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Robust Optimal Power Control and Subcarrier Allocation in Uplink OFDMA Network With Assistance of Mobile Relay

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ABSTRACT Compared with the traditional fixed relay assisted communication network, the mobile relay assisted wireless communication network has greater communication coverage and better flexibility. It enables to extend the lifetime of a communication system and improve the throughput of uses. Due to the time-varying nature of the actual communication environment and the existence of various interferences, there are uncertain factors in the communication channel that affect the quality of service of users. In this paper, we study the energy efficiency maximization problem based on power control, mobile relay selection, and subcarrier allocation under uncertain channel. The proposed mobile relay selection and subcarrier allocation algorithm improves the energy efficiency of the system while ensuring the normal communication of mobile users. Probabilistic constraints are introduced into the optimization problem to describe the uncertain channel, and after the mathematical transformation, it becomes a solvable form. The subcarrier allocation algorithm and distributed robust power control algorithm are also presented. Simulation results show that the improved system energy efficiency has been achieved and the proposed algorithm behaves better scalability and robustness under dynamic communication environment.

INDEX TERMS Wireless networks, mobile relay, power control, subcarrier allocation, robust optimization.

I. INTRODUCTION

In recent years, with the rapid development and employment of wireless Internet of Things(IoT) and data services in the industrial sectors such as in power systems, more and more intelligent devices are connected to the wireless network. More quality of service (QoS) requirements are proposed [1]–[3]. For instance, in power systems, the reliability and speed of data transmission are principal concerns [4]; the security and privacy-preserving have been payed more attentions [5]–[8]. There are also lots of typical applications of IoT, such as Wireless Sensor Networks (WSNs) [9]–[11]. However, due to the influence of distance, occlusion, fading and other factors, users cannot rely on direct transmission to meet the communication quality requirements. Relay-assisted wireless communication networks can extend the communication range and reschedule the communication resources. Thus the optimization of system performance in relay mode has attracted more and more attentions of many scholars. Literature [12] considers a relay-assisted multi-user IoT network to maximize total network throughput. Literature [13] proposes the time-frequency resource block optimization scheduling strategy combining the optimal time and energy allocation to improve the total throughput of the system. In [14], the wireless information and energy co-transmission system is studied with the assistance of relay in wireless body area network, considering to collect energy from the RF signals sent by other nodes, and then use the collected energy to forward information. Literature [15] studies the problem of maximizing the throughput of a relay network for simultaneous wireless information and power transmission in the case of a direct link between the source node and the destination node.

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Although the throughput is an important indicator to measure system performance, due to the diversity and universality of wireless communication services in recent years, mobile devices relying on battery power have been increasing rapidly, and how to reduce energy consumption and extend battery working time have attracted much more attentions. Therefore, the energy efficiency (EE) of the system becomes the key problem that needs to be solved [16]–[18]. Literature [19] studies a joint resource allocation scheme of communication duration and power level for relay assisted wireless power communication system, which attempts to maximize system energy efficiency. In literature [20], energy efficiency in multiple relaying-assisted OFDM systems is studied, where the decode-and forward (DF) relay beamforming is adopted to help information transmission. Literature [21] studies energy-efficient combined subcarrier pairing, subcarrier allocation and power allocation algorithms to improve the energy efficiency of multi-user amplify-and-forward (AF) relay network. At the same time, it ensures the quality of service required by users and satisfies users' quality of service (QoS) requirements through the concept of ''network price''. Literature [22] maximizes energy efficiency by optimizing the allocation of wireless resources in large multi-user multi-carrier orthogonal frequency division multiple access (OFDMA) systems.

Although literatures [15], [19]–[22] focus on how to optimize relay-assisted wireless networks to achieve maximum system energy efficiency, these works all solve the optimization problem under the ideal channel model with the assumption that the perfect channel state information is available for all users. However, in the real communication environment, it is difficult to obtain accurate channel state information. In order to make the communication model more consistent with the actual communication environment, the uncertain channel gain needs to be taken into account in the optimization problem [23], [24]. Literature [25] proposes a joint relay selection and power allocation algorithm under uncertain channels, which provides a resource allocation scheme for DF cellular relay network under uncertain channels. Literature [26] analyzed the influence of fading and channel estimation error in cellular decoding, forwarding and relay networks with multiple antennas deployed on base stations. For multi-user and multi-relay scenarios, the closed form expression of outage probability is obtained and the global optimal solution to maximize spectral efficiency is given. Literature [27], considering the imperfect channels state information, studies the synchronous wireless information and power transmission network in the multi-input multi-output DF relay system. Literature [28] proposes a robust power allocation and access control scheme to improve the QoS for restricted users in a DF cooperative cellular system based on selective relay. In OFDMA network, reasonable allocation of subcarriers can also improve the energy efficiency of the system. Literature [29] studies the resource joint optimization of subcarrier allocation, subcarrier pairing and power allocation, so as to maximize the energy efficiency of the system in the DF relay-assisted OFDMA system with untrusted users. Literature [30] studies the energy efficiency maximization in downlink OFDMA networks assisted by relay, and carries out joint optimization for power allocation, subcarrier allocation and pairing. Literature [31] designs an energy saving resource allocation scheme for orthogonal frequency division multiple access cellular wireless network with multi-user collaboration. Considering the QoS requirements of users, the combined relay selection, subcarrier pairing, and power allocation algorithms are designed to maximize the energy efficiency of the system. In reference [32], a resource allocation algorithm based on joint subcarrier pairing and allocation is proposed to solve the power minimization problem in multi-user cooperative relay systems. It is verified that the algorithm can effectively pair and allocate subcarriers to minimize the transmission power of the system when the target rate of the user is satisfied.

