QoS Guarantees in NOMA-based Wireless Powered Mobile Communications

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***Abstract*— A Non-Orthogonal Multiple Access (NOMA)-based Wireless Powered Communication Network (WPCN) system is studied in this work where, at each time frame, an access point firstly performs Wireless Power Transfer (WPT) to energize the battery of mobile terminals (phase 1) and then, receives information from terminals in uplink by employing NOMA (phase 2). We formulate the total data rate maximization problem with Quality of Service (QoS) guarantees where the Successive Interference Cancellation (SIC) decoding order and phase 1/phase 2 time duration are optimized. Our main contributions are the assumption of more realistic aspects in the system modeling compared to prior art as well as the proposal of optimum and heuristic solutions to the aforementioned problem. According to our simulation results, one of our proposed heuristic presents quasi-optimum performance at the cost of a lower increase in computational complexity.**

***Keywords*— Energy Harvesting, Non-Orthogonal Multiple Access, Successive Interference Cancellation, Quality of Service.**

I. Introduction

Wireless communications area is one of the top fastest growing industries nowadays. Fifth Generation (5G) commercial deployment is ramping up worldwide while the first efforts to propose the new Sixth Generation (6G) networks are already taking place. The evolution of wireless networks is important in order to cope with the growing number of mobile subscriptions and data traffic. According to Ericsson Mobility Report [1], there will be 8.9 billion mobile subscriptions in 2025 (not including Internet of Things (IoT) devices), out of which around 90 percent will be for mobile broadband. For cellular IoT and short-range IoT, the estimation is that there will be 5 billion and 19.5 billion connections in 2025, respectively. When data traffic is regarded, Ericsson projects that global mobile traffic will reach 160 Exabytes per month in 2025 which represents a growth by a factor of 4.

Motivated by those prospects, wireless networks must increase their spectral and energy efficiencies in current and future generations in order to cope with those challenges. In order to achieve these objectives, multiple solutions/technologies are already present in 5G, e.g., massive Multiple Input Multiple Output (MIMO) and ultra-dense deployment, whereas others such as such as Energy Harvesting (EH) and Non-Orthogonal Multiple Access (NOMA) are promising candidates to the next wireless standards .

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EH is a subarea of energy efficiency that represents a new paradigm on how mobile devices are energized. With EH, network nodes are able to collect energy from natural sources or produced by man-made activities. Specifically, with Wireless Power Transfer (WPT), transceivers are able to recharge their batteries by harvesting energy from electromagnetic waves. In Wireless Powered Communication Network (WPCN), battery of mobile nodes can be replenished by employing the WPT technique.

Multiple access technologies are at the core of the solutions to increase spectral efficiency in wireless networks. NOMA is a multiple access technology that is able to reuse the same time-frequency resource with multiple connections. In power-domain NOMA, multiple symbols are transmitted at the same time with different power levels; the so called superposition coding. At the receiver, Successive Interference Cancellation (SIC) is employed where the interference is sequentially cancelled depending on the decoding order.

In this article, we study Radio Resource Allocation (RRA) strategies applied to modern wireless network deployment that combines both NOMA and WPCN technologies. RRA is an important functionality in wireless networks that manages scarce radio resources that include power, frequency channels, among others. The remaining of the article is organized as follows. In Section II we present a literature review where related articles are discussed and our main contributions are presented. The system model and main assumptions of the studied scenario are shown in Section III. In Section IV we formulate the optimization problem and discuss a method to obtain the optimal solution. Low-complexity solutions are presented in Section V. Finally, a performance evaluation of the proposed solutions and main conclusions are presented in Sections VI and VII, respectively.

II. Literature Review

As previously mentioned, in this article we consider WPCN where the time frame is divided into two phases: phase 1, where the access point sends power to terminals through WPT; and phase 2, where the terminals use the power received in phase 1 and transmit information to the access point. The interested reader can see [2] and [3] for deep surveys on NOMA and EH.

