Multiobjective Optimization for Resource Allocation in Full-duplex Large Distributed MIMO Systems

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***Abstract*—The most conflicting key variables in wireless networks are energy efficiency (EE) and spectral efficiency (SE). In this paper, we propose an energy-efficient allocation algorithm of network resources for multi-input multi-output networks distributed with large-scale antenna systems. We formulate a multiobjective optimization problem (MOOP) to maximize the EE of each distinct user and to show the EE–SE trade-off as a MOOP. To find the Pareto optimal solution, we transform this MOOP into single-objective optimization problem (SOOP) through Tchebycheff scalarization and by exploiting it with Dinkelbach's method. To solve the SOOP, we apply a joint antenna selection and user scheduling (JASUS) algorithm for the joint allocation of antenna scheduled users solved through an iterative approach. The power allocations are applied distinctly for individual cell users by a subgradient iterative method to simplify the SOOP further and improve the EE. The simulation results reveal that our proposed MOOP has a fast convergence, achieving maximum EE after a few iterations. Additionally, our proposed methods unveil an interesting trade-off between EE and SE at a faster speed and demonstrate that an important performance gain is achieved by using the proposed algorithm.**

***Index Terms*—antenna, convergence, energy efficiency, optimization, uplink.**

I. INTRODUCTION

Advanced fifth-generation (5G) communication networks support many architectures. The growing power consumption among these networks has raised concerns regarding the investigation of 5G communication systems. Owing to increasing energy costs and rising levels of greenhouse gases, energy-efficient wireless communication has drawn great interest in the wireless research community. Therefore, reducing energy consumption along with increasing data transmission rates is crucial for the development of future wireless communication networks [1, 2]. EE is expressed as the ratio of maximum achievable throughput of all users to overall power consumption. Over the years, many techniques have been studied for enhancing EE performance in wireless communication networks [3].

More recently, massive multi-input multi-output (MIMO) systems have been thoroughly investigated to enhance the EE and SE of wireless communication networks. Massive MIMO systems with a very large number of numerous antennas can successfully overcome small-scale distortion, fast fading of channels, and receiver noise [4–7]. By contrast, distributed antenna systems (DASs) are one of the new technologies available for enhancing EE and SE in wireless communications. The DAS is an attractive and inspiring candidate for 5G wireless communication networks, such as cloud radio access networks (C-RANs) [8-9]. A large-scale DAS (L-DAS) is employed with a DAS over different base stations (BSs) located in various cells or from radio remote heads (RRHs) in the cell that can ease high propagation loss by using numerous geographically antenna systems.

The performance of a wireless network can be calculated by capacity, SE, and EE. Recently, the EE-SE trade-off investigation has gained much attention [10-14]. In wireless communication SE shows how efficiently the bandwidth is used while the EE refers to way of limiting the energy consumption. It is well-known that maximizing EE and SE are conflicting objectives and there exists a fundamental trade-off between them [10-14]. The EE-SE trade-off, therefore, reveals the theoretical performance boundary of a communication system. To meet the need for energy-efficient 5G wireless communication, DASs have been studied for optimization of EE [9–15]. The optimum energy-efficient power allocation approach has been considered in a generalized DAS [16–20]. He *et al.* explained the problem of EE maximization with proportional equality taken into consideration [21]. An EE optimization of joint antenna selection and power allocation was conducted in which multiple sectored antennas were suggested for high EE [22-23]. SE–EE trade-off in DASs was examined for a single user. Power allocation was achieved by an optimal closed-form solution [15]. Li *et al.* also performed joint allocation of antenna selection and power for a multiuser DAS system [17]. They also proposed energy-efficient power allocation in a C-RAN with minimum capacity and per-antenna power constraints [18]. In a DAS, antenna selection plays a significant role in maximizing the system's EE. A proper antenna selection method can significantly improve EE in a communication network. Usually, antennas are equally distributed, while some are far distant from users. These more-distant antennas consume a considerable power without having any significant impact on the overall capacity. In the case of multiple cells, the nodes of each cell may interfere with one another and even reduce the capacity [24–25]. Furthermore, there is limited research on the

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performance of L-DASs under some channel parameters, shadowing, and fading. Therefore, a proper antenna selection method can significantly improve EE of a massive MIMO network.

In this paper, we focus on the performance of an L-DAS network under constraints such as path loss, fading, and other-cell interference. Results are obtained for practical situations such as user scheduling and various antenna architectures [27-28]. We propose a simple and fast converging algorithm for solving the multiobjective optimization problem (MOOP) for the energy-efficient allocation of resources, e.g., selection of antenna and user scheduling with power allocation in full-duplex (FD) MIMO L-DASs. We also examine the EE–SE trade-off in L-DAS networks. The solution of the optimization problem is expressed as a Pareto optimal set based on the MOOP [29–32].

The formulated MOOP is nonconvex and a bit tedious to handle. To tackle this problem, the weighted Tchebycheff method is used to convert it into an equivalent single-objective optimization problem (SOOP). The SOOP obtained is a fractional function of several functions, and this function is further solved by an iterative algorithm and subproblem approach [33-39]. The Pareto optimal solution is derived by applying a dual-Lagrangian method that fulfills the Karush–Kuhn–Tucker (KKT) condition. The Lagrangian multipliers are obtained and iteratively simplified using the subgradient method. The simulation results demonstrate that the proposed MOOP optimization approach has superior performance and convergence speed. The rest of this paper is organized as follows. Section II details the system model adopted in the present work. The MOOP formulation and its Pareto optimal solution are derived in Section III and Section IV. The simulation results are discussed in Section V. Finally, we conclude our work in Section VI.

II. System Model

We consider L cells where N RRHs in each cell work in FD mode. The data are transmitted to distributed users in the downlink and received independently at the same time from these users in the uplink mode. Each RRH is provided with U colocated antennas. The $K_{\max}$ users are randomly distributed in each cell with a single antenna.

A. Uplink Transmission

The uplink channel vector between the mth user in the jth cell to the RRHs in the ith BS is expressed as

$$\mathbf{g}_{ijm} = \mathbf{\Psi}_{ijm}^{1/2}\mathbf{h}_{ijm} \tag{1}$$

where, $\mathbf{\Psi}_{ijm} = \operatorname{diag}\left(\left[\psi_{i1jm},\ldots,\psi_{iNjm}\right]\right)\otimes \mathbf{I}_U$, $\psi_{injm} \triangleq cd_{injm}^{-\alpha}$, and $\mathbf{h}_{ijm} = \left[\mathbf{h}_{i1jm}^T,\ldots,\mathbf{h}_{iNjm}^T\right]^T$. The symbol $(\cdot)^{\mathrm{T}}$ denotes the transpose, ψ_{injm} is the large-scale fading coefficient between the mth user in the jth cell to the nth RRH in the ith cell, $\otimes$ signifies the Kronecker product, and c and α denote the path loss and the path loss exponent at the reference distance d, respectively.

