Adaptive Energy-Efficient Power Allocation in Green Interference Alignment Based Wireless Networks

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Abstract—Interference alignment (IA) is a promising technique for interference management in wireless networks. However, the sum rate may fall short of the theoretical maximum especially at low signal-to-noise ratio (SNR) levels since IA mainly concentrates on mitigating the interference, instead of improving the quality of desired signal. Moreover, most of the previous works focused on improving spectrum efficiency, but the energy efficiency aspect is largely ignored. In this paper, an adaptive energy-efficient IA algorithm is proposed through power allocation and transmission-mode adaptation for green IA-based wireless networks. The power allocation problem for IA is first analyzed, then we propose a power allocation scheme that optimizes the energy efficiency of IA-based wireless networks. When SNR is low, the transmitted power of some users may become zero. Thus the users with low transmitted power are turned into the sleep mode in our scheme to save energy. The transmitted power and transmission mode of the remaining active users are adapted again to further improve the energy efficiency of the network. To guarantee the interests of all the users, fairness among users is also considered in the proposed scheme. Simulation results are presented to show the effectiveness of the proposed algorithm in improving the energy efficiency of IA-based wireless networks.

Index Terms—Interference alignment, energy efficiency, power allocation, transmission-mode adaptation, fairness

I. INTRODUCTION

INTERFERENCE alignment (IA) is an emerging technique for interference management in wireless networks [1], [2]. In IA-based wireless networks, the transmitted signals are coordinated to concentrate interferences in certain subspaces at the unintended receivers, and thus interference-free subspaces are opened up for the desired signal at each receiver [3]. In [1], degrees of freedom (DoFs) and sum rate of the K-user IA-based network were analyzed. Based on the reciprocity of wireless networks, some iterative distributed algorithms were proposed for IA in [4]. Due to its promising performance in

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solving the interference problem in multiuser communication systems, IA has been applied to several wireless networks successfully [5], [6], [7], [8], [9]. However, there are still some challenges when IA is leveraged in practical networks that may be summarized as follows [10]:

- The received signal-to-interference-plus-noise ratio (SINR) may decrease in IA-based networks [4], [11], [12], [7], [8], [13], and thus quality of service (QoS) of the systems cannot be satisfied.
- The closed-form expressions of the IA solutions are difficult to obtain, especially when the number of users K is larger than 3. Furthermore, easy-implemented algorithms with reliable performance should be designed [4], [14], [15].
- Accurate channel state information (CSI) of the whole network should be available at all the transceivers to get the solutions of IA, which is difficult to achieve in practical wireless systems [16], [17], [18], [19], [20].

One of the most challenging issues mentioned above is the SINR decrease, because it will affect the QoS and sum rate of the network directly. The sum rate over interference channel when using IA can approach the channel' sum capacity at very high signal-to-noise ratio (SNR). However, it may fall short of the theoretical maximum at moderate and low SNRs [10], [12], since IA mainly concentrates on mitigating the interference, without involving the quality of desired signal.

Several research works have been conducted to improve the sum rate or QoS of IA-based networks at low SNR through improving the quality of desired signal [4], [11], [12], [7], [8], [13]. A Max-SINR algorithm for IA was proposed in [4] to maximize the SINR of the received signal, and thus improve the sum rate of interference networks especially at low SNR. However, its advantage tends to be lost when SNR becomes larger. The authors of [11] proposed an iterative IA algorithm that aims at finding the solutions maximizing the average sum rate. The reason why the received SINR in IA-based networks decreases dramatically at low SNR was analyzed in [12], and an antenna-switching IA scheme was proposed to improve the sum rate. In [7], [8], [13], resources in the network were scheduled properly to optimize the performance of IA, however, they are effective only when additional resources are available in the network to allocate. Note that in the above-mentioned research works, namely [4], [11], [12], [7], [8], [13], equal power allocation scheme is adopted in the IA-based networks. Power allocation can be an important side to

leverage to further improve the sum rate of IA.

Power allocation (PA) can be utilized to optimize the throughput of the wireless network through allocating appropriate transmitted power to each user[21]. Waterfilling algorithm is a famous strategy to achieve optimal power allocation [22], which is easy to realize. However, when the structure of the network and the objective function become more complex, waterfilling algorithm is no longer suitable to be used, and more complex optimization problem should be solved [23], [24]. As green communication becomes more and more important for the next generation wireless network, power allocation has also been leveraged to optimize the *energy efficiency* (EE) of the network [25], [26].

Recently, power allocation and control have also been applied to IA to improve its performance [27], [28], [29]. An improved blind IA was proposed in [27], which can increase the SINR by simply changing the power allocation in the transmitted signal. The authors of [28] proposed a distributed power control algorithm for IA-based wireless networks, in order to guarantee the data transmission at a fixed data rate for each user. A PA scheme was proposed for IA in [29] through using grid search and game theory, and the sum rate of the network can be optimized. However, all of these PA algorithms for IA focus on optimizing the sum rate, i.e., spectrum efficiency, instead of energy efficiency.

Nowadays, due to the rapidly rising energy costs and contributions to global CO_2 emissions, energy efficiency is becoming an important design criterion in green wireless communications [30], [25], [31], [32]. Thus dramatic improvements in EE will be needed, and new tools for optimizing the EE of the wireless networks will be essential. Although some excellent works have been done on IA-based wireless networks, to the best of our knowledge, the EE issue is largely ignored in the existing IA studies.

In this paper, we propose an adaptive energy-efficient interference alignment (AEEIA) algorithm for green IA-based wireless networks. The main contributions of this paper are summarized as follows.

- Unlike the existing works that focused on spectrum efficiency, we have done some fundamental research on the energy efficiency aspect of linear IA-based wireless networks in this paper.
- The spectrum-efficient power allocation problem for IA-based wireless networks is analyzed in detail, and an energy-efficient power allocation algorithm is then proposed specially for IA.
- It is shown that, when SNR is low, the transmitted power of some users may become zero. Therefore, based on the results of PA, a dynamic user sleep mode control (DUSMC) algorithm is proposed to improve the EE of IA-based networks.
- To further improve the EE of IA-based wireless networks, a transmission-mode adaption algorithm is proposed according to the results of DUSMC, and the transmitted power of active users is reallocated.
- In the proposed AEEIA algorithm, users with low transmitted power will be switched into the sleep mode to improve energy efficiency. Fairness among users is also

studied in the proposed algorithm.

The rest of the paper is organized as follows. In Section II, the system model is presented. The PA algorithm is proposed to improve IA's EE in Section III. In Section IV, the DUSMC algorithm is proposed based on the results of PA. The transmission-mode adaption algorithm is proposed to further improve the EE of IA-based networks in Section V, and then the procedure of the proposed AEEIA algorithm is presented. Fairness among users of the proposed AEEIA algorithm is studied in Section VI. In Section VII, simulation results are discussed. Finally, conclusions and future work are presented in Section VIII.

Notation: $\mathbf{I}_d$ represents the $d \times d$ identity matrix. $\mathbf{A}^{\mathrm{T}}$, $\mathbf{A}^{\dagger}$, $\mathbf{A}_{\star d}$, $(\mathbf{A})_{ij}$, and $|\mathbf{A}|$ are the transpose, the Hermitian transpose, the dth column, the ijth element, and the determinant of matrix $\mathbf{A}$, respectively. $\|\mathbf{a}\|$ and $(\mathbf{a})_d$ are the ℓ^2-norm and the dth element of vector $\mathbf{a}$, respectively. $|a|$ is the absolute value of complex number a. $\mathbb{C}^{M \times N}$ is the space of complex $M \times N$ matrices. $\mathcal{CN}(\mathbf{a}, \mathbf{A})$ is the complex Gaussian distribution with mean $\mathbf{a}$ and covariance matrix $\mathbf{A}$. $\mathbb{E}(\cdot)$ stands for expectation.

II. System Description

Consider a K-user interference channel consisting K transmitters and K receivers. There exists a one-to-one correspondence between transmitters and receivers. Each transmitter of a certain user only wants to communicate with its corresponding receiver, and vice versa. In the network, $M^{[k]}$ and $N^{[k]}$ antennas are equipped at the kth transmitter and receiver, respectively. When linear IA is performed through using precoding and interference suppression matrices [1], [4], the received signal with $d^{[k]}$ data streams at the kth receiver can be expressed as

$$\mathbf{y}^{[k]}(n) = \mathbf{U}^{[k]\dagger}(n)\mathbf{H}^{[kk]}(n)\mathbf{V}^{[k]}(n)\mathbf{x}^{[k]}(n)$$
$$+ \sum_{j=1, j \neq k}^{K} \mathbf{U}^{[k]\dagger}(n)\mathbf{H}^{[kj]}(n)\mathbf{V}^{[j]}(n)\mathbf{x}^{[j]}(n) + \mathbf{U}^{[k]\dagger}(n)\mathbf{z}^{[k]}(n). \quad (1)$$