In [4] the authors considered the optimization of harvesting interval (phase 1 length) and power allocation in uplink. Three optimization objectives were studied: max–min, proportional, and harmonic fairness. The original non-convex problems were converted to convex ones and solved by efficient methods.

However, the authors assumed fixed decoding order in SIC which degrades the system performance and Quality of Service (QoS) as some users may experience the interference levels differently.

In [5], among other contributions, the authors studied the problem of maximizing the total system data rate in uplink with fixed SIC decoding order. In this case, only the phase 1 time length is optimized (harvesting time interval). The authors also consider a different flavour of NOMA that employs the principle of time-sharing where the order of decoding for the terminals is changed for specific fractions of phase time length. In this problem, besides optimizing phase 1 time length, the authors also optimizes the time-sharing for SIC decoding assuming the terminals have the same data rate requirement in uplink (homogeneous data rate requirement). Note that in time-sharing NOMA, multiple time-sharing lengths and SIC decoding orders should be reported to the terminals within a single frame. This leads to a high signaling and computational complexity burden.

Fairness is also the main objective in [6], [7]. In [6] the authors considered the problem of maximizing proportional fairness in time-sharing NOMA WPCN scenario. The formulated optimization problem is solved by using Lagrange dual decomposition method. In [7], the authors solve the alpha-fair utility maximization by allocating time, transmit power and information/power split ratio in downlink and uplink with Simultaneous Wireless Information and Power Transfer (SWIPT). However, the authors consider Time Division Multiple Access (TDMA) instead of NOMA. As shown in [2], NOMA is much more efficient in terms of capacity region.

In this article, we consider the problem of total data rate maximization subject to uplink data rate requirements. Although fairness is relevant in the context of wireless networks, it cannot guarantee minimum data rate requirements or QoS. Among the presented works, only [5] considers this problem. However, homogeneous data rate requirements is assumed. In our work, we consider a more practical assumption that the terminals can have different data rate requirements (heterogeneous QoS). Furthermore, all presented works in this section consider that the phase 1 and 2 lengths in WPCN is a continuous real number. In practical networks, the time frame is split into discrete time intervals, the so called time slots. The modeling of this aspect changes the nature of the optimization problem from continuous optimization problems to discrete optimization ones. Finally, differently of the presented previous works that assume fixed SIC decoding order in conventional NOMA, in this work we include this in the optimization framework.

III. System Model

We consider a WPCN setup where there is an access point located at the center of a cell with circular area and multiple terminals uniformly distributed in the cell area. In WPCN, the time is arranged in time frames. Every time frame is split into two phases. The first phase consists in the energy transfer where the access point provides power to the terminals by means of WPT. In the second phase, the terminals transmit information using the harvested energy from phase 1 following the harvest-then-transmit protocol [6]. Differently of the articles presented in Section II, we assume that each time frame is divided into multiple (discrete) time slots. Therefore, the time length of phases 1 and 2 should be expressed in number of time slots. Our scenario is illustrated in Fig. 1, where the number of time slots for energy transfer is 4 and the number of slots for uplink data transmission is 6 in a frame of 10 slots.

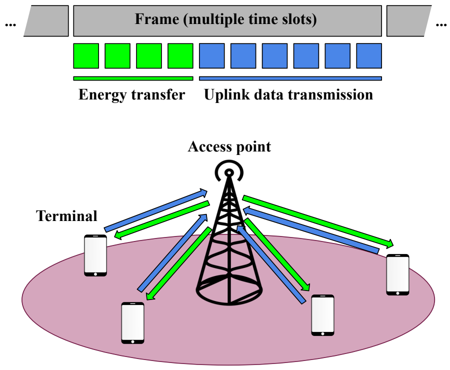

Fig. 1: NOMA-based WPCN system model.