Moreover, $\mathbf{h}_{injm}$ is small-scale fading coefficient which represents $U \times 1$ independent and identically distributed zero-mean circularly symmetric complex Gaussian random variables with unit variance.

We consider the worst-case scenario of pilot reuse and contamination in which each cell reuses the same set pilot sequences that are mutually orthogonal.

For simplicity, we denote the orthogonal pilot set in each cell by $\mathbf{X}_{\mathrm{P}}$ [1], [4]. Hence, the received signal at the baseband processing unit (BPU) of the ith cell is expressed as

$$\mathbf{Y}_{\mathrm{P}i} = \mathbf{G}_{ii}\mathbf{X}_{\mathrm{P}} + \sum_{l\neq i}\mathbf{G}_{il}\mathbf{X}_{\mathrm{P}} + \mathbf{Z}_{\mathrm{P}i} \tag{2}$$

Here, $G_{il} = \left[g_{il1}, g_{il2},\ldots, g_{ilK_{\max}}\right]$ is the channel matrix of all users in the lth cell to all the RRHs of the ith cell. The symbol $\mathbf{Z}_{\mathrm{P}i}$ denotes noise matrix independent and identically distributed zero-mean circularly symmetric complex Gaussian random variables with variance $1/\sigma_{\mathrm{p}}$, where σ_{P} denotes the signal-to-noise ratio.

The BPU of the ith cell traces the channel vector $\mathbf{g}_{ijm}$ after tallying the received signal and pilot sequence of the mth user given by

$$\mathbf{y}_{\mathrm{P}im} = \mathbf{g}_{ijm} + \sum_{k\neq j}\mathbf{g}_{ikm} + \mathbf{z}_{\mathrm{P}im} \tag{3}$$

where, y_{Pim} and z_{Pim} are the mth columns of $\mathbf{Y}_{\mathrm{P}i}$ and Z_{Pi}, respectively. The minimum mean-square error (MMSE) $\hat{\mathbf{g}}_{ijm}$ in $\mathbf{g}_{ijm}$ is expressed as

$$\hat{\mathbf{g}}_{ijm} = \mathbf{\Psi}_{ijm}\mathbf{Q}_{im}^{-1}\mathbf{y}_{\mathrm{P}im} \tag{4}$$

B. Downlink Transmission

We used the maximum ratio transmission beamforming technique. The precoding vector $\mathbf{w}_{jm}$ of the mth user in the jth cell is expressed by

$$\mathbf{w}_{jm} = \sqrt{\zeta_{jm}}\hat{\mathbf{g}}_{jjm} \tag{5}$$

where, ζ_{jm} is the normalization constant given by $\zeta_{jm} = \dfrac{1}{\mathbb{E}\left[\mathbf{w}_{jm}^{\mathrm{H}}\mathbf{w}_{jm}\right]}$. In FD mode, the downlink received signal at the mth user in the jth cell contributes to the uplink co-channel interference given by [1].

$$y_{jm} = \sum_{i=1}^{L}\mathbf{g}_{ijm}^{\mathrm{H}}\sum_{k=1}^{K_{Di}}\sqrt{\zeta_{ik}P_{ik}}\mathbf{w}_{ik}x_{ik} + \sum_{i=1}^{L}\sum_{k=1}^{K_{Ui}} q_{ikjm}s_{ik} + \mathbf{n}_{jm} \tag{6}$$

where, x_{ik} indicates the data symbol for the kth user in the ith cell, which follow a complex Gaussian distribution with a random variable with zero mean and unit variance. $s_{ik} = \sqrt{t_{ik}}d_{ik}$ is the transmission signal of the kth uplink user in the ith cell. t_{ik} and d_{ik} denote the transmission power and transmitted data sent from the kth uplink user to the RRH in the ith cell, respectively; q_{ikjm} represent the channel coefficients between the downlink mth user in the jth cell and the uplink kth user in the ith cell; and n_{jm} is the additive white Gaussian noise at the mth user in the jth cell. The maximum throughput of the mth user in the jth cell is given by [1].

$$r_{jm} = \log_2\left(1+\frac{\left|\sqrt{\zeta_{jm}P_{jm}}\mathbf{g}^{\mathrm{H}}_{jjm}\hat{\mathbf{g}}_{jjm}\right|^2}{\sum\limits_{(lk)\neq(jm)}\left|\sqrt{\zeta_{jm}P_{jm}}\mathbf{g}^{\mathrm{H}}_{ljm}\hat{\mathbf{g}}_{llk}\right|^2+\sum\limits_{i=1}^{L}\sum\limits_{k=1}^{K_{\mathrm{U}i}}t_{ik}\left|q_{ikjm}\right|^2+\delta^2_{n_{jm}}}\right) \tag{7}$$

Here, the fractional term represent signal to noise plus interference ratio (SINR), $\delta^2_{n_{jm}}$ is the noise variance at the mth user in the jth cell. Now, we define the SE of the system, which is equal to the total system throughput per unit bandwidth as

$$\eta_{SE} = \Re(\mathbf{P},\mathbf{A},\,\mathbf{U}) = \sum_{j=1}^{L}\sum_{m\in U_j} r_{jm}\left(\mathbf{P},\mathbf{A},\mathbf{U}\right) \tag{8}$$

where, $\mathbf{P}=\mathrm{vec}\left(\mathbf{P}_1,\mathbf{P}_2,\ldots,\mathbf{P}_L\right)$ is the transmission power of all the scheduled users in L cells; $\mathbf{P}_j=\mathrm{diag}\left(P_{j1},P_{j2},\ldots,P_{jK}\right)$ denotes the transmission power of K out of $K_{\max}$ scheduled users in the jth cell; and $\mathbf{U}=\left(\mathbf{U}_1,\mathbf{U}_2,\ldots,\mathbf{U}_L\right)$ and $\mathbf{A}=\left(\mathbf{A}_1,\mathbf{A}_2,\ldots,\mathbf{A}_L\right)$ denote the set of scheduled users and antennas selected in L cells, respectively. The overall power consumption is the linear sum of all transmission-power-dependent terms of all selected antennas and independent power (P_c) contributions per cell [10]. The total power consumption of the system is expressed as

$$\mathrm{P}_{\mathrm{tot}}=\mathrm{P}\left(\mathbf{P},\mathbf{A},\mathbf{U}\right)=\upsilon\sum_{j=1}^{L}\sum_{a_i^j\in A_j}\frac{1}{\beta}P^j_{a_i}+\sum_{j=1}^{L}P_c \tag{9}$$

Here a_i^j is the ith antenna in the jth cell, υ indicates the power loss coefficient $(\upsilon>1)$, β denotes the efficiency of the power amplifier, and $P^j_{a_i}$ indicates the transmission power of the ith antenna in the jth cell. Accordingly, the EE of the whole network can be expressed as [27].

$$\eta\left(\mathbf{P},\mathbf{A},\mathbf{U}\right)=\frac{\eta_{SE}}{\mathrm{P}_{\mathrm{tot}}}=\frac{\Re\left(\mathbf{P},\mathbf{A},\mathbf{U}\right)}{\upsilon\sum\limits_{j=1}^{L}\sum\limits_{a_i^j\in A_j}\frac{1}{\beta}P^j_{a_i}+\sum\limits_{j=1}^{L}P_c} \tag{10}$$

As already mentioned, SE and EE are conflicting metrics in an L-DAS. Maximizing the SE of the system is equivalent to utilizing all the available resources, e.g., transmission power and all antennas. Therefore, the EE of the system may degrade drastically as a result of severe power consumption. In such cases, maximizing SE or EE may not work out to satisfy the QoS requirement. Therefore, investigation of EE–SE trade-off becomes important. SE–EE trade-off is achieved by solving a simplified MOOP in which the total power consumption is minimized, and SE is maximized over various weight parameters [23].

