Optimal Resource Allocation for MC-NOMA in SWIPT-Enabled Networks

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***Abstract*— In this letter, we study a receiver architecture technique for joint resource allocation in a downlink (DL) multi-user multi-carrier non-orthogonal multiple access (MC-NOMA) network with simultaneous wireless information and power transfer (SWIPT). In this framework, the subcarrier set is partitioned into two groups that are assigned to perform information decoding (ID) and energy harvesting (EH) at the receiver side based on the optimization problem. This letter seeks to maximize energy harvesting while meeting a minimum data-rate requirement for each user. The underlying optimization problem is mixed-integer non-linear programming (MINLP). To that end, we employ the monotonic optimization approach to obtain an optimal resource allocation policy. A suboptimal solution is also presented. Simulation results demonstrate that our proposed algorithm achieves excellent performance as compared to other works described in the literature.**

***Index Terms*— Simultaneous wireless information and power transfer (SWIPT), energy harvesting (EH), information decoding (ID), non-orthogonal multiple access (NOMA), mixed-integer non-linear programming (MINLP), monotonic optimization.**

I. Introduction

NON-ORTHOGONAL multiple access (NOMA) has been suggested as one of the fundamental techniques for fifth generation (5G) cellular networks and beyond. It should make it possible to enhance the spectral efficiency (SE) and also permits some degree of multiple access interference [1]. In general, NOMA schemes are designed to concurrently serve two or more users in a single resource block and can be categorized in two main classes: single-carrier NOMA (SC-NOMA) and multi-carrier NOMA (MC-NOMA). To distinguish between the users and eliminate the predicted interference, successive interference cancellation (SIC) is employed to achieve better overall fairness, throughput, and most importantly, SE in NOMA networks.

In addition to improving SE, energy efficiency (EE), another critical performance indicator in practical wireless networks, also needs to be ameliorated. To meet the challenging demand of enhancing the system's EE, simultaneous wireless information and power transfer (SWIPT) has been proposed. This is a way to diminish power consumption in the network by providing an alternative green energy source [2], [3]. In this regard, a great deal of research has been conducted on the deployment of SWIPT in various types of wireless communication networks. More specifically, [4] studied a resource allocation design in a single-user SWIPT-enabled orthogonal frequency division multiplexing (OFDM) system to maximize the harvested energy. The subcarriers' set was partitioned into two subsets: one subset for performing information decoding (ID) and another for energy harvesting (EH). This made it possible to avoid using a splitter – unlike in the more traditional SWIPT architectures, power splitting (PS) and time switching (TS). However, TS and PS receiver architectures were adopted in [5] to address the weighted sum-rate maximization problem by varying the power allocation and the TS/PS ratios in a multi-user SWIPT-enabled orthogonal frequency division multiple access (OFDMA) network. The resource allocation algorithm design for EE maximization was also studied in [6] to jointly optimize subcarrier assignment and power allocation, as well as the PS ratios in an OFDMA system, by using SWIPT. The resource allocation design is also useful for contributing not only to EE through SWIPT but also to SE through NOMA in SWIPT-enabled NOMA cellular networks. With this in mind, [7]–[9] proposed SWIPT-assisted NOMA networks to improve the system's EE and SE. The authors of [7] considered TS-based SWIPT-aided SC-NOMA in which the EE maximization problem was investigated by jointly optimizing power allocation and TS control. In [8], a multi-objective optimization approach in a PS-based SWIPT SC-NOMA was investigated to maximize the sum-rate at the same time as the harvested energy. Subcarrier allocation and power control optimization in the MC-NOMA system with SWIPT as a way to suboptimally maximize EE under minimum data-rate and maximum interference constraints were addressed in [9].

Most of the previous works focused on the SWIPT system based on conventional receiver architectures. The authors are unaware of any studies on harvesting energy in SWIPT-enabled MC-NOMA networks without using a splitter. Inspired by these observations, we aim to develop an energy harvesting optimization model for the SWIPT-assisted MC-NOMA network by partitioning the subcarrier set into ID and EH subsets. Thus, the main contributions of this letter can be summarized as follows:

- We examine a resource allocation design that includes subcarrier assignment and power allocation for a simple scenario that is well-known in the literature. Our innovation is capturing the essential characteristics of SWIPT-assisted NOMA networks.
- We propose a low-complexity receiver that does not require a splitter to perform appropriately; the receiver uses neither TS nor PS technique.
- We analyze how the proposed resource allocation algorithm performs with existing schemes.

