Energy Efficiency Maximization Via Joint Sub-Carrier Assignment and Power Control for OFDMA Full Duplex Networks

Rojin Aslani, Student Member, IEEE, Mehdi Rasti, Member, IEEE, and Ata Khalili, Student Member, IEEE

Abstract—In this paper, we develop an energy efficient resource allocation scheme for orthogonal frequency division multiple access (OFDMA) networks with in-band full-duplex (IBFD) communication between the base station and user equipments (UEs) considering a realistic self-interference (SI) model. Our primary aim is to maximize the system energy efficiency (EE) through a joint power control and sub-carrier assignment in both the downlink (DL) and uplink (UL), where the quality of service requirements of the UEs in DL and UL are guaranteed. The formulated problem is non-convex due to the non-linear fractional objective function and the non-convex feasible set which is generally intractable. In order to handle this difficulty, we first use fractional programming to transform the fractional objective function to the subtractive form. Then, by employing Dinkelbach method, we propose an iterative algorithm in which an inner problem is solved in each iteration. Applying majorization-minimization approximation, we make the inner problem convex. Also, by introducing a penalty function to handle integer sub-carrier assignment variables, we propose an iterative algorithm for addressing the inner problem. We show that our proposed algorithm converges to the locally optimal solution which is also demonstrated by our simulation results. In addition, simulation results show that by applying the IBFD capability in OFDMA networks with efficient SI cancellation techniques, our proposed resource allocation algorithm attains a 75% increase in the EE as compared to the half-duplex system.

Index Terms—OFDMA cellular networks; in-band full-duplex; energy efficiency; joint resource allocation; power control; sub-carrier assignment; majorization-minimization.

I. INTRODUCTION

Nowadays, the fast development of wireless communication technologies increases energy consumption and carbon emission which raises concerns across the globe. According to [1], it is estimated that the percentage of the global carbon emission due to the information and communication technologies is 5% which increases significantly in coming years, and the situation will intensify with the arrival of 5G networks in the near future. Moreover, it is reported that network operators spend more than 10 billion dollars a year on electricity [2]. Therefore, due to the importance of energy consumption in terms of environmental impact and cost, energy efficiency (EE) will be a significant feature in 5G wireless networks [3], on which we focus in this paper.

Recently, there have been some research efforts to design energy efficient resource allocation schemes for orthogonal frequency division multiple access (OFDMA) cellular networks [4]-[11]. The authors of [4] addressed the joint problem of user scheduling and power control to maximize the EE in the downlink (DL) of OFDMA cellular networks. In [5], an energy efficient resource allocation algorithm with proportional fairness is developed for DL multi-user OFDMA systems with distributed antennas. A low-complexity sub-optimal algorithm is developed in [6], which allocates sub-carriers and power for the EE maximization considering constraints of bit error rates, proportional fair data rates and total transmit power of remote access units. Applying the Lagrangian dual decomposition technique, an energy efficient sub-carrier assignment and power control scheme is proposed in [7], which aims at maximizing the EE. In [7], the authors designed the joint relay selection, pairing, sub-carrier assignment and power control algorithms for maximizing the system EE with quality of service (QoS) considerations. Dinkelbach method is employed in [7] to tackle the non-linear fractional objective function and an optimal solution to relaxed problem is presented. In [8]-[9], resource allocation schemes are proposed for EE maximization in the DL of OFDMA cellular networks with energy harvesting capability for the base station (BS) or user equipments (UEs). The resource allocation schemes to maximize the EE in the uplink (UL) of OFDMA wireless networks are developed in [10]-[11].

Most of the proposed resource allocation schemes in the literature for OFDMA cellular networks are devoted to either the DL or UL transmission. In fact, in most works, it is implicitly considered that the DL and UL channels operate in half-duplex (HD) mode or out-band full-duplex (OBFD) mode, where a radio transceiver can either transmit or receive at different times on the same frequency band or on different frequency bands at the same time, respectively. Recent advances in signal processing techniques have challenged this presumption and indicated the practicability of in-band full-duplex (IBFD) communication, where a radio transceiver simultaneously transmits and receives on the same frequency band. But, the notion of concurrent transmission and reception in a node makes self-interference (SI) in IBFD systems which is a portion of the transmitted signal of an IBFD node received by itself, so interfering with the desired signal received at the same time. Therefore, the key requirement to implement the IBFD communication is applying self-interference cancellation (SIC) methods. There are variant SIC methods presented in the literature (e.g., see [12] and [13]). Equipped with SIC
methods, the IBFD communication has attracted a growing interest from both industrial and academic world, due to its potential of doubling the spectral efficiency. However, there are few efforts for redesigning the resource allocation algorithms in IBFD cellular networks. The authors of [14]−[21] apply the IBFD capability to OFDMA wireless networks employing different architectures. In particular, IBFD cellular networks can be categorized into two-node and three-node architectures [14]. In two-node architecture, referred also as bidirectional, both nodes, i.e., the BS and the UEs have IBFD capability. However, in three-node architecture, only the BS is IBFD-capable and the UEs work in the HD mode. In [14], the outage probability of an IBFD cellular network for both cases of the two-node and three-node architectures is analytically characterized. In [15]−[20], it is assumed that the three-node architecture is employed in IBFD cellular networks. In [15] and [16], resource allocation schemes are proposed for a relay assisted OFDMA DL cellular network in which the relays are IBFD-capable. In [17]−[21], resource allocation schemes are proposed for both the UL and DL of OFDMA networks with IBFD capability. A joint power control and sub-carrier assignment algorithm is proposed in [17] for the system sum-rate maximization subject to the maximum transmit power and sub-carrier assignment constraints. A greedy sub-carrier assignment algorithm and an iterative water-filling power control algorithm were proposed in [17]. The problem of the EE maximization is addressed in [18] in which two different SI models are considered: constant and linear SI model. Then, an optimal algorithm to achieve the maximum EE via a Lagrangian joint optimization of power control and sub-carrier assignment is developed for constant SI model. Also, a Lagrangian joint optimization of power control and sub-carrier assignment constraints. A greedy sub-carrier assignment algorithm and an iterative water-filling power control algorithm were proposed in [17]. The problem of the EE maximization is addressed in [18] in which two different SI models are considered: constant and linear SI model.

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maximize the weighted system sum-rate in a multicarrier non-orthogonal multiple access network. The two-node architecture for IBFD networks is considered in [21], where it is assumed that SIC methods are able to cancel the SI almost completely, then the authors propose an iterative algorithm to jointly optimize the power control and sub-carrier assignment with the aim of maximizing the system sum-rate.

In this work, we focus on designing the energy efficient resource allocation scheme for joint power control and sub-carrier assignment in both the UL and DL of OFDMA networks with IBFD capability. Similar to [21], we assume that the two-node architecture is employed in IBFD cellular network (opposing with [17]-[20] where the three-node architecture is employed). We further consider a more realistic assumption on the SI model in the BS and UEs. In fact, there are two main assumptions on the SI model in the literature: 1) constant SI independent of the transmit power [18], [21], which has less complexity but is not the case in practice, 2) varying SI proportional to the transmit power [18], [20], [22]-[24], [43]-[47], leading to the complex but realistic problem formulations, which is adopted in our paper for modeling the SI in both the BS and UEs. Although the assumption of SI proportional to the transmit power is more realistic, it invokes non-convexity, making the designing of energy efficient resource allocation schemes more challenging in comparison with [21]. To the best of our knowledge, there is no work in the literature that proposes a joint energy efficient resource allocation scheme for both the UL and DL of OFDMA cellular networks with IBFD-capable BS and UEs, and with a practical SI model that is proportional to the transmit power (see Table I). The contributions of this work are summarized as follows:

- We present a system model for the OFDMA network with IBFD capability in which all UEs and the BS operate in the IBFD mode and the UL transmission from a given UE to the BS and the DL transmission from the BS to that UE occur simultaneously in the same frequency band. We suppose that the SI in both the BS and UEs are proportional to their transmit power and they have different SIC capabilities as is the case in reality. We also formally state the EE maximization problem subject to the maximum transmit power of the UEs and BS and the QoS requirement of the UEs in the UL and DL. To the best of our knowledge, this problem has not been considered in the literature for OFDMA cellular networks with IBFD capability for both the BS and UEs.

- We propose a joint solution to the sub-carrier assignment and power control in the ULs and DLs considering QoS provisioning. To do this, we first use the fractional programming to deal with the fractional objective function of the EE. Then, we apply Dinkelbach algorithm to address the problem in which an inner optimization problem should be solved in each iteration. Applying the majorization-minimization (MM) algorithm, we make the inner problem convex. Also, by introducing a penalty function, we handle the integer sub-carrier assignment variables. Finally, we solve the obtained convex optimization problem using off-the-shelf software packages, e.g., CVX.