III. Problem Formulation

The objective of our work is optimization of the EE of each user and improved EE–SE trade-off. The equivalent MOOP can be formulated by maximizing the EE and SE of each user simultaneously, which is expressed as the following equation:

$$\max_{\mathbf{P},\mathbf{A},\mathbf{U}}\left[\eta\left(\mathbf{P},\mathbf{A},\mathbf{U}\right),\Re\left(\mathbf{P},\mathbf{A},\mathbf{U}\right)\right] \tag{11}$$

s.t.

$$(\mathrm{C1}):r_{jm}\left(\mathbf{P},\mathbf{A},\mathbf{U}\right)\geq R_{\min}\;\;\forall j,m\in\mathbf{U}_j, \tag{12}$$

$$(\mathrm{C2}):\mathbf{P}_{jm}>0\;\;\;\forall j,m\in\mathbf{U}_j \tag{13}$$

$$(\mathrm{C3}):\sum_{i=U\times(n-1)+1}^{nU}\mathbf{P}^j_{a_i}\leq\mathbf{P}_{n,\max}\;\;\;\forall n,j \tag{14}$$

$$(\mathrm{C4}):\mathbf{A}_j\subset\mathbf{A}_j,\;\forall j \tag{15}$$

$$(\mathrm{C5}):\mathbf{U}_j\subset\mathbf{U}_j,\;\;\forall j \tag{16}$$

$$(\mathrm{C6}):P^j_{a_i}=0\;\;\;\forall j,a_i^j\notin\mathbf{A}_j \tag{17}$$

In (11), constraint C1 represents the minimum bit rate of all selected users. In C2, we impose a limit for the users to transmit power. C3 imposes a constraint on the overall transmission power of a given RRH. C4 and C5 address antenna and user selection. C6 indicates zero transmission power for all antennas without transmission.

IV. Proposed Solution

It is obvious that the aforementioned MOOP has a nonconvex objective in C1 and C2. Consequently, we implement a method to solve it by using two subproblems with regard to A and U, as well as with regard to P. Now, problem (11) is compressed to an optimization problem subjected to A and U for an initial feasible P that satisfies constraints C2, C3, and C6. Therefore, we propose an easy and effective joint antenna selection and user scheduling (JASUS) algorithm for A and U. We denote this as subproblem 1. Then, we solve subproblem 2 by obtaining the suboptimal P that satisfies C1–C3 and C6. Here, we transform the objective function from fractional to a subtractive form and find a suboptimal solution using Dinkelbach's method [38].

A. JASUS Algorithm

We propose a JASUS algorithm that can easily be employed in an L-DAS. The basic idea is based upon a greedy algorithm that successively removes the worst antenna (i.e., the one causing performance degradation) at each iteration (t). Meanwhile, at each iteration, it successively selects the set of users that experiences a promising level of orthogonality. The algorithm seeks to construct three parts. It starts by initializing the set of all antennas in sequence independently in all L cells. In a similar way to the antenna set A^t we calculate user set U^t.

After the antenna and user selections are made, the iterative process starts by updating them one by one based on the maximum achievable throughout criteria. The entire process is repeated for the next network cell until convergence is reached.

Algorithm 1. JASUS Algorithm

1. Initialization: $\mathbf{U}^0$ and $\mathbf{A}^0$.
2. $\mathrm{d}_\mathrm{m}=\mathrm{diag}\left(\hat{\mathrm{G}}^\mathrm{H}\hat{\mathrm{G}}\right)_\mathrm{m}$. Let antenna M with the largest $\left|d_m\right|$ be used to create A^0.
3. According to A^0, calculate $d_k=\mathrm{diag}\left(\hat{G}_{U_{all}A^0}\hat{G}^H_{U_{all}A^0}\right)_k$,
4. Select the users $(K\leq M)$ with largest $\left|d_k\right|$

5. Create U^0.
6. Let t = 0, where $t_{\max}$ = maximum number of iterations, $\mathbf{U}^{t-1}=\varnothing$, $\mathbf{A}^{t-1}=\varnothing$, $\boldsymbol{T}^{t\text{-}1}=\{A^0,U^0\}$, $\boldsymbol{B}_a^t=\{A^0\}$, and $\boldsymbol{B}_u^t=\{U^0\}$.
7. Iterative updating of antenna and user:
8. **While** $\mathbf{U}^t \neq \mathbf{U}^{t-1}$, $\mathbf{A}^t \neq \mathbf{A}^{t-1}$
9. **do**
10. $a_i^{t*}=\underset{a_i^t\in\mathbf{A}^t}{\operatorname{argmin}}\left\|\hat{G}_{U^t\,\mathbf{A}_i^t}\right\|_F$
11. Formulate $\mathbf{A}^t_{\backslash a_i^{t*}}$
12. Find $a_i^*=\underset{a_i\in(\mathbf{A}^t)^c}{\operatorname{argmax}}\left\|\hat{\mathbf{G}}^t_{U_{a_i}}\right\|_F$
13. **If** $\eta\left(\mathbf{A}^t_{\backslash a_i^{t*}}\cup\{a_i^*\},\mathbf{U}^t\right)>\eta\left(\boldsymbol{B}_a^t,\boldsymbol{B}_u^t\right)$
14. **Then U**pdate $\mathbf{A}^{t+1}=\mathbf{A}^t_{\backslash a_i^{t*}}\cup\{a_i^*\}$, $\boldsymbol{B}_a^{t+1}=\mathbf{A}^{t+1}$ and $\boldsymbol{T}^{t+1}=\boldsymbol{T}^t\cup a_i^{t*}$.
15. **Else**
16. $\mathbf{A}^{t+1}=\mathbf{A}^t$
17. End if
18. Find $u_i^{t*}=\underset{u_i^t\in U^t}{\arg\max}\,\eta\left(\boldsymbol{B}_a^{t+1},\boldsymbol{B}_u^t\right)$
19. Formulate $\mathbf{U}^t_{\backslash u_i^{t*}}$
20. **If** $\eta\left(\mathbf{A}^{t+1},\mathbf{U}^t_{\backslash u_i^{t*}}\cup\{u_i^*\}\right)>\eta\left(\boldsymbol{B}_a^{t+1},\boldsymbol{B}_u^t\right)$
21. **Then** Update $\mathbf{U}^{t+1}=\mathbf{U}^t_{\backslash u_i^{t*}}\cup\{u_i^*\}$
22. **Else**
23. Update $\mathbf{U}^{t+1}=\mathbf{U}^t$
24. **End if**
25. t = t + 1
26. Until $t=t_{\max}$

