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Energy-Efficient Opportunistic Multi-Carrier NOMA-based Resource Allocation for Beyond 5G (B5G) Networks

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Abstract

The interplay between the non-orthogonal multiple access (NOMA) and the opportunistic cognitive radio (CR)-based orthogonal frequency multiple access (OFDMA) has been recently realized as a promising paradigm to support the unprecedented massive connectivity demands of future beyond fifth-generation (B5G) wireless communication systems. In such systems, which are called multi-carrier NOMA CR-based systems, each licensed band reserved for primary users can be opportunistically utilized based on power-domain NOMA to serve a group of secondary users simultaneously. An important challenge in this domain is how to provide energy-efficient resource allocation techniques that attempt to strike a balance between the total throughput (i.e., the achieved sum-rate) and the power required to achieve that rate while satisfying network QoS demands and being aware of the unique characteristics of the CR operating environment. In this paper, we propose an energy-efficient resource allocation technique for multi-carrier NOMA CR-based systems, which aims at maximizing the overall energy efficiency (EE) of the system under a set of CR and NOMA constraints. The EE maximization problem is shown to be a fractional non-convex optimization, which is, in general, hard to optimize. To deal with

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the fractional and the non-convexity nature of the formulated EE maximization problem, we exploit the Dinkelbach's algorithm to transfer the EE problem to a parameterized optimization problem. Then we use an iterative optimization approach to obtain the solution for the EE maximization problem. Simulation results reveal that this EE maximization-based resource allocation technique outperforms the existing resource allocation techniques in terms of the overall EE of the system while striking a good balance between the sum-rate and the transmit power consumption.

Index Terms

Beyond 5G (B5G) networks, energy efficiency (EE), Cognitive radio (CR), non-orthogonal multiple access (NOMA), Multi-carrier.

I. Introduction

Due to the rapid development of future wireless communication systems such as beyond fifth-generation (B5G) or 6G networks, explosive growth in the number of wireless devices is inevitable [1], [2]. This, as a result, brings up huge challenges to tackle the issues associated with the massive number of connected devices. In fact, the challenges include; developing smart communication technologies, aligning with the smart nature of the B5G and 6G networks [1], [3], [4], proposing efficient multiple access (MA) techniques to serve a large number of users [5], [6], and finally, addressing the issues associated with a high rise in power consumption in such emerging wireless networks [7]. Significant research efforts have been dedicated to deal with these challenges by proposing efficient communication technologies.

Among several proposed technologies, cognitive radio (CR) technology has been considered as a potential candidate to enable massive connectivity in next-generation (e.g., B5G and 6G) communication networks [8], [9]. In CR technology, the licensed bandwidth owned by the primary users (PUs), can be utilized by next-generation wireless-unlicensed- devices smartly and opportunistically [10]. With this, the wireless devices can be considered as secondary users (SUs), which seek opportunistic utilization of the available PU's bandwidth without interrupting the PUs' communication activities [9]. In fact, CR communication can be realized through four functional phases, namely spectrum sensing, decision, sharing, and mobility [11]. It has been shown that the practical deployment of CR technology cannot be achieved without developing efficient MA techniques [12]. Therefore, several MA techniques have been proposed to handle the access issues of CR-based future wireless networks, such as orthogonal frequency division multiple access (OFDMA) [13], space domain multiple access (SDMA) [14], non-orthogonal multiple access (NOMA), and the hybrid MA techniques. Specifically, the combination of power-domain NOMA and OFDMA, referred to as hybrid OFDMA-NOMA, has been recently considered as a promising technique to support the massive connectivity of the CR-based future networks [15], [16]. On one hand, the integration between NOMA and OFDMA offers an additional degree of freedom as the power and frequency domains are utilized to serve a larger number of users [15] [16]. On the other hand, due to the computational complexity of employing SIC in dense networks, employing NOMA alone introduces several practical challenges [16]. With the hybrid OFDMA-NOMA system, NOMA is only exploited to serve a few users within each cluster (i.e., sub-band), which overcomes the practical challenges of employing SIC. In particular, this can be achieved by dividing the available bandwidth into a set of sub-channels, in which power-domain NOMA is utilized to serve a group of users within each sub-channel through utilizing superposition coding (SC) [17]. This combination introduces an additional degree of freedom and can efficiently utilize the available resources. The CR-based future wireless networks that employ hybrid OFDMA-NOMA techniques are referred to as multi-carrier NOMA CR-based systems throughout this paper.

It is known that the multi-carrier NOMA CR-based system can support a massive number of users. However, this cannot be achieved without significant power consumption. The increase in power consumption has several undesirable outcomes, including the economic and environmental concerns [18]. These concerns have attracted both academia and industry to explore further research directions to tackle the considerable increase in the power consumption [19]. In fact, existing proposed solutions that deal with the power consumption issue in wireless networks can be divided into two categories. The first category focuses on the further deployment of green energy resources to feed wireless communication infrastructure. The green resources include solar and wind resources along with existing conventional power resources [20]. Furthermore, the simultaneous wireless power and information transfer (SWIPT) has also been considered as an additional green power resource [21], [22]. The aforementioned solutions require severe modification to the existing communication systems. Unlike the first category, the second category proposes energy-efficient communication protocols and mechanisms without modifying existing wireless systems. Such protocols and mechanisms intelligently allocate the available power resources in the network such that the energy efficiency (EE) of the system is improved [18], [23]. In particular, EE is defined as the ratio between the achieved sum-rate and the corresponding consumed power that is required to achieve this sum-rate [24]. In addition, EE strikes a good balance between the two conflicting metrics, namely the sum rate and the transmit power consumption [25] [26] [27]. The EE can be viewed as the performance metric that aims to attain the best achievable rate with minimum power consumption.