- Extensive simulation results show the convergence of our proposed algorithm to the locally optimal solution and outperforming other resource allocation schemes proposed in [5], [18], [21] and [29]. Also, our simulation results reveal the effect of several factors such as the minimum data rate requirement of UEs, the maximum transmit power, the cell size, and the SI on the EE of the IBFD system. Our numerical results demonstrate that by applying IBFD capability in OFDMA networks with efficient SIC techniques, our proposed resource allocation scheme can operate 75% more energy efficiently than that of the HD system proposed in [5]. Also, our proposed algorithm performs 20% and 35% better than the algorithms proposed in [18] to maximize EE in IBFD systems with linear and constant SI model, respectively.

The summary of the related works and comparison with our proposed approach is presented in Table I. The rest of this paper is organized as follows. In Section II, we introduce the system model and formulate the problem. Our proposed method for addressing the stated problem is presented in Section III. The numerical results and conclusion are presented in Sections IV and V, respectively.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

We consider a single-cell OFDMA network with one BS and $N$ UEs, the set of which is denoted by $\mathcal{N} = \{1, 2, \cdots, N\}$. The system’s total bandwidth is divided to $K$ sub-carriers perfectly orthogonal to each other, and let $\mathcal{K} = \{1, 2, \cdots, K\}$ denote the set of sub-carriers.

We assume that all the UEs and the BS operate in the IBFD mode and the UL and DL data transmission are simultaneously performed in the same frequency band. Assuming the separate antenna architecture for IBFD nodes presented in [12], the BS and UEs are both equipped with two antennas in which the transmit and receive signals in the UL and DL use a dedicated antenna, both operating in the same frequency band.
Let \( h_{n,k} \) denote the UL channel gain from the \( n \)th UE to the BS on the \( k \)th sub-carrier and \( g_{n,k} \) denote the DL channel gain from the BS to the \( n \)th UE on the \( k \)th sub-carrier (see Fig. 1). Also, \( p_{n,k}^u \) and \( p_{n,k}^d \) denote the transmit power of \( n \)th UE for transmitting the information signal to the BS on sub-carrier \( k \) in the UL and the transmit power of the BS for transmitting the information to the \( n \)th UE on sub-carrier \( k \) in the DL, respectively. The binary-valued sub-carrier assignment, \( x_{n,k} \in \{0, 1\} \) represents sub-carrier assignment for the \( n \)th UE on sub-carrier \( k \) and is defined as
\[
x_{n,k} = \begin{cases} 
1, & \text{if the } k \text{th sub-carrier is assigned to the } n \text{th UE} \\
0, & \text{otherwise}.
\end{cases}
\]

The vector \( x \in \mathbb{R}^{NK \times 1} \) represents the sub-carrier assignment of all the UEs and the vector \( p = [p^u, p^d]^T \) represents the transmit power of UEs and BS, where \( p^u = [p_{n,k}^u]^T, n \in N, k \in K \) is the UEs transmit power vector in UL and \( p^d = [p_{n,k}^d]^T = [p^n_{k,n}]_{N \times K} \) is the BS transmit power vector in DL. Considering a combination of the passive and active SIC methods [43] for all the UEs and BS, we assume that the residual SI is proportional to the transmit power (similar to [14], [20], [22]-[24] and [34]-[37]). It should be noted that in practice, SI cannot be canceled completely even if the SI channel is perfectly known at the IBFD BS as well as IBFD UEs due to the limited dynamic range of the receiver [42]. Thus, the residual SI after cancellation at the receive antennas can be modeled as an independent zero-mean Gaussian distortion noise whose variance is proportional to the received power of the antenna [20], [42]. Assuming different SIC capabilities in the BS and UEs, the SI power at the BS and the \( n \)th UE is represented by \( \delta_{\text{BS}}[p^u], \delta_{\text{BS}}[p^d] \) and \( \gamma_{n}^u[p^u], \gamma_{n}^d[p^d] \), respectively, where \( 0 < \delta_{\text{BS}} \ll 1 \) and \( 0 < \gamma_{n} \ll 1 \) are constants modeling the quality of the SI at the BS and the \( n \)th UE, respectively. \( \delta_{\text{BS}}^n, \gamma_{n}^u, \gamma_{n}^d \) denote the SI channel gain at the BS and \( n \)th UE, respectively. The noise is assumed to be additive white Gaussian noise (AWGN) whose power is \( N_{\text{BS}} \) at the BS and \( N_n \) at the \( n \)th UE. In addition, we assume that the global channel state information (CSI) of all channels is available at the BS so as to unveil the performance upper bound of IBFD OFDMA wireless networks [20]. Given the sub-carrier assignment vector \( x \) and the transmit power vector \( p \), the UL SINR of the \( n \)th UE at the BS receiver on the \( k \)th sub-carrier denoted by \( \gamma_{n,k}^u \) is obtained as
\[
\gamma_{n,k}^u(x, p) = \frac{p_{n,k}^u x_{n,k} h_{n,k}}{\delta_{\text{BS}}^n |x_n|^2 p_{n,k}^u x_{n,k} + N_{\text{BS}}}. \tag{2}
\]

Similarly, given the sub-carrier assignment vector \( x \) and the transmit power vector \( p \), the DL SINR of the \( n \)th UE on the \( k \)th sub-carrier denoted by \( \gamma_{n,k}^d \), is obtained as
\[
\gamma_{n,k}^d(x, p) = \frac{p_{n,k}^d x_{n,k} g_{n,k}}{\delta_{n}^u |x_n|^2 p_{n,k}^d x_{n,k} + N_n}. \tag{3}
\]

According to the Shannon formula, the achievable instantaneous UL and DL transmission rates (bps/Hz) for \( n \)th UE on \( k \)th sub-carrier are given by
\[
R_{n,k}^u(x, p) = \log \left( 1 + \gamma_{n,k}^u(x, p) \right), \tag{4}
\]
and
\[
R_{n,k}^d(x, p) = \log \left( 1 + \gamma_{n,k}^d(x, p) \right), \tag{5}
\]
respectively. Let \( R_{n,k}^u(x, p) \) denote the UL transmission rate of the \( n \)th UE, i.e., \( R_{n,k}^u(x, p) = \sum_{l \in K} R_{n,k}^u(x, p) \) and let \( R_{n,k}^d(x, p) \) denote the DL transmission rate of the \( n \)th UE, i.e., \( R_{n,k}^d(x, p) = \sum_{l \in K} R_{n,k}^d(x, p) \). The transmission rate of the \( n \)th UE is obtained by \( R_n(x, p) = R_{n,k}^u(x, p) + R_{n,k}^d(x, p) \). The total system sum-rate denoted by \( R(x, p) \) is obtained by \( R(x, p) = \sum_{n \in N} R_n(x, p) \). The total system power consumption denoted by \( P_T(x, p) \) is formed as
\[
P_T(x, p) = P_{\text{BS}}^c + \sum_{n \in N} P_{n}^c + \sum_{n \in N, k \in K} x_{n,k} \left( \frac{1}{\epsilon_n} p_{n,k}^u + \frac{1}{\epsilon_{\text{BS}}} p_{n,k}^d \right), \tag{6}
\]
where \( \epsilon_n \in (0, 1) \) and \( \epsilon_{\text{BS}} \in (0, 1) \) are the power amplifier efficiency of the \( n \)th UE and the BS, respectively [32]. \( P_{\text{BS}}^c \) and \( P_{n}^c \) are the fixed circuit power consumed by the BS and the \( n \)th UE, respectively. Indeed, we consider the transmit power of the BS and UEs as well as their circuit power consumption. We define the EE criterion as the ratio of the total system sum-rate to the total system power consumption given by
\[
EE(x, p) = \frac{R(x, p)}{P_T(x, p)}. \tag{7}
\]

### B. Problem Formulation

We formally state the joint optimization problem of sub-carrier assignment and power control to maximize the EE subject to constraints of the transmit power of both the UEs and BS and the QoS requirements for each UEs at the DL and UL, that is:

\[
\begin{align*}
\text{maximize} & \quad EE(x, p) \\
\text{subject to} & \quad \sum_{n \in N} x_{n,k} \leq 1, \quad \forall k \in K \quad (8-1) \\
& \quad \sum_{k \in K} p_{n,k} x_{n,k} \leq P_n, \quad \forall n \in N \quad (8-2) \\
& \quad \sum_{n \in N} \sum_{k \in K} p_{n,k} x_{n,k} \leq P_{\text{BS}}, \quad (8-3) \\
& \quad R_{n,k}^u(x, p) \geq R_n^u, \quad \forall n \in N \quad (8-4) \\
& \quad R_{n,k}^d(x, p) \geq R_n^d, \quad \forall n \in N \quad (8-5) \\
& \quad p_{n,k}^u, p_{n,k}^d \geq 0, \quad \forall n \in N, k \in K \quad (8-6) \\
& \quad x_{n,k} \in \{0, 1\}, \quad \forall n \in N, k \in K \quad (8-7)
\end{align*}
\]

where constraint (8-1) ensures the exclusive sub-carrier assignment in OFDMA system. The feasibility of transmit power of the UEs and BS are indicated by constraints (8-2) and (8-3), respectively, in which \( P_n \) and \( P_{\text{BS}} \) are the maximum transmit power of the \( n \)th UE and the BS, respectively. Constraints (8-4) and (8-5) guarantee the QoS requirement for each UEs at the UL and DL, respectively, where the specific required rates

1. C denote the set of complex number.

2. In fact, we assume that the BS attains the UL CSI by listening to the sounding reference signal transmitted by the UEs and the DL CSI through the channel quality indicator (CQI) feedback from the UEs [21].
of the UEs in the UL and DL need to be satisfied. Constraint (8-6) corresponds to the non-negative transmit power for the UEs and BS. Finally, constraint (8-7) is an integer constraint for sub-carrier assignment to the UEs.

