A Heuristic for Mixed Integer and Nonlinear Programming in a WPCN-NOMA Scenario with Imperfect SIC

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Abstract— **This paper presents a wireless powered communication network (WPCN) that features a power beacon (PB) with multiple antennas for power transfer to single-antenna terminals employing energy harvesting (EH). These terminals use non-orthogonal multiple access (NOMA) to transmit their data to a single-antenna access point (AP), in an imperfect successive interference cancellation (SIC) scenario. The objective of this work is to propose a heuristic method that maximizes the throughput of the terminals subject to a quality-of-service (QoS) conditions. To this end, comparisons of the heuristic method with branch-and-bound (BB) through simulations are carried out. The results demonstrated that proposed method yields better results in terms of throughput and energy efficiency compared to the BB algorithm, by optimizing the power for each terminal.**

Keywords— **energy harvesting (EH), imperfect successive interference cancellation (SIC), non-orthogonal multiple access (NOMA), wireless powered communication network (WPCN), wireless power transfer (WPT).**

I. INTRODUCTION

In recent years, wireless communications have experienced advancements in connectivity that will enable a future where most electronic devices will be connected to the network. The deployment of fifth generation (5G) networks has been a primary catalyst for the phenomenon of hyperconnectivity, in such a manner that by the fourth quarter of 2023 it had reached approximately 1.6 billion mobile subscriptions [1]. In this conducive environment, the Internet of Things gains ground, particularly one of its branches, the wireless sensor network (WSN). This network consists of low-power sensors that sporadically monitor environmental conditions. Thus, the sensors are typically in sleep mode [2].

These sensors are specific cases of Internet of Things devices adapted for ambient energy. According to [3], these devices, which harvest energy through radio waves, either lack a battery or have a low-capacity battery, such as a capacitor. In this context, wireless powered communication network (WPCN) is a suitable network because the time frame is split into two phases. In the phase 1, a power beacon (PB), i.e., an access point (AP) aimed at power transfer, broadcasts an energy signal where devices perform energy harvesting (EH). In phase 2, the devices send their information to another AP using a multiple access technique. As it is crucial to increase bandwidth and decrease latency in IoT systems [4], non-orthogonal multiple access (NOMA) is considered because as reported in [5], NOMA outperforms other orthogonal multiple access schemes in terms of these criteria. Also, a PB with multiple antennas and beamforming is considered to increase spatial streams, improve channel efficiency, increase signal strength, and reduce interference [4]. In this work, these devices are referred to as terminals.

The scheme studied by [6] considered a single-antenna co-located PB and AP, and multiple single-antenna terminals. The work compared multiple access techniques such as NOMA and time division multiple access (TDMA) in order to maximize the total system data throughput, i.e., the sum of each terminal data rate. In a NOMA configuration, it was assumed that the AP perfectly decodes the terminals' data by using successive interference cancellation (SIC). The work focused on maximizing the total system rate without concern for the discrepancy between terminal data rates. It was shown that NOMA improves fairness compared to methods employing conventional orthogonal schemes.

The study presented by [7] considered a WPCN network with a multiple antenna co-located PB and AP and multiple single-antenna terminals. The work compared TDMA and space division multiple access (SDMA) and their respective impacts on the energy efficiency of the network. To this end, several optimization problems were addressed, with the objective of maximizing the network's energy efficiency. It was demonstrated that when there is no data rate restriction for terminals, TDMA outperforms SDMA.

In [8], a WPCN-NOMA system model with a single-antenna co-located PB and AP and multiple single-antenna terminals is investigated in the presence of imperfections in the SIC process. The work evaluates the impact of the SIC decoding order and the time duration where the AP transfers power to the terminals in a configuration without quality of service (QoS) restrictions imposed on the terminals. Consequently, a suboptimal solution based on analytical insights was proposed to enhance the system throughput. Other works, such as [9] and [10], utilize intelligent reflecting surface (IRS) and both employ a configuration similar to that presented in [8], with the exception that [10] considers the use of co-located PBs and APs that are unmanned aerial vehicles (UAVs). The objective of [9] is to maximize the system throughput with QoS restrictions on the terminals by employing a genetic algorithm

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(GA). In contrast, the objective of [10] is to maximize the minimum throughput by employing a semi-definite relaxation (SDR).