Consider a terminal set $\mathcal{J} = \{1, \cdots, J\}$ where J is the number of terminals. Assume that the number of slots dedicated to energy transfer and data transmission are $n^{\mathrm{e}} \in \{1, \cdots, N-1\}$ and $n^{\mathrm{i}} \in \{1, \cdots, N-1\}$, respectively, where N is the number of slots in a time frame and $n^{\mathrm{e}} + n^{\mathrm{i}} = N$. Each slot has a time length equal to T^{s} and the time length of a frame is $T^{\mathrm{f}} = N \cdot T^{\mathrm{s}}$.

When radio propagation is concerned, we assume a block fading channel where the fading process is approximately constant over the duration of a frame as it is considered in [4], [5], [6], [7]. More details on our channel model is presented in Section VI. Assume that g_j is the channel gain between the access point and terminal j for both directions (uplink and downlink). We consider that the access point transmits with a constant power P. The amount of energy harvested by terminal j when n^{e} slots are employed for phase 1 of a specific frame is given by

$$E_{j,n^{\mathrm{e}}} = P \cdot \eta \cdot g_j \cdot n^{\mathrm{e}} \cdot T^{\mathrm{s}}, \tag{1}$$

where $0 \leq \eta \leq 1$ is the energy harvesting efficiency that assumes 1 for maximum efficiency and 0 for no energy harvesting capability. The available transmit power for terminal j in phase 2 when phase 1 lasts n^{e} slots is $P_{j,n^{\mathrm{e}}} = (E_{j,n^{\mathrm{e}}}) \,/\, (T^{\mathrm{s}} \cdot (N - n^{\mathrm{e}}))$.

In the second phase, where uplink data transmission takes place, we assume that NOMA is employed and, therefore, terminals simultaneously transmit their data and the access point performs SIC by assuming a certain decoding order. We assume that $\rho_p \in \mathcal{M}$ is the p^{th} permutation of the elements on $\mathcal{J}$, i.e., the available terminals in the system, and $\mathcal{M}$ is the set of all possible permutations. The total number of permutations, M, is given by $M = J!$. The i^{th} element of permutation p is represented by $\rho_{p,i}$. For example, for $J = 3$ we have $M = 3! = 6$ and $\mathcal{M} =$

$\{(1,2,3),(2,1,3),(3,2,1),(3,1,2),(1,3,2),(2,3,1)\}$. In this example, $\rho_{3,2}=2$, i.e., terminal 2.

According to those definitions, the achievable data rate on uplink for terminal $\rho_{p,i}$, i.e., the i^{th} terminal of permutation p, when assuming the SIC decoding order following permutation ρ_p and n^{e} slots for energy harvesting is given by

$$r_{\rho_{p,i},n^{\text{e}},p} = \frac{B\cdot n^{\text{i}}}{N}\log_2\left(1+\frac{P_{\rho_{p,i},n^{\text{e}}}\cdot g_{\rho_{p,i}}}{\sum\limits_{k=i+1}^{J}\left(P_{\rho_{p,k},n^{\text{e}}}\cdot g_{\rho_{p,k}}\right)+\sigma^2}\right), \tag{2}$$

where B is the system bandwidth and σ^2 is the thermal noise power. According to (2), the data sent by the first terminal to have its data decoded experiences interference from all other transmissions, while the data sent by the last terminal to have its data decoded is impaired only by the thermal noise.

IV. Problem Formulation

In this article we study the problem of maximizing the total data rate in uplink subject to minimum data rate requirements, i.e., QoS. Before presenting the optimization problem, let us first define some relevant variables. Assume that $x_{n^{\text{e}},p}$ is a binary optimization variable that assumes 1 if the number of slots for phase 1 is $n^{\text{e}}\in\{1,\cdots,N-1\}$ and the p^{th} permutation is chosen for SIC decoding order, and 0 otherwise. We assume that terminal j has a data rate requirement equal to R_j. We highlight here that we assume a heterogeneous data rate requirement since R_j can differ for different terminals.

