Resource Allocation for Simultaneous Wireless Information and Power Transfer Systems: A Tutorial Overview

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Abstract—Over the last decade, simultaneous wireless information and power transfer (SWIPT) has become a practical and promising solution for connecting and recharging battery-limited devices, thanks to significant advances in low-power electronics technology and wireless communications techniques. To realize the promised potentials, advanced resource allocation design plays a decisive role for revealing, understanding, and exploiting the intrinsic rate-energy tradeoff capitalizing on the dual use of radio frequency (RF) signals for wireless charging and communication. In this paper, we provide a comprehensive tutorial overview of SWIPT from the perspective of resource allocation design. The fundamental concepts, system architectures, and RF energy harvesting (EH) models are introduced. In particular, three commonly adopted EH models, namely the linear EH model, the nonlinear saturation EH model, and the nonlinear circuit-based EH model are characterized and discussed. Then, for a typical wireless system setup, we establish a generalized resource allocation design framework which subsumes conventional resource allocation design problems as special cases. Subsequently, we elaborate on relevant tools from optimization theory and exploit them for solving representative resource allocation design problems for SWIPT systems with and without perfect channel state information (CSI) available at the transmitter, respectively. The associated technical challenges and insights are also highlighted. Furthermore, we discuss several promising and exciting future research directions for resource allocation design for SWIPT systems intertwined with cutting-edge communication technologies, such as intelligent reflecting surfaces, unmanned aerial vehicle, mobile edge computing, federated learning, and machine learning.

Index Terms—Wireless power transfer, SWIPT, resource allocation, optimization.

I. INTRODUCTION

A. Overview of Wireless Power Transfer

The advancements of wireless technologies over the past decades have triggered a massive growth in the number of wireless devices and sensors, such as smartphones, tablets, earbuds, wearable sensors, and wireless environmental monitoring sensors, fueling the rapid development of the Internet-of-Things (IoT) [1] and massive machine type communications (mMTC) [2]. Nowadays, these widely deployed wireless devices are often battery-powered while battery capacities are usually limited which creates a serious performance bottleneck in realizing ubiquitous wireless communication networks. In particular, the regular manual battery replacement and wired recharging can be costly, cumbersome, dangerous, or even not possible, e.g., for biomedical implants, which significantly limits the lifetime of wireless networks and increases the network operational costs. In this regard, a viable solution for extending the lifetime of wireless devices is to allow them to scavenge energy from diverse renewable energy sources, e.g., solar, wind, geothermal, and vibration. However, energy harvesting (EH) from these resources has its own limitations. In fact, natural energy sources are usually intermittent and uncontrollable and thus EH from natural sources for powering communication may lead to unstable communication services [3], [4]. As an alternative, near-field contactless charging technologies, including inductive and magnetic resonant coupling, enable on-demand energy supply, while the range of energy transmission is quite limited [5], [6]. Moreover, laser-based wireless charging is also a potential technology to achieve efficient power delivery over long distances [7]. Unfortunately, this technique requires a line-of-sight (LoS) link and accurate laser beam alignment between transceivers, which may not always be possible in practice.

In contrast, radio frequency (RF) wireless power transfer (WPT), where wireless devices harvest energy from ambient electromagnetic (EM) waves, is a promising technology to provide a stable and controllable wireless energy supply for battery-limited wireless devices. Moreover, WPT [8] is applicable in non-LoS (NLoS) environments and allows for flexibility in transceiver deployment. Indeed, thanks to the continuous advancement of low-power electronics technology, the harvested energy is sufficient to support various types of emerging systems.
wireless devices and applications, such as radio frequency identification (RFID) tags and wearable sensors. Furthermore, since radio signals can be used for transferring both information and power, simultaneously or asynchronously, it is expected that the integration and joint design of WPT and wireless communication systems can enable perpetual sustainability of wireless networks. Depending on how WPT is combined with communications, several general system architectures can be distinguished [8]–[16]:

- Simultaneous wireless information and power transfer (SWIPT) systems convey both information and power at the same time and in the same frequency band using the same radio signals [8].
- Wireless powered communication (WPC) systems deliver wireless energy to power communication devices [9], [10]. Then, the energy harvested by these devices is utilized for transferring their information to information decoding receivers.
- In wireless powered relaying (WPR) systems, a source node delivers both information and power to an energy-limited relay node via SWIPT [11]. The relay node harvests energy and decodes information from the received signals. In turn, the wirelessly-powered relay assist the end-to-end communications by forwarding the source information to the destination node.
- Wireless powered backscatter communication (WPBC) systems convey energy to a wireless tag device [12]. Then, the wirelessly-powered tag reflects and modulates the incoming RF signal for communication with a tag reader.
- Wireless powered mobile edge computing (WPMEC) systems energize resources-constrained mobile edge computing (MEC) devices via WPT [13], [14]. Following the harvest-then-offload protocol, the MEC devices can offload computation-intensive tasks to the edge cloud or servers [15], [16] exploiting the harvested energy.

In this paper, we focus on resource allocation design for SWIPT systems as this system architecture serves as a fundamental building block for the other types of WPT-based systems. Besides, as the name suggests, SWIPT implies the dual use of radio signals, which leads to an essential and non-trivial tradeoff between wireless information transfer (WIT) and WPT, known as rate-energy tradeoff. To unlock the potential of SWIPT, resource allocation plays a decisive role in optimizing this tradeoff to achieve certain design goals. However, resource allocation design for SWIPT systems is challenging as the dual use of radio signals in the same link introduces severe coupling between WIT and WPT. Moreover, focusing on SWIPT systems facilitates the investigation of concrete resource allocation design methodologies. These methodologies can then serve as a fundamental platform, which can be extended to other WPT-based system architectures with proper modifications. We refer interested readers for more details on resource allocation design for the other four system architectures to [9]–[17].

![Fig. 1. A SWIPT system with separated and co-located ID and EH Rxs.](image)

B. Fundamentals of SWIPT Systems

In a SWIPT system, as shown in Fig. 1, energy harvesting receivers (EH Rxs) harvest RF energy and information decoding receivers (ID Rxs) decode the information contained in the signals emitted by the transmitter (Tx). The EH Rxs and the ID Rxs may be physically separated or co-located in the same user equipment depending on the application [8]. For separated Rxs, ID and EH are performed based on different received signals at physically separated sites. In contrast, a co-located Rx comprises both ID and EH hardware modules, which need to share the received RF signals at the analog front-end. Unfortunately, practical circuits for EH cannot extract information [3] and vice versa. As a compromise solution, several Rx architectures have been proposed [8] for exploiting the received RF signals for EH and ID:

- Time-switching (TS): TS co-located Rxs switch in time between the ID and EH hardware modules, which are synchronized with the Tx. The TS co-located Rx architecture requires the optimization of the TS sequences to achieve a desired rate-energy tradeoff.
- Power-splitting (PS): PS co-located Rxs split the power of the received signal into two power streams, where one stream with PS ratio $\rho$ is fed to the ID Rx and the other stream with PS ratio $1 - \rho$ is fed to the EH Rx.
- Antenna-switching (AS): When the co-located Rxs are equipped with multiple antennas, an AS co-located Rx architecture can be adopted, where a subset of the antennas are selected for EH only, while the remaining antennas are solely used for ID. Determining the optimal AS policy is critical to balance between wireless charging and the beamforming gain for ID.

We note that these three co-located Rx architectures can be combined in different ways, depending on the specific system setups and hardware constraints. For example, the PS and AS co-located Rx architectures can be combined by equipping a power splitter at each receive antenna. Not surprisingly, sharing the received signals at the co-located Rx incurs a tradeoff between information transfer and EH. Moreover, the signal sharing policy at co-located Rxs has to be jointly designed with the resource allocation at the Tx to achieve a favorable rate-energy tradeoff.
C. Resource Allocation Design for SWIPT Systems

Resource allocation is a key concept for improving wireless system performance by making the best use of limited resources based on the available system information. Resource allocation design has been extensively studied in the context of conventional data communication networks [18]–[20]. In general, wireless system resources are power, the available bandwidth and time, as well as space if multiple antennas are deployed. The system information exploited for resource allocation design includes channel state information (CSI), queue state information, and quality-of-service (QoS) requirements. On the other hand, different system design objectives can be set, e.g., maximizing the system sum-rate, maximizing the system energy efficiency, or minimizing the system power consumption, depending on the specific application scenario. However, resource allocation design for SWIPT systems differs from that in conventional wireless systems in several aspects. First, compared to ID Rxs, the mathematical EH models needed to capture the input-output characteristic of practical EH circuits at the EH Rxs are substantially more complicated, which imposes a great challenge for resource allocation design. Second, energy-based performance metrics, such as the harvested energy and WPT efficiency, are as important as data rate-based metrics. Third, in conventional data communication systems, co-channel interference is harmful and limits the system performance. Hence, it should be suppressed or mitigated during resource allocation design. In contrast, in SWIPT systems, strong interference is a vital energy source for energy-limited receivers and could be harvested to facilitate WPT.

In the following, we briefly overview seminal works on resource allocation design for SWIPT systems. Different SWIPT system architectures were first proposed in [8] for a multiple-input multiple-output (MIMO) broadcasting system. Corresponding resource allocation design problems were formulated for maximization of the achievable rate-energy region [8]. Based on the framework in [8], the authors in [21]–[23] developed schemes for optimal time/antenna-switching and/or optimal power splitting to achieve various tradeoffs between WIT and WPT. Furthermore, extending SWIPT to multi-user communication systems is desirable as the property of one-to-many charging can be exploited for increasing the lifetime of a large number of wireless devices, e.g., wireless sensors in IoT networks. In SWIPT-based multi-user communication systems, the resource allocation can be designed to exploit the multi-user diversity originating from the independent channel fading of different users to optimize the system performance taking into account certain constraints. Examples of such designs include maximizing the weighted sum-power transferred to EH Rxs under minimum signal-to-interference-plus-noise ratio (SINR) requirements for ID Rx [24] or minimizing the total transmit power under SINR and EH constraints [25]. Moreover, compared with narrowband systems, applying SWIPT techniques in multi-carrier communications offers the opportunity to exploit frequency diversity as the frequency domain offers extra degrees of freedom (DoF) for flexible and efficient resource allocation design. For example, orthogonal frequency-division multiple access (OFDMA) has been applied in SWIPT-based multi-user communication systems [26]–[28], where ID Rxs retrieve their information from the received signals on subcarriers allocated to them, while EH Rxs harvest the energy from the signals received on all subcarriers. Besides, a multi-objective optimization (MOO) framework can be adopted to handle the conflicting system design goals of providing communication services while guaranteeing EH performance [29], [30].

All the above studies assumed that perfect CSI is available at the Tx, which is challenging to acquire in practice due to channel estimation errors, feedback delays, and quantization noises. In practice, imperfect CSI at the transmitter (CSIT) usually leads to substantial performance degradation and system outages. In SWIPT systems, the resulting channel uncertainty affects the performance of both WPT and WIT, and consequently system outages may happen more frequently compared to conventional communication systems. In fact, SWIPT systems generally require a joint transceiver design and the coupling between WIT and WPT makes the resource allocation design more sensitive to CSIT errors. Thus, robust resource allocation design is critical for achieving high SWIPT system performance in the presence of channel uncertainty [31]–[36]. For instance, the authors in [34] maximized the worst-case harvested direct current (DC) power for the EH Rxs while guaranteeing a minimum data rate for the ID Rxs for all possible channel realizations. When the channel uncertainty is not taken into account for resource allocation design, frequent violations of the minimum required data rate constraint of the ID Rxs occur [34]. In contrast, the authors’ robust design guarantees the performance of the SWIPT system even in the presence of channel uncertainty, at the expense of sophisticated resource allocation.