This paper encompasses a broader range of topics than previous studies, employing a WPCN-NOMA network with separated PB and AP, where the first has multiple antennas, while the second has a single antenna and presents imperfection in the SIC process. Furthermore, in our system, we impose QoS restrictions on our single-antenna terminals. The objective is to maximize the system throughput. In order to achieve this objective, we propose a heuristic method that optimizes: the time duration for phase 1, the SIC decoding order and the power allocated for each terminal.

The remainder of this work is organised as follows. First, the system model is presented in Section II. Then, we formulate our optimization problem in Section III. Subsequently, we propose the heuristic method in Section IV. Then, we compare the performance of the proposed method with Branch-and-Bound (BB) in Section V. Finally, we present our conclusions in Section VI.

Notation: Scalars, vectors and matrices are represented as a, $\mathbf{a}$, $\mathbf{A}$. The following operations: $(.)^T$, $(.)^H$, $\|.\|$, $\mathbb{E}(.)$ and $|.|$ stand for transpose, conjugate transpose, l^2 norm, expectation and the modulus, respectively.

II. SYSTEM MODEL

We assume a WPCN composed of a multiple-antennas PB in the center of a circular area where single-antenna terminals are uniformly distributed. At the corner of the circular area there is a single-antenna AP. We assume that the time frame is split in multiple slots, where the time frame length is lower than the channel coherence interval. A WPCN network using a time division duplex (TDD) scheme is adopted with two phases: phase 1, where the energy is transfer from the PB to the terminals, and phase 2, where the data is transmitted from the terminals to the AP. Thus, in a frame, n^{e} slots are used for phase 1, and n^{i} slots are used for phase 2, such that the sum of n^{e} and n^{i} results in the total number of slots in a frame, N. Figure 1 illustrates the described scenario.

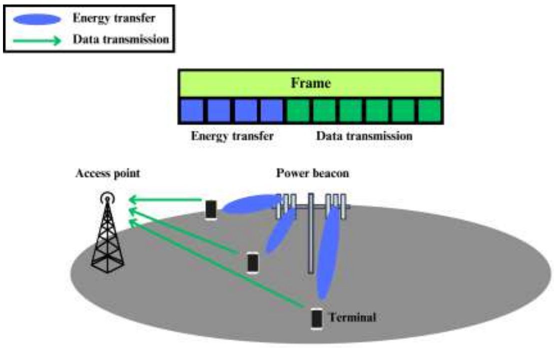

Fig. 1. System model illustration.

Before starting the phase 1 modeling, we define some important variables for the model. Let terminal $j \in \mathcal{J} = \{1, 2, \cdots, J\}$, where J is the number of terminals, M is the number of antenna elements in the PB. The slots $n^{\mathrm{e}}, n^{\mathrm{i}} \in \mathcal{N} = \{1, \cdots, N-1\}$, such that $n^{\mathrm{e}} + n^{\mathrm{i}} = N$. This shows that the two phases will always use at least one slot. We consider the duration of a slot to be T^{s}, so the time interval of a frame is $T^{\mathrm{f}} = NT^{\mathrm{s}}$.

Another consideration is that all sub-channels in both phases are modeled by a Rayleigh distribution whose random variables are independent and identically distributed [7][11]. Thus, the frequency response of the channel in phase 1 between antenna m of the PB and terminal j is defined as

$$h_{j,m} = \sqrt{1/2} \cdot (a_{j,m} + jb_{j,m}) \cdot \sqrt{10^{-3}/d^{\phi}_{PB-j}}, \quad (1)$$