In (1), $\mathbf{H}^{[kj]}(n) \in \mathbb{C}^{N^{[k]} \times M^{[j]}}$ is the channel coefficient matrix between the jth transmitter and the kth receiver in time slot n. Each entity of $\mathbf{H}^{[kj]}(n)$ is independent and identically distributed (i.i.d.), and follows $\mathcal{CN}(0, 1)$. Block fading channel is used in this paper [33], thus the channel remains constant over each time slot. For clarity, the time slot number n is henceforth suppressed. $\mathbf{V}^{[k]}$ and $\mathbf{U}^{[k]}$ are unitary $M^{[k]} \times d^{[k]}$ precoding matrix and $N^{[k]} \times d^{[k]}$ interference suppression matrix of user k respectively, i.e., $\mathbf{V}^{[k]\dagger}\mathbf{V}^{[k]} = \mathbf{I}_{d^{[k]}}$ and $\mathbf{U}^{[k]\dagger}\mathbf{U}^{[k]} = \mathbf{I}_{d^{[k]}}$. $\mathbf{x}^{[k]} = \left[x_1^{[k]}, x_2^{[k]}, \ldots, x_{d^{[k]}}^{[k]}\right]^{\mathrm{T}}$ is the transmitted signal vector consisting $d^{[k]}$ data streams at the kth transmitter, and the $d^{[k]}$ independent data streams are multiplexed and transmitted between the kth transmitter and receiver. $\mathbf{x}^{[k]}$ has a transmitted power constraint $P_t^{[k]}$, i.e., $\mathbb{E}\left[\|\mathbf{x}^{[k]}\|^2\right] = P_t^{[k]}$. $\mathbf{z}^{[k]} \in \mathbb{C}^{N^{[k]} \times 1}$ is the additive white Gaussian noise (AWGN) vector with distribution $\mathcal{CN}(\mathbf{0}, \sigma^2 \mathbf{I}_{N^{[k]}})$, where σ^2 is the power of the AWGN at each antenna of the receivers.

When IA is feasible [34], the interferences in the network can be completely eliminated if the following conditions are satisfied [4]

$$\mathbf{U}^{[k]\dagger}\mathbf{H}^{[kj]}\mathbf{V}^{[j]} = 0, \ \forall j \neq k, \tag{2}$$

$$\text{rank}\left(\mathbf{U}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{V}^{[k]}\right) = d^{[k]}. \tag{3}$$

The desired signals of the kth user can be viewed as received through a $d^{[k]} \times d^{[k]}$ full rank channel matrix $\overline{\mathbf{H}}^{[kk]} \triangleq \mathbf{U}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{V}^{[k]}$, and (1) can be rewritten as

$$\mathbf{y}^{[k]} = \overline{\mathbf{H}}^{[kk]}\mathbf{x}^{[k]} + \overline{\mathbf{z}}^{[k]}, \tag{4}$$

where $\overline{\mathbf{z}}^{[k]} = \mathbf{U}^{[k]\dagger}\mathbf{z}^{[k]}$, and it also follows the distribution $\mathcal{CN}(\mathbf{0}, \sigma^2 \mathbf{I}_{d^{[k]}})$.

The closed-form expression of the precoding matrix $\mathbf{V}$ in IA is usually difficult to obtain, especially when the number of users in the IA-based network, K, is larger than 3 [3]. In order to develop methods to obtain the solutions of IA as the number of users increase, several distributed algorithms are proposed, including minimizing interference leakage (MinIL) and Max-SINR algorithms [4], which are adopted in this paper.

In pursuing the matrices $\mathbf{U}^{[k]}$ and $\mathbf{V}^{[k]}$, IA only focuses on condition (2) to eliminate the interferences, and does not involve the direct channel $\mathbf{H}^{[kk]}$ to maximize the desired signal power within the desired signal subspace [17]. Thus several IA algorithms have been proposed to further improve the performance of the conventional linear IA-based networks [4], [11], [12], [7], [8], [13].

Based on the above analysis, the sum rate of the IA-based network with perfect solutions can be denoted as

$$SR_p = \sum_{k=1}^{K} R^{[k]} = \sum_{k=1}^{K} \log_2 \left| \mathbf{I}_{d^{[k]}} + \frac{P_t^{[k]}}{d^{[k]}\sigma^2}\overline{\mathbf{H}}^{[kk]}\overline{\mathbf{H}}^{[kk]\dagger} \right|, \tag{5}$$

where $R^{[k]}$ is the transmission rate of user k.

However, condition (2) is difficult to satisfy perfectly when K is large. In practical systems, easy-implemented iterative IA algorithms are usually adopted, and thus interferences cannot be eliminated ideally. Furthermore, the CSI used in IA-based networks cannot be perfectly estimated and fed back, which will also lead to the imperfect solutions [16], [17], [18], [19], [20]. In these cases, the sum rate of the IA-based network with imperfect solutions can be expressed as

$$SR_{imp} = $$
$$\sum_{k=1}^{K} \log_2 \left| \mathbf{I}_{d^{[k]}} + \mathbf{U}^{[k]\dagger}\mathbf{Q}^{[k]}\mathbf{U}^{[k]}\left(\mathbf{U}^{[k]\dagger}\left(\sigma^2\mathbf{I}_{N^{[k]}} + \widetilde{\mathbf{Q}}^{[k]}\right)\mathbf{U}^{[k]}\right)^{-1} \right|. \tag{6}$$

In (6), we have

$$\mathbf{Q}^{[k]} = \frac{P_t^{[k]}}{d^{[k]}}\mathbf{H}^{[kk]}\mathbf{V}^{[k]}\mathbf{V}^{[k]\dagger}\mathbf{H}^{[kk]\dagger}, \tag{7}$$

and

$$\widetilde{\mathbf{Q}}^{[k]} = \sum_{j=1,j\neq k}^{K} \frac{P_t^{[j]}}{d^{[j]}}\mathbf{H}^{[kj]}\mathbf{V}^{[j]}\mathbf{V}^{[j]\dagger}\mathbf{H}^{[kj]\dagger}. \tag{8}$$

In most previous works, the transmitted power of each user in IA-based networks is set to be equal, i.e., $P_t^{[k]} = P_t, \forall k = 1, 2, \ldots, K$. Thus power allocation can be leveraged to further improve the performance of IA-based networks with adaptive transmitted power of each user.

III. SPECTRUM-EFFICIENT AND ENERGY-EFFICIENT POWER ALLOCATION ALGORITHMS FOR IA-BASED NETWORKS

Only a few research works have been concentrated on power allocation or control for IA-based wireless networks to improve the sum rate or guarantee the transmission rate of each user [27], [28], [29]. In this section, the PA problem in IA will be analyzed specifically, and two PA algorithms aiming at maximizing the spectrum efficiency of the network are proposed for the MinIL IA algorithm and Max-SINR algorithm, respectively [1], [4]. To the best of our knowledge, energy efficiency aspect of IA has been largely ignored in existing IA studies, and thus a PA algorithm aiming at optimizing the EE of IA is proposed in this paper. Besides, this paper mainly focuses on the PA between different users instead of DoFs, thus it is assumed that there is only one data stream for each user in the remaining parts of this paper[1].

A. Spectrum-Efficient Power Allocation

In Section II, equal transmitted power P_t is allocated to each user as usually assumed. However, this may hinder the improvement of the performance of IA-based networks. In this section, we assume that the sum transmitted power of all the users is constrained to be lower than a constant, i.e., $\sum_{k=1}^{K} P_t^{[k]} \leq P_t^{max}$.

Thus the PA problem to optimize the spectrum efficiency of IA-based networks can be formulated as follows according to (9).

$$\max_{P_t^{[1]}, P_t^{[2]}, \ldots, P_t^{[K]}} \sum_{k=1}^{K} \log_2\left(1 + \frac{\left|\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}\right|^2 P_t^{[k]}}{\sum\limits_{j=1,j\neq k}^{K}\left|\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kj]}\mathbf{v}^{[j]}\right|^2 P_t^{[j]} + \sigma^2}\right)$$

$$s.t. \quad P_t^{[k]} \geq 0, \ \forall k = 1, 2, \ldots, K$$
$$\sum_{k=1}^{K} P_t^{[k]} \leq P_t^{max}. \tag{9}$$

The optimization problem described in (9) is somewhat difficult to solve, because it involves the remaining interferences. In MinIL IA algorithms, e.g., closed-form IA [1] and iterative IA [4], solutions are achieved to force interferences to be zero, thus the optimization problem in (9) can be simplified into a waterfilling strategy with random distributed noise levels.

Theorem 1: In a K-user IA-based network with 1 data stream each user, if the interferences are eliminated perfectly, the spectrum-efficient optimization problem for PA can be deemed as a waterfilling power allocation strategy with the noise level of user k equal to $\frac{\sigma^2}{|h_k|^2}$, where $|h_k|^2 = \left|\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}\right|^2$ follows exponential distribution.