II. System Model

We consider a downlink (DL) SWIPT-assisted MC-NOMA network consisting of one access point (AP) and K mobile users where each mobile receiver can harvest energy from

Manuscript received June 1, 2020; accepted June 18, 2020. Date of publication June 23, 2020; date of current version October 9, 2020. The associate editor coordinating the review of this letter and approving it for publication was H. Zhang. *(Corresponding author: Jalal Jalali.)*

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Digital Object Identifier 10.1109/LCOMM.2020.3004418

the transmitted signal. It is assumed that the entire frequency band is divided into N subcarriers, each with a bandwidth of $\mathscr{B}$. The set of subcarriers and users are denoted by $\mathcal{N} = \{1, 2, \ldots, Z, Z+1, \ldots, N\}$ and $\mathcal{K} = \{1, 2, \ldots, K\}$, respectively. Let $\mathcal{N}_I = \{1, 2, \ldots, Z\}$ denote the set of subcarriers for ID, and the remaining subcarriers $\mathcal{N}_E = \mathcal{N} - \mathcal{N}_I$ for EH.[1] Hence, the subcarriers' assignment variables are given by

$$a_{n,k} = \begin{cases} 1, & \text{if ID subcarrier } n \text{ is assigned to user } k, \\ 0, & \text{otherwise,} \end{cases}$$

$$b_{n,k} = \begin{cases} 1, & \text{if EH subcarrier } n \text{ is assigned to user } k, \\ 0, & \text{otherwise.} \end{cases}$$

Let $h_{n,k}$ denote the DL channel coefficient from the AP to the k^{th} user over the subcarrier n. We further assume that perfect channel state information (CSI) is available at a centralized resource allocator for the purpose of designing a resource allocation policy.[2] Without losing generality, it is assumed that the channel gains should satisfy the following sorting condition: $|h_{n,1}|^2 \leq \ldots \leq |h_{n,k}|^2 \leq \ldots \leq |h_{n,K}|^2$. It is worth noting that in single-input single-output NOMA systems the optimal decoding order among users is characterized according to the channel gains; each user employs SIC to mitigate the interference created by other users and improve performance [1]. By denoting $p_{n,k}$ as the transmitted power of AP to the k^{th} user over the subcarrier n, the DL signal to interference plus noise ratio (SINR) of the k^{th} user can be written as

$$\gamma_{n,k} = \frac{a_{n,k} p_{n,k} |h_{n,k}|^2}{\sum_{i=k+1}^{K} a_{n,i} p_{n,i} |h_{n,k}|^2 + \sigma_{n,k}^2}, \tag{1}$$

where $\sigma_{n,k}^2$ denotes the additive noise power. Accordingly, the data-rate of k^{th} user over the subcarrier n can be expressed as

$$R_{n,k} = \log_2\Big(1 + \gamma_{n,k}\Big). \tag{2}$$

For facilitating the presentation, we denote $\mathbf{p} \in \mathbb{R}^{1\times KN}$ and $\mathbf{a} \in \mathbb{R}^{1\times KZ}$ as vectors of optimization parameters. Consequently, the data-rate of k^{th} user is given by

$$R_k(\mathbf{a}, \mathbf{p}) = \sum_{n\in\mathcal{N}_I} R_{n,k}. \tag{3}$$

To ensure users' quality of service (QoS), a minimum data-rate denoted by $R_{\min}$ should be provided for each user as follows

$$R_k(\mathbf{a}, \mathbf{p}) \geq R_{\min}, \quad \forall k \in \mathcal{K}. \tag{4}$$

Furthermore, the harvested energy can be stated as

$$\mathrm{EH}(\mathbf{b}, \mathbf{p}) = \sum_{k\in\mathcal{K}} \epsilon_k \Bigg(\sum_{n\in\mathcal{N}_E} b_{n,k} p_{n,k} |h_{n,k}|^2 + \sigma_{n,k}^2 \Bigg), \tag{5}$$

where $\mathbf{b} \in \mathbb{R}^{1\times K(N-Z)}$ and ϵ_k is the power efficiency of the k^{th} user capable of harvesting energy. The main objective of this letter is to assign subcarrier(s) and to allocate power(s), for each user – in order to maximize the total harvested energy. Thus, the optimization problem can be formulated as

$$\max_{\mathbf{a},\mathbf{b},\mathbf{p}} \ \mathrm{EH}(\mathbf{b}, \mathbf{p}) \tag{6a}$$