ALGORITHM 2. ITERATIVE ALGORITHM FOR FLAG CONVERGENCE

1. Initialization: Iteration number t = 0, flag = 1, weight coefficient = ϕ
2. **While** flag, flag > 0.01, **do**
3. **Update** t = t + 1;
4. According to $\mathbf{A}^{t+1}$, $\mathbf{U}^{t+1}$
5. Calculate from Algorithm 1 $(\mathbf{A}^t,\mathbf{U}^t);\forall f\in\{A,U\}$;
6. Calculate flag $\Delta f=\max_{j,m}\left|f_{j,m}^t - f_{j,m}^{t\text{-}1}\right|$;
7. **End while**

B. Proposed MOOP Algorithm

The equivalent MOOP can be formulated by maximizing the SE of the network for each user and minimizing the total power consumed simultaneously, which is expressed as the following equations:

$$\max f_1(\mathbf{P})=\sum_{j=1}^{L}\sum_{m\in U_j} r_{jm}(\mathbf{P})$$
$$\min f_2(\mathbf{P})=\mathrm{P}(\mathbf{P}) \tag{18}$$
$$\text{s.t. (C1)–(C3) and (C6)} \tag{19}$$

In this section, multiple objectives can be linearly coupled as a SOOP by using a weighting parameter that indicates the trade-off among multiobjective [40-42]. To solve above problem, we apply the concept of Pareto optimal. In above problem, the weighted Tchebycheff method can be regarded as EE-SE tradeoff among users. It is most effective method to solve MOOP. It is difficult to achieve Pareto optimal resource allocation from the above problem (18). Therefore, to transform the MOOP into a SOOP, we adopt the weighted Tchebycheff technique [37]:

$$\min_{\mathbf{P},\mathbf{A},\mathbf{U}}\max\left\{\phi f_1(\mathbf{P}),(1-\phi)f_2(\mathbf{P})\right\} \tag{20}$$
$$\text{s.t. (C1)–(C3) and (C6)} \tag{21}$$

Here, ϕ is a vector of weights. The above problem (20) is an example fractional programming, in which the maximum of numerous fractions is minimized [43-49]. Problem (20) can be converted into a quasiconvex problem by using the following approach given in [42], [50].

C. Dual-Lagrangian Analysis and KKT Conditions

The Lagrange dual multiplier method is an efficient tool for optimization problems [21]. Thus, we first derive the Lagrangian function to solve (20) is Pareto optimal which can be derived from constraint (21).

$$\begin{aligned}
&L(P_{jm},\lambda_m,\mu_m,\tau_m)\\
&=\phi\sum_{j=1}^{L}\log_2\left(1+\frac{\left|\sqrt{\zeta_{jm}P_{jm}}\mathbf{g}_{jjm}^{\mathrm{H}}\hat{\mathbf{g}}_{jjm}\right|^2}{\sum\limits_{(l,k)\neq(j,m)}\left|\sqrt{\zeta_{lk}P_{lk}}\mathbf{g}_{ljm}^{\mathrm{H}}\hat{\mathbf{g}}_{llk}\right|^2+\sum\limits_{i=1}^{L}\sum\limits_{k=1}^{K_{\mathrm{U}i}}t_{ik}\left|q_{ikjm}\right|^2+\delta_{n_{jm}}^2}\right)\\
&-\phi)\left(\upsilon\sum_{j=1}^{L}\sum_{a_i^j\in A_j}\frac{1}{\beta}P_{a_i}^j+\sum_{j=1}^{L}P_c\right)\\
&+\left[\lambda_m\left\{\sum_{j=1}^{L}\log_2\left(1+\frac{\left|\sqrt{\zeta_{jm}P_{jm}}\mathbf{g}_{jjm}^{\mathrm{H}}\hat{\mathbf{g}}_{jjm}\right|^2}{\sum\limits_{(l,k)\neq(j,m)}\left|\sqrt{\zeta_{lk}P_{lk}}\mathbf{g}_{ljm}^{\mathrm{H}}\hat{\mathbf{g}}_{llk}\right|^2+\sum\limits_{i=1}^{L}\sum\limits_{k=1}^{K_{\mathrm{U}i}}t_{ik}\left|q_{ikjm}\right|^2+\delta_{n_{jm}}^2}\right)-R_{\min}\right\}\right]\\
&+\mu_m\sum_{j=1}^{L}P_{jm}-\sum_{m\in\mathbf{U}_j}\tau_m\left(\sum_{a_i^j\in\mathrm{RRH}_n}P_{a_i}^j-P_{\max}\right)
\end{aligned} \tag{22}$$

where, λ_m, μ_m, and τ_m are the positive Lagrangian multipliers. Now, by applying KKT conditions, the closed-form expression for P_{jm} can be obtained by taking derivative of is given by $L(P_{jm},\lambda_m,\mu_m,\tau_m)$ with respect to P_{jm} and setting it to zero which is given by

$$\frac{\partial L}{\partial P_{jm}}=\left[\begin{array}{l}\dfrac{1+\mu_m}{\left(\left(\eta\left(\dfrac{\upsilon}{\beta}\right)\left\|\mathbf{W}_{A_j u_m^j}\right\|^2+\sum\limits_{a_i^j\in A_j}\tau_m\left|\mathbf{W}_{a_i^j u_m^j}\right|^2+\lambda_m\right)+\lambda_m\right)\ln 2}\\ +\phi-\dfrac{\left(1/\sigma_{\mathrm{DL}}\right)}{\zeta_{jm}\varepsilon_{jm}}\end{array}\right] \tag{23}$$

Then we apply the sub-gradient method [49] to update the parameters. Repeating the process until Lagrangian function converges. In each cell, the gradient update equations can be defined as

$$\lambda_m(t+1) = \left\{ \lambda_m(t) - \xi(t) \times \left(\hat{r}_{jm} - R_{\min} \right) \right\} \quad (24)$$

$$\mu_m(t+1) = \left\{ \mu_m(t) - \xi(t) \times \upsilon \sum_{j=1}^{L} \sum_{a_i^j \in A_j} \frac{1}{\beta} P_{a_i}^j + \sum_{j=1}^{L} P_c \right\} \quad (25)$$

$$\tau_m(t+1) = \left\{ \tau_m(t) - \xi(t) \times \left(P_{\max} - \sum_{a_i^j \in \mathrm{RRH}_n} P_{a_i}^j \right) \right\} \quad (26)$$

Here, $\xi \geq 0$ is the iterative step size of λ_m, μ_m, and τ_m, and t is the iteration index. The gradient updates of (24), (25) and (26) are assured to converge to the optimal λ_m, μ_m, and τ_m, on the assumption that $\xi(t)$ is chosen. In this paper we consider $\xi(t) = \frac{0.1}{\sqrt{t}}$. In the successive iterations, the optimal values of λ_m, μ_m, and τ_m are used to determine P_{jm}. The iterative process continues until convergence.