Proof: Denote $h_k \triangleq \mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}$. If perfect IA can be obtained, the interferences are thus completely eliminated, and

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[1]The PA problem among data streams of user k in IA-based networks can be easily extended, which can be deemed as the PA problem among $d^{[k]}$ antennas at the transmitter in the MIMO system of channel $\overline{\mathbf{H}}^{[kk]}$ with perfect CSI at transmitter and receiver [22], [35]. It is out the scope of this paper.

the optimization problem in (9) can be rewritten as

$$\max_{P_t^{[1]},P_t^{[2]},\ldots,P_t^{[K]}} \sum_{k=1}^{K} \log_2\left(1+\frac{|h_k|^2}{\sigma^2}P_t^{[k]}\right)$$

$$s.t. \qquad P_t^{[k]} \geq 0, \ \forall k=1,2,\ldots,K$$

$$\sum_{k=1}^{K} P_t^{[k]} \leq P_t^{max}. \qquad (10)$$

In the design of $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$, it only concentrates on the condition in (2) without considering $\mathbf{H}^{[kk]}$ in (3). Thus $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ are i.i.d., and independent of $\mathbf{H}^{[kk]}$, and we can obtain

$$\mathbb{E}\left(|h_k|^2\right) = \mathbb{E}\left[\sum_{i=1}^{N^{[k]}}\sum_{j=1}^{M^{[k]}}\left|\left(\mathbf{u}^{[k]}\right)_i\right|^2\left|\left(\mathbf{v}^{[k]}\right)_j\right|^2\left|\left(\mathbf{H}^{[kk]}\right)_{ij}\right|^2\right]$$

$$= \mathbb{E}\left[\sum_{i=1}^{N^{[k]}}\left|\left(\mathbf{u}^{[k]}\right)_i\right|^2\right]\mathbb{E}\left[\sum_{j=1}^{M^{[k]}}\left|\left(\mathbf{v}^{[k]}\right)_j\right|^2\right]\mathbb{E}\left[\left|\left(\mathbf{H}^{[kk]}\right)_{ij}\right|^2\right].(11)$$

As mentioned in Section II, $\left(\mathbf{H}^{[kk]}\right)_{ij}$ is i.i.d. $\mathcal{CN}(0,1)$, and $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ are unitary vectors, i.e., $\sum_{i=1}^{N^{[k]}}\left|\left(\mathbf{u}^{[k]}\right)_i\right|^2 = 1$ and $\sum_{j=1}^{M^{[k]}}\left|\left(\mathbf{v}^{[k]}\right)_j\right|^2 = 1$. Thus we can achieve

$$\mathbb{E}(|h_k|^2) = \mathbb{E}\left[\left|\left(\mathbf{H}^{[kk]}\right)_{ij}\right|^2\right] = 1. \qquad (12)$$

Therefore, h_k is a complex Gaussian random variable with zero mean and variance equal to 1, and $|h_k|^2$ follows exponential distribution.

Observing the optimization problem in (10), we can see that it is similar to the PA problem in multiple parallel channels. The difference is that the noise level of user k in the PA of IA-based networks is equal to $\frac{\sigma^2}{|h_k|^2}$. Thus it can be solved by the famous waterfilling PA strategy [22], and its closed-form solution can be expressed as

$$P_{t\_opt}^{[k]} = \left(\mathcal{V} - \frac{\sigma^2}{|h_k|^2}\right)^+, \qquad (13)$$

where $x^+ \triangleq \max(x,0)$, and $\mathcal{V}$ should satisfy

$$\sum_{k=1}^{K}\left(\mathcal{V} - \frac{\sigma^2}{|h_k|^2}\right)^+ = P_t^{max}. \qquad (14)$$

In (13), $P_{t\_opt}^{[k]}$ is the optimal transmitted power allocated for user k, and $|h_k|^2$ follows exponential distribution. ∎

Remark 1: In practical networks using MinIL IA algorithms, the interferences among users cannot be eliminated perfectly. However, the remaining part of the interference is trivial, and will not affect the spectrum efficiency of PA strategy obviously. Thus, the objective function in (10) can be applied to MinIL IA algorithms with little interference remaining.

In MinIL IA algorithms, the PA optimization problem can be simplified as (10) and solved by the waterfilling strategy, because $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$ are designed according to condition (2) and interferences can be assumed to be eliminated perfectly. The MinIL IA algorithms make no attempt to improve the desired signal power according to $\mathbf{H}^{[kk]}$, and thus it is not optimal at intermediate and low SNR levels.

On the contrary, if the Max-SINR algorithm for IA is leveraged to obtain the solutions of $\mathbf{u}^{[k]}$ and $\mathbf{v}^{[k]}$, condition (3) is also involved together with (2) to optimize the SINR of desired signal [4]. However, perfect alignment of interference is sacrificed in the Max-SINR algorithm, and there is some nontrivial interference remaining. Thus, the objective function (10) of the PA optimization cannot be adopted in Max-SINR algorithm, and we should use the more complicated objective function in (9) to solve it, in which the remaining interference is considered. There are many simple but effective methods for solving the optimization problems [36]. In the simulations of this paper, the interior-point method is adopted.

B. Energy-Efficient Power Allocation

The spectrum efficiency of IA-based networks can be optimized by the PA algorithms in (9) and (10), however, the energy efficiency is ignored. EE becomes an important design criterion recently in wireless communications due to rapidly rising energy consumption in information and communication technology.

Assume that in each time slot with duration T, the solutions of IA are first calculated in duration T_1, and then the transmission is performed in duration T_2. $T = T_1 + T_2$, and $T_1 \ll T_2$. The EE of IA-based networks can be defined as the transmitted information in unit frequency per Joule energy consumption (bits/Hz/Joule), and thus the PA problem aiming at maximizing the EE when interferences are assumed to be perfectly eliminated can be expressed as (15) (on the next page).

In (15), $P^{[k]}$ is the total power consumption of user k, and it comprises the transmitter-circuit power consumption $P_{ct}^{[k]}$, the receiver-circuit power consumption $P_{cr}^{[k]}$, and the transmitted power $P_t^{[k]}$ [37], [31]. As $T_1 \ll T_2$, the energy consumption in the duration T_1 of each time slot to obtain the solutions of IA is ignored when calculating the EE of the IA-based network in this paper.

To analyze the EE of the spectrum-efficient and energy-efficient PA algorithms in (10) and (15), the EE and average transmitted power of the IA-based networks are compared in Fig. 1 and Fig. 2, respectively. In these two figures, there are $K = 3$ users with 2 antennas equipped at each transceiver. $P_{cr}^{[k]}$, $P_{ct}^{[k]}$ and P_t^{max} are set to 112mW, 98mW and 300mW, respectively [37], [31].

From the results in Fig. 1, we can see that the energy-efficient PA algorithm in (15) can further improve the EE of IA-based networks compared to the spectrum-efficient PA algorithm in (10). The power allocation of the two algorithms is depicted in Fig. 2. From the results, we can see that when SNR is low, the throughput of the network is more important than the transmitted power consumed for both the EE and SE of the network, and the averaged transmitted power of the network is equal to its maximum, P_t^{max}. On the other hand, when SNR becomes larger, the throughput of the network becomes much higher, and the transmitted power consumed is much more important than the throughput of the network when the EE of the network is optimized. Thus the average transmitted power of the network in the energy-efficient PA

$$\max_{P_t^{[1]}, P_t^{[2]}, \ldots, P_t^{[K]}} \frac{\sum_{k=1}^{K} R^{[k]}}{\sum_{k=1}^{K} P^{[k]}} = \frac{\sum_{k=1}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2} P_t^{[k]}\right) \cdot T_2}{\sum_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]}\right) \cdot T_1 + \sum_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_t^{[k]}\right) \cdot T_2}$$

$$= \frac{\sum_{k=1}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2} P_t^{[k]}\right)}{\sum_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]}\right) \cdot \frac{T_1}{T_2} + \sum_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_t^{[k]}\right)} \approx \frac{\sum_{k=1}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2} P_t^{[k]}\right)}{\sum_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_t^{[k]}\right)}$$

$$s.t. \quad P_t^{[k]} \geq 0, \ \forall k = 1, 2, \ldots, K$$

$$\sum_{k=1}^{K} P_t^{[k]} \leq P_t^{max}, \tag{15}$$
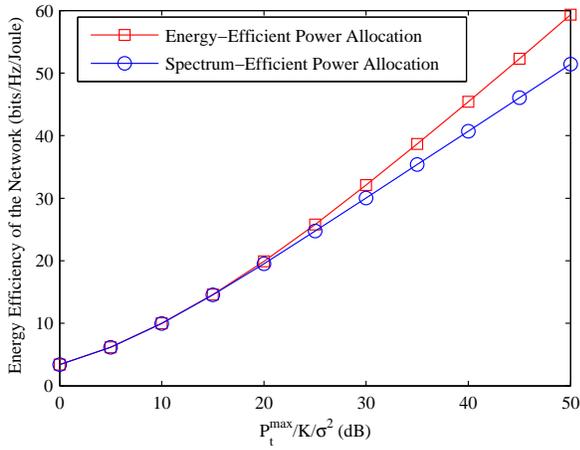
Fig. 1. Energy efficiency comparison in IA-based networks with spectrum-efficient and energy-efficient power allocation algorithms.
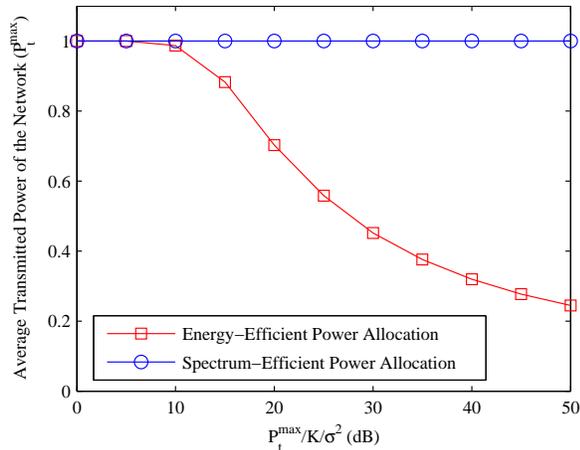
Fig. 2. Average transmitted power comparison in IA-based networks with spectrum-efficient and energy-efficient power allocation algorithms.

algorithm becomes lower with larger SNR. For the spectrum-efficient PA algorithm, the transmitted power of the network is all equal to P_t^{max} with different SNRs, since only the spectrum efficiency of the network is optimized.

