Weighted Sum-SINR and Fairness Optimization for SWIPT-Multigroup Multicasting Systems with Heterogeneous Users

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The development of next generation wireless communication systems focuses on the expansion of existing technologies, while ensuring an accord between various devices within a system. In this paper, we target the aspect of precoder design for simultaneous wireless information and power transmission (SWIPT) in a multi-group (MG) multicasting (MC) framework capable of handling heterogeneous types of users, viz., information decoding (ID) specific, energy harvesting (EH) explicit, and/or both ID and EH operations concurrently. Precoding is a technique well-known for handling the inter-user interference in multi-user systems, however, the joint design with SWIPT is not yet fully exploited. Herein, we investigate the potential benefits of having a dedicated precoder for the set of users with EH demands, in addition to the MC precoding. We study the system performance of the aforementioned system from the perspectives of weighted sum of signal-to-interference-plus-noise-ratio (SINR) and fairness. In this regard, we formulate the precoder design problems for (i) maximizing the weighted sum of SINRs at the intended users and (ii) maximizing the minimum of SINRs at the intended users; both subject to the constraints on minimum (non-linear) harvested energy, an upper limit on the total transmit power and a minimum SINR required to close the link. We solve the above-mentioned problems using distinct iterative algorithms with the help of semi-definite relaxation (SDR) and slack-variable replacement (SVR) techniques, following suitable transformations pertaining the problem convexification. The main novelty of the proposed approach lies in the ability to jointly design the MC and EH precoders for serving the heterogeneously classified ID and EH users present in distinct groups, respectively. We illustrate the comparison between the proposed weighted sum-SINR and fairness models via simulation results, carried out under various parameter values and operating conditions.

***Index Terms*—Multi-group (MG) multicast (MC) precoding, simultaneous wireless information and power transfer (SWIPT), system fairness, weighted sum-SINR optimization.**

I. INTRODUCTION

A. Motivation

THE evolving techniques in short distance wireless communications aim to address several existing problems while taking into consideration the increasing performance and capacity needs, complex hardware circuitry, and demands for even more efficient services. The continuous drainage of batteries due to heavy operations also poses an additional difficulty, both in terms of power consumption as well as management of radio resources. In order to address these issues, power optimization and introduction of energy harvesting (EH) capabilities in devices seem promising [1], [2]. It is also essential to ensure the co-existence of heterogeneous devices within the same wireless networks, where they can garner maximum benefits. Additionally, an efficient allocation of network resources is desired for ultra-low power devices, such as wireless sensor network (WSN) nodes, Internet-of-Things (IoT) devices, etc., [3]–[5].

The research leading to these results has received funding from the Luxembourg National Research Fund (FNR), Luxembourg, under the FNR-FNRS bilateral - InWIP-NET: Integrated Wireless Information and Power Networks (R-AGR-0700-10-V).

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B. Related Works

The benefits of adopting Multiple-Input Single-Output (MISO) frameworks for ID specific users were shown in [6]. In [7], *Varshney* discussed about the possibility of using radio-frequency (RF) based simultaneous wireless information and energy transmission (SWIPT), which was later investigated in [1], [8] with multi-user MISO scenario. Several receiver architectures for SWIPT have been proposed in the literature based on time-switching (TS), power-spliting (PS), or separated architecture (SA) [9]. Due to the complex circuitries and additional optimization parameter(s), realization of TS and PS based receiver architectures is difficult from practical viewpoint [10]. Thus, the adoption of SA-based SWIPT receivers with simple working criteria seems promising, wherein the corresponding ID and EH operations can be handled separately within the same receiver device. As a developmental process, it is additionally important to focus on system designs that can handle distinct user types like information decoding (ID) specific, explicit to EH, and the ones performing joint ID and EH operations.

Another promising technology to meet the challenges described is transmit precoding for multi-user MISO systems, which aims at the enhancement of channel capacity and diversity [11], [12]. In order to substantially improve the system performance, Multi-group (MG) Multicasting (MC) has emerged as another potentially viable technique, whose benefits were demonstrated in [13], [14]. The practical limitations of MG-MC scenarios were discussed in [11], where the precoding problem was found to be NP-hard, even for a single group multicast. It is noteworthy that the MG-MC

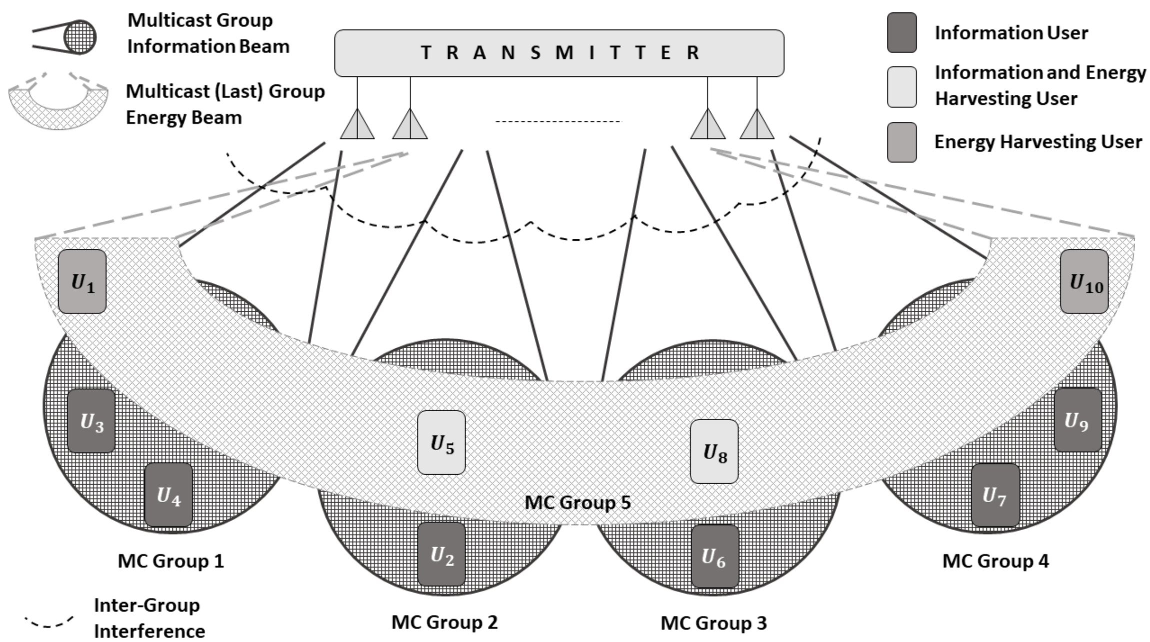


Fig. 1: System model comprising a dedicated precoder to serve the set of users with EH demands, in addition to the MC precoding.

framework has gathered tremendous interest recently, and is found to be more suitable for upcoming technique of rate-splitting [15]. Recent works focusing on SWIPT in MG-MC scenarios assume a linear EH operation at the corresponding module [16]–[18]. Noticeably, the above-mentioned works neither consider the co-existence of heterogeneous user types within the MG-MC framework, nor do they investigate the non-linearity at the EH module. The authors in [19], [20] established the superior performance of the separate precoder design for serving the heterogeneous users over the joint and per-user precoder designs. The corresponding investigation was carried out keeping the respective sum-transmit power and sum-harvested energy optimizations in focus. In contrast to the related works in the literature [19], [20], we present in this paper a framework for joint ID and EH precoder designs from the perspectives of weighted sum of signal-to-interference-plus-noise-ratio (SINR) and fairness optimization. In the following section, we present a discussion to motivate the aspects considered for investigation in this work.

C. More discussion on the key aspects in focus

The MG-MC framework is found to be a useful methodology for tackling the distinct information needs at various users. The ID users demanding same information may be categorized under a certain group, while there may be various other possibilities of group formations in-line with such a scheme of user categorization. In this context, the overall system is well-organized to efficiently carry out further investigation with techniques like beamforming / precoder designing and user scheduling [20]–[22]. The precoder design problem in MG-MC with consideration of heterogeneous users having ID, EH and/or both, have not been investigated widely in the literature and is hence considered for analysis in this work.

In order to carry out the analysis of the considered MG-MC framework, certain metrics based on transmit power, harvested energy, or information rate/SINR may be optimized under certain sets of constraints. The SINR-based optimization methods have been used to investigate the performance of multiple-input multiple-output (MIMO) and multiple access systems [23], [24]. This approach based on the SINR-optimization provides an alternative perspective to the widely adopted rate-based method for investigation. In this vein, it is noteworthy that in the case of weighted sum-SINR, the weighing terms which introduces dimensional stability during performance evaluation. However in such cases, instances with unfair resource allocation is very common due to the targeted sum metric. For example, a user present near the transmit source may be allocated better resources in comparison to a user placed far away from the transmit source such that the feasibility criteria at the latter is barely met. This inequitable allocation of resources needs to be addressed, and hence a fairness optimization is necessary in this context [25]. However, this comes at a cost of compromised overall performance, but each user gets a fair share of the resources. More details will be discussed in the later sections. In the following, we describe the main contributions and novelty of this work.

D. Contributions

In this paper, we adopt a system model comprising a dedicated precoder serving a set of users with EH demands, in addition to the MC precoding, whose efficiency was established in [19], [20]. Specifically, we analyze a SWIPT-enabled MISO MG-MC precoding system with the consideration of the co-existential aspect of heterogeneous user types, wherein a transmit source is assumed to be equipped with an array of antennas which serves multiple users via beamforming through adequate precoders. In this context, we formulate the optimization problems to (i) maximize the weighted sum of SINR at the intended users, and (ii) maximize the minimum of SINR at the intended users, both subjected to certain quality-of-service (QoS) constraints. The non-linear EH constraint and the non-convex objective of the aforementioned problem lead to mathematical intractability. We perform adequate transformation of the non-linear EH constraint to a linear one, and convexify the problems with the help of semi-definite relaxation (SDR) and slack variable replacement (SVR) techniques. Particularly, the main contributions and novelty of this work are listed below.

1) We consider an MG-MC precoding framework to study the possibility of co-existence between heterogeneous users capable of ID, EH, and joint ID and EH operations, while investigating the system performance from two perspectives, i.e., the weighted sum-SINR and fairness, respectively. In this context, it is important to mention that most existing works do not consider co-existence of multiple user types for analysis, while additionally taking into consideration the perspectives of weighted sum-SINR and fairness optimizations.
2) We formulate two problems for optimal precoder designs, viz., (i) maximization of weighted sum-SINR and (ii) a fairness problem targeting the maximization of minimum SINR; both subjected to some QoS constraints. In comparison to other works, this paper provides more practically oriented problem formulations as mentioned above, with the consideration of a non-linear EH constraint.
3) In order to solve the aforementioned precoder design problems, we propose suitable solutions in the form of iterative algorithms based on alternating variable optimization using the SDR and SVR methods. On the other hand, simpler problems with linear EH constraint are considered in most of the existing works that analyze the MG-MC framework.
4) Considering the existing works in the literature, it is noteworthy that an investigative comparison between the proposed schemes (i.e., the weighted sum-SINR and fairness) with heterogeneous users (including EH users having non-linear EH modules) has not been presented so far. We show the effectiveness of the proposed methods under the consideration of separate information and/or energy precoder design, both in terms of maximization of weighted sum-SINR and maximization of minimum SINR at the intended users. Specifically, we consider the performance metrics of minimum spectral efficiency, sum-SINR, and Jain's fairness index for our evaluation.