Furthermore, integrating other cutting-edge technologies, such as full-duplex [37], [38], coordinated multipoint (CoMP) [39], physical layer security [40], [41], and relaying technologies [42], [43], into SWIPT systems is expected to further improve the system performance while introducing new resource allocation design challenges. For instance, by leveraging macro-diversity, CoMP [39] can extend the service areas of both WIT and WPT without increasing the overall transmit power [44]. However, the power loss in delivering power from the central processor to distributed remote radio heads and the corresponding backhaul capacity limitation for conveying data have to be considered for resource allocation design [45]. Interested readers may refer to [37], [38], [40]–[43] and the references therein for more details.

In the early stages of research on resource allocation design for SWIPT systems, most of the works assumed a simple linear EH model. Yet, from the micro-electronics literature [46], [47], it is well-known that the EH circuits converting the received RF energy into electrical energy exhibit strong nonlinearities, especially for high RF input powers. Therefore, adopting a linear EH model for resource allocation design may introduce a model mismatch, which degrades the system performance [48]–[51]. The authors in [49] firstly identified the implications of the nonlinearity of EH circuits for SWIPT system design and proposed a nonlinear saturation EH model, which leads to
tractable problem formulations for resource allocation design. In particular, the nonlinear saturation EH model provides a relationship between the average received RF power and the average harvested DC power for a given input distribution. Most recently, several works [48, 52] proposed nonlinear circuit-based EH models, which characterize the relationship between the instantaneous received RF power and the instantaneous harvested DC power. These nonlinear circuit-based EH models allow the optimization of the input distribution whereas both the linear EH model and the nonlinear saturation EH model do not. In general, improving the EH circuit modeling accuracy can improve SWIPT system performance while it generally reduces the tractability of resource allocation design. A comprehensive treatment of the relation between EH modeling accuracy and the resulting resource allocation design is not available in the literature, yet.

D. Objective and Organization

The main objective of this paper is to review and discuss resource allocation design for SWIPT systems. There have been several overview papers on SWIPT [3], [53]–[56]. The early works in [53, 54] relied on the simple linear EH model, whose practicality has been questioned since that time. The authors of [55] provided an overview of the main communication and signal processing techniques for SWIPT systems for both the linear EH model and the nonlinear EH model. However, the role of resource allocation for the joint design of the WPT and WIT subsystems was not highlighted. Also, the authors of [3] investigated how the receiver architecture and the modeling of the energy harvesters affect the rate-energy tradeoff in SWIPT systems. Most recently, the authors of [56] discussed possible applications of future wireless-powered networks, including computing, sensing, and edge learning. Nevertheless, the existing tutorial-style overview papers on SWIPT [3], [53]–[56] did not focus on resource allocation design, which motivates this paper.

The remainder of this paper is organized as follows. Section II introduces the EH models developed for resource allocation in SWIPT systems. Section III proposes a general resource allocation design framework for SWIPT systems and outlines corresponding solution methodologies. Section IV presents three robust resource allocation design approaches to combat the channel uncertainty in SWIPT systems. Potential future research directions are discussed in Section V, and Section VI concludes this paper.

II. ENERGY HARVESTING MODELS

To facilitate resource allocation design for spectrally-efficient and energy-efficient SWIPT-based systems, it is necessary to characterize the input-output relationship of RF-based EH circuits via a suitable model [3]. A practical RF-based EH circuit, known as a rectenna, comprises an antenna and a rectifier [47, 57], see Fig. 2. The rectifying circuit typically includes a matching network, diodes, and a low-pass filter, which converts the received RF energy into electrical energy [47, 57]. Subsequently, the scavenged DC power can be stored in a battery for future use, e.g., for data transmission or signal processing. We note that the load resistance representing, e.g., an energy storage module, is part of the low-pass filter and is not explicitly shown in Fig. 2.

To quantify the performance of an RF-based EH circuit, its RF-to-DC energy conversion efficiency has to be accurately modeled and analyzed. In the following, we present three commonly adopted EH models striking a balance between modeling accuracy and modeling tractability.

A. Linear EH Model

In the conventional linear EH model, e.g., [27, 40, 58, 59], the average harvested power at the EH receiver, \( P_{\text{out}}^{\text{Linear}} \), is modeled by the following linear equation:

\[
 P_{\text{out}}^{\text{Linear}} = \eta P_{\text{Rx}},
\]

where \( P_{\text{Rx}}^{\text{EH}} \) denotes the average power of the input RF signals for EH and \( 0 < \eta \leq 1 \) is the constant power conversion efficiency. Its value can be obtained by curve fitting based on measured harvested DC power data. According to (1), the harvested power at the EH Rx is linearly and directly proportional to the received RF power. This linear model was commonly adopted in the early works on SWIPT, e.g., [60, 61], as it facilitates simple resource allocation design and performance analysis. Yet, this model is not accurate as the output power of the EH circuit is not bounded even for large RF input powers.

B. Nonlinear Circuit-based EH Model

Practical RF-based EH circuits inevitably introduce nonlinearities for the end-to-end WPT due to the nonlinear components required for converting the RF signal to DC power [46, 47]. Considering the single-diode EH circuit shown in Fig. 2, the authors proposed an approximate closed-form expression for the output DC power with respect to (w.r.t.) the instantaneous received RF power assuming a sinusoidal input excitation signal². In particular, the instantaneous harvested DC power is given by [48]

\[
 P_{\text{out}}^{\text{CIR}}(\beta) = \min \left( \frac{1}{\zeta} W_{0}(\zeta e^{\beta^2/2}) - 1 \right)^{2} I_{L}^{2} R_{L}, \frac{B_{v}^{2}}{4R_{L}} \right),
\]

where \( \beta \cong \sqrt{2B|h_{E}|x}, \ x \in \mathbb{C} \) denotes the transmitted complex symbol, and \( h_{E} \in \mathbb{C} \) is the channel gain from the Tx

²As shown in [48, Eq. (1)], the received RF signal is typically narrowband as the bandwidth is usually much smaller than the carrier frequency. Therefore, a sinusoidal input excitation signal is sufficient for characterizing the EH circuit. Moreover, despite the assumed fixed sinusoidal input excitation signal, (2) enables waveform design via optimization of the distribution of the input symbols \( x \).
allocation algorithm design by striking a balance between EH model was proposed in [49]–[51] to facilitate resource from specific implementation details, a parametric nonlinear different types of EH circuits. To isolate the system model and the resulting mathematical expressions are different for of the EH circuits (e.g., the circuit schematic in [48, Fig. 2])

C. Nonlinear Saturation EH Model

Although the above circuit-based model can accurately capture the nonlinear input-output relationship of a practical EH circuit, the corresponding analytical expressions make resource allocation design very challenging. Indeed, such a tailor-made method relies on specific implementation details of the EH circuits (e.g., the circuit schematic in [48, Fig. 2]) and the resulting mathematical expressions are different for different types of EH circuits. To isolate the system model from specific implementation details, a parametric nonlinear EH model was proposed in [49]–[51] to facilitate resource allocation algorithm design by striking a balance between resource modeling accuracy and tractability. In particular, for an arbitrary received RF signal with average power $P_{RX}^{EH}$, the average harvested DC power, $P_{out}^{Sat}$, is modeled as:

$$P_{out}^{Sat} = \frac{[\Psi - P_{Sat}^{EH}]}{1 - \Omega}, \quad \Omega = \frac{1}{1 + \exp(ab)}$$

where $\Psi = \frac{P_{Sat}^{EH}}{1 + \exp(-a(P_{RX}^{EH} - b))}$ is a logistic (sigmoid) function and its input $P_{RX}^{EH}$ represents the average received RF power for EH. Parameter $P_{Sat}$ is a positive constant representing the maximum available power at the output of the energy harvester when the EH circuit is saturated due to an exceedingly large input RF power. Constant $a$ denotes the nonlinear charging rate w.r.t. the input power and constant $b$ is related to the minimum turn-on voltage of the EH circuit modeling the circuit sensitivity. These three parameters jointly determine the shape of the logistic function which depends on the physical characteristics of the RF EH circuit and their values can be estimated by applying standard curve fitting algorithms. Moreover, parameters $a$ and $b$ depend on the excitation waveform and have to be determined for a given input distribution. More importantly, the saturation model in (3) is a continuous quasi-convex function which is generally more tractable than the circuit-based EH model for resource allocation design, cf. [65], [66].

In Fig. 3, we show an example for curve fitting based on the measurement data in [46] for both the linear EH model and the nonlinear saturation EH model. As can be observed, the parametric nonlinear model closely matches the experimental results provided in [46] for the RF power harvested by a practical EH circuit. In contrast, the conventional linear RF EH model fails to capture the nonlinear nature of practical EH circuits, especially in the high received RF power regime. We note that the received RF power that leads to saturation depends on the EH circuit used. While the circuit considered in [46] causes saturation for received RF powers exceeding $P_{RX}^{EH} = 14.5$ dBm, the circuits reported in [67] and [52], [68] saturate already for $P_{EH}^{RX} = -5$ dBm and $P_{RX}^{EH} = 0$ dBm, respectively.

To summarize, Table I provides a comparison of the three considered RF-based EH models. In general, both the linear EH model and the nonlinear saturation EH model are more tractable for resource allocation design due to their simple input-output relationship. In particular, the nonlinear saturation EH model can accurately capture the receiver sensitivity and output DC power saturation of practical RF-based EH circuits. However, since the curve fitting for finding the model parameters has to be performed for a given input distribution, this model does not allow the optimization of the input distribution. In contrast, although the circuit-based model generally leads to more complicated expressions for the harvested power, it offers the possibility to jointly optimize the resource allocation and the input distribution for improving the system performance. Indeed, depending on the setting, all models discussed in this section may be acceptable approximations of the behavior of a practical energy harvester. The system designer has to decide which model provides the best tradeoff between resource

![Fig. 3. A comparison between measurement data from [46], the average harvested DC power for the nonlinear saturated model in (3) and the conventional linear EH model in (1). The model parameters are obtained by curve fitting via least square algorithm with $P_{Sat}^{EH} = 0.024$ Watt, $b = 0.014$, $a = 150$, and $\eta = 0.474$.](image)
allocation design complexity and performance for a given application.

D. Other Nonlinear EH Models

In addition to the nonlinear EH models discussed in Sections II-B and II-C, the authors in [69] proposed a tractable Taylor expansion-based EH model accounting for the nonlinear diode characteristics for a multisine excitation signal. In particular, this model expresses the harvested DC power in terms of a time average of a polynomial of the input RF signal. Yet, compared with the nonlinear circuit-based EH model, the model in [69] assumes a perfect matching network between the antenna and the rectifier and ignores the reverse-bias breakdown mode of the rectifying diode. Moreover, although the EH models in Sections II-B, II-C, and [69] capture the nonlinearity of EH circuits, they still have limitations. For instance, since a non-zero time is required for ramping up/down the voltage across the reactive elements of realistic EH circuits before reaching the steady state, EH circuits are not memoryless [70]. One possible approach for handling this issue is to model the dynamic of the EH circuit by a Markov decision process (MDP), e.g., [71]. On the other hand, the imperfection of hardware components introduces further nonlinearities to the input-output relationship of practical EH circuits [70], [71]. Since an accurate analytical model for capturing all nonlinear effects is generally not tractable, a machine learning (ML)-based approach to adaptively model the nonlinear characteristics of practical EH circuits can be adopted [71]. Nevertheless, such an ML approach models the EH circuit as a black box which generally offers limited insights for SWIPT system design.