V. SIMULATION RESULTS

We present the simulation results of our proposed MOOP optimization in this section. The convergence performance of our proposed algorithms is also estimated through simulation results. We consider that the RRHs with two antennas (U = 2) are fixed in a square grid. The number of RRHs (N) and number of selected antennas (M) are fixed in the range of 100–1000. The number of cells (L) is 4. The maximum number of users ($K_{\max}$ out of K) is 4–20. The power amplifier efficiency is 0.37 [51-53]. The distribution of users in the cell is uniform. The independent transmission power per cell (P_c) is 40 W. Under the framework of the path loss model, the path loss exponent α is 3.7. We also assume a power loss coefficient ν of 2.63 [17]. Parameter c is fixed to 1, and the downlink signal-to-noise ratio (σ_{DL}) is set to 30 dB. The minimum bit rate is 1 bit/s/Hz.

Fig. 1 shows the graph of EE versus the number of iterations performed to achieve the maximum converged value of EE. It can be noticed that the convergence speed of our algorithm for different numbers of K and M is high. The values of $P_{\max}$ of each RRH are different, e.g., 0 dB, 5 dB, and 0 dB. When $P_{\max}$ = 0 dB, there is no power scaling at the BS and users. So, in this case, the fractional term in equation (7) tends to infinity, the harmful effects of noise and interference terms all diminish, while the desired signal is maintained.

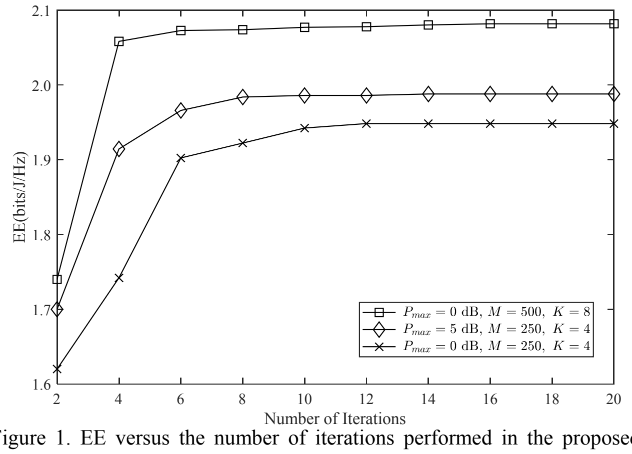

Figure 1. EE versus the number of iterations performed in the proposed algorithm

We can observe that our approach always achieves maximum EE within a few iterations. For M = 500 antennas, K = 8, and $P_{\max}$ = 0 dB, the maximum EE achieved is 1.9 bits/J/Hz. Similarly, for M = 250 and K = 4, the EE is maximum for $P_{\max}$ = 5 dB compared to $P_{\max}$ = 0 dB is highly efficient in achieving its optimal EE rapidly. Therefore, the proposed MOOP resource allocation scheme achieves maximum EE quickly.

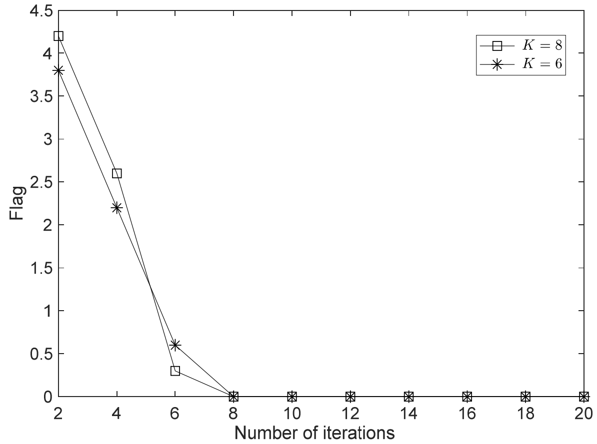

Figure 2. Convergence with regard to different initial values of users

Fig. 2 provides insight into the convergence performance of Algorithm 1. The calculated flag value according to Algorithm 2 indicates the accuracy of the convex procedure for determining SE. The plot of flag convergence versus number of iterations for various users according to different initial users (Algorithm 1) is given in Fig. 2. The ordinate in Fig. 2 denotes the change in the number of the convergence flag. The smaller the number of the flag convergence, the better is the accuracy of the convex approximation. It can be observed that our algorithm (Algorithm 2) converges very quickly, and with the increase in users, it has a minor impact on the speed of convergence.

When the flag convergence value is zero, the allocated power according to Dinkelbach's method remains the same irrespective of the number of iterations and users. This observation, together with the previous result, ensures that proposed Algorithms 1 and 2 are applicable in FD-MIMO-enabled L-DAS networks.

Fig. 3 shows the SE–EE trade-off where the number of antennas installed at the BPU is different. It can be clearly seen from this figure that the EE is a concave function of the SE. Moreover, also apparent is that the maximum value of the EE and SE improves and diminishes with the number of antennas increasing from 80 to 120. This means that SE–EE trade-off is maximum with fewer antennas and vice versa. Alternatively, the consumption of energy of the system also spikes as the quantity of antennas rises. Interestingly, the density of available spatial channels improves with more antennas installed at the BPU. The spatial channel density raises the throughput and thereby the SE. In addition, having a greater number of existing antennas leads to higher energy consumption, and the network EE decreases, to some extent, after achieving a maximum accordingly.

Furthermore, we evaluated the optimal performance of our proposed multiobjective algorithms (Algorithm 1 and Algorithm 2) by comparing our approach with the standard exhaustive search method for optimization problems.

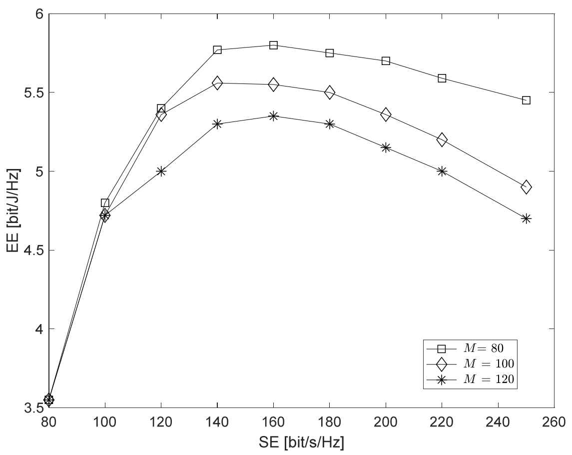

Figure 3. EE versus SE with different numbers of antennas

We chose a small scale because of the exponential computational complexity requirement of exhaustive search, considering small-scale users, e.g., K = 8 and N = 4. Fig. 4 shows the performance comparison of the EE–SE trade-off proposed by our algorithm and the reference exhaustive search method. We can observe that the performance of our proposed MOOP algorithm is very close to that of the exhaustive search method with regard to EE–SE trade-off.

