α_i is the control gain of standard power control, which is used to limit the magnitude of power variation between two adjacent time slots. Does not cause users to increase or decrease transmit power values excessively due to sudden changes in channel conditions. It avoids the degradation of the whole network communication performance due to the steep change of transmit power of one user. And each user can also set the value according to its own situation. Its decibel form can be expressed as:

$$\bar{p}_i(k+1) = \bar{p}_i(k) + \alpha_i [\bar{\gamma}_i^*(k) - \bar{\gamma}_i(k)] \tag{14}$$

It is assumed that the initial power values $\bar{p}_i(0)$ for each sub-user are independent of each other.

We formulate the power allocation of the CR-NOMA as a control problem based on state-space model. In order to satisfy the communication needs for both SUs and PUs, we introduce an auxiliary variable $\gamma_i^*(k)$ defined as the target SINR controlled by our proposed controller for SU adjusting allocated power to meet the following control goals:

1)The instantaneous $\gamma_i(k)$ tracks target $\gamma_i^*(k)$.

2) $\gamma_i^*(k)$ ensures the interference power to PU under interference temperature threshold.

3)The target $\gamma_i^*(k)$ is feasible at moment k, namely each SU can satisfy its own minimum communication requirement if $\gamma_i(k)$ reaches $\gamma_i^*(k)$.

To achieve the above goal, we introduce a control variable $u_i(k)$ for the ith SU link is formulated as:

$$\bar{\gamma}_i^*(k+1) = \bar{\gamma}_i^*(k) + u_i(k) \tag{15}$$

$u_i(k)$ is the controller that needs to be designed.

Assuming that the channel parameters of each link do not change during the N time slots of packet transmission, according to (6), (14), (15), we obtain following adjustable SINR:

$$\bar{\gamma}_i(k+1) = (1-\alpha_i)\bar{\gamma}_i(k) + \alpha_i \bar{\gamma}_i^*(k) \tag{16}$$

From goal of the control strategy, the target SINR of each SU is achieved under the condition that the interference temperature constraint should be ensured. To reach this purpose, we substitute (14) into (9) to obtain the interference power

$$\bar{I}_i(k+1) = \bar{I}_i(k) + \alpha_i [\bar{\gamma}_i^*(k) - \bar{\gamma}_i(k)] \tag{16}$$

Our aim is to select power control sequence $\{p_i(k)\}$ such that the actual SINR of SU must approach as closely as possible to the target one defined by (15) subject to the given interference temperature constraint . To realize this goal, we let the distance between the interference temperature threshold and the actual value $\left|\overline{I}_{avg}-\overline{I}_i(k)\right|$ and the one between the target SINR and the actual value $\left|\overline{\gamma}_i^*(k)-\overline{\gamma}_i(k)\right|$ be as small as possible during a period of time T with N samplings. Thus, the following two state variables are introduced:

$$\overline{\varepsilon}_i^s(k)=\overline{\gamma}_i^*(k)-\overline{\gamma}_i(k) \quad (17)$$

$$\overline{\varepsilon}_i(k)=\overline{I}_{avg}-\overline{I}_i(k) \quad (18)$$

According to the formula. (15), (16), and (17), the dynamic difference equations for the two state variables mentioned above can be derived as:

$$\overline{\varepsilon}_i^s(k+1)=(1-\alpha_i)\overline{\varepsilon}_i^s(k)+\mu_i(k) \quad (19)$$

$$\overline{\varepsilon}_i(k+1)=-\alpha_i\overline{\varepsilon}_i^s(k)+\overline{\varepsilon}_i(k) \quad (20)$$

We define a two-element state vector $x_i(k)=[\overline{\varepsilon}_i^s(k),\overline{\varepsilon}_i(k)]^T$ for SU link i. Because there is the same control process for each link, the index i can be dropped for simplicity in the design of the controller. Thus, combining (20) and (21) we build the general state-space model for SU link i as:

$$x_i(k+1)=A_ix_i(k)+B_i\mu_i(k) \quad (21)$$

where coefficient matrixes are $A_i=\begin{bmatrix}1-\alpha_i & -\alpha_i\\ -\alpha_i & 0\end{bmatrix}$ and $B_i=\begin{bmatrix}1\\0\end{bmatrix}$ with their own appropriate dimensions. Since the controllability matrix $\begin{bmatrix}B_i & AB_i\end{bmatrix}=\begin{bmatrix}1 & 1-\alpha_i\\ 0 & -\alpha_i\end{bmatrix}$ is full rank, it can be shown that the linear discrete constant system described by Eq. (22) is controllable. Therefore, for this dynamic system, a feasible controller can be found to make the closed-loop control system stable and the control output achieves a certain control target.