$$s.t.\ C_1: \sum_{k\in\mathcal{K}} a_{n,k} \leq L, \quad \forall n \in \mathcal{N}_I, \tag{6b}$$

$$C_2: \sum_{k\in\mathcal{K}} b_{n,k} \leq 1, \quad \forall n \in \mathcal{N}_E, \tag{6c}$$

$$C_3: \sum_{k\in\mathcal{K}} \sum_{n\in\mathcal{N}} (a_{n,k} + b_{n,k}) p_{n,k} \leq p_{\max}, \tag{6d}$$

$$C_4: R_k(\mathbf{a}, \mathbf{p}) \geq R_{\min}, \quad \forall k \in \mathcal{K}, \tag{6e}$$

$$C_5: a_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}_I,\ k \in \mathcal{K}, \tag{6f}$$

$$C_6: b_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}_E,\ k \in \mathcal{K}. \tag{6g}$$

In this optimization problem, C_1 indicates that ID subcarriers can be assigned to at most L users, where L is the reuse factor. The constraint C_2 assigns EH subcarriers to users. C_3 states the power constraint for AP with a maximum transmitted power allowance of $p_{\max}$. C_4 guarantees the QoS for each user. Finally, keeping in mind that subcarrier assignment variables are binary, C_5 and C_6 ensure that different subcarriers take their values from a binary set, that is, whether a given subcarrier is going to be selected to maximize the harvested energy. One can easily conclude that the optimization problem (6) is a non-convex mixed-integer nonlinear programming (MINLP) [11]. In general, it is impossible to find an optimal solution for a non-convex MINLP. However, in the next section, we adopt an approach to find a globally optimal and a suboptimal solution for this system.

III. Solution of the Optimization Problem

In the following, an optimal resource allocation algorithm based on the monotonic optimization method [12] is proposed for solving the non-convex problem in (6). A suboptimal solution is also provided which achieves close-to-optimum performance with lower complexity.

A. Optimal Solution

In this subsection, we propose a joint power allocation and subcarrier assignment algorithm that uses the monotonic approach to yield an optimal solution for the optimization problem in (6). The multiplication of two variables in the objective function of the problem in (6a), as well as the constraints, are the obstacles to designing an efficient resource allocation algorithm. Since the multiplications $a_{n,k}p_{n,k}$ and $b_{n,k}p_{n,k}$ in (6d) are non-convex, we define the product terms as $\tilde{p}_{n,k} = a_{n,k}p_{n,k}$ and $\tilde{q}_{n,k} = b_{n,k}p_{n,k}$. Therefore, the optimization problem in (6) can be recast in equivalent form as

$$\max_{\mathbf{a},\mathbf{b},\mathbf{p},\tilde{\mathbf{p}},\tilde{\mathbf{q}}} \ \mathrm{EH}(\tilde{\mathbf{q}}) \tag{7a}$$

$$s.t.\ C_3: \sum_{k\in\mathcal{K}} \sum_{n\in\mathcal{N}} \tilde{p}_{n,k} + \tilde{q}_{n,k} \leq p_{\max}, \tag{7b}$$

$$C_4: R_k(\tilde{\mathbf{p}}) \geq R_{\min}, \quad \forall k \in \mathcal{K}, \tag{7c}$$

$$C_7: \tilde{p}_{n,k}, \tilde{q}_{n,k} \geq 0, \quad \forall n \in \mathcal{N}_E,\ n \in \mathcal{N}_I,\ k \in \mathcal{K}, \tag{7d}$$

$$C_1, C_2, C_5, C_6, \tag{7e}$$

[1]The optimal value of the subcarrier sets for ID and EH operations is done based on [4] but is omitted here due to limited space limitations. Note that a portion of the spectrum is used for ID while the remaining portion is exploited for EH. This requires a demand for the use of two separate filters at receivers [10].

[2]It is assumed the AP broadcasts orthogonal preambles, pilot signals, in the DL to the users. Then, through a feedback channel, each user estimates the CSI and transfers this information back to the AP. Afterward, the corresponding AP listens to the sounding reference signals communicated by users and sends the CSI to the centralized controller for the resource allocation design.