Motivations and Contributions

The multi-carrier NOMA CR-based systems have the potential capabilities to support a massive number of users. Therefore, considering the EE-based resource allocation technique is of importance. To the best of the authors' knowledge, the EE-based resource allocation technique for multi-carrier NOMA CR-based systems has not been considered in the literature. Therefore, this paper considers an energy-efficient resource allocation technique for a downlink multi-carrier NOMA CR-based system. With this resource allocation technique, an EE optimization framework is formulated to allocate the available power at the base station, such that the overall EE of the system is maximized under a set of constraints. These constraints include the QoS requirements for SUs in the system and relevant CR and NOMA constraints. However, due to the non-convexity nature of the formulated EE optimization framework, the Dinkelbach's algorithm is utilized to obtain the solution of this fractional non-convex optimization framework. We provide an efficient approach to examine the feasibility of the EE maximization framework prior to solving it. Furthermore, extensive simulations are carried out to validate the effectiveness of the proposed resource allocation technique, comparing their performance with that of the existing conventional resource allocation techniques in terms of the achieved EE. In addition, the achieved EE trend against the change in several parameters is also studied in the simulation results.

Related Work

Over the past few years, several works investigated the potential capabilities of single-carrier NOMA CR-based systems. For example, a single-carrier NOMA CR-based system was studied in [28], in which maximizing the number of served SUs while meeting a set of relevant constraints was considered. Furthermore, the authors in [29] proposed an EE maximization design for a single-carrier NOMA CR-based system. On the other hand, ongoing research studies have investigated the multi-carrier NOMA CR-based systems and their potential to implement future wireless networks. For example, a power minimization resource allocation technique for a multi-carrier NOMA CR-based system was considered in [13]. This design aimed to minimize the power required for transmission while achieving a set of quality-of-service (QoS) constraints.

Paper Organization

The remainder of the paper is organized as follows. In Section II, we present the multi-carrier NOMA CR-based system model and formulate the EE maximization problem. In Section III, we provide a feasibility check and the proposed methodology to solve the EE maximization problem. Section IV provides the simulation setup, results, and discussions. Finally, Section V concludes the paper.

II. System Model and Problem Formulation

A. System Model

We consider a downlink multi-carrier NOMA CR-based system, as shown in Fig. 1. In this system, a single-antenna CR base-station (CR-BS) communicates with L single-antenna SUs. Hence, the available PU bandwidth, B, which is divided into K sub-bands is opportunistically available for CR communication. As such, $B = \sum_{i=1}^{K} B_i$, where B_i represents the i^{th} sub-band, $\forall i \in \mathcal{K} = \{1, 2, \cdots, K\}$. To utilize the available sub-bands efficiently, each of them is dedicated to serve a group of users (i.e., cluster) through the power domain NOMA. The number of clusters is equal to the number of the available sub-bands, such as B_i is dedicated to serve the i^{th} cluster C_i. Furthermore, the number of users at each cluster is denoted as L_i, such that $L = \sum_{i=1}^{K} L_i$, whereas $u_{l,i}$ denotes the l^{th} user in the i^{th} cluster, $\forall l \in \mathcal{L}_i = \{1, 2, \cdots, L_i\}$. In this cluster-based scenario, selecting users inside each cluster (i.e., clustering) is a key element that determines the overall system performance. Therefore, the details of clustering are discussed in the following section.

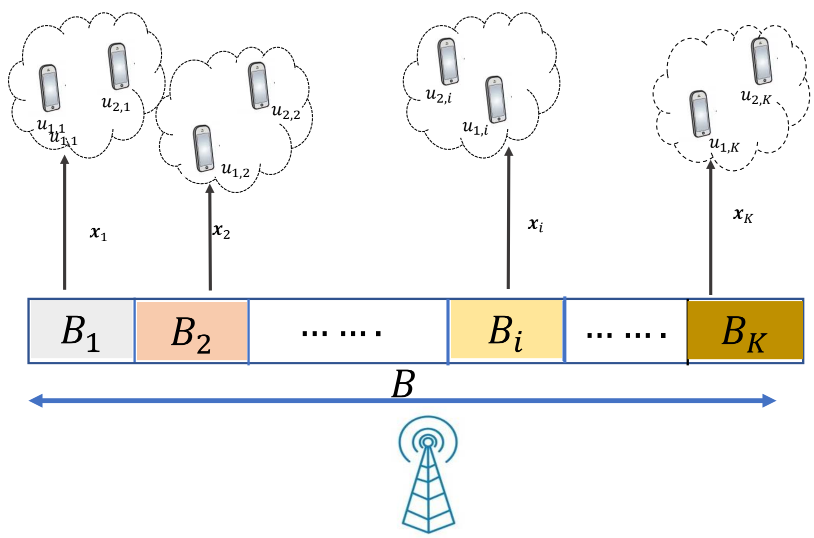

Fig. 1: A multi-carrier NOMA in CR system, with two users at each cluster, i.e., $L_i = 2$.