III. OUR PROPOSED RESOURCE ALLOCATION SCHEME FOR EE MAXIMIZATION

Optimization problem (8) contains a non-convex objective function and non-linear constraints with a combination of binary and continuous variables, i.e., $x$ and $p$, respectively. Specifically, (8) is a non-convex mixed-integer nonlinear programming (MINLP) optimization problem and so it is hard to solve at its original form. Thus we need to propose an efficient algorithm for addressing (8) with reasonable computational complexity.

To evade the high complexity of the MINLP problem in (8), we reformulate it into a more mathematically tractable one where its time complexity is polynomial. The first concern to address the problem (8) is the coupled UL and DL power control and sub-carrier assignment variables in both the objective function and constraints. This makes obtaining a solution for problem (8) complicated. To tackle this issue, we define two new auxiliary transmit power variables and redefine the problem based on them. The next concern for addressing the problem is the fractional objective function of EE. We employ the fractional programming technique to tackle the integer variables issue. Finally, we use the Dinkelbach algorithm to address the problem in subtractive form of the objective function. In each iteration of Dinkelbach algorithm, an inner optimization problem requires to be solved. To address the inner problem, we first make it convex by applying MM algorithm [39]. Next, we treat the integer variables and constraints on the sub-carrier assignment variables which create a disjoint feasible solution set that is an obstacle to solve the problem. Using abstract Lagrangian duality and introducing a penalty function, we propose a technique to tackle the integer variables issue. Finally, we obtain a convex optimization problem with continuous feasible set which can be solved by using tools for solving convex problems such as CVX [30], [31]. The details of our proposed method for addressing the optimization problem stated in (8) will be explained in what follows.

A. Tackling the Coupled Variables in Problem (8)

As mentioned before, the first step to address problem (8) is to tackle the coupled UL and DL power control and sub-carrier assignment variables in constraints (8-2) (8-5) as well as the objective function. To do this, we first define two new auxiliary power variables $\tilde{p}_{n,k}^u$ and $\tilde{p}_{n,k}^d$ as

$$\tilde{p}_{n,k}^u = p_{n,k}^u, \quad \forall n \in \mathcal{N}, k \in \mathcal{K};$$

$$\tilde{p}_{n,k}^d = p_{n,k}^d, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}. \quad (9)$$

Then, replacing the original power variables $p$ by auxiliary power variables $\tilde{p} = [\tilde{p}^u, \tilde{p}^d]^T$, where $\tilde{p}^u = [\tilde{p}_{n,k}^u]_{N \times K}$ and $\tilde{p}^d = [\tilde{p}_{n,k}^d]_{N \times K}$, in constraints (8-2) and (8-5), they are reformulated as

$$\sum_{n \in \mathcal{N}} \tilde{p}_{n,k}^u \leq P_n, \quad \forall n \in \mathcal{N}, \quad (8-2-1)$$

and

$$\sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \tilde{p}_{n,k}^d \leq P_{BS}, \quad (8-3-1)$$

respectively. Now, we add two following constraints:

$$\tilde{p}_{n,k}^u \leq x_{n,k} P_n, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, \quad (8-2-2)$$

and

$$\tilde{p}_{n,k}^d \leq x_{n,k} P_{BS}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}. \quad (8-3-2)$$

The constraint (8-2-2) ensures that if the sub-carrier $k$ is not assigned to the $n$th UE, i.e., $x_{n,k}=0$, the transmit power of the $n$th UE on the sub-carrier $k$ is also zero, i.e., $\tilde{p}_{n,k}^d=0$. Also, if $x_{n,k}=1$, then $\tilde{p}_{n,k}^u$ at most can reach $P_n$. Similarly, the constraint (8-3-2) ensures that if the sub-carrier $k$ is not assigned to the BS for transmitting information to the $n$th UE, i.e., $x_{n,k}=0$, the transmit power of the BS on the sub-carrier $k$ is also zero, i.e., $\tilde{p}_{n,k}^d=0$. Also, if $x_{n,k}=1$, then $\tilde{p}_{n,k}^d$ at most can reach $P_{BS}$. In addition, the constraint (8-6) is rewritten as

$$\tilde{p}_{n,k}^u, \tilde{p}_{n,k}^d \geq 0, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}. \quad (8-6-1)$$

Now, we rewrite constraints (8-4) and (8-5) as

$$\bar{R}_n^u(x, \tilde{p}) \geq \bar{R}_n^u, \quad \forall n \in \mathcal{N}, \quad (8-4-1)$$

and

$$\bar{R}_n^d(x, \tilde{p}) \geq \bar{R}_n^d, \quad \forall n \in \mathcal{N}, \quad (8-5-1)$$

respectively, where $\bar{R}_n^u(x, \tilde{p}) = \sum_{k \in \mathcal{K}} \log (1 + \gamma_{n,k}^u(x, \tilde{p}))$, in which $\gamma_{n,k}^u(x, \tilde{p}) = \frac{\tilde{p}_{n,k}^u h_{n,k}}{\tilde{p}_{BS} + N}_{BS}$ obtained by replacing $p_{n,k}^u x_{n,k}$ by $\tilde{p}_{n,k}^u$ and $p_{n,k}^d x_{n,k}$ by $\tilde{p}_{n,k}^d$ in the UL SINR and the UL transmission rate function in (2) and (4), respectively. Similarly, $\bar{R}_n^d(x, \tilde{p})$ is found.

Now, we tackle the coupled UL and DL power control and sub-carrier assignment variables in the objective function of problem (8). To do this, we rewrite the total system sum-rate as

$$\bar{R}(x, \tilde{p}) = \sum_{n \in \mathcal{N}} \left( \bar{R}_n^u(x, \tilde{p}) + \bar{R}_n^d(x, \tilde{p}) \right), \quad (10)$$

where, $\bar{R}_n^u(x, \tilde{p})$ and $\bar{R}_n^d(x, \tilde{p})$ are described in (8-4-1) and (8-5-1), respectively. Also, we rewrite the total system power consumption in (6) as

$$\bar{P}^T(x, \tilde{p}) = P_{BS} + \sum_{n \in \mathcal{N}} P_n + \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \left( \frac{1}{\epsilon_{BS}} \tilde{p}_{n,k}^d + \frac{1}{\epsilon_{BS}} \tilde{p}_{n,k}^d \right). \quad (11)$$

Finally, we rewrite the EE criterion in (7) as

$$\bar{E}(x, \tilde{p}) = \frac{\bar{R}(x, \tilde{p})}{\bar{P}^T(x, \tilde{p})}. \quad (12)$$

To achieve the globally optimal solution of original problem (8), an exhaustive search is required, entailing a complexity of $O(N^K)$ which is computationally infeasible for $N \gg 1$ and $K \gg 1$.  

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After applying the mentioned steps, problem (8) is reformulated as
\[
\begin{align*}
\text{maximize} & \quad \tilde{E}(x, \tilde{p}) \\
\text{subject to} & \quad (8-1), (8-2-1), (8-2-2), (8-3-1), (8-3-2), \\
& \quad (8-4-1), (8-5-1), (8-6-1) \text{ and } (8-7).
\end{align*}
\]

The problem (13) is an optimization problem with decoupled variables. However, it is still non-convex due to the non-convexity of the fractional objective function and constraints (8-4-1) and (8-5-1) as well as the combinatorial constraint (8-7) on the sub-carrier assignment variables. In the next subsections, we first describe a technique to treat the fractional objective function in problem (13), then we tackle the non-convexity of constraints (8-4-1), (8-5-1) and finally, we propose a technique to handle the integer sub-carrier assignment variables in (8-7).