IV. DYNAMIC USER SLEEP MODE CONTROL IN ENERGY-EFFICIENT IA-BASED NETWORKS

In this section, we first discuss the power allocation problem in IA-based networks. Then, we propose a dynamic user sleep mode control algorithm based on power allocation.

A. Discussions of the Power Allocation Results

The EE of IA-based networks can be significantly improved when the PA algorithm in (15) is leveraged. In this subsection, its results are further discussed in *Remark 2*. From the results in Fig. 1 and Fig. 2, we can know that the PA in algorithms (10) and (15) is almost the same when SNR is low.

Remark 2: At low SNR, the water level is shallow, and the noise levels are much higher than the received power of desired signal. Thus the transmission rate with allocating all the power to the strongest user (lowest noise level) approximates to the optimal sum rate exploiting objective function (15), and it can be denoted as

$$\begin{aligned} SR_{sole} &= \log_2\left(1 + \frac{|h_{max}|^2}{\sigma^2} P_t^{max}\right) \\ &\approx \sum_{k=1}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2} P_{t\_opt}^{[k]}\right), \end{aligned} \tag{16}$$

where $|h_{max}|^2 = \max(|h_1|^2, |h_2|^2, \ldots, |h_K|^2)$, and $P_{t\_opt}^{[k]}$ is the optimal transmitted power of user k solved by (15).

From the analysis in *Remark 2*, we can know that, when SNR becomes lower, the PA strategy tends to select the strongest user/users to communicate. Thus we further study the probability of low-power users in a 3-user IA-based network with 2 antennas equipped at each transceiver, and the results are shown in Fig. 3. In the figure, the threshold λ, below which one user can be deemed as low-power user, is set to 5%, 10%, and 20% of the average transmitted power per user $\frac{1}{K} \sum_{k=1}^{K} P_{t\_opt}^{[k]}$, respectively.

From the results in Fig. 3, it is shown that, when average SNR becomes lower, the PA of IA tends to allocate more power to the stronger user with lower noise level. When $P_t^{max}/K/\sigma^2$ is below -20dB, the transmitted power will be almost allocated to only one user definitely. Besides, the value
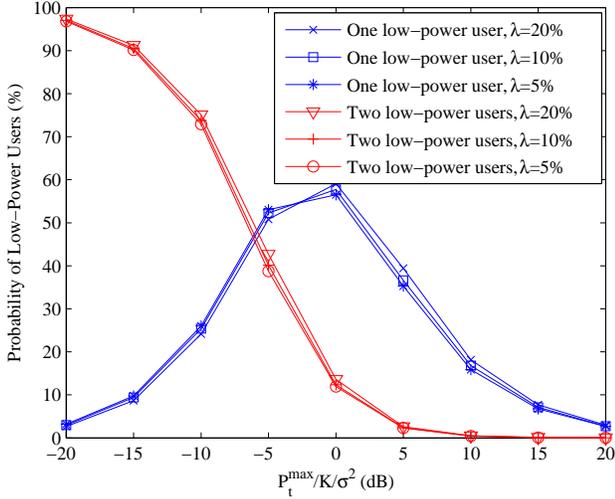
Fig. 3. Probability of low-power users in a 3-user IA-based network with 2 antennas at each transceiver. The threshold λ is set to 5%, 10%, and 20%, respectively.

of the threshold λ will not affect the number of low-power users obviously.

Therefore, we want to study the following question: Can we further improve the energy efficiency of IA-based networks based on the results of the power allocation?

B. Dynamic User Sleep Mode Control Algorithm Based on Power Allocation

When the objective function in (15) is exploited in MinIL IA algorithms, the EE of IA-based networks can be expressed as

$$EE_{IA} = \frac{\sum\limits_{k=1}^{K} R^{[k]}}{\sum\limits_{k=1}^{K} P^{[k]}} = \frac{\sum\limits_{k=1}^{K} \log_2 \left(1 + \frac{|h_k|^2}{\sigma^2} P_{t\_opt}^{[k]} \right)}{\sum\limits_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_{t\_opt}^{[k]} \right)}, \quad (17)$$

where $P_{t\_opt}^{[k]}$ is the optimal transmitted power of user k.

From the analysis in *Remark 2* and results in Fig. 3, it is shown that, when SNR is low, it tends to allocate all the transmitted power to the strongest users. Thus the transmission rate of the other users with low transmitted power is getting close to 0; however their circuit power is still consumed.

Thus a proper threshold $\lambda \in (0,1)$ can be set. If the optimal transmitted power of user k, $P_{t\_opt}^{[k]}$, is lower than $\lambda \cdot \frac{1}{K} \sum_{k=1}^{K} P_{t\_opt}^{[k]}$ in one time slot, the transmission of user k is terminated in this time slot, and it is switched into the sleep mode [37]. The circuit power can be saved in the proposed dynamic user sleep mode control (DUSMC) algorithm based on the results of PA when there exist some low-power users, and the EE of IA-based networks can be consequently improved.

Define $\mathcal{S}$ as the set that contains the users in the sleep mode in the time slot, and it can be expressed as

$$\mathcal{S} = \left\{ k : P_{t\_opt}^{[k]} < \lambda \cdot \frac{1}{K} \sum_{k=1}^{K} P_{t\_opt}^{[k]}, k = 1, 2, \cdots, K \right\}. \quad (18)$$

Thus the EE in (17) can be enhanced by the DUSMC algorithm as

$$EE_{DUSMC} = \frac{\sum\limits_{k=1,k \notin \mathcal{S}}^{K} \log_2 \left(1 + \frac{|h_k|^2}{\sigma^2} P_{t\_opt}^{[k]} \right)}{\sum\limits_{k=1,k \notin \mathcal{S}}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_{t\_opt}^{[k]} \right) + \sum\limits_{k \in \mathcal{S}} P_s^{[k]}}, \quad (19)$$

where $P_s^{[k]}$ is the power consumption of user k when it is in the sleep mode.

In the sleep mode, the power consumption of users in IA-based networks mainly results from the leaking current of the switching transistors with the circuits properly designed [37]. The power consumption of leaking current is usually much lower than the circuit power consumption in the active mode, and thus it is neglected in the proposed algorithms in this paper, i.e., $P_s^{[k]} = 0$. The analysis and simulation can be easily modified when the power consumption in the sleep mode is considered. Thus we can obtain

$$EE_{DUSMC} \approx \frac{\sum\limits_{k=1,k \notin \mathcal{S}}^{K} \log_2 \left(1 + \frac{|h_k|^2}{\sigma^2} P_{t\_opt}^{[k]} \right)}{\sum\limits_{k=1,k \notin \mathcal{S}}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_{t\_opt}^{[k]} \right)} \geq EE_{IA}. \quad (20)$$

In (20), the second equality holds when $\mathcal{S} = \varnothing$.

The value of threshold λ is important in the DUSMC algorithm, and it will affect the EE of IA-based wireless networks. It is analyzed in detail in Theorem 2.

Theorem 2: In the DUSMC algorithm with the same circuit power for each user, if $0 < \lambda_1 < \lambda_2 \ll 1$, then $EE_{DUSMC}(\lambda_1) \leq EE_{DUSMC}(\lambda_2)$.

Proof: Define $\mathcal{S}_1$ and $\mathcal{S}_2$ as the sets of the sleep-mode users corresponding to λ_1 and λ_2, respectively. From the definition of $\mathcal{S}$ in (18), we can know that $\mathcal{S}_1 \subseteq \mathcal{S}_2$ with Q elements in $\mathcal{S}_1$. Without loss of generality, we assume that $\mathcal{S}_2 \setminus \mathcal{S}_1 = \{1, 2, \ldots, i\}, i \geq 1$ when $\mathcal{S}_1 \subset \mathcal{S}_2$. Thus from (20) we can obtain

$$EE_{DUSMC}(\lambda_1) = \frac{\sum\limits_{k=1,k \notin \mathcal{S}_1}^{K} \log_2 \left(1 + \frac{|h_k|^2}{\sigma^2} P_{t\_opt}^{[k]} \right)}{\sum\limits_{k=1,k \notin \mathcal{S}_1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_{t\_opt}^{[k]} \right)}. \quad (21)$$

Assume that the circuit power consumption of all the users is the same, and we have $P_{ct}^{[1]} = P_{ct}^{[2]} = \cdots = P_{ct}^{[K]} = P_{ct}$ and $P_{cr}^{[1]} = P_{cr}^{[2]} = \cdots = P_{cr}^{[K]} = P_{cr}$.

(1) $\mathcal{S}_1 = \mathcal{S}_2$

The users in the sleep mode with thresholds λ_1 and λ_2 are the same, thus we have $EE_{DUSMC}(\lambda_1) = EE_{DUSMC}(\lambda_2)$.