Considering the above, the CR-BS transmits the superimposed signal, x_i, to the users in cluster C_i over the sub-band B_i, namely $\{u_{1,i}, \cdots, u_{L_i,i}\}$. The superimposed signal, x_i, can be written as:

$$x_i = \sum_{l=1}^{L_i} \sqrt{p_{l,i}} s_{l,i}, \quad \forall i \in \mathcal{K}, \tag{1}$$

where $s_{l,i}$ and $p_{l,i}$ represent the symbol intended to $u_{l,i}$ and the corresponding power allocation, respectively. The received signal at $u_{l,i}$, $\forall l \in \mathcal{L}_i$, $\forall i \in \mathcal{K}$, can be written as follows:

$$y_{l,i} = h_{l,i} x_i + n_{l,i}, \tag{2}$$

where $h_{l,i}$ denotes the channel coefficients between the CR-BS and $u_{l,i}$. It is assumed that the CR-BS and $u_{l,i}$ have the perfect channel state information (CSI). Furthermore, $n_{l,i}$ is the additive white Gaussian noise with zero mean and variance σ^2. As the SUs in each cluster are served based on power-domain NOMA, the ordering of users has a considerable impact on the power allocation at each cluster [30]. Therefore, the performance of the multi-carrier NOMA CR-based system depends on the user-ordering within each cluster. Without loss of generality, the users in each cluster are ordered as follows:

$$|h_{1,i}|^2 \geq |h_{2,i}|^2 \geq \ldots |h_{L_i,i}|^2, \quad \forall i \in \mathcal{K}. \tag{3}$$

Note that $|h_{l,i}|^2$ represents the channel gain of the channel coefficients $h_{l,i}$. Given the ordering in (3), the weaker users (i.e., users with lower channel gains) should be allocated higher power levels compared to that of the stronger users (i.e., users with stronger channel gains) [30]. This can be achieved through imposing the following constraint:

$$p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. \tag{4}$$

Note that the stronger users within each cluster perform successive interference cancellation (SIC) to decode and subtract the messages intended for weaker users prior to decoding their own messages [31]. The message intended to $u_{l,i}$ is decoded at the stronger users, namely $\{u_{1,i}, \cdots, u_{l-1,i}\}$. Thus, the achieved signal-to-interference-and-noise-ratio (SINR) can be defined as

$$\text{SINR}_{l,i}^{j} = \frac{|h_{j,i}|^2 p_{l,i}}{|h_{j,i}|^2 \sum_{s=1}^{l-1} p_{s,i} + n_{j,i}^2}, \quad \forall i \in \mathcal{K}, \ \forall L \in \mathcal{L}_i, \ \forall j \in \{1, 2, \ldots, l-1\}, \tag{5}$$

where $\text{SINR}_{l,i}^{j}$ denotes the SINR of the message intended to $u_{l,i}$ at the stronger user $u_{j,i}$, such that $j \leq l$. Furthermore, $u_{l,i}$ also decodes its own message with the following SINR:

$$\text{SINR}_{l,i}^{l} = \frac{|h_{l,i}|^2 p_{l,i}}{|h_{l,i}|^2 \sum_{s=1}^{l-1} p_{s,i} + n_{l,i}^2}, \quad \forall i \in \mathcal{K}, \ \forall L \in \mathcal{L}_i. \tag{6}$$

Based on this definition, the SINR of the message intended to $u_{l,i}$ can be defined as [18], [32]:

$$\text{SINR}_{l,i} = \min\left\{\text{SINR}_{l,i}^{1}, \cdots, \text{SINR}_{l,i}^{l}\right\}, \quad \forall i \in \mathcal{K}, \ \forall L \in \mathcal{L}_i. \tag{7}$$

Therefore, the achieved rate at $u_{k,i}$ can be written as

$$R_{l,i} = B_i \log_2\left(1 + \text{SINR}_{l,i}\right), \quad \forall i \in \mathcal{K}, \ \forall L \in \mathcal{L}_i, \tag{8}$$

and thus, the overall achieved sum-rate is given by

$$R_{\text{sum}} = \sum_{l=1}^{L_i} \sum_{k=1}^{C} R_{l,i}. \tag{9}$$

The overall EE of the system can be defined as follows [24]:

$$\text{EE} = \frac{R_{\text{sum}}}{\frac{1}{\epsilon} P_t + P_l}, \tag{10}$$

where P_t and P_l represent the total required power for transmission, and the power losses at the CR-BS, respectively, such that $P_t = \sum_{i=1}^{K} \sum_{l=1}^{L_i} p_{l,i}$. Furthermore, ϵ is the efficiency of power amplifier at the CR-BS, and has a maximum value of one, i.e., $0 \leq \epsilon \leq 1$ [25], [33].

B. Clustering Approach

It is crucial to determine which users are grouped into different clusters. Considering the practical implementation of employing SIC in dense networks, two users per cluster is assumed throughout the rest of this paper. However, the analysis provided throughout this paper is applicable for any number of users per cluster. First, as the stronger users in each cluster need to perform SIC [17], having more users (i.e., more than two users) per cluster will introduce significant computational complexity, which is not desirable for practical implementation of NOMA and B5G wireless systems [31], [34]. Second, as the decoding of the signals intended for the weaker users (i.e., SIC) is sequentially performed at each stronger user, grouping more users into each cluster increases the latency, which will not meet the requirements of the delay-sensitive applications in future wireless networks. Third, the clusters with more users are more likely to suffer from error propagation due to successive decoding in SIC. Considering the issues mentioned earlier, two users per cluster is recommended to realize the practical implementation of NOMA. In addition, this is widely adopted in several previous works dealt with NOMA systems, e.g., [35]–[37].

While determining the clusters through the exhaustive search can offer the optimal clustering strategy, it will raise practical concerns in terms of the implementation of SIC. Therefore, the grouping strategy used in this paper considers the channel gain differences to enable the successful implementation of SIC. This clustering strategy has been widely utilized in the literature [38], [39], and we denote this grouping strategy as π throughout this paper. Similar to the most existing works in the literature, the grouping strategy employed in this paper chooses users with a higher difference in their channel gains. The analysis provided in the paper is still applicable for any grouping strategy. We have utilized the same grouping strategy for the proposed EE maximization framework and the other benchmark resource allocation techniques for a fair comparison.

