Energy Efficiency Optimization: Joint Antenna-Subcarrier-Power Allocation in OFDM-DASs

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***Abstract*— Due to environmental concerns of rising energy consumption caused by explosive growth in the demands of wireless multimedia services, energy efficiency has become an important consideration in the design of future wireless communication systems. In this paper, we investigate and propose an energy-efficient scheme of joint antenna-subcarrier-power allocation for min-rate guaranteed services in the downlink multiuser orthogonal frequency division multiplexing distributed antenna systems (OFDM-DASs) with limited backhaul capacity. Our aim is to maximize the energy efficiency in an OFDM-DAS based on the constraints of users' Quality of Service, subcarrier reuse, backhaul capacity, and remote antenna units' transmit power. By exploring the properties of the complex nonconvex energy efficiency optimization problem, we transform the problem into an equivalent problem based on fractional programming, and then, use the alternating direction multiplier method to decompose the problem into a series of simpler subproblems, where their optimal or suboptimal solutions can be easily achieved. We propose the corresponding low-complexity methods to solve the subproblems and, then, the whole problem. The numerical results demonstrate the effectiveness of the proposed low-complexity energy-efficient scheme and illustrate the fundamental tradeoff among energy consumption, spectral efficiency, and energy efficiency.**

***Index Terms*— Energy efficiency, OFDM distributed antenna system, quality of service, resource allocation.**

I. INTRODUCTION

GREENHOUSE gas emissions have been regarded as a global threat to environment and sustainable development, and they have increased rapidly with industrial revolution and are projected to rise sharply if no significant prevention measures are taken. Currently, the telecommunication industry sector accounts for about 2% of the greenhouse gas footprint [1]. For wireless communications, the significant environmental impact is mostly caused by high energy consumption, especially at cellular base stations (BSs). Moreover, reducing the energy consumption can save the operational expense of mobile network operators. Besides, future communication systems are required to provide higher data rate with limited resources due to the explosive demands of multimedia services [2]–[5]. Thus, advanced network deployment schemes and wireless transmission techniques are required to achieve the performance metrics such as spectral efficiency and energy efficiency.

The distributed antenna system (DAS), a kind of distributed multiple input multiple output (MIMO) system, has been introduced as a promising technique for future wireless systems to increase data transmission rate (or spectral efficiency), extend coverage, enhance link reliability and provide flexible utilization of spatial degrees of freedom [6]–[11]. In a DAS, the remote antenna units (RAUs) are geographically distributed and connected to a BS or a central unit in a cell via optical fibers or cables [6]–[11], which is different from conventional collocated antenna systems with centrally collocated antennas, i.e., collocated MIMO systems [12]. In principle, such a DAS can emulate any collocated MIMO technique feasible [13], [14]. Besides, compared with the collocated MIMO system, a cell in a DAS can be divided into several smaller sectors, and access link distances between RAUs and mobile users can be reduced together with transmit power and co-channel interference. This is particular true for mobile users near the edge of a cell and the system performance can be enhanced [9], [10]. Moreover, as compared with collocated massive MIMO systems in [13]–[15], if the DAS technique can be made scalable (i.e., distributed massive MIMO system), it can provide arguably the most effective means of realizing truly massive MIMO systems considering the benefits of distributed massive MIMO systems such as: a) acquiring high-quality channel state information (CSI) seems to be easier considering the factors such as mobility, Doppler shifts, phase noise and clock synchronization; b) a distributed massive MIMO system can offer substantial reduction in path loss and provide some diversity against shadow fading due to the decrease of access

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link distance, thereby reducing transmit power and interference. Due to the potentials of DASs, they have drawn much attention in academic research and industrial standardization, such as Long Term Evolution (LTE) Advanced and IEEE 802.16 Worldwide Interoperability Microwave Access (WiMAX) [16]. Besides, the technique of DASs is similar to small cells in 5G systems, but differs from small cell solutions with distributed control because availability of the central processing entity in the DAS allows joint processing of network-wide resource utilization and a lower interference level, which yields better system performance [17]. On the other hand, orthogonal frequency division multiplexing (OFDM) technology can improve the spectral efficiency of mobile cellular systems and has been widely used in various wireless standards such as LTE Advanced and IEEE 802.16 WiMAX [16]. Thus, it is of great benefit to combine the above two technologies together, i.e., OFDM-DASs.

However, to achieve the potential performance gains of an OFDM-DAS, especially on spectral efficiency and energy efficiency, proper resource allocation schemes are crucial. There are several studies focusing on energy efficiency in OFDM systems or DASs. The survey in [18] discussed the state-of-the-art research on energy-efficient wireless networks including OFDM systems. In [19], an energy-efficient resource allocation scheme in a single-cell OFDM system was proposed, but the considered antennas were not distributed but centrally collocated at the BS. The study in [20] compared the energy efficiency for DASs with different number and locations of antennas, but it did not consider the impact of transmit power on energy efficiency. In [21], energy efficiency comparison between orthogonal and co-channel resource allocation schemes in DASs was analyzed based on users' SNR, but only path loss was considered in the channel model. In [8], the tradeoff between spectral efficiency and energy efficiency was investigated for the downlink multiuser DASs with proportional rate constraints. In [22], different power allocation criteria, consisting of maximum spectral efficiency, minimum sum transmit power and maximum energy efficiency, were studied for the downlink DASs. However, the studies in [8] and [22] did not consider the combination between DASs and OFDM technology. In [10], energy-efficient resource allocation was studied for OFDM-DASs with proportional fairness. The studies in [23] and [24] developed energy-efficient power optimization schemes for interference-limited OFDM-based systems. However, the studies in [10], [23], and [24] do not consider the users' required minimum data rate to guarantee their service demands as well as the limit of backhaul link capacity. In [25], the tradeoff between energy efficiency and spectrum efficiency was studied in downlink OFDMA networks, where subcarrier reuse was not considered. In [26], an energy-efficient resource allocation scheme was proposed for multi-cell OFDMA systems with limited backhaul capacity, where the power consumed by sending data was not considered. As well, most of the above studies do not consider the joint resource optimization. To the best of the authors' knowledge, the problem of energy-efficient resource allocation for min-rate guaranteed services in OFDM-DASs with limited backhaul capacity has not been explored as well as the problem of corresponding joint antenna-subcarrier-power allocation.

To fill this gap, this paper focuses on the energy-efficient joint antenna-subcarrier-power allocation for min-rate guaranteed services in multiuser OFDM-DASs with limited backhaul capacity. Besides, it is necessary to consider the downlink transmission in an OFDM-DAS since RAUs are the primary energy consumers. Moreover, the considered channels in an OFDM-DAS consist of small-scale and large-scale fading. The complex energy efficiency optimization problem is formulated by maximizing the energy efficiency in an OFDM-DAS mainly based on the constraints of users' QoS (e.g., required minimum data rate), subcarrier reuse, backhaul link capacity and RAUs' transmit power. By exploring the properties of the optimization problem, we first transform the problem into an equivalent problem according to the theory of fractional programming, then use the alternating direction multiplier method (ADMM) [27] to decompose the original problem into a series of subproblems, and finally propose the corresponding low-complexity methods to solve the subproblems as well as the original energy efficiency optimization problem. Different from previous works, this paper investigates the energy-efficient resource allocation scheme with the following contributions:

- This paper first explores the energy-efficient schemes of joint antenna-subcarrier-power allocation for min-rate guaranteed services in downlink multiuser OFDM-DASs with limited backhaul capacity.
- This paper first transforms the complex three-dimensional (antenna, subcarrier and power) mixed 0-1 optimization problem into one-dimensional (power) optimization problem by exploring the inner mathematical relation between power allocation and joint selection of antennas and subcarriers, then transforms the problem into an equivalent problem based on nonlinear fractional programming, and finally uses ADMM to split the complex nonconvex problem into a series of simpler subproblems where their optimal or suboptimal solutions can be easily obtained. Some of these subproblems can be solved separately with low complexity.
- Based on several derived properties, a suboptimal iterative algorithm is developed and evaluated to realize the corresponding energy efficiency optimization in OFDM-DASs.

The rest of this paper is organized as follows. In Section II, we describe the system model and then formulate and transform the energy efficiency optimization problem. In Section III, we decompose the nonconvex optimization problem into four subproblems and solve these subproblems. In Section IV, we provide upper bound analysis of energy efficiency in an OFDM-DAS, and provide the analysis of some parameters' choice as well as some baseline schemes for comparison. Numerical results are shown to evaluate the performance of the proposed resource allocation

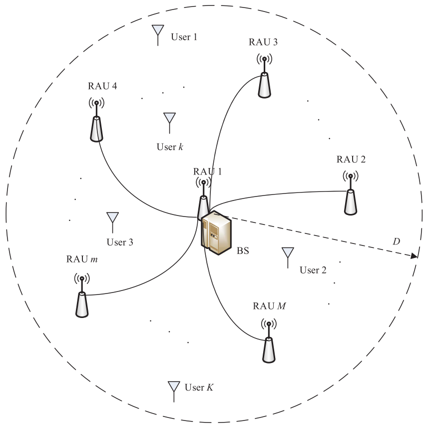


Fig. 1. A single-cell OFDM-DAS model.

scheme in Section V. Finally, Section VI makes the conclusions.

II. System Model and Problem Formulation

In this section, we describe the OFDM-DAS model, and then formulate and transform the energy efficiency optimization problem for joint antenna-subcarrier-power allocation.