Further sections of this paper are organized as follows. Section II provides an introduction to the system model. The maximization of weighted sum-SINR scheme is presented in Section III, while the max-min SINR scheme is discussed in Section IV. Numerical results are shown in Section V, followed by concluding remarks in Section VI.

Notation: In the remainder of this paper, bold face lower case and upper case characters denote column vectors and matrices, respectively. The operators $(\cdot)^H$ and $|\cdot|$ correspond to the conjugate transpose and the absolute value, respectively.

II. System Model

We consider an M antennas equipped transmitter designated to serve L users $(\mathcal{U}_1,\ldots,\mathcal{U}_L)$. The users are assumed to be of heterogeneous types, viz., information decoding (ID) only, energy harvesting (EH) only, and users capable of performing both ID and EH concurrently. The receiver devices with exclusive operations of ID or EH are assumed to have a single antenna for reception (due to low-cost) while the devices performing joint ID and EH are assumed to be equipped with two separate RF chains to carry out the respective desired operations. This kind of receive scheme is often termed as SA for enabling joint information processing and energy harvesting at the receiver [9], as explained previously.

Herein, we adopt a SWIPT-enabled MG-MC system for our analysis where the joint designs of MC precoders and a specific energy-providing precoder are intended. The benefits of the considered system were established over the joint and per-user precoder designs recently [19], [20]. In the considered system, the ID specific users are categorized within G MC groups while the EH users are classified under an additional (last) group. Therefore, we aim at designing at least $(G+1)$ precoders. The basic layout of the considered system model is depicted in Fig. 1.

Let $\mathcal{G}_\ell$ denote the ℓ^{th} multicast group of users. We assume the MC groups and the additional (last) EH group to be known in this work. The ID users within the MC groups listen only to the common signals intended for their corresponding groups. It implies that $\mathcal{G}_\ell \cap \mathcal{G}_k = \varnothing, \forall \ell, k = \{1,\ldots,G+1\}$ and $\ell \neq k$. However, the EH users harvest energy using all the possible (available) multicast signals[1].

The transmitter emits the signal $\mathbf{x}(t) = \sum_{\ell=1}^{G+1} \mathbf{w}_\ell s_\ell(t)$ via an antenna array, where $\mathbf{w}_\ell$ corresponds to the $M \times 1$ complex precoding weight vector for the users in group $\mathcal{G}_\ell$, and $s_\ell(t)$ represents the ID- and/or EH-specific signal. We assume mutually uncorrelated ID and EH signals for each group $\{s_\ell(t)\}_{\ell=1}^{G+1}$ with zero mean and unit variance, $\sigma_{s_\ell}^2 = 1$. The corresponding ID and/or EH signals may be separately designed according to the framework proposed in [26]. Distinct ID and EH signal forms motivate the use of SA-based devices. The total transmitted power can thus be given by: $\sum_{\ell=1}^{G+1} \mathbf{w}_\ell^H \mathbf{w}_\ell$.

The i^{th} user receives the signal: $y_i(t) = \mathbf{h}_i^H \mathbf{x}(t) + n_{R,i}(t)$, where $\mathbf{h}_i$ is the $M \times 1$ conjugated channel vector for the corresponding receiver and $n_{R,i}(t)$ is the additive zero mean Gaussian noise at the corresponding i^{th} user's receiving antenna equipment with a noise variance of $\sigma_{R,i}^2$. The source signals are uncorrelated with $n_{R,i}(t)$.[2] The input signal to the ID module of the i^{th} receiver equipment is expressed as

$$y_{D,i}(t) = \left(\mathbf{h}_i^H \mathbf{x}(t) + n_{R,i}(t)\right) + n_{D,i}(t), \tag{1}$$

[1]The other MCs are primarily taken into consideration due to interference causing side-lobes other than the desired MC, which is beneficial for EH.

[2]In practice, the antenna noise $n_{R,i}(t) \in \mathcal{CN}(0, \sigma_{R,i}^2)$ has a negligible impact on the signals intended for both the ID and EH modules [27].

where $n_{D,i}(t)$ is the additional zero-mean Gaussian noise with a variance of $\sigma^2_{D,i}$ incurred due to the circuitry and other relevant operations at the ID block of the i^{th} receiver.[3] For i^{th} receiver as a part of ℓ^{th} MC group $\mathcal{G}_\ell$, the SINR is given by the following expression

$$\Upsilon_i = \frac{|\mathbf{w}_\ell^H \mathbf{h}_i|^2}{\sum_{\substack{k=1\\k\neq\ell}}^{G+1} |\mathbf{w}_k^H \mathbf{h}_i|^2 + \sigma^2_{R,i} + \sigma^2_{D,i}}, \forall \ell = \{1,\ldots,G\}. \quad (2)$$

The signal dedicated for EH block of the i^{th} receiver is

$$y_{E,i}(t) = \mathbf{h}_i^H \mathbf{x}(t) + n_{R,i}(t). \quad (3)$$

Therefore, the linear EH operation at the EH unit of i^{th} receiver is given as: $\mathcal{E}_i^{\mathcal{L}} = \zeta_i\big(\sum_{\ell=1}^{G+1} |\mathbf{w}_\ell^H \mathbf{h}_i|^2 + \sigma^2_{R,i}\big)$, where $0 < \zeta_i \leq 1$ is the energy conversion efficiency of the corresponding receiver. Noticeably, $\mathcal{E}_i^{\mathcal{L}}$ is theoretically valid for numerical evaluations, however its practical relevance is questionable. This calls for the adoption of a sigmoidal function based non-linear EH model [29], [30], defined as

$$\mathcal{E}_i^{\mathcal{N}} = \frac{\mathcal{E}'}{1-\phi} \cdot \left(\frac{1}{1+e^{\left(-\alpha(\sum_{\ell=1}^{G+1} |\mathbf{w}_\ell^H \mathbf{h}_i|^2) + \alpha\beta\right)}} - \phi \right), \quad (4)$$

where $\phi \triangleq \frac{1}{1+\exp(\alpha\beta)}$, the constant $\mathcal{E}'$ is obtained by determining the maximum harvested energy on the saturation of the energy harvesting circuit, and α and β are specific to the capacitor and diode turn-on voltage metrics at the EH circuit. Note that the similar sigmoidal function based non-linear EH model was also adopted for investigation in [31]–[33]. Further, we assume normalized time slots to use the terms *power* and *energy* interchangeably.

To proceed, we intend to investigate the performance of the considered framework using a weighted sum-SINR (WSS) scheme and a Max-Min SINR (MMS) based fairness model. In this context, we first develop the formulation for maximizing the weighted sum-SINR of the intended users under minimum harvested energy and total transmit power limitation. To use the corresponding solution as a benchmark for comparison, we then formulate a fairness scheme to maximize the minimum of SINR at the intended users under the same set of QoS constraints as in the previous problem. It is noteworthy that the proposed fairness scheme may come in handy for the ultra-low power devices such as WSN nodes or IoT devices. In this regard, it is important to ensure an impartial allocation of the network resources. To measure the degree of fairness among the two schemes (i.e., WSS and MMS), we make use of the Jain's fairness index [34].

In order to measure the fairness of the two proposed schemes viz., WSS and MMS, we make use of the Jain's fairness index [34], defined as

$$\mathcal{J}(\Upsilon_1, \Upsilon_2, \ldots, \Upsilon_{\hat{n}}) = \frac{\left(\sum_{i=1}^{\hat{n}} \Upsilon_i\right)^2}{\hat{n} \cdot \sum_{i=1}^{\hat{n}} \Upsilon_i^2}, \quad (5)$$

[3]In case of ID, $\sigma^2_{R,i}$ is generally much smaller than the noise power introduced by the baseband processing circuit, i.e., $\sigma^2_{D,i}$, and thus even lower than the average power of the received signal [27], [28]. As a consequence, the antenna noise $n_{R,i}(t)$ may be neglected.

where Υ_i denotes the SINR at the i^{th} ID user and $\hat{n}$ is the total number of ID users. In simple terms, the Jain's fairness index in (5) rates the fairness of a set of values where there are $\hat{n}$ ID users, and Υ_i is the SINR for the i^{th} connection. It is noteworthy that the output ranges from $\frac{1}{\hat{n}}$ (worst case) to 1 (best case), and the value is maximum when all users receive the same (or equal) allocation. This index is $\frac{\hat{k}}{\hat{n}}$ when $\hat{k}$ users share the resources equally while the remaining $\hat{n}-\hat{k}$ users receive zero distribution. The succeeding sections provide more insights on the above-mentioned problems and their solutions.

III. Weighted Sum-SINR (WSS) Maximization

In this section, we formulate the optimization problem to maximize the weighted sum of SINR by the intended users, subjected to constraints on minimum (non-linear) EH demands, a maximum limitation on the total transmit power and a minimum SINR threshold. The overall optimization problem to ensure the co-existence of three user types with the MG-MC precoding scheme can subsequently be written in its mathematical form as follows

$$(P1): \max_{\{\mathbf{w}_k\}_{k=1}^{G+1}} \sum_{i=1}^{\hat{n}} \omega_i \Upsilon_i \quad (6)$$

$$\text{s.t.} \ (C1): \mathcal{E}_j^{\mathcal{N}} \geq \xi_j, \ \ \forall j \in \mathcal{G}_{G+1}, \quad (7)$$

$$(C2): \Upsilon_i \geq \gamma_i, \ \ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \quad (8)$$

$$(C3): \sum_{\ell=1}^{G+1} \mathbf{w}_\ell^H \mathbf{w}_\ell \leq \mathrm{P}_{\text{Max}}, \quad (9)$$

where $\Upsilon_i = \frac{\mathbf{w}_\ell^H \mathbf{H}_i \mathbf{w}_\ell}{\sum_{\substack{k=1\\k\neq\ell}}^{G+1} \mathbf{w}_k^H \mathbf{H}_i \mathbf{w}_k + \sigma^2_{R,i} + \sigma^2_{D,i}}$, ω_i is the corresponding weight, $\forall i \in \mathcal{G}_\ell$, $\forall \ell \in \{1,\ldots,G\}$, ξ_j is the demanded harvested energy at j^{th} user (where i can be equal to j for some cases, in general), γ_i is the SINR threshold at the i^{th} user, P_{Max} is the maximum transmit power limit, and $\mathbf{H}_i = \mathbf{h}_i \mathbf{h}_i^H$.