The above works all focus the communication scene with the assistance of fixed relay. For mobile end users, when the distance between users is far from the relay or there are blocking factors in the middle of the link, the flexibility of fixed relay communication network is poor and it cannot continue to meet the needs of mobile users. The flexibility of the communication network is greatly enhanced if a mobile user acts as a relay. In literature [33], to maximize the total energy efficiency of system in the mobile relay-assisted terminal straight through device-to-device (D2D) scenario, the combined power control, channel allocation and mobile relay selection schemes are proposed. However, this scheme assumes that the channel information is accurate and measurable, which is difficult to satisfy in the actual communication environment. Literature [34] studies the mobile relay selection algorithm of cooperative diversity in distributed environment. In the AF cooperative communication mode, a dynamic selection strategy for power allocation and relay based on channel statistical state information is presented. Also, the uncertainty of subcarrier allocation and channel is not considered, so the throughput and robustness of the system will be reduced.

In view of the deficiency of the above literature, taking the uncertain channel gains into consideration, a joint and distributed resource allocation scheme is proposed, including power control, subcarrier allocation and mobile relay selection. The uncertain channel is introduced into the optimization problem in the form of outage probability constraint, so as to improve the robustness of the system under the dynamic environment. The selection of mobile relay and the allocation of subcarriers not only improve the system's energy efficiency, but also greatly improves the system's flexibility compared with fixed relay-assisted communication networks. At the same time, the distributed algorithm effectively reduces the information exchange.

II. SYSTEMS MODEL

The uplink mobile relay-assisted communication network is considered in this paper as shown in Figure 1. The system

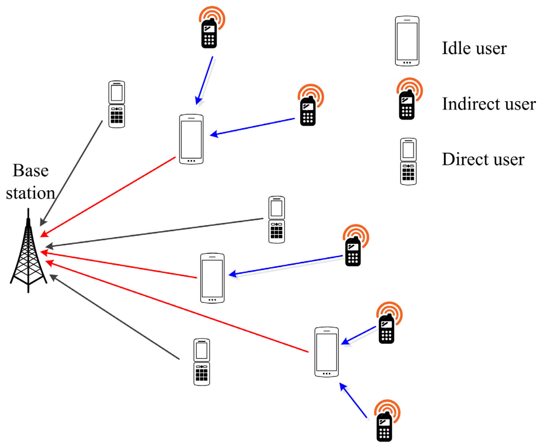

FIGURE 1. System model.

model contains one base station (BS), N direct users whose achievable rate is greater than the minimum rate denoted as R_{min}, I indirect users whose achievable rate is lower than R_{min}. It means that the indirect users cannot meet the minimum rate requirement through direct transmission due to distance, occlusion and other factors. There are also J free users that can act as mobile relays. It is also assumed that the communication channel is divided into L available subcarriers. The OFDMA access technology is employed in the system, and each communication link is independent from each other without the same frequency interference. Users need to upload their own information to the BS. In addition, the mobile relay node works in DF half-duplex mode, and only the transmission within a communication duration T is studied here. It is noted that if it is extended to the full-duplex case, the interference management will be the important issue to be solved. Specially, the self-interference cancelation also should be considered. It is assumed that a communication duration T is divided into two identical time slots. In the first slot, the idle user acts as a mobile relay, and the indirect user i sends data to the relay. In the second slot, the direct user sends data directly to the base station, while the mobile relay forwards the received information to the base station. Because mobile relay multiplies the subcarriers of the indirect user and uses different subcarriers between the indirect user and the direct user, there is no co-frequency interference in the second time slot.

In the actual communication environment, the channel state often changes dynamically, and it is difficult to obtain the accurate channel gain. In order to ensure the communication quality of the system under dynamic changing environment, channel estimation error needs to be considered. The expression of uncertain channel gain based on Rayleigh fading is as follows.

$$G^l_{i,j} = \overline{G}^l_{i,j} + \Delta G^l_{i,j}, \tag{1}$$

$$G^l_{j,b} = \overline{G}^l_{j,b} + \Delta G^l_{j,b}, \tag{2}$$

$$G^l_{n,b} = \overline{G}^l_{n,b} + \Delta G^l_{n,b}, \tag{3}$$

where $\overline{G}^l_{i,j}$, $\overline{G}^l_{j,b}$, $\overline{G}^l_{n,b}$ are the estimated channel gains from indirect user i to mobile relay j, from mobile relay j to base station, from direct user n to base station, on the lth subcarrier, respectively. $\Delta G^l_{i,j}$, $\Delta G^l_{j,b}$, $\Delta G^l_{n,b}$ represent the corresponding channel gain estimation errors, respectively, and obey the exponential distribution of parameter $\lambda = 1$ [27]. The probability density function is:

$$\varphi(x) = e^{-\lambda x}. \tag{4}$$

In the first slot, the SNR from the indirect user i to the mobile relay j is

$$SNR^l_{i,j} = \frac{P^l_{i,j} G^l_{i,j}}{N_0}, \tag{5}$$

where N_0 is the background noise. In the second slot, the SNR from direct user n to base station and SNR from mobile relay j to base station are respectively

$$SNR^l_{n,b} = \frac{P^l_{n,b} G^l_{n,b}}{N_0}, \tag{6}$$

$$SNR^l_{j,b} = \frac{P^l_{j,b} G^l_{j,b}}{N_0}. \tag{7}$$

Taking the channel estimation error into account in the channel gain expression, equation (6), (7) are rewritten as

$$SNR^l_{n,b} = \frac{P^l_{n,b}(\overline{G}^l_{n,b} + \Delta G^l_{n,b})}{N_0}, \tag{8}$$

$$SNR^l_{j,b} = \frac{P^l_{j,b}(\overline{G}^l_{j,b} + \Delta G^l_{j,b})}{N_0}. \tag{9}$$