A. Downlink OFDM-DAS Model

As shown in Fig. 1 [8]–[10], we consider the downlink transmissions of a single-cell N-subcarrier OFDM-DAS from a single-antenna BS, connected with $M-1$ single-antenna RAUs through capacity-limited cables or optical fibers, to K single-antenna users. Here, the BS is a central unit that can perform all computations, and can be regarded as a special RAU and denoted by RAU 1; therefore, there are M RAUs in the OFDM-DAS. Without loss of generality, the cell shape is assumed to be a circle with radius D. Assuming the global CSI is available at RAU 1 and shared among all RAUs, RAU 1 designs the resource allocation strategy and broadcasts it by control signals to the other RAUs via the capacity-limited backhaul links. Note that the consumed energy by exchanging CSI and other overhead such as control signals are relatively less significant than the energy consumed for data transmission [26]. Denote subcarriers' set by $\mathcal{N} = \{1, 2, \ldots, N\}$, RAUs' set by $\mathcal{M} = \{1, 2, \ldots, M\}$ and users' set by $\mathcal{K} = \{1, 2, \ldots, K\}$. In the system, the allocated subcarriers have an identical bandwidth and are non-overlapping. Universal frequency reuse is assumed, and the M RAUs share a total bandwidth of B. Thus, the sub-bandwidth of each subcarrier is $B_s = \frac{B}{N}$ if subcarrier spacing is not considered. Moreover, each user is served by a specific group of subcarriers and RAUs. Denote $\{\delta_{k,m,n}\}$ as the indictors of joint selection of RAUs (or antennas) and subcarriers to users. Specifically, if user k is served by RAU m and subcarrier n, denote $\delta_{k,m,n} = 1$; otherwise, $\delta_{k,m,n} = 0$.

By allowing several RAUs to transmit to one user in a coordinated fashion, e.g., using the technique of maximum ratio transmission (MRT) [22], [28], [29], the signal-to-interference-plus-noise ratio (SINR) of user k on subcarrier n from all the RAUs can be expressed as

$$\rho_{k,n} = \frac{\sum_{m=1}^{M} \delta_{k,m,n} p_{k,m,n} \mid h_{k,m,n} \mid^2}{\sigma_N^2 + I_{k,n}}, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N} \tag{1}$$

where $p_{k,n,m}$ and $h_{k,n,m}$ indicate the transmit power and the composite channel coefficient from RAU m to user k on subcarrier n, respectively; σ_N^2 denotes the power of the zero-mean additive white Gaussian noise (AWGN) at the receiver input; $I_{k,n} = \sum_{j=1,j\neq k}^{K} \sum_{m=1}^{M} \delta_{j,m,n} p_{j,m,n} \mid h_{j,m,n} \mid^2$ is the interference power of user k on subcarrier n.

Moreover, the composite channel gain consists of small-scale fading and large-scale fading, which is expressed as [31]

$$h_{k,m,n} = \sqrt{\frac{c}{d_{k,m}^{\gamma}}} \cdot \sqrt{s_{k,m}} \cdot g_{k,m,n}, \quad \forall k \in \mathcal{K},\ \forall m \in \mathcal{M},\ \forall n \in \mathcal{N} \tag{2}$$

where $d_{k,m}$ is the distance in kilometer between RAU m and user k, $\gamma \in [3, 5]$ is the path loss exponent, c is the median of the mean path gain at a reference distance $d_0 = 1$km, $s_{k,m}$ is the log-normal shadow fading coefficient, i.e., $10 \lg s_{k,m} \sim \mathcal{N}(0, \sigma_{sh}^2)$, where σ_{sh} is the corresponding standard deviation, and $g_{k,n,m}$ is the small-scale channel fading coefficient from RAU m to user k on subcarrier n. Thus, we can get the channel capacity of user k on subcarrier n as

$$r_{k,n} = B_s \log_2(1 + \rho_{k,n}), \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}. \tag{3}$$

However, as analyzed in [29] and [30], due to the interference power, the data rate function $r_{k,n}$ brings two difficulties to formulate the resource allocation problem: 1) it leads to a nonconvex optimization problem which is NP-hard, thus it may be impossible to find a global optimal solution even by centralized optimization and the design of a distributed algorithm will be even more difficult if possible; 2) it can be quite difficult to attain the exact expression of the rate function $r_{k,n}$. Thus, as similar to [19], [29], and [30], we consider to utilize an upper bound of the interference power $I_{k,n}$, which is denoted by I, to derive an approximate capacity function, i.e., $\widetilde{r}_{k,n} = B_s \log_2 (1 + \frac{\sum_{m=1}^{M} p_{k,m,n} |h_{k,m,n}|^2}{\sigma_N^2 + I}) \leq r_{k,n}$. The key benefit of the approximate rate function $\tilde{r}_{k,n}$ is that it becomes concave and is computable without accurate knowledge of the CSI $h_{k,m,n}$ for the enormous interfering antennas, thereby solving the above two difficulties. Besides, as similar to [30] and [19], we introduce an interference temperature constraint as

$$I_{k,n} \leq I, \quad \forall k \in \mathcal{K},\ \forall n \in \mathcal{N}. \tag{4}$$

Thus, by varying the value of I,[1] the system is able to control the amount of interference on each subcarrier to improve the system performance [19], [30].

Then we can write the overall data rate of user k as

$$R_k = \sum_{n=1}^{N} \widetilde{r}_{k,n}, \quad \forall k \in \mathcal{K}. \tag{5}$$

[1]As similar to [30] and [19], the maximum interference temperature parameter I is not an optimization variable in the proposed framework. However, a proper value of I can be found via simulation in an off-line manner.

Specifically, for $\forall k \in \mathcal{K}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}$, the mathematical relation between the power allocation and the joint selection of RAUs (or antennas) and subcarriers satisfies

$$\begin{cases} p_{k,m,n} > 0 \Leftrightarrow \delta_{k,m,n} = 1, \\ p_{k,m,n} = 0 \Leftrightarrow \delta_{k,m,n} = 0 \end{cases} \tag{6}$$

which indicates that the joint selection of a pair of a RAU and subcarrier for a user depends on whether positive transmit power is allocated from the RAU to the user on the subcarrier or not.

Then for $\forall k \in \mathcal{K}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}$, we can get

$$\delta_{k,m,n} = \text{sign}(p_{k,m,n}) \text{ and } \delta_{k,m,n} p_{k,m,n} = p_{k,m,n} \tag{7}$$

where $\text{sign}(x) \triangleq \begin{cases} 1, & \text{if } x > 0, \\ 0, & \text{if } x = 0, \end{cases}$ $(x \geq 0)$ is the step function.

Thus, based on (7), we can equally transform the joint antenna-subcarrier-power allocation into the power allocation.

B. Energy Efficiency of an OFDM-DAS

We model the total power consumption P_{Total} in an OFDM-DAS as the sum of two dynamic terms and two static terms as [25], [26]

$$P_{\text{Total}} = \frac{P_T}{\tau_d} + \tau_r \cdot \sum_{k=1}^{K} R_k + M \cdot P_c + (M-1) \cdot P_{BH} \tag{8}$$

where $P_T = \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} p_{k,m,n}$ is the total transmit power, τ_d is the drain efficiency of the radio frequency power amplifier, τ_r is the dynamic circuit power per unit data rate, P_c is the static circuit power per RAU, and P_{BH} is the average consumed power per backhaul link.

Similar to many works such as [8], [10], [18], [19], [22], [24]–[26], and [33], the energy efficiency (unit: bits/J/Hz) of an OFDM-DAS is defined as the ratio of the sum capacity to the sum consumed power as

$$\eta_{EE} = \frac{\frac{1}{B_s} \sum_{k=1}^{K} R_k}{P_{\text{Total}}}. \tag{9}$$

C. Problem Formulation

Our objective is to maximize the energy efficiency in an OFDM-DAS based on joint antenna-subcarrier-power allocation for min-rate guaranteed services. The overall optimization problem is formulated as

$$\max_{\mathbf{P} \in \mathbb{R}^{K \times M \times N}} \eta_{EE} \tag{10a}$$

$$\text{s.t. } p_{k,m,n} \geq 0, \quad \forall k \in \mathcal{K}, \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}, \tag{10b}$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} p_{k,m,n} \leq p_m^{\max}, \quad \forall m \in \mathcal{M}, \tag{10c}$$

$$R_k \geq C_k^{\min}, \quad \forall k \in \mathcal{K}, \tag{10d}$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} \delta_{k,m,n} \widetilde{r}_{k,n} \leq C_m^{\max}, \quad \forall m \in \mathcal{M} \setminus \{1\}, \tag{10e}$$

$$\delta_{k,m,n} = \text{sign}(p_{k,m,n}), \quad \forall k \in \mathcal{K}, \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}, \tag{10f}$$

$$\sum_{k=1}^{K} \delta_{k,m,n} \leq 1, \quad \forall \ n \in \mathcal{N}, \ \forall m \in \mathcal{M}, \tag{10g}$$

$$\sum_{j=1, j \neq k}^{K} \sum_{m=1}^{M} p_{j,m,n} \mid h_{j,m,n} \mid^2 \leq I, \quad \forall k \in \mathcal{K}, \ \forall n \in \mathcal{N} \tag{10h}$$

where $\mathbf{P} = \{p_{k,m,n}\}^{K \times M \times N}$, $p_m^{\max}$ and $C_k^{\min}$ denote the maximum transmit power of RAU m and the required minimum transmission rate of user k, respectively. The constraint in (10e) gives the limit on the maximum sum data rate of RAU m $(m \neq 1)$ due to the limited backhaul link capacity $C_m^{\max}$ between BS/RAU 1 and RAU m. If the backhaul link capacity is much greater than the wireless link capacity, then (10e) always holds. The constraint in (10g) is to make sure that each pair of a RAU and subcarrier can serve one user at most. Besides, the power constraints in (10b) and (10c) imply that

$$0 \leq p_{k,m,n} \leq p_m^{\max}, \quad \forall k \in \mathcal{K}, \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}. \tag{11}$$

Clearly, the problem in (10) is a mixed 0-1 nonconvex optimization problem and thus is NP-hard. Denote $\mathcal{P}$ as the feasible solution set of the problem in (10).

D. Transformation of the Optimization Problem

The problem in (10) can be regarded as a nonlinear fractional programming problem [34]. Denote the maximum energy efficiency η_{EE}^* of the considered system as

$$\eta_{EE}^* = \frac{R_{\text{Total}}(\mathbf{P}^*)}{P_{\text{Total}}(\mathbf{P}^*)} = \max_{\mathbf{P} \in \mathcal{P}} \left\{ \frac{R_{\text{Total}}(\mathbf{P})}{P_{\text{Total}}(\mathbf{P})} \right\} \tag{12}$$

where $R_{\text{Total}}(\mathbf{P}) = \frac{1}{B_s} \sum_{k=1}^{K} R_k(\mathbf{P})$. To achieve η_{EE}^*, we introduce the following theorem proved in [19], [26], and [34].