where $a_{j,m}, b_{j,m} \sim \mathcal{N}(0,1)$, d_{PB-j} is the distance between the PB and terminal j, and ϕ is the path loss coefficient. Thus, the subchannel $h_{j,m}$ is an element of the jth row and mth column of the channel matrix $\mathbf{H} \in \mathcal{C}^{J\times M}$. We define $\mathbf{h}_j \in \mathcal{C}^{1\times M}$ as the row vector of the jth row of matrix $\mathbf{H}$, thus $\mathbf{H} = [\mathbf{h}_1^T, \cdots, \mathbf{h}_J^T]^T$. Let y_j be the signal arriving at terminal j, the jth component of vector $\mathbf{y} \in \mathcal{C}^{J\times 1}$. We consider the precoding matrix $\mathbf{W} \in \mathcal{C}^{M\times J}$ as the matched filter solution, that is, $\mathbf{W} = [\mathbf{h}_1^H/\|\mathbf{h}_1^H\|, \cdots, \mathbf{h}_J^H/\|\mathbf{h}_J^H\|]$. Thus, the kth column vector of the precoding matrix $\mathbf{W}$ is $\mathbf{w}_k = \mathbf{h}_k^H/\|\mathbf{h}_k^H\|$. Thus, the signal vector $\mathbf{y}$ is given as

$$\mathbf{y} = \mathbf{HWx} + \mathbf{n}, \quad (2)$$

where $\mathbf{n} \sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I})$ is the additive white gaussian noise (AWGN) with noise power, σ^2, and $\mathbf{x} = s[\sqrt{\alpha_1 P}, \cdots, \sqrt{\alpha_J P}]^T \in \mathcal{R}^{J\times 1}$, where s is a baseband signal and $\alpha_j \in \mathbf{R}$ is the power allocation of the system for terminal j, satisfying the constraints $\sum_{j=1}^{J} \alpha_j = 1$ and $0 \leq \alpha_j \leq 1, \forall j \in \mathcal{J}$. Moreover, P is the total power that the PB uses for phase 1. We define the power weight vector as $\boldsymbol{\alpha} = [\alpha_1, \cdots, \alpha_J]^T \in \mathcal{R}^{J\times 1}$. Therefore, the power transferred to terminal j is the element in the jth row and jth column of the covariance matrix $\mathbb{E}(\mathbf{y}\mathbf{y}^H)$ which is given by

$$\bar{P}j = \sum_{k=1}^{J} \alpha_k P \left| \frac{\mathbf{h}_j \mathbf{h}_k^H}{\|\mathbf{h}_k^H\|} \right|^2 + \sigma^2. \quad (3)$$

Thus, the useful energy for terminal j during phase 1 is given by $E_{j,n^{\mathrm{e}}} = \eta \cdot n^{\mathrm{e}} \cdot T^{\mathrm{s}} \cdot \bar{P}_j$, where $0 \leq \eta \leq 1$ represents the energy conversion efficiency performed by the terminal.

We assume that all energy stored in phase 1 of each terminal is fully utilized in phase 2. Thus, the data transmission power during phase 2 for terminal j is $P_{j,n^{\mathrm{e}}} = E_{j,n^{\mathrm{e}}}/\left((N - n^{\mathrm{e}})T^{\mathrm{s}}\right)$.

The channel modeling between terminal j and the AP in phase 2 follows the Rayleigh fading model. Thus, the channel gain in phase 2 for each terminal j is given by $g_j = c_j \cdot 10^{-3}/d^{\phi}_{j-AP}$, where c_j has an exponential distribution with unit mean and d_{j-AP} is the distance between terminal j and the AP.

During phase 2, terminals transmit their data to the AP using NOMA. To decode the data, the AP employs SIC that defines a decoding order. Regarding the various permutation orders, we define $\mathcal{P}$ as the ordered set of all permutations of the J terminals. The pth element of $\mathcal{P}$ is ρ_p, which is the pth permutation of the terminals. Additionally, ρ_p^i is the terminal in position i of the pth permutation of $\mathcal{P}$. For example, suppose there are three terminals identified by the letters S, T, and U. Then, the set of permutations $\mathcal{P}$ is $\{(S,T,U),(S,U,T),(T,S,U),(T,U,S),(U,S,T),(U,T,S)\}$. Thus, the terminal in the 2nd position of the 3rd permutation is $\rho_3^2 = S$.

Thus, we define in Equation (4) $r_{\rho_p^i, n^{\mathrm{e}}, p}(\epsilon)$ as the data rate for the terminal in position i of permutation p when using n^{e} slots [8], where B is the considered bandwidth, $\epsilon \in [0,1]$ is the fractional error factor (FEF) modeling the interference of signals imperfectly canceled by the AP.