**B. Transforming the Fractional Objective Function in (13)**

In this section, we tackle the fractional objective function of (13). Suppose \( F \) is the set of feasible solutions to problem (13) spanned by constraints (8-1), (8-2-1), (8-2-2), (8-3-1), (8-3-2), (8-4-1), (8-5-1), (8-6-1) and (8-7). We denote \( q^* \) as the optimal EE as the optimal EE in problem (13) represented as
\[
q^* = \frac{\tilde{R}(x^*, \tilde{p}^*)}{P^T(x^*, \tilde{p}^*)} = \max_{p, x \in F} \frac{\tilde{R}(x, \tilde{p})}{P^T(x, \tilde{p})},
\]
where \( x^* \) and \( \tilde{p}^* \) are the optimal sub-carrier assignment and the optimal transmit power control for problem (13), respectively. Now, we employ the following theorem borrowed from non-linear fractional programming [25] to address (13).

**Theorem 1.** [25] The resource allocation policy attains the optimal EE, i.e., \( q^* \), if and only if
\[
\max_{p, x \in F} \tilde{R}(x, \tilde{p}) - q^* P^T(x, \tilde{p}) = \tilde{R}(x^*, \tilde{p}^*) - q^* P^T(x^*, \tilde{p}^*) = 0,
\]
for \( \tilde{R}(x, \tilde{p}) \geq 0 \) and \( P^T(x, \tilde{p}) \geq 0 \), where \( x^* \) and \( \tilde{p}^* \) yield the optimal solution to problem (13).

**Proof.** The proof is directly obtained from [25]. \( \square \)

A necessary and sufficient condition to obtain the optimal resource allocation policy for problem (13) is described in Theorem 1. The above theorem states that for the fractional objective function of problem (13), there is a transformed objective function in subtractive form (i.e., maximize \( \tilde{R}(x, \tilde{p}) - q^* P^T(x, \tilde{p}) \)), which shares the same resource allocation policy. Therefore, we focus on this transformed objective function in the rest of this paper.

**C. Iterative Dinkelbach Algorithm to Address Problem (13) with Transformed Objective Function**

In this section, we propose an iterative algorithm known as Dinkelbach method [25] for addressing problem (13) with a transformed objective function. The proposed scheme is given in Algorithm 1.

| Algorithm 1: Iterative Resource Allocation Algorithm (Dinkelbach Method) |
|-------------------------------|
| **Require:** i = 0, q0 = 0, Δ > 0 |
| 1: i : Dinkelbach iteration index |
| 2: qi : Dinkelbach parameter |
| 3: Δ : The maximum allowed tolerance for convergence of Dinkelbach Method |
| 4: while qi - qi-1 > Δ do |
| 5: Solve problem (16) using Algorithm 2 and obtain resource allocation policy \{\tilde{p}_i^*, x_i^*\} |
| 6: Set i = i + 1 |
| 7: Set qi = \frac{\tilde{R}(x_i^*, \tilde{p}_i^*)}{P^T(x_i^*, \tilde{p}_i^*)} |
| 8: end while |
| 9: Set \{\tilde{p}_i^*, x_i^*\} = \{\tilde{p}_{i-1}^*, x_{i-1}^*\} |
| 10: return \tilde{p}_i^*, x_i^* |

In accordance with Algorithm 1, given parameter qi in iteration i of Dinkelbach method, the following optimization problem should be solved:
\[
\begin{align*}
\text{maximize} & \quad \tilde{R}(x, \tilde{p}) - q_i P^T(x, \tilde{p}) \\
\text{subject to} & \quad (8-1), (8-2-1), (8-2-2), (8-3-1), (8-3-2), \\
& \quad (8-4-1), (8-5-1), (8-6-1) \text{ and } (8-7).
\end{align*}
\]

Then, qi is updated by \( qi = \frac{\tilde{R}(x_i^*, \tilde{p}_i^*)}{P^T(x_i^*, \tilde{p}_i^*)} \), where \( \{\tilde{p}_i^*, x_i^*\} \) is the resource allocation policy corresponding to problem (16). The algorithm is terminated when qi converges and so the solution to problem (13), i.e., \( \{\tilde{p}_i^*, x_i^*\} \), is eventually achieved.

The proposed algorithm converges to the optimal solution of problem (13), if we are able to solve the inner problem (16) in each iteration. The convergence proof is similar to the proof given in [24]. However, as the inner problem (16) is a non-convex problem, we employ MM approach by constructing a sequence of surrogate functions using Taylor approximation to make it convex. So, the proposed algorithm converges to a locally optimal solution of the problem (13). Also, our simulation results show that our proposed algorithm closely achieves the globally optimal solution. In the next subsection, we derive the solution to the problem (16).

**D. Solving the Optimization Problem (16)**

In this section, we obtain our proposed resource allocation policy for addressing problem (16). To do this, we first make the problem (16) convex by applying MM algorithm and then we handle the integer sub-carrier assignment variables by using abstract Lagrangian duality.

Although, we addressed the issue of the coupled variables in constraints (8-4-1) and (8-5-1), they are still non-convex due to the logarithmic rate function. In order to handle this issue, we employ MM algorithm [39] to make constraints (8-4-1) and (8-5-1) convex as explained in what follows. First, by replacing \( \tilde{R}_n(x, \tilde{p}) \) in (8-4-1), we have
\[
\sum_{k \in K} \log \left(1 + \frac{\tilde{p}_{n,k} h_{n,k}}{\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}}\right) \geq R_n^a, \quad \forall n \in \mathcal{N}.
\]

Re-arranging this relation, we rewrite it as
\[
\sum_{k \in K} \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) - \sum_{k \in K} \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) \geq R_n^a, \quad \forall n \in \mathcal{N}. \quad (17)
\]

We redefine the left side of the above equation as a difference of convex functions (DC) as
\[
f_1^a(x, \tilde{p}) - f_2^a(x, \tilde{p}) \geq R_n^a, \quad \forall n \in \mathcal{N}, \quad (18)
\]
where, \( f_1^a(x, \tilde{p}) = \sum_{k \in K} \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) \)
and \( f_2^a(x, \tilde{p}) = \sum_{k \in K} \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) \)
and both \( f_1^a(x, \tilde{p}) \) and \( f_2^a(x, \tilde{p}) \) are concave, the subtraction of two
concave functions is not necessarily concave [39]. To obtain a concave
approximation for the constraint [13], we apply MM algorithm [39] and construct
a surrogate function for \( f_2^a(x, \tilde{p}) \)
using first order Taylor approximation as
\[
\tilde{f}_2^a(x, \tilde{p}) = f_2^a(x, \tilde{p}^{(t-1)}) + \nabla_{\tilde{p}} f_2^a(x, \tilde{p}^{(t-1)}) (\tilde{p} - \tilde{p}^{(t-1)}), \quad (19)
\]
where, \( \tilde{p}^{(t-1)} \) is the solution of the problem at \((t-1)\)th
iteration, and \( \nabla_{\tilde{p}} \) is the gradient operation with respect to \( \tilde{p} \).
Approximation [19] satisfies the MM principles and makes a
tight lower bound of \( R_n^a(x, \tilde{p}) \) [39]. Now, we have the
following constraint which is convex:
\[
f_1^a(x, \tilde{p}) - \tilde{f}_2^a(x, \tilde{p}) \geq R_n^a, \quad \forall n \in \mathcal{N}. \quad (8-4-2)
\]

Similarly, constraint (8-5-1) is rewritten as the following convex constraint:
\[
f_1^a(x, \tilde{p}) - \tilde{f}_2^a(x, \tilde{p}) \geq R_n^a, \quad \forall n \in \mathcal{N}, \quad (8-5-2)
\]
where, \( f_1^a(x, \tilde{p}) \) and \( \tilde{f}_2^a(x, \tilde{p}) \) are obtained in a similar way of
obtaining \( f_2^a(x, \tilde{p}) \) and \( \tilde{f}_2^a(x, \tilde{p}) \) as explained.
Now, we treat the non-convex total system sum-rate function, i.e. \( \sum_{k \in K} R_n^a(x, \tilde{p}) \) in the objective function of problem (16). Replacing \( R_n^a(x, \tilde{p}) \) and \( \tilde{R}_n^a(x, \tilde{p}) \) from (8-4-1) and (8-5-1), respectively, we rewrite (10) as
\[
\tilde{R}(x, \tilde{p}) = \sum_{n \in \mathcal{N}} \sum_{k \in K} \left[ \log \left(1 + \frac{\tilde{p}_{n,k} h_{n,k}}{\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}}\right) + \log \left(1 + \frac{\tilde{p}_{n,k} g_{n,k}}{\delta_{n} |\mathbf{h}|^2 + \tilde{p}_{n,k} g_{n,k}}\right) \right].
\]