III. RESOURCE ALLOCATION DESIGN FOR SWIPT SYSTEMS

In this section, we introduce a representative SWIPT system model and establish a general resource allocation design framework. Solution methodologies for addressing the formulated problem are introduced for the EH models considered in Section II. We first investigate the resource allocation design based on the linear EH model in (1) and the nonlinear saturation EH model in (3), where we assume a Gaussian input distribution. Then, we extend our consideration to the nonlinear circuit-based EH model in (2). Finally, a simulation example is presented to illustrate the effectiveness of the introduced methodologies and to unveil insights for SWIPT system designs.

A. System Model

We consider a multi-user multiple-input single-output (MISO) SWIPT system, where a Tx equipped with \( N_t \) antennas serves \( K \) single-antenna users. We assume each user is equipped with a co-located PS Rx. This is because the rate-energy region of SWIPT systems employing PS Rxs is convex and subsumes that of SWIPT systems employing TS Rxs for both the linear EH model and the nonlinear saturation EH model [3] [52]. In fact, TS Rxs can be mimicked by forcing the PS ratio to 1 and 0 across time. Note that fixing the PS ratio to 1 and 0 can also emulate the case of separated Rxs.

The baseband transmitted signal is given by

\[
x = \sum_{k=1}^{K} w_k s_k + v, \tag{4}
\]

where \( s_k \sim \mathcal{CN}(0, 1), k \in K = \{1, \ldots, K\} \), denotes the modulated symbol intended for user \( k \) and \( w_k \in \mathbb{C}^{N_t \times 1} \) is the corresponding WIT beamforming vector. Here, \( \mathbb{C}^{A \times B} \) stands for the set of \( A \times B \) complex matrices and \( \mathcal{CN}(\mu, \sigma^2) \) denotes the circularly symmetric complex Gaussian (CSCG) distribution with mean \( \mu \) and variance \( \sigma^2 \). Vector \( v \in \mathbb{C}^{N_t \times 1} \) is an energy signal that is modeled as a complex pseudo-random sequence with covariance matrix \( V = \mathcal{E}(vv^H) \), where \( (\cdot)^H \) stands for the Hermitian transpose of a vector or matrix. Let us denote the vector characterizing the baseband equivalent frequency flat fading channel from the Tx to user \( k \) as \( h_k \in \mathbb{C}^{N_t \times 1} \). The baseband received signal at user \( k \) is given by

\[
y_k = h_k^H \left( \sum_{k' = 1}^{K} w_{k'} s_{k'} + v \right) + n_k^A, \tag{5}
\]

where \( n_k^A \sim \mathcal{CN}(0, \sigma^2_A) \) denotes the additive white Gaussian noise (AWGN) at the receive antennas with power \( \sigma^2_A \). For now, we assume that the CSI is perfectly known at the Tx and the users. The extension to the case of imperfect CSI will be discussed in Section IV. Ignoring the antenna noise power [3] as its contribution to the harvested power is negligible, the received RF power at user \( k \) is equal to the equivalent baseband signal power, which is given by

\[
P_{k,Rx} = \mathcal{E}(||y_k||^2) = \sum_{k' = 1}^{K} \text{Tr} \left( W_{k'} H_k \right) + \text{Tr} \left( VH_k \right), \tag{6}
\]

where \( \text{Tr}(\cdot) \) is the trace of a matrix, \( W_{k'} = w_{k'} w_{k'}^H \), and \( H_k = h_k h_k^H \). User \( k \) splits its received signal at the analog RF front-end with a PS ratio \( (1 - \rho_k) \) for EH, i.e., \( P_{\text{EH}}^{k,Rx} = (1 - \rho_k) P_{k,Rx} \). Note that both the desired signal and the inter-user interference (IUI) contribute to \( P_{\text{EH}}^{k,Rx} \). For the linear EH model, the harvested DC power at user \( k \) is given by

\[
P_{k,\text{out}} = \eta P_{k,Rx}^{\text{EH}}. \tag{7}
\]

\(^3\)Theoretically, a deterministic energy signal is as effective as a random one in terms of WPT [3]. Yet, the latter can be easily shaped to satisfy potential constraints on the spectrum mask.
In contrast, for the nonlinear saturation EH model, the harvested DC power at user $k$ is given by

$$P_{k,\text{out}} = \frac{[\Psi_k - P_{\text{Sat}}^k \Omega]}{1 - \Omega},$$

(8)

where $\Psi_k = \frac{1}{1 + \exp\left(-a(P_{\text{EH}}^k - b)\right)}$. Besides, user $k$ decodes its information based on the other power stream with a PS ratio $\rho_k$ and the corresponding achievable rate is given by

$$R_k = \log_2 \left(1 + \frac{\rho_k \Tr(W_k H_k)}{\rho_k \left(\Tr\left(\sum_{k' \neq k} W_{k'} H_{k'} + V H_k + \sigma^2 I + \sigma^2_{\text{p}}\right)\right)}\right),$$

(9)

where $\sigma^2_{\text{p}}$ denotes the power of the AWGN introduced by the overall signal processing including the power splitting and the RF-to-baseband signal conversion at the ID Rx. Furthermore, we define the total power consumption minus the harvested DC power of SWIPT systems as

$$P_{\text{Sys}} = P_C + \xi \Tr\left(\sum_{k=1}^{K} W_k + V\right) - \sum_{k=1}^{K} P_{k,\text{out}},$$

(10)

where $P_C$ comprises the constant circuit power consumption of both the Tx and the $K$ users. Here, $\xi \Tr\left(\sum_{k=1}^{K} W_k + V\right)$ is the power dissipation of the power amplifier of the Tx and $\frac{\xi}{2}$ with $\xi \geq 1$ is the power amplifier efficiency. Although $P_{k,\text{out}}$ might be much smaller compared with the first and second terms in (10), $P_{\text{Sys}}$ is physically meaningful as it represents the net power consumption of the SWIPT system \[27\], \[72\].

Next, we define two important utility functions for the considered system, i.e., the WIT and WPT efficiencies, which are given by

$$U_{\text{WIT}}^{\text{Eff}}(\rho_k, W_k, V) = \frac{R_{\text{WS}}(\rho_k, W_k, V)}{P_D(W_k, V) - P_{\text{EH}}(\rho_k, W_k, V)}$$

and

$$U_{\text{WPT}}^{\text{Eff}}(\rho_k, W_k, V) = \frac{P_{\text{EH}}(\rho_k, W_k, V)}{P_D(W_k, V)},$$

(11)

(12)

respectively, where $R_{\text{WS}}(\rho_k, W_k, V) = \sum_{k=1}^{K} a_k R_k$ represents the weighted system sum-rate, $P_D(W_k, V) = P_C + \xi \Tr\left(\sum_{k=1}^{K} W_k + V\right)$ denotes the power dissipation required for wireless information and power transfer, and $P_{\text{EH}}(\rho_k, W_k, V) = \sum_{k=1}^{K} P_{k,\text{out}}$ is the total power harvested by all users. Here, $\alpha_k \geq 0, \forall k$, are non-negative weights which account for the priorities of different users and their values can be set to facilitate fairness in resource allocation. The system WIT efficiency $U_{\text{WIT}}^{\text{Eff}}$ denotes the number of bits delivered while consuming one joule of net energy \[73\]. The system WPT efficiency $U_{\text{WPT}}^{\text{Eff}}$ represents the amount of harvested power while consuming one Watt of system power. The former utility function is often adopted for the conventional communication-centric resource allocation designs, e.g., \[59\], \[60\], \[74\], while the latter one is suitable for power-centric designs \[75\], \[76\]. Besides, the two utility functions in (11) and (12) can be jointly considered in a MOO framework \[29\], \[77\]. In general, MOO aims to provide a set of Pareto optimal resource allocation policies. In particular, a resource allocation policy is Pareto optimal if there is no other policy that improves at least one of the objectives without detriment to the other objectives \[29\]. There are various methods to handle MOO programming (MOOP) problems \[29\]. The crux of MOO methods is to convert MOOP to single-objective optimization programming (SOOP) via some parametric transformation such that the Pareto optimal set can be found by solving the SOOP problem. For example, one can adopt the weighted Tchebycheff method to investigate the tradeoff between the WIT and WPT efficiencies for SWIPT systems as in \[29\]. Without loss of generality, we consider SOOP in the following for illustration.

### B. Problem Formulation

One possible design goal for resource allocation in SWIPT systems is the maximization of the WIT efficiency. This leads to the following optimization problem:

$$\begin{align*}
\max_{\rho_k, W_k, V} & \quad U_{\text{WIT}}^{\text{Eff}}(\rho_k, W_k, V) \\
\text{s.t.} & \quad \sum_{k=1}^{K} \Tr(W_k) + \Tr(V) \leq P_{\text{max}}, \\
& \quad R_k = R_{\text{req}}, \quad \forall k, \\
& \quad P_{k,\text{out}} \geq P_{k,\text{req}}, \quad \forall k, \\
& \quad U_{\text{WPT}}^{\text{Eff}}(\rho_k, W_k, V) \geq P_{\text{req}}^{\text{WPT}}, \\
& \quad \text{Rank}(W_k) \leq 1, \quad \forall k, \\
& \quad W_k, V \succeq 0, \quad \forall k, 
\end{align*}$$

where $\mathbb{H}^{n \times n}$ stands for the set of $A \times A$ complex Hermitian matrices. Constraint C1 limits the average transmit power to the available power budget $P_{\text{max}}$ of the Tx. Constraint C2 is an individual QoS constraint for user $k$ and constant $R_{\text{req}}$ is the corresponding minimum required data rate. Constraint C3 is the individual EH constraint for user $k$ and $P_{k,\text{req}}$ is the corresponding minimum required harvested DC power. Constraint C4 guarantees that the WPT efficiency does not fall below a given threshold $P_{\text{req}}^{\text{WPT}}$. Constraint C5 jointly with $W_k \in \mathbb{H}^{n \times n}$ is imposed to guarantee that $W_k = w_k w_k^H$ holds after optimization. Constraint C6 ensures that $W_k$ and $V$ are positive semidefinite matrices.

Problem formulation $P_{\text{WIT}}$ intends to make the WIT as efficient as possible under constraints on the WPT efficiency and minimum requirements for the harvested power and the data rate. $P_{\text{WIT}}$ is of practical interest when the circuit power consumptions for WIT and WPT are non-negligible or even overwhelming compared to the transmit power, which might be the case, e.g., for SWIPT systems operating in the millimeter wave frequency bands \[78\]. The formulated problem $P_{\text{WIT}}$ allows not only the investigation of the rate-energy tradeoff \[3\] but also of the tradeoff between the WPT and WIT efficiencies. Note that one can swap the objective...
function with constraint C4 when the WPT efficiency is more critical for achieving the design objectives of the overall system. The problem solving methodology detailed in Section III-C can be adopted to address both problems.