It is clear that the formulated problem $(P1)$ is not convex because of the SINR and non-linear EH expressions, and is hence intractable. We define $\mathbf{W}_\ell = \mathbf{w}_\ell \mathbf{w}_\ell^H$ and with the help of this notation, $(P1)$ can be represented using semi-definite relaxation (SDR) and slack-variable replacement (SVR) as follows

$$(P2): \max_{\substack{\{\tau_i\}_{i=1}^{\hat{n}}\\ \{\mathbf{W}_\ell\}_{\ell=1}^{G+1}}} \sum_{i=1}^{\hat{n}} \omega_i \tau_i \quad (10)$$

$$\text{s.t.} \ (C1): \sum_{\ell=1}^{G+1} \mathrm{Tr}\{\mathbf{H}_j \mathbf{W}_\ell\} \geq \frac{\xi'_j}{\zeta_j} - \sigma^2_{R,j}, \ \forall j \in \mathcal{G}_{G+1}, \quad (11)$$

$$(C2): \mathrm{Tr}\{\mathbf{H}_i \mathbf{W}_\ell\} - \upsilon \sum_{k\neq\ell} \mathrm{Tr}\{\mathbf{H}_i \mathbf{W}_k\} \geq \tau_i(\sigma^2_{R,i} + \sigma^2_{D,i}), \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \quad (12)$$

$$(C3): \tau_i \geq \gamma_i, \ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \quad (13)$$

$$(C4): \sum_{\ell=1}^{G+1} \mathrm{Tr}\{\mathbf{W}_\ell\} \leq \mathrm{P}_{\text{Max}}, \quad (14)$$

$$(C5): \mathbf{W}_\ell \succcurlyeq 0, \quad (15)$$

where τ_i is the introduced slack-variable corresponding to the i^{th} receiver as a part of ℓ^{th} MC group $\mathcal{G}_\ell$ (to be optimized), and other parameters have same definitions as before.[4] Note that $(C1)$ is a linear constraint introduced to simplify the problem. Proof for the corresponding transformation is provided in Appendix A of [19], [20]. It is clear from $(P2)$ that joint optimization of $\tau_i,\ \forall i \in \mathcal{G}_\ell,\ \forall \ell \in \{1,\dots,G\}$ and $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$ is cumbersome and hence a direct solution cannot be obtained via existing convex optimization solvers (e.g., CVX [35], [36]). However, an iterative approach with alternating parameter optimization may provide an appreciable (sub-optimal) solution, where the execution is anticipated to be within polynomial time. In this regard, we propose the weighted sum-SINR (WSS) algorithm with alternating optimizations of $\tau_i,\ \forall i \in \mathcal{G}_\ell,\ \forall \ell \in \{1,\dots,G\}$ and $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$. In Algorithm 1, we choose the initial point of the each slack variable τ_i same as the minimum SINR demand, γ_i, to ensure the problem feasibility. Concerning the convergence of the algorithm, we observe that $(P2)$ is convex[5] for individual sub-problems with fixed $\tau_i,\ \forall i \in \mathcal{G}_\ell,\ \forall \ell \in \{1,\dots,G\}$ to optimize $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$, and then with fixed (pre-determined) $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$ to optimize $\tau_i,\ \forall i \in \mathcal{G}_\ell,\ \forall \ell \in \{1,\dots,G\}$, respectively, on an alternating basis. For the given transmit power limitation, the objective function increases with each progressing iteration, and is guaranteed to converge to an optimal value after several runs. Hence, the proof of convergence is straightforward.

Suppose that the CVX solver incurs the computational complexities of $\kappa_1(G+1,M)$ orders for carrying out the operations 3: to 10:, and $\kappa_2(M)$ orders to process 11: to 19:, respectively, corresponding to Algorithm 1. Consequently, the overall computation complexity for the proposed algorithm is given by $\mathcal{O}\Big(\big(L^5 \cdot G^3 \cdot (G+1)^4\big)^{\big(\kappa_1(G+1,M)+\kappa_2(M)\big)}\Big)$.

Concerning the solution of the relaxed problem in $(P2)$, it cannot be denied that multi-rank possibilities remain probable due to SDR. Therefore, the Gaussian randomization technique [11] is employed to curtail the (possible) multi-ranked $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$ into a unit rank, which in-turn induces additional computational complexities. In order to compensate for the incurred losses, we first define the vector indicating the direction of ℓ^{th} precoder as $\widetilde{\mathbf{w}}_\ell = \frac{\mathbf{w}_\ell}{||\mathbf{w}_\ell||_2}$ and in order to avoid any instance of multi-rank solutions, we reformulate $(P2)$ to obtain the problem $(P3)$, as follows

[4]We use the short notation: $\forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}$, to equivalently represent: $\forall i \in \mathcal{G}_\ell,\ \forall \ell \in \{1,\dots,G\}$.

[5]The objective function in $(P2)$ is affine, since the sum of affine metrics is affine. In addition, an affine function can be considered both convex as well as concave. Thus, the maximization of an affine function under convex set of constraints is a convex problem.

Algorithm 1 Weighted Sum-SINR (WSS) Maximization Scheme

1: **Initialize**: $\tau_i = \gamma_i$, ξ_i, P_{Max}, $\bar{n}$ = 1, and ϵ : threshold limit;
2: **REPEAT**
3: Given $\tau_i,\ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}$, solve (10)-(15) to get $\{\mathbf{W}_\ell(\bar{n})\}_{\ell=1}^{G+1}$;
4: **IF** $(\tau_i(\bar{n}) - \tau_i(\bar{n}-1) \le \epsilon)$ & $(\bar{n} > 2)$
5: Convergence_1 = **TRUE**;
6: **RETURN:** $\{\mathbf{W}_\ell^\star\}_{\ell=1}^{G+1} = \{\mathbf{W}_\ell(\bar{n}-1)\}_{\ell=1}^{G+1}$,
7: $\tau_i^\star = \tau_i(\bar{n}-1),\ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}$;
8: **ELSE**
9: Convergence_1 = **FALSE**;
10: **END IF**
11: Given $\{\mathbf{W}_\ell(\bar{n})\}_{k=1}^{G+1}$, solve (10)-(15) to get $\tau_i(\bar{n})$;
12: **IF** $(\tau_i(\bar{n}) - \tau_i(\bar{n}-1) \le \epsilon)$ & $(\bar{n} > 2)$
13: Convergence_2 = **TRUE**;
14: **RETURN:** $\tau_i^\star = \tau_i(\bar{n}-1),\ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}$,
15: $\{\mathbf{W}_\ell^\star\}_{\ell=1}^{G+1}$ = $\{\mathbf{W}_\ell(\bar{n}-1)\}_{\ell=1}^{G+1}$;
16: **ELSE**
17: $\tau_i(\bar{n}+1) = \tau_i(\bar{n}),\ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}$, and $\bar{n}$ = $\bar{n}$ + 1;
18: Convergence_2 = **FALSE**;
19: **END IF**
20: **UNTIL** Convergence_1 = **TRUE** & Convergence_2 = **TRUE**.

$$(P3):\ \max_{\substack{\{\tau_i\}\\ \{\mathrm{p}_\ell\}_{\ell=1}^{G+1}}}\ \sum_{i=1}^{\hat{n}} \omega_i \tau_i \tag{16}$$

$$\text{s.t.}\ \ (C1): \zeta_j\Big(\sum_{\ell=1}^{G+1} |\widetilde{\mathbf{w}}_\ell^H \mathbf{h}_j|^2 \mathrm{p}_\ell + \sigma_{R,j}^2\Big) \ge \xi_j',\ \ \forall j \in \mathcal{G}_{G+1}, \tag{17}$$

$$(C2): \frac{|\widetilde{\mathbf{w}}_\ell^H \mathbf{h}_i|^2 \mathrm{p}_\ell}{\sum_{k\neq\ell} |\widetilde{\mathbf{w}}_k^H \mathbf{h}_i|^2 \mathrm{p}_k + \sigma_{R,i}^2 + \sigma_{D,i}^2} \ge \tau_i, \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \tag{18}$$

$$(C3): \tau_i \ge \gamma_i,\ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \tag{19}$$

$$(C4): \sum_{\ell=1}^{G+1} \mathrm{p}_\ell \le \mathrm{P}_{\text{Max}}, \tag{20}$$

where p_ℓ is the power term associated to the ℓ^{th} precoder with $\widetilde{\mathbf{w}}_\ell$ as its direction, and other terms have the same meaning as defined previously. In other words, the scalar p_ℓ is optimized in the direction of $\widetilde{\mathbf{w}}_\ell$. Thereafter, the solution to $(P3)$ can be obtained via CVX solver, using the similar alternating parameter optimization approach as in Algorithm 1. In this context, the overall computation complexity for the updated algorithm is given by $\mathcal{O}\Big(\big(L \cdot (G+1)\big)^{\big(\kappa_1(G+1,M)+\kappa_2(M)\big)}\Big)$.

The proposed algorithm is developed to tackle the novel problem formulation of WSS from the MG-MC perspective. In this context, the main problem is further reduced with the help of SDR and SVR methods to simplify the implementation process based on the compatibility with existing convex optimization solvers (e.g., CVX). The algorithm is based on an iterative method, where the initialization point is important for convergence. The best way is to start with the lowest possible feasible points of 'τ_i' and the algorithm keeps working until a convergence is reached. However, the convergence rate can be improved by choosing an adequate starting points based on the selection of parameters. One possibility in this context may be via machine learning techniques wherein several experiments may be carried out to train a prediction model based on different parameter selections. When the prediction model is in use, the predicted values may be used to fasten the convergence procedure. This possibility is currently out of the scope of this paper and may be considered for future works.

It is clear that the WSS scheme is developed as an effective method to tackle the assertive network demands. However, there are some possibilities of unbalanced resource allocations due to the weighted sum-SINR as the objective. In simple terms, this implies that some users may obtain high SINRs while certain other users may get very low yield of SINR (for carrying out the corresponding ID operation), enough to satisfy the corresponding weighted sum-objective based optimization problem. Therefore, we seek an alternative approach to ensure a fair distribution of network resources which may, however, enforce a compromise on the overall system performance. Consequently, a fair resource allocation would make sure that all the concerned nodes receive equal share of network assets without any discrimination criteria like e.g., distance, power, etc. More specifically, we are interested in the users which may either be placed distant from the transmit source or receive very small amount of power just enough to satisfy the minimum demanded constraints of the concerned nodes. In this case, the devices closer to the transmitter may leverage better services due to some practical reasons, e.g., their placements. This phenomenon may in-turn adversely affect the performance at the other concerned nodes within the system, that are placed far apart from the transmit source. In order to address this concern, we present in the following section a fairness scheme to maximize the minimum of SINR at the intended ID users.