Two points can be noticed from this graph. First, EE is a concave function of SE, as already proved above. Second, the EE performance proposed through our MOOP Algorithms 1 and 2 is superior to that of other algorithms such as existing exhaustive search methods. Therefore, it can be inferred that the algorithm developed in this study offers better speed and convergence to achieve the optimum EE and a better EE–SE trade-off. The SE increases while the EE increases at a slower rate owing to the increasing transmission power and number of available antennas. Power consumption is higher when the number of BSs increases, which confirms that EE first increases and then exhibits a decreasing trend with more antennas.

Fig. 5 shows the EE versus the number of antennas for various users (K = 4, 8, and 16). It is verified that the EE first increases to a maximum and then decreases when the number of transmission antenna varies from 100 to 1000. Maximum EE is achieved at M = 400 for all cases. If we compare the EE for different numbers of users (K = 4, 8, and 16), we see that it increases with the number of users in the cell.

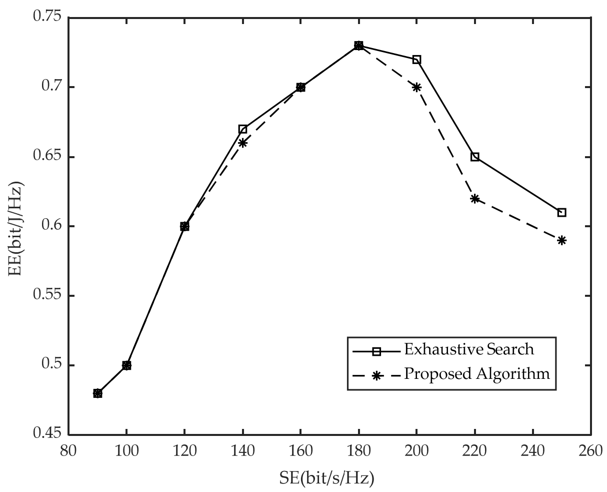

Figure 4. EE–SE trade-off

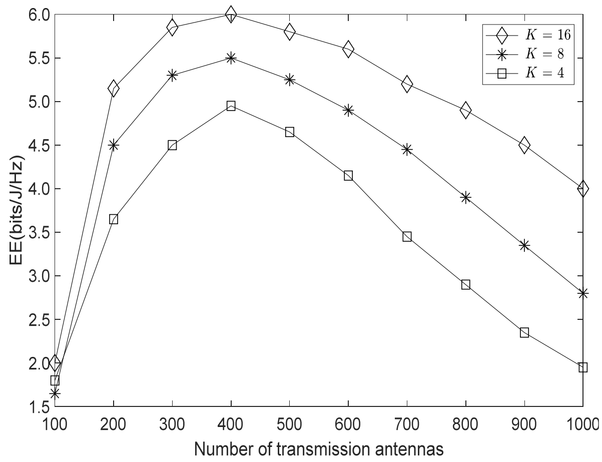

Figure 5. EE versus number of antennas

The EE improves when the number of antennas varies from M = 100 to 400. During the increase in the number of antennas to up to 400, the number of users, K = 16, 8, and 4, the maximum EE can be achieved, at EE = 6, 5.5, and 4.8 bits/J/Hz. However, EE further drops from M = 400 to 1000 owing to the progressive increase in power consumption associated with the more extensive antenna network.

Fig. 6 presents the SE versus the total number of antennas at the BSs. We observe that SE increases when the number of antennas increases from M = 100 to 1000. This means that a large number of antennas is beneficial for achieving higher SE.

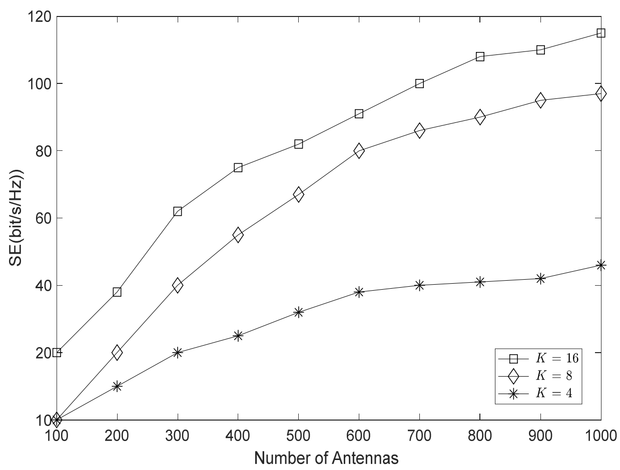

Figure 6. SE versus number of antennas

If we compare the SE for different numbers of users (K = 4, 6, and 16), SE increases slowly for K = 4 while SE increases rapidly when K = 8 and 16. The SE is 42 bits/s/Hz for K = 4, 97 bits/s/Hz for K = 8, and 118 bits/s/Hz for K = 16.

As expected, the SE is maximum (118 bits/s/Hz) when K =16 and M = 1000, indicating that an increase in the number of users increases SE proportionally when M varies from M = 100 to 1000. An exponential variation is observed for K = 8 and 16 while the rate of increase in SE is slightly lower for a small number of users (K = 4). This implies that, by simultaneously serving many users in the L-DAS cell, we can increase SE effectively.

VI. Conclusion

In modern wireless communication networks, the trade-off between SE and EE is very important for energy efficiency optimization, owing to the conflicting nature of EE and SE with fixed radio resources. Individual optimization of SE or EE becomes a challenging task when a large number of distributed users exist in a network with a number of conflicting variables. Therefore, we formulated a multiobjective optimization problem in this work for an L-DAS network. We studied EE optimization by JASUS by maximizing SE and minimizing total power consumption simultaneously. Further, we studied the SE–EE trade-off and optimality of our algorithm by flag convergence methods and compared the results with those of the exhaustive search method, which serves as a benchmark. Therefore, joint optimization of EE and SE can be achieved by maximizing SE and minimizing the total power consumption simultaneously

In this study, we developed a resource allocation algorithm for multi-cell MIMO L-DASs in FD mode. We proposed a MOOP framework based on the weighted Tchebycheff method to study the multiobjective optimization of EE and trade-off between EE and SE. The nonconvex MOOP was transformed into an equivalent SOOP and solved optimally to get the Pareto solution set. Furthermore, we examined the relationship between EE and SE for an L-DAS. We used an antenna selection and user scheduling method based on large-scale fading to minimize power consumption and to improve EE. We also used a subgradient method to obtain power allocation. The results demonstrate that the proposed algorithm converged quickly within several iterations in MIMO L-DASs, in terms of EE–SE performance.