Due to the bottleneck effect between the two hops, in order to get the maximum rate of the communication link, it is reasonable to let the transmitting rates of two hops are same, i.e. $r^l_{i,j} = r^l_{j,b}$. Therefore, the SNR of the i indirect user to the base station link can be equivalent to

$$SNR^l_{i,j} = SNR^l_{j,b}. \tag{10}$$

According to equation (9), the transmitting power of the i indirect user is

$$P^l_{i,j} = \frac{P^l_{j,b} G^l_{j,b}}{G^l_{i,j}} \tag{11}$$

The data transmission rate from the indirect user to the base station is

$$R^l_{i,j,b} = \frac{W}{2}\log_2(1 + SNR^l_{j,b}), \tag{12}$$

where W is the bandwidth. The data transmission rate from the direct user to the base station is

$$R^l_{n,b} = \frac{W}{2}\log_2(1 + SNR^l_{n,b}). \tag{13}$$

Thus, the total data transmission rate of the system in a communication duration is:

$$R_{sum} = \sum_{l=1}^{L} \rho^l_{i,n}(\sum_{i=1}^{I}\sum_{j=1}^{J} a_{i,j} R^l_{i,j,b} + \sum_{n=1}^{N} R^l_{n,b}), \tag{14}$$

where, $\rho_{I,n}^{L}$ is the indicator for subcarrier selection, $\rho_{i,n}^{l} \in \{0, 1\}$, $a_{i,j}$ is indicator for relay selection, $a_{i,j} \in \{0, 1\}$. The total power consumption of the system in a communication duration is:

$$P_{sum} = P_{SC} + \sum_{l=1}^{L} \rho_{i,n}^{l} \left(\sum_{i=1}^{I} \sum_{j=1}^{J} a_{i,j}(P_{i,j}^{l} + P_{j,b}^{l}) + \sum_{n=1}^{N} P_{n,b}^{l} \right), \quad (15)$$

where P_{SC} is the fixed power consumption of circuit system. The system energy efficiency is defined as the ratio of the total system rate to the total system power consumption, i.e.

$$EE = \frac{R_{sum}}{P_{sum}}. \quad (16)$$

In this paper, it attempts to maximize system energy efficiency by scheduling resources, such as transmitting power, subcarrier and mobile relays. The optimization problem formulation and solution of will be described in detail below.

III. OPTIMIZATION PROBLEM AND SOLUTION

This section will combine strategies such as mobile relay selection, power allocation, and subcarrier allocation to maximize the energy efficiency of uplink network systems. The strategy is composed of three parts. First, the optimal choice of mobile relay is determined, second, the uncertain probability constraint is transformed into the solvable form by means of outage probability threshold constraint, finally, the subcarrier allocation strategy is designed to make full use of channel resources to achieve the optimal energy efficiency of the system.

A. OPTIMAL MOBILE RELAY SELECTION

Since the distribution of users with idle state is random, in order to ensure the communication quality between indirect users and base stations, it is necessary to determine which idle users can be used as mobile relays for information decoding and forwarding. The basic requirement is that idle users should be between indirect users and base stations. Secondly, the bottleneck effect between the two hops is considered as the constraint of relay system, that is, the end-to-end transmission rate depends on the minimum transmission rate in the two hops. In order to maximize the data transmission rate of the whole link, we have $SNR_{i,j}^{l} = SNR_{j,b}^{l}$. Thus the power of the indirect user can be represented by the power of the mobile relay. Since the transmitting power of the indirect user varies according to the choice of mobile relay, the maximum transmitting power is limited by setting a power threshold to help find a suitable mobile relay. Finally, the mobile relay is selected based on the maximization of system energy efficiency. The optimal mobile relay selection algorithm is shown in Algorithm 1.

Algorithm 1 Mobile Relay Selection Algorithm

1: Idle user categorizing.
i) User i sends HELLO message within its coverage and sets up the idle user set.
ii) Take the idle users satisfying $d_{j,b} < d_{i,b}$ as the candidates of mobile relays, where $d_{j,b}$ is the distance from the idle user to the base station.
2: Candidate relay screening.
i) User i tests with maximum transmitting power P_{max}, and remove inappropriate mobile relays.
ii) Establish the relay candidate set of indirect user i denoted as $\mathcal{C}$.
3: Relay Selecting.
Take $j^* = \arg\max_{i,j} EE_j$ as a criterion to determine the best relay in set $\mathcal{C}$.

B. ROBUST OPTIMIZATION PROBLEM DESCRIPTION AND NON-CONVEX PROBLEM TRANSFORMATION

Combined with the above optimization objectives and system constraints, the following robust optimization problem is established.

$$P1: \max_{P_{j,b}^{l}, P_{n,b}^{l}, \rho_{i,n}^{l}, a_{i,j}} EE$$
$$s.t. \begin{cases} (C.1) 0 \leq P_{i,j}^{l}, P_{j,b}^{l}, P_{n,b}^{l} \leq P_{max}^{l}, & \forall i, j, n \\ (C.2) \Pr[SNR_{j,b}^{l} \leq SNR_{th}] \leq \varepsilon, & \forall j \\ (C.3) \Pr[SNR_{n,b}^{l} \leq SNR_{th}] \leq \varepsilon, & \forall n \\ (C.4) \sum_{j=1}^{J} a_{i,j} = 1, & \forall i \\ (C.5) a_{i,j} \in \{0, 1\}, & \forall i, j \\ (C.6) \sum_{l=1}^{L} \rho_{i,n}^{l} = 1, & \forall i, n \\ (C.7) \rho_{i,n}^{l} \in \{0, 1\}, & \forall i, j \end{cases} \quad (17)$$

where P_{max}^{l} is the maximum transmitting power threshold of user, SNR_{th} is the signal-to-noise ratio threshold. The constraint (C.1) limits the maximum transmitting power of each user. Constraint (C.2) ensures that the outage probability of mobile relay to base station link is lower than the given threshold value. Constraint (C.3) ensures that the outage probability of the direct user to the base station link is lower than the given threshold value. The constraint (C.4) requires any indirect user to select only one mobile relay. Constraint (C.5) ensures that a mobile relay can only serve one indirect user within a communication duration. Constraint (C.6) ensures that a user can only use one subcarrier for communication within a communication duration. Constraint (C.7) ensures that any subcarrier can be occupied by only one user within a communication duration.