III. PROBLEM FORMULATION

We formulate the problem with the objective of maximizing the sum of the data rates of each terminal during phase 2 while satisfying the QoS constraints, which in this work are defined as the data rates, R_j, that lower bound the data rates of each terminal j. We define $\boldsymbol{\alpha}$ as a continuous vector optimization variable where its component j indicates the transmission power from the PB to terminal j during phase 1, and $x_{n^{\mathrm{e}},p}$ as a binary optimization variable that is 1 for the optimal $n^{\mathrm{e}*}$ and p^* which solve the optimization problem and 0 otherwise. The optimization problem is modeled as

$$\max_{x_{n^{\mathrm{e}},p},\boldsymbol{\alpha}} \left\{ \sum_{n^{\mathrm{e}}=1}^{N-1} \sum_{p=1}^{P} \sum_{j=1}^{J} \left(r_{j,n^{\mathrm{e}},p}(\epsilon) \cdot x_{n^{\mathrm{e}},p} \right) \right\}, \tag{5a}$$

$$\text{s.t.} \sum_{n^{\mathrm{e}}=1}^{N-1} \sum_{p=1}^{P} \left(r_{j,n^{\mathrm{e}},p}(\epsilon) \cdot x_{n^{\mathrm{e}},p} \right) \geq R_j, \ \forall j \in \mathcal{J}, \tag{5b}$$

$$\sum_{n^{\mathrm{e}}=1}^{N-1} \sum_{p=1}^{P} x_{n^{\mathrm{e}},p} = 1, \tag{5c}$$

$$\mathbf{1}^T \boldsymbol{\alpha} = 1, \tag{5d}$$

$$\mathbf{0} \preceq \boldsymbol{\alpha} \preceq \mathbf{1}. \tag{5e}$$

The objective function presented in Equation (5a) is the system capacity at the AP at the end of phase 2. The constraints presented in Equation (5b) model the QoS constraints. Constraint (5c) models the uniqueness of the solution for the binary optimization variable, $x_{n^{\mathrm{e}},p}$. Constraint (5d) indicates that the sum of the transmitted powers during phase 1 is fully utilized. Constraint (5e) indicates that the power to be transmitted to each terminal in phase 1 is confined to the interval $[0,1]$. Since the problem includes both binary and continuous optimization variables, it falls into the category of mixed integer nonlinear programming (MINLP). Therefore, it is a problem of difficult resolution, as analyzing only the binary optimization variable, there are $(N-1) \cdot J!$ possible solutions.

IV. PROPOSED LOW COMPLEXITY HEURISTIC METHOD

To solve the problem (5), we have devised a heuristic method that provides an approximate solution. This approximation is based on three hypotheses:

- The problem (5) can be decomposed into two subproblems: one integer linear problem (ILP) subproblem with optimization variable $x_{n^{\mathrm{e}},p}$, and one nonlinear subproblem with optimization variable $\boldsymbol{\alpha}$.
- The ILP subproblem can be solved based on the power of the data received at the AP from each of the J terminals.
- The nonlinear subproblem is convex in $\boldsymbol{\alpha}$.

In the ILP subproblem, we consider the continuous optimization variable $\boldsymbol{\alpha}$ to be equal to the vector $[1/J, \cdots, 1/J]^T \in \mathcal{R}^{J \times 1}$. Thus, this subproblem is modeled as follows:

$$\max_{x_{n^{\mathrm{e}},p}} \left\{ \sum_{n^{\mathrm{e}}=1}^{N-1} \sum_{p=1}^{P} \sum_{j=1}^{J} \left(r_{j,n^{\mathrm{e}},p}(\epsilon) \cdot x_{n^{\mathrm{e}},p} \right) \right\}, \tag{6a}$$

$$\text{s.t.} \sum_{n^{\mathrm{e}}=1}^{N-1} \sum_{p=1}^{P} \left(r_{j,n^{\mathrm{e}},p}(\epsilon) \cdot x_{n^{\mathrm{e}},p} \right) \geq R_j, \ \forall j \in \mathcal{J}, \tag{6b}$$

$$\sum_{n^{\mathrm{e}}=1}^{N-1} \sum_{p=1}^{P} x_{n^{\mathrm{e}},p} = 1. \tag{6c}$$