IV. Proposed Max-Min SINR (MMS) SWIPT Scheme

Herein, we formulate the optimization problem to maximize the minimum of the SINR values subjected to constraints on minimum (non-linear) EH demands, a maximum limitation on the total transmit power and a minimum SINR threshold. The overall optimization problem can subsequently be written in its mathematical form as follows

$$(P4): \max_{\{\mathbf{w}_k\}_{k=1}^{G+1}} \min \ \Upsilon_i, \ \ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G} \tag{21}$$

$$\text{s.t.} \ \ (C1): \mathcal{E}_j^{\mathcal{N}} \geq \xi_j, \ \ \forall j \in \mathcal{G}_{G+1}, \tag{22}$$

$$(C2): \Upsilon_i \geq \gamma_i, \ \ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \tag{23}$$

$$(C3): \sum_{\ell=1}^{G+1} \mathbf{w}_\ell^H \mathbf{w}_\ell \leq \mathrm{P}_{\text{Max}}, \tag{24}$$

where the involved parameters have same definitions as defined previously. It is clear that the formulated problem $(P4)$ is non-convex because of the SINR and non-linear EH expressions, and is hence intractable. Making use of the previously defined variables $\mathbf{W}_\ell = \mathbf{w}_\ell \mathbf{w}_\ell^H$, $(P4)$ can be represented using semi-definite relaxation (SDR) and slack-variable replacement (SVR) as follows

Algorithm 2 Max-Min SINR (MMS) Scheme

1: **Initialize**: $\upsilon = \gamma_i$, ξ_i, P_{Max}, $\bar{n}$ = 1, and ϵ as the threshold limit;
2: **REPEAT**
3: Given υ, solve (25)-(30) to obtain $\{\mathbf{W}_\ell(\bar{n})\}_{\ell=1}^{G+1}$;
4: **IF** $(\upsilon(\bar{n}) - \upsilon(\bar{n}-1) \leq \epsilon)$ & $(\bar{n} > 2)$
5: Convergence_1 = **TRUE**;
6: **RETURN** $\{\mathbf{W}_\ell^\star\}_{\ell=1}^{G+1} = \{\mathbf{W}_\ell(\bar{n}-1)\}_{\ell=1}^{G+1}$, $\upsilon^\star = \upsilon(\bar{n}-1)$;
7: **ELSE**
8: Convergence_1 = **FALSE**;
9: **END IF**
10: Given $\{\mathbf{W}_\ell(\bar{n})\}_{k=1}^{G+1}$, solve (25)-(30) to get $\upsilon(\bar{n})$;
11: **IF** $(\upsilon(\bar{n}) - \upsilon(\bar{n}-1) \leq \epsilon)$ & $(\bar{n} > 2)$
12: Convergence_2 = **TRUE**;
13: **RETURN** $\upsilon^\star = \upsilon(\bar{n}-1)$, $\{\mathbf{W}_\ell^\star\}_{\ell=1}^{G+1}$ = $\{\mathbf{W}_\ell(\bar{n}-1)\}_{\ell=1}^{G+1}$;
14: **ELSE**
15: $\upsilon(\bar{n}+1) = \upsilon(\bar{n})$, and $\bar{n}$ = $\bar{n}$ + 1;
16: Convergence_2 = **FALSE**;
17: **END IF**
18: **UNTIL** Convergence_1 = **TRUE** & Convergence_2 = **TRUE**.

$$(P5): \max_{\upsilon, \{\mathbf{W}_\ell\}_{\ell=1}^{G+1}} \ \upsilon \tag{25}$$

$$\text{s.t.} \ \ (C1): \sum_{\ell=1}^{G+1} \mathrm{Tr}\{\mathbf{H}_j \mathbf{W}_\ell\} \geq \frac{\xi_j'}{\zeta_j} - \sigma_{R,j}^2, \ \forall j \in \mathcal{G}_{G+1}, \tag{26}$$

$$(C2): \mathrm{Tr}\{\mathbf{H}_i \mathbf{W}_\ell\} - \upsilon \sum_{k \neq \ell} \mathrm{Tr}\{\mathbf{H}_i \mathbf{W}_k\} \geq \upsilon(\sigma_{R,i}^2 + \sigma_{D,i}^2), \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \tag{27}$$

$$(C3): \upsilon \geq \gamma_i, \ \forall i \in \mathcal{G}_\ell|_{\ell=1}^{G}, \tag{28}$$

$$(C4): \sum_{\ell=1}^{G+1} \mathrm{Tr}\{\mathbf{W}_\ell\} \leq \mathrm{P}_{\text{Max}}, \tag{29}$$

$$(C5): \mathbf{W}_\ell \succcurlyeq 0, \tag{30}$$

where υ is the introduced slack-variable to indicate the minimum SINR threshold (to be optimized), and other parameters have same definitions as before. It is noteworthy that $(C1)$ is a linear constraint introduced to simplify the problem and its proof is provided in Appendix A of [19], [20]. Due to the joint optimization of υ and $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$, a direct solution is difficult to compute using the existing convex optimization solvers (e.g., CVX [35], [36]). Yet again, an iterative approach with alternating parameter optimization may provide an appreciable (sub-optimal) solution, where the execution is anticipated to be within polynomial time. In this regard, we propose a Max-Min SINR (MMS) based fairness scheme for SWIPT algorithm with alternating optimization of υ and $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$, and vice-versa. The corresponding solution is summarized in Algorithm 2. Consequently, the proof of convergence follows the similar fashion as discussed in the previous section.

Assuming that the CVX solver incurs the computational complexities of $\kappa_1(G+1, M)$ orders for carrying out the operations 3: to 10:, and $\kappa_2(M)$ orders to process 11: to 19:, respectively, corresponding to Algorithm 2. Consequently, the overall computation complexity for the proposed algorithm is given by $\mathcal{O}\Big(\big(L^4 \cdot G^2 \cdot (G+1)^4\big)^{\big(\kappa_1(G+1,M)+\kappa_2(M)\big)}\Big)$.

Due to the SDR, possibilities of obtaining a muti-rank solution cannot be ruled out. Hence, the Gaussian randomization technique [11] is employed in this regard to downsize the multi-ranked $\{\mathbf{W}_\ell\}_{\ell=1}^{G+1}$ into a unit rank. Following this, we define the vector indicating the direction of ℓ^{th} precoder as $\widetilde{\mathbf{w}}_\ell = \frac{\mathbf{w}_\ell}{||\mathbf{w}_\ell||_2}$. Therefore, we reformulate $(P5)$ and obtain the problem $(P6)$, as follows

$$(P6): \max_{\upsilon, \{\mathrm{p}_\ell\}_{\ell=1}^{G+1}} \ \upsilon \tag{31}$$

$$\text{s.t.} \ (C1): \zeta_j \left(\sum_{\ell=1}^{G+1} |\widetilde{\mathbf{w}}_\ell^H \mathbf{h}_j|^2 \mathrm{p}_\ell + \sigma_{R,j}^2 \right) \geq \xi_j', \ \forall j \in \mathcal{G}_{G+1}, \tag{32}$$

$$(C2): \frac{|\widetilde{\mathbf{w}}_\ell^H \mathbf{h}_i|^2 \mathrm{p}_\ell}{\sum_{k \neq \ell} |\widetilde{\mathbf{w}}_k^H \mathbf{h}_i|^2 \mathrm{p}_k + \sigma_{R,i}^2 + \sigma_{D,i}^2} \geq \upsilon, \forall i \in \mathcal{G}_\ell|_{\ell=1}^G, \tag{33}$$

$$(C3): \upsilon \geq \gamma_i, \ \forall i \in \mathcal{G}_\ell|_{\ell=1}^G, \tag{34}$$

$$(C4): \sum_{\ell=1}^{G+1} \mathrm{p}_\ell \leq \mathrm{P}_{\text{Max}}, \tag{35}$$

where p_ℓ is the power term associated to the ℓ^{th} precoder with $\widetilde{\mathbf{w}}_\ell$ as its direction, and other terms have the same meaning as defined previously. Intuitively, the scalar p_ℓ is optimized in the direction of $\widetilde{\mathbf{w}}_\ell$. Due to the convex nature of $(P6)$, its solution can be obtained directly via CVX solver, using the similar alternating parameter optimization approach in-line with the Algorithm 2. Correspondingly, the overall computation complexity for the updated algorithm is given by $\mathcal{O}\big((G+1)^{\left(\kappa_1(G+1,M)+\kappa_2(M)\right)}\big)$. The solution of $(P6)$ guarantees a unit-rank solution for all the precoding weight vectors and also compensates for any losses that may have been incurred following the aforementioned Gaussian randomization process. The performance analyses of the proposed schemes (viz., WSS and MMS) is carried out with the help of numerical results in the next section.

V. Simulation Results

In this section, we present the performance benefits of the WSS and MMS schemes under the considered framework targeting the design of a dedicated precoder to serve the set of users with EH demands, in addition to the MC precoding. To solve the simplified convex problems, we make use of the convex programming tool CVX [35], [36], with solutions obtained via SEDUMI solver.

A. Simulation Environment

We assume an ITU-R indoor model (2-floor office scenario) to generate channel realizations with the path-loss exponent given by [37]

$$\text{PL (in dB)} = 20\log_{10}(F) + N\log_{10}(\mathrm{D}) + P_f(n) - 38, \tag{36}$$

where F is the operational frequency (in MHz), N is the distance power loss coefficient, D is the separation distance (in metres) between the transmitter and end-user(s) (with D $>$ 1m), $P_f(n)$ = 15 + 4 (n-1) is the floor penetration loss factor (in dB), and n is the number of floors between the transmitter and the end-user(s) (with $n \geq 0$). Specifically, the chosen parametric values are F = 2 GHz, D = 5m (unless specified otherwise), N = 30, and $P_f(2)$ = 19 dB. The transmitter is assumed to be equipped with M = 20 antennas (unless specified otherwise) while K = 10 users are distributed within $(G+1)$ = 5 multicasting groups as follows: $\mathcal{G}_1$ = $\{\mathcal{U}_3,\mathcal{U}_4\}$, $\mathcal{G}_2$ = $\{\mathcal{U}_2,\mathcal{U}_5\}$, $\mathcal{G}_3$ = $\{\mathcal{U}_6,\mathcal{U}_8\}$, $\mathcal{G}_4$ = $\{\mathcal{U}_7,\mathcal{U}_9\}$, and $\mathcal{G}_5$ = $\{\mathcal{U}_1,\mathcal{U}_5,\mathcal{U}_8,\mathcal{U}_{10}\}$, where $\mathcal{G}_5$ is the energy harvesting group of users while the remaining ($\mathcal{G}_1$,. . ., $\mathcal{G}_4$) groups are comprised of information users. Note that an additional antenna gain of 10 dB is added to take the directivity of the transmit antennas into account. We set to $\sigma_{R,i}^2$ = -110 dBW, $\sigma_{D,i}^2$ = -80 dBW and ζ_i = 0.6. The constants corresponding to the non-linear EH circuit are chosen as $\mathcal{E}'$ = 2.8 mJ, α = 1500, and β = 0.0022 [29], [30]. For simplicity, we assume unity weights, i.e., $\omega_i = 1$, $\gamma_i = \gamma$, $\forall i \in \mathcal{G}_\ell|_{\ell=1}^G$ and $\xi_j = \xi$, $\forall j \in \mathcal{G}_{G+1}$.

B. Numerical Evaluation

We present herein the simulation results in two parts, considering the parameter definitions as in the previous section. Correspondingly, we first perform a general investigation on the performances of the proposed MMS and WSS schemes over their individual benchmarks (described below). Next, we perform a rigorous comparison between the proposed MMS and WSS schemes with several parameter alterations.