Additionally, the problem in (13) provides a general unifying framework which subsumes existing resource allocation designs as special cases [24], [65], [74]. For example, by omitting $P_{D}$ ($W_{k}, V$) and $P_{EH}$ ($\rho_{k}, W_{k}, V$) in the objective function of (13), the resulting problem formulation becomes the conventional weighted sum-rate maximization problem [74]:

| $P_{Rate}$: Rate Maximization |
|--------------------------------|
| maximize $R_{WS}$ ($\rho_{k}, W_{k}, V$) s.t. C1-C6. (14) |

$P_{Rate}$ is suitable for optimization of systems with demanding requirements on the data rate, such as SWIPT systems operating in mobile cellular networks. On the other hand, when there is a stringent constraint on the power consumption of the Tx, such as in unmanned aerial vehicle (UAV)-enabled SWIPT systems [79], $R_{WS}$ ($\rho_{k}, W_{k}, V$) and $P_{D}$ ($W_{k}, V$) can be removed from the objective function of (13) such that the problem degenerates to a power minimization problem [65]:

| $P_{Power}$: Power Minimization |
|----------------------------------|
| minimize $P_{D}$ ($W_{k}, V$) s.t. C1-C6. (15) |

Furthermore, for applications where wireless charging is the key for prolonging the lifetime of battery-limited users, e.g., IoT systems [80] and Internet of Everything (IoE) networks [81], $R_{WS}$ ($\rho_{k}, W_{k}, V$) and $P_{D}$ ($W_{k}, V$) can be omitted in the objective function of (13) to maximize the total harvested power [24]:

| $P_{EH}$: Harvested Power Maximization |
|----------------------------------------|
| maximize $P_{EH}$ ($\rho_{k}, W_{k}, V$) s.t. C1-C6. (16) |

The above formulated problems are typical instances of SWIPT resource allocation design problems. From an optimization point of view, problems $P_{Power}$ and $P_{EH}$ are easier to solve compared with $P_{WIT}$ and $P_{Rate}$ due to their simpler objective functions. Nevertheless, $P_{Power}$ and $P_{EH}$ are also non-convex and the non-convexity arises from the coupling between the PS ratio $\rho_{k}$ and the beamforming matrices ($W_{k}, V$) and from the rank-one constraint C5. $P_{WIT}$ and $P_{Rate}$ are more challenging to solve due to the additional non-convexity introduced by IUI. The fractional objective function further contributes to the degree of difficulty involved in solving $P_{WIT}$. In fact, solving $P_{WIT}$, $P_{Rate}$, $P_{Power}$, and $P_{EH}$ is NP-hard [82]. Thus, finding the globally optimal solution is challenging and entails prohibitive complexity. Global optimization approaches, such as monotonic optimization [83]–[86] and branch-and-bound (BnB) [20], [87], can be used to find the optimal solutions of the formulated problems. In particular, monotonic optimization targets a subset of non-convex optimization problems described in terms of monotonic functions and difference of monotonic (d.m.) functions. This subsumes a large number of non-convex optimization problems as most non-convex functions, including the fractional functions in (11) and (12), can be transformed to d.m. functions, as is detailed in [85], [86]. On the other hand, BnB is also a widely adopted approach that successively divides the feasible region (Branch) into subregions and systematically discards non-promising subregions based on lower bounds or upper bounds (Bound) [87]. This partial enumeration strategy can be used to solve a wide array of global optimization problems, including monotonic optimization problems [88]. BnB algorithms converge to globally optimal solutions in a finite number of iterations if the branching operation is consistent and the selection operation is bound improving [20]. Yet, BnB usually has a lower speed of convergence compared to monotonic optimization as it cannot exploit the structure of the optimization problem. The computational complexity of both methods is generally exponential w.r.t. the number of input variables. More details on monotonic and BnB optimization for resource allocation design can be found in [20], [85]–[87].

A common approach to handle fractional objective functions is Dinkelbach’s method [89], [90]. With this method, the fractional objective function is equivalently transformed into a subtractive form by introducing an auxiliary parameter. The resulting subtractive optimization problem is solved in an inner loop and the auxiliary parameter is iteratively updated in an outer loop. If the resulting inner optimization problem can be solved globally, the corresponding algorithm converges to the globally optimal solution of the original problem. However, if the transformed optimization problem in subtractive form is also non-convex, usually only a suboptimal solution of the inner optimization problem can be obtained with an affordable computational complexity, e.g., by using successive convex approximation (SCA) [20] or the weighted sum mean square error (WSMSE) method [91]. In this case, the convergence of Dinkelbach’s method cannot be guaranteed. Moreover, it is well known that Dinkelbach’s method can only handle a single fractional objective function [73]. For instance, $R_{WS}$ ($\rho_{k}, W_{k}, V$) in $P_{WIT}$ and $P_{Rate}$ is a sum of logarithms of fractional functions and thus Dinkelbach’s method is not applicable. Moreover, even for $P_{Power}$ and $P_{EH}$, the multiplication of $\rho_{k}$ and ($W_{k}, V$) in $P_{out}$ and $R_{k}$ prevents the application of Dinkelbach’s method. Hence, in this paper, we exploit the fractional programming (FP) method recently proposed in [92] which can handle the fractional/multiplicative functions and even the function of fractional/multiplicative functions more flexibly. Similar to Dinkelbach’s method, FP also introduces auxiliary parameters to decouple the optimization variables and updates the optimization variables and auxiliary parameters iteratively. However, the adopted quadratic transformation [92], [93] for FP is more flexibly such that the resultant inner optimization problem is usually convex. Therefore, the FP method is guaranteed to converge to a stationary point of the original optimization problem and
also enjoys a polynomial-time computational complexity. In the following, we first present a solution methodology for optimization problem \( P_{\text{WIT}} \) based on the quadratic transformation \([92], [93]\), which can handle the severe variable coupling and can be readily used for developing a concrete algorithm for resource allocation. Then, the solutions for \( P_{\text{Rate}}, P_{\text{Power}}, \) and \( P_{\text{EH}} \) can be obtained by omitting the corresponding terms in the algorithm accordingly, since \( P_{\text{WIT}} \) subsumes the other three problems.

C. Solution Methodology for \( P_{\text{WIT}} \)

FP is based on the quadratic transformation recently proposed in \([92]\), which introduces an auxiliary variable to convert a fractional form function into an equivalent subtractive form, i.e.,

\[
\max_x f_{\text{Obj}}(x) \quad \text{s.t. } f_i(x, y_i, \text{Cons}) \geq f_i, \text{Convex}(x), \forall i,
\]

\[
\Leftrightarrow \max_{x \in X, y_i, \text{Obj}_i} 2y_i \sqrt{f_{\text{Obj}}(x)} - y_i^2 g_{\text{Obj}}(y_i)(x)
\]

s.t. \( 2y_i, \text{Cons} \geq f_i, \text{Convex}(x), \forall i, \)

where \( y_{\text{Obj}}, y_i, \text{Cons} \in \mathbb{R} \) are auxiliary variables and \( f_i, \text{Convex}(x) \) is a convex function w.r.t. \( x \). The proof of the equivalence between \( 17 \) and \( 18 \) is provided in \([92]\). When \( f_{\text{Obj}}(x) \) and \( f_i(x, y_i, \text{Cons}) \) are concave functions w.r.t. \( x \), \( g_{\text{Obj}}(y_i) \) and \( g_{\text{Cons}}(y_i) \) are convex functions w.r.t. \( x \), and \( X \) is a convex set, the subtractive functions \( 2y_i \sqrt{f_{\text{Obj}}(x)} - y_i^2 g_{\text{Obj}}(y_i)(x) \) and \( 2y_i, \text{Cons} \geq f_i, \text{Convex}(x) \) are concave functions w.r.t. \( x \). Then, the resulting problem in \( 18 \) is a convex optimization problem for given \( y_{\text{Obj}} \) and \( y_i, \text{Cons} \). Moreover, for given \( x \), the optimal auxiliary variables are given by

\[
y_{\text{Obj}} = \sqrt{f_{\text{Obj}}(x)} \quad \text{and} \quad y_i, \text{Cons} = \sqrt{f_i, \text{Cons}(x)} \quad (19)
\]

respectively.

As a result, an iterative algorithm can be developed to update \( x \) and \( (y_{\text{Obj}}, y_i, \text{Cons}) \) in an alternating manner. Note that this algorithm is guaranteed to converge to a suboptimal solution of the original problem in \( 17 \) if the transformed problem in \( 18 \) can be solved globally. We refer interested readers to \([92], [93]\) for a detailed proof of the convergence. Furthermore, the algorithm has a polynomial-time computational complexity, which is well-suited for real-time implementation.

In the following, we show how to perform the quadratic transformation to obtain a suboptimal solution of \( P_{\text{WIT}} \) for both the linear EH model and the nonlinear saturation EH model.

1) Linear EH model: In this section, we transform \( P_{\text{WIT}} \) into an equivalent optimization problem, which is suitable for applying the quadratic transformation. Then, an iterative algorithm is developed to achieve a stationary point of \( P_{\text{WIT}} \). In the objective function of \( P_{\text{WIT}} \), we can observe that the numerator is not a concave function w.r.t. the optimization variables due to the IUI and the denominator is not a convex function w.r.t. the optimization variables due to the coupling between \( \rho_k \) and \((W_k, V)\). To address these challenges, we introduce two auxiliary optimization variables \( \gamma_k \) and \( P_{k,\text{out}} \) and add two corresponding constraints:

\[
C7: \quad \text{Tr} (W_k H_k) + \sum_{k' \neq k} \frac{\text{Tr} (W_k H_k + V H_k)}{\rho_k} \geq \gamma_k \quad \text{and}
\]

\[
C8: \quad \eta \frac{\sum_{k'=1}^{K} W_k H_k + V H_k}{P_{k,\text{out}}} \geq \frac{1}{(1 - \rho_k)}, \forall k \quad (20)
\]

It can be verified that constraints \( C7 \) and \( C8 \) are satisfied with equality at the optimal point. Then, the problem in \( 13 \) can be rewritten as follows:

\[
\min_{W_k, V} \max_{0 \leq \rho_k \leq 1, \gamma_k, P_{k,\text{out}} \leq V} \sum_{k=1}^{K} \alpha_k \log_2 (1 + \gamma_k)
\]

s.t. \( C1: C3, C5-C8 \)

\[
C2: \gamma_k \geq 2^{R_k, \text{req}} - 1, \forall k,
\]

\[
C4: \quad \sum_{k=1}^{K} P_{k,\text{out}} \geq \text{WPT}_{\text{req}} P_{0} (W_k, V).
\]

Adopting the quadratic transformation in \( 17 \) and \( 18 \), the problem in \( 21 \) can be transformed into the following equivalent optimization problem:

\[
\min_{W_k, V} \max_{0 \leq \rho_k \leq 1, \gamma_k, P_{k,\text{out}} \leq V, \beta_{\text{Obj}}, \beta_{k,\text{C7}}, \beta_{k,\text{C8}}} \sum_{k=1}^{K} \alpha_k \log_2 (1 + \gamma_k)
\]

s.t. \( C1-C5 \)

\[
C7: \quad G_{\text{C7}} (W_k, V, \rho_k, \beta_{k,\text{C7}}) \geq \gamma_k, \forall k,
\]

\[
C8: \quad G_{\text{C8}} (W_k, V, P_{k,\text{out}}, \beta_{k,\text{C8}}) \geq \frac{1}{(1 - \rho_k)}, \forall k,
\]

where \( \beta_{\text{Obj}}, \beta_{k,\text{C7}}, \beta_{k,\text{C8}} \in \mathbb{R} \) denote the auxiliary variables corresponding to the objective function, \( C7 \), and \( C8 \), respectively. The corresponding subtractive functions \( G_{\text{Obj}}, G_{\text{C7}}, \) and \( G_{\text{C8}} \) are given in \( 22 \) at the top of next page.