For the channel probability constraint (C.2) and (C.3), the uncertain interrupt probability constraint will be converted into a treatable form through the following theorem.

Theorem 1: For $\forall l \in L$*, the outage probability of mobile relay j to the base station on the lth subcarrier is equivalent to* $\ln(1-\varepsilon)P_{j,b}^l + SNR_{th}N_0 - \overline{G}_{j,b}^l \leq 0$.

Proof: Considering that the channel gain of uncertainty is $G = \overline{G} + \Delta G$, where ΔG follows the exponential distribution of parameter $\lambda = 1$, combined with eq. (4), the outage probability (C.2) can be expressed as

$$\Pr[SNR_{j,b}^l \leq SNR_{th}] = \int_0^A e^{-x}dx \leq \varepsilon, \tag{18}$$

where $A = \frac{SNR_{th}N_0}{P_{j,b}^l} - \overline{G}_{j,b}^l$. After the integral, the following equation can be obtained

$$1 - e^{-A} \leq \varepsilon \Rightarrow \ln(1-\varepsilon)P_{j,b}^l + SNR_{th}N_0 - \overline{G}_{j,b}^l \leq 0. \tag{19}$$

Thus, the outage probability under uncertain channel gains, $\Pr[SNR_{j,b}^l \leq SNR_{th}] \leq \varepsilon$, is equivalent to $\ln(1-\varepsilon)P_{j,b}^l + SNR_{th}N_0 - \overline{G}_{j,b}^l \leq 0$.

The proof is end. □

Similarly, the constraint (C.2) can also be transformed into a deterministic constraint, then the problem **P1** is transformed to the optimization problem **P2**.

$$P2: \max_{P_{j,b}^l, P_{n,b}^l, \rho_{i,n}^l, a_{i,j}} EE$$
$$s.t. \begin{cases} (C.1)\, 0 \leq P_{i,j}^l, P_{j,b}^l, P_{n,b}^l \leq P_{max}^l, \\ \qquad \forall i, j, n \\ (C.2)\, \ln(1-\varepsilon)P_{j,b}^l + SNR_{th}N_0 - \overline{G}_{j,b}^l \leq 0, \\ \qquad \forall j \\ (C.3)\, \ln(1-\varepsilon)P_{n,b}^l + SNR_{th}N_0 - \overline{G}_{n,b}^l \leq 0, \\ \qquad \forall n \\ (C.4) \sum_{j=1}^{J} a_{i,j} = 1, \\ \qquad \forall i \\ (C.5)\, a_{i,j} \in \{0,1\}, \\ \qquad \forall i, j \\ (C.6) \sum_{l=1}^{L} \rho_{i,n}^l = 1, \\ \qquad \forall i, n \\ (C.7)\, \rho_{i,n}^l \in \{0,1\}, \\ \qquad \forall i, j \end{cases} \tag{20}$$

After examining the second derivative of the objective function of the optimization problem **P2**, the convexity of the optimization problem cannot be determined by Hessian matrix, and the optimal solution of the fractional non-convex optimization problem is difficult to be obtained. We use Dinkelbach method to solve this non-convex problem. The fractional form of the optimization problem **P2** can be converted to the subform by the Dinkelbach method [35]. That is, the energy efficiency expression in the objective function can be written as $F(q) = R_{sum} - qP_{sum}$, where q is a non-negative parameter, and it plays a role as a penalty factor in resource scheduling. Note that when $q \to 0$, this means that the penalty for using a resource is almost zero, and the efficiency resource allocation problem of the objective function $F(q) = R_{sum} - qP_{sum}$ reduces to a summation rate maximization problem. But for the extreme case of $q \to \infty$, there is no resource allocation strategy that could maximize the objective function $F(q) = R_{sum} - qP_{sum}$. Therefore, the optimal parameter q^* can be expressed as

$$\begin{aligned} q^* &= \frac{R_{sum}(P_{j,b}^{l*}, P_{n,b}^{l*}, \rho_{i,n}^{l*}, a_{i,j}^*)}{P_{sum}(P_{j,b}^{l*}, P_{n,b}^{l*}, \rho_{i,n}^{l*}, a_{i,j}^*)} \\ &= \max_{P_{j,b}^l, P_{n,b}^l} \frac{R_{sum}(P_{j,b}^{l*}, P_{n,b}^{l*}, \rho_{i,n}^{l*}, a_{i,j}^*)}{P_{sum}(P_{j,b}^{l*}, P_{n,b}^{l*}, \rho_{i,n}^{l*}, a_{i,j}^*)}. \end{aligned} \tag{21}$$

For equation (21), if and only if the following equation is true, the energy efficiency of the system can reach the optimum.

$$\begin{aligned} &\max_{P_{j,b}^l, P_{n,b}^l} F(q^*) \\ &= \max_{P_{j,b}^l, P_{n,b}^l} \{R_{sum}(P_{j,b}^l, P_{n,b}^l, \rho_{i,n}^{l*}, a_{i,j}^*) \\ &\quad - q^* P_{sum}(P_{j,b}^l, P_{n,b}^l, \rho_{i,n}^{l*}, a_{i,j}^*)\} \\ &= \{R_{sum}(P_{j,b}^{l*}, P_{n,b}^{l*}, \rho_{i,n}^{l*}, a_{i,j}^*) \\ &\quad - q^* P_{sum}(P_{j,b}^{l*}, P_{n,b}^{l*}, \rho_{i,n}^{l*}, a_{i,j}^*)\} \\ &= 0. \end{aligned} \tag{22}$$

By iteration, the value of q converges to the optimal value of q^* based on Dinkelbach method. Obviously, the second derivative of $F(q*)$ is greater than zero, so the transformed objective function is convex. Therefore, the original non-convex problem **P2** can be transformed into problem **P3** according to Eq. (22).

$$\begin{aligned} P3: \max_{P_{j,b}^l, P_{n,b}^l} &\{R_{sum}(P_{j,b}^l, P_{n,b}^l, \rho_{i,n}^{l*}, a_{i,j}^*) \\ &- q^* P_{sum}(P_{j,b}^l, P_{n,b}^l, \rho_{i,n}^{l*}, a_{i,j}^*)\} \\ s.t.\ &(C.1 - C.7). \end{aligned} \tag{23}$$

After converting the original non-convex problem to a convex problem, the dual decomposition method could be used to find the optimal solution for **P3**.

