Abstract—In this paper, we consider the resource allocation problem for energy efficiency (EE) - spectral efficiency (SE) trade-off. Unlike traditional research that uses the EE as an objective function and imposes constraints either on the SE or achievable rate, we propose a multiobjective optimization approach that can flexibly switch between the EE and SE functions or change the priority level of each function using a trade-off parameter. Our dynamic approach is more tractable than the conventional approaches and more convenient to realistic communication applications and scenarios. We prove that the multiobjective optimization of the EE and SE is equivalent to a simple problem that maximizes the achievable rate/SE and minimizes the total power consumption. Then we apply the generalized framework of the resource allocation for the EE-SE trade-off to optimally allocate the subcarriers’ power for orthogonal frequency division multiplexing (OFDM) with imperfect channel estimation. Finally, we use numerical results to discuss the choice of the trade-off parameter and study the effect of the estimation error, transmission power budget and channel-to-noise ratio on the multiobjective optimization.

Index Terms—Energy efficiency, spectral efficiency, multiobjective optimization, OFDM, imperfect CSI, LMMSE.

I. INTRODUCTION

The dramatic growth of wireless communication services and applications represents the main driving force to expand the existing wireless infrastructure and to deploy new systems. Although the communication networks may be able to support the increasing demand of high data rate and ubiquitous services, the energy consumption increases significantly especially at the base stations. This accounts for most of the energy consumption of cellular networks, which represents an important contribution of the information and communication technology industry to the global CO₂ emission [1], [2]. Therefore, wireless communication systems have to be designed based on green metrics that reduce the energy consumption wisely, along with the associated CO₂ emission [1], [2]. Energy efficiency (EE) is a widely used green communication metric, defined either as the number of successfully delivered bits per unit energy, which we adopt in this paper, or its inverse [3]. Although EE is the major design metric for environment-friendly future wireless communication systems, it conflicts with other traditional metrics such as spectral efficiency (SE) in bit/sec/Hz [4]. The trade-off between EE and SE states that the available system’s resources cannot be optimized to improve both EE and SE simultaneously.

Considering the trade-off between the EE and SE in allocating the available resources is a timely and important problem. Attention has recently started to be paid for both single carrier [5], [6] and multicarrier transmission systems [7]. The previously mentioned resource allocation problems that deal with the EE-SE trade-off are suitable to fixed objective scenarios and can not deal with the dynamic changes of the design objectives. These traditional approaches use EE as the objective function and impose constraints on the SE, the transmit power and the fairness for multiple access systems. On the other hand, there are scenarios in wireless communication systems in which we need to change the optimization objective function dynamically according to the surrounding circumstances or application requirements.

A motivating scenario is when renewable energy sources are used in addition to diesel generators in base stations to generate the required electrical energy [8]. In such a scenario, when the base station is powered by clean energy sources (i.e., renewable sources), adopting EE as a design metric does not have a green advantage, as the base station is working now with zero CO₂ emissions. Thus, it is more beneficial to improve other quality of service (QoS) metrics, such as SE. On the other hand, when the surrounding environment varies, diesel generators are used to compensate for the shortage of the renewable sources or even replace them. Therefore, considering the EE as the objective function becomes inevitable when the diesel generator is the only energy source, while a multiobjective function taking into account the EE and SE is used when both sources are employed. In the latter case, the priority of each function is chosen according to the contribution of each energy source in powering the base station.

In this paper, inspired by the green communication trend and considering the variations of the objective functions according to the provided service or surrounding environment, we use the multiobjective optimization to solve the resource allocation problem for the EE-SE trade-off. First, we propose a general framework to solve the multiobjective optimization of EE and SE for a general communication system and prove that it is equivalent to the multiobjective optimization problem of minimizing the total power consumption and maximizing the
SE or achievable rate. Then, we apply the derived framework to orthogonal frequency division multiplexing (OFDM) with estimated CSI.