1) Performance measure of MMS and WSS schemes with respect to their corresponding individual Benchmarks

In this section, we investigate the performances of MMS and WSS schemes with respect to the individual benchmark methods targeting an equal power limitation at each precoder. Specifically, we alter the individual constraints $(C3)$ in $(P1)$ and $(P4)$, respectively, by the following

$$(C3): \mathbf{w}_\ell^H \mathbf{w}_\ell \leq \frac{\mathrm{P}_{\text{Max}}}{G+1}, \forall \ell = \{1, \cdots, G+1\}. \tag{37}$$

Next, the constraints $(C4)$ in $(P2)$ and $(P5)$ are respectively modified as follows

$$(C4): \mathrm{Tr}\{\mathbf{W}_\ell\} \leq \frac{\mathrm{P}_{\text{Max}}}{G+1}, \forall \ell = \{1, \cdots, G+1\}. \tag{38}$$

Finally for the power refinement process, the constraints $(C4)$ in $(P3)$ and $(P6)$ are respectively to be altered by

$$(C4): \mathrm{p}_\ell \leq \frac{\mathrm{P}_{\text{Max}}}{G+1}, \forall \ell = \{1, \cdots, G+1\}. \tag{39}$$

The above-mentioned updates to the constraints in the corresponding problems accounts for our benchmark methods with equal power limitation at each of the intended precoder (to be designed). In this context, we refer to the corresponding benchmark schemes as WSS-EQ and MMS-EQ.

We now compare the performances of the proposed MMS and WSS methods with respect to MMS-EQ and WSS-EQ benchmark schemes. In this context, we first illustrate in Fig. 2 the performance of the MMS and WSS with respect to MMS-EQ and WSS-EQ schemes in terms of minimum spectral efficiency [in bps/Hz][6] versus number of transmit antennas

[6]The minimum spectral efficiency (corresponding to the minimum SINR) is defined as $\min\big(\log_2(1+\Upsilon_i)\big), \forall i \in \mathcal{G}_\ell, \ \forall \ell \in \{1, \ldots, G\}$.

Distance (D) & Scheme → Number of Antennas (M) ↓	D = 5m		D = 7.5m	
	MMS	WSS	MMS	WSS
8	1.0000	0.8730	1.0000	0.8907
12	1.0000	0.9436	1.0000	0.9574
16	1.0000	0.9477	1.0000	0.9595
20	1.0000	0.9729	1.0000	0.9843

TABLE I: Jain's fairness indices for the MMS and WSS schemes in terms of variation in distances and the number of transmit antennas, where γ = 0.1 dB, ξ = 10 nJ and P_{Max} = 1.5 W.

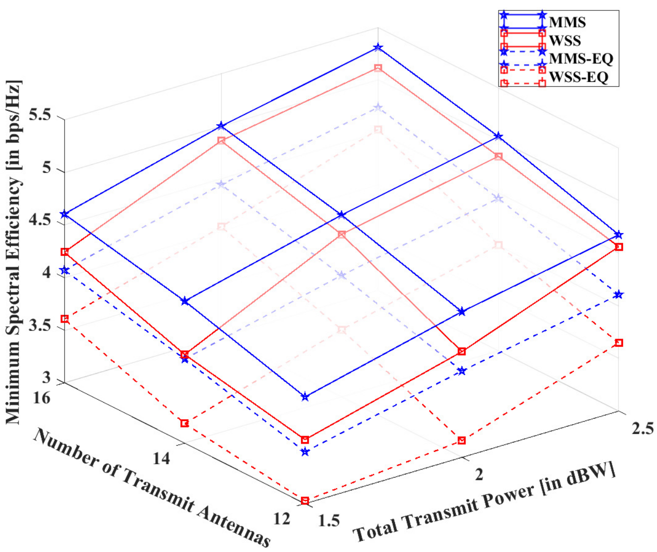


Fig. 2: Performance analysis of the MMS and WSS with respect to MMS-EQ and WSS-EQ schemes in terms of minimum spectral efficiency [in bps/Hz] versus number of transmit antennas and total transmit power, where γ = 0.1 dB, ξ = 10 nJ.

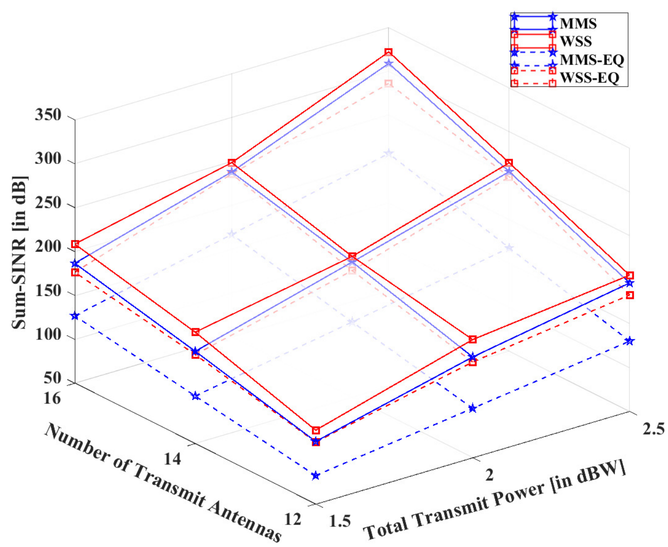


Fig. 3: Performance analysis of the MMS and WSS with respect to MMS-EQ and WSS-EQ schemes in terms of sum-SINR [in dB] (optimized) versus number of transmit antennas and total transmit power, where γ = 0.1 dB, ξ = 10 nJ.

and total transmit power, where γ = 0.1 dB, ξ = 10 nJ. We observe that for all the considered schemes, the individual performances increase with growing antenna numbers as well as with the increasing transmit power values. We observe a superior performance of MMS over its corresponding benchmark MMS-EQ, while the WSS scheme is found to perform significantly better than its corresponding benchmark of WSS-EQ. As evident, we infer that the MMS scheme outperforms the WSS in terms of minimum spectral efficiency measure, which will be further scrutinized in the succeeding section.

In Fig. 3, we depict the performance analysis of the MMS and WSS with respect to MMS-EQ and WSS-EQ schemes in terms of sum-SINR [in dB] (optimized) versus number of transmit antennas and total transmit power, where γ = 0.1 dB, ξ = 10 nJ. Herein, we observe that the significant benefits of the WSS and MMS schemes over their respective benchmarks of WSS-EQ and MMS-EQ for growing antenna numbers as well as with the increasing transmit power values. The WSS schemes is found to outperform the MMS scheme in terms the of sum-SINR metric, with further investigation to be carried out in the subsequent section.

2) Comparison between the MMS and WSS Schemes

After having shown the superior benefits of the MMS and WSS schemes over their respective benchmark schemes of MMS-EQ and WSS-EQ in the previous section, we now present a rigorous analysis to study the performances of the two proposed schemes with variation in different operational parameters. The corresponding investigation is as follows.

Table I summarizes the behavior of the resource allocations performed via two proposed algorithms for MMS and WSS using the Jain's faineness index model, according to (5). Herein, the evaluation of MMS and WSS techniques is performed in terms of variation in distances and the number of transmit antennas, where γ = 0.1 dB, ξ = 10 nJ and P_{Max} = 1.5 W. It is seen that the proposed MMS algorithm provides the best case possibility of resource allocation for any kind of antenna set-up (provided that the feasibility is ensured). This implies that the resources are shared equally among the involved users. In the case of WSS scheme, an irregular distribution of resources is implied from the outcomes. However, it is noted that the fairness measure for WSS improves with increasing number of antennas. From the general trend, it is noteworthy that a fair distribution of resources (best case) may be ensured via both MMS and WSS algorithms when the number of antennas

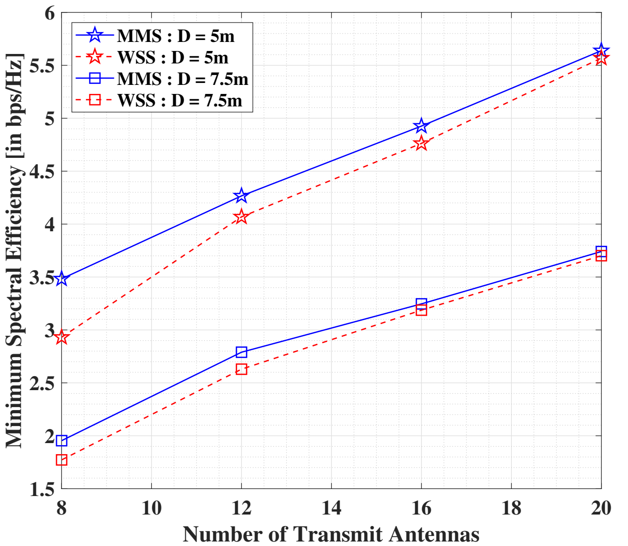


Fig. 4: Performance analysis of the MMS and WSS schemes in terms of minimum spectral efficiency [in bps/Hz] (optimized) versus the number of transmit antennas with the variation in distance, where γ = 0.1 dB, ξ = 10 nJ and P_{Max} = 1.5 W.

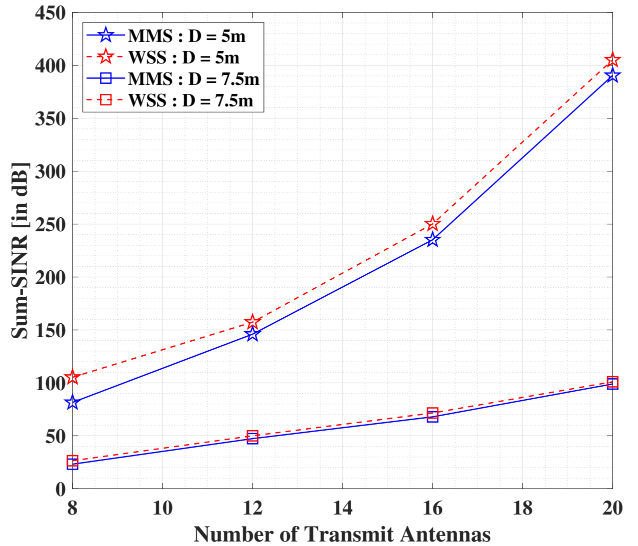


Fig. 5: Performance analysis of the MMS and WSS schemes in terms of sum-SINR [in dB] (optimized) versus the number of transmit antennas with the variation in distance, where γ = 0.1 dB, ξ = 10 nJ and P_{Max} = 1.5 W.

is sufficiently large.

Fig. 4 shows the variation in minimum spectral efficiency [in bits-per-second-per-Hertz (bps/Hz)] with increasing number of array antennas at the transmitter for γ_i = 0.1 dB, ξ_i = 10 nJ and P_{Max} = 1.5 W. Herein, we compare the performances of the proposed MMS and WSS schemes. It is observed that the system performance for both techniques improve considerably in terms of minimum spectral efficiency with the increase in number of transmit array antennas. As expected, MMS scheme is found to perform appreciably better in comparison to the WSS scheme in this context with D = 5m. Furthermore, a similar trend is observed when the distance between the transmitter and end-users is increased to D = 7.5m. However, an expected increase in the minimum spectral efficiency is also seen for both the schemes in this case.