C. Problem Formulation and Design Constraints

We now formulate the EE maximization framework for the multi-carrier NOMA CR-based system. However, we first shed some light on the relevant constraints for efficient utilization of this resource allocation technique.

1) Design constraints: When considering the EE maximization of the multi-carrier NOMA CR-based systems, a set of constraints should be satisfied to meet the SUs' requirements and enable the successful implementation of NOMA and CR transmission. We provide the details of these constraints in the following:

- Requirements and design constraints of SUs:

  While the objective of the EE based resource allocation technique is to maximize EE, this design has to ensure a set of QoS requirements and design constraints for the SUs that take into consideration the unique characteristics of the CR networks operating environment, which are

  - Minimum rate requirement for each SU:

    The rate requirement for each SU l in each cluster i ($R_{l,i}$) can be achieved through imposing the following constraint:

    $$R_{l,i} \geq R_{\min}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, \tag{11}$$

    where $R_{\min}$ is the minimum rate requirement of each SU, determined by the application layer.

  - Success probability requirement:

    The success probability of each SU l in cluster i ($P_{suc;l,i}$) must be greater than or equal to a given success probability threshold γ, where γ is application dependent. This can be maintained by imposing the following constraint:

    $$P_{suc;l,i} \geq \gamma, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i. \tag{12}$$

    In particular, the probability of success for the SU l in cluster i can be computed as:

    $$P_{suc;l,i} \triangleq \exp\left(-\frac{S}{R_{l,i}\mu_i}\right) \geq \gamma, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, \tag{13}$$

    where μ_i is the average idle period of the i^{th} PU channel and S is the packet length. After some algebraic manipulations and defining $v = -\ln(\gamma)$, (13) can be re-written as a function of the achieved rate as

    $$R_{l,i} \geq \frac{S}{v\mu_i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i. \tag{14}$$

Accordingly, the minimum rate and the probability of success constraints (i.e., (11) and (12)) can be combined into a single constraint as follows:

$$R_{l.i} \geq \max\left\{R_{\min}, \frac{S}{v\mu_i}\right\} = r_{l,i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, \tag{15}$$

where $r_{j,i} = \max\left\{R_{\min}, \frac{S}{v\mu_i}\right\} = R_{l,i}$ is the required rate demand by the CR system that ensures the satisfaction of the probability of success (γ) and the minimum rate demand ($R_{\min}$) requirements.

- The power mask constraints on SU transmissions:

  To maintain the PU activities with certain quality over the sub-channel C_i, each CR transmission over C_i should utilize a controlled transmission power. This can be maintained through imposing the following constraint:

$$\sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\text{mask},i}, \quad \forall i \in \mathcal{K}, \tag{16}$$

  where $P_{\text{mask},i}$ is the maximum transmit power that can be utilized over C_i.

- NOMA requirements and constraints:
  - SIC requirement:

    To implement SIC, it is required that the power levels of the received signals intended for the weaker SUs should be higher than that of the signals associated with the stronger SUs. This can be ensured through allocating higher power levels to SUs with weaker channel gains [31]. Accordingly, the following SIC constraint should be satisfied:

$$p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. \tag{17}$$

  - Maximum power budget at the CR-BS:

    The transmit power at the CR-BS, P_t, should not exceed the maximum power budget at the CR-BS, $P_{\max}$. This can be ensured with the following constraint:

$$P_t = \sum_{i=1}^{K} \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\max}. \tag{18}$$

D. Problem Formulation

Given the aforementioned constraints, the EE optimization framework for the multi-carrier NOMA CR-based system, can be formulated as follows:

$$
\begin{aligned}
\textbf{P1:}\ \underset{\{p_{l,i}\}_{\forall l,\forall i}}{\text{maximize}} \quad & \text{EE} && \text{(19a)}\\
\text{subject to} \quad & R_{l,i} \geq r_{l,i},, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(19b)}\\
& \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\text{mask},i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(19c)}\\
& \sum_{i=1}^{K} \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\max}, && \text{(19d)}\\
& p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. && \text{(19e)}
\end{aligned}
$$

An observation of the above formulation suggests that several challenges need to be addressed to solve **P1**, and we summarize these challenges in the following discussion. Firstly, it is evident that the EE optimization problem, **P1**, is non-convex in nature and thus cannot be solved directly using the conventional optimization techniques. Secondly, the objective function of this problem, EE, is a fractional function, which introduces additional complexity to solve it. Furthermore, due to the total power constraint in (19d), the EE optimization problem might turn out to be infeasible when the available power budget, $P_{\max}$, is not sufficient to support the minimum rate requirements, i.e., QoS constraints in (19b). These challenges are discussed and simplified in the following section.