Rearranging (20), we rewrite it as
\[
\tilde{R}(x, \tilde{p}) = \sum_{n \in \mathcal{N}} \sum_{k \in K} \left[ \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) + \log (\delta_{n} |\mathbf{h}|^2 + \tilde{p}_{n,k} g_{n,k}) - \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) - \log (\delta_{n} |\mathbf{h}|^2 + \tilde{p}_{n,k} g_{n,k}) \right].
\]

We redefine the above equation as a DC as
\[
\tilde{R}(x, \tilde{p}) = f(x, \tilde{p}) - g(x, \tilde{p}), \quad (22)
\]
where, \( f(x, \tilde{p}) = \sum_{n \in \mathcal{N}} \sum_{k \in K} \left( \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) + \log (\delta_{n} |\mathbf{h}|^2 + \tilde{p}_{n,k} g_{n,k}) \right) \)
and \( g(x, \tilde{p}) = \sum_{n \in \mathcal{N}} \sum_{k \in K} \left( \log (\delta_{\text{BS}} |\mathbf{h}|^2 + \tilde{p}_{n,k} h_{n,k}) + \log (\delta_{n} |\mathbf{h}|^2 + \tilde{p}_{n,k} g_{n,k}) \right) \).

After applying the mentioned steps, the problem (16) is reformulated as
\[
\max_{\tilde{p}, \mathbf{x}} f(x, \tilde{p}) - g(x, \tilde{p}) - q_l \tilde{p}_l^T (x, \tilde{p}) \quad (23)
\]
subject to (8-1), (8-2-1), (8-2-2), (8-3-1), (8-3-2), (8-4-2), (8-5-2), (8-6-1) and (8-7).

Next, we handle the issue of incorporating integer variables on the objective function as well as constraints. To do this, we first relax the sub-carrier assignment variable \( x_{n,k} \) to be a real value between zero and one alternative to a binary value. So, the constraint (8-7) is rewritten as
\[
\sum_{n \in \mathcal{N}} \sum_{k \in K} (x_{n,k} - (x_{n,k})^2) \leq 0. \quad (8-8)
\]
This constraint is satisfied for binary values, i.e., \( x_{n,k} \in \{0, 1\} \).
Adding the new constraint (8-8) to the problem (23), the new optimization problem is:
\[
\max_{\tilde{p}, \mathbf{x}} f(x, \tilde{p}) - g(x, \tilde{p}) - q_l \tilde{p}_l^T (x, \tilde{p}) \quad (24)
\]
subject to (8-1), (8-2-1), (8-2-2), (8-3-1), (8-3-2), (8-4-2), (8-5-2), (8-6-1), (8-7) and (8-8).

However, the constraint (8-8) is not convex. In order to treat the
non-convexity of (8-8), using the abstract Lagrangian duality, we add the constraint (8-8) as a penalty term to the objective function of problem (24). More specifically, the abstract Lagrangian function of problem (24) with only one
Lagrangian multiplier to handle the non-convex constraint (8-8) is given by
\[
\mathbf{L}(x, \tilde{p}) = f(x, \tilde{p}) - g(x, \tilde{p}) - q_l \tilde{p}_l^T (x, \tilde{p}) - \lambda \sum_{n \in \mathcal{N}} \sum_{k \in K} (x_{n,k} - (x_{n,k})^2), \quad (25)
\]
where \( \lambda \) acts as a penalty factor to penalize the objective function when the value of \( x_{n,k} \) is not binary. Letting the feasible set spanned by constraints (8-1), (8-2-1), (8-2-2), (8-3-1), (8-3-2), (8-4-2), (8-5-2), (8-6-1) and (8-7) be denoted by \( D \), the problem (24) is expressed by \( \max_{(\tilde{p}, x) \in D} \mathbf{L}(x, \tilde{p}) \), while its dual problem is
\[
\min_{\lambda \geq 0} \max_{(\tilde{p}, x) \in D} \mathbf{L}(x, \tilde{p}); \quad \forall \lambda \geq 0 \quad (D). \quad (40)
\]
Note that, in general, there is a duality gap, i.e., \( \max_{(\tilde{p}, x) \in D} \mathbf{L}(x, \tilde{p}) \leq \min_{\lambda \geq 0} \max_{(\tilde{p}, x) \in D} \mathbf{L}(x, \tilde{p}) \) [40], [41].

4The objective function of problem (23) is still non-concave which later becomes concave using MM algorithm in (20).
Proposition 1. For adequately large values of penalty factor, i.e., \( \lambda \), the optimization problem \((24)\) is equivalent to the following problem:

\[
\begin{align*}
\text{maximize} & \quad L(x, \tilde{p}) \\
\text{subject to} & \quad \tilde{p}, x \in D.
\end{align*}
\]

\( (26) \)

Proof. The proof is given in the Appendix A.

However, the objective function of problem \((26)\) is still non-concave. In order to handle this issue, we apply MM algorithm. To do this, we first redefine the objective function of \((26)\) as

\[
L(x, \tilde{p}) = e_1(x, \tilde{p}) - e_2(x, \tilde{p}),
\]

\( (27) \)

where, 

\[
e_1(x, \tilde{p}) = f(x, \tilde{p}) - q_i \tilde{p}^T (x, \tilde{p}) - \lambda \sum_{n \in N} \sum_{k \in K} x_{n,k}
\]

and

\[
e_2(x, \tilde{p}) = g(x, \tilde{p}) - \lambda \sum_{n \in N} \sum_{k \in K} (x_{n,k})^2.
\]

In fact, although both \( e_1(x, \tilde{p}) \) and \( e_2(x, \tilde{p}) \) are concave, the subtraction of them is not necessarily concave \[39\]. It is obvious that the objective function of \((27)\) belongs to the class of DC programming. To obtain a concave approximation for the objective function in \((27)\), we apply MM approach \[39\] and construct a sequence of surrogate functions for \( e_2(x, \tilde{p}) \) using first order Taylor approximation as

\[
\tilde{e}_2(x, \tilde{p}) = e_2(x^{(t-1)}, \tilde{p}^{(t-1)}) + \nabla \tilde{p} \tilde{e}_2^T(x^{(t-1)}, \tilde{p}^{(t-1)}) (\tilde{p} - \tilde{p}^{(t-1)}) + \nabla_x \tilde{e}_2^T(x^{(t-1)}, \tilde{p}^{(t-1)}) (x - x^{(t-1)}),
\]

\( (28) \)

where, \( \tilde{p}^{(t-1)} \) and \( x^{(t-1)} \) are the solution of the problem at \((t-1)\)th iteration and \( \nabla \tilde{p} \) and \( \nabla_x \) present the gradient operation with respect to \( \tilde{p} \) and \( x \), respectively. Since \( e_2(x, \tilde{p}) \) is a concave function, due to the first order condition \[31\], we have \( \tilde{e}_2(x, \tilde{p}) \geq e_2(x, \tilde{p}) \) which shows that \( \tilde{e}_2(x, \tilde{p}) \) makes a tight lower bound of \( L(x, \tilde{p}) \) \[39\] as summarized in the following Proposition.

Proposition 2. The approximation \((28)\) satisfies MM principles and makes a tight lower bound of \( L(x, \tilde{p}) \) which results in a sequence of improved solutions for problem \((26)\) and yields a locally optimal solution.

Proof. The proof is given in the Appendix B.

Now, the objective function \( L(x, \tilde{p}) = e_1(x, \tilde{p}) - \tilde{e}_2(x, \tilde{p}) \) is a concave function at each iteration. Finally, we obtain the following problem:

\[
\begin{align*}
\text{maximize} & \quad e_1(x, \tilde{p}) - \tilde{e}_2(x, \tilde{p}) \\
\text{subject to} & \quad \tilde{p}, x \in D.
\end{align*}
\]

\( (29) \)

The problem in \((29)\) is a convex optimization problem at each iteration, it can be solved efficiently using the optimization package including interior point method such as CVX \[30\], \[31\]. Therefore, we apply an iterative algorithm to tighten the obtained lower bound where the solution of \((29)\) in iteration \((t+1)\) is used as the initial point for the next iteration \((t+1)\). This iterative algorithm continues until reaches to a locally optimum point \( \tilde{p}^{(t)} \) of problem \((26)\) or equivalently problem \((24)\) in a polynomial time complexity \[20\], \[40\]. The detailed scheme is provided in Algorithm 2.