In Fig. 5, we depict the performances of MMS and WSS algorithms in terms of optimized sum-SINR versus the number of transmit antennas with the variation in distance, where γ = 0.1 dB, ξ = 10 nJ and P_{Max} = 1.5 W. We observe an increase in the aggregated SINR of the involved ID users, for growing number of antenna numbers in general. Herein, the WSS scheme is found to perform slightly better than MMS in terms of sum-SINR. This is due to the impartial resource allocation in case of WSS, which implies certain set of users will be allocated better resources while the remaining would obtain the least. The operation of fair resource allocation via MMS incurs some performance losses due to an (enforced) equal resource distribution. Additionally, the performances of both MMS and WSS are expected to be identical at set-ups with large distances between the transmitter and involved devices, which is due to the hard limitation on the total transmit power.

Table II characterizes the fairness measure of the proposed MMS and WSS schemes in terms of minimum harvested energy requirement and maximum transmit power limitation, where γ = 0.1 dB and D = 5m. We observe that the MMS algorithm provides the best case of Jain's fairness index for different values of harvested energy demands and total limit on the transmit power. On the other hand, the output via WSS scheme is found to be marginally lower than the one of MMS for lower values of harvested energy demands under a low transmit power budget. Whereas, the phenomenon of unfair resource distribution is clearly inferred from the case wherein the harvested energy demand is high while the transmit power budget is low. In the case of increasing transmit power budget, the fairness criteria for WSS is seen to improve significantly.

In Fig. 6, we illustrate the effect on the minimum spectral efficiency (in bps/Hz) with the increase in the maximum transmit power and harvested energy demand. Herein, we draw a comparison between the proposed MMS and WSS schemes assuming γ = 0.1 dB and D = 5m. We observe that the minimum optimized spectral efficiency increases with increasing transmit power values for both the cases. However, the effect of rate-energy (R-E) trade-off is also seen; which implies that the minimum optimized spectral efficiency threshold decreases with increase in the harvested energy demand, while vice-versa holds true as well.

Fig. 7 presents the performances of the MMS and WSS schemes in terms of the optimized sum-SINR versus the maximum transmit power limitation with variation in the harvesting energy demands of users, where γ = 0.1 dB and D = 5m. We observe an overall increase in the sum-SINR of the ID users for growing transmit power budget, with WSS performing marginally better than MMS. Additionally, the behavior of both WSS and MMS follows an incremental trend when the harvested energy demand is low, while the performance is seen to degrade otherwise. In the latter case, MMS is found to suffer significant performance losses when the demanded harvesting energy is very high with regard to

Min. HE Req. (ξ) & Scheme → Max. Transmit Power (P_{Max}) ↓	ξ = 1 nJ		ξ = 100 nJ	
	MMS	WSS	MMS	WSS
1.0 W	1.0000	0.9326	1.0000	0.6284
1.5 W	1.0000	0.9402	1.0000	0.8438
2.0 W	1.0000	0.9871	1.0000	0.9646
2.5 W	1.0000	0.9896	1.0000	0.9880

TABLE II: Jain's fairness indices for the MMS and WSS schemes in terms of minimum harvested energy requirement and maximum transmit power limitation, where γ = 0.1 dB and D = 5m.

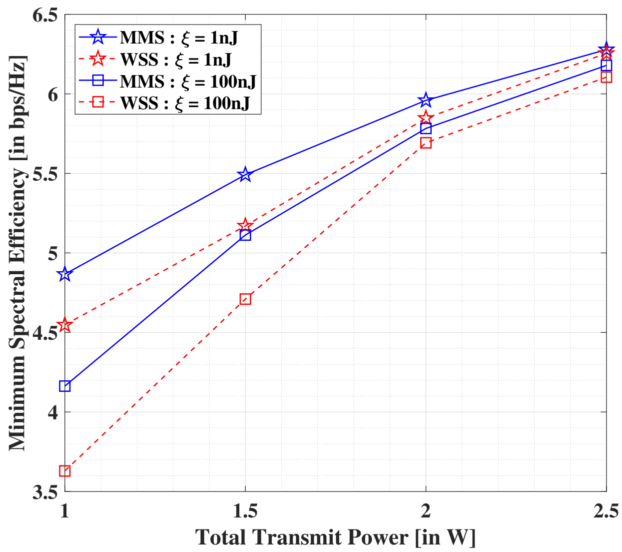


Fig. 6: Performance analysis of the MMS and WSS schemes in terms of minimum spectral efficiency (optimized) versus maximum transmit power limitation with variation in the harvesting energy demands of users, where γ = 0.1 dB and D = 5m.

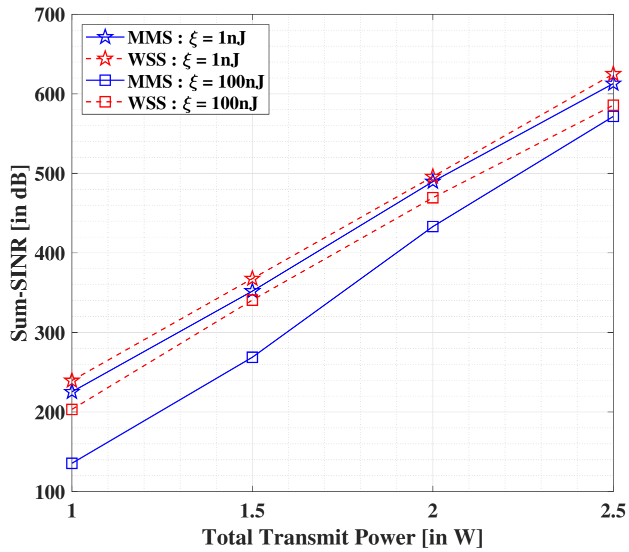


Fig. 7: Performance analysis of the MMS and WSS schemes in terms of sum-SINR (optimized) versus the maximum transmit power limitation with variation in the harvesting energy demands of users, where γ = 0.1 dB and D = 5m.

the hard-constrained total transmit power budget.

C. Further investigation with variable users' categorization

Herein, we intend to further investigate the performance of the proposed WSS and MMS schemes under the consideration of a variety of test-cases, with differing user categorizations within the MG and EH groups. For analytical convenience, we now fix a single group $\mathcal{G}_1$ for the ID users for MC operation and another group $\mathcal{G}_2$ comprising the EH users. In this context, let us first assume a scenario setting with incremental ID users, comprised as follows : $\varpi_1 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_{10}\}\}$, $\varpi_2 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \ldots, \mathcal{U}_4\}, \mathcal{G}_2 = \{\mathcal{U}_{10}\}\}$, $\varpi_3 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \ldots, \mathcal{U}_6\}, \mathcal{G}_2 = \{\mathcal{U}_{10}\}\}$, $\varpi_4 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \ldots, \mathcal{U}_8\}, \mathcal{G}_2 = \{\mathcal{U}_{10}\}\}$, and $\varpi_5 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \ldots, \mathcal{U}_{10}\}, \mathcal{G}_2 = \{\mathcal{U}_{10}\}\}$. As clearly indicated in the typesetting, we consider an incremental trend of ID users, where a couple of ID users are added to each incremental setting of ϖ_i, with $i = 1, \ldots, 5$. We additionally assume the presence of single user ($\mathcal{U}_{10}$) in the EH group ($\mathcal{G}_2$) throughout, for this case. The performance measures of the proposed WSS and MMS schemes are represented in Fig. 8 as bar-plots, where γ = 0.1 dB, ξ = 10 nJ, M = 16, P_{Max} = 1.5 W, and D = 5m. In Fig. 8 (a), we plot the results corresponding to the minimum SINR (in dB) obtained via WSS and MMS schemes, with variation in the users' categorization as considered above. We observe that the min-SINR for both the scenarios (i.e., WSS and MMS) decreases with increasing number of ID users in $\mathcal{G}_1$. This decrease in the min-SINR is due to the corresponding additions of ID users, which implies that the limited power resources have to be distributed accordingly. However, the MMS technique shows considerable advantages of WSS in terms of fairness measure. The bar-plot in Fig. 8 (b) shows an incremental trend for both WSS and MMS schemes. Due to the upsurge in the number of ID users, more resources are bound to be utilized for the ID users in comparison to the EH user at each incremental stage. Herein, the sum-SINR obtained via MMS scheme is found to be lower than the one obtained via WSS. This may be inferred as the trade-off for ensuring a fair allocation of the resources, while also observing the aspect of rate-energy (R-E) trade-off wherein certain amount of power is seen to shift towards the increasing ID users at each growing stage of the scenario set-up.

The second analysis involves the selection of incremental sets of the EH users, composed as follows: $\varsigma_1 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_1, \mathcal{U}_2\}\}$, $\varsigma_2 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_1, \ldots, \mathcal{U}_4\}\}$, $\varsigma_3 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_1, \ldots, \mathcal{U}_6\}\}$,

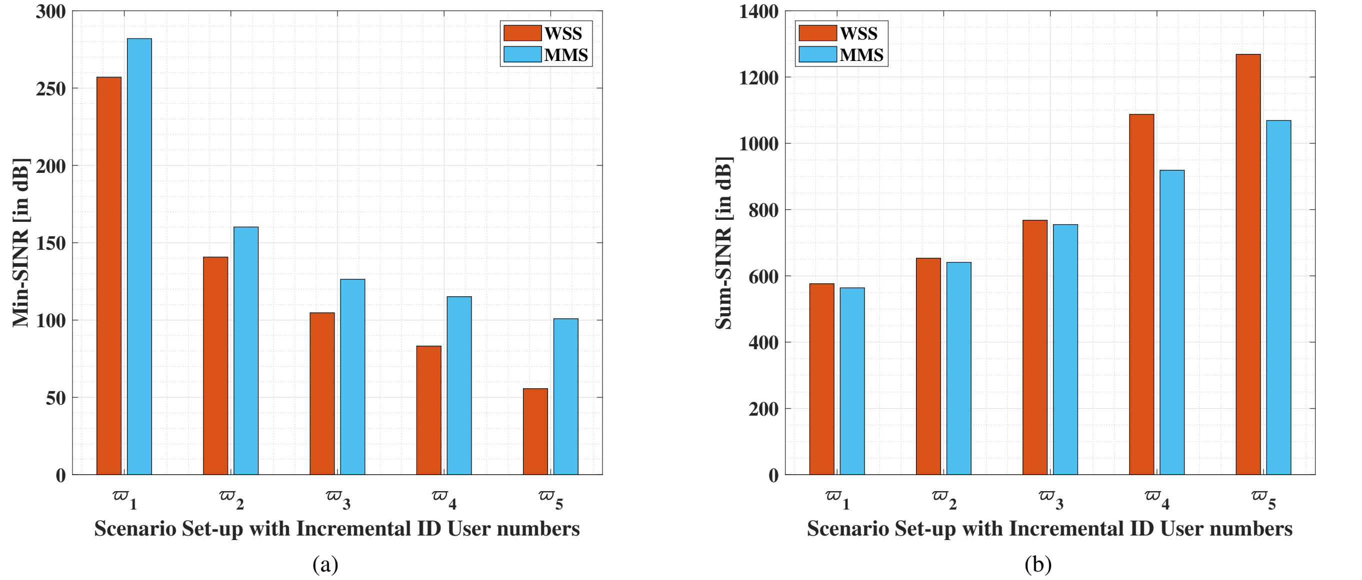


Fig. 8: The scenario setting with incremental ID users to study the variation according to (a) Min-SINR and (b) Sum-SINR, corresponding to the ID users based on the WSS and MMS schemes, where γ = 0.1 dB, ξ = 10 nJ, M = 16, P_{Max} = 1.5 W, and D = 5m.