C. THE SOLUTION OF ROBUST OPTIMIZATION PROBLEM

Since the optimization problem **P3** is a convex optimization problem with the fixed subcarrier and relay selection, the Lagrangian multiplier method can be used to solve the optimization problem. the Lagrangian function is shown as

$$\begin{aligned} &L(P^l_{j,b}, P^l_{n,b}, \rho^{l*}_{i,n}, a^*_{i,j}) \\ &= \sum_{l=1}^{L} \rho^l_{i,n}\Big(\sum_{i=1}^{I}\sum_{j=1}^{J} a_{i,j}R^l_{i,j,b} + \sum_{n=1}^{N} R^l_{n,b}\Big) \\ &\quad - q\Big(P_{SC} + \sum_{l=1}^{L}\rho^l_{i,n}\big(\sum_{i=1}^{I}\sum_{j=1}^{J} a_{i,j}(P^l_{i,j} + P^l_{j,b}) + \sum_{n=1}^{N} P^l_{n,b}\big)\Big) \\ &\quad + \lambda_1\Big(P_{max} - \sum_{l=1}^{L}\rho^l_{i,n}\big(\sum_{i=1}^{I}\sum_{j=1}^{J} a_{i,j}(P^l_{i,j} + P^l_{j,b}) + \sum_{n=1}^{N} P^l_{n,b}\big)\Big) \\ &\quad + \lambda_2\Big(P_{max} - \sum_{l=1}^{L}\rho^l_{i,n}\sum_{n=1}^{N} P^l_{n,b}\Big) \\ &\quad - \mu_1\big(\ln(1-\varepsilon)P^l_{j,b} + SNR_{th}N_0 - \overline{G}^l_{j,b}\big) \\ &\quad - \mu_2\big(\ln(1-\varepsilon)P^l_{n,b} + SNR_{th}N_0 - \overline{G}^l_{n,b}\big), \end{aligned} \tag{24}$$

where $\lambda_1, \lambda_2, \mu_1, \mu_2$ are the Lagrangian multipliers.

The corresponding Lagrangian dual function is

$$g(\boldsymbol{\lambda}, \boldsymbol{\mu}) \triangleq \max_{P^l_{j,b}, P^l_{n,b}, \rho^l_{i,n}, a_{i,j}} L(P^l_{j,b}, P^l_{n,b}, \rho^{l*}_{i,n}, a^*_{i,j}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \quad s.t.\ (C.1 - C.7). \tag{25}$$

This dual optimization problem can be rewritten as

$$\begin{aligned} &\min_{\boldsymbol{\lambda},\boldsymbol{\mu}\geq 0} g(\boldsymbol{\lambda}, \boldsymbol{\mu}) \\ &\triangleq \min_{\boldsymbol{\lambda},\boldsymbol{\mu}\geq 0} \max_{P^l_{j,b}, P^l_{n,b}, \rho^l_{i,n}, a_{i,j}} L(P^l_{j,b}, P^l_{n,b}, \rho^{l*}_{i,n}, a^*_{i,j}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \\ &\quad s.t.\ (C.1 - C.7). \end{aligned} \tag{26}$$

For problem (26), the Karush-Kuhn-Tucker (KKT) conditions can be used to obtain the optimal solution of the optimization problem. Then the optimal mobile relay selection and sub-carrier assignment algorithm are used to obtain the optimal mobile relay and sub-carrier pairing.

Since the Lagrangian dual problem is a convex optimization problem, the first partial derivative of formula (24) is obtained and set to zero in the case of fixed subcarriers and mobile relays to obtain the optimal transmission power, i.e.,

$$\begin{aligned} &P^{l*}_{j,b}(t+1) \\ &= \arg\max_{P^l_{j,b}} L(P^l_{j,b}, P^l_{n,b}, \rho^{l*}_{i,n}, a^*_{i,j}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \\ &= \left[\frac{1/(2\ln 2)}{[\lambda_1 - \mu_1(\overline{G}^l_{j,b} - \ln(1-\varepsilon)) + q(1 + \frac{\overline{G}^l_{j,b}}{\overline{G}^l_{i,j}})]} - \frac{N_0}{\overline{G}^l_{j,b}}\right]^+, \end{aligned} \tag{27}$$

$$\begin{aligned} &P^{l*}_{n,b}(t+1) \\ &= \arg\max_{P^l_{n,b}} L(P^l_{j,b}, P^l_{n,b}, \rho^{l*}_{i,n}, a^*_{i,j}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \\ &= \left[\frac{1/\ln 2}{[\lambda_2 - \mu_2(\overline{G}^l_{n,b} - \ln(1-\varepsilon)) + q]} - \frac{N_0}{\overline{G}^l_{n,b}}\right]^+, \end{aligned} \tag{28}$$

where, $[\cdot]^+ = \max\{0, \cdot\}$, it denotes that the optimal power should be greater than zero. After the optimal transmission power solution is obtained, the mobile relay selection algorithm needs to be called again to select the optimal mobile relay, and then the subcarrier allocation algorithm is used to obtain the optimal subcarrier pairing.