III. Proposed Methodology

A. Feasibility Check

The optimization problem **P1** turns out to be infeasible when the available power budget, $P_{\max}$, cannot support the minimum rate requirements constraints in (19b). Therefore, it is important to carry out a feasibility check for **P1** prior to solving it. In fact, this check can be performed by finding the minimum transmit power ($P_t^{\min}$) that is required to meet the minimum rate requirements of the system. This can be determined by solving the following power minimization (P-Min) problem:

$$
\begin{aligned}
\textbf{P2:}\ P_t^{\min} = \underset{p_{l,i},\ \forall l,\forall i}{\text{minimize}} \quad & \sum_{i=1}^{K} \sum\nolimits_{l=1}^{L_i} p_{l,i} && \text{(20a)}\\
\text{subject to} \quad & R_{l,i} \geq r_{\min}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(20b)}\\
& \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\text{mask},i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(20c)}\\
& p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. && \text{(20d)}
\end{aligned}
$$

Note that the solution of the P-min optimization framework can be found in [13], while also its solution can be reached throughout this paper. In fact, when solving **P2**, the minimum required power to satisfy the minimum rate constraints, $P_t^{\min}$, is evaluated. With this, the original EE optimization problem, **P1**, is feasible and thus, worthy to solve if the available power budget at the CR-BS is greater than the minimum transmit power required to achieve the QoS constraints, i.e., $P_{\max} \geq P_t^{\min}$. Otherwise, the original problem is infeasible and cannot be solved for the given constraints. To handle this infeasibility issue, the CR-BS alternatively switches to the sum-rate maximization (SRM) design, which can be formulated as follows:

$$\begin{aligned}
\textbf{P3:}\quad & \underset{p_{l,i},\ \forall l, \forall i}{\text{maximize}} && R_{\text{sum}} && \text{(21a)}\\
& \text{subject to} && \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\text{mask},i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(21b)}\\
& && \sum_{i=1}^{K}\sum_{l=1}^{L_i} p_{l,i} \leq P_{\max}, && \text{(21c)}\\
& && p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. && \text{(21d)}
\end{aligned}$$

Note that the SRM optimization problem aims to maximize the achieved sum-rate for the given power constraints, where the QoS constraints are dropped. The SRM optimization problem is always feasible and can be solved for any power budget at the CR-BS. Without loss of generality, we provide an approach to solve the EE optimization problem, given that it is feasible under the given constraints.

B. Proposed Solution

The EE maximization framework **P1** is non-convex fractional problem, and thus, the existing softwares cannot be used to solve it. Therefore, we utilize the Dinkelbach's algorithm along with SCA approach to solve **P1**. In the Dinkelbach's algorithm [40], a non-negative variable, namely ξ is introduced to transform the fractional objective function, EE, into a non-fractional, i.e., parameterized, one. For ease of reference, we introduce the functions $f_1(p_{l,i})$ and $f_1(p_{l,i})$, such as $f_1(p_{l,i}) = R_{\text{sum}}$, and $f_1(p_{l,i}) = (\frac{1}{\epsilon}P_t + P_l)$. With this transformation, the parametrized non-fractional objective function can be written as follows:

$$\text{EE}_P = f_1(p_{l,i}) - \xi f_2(p_{l,i}), \tag{22}$$

where EE_P is the parameterized version of EE. The parametrized EE optimization problem can be written as

$$\begin{aligned}
\textbf{P4:} \quad \underset{\{p_{l,i}\}_{\forall l,\ \forall i},\ \xi}{\text{maximize}} \quad & \text{EE}_P = f_1(p_{l,i}) - \xi f_2(p_{l,i}) && \text{(23a)}\\
\text{subject to} \quad & R_{l,i} \geq r_{l,i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(23b)}\\
& \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\text{mask},i}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, && \text{(23c)}\\
& \sum_{i=1}^{K} \sum\nolimits_{l=1}^{L_i} p_{l,i} \leq P_{\max}, && \text{(23d)}\\
& p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. && \text{(23e)}
\end{aligned}$$

Let us first point out that $p^*_{l,i}$ and $p^*_{2,i}, \forall i$ are the solutions of the non-parametrized optimization framework, **P1**. Now, we invoke the relationship between the original non-parameterized problem **P1** and the parameterized one **P4**, through providing the following theorem [40]:

Theorem 1: The optimal value of the parameterized optimization problem **P4** is zero, i.e.,

$$\underset{p_{l,i},\xi}{\text{maximize}} \quad f_1(p_{l,i}) - \xi f_2(p_{l,i}) = f_1(p^*_{l,i}) - \xi^* f_2(p^*_{l,i}) = 0,$$

and this optimal value occurs only when $\xi^* = \frac{f_1(p^*_{l,i})}{f_2(p^*_{l,i})}$.

It is worth mentioning that the proof of Theorem 1 can be found in [18], [40]. Based on Theorem 1, determining the solution of the original non-parametrized optimization problem **P1** can be alternatively achieved through solving the parameterized optimization problem for the optimization parameters $p_{l,i}$ and ξ. However, due to the joint nature of the optimization parameters $p_{l,i}$ and ξ, an alternating optimization approach is utilized to handle this issue. With this approach, an initial value of ξ is assumed, i.e., $\xi^{(0)} = 0$, then **P4** is solved for this initial value, and the optimization parameters $p_{l,i}$ are evaluated using the SCA as it is introduced in the subsequent discussion. Then, the value of ξ is updated based on the solution obtained in the previous iteration; the update role can be written as

$$\xi^{(n)} = \frac{f_1\left(p_{l,i}^{(n-1)}\right)}{f_2\left(p_{l,i}^{(n-1)}\right)}, \tag{24}$$

where $(\cdot)^{(n)}$ denotes the value of $(\cdot)$ at the n^{th} iteration. This iterative process continues until the absolute difference between two consecutive values is less than a pre-defined threshold.