Theorem 1: The maximum energy efficiency η_{EE}^* is achieved if and only if

$$\begin{aligned} &\max_{\mathbf{P} \in \mathcal{P}} \{R_{\text{Total}}(\mathbf{P}) - \eta_{EE}^* P_{\text{Total}}(\mathbf{P})\} \\ &\quad = R_{\text{Total}}(\mathbf{P}^*) - \eta_{EE}^* P_{\text{Total}}(\mathbf{P}^*) = 0 \end{aligned}$$

for $R_{\text{Total}}(\mathbf{P}) \geq 0$ and $P_{\text{Total}}(\mathbf{P}) > 0$.

Thus, based on *Theorem 1*, for the objective function (10a) in fractional form, there exists an equivalent objective function in subtractive form, e.g., $\Omega R_{\text{Total}}(\mathbf{P}) - (1-\Omega) P_{\text{Total}}(\mathbf{P})$ where $\Omega = \frac{1}{1+\eta_{EE}}$. We define a new optimization problem as

$$\min_{\mathbf{P} \in \mathbb{R}^{K \times N \times M}} F(\mathbf{P}, \Omega) = -\frac{\Omega}{B_s} \sum_{k=1}^{K} R_k + (1-\Omega) P_{\text{Total}} \tag{13a}$$

s.t. the same with (10c)-(10g) and (11) (13b)

where $\Omega \in [0, 1]$ is introduced as a weighted parameter. Thus, by using the method in [34] to iteratively solve the problem in (13) with an equivalent objective function, the overall energy efficiency optimization problem in (10) can be solved and the details will be introduced in the next section. Then we can only focus on solving the problem in (13) for a given Ω. Specifically, $F(\mathbf{P}, \Omega) \triangleq \varphi_1 \sum_{k=1}^{K} f_k(\mathbf{P}) + \varphi_2 \sum_{i=1}^{K} \sum_{m=1}^{M} \sum_{n=1}^{N} p_{k,m,n} + P_{\text{cons}}$, where $f_k(\mathbf{P}) = \frac{1}{B_s} R_k(\mathbf{P})$, $\varphi_1 = (1-\Omega)\tau_r B_s - \Omega = \frac{\eta_{EE} \cdot \tau_r \cdot B_s - 1}{1+\eta_{EE}} < 0$ based on (8) and (9), $\varphi_2 = \frac{(1-\Omega)}{\tau_d} > 0$ and $P_{\text{cons}} = \tau_d \, \varphi_2 [M P_c + (M-1) P_{BH}]$.

III. Solutions to the Optimization Problem

In this section, we will address the challenges of solving the optimization problem in (13) and then the whole energy efficiency optimization problem in (10). We first decompose the complex problem in (13) into several simpler subproblems based on ADMM, and then propose efficient algorithms for solving these subproblems. Finally, an iterative method is provided to solve the whole problem in (10).

A. ADMM-Based Decomposition

We apply the ADMM [27], [35]–[38] to solve the transformed optimization problem in (13). ADMM has become widely popular in modern big data related problems arising in machine learning, computer vision, signal processing, networking and so on. It is a powerful optimization technique that combines the benefits of dual decomposition and method of multipliers to solve convex or nonconvex problems. Besides, the method often exhibits faster convergence than traditional primal-dual type algorithms such as the dual ascent algorithm or the methods of multipliers [35]. The basic idea of ADMM is to decompose a large (and probably difficult) problem into a set of (simpler to solve) subproblems and cleverly combine their solutions in a principled manner to recover the solution of the original problem [36]. Generally, the decomposed subproblems only consider part of all the constraints in the original problems. In other words, all the constraints are divided into some groups to form simpler subproblems, and the inequality constraints are transformed into equality constraints in some manners and then added into the optimization objective in a penalty manner.

The constraints of the studied problem in (13) are large-scale and consist of linear constraints (i.e., (10c), (10h) and (11)), non-linear constraints (i.e., (10d)), binary constraints (i.e., (10f) and (10g)) and mixed binary non-linear constraints (i.e., (10e)). Thus, it is very challenging to solve the problem with widely used regular methods of multipliers based on dual decomposition, especially for joint optimization. Considering the advantages of ADMM, ADMM is an appropriate approach to solve such a complex energy efficiency optimization problem in (13). Thus, based on the idea of ADMM, we divide the constraints in (13) into three groups and define three sets as

$$\mathcal{S}_P = \left\{\mathbf{P} \in \mathbb{R}^{K\times M\times N} \middle| (10d), (10h) \text{ and } (11)\right\}, \tag{14}$$

$$\mathcal{S}_Q = \left\{\mathbf{P} \in \mathbb{R}^{K\times M\times N} \middle| (10c) \text{ and } (11)\right\}, \tag{15}$$

$$\mathcal{S}_Z = \left\{\mathbf{P} \in \mathbb{R}^{K\times M\times N} \middle| (10e) - (10g) \text{ and } (11)\right\}. \tag{16}$$

Clearly, the sets $\mathcal{S}_P$ and $\mathcal{S}_Q$ are continuous, while the set $\mathcal{S}_Z$ is discrete. Specifically, $\mathbf{P} \in \mathcal{S}_P$, $\mathbf{P} \in \mathcal{S}_Q$ and $\mathbf{P} \in \mathcal{S}_Z$ aim at satisfying the constraints of users' required minimum transmission rates as well as interference, RAUs' maximum transmit power, and subcarrier allocation as well as the backhaul link capacity, respectively. As a result, any feasible solution $\mathbf{P}$ to the problem in (13) should be in the intersection of the above three sets, i.e., all $\mathbf{P} \in \mathcal{S}_P, \mathbf{P} \in \mathcal{S}_Q$ and $\mathbf{P} \in \mathcal{S}_Z$ hold. Then the problem in (13) becomes

$$\min_{\mathbf{P}\in\mathcal{S}_\mathbf{P}} F(\mathbf{P}, \Omega) \tag{17a}$$
$$s.t.\ \mathbf{P} \in \mathcal{S}_Q, \tag{17b}$$
$$\mathbf{P} \in \mathcal{S}_Z \tag{17c}$$

which is equivalent to

$$\min_{\mathbf{P}\in\mathcal{S}_\mathbf{P},\mathbf{Q}\in\mathcal{S}_\mathbf{Q},\mathbf{Z}\in\mathcal{S}_\mathbf{Z}} F(\mathbf{P}, \Omega) \tag{18a}$$
$$s.t.\ \mathbf{P} = \mathbf{Q}, \tag{18b}$$
$$\mathbf{P} = \mathbf{Z} \tag{18c}$$

where $\mathbf{Q} \in \mathbb{R}^{K\times M\times N}$ and $\mathbf{Z} \in \mathbb{R}^{K\times M\times N}$ are introduced variable matrices. Thus, the problem in (13) is equally transformed to the problem as shown in (18) with two equality constraints.

Then the problem in (18) can be turned into a minimization problem by introducing the augmented Lagrangian function as

$$\begin{aligned}\mathcal{L}&(\mathbf{P}, \Omega, \mathbf{Q}, \mathbf{Z}, \mathbf{L}, \mathbf{U}, \theta)\\ &= F(\mathbf{P}, \Omega) + \langle \mathbf{P} - \mathbf{Q}, \mathbf{L}\rangle\\ &\quad + \langle \mathbf{P} - \mathbf{Z}, \mathbf{U}\rangle + \frac{\theta}{2}(\|\mathbf{P} - \mathbf{Q}\|_2^2 + \|\mathbf{P} - \mathbf{Z}\|_2^2)\end{aligned} \tag{19}$$

where $\mathbf{L}, \mathbf{U} \in \mathbb{R}^{K\times M\times N}$ are the corresponding Lagrange multiplier matrices for constraints (18b) and (18c), respectively; $\theta > 0$ is a quadratic penalty scalar; $\langle \mathbf{x}, \mathbf{y}\rangle$ denotes the sum of all the elements of $\mathbf{x} \circ \mathbf{y}$ and $\circ$ denotes the Hadamard product.

By using ADMM-based decomposition, the joint optimization problem w.r.t. the augmented Lagrangian function in (19) can be decomposed into the following four subproblems:

1) Subproblem 1: Optimization of $\mathbf{P}$ under fixed Ω, $\mathbf{Q}$, $\mathbf{Z}$, $\mathbf{L}$, $\mathbf{U}$ and θ, which can be formulated as

$$\min_{\mathbf{P}\in\mathcal{S}_\mathbf{P}} F(\mathbf{P}, \Omega) + \theta\|\mathbf{P} - \mathbf{C}_P\|_2^2 \tag{20}$$

where $\mathbf{C}_P \triangleq \frac{1}{2}(\mathbf{Q} - \frac{\mathbf{L}}{\theta} + \mathbf{Z} - \frac{\mathbf{U}}{\theta})$ is a constant matrix w.r.t. $\mathbf{P}$.

2) Subproblem 2: Optimization of $\mathbf{Q}$ under fixed $\mathbf{L}$, $\mathbf{U}$ and θ, which can be formulated as

$$\min_{\mathbf{Q}\in\mathcal{S}_\mathbf{Q}} \|\mathbf{Q} - \mathbf{C}_Q\|_2^2 \tag{21}$$

where $\mathbf{C}_Q \triangleq \mathbf{P}^* + \frac{\mathbf{L}}{\theta}$ is a constant matrix w.r.t. $\mathbf{Q}$, and $\mathbf{P}^*$ is the optimal solution of (20).

3) Subproblem 3: Optimization of $\mathbf{Z}$ under fixed $\mathbf{L}$, $\mathbf{U}$ and θ, which can be formulated as

$$\min_{\mathbf{Z}\in\mathcal{S}_\mathbf{Z}} \|\mathbf{Z} - \mathbf{C}_Z\|_2^2 \tag{22}$$

where $\mathbf{C}_Z \triangleq \mathbf{P}^* + \frac{\mathbf{U}}{\theta}$ is a constant matrix w.r.t. $\mathbf{Z}$, and $\mathbf{P}^*$ is also the optimal solution of (20).

4) Subproblem 4: Updating of $\mathbf{L}$, $\mathbf{U}$ and θ with given $(\mathbf{P}^*, \mathbf{Q}^*, \mathbf{Z}^*)$, where $\mathbf{Q}^*$ and $\mathbf{Z}^*$ are the optimal solutions of (21) and (22), respectively.