Once a suboptimal solution $\widetilde{n^{\mathrm{e}}}$ and $\widetilde{p}$ forming the solution $x_{\widetilde{n^{\mathrm{e}}},\widetilde{p}}$ for the subproblem (6) is found, the following convex subproblem is solved:

$$\max_{\boldsymbol{\alpha}} \left\{ R_T(\boldsymbol{\alpha_0}) + \gamma \boldsymbol{\nabla}^T \left(R_T(\boldsymbol{\alpha_0}) \right) (\boldsymbol{\alpha} - \boldsymbol{\alpha_0}) \right\}, \tag{7a}$$

$$\text{s.t.} \ \mathbf{C}\boldsymbol{\alpha} \preceq \mathbf{d}, \tag{7b}$$

$$\mathbf{1}^T \boldsymbol{\alpha} = 1, \tag{7c}$$

$$\mathbf{0} \preceq \boldsymbol{\alpha} \preceq \mathbf{1}, \tag{7d}$$

where γ is a tune parameter, $R_T(\boldsymbol{\alpha_0})$ is the system capacity for $\boldsymbol{\alpha_0}$ and is obtained when summing the data rates of the J terminals for $\widetilde{n^{\mathrm{e}}}$ and $\widetilde{p}$. Thus, the objective function (7a) is the tangent plane of the system capacity at point $\boldsymbol{\alpha_0}$. Constraint (7b), forming a half-space, is obtained when simplifying the QoS inequalities $r_{j,\widetilde{n^{\mathrm{e}}},\widetilde{p}} \geq R_j$. The constraints related to the variable $\boldsymbol{\alpha}$ from problem (6) are maintained. Note that problem (7) is convex since the objective function is affine and the constraints form a polyhedron. To solve problem (6), we propose a heuristic method with the following assumptions: the AP has channel state information (CSI) of the channels for phases 1 and 2, $\alpha_j = 1/J, \forall j \in \mathcal{J}$, and the FEF, ϵ, is known. The heuristic method starts with the idea that the order of terminals performed by the SIC process can be found by arranging in descending order the powers of the messages from terminals arriving at the AP, $g_j \bar{P}_j$. Although we do not know the power of each message, we know that the power of each message depends only on the CSI, as can be observed in the following equation.

$$g_j \bar{P}_j = g_j \sum_{k=1}^{J} \alpha_k P \left| \frac{\mathbf{h}_j \mathbf{h}_k^H}{\|\mathbf{h}_k^H\|} \right|^2,$$

$$g_j \bar{P}_j \propto \left(d_j = g_j \sum_{k=1}^{J} \left| \frac{\mathbf{h}_j \mathbf{h}_k^H}{\|\mathbf{h}_k^H\|} \right|^2 \right). \tag{8}$$

Note that the constant P and the hypothesis $\alpha_k = 1/J$ do not affect the proportionality of Equation (8). Once the permutation $\widetilde{p}$ is found, we vary n^{e} in Equation (4) and choose the n^{e} that yields the highest capacity, i.e., the highest sum of $r_{j,n^{\mathrm{e}},\widetilde{p}}$ while respecting the QoS constraints. In this way, Algorithm 1 presents the pseudo-code of the proposed heuristic method.

With $\widetilde{p}$ and $\widetilde{n^{\mathrm{e}}}$ found, the complex problem of Equation (7) can be solved for the optimization variable $\boldsymbol{\alpha}$ using interior point methods found in various optimization packages.

$$r_{\rho_p^i,n^{\mathrm{e}},p}\left(\epsilon\right)=\frac{B\cdot n^{\mathrm{i}}}{N}\log_2\left(1+\left(P_{\rho_p^i,n^{\mathrm{e}}}\cdot g_{\rho_p^i}\right)\Bigg/\left(\underbrace{\epsilon\sum_{k\leq i-1}\left(P_{\rho_p^k,n^{\mathrm{e}}}\cdot g_{\rho_p^k}\right)}_{\text{Interferences due to imperfect SIC}}+\sum_{k\geq i+1}\left(P_{\rho_p^k,n^{\mathrm{e}}}\cdot g_{\rho_p^k}\right)+\sigma^2\right)\right) \tag{4}$$

Algorithm 1: Heuristic method for the problems in Equations (6) and (7).