REFERENCES

[1] J. Li, D. Wang, P. Zhu, J. Wang, X. You, "Downlink spectral efficiency of distributed massive MIMO systems with linear beamforming under pilot contamination," IEEE Trans. Veh. Technol., vol. 67, pp. 1130–1145, 2018. doi:10.1109/ACCESS.2020.3009657

[2] J. B. Rao, A. O. Fapojuwo, "A survey of energy efficient resource management techniques for multicell cellular networks," IEEE Commun. Survey Tuts, vol. 16, pp. 154–180, 2014. doi:10.1109/SURV.2013.042313.00226

[3] C. Pan, H. Zhu, N. Gomes, J. Wang, "Joint user selection and energy minimization for ultra-dense multi-channel C-RAN with incomplete CSI," IEEE J. Sel. Areas Commun., vol. 35, pp. 1809–1824, 2017. doi:10.1109/JSAC.2017.2710858

[4] A. Khansefid and H. Minn, "On channel estimation for massive MIMO with pilot contamination,'' IEEE Commun. Lett., vol. 19, no. 9, pp. 1660–1663, Sep. 2015

[5] J. B. Rao and A. O. Fapojuwo, "An analytical framework for evaluating spectrum/energy efficiency of heterogeneous cellular networks," IEEE Trans. Veh. Technol., vol. 65, no. 5, pp. 3568–3584, May 2016. doi:10.1109/JSAC.2013.130503

[6] H. Zhu, S. Wang, and D.Chen, "Energy-efficient user association for heterogenous cloud cellular networks," in Proc. IEEE Globecom Workshops, Dec. 2012, pp. 273–278. doi:10.1109/TVT.2016.2574899

[7] S. Cui, A. Goldsmith, and A. Bahai, "Energy-efficiency of MIMO and cooperative MIMO techniques in sensor networks," IEEE J. Sel. Areas Commun., vol. 22, no. 6, pp. 1089–1098, 2004. doi:10.1109/JSAC.2004.830916

[8] J. Tang, W. P. Tay, T. Q. S. Quek, and B. Liang, "System cost minimization in cloud RAN with limited front haul capacity," IEEE Trans. Wireless Commun., vol. 16, no. 5, pp. 3371–3384, 2017. doi:10.1109/TWC.2017.2682079

[9] H. Ren, N. Liu, C. Pan, C. He, "Energy efficiency optimization for MIMO distributed antenna systems," IEEE Trans. Veh. Technol., vol. 66, pp. 2276–2288, 2017

[10] J. Vilardebo, I. Ana, M. Najar, "Energy efficient communications over the AWGN relay channel," IEEE Trans. Wireless Commun., vol. 9, no. 1, pp. 32–37, Jan. 2010

[11] D. Feng, C. Jiang, G. Lim, J. Cimini, L.J., G. Feng, and G. Li, "A survey of energy-efficient wireless communications," IEEE Commun. Survey Tutorial, vol. 15, no. 1, pp. 167–178, Feb. 2013. doi:10.1109/SURV.2012.020212.00049

[12] X. Hong, J. Yu, C.-X. Wang, et. al. "Energy-spectral efficiency trade-off in virtual MIMO cellular systems," IEEE J. Sel. Areas Commun., vol. 31, no. 10, pp. 2128–2140, Oct. 2013. doi:10.1109/JSAC.2013.131013

[13] S. Huang, H. Chen, J. Cai and F. Zhao, "Energy efficiency and spectral efficiency trade-off in amplify-and-forward relay networks," IEEE Trans. Veh. Technol., vol. 62, no. 9, pp. 4366–4378, Nov. 2013. doi:10.1109/TVT.2013.2269695

[14] X. Hong, J. Wang, C.-X. Wang, and J. Shi, "Cognitive radio in 5G: A perspective on energy-spectral efficiency trade-off," IEEE Commun. Mag., vol. 52, no. 7, pp. 46–53, July 2014. doi:10.1109/MCOM.2014.6852082

[15] H. Kim, S.R. Lee, C. Song, I. Lee, "Optimal power allocation for energy efficiency maximization in distributed antenna systems," in Proc. IEEE Int. Conf. Communication - Wireless Communications Symposium, Budapest, Hungary, 9-13 June 2013, pp. 5769–5773.doi:10.1109/TCOMM.2014.2385772

[16] T. Edler and S. Lundberg, "Energy efficiency enhancements in radio access networks," Ericsson Review, no, 1, pp. 42-51, Jan 2004. http://www.ericsson.com/ericsson/corpinfo/publications/review/200401/files/2004015.pdf

[17] P. Li, T. Chang, K. Feng, "Energy-efficient power allocation for distributed large-scale MIMO cloud radio access networks," in Proc. IEEE Wireless Communications and Networking Conference, Istanbul, Turkey, April 6-9, 2014, pp. 1856-1861. doi:10.1109/TVT.2014.2379922

[18] W. Feng, Y. Chen, N. Ge, J. Lu, "Optimal energy-efficient power allocation for distributed antenna systems with imperfect CSI," IEEE Trans. Veh. Technol., vol. 65, pp. 7759–7763, 2016. doi:10.1109/TVT.2015.2497140

[19] J. Joung, Y. Chia, S. Sun, "Energy-efficient, large-scale distributed-antenna system (L-DAS) for multiple users," IEEE J. Sel. Top. Signal Process, vol. 8, pp. 954-965, 2014. doi: 10.1109/JSTSP.2014.2309942

[20] H.L. Zhu, J.Z. Wang, "Resource allocation in OFDMA-based distributed antenna systems," In Proc. IEEE Int. Conf. Communications in China (ICCC), Xian, China, 12-14 Aug 2013, pp. 565–570. doi:10.1109/ICCChina.2013.6671178

[21] C. He, G.Y. Li, F.C. Zheng, X. You, "Energy-efficient resource allocation in OFDM systems with distributed antennas," IEEE Trans. Veh. Technol. vol. 63, pp. 1223–1231, 2014. doi:10.1109/TVT.2013.2282373

[22] C. He, B. Sheng, P. Zhu, X. You, "Energy efficiency and spectral efficiency tradeoff in downlink distributed antenna systems," IEEE Wireless Commun. Lett., vol. 1, no. 3, pp. 153–156, 2012. doi:10.1109/WCL.2012.022812.120048

[23] B. Dai, W. Yu, "Energy efficiency of downlink transmission strategies for cloud radio access networks," IEEE J. Sel. Areas Commun., vol. 34, pp. 1037–1050, 2016. doi:10.1109/JSAC.2016.2544459

[24] H. Kim, S.R. Lee, K. J. Lee, "Transmission schemes based on sum rate analysis in distributed antenna systems," IEEE Trans. Wirel. Commun., vol. 11, pp. 1201–1209, 2012. doi:10.1109/TWC.2012.011812.111008

[25] Z. Lei, Y. S. Ji, K. Yang, "Energy efficient resource allocation in mobile networks with distributed antenna transmission," Mobile Netw. Appl. vol. 17, pp. 36–44, 2012. doi:10.1007/s11036-011-0306-6