After the ADMM-based decomposition, Subproblem 1 is convex and can be solved by using optimization techniques (e.g., sub-gradient method) as shown in Section III-B. Subproblem 2 is convex and can be solved with an efficient distributed algorithm as shown in Section III-C. Subproblem 3 is a discrete nonconvex optimization problem but its solution can be easily achieved as shown in Section III-D. Subproblem 4 is solved by updating $\mathbf{L}$, $\mathbf{U}$ and θ according to the rules of ADMM, and thus the problem in (18) can be solved as shown in Section III-E. At last, the whole energy efficiency joint optimization problem can be solved with an iterative method as shown in Section III-F.

Thus, by using ADMM, solving the original complex nonconvex problem is decomposed into solving a set of simpler subproblems where their optimal or suboptimal solutions can be easily achieved. Moreover, Subproblem 2 and Subproblem 3 can be solved in parallel. Note that since the original complex problem is nonconvex, the final solution will be suboptimal.

B. Solutions to Subproblem 1

Subproblem 1 in (20) can be rewritten as

$$\min_{\mathbf{P}\in\mathbb{R}^{KN\times M}} \varphi_1 \sum_{k=1}^{K} f_k(\mathbf{P}) + \varphi_2 \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N} p_{k,m,n} + \theta\|\mathbf{P}-\mathbf{C}_P\|_2^2 \tag{23a}$$

$$s.t.\ 0 \le p_{k,m,n} \le p_m^{\max}, \quad \forall k\in\mathcal{K},\ \forall m\in\mathcal{M},\ \forall n\in\mathcal{N}, \tag{23b}$$

$$-f_k(\mathbf{P}) + \frac{C_k^{\min}}{B_s} \le 0, \quad \forall k\in\mathcal{K}, \tag{23c}$$

$$\sum_{j=1,j\neq k}^{K}\sum_{m=1}^{M} p_{j,m,n} \mid h_{j,m,n}\mid^2 \le I, \quad \forall k\in\mathcal{K},\ \forall n\in\mathcal{N} \tag{23d}$$

which is a convex optimization problem w.r.t. $\mathbf{P}$. Thus, by applying standard optimization techniques in [39], we can obtain the Lagrangian function for Subproblem 1 in (23) as

$$\begin{aligned}
&\mathcal{L}_1(\mathbf{P},\boldsymbol{\mu})\\
&= \theta\|\mathbf{P}-\mathbf{C}_P\|_2^2 + \sum_{k=1}^{K}(\varphi_1-\mu_k)\, f_k(\mathbf{P})\\
&\quad + \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N}\Big(\varphi_2 p_{k,m,n} + \lambda_{k,n}\sum_{j=1,j\neq k}^{K} p_{j,m,n}\mid h_{j,m,n}\mid^2\Big)\\
&\quad + \frac{1}{B_s}\sum_{k=1}^{K}\mu_k C_k^{\min} - \sum_{k=1}^{K}\sum_{n=1}^{N}\lambda_{k,n} I
\end{aligned} \tag{24}$$

where $\boldsymbol{\mu}$ is the Lagrange multiplier vector for the constraint (23c) with elements $\mu_k, \forall k\in\mathcal{K}$, and $\boldsymbol{\lambda}$ is the Lagrange multiplier matrix for the constraint (23d) with elements $\lambda_{k,n}$, $\forall k\in\mathcal{K}, \forall n\in\mathcal{N}$.

After differentiating $\mathcal{L}_1(\mathbf{P},\boldsymbol{\mu})$ w.r.t. $\mathbf{P}$, for $\forall k\in\mathcal{K}$, $\forall m\in\mathcal{M}, \forall n\in\mathcal{N}$, we get

$$\begin{aligned}
\frac{\partial\mathcal{L}_1}{\partial p_{k,m,n}} &= 2\theta[p_{k,m,n}-(\mathbf{C}_P)_{k,m,n}] + \lambda_{k,n}(K-1)\mid h_{k,m,n}\mid^2\\
&\quad + \frac{\varphi_1-\mu_k}{\ln 2}\frac{H_{k,m,n}}{\sum_{m=1}^{M} H_{k,m,n}p_{k,m,n}+1} + \varphi_2
\end{aligned} \tag{25}$$

where $H_{k,m,n} = \frac{|h_{k,m,n}|^2}{\sigma_N^2+I}$.

Algorithm 1 Subgradient Algorithm for Solving Subproblem 1 w.r.t. $\mathbf{P}$

Input: φ_1, φ_2, I, σ_N^2, $(h_{k,m,n})_{K\times M\times N}$, $(p_m^{\max})_{M\times 1}$, $\mathbf{C}_P$, θ, $\mathbf{P}_{ini}$.
Initialize $t=0$, $\boldsymbol{\mu}^{(0)} = 0.01\times\mathbf{1}_{K\times 1}$, convergence precision $\varrho = 10^{-4}$, maximum iterations $N_{\max}=20$, $\mathbf{P}^{(0)} = \mathbf{P}_{ini}$.
while $(\boldsymbol{\mu},\boldsymbol{\lambda})$ not converge **do**
  while not exceed $N_{\max}$ or $\mathbf{P}$ not converge **do**
    Update $\mathbf{P}^{(t)}$ based on (28).
  end while
  Set $t\leftarrow t+1$.
  Update $\boldsymbol{\mu}^{(t)}$ and $\boldsymbol{\lambda}^{(t)}$ according to (26) and (27), respectively.
  Check the convergence condition: $\|\boldsymbol{\mu}^{(t)}-\boldsymbol{\mu}^{(t-1)}\|_\infty \le \varrho$ and $\|\boldsymbol{\lambda}^{(t)}-\boldsymbol{\lambda}^{(t-1)}\|_\infty \le \varrho$.
end while
Output: $\mathbf{P}$.

Then we employ the subgradient method to get the optimal solution of the approximate problem. The multipliers $(\boldsymbol{\mu},\boldsymbol{\lambda})$ can be updated for $\forall k\in\mathcal{K}, \forall n\in\mathcal{N}$ in each step as

$$\mu_k^{(t+1)} = \big[\mu_k^{(t)} + \xi^{(t)}\big(\frac{C_k^{\min}}{B_s} - f_k^{(t)}\big)\big]^+, \tag{26}$$

$$\lambda_{k,n}^{(t+1)} = \big[\lambda_{k,n}^{(t)} + \xi^{(t)}\big(\sum_{j=1,j\neq k}^{K}\sum_{m=1}^{M} p_{j,m,n}^{(t)}\mid h_{j,m,n}\mid^2 - I\big)\big]^+ \tag{27}$$

where t is the iteration index, and $\xi^{(t)}$ is a small positive step size in the t-th iteration, and $[x]^+ \triangleq \max\{x,0\}$. The convergence to the optimal multipliers of the subgradient method can be guaranteed if the steps $\xi^{(t)}$ are chosen to be sufficiently small [39], e.g., $\xi^{(t)} = \frac{100(1+K)}{t+K}$.

Moreover, given $(\boldsymbol{\mu}^{(t)},\boldsymbol{\lambda}^{(t)})$, the elements of $\mathbf{P}^*$ can be updated as

$$p_{k,m,n}^{(t)} = \min\{[T_{k,m,n}^{(t)}]^+, p_m^{\max}\}, \quad \forall k\in\mathcal{K},\ \forall m\in\mathcal{M},\ \forall n\in\mathcal{N} \tag{28}$$

where $T_{k,m,n}^{(t)} = \frac{b_{k,m,n}^{(t)}+\sqrt{[b_{k,m,n}^{(t)}]^2+4H_{k,m,n}a_{k,m,n}^{(t)}}}{2H_{k,m,n}}$, $b_{k,m,n}^{(t)} = c_{k,m,n}^{(t)} H_{k,m,n} - \sum_{j=1,j\neq m}^{M} H_{k,j,n}p_{k,j,n}^{(t)} - 1$, $a_{k,m,n}^{(t)} = c_{k,m,n}^{(t)}[\sum_{j=1,j\neq m}^{M} H_{k,j,n}p_{k,j,n}^{(t)} + 1] + \frac{\mu_k^{(t)}-\varphi_1}{2\theta\ln 2}H_{k,m,n}$, and $c_{k,m,n}^{(t)} = (\mathbf{C}_P)_{k,m,n} - \frac{1}{2\theta}[\lambda_{k,n}^{(t)}(K-1)\cdot\mid h_{k,m,n}\mid^2 + \varphi_2]$.

Thus, the process of the subgradient algorithm for solving Subproblem 1 is described in Algorithm 1, and its complexity and convergence analysis can be referred to [39]. Algorithm 1 includes an inner loop and an outer loop. Given the Lagrangian multipliers $(\boldsymbol{\mu},\boldsymbol{\lambda})$ at each iteration, the inner loop calculates $\mathbf{P}$, which is convergent to the unique optimal solution due to the convexity of (24). Moreover, the achieved solution $\mathbf{P}$ with Algorithm 1 is optimal for Subproblem 1.

C. Solutions to Subproblem 2

Since the variables of Subproblems 2 are three-dimensional, we can transform them into two-dimensional variables and rewrite the constraints in $\mathcal{S}_Q$ by defining the following sets, matrices and vectors as

Algorithm 2 Distributed Algorithm for Solving Subproblem 2 w.r.t. $\mathbf{Q}$

Input: $\mathbf{P}$, $\mathbf{L}$, θ, $(p_m^{\max})_{M\times 1}$.
Initialize $\mathbf{Q} = \mathbf{0}_{K\times M\times N}$, $\widetilde{\mathbf{Q}} = \mathbf{0}_{KN\times M}$, $\widetilde{\mathbf{C}}_Q = \mathbf{0}_{KN\times M}$, $\mathbf{q} = \mathbf{0}_{KN\times 1}$, $p^{\max} = 0$.
Calculate $\mathbf{C}_Q$ and transform it into $\widetilde{\mathbf{C}}_Q$.
for $m = 1$ to M **do**
  Set $\boldsymbol{\phi} \leftarrow (\widetilde{\mathbf{C}}_Q)_m$, $p^{\max} \leftarrow p_m^{\max}$.
  Sort $\boldsymbol{\phi}$ into $\boldsymbol{\pi}$ in a descending order.
  Find the number $\chi = \max\{j \in \mathcal{J} | \pi_j - \frac{1}{j}\big(\sum_{r=1}^{j}\pi_r - p^{\max}\big) > 0\}$.
  Calculate $\mathbf{q}$ as $q_j = \min\{\big[\phi_j - \frac{1}{2}\omega\big]^+, p^{\max}\}$ for $\forall j$, where $\omega = \big[\frac{2}{\chi}\big(\sum_{r=1}^{\chi}\pi_r - p^{\max}\big)\big]^+$.
  Set $\widetilde{\mathbf{Q}}_m \leftarrow \mathbf{q}$.
end for
Transform $\widetilde{\mathbf{Q}}$ into $\mathbf{Q}$.
Output: $\mathbf{Q}$.