The rest of the paper is organized as follows. In Section II, we introduce the EE-SE multiobjective optimization general framework. In Section III, we define the model for the OFDM system with estimated CSI and apply the proposed approach to allocate the power for the OFDM subcarriers considering the EE-SE tradeoff. Then, we present numerical simulation results in Section IV and conclude the paper in Section V.

Regarding the notation, bold face letters refer to vectors (lower case) or matrices (upper case). The superscripts $H$ and $T$ represent the conjugate transpose and transpose operation, respectively, $|\cdot|$ denotes the absolute value, and $\hat{\cdot}$ denotes the estimate value.

II. EE-SE TRADE-OFF USING MULTIOBJECTIVE OPTIMIZATION

Optimizing EE or SE under a given set of constraints is suitable only for a specific communication scenario/application or under static environmental circumstances. In this section, we use a multiobjective optimization problem of EE and SE to deal with the dynamic change of design conditions, where tuning the objective functions becomes indispensable. Let us consider a communication system that is used to deliver information with a spectral efficiency $\eta_{SE}$ bit/sec/Hz. We assume $N$ resources that have to be allocated that may include power sources, subcarriers, antennas, users, relays, bandwidth, etc, and denoted them as $x = [x_1, x_2, ..., x_N]^T$. Among these resources, we assume $M$ signal sources that may be obtained from antennas, subcarriers and/or distributed communication nodes. The total power consumed to deliver the required data consists of the transmitted power $p = [p_1, p_2, ..., p_M]^T$, and the power consumption at the power amplifiers, and all circuits used in the communication scenario. The EE is expressed as

$$\eta_{EE}(x) = \frac{C(x)}{\sum_{m=1}^{M} f_m(x) + p_c},$$

where $f_m(x)$ is the variable power consumption term of the $m$th power source, $p_c$ is the constant power consumption term due to all circuits in the communication system, and $C(x)$ is the achievable rate, which is related to the SE as $C(x) = B\eta_{SE}(x)$, where $B$ is the transmission bandwidth. We formulate the multiobjective optimization problem as

$$\min_{x} \eta_{EE}^{-1}(x) \quad \text{and} \quad \min_{x} \eta_{SE}^{-1}(x).$$

We employed the weighted sum method to deal with the trade-off multiobjective using the trade-off parameter, $\beta$, with $0 \leq \beta \leq 1$, which describes the priority of each objective function as follows,

$$L_{EE-SE} = \beta \theta_{EE} \eta_{EE}^{-1}(x) + (1 - \beta) \theta_{SE} \eta_{SE}^{-1}(x) \quad 0 < \beta < 1,$$

where $\theta_{EE}$ and $\theta_{SE}$ are normalization factors used to have the same range for the objective functions.$^1$ It is well known that $C(x)$ is a logarithmic function which is often a strictly-concave function in $x$. Thus, the multiobjective function in (3) can provide a complete PF since objective functions are quasi-convex with at least one function being strictly quasi-convex, i.e., $-qC(x)$ [9, Ch. 1, pp. 4-11]. The non-convex non-linear fractional objective function in (3) can be transformed to the following equivalent convex function using the Dinkelbach approach [10]

$$L_{EE-SE,1} = \beta \theta_{EE} \left( \sum_{m=1}^{M} f_m(x) + p_c \right) + (1 - \beta) \theta_{SE} B - qC(x),$$

where $q$ is a constant parameter that represents the minimum value of (3) at a specific $\beta$ [10]. The optimal resource allocation solution of the objective function in (4) can be computed by following the Dinkelbach-based iterative approach in [10] for a given priority $\beta$. At $\beta = 0$, we do not need to follow the iterative approach because the problem translates into the SE maximization, and reduces to the well known water filling problem. In other words, to draw the PF curve for this multiobjective function, we need to apply the Dinkelbach-based iterative algorithm for each point (priority value) in the PF except at the maximum SE solution. In the following, we prove that the EE-SE PF can be obtained by solving a simplified multiobjective problem of total power consumption and achievable rate or SE.