In particular, the parameterized optimization framework for a given ξ is still non-convex. Therefore, the SCA approach is utilized here to deal with this non-convexity issue. In SCA approach [41], the original non-convex optimization problem is approximated with a lower-bound convex problem through approximating each non-convex term with a linear (i.e., convex-concave) one [42]. The approximated problem is solved for a set of iterations until the required accuracy is achieved. This SCA approach has been utilized to solve a different set of optimization frameworks in wireless communications, such as [32], [43], [44]. The non-convexity of the parameterized optimization framework is due to the non-convex term $R_{i,j}$, which appears in the objective function and some of the constraints. Therefore, we tackle this non-convexity issue by introducing a linear slack variable $\eta_{j,i}$ to approximate $R_{i,j}$, such that

$$R_{i,j} \geq \eta_{i,j}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i. \tag{25}$$

With this slack variable, the non-convex part of objective function in the parameterized optimization problem **P4**, turns out to be convex. However, a new non-convex constraint is introduced to the problem. To handle this non-convexity issue, a set of additional slack variables is incorporated, as follows:

$$(1 + \text{SINR}_{i,j}) \geq a_{i,j}, \quad \forall i \in \mathcal{K}, \forall L \in \mathcal{L}_i, \tag{26a}$$

$$a_{i,j} \geq 2^{\eta_{i,j}}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i, \tag{26b}$$

while the constraint in (26b) is convex [32], the constraint in (26a) is not convex. To handle the non-convexity issue of this constraint, we first rewrite it as

$$\Big(1 + \min\Big\{\text{SINR}_{l,i}^{1}, \cdots, \text{SINR}_{l,i}^{l}\Big\}\Big) \geq a_{l,i}, \quad \forall i \in \mathcal{K},\ \forall l \in \mathcal{L}_i. \tag{27}$$

Thus, the constraint in (27) can be expressed as

$$\text{SINR}_{l,i}^{j} \geq (a_{l,j} - 1), \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i,\ \forall j \in \{1, 2, \ldots, l-1\}. \tag{28}$$

With this, the new slack variable $\theta_{i,j}$ is introduced, such that

$$\frac{|h_{j,i}|^2 p_{l,i}}{|h_{j,i}|^2 \sum_{s=1}^{l-1} p_{s,i} + \sigma_{j,i}^2} \geq \frac{\big(a_{l,i} - 1\big)\sqrt{\theta_{l,i}}}{\sqrt{\theta_{l,i}}}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i,\ \forall j \in \{1, 2, \ldots, l\}. \tag{29}$$

Note that the constraint in (29) can be further decomposed into two parts, as follows:

$$|h_{j,i}|^2 p_{l,i} \geq \big(a_{l,i} - 1\big)\sqrt{\theta_{l,i}}, \quad \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i,\ \forall j \in \{1, 2, \ldots, l\}, \tag{30}$$

$$|h_{j,i}|^2 \sum_{s=1}^{l-1} p_{s,i} + \sigma_{j,i}^2 \leq \sqrt{\theta_{l,i}},\ \forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i,\ \forall j \in \{1, 2, \ldots, l\}. \tag{31}$$

To deal with the non-convexity issues of the constraints in (30) and (31), the left-hand sides of them are replaced with their corresponding lower-bound approximations through using the first-order Taylor series expansions. With this approximation, these constraints can be rewritten as

$$|h_{j,i}|^2 p_{l,i} \geq \big(a_{l,i}^{(n)} - 1\big)\sqrt{\theta_{l,i}^{(n)}} + \sqrt{\theta_{l,i}^{(n)}}\Big(a_{l,i} - a_{l,i}^{(n)}\Big) + \frac{1}{2\sqrt{\theta_{l,i}^{(n)}}}\big(a_{l,i}^{(n)} - 1\big)\Big(\theta_{l,i} - \theta_{l,i}^{(n)}\Big),$$
$$\forall i \in \mathcal{K},\ \forall L \in \mathcal{L}_i,\ \forall j \in \{1, 2, \ldots, l\}, \tag{32}$$

$$|h_{j,i}|^2 \sum_{s=1}^{l-1} p_{s,i} + \sigma_{j,i}^2 \leq \sqrt{\theta_{l,i}^{(n)}} + \frac{1}{2\sqrt{\theta_{l,i}^{(n)}}} \left(\theta_{l,i} - \theta_{l,i}^{(n)}\right), \quad \forall i \in \mathcal{K}, \forall L \in \mathcal{L}_i, \forall j \in \{1, 2, \ldots, l\}. \quad (33)$$

Incorporating these multiple slack variables, the non-convex term $R_{l,i}$ which appears in the in parameterized optimization problem **P4** has been replaced with a convex term $\eta_{j,i}$ subject to the convex constraints in (26b), (32), and (33). The non-convex optimization problem **P4** can be approximated with the following convex optimization problem:

$$\begin{aligned}
\textbf{P5:} \quad \underset{p_{l,i},\ \forall l, \forall i}{\text{maximize}} \quad & \sum_{l=1}^{L_i} \sum_{k=1}^{C} \eta_{l,i} - \xi \left(\frac{1}{\epsilon} \Big(\sum_{i=1}^{K} \sum_{l=1}^{L_i} p_{l,i} \Big) + P_l \right) && \text{(34a)} \\
\text{subject to} \quad & R_{l,i} \geq r_{l,i},, \ \forall i \in \mathcal{K}, \forall L \in \mathcal{L}_i, && \text{(34b)} \\
& \textstyle\sum_{l=1}^{L_i} p_{l,i} \leq P_{\text{mask},i}, \ \forall i \in \mathcal{K}, \forall L \in \mathcal{L}_i, && \text{(34c)} \\
& \sum_{i=1}^{K} \textstyle\sum_{l=1}^{L_i} p_{l,i} \leq P_{\max}, && \text{(34d)} \\
& p_{L_i,i} \geq \cdots \geq p_{2,i} \geq p_{1,i}, \quad \forall i \in \mathcal{K}. && \text{(34e)}
\end{aligned}$$

We can confirm that the approximated optimization problem **P5** is convex and thus can be solved using the convex software, such as CVX [45]. The proposed iterative algorithm to solve the original non-convex optimization problem **P1** is summarized in Algorithm 1.