- $\mathcal{J} = \{1, 2, \ldots, KN\}$. $\widetilde{\mathbf{Q}}, \widetilde{\mathbf{C}}_Q \in \mathbb{R}^{KN\times M}$, denoting the transformation of $\mathbf{Q}$ and $\mathbf{C}_Q$, respectively. Here, $\widetilde{Q}_{i,m} = Q_{k_i,m,n_i}$, $(\widetilde{C}_Q)_{i,m} = (C_Q)_{k_i,m,n_i}$ for $\forall i \in \mathcal{J}, \forall m \in \mathcal{M}$, $k_i \in \mathcal{K}, n_i \in \mathcal{N}$. Specifically, $i = N \times (k_i - 1) + n_i$, $n_i = \mathrm{mod}(i-1, N) + 1$ and $k_i = \frac{i-n_i}{N} + 1$, where $\mathrm{mod}(x, y)$ is the reminder function of x/y.
- $\mathbf{e}_m \in \{0, 1\}^{M\times 1}$, $\forall m \in \mathcal{M}$, where only the m-th element is one, and others are zeros.

Thus, Subproblem 2 can be rewritten as

$$\min_{\widetilde{\mathbf{Q}}} \ \|\widetilde{\mathbf{Q}} - \widetilde{\mathbf{C}}_Q\|_2^2 \tag{29a}$$
$$s.t. \ \|\widetilde{\mathbf{Q}}\mathbf{e}_m\|_1 \leq p_m^{\max}, \quad \forall m \in \mathcal{M} \tag{29b}$$
$$\widetilde{Q}_{i,m} \geq 0, \quad \forall i \in \mathcal{J}, \ \forall m \in \mathcal{M}, \tag{29c}$$
$$\widetilde{Q}_{i,m} \leq p_m^{\max}, \quad \forall i \in \mathcal{J}, \ \forall m \in \mathcal{M}. \tag{29d}$$

With $\mathbf{P} \succeq 0, \mathbf{L}$ and $\theta > 0$ given, i.e., $\widetilde{\mathbf{C}}_Q$ given, Subproblem 2 in (29) can be split into M subproblems, and the m-th subproblem is w.r.t. the m-th column of $\widetilde{\mathbf{Q}}$ for $\forall m \in \mathcal{M}$. Particularly, each subproblem is in the form as

$$\min_{\mathbf{q}\in\mathbb{R}^J} \ \|\mathbf{q} - \boldsymbol{\phi}\|_2^2 \tag{30a}$$
$$s.t. \ \|\mathbf{q}\|_1 \leq p^{\max}, \tag{30b}$$
$$q_j \geq 0, \quad \forall j \in \mathcal{J}, \tag{30c}$$
$$q_j \leq p^{\max}, \quad \forall j \in \mathcal{J}. \tag{30d}$$

For the m-th subproblem of Subproblem 2, the corresponding $(\mathbf{q}, \boldsymbol{\phi}, p^{\max})$ is equal to $(\widetilde{\mathbf{Q}}_m, (\widetilde{\mathbf{C}}_Q)_m, p_m^{\max})$, where $\widetilde{\mathbf{Q}}_m$ and $(\widetilde{\mathbf{C}}_Q)_m$ denote the m-th column vector of $\widetilde{\mathbf{Q}}$ and $\widetilde{\mathbf{C}}_Q$, respectively.

Thus, solving Subproblem 2 is equivalent to solving M subproblems in (30) in parallel. Clearly, the optimization problem in (30) is convex and its closed-form optimal solution can be obtained by using the low-complexity method in [40]. The process of the distributed algorithm for solving Subproblem 2, with $\mathbf{P}, \mathbf{L}$ and θ fixed, is described in Algorithm 2. Algorithm 2 can also be operated in parallel with computation complexity $O(KNM\log(KN))$ bounded by sorting $\boldsymbol{\phi}$.

Algorithm 3 Heuristic Algorithm for Solving Subproblem 3 w.r.t. $\mathbf{Z}$

Input: C_Z, $(C_m^{\max})_{M\times 1}$ where $C_1^{\max} = +\infty$, $(p_m^{\max})_{M\times 1}$.
Calculate the results in the case of unlimited backhaul capacity, i.e., $\mathcal{S}_0$, $\mathcal{S}_m$ for $\forall m \in \mathcal{M}$, and $\mathbf{Z}$.
while $\mathbf{Z}$ not feasible **do**
  Calculate $\widetilde{r}_{k,n}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}$.
  Check the feasibility of $\mathbf{Z}$.
  Find $m^* = \arg\max_{m\in\mathcal{M}}\big\{\sum_{(k,n)\in\mathcal{S}_m}\widetilde{r}_{k,n}(\mathbf{Z}) - C_m^{\max}\big\}$ and $(k^*, n^*) = \arg\min_{(k,n)\in\mathcal{S}_{m^*}}\big\{z_{k,m^*,n}\big\}$.
  if $\sum_{(k,n)\in\mathcal{S}_{m^*}}\widetilde{r}_{k,n}(\mathbf{Z}) \geq C_{m^*}^{\max} + \widetilde{r}_{k^*,n^*}$ **then**
    Set $z_{k^*,m^*,n^*} = 0$, $\mathcal{S}_{m^*} \leftarrow \mathcal{S}_{m^*} \setminus \{(k^*, n^*)\}$, $\mathcal{S}_0 \leftarrow \mathcal{S}_0 \setminus \{(k^*, m^*, n^*)\}$.
  else
    Set $z_{k^*,m^*,n^*} = \frac{1}{H_{k^*,m^*,n^*}}\big[(2^\lambda - 1)\sigma_{k^*,n^*}^2 - \sum_{m=1,m\neq m^*}^{M} H_{k^*,m,n^*}\cdot z_{k^*,m,n^*}\big]$ where $\lambda = \frac{1}{B_s}\big[C_{m^*}^{\max} - \sum_{(k,n)\in\mathcal{S}_{m^*}\setminus\{(k^*,n^*)\}}\widetilde{r}_{k,n}(\mathbf{Z})\big]$.
  end if
end while
Output: $\mathbf{Z}$.

D. Solutions to Subproblem 3

With $\mathbf{P} \succeq 0, \mathbf{U}$ and $\theta > 0$ given, i.e, $\mathbf{C}_Z$ given, Subproblem 3 is rewritten as

$$\min_{\mathbf{Z}} \ \|\mathbf{Z} - \mathbf{C}_Z\|_2^2 \tag{31a}$$
$$s.t. \ \sum_{k=1}^{K}\sum_{n=1}^{N}\delta_{k,m,n}\cdot\widetilde{r}_{k,n}(\mathbf{Z}) \leq C_m^{\max}, \quad \forall m \in \mathcal{M}\setminus\{1\}, \tag{31b}$$
$$\sum_{k=1}^{K}\delta_{k,m,n} \leq 1, \quad \forall n \in \mathcal{N}, \ \forall m \in \mathcal{M}, \tag{31c}$$
$$\delta_{k,m,n} = \mathrm{sign}(z_{k,m,n}), \quad \forall k \in \mathcal{K}, \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}, \tag{31d}$$
$$0 \leq z_{k,m,n} \leq p_m^{\max}, \quad \forall k \in \mathcal{K}, \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}. \tag{31e}$$

Define $(\mathbf{C}_Z)_{m,n} = \{(\mathbf{C}_Z)_{k,m,n}\}_{K\times 1}$, $k_{m,n} = \arg\max_{k\in\mathcal{K}}\{(\mathbf{C}_Z)_{k,m,n}\}$, $\forall m \in \mathcal{M}$, $\forall n \in \mathcal{N}$, and the set $\mathcal{S}_0$ with elements $(k_{m,n}, m, n)$. Then to solve Subproblem 3, we discuss two cases of whether the backhaul link capacity is unlimited or limited as following.

1) Unlimited Backhaul Capacity: If the backhaul link capacity is much greater than the wireless link capacity, then (31b) always holds and can be not considered to solve Subproblem 3. In this case, it is not hard to get the closed form of the optimal solution $\mathbf{Z}^*$ to Subproblem 3, i.e., for $\forall k \in \mathcal{K}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}$, we have

$$z_{k,m,n}^* = \begin{cases} \min\{\big[(\mathbf{C}_Z)_{k,m,n}\big]^+, p_m^{\max}\}, & \text{if } (k, m, n) \in \mathcal{S}_0 \\ 0, & \text{otherwise.} \end{cases} \tag{32}$$

2) Limited Backhaul Capacity: In this case, (31b) needs to be considered to solve Subproblem 3 and we aim to

Algorithm 4 ADMM for Solving the Problem in (18)