Consider the objective function in (4) for a given $\beta$, the term $(1 - \beta) \theta_{SE} B$ is considered constant. Thus, omitting this term does not change the problem solution and the following alternative objective function is used instead,

$$L_{EE-SE,2} = \beta \theta_{EE} \left( \sum_{m=1}^{M} f_m(x) + p_c \right) - qC(x).$$

Dividing the objective function $L_{EE-SE,2}$ by $\beta \theta_{EE}$ gives another equivalent objective function that has the same solution and is expressed as

$$L_{EE-SE,3} = \left( \sum_{m=1}^{M} f_m(x) + p_c \right) - \frac{q}{\beta \theta_{EE}} C(x).$$

The quantity $q/(\beta \theta_{EE})$ is a positive constant and is equivalently replaced by $(1 - \alpha)/\alpha$, for $0 < \alpha < \alpha_{EE} < 1$, where $(1 - \alpha_{EE})/\alpha_{EE} = q/\theta_{EE}$; as such, (6) becomes

$$L_{EE-SE,4} = \left( \sum_{m=1}^{M} f_m(x) + p_c \right) - \frac{(1 - \alpha)}{\alpha} C(x).$$

Multiplying the objective function in (7) by $\alpha$ yields the

$^1$The normalization factor depends on the system parameters such as the maximum power budget and average CSI.
following equivalent objective function
\[
L_{\text{EE–SE,5}} = \alpha \left( \sum_{m=1}^{M} f_m(x) + p_c \right) - (1 - \alpha) C(x) \tag{8}
\]
\[
\equiv \min_x \left( \sum_{m=1}^{M} f_m(x) + p_c \right) \quad \text{and} \quad \max_x C(x). \tag{9}
\]
The objective function written in (8) represents a multiobjective function that aims to minimize the total power consumption and maximize the achievable rate using the trade-off parameter \( \alpha \), as presented in (9). Thus, the PF curve for the EE-SE multiobjective optimization can be drawn equivalently by considering the multiobjective optimization of the total power consumption and the achievable rate or SE for a specific weighted factor range of the second problem, i.e., \( 0 < \alpha < \alpha_{\text{EE}} \). Based on this proved fact, the optimization solution of the EE-SE problem in (2) can be obtained from,
\[
\min_{\theta_p} \frac{\alpha}{\theta_c} \left( \sum_{m=1}^{M} f_m(x) + p_c \right) - \frac{(1 - \alpha)}{\theta_c} C(x), \tag{10}
\]
where \( \theta_p \) and \( \theta_c \) are the normalization factors\(^3\) for the power and the achievable rate objective functions, respectively. The multiobjective problem in (10) reduces to achievable rate or SE maximization at \( \alpha = 0 \), and to power minimization at \( \alpha = 1 \), while the energy efficient solution is achieved at \( \alpha_{\text{EE}} \). Therefore, we can obtain the EE-SE PF by changing \( \alpha \) from 0 to \( \alpha_{\text{EE}} \). It is worth emphasizing that we do not need to use the Dinkelback-based iterative algorithm except at \( \alpha = \alpha_{\text{EE}} \), which reduces the complexity of the original problem.

III. EE-SE Trade-off for OFDM with Estimated CSI

A. System model

OFDM is widely utilized in many wireless systems, including the IEEE 802.11 family of standards, LTE/LTE-A, and others. OFDM is chosen over a single carrier solution because it is well suited for wideband transmission and supports higher data rates with reduced equalizer complexity. Thus, we consider a single-link OFDM wireless communication system with single-antenna equipped nodes. The channel is assumed to change slowly and is modeled as a finite impulse response system with order equal to \( L \), \( h = [h(0), h(1), \ldots, h(L)]^T \), where each channel tap is assumed to be complex Gaussian distributed with zero-mean and variance \( \sigma_n^2 \). The noise at the receive-side is modeled as additive white Gaussian noise (AWGN) with zero-mean and correlation matrix equal to \( \sigma_n^2 I \).