The resulting subtractive functions in \( 23 \) are concave w.r.t. the optimization variables for given auxiliary variables. Except for constraint \( C5 \), the problem in \( 22 \) is a convex optimization problem given the auxiliary variables. On the other hand, given \((W_k, V, \gamma_k, P_{k,\text{out}})\), the optimal auxiliary variables can be
where the optimal WIT beamformer, $\mathbf{w}^\ast_k$, is sufficient to maximize the WIT and WPT efficiencies simultaneously in SWIPT systems.\footnote{Note that if the energy signal $\mathbf{v}$ is known at the ID Rxs, it can be canceled at user $k$ to further improve the spectral efficiency \cite{11}. In such a case, the energy signal can in fact improve the WPT performance, i.e., a non-zero $\mathbf{v}$ is generally optimal.}

\subsection{2) Nonlinear Saturation EH Model:} For the nonlinear saturation EH model in \cite{8}, constraint C8 in \cite{20} needs to be reformulated accordingly. Besides, we need to additionally introduce an optimization variable $P_{k,Rx}^{EH}$ to facilitate the quadratic transformation. In this case, the problem in \cite{15} can be rewritten as follows:

\begin{equation}
\begin{aligned}
\mathcal{P}_{\text{WIT}}: \text{WIT Efficiency Maximization with Nonlinear Saturation EH Model} \\
\text{maximize} & \sum_{k=1}^{K} \alpha_k \log_2 (1+\gamma_k) - \frac{P_{D} (\mathbf{W}_k, \mathbf{V}) - \sum_{k=1}^{K} P_{k,\text{out}}}{P_D (\mathbf{W}_k, \mathbf{V})} \\
\text{subject to} & \sum_{k=1}^{K} P_{k,\text{out}} = 0, \gamma_k \geq \frac{1}{1-P_{k,\text{out}}}, \forall_k, \\
& \mathcal{C}_{7} - \mathcal{C}_{8} \in \{0, 1\}, \forall_k, \forall_{\mathbf{V}, \mathbf{W}} \\
& \mathcal{C}_{8a}: \sum_{k'=1}^{K} \text{Tr} (\mathbf{W}_{k'} \mathbf{H}_k + \mathbf{V} \mathbf{H}_k) + \sigma_k^2 + \frac{\eta_k}{\rho_k} \geq 1, \forall_k, \\
& \mathcal{C}_{8b}: \frac{1}{1+\exp \left[-\frac{a}{P_{k,Rx}^{EH}} \mathbf{b} \right]} \geq \frac{P_{k,\text{out}}}{P_{\text{Sat}}} (1-\Omega) + \Omega, \forall_k.
\end{aligned}
\end{equation}

Now, the quadratic transformation can be used to transform the problem in \cite{25} into an equivalent subtractive form by introducing auxiliary variables associated with the objective function, C7, C8a, and C8b. Comparing \cite{21} and \cite{25}, we can observe that C8a in \cite{25} is equivalent to C8 in \cite{21} when the RF-to-DC conversion does not cause any energy loss, i.e., $\eta = 1$. In fact, the difference between \cite{21} and \cite{25} is the additional constraint C8b in \cite{25}. The similar structure of both problems implies that the SDP relaxation is also tight for \cite{25}. This is formally stated in the following corollary.

\textbf{Corollary 1:} Assuming that the channel vectors of all users, $\mathbf{h}_k, \forall_k$, are mutually statistically independent, given $\mathbb{B}_{\text{Obj}}, \mathbb{B}_{\text{C7}}, \mathbb{B}_{\text{C8}}$, and $P_{\text{max}} > 0$, the optimal WIT beamforming matrices $\mathbf{W}_k^\ast$ of the relaxed version of the problem in \cite{25} are rank-one, i.e., $\text{Rank} (\mathbf{W}_k^\ast) \leq 1, \forall_k$, with probability one. Furthermore, the optimal WPT beamformer is $\mathbf{v}^\ast = 0$, where 0 denotes the vector with all zero entries.

\textbf{Proof:} See Appendix for a proof of Theorem 1. $\blacksquare$

According to Theorem 1 the SDP relaxation is tight. Moreover, when the energy signal cannot be canceled at the Rxs, a dedicated WPT signal $\mathbf{v}$ is not needed for maximizing the WIT efficiency despite the EH constraint. In fact, it has been demonstrated that, for the linear EH model, the CSCG input distribution is optimal in terms of both WIT and WPT \cite{3}. Therefore, the optimal WIT beamformer, $\mathbf{w}^\ast_k$, is sufficient to maximize the WIT and WPT efficiencies simultaneously in SWIPT systems.\footnote{Note that if the energy signal $\mathbf{v}$ is known at the ID Rxs, it can be canceled at user $k$ to further improve the spectral efficiency \cite{11}. In such a case, the energy signal can in fact improve the WPT performance, i.e., a non-zero $\mathbf{v}$ is generally optimal.}
given the auxiliary variables, the problem in (25) can be solved globally via SDR. Moreover, the additional constraint C8b in (25) implies that the resource allocation design based on the linear EH model may outperform that based on the nonlinear saturation EH model if the EH circuit was actually linear. However, in practice, the resource allocation design based on the linear EH model suffers from a model mismatch and the expected system performance is not achievable, as shown in Section III-D.

3) Nonlinear Circuit-based EH Model: Adopting a nonlinear circuit-based EH model requires the joint design of the input distribution and the resource allocation. The optimal input distribution that maximizes the WIT performance under an EH constraint is unique, discrete, and finite [48]. However, finding the optimal input distribution to maximize a general utility function, such as (11), typically results in an intractable problem. Also, the coupling of the input distribution and the resource allocation variables imposes a challenge for optimization.

In the following, we propose an iterative suboptimal design approach, where the input distribution and the resource allocation are designed in an alternating manner. In particular, in the \( i \)-th iteration, given the resource allocation policy \( \begin{pmatrix} W_k^i, V_k^i, \rho_k^i \end{pmatrix} \), the optimal input distribution enjoying the highest WIT efficiency is numerically determined. Motivated by the fact that the optimal input distribution for WIT is the zero-mean CSG distribution and the optimal input distribution for WPT has an on-off characteristic [3], [48], we propose the following channel input:

\[
s_k = \sqrt{\alpha_{k,1} s_{k,1} + \alpha_{k,E}^* s_{k,E}}, \tag{26}
\]

where \( s_{k,1} \) denotes the information-bearing symbols for user \( k \) following a zero-mean CSG distribution and \( s_{k,E} \) denotes the energy-bearing symbols for user \( k \) following an on-off distribution. Here, \( \alpha_{k,1}, \alpha_{k,E} \geq 0 \) represent the powers allocated for WIT and WPT to user \( k \) in the \( i \)-th iteration, respectively. To facilitate the joint design, we assume all user devices employ the same EH circuits and \( \alpha_{k,1} = \alpha_{k',1} \) and \( \alpha_{k,E} = \alpha_{k',E} \), \( \forall k \neq k' \). Assuming the impulsive signal \( s_{k,E} \) can be canceled at the Rx via successive interference cancellation (SIC), the reachable rate is given by (9) if only the CSGC signal is used for WIT. Given \( \begin{pmatrix} W_k^i, V_k^i, \rho_k^i \end{pmatrix} \), we can employ the nonlinear circuit-based EH model in (2) to simulate the harvested DC power and numerically select the optimal power allocation, \( \begin{pmatrix} \alpha_{k,1}^i, \alpha_{k,E}^i \end{pmatrix} \), which yields the highest WIT efficiency. Then, the model parameters of the nonlinear saturation EH model in (3) can be updated by curve fitting based on the harvested DC power obtained from the nonlinear circuit-based EH model for the optimized input distribution. The resource allocation for the \( (i+1) \)-th iteration is designed based on the selected input distribution and the updated nonlinear saturation EH model, where problem formulation (25) and the corresponding solution methodologies are applicable.

D. Simulation Result for an Exemplary SWIPT System

In this section, we provide a simulation result for an exemplary SWIPT system to reveal some insights for resource allocation design. The average system WIT efficiency \( U_{\text{WIT}}^{\text{Eff}} \) is evaluated for different minimum required WPT efficiencies \( \text{WPT}_{\text{req}}^{\text{Eff}} \) in Fig. 4. We set \( v = 0 \) and adopt maximum ratio transmission (MRT) precoding for the initialization of the resource allocation algorithm described in Sections III-C1 and III-C2, i.e., \( w_k = h_k, \forall k \). All simulation parameters are provided in Table II. Here, the EH model parameters are obtained by curve fitting based on the measurement data in [46], cf. Fig. 3. We solve the WIT maximization problem \( P_{\text{WIT}} \) for both the linear EH model and the nonlinear saturation EH model in (21) and (25), respectively. As the required WPT efficiency increases, we observe from Fig. 4 that the system WIT efficiencies for both EH models decrease since more resources have to be dedicated to WPT. We can further observe that the system WIT efficiency for the linear EH model is higher than that for the nonlinear saturation EH model since the latter model usually leads to an additional constraint for resource allocation compared to the former one, as shown in (21) and (25). However, linear RF-to-DC conversion is not realizable due to the inevitable nonlinearity of EH circuits. To show the impact of the resulting resource allocation mismatch, we solve the WIT maximization problem \( P_{\text{WIT}} \) based on the linear EH model and evaluate the resulting system performance for the nonlinear saturation EH model ("\( P_{\text{WIT}} \): model mismatch"). Note that we set the system WIT efficiency to zero when any QoS or EH constraint cannot be satisfied to account for the corresponding penalty. Since at least one of the QoS and EH constraints in (21) is active at the optimal point, the resource allocation policy designed based on the linear EH model inevitably leads to system outages when employed in a practical SWIPT system with nonlinear EH. Furthermore, for comparison, we solve the rate maximization problem \( P_{\text{Rate}} \) based on the nonlinear saturation EH model in (13). We observe that maximizing the system sum-rate results in a lower WIT efficiency in the low WPT efficiency regime while it achieves almost the optimal WIT efficiency in the high WPT efficiency regime. In fact, as indicated in (12), to achieve a high WPT efficiency, a low transmit power and a high PS ratio for EH are needed, and vice versa. Therefore, in the low WPT efficiency regime, maximizing the system
sum-rate causes the SWIPT system to operate in the high power regime and thus it decreases the WIT efficiency due to the diminishing return in spectral efficiency when allocating more transmit power. In contrast, in the high WPT efficiency regime, maximizing the system sum-rate cannot exhaust the power budget at the Tx as only a small transmit power can be afforded due to the stringent WPT efficiency constraint. In the low power regime, the spectral efficiency increases almost linearly w.r.t. the transmit power and thus transmitting all the allowable power is the most energy-efficient option.

### IV. Resource Allocation Design for SWIPT Systems with Imperfect CSIT

The resource allocation design problems for SWIPT systems formulated above are based on the assumption of perfect CSIT. However, in the presence of CSIT errors, resource allocation design for SWIPT systems suffers from substantial performance degradation, which calls for robust designs. In this section, we introduce three different approaches to robust resource allocation design: namely average robust design [31], outage-constrained robust design [32], [33], and worst-case robust design [34]–[36]. We first discuss how to incorporate channel uncertainty in the problem formulation to make the resource allocation robust. Then, corresponding solution methodologies are discussed and examples for outage-constrained and worst-case robust designs are provided for illustration.

#### A. CSIT Error Model

To capture the imperfection of CSIT, we model the channel from the Tx to user $k$ as

$$h_k = \hat{h}_k + \Delta h_k, \forall k,$$

where $\hat{h}_k$ denotes the estimate of $h_k$ and $\Delta h_k$ is the corresponding CSIT error. In the literature, there are generally two approaches for modeling CSIT errors [31]–[36]:

- **Statistical CSIT Error Model** [31]–[33]:
  $$\Delta h_k \sim \mathcal{CN}(0, \sigma^2_{\Delta h_k} I_N),$$
  where $\sigma^2_{\Delta h_k}$ is the variance of the channel estimation error of user $k$ and $\mathcal{CN}(\mu, \Sigma)$ denotes the CSCG distribution with mean $\mu$ and variance $\Sigma$.