Algorithm 1: Solving EE maximization problem for multi-carrier NOMA CR-based system using the Dinkelbach's algorithm and SCA approach

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Step 1: For each busy channel i, set the $p_{l,i}$ = 0 and the required rate demand for the users served by channel i to 0

Step 2: Group the SUs based on the proposed clustering strategy π

Step 3: Check the feasibility of the EE maximization framework

Step 4: Initialization of Dinkelbach's algorithm, i.e., $\xi^{(0)} = 0$

Step 5: Repeat

1) Solve the approximated optimization problem **P5** iteratively
2) Repeat the previous step until the required accuracy is achieved

Step 6: Update ξ following the rule in (24)

Step 7: Go to Step 3 until the required accuracy is achieved.

The Complexity Analysis: The solution of the original fractional optimization problem **P1** is determined through firstly employing the Dinkelbach's algorithm to transform it to the non-fractional (i.e., parameterized) optimization problem **P4**. Next, with the proposed SCA approach, the first-order Taylor series expansion is exploited to transform the non-convex optimization problem **P4** to a convex one, namely **P5**. Accordingly, the complexity of obtaining the solution of the original problem is determined based on the complexity of solving the approximated optimization problem **P5**. In fact, the optimization problem **P5** is a linear program. Thus, CVX solves this linear program using the the Dantzig's simplex method [41] for several iterations. In particular, at each iteration, the complexity of solving **P5** is upper-bounded by $\mathcal{O}(A^2B)$ [32], where A and B represent the numbers of constraints and the optimization parameters, respectively. The solution of the original problem is attained with two iterative algorithms, which are, 1) an iterative algorithm to obtain the solution **P5** for given ξ, and 2) an iterative algorithm to obtain the value of the non-negative slack variable ξ. Therefore, the overall complexity of solving the original problem can be defined as $\mathcal{O}\bigg(A^2B\log(\frac{1}{v})\log(\frac{1}{z})\bigg)$, where v and z denote the required accuracy of the iterative algorithms.

IV. Simulation Results

A. Simulation Setup

In this section, we examine the performance of the proposed EE maximization resource allocation technique for the considered multi-carrier NOMA CR-based system, comparing the performance with two benchmark conventional resource allocation techniques. These benchmark schemes are the P-min and the SRM resource allocation techniques, which are demonstrated in **P2** and **P3**, respectively. In these simulations, a set of ten SUs, i.e., L = 10, is considered, assuming that these SUs are uniformly distributed in a circle with a 20-meter-radius around the CR-BS. Furthermore, the SUs are divided into five clusters, with each cluster containing two users, i.e., L_i = 2. The simulation parameters are summarized in Table I. Note that the CVX toolbox from MATLAB is utilized to generate all simulation results, where the results are averaged over 1000 iterations.

B. Simulation Results

We provide numerical simulations to evaluate the performance of the proposed EE maximization resource allocation technique against several design parameters, such as the maximum power at the CR-BS P_{max}, the probability of success γ, and the idle probability P_{idle}. In particular, the performance metrics, namely the overall energy efficiency of the system EE, the overall sum-rate of the system R_{sum}, and the total required power for transmission P_t are evaluated for the proposed EE resource allocation

TABLE I: Simulation Parameters.

Parameter	**Value**
Number of users (L)	10
Number of clusters (C)	5
Number of users in each cluster (L_i)	2
Maximum power (P_{max}) [Watt]	5
Power mask $\left(P_{\text{mask},i},\ \forall i\right)$, [Watt]	1
Path loss exponent (n)	3
Noise Variance (σ^2) [dBm/Hz]	-107
Probability of success threshold (γ)	0.85, 0.9
Packet length (S) [Bits]	2
R_{min} [Mbps]	2.5
Bandwidth (B) [MHz]	50
Idle Period (μ_i) [Seconds]	[0.05 0.1 0.03 0.045 0.05]
Channel Availability Duration (μ) [Seconds]	0.5
Idle Probability (P_{idle})	0.5, 0.9

technique, and they are compared with that of the benchmarks resource allocation techniques. This, as a result, provides a comprehensive understanding of these designs and, thus, demonstrates the superiority of the proposed EE maximization design.