At the transmitter, we assume a serial data sequence that is divided into blocks, processed by a given precoded matrix and loaded to \( M \) subcarriers. The transmitted training pilot symbols \( x_p \) are inserted in the transmitted data with a known pattern. The receiver is assumed to be equipped with the LMMSE channel estimator that gives \( \hat{H} = (\sigma_n^2 R_c^{-1} + X_p^H X_p)^{-1} X_p^H x_t \) [11], where \( x_t \) is the received signal block and \( X_p \) is an \( M \times (L+1) \) column wise circulant matrix with the first column equal to \( x_p \). The estimated CSI is assumed to be sent through a reliable feedback channel to the transmitter. The subchannel estimates are computed as \( \hat{H}(1), \hat{H}(W), \ldots, \hat{H}(W^{M-1})]^T = \sqrt{M} F L \hat{H} \) [11], where \( \hat{H}(W^{m-1}) \) is the \( m \)th subcarrier channel estimate, \( W = \exp(j2\pi/M) \), \( F_L \) is the first \( L + 1 \) submatrix of \( F \), and \( F \) is the \( M \times M \) discrete Fourier transform matrix.

The achievable rate is expressed in terms of the channel estimate across subcarriers similarly to [11], while considering the powers per subcarriers \( p \),
\[
C(p) = \Delta f \sum_{m=1}^{M} \log_2 \left( 1 + \frac{|\hat{H}(W^m)|^2 G p_m}{\sigma_{\Delta H}^2 G p_m + \sigma_n^2} \right), \tag{11}
\]
where \( \Delta f = B/M \) is the subcarrier bandwidth, \( p_m \) is the \( m \)th subcarrier power, \( G \) is the large scale fading power coefficient, and \( \sigma_{\Delta H}^2 \) is the estimation error variance, which can be expressed as \( \sigma_{\Delta H}^2 = \left( L + 1 \right) \sigma_n^2 \sigma_n^2 / (\sigma_n^2 + \sigma_H^2 G p) \) [11], with \( p \) as the pilots’ transmitted power, and \( \sigma_n^2 \) is the AWGN noise variance.