- **Bounded CSIT Error Model** [33]–[36]:
  $$\|\Delta h_k\| \leq e_{h_k},$$
  where $e_{h_k}$ denotes the maximum value of the norm of the CSIT error of user $k$.

The statistical CSIT error model assumes the CSIT errors, which may be caused by a noising estimation process, can be approximated by a Gaussian random variable [31]–[33]. In contrast, for the bounded CSIT error model, the CSIT error is assumed to be within a known norm-bounded set, without any assumption on its distribution [33]–[36]. One typical application scenario of the bounded CSIT error model is to capture CSI errors resulting from quantization. For robust resource allocation design based on the bounded CSIT error model, certain constraints have to be satisfied for all possible errors within the uncertainty set, which ultimately leads to a worst-case design. On the other hand, with the statistical CSIT error model, the resource allocation can be made robust w.r.t. the average system performance or performance outages, which leads to average robust designs and outage-constrained robust designs, respectively. These different approaches will be discussed in detail in the following.

#### B. Average Robust Design

This design methodology aims to maximize the average system performance with a constraint on the average QoS based on the statistical CSIT error model [31]. For instance, the average robust design problem corresponding to the problem in [13] can be formulated as follows:

$$\max_{0 \leq P_k \leq 1, \forall k} \mathbb{E} \left[ R_{k} | \bar{h}_k \right]$$

subject to:

$$\begin{align*}
C1: & \quad 0 \leq P_k \leq 1, \forall k \in V_n \\
C2: & \quad \mathbb{E} \left[ R_k | \bar{h}_k \right] \geq R_k | \text{req}, \forall k \\
C3: & \quad \mathbb{E} \left[ \bar{h}_k \right] \geq P_k | \text{req}, \forall k \\
C4: & \quad \mathbb{E} \left[ \bar{h}_k \right] \geq P_D (W_k, V) WPT_{\text{req}}^\text{WPT}
\end{align*}$$

where the expectation is taken over the CSIT error distribution in [25]. Note that this kind of problem formulation does not penalize instantaneous QoS outages, as long as the desired average performance is achieved. However, it is usually challenging to obtain a closed-form expression for the average performance metric, such as the system sum-rate in [30] or the WIT efficiency in [13], which limits the applicability of the average robust design methodology. One possible approach to resolve this issue is the Monte Carlo method [96], where the average system performance

| TABLE II | SYSTEM PARAMETERS. |
|-----------|-------------------|
| Number of users | $K = 3$ |
| Path loss exponent | 2.5 |
| Multipath fading distribution | Rician fading |
| Antenna noise power | $\sigma_N^2 = -100 \text{ dBm}$ |
| Minimum harvested DC power | $P_{k, \text{req}} = 1 \mu W$ |
| Minimum rate requirement | $R_{k, \text{req}} = 1 \text{ bit/s/Hz}$ |
| Circuit power consumption | $P_C = 1 \text{ W}$ |
| Outage probability | $\kappa_{R_k} = \kappa_{P_k} = \kappa_{\text{EH}} = 0.001 \sim 0.1$ |
| EH model parameters | $\eta = 0.474, P_{\text{max}} = 0.024 \text{ W, } b = 0.014, a = 150$ |

$P_{\text{max}}$ is the maximum allowable power is the most energy-efficient option.
metric in the objective function and the constraints are approximated by the corresponding empirical mean via random sampling of the channel based on the CSIT error distribution \[96\]. For instance, the average system sum-rate in (30) can be approximated by 
\[ E_{\Delta h_k} \left\{ R_{WS}(\rho_k, W_k, V) \right\} \approx \frac{1}{\hat{I}} \sum_{i=1}^{\hat{I}} R_{WS}(\rho_k, W_k, V) \big|_{h_k = 0} + \Delta h_k, \]
where \( \Delta h_k \) denotes the \( i \)-th sample of the CSIT error according to (28) and \( \hat{I} \) is the total number of samples. Yet, this approach increases the computational complexity for solving (30).

### C. Outage-constrained Robust Design

This design approach optimizes a probabilistic or deterministic objective function while guaranteeing the probabilities with which the QoS and EH requirements are satisfied \[32\], \[33\]. Outage-constrained robust designs are suitable for application scenarios which can tolerate system performance outages while requiring a limit to the frequency of their occurrence. For instance, for problem (15), we may minimize the system power consumption under probabilistic QoS and EH constraints:

\[
\begin{align*}
\text{minimize} & \quad P_D(W_k, V) \\
\text{subject to} & \quad 0 \leq \rho_k \leq \frac{1}{M}, \quad W_k, V \in \mathbb{H}^{N_k \times M} \\
\text{s.t.} & \quad C1, C5, C6, \\
C2: & \quad \Pr_{\Delta h_k} \left\{ R_k \geq R_{k,req} | \hat{h}_k \right\} \geq 1 - \kappa_Rk, \quad \forall k, \\
C3: & \quad \Pr_{\Delta h_k} \left\{ P_{k,\text{out}} \geq P_{k,req} | \hat{h}_k \right\} \geq 1 - \kappa_{P,k}, \quad \forall k, \\
C4: & \quad \Pr_{\Delta h_k} \left\{ \ell_{\text{WPT}}(\rho_k, W_k, V) \geq \text{WPT}^{\text{Eff}}_{\text{req}} | \hat{h}_k \right\} \geq 1 - \kappa_{\text{EH}}.
\end{align*}
\]

Constraints C2-C4 ensure that the probabilities of satisfying the QoS and EH requirements are higher than those given corresponding thresholds. Here, \( 0 \leq \kappa_Rk, \kappa_{P,k}, \kappa_{\text{EH}} \leq 1 \) denote the maximum tolerable outage probabilities for given constraints on the target data rate, harvested power, and WPT efficiency, respectively. The probabilistic constraints in C2-C4 do not admit simple closed-form expressions, which is typical for this kind of problem formulation and imposes a challenge for robust resource allocation design \[97\]. Fortunately, since the probabilistic constraints C2-C4 can be transformed into complex Gaussian quadratic forms, the problem can be reformulated to obtain another type of robust formulation, namely a safe convex approximation of the original problem (31) \[97\]. This convex approximation approach is based on the large deviation inequality for complex Gaussian quadratic forms, i.e., the Bernstein-type inequality, which bounds the probability that a sum of random variables deviates from its mean \[97\]. To begin, let us recall the following lemma.

**Lemma 1 (Bernstein-type inequality \[97\]):** Consider the following random variable \( f(t) = t^H Q t + 2 R (t^H u) \), where \( t \sim \mathcal{CN}(0, I_M) \), \( Q \in \mathbb{H}^{M \times M} \), and \( u \in \mathbb{C}^{M \times 1} \). For all \( \kappa > 0 \), the following inequality holds:

\[
\Pr \{ f(t) \geq \Upsilon(\kappa) \} \geq 1 - e^{-\kappa},
\]

where \( \Upsilon(\kappa) = \text{Tr}(Q) - \sqrt{2\kappa} \sqrt{||Q||_F^2 + 2||u||^2 - \kappa \lambda^+(Q)}, \)
\( || \cdot ||_F^2 \) denotes the matrix Frobenius norm, \( \lambda^+(Q) = \max \{ \lambda_{\max}(-Q), 0 \} \), and \( \lambda_{\max}(\cdot) \) denotes the maximum eigenvalue of a matrix. Since \( \Upsilon(\kappa) \) is monotonically decreasing, the Bernstein-type inequality in (32) can be rewritten as follows

\[
\Pr \{ f(t) + g \geq 0 \} \geq 1 - e^{-\Upsilon^{-1}(\cdot - g)},
\]

where \( \Upsilon^{-1}(\cdot) \) denotes the inverse function of \( \Upsilon(\cdot) \).

The Bernstein-type inequality provides a lower bound for \( \Pr \{ f(t) + g \geq 0 \} \) and \( e^{-\Upsilon^{-1}(\cdot - g)} \leq \tau \) implies \( \Pr \{ f(t) + g \geq 0 \} \geq 1 - \tau \), where \( 0 \leq \tau < 1 \) is a constant. Due to the intractability of the probabilities in C2-C4 in (31), it is generally a formidable challenge to analyze the tightness of Bernstein-type inequalities. However, a comparative analysis has been provided in \[97\], which showed that the Bernstein-type inequality is tighter compared with two other bounds, i.e., the sphere bound and the decomposition-based large deviation inequality \[97\].

In the following, we discuss how to handle constraint C2 in (31) based on the Bernstein-type inequality introduced in Lemma 1.

In particular, substituting (27) for \( R_k \) in C2, we have

\[
\Pr_{\Delta h_k} \left\{ R_k \geq R_{k,req} | \hat{h}_k \right\} \geq 1 - \kappa_Rk \\
\iff \Pr_{\Delta h_k} \left\{ t_k^H Q_k t_k + 2 R (t_k^H u_k) + g_k \geq 0 \right\} \geq 1 - \kappa_Rk,
\]

where \( t_k = \frac{\Delta h_k}{\sigma_{g_k}^2} \sim \mathcal{CN}(0, I_{N_k}), \) \( Q_k = W_k - (2 R_{k,req} - 1) \left( \sum_{k' \neq k} W_{k'} + V \right), \) \( u_k = \frac{Q_k^H h_k}{\sigma_{g_k}^2}, \) and \( g_k = h_k^H Q_k h_k - (2 R_{k,req} - 1) \left( \sigma_{g_k}^2 + \frac{N_k}{\sigma_{g_k}^2} \right). \) According to (33), (34) is always satisfied if the following inequality holds

\[
e^{-\Upsilon^{-1}(\cdot - g_k)} \leq \kappa_Rk \\
\iff \text{Tr}(Q_k) - 2 \ln \left( \frac{1}{\kappa_Rk} \right) \sqrt{||Q_k||_F^2 + 2||u_k||^2} \\
+ \ln (\kappa_Rk) \lambda^+(Q_k) + g_k \geq 0.
\]

By introducing suitable slack variables, the constraint in (33) can be transformed into the following linear matrix inequality (LMI) and second-order cone (SOC) constraints:

\[
\text{Tr}(Q_k) - 2 \ln \left( \frac{1}{\kappa_Rk} \right) d_k + \ln (\kappa_Rk) z_k + g_k \geq 0, \\
\sqrt{||Q_k||_F^2 + 2||u_k||^2} \leq d_k, \\
z_k N_k + Q_k \geq 0, \quad z_k \geq 0,
\]

which can be handled by convex optimization approaches.