where $\tilde{\mathbf{p}}$ and $\tilde{\mathbf{q}}$ are the collections of $\tilde{p}_{n,k}$'s and $\tilde{q}_{n,k}$'s, respectively. Furthermore, the objective function (7a) and the constraint (7c) are

$$\text{EH}(\tilde{\mathbf{q}}) = \sum_{k\in\mathcal{K}} \epsilon_k \bigg(\sum_{n\in\mathcal{N}_E} \tilde{q}_{n,k}|h_{n,k}|^2 + \sigma_{n,k}^2 \bigg), \tag{8}$$

$$R_k(\tilde{\mathbf{p}}) = \sum_{n\in\mathcal{N}_I} \log_2\left(1 + \frac{\tilde{p}_{n,k}|h_{n,k}|^2}{\sum_{i=k+1}^{K}\tilde{p}_{n,i}|h_{n,k}|^2 + \sigma_{n,k}^2}\right). \tag{9}$$

It can be observed that problem (7e) is not a monotonic optimization problem due to the non-monotonic constraint (7c). However, in order to find the hidden monotonicity, let us rewrite the constraint (7c) as $[f_k^+(\tilde{\mathbf{p}}) - f_k^-(\tilde{\mathbf{p}})] \geq R_{\min}$ where

$$f_k^+(\tilde{\mathbf{p}}) = \sum_{n\in\mathcal{N}_I}\log_2\Big(\sum_{i=k+1}^{K} \tilde{p}_{n,i}|h_{n,k}|^2 + \tilde{p}_{n,k}|h_{n,k}|^2 + \sigma_{n,k}^2 \Big), \tag{10}$$

$$f_k^-(\tilde{\mathbf{p}}) = \sum_{n\in\mathcal{N}_I} \log_2\Big(\sum_{i=k+1}^{K} \tilde{p}_{n,i}|h_{n,k}|^2 + \sigma_{n,k}^2 \Big). \tag{11}$$

Although the constraint (7c) is expressed as the difference of increasing functions, the problem is still not monotonic. Therefore, we rewrite the constraint (7c) as the difference of two increasing non-negative functions $f^+(\tilde{\mathbf{p}})$ and $f^-(\tilde{\mathbf{p}})$. In this regard, we define $f^+(\tilde{\mathbf{p}}) = \min_{k\in\mathcal{K}}[f_k^+(\tilde{\mathbf{p}}) + \sum_{j\neq k}^{K} f_j^-(\tilde{\mathbf{p}})]$ and $f^-(\tilde{\mathbf{p}}) = \sum_{j=1}^{K} f_j^-(\tilde{\mathbf{p}}) + R_{\min}$. As a result, (7c) would be transformed to $f^+(\tilde{\mathbf{p}}) - f^-(\tilde{\mathbf{p}}) \geq 0$. By introducing the auxiliary variable s, the optimization problem can then be restated as follows

$$\max_{\mathbf{a},\mathbf{b},\mathbf{p},\tilde{\mathbf{p}},\tilde{\mathbf{q}},s} \ \text{EH}(\tilde{\mathbf{q}}) \tag{12a}$$

$$s.t.\ C_1 - C_3, C_5 - C_7, \tag{12b}$$

$$C_8 : f^+(\tilde{\mathbf{p}}) + s \geq f^-(\boldsymbol{p}_{\max}), \tag{12c}$$

$$C_9 : f^-(\tilde{\mathbf{p}}) + s \leq f^-(\boldsymbol{p}_{\max}), \tag{12d}$$

$$C_{10} : 0 \leq s \leq f^-(\boldsymbol{p}_{\max}) - f^-(\mathbf{0}). \tag{12e}$$

As a consequence, the feasible set of problem (12) can be expressed as the intersection of the following two sets

$$\mathcal{G} = \Big\{ (s, \tilde{\mathbf{p}}, \tilde{\mathbf{q}}) : \tilde{\mathbf{p}} \preceq \boldsymbol{p}_{\max},\ C_1 - C_3,\ C_9,\ C_{10} \Big\}, \tag{13}$$

$$\mathcal{H} = \Big\{ (s, \tilde{\mathbf{p}}, \tilde{\mathbf{q}}) : \tilde{\mathbf{p}} \succeq \mathbf{0},\ C_7,\ C_8 \Big\}, \tag{14}$$

where $\mathcal{G}$ and $\mathcal{H}$ are normal and co-normal sets, respectively, in the hyper-rectangle [13]

$$\big[0, f^-(\tilde{\mathbf{p}}_{\max}) - f^-(\mathbf{0})\big] \times \big[0, \tilde{\mathbf{p}}_{\max}\big]. \tag{15}$$

Thus, problem (12) is a monotonic problem in a canonical form. This means it is possible to globally solve the monotonic optimization (12) by utilizing the outer polyblock approximation approach [12], [13]. The computational complexity of the monotonic approach, which depends heavily on the structure of $\mathcal{G}$, is too high but can serve as a benchmark. In the next subsection, we provide a suboptimal solution for striking a balance between complexity and performance gain.