Algorithm 2 Iterative Algorithm to Solve Inner Problem (MM Method)

| Require: | i, q_i, t = 0, T_{max}, \lambda, \tilde{p}^{(0)}, x^{(0)} |
|----------|-----------------------------------------------|
| 1: | i : Dinkelbach iteration index |
| 2: | q_i : Dinkelbach parameter |
| 3: | t : MM iteration index |
| 4: | T_{max} : Maximum number of iterations |
| 5: | \lambda >> 1 : Penalty factor |
| 6: | \tilde{p}^{(0)}, x^{(0)} : Initial value of \tilde{p} and x in iteration 0 |
| repeat | |
| 7: | Solve problem \((29)\) using CVX and obtain resource allocation policy \{\tilde{p}^{(t,i)}, x^{(t,i)}\} |
| 8: | \text{Calculate } f_2^p(x, \tilde{p}^{(t,i)}), \nabla \tilde{p} f_2^T(x, \tilde{p}^{(t,i)}), f_1^p(x, \tilde{p}^{(t,i)}), \nabla \tilde{p} f_1^T(x, \tilde{p}^{(t,i)}), e_2(x^{(t,i)}, \tilde{p}^{(t,i)}), \nabla \tilde{p} e_2^T(x^{(t,i)}, \tilde{p}^{(t,i)}) \text{ and } \nabla_x e_2^T(x^{(t,i)}, \tilde{p}^{(t,i)}) |
| 9: | Set \( t = t + 1 \) |
| until | Convergence or \( t = T_{max} \) |
| 10: | Solve problem \((29)\) using CVX and obtain resource allocation policy \{\tilde{p}^{(t,i)}, x^{(t,i)}\} |
| 11: | \text{return } \tilde{p}^{(t,i)}, x^{(t,i)} |

1) Feasibility and Initial Feasible Allocation:

The optimization problem \((29)\) is feasible since there exists an initial point, i.e., \( \tilde{p}^{(0)}, x^{(0)} \), which holds all of the constraints in \( D \). However, the iterative algorithm \[2\] needs to find an appropriate initialization vector for the sub-carrier assignment and power control. The difficulty lies in how the initial point meets the QoS constraints \[8.4.2\] and \[8.5.2\]. To meet these constraints, we assume that the UEs and BS have complete SIC capability, and so, there exists only noise in the system. For the considered system, we obtain the initial point \( x^{(0)} \) and \( \tilde{p}^{(0)} \) in two steps. In step one, we assume that each sub-carrier is assigned to a UE with highest channel gain which gives the initial sub-carrier assignment, i.e., \( x^{(0)} \). In step two, for the initial sub-carrier assignment policy \( x^{(0)} \) obtained in step one, we find the initial power control policy, i.e., \( \tilde{p}^{(0)} \), obtained by solving the classic water-filling problem using CVX.

2) Computational Complexity Analysis:

The computational complexity of the proposed scheme in each iteration of the Dinkelbach method in Algorithm \[1\] is dominated by the MM algorithm proposed in Algorithm \[2\]. Since the optimization problem \((29)\) consists of \( NK \) variables and \( 3NK + 3N + K + 1 \) linear convex constraints, its time complexity is given by \((NK)^4 \) which is polynomial time complexity \[41\]. Therefore, the overall complexity of our proposed scheme is of order \( O(I_{Dinkelbach} I_{MM}(NK)^4) \), where \( I_{Dinkelbach} \) and \( I_{MM} \) are the number of iterations required for reaching convergence in Dinkelbach and MM method, respectively. More specifically, \( I_{MM} \) is the required iterations for the D.C. programming with the interior point method employed by CVX to solve problem \((29)\) given by \( I_{MM} = \log \frac{2NK + 3N + K + 1}{t^{(0)}}, \) where \( t^{(0)} \) is the
initial point, $0 < \lambda \ll 1$ is the stopping criterion, and $\xi$ is used for updating the accuracy of the method [31], [44].

In this section, we propose a novel resource allocation scheme for OFDMA networks with IBFD capability in both the BS and UEs. We maximized the EE while considering data rate requirements of UEs in DL and UL. Note that the proposed scheme can be applied to the multi-cell systems in which the UL transmission of the UEs and DL transmission of the BSs in a cell cause the inter-cell interference to the UEs and BSs in neighboring cells. In IBFD cellular networks with two-node architecture, the cell-edge UEs associated with different BSs can give severe inter-cell interference to each other [27]. To address this issue, simultaneous interference management in the BSs and UEs by employing the sub-carrier assignment, power control and user association in the resource allocation policy is required.

IV. Numerical Results

In this section, we evaluate our proposed resource allocation scheme and compare it with existing schemes proposed in [5], [18], [21], and [29] to demonstrate the efficacy of our scheme. We consider a single-cell system where the BS is placed at the midpoint of a square cell and the UEs are generated randomly inside the cell. The number of UEs and sub-carriers are set as $N = 10$ and $K = 16$, respectively. The channel gains are independent and generated by applying Rayleigh fading, Log-Normal shadowing with standard deviation of 8 dB, illustrated by an exponentially distributed random variable of unit mean, and the path loss model $PL(d) = PL_0 + 10\theta \log_{10} d$. Here, $d$ is the distance between the corresponding UE and the BS, $\theta$ is the path loss exponent, and $PL_0$ is the constant path loss coefficient which depends on the average channel attenuation and antenna characteristics [33]. For the power consumption model, we set the constant circuit power consumed by the BS and UEs as $P_{BS}^c = 30$ dBm and $P_{n}^c = 20$ dBm, respectively (as in [7] and [8]). The power amplifier efficiency of the BS and UEs are set as $\epsilon_{BS} = 30\%$ and $\epsilon_n = 20\%$ (as in [33] and [34]), respectively. We set the maximum transmit power of the BS and UEs as $P_{BS}^m = 42$ dBm and $P_n^m = 23$ dBm, similar to [8], [17] and [33]. Parameters of the SIC constant for the BS and UEs are set as $\delta_{BS} = -100$ dB and $\delta_n = -70$ dB, as in [13], [14], [35] and [36]. The fading coefficients of the SI channel at the BS and UEs (i.e., $l_{BS}$ and $l_n$) are generated as independent and identically distributed Rician random variables with Rician factor 5 dB, similar to [20] and [33]. Furthermore, the penalty factor to handle the integer sub-carrier assignment variables in our proposed scheme is set as $\lambda = 10^{\log_{10}(\frac{P_{BS}^m}{\epsilon_{BS}})}$. The minimum data rate requirement in UL and DL for the $n$th UE are set as $R_n^u = R_n^d = 2$ bps/Hz. Other parameters such as the noise power and the sub-carrier bandwidth are set as $-120$ dBm and 180 KHz, similar to [9], [17], [21] and [38]. The default values of all parameters used in the simulations are summarized in Table II. Unless mentioned otherwise, the default values are used. In all scenarios, the numerical results are obtained by averaging over 100 independent snapshots with randomly generated UEs’ locations.

| Parameter           | Value      |
|---------------------|------------|
| Cell diameter       | 250 m      |
| Number of UEs ($N$) | 10         |
| Number of sub-carriers ($K$) | 10 |
| Noise power at the BS and UEs ($\mathcal{N}_{BS}, N_n$) | $-120$ dBm |
| Sub-carrier bandwidth | 180 KHz |
| Path loss exponent ($\theta$) | 3.76 |
| Constant path loss coefficient ($PL_0$) | 128.1 dB |
| SIC constant for the BS ($\delta_{BS}$) | $-100$ dB |
| SIC constant for the UEs ($\delta_n$) | $-70$ dB |
| Fading coefficient of the SI channel | Rician factor 5 dB |
| Power amplifier efficiency of the BS ($\epsilon_{BS}$) | 30% |
| Power amplifier efficiency of the $n$th UE ($\epsilon_n$) | 20% |
| Constant power consumed by the BS ($P_{BS}^c$) | 30 dBm |
| Constant power consumed by the $n$th UE ($P_n^c$) | 20 dBm |
| Maximum transmit power of the BS ($P_{BS}^m$) | 42 dBm |
| Maximum transmit power of the $n$th UE ($P_n^m$) | 23 dBm |
| Minimum data rate requirement in UL ($R_n^u$) | 2 bps/Hz |
| Minimum data rate requirement in DL ($R_n^d$) | 2 bps/Hz |
| The penalty factor ($\lambda$) | $10^{\log_{10}(\frac{P_{BS}^m}{\epsilon_{BS}})}$ |

Fig. 2. Average system EE (bits/Joule/Hz) versus the number of iterations for different levels of data rate requirements in UL and DL ($R_n^u$, $R_n^d$).