In other words, the constraints in (36) impose a convex restriction for the probabilistic constraint C2 in (31). Applying a similar transformation procedure to constraints C3 and C4 in (31), the resulting problem can be directly handled by the methodologies introduced in Section III-C.
### D. Worst-case Robust Design

This approach is based on the bounded CSIT error model in (29) and optimizes the worst-case system performance under worst-case QoS constraints [35], [36]. For example, the problem in (16) can be reformulated as follows:

| Power Maximization | Worst-case Robust Design for Harvested EH |
|---------------------|------------------------------------------|
| maximize $\min_{\Delta h_k, \forall k} C(\rho_k, W_k, V)$ | $\hat{C}_2$ : $\min R_k \geq R_{k,\text{req}}, \forall k$, |
| s.t. $C1$, $C5$, $C6$, | $\hat{C}_3$ : $\min P_{k,\text{out}} \geq P_{k,\text{req}}, \forall k$, |
| $\hat{C}_4$ : $\min_{\Delta h_k, \forall k} \sum_{k=1}^{K} P_{k,\text{out}} \geq P_{\text{D}}(W_k, V)$ | $\hat{W}_{\text{Eff}}^{\text{WPT}}$ |

where $\Delta h_k$ follows (29) and the min in the objective function and constraints $\hat{C}2$-$\hat{C}4$ is over the CSIT error which leads to a guaranteed worst-case performance. Due to the imperfect CSIT, there are infinitely many possibilities for the objective function and constraints $\hat{C}2$-$\hat{C}4$ in (37). This obstacle can often be circumvented by exploiting a complex Gaussian quadratic form inequality [95]. To this end, the implication in the following lemma is useful to obtain tractable restrictions for $\hat{C}2$-$\hat{C}4$:

**Lemma 2 (S-Procedure [95]):** Let a function $f_m(t), m \in \{1, 2\}, t \in \mathbb{C}^{N \times 1}$, be defined as

$$f_m(t) = t^H A_m t + 2\Re\{b_m^H t\} + c_m,$$  

where $A_m \in \mathbb{H}^N$, $b_m \in \mathbb{C}^{N \times 1}$, and $c_m \in \mathbb{R}^{1 \times 1}$. Then, the implication $f_1(t) \leq 0 \Rightarrow f_2(t) \leq 0$ holds if and only if there exists a variable $\epsilon \geq 0$ such that

$$\epsilon \begin{bmatrix} A_1 & b_1 \\ b_1^H & c_1 \end{bmatrix} - \begin{bmatrix} A_2 & b_2 \\ b_2^H & c_2 \end{bmatrix} \succeq 0,$$  

provided that there exists a point $\hat{t}$ such that $f_k(\hat{t}) < 0$.

Note that the worst-case robust design approach is preferable for mission-critical applications where the QoS and EH constraints cannot be violated even in the presence of CSIT uncertainty. In the following, we show exemplarily how to handle constraint $\hat{C}2$ in (37) employing the S-Procedure in Lemma 2. In particular, we define the optimization variable:

$$\hat{\gamma}_k = \min_{\Delta h_k} \frac{\rho_k \Tr(W_k H_k)}{\rho_k \left( \Tr(\sum_{k' \neq k} W_{k'} H_{k'} + V H_k) + \sigma_A^2 + \sigma_P^2 \right)}, \forall k,$$  

such that constraint $\hat{C}2$ in (37) can be rewritten as:

$$\hat{C}2a : \hat{\gamma}_k \geq 2^{\hat{R}_{k,\text{req}}} - 1, \forall k,$$

$$\hat{C}2b : \min_{\Delta h_k} f_2(\Delta h_k) \leq 0,$$

where $f_2(\Delta h_k) = \Delta h_k^H \Omega_k \Delta h_k + 2\Re\{\hat{h}_k^H \Omega_k \Delta h_k\} + y_k$, $\Omega_k = \left( \sum_{k' \neq k} W_{k'} + V \right) \frac{\hat{h}_k^H}{\hat{h}_k}$, and $y_k = \hat{h}_k^H \Omega_k \hat{h}_k + \sigma_A^2 + \sigma_P^2$. According to Lemma 2, we define $f_1(\Delta h_k) = \|\Delta h_k\|^2 = \Delta h_k^H \Delta h_k \leq \epsilon_k$, and $f_2(\Delta h_k) \leq 0$ holds if and only if

$$\hat{C}2b : \Xi = \left[ \epsilon_k I - \Omega_k - \Omega_k^H \hat{h}_k \bar{h}_k^H \Omega_k \right] \geq 0,$$

where $\epsilon_k \geq 0$. We note that to maximize the total power harvested by all users, constraint $\hat{C}2b$ will be satisfied with equality at the optimal point, i.e., $\hat{\gamma}_k = 2^{R_{k,\text{req}}} - 1$. Introducing an auxiliary variable $\frac{1}{\hat{C}2b} \geq \frac{1}{\epsilon_k}$, the inequality in (42) can be transformed into an LMI. Applying the transformation procedure above to constraints $C3$ and $C4$ in (37), the resulting problem can be handled by the quadratic transformation and SDR approaches discussed in Section III-C.

### E. Complexity Analysis and Implementation Details

In this section, we analyze the computational complexity of the introduced solution methodology and discuss some practical aspects arising in its implementation.

The proposed algorithms are based on the quadratic transformation and SDR. Since the auxiliary variables are updated based on closed-form expressions, e.g., (24), the computational complexity of the proposed optimization methods is dominated by the SDP required for solving the transformed problems in subtractive form for given auxiliary variables. It is well-known that SDP has a polynomial worst-case computational complexity [98]. In particular, when the interior-point method is employed, the worst-case complexity of SDP is $O\left(\sqrt{N_{\text{Var}}} (N_{\text{Cons}} N_{\text{Var}}^2) \log \left( \frac{1}{\epsilon_{\text{SDP}}} \right) \right)$, where the big-O notation $O(\cdot)$ describes the order of computational complexity, $N_{\text{Var}}$ denotes the number of optimization variables, $N_{\text{Cons}}$ denotes the number of constraints, and $\epsilon_{\text{SDP}} > 0$ specifies the accuracy of SDP. Considering this, the worst-case computational complexity for solving (22) is

$$O\left( \sqrt{3K(1+K)N_{\text{Var}}^2} [(4K+2)(3K+(1+K)N_{\text{Var}}^2) \log \left( \frac{1}{\epsilon_{\text{SDP}}} \right) \right].$$

As can be observed, the computational complexity of the proposed algorithm scales with $N_{\text{Var}}^5$ and $K^{3.5}$.

To implement the proposed resource allocation design, all users first have to inform the Tx of the SWIPT system about their minimum required data rates and their minimum required EH powers via dedicated feedback links. Then, the Tx has to acquire the CSI through uplink training by exploiting the channel reciprocity in time division duplexing (TDD) systems or through downlink training and feedback in frequency division duplexing (FDD) systems [100]. Compared with conventional wireless Rxs, EH Rxs are usually more severely power-limited and thus the required uplink training or feedback leads to higher channel estimation errors. Therefore, it is imperative to take the CSIT errors into account for the design of robust resource allocation algorithms, as explained earlier in this section. The resource allocation design is computed at the Tx in a centralized manner. The obtained beamforming vectors are used to generate the transmit signal, while the obtained PS ratios are informed to all users via dedicated control links for splitting the received RF signal for EH and ID.
the total transmit power versus the CSIT error uncertainty simulation parameters are taken from Table II. Fig. 5 shows in (31), considering a nonlinear saturation EH model. All methods to minimize the total transmit power, i.e., the problem and outage-constrained robust resource allocation designs.

Fig. 5. Average total transmit power versus the CSIT error with worst-case κ

\[ \kappa \]

outage probabilities, i.e., \( \kappa_{\text{EH}} \), \( \kappa_P \), and \( \kappa_{\text{EH}} \) become smaller, as the QoS and EH outage constraints become more stringent.

\[ \kappa \]

V. Future Research Directions

In this section, we discuss some potential research directions for resource allocation design in SWIPT systems, including the joint waveform and resource allocation design, intelligent reflecting surface (IRS)-assisted SWIPT systems, SWIPT-enabled MEC systems, and the role of ML.

A. Joint Waveform and Resource Allocation Design

While resource allocation design for SWIPT systems has been extensively studied in the literature [21]–[23], [37], [38], [40]–[43], joint waveform and resource allocation design for the nonlinear circuit-based EH model is still an open problem. As mentioned in Section III-C, the optimal waveform for maximizing the total harvested power is usually deterministic [3] or follows a discrete finite distribution [48], which is different from the widely-adopted CSCG signal for conventional WIT. In fact, it is expected that exploiting the nonlinearity can enlarge the rate-energy tradeoff region [3]. Firstly, how to design the waveform for optimization of a generalized system utility function is still unknown. Secondly, for resource allocation design, closed-form expressions for the achievable rate and the harvested DC power are needed, but are usually not available or cumbersome when the signals depart from the conventional CSCG distribution. Thirdly, for waveform design, essentially an optimal input distribution has to be found while conventional resource allocation designs are parametric in nature. Therefore, the coupling of resource allocation and waveform design calls for a general parametric input distribution, which can lead to a tractable performance characterization for SWIPT systems. This would allow the joint design of the waveform and the resource allocation for improving the system performance. Moreover, waveform optimization for multi-carrier SWIPT systems is even more challenging. In particular, WPT has to be carried out based on the time-domain waveform in passband, while for WIT, the adopted signal on each subcarrier is relevant. In addition, frequency-selective fading provides frequency diversity, which also needs to be taken into account for joint resource allocation and waveform optimization. For instance, power allocation in the frequency domain affects both the system sum-rate and the WIT efficiency [101]. On the other hand, power allocation across subcarriers might be an effective approach to alter the distribution of the time-domain signal waveform which can be exploited to improve the WPT efficiency. Moreover, if multiple antennas are available at the EH Rx, the energy combining can be performed either at the RF or the DC level [102]. Besides, the Tx/Rx beamforming, the waveform, and the resource allocation should be jointly optimized to strike a balance between WPT and WIT, particularly if nonlinear EH models are employed [103]. However, this area of research is still largely unexplored.

B. IRS-assisted SWIPT

Recently, IRSs have been proposed to enable the establishment of a programmable radio environment and have attracted extensive attention from the wireless research community [104], [105]. By exploiting a large number of low-cost passive elements that can reflect the signals with adjustable amplitudes and phase shifts [104], [105]. IRSs have the potential to establish favorable communication links for both ID and EH Rxs that would otherwise be blocked or in deep fades [75]. Owing to their capability to reconfigure the channel and their limited power consumption, IRSs are a promising candidate for enabling intelligent and energy-efficient SWIPT [106]. However, to fully unleash the potentials of IRSs in improving SWIPT system performance, the reflection coefficients of the IRSs have to be jointly designed with the WIT and WPT beamforming at the transmitter, which introduces new challenges for resource allocation design. Besides, the passivity of the IRS
elements introduces additional highly non-convex constraints, e.g., unit modulus constraints or binary constraints, which makes the resource allocation design in IRS-assisted SWIPT systems more challenging [107]. Moreover, if the nonlinear circuit-based EH model is adopted, the amalgamation of SWIPT and IRS calls for joint waveform, resource allocation, and passive beamforming design, which is still an open problem.

C. UAV-enabled SWIPT

One critical issue of SWIPT systems is the limited WPT efficiency due to the severe wireless propagation loss, especially when the EH Rxs are far from the Tx. Besides, since the EH Rxs close to the Tx can harvest significantly higher amounts of power than remote EH Rxs, fairness issues arise for resource allocation in SWIPT systems. With the recent advancement of UAV manufacturing technologies and the resulting substantial cost reductions, low-altitude UAVs become a potential mobile platform for providing highly efficient and fair SWIPT for massive EH Rxs distributed over a large area, e.g., UAV-enabled IoT systems [108], [109]. In particular, UAV-enabled SWIPT provides an effective approach to combat channel fading as it can establish a LoS link to the EH Rxs with high probability [110]. Moreover, benefiting from its high maneuverability, the UAV’s trajectory can be designed to adapt to the actual signal propagation environment and EH Rx distribution, which provides additional design DoFs for resource allocation in SWIPT systems. Nevertheless, several critical issues have to be taken into account for resource allocation. Firstly, the UAV’s trajectory affects the performances of both WIT and WPT significantly and thus has to be jointly designed with the optimal resource allocation. For instance, when considering the nonlinear saturation EH model, the UAV does not need to fly closer to EH Rxs whose received RF power is already in the saturation regime. Moreover, when serving a large number of EH Rxs over a large area, it is impractical for the UAV to cruise over the devices one-by-one due to its limited flight duration [79]. As a remedy, device grouping can be performed such that the UAV’s trajectory can be designed based on the distribution of the formed EH Rx clusters. Deploying multiple UAVs for SWIPT is also a viable option to address this issue. However, how to efficiently coordinate WIT, WPT, and trajectory design is a new problem to be tackled.