According to those definitions, the studied optimization problem can be formulated as

$$\max_{x_{n^{\text{e}},p}}\left\{\sum_{n^{\text{e}}=1}^{N-1}\sum_{p=1}^{M}\sum_{j=1}^{J}\left(r_{j,n^{\text{e}},p}\cdot x_{n^{\text{e}},p}\right)\right\}, \tag{3a}$$

$$\text{s.t.}\ \sum_{n^{\text{e}}=1}^{N-1}\sum_{p=1}^{M}\left(r_{j,n^{\text{e}},p}\cdot x_{n^{\text{e}},p}\right)\geq R_j,\ \ \forall j\in\mathcal{J}, \tag{3b}$$

$$\sum_{n^{\text{e}}=1}^{N-1}\sum_{p=1}^{M}x_{n^{\text{e}},p}=1. \tag{3c}$$

In problem (3), the objective stated in equation (3a) represents the total uplink data rate. Constraint (3b) represents the per-terminal QoS constraint. In constraint (3c) we assure that only one n^{e} and permutation p is selected. Problem (3) is combinatorial and belongs to the class of Integer Linear Program (ILP) that in general are very hard to solve optimally for large input variables. The use of exhaustive search or brute force requires the full enumeration of all possible instances of the optimization variable, $x_{n^{\text{e}},p}$, evaluation of feasibility according to problem constraints and evaluation of the optimization objective for each instance. According to our model, the optimization variable has a length equal to $M\cdot(N-1)$. As $M = J!$, the number of possible instances in optimization grows exponentially with J. Fortunately, Branch-and-Bound (BB) algorithm can be employed to reduce the average computational complexity to obtain the optimal solution (at least for low and moderated input sizes) [8]. BB avoids the evaluation of all possible instances of the optimization variable by checking solutions against upper and lower estimated bounds and, then, pruning part of the search space.

V. Low-Complexity Solutions

Although the solution obtained by BB algorithm presents a much lower average computational complexity than the exhaustive search approach, it still has an exponential worst-case computational complexity. Motivated by this, we propose a low-complexity solution for this problem according with reasonable and insightful observations.

First of all, consider a fixed value of n^{e} and any decoding order following a permutation $p^*\in\mathcal{M}$ where the first terminal whose information is decoded is k_1, the second one is k_2, and so on, i.e., $p^*=(k_1,\cdots,k_J)$. Then, the total data rate in uplink, R^{T}, can be written as [5]

$$\begin{aligned} R^{\text{T}} &= \sum_{j=1}^{J}\left(\frac{B\cdot n^{\text{i}}}{N}\log_2\left(1+\frac{P_{k_j,n^{\text{e}}}\cdot g_{k_j}}{\sum\limits_{w=j+1}^{J}\left(P_{k_w,n^{\text{e}}}\cdot g_{k_w}\right)+\sigma^2}\right)\right)\\ &= \frac{B\cdot n^{\text{i}}}{N}\log_2\left(1+\frac{\sum_{j=1}^{J}P_{k_j,n^{\text{e}}}\cdot g_{k_j}}{\sigma^2}\right). \end{aligned} \tag{4}$$

As can be seen from the final result in equation (4), the total uplink data rate depends on the fixed values (n^{i}, B, σ^2 and N) as well as on the term $\sum_{j=1}^{J}P_{k_j,n^{\text{e}}}\cdot g_{k_j}$. Note that, independently of the assumed permutation p^*, this last term returns the same result. Therefore, the total uplink data rate does not depend on the assumed SIC decoding order, i.e., terminal permutation, but only on the time length of phase 2, n^{i}, and consequently, time length of phase 1, n^{e}. In this sense, the total data rate maximization would be trivial if there were no QoS constraints. However, the decoding order or terminal permutation is of utmost importance to assure the heterogeneous uplink data rate requirements.