The above completes the state space modeling of the dynamic power control problem for CR-NOMA and gives its state space expression (22). The following will give how to design a reasonable target SINR regulator. Maximize the SU communication performance while satisfying the interference temperature constraint.

4.2. Lqr-Based Target Sinr Regulaator Design

In order to achieve control objectives, we define a cost function as:

$$J_i=\frac{1}{2}\sum_{k=0}^{N-1}\left\{x_i^T(k)Q_ix_i(k)+u_i(k)r_iu_i(k)\right\} \quad (22)$$

where $Q_i=\begin{bmatrix}\rho_i^{ss} & 0\\ 0 & \rho_i^{l_{\min}}\end{bmatrix}$ and r_i are both control weights, whose value can be adjusted according to the control requirements. These weights decide whether the corresponding element is important or not.

Precisely ρ_i^{ss} and $\rho_i^{l_{\min}}$ help us to pay more attention to the SINR and interference temperature threshold tracking in particular. And r_i means controller limited. In our CR-

NOMA, PU allows SUs to temporarily utilize its given primary spectrum without interrupting its communication. This often depends on a fixed IT threshold limitation. Thus we assign $\rho_i^{l_{\min}}$ is larger than ρ_i^{ss} and r_i for better tracking of the interference temperature a priori, which means that SU can better use available spectrum resources. The power control based on the above state-space model can be formulated as a state feedback control problem in different forms with or without considering channel gain fluctuation, which is to find a control gain to satisfy the communication requirement for both PU and SUs.

$$\min_{u_i} J_i=\frac{1}{2}\sum_{k=0}^{N-1}\{x_i^T(k)Q_ix_i(k)+u_i(k)r_iu_i(k)\}$$

$$s.t.\ \ x_i(k+1)=A_ix_i(k)+B_iu_i(k)$$

And the controller of the discrete-time LQR problem is given as:

$$u_i(k)=-K_ix_i(k) \quad (23)$$

This makes the closed-loop system stable and minimizes the control output performance index equation (23). The optimal state feedback controller gain can be derived from the LQR principle as:

$$K_i=[r_i+(B_i)^TP_iB_i]^{-1}(B_i^2)^TP_iA_i \quad (24)$$

P_i is the unique positive definite solution of the following discrete Riccati matrix algebraic equation:

$$P_i=Q_i+A_i^TP_iA_i-A_i^TP_iB_i[r_i+(B_i)^TP_iB_i]^{-1}(B_i)^TP_iA_i \quad (25)$$

Table 1. Dynamic Power Control Algorithm Based on LQR

At the kth time slot, each sub-user performs the following operations:
step 1. Measurement of instantaneous SINR;
step 2. Obtain interference information for all PUs;
step 3. Select the most vulnerable primary user $l_{\min}$;
step 4. Input the current instantaneous SINR, the target SINR and the most vulnerable primary user interference information into the state space model equation (22) and calculate the optimal state feedback control law equation (25).
step 5. Update target SINR;
step 6. Adjusting the transmit power value using the standard power control equation (15) to track the new target SINR.
step 7. Return to step 1 for transmit power control of the k+1th time slot.

4.3. Ftpc Power Allocation Algorithm

In order to show the superiority of the algorithm proposed in this paper, the FTPC power allocation algorithm is compared with it. The FTPC algorithm is specified as follows:

$$\upsilon_j=\frac{1}{\sum_{k=1}^{M}q_k^{-\nu_f}}q_j^{-\nu_f} \quad (26)$$

ν_f is the attenuation factor, which ranges from $0\le\nu_f\le 1$. When $\nu_f=0$, according to (28), it is obvious that the power factor of each SU is equal, and at this point, FTPC is equal power distribution. As the value of ν_f increases, more power is allocated to users with poorer channel conditions, which is consistent with the idea of

NOMA.

In addition to the FTPC algorithm, the power allocation algorithm of the genetic algorithm was also simulated. It is also compared with the algorithm of this paper and the superiority of the algorithm is proved by the simulation results.