D. Mobile Edge Computing and Federated Learning

The IoE era represents the next wave of the wireless revolution [1], and will connect billions of devices, objects, and machines [81]. This trend is driving a paradigm shift in wireless communications, from “connecting humans” to “connecting things”. To realize this novel paradigm, a technological breakthrough towards a new generation of low-energy mobile devices with improved processing capability is required. To prolong the battery life and to minimize the processing delay, partial computation tasks that are supposed to be processed locally at mobile devices are offloaded to nearby servers located at the edge of the wireless networks [111]. In such MEC systems, SWIPT can work concurrently to further increase the lifetime of the batteries of the mobile devices and relieve the burden of power-limited wireless systems. The integration of MEC and SWIPT in modern wireless systems has received much attention from both industry and academia [112]. In particular, proper resource allocation algorithms are needed to jointly design the offloading decision, beamforming, and covariance matrix of the transmitted energy signals for transmit power minimization, EH energy maximization, rate maximization, or task completion time minimization. The resulting optimization problems are typically non-convex mixed integer nonlinear programs (MINLPs) and efficient solutions have to be developed.

Originating from a similar idea as MEC, federated learning (FL) has been proposed where the computation abilities of the mobile users are typically specialized for training a deep learning model. Without directly offloading the raw data of the clients to the edge server, FL is a promising approach for training a deep learning model while preserving data privacy. In particular, during the training process of FL, the mobile users need to train a learning model locally and transmit the model information to the edge server to build consensus [113]. However, periodically training a deep learning model and transmitting the bulky model is computation- and communication-intensive. Therefore, equipping mobile users with the ability of EH for prolonging the battery usage is a promising approach to enable FL in future intelligent wireless networks [114]. In this regard, an important task in SWIPT-based FL is to optimize the portion of harvested energy allocated to communication with the edge server and local computation, respectively. In addition, the integration of SWIPT and conventional energy-saving techniques in FL, e.g., model compression, adaptive transmission, and hierarchical FL [115], needs further investigation.

E. Machine Learning-based Design

Effective resource allocation design is critical for realizing efficient utilization of the available resources within a complex environment. Conventional design methodologies based on mathematical optimization may not be directly applicable to large-scale SWIPT networks as the complexity of the optimal designs often scales exponentially with the network size. As a remedy, ML is a promising tool as it can be used to optimize large-scale systems without relying on analytical models [115], [116]. Recently, several papers have exploited ML for solving communication-centric resource allocation design problems in conventional wireless networks [117]– [119]. In fact, deep learning networks can be leveraged to characterize the complicated mapping relations between given wireless channel conditions and the corresponding resource allocation for SWIPT systems [120]. The samples/labels for learning are typically generated by conventional optimal iterative algorithms, e.g., monotonic optimization [85], which may be computationally challenging. However, as a large number of samples are typically needed for training an accurate model, how to reduce the sample size while maintaining inference accuracy is a crucial task. Furthermore, ML can be applied to characterize complicated nonlinear EH models
\( L = \left( \frac{\beta_{\text{Obj}}^2}{\beta_{\text{Obj}}} \xi + \alpha_{C1} + \alpha_{C4} E_{\text{req}}^H \right) \text{Tr} \left( \sum_{k=1}^{K} W_k + V \right) - \sum_{k=1}^{K} \text{Tr} (\Lambda_{k,C6} W_k) - \text{Tr} (\Lambda_{v,C6} V) \) (43)

Specifically, while different EH models have been proposed to characterize energy harvesters, there still exists a tradeoff between characterizing energy harvesters, e.g., neural network-based long short-term memory (LSTM) [122], efficient optimization of SWIPT systems will become feasible. Deep reinforcement learning (DRL), which is a combination of reinforcement learning and deep neural networks, is a useful tool for resource allocation design for SWIPT systems which can exploit information and exhibit state transition features, e.g., SWIPT systems with limited energy buffers at the Tx or EH Rxs [123], [124]. In particular, when applying SWIPT to dynamic systems, such as UAV networks, the resource allocation design problem can be modeled as an MDP and DRL can be used for maximizing the long-term system reward. However, in the presence of a large number of EH nodes, DRL requires extensive signaling to feedback the global system state to all EH nodes. In this case, a multi-agent reinforcement learning (MARL) approach can facilitate the learning of the online resource allocation policy in a distributed fashion [125]. These aspects are interesting directions for future research.

VI. CONCLUSIONS

This paper provided a tutorial overview on resource allocation design for SWIPT systems. First, the recent literature on SWIPT systems was reviewed with an emphasis on Rx architectures, EH models, and resource allocation design. Three widely-adopted EH models, namely the linear EH model, the nonlinear saturation EH model, and the nonlinear circuit-based EH model, were characterized and their significant impact on resource allocation design was highlighted. For a typical SWIPT downlink system, we established a generalized resource allocation design framework which subsumes existing designs as special cases. Then, focusing on the WIT efficiency maximization problem for both the linear EH model and the nonlinear saturation EH model, we developed an efficient suboptimal solution employing quadratic transformation, which can handle the severe variable coupling typical for SWIPT and can be readily used for developing a concrete resource allocation algorithm. Besides, the joint design of the input distribution and the resource allocation for the nonlinear circuit-based EH model was discussed. To reduce the severe performance degradation suffered by SWIPT systems in the case of channel uncertainty, three robust resource allocation design methodologies were considered. Simulation results for exemplary SWIPT systems demonstrated the effectiveness of the proposed solution methodologies and provided several insights for SWIPT system design: 1) resource allocation design for SWIPT systems based on the linear EH model leads to inevitable system outages in practice due to the EH model mismatch; 2) a resource allocation maximizing the system sum-rate can achieve the same performance as maximizing the WIT efficiency when the required system WPT efficiency is sufficiently high; 3) robust resource allocation design in the presence of CSIT errors requires significantly higher transmit powers than the case with perfect CSIT, in particular for worst-case robust designs. Last but not the least, future research directions for resource allocation in SWIPT systems were highlighted, including joint waveform and resource allocation design, IRS-assisted SWIPT systems, UAV-enabled SWIPT systems, applications in emerging MEC systems, and the role of ML.

APPENDIX - PROOF OF THEOREM 1

For given \((\beta_{\text{Obj}}, \beta_{k,C7}, \beta_{k,C8})\), the SDP relaxed problem in [22] is convex w.r.t. the remaining optimization variables and satisfies Slater’s constraint qualification [95]. Therefore, strong duality holds and solving the dual problem is equivalent to solving the primal problem [95]. In the following, we prove Theorem 1 by exploiting the Karush-Kuhn-Tucker (KKT) conditions of [22]. To start with, the Lagrangian function of the primal problem in [22] is given by (43), shown at the top of this page, where \(\alpha_{C1}, \alpha_{C4}, \alpha_{k,C7}, \alpha_{k,C8} \geq 0\) are the Lagrange multipliers associated with constraints C1, C4, C7, and C8, respectively, \(\Lambda_{k,C6}, \Lambda_{v,C6} \in \mathbb{C}^{N_i \times N_i}\) are the Lagrange multiplier matrices for the positive semidefinite constraint C6 for matrices \(W_k\) and \(V\), respectively, and \(\vartheta\) denotes the collection of terms that are independent of \((W_k, V)\). The dual problem of [22] is given by

\[
\text{maximize} \quad \alpha_{C1}, \alpha_{C4}, \alpha_{k,C7}, \alpha_{k,C8} \geq 0, \quad \Lambda_{k,C6}, \Lambda_{v,C6} \geq 0 \quad \text{subject to} \quad 0 \leq p_k \leq P_{k,\text{out}}, \quad \text{inf}_{W_k, V \in \mathbb{H}^{N_i \times N_i}} L, \quad (44)
\]

The KKT conditions for the optimal \((W_k^*, V^*)\) are obtained as follows:

\[
\begin{align*}
K1 : & \quad \alpha_{C1}^* \geq 0, \alpha_{C4}^* \geq 0, \alpha_{k,C7}^* \geq 0, \alpha_{k,C8}^* > 0, \\
K2 : & \quad \Lambda_{k,C6}^*, \Lambda_{v,C6}^* \geq 0, \\
K3 : & \quad \text{Tr} (\Lambda_{k,C6}^* W_k^*) = 0, \text{Tr} (\Lambda_{v,C6}^* V^*) = 0, \\
K4 : & \quad \nabla_{W_k} L = 0, \text{ and} \\
K5 : & \quad \nabla_{V} L = 0, \quad (45)
\end{align*}
\]

where \(\nabla_{W_k} L\) and \(\nabla_{V} L\) denote the gradients of the Lagrangian function \(L\) w.r.t. matrices \(W_k^*\) and \(V^*\), respectively.
By examining K4 and K5 in (45), we have

\[
\nabla W_k^L = \Lambda^*_{v,C6} - \Lambda^*_{k,C6} - \alpha^*_{k,C7} \beta_k C7 H_k \frac{1}{\sqrt{\text{Tr}(W_k^T H_k)}} \quad \text{and} \\
\Lambda^*_{v,C6} = \left( \beta^2_{0,d} e^{\frac{-1}{2}c_{1v}^2 + \alpha C4 E_{\text{Rec}}^SEF_k} I_N + \sum_{k'=1}^{K} \alpha_{k',C7} \beta_{k',C7} H_{k'} \right) \Lambda^*_{k,C6} \frac{K-1}{\sqrt{\text{Tr}(K) \sum_{k'=1}^{K} W_{k'}^T H_{k'}} + \eta H_k} \frac{\eta H_k}{\sqrt{\text{Tr}(K) \sum_{k'=1}^{K} W_{k'}^T H_{k'}} + \eta H_k},
\]

(46)

respectively. Moreover, based on [24, Proposition 3.1], \( \Lambda^*_{v,C6} \) is a full-rank matrix with probability one, i.e., \( \text{Rank}(\Lambda^*_{v,C6}) = N_v \), when the channels, \( h_k, \forall k \), are mutually statistically independent. Therefore, from the complementary slackness condition in K3, we obtain \( v^* = 0 \).

Furthermore, by exploiting K4 and (46) and a basic inequality for the ranks of matrices, we have

\[
\text{Rank}(\Lambda^*_{v,C6}) \leq \text{Rank}(\Lambda^*_{k,C6}) + \text{Rank} \left( \left( \alpha_{k,C7} \beta_{k,C7} \frac{1}{\sqrt{\text{Tr}(W_k^T H_k)}} \right) H_k \right) \Rightarrow \text{Rank}(\Lambda^*_{k,C6}) \geq N_k - 1.
\]

Moreover, \( W_k^L \neq 0 \) is required to satisfy QoS constraint C2 for each user. Thus, considering K3, \( \Lambda^*_{v,C6} \) cannot be full-rank. Hence, \( \text{Rank}(\Lambda^*_{k,C6}) = N_k - 1 \) and \( \text{Rank}(W_k^L) = 1 \), which completes the proof.  

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5Note that the above proof does not imply the uniqueness of the optimal solution of the relaxed problem in (42). There may be multiple optimal solutions that all satisfy the KKT conditions in (45) and achieve the same objective value. Nevertheless, as shown above, all optimal solutions are rank-one with probability one.
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