Input: Ω, I, σ_N^2, $(h_{k,m,n})_{K\times M\times N}$, $(p_m^{\max})_{M\times 1}$, B_s, $(C_k^{\min})_{K\times 1}$, $(C_m^{\max})_{M\times 1}$, P_{cons}.
Initialize $\tau = 0$, $\mathbf{P}^{(0)} = \mathbf{0}_{KN\times M}$, $\Omega^{(0)} = 0.1$, $\mathbf{Q}^{(0)} = \mathbf{0}_{KN\times M}$, $\mathbf{Z}^{(0)} = \mathbf{0}_{KN\times M}$, $\mathbf{L}^{(0)} = 0.02\times\mathbf{1}_{KN\times M}$, $\mathbf{U}^{(0)} = 0.01\times\mathbf{1}_{KN\times M}$, $\theta^{(0)} = 10^{-3}$, $\theta^{\max} = 10^6$, $\Delta = 1.2$, $\varepsilon = 10^{-4}$.
while not converge **do**
  Update $\mathbf{P}^{(\tau)}$ by solving Subproblem 1.
  Update $\mathbf{Q}^{(\tau)}$ by solving Subproblem 2.
  Update $\mathbf{Z}^{(\tau)}$ by solving Subproblem 3.
  Set $\tau \leftarrow \tau + 1$.
  Update $\mathbf{L}^{(\tau)}, \mathbf{U}^{(\tau)}$ and $\theta^{(\tau)}$ according to (34), (35) and (36), respectively.
  Check the convergence conditions: $\|\mathbf{P}^{(\tau)} - \mathbf{Q}^{(\tau)}\|_\infty \le \varepsilon$ and $\|\mathbf{P}^{(\tau)} - \mathbf{Z}^{(\tau)}\|_\infty \le \varepsilon$.
end while
Output: $\mathbf{P}$.

provide a suboptimal solution considering the nonconvexity of Subproblem 3. Based on the above results in the case of unlimited backhaul capacity, we set $\{\delta_{k,m,n}\}$ as: if $(k,m,n) \in \mathcal{S}_0$, then $\delta_{k,m,n} = 1$; otherwise, $\delta_{k,m,n} = 0$. Define sets $\mathcal{S}_m$ with elements (k,n) satisfying $(k,m,n) \in \mathcal{S}_0$. Thus, Subproblem 3 can be transformed as

$$\min_{\mathbf{Z}} \|\mathbf{Z} - \mathbf{C}_Z\|_2^2 \tag{33a}$$

$$s.t. \sum_{(k,n)\in\mathcal{S}_m} \widetilde{r}_{k,n}(\mathbf{Z}) \le C_m^{\max}, \quad \forall m \in \mathcal{M}\setminus\{1\}, \tag{33b}$$

$$0 \le z_{k,m,n} \le p_m^{\max}, \quad \forall (k,m,n) \in \mathcal{S}_0, \tag{33c}$$

$$z_{k,m,n} = 0, \quad \forall (k,m,n) \notin \mathcal{S}_0 \tag{33d}$$

which is also a nonconvex problem. Then we can obtain a suboptimal solution to the problem in (33) by using a heuristic method as shown in Algorithm 3 and its complexity is $O(KMN)$.

In all, to solve Subproblem 3, we provide a closed-form optimal solution in the case of unlimited backhaul capacity, and provide a suboptimal solution with Algorithm 3 in the case of limited backhaul capacity.

E. Solutions to Subproblem 4

With $\mathbf{P}, \mathbf{Q}$ and $\mathbf{Z}$ given, Subproblem 4 aims to update the multipliers $\mathbf{L}, \mathbf{U}$ and the quadratic penalty scalar θ. With ADMM, they can be updated in each step as

$$\mathbf{L}^{(\tau+1)} = \mathbf{L}^{(\tau)} + \theta^{(\tau)}\big(\mathbf{P}^{(\tau)} - \mathbf{Q}^{(\tau)}\big), \tag{34}$$

$$\mathbf{U}^{(\tau+1)} = \mathbf{U}^{(\tau)} + \theta^{(\tau)}\big(\mathbf{P}^{(\tau)} - \mathbf{Z}^{(\tau)}\big), \tag{35}$$

$$\theta^{(\tau+1)} = \max\big\{\theta^{\min}, \Delta\cdot\theta^{(\tau)}\big\} \tag{36}$$

where τ denotes the iteration index, $\theta^{\max}$ is a relatively large scalar and $\Delta > 1$ is a scalar. The ADMM process for solving the whole problem in (18) is described in Algorithm 4. Given the multipliers $\mathbf{L}, \mathbf{U}$ and the quadratic penalty scalar θ, Algorithm 4 updates $\mathbf{P}$, $\mathbf{Q}$ and $\mathbf{Z}$ by solving Subproblem 1, Subproblem 2 and Subproblem 3, respectively. Besides, the updating of $\mathbf{Q}$ and $\mathbf{Z}$ can be simultaneously operated in parallel to enhance the algorithm's efficiency. ADMM converges to the corresponding suboptimal solution of the problem in (18) [27], [35]–[38]. Let ε be the convergence precision of Algorithm 4.

Algorithm 5 Iterative Algorithm for Solving the Whole Problem w.r.t. $\mathbf{P}$ and Ω

Input: $\mathbf{P}_{ini}$.
Initialize $\Omega = 0.1$, convergence precision $\zeta = 10^{-3}$.
while Ω not converge **do**
  Update $\mathbf{P}$ by solving the problem in (18) with ADMM.
  Calculate η_{EE} based on (9).
  Update $\Omega = \frac{1}{1+\eta_{EE}}$.
end while
Output: $\mathbf{P}$, Ω, η_{EE}.

Moreover, for the initialization of the multipliers $\mathbf{U}$ and $\mathbf{L}$, they can be set as random values. For the scalars θ, $\theta^{\max}$ and Δ, θ is usually initialized as a small value, e.g., $\theta^{(0)} = 10^{-3}$; $\theta^{\max}$ is set as a relatively large value, e.g., $\theta^{\max} = 10^6$, which is usually not reached when the algorithm converges and stops; Δ is set neither too small nor too large based on the algorithm's convergence rate, e.g., $\Delta = 1.2$. Most importantly, using different feasible initializations, ADMM always converges but requires various numbers of iterations to converge, the complexity and convergence analysis of which can be referred to [27] and [35]–[38].

F. Solutions to Energy Efficiency Maximization Problem

To solve the overall energy efficiency optimization problem in (10), we use the iterative method in [34] as shown in Algorithm 5 to iteratively solve the problem in (18). Algorithm 5 converges to the maximum energy efficiency w.r.t. $\mathbf{P}$ and its convergence proof can be referred to [19], [26], and [34]. However, the finally achieved solution is suboptimal from the perspective of joint optimization since the problem in (18) is nonconvex.

IV. Theoretical Analysis and Comparison

In this section, we provide the analysis of upper bound of energy efficiency in an OFDM-DAS, and provide a simple choice of maximum interference temperature I as well as three baseline schemes for the comparison with the proposed scheme.

A. Upper Bound Analysis of Energy Efficiency

By using the finite form of Jensen's Inequality, we have

$$\begin{aligned} R_{\text{total}} &= \frac{1}{B_s}\sum_{k=1}^{K} R_k = \sum_{k=1}^{K}\sum_{n=1}^{N}\log_2\Big(1+\frac{\sum_{m=1}^{M} p_{k,m,n}|h_{k,m,n}|^2}{\sigma_N^2 + I}\Big) \\ &\le KN\log_2\Big(1+\frac{\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N} p_{k,m,n}|h_{k,m,n}|^2}{KN\,(\sigma_N^2+I)}\Big) \\ &\le KN\log_2\big(1+\widetilde{H}\cdot P_{\text{T}}\big) \end{aligned}$$

where $\widetilde{H} = \frac{1}{KN\,(\sigma_N^2+I)}\max_{k\in\mathcal{K},m\in\mathcal{M},n\in\mathcal{N}}\{|h_{k,m,n}|^2\}$ and $P_{\text{T}} = \sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N} p_{k,m,n} \in \mathcal{X} \triangleq \big[0, \sum_{m=1}^{M} p_m^{\max}\big]$. Thus, the energy efficiency of an OFDM-DAS in (9) satisfies

$$\eta_{EE} \le \frac{\beta_1 \log_2\left(1+\widetilde{H}\cdot P_{\mathrm{T}}\right)}{P_{\mathrm{T}}+\beta_2 \log_2\left(1+\widetilde{H}\cdot P_{\mathrm{T}}\right)+\beta_3} \triangleq g(P_{\mathrm{T}}) \quad (37)$$

where $\beta_1 = \tau_d KN$, $\beta_2 = \tau_d \tau_r B_s KN$ and $\beta_3 = \tau_d[M\cdot P_c + (M-1)\cdot P_{BH}]$.

Moreover, $g(P_T)$ $(P_T \in \mathcal{X})$ is either strictly increasing or first strictly increasing and then strictly decreasing with the increase of P_T. To get the maximum value of $g(P_T)$, denoted by $g_{\max} = \max_{P_T\in\mathcal{X}} g(P_T)$, it is not difficult to show that $\widetilde{P}_T = \arg\max_{P_T\in\mathcal{X}} g(P_T) = \min\{\widetilde{y}, \sum_{m=1}^{M} p_m^{\max}\}$, where $\widetilde{y}$ is the only nonnegative root of the equation $[y+(\widetilde{H})^{-1}]\cdot \ln 2\cdot\log_2(1+\widetilde{H}\cdot y) - y - \beta_3 = 0, y \ge 0$, and can be obtained with the widely used bisection method. Clearly, we have $\eta_{EE} \le g(P_T) \le g_{\max}$. Thus, $g_{\max}$ is an upper bound of energy efficiency η_{EE}. Note that the upper bound $g_{\max}$ is loose to some extent due to the strict conditions on making the above derived inequalities become equalities, but it provides a limit on the energy efficiency that the system can achieve. Besides, the upper bound $g_{\max}$ can be predetermined and is either a constant or increasing to a constant with the increase of P_T.

B. Choice of Maximum Interference Temperature I

To choose a proper maximum interference temperature I, we provide a simple method by deriving a lower bound of I based on the analysis of the constraints in the system. By adding up all the constraints in (10h), we can get $\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N} p_{k,m,n}|h_{k,m,n}|^2 \le \frac{KN}{K-1}I$. By adding up all the constraints in (10d), we can get $\frac{1}{B_s}\sum_{k=1}^{K} C_k^{\min} \le \sum_{k=1}^{K}\sum_{n=1}^{N}\log_2\left(1+\frac{\sum_{m=1}^{M} p_{k,m,n}|h_{k,m,n}|^2}{\sigma_N^2+I}\right) \le KN\log_2\left(1+\frac{\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{n=1}^{N} p_{k,m,n}|h_{k,m,n}|^2}{KN(\sigma_N^2+I)}\right)$.