In order to obtain the optimal subcarrier pairing, only the items with subcarrier pairing coefficient indicator $\rho^l_{i,n}$ in optimization problem (25) need to be integrated together, and optimization problem (25) can be transformed into the following formula:

$$g(\boldsymbol{\lambda}, \boldsymbol{\mu}) \triangleq \max_{P^l_{j,b}, P^l_{n,b}, \rho^l_{i,n}, a_{i,j}} \sum_{l=1}^{L} \rho^l_{i,n}H^l_{i,n} + C(P^l_{j,b}, P^l_{n,b}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \quad s.t.\ (C.1 - C.7), \tag{29}$$

where, $H^l_{i,n}$ is the integration with the $\rho^l_{i,n}$ revelent items, $C(P^l_{j,b}, P^l_{n,b}, \boldsymbol{\lambda}, \boldsymbol{\mu})$ is the integration with the $\rho^l_{i,n}$ irrelevant items. The sub-carrier assignment problem in the optimization problem (29) can be solved with the standard Hungarian algorithm [36]. The Lagrangian multiplier iteration and the distributed energy efficiency maximization robust power control algorithm proposed in this paper are presented below. First of all, the Lagrangian multipliers are updated using the subgradient descent method $\lambda_1, \lambda_2, \mu_1, \mu_2$:

$$\lambda_1(t+1) = [\lambda_1(t) - \epsilon_1(P^l_{max} - P^l_{j,b})]^+, \tag{30}$$

$$\lambda_2(t+1) = [\lambda_2(t) - \epsilon_2(P^l_{max} - P^l_{n,b})]^+, \tag{31}$$

$$\mu_1(t+1) = [\mu_1(t) - \epsilon_3((\overline{G}^l_{j,b} - \ln(1-\varepsilon))P^l_{j,b} - SNR_{th}N_0)]^+, \tag{32}$$

$$\mu_2(t+1) = [\mu_2(t) - \epsilon_4((\overline{G}^l_{n,b} - \ln(1-\varepsilon))P^l_{n,b} - SNR_{th}N_0)]^+, \tag{33}$$

where, $\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4$ are the step sizes which are positive, t is the number of iterations. Given the initial value of penalty factor q, equations (27)-(33) can be used to obtain the optimal solution through multiple iterations. At this point, the optimization problem is solved, and the distributed power control algorithm for joint mobile relay and subcarrier allocation is presented below.

D. DISTRIBUTED POWER CONTROL ALGORITHM

In this section, for wireless communication networks with OFDMA access, a robust distributed power control algorithm is proposed by combining mobile relay selection, subcarrier and power allocation to maximize system energy efficiency. Through iteration, the algorithm is able to obtain quickly the optimal power $P^{l*}_{j,b}$, $P^{l*}_{n,b}$ and Dinkelbach coefficient q, at the same time get the best mobile relay selection $a^*_{i,j}$ and subcarrier allocation $\rho^{l*}_{i,n}$. The details are shown in Algorithm 2.

It is worth noting that before the optimal power control algorithm is carried out, the mobile relay shall be screened first, and the obtained mobile relay shall be substituted into the inner loop for optimal power allocation and multiplier iteration until it converges. After the end of the inner loop,

Algorithm 2 Distributed Robust Power Control Algorithm

1: Initializing $P^l_{j,b}$, $P^l_{n,b}$, P^l_{max}, setting parameters ε.
2: Selecting the mobile relay using Algorithm 1, and determine $a_{i,j}$.
3: Setting out loop parameter Z_{Max}, $q(1)$, $\rho^l_{i,n}$.
4: Setting inner loop parameter T_{max}.
5: According to equations (27) and (28), update the powers $P^l_{j,b}(t)$, $P^l_{n,b}(t)$.
6: According to equations (30)-(33), update the multipliers $\lambda_1(t)$, $\lambda_2(t)$, $\mu_1(t)$, $\mu_2(t)$, then update $t = t + 1$.
7: If the powers $P^l_{j,b}(t)$, $P^l_{n,b}(t)$ and the multipliers $\lambda_1(t)$, $\lambda_2(t)$, $\mu_1(t)$, $\mu_2(t)$ are converged, or $t > T_{max}$, go to Step 6, otherwise go to Step 4.
8: Updating $q(z)$ according to formula (21) with the converged power and Lagrange multipliers.
9: Solving problem (29) and updating $a_{i,j}(z)$ and $\rho^l_{i,n}(z)$.
10: updating $z \leftarrow z + 1$.
11: If $q(z)$, $a_{i,j}(z)$ and $\rho^l_{i,n}(z)$ are converged or $z > Z_{max}$, go to Step 8, otherwise go to Step 3.
12: End.

the optimal energy efficiency value, optimal relay selection and subcarrier distribution are obtained by using the obtained optimal power value. In the iteration process of user power, it is not necessary to know all user information, but only rely on local information, such as information of indirect user to corresponding mobile relay link, information of mobile relay to base station and information of direct user to base station.

IV. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

This section will verify the performance of the proposed optimization algorithm through simulation. The parameters used in the simulation are as follows: there are one base station, four indirect users, four direct users and seven idle users as candidates for mobile relay, eight available subcarriers. The locations are as follows, the coordinate is (0,0)(unit:m), coordinates of indirect users are (50,180), (110,170), (150,130), (180,100), the coordinates of direct users are (30,-128), (110,170), (150,130), (180,100), respectively. Other used parameters are listed in Table 1. It is assumed that the channel gain is composed of estimated $\overline{G}$ and estimated channel error ΔG, the estimation of channel gain is denoted as $\overline{G} = Kd^{-x}$, where x is path loss coefficient, which is determined according to the corresponding link as shown in Table 1. K is the fixed gain loss of the corresponding link, and d is the distance between nodes. ΔG is generated based on the Monte Karlo method following the exponential distribution to simulate the dynamic channel gain in the simulation.

The power convergence performance of direct communication users and mobile relays are given in Fig.2 and Fig.3, respectively. In the simulations, the outage probability threshold is set as $\varepsilon = 0.2$, and the maximum powers of mobile relays and direct communication users are same, $P_{max} = 0.5$W. It is found that both $P^l_{n,b}$ and $P^l_{j,b}$ converge quickly, about 25 iterations. It can be seen that the algorithm has good convergence.