(2) $\mathcal{S}_1 \subset \mathcal{S}_2$

Assume that the total transmitted power of the users with threshold λ_2 is $P_{t\_\lambda_2}$, (21) can be rewritten as (22) (on the next page). In (22), when $0 < \lambda_1 < \lambda_2 \ll 1$, we have $P_{t\_opt}^{[j]} \ll P_{t\_opt}^{[k]}$ and $|h_j|^2 \ll |h_k|^2$, $k \in \{1, 2, \ldots, K\} \setminus$

$$EE_{DUSMC}(\lambda_1) = \frac{\sum\limits_{k=1,k\notin\mathcal{S}_2}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2}P_{t\_opt}^{[k]}\right) + \sum\limits_{j=1}^{i} \log_2\left(1 + \frac{|h_j|^2}{\sigma^2}P_{t\_opt}^{[j]}\right)}{(K-Q-i)(P_{ct}+P_{cr}) + i(P_{ct}+P_{cr}) + P_{t\_\lambda_2} + \sum\limits_{j=1}^{i}P_{t\_opt}^{[j]}}. \tag{22}$$
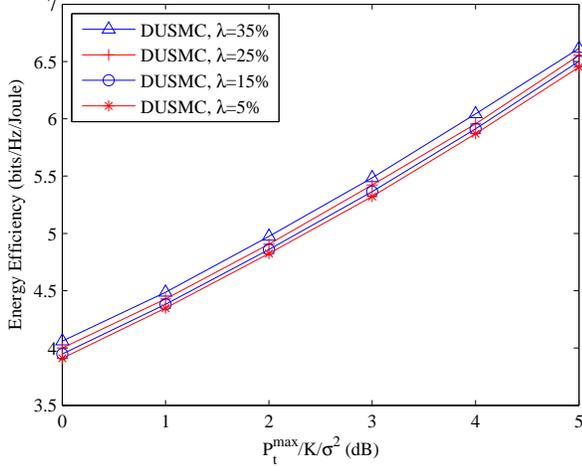

Fig. 4. Energy efficiency comparison of a 3-user IA-based network when the DUSMC algorithm is performed with λ equal to 5%, 15%, 25%, and 35%, respectively.

$\mathcal{S}_2, j = 1, 2, \ldots, i$. Thus (22) can be changed into

$$\begin{aligned}
EE_{DUSMC}(\lambda_1) &\approx \frac{\sum\limits_{k=1,k\notin\mathcal{S}_2}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2}P_{t\_opt}^{[k]}\right)}{(K-Q-i)(P_{ct}+P_{cr}) + i(P_{ct}+P_{cr}) + P_{t\_\lambda_2}} \\
&< \frac{\sum\limits_{k=1,k\notin\mathcal{S}_2}^{K} \log_2\left(1 + \frac{|h_k|^2}{\sigma^2}P_{t\_opt}^{[k]}\right)}{(K-Q-i)(P_{ct}+P_{cr}) + P_{t\_\lambda_2}} \\
&= EE_{DUSMC}(\lambda_2). \tag{23}
\end{aligned}$$

∎

In Theorem 2, it is reasonable to assume $0 < \lambda_1 < \lambda_2 \ll 1$ in practical wireless communication systems to guarantee the fairness among users in IA-based wireless networks, i.e., we switch the user to the sleep mode only when the allocated transmitted power is extremely low.

The energy efficiency of a 3-user IA-based network when the DUSMC algorithm is performed with different values of λ is shown in Fig. 4. From the results, we can see that the energy efficiency of the IA-based network increases with larger λ, which is consistent with Theorem 2. However the difference of the energy efficiency with different values of λ is trivial.

Besides, although the value of threshold λ can affect the EE of IA-based networks, the number of sleep-mode users changes slightly according to the results in Fig. 3. Thus λ is set to 5% in the simulations part of this paper.

The analysis in this subsection uses the objective function (15) of MinIL IA algorithms for simplicity of analysis, and it can also be extended to Max-SINR algorithm similarly if the remaining interference is not marginal.

V. TRANSMISSION-MODE ADAPTATION BASED ON THE DUSMC ALGORITHM

In the DUSMC algorithm, when $\mathcal{S} \neq \varnothing$, some low-power users switch into the sleep mode based on the results of PA, and the EE can be improved. The number of active users N_a is smaller than the feasible number of users K [34], i.e., $N_a < K$, and the desired signal subspace is thus expanded. We can fully exploit the expanded desired signal subspace to further improve the EE of IA-based wireless networks. Therefore, a transmission-mode adaption algorithm is proposed in this section.

A. $N_a > 1$

If there are more than one active users remaining after the DUSMC algorithm is performed, we can obtain the solutions of IA again through using the Max-SINR algorithm [4] and reallocate the transmitted power of N_a active users according to the objective function (9) to further improve the EE of IA-based networks.

Assume that the regenerated solutions with the Max-SINR algorithm is $\hat{\mathbf{u}}^{[k]}$ and $\hat{\mathbf{v}}^{[k]}$, $k = 1, 2, \ldots, K, k \notin \mathcal{S}$, and we can express the SINR of user k without PA and DUSMC algorithm as in (24) (on the next page). PA is not considered here for simplicity of analysis.

The second inequality in (24) holds because the subspace of the desired signal is expanded as the number of users that share the whole signal subspace decreases, and the Max-SINR algorithm is leveraged to involve the power of the desired signal and interference simultaneously and fully exploit the subspace resource.

After $\hat{\mathbf{u}}^{[k]}$ and $\hat{\mathbf{v}}^{[k]}$ are achieved by the Max-SINR algorithm, $k \notin \mathcal{S}$, energy-efficient PA algorithm is reused to obtain the final solutions as (25) (on the next page).

B. $N_a = 1$

If there is only one active user remaining after the DUSMC algorithm, we can know that it is equivalent to a single-input and single-output (SISO) Rayleigh fading channel from the proof of Theorem 1. Thus the advantage of multiple-input and multiple-output (MIMO) disappears even when there is only one user communicating in the IA-based network.

Therefore, we should change the transmission mode from IA to MIMO when there is only one user after the DUSMC algorithm is performed. The user with the highest transmission rate of MIMO mode will be selected solely to communicate in the time slot, and it can be expressed as [22], [35]

$$R_{MIMO} = \max_i \left(\log_2\left|\mathbf{I}_{N^{[i]}} + \frac{P_t^{max}}{\sigma^2}\mathbf{H}^{[ii]}\mathbf{B}^{[i]}\mathbf{H}^{[ii]\dagger}\right|\right), \tag{26}$$

$$SINR^{[k]} = \frac{\left|\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}\right|^2 P_t^{max}/K}{\left|\sum\limits_{j=1,j\neq k}^{K}\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kj]}\mathbf{v}^{[j]}\right|^2 P_t^{max}/K + \sigma^2} < \frac{\left|\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}\right|^2 P_t^{max}/K}{\left|\sum\limits_{j=1,j\neq k,j\notin\mathcal{S}}^{K}\mathbf{u}^{[k]\dagger}\mathbf{H}^{[kj]}\mathbf{v}^{[j]}\right|^2 P_t^{max}/K + \sigma^2}$$

$$< \frac{\left|\widehat{\mathbf{u}}^{[k]\dagger}\mathbf{H}^{[kk]}\widehat{\mathbf{v}}^{[k]}\right|^2 P_t^{max}/K}{\left|\sum\limits_{j=1,j\neq k,j\notin\mathcal{S}}^{K}\widehat{\mathbf{u}}^{[k]\dagger}\mathbf{H}^{[kj]}\widehat{\mathbf{v}}^{[j]}\right|^2 P_t^{max}/K + \sigma^2} = \widehat{SINR}^{[k]}. \tag{24}$$

$$\max_{P_t^{[k]},k\notin\mathcal{S}} \frac{\sum\limits_{k=1,k\notin\mathcal{S}}^{K}\log_2\left(1 + \frac{\left|\widehat{\mathbf{u}}^{[k]\dagger}\mathbf{H}^{[kk]}\widehat{\mathbf{v}}^{[k]}\right|^2 P_t^{[k]}}{\sum\limits_{j=1,j\neq k,k\notin\mathcal{S}}^{K}\left|\widehat{\mathbf{u}}^{[k]\dagger}\mathbf{H}^{[kj]}\widehat{\mathbf{v}}^{[j]}\right|^2 P_t^{[j]} + \sigma^2}\right)}{\sum\limits_{k=1,k\notin\mathcal{S}}^{K}\left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_t^{[k]}\right)}$$

$$s.t. \quad P_t^{[k]} \geq 0, \ \forall k = 1,2,\ldots,K, k \notin \mathcal{S}$$

$$\sum_{k=1,k\notin\mathcal{S}}^{K} P_t^{[k]} \leq P_t^{max}. \tag{25}$$

where $i = 1,2,\ldots,K$. Assume that user k is the selected one in (26).