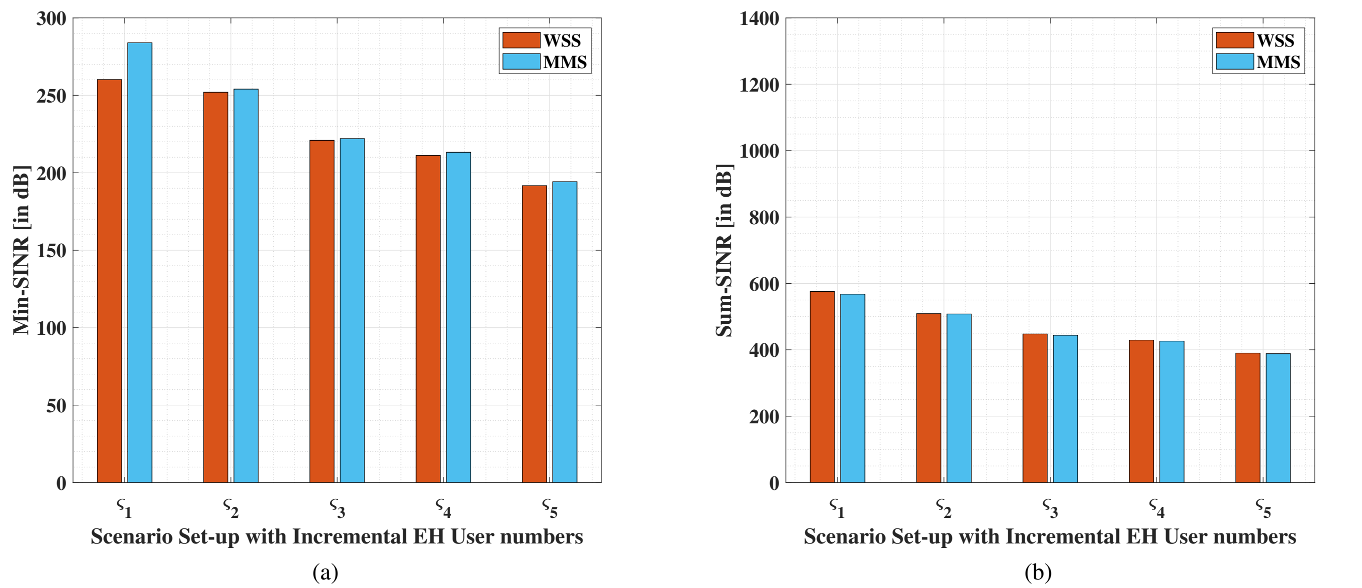
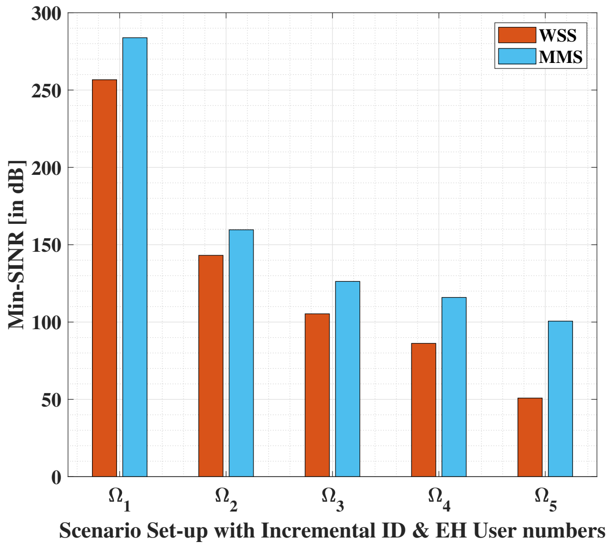


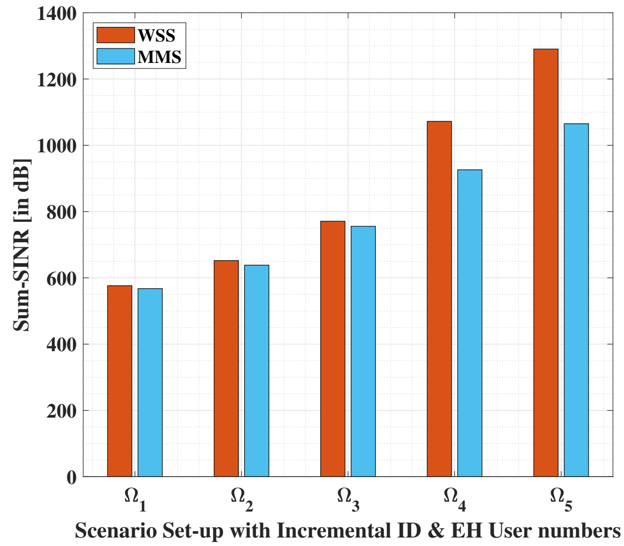
Fig. 9: The bar-plots to depict the outcome of the scenario setting with incremental EH users according to (a) Min-SINR and (b) Sum-SINR, corresponding to the ID users based on the WSS and MMS schemes, where γ = 0.1 dB, ξ = 100 nJ, M = 16, P_{Max} = 1.5 W, and D = 5m.

$\varsigma_4 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_1, \ldots, \mathcal{U}_8\}\}$, and $\varsigma_5 := \{\mathcal{G}_1 = \{\mathcal{U}_1, \mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_1, \ldots, \mathcal{U}_{10}\}\}$. In this case, we choose an incremental trend of EH users, where a couple of EH users are added to each incremental stage of ς_i, with $i = 1, \ldots, 5$. The MC group $\mathcal{G}_1$ is assumed to be fixed, having a couple of ID users (i.e., $\mathcal{U}_1$ and $\mathcal{U}_2$)[7] throughout. We show in Fig. 9 the results corresponding to the proposed WSS and MMS schemes, with γ = 0.1 dB, ξ = 100 nJ, M = 16, P_{Max} = 1.5 W, and D = 5m. The bar plots in Fig. 9 (a) follows a decreasing trend for both WSS and MMS schemes with each increasing stage of scenario set-up. Intuitively, an increase in the number of EH users would divert more resources towards the latter. The performance of MMS scheme is found to be superior to WSS scheme in terms of min-SINR. Fig. 9 (b) presents the results corresponding to the sum-SINR with respect to each incremental stage of the scenario setting, where a decreasing trend is obtained for both WSS and MMS schemes. However, the performance of WSS scheme is found to be marginally better than MMS scheme. Understandably, this trend is justified since we need to keep the EH demand high so as to be

[7]We choose the lowest number of elements so as to be able to perform the corresponding minimum and sum operations for these entities.



(a)



(b)

Fig. 10: The scenario setting with incremental ID and EH users to study the variation according to (a) Min-SINR and (b) Sum-SINR, corresponding to the ID users based on the WSS and MMS schemes, where γ = 0.1 dB, ξ = 10 nJ, M = 16, P_{Max} = 1.5 W, and D = 5m.

able to distinguish between the results. For both the cases, the decreasing trends may be interpreted according to the well-known R-E trade-off pertaining the SWIPT systems.

Finally, we assume the case with jointly incremental ID and EH users at each stage of the scenario set-up, comprised as follows: $\Omega_1 := \{\mathcal{G}_1 = \{\mathcal{U}_1,\mathcal{U}_2\}, \mathcal{G}_2 = \{\mathcal{U}_1,\mathcal{U}_2\}\}$, $\Omega_2 := \{\mathcal{G}_1 = \{\mathcal{U}_1,\ldots,\mathcal{U}_4\}, \mathcal{G}_2 = \{\mathcal{U}_1,\ldots,\mathcal{U}_4\}\}$, $\Omega_3 := \{\mathcal{G}_1 = \{\mathcal{U}_1,\ldots,\mathcal{U}_6\}, \mathcal{G}_2 = \{\mathcal{U}_1,\ldots,\mathcal{U}_6\}\}$, $\Omega_4 := \{\mathcal{G}_1 = \{\mathcal{U}_1,\ldots,\mathcal{U}_8\}, \mathcal{G}_2 = \{\mathcal{U}_1,\ldots,\mathcal{U}_8\}\}$, and $\Omega_5 := \{\mathcal{G}_1 = \{\mathcal{U}_1,\ldots,\mathcal{U}_{10}\}, \mathcal{G}_2 = \{\mathcal{U}_1,\ldots,\mathcal{U}_{10}\}\}$. Herein, we add a couple of ID and EH users each within the corresponding groups (i.e., $\mathcal{G}_1$ and $\mathcal{G}_2$, respectively) at each growing stage of Ω_i, where $i = 1,\ldots,5$. With these settings, we illustrate the performance measures of the proposed WSS and MMS schemes in Fig. 10 by keeping γ = 0.1 dB, ξ = 10 nJ, M = 16, P_{Max} = 1.5 W, and D = 5m. In Fig. 10 (a), we present the bar-plots corresponding to the min-SINR obtained with the help of the proposed WSS and MSS schemes. We observe a decreasing trend at each incremental stage of the system setting with jointly increasing numbers of ID and EH users. The decrease is due to the distribution of resources amongst the correspondingly growing user numbers. Similar to the previous outcomes, we see the performance benefits of the MSS scheme over the WSS, concerning the min-SINR investigation. We then show in Fig. 10 (b) the comparison between the proposed WSS and MMS schemes from the sum-SINR perspective. Herein, we observe a growing trend with each incremental stage of the scenario set-up for both WSS and MMS schemes. Due to the upsurge in the number of users, the sum-SINR increases because the corresponding precoders are able to handle more number of ID and EH users, respectively, using potent methods. In other words, the EH users may benefit from the signals intended for the nearby ID users, where they can harvest their demanded share of energy more efficiently. This aspect may further facilitate in efficient power allocation at the precoder devices, which may significantly enhance the system performance, as inferred from the results. From the perspective of sum-SINR, we find that the WSS scheme outperforms the MMS scheme which however, cannot always guarantee a fair distribution of the available resources.

D. *Intuitive interpretation of the obtained results*

We have presented two perspectives for analysing the considered MG-MC system wherein a dedicated precoder serves the set of EH users, in addition to the MC precoding. The two possibilities are rigorously investigated from different aspects concerning the utilization of MMS and WSS schemes. Herein, we provide an intuitive analysis to the presented numerical solutions. It is clear that the MMS scheme targets the fairness aspect, wherein we showed its effectiveness in terms of minimum-spectral efficiency/minimum-SINR at the intended users. Naturally, this methodology is more suitable for systems wherein the concerned nodes are scattered around at random distances from the transmitter, and fairness optimization is of paramount interest. On the other hand, the WSS scheme is found to be more effective in terms of sum-SINR concerning the overall system. Intuitively, such a technique (WSS) may be employed in the same system with scattered users (as mentioned above), however, compromised from the users' fairness perspective measure. More specifically, the performance per user is overshadowed by the overall collective performance of the system. This, however, is the matter of choice for the network operator, wherein either of the two schemes may be employed according to the users', network's and service provider's requirements.