B. Suboptimal Solution

In this subsection, we propose a low-complexity suboptimal scheme, which yields a locally optimal solution for the optimization problem in (6). We should remark that the multiplication of two variables in the objective function of the problem, as well as the constraints in (6) make the implementation of a computationally efficient resource allocation algorithm difficult. To manage this, we adopt the big-M formulation [14] to decouple the product terms in $\tilde{p}_{n,k} = a_{n,k}p_{n,k}$ and $\tilde{q}_{n,k} = b_{n,k}p_{n,k}$. Therefore, the following additional constraints are imposed as

$$C_7 : \tilde{p}_{n,k} \leq p_{\max} a_{n,k}, \quad \forall n \in \mathcal{N}_I,\ k \in \mathcal{K}, \tag{16}$$

$$C_8 : \tilde{q}_{n,k} \leq p_{\max} b_{n,k}, \quad \forall n \in \mathcal{N}_E,\ k \in \mathcal{K}, \tag{17}$$

$$C_9 : \tilde{p}_{n,k} + \tilde{q}_{n,k} \leq p_{\max}, \quad \forall n \in \mathcal{N},\ k \in \mathcal{K}, \tag{18}$$

$$C_{10} : \tilde{p}_{n,k} \geq p_{n,k} - (1 - a_{n,k})p_{\max}, \quad \forall n \in \mathcal{N}_I,\ k \in \mathcal{K}, \tag{19}$$

$$C_{11} : \tilde{q}_{n,k} \geq q_{n,k} - (1 - b_{n,k})p_{\max}, \quad \forall n \in \mathcal{N}_E,\ k \in \mathcal{K}, \tag{20}$$

$$C_{12} : \tilde{p}_{n,k} \geq 0, \quad \forall n \in \mathcal{N}_I,\ k \in \mathcal{K}, \tag{21}$$

$$C_{13} : \tilde{q}_{n,k} \geq 0, \quad \forall n \in \mathcal{N}_E,\ k \in \mathcal{K}. \tag{22}$$

The integer constraints C_5 and C_6 in optimization problem (6) are non-convex. For that reason, we rewrite these constraints in their equivalent form as

$$\dot{C}_5 : 0 \leq a_{n,k} \leq 1, \quad \forall n \in \mathcal{N}_I,\ k \in \mathcal{K}, \tag{23}$$

$$\ddot{C}_5 : \sum_{k\in\mathcal{K}} \sum_{n\in\mathcal{N}_I} a_{n,k} - (a_{n,k})^2 \leq 0, \tag{24}$$

$$\dot{C}_6 : 0 \leq b_{n,k} \leq 1, \quad \forall n \in \mathcal{N}_E,\ k \in \mathcal{K}, \tag{25}$$

$$\ddot{C}_6 : \sum_{k\in\mathcal{K}} \sum_{n\in\mathcal{N}_E} b_{n,k} - (b_{n,k})^2 \leq 0. \tag{26}$$

These transformations make integer optimization variables continuous with values between zero and one. The original problem in (6) can therefore be rewritten as

$$\max_{\mathbf{a},\mathbf{b},\mathbf{p},\tilde{\mathbf{p}},\tilde{\mathbf{q}}} \ \text{EH}(\tilde{\mathbf{q}}) \quad s.t.\ C_1 - C_4, \dot{C}_5, \ddot{C}_5, \dot{C}_6, \ddot{C}_6, C_7 - C_{13}. \tag{27}$$

Note that the optimization problem in (27) is a continuous optimization problem. However, we need to obtain integer solutions for $a_{n,k}$ and $b_{n,k}$. To this end, we add a penalty term to the objective function, and relax the integer variable to take any values from zero to one. Thus, the problem can be restated as follows

$$\max_{\mathbf{a},\mathbf{b},\mathbf{p},\tilde{\mathbf{p}},\tilde{\mathbf{q}}} L(\mathbf{a}, \mathbf{b}, \mathbf{p}, \tilde{\mathbf{p}}, \tilde{\mathbf{q}}, \boldsymbol{\lambda}) \quad s.t.\ C_1 - C_4, \dot{C}_5, \dot{C}_6, C_7 - C_{13}, \tag{28}$$