B. Optimal power loading for the OFDM systems with estimated CSI

In this subsection, we consider the multiobjective optimization problem of EE-SE trade-off for the OFDM system with imperfect CSI. Since the achievable rate is a strictly concave function, it is strictly quasi-concave [12] and the proposed framework in Section II provides a complete PF curve. The simplified power loading problem for the EE-SE trade-off is defined as
\[
\min_p \frac{\alpha}{\theta_p} \left( \sum_{m=1}^{M} p_m + p_c \right) - \frac{(1 - \alpha)}{\theta_c} C(p) \tag{12}
\]
subject to
\[
C1 : \sum_{m=1}^{M} p_m \leq P_T,
\]
\[
C2 : C(p) \geq R_{\text{min}},
\]
\[
C3 : p_m \geq 0, \ m = 1, 2, \ldots, M,
\]
where \( \kappa \) is a constant which depends on the power amplifier efficiency. The constraints imposed in (12) represent the following: \( C1 \) reflects the total power budget of the proposed system \( (P_T) \), \( C2 \) is related to the minimum rate constraint \( (R_{\text{min}}) \) that is used for rate sensitive applications, and \( C3 \) guarantees positive power. The Lagrangian problem of (12) is written as,
\[
L_{\text{EE–SE,con}} = \frac{\alpha}{\theta_p} \left( \sum_{m=1}^{N} p_m + p_c \right) - \frac{(1 - \alpha)}{\theta_c} C(p) + \lambda_1 \left( \sum_{m=1}^{M} p_m - P_T + y_1 \right) + \lambda_2 \left( R_{\text{min}} - \Delta f \sum_{m=1}^{N} \log_2 \left( 1 + \frac{|\hat{H}(W^m)|^2 G p_m}{\sigma_{\Delta H}^2 G p_m + \sigma_n^2} \right) + y_2 \right), \tag{13}
\]
where we introduce two slack variables \( y_1 \) and \( y_2 \) to transform the inequality constraints to equality constraints. By differentiating \( L_{\text{EE–SE,con}} \) with respect to \( p_m, m = 1, 2, \ldots, M, \lambda_1, \lambda_2, y_1 \) and \( y_2 \), and equating the results to zero, we obtain the
following equations,
\begin{equation}
\frac{(\sigma_{\Delta H}^2 G + \sigma_n^2)^2}{|\hat{H} (Wm)|^2 G \sigma_n^2} \left[ 1 + \left( \frac{2|\hat{H} (Wm)|^2 G \sigma_n^2}{\sigma_{\Delta H}^2 G + \sigma_n^2} \right) \right] = \left( \frac{\theta_i (1 - \alpha + \lambda_2) \Delta f}{(\theta_i \rho \kappa + \lambda_1 \theta_i) \ln 2} \right),
\end{equation}
\begin{equation}
R_{\min} = \Delta f \sum_{m=1}^{M} \log_2 \left( 1 + \frac{2|\hat{H} (Wm)|^2 G \sigma_n^2}{\sigma_{\Delta H}^2 G + \sigma_n^2} \right) + y_2^2 - 2 \lambda_1 y_1 + 0, \quad \text{and} \quad 2 \lambda_2 y_2 = 0.
\end{equation}

The $m$th subcarrier power is computed from (14) as
\begin{equation}
p_{\text{EE},m} = \rho_m \left[ \frac{1}{1 + \left( \frac{2|\hat{H} (Wm)|^2 G \sigma_n^2}{\rho_m (2 \sigma_{\Delta H}^2 G + |\hat{H} (Wm)|^2)}) \right) - 1 \right],
\end{equation}
where
\begin{equation}
\rho_m = \frac{\sigma_{\Delta H}^2 G}{2 \sigma_{\Delta H}^2 G + |\hat{H} (Wm)|^2}.
\end{equation}

From (17), the values of $\lambda_1$, $\lambda_2$, $y_1$, $y_2$ give four possible cases, Case 1: $\lambda_1 = 0$ and $\lambda_2 = 0$, Case 2: $y_1 = 0$ and $\lambda_2 = 0$, Case 3: $\lambda_1 = 0$ and $y_2 = 0$, and Case 4: $y_1 = 0$ and $\lambda_2 = 0$. The cases with $\lambda_i = 0$, $i = 1, 2$ refer to the unconstrained problem, where the solution may satisfy the problem constraint(s), $\sum_{m=1}^{M} p_m = P_T$ and/or $C(x)$ $\geq R_{\min}$ in (12) or not. On the other hand, the cases with $y_i = 0$ and the corresponding $\lambda_i \neq 0$, $i = 1, 2$ describe the scenarios when the inequality constraints are valid with equality, that is $\sum_{m=1}^{M} p_m = P_T$ and/or $C(x)$ $= R_{\min}$. Based on these cases, we introduce Algorithm I as described below:

- **Steps 1 to 2**: for a desired $\alpha$, we first consider the unconstrained problem (Case 1 above) and find the corresponding solution of the subcarriers power from (18). The obtained solution is feasible only if it meets the problem constraints.

- **Steps 3 to 4**: if the power constraint is violated and the rate constraint is satisfied, then the subcarriers power solution is found based on Case 2. This alternative solution becomes feasible only if it satisfies the rate constraint.