The relationship of the real outage probability and the target outage probability threshold is shown in Fig.4. Note that each curve in the simulation is averaged of 50000 independent channel experiments. It is found that the real outage probability of each user is lower than the target outage threshold, and the robustness against changing channel gains is guaranteed. In the actual communication environment, the user adapts to the changes of the environment by constantly adjusting the transmitting power and has better anti-interference ability.

The scalability of the algorithm is verified by changing system parameters and system topology, respectively.

TABLE 1. Simulation parameters.

parameter	value
Bandwidth W	10MHz
Path loss coefficient α	3.5
Path loss coefficient β, γ	4.0
Fixed fading $K_{i,j}$	0.6
Fixed fading $K^l_{j,b}$, $K^l_{n,b}$	random number in (0,1)
Background noise N_0	10^{-10}
Maximum transmitting power P^l_{max}	0.5W
Iteration step size ϵ_1, ϵ_3	1
Iteration step size ϵ_2, ϵ_4	0.01

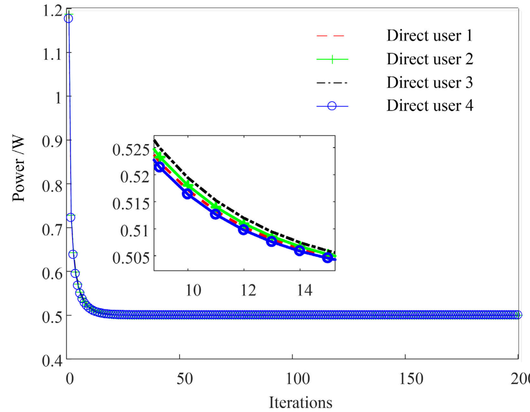

FIGURE 2. Power of direct communication users.

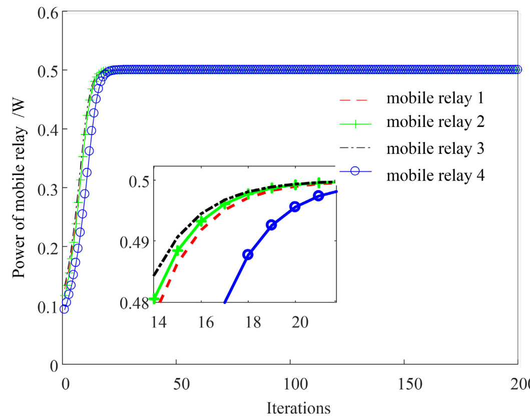

FIGURE 3. Power of mobile relays.

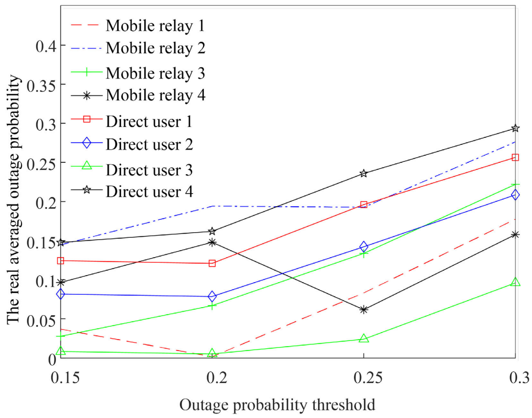

FIGURE 4. The real outage probability vs the outage threshold.

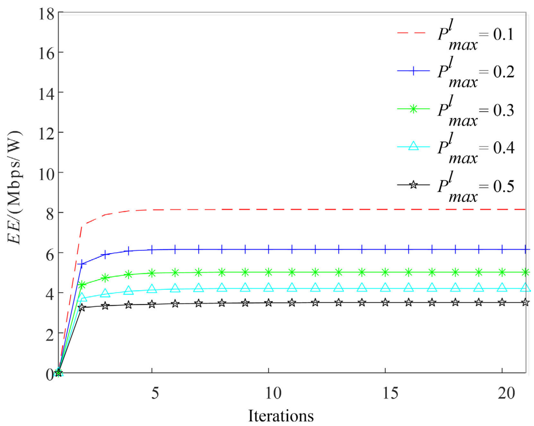

FIGURE 5. The energy efficiency with different P_{max}.

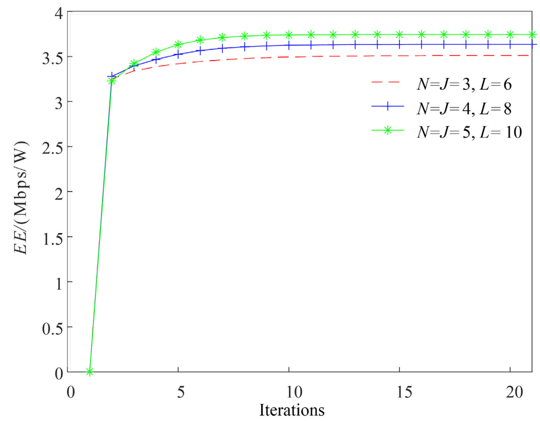

FIGURE 6. The energy efficiency with different topologies.

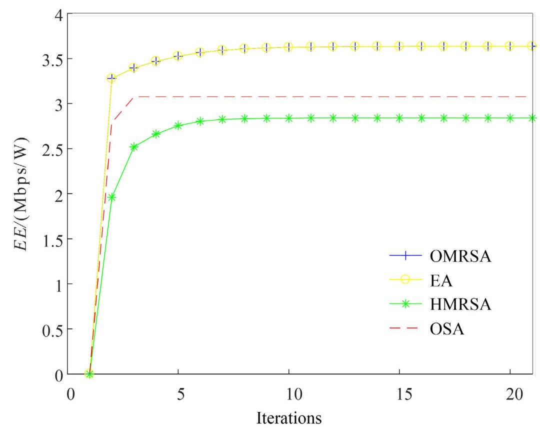

FIGURE 7. Performance comparison of different relay selection algorithms.