where $L(\mathbf{a}, \mathbf{b}, \mathbf{p}, \tilde{\mathbf{p}}, \tilde{\mathbf{q}}, \boldsymbol{\lambda})$ is the *abstract Lagrangian duality* [15] associated to (27) and is equal to

$$\text{EH}(\tilde{\mathbf{q}}) - \lambda_1\big(U(\mathbf{a}) - \mathcal{U}(\mathbf{a})\big) - \lambda_2\big(V(\mathbf{b}) - \mathcal{V}(\mathbf{b})\big), \tag{29}$$

where $U(\mathbf{a}) = \sum_k \sum_n a_{n,k}, \mathcal{U}(\mathbf{a}) = \sum_k \sum_n (a_{n,k})^2$, $V(\mathbf{b}) = \sum_k \sum_n b_{n,k}$, and $\mathcal{V}(\mathbf{b}) = \sum_k \sum_n (b_{n,k})^2$ are all convex functions. Moreover, λ_1 and λ_2, collected as $\boldsymbol{\lambda}$, are the penalty factors that penalize the objective function when $a_{n,k}$ and $b_{n,k}$ are not integer values. However, the optimization problem in (28) is still a non-convex optimization problem. To make a convex approximation for the objective function, we adopt Majorization Minimization (MM) algorithm [16] by constructing a surrogate function via a first-order Taylor approximation as

$$\mathcal{U}(\mathbf{a}) \simeq \mathcal{U}(\mathbf{a}^{t-1}) + \nabla_{\mathbf{a}}\mathcal{U}(\mathbf{a}^{t-1}).(\mathbf{a} - \mathbf{a}^{t-1}) \triangleq \tilde{\mathcal{U}}(\mathbf{a}), \tag{30}$$

$$\mathcal{V}(\mathbf{b}) \simeq \mathcal{V}(\mathbf{b}^{t-1}) + \nabla_{\mathbf{b}}\mathcal{V}(\mathbf{b}^{t-1}).(\mathbf{b} - \mathbf{b}^{t-1}) \triangleq \tilde{\mathcal{V}}(\mathbf{b}), \quad (31)$$

where t denotes the iteration number, $\mathbf{a}^{t-1}$ and $\mathbf{b}^{t-1}$ are the solutions of the problem at $(t-1)^{th}$ iteration, and $\nabla_\square$ represents the gradient with respect to $\square$. Approximations (30) and (31) satisfy the MM principles and are a tight upper bound of $\mathcal{U}(\mathbf{a})$ and $\mathcal{V}(\mathbf{b})$ [17]. As for the last step, we need to make a convex solution for the minimum data-rate because the co-channel interference exists in the rate function. To handle the non-convexity of the rate functions, we restate the rate function as $R_k(\tilde{\mathbf{p}}) = f_k^+(\tilde{\mathbf{p}}) - f_k^-(\tilde{\mathbf{p}})$, and similarly employ the MM approach via a first-order Taylor approximation as $f_k^-(\tilde{\mathbf{p}}) \simeq f_k^-(\tilde{\mathbf{p}}^{t-1}) + \nabla_{\tilde{\mathbf{p}}} f_k^-(\tilde{\mathbf{p}}^{t-1}).(\tilde{\mathbf{p}} - \tilde{\mathbf{p}}^{t-1}) \triangleq \tilde{f}_k^-(\tilde{\mathbf{p}})$. Consequently, the lower bound of $R_k(\tilde{\mathbf{p}})$ would be $\tilde{R}_k(\tilde{\mathbf{p}}) = f_k^+(\tilde{\mathbf{p}}) - \tilde{f}_k^-(\tilde{\mathbf{p}})$. So, using the MM approach and constructing a sequence of surrogate functions at the t^{th} iteration, we solve the following convex problem as follows

$$\max_{\mathbf{a},\mathbf{b},\mathbf{p},\tilde{\mathbf{p}},\tilde{\mathbf{q}}} \mathrm{EH}(\tilde{\mathbf{q}}) - \lambda_1\big(U(\mathbf{a}) - \tilde{\mathcal{U}}(\mathbf{a})\big) - \lambda_2\big(V(\mathbf{b}) - \tilde{\mathcal{V}}(\mathbf{b})\big)$$
$$s.t.\ \tilde{R}_k(\tilde{\mathbf{p}}) \geq R_{\min},\ \ \forall k \in \mathcal{K},\ \text{and}\ C_1 - C_3, \dot{C}_5, \dot{C}_6, C_7 - C_{13}. \quad (32)$$

It is worth mentioning that the optimization problem (32) is convex and can be solved efficiently via the interior point methods. The MM approach produces a sequence of improved feasible solutions, which will ultimately converge to a locally optimal solution $(\mathbf{a}^*, \mathbf{b}^*, \mathbf{p}^*, \tilde{\mathbf{p}}^*, \tilde{\mathbf{q}}^*)$ using standard convex program solvers such as CVX.