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Data: $K$, $\mathbf{h}_j$, $\mathbf{g}_j$, $\boldsymbol{\alpha}_0 = (1/J)\mathbf{1}$, $P$, $\epsilon$, $\forall j \in \mathcal{J}$
Result: $\widetilde{p}$, $n^{\mathrm{e}}$, $\widetilde{\boldsymbol{\alpha}}$
For all $j \in \mathcal{J}$, calculate the expression in Equation (8) and store the value in the ordered set $\mathcal{D}$;
Sort in descending order the elements of $\mathcal{D}$;
To construct $\widetilde{p}$, relate the elements of D to the position of the terminals;
while $n^e, i \in \mathcal{N}$ do
    $S_i = \sum_{j=1}^{J} r_{j,n^{\mathrm{e}},\widetilde{p}}$;
    if $n^e$ satisfies Equation (6b) then
        Store $S_i$ in $\mathcal{S}$ (The set that stores the capacity of the system);
    else
        Store 0 in $\mathcal{S}$;
Set $\widetilde{n^{\mathrm{e}}}$ as the position in $\mathcal{S}$ which has the biggest value;
Set k equal to zero;
do
    Solve for $\widetilde{\boldsymbol{\alpha}}$ the problem in Equation (7). Set $\boldsymbol{\alpha}_0 := \widetilde{\boldsymbol{\alpha}}$;
    Set $k := k + 1$;
until convergence or $k = K$;
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V. PERFORMANCE ANALYSIS

The system described in Section II has 5 terminals distributed uniformly within a circular cell with a radius of 10 m, where the AP is located 8 m from its center. Additionally, the minimum distance between the terminals and both the AP and the PB is 1 m. The PB, which can have 1, 8, or 256 antennas, transmits at a power of 10 W. The channel bandwidth is 1 MHz [8]. The frame has 20 slots, the energy harvesting efficiency is 0.5, the noise power is -104 dBm and the pathloss exponent is equal to 3. The fractional error factors analyzed are $\{0, 10^{-4}, 10^{-3}, 10^{-2}, 2.10^{-2}, 3.10^{-2}, 4.10^{-2}, 5.10^{-2}\}$, and the required rates are $\{0, 100, 200, 300, 400, 500\}$ kbps. To ensure statistical reliability, 1000 Monte Carlo realizations are conducted.

In the simulations, we compare the results of the combinatorial problem (6) using the BB algorithm with the results of the approximation performed on the mixed problem (5), solved by our method. These solutions are designated as equal power allocation and branch-and-bound (EPA-BB) and adaptive power allocation and heuristic (APA-H), respectively. To assess the relative merits of the two algorithms, we analyzed several metrics, including system throughput, i.e., the total data rate of the terminals at the conclusion of phase 2 and is a key metric for determining which method optimizes the objective function (6a) the most. Another indicator is the average number of slots dedicated to phase 1, n^{e}, providing insight into the relative energy efficiency of the two algorithms. Finally, we considered the computational complexity to compare the BB algorithm with the heuristic method in terms of their search space.

Firstly, we examine the throughput as a function of the FEF for a requested rate of 300 kbps in Fig. 2 and 3. The curves for both configurations decline rapidly as the interference increases due to greater FEF. However, the APA-H configuration outperforms the EPA-BB configuration, especially with multiple antennas in the PB, enhancing diversity. When the FEF is zero, the greatest gains are observed, as sorting in descending order is highly effective, as demonstrated in [12].

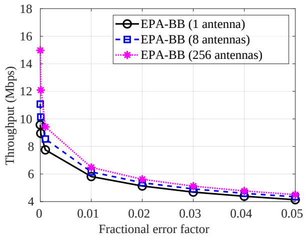

Fig. 2. Throughput versus FEF (BB).