It is found from Fig.5 that with the increase of P_{max}, the energy efficiency of the system decreases. This is because with the increase of P_{max}, the user's data transmission rate also increases, but the rate of data transmission is less than the rate of power growth. Because the system energy efficiency value is the ratio of the system rate to the power. Thus, the energy efficiency of the system decreases with the increase of P_{max}. Fig. 6 is the simulation results of the system under three different topologies, where $N = J = 3, L = 6$ denote that there are 3 indirect users assisted by 3 mobile relays in the system, and there are 3 direct users and 6 subcarriers in the system. It can be seen from Fig. 6 that the energy efficiency of the system converges quickly under three different topologies, and the energy efficiency value of the system increases with the increase of the system size. Therefore, it can be seen that the system can converge to the optimal value rapidly under different parameters and topologies, and the system has good scalability.

In Figure 7, four different mobile relay selection algorithms are compared to verify the performance of the proposed algorithm. It can be clearly seen from the figure that with the same system parameters, the system performance of the optimal mobile relay selection algorithm (OMRSA) proposed in this paper is consistent with that of the exhaustive algorithm (EA) and superior to the other two algorithms. The mobile relay selection algorithm proposed in this paper can get the optimal mobile relay through about three computational cycles, and the computational complexity is much lower than that of exhaustive algorithm. However, the heuristic mobile relay selection algorithm (HMRSA) in literature [34], namely the single relay node selection strategy, is that indirect users tentatively choose idle users as mobile relays. While the order selection algorithm (OSA) is executed after the first two steps of the optimal relay selection algorithm, namely first judge whether the distance between idle users and base station is less than that of indirect users to the base station, and then examine whether the transmitting power determined by idle user is lower than the maximum power threshold. After that, indirect users select idle users as their mobile relays in the order of the distance from idle users to base stations from small to large. These two comparison algorithms are easy to implement, but the efficiency of the system is not satisfactory. Simulation results show that the optimal mobile relay selection algorithm proposed in this paper can achieve higher energy efficiency.

Figure 8 shows the performance comparisons of four different subcarrier allocation algorithms under the same

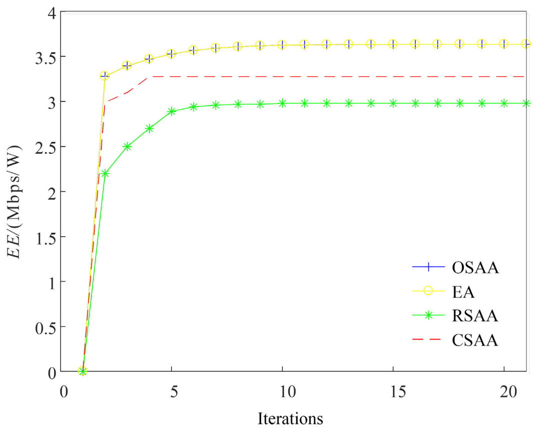

FIGURE 8. Performance comparison of different subcarrier allocation algorithms.

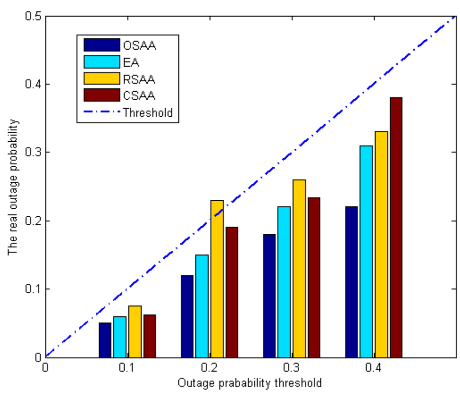

FIGURE 9. Outage probability comparison of different subcarrier allocation algorithms.

parameters. As can be seen from the figure, the energy efficiency value obtained by the optimal subcarrier allocation algorithm (OSAA) proposed in this paper is the same as that obtained by the exhaustive algorithm (EA), which indicates that the proposed subcarrier allocation algorithm is optimal. But the algorithm complexity of the exhaustive method is $O(n!)$, the complexity of our proposed algorithm is $O(n^3)$. When n is large, the algorithm complexity of the exhaustive method is much higher than that of the algorithm proposed in this paper. The algorithm complexity of the random subcarrier allocation algorithm (RSAA) and the channel sequential allocation algorithm (CSAA) proposed in [37] is $O(1)$. Although the complexity of these two algorithms is low, the energy efficiency value of the system obtained is not ideal. Considering the complexity of the algorithm and the system energy efficiency, the optimal subcarrier allocation algorithm proposed in this paper has better performance and it is more practical. Also the real outage probability comparisons of four algorithms are given in Figure 9. It is found that the proposed OSAA scheme is with the lowest outage probability compared with other algorithms. Moreover, when $\varepsilon = 0.2$, the RSAA shows worse performance because the real outage probability exceeds the threshold.

V. CONCLUSION

In this paper, we consider the energy efficiency maximization based on power allocation, mobile relay selection and subcarrier allocation with uncertain channels. It maximizes the energy efficiency of the system on the premise of ensuring the communication quality of mobile end users. The optimal mobile relay selection algorithm proposed in this paper selects the optimal mobile terminal users as relays to assist indirect users in information transmission. The energy efficiency of the system is further improved by using subcarrier and power allocation algorithm. We describe the uncertain channel as a form of outage probability, transform the probability constraint with uncertain channel gain into a deterministic form that is easy to be solved by mathematical processing, and propose a distributed power control algorithm to determine the optimization solutions. Simulation results verify the advantages of the proposed algorithm in energy efficiency improvement, scalability and robustness under dynamic environment. In this paper, only the half-duplex scenario is considered, how to extend to the full-duplex case will the future work.

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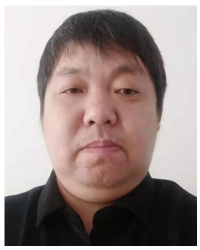

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