[26] Y. Wang, J. Yan, D. Li, Z. Shi, Y. Guo, W. Wu, "Energy efficient joint user scheduling and transmit beamforming in downlink DAS," IEEE Trans. Wirel. Commun., vol. 25, pp. 3223-3237, 2019. doi:10.1007/s11276-018-1714-3

[27] J. Xu, P. Zhu, J. Li, X. You, "Energy efficiency optimization for MIMO distributed antenna systems with pilot contamination," IEEE Access, vol. 6, pp. 24157–24170, 2018. doi:10.1109/TCOMM.2016.2593924

[28] Y.Hao, Q. Ni, H. Li, S. Hou, "On the energy and spectral efficiency tradeoff in massive MIMO-enabled hetnets with capacity-constrained backhaul links," IEEE Trans. Commun., vol. 65, pp. 4720 – 4733, 2017. doi:10.1109/TCOMM.2017.2730867

[29] X. Wang, D. Zhang, K. Xu, et al. "On the energy/spectral efficiency of multi-user full-duplex massive MIMO systems with power control." J Wireless Com Network., vol. 82, pp.1-17, 2017. doi:10.1186/s13638-017-0864-9

[30] H. Q. Ngo, E. G. Larsson, T. L. Marzetta, "Energy and spectral efficiency of very large multiuser MIMO systems," IEEE Trans.

Commun., vol. 64, no. 4, pp. 1436–1449, 2013. doi:10.1109/TCOMM.2013.020413.110848

[31] S. Sharma, W. Yoon, “Multi-objective energy efficient resource allocation for WPCN,” Int. J. Eng. Res & Tech., vol. 11, pp. 2035-2043, 2018

[32] G. Yu, Y. Jiang, L. Xu, G.Y. Li, “Multi-objective energy-efficient resources allocation for multi-RAT heterogeneous networks,” IEEE J. Sel. Areas Commun. vol.13, pp. 2118-2126, 2015. doi:10.1109/JSAC.2015.2435374

[33] S. Jabbar, Y. Li, “Analysis and evaluation of performance gains and tradeoffs for massive MIMO systems,” Appl. Sci., vol. 6, pp. 268, 2016

[34] O. Amin, E. Bedeer, M.H. Ahmed, O.A. Dobre, “Energy efficiency–spectral efficiency tradeoff: A multiobjective optimization approach,” IEEE Trans. Veh. Technol., vol. 65, pp. 1975–1981, 2016. doi:10.1109/TVT.2015.2425934

[35] Y. Chen, S. Zhang, S. Xu, and G. Y. Li, “Fundamental trade-offs on green wireless networks,” IEEE Commun., Mag., vol. 49, no. 6, pp. 30–37, 2011. doi:10.1109/MCOM.2011.5783982

[36] A. Khalili, M.R. Mili, M. Rasti, S. Parsaeefard, D.W.K. Ng, “Antenna selection strategy for energy efficiency maximization in uplink OFDMA networks: a multi-objective approach,” IEEE Trans. Wirel. Comm., vol. 19, pp. 595-609, 2020. doi: 10.1109/TWC.2019.294683

[37] P. Gatchou, A. Zarei, A. El-Sharkawi, “Pareto multi objective optimization,” in Proc. 13th Int. Conf. Intelligent Systems Application to Power Systems, Arlington, VA, USA, 6–10 November 2005, pp. 84–91. doi: 10.1109/ISAP.2005.1599245

[38] F. Liu, Q. Yang, Q. He, K-S Kwak, “Energy efficiency and spectral efficiency tradeoff in downlink OFDMA systems with imperfect CSI,” AEU Int J Electron Commun., vol. 85, pp. 54-58, 2018. doi:10.1016/j.aeue.2017.12.015

[39] W. Dinkelbach, “On nonlinear fractional programming,” Manage. Sci. vol. 13, pp. 492-498, 1967. doi:10.1287/mnsc.13.7.492

[40] D.W.K. Ng, R. Schober, “Max-min fair wireless energy transfer for secure multiuser communication systems,” in Proc. IEEE Inf. Theory Workshop, Nov. 2014, pp. 326–330. doi:10.1109/ITW.2014.6970847

[41] D. W. K. Ng, E. S. Lo, R. Schober, “Multi-objective resource allocation for secure communication in cognitive radio networks with wireless information and power transfer,” IEEE trans. Veh. Technol., vol. 65, pp. 3166-3184, 2015

[42] L. Xu, G. Yu, Y. Jiang, “Energy-efficient resource allocation in single-cell OFDMA systems: multi-objective approach,” IEEE Trans. Wirel. Commun., vol. 14, pp. 5848–5858, 2015. doi:10.1109/TWC.2015.2443104

[43] R.T. Marler, J.S. Arora, “Survey of multi-objective optimization methods for engineering,” Struct. Multidisc. Optim., vol. 26, pp. 369–395, 2004

[44] W. Yu, R. Lui, “Dual Methods for nonconvex spectrum optimization of multicarrier systems,” IEEE Trans. Commun., vol. 54, no. 7, pp. 1310-1322, Jul. 2006. doi:10.1109/TCOMM.2006.877962

[45] K. Miettinen, Some methods for nonlinear multi objective optimization. In International conference on evolutionary multi-criterion optimization, 2001 March 7 (pp. 1–20). Berlin: Springer, 2001. doi:10.1007/3-540-44719-9_1

[46] M. Ehrgott, J. Ide, A. Schobel, “Minmax robustness for multiobjective optimization problems,” Eur. J. Oper. Res. vol. 239, pp. 17–31, 2014. doi:10.1016/j.ejor.2014.03.013

[47] H. Li, Q. Zhang, “Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II,” IEEE Trans., Evol., Comput, vol.13, no. 2, pp. 284-302, 2009. doi:10.1071/AP09004

[48] R. T. Rockafellar, Lagrange multipliers and optimality. SIAM Review, vol. 35, pp. 183–283, 1993

[49] W. Rudin. Principles of Mathematical Analysis. McGraw-Hill, 1976

[50] D. Palomar, M. Chiang, “A tutorial on decomposition methods for network utility maximization,” IEEE J. Sel. Areas Commun., vol. 24, no. 8, pp. 1439–1451, 2006. doi:10.1109/JSAC.2006.879350

[51] S. Boyd, L. Vandenberghe, Convex Optimization. Cambridge University Press, Cambridge, UK, 2004

[52] N. N. Moghadam, G. Fodor , M. Bengtsson D. J. Love , “On the energy efficiency of MIMO hybrid beamforming for millimeter-wave systems with nonlinear power amplifiers,” IEEE Trans. Wirel. Commun., vol. 17, no. 11, 2018

[53] A. Ahmad Khan, P. Uthansakul, P. Duangmanee, M. Uthansakul, “Energy efficient design of massive MIMO by considering the effects of nonlinear amplifiers,” Energies. vol.11, no. 5, 2018. doi:10.3390/en11051045