IV. Complexity Analysis

In this section, the computational complexity for the two solution approaches is analyzed. The computational complexity of the optimal solution, adopting a monotonic approach that uses the polyblock algorithm, depends on the dimensions of the problem. Let consider the dimension of the optimization problem to be D_1, the number of iterations in the overall polyblock algorithm for convergence D_2, and the number of iterations for the projection of each vertex D_3. Consequently, the complexity order of the monotonic approach is that of $\mathcal{O}(D_2(D_1 \times D_2 + D_3))$ [13]. In general, the global solution of a problem with a large number of variables can be only a benchmark for the low-complexity suboptimal approach. However, as the suboptimal approach shows, the joint optimization problem (32) involves KN variables and $5NK + N + K$ linear constraints. Thus, it can be concluded that the overall computational complexity of this optimization problem is $\mathcal{O}(NK)^2(5NK + N + K)$. This is asymptotically equal to $\mathcal{O}(NK)^3$, which is a polynomial time complexity [17].

V. Simulation Results

This section evaluates the performance gain of the proposed scheme through extensive simulations. We study a single-cell SWIPT-assisted MC-NOMA network with $K = 4$ randomly located DL users between the reference distance of 3 to 10 meters based on a uniform distribution [6]. We further assume a frequency-selective fading channel, where the central carrier frequency is set to 3 GHz with a 180 kHz bandwidth of each subcarrier. The number of subcarriers is $N = 16$, where the optimal set cardinality of subcarriers for ID and

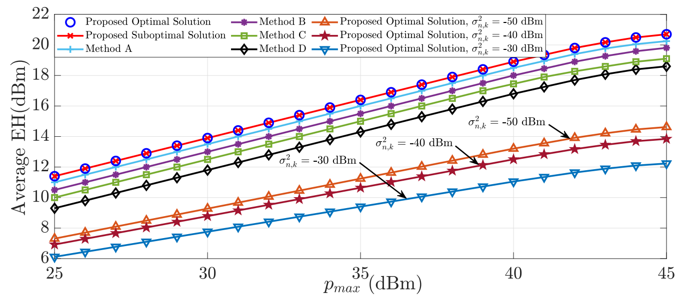

Fig. 1. Average harvested energy versus $p_{\max}$.

EH is evaluated based on [4]. The variance of the background noise at the receiver is equal to $\sigma^2_{n,k} = -120$ dBm throughout the simulations. Since a line-of-sight signal is expected in the received signal, the small-scale fading channel is modeled as Rician fading with Rician factor $J = 3$ dB. The 3GPP path loss model is also used with path loss exponent 2.8 [18]. The power conversion efficiency of all users is assumed to be the same and equal to $\epsilon_k = 0.3$. The target transmission rate is $R_{\min} = 1\ bps/Hz$, unless otherwise stated. Moreover, we conduct Monte Carlo simulations by generating random realizations of the channel gains to obtain the average EH of the network.

Fig. 1 shows the total harvested energy versus the maximum transmitted power $p_{\max}$. As can be observed, the average harvested energy grows monotonically as $p_{\max}$ increases. However, the slope of the curves starts to decline as the maximum transmit power increases to very high values. Besides, the harvested energy for the lower values of $p_{\max}$ is low compared to the higher values due to the inability of the AP to contribute to EH because it is forced to ensure QoS requirements. For the higher values of $p_{\max}$, the AP can thus help users harvest more energy since fewer subcarriers are assigned to ID and more to EH. Furthermore, Fig. 1 shows that the proposed suboptimal scheme closely approaches the optimal solution. This figure also shows that as the noise variance increases, the average harvested energy decreases. This is because more subcarriers with more power are needed to meet the QoS constraint (i.e., to be assigned to ID) once the noise variance significantly boosts the denominator of the data-rate function. For comparison, Fig. 1 also investigates the average EH of four methods. Method A investigates the proposed optimal solution based on the OFDMA scheme in which each subcarrier is assigned to at most one user, i.e., $L = 1$, and power allocation is optimized according to the resource allocation design. Method B studies the proposed method in [4], where subcarrier sets are determined based on the optimization problem for EH whereas the rest are assigned to ID with an imposed QoS requirement. Method C examines the proposed method in [5] in which each subcarrier set is divided into two subsets. Specifically, one subset is employed for EH, and the other for ID while considering a fixed PS. Method D is the proposed algorithm based on the MC-NOMA scheme, where the subcarrier is assigned randomly, and the power is optimized based on our proposed scheme.