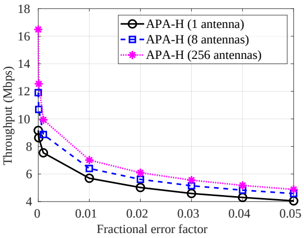

Fig. 3. Throughput versus FEF (Heuristic).

Figs. 4 and 5 show the throughput as a function of the requested data rate for a fixed FEF equal to 0.01. We note that for a null requested data rate, the EPA-BB generates a higher throughput. One reason for this is that the null requested rate imposes a stricter constraint (7b) because the vector $\mathbf{d}$ becomes null. However, as the requested rate increases, we observe that the APA-H configuration generates higher throughput for more than one antenna.

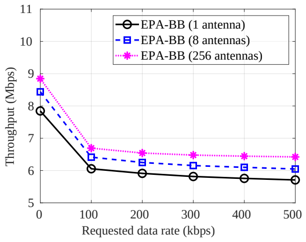

Fig. 4. Throughput versus requested data rate (BB).

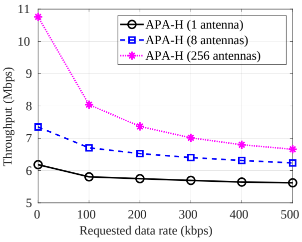

Fig. 5. Throughput versus requested data rate (Heuristic).

In Figs. 6 and 7, we present the relationship between the average number of slots for phase 1 and the requested data rates for a null FEF and for the EPA-BB and APA-H configurations. For both figures, we note that n^{e} decreases when we increase the number of antennas. One explanation for this is that increasing the number of antennas enhances the system's diversity, meaning more copies of the transmitted signal reach the terminals, thereby increasing the received power at each terminal. Consequently, there is a reduction in the number of slots used for phase 1, because more power reaches the terminals due to the number of antennas at the PB. In Fig. 7, we observe a reduction in the amount of n^{e} compared to Fig. 6. This indicates that adaptive power allocation for the terminals increases the energy efficiency of the PB.

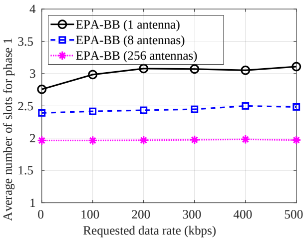

Fig. 6. Average n^{e} versus requested data rate (BB).

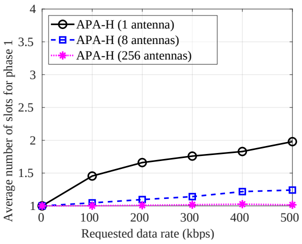

Fig. 7. Average n^{e} versus requested data rate (Heuristic).

Finally, with regard to computational complexity, the most computationally demanding scenario for the BB method is the exhaustive search case, as demonstrated in [13]. For the heuristic method, the most unfavourable scenario occurs when it is necessary to examine all possible values of n^{e} during the K iterations to solve the linear problem 7 using the simplex method, which has a worst-case complexity of 2^d where d is the number of variables, as stated in [14]. The worst-case scenario for both methods is presented in Table I.

TABLE I

ALGORITHM COMPUTATIONAL COMPLEXITY.

`Algorithm`	`Computational complexity`
`EPA-BB`	$\mathcal{O}\left((N-1)J!\right)$
`APA-H`	$\mathcal{O}\left(K(N-1)2^J\right)$

To illustrate, if we consider seven terminals, $N = 20$, and convergence occurring in $K = 20$ iterations, the APA-H heuristic has a computational complexity that is 49.21% lower than that of the EPA-BB algorithm.

VI. CONCLUSIONS

In this article, we present a scenario involving EH in a WPCN-NOMA network. The evaluated scenario is composed by a multiple-antennas PB, serving multiple terminals employing EH in phase 1 and an AP performing NOMA with imperfect SIC in phase 2. Thus, we propose a heuristic method that maximizes data throughput subject to QoS constraints for all terminals through adaptive power allocation. The simulations results indicated that, for multiple antennas in the PB, the power allocation performed by the heuristic method generated higher throughput than the BB method, which did not perform any power allocation. Furthermore, it was observed that the proposed heuristic method increase energy efficiency while reduces computational complexity when compared to the BB method.

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