- **Steps 5 to 6**: if the power constraint is satisfied and the rate constraint is violated, then we use Case 3 in finding the solution and investigate the feasibility of the new solution by checking the power constraint.

- **Steps 7 to 8**: when the solution based on Case 1 violates both constraints, a feasible solution does not exist because we need more power than the available budget to meet the rate requirement.

The values of $\lambda_1$ in step 4 and $\lambda_2$ in step 6 are computed from the total power equality constraint ($\sum_{m=1}^{M} p_m = P_T$)

\begin{algorithm}
1: **INPUT** $\alpha$.
2: Set $\lambda_1$ and $\lambda_2$ to zero in (17) and find $p_{\text{EE},m}$ from (18).
3: **if** the power constraint is violated and the rate constraint is satisfied **then**
4: Set $\lambda_2$ to zero in (17) and find non-negative $\lambda_1$ such that equality power constraint is satisfied from (18). If the rate constraint is violated, then set $p_{\text{EE},m} = 0$.
5: **else** if the power constraint is satisfied and the rate constraint is violated **then**
6: Set $\lambda_1$ to zero in (17) and find non-negative $\lambda_2$ such that equality rate constraint is satisfied from (18). If the power constraint is violated, then set $p_{\text{EE},m} = 0$.
7: **else** if the power constraint is violated and the rate constraint is violated **then**
8: Set $p_{\text{EE},m} = 0$.
9: **end if**
10: **OUTPUT** $p_{\text{EE},m}$.
\end{algorithm}

The computational complexity of Algorithm I is analyzed based on the fact that the bisection method is used to find $\lambda_1$, with a starting interval of $[\lambda_{1, U}, \lambda_{1, L}]$, $i = 1, 2$; as such, step 2 is of complexity $O(N)$. Step 4 is of complexity $O(N \log_2 (\frac{\Delta A_1}{\epsilon_1}))$ [14], where $\Delta A_1$ is the range between the lower and upper bounds of $\lambda_1$, expressed as $\Delta A_1 = \lambda_{1, U} - \lambda_{1, L}$ and $\epsilon_1$ is the solution accuracy. Similarly, step 6 is of complexity $O(N \log_2 (\frac{\Delta A_2}{\epsilon_2}))$, where $\Delta A_2$ is the range between the lower and upper bounds of $\lambda_2$, written as $\Delta A_2 = \lambda_{2, U} - \lambda_{2, L}$ and $\epsilon_2$ is the solution accuracy. Thus, the complexity of Algorithm I is calculated as $O(N) + \max \left( O(N \log_2 (\frac{\Delta A_1}{\epsilon_1})), O(N \log_2 (\frac{\Delta A_2}{\epsilon_2})) \right) = O(N \log_2 (\frac{\Delta A_1}{\epsilon_1})).$

The EE solution is found at $\alpha = \alpha_{\text{EE}}$ and computed by applying the Dinkelbach method [10]; for this case, we develop Algorithm II, which iteratively uses Algorithm I to compute the EE power loading solution $p_{\text{EE},m}$ and $\alpha_{\text{EE}}$ that satisfy $L_{\text{EE},\text{SE},\text{con}} (p, \alpha_{\text{EE}}) = 0$. Algorithm II starts with an initial value of $\alpha_{\text{EE}}$ equal to $\alpha_{\text{initial}}$ and employs an error tolerance of $\delta$.

\begin{algorithm}
1: **INPUT** $\alpha_{\text{initial}}, \delta$.
2: Set $\alpha_{\text{EE}} = \alpha_{\text{initial}}$.
3: **while** $L_{\text{EE}, \text{SE}} < -\delta$ **do**
4: Find $p_{\text{EE},m} (\alpha_{\text{EE}})$ from Algorithm I.
5: Calculate $\alpha_{\text{EE}} = \frac{\theta_i C(p)}{\theta_i C(p) + \theta_i C(p)}$ and update $L_{\text{EE},\text{SE}}$.
6: **end while**
7: **OUTPUT** $p_{\text{EE},m}$ and $\alpha_{\text{EE}}$.
\end{algorithm}