The CSI of the network is available at all the transceivers due to the requirements of IA, thus in (26) the transmitted power at each antenna can be optimized through using the waterfilling strategy. The optimal signal covariance $\mathbf{B}^{[k]} = \widetilde{\mathbf{V}}^{[k]}\mathbf{S}^{[k]}\widetilde{\mathbf{V}}^{[k]\dagger}$, and $\widetilde{\mathbf{V}}^{[k]}$ can be obtained by singular value decomposition of the channel matrix as $\widetilde{\mathbf{U}}^{[k]}\mathbf{D}^{[k]}\widetilde{\mathbf{V}}^{[k]\dagger} = \mathbf{H}^{[kk]}$. The optimal diagonal PA matrix $\mathbf{S}^{[k]} = \mathrm{diag}\left(s_1,\ldots,s_{\min(M^{[k]},N^{[k]})},0,\ldots,0\right)$. The optimal PA among antennas of user k can be achieved through using the waterfilling strategy as

$$s_i = \left(\mu - \frac{\sigma^2}{P_t^{max}\delta_i^{[k]2}}\right)^+, i = 1,\ldots,\min\left(M^{[k]},N^{[k]}\right). \tag{27}$$

In (27) $\delta_1^{[k]},\ldots,\delta_{\min(M^{[k]},N^{[k]})}^{[k]}$ are the diagonal elements of $\mathbf{D}^{[k]}$, and μ should satisfy

$$\sum_{i=1}^{\min(M^{[k]},N^{[k]})} s_i = 1. \tag{28}$$

C. Procedure of the Proposed Adaptive Energy-Efficient IA Algorithm

Based on the PA algorithms in Section III, the DUSMC algorithm in Section IV and transmission-mode adaption in Subsections V-A and V-B, we propose an AEEIA algorithm, which can be represented in Algorithm 1.

In Step 1 of Algorithm 1, the MinIL IA algorithm is applied to avoid high computational complexity, and the corresponding algorithm can be similarly obtained if the

Max-SINR algorithm is leveraged.

Algorithm 1 - AEEIA Algorithm without Fairness
1:   Time slot n in a frame starts.   Solutions of IA are calculated through MinIL IA.
2:   Energy-efficient PA is performed through (15).
3:   The DUSMC algorithm is performed.
4:   **If** $\mathcal{S} \neq \varnothing$ and $N_a > 1$, **then**
5:      Solutions of IA is recalculated by Max-SINR algorithm.   Transmitted power is reallocated according to (25).
6:   **Elseif** $\mathcal{S} \neq \varnothing$ and $N_a = 1$, **then**
7:      MIMO transmission mode is adopted.   Transmitted power of each antenna is allocated by (26).
8:   **End if**
9:   Transmission of one time slot begins.   After the duration T, the time slot ends.
10:   **If** $n = N_f$, **then**
11:      $n = 1$ and a new frame starts. N_f is the number of time slots in one frame.
12:   **Else**
13:      $n = n + 1$.
14:   **End if**
15:   Go back to Step 1.

VI. FAIRNESS AMONG USERS IN THE ADAPTIVE ENERGY-EFFICIENT IA ALGORITHM

In the above sections, fairness among the users in IA-based networks is not considered. In the ideal situation with the same fading statistics of all the users, the long-term throughput of each user is almost the same, and the fairness can be guaranteed [22]. However, when the statistics of the channel are not symmetric, or channel fading is low, it may be highly unfair in the proposed AEEIA algorithm, since the throughput of some users may be quite low. Furthermore, when SNR
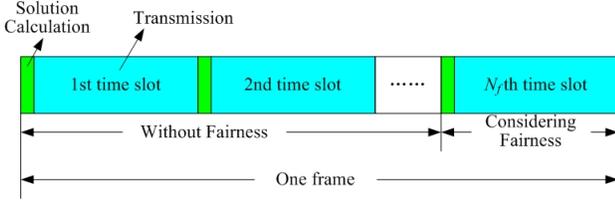
Fig. 5.   One-frame time structure of the proposed AEEIA algorithm considering fairness.

Fig. 6.   The relationship of the mentioned algorithms in this paper.

becomes lower, the proposed algorithm becomes more unfair. Thus the fairness among users in IA-based networks should be considered when the proposed AEEIA algorithm is performed.

A. AEEIA Algorithm Considering Fairness

In this section, fairness is studied in the proposed AEEIA algorithm. One-frame time structure of the proposed fair AEEIA algorithm is depicted in Fig. 5.

In the figure, one frame consists of N_f time slots, and the duration of each time slot is equal to T. In each time slot, the optimal solutions are considered first in duration T_1, and then transmission is performed in duration T_2. $T = T_1 + T_2$. When fairness is considered in the scheme, the first $N_f - 1$ time slots are carried out without fairness, and in the N_fth time slot, fairness is considered.

The throughput of the first $N_f - 1$ time slots of the kth user in one frame can be expressed as

$$\mathcal{T}^{[k]} = \sum_{n=1}^{N_f-1} R^{[k]}(n) \cdot T_2, \ k = 1, 2, \ldots, K. \quad (29)$$

The fairness factor of the kth user in the nth time slot can be denoted as

$$\alpha^{[k]}(n) = \begin{cases} 1, & n = 1, 2, \ldots N_f - 1 \\ \dfrac{K \cdot \dfrac{1}{\mathcal{T}^{[k]}}}{\displaystyle\sum_{i=1}^{K} \dfrac{1}{\mathcal{T}^{[i]}}}, & n = N_f \end{cases} \quad (30)$$

and $\sum_{k=1}^{K} \alpha^{[k]}(n) = K$ to be consistent with (15).

Thus when fairness is considered in the N_fth time slot of one frame, the energy-efficient PA algorithm of (15) in time slot n of each frame can be revised as

$$\max_{P_t^{[1]}, P_t^{[2]}, \ldots, P_t^{[K]}} \frac{\displaystyle\sum_{k=1}^{K} R^{[k]}}{\displaystyle\sum_{k=1}^{K} P^{[k]}} = \frac{\displaystyle\sum_{k=1}^{K} \alpha^{[k]}(n) \log_2\left(1 + \frac{|h_k|^2}{\sigma^2} P_t^{[k]}\right)}{\displaystyle\sum_{k=1}^{K} \left(P_{ct}^{[k]} + P_{cr}^{[k]} + P_t^{[k]}\right)}$$

$$s.t. \quad P_t^{[k]} \geq 0, \ \forall k = 1, 2, \ldots, K$$

$$\sum_{k=1}^{K} P_t^{[k]} \leq P_t^{max}. \quad (31)$$

In (31), when $\alpha^{[k]}(N_f)$ is large, it means the throughput of user k is low in the first $N_f - 1$ time slots of the frame, and more opportunity will be given to user k to transmit in the N_f time slot.
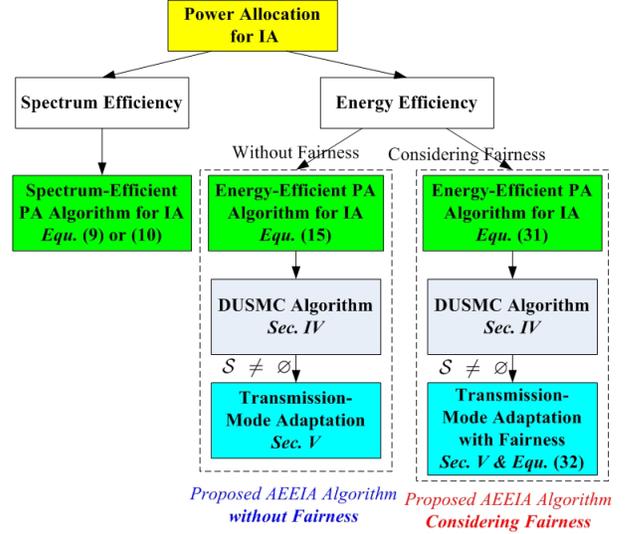
In the N_fth time slot, (26) should also be revised as

$$R_{MIMO} = \log_2 \left| \mathbf{I}_{N^{[k_a]}} + \frac{P_t^{max}}{\sigma^2} \mathbf{H}^{[k_a k_a]} \mathbf{B}^{[k_a]} \mathbf{H}^{[k_a k_a]\dagger} \right|, \quad (32)$$

where user k_a is the only active user not in $\mathcal{S}$.

Remark 3: The reason why the fair AEEIA algorithm is performed once every N_f time slots is to optimize the energy efficiency and guarantee the fairness simultaneously. When N_f becomes larger, fairness among users becomes less important compared to energy efficiency.

B. Procedure and Summary of the Proposed AEEIA Algorithm Considering Fairness

The procedure of the proposed AEEIA algorithm with fairness can be represented in Algorithm 2.

To further explain the relationship of the mentioned algorithms in this paper, they are summarized in Fig. 6. Different objectives can be optimized in the power allocation for IA. When the spectrum efficiency of the IA-based network is optimized, the spectrum-efficient PA algorithm in (9) or (10) should be applied. On the contrary, when the energy efficiency is optimized, the energy-efficient PA algorithm in (15) or (31) can be leveraged. (15) is used when fairness is not considered, while (31) is suitable for the case when fairness is harnessed. Subsequently, the DUSMC algorithm is performed based on the results of the energy-efficient PA. At last, transmission-mode adaptation is applied after the DUSMC algorithm when $\mathcal{S} \neq \varnothing$. (26) or (32) is adopted when $N_a = 1$ without or with fairness, respectively. With the solutions of the proposed AEEIA algorithm without fairness or considering fairness, the transmission of the time slot may start.

Therefore, fairness needs not to be considered when channel fading statistics are symmetric, users are not sensitive to the delay, or SNR is high. However, when the channel statistics are not symmetric, users are sensitive to the delay, or SNR becomes lower, fairness should be involved.