5. Simulation Analysis

Downlink energy efficiency optimization for CR-NOMA network. SUs are randomly distributed in a cell with a radius of 400m. The minimum distance between the SU base station and SUs is 50m. The system bandwidth is 5MHz, the total noise power at the receiver is -75dBm and the power consumed by the circuit is 30dBm. The number of PUs in the cell is 5, and the maximum tolerable interference power value for each PU is -30dBm. The channel gain model is $h_i = H_{i,m} d_i^{(-\eta/2)}$, and $H_{i,m}$ is a Gaussian random variable with mean 0 and variance 1. d_i is the distance from SU i to the SU base station η is the link fading factor In addition, the weighting parameters of the control performance index equation (23) are set to $\rho_i^{ss} = 1$, $\rho_i^{l_{\min}}$ =6, r_i =1, and the control gain a=0.2 for standard power control. During the simulation, the FTPC power allocation algorithm and genetic algorithm are used to compare the algorithms.

In order to comprehensively investigate the performance of the proposed algorithm, the relationship between the program running time, the number of iterations of convergence of the algorithm, the average system energy efficiency and the minimum signal-to-noise ratio, the total power of the sub-user base station, and the maximum tolerable power of the primary user during the simulation are given in this paper. The average system energy efficiency is the long time average of the system energy efficiency.

Fig 2 depicts the iterative convergence process of the proposed algorithm and the genetic algorithm for different base station total power cases, where the number of multiplexed users is 3. It can be seen that the average system energy efficiency of both algorithms gradually increases with the increase in the number of iterations and converges to a fixed value. The energy efficiency of the proposed algorithm fluctuates greatly in the first few iterations, but it can be stabilized quickly with the increase of iterations. The genetic algorithm has less fluctuation in energy efficiency in the iterations, but the convergence speed is slower than the proposed algorithm. From the figure, we can see that the proposed algorithm can reach the optimal system energy efficiency in 20 iterations. In contrast, the genetic algorithm requires 40 iterations to reach the optimal system energy efficiency, and the proposed algorithm has a slightly better system energy efficiency than the genetic algorithm. Table 2 gives the time consumed to run the simulation program for the proposed and genetic algorithms for the number of iterations 1, 2, ..., and 6, respectively.

From table 2, we can see that the running time of the simulation program of the proposed algorithm is about 1/3 of that of the genetic algorithm. Because the simulation program operation time can directly reflect the complexity of the algorithm. It can be seen that the time complexity of the proposed algorithm is lower than the time complexity of the genetic algorithm. Therefore, the proposed algorithm has the characteristics of fast convergence and low time complexity.

Table 2. Comparison of The Proposed Algorithm and The Genetic Algorithm at Different Time Complexities

Methods /Running time/s	1	2	3	4	5	6
The proposed algorithm	0.19	0.22	0.25	0.28	0.31	0.33
Genetic Algorithm	0.62	0.68	0.75	0.82	0.90	0.98