Thus, based on the above two derived inequalities, we can get $\frac{1}{B_s}\sum_{k=1}^{K} C_k^{\min} \le KN\log_2(1+\frac{I}{(K-1)(\sigma_N^2+I)})$. Then we can get

$$\frac{I}{\sigma_N^2} \ge \frac{(K-1)\varpi}{1-(K-1)\varpi} \ge 0 \quad (38)$$

where $\varpi = 2^{\frac{1}{KNB_s}\sum_{k=1}^{K} C_k^{\min}} - 1$. Thus, the above in (38) provides a necessary condition that a chosen proper I needs to satisfy.

C. Baseline Schemes

To the best of the authors' knowledge, this paper presents the first study of the formulated problem in (10) and other energy-efficient resource allocation schemes in existing studies cannot be directly applied to solve the problem in (10). Thus, from the perspective of optimization, we theoretically compare our proposed resource allocation scheme with two other resource allocation schemes with different optimization objectives in the same OFDM-DAS, denoted as Scheme 1 and Scheme 2, respectively. Besides, we carefully modify the adopted method in [19] to solve the energy-efficient resource allocation problem in this paper, denoted as Scheme 3. The three baseline schemes are described as follow:

- Scheme 1: To minimize the overall transmit power for min-rate guaranteed services as similar in [22] and [41], the problem of which can be expressed as

$$\min_{\mathbf{P}\in\mathbb{R}^{K\times N\times M}} P_T = \sum_{k=1}^{K}\sum_{n=1}^{N}\sum_{m=1}^{M} p_{k,n,m} \quad (39a)$$

$$s.t. \text{ the same with (10b)-(10h).} \quad (39b)$$

- Scheme 2: To maximize the overall transmission data rate for min-rate guaranteed services as similar in [22], [42], and [43], the problem of which can be expressed as

$$\max_{\mathbf{P}\in\mathbb{R}^{K\times N\times M}} \sum_{k=1}^{K} R_k \quad (40a)$$

$$s.t. \text{ the same with (10b)-(10h).} \quad (40b)$$

Scheme 3: Based on the main idea of the used method in [19] by relaxing the binary variables, we carefully modify it to solve the same energy efficiency optimization problem in this paper.

In terms of Scheme 1, Scheme 2 and Scheme 3 used for comparison with our proposed scheme, we provide some remarks as below.

Remark 1: Scheme 1 can be regarded as one special case of our proposed scheme by setting $\Omega = 0$ and $\tau_r = 0$ in (13a), since minimizing the overall power consumption P_{Total} is equivalent to minimizing sum transmit power P_T based on (8). Scheme 2 can also be regarded as one special case of our proposed scheme by setting $\Omega = 1$ and $\tau_r = 0$ in (13a).

Remark 2: The proposed scheme is usually the case where $0 < \Omega < 1$, which indicates the tradeoff between energy consumption and spectral efficiency, thereby achieving high energy efficiency while improving spectral efficiency compared with Scheme 1 and reducing energy consumption compared with Scheme 2.

Remark 3: The relaxation of binary variables for the selection of RAUs or subcarriers in Scheme 3 is a widely used method to solve similar types of mixed 0-1 optimization problem. However, the proposed scheme can avoid the relaxation by exploring the inner mathematical relation between the power allocation and the joint selection of RAUs and subcarriers as shown in (6) and (7), which provides some new insights in designing joint resource allocation schemes.

Thus, based on *Remark 1*, both Scheme 1 and Scheme 2 are the special cases of our proposed scheme, and they can also be achieved by using our proposed Algorithm 4 to get suboptimal solutions due to the nonconvexity of the problems in (39) and (40).

V. NUMERICAL RESULTS

In this section, we evaluate the performance of our proposed energy-efficient joint antenna-subcarrier-power allocation scheme in an OFDM-DAS by comparing the proposed

TABLE I
SYSTEM PARAMETERS

Parameter	Parameter value
System bandwidth B	2.5 MHz
Number of RAUs M	4
Number of subcarriers N	128
Carrier Center Frequency	2.5 GHz
Cell radius D	1km
Path loss exponent γ	3.7
Lognormal shadowing σ_{sh}	8 dB
Noise power density	-174 dBm/Hz
Drain efficiency τ_d	20%
Backhaul link capacity $C^{\max}$	50 Mbps
Dynamic circuit power per unit rate τ_r	2 W/Mbps
Static circuit power per RAU P_c	30 dBm
Average power per backhaul link P_{BH}	40 dBm

TABLE II
MIN-RATE CONSTRAINTS

Rate levels	Minimum rate value	Number of users
Level 1	64Kbps	K_1
Level 2	128Kbps	K_2
Level 3	384Kbps	K_3
Level 4	1024Kbps	K_4

scheme with Scheme 1, Scheme 2 and Scheme 3 via Monte-Carlo simulations. As in [8]–[10], we set the polar coordinate of the center BS/RAU 1 as $(0, 0)$ and the other RAUs' polar coordinates as $(\frac{3-\sqrt{3}}{2}D, \frac{2\pi(m-2)}{M-1})$, $m = 2, ..., M$. Besides, the users are assumed to be uniformly distributed in the cell. The RAUs have the identical maximum transmit power and backhaul link capacity, i.e., $p_m^{\max} \equiv p^{\max}$ for $\forall m \in \mathcal{M}$, and $C_m^{\max} \equiv C^{\max}$ for $\forall m \in \mathcal{M} \setminus \{1\}$. Different categories of users' services require different levels of minimum transmission rates. For illustration purpose, the system parameters and min-rate constraints are shown in Table I based on [8]–[10], [25], and [26], and Table II [44], respectively. In Table II, four different levels of service requirements are considered, i.e., they may be VoIP (Level 1), web-browsing (Level 2), video-watching (Level 3) and file-download (Level 4) [44]. As a result, we have $\sum_{i=1}^{4} K_i = K$ in Table II. Without loss of generality, we assume that the given users' rate levels are in the ascending order and increase with the users' indices. After the joint resource allocation solution is derived, we substitute it into the original rate function $r_{k,n}$ in (3) to compute the achievable sum data rate, sum consumed power as well as energy efficiency in the system. All the simulation results are averaged over 100 random channel realizations.

A. Effects of Different Maximum Interference Temperature I

In this section, we explore the effects of the value of I on the system energy efficiency. Seen from Section II-A, the maximum interference temperature I, which is the key for making the data rate function concave and easier to attain its exact expression as well as making the problem in (10) much easier to solve, is very important in the proposed energy-efficient resource allocation scheme. The value of I gives a limit on the received interference power from other pairs of

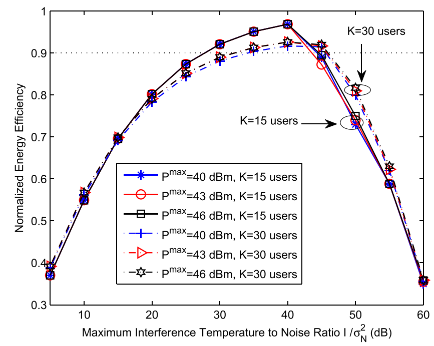


Fig. 2. Normalized energy efficiency versus maximum interference temperature to noise ratio I/σ_N^2 for different maximum transmit power $p^{\max}$ and user number K.

RAUs and users by controlling the amount of interference temperature[2] [19], [30]. Fig. 2 compares the normalized energy efficiency of the proposed scheme versus the value of I for different maximum transmit power $P^{\max}$ and user number K. Here, all the required minimum data rates of the users are set at Level 2. Besides, the x-axis is the interference temperature to noise ratio I/σ_N^2, while the y-axis is normalized by an upper bound on the energy efficiency in the system.[3] From Fig. 2, for a wide range of I/σ_N^2 values, we can achieve more than 90% of the upper bound performance while achieving the benefits of introducing I. Moreover, the choice of I is mainly dependent on the user number, which can be explained that a greater value of I/σ_N^2 can be tolerated for a larger number of users since the selected users can better deal with the co-channel interference in each subcarrier due to multiuser diversity [19], [30]. As well, the optimal value of I/σ_N^2 is not sensitive to $p^{\max}$ when $p^{\max}$ is relatively large.

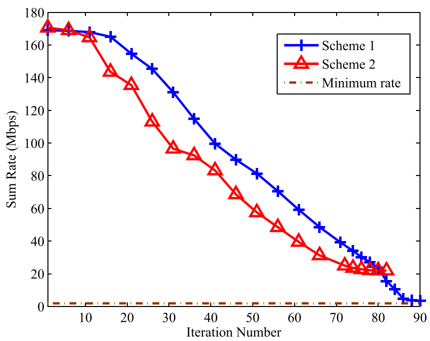
In the following evaluations, a fixed value of I is chosen for the proposed scheme in each simulation point so that we always achieve more than 90% of the average energy efficiency of the upper bound performance.

B. Convergence Performance of Algorithms

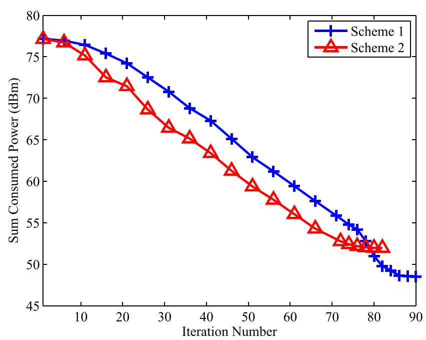
Figures 3 and 4 illustrate the evaluation of ADMM in Algorithm 4 and the adopted iterative method in Algorithm 5, respectively. Here, we set the user number $K = 8$, users' required rate levels $(K_1, K_2, K_3, K_4) = (4, 2, 1, 1)$ and the maximum transmit power $p^{\max} = 36\,$dBm. Besides, since the parameter Ω is fixed in Algorithm 4, we use Scheme 1 and Scheme 2 to evaluate the convergence performance of Algorithm 4. As shown in Fig. 3, Algorithm 4 converges at most 90 iterations. Specifically, In Scheme 1, both sum rate and sum consumed power decrease significantly in [10, 70] iterations and then gradually converge to satisfy the given convergence precision. In Scheme 2, both sum rate and sum

[2] In practice, proper values of I for implementing the proposed scheme can be found in an off-line manner.

[3] To obtain the upper bound, we remove the constraints in (10f), (10g) and (10h) from the problem in (10), and solve the problem by using the method in Algorithm 5 and the high-complexity near-optimal spectrum balancing method from [45]. Note that the method in [45] for solving non-convex optimization problems in multiuser systems converges slowly and is computationally infeasible for large-scale systems [19].