Algorithm 2 - AEEIA Algorithm Considering Fairness

1:	Time slot n in a frame starts.
	Solutions of IA are calculated through MinIL IA.
2:	Energy-efficient PA with fairness is performed by (31).
3:	The DUSMC algorithm is performed.
4:	**If** $\mathcal{S} \neq \varnothing$ and $N_a > 1$, **then**
5:	Solutions of IA is recalculated by Max-SINR algorithm.
	Transmitted power is reallocated according to (25).
6:	**Elseif** $\mathcal{S} \neq \varnothing$ and $N_a = 1$, **then**
7:	MIMO transmission mode is adopted.
8:	**If** $n \neq N_f$, **then**
9:	Transmitted power of each antenna is allocated by (26).
10:	**Else**
11:	Transmitted power of each antenna is allocated by (32).
12:	**End if**
13:	**End if**
14:	Transmission of one time slot begins.
	After the duration T, the time slot ends.
15:	**If** $n = N_f$, **then**
16:	$n = 1$ and a new frame starts.
	N_f is the number of time slots in one frame.
17:	**Else**
18:	$n = n + 1$.
19:	**End if**
20:	Go back to Step 1.

VII. SIMULATION RESULTS AND DISCUSSIONS

In the simulations, we consider a K-user IA-based network with 1 data stream for each user. All the channels are under slow Rayleigh block fading [33]. Perfect CSI is assumed to be available at each transceiver.

According to [37], [31], the transmitter-circuit power consumption $P_{ct}^{[k]}$, receiver-circuit power consumption $P_{cr}^{[k]}$, and sleep-mode power consumption $P_s^{[k]}$ of all the users are set to 98mW, 112mW, and 0mW, respectively. P_t^{max}/K is set to 20dbmW, and thus the constrained total transmitted power of the network (also the maximum transmitted power of each user) is equal to $100K$ mW. The threshold λ is set to 5%. In Step 1 of the proposed AEEIA algorithm, iterative MinIL IA algorithm is used to obtain the solutions of IA. The interior-point method is adopted to solve the problems in (9), (15), (25) and (31) [36].

A. Spectrum Efficiency and Energy Efficiency

We consider a 3-user IA-based network with 2 antennas equipped at each transceiver, and the spectrum efficiency and energy efficiency are studied.

In Fig. 7 and Fig. 8, we compare the spectrum efficiency of the MinIL IA algorithm with equal transmitted power, the MinIL IA algorithm with spectrum-efficient and energy-efficient PA, the DUSMC algorithm, and the proposed AEEIA algorithm. The spectrum efficiency in Fig. 7 and Fig. 8 is linearly and logarithmically scaled, respectively. From the results in Fig. 7, we can see that when SNR is high, the spectrum efficiency of the proposed AEEIA algorithm, DUSMC algorithm, and MinIL IA algorithm with energy-efficient PA is lower than that of the MinIL IA algorithm with equal transmitted power and MinIL IA algorithm with spectrum-efficient PA. This is because when SNR is high, the energy-efficient PA can save transmitted power to improve the energy
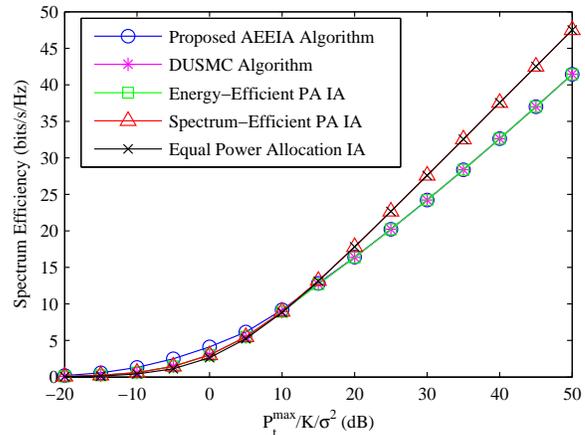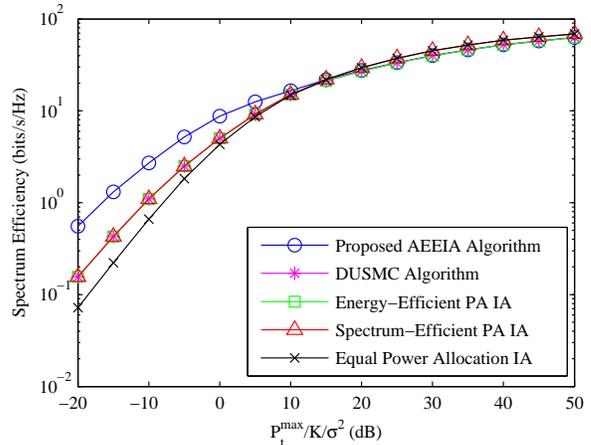

Fig. 7. Spectrum Efficiency comparison of different algorithms in a 3-user IA-based network with 2 antennas at each transceiver. The threshold λ is set to 5%. Spectrum efficiency is linearly scaled.
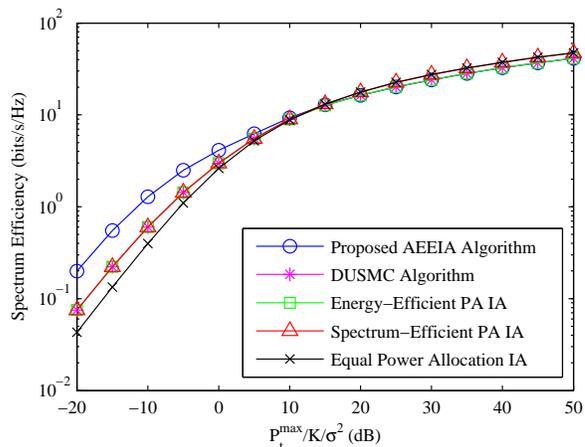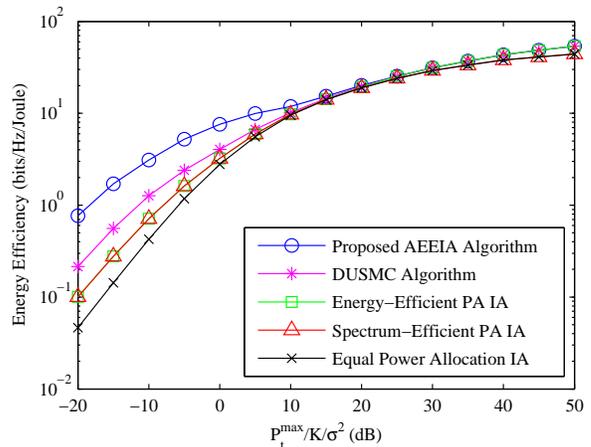

Fig. 8. Spectrum Efficiency comparison of different algorithms in a 3-user IA-based network with 2 antennas at each transceiver. The threshold λ is set to 5%. Spectrum efficiency is logarithmically scaled.

efficiency. From the results in Fig. 8, it is shown that when SNR is low, the spectrum efficiency can be significantly improved by the proposed AEEIA algorithm, and the spectrum efficiency of the DUSMC algorithm, MinIL IA algorithm with spectrum-efficient and energy-efficient PA is almost the same, which is lower than that of the AEEIA algorithm. In addition, we can observe that, when SNR is lower, the throughput of the proposed AEEIA algorithm is even higher than that of the spectrum-efficient PA, due to DUSMC and transmission-mode adaptation; when SNR becomes larger, there is no need to allocate too much power to each transmitter, because the throughput is high enough to support the transmission of the network, and energy efficiency is more important in this situation. Furthermore, the throughput of the network when the proposed AEEIA algorithm is used is better than that when the spectrum-efficient PA is applied at low SNRs. Only when $P_t^{max}/K/\sigma^2$ is larger than 10dB, the throughput of the proposed AEEIA algorithm becomes to be lower than that of the spectrum-efficient PA, which is larger than 10bits/s/Hz.
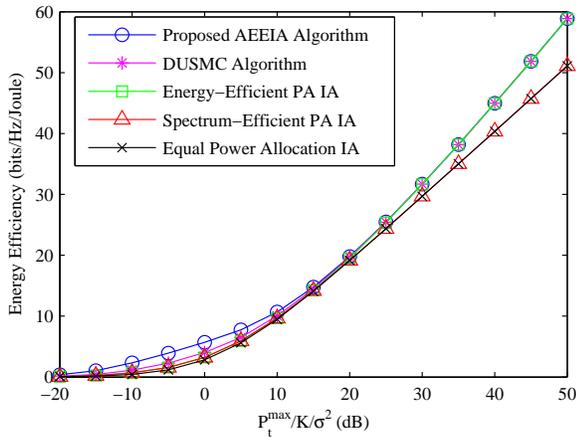
Fig. 9. Energy efficiency comparison of different algorithms in a 3-user IA-based network with 2 antennas at each transceiver. The threshold λ is set to 5%. Energy efficiency is linearly scaled.