Based on the presented observations, we proposed our first heuristic solution, *heuristic 1*, with the following steps. In the first step, we evaluate R^{T} in equation (4) for n^{e} from 1 to $N-1$ and choose the value of n^{e} that maximizes R^{T}. Then, based on the chosen value for n^{e} we should decide the decoding order or terminal permutation. Our idea is to calculate the worst-case achieved data rate for each terminal j, R_j^{w} when it is the first to get its data decoded in SIC decoding process as follows

$$R_j^{\text{w}} = \frac{B\cdot n^{\text{i}}}{N}\log_2\left(1+\frac{P_{j,n^{\text{e}}}\cdot g_j}{\sum\limits_{\forall w\neq j}\left(P_{w,n^{\text{e}}}\cdot g_w\right)+\sigma^2}\right) \tag{5}$$

Based on this, we calculate a priority for terminal j as follows

$$p_j = R_j^{\text{w}}/R_j. \tag{6}$$

Once the terminal priorities are calculated according to equation (6), the decoding order is defined by sorting $p_j\ \forall j\in\mathcal{J}$ in descending order, i.e., the terminal with highest value for p_j has its data decoded first, and so on. The main idea

Algorithm 1: Heuristic solution 1

Input: $\mathcal{S}$ (Set with possible values for n^{e})
for $i \in \mathcal{S}$ **do**
    Calculate R^{T} for $n^{\text{e}} = i$ and store in $R^{\text{T}}(i)$
end
$n^{\text{e}*} = \arg\max_{i \in \mathcal{S}} \left(R^{\text{T}}(i)\right)$
Calculate terminal priority, $p_j \; \forall j \in \mathcal{J}$ for $n^{\text{e}} = n^{\text{e}*}$ according to equation (6);
Obtain SIC decoding sequence, permutation p^*, by sorting $p_j \; \forall j \in \mathcal{J}$ in descending order
Test solution feasibility, i.e., if the QoS constraints in equation (3b) are satisfied with $n^{\text{e}*}$ and p^*
if *solution feasible* **then**
    Output: $n^{\text{e}*}$ and p^*
end
if *solution infeasible* **then**
    Output: 0
end

Algorithm 2: Heuristic solution 2

Input: none
Run Algorithm 1 with input $\mathcal{S} = \{1, \cdots, N-1\}$ and get output on $\beta = (n^{\text{e}*}, p^*)$ for feasible solution or $\beta = 0$ for infeasible solution
if $\beta \neq 0$ **then**
    Output: β
end
while $(\beta = 0)$ *and* $(\mathcal{S}$ *is not empty*$)$ **do**
    $\mathcal{S} = \mathcal{S} - \{n^{\text{e}*}\}$
    Run Algorithm 1 with input $\mathcal{S}$ and get output on $\beta = (n^{\text{e}*}, p^*)$ for feasible solution or $\beta = 0$ for infeasible solution
end
Output: β

behind this procedure is to let the terminal with highest value for p_j, i.e., best channel conditions (R_j^{w}) and/or lowest data rate requirements (R_j), have its data decoded firstly. This terminal will experience interference from all other concurrent transmissions. On the other hand, the terminal with lowest value for p_j, i.e., worst channel conditions (R_j^{w}) and/or highest data rate requirements (R_j), should have its data decoded lastly. This terminal will experience a noise-limited channel as SIC is applied to cancel the interference coming from all other terminals.

After that, we should evaluate if the chosen values for n^{e} and SIC decoding order are able to satisfy the QoS requirements stated in equation (3b). If so, our solution is able to find a feasible solution to problem (3). Heuristic 1 is summarized in Algorithm 1 assuming that $\mathcal{S}$ is set to $\{1, \cdots, N-1\}$.