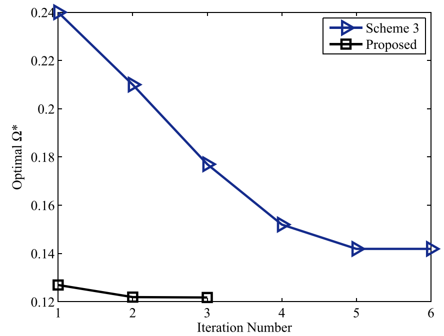


(a) Sum rate

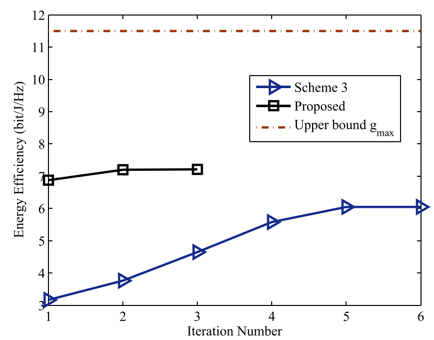


(b) Sum consumed power

Fig. 3. Sum rate and sum consumed power versus iteration number with Algorithm 4, where $p^{\max} = 36\,\text{dBm}$.



(a) Ω



(b) Energy efficiency

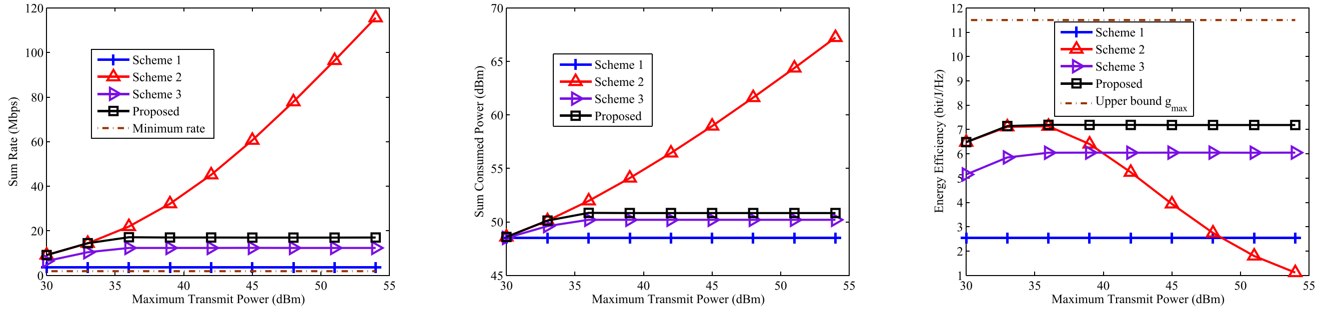
Fig. 4. Ω and energy efficiency versus iteration number with Algorithm 5, where $p^{\max} = 36\,\text{dBm}$.

consumed power also rapidly decrease in [10, 80] iterations and then gradually converge. Besides, at the beginning of the iterative procedure of Algorithm 4, given the upper bound of sum transmit power (i.e., $M \cdot P^{\max}$), both sum rate and sum consumed power may be relatively large since the obtained power matrix $\mathbf{P}$ only satisfies part of all the considered constraints. Seen from Fig. 4, the parameter $\boldsymbol{\Omega}$ and energy efficiency in the adopted Algorithm 5 converge within 3 iterations while those in Scheme 3 need 6 iterations to converge, which indicates that the proposed scheme has better convergence performance than Scheme 3.

C. Effects of Different Maximum Transmit Power

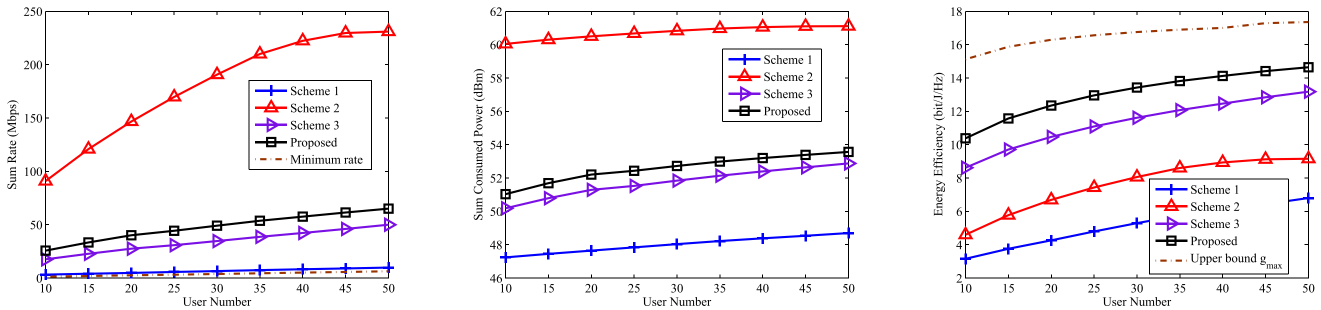
Figure 5 compares the system's sum rate, sum consumed power and energy efficiency versus maximum transmit power $p^{\max}$ in the considered four schemes. Here, we also set the user number $K = 8$ and users' required rate levels $(K_1, K_2, K_3, K_4) = (3, 2, 1, 2)$. From Fig. 5, as the maximum transmit power increases, Scheme 1 only achieves the identical corresponding sum rate that is slightly greater than the required minimum sum rate, consumes identical corresponding sum transmit power, and thus respectively achieves identical corresponding energy efficiency. However, with the increase of maximum transmit power in Scheme 2, both the sum rate and sum consumed power increase significantly, while the achieved energy efficiency firstly increases to a maximum value (at $p^{\max} = 36$ dBm) and then decreases significantly. Moreover, in Scheme 3 and the proposed scheme, all the achieved sum rate, consumed sum transmit power and achieved energy efficiency firstly increase to be maximum and then become constants as the maximum transmit power increases. Most importantly, the energy efficiency with the proposed scheme is no less than or much higher than that with Scheme 1, Scheme 2 and Scheme 3, that is, the proposed scheme has the best performance on energy efficiency. Specifically, when the maximum transmit power is relatively low (i.e., less than 36 dBm), the achieved energy efficiency by Scheme 2 and the proposed scheme is very close for any fixed maximum transmit power, which indicates that the proposed scheme is approximate to Scheme 2. However, when the maximum transmit power is relatively high (e.g. greater than 36 dBm) and increases, the difference between the energy efficiency achieved by Scheme 2 and the proposed scheme significantly goes up.

Specifically, given the maximum transmit power $p^{\max} = 36$dBm where all the considered four schemes achieve their maximum energy efficiency, compared with Scheme 1, the proposed scheme achieves 383.3% higher sum rate, consumes 71.4% higher sum consumed power, but achieves 183.4% higher energy efficiency. Besides, compared with Scheme 2, the proposed scheme achieves 22.0% less sum rate, consumes 22.9% less sum consumed power, but achieves 0.8% higher energy efficiency, respectively. Compared with Scheme 3, the proposed scheme achieves 38.7% higher sum rate, consumes 15.9% higher sum consumed power, but achieves 18.0% higher energy efficiency, respectively. Therefore, the proposed scheme can effectively achieve the fundamental tradeoff among the spectral



(a) Sum rate (b) Sum consumed power (c) Energy efficiency

Fig. 5. Sum rate, sum consumed power and energy efficiency versus maximum transmit power $p^{\max}$.



(a) Sum rate (b) Sum consumed power (c) Energy efficiency

Fig. 6. Sum rate, sum consumed power and energy efficiency versus user number, where $p^{\max} = 46$dBm.

efficiency, energy consumption and energy efficiency in the OFDM-DAS.

D. Effects of Different User Numbers

Figure 6 compares the system's sum rate, sum consumed power and energy efficiency versus user number in the considered four schemes. Here, we set the maximum transmit power $p^{\max} = 46\,$dBm and all the users' required minimum data rate levels are at Level 2, i.e., $(K_1, K_2, K_3, K_4) = (0, K, 0, 0)$. From Fig. 6, as the user number increases, all the sum rate, sum consumed power and energy efficiency in all the four schemes increase. In particular, with the increase of user number, Scheme 1 achieves gradually increasing sum rate that is slightly greater than the required minimum sum rate, while the sum rate in Scheme 2 is first rapidly increasing and then nearly keep unchanged due to the limits of interference and backhaul link capacity. Mostly importantly, Scheme 3 and the proposed scheme outperforms Scheme 1 and Scheme 2 on energy efficiency, but the proposed scheme achieves the best performance on energy efficiency among the four schemes.

Specifically, given the user number $K = 15$, compared with Scheme 1, the proposed scheme achieves 718.1% higher sum rate, consumes 165.5% higher sum consumed power, but achieves 208.1% higher energy efficiency. Compared with Scheme 2, the proposed scheme achieves 72.4% less sum rate, consumes 86.2% less sum consumed power, but achieves 100.3% higher energy efficiency. Besides, compared with Scheme 3, the proposed scheme achieves 46.8% higher sum rate, consumes 23.0% higher sum consumed power, but achieves 18.8% higher energy efficiency. Therefore, the proposed scheme can also achieve the effective tradeoff among the spectral efficiency, energy consumption and energy efficiency in the OFDM-DAS.

VI. Conclusions

In this paper, we have explored the energy-efficient joint antenna-subcarrier-power allocation for min-rate guaranteed services in the downlink multiuser OFDM-DASs with limited backhaul capacity, transformed the problem into an equivalent problem based on nonlinear fractional programming, used ADMM to split the transformed optimization problem into a series of simpler subproblems where their optimal or suboptimal solutions can be easily achieved, and proposed the corresponding methods to solve the subproblems with low complexity as well as the whole problem to achieve energy efficiency performance gains in OFDM-DASs. Numerical results have shown that the proposed algorithm has good convergence performance. Moreover, compared with Scheme 1 (to minimize the overall transmit power), Scheme 2 (to maximize the overall transmission data rate) and Scheme 3 (modified from the used method in [19]), the proposed suboptimal scheme achieves good performance on energy efficiency as well as spectral efficiency and energy consumption, which is important in designing energy-efficient wireless communication systems.

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