VI. Conclusion

We considered a precoder design problem for SWIPT-enabled MG-MC systems with heterogeneous wireless user types that are capable of performing ID only, EH only, and joint ID and EH. In this regard, we proposed and formulated two optimization problems based on the maximization of weighted sum-SINR and the maximization of minimum SINR of the intended users. Herein, we sought suitable precoder designs that could either maximize the weighted sum-SINR or maximize the minimum of SINR, both subjected to the constraints on minimum EH and SINR demands at the respective users, along with an overall transmit power limitation. Furthermore, both the problems were solved and analyzed using the semidefinite relaxation and slack variable replacement techniques under a separate multicating and energy precoder design, respectively summarized in the form of iterative algorithms. Superior performance of MMS was shown over WSS in terms of fair resource allocations, whereas WSS was found to perform marginally better in the other case focusing on maximization of sum-SINR. However, both the techniques may find their applications in the IoT systems accordingly, based on the two proposed perspectives of resource allocation.

Acknowledgment

The authors would like to thank Mr. Ashok Bandi, Dr. Thang X. Vu and Dr. Steven Kisseleff for their help and efforts in the form of fruitful discussions, which were valuable for enhancement of some details in the manuscript.

References

[1] Q. Shi, L. Liu, W. Xu, and R. Zhang, "Joint Transmit Beamforming and Receive Power Splitting for MISO SWIPT Systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 6, pp. 3269–3280, June 2014.

[2] S. Gautam and P. Ubaidulla, "Relay Selection and Transceiver Design for Joint Wireless Information and Energy Transfer in Cooperative Networks," in *85th Veh. Tech. Conf. (Spring)*. IEEE, 2017, pp. 1–5.

[3] J. Feng, L. Zhao, J. Du, X. Chu, and F. R. Yu, "Energy-Efficient Resource Allocation in Fog Computing Supported IoT with Min-Max Fairness Guarantees," in *2018 IEEE International Conference on Communications (ICC)*, 2018, pp. 1–6.

[4] S. Gautam and T. X. Vu and S. Chatzinotas and B. Ottersten, "Joint wireless information and energy transfer in cache-assisted relaying systems," in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, 2018, pp. 1–6.

[5] N. Janatian, I. Stupia, and L. Vandendorpe, "Optimal resource allocation in ultra-low power fog-computing SWIPT-based networks," in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, 2018, pp. 1–6.

[6] R. Tandon, S. A. Jafar, S. Shamai, and H. V. Poor, "On the Synergistic Benefits of Alternating CSIT for the MISO Broadcast Channel," *IEEE Trans. Inf. Theory*, vol. 59, no. 7, pp. 4106–4128, July 2013.

[7] L. R. Varshney, "Transporting information and energy simultaneously," in *IEEE Int. Symp. Inf. Theory*, July 2008, pp. 1612–1616.

[8] M. R. A. Khandaker and K. Wong, "SWIPT in MISO Multicasting Systems," *IEEE Wireless Commun. Lett.*, vol. 3, no. 3, pp. 277–280, June 2014.

[9] Z. Ding, C. Zhong, D. W. K. Ng, M. Peng, H. A. Suraweera, R. Schober, and H. V. Poor, "Application of smart antenna technologies in simultaneous wireless information and power transfer," *IEEE Comm. Mag.*, vol. 53, no. 4, pp. 86–93, April 2015.

[10] T. D. P. Perera, D. N. K. Jayakody, S. K. Sharma, S. Chatzinotas, and J. Li, "Simultaneous Wireless Information and Power Transfer (SWIPT): Recent Advances and Future Challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 264–302, 2018.

[11] N. D. Sidiropoulos and T. N. Davidson and, "Transmit beamforming for physical-layer multicasting," *IEEE Trans. Signal Process.*, vol. 54, no. 6, pp. 2239–2251, June 2006.

[12] J. Krivochiza, J. M. Duncan, S. Andrenacci, S. Chatzinotas, and B. Ottersten, "FPGA Acceleration for Computationally Efficient Symbol-Level Precoding in Multi-User Multi-Antenna Communication Systems," *IEEE Access*, vol. 7, pp. 15509–15520, 2019.

[13] E. Karipidis, N. D. Sidiropoulos, and Z. Luo, "Quality of Service and Max-Min Fair Transmit Beamforming to Multiple Cochannel Multicast Groups," *IEEE Trans. Signal Process.*, vol. 56, no. 3, pp. 1268–1279, 2008.

[14] D. Christopoulos, S. Chatzinotas, and B. Ottersten, "Weighted Fair Multicast Multigroup Beamforming under Per-antenna Power Constraints," *IEEE Trans. Signal Process.*, vol. 62, no. 19, pp. 5132–5142, 2014.

[15] H. Chen, D. Mi, B. Clerckx, Z. Chu, J. Shi, and P. Xiao, "Joint Power and Subcarrier Allocation Optimization for Multigroup Multicast Systems With Rate Splitting," *IEEE Trans. Veh. Technol.*, vol. 69, no. 2, pp. 2306–2310, 2020.

[16] Ö. T. Demir and T. E. Tuncer, "Multi-group multicast beamforming for simultaneous wireless information and power transfer," in *23rd European Sig. Processing Conf. (EUSIPCO)*, Aug 2015, pp. 1356–1360.

[17] Ö. T. Demir and T. E. Tuncer, "Antenna Selection and Hybrid Beamforming for Simultaneous Wireless Information and Power Transfer in Multi-Group Multicasting Systems," *IEEE Trans. Wireless Comm.*, vol. 15, no. 10, pp. 6948–6962, Oct 2016.

[18] M. Alodeh, D. Spano, A. Kalantari, C. G. Tsinos, D. Christopoulos, S. Chatzinotas, and B. Ottersten, "Symbol-Level and Multicast Precoding for Multiuser Multiantenna Downlink: A State-of-the-Art, Classification, and Challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 1733–1757, thirdquarter 2018.

[19] S. Gautam, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Wireless Multi-group Multicast Precoding with Selective RF Energy Harvesting," in *2019 27th European Signal Processing Conference (EUSIPCO)*, 2019, pp. 1–5.

[20] S. Gautam, E. Lagunas, A. Bandi, S. Chatzinotas, S. K. Sharma, T. X. Vu, S. Kisseleff, and B. Ottersten, "Multigroup Multicast Precoding for Energy Optimization in SWIPT Systems With Heterogeneous Users," *IEEE Open Journal of the Communications Society*, vol. 1, pp. 92–108, 2020.

[21] X. Jia, C. Zhang, J. Kang and I. Kim, "Joint Beamforming Design and Time Allocation for Wireless Powered Asymmetric Two-Way Multirelay Network," *IEEE Trans. Veh. Technol.*, vol. 67, no. 10, pp. 9641–9655, 2018.

[22] A. Bandi, R. Bhavani Shankar Mysore, S. Chatzinotas and B. Ottersten, "Joint User Grouping, Scheduling, and Precoding for Multicast Energy Efficiency in Multigroup Multicast Systems," *IEEE Trans. Wireless Commun.*, pp. 1–1, 2020.

[23] M. C. H. Lim, D. C. McLernon and M. Ghogho, "Weighted harmonic mean SINR maximization for the MIMO downlink," in *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, 2009, pp. 2381–2384.

[24] L. Wei and D. A. Pados, "Optimal Orthogonal Carriers and Sum-SINR/Sum-Capacity of the Multiple-Access Vector Channel," *IEEE Trans. Commun.*, vol. 60, no. 5, pp. 1188–1192, 2012.

[25] D. Julian, M. Chiang, D. O'Neill and S. Boyd, "QoS and fairness constrained convex optimization of resource allocation for wireless cellular and ad hoc networks," in *Proceedings.Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies*, 2002, vol. 2, pp. 477–486.

[26] B. Clerckx and E. Bayguzina, "Waveform Design for Wireless Power Transfer," *IEEE Trans. Signal Process.*, vol. 64, no. 23, pp. 6313–6328, 2016.

[27] L. Liu, R. Zhang, and K. Chua, "Wireless Information and Power Transfer: A Dynamic Power Splitting Approach," *IEEE Trans. Commun.*, vol. 61, no. 9, pp. 3990–4001, 2013.

[28] S. Gautam, J. Krivochiza, A. Haqiqatnejad, S. Chatzinotas, and B. Ottersten, "Boosting SWIPT via Symbol-Level Precoding," in *Proc. 21st IEEE International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2020, https://orbilu.uni.lu/handle/10993/43218#ft, [Online].

[29] J. Guo, H. Zhang, and X. Zhu, "Theoretical analysis of RF-DC conversion efficiency for class-F rectifiers," *IEEE Trans. Microw. Theory Techn.*, vol. 62, no. 4, pp. 977–985, 2014.

[30] S. Gautam, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Relay Selection and Resource Allocation for SWIPT in Multi-User OFDMA Systems," *IEEE Trans. Wireless Commun.*, vol. 18, no. 5, pp. 2493–2508, 2019.

[31] J. Kang, I. Kim, and D. I. Kim, "Wireless Information and Power Transfer: Rate-Energy Tradeoff for Nonlinear Energy Harvesting," *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 1966–1981, 2018.
[32] J. Kang, C. Chun, I. Kim, and D. I. Kim, "Dynamic Power Splitting for SWIPT With Nonlinear Energy Harvesting in Ergodic Fading Channel," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 5648–5665, 2020.
[33] J. Kang, I. Kim, and D. I. Kim, "Mode Switching for SWIPT Over Fading Channel With Nonlinear Energy Harvesting," *IEEE Wireless Commun. Lett.*, vol. 6, no. 5, pp. 678–681, 2017.
[34] R. K. Jain, D.-M. W. Chiu, and W. R. Hawe, "A Quantitative Measure Of Fairness And Discrimination For Resource Allocation In Shared Computer Systems," *Eastern Research Laboratory, Digital Equipment Corporation, Hudson, MA*, 1984.
[35] M. Grant and S. Boyd, "CVX: Matlab software for disciplined convex programming, version 2.1," http://cvxr.com/cvx, Mar. 2014.
[36] M. Grant and S. Boyd, "Graph implementations for nonsmooth convex programs," in *Recent Advances in Learning and Control*, V. Blondel, S. Boyd, and H. Kimura, Eds., Lecture Notes in Control and Information Sciences, pp. 95–110. Springer-Verlag Limited, 2008, http://stanford.edu/~boyd/graph_dcp.html.
[37] P. Series, "Propagation data and prediction methods for the planning of indoor radiocommunication systems and radio local area networks in the frequency range 900 MHz to 100 GHz," *Recommendation ITU-R*, pp. 1238–7, 2012.

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