From the complexity discussion of Algorithm I, the complexity of step 4 in Algorithm II is $O(N \log_2 (\frac{\Delta A_1}{\epsilon_1}));$ hence, the complexity of Algorithm II is of the order
\( O(\alpha_{\text{EE}} N \log_2(\frac{N_{\alpha_{\text{EE}}}}{c})) \), where \( N_{\alpha_{\text{EE}}} \) is the number of required iterations to update \( \alpha_{\text{EE}} \).

It is worth noting that the trade-off parameter \( \alpha \) is adjusted to obtain a required priority of the objective functions. To optimize the SE objective function, we impose \( \alpha = 0 \), while to optimize EE, we use \( \alpha_{\text{EE}} \) that can be found from \( \mathcal{L}_{\text{EE-SE,con}} = 0 \), which is similar to finding \( q \) in solving the EE problem. On the other hand, for a specific priority to EE or SE, \( \alpha \) can be chosen according to the average performance of EE-SE trade-off that is discussed in the next section.

IV. SIMULATION RESULTS

In this section, we provide a numerical evaluation of the proposed multiobjective optimization problem for an OFDM system with imperfect channel estimation. The simulation parameters are considered for base stations listed in [15].

Simulation Example 1: In the first simulation example, we study the EE and SE behavior versus \( \alpha \) without imposing the transmission rate constraint, which is implemented by setting \( \lambda_2 = 0 \) in Algorithm I, and assuming different ratios of the maximum useful transmission power budget ratio to the total power consumption at the base station \( (P_T/\theta_p) \) in Fig. 1. We assume a good channel quality with the channel-to-noise ratio (CNR) equal to 20 dB and accurate channel estimate with the MMSE of 0.001.

First, we investigate the choice of the trade-off parameter \( \alpha \) to achieve a given priority level for either EE or SE assuming a sufficient power budget with \( P_T/\theta_p = 0.11 \) in Fig. 1. For \( \alpha = 0 \), the solution reduces to the maximum SE or achievable rate, and for \( \alpha = 1 \), the scenario reduces to the minimum transmitted power. On the other hand, maximum average EE is achieved at \( \alpha = \alpha_{\text{EE}} = 0.5 \). As \( \alpha \) increases from zero to \( \alpha_{\text{EE}} \), the EE increases and SE decreases, while both EE and SE decrease when \( \alpha \) changes from \( \alpha_{\text{EE}} \) to 1; thus, the former represents the region of interest. The average results depicted in Fig. 1 are used as a guide to choose \( \alpha \) in order to achieve a predetermined average EE or SE performance. For example, if it is required to design the system for a green perspective while satisfying the average SE to 4.5 bit/sec/Hz, then we choose \( \alpha = 0.35 \), while if the design targets to maximize the SE while keeping minimum average EE to 4 kb/J, then we choose \( \alpha = 0.1 \).

Additionally, we aim to study the effect of the useful transmission power ratio, i.e., \( P_T/\theta_p \). For a large transmitted power budget \( (P_T/\theta_p = 0.11) \), we observe the expected trade-off between EE and SE versus \( \alpha \). On the other hand, the unavailability of sufficient transmission power budget limits the SE from improving as \( \alpha \) decreases and limits the EE curve from its expected trend, i.e., having a maximum at \( \alpha_{\text{EE}} \) and reducing as \( \alpha \) decreases. Accordingly, and as can be noted from Fig. 1, communication systems with low transmission power efficiency, i.e., very small \( P_T/\theta_p \) values, have a nearly constant EE and SE performance versus \( \alpha = 0 \rightarrow \alpha_{\text{EE}} \), which makes the EE solution equivalent to the SE solution.