We also proposed an alternative solution, *heuristic 2*, based on heuristic 1. Our main idea is to create an iterative process that chooses a new value for n^{e} every time heuristic 1 returns an infeasible solution. The idea here is to smoothly degrade the total uplink data rate in order to increase the probability of satisfying the QoS of all terminals. Heuristic 2 is shown in Algorithm 2.

VI. Results and Performance Evaluation

The system model presented in Section III was implemented in a computer simulator. Our simulation setup consists of an access point located in the center of a cell with a radius equal to 10 m. The transmit power of the access point is 5 W. The number of time slots used in the simulation is 20 while the channel bandwidth is of 1 MHz. There are 5 terminals in the system that are uniformly distributed in a ring-shaped area with inner radius equal to 1 m and outer radius equal to the cell radius. The time frame length is equal to 2 ms and the noise power is -104 dBm. The channel gain between the access point and terminal j is given by $10^{-3} \cdot X \cdot d_j^{-3}$ where d_j is the distance between terminal j and the access point in meters and X is an exponentially distributed random variable with unit mean. The energy harvesting efficiency is equal to 0.5. We perform Monte Carlo simulations with 3,000 repetitions so as to obtain statistical confidence. Most of the simulation parameters were taken from [7].

We consider benchmark solutions to compare with our two proposed heuristics. The first one is obtained from [5]. In this solution the authors assume that n^{e} is a continuous variable, $n^{\text{e,cont}}$, between 0 and 1 that represents the fraction of the time frame devoted to phase 1. It is given by

$$n^{\text{e,cont}} = N - \frac{\dfrac{\eta \cdot P \cdot \sum\limits_{j=1}^{J} g_j}{\sigma^2}}{\dfrac{\eta \cdot P \cdot \sum\limits_{j=1}^{J} g_j}{\sigma^2} + \dfrac{\left(\dfrac{\eta \cdot P \cdot \sum_{j=1}^{J} g_j}{\sigma^2} - 1\right)}{W_0\left(\dfrac{\eta \cdot P \cdot \sum_{j=1}^{J} g_j - 1}{e}\right)} - 1}, \quad (7)$$

where $W_0(\cdot)$ returns the main branch of the Lambert W function. As we consider a slotted time frame, we convert the result of $n^{\text{e,cont}}$ from equation (7) by rounding $n^{\text{e,cont}} \cdot N$ to the nearest integer. The decoding order employed in [5] for conventional NOMA is the one obtained after sorting the terminals by channel gains in descending order (fixed permutation). The other benchmark solution is the optimal solution of problem (3) obtained by the solver CPLEX that is capable of solving ILP.

In order to model the heterogeneous QoS, at each Monte Carlo repetition, we assume that the required data rate of the terminal j, R_j, are drawn from a uniform distribution within the interval $\left[\bar{R} - \alpha \cdot \bar{R}, \bar{R} + \alpha \cdot \bar{R}\right]$ where $\bar{R}$ is the mean required data rate and α is the data rate deviation. Note that $\alpha = 0$ reduces the required data rate to the homogeneous case, i.e., $R_1 = R_2 = \cdots = R_J$. $\bar{R}$ is varied in the simulation in order to emulate the system load.

In Fig. 2 we present the outage rate versus the mean required data rate assuming data rate deviation equal to 0.9. First of all, the outage rate increases as the average data rate augments since the space of feasible solutions becomes smaller, i.e., it is harder to satisfy the QoS of terminals. The solution from [5] presents the worst outage rate followed by heuristic 1. Basically, the solution in [5] presents a limited performance since the SIC decoding order is not optimized. On the other hand, the best outage rate is achieved obviously by the optimum solution closely followed by heuristic 2. Although both heuristics 1 and 2 optimize the SIC decoding order, heuristic 2 has an additional iterative step where the length of phase 1 can be adapted.