Our proposed method clearly outperforms the other benchmark algorithms due to the joint optimization framework. This also shows that in the MC-NOMA scheme, more than one user can be assigned to an ID subcarrier. Hence the number

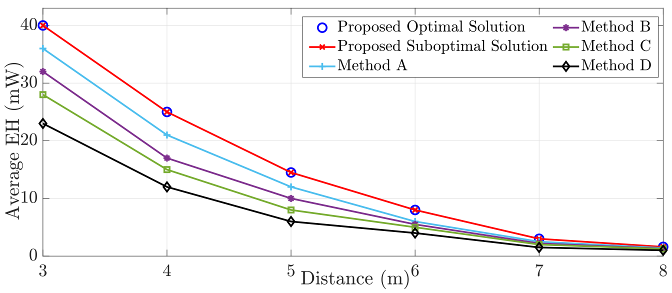

Fig. 2. Average harvested energy versus distance.

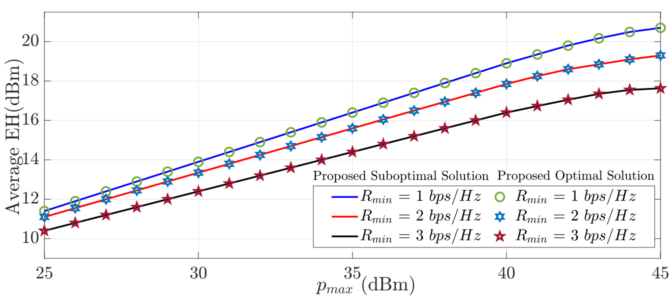

Fig. 3. Average harvested energy versus $p_{\max}$ for different minimum data-rate requirements.

of EH subcarriers increases in order to maximize the harvested energy. In fact, in the MC-NOMA scheme, due to the orthogonal assignment of the subcarriers, the spectrum resource would be underutilized, so more subcarriers are allocated for EH than in the OFDMA scheme. It can be noted that Method A performs better in comparison to Methods B and C because the subcarrier assignment and power allocation were designed together. Method B is also better than method C since the power allocation and subcarrier assignment of Method B is based on a heuristic algorithm, while in method C, each subcarrier is divided into two parts with fixed PS ratios. In particular, in method C, each subcarrier uses the same PS ratios for ID and EH, which results in a degradation of the performance gain. It should be noted that Method D performs worse than all the others since the subcarrier is assigned randomly, causing an increase in interference level. More subcarriers need to be assigned to users to meet the data-rate requirement, which reduces the amount of harvested energy.

Fig. 2 depicts the harvested energy versus the distance between transmitter and receiver. It is observed that as the distance increases, the harvested energy decreases. This is because increasing the distance weakens the channel strength, so more subcarriers with more power need to be assigned to meet the minimum required data-rate. Hence, less energy is harvested by users. Once the minimum data-rate is met, the rest of the subcarriers are used for EH. It should be noted that the Methods A-D are the same as those defined earlier.

Fig. 3 illustrates the harvested energy versus $p_{\max}$ for different data-rate requirements. It can be seen that less energy is harvested by increasing $R_{\min}$. The reason for this is quite evident. Considering a fixed $p_{\max}$ at the AP, more subcarriers with more power would need to be assigned to each user when the minimum data-rate requirement becomes larger. This means fewer subcarriers will be assigned for EH and less power will be allocated, which results in less energy being harvested by users.

VI. Conclusion

This letter investigates the problem of subcarrier allocation and power control for the SWIPT-assisted MC-NOMA system to maximize EH while considering the minimum data-rate required for each user. In the proposed algorithm, the receivers did not need a splitter to perform appropriately, which means that no TS or PS was utilized at the receiver. The problem studied was mixed-integer non-convex, which is generally intractable. To circumvent the difficulty and obtain a globally optimal solution, the monotonic optimization approach was proposed. A low-complexity suboptimal scheme, which achieves a close-to-optimal solution, was also studied. Simulation results demonstrated that the designed algorithms performed better than other algorithms described in the literature. Our future work concerns the extension of the presented system model to multi-cell and multi-antenna scenarios.

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