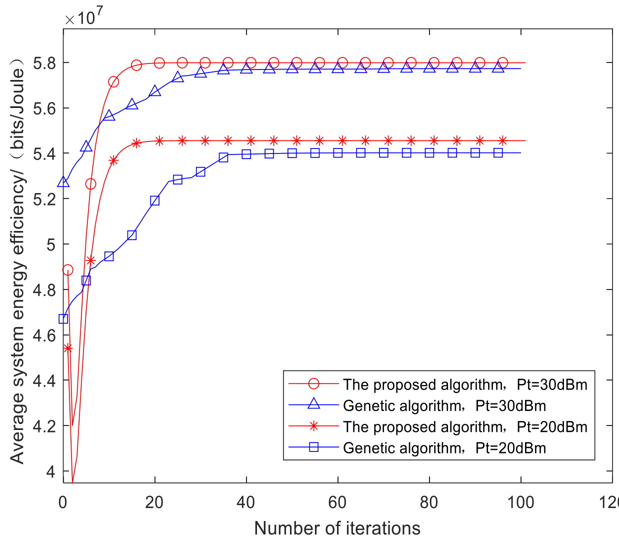

Fig.2 Iterative convergence process

Fig 3 depicts the average system energy efficiency versus the minimum signal to interference plus noise ratio $SINR_{\min}$, where the number of multiplexed users is 3. From figure 3, it can be seen that the average system performance of the proposed algorithm, genetic algorithm, and FTPC power allocation algorithm gradually decreases as $SINR_{\min}$ increases. The reason for the above phenomenon is that the larger $SINR_{\min}$ indicates that the system needs to allocate more power to users with weaker channel gain to meet their SINR requirements, while only less power is allocated to users with stronger channel gain. This situation leads to an increase in throughput for users with weak channel gain and a decrease in throughput for users with strong channel gain. However, the increase in sub-channel throughput is less than the decrease in sub-channel throughput, resulting in a decrease in system throughput. The maximum transmits the power of the SU base station remains unchanged, and thus the system energy efficiency is reduced. The energy efficiency of the FTPC algorithm is significantly lower than that of the genetic algorithm and the proposed algorithm. This is due to the fact that the FTPC algorithm only allocates power according to the channel conditions of each subscriber. In the case that the minimum SINR requirement can be met for normal communication, there will be a situation where power is wasted by over-allocating power to users, and the available allocated power cannot be maximized.

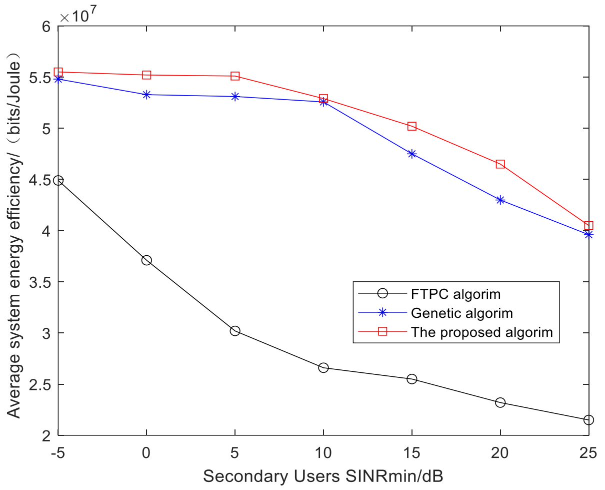

Fig.3 Average system energy efficiency versus minimum signal-to-noise ratio

Figure 4 depicts the relationship between the average system energy efficiency and the maximum tolerable power I_m of the PU. It can be seen from Fig.4 that the average system energy efficiency first increases with the increase of I_m. After it increases to a certain value, the average system energy efficiency reaches and converges to the optimal value. When I_m is less than -90dBm, it is meaningless to calculate the SUs system because the power obtained by the SUs cannot meet its own demand. When the value of I_m increases gradually, the available power of the base station also increases gradually. Until the available power of the base station is equal to the total power of the base station, the average system energy efficiency no longer increases. Moreover, as I_m increases, the average system energy efficiency of the proposed algorithm is slightly higher than that of the genetic algorithm and FTPC algorithm. The simulation results show that the proposed algorithm is more suitable for the application scenario where the maximum tolerable power of the PUs is larger.

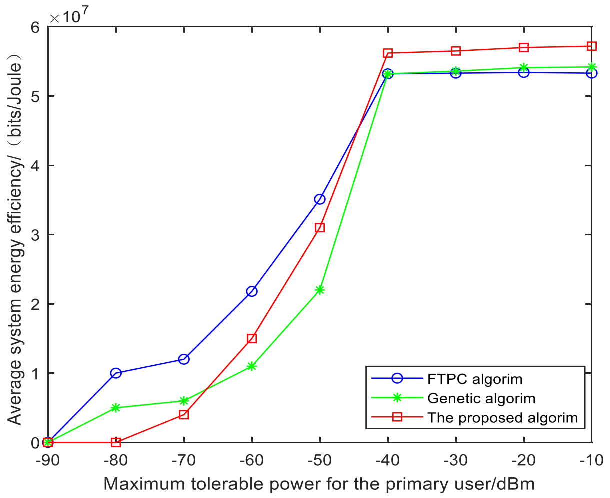

Fig. 4 Average system energy efficiency versus maximum tolerable power for the primary user

6. Conclusion

In this paper, we combine a CR network with NOMA and propose a new power allocation algorithm for this hybrid network, which makes the energy efficiency of the SU network optimal. The article considers in detail the power of the primary transmitter, the number of PUs, the number of SUs, the channel gain, and the SINR situation while allocating power to the SUs. The power of the SUs is constrained by ensuring that the PUs can communicate properly. To show its superiority, it is compared with the more classical genetic algorithm and FTPC algorithm. The simulation results show that the proposed algorithm, with fast convergence and low time complexity, has a higher average system energy efficiency than the genetic algorithm and FTPC algorithm. In this paper, a new idea is mainly proposed for CR-NOMA power allocation with a perfect channel. However, most of them are non-perfect channels in practice, and next, uncertain channels will be studied and analyzed.

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