Fig. 11. Spectrum Efficiency comparison of different algorithms in a 5-user IA-based network with 3 antennas at each transceiver. The threshold λ is set to 5%.
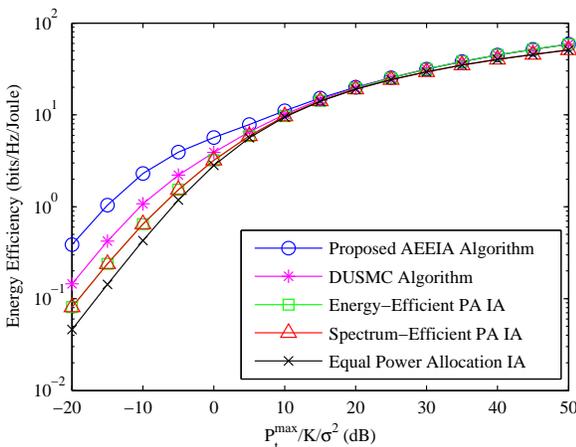
Fig. 10. Energy efficiency comparison of different algorithms in a 3-user IA-based network with 2 antennas at each transceiver. The threshold λ is set to 5%. Energy efficiency is logarithmically scaled.

Fig. 12. Energy efficiency comparison of different algorithms in a 5-user IA-based network with 3 antennas at each transceiver. The threshold λ is set to 5%.

In Fig. 9 and Fig. 10, we compare the energy efficiency of the MinIL IA algorithm with equal transmitted power, MinIL IA algorithm with spectrum-efficient and energy-efficient PA, DUSMC algorithm, and the proposed AEEIA algorithm. The energy efficiency in Fig. 9 and Fig. 10 is linearly and logarithmically scaled, respectively. From the results in Fig. 9, we can see that when SNR is high, the energy efficiency of the proposed AEEIA algorithm, DUSMC algorithm, and MinIL IA algorithm with energy-efficient PA is almost the same and much better than that of the MinIL IA algorithm with equal transmitted power and MinIL IA algorithm with spectrum-efficient PA. From the results in Fig. 10, it is shown that when SNR is low, the energy efficiency of the proposed AEEIA algorithm is much higher than that of the DUSMC algorithm, and the energy efficiency of the DUSMC algorithm is higher than that of the MinIL IA algorithm with energy-efficient and spectrum-efficient PA. The energy efficiency of the MinIL IA algorithm with equal transmitted power is the lowest among these algorithms when SNR is low.

Fig. 7 and Fig. 9 can show the spectrum and energy efficiency, respectively, with higher SNR more clearly due to the linearly scaled Y-axis. The spectrum and energy efficiency is depicted more obviously when SNR is lower in Fig. 8 and Fig. 10, respectively, due to the logarithmically scaled Y-axis. For the conciseness and simplicity of the paper, logarithmically scaled Y-axis is adopted in the following when spectrum efficiency and energy efficiency are studied.

B. Performance with More Users

In this subsection, the performance of the algorithms with more users involved in the network is studied. $K = 5$, and 3 antennas are equipped at each transceiver. The spectrum efficiency and energy efficiency of the algorithms are compared in Fig. 11 and Fig. 12. In the simulation, the iterative MinIL IA algorithm [4] is adopted.

From the results we can observe that when $P_t^{max}/K/\sigma^2$ is below 15dB, the proposed AEEIA algorithm can achieve both the best spectrum efficiency and energy efficiency performance, and when $P_t^{max}/K/\sigma^2$ is larger than 20dB, the

spectrum efficiency of the proposed AEEIA algorithm is lower than that of the IA algorithms with spectrum-efficient PA and equal transmitted power. This is because the proposed energy-efficient IA algorithm mainly focuses on the energy efficiency of the network, and there is no need to allocate all the power (equal to P_t^{max}) to the users when SNR is high. Consequently, the energy efficiency of the proposed AEEIA algorithm is always optimal among all these algorithms whenever SNR is high or low.

C. Fairness

In the above simulations, fairness is not involved in the proposed AEEIA algorithm. In this subsection, fairness is considered. To quantify fairness, Jain's index is leveraged to compare the fairness of the proposed algorithms [38]. For a given length-K vector $\mathbf{tp}$ of non-negative real entries $\{tp_k\}_{k=1}^{K}$, the Jain's fairness index J of vector $\mathbf{tp}$ can be expressed as

$$J(\mathbf{tp}) = \frac{\left(\sum_{k=1}^{K} tp_k\right)^2}{K\sum_{k=1}^{K} tp_k^2}. \qquad (33)$$

From the definition in (33) we can know that $\frac{1}{K} \leq J(\mathbf{tp}) \leq 1$. $J(\mathbf{tp}) = \frac{1}{K}$ is the least fair allocation in which the benefit is allocated to one sole user, while $J(\mathbf{tp}) = 1$ means the fairest allocation in which the users receive the same benefit. If we define tp_k as the throughput of user k in the IA-based network, (33) can be exploited as a metric to measure the fairness of the proposed algorithms.

A 3-user IA-based network with 2 antennas equipped at each transceiver is adopted in the simulation. The spectrum efficiency, energy efficiency and Jain's fairness index of the proposed AEEIA algorithm with and without fairness are compared in Fig. 13, Fig. 14 and Fig. 15, respectively. The cases when $N_f = 2, 4, 8$ and 16 of the algorithm with fairness are shown in the figures, and the equal power allocated IA is also included. In Fig. 13, Fig. 14 and Fig. 15, quasi-static Rayleigh fading channel is considered, i.e., the channel is almost unchanged during each frame as shown in Fig. 5. When time-varying fading channel is adopted, the channel tends to be ergodic, and the problem of fairness is not so obvious. When quasi-static fading channel is utilized, the channel becomes asymmetric, and it will be more unfair. Thus by adopting the quasi-static Rayleigh fading channel in the simulation, the fairness of the algorithms can be demonstrated more clearly.

From the simulation results in Fig. 13, Fig. 14 and Fig. 15, it is shown that when fairness is considered in the proposed AEEIA algorithm, fairness among the users can be improved significantly with a little sacrifice of the spectrum efficiency and energy efficiency. The Jain's fairness index can be increased with smaller N_f, while spectrum efficiency and energy efficiency are increased when N_f becomes larger. Furthermore, the spectrum efficiency and energy efficiency of the proposed algorithm considering fairness is close to that of the proposed algorithm without fairness even when $N_f = 2$,
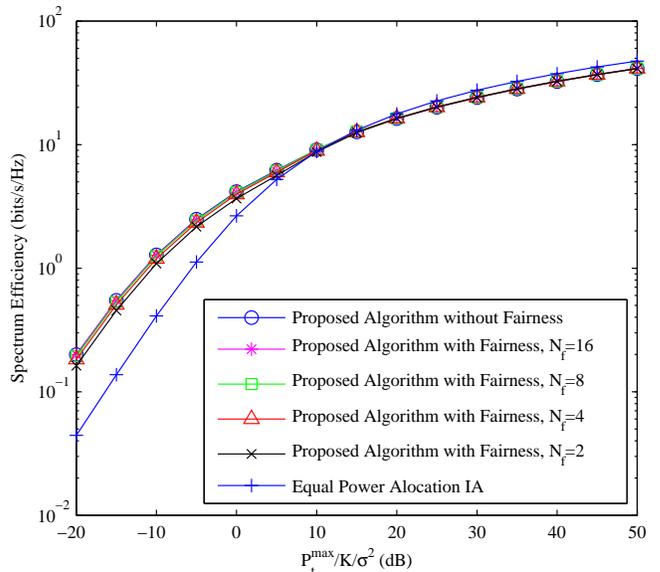
Fig. 13. Spectrum Efficiency comparison of the proposed AEEIA algorithm with and without fairness, when $K = 3$. N_f is equal to 2, 4, 8 and 16, respectively when fairness is considered.
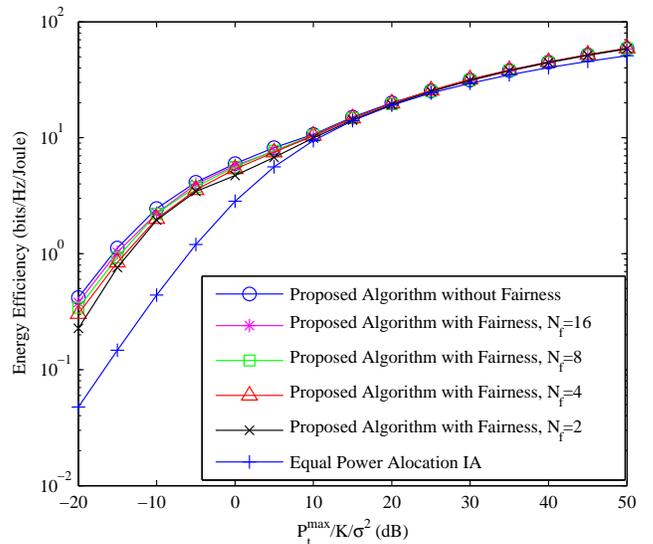
Fig. 14. Energy Efficiency comparison of the proposed AEEIA algorithm with and without fairness, when $K = 3$. N_f is equal to 2, 4, 8 and 16, respectively when fairness is considered.

and the Jain's fairness index of the proposed algorithm with $N_f = 2$ is much larger than that of the equal power allocation IA when $P_t^{max}/K/\sigma^2$ is larger than -5dB. Thus the proposed AEEIA algorithm considering fairness in (31) can significantly improve the fairness of the AEEIA algorithm for IA-based networks while guaranteeing the spectrum efficiency and energy efficiency of the network.

VIII. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed an AEEIA algorithm to improve the energy efficiency of IA-based wireless networks.

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