A. Convergence of Our Proposed Algorithm

First, we consider a system with different levels of data rate requirements in UL and DL. Fig. 2 demonstrates the average system EE versus the number of iterations, for different minimum data rate requirements of the UEs in UL and DL ($R_n^u$, $R_n^d$). From Fig. 2 it can be seen that the EE is monotonically non-decreasing function. Fig. 2 also shows the overall convergence of our proposed iterative algorithm. As observed in this figure, our proposed algorithm converges to a stationary point after 20 iterations. Hence, in the following case studies, we show the performance of our proposed algorithm for 20 iterations. From Fig. 2 we also see that increasing the minimum data rate requirements of the UEs causes the average system EE to decrease. In fact, average EE has the highest value for the case of $R_n^u = R_n^d = 0$ bps/Hz. The reason is that without the limitation on the data rate requirement for all UEs, the sub-carriers are assigned to
the UEs with high channel gains in UL and DL which results in a higher system data-rate and a lower power consumption. Therefore, a higher average EE is achieved in a system without constraints on the QoS requirement for the UEs. To get in insight, we investigate the effect of the minimum data rate requirement on the EE as follows.

Fig. 3 demonstrates the average system EE versus the levels of minimum data rate requirements in UL and DL, i.e., $R_n^d = R_n^u$, for different SIC constant of the BS ($\delta_{BS}$). From this figure, we observe that increasing the minimum data rate requirements of the UEs in UL and DL, i.e., $R_n^u$, $R_n^d$, leads to a decreased system EE. However, as $R_n^u$ and $R_n^d$ increase, the decline in the system EE becomes more significant. The reason is that as the minimum data rate requirement is low, the required transmit power to satisfy the QoS constraint is also low leading to lower total system power consumption and subsequently lower EE. In particular, as the minimum data rate requirement in UL and DL increases, the UEs and BS have to increase their transmit power in all of channels including low quality channels to satisfy the QoS requirement constraints in UL and DL, respectively. This results in a decreased system data rate and an increased total system power consumption which leads to a decreased system EE.

### B. Probability of Feasibility

Now, we investigate that for what levels of data rate requirements in UL and DL, the stated EE maximization problem is feasible. It is notable that for all simulation scenarios, if the UL and DL transmission rates for each UE do not meet the minimum data rate requirement in UL and DL, respectively, the optimization problem (29) is infeasible and so the total system sum-rate is equal to zero leading to zero system EE. To clarify more, we compare the probability of feasibility for our proposed algorithm with four different resource allocation schemes including the exhaustive search result. As the exhaustive search is a time consuming method, we consider a system with small number of UEs and sub-carriers, i.e., $N = 2$ and $K = 4$. Fig. 4 demonstrates the probability of feasibility versus the levels of data rate requirements in UL and DL, i.e., $R_n^u = R_n^d$, for different algorithms ($N = 2$ and $K = 4$).

### C. The Effect of SIC on the EE for Different Cell Diameters

In this scenario, we consider a system in which the SIC constant of the UEs ($\delta_u$) is set as -70 dB. Fig. 5 demonstrates the average system EE versus the SIC constant of the BS for different cell diameters. We see that the average EE decreases with increasing the cell diameter. The reason is that as the cell diameter increases, the system data rate decreases and the transmit powers of both the UEs and BS increase resulting in a decreased system EE. From Fig. 5, we also observe that small values of the SIC constant of the BS results in an increased system EE. On the other hand, to achieve a certain amount of system EE, as the cell diameter increases, the SIC constant should be decreased which implies that more efficient SIC methods should be employed in long-distance communications. These results suggest that the IBFD...
D. The Effect of Maximum Transmit Power on the EE

Now, we consider a system in which the maximum transmit power of the $n$th UE is set as $\mathcal{P}_n = 23 \, \text{dBm}$. Fig. 6 shows the average system EE versus the maximum transmit powers of the BS ($\mathcal{P}_{\text{BS}}$) for our proposed algorithm and two Baseline algorithms. We observe that the average system EE by applying our proposed algorithm increases by rising maximum transmit power of the BS. In fact, the average system EE of our proposed algorithms is a monotonically non-decreasing function of the maximum transmit power. However, the rate of the increase in EE is declined as the maximum transmit power becomes larger until the EE achieves a constant in the high transmit power regime. Particularly, starting from a small value of $\mathcal{P}_{\text{BS}}$, the system EE first increases with increasing $\mathcal{P}_{\text{BS}}$ and then saturates when $\mathcal{P}_{\text{BS}} \geq 42 \, \text{dBm}$. The reason is that applying our proposed algorithm, when the maximum system EE is obtained, a further increase in the maximum transmit power does not affect the EE. In fact, although the higher values for transmit power increases the system total power consumption, they also cause the system data rate to rise. When the maximum available power of the BS is higher than certain levels, only a portion of the power contributes to keeping the EE at its maximum level, therefore the EE for higher value of the transmit power is constant. In Fig. 6, the performance of upper bound is also illustrated. To find the upper bound, we consider a system with complete SIC capability for the BS and UEs and then we obtain the system EE for the different maximum transmit power levels of the BS. From this figure, we see that our proposed algorithm achieves over 90% of the upper bound performance. Also, as the optimal solution of problem (5) is located between the upper bound performance and the solution of our proposed algorithm, we can conclude that our proposed algorithm closely achieves the globally optimal solution. This observation highlights the tightness of the MM approximation used for making the stated problem convex in our paper.

Fig. 6 also contains the average system EE of two other resource allocation algorithms: algorithms proposed in [21] for the system data-rate maximization in an FD system and [29] for the aggregate power consumption minimization in an FD system. It can be observed that our proposed algorithm outperforms the other algorithms proposed in [21] and [29]. The reason is that the algorithm proposed in [21] uses excess power to increase the system data-rate by sacrificing EE, particularly in the high transmit power regime. On the other hand, the algorithm proposed in [29] just considers the total system power consumption and after it reaches a certain system data-rate which satisfies the data rate constraints of UEs, it stops and does not use the executive power to increase the EE.

E. Comparing the Performance of Our Proposed Algorithm with Existing Algorithms

Finally, we compare the performance of our proposed algorithm with other related algorithms. For this purpose, we consider five schemes proposed in [5], [18], [21] and [29] as well as the upper bound performance. As aforementioned, the stated problem for maximizing the EE in full-duplex (FD) systems with proportional SI has not been considered in the literature. Therefore, we compare our proposed algorithm with different scenarios available in the literature: we compare with [5] for the EE maximization in an HD system, with [18] for the EE maximization in an FD system with linear and constant SI, with [21] for the system data-rate maximization in an FD system, with [29] for the aggregate power consumption minimization in an FD system and with upper bound performance which finds the optimal EE in a system with complete SIC capability for the BS and UEs (See Fig. 6). In these comparisons, the number of sub-carriers is set as $K = 16$, which are assigned simultaneously to the UEs.
average energy efficiency (bits/Joule/Hz) and it has the closest performance to the upper bound performance. As observed in Fig. 7, our proposed algorithm outperforms the other algorithms proposed in [21], the problem of aggregate power minimization in FD systems [29] and the data rate maximization in FD systems [21], the problem of EE maximization in FD systems with constant SI [18], the problem of system data rate maximization in FD systems with linear SI [18], the problem of EE maximization in FD systems with proportional SI (i.e., for the algorithm proposed in [5]), the problem of EE maximization in an HD system. As in reality, we assume that the SI exists and it is proportional to the transmit power with Rician distribution for SI channels in our FD system model. In the proposed algorithm in [18], to maximize the EE in FD systems with constant SI model, the SI was constant. Therefore, to carry out a fair comparison with our proposed algorithm, we include the SI proportional to the transmit power in data rate calculations of [18] with constant SI model. We also compare our proposed algorithm with heuristic algorithm proposed in [18] for linear SI model. Fig. 7 demonstrates the average system EE versus the SIC constant of the BS for seven different scenarios: the problem of EE maximization in FD systems with proportional SI (i.e., our proposed algorithm), the problem of EE maximization in HD systems [5], the problem of EE maximization in FD systems with linear SI [18], the problem of EE maximization in FD systems with constant SI [18], the problem of system data rate maximization in FD systems [21], the problem of aggregate power minimization in FD systems [29] and the upper bound performance. As observed in Fig. 7, our proposed algorithm outperforms the other algorithms proposed in the literature and it has the closest performance to the upper bound. More specifically, the EE achieved by our proposed algorithm that maximizes EE with proportional SI is more than that achieved by the algorithms proposed to maximize the system data rate and minimize the aggregate power. The reason is that the algorithms proposed to maximize the system data rate and minimize the aggregate power just optimize the system data rate and total power consumption, respectively while our proposed algorithm optimizes both of them which leads to a higher EE. In addition, as observed in Fig. 7, our proposed algorithm performs 20% and 35% better than the algorithms proposed to maximize EE in FD systems with linear and constant SI model, respectively. The reason is that the algorithm proposed in [13] for linear SI model is a heuristic algorithm which decouples the problem into two sub-problems of power control and sub-carrier assignment, while our proposed algorithm finds sub-carrier assignment and power control policy jointly and it closely achieves the globally optimal solution (See Fig. 6). In addition, although the algorithm proposed in [13] for constant SI model finds an optimal solution, it does not have a good performance in a realistic system where the SI is proportional to the transmit power. The important observation from Fig. 7 is that by applying the IBFD capability with efficient SIC techniques, i.e., $\delta_{BS} \leq -100$ dB and $\delta_n \leq -70$ dB, our resource allocation scheme can operate 75% more energy efficiently than that in HD systems. The reason is that although algorithms that maximize EE in HD systems achieve a lower power consumption, a two-fold data rate is achieved by algorithms that maximize EE in FD systems. The same results are also obtained for SIC constant of the UEs which omitted due to similarity.