In Fig. 3 we plot the outage rate from another point of view; in terms of the data rate deviation. We can notice that

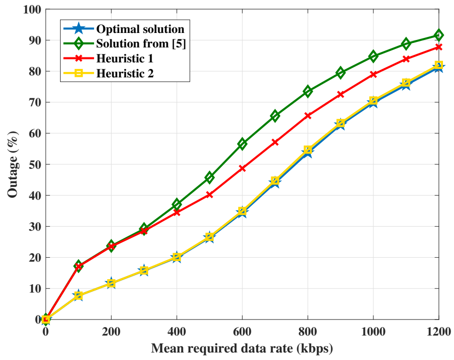

Fig. 2: Outage rate versus mean required data rate assuming data rate deviation equal to 0.9.

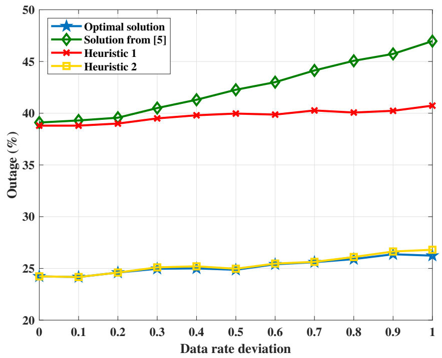

Fig. 3: Outage rate versus data rate deviation assuming mean data rate equal to 500 kbps.

the heuristic solutions 1 and 2 as well as the optimal solution are almost insensitive to data rate deviation. The optimization of SIC decoding order is capable of finding feasible solutions even when the required data rates of different terminals are set apart. However, the solution from [5] presents an outage rate with a steeper slope. Furthermore, we can see that when $\alpha = 0$ (homogeneous data rate requirement), heuristic 1 and solution from [5] presents similar results. An interesting conclusion that can be obtained from this is that fixed SIC decoding order is not able to reduce the outage rate as the data rate deviation increases.

Although both proposed heuristics present a much lower complexity than the optimal solution, it is clear from section V that heuristic 2 has a higher computational complexity compared to heuristic 1 since n_{e} is iteratively adapted in the former. In Fig. 4, we present the average number of iterations in heuristic 2 versus the mean required data rate assuming data rate deviation of 0.9 for different transmit power values. As we can see, the average number of iterations increases as the required data rate augments since the problem becomes harder to solve. Moreover, the outage rate decreases as we increase the available transmit power. From equations (1) and (2), we can see that the increase in transmit power has a positive effect in the achievable data rates, thus, decreasing the outage rates. Finally, we highlight that the average number of iterations is very small and not higher than 2 in the simulated load range.

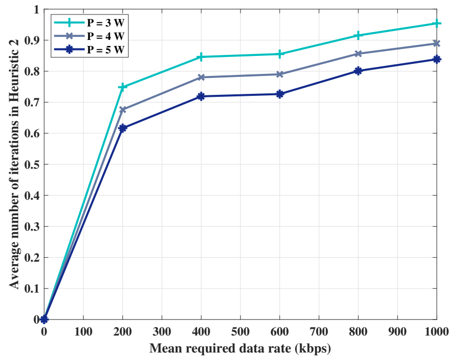

Fig. 4: Average number of iterations to update n_{e} in Heuristic 2 versus mean required data rate asusming data rate deviation equal to 0.9.

Therefore, we conclude that heuristic 2 presents an excellent performance/complexity trade-off when compared to the other solutions.

VII. Conclusions and Perspectives

In this article we optimize the SIC decoding order and time allocation for power transfer/data transmission in an NOMA-based WPCN network. Differently from previous works, we consider practical assumptions: the time frame is discretized in time slots and terminals have heterogeneous data rate requirements. Then, we provide the optimal solution to the total data rate maximization with (heterogeneous) QoS guarantees. In order to reduce complexity, we propose two heuristics based on reasonable assumptions. From the simulation results, we have shown that our second proposed heuristic presents a quasi-optimal performance. Furthermore, our two heuristic solutions outperform a benchmark solution from the literature.

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