Simulation Example 2: To study the effect of circuitry power consumption, we assume the scenario discussed in the previous simulation example with \( P_T/\theta_p = 0.11 \), and then let \( p_c \) equal 100 W and 20 W in addition to its original value of 300 W, to investigate its effect on the EE-SE trade-off. From the results presented in Fig. 2, it can be seen that EE improves as \( p_c \) decreases because the total power consumption cost to transmit data decreases. For \( \alpha = 0 \) the optimization problem reduces to SE maximization, and we observe equal maximum SE regardless of the value of \( p_c \) because SE does not depend on the circuitry power consumption, while for \( \alpha > 0 \), the objective function becomes a linear combination between EE and SE and thus depends on \( p_c \). Therefore, both EE and SE change with \( p_c \) for \( \alpha > 0 \), where EE improves as \( p_c \) decreases, while SE improves as \( p_c \) increases because both functions are contradicting. The value of \( \alpha_{\text{EE}} \) increases as \( p_c \) decreases, specifically maximum EE is found at \( \alpha_{\text{EE}} = 0.5, 0.6 \) and 0.7 for \( p_c = 20 \text{ W}, 100 \text{ W} \) and 300 W. This shows that communication systems with large \( p_c \) are willing to spend more transmission power to guarantee the successful delivery of the data and improve EE, while systems with small \( p_c \) tend to use less transmission power to improve EE.

Simulation Example 3: In this example, we study the effect
of rate constraint on the EE-SE multiobjective problem. For this purpose, we consider the scenario with sufficient power budget, i.e., $P_T/\theta_p = 0.11$, and plot EE and SE versus $\alpha$ for different rate constraints in Fig. 3, where $\eta_{SE,\min}$ is the SE corresponding to the minimum rate, expressed as $\eta_{SE,\min} = R_{\min}/B$. Unlike the unconstrained rate case from which the SE curve decreases as $\alpha$ increases and reaches zero at $\alpha = 1$, the constrained SE curves do not go below the floor of the predetermined constraints, which is either 2.3 or 4.6 b/s/Hz. The EE curves are affected by the rate constraint starting from the rate breaking point, defined as the point in which the SE starts to have a constant flooring behavior while $\alpha$ increases. Particularly, if the rate breaking point is located before the maximum EE point, then both the EE peak and the decreasing part of the curve are affected, which is the case of $\eta_{SE,\min} = 4.6$ b/s/Hz; otherwise, only the decreasing part of the EE is affected and achieves larger EE when compared with the unconstrained case, which is the case of $\eta_{SE,\min} = 2.3$ b/s/Hz. If the rate breaking point lies outside our region of interest, then the rate constraint does not affect apparently the EE and SE average curves in this region.

Simulation Example 4: To study the effect of the channel estimation error on the trade-off between EE and SE, we plot the PF curve of EE and SE for $P_T/\theta_p = 0.11$ assuming unconstrained rate problem and different MMSE values in Fig. 4. One can notice that the having a good channel estimator is important to achieve a good EE-SE curve. Specifically, channel estimators with maximum MMSE of 0.001 are needed to achieve near optimal EE-SE relation. SE shows more sensitivity to estimation errors than EE, where SE loses around 30% from its performance as the MMSE decreases from 0.001 to 0.01, while EE loses only 5% from its performance.

V. CONCLUSION

In this paper, we introduced the general framework of the multiobjective optimization to deal with the resource allocation problem for any communication system while considering the EE-SE trade-off. We proved the necessary conditions that the weighted sum method provides the optimal EE-SE trade-off relationship. The multiobjective optimization of the EE-SE is equivalent to the multiobjective problem that minimizes the total power consumption and maximizes the SE or achievable rate. We applied the proposed framework to the OFDM system with estimated CSI and proposed a power loading algorithm to achieve the optimal EE-SE relationship. Through simulation examples, we explained how to select the trade-off parameter to switch between different practical communication scenarios, with different design requirements.

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