V. CONCLUSIONS

We have studied the EE maximization problem subject to the maximum transmit power of the BS and UEs, while satisfying QoS requirements of the UEs at UL and DL in OFDMA IBFD networks. We addressed this problem by proposing an algorithm for jointly optimizing the power control and sub-carrier assignment in the UL and DL. As the formulated optimization problem was non-convex, solving it in original form was difficult. Thus, we first reformulated it in a problem by decoupling the transmit power and sub-carrier assignment variables. Then by applying Dinkelbach method, we transformed the fractional objective function to a subtractive form. Next, we made the inner problem in each iteration of Dinkelbach algorithm convex by using MM algorithm and handled the integer sub-carrier assignment variables by applying abstract Lagrangian duality and introducing a penalty function. We showed that MM approximation used for making the inner problem convex is a tight lower band of the original inner problem. Finally, we proposed an iterative resource allocation scheme to solve the inner problem which converges to the locally optimal solution. Simulation results showed that our proposed algorithm quickly converges and outperforms current schemes in the literature such as the algorithm proposed to minimize the aggregate power or maximize the system data rate. Also, our simulation results demonstrated that by applying the IBFD capability in cellular networks with efficient SIC techniques, the resource allocation scheme can operate 75% more energy efficiently than that in an HD system. An interesting future work includes considering the case of multi-antenna BS which requires joint beamforming design, sub-carrier assignment and power control solutions.
A. Proof of Proposition 2

We start the proof of Proposition 1 by using the abstract Lagrangian duality. The primal problem of (24) is written as

\[ p^* = \max_{(p, x) \in D} \min_{\lambda} L(x, p, \lambda), \quad (30) \]

where the dual problem of (24) is given by

\[ d^* = \min_{\lambda} \max_{(p, x) \in D} L(x, p, \lambda) = \min_{\lambda} \theta(\lambda), \quad (31) \]

where \( \theta(\lambda) \) is defined as \( \theta(\lambda) = \max_{(p, x) \in D} L(x, p). \) Based on the weak duality theorem, we have the following equality:

\[ p^* = \max_{(p, x) \in D} \min_{\lambda} L(x, p, \lambda) \leq \min_{\lambda} \theta(\lambda) = d^*. \quad (32) \]

It should be noted that for \( \bar{p}, x \in D, \) we have two cases where each case should be studied.

**Case 1:** Assume that at the optimal point, we have:

\[ \sum_{\forall n \in N} \sum_{\forall k \in K} (x_{n,k} - (x_{n,k})^2) = 0. \quad (33) \]

In this case, \( d^* \) is also a feasible solution of (24). Accordingly, substituting the optimal value of \( \lambda, \) i.e., \( \lambda^*, \) into the optimization problem (24) leads to the following equation:

\[ d^* = \theta(\lambda^*) = \max_{(p, x) \in D} \min_{\lambda} L(x, p, \lambda) = p^*. \quad (34) \]

Furthermore, referring to (25), in this region \( \theta(\lambda) \) is a monotonically decreasing function with respect to \( \lambda \). On the other hand, it is specified that \( d^* = \min_{\lambda} \theta(\lambda). \) Hence, we have:

\[ d^* = \theta(\lambda), \quad \forall \lambda \geq \lambda^*. \quad (35) \]

Equation (35) indicates that for any value of \( \lambda \geq \lambda^*, \) the solution of (26) leads the optimal solution of (24).

**Case 2:** Assume that, \( x_{n,k} \) take values \( 0 < x_{n,k} < 1, \) causing:

\[ \sum_{\forall n \in N} \sum_{\forall k \in K} (x_{n,k} - (x_{n,k})^2) > 0. \quad (36) \]

In this case, referring to (25) and \( \theta(\lambda), \) at the optimal point \( \theta(\lambda^*) \) tends to \( -\infty. \) However, this may not happen as it contradicts with primal solution (i.e., \( \max_{\lambda} \min L(x, p, \lambda) \)) which states that \( \theta(\lambda^*) \) is bounded from below by solution of (24) which is always greater than zero. Thus, at the optimal point, we have \( \sum_{\forall n \in N} \sum_{\forall k \in K} (x_{n,k} - (x_{n,k})^2) = 0, \) and the result for the first case is hold. This completes the proof.

B. Proof of Proposition 3

The approximation (28) makes a tight lower bound of \( L(x, \bar{p}). \) Since \( e_2(x, \bar{p}) \) is a concave function, the gradient of \( e_2(x, \bar{p}) \) is upper-gradient (31) as follows:

\[ e_2(x, \bar{p}) = \dot{e_2}(x, \bar{p}). \quad (37) \]

It is noteworthy that \( e_1(x, \bar{p}) - e_2(x, \bar{p}) \geq e_1(x, \bar{p}) - \dot{e_2}(x, \bar{p}). \) Moreover, the equality holds when \( x = x^{(t-1)} \) and \( \bar{p} = \bar{p}^{(t-1)} \) which shows the tightness of the lower bound. In addition, we can conclude that the solution obtained by incorporating MM approximation would be improved at the end of each iteration. The objective function of (25) in \( t \)-th iteration is \( e_1(x^{(t)}, \bar{p}^{(t)}) - e_2(x^{(t)}, \bar{p}^{(t)}) \). Hence, we have the following equation:

\[ e_1(x^{(t+1)}, \bar{p}^{(t+1)}) - e_2(x^{(t+1)}, \bar{p}^{(t+1)}) \geq e_1(x^{(t+1)}, \bar{p}^{(t+1)}) - e_2(x^{(t)}, \bar{p}^{(t)}) - \nabla_{x} e_2(x^{(t)}, \bar{p}^{(t)}) (x^{(t)} - x^{(t+1)}) = \min_{\bar{p} \in \mathcal{P}} (e_1(x, \bar{p}) - e_2(x, \bar{p})) \]

Thus, by solving the convex lower bound in (29), the proposed iterative algorithm generates a sequence of feasible solutions, i.e., \( \bar{p}^{(t+1)} \) and \( x^{(t+1)}. \) One may conclude that the solution of (26) would be improved and takes larger values as iterations continue which yields a locally optimal solution.

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Rojin Aslani (S’19) received her B.Sc. degree in Information Technology Engineering from University of Tabriz, Tabriz, Iran, in 2011 and her M.Sc. degree in Information Technology Engineering (Computer Networks) from Amirkabir University of Technology, Tehran, Iran, in 2013. She is pursuing the Ph.D. degree in Computer Engineering (Computer Networks) in Amirkabir University of Technology, Tehran, Iran. Currently, she is a visiting research scholar at the Department of Electrical and Computer Engineering, University of Nevada, Las Vegas, NV, USA. Her current research area include resource allocation in wireless networks, vehicular communications, and optimization.

Mehdi Rasti (S’08-M’11) received his B.Sc. degree from Shiraz University, Shiraz, Iran, and the M.Sc. and Ph.D. degrees both from Tarbiat Modares University, Tehran, Iran, all in Electrical Engineering in 2001, 2003 and 2009, respectively. From November 2007 to November 2008, he was a visiting researcher at the Wireless@KTH, Royal Institute of Technology, Stockholm, Sweden. From September 2010 to July 2012, he was with Sharif University of Technology, Shiraz, Iran, after that he joined the Department of Computer Engineering and Information Technology, Amirkabir University of Technology, Tehran, Iran, where he is now an assistant professor. From June 2013 to August 2013, and from July 2014 to August 2014 he was a visiting researcher in the Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB, Canada. His current research interests include radio resource allocation in wireless networks and network security.

Ata Khalili (S’18) received the B.Sc. degree and M.Sc. degree with first class honors in Electronic Engineering and Telecommunication Engineering from the Shahed University in 2016 and 2018, respectively. He is now working as a visiting researcher in the Department of Computer Engineering and Information Technology, Amirkabir University of Technology, Tehran, Iran. His research interests include convex and non-convex optimization, resource allocation in wireless communication, Green communication, and mobile edge computing.