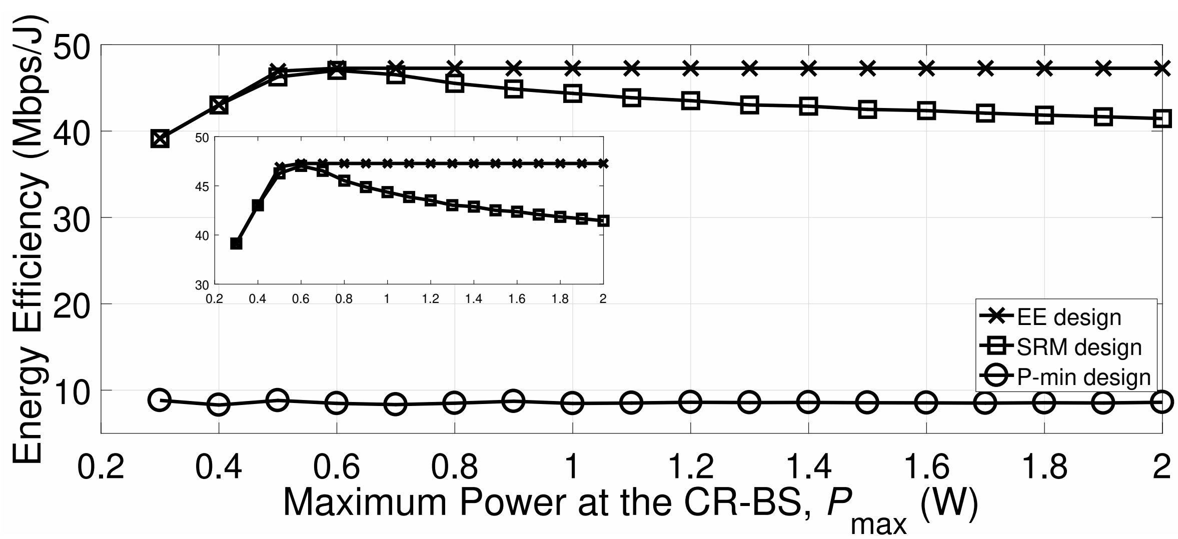
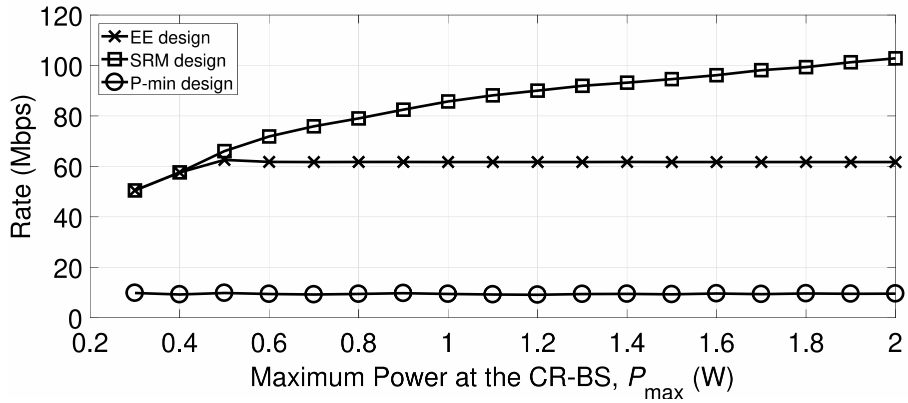


Fig. 2: The achieved EE for the proposed EE design and the benchmark schemes against different available power budget P_{max}, with P_{idle} = 0.5.

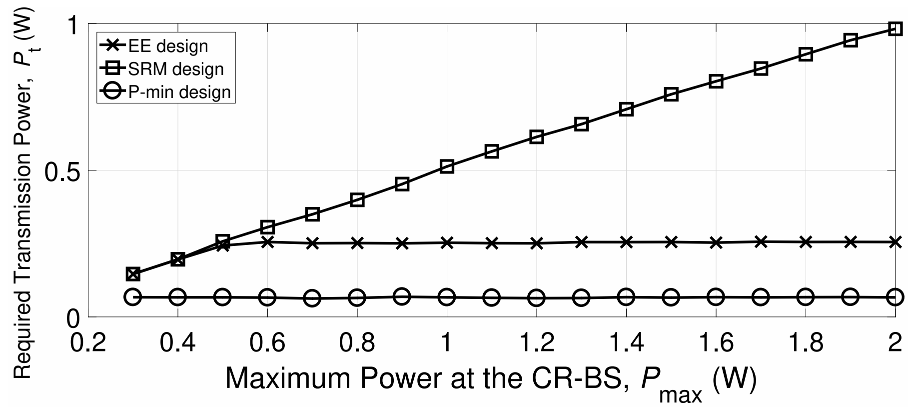
Fig. 2 illustrates the achieved EE for the different resources allocation techniques against the available power budget P_{max} with $\gamma = 0.85$ and P_{idle} = 0.5. As seen in Fig. 2, the proposed EE resource allocation technique outperforms the benchmark schemes in terms of the achieved EE. In particular, both the EE and the SRM based designs show similar performance in terms of EE until reaching a critical power level, referred to as the green power in the literature. When the available power budget P_t exceeds the green power, the achieved EE for the SRM design starts decaying. However, the proposed EE-based design's achieved EE remains almost constant, with an optimal EE achieved with the green power. This is due to the fact that the SRM design aims to maximize the sum-rate, which is achieved by using all the available power budget at the CR-BS, which as a result, degrades the achieved EE. In contrast, in the proposed EE design, the maximum achieved EE is attained at the green power, i.e., $P_{\max} = 0.7$ W. This EE performance reflects the best trade-off between the achieved sum rate and the corresponding power consumption. In fact, due to the fractional nature of the EE design, the optimal EE is achieved at a certain transmit power, referred to as the green power. Therefore, the EE design consumes only this power to achieve its optimal value, which as a result causes saturation in the achieved EE even with the increase of the available power. The lowest EE is achieved with the P-min design compared to that of the EE and the SRM designs. This is due to the fact that the P-min design requires a certain minimum transmit power P_t to achieve the QoS constraints. This leads to a fixed EE as the required power to achieve the QoS requirements remains constant, which explains the constant EE in the P-min design.

To further understand the results provided in Fig. 2, we compare the achieved sum-rate R_{sum} and the corresponding required power P_t for the proposed EE design and the other benchmark designs in Fig. 3. It can be observed from Fig. 3a and Fig. 3b that the achieved sum-rate and the corresponding required power for the EE design saturate when the available power $P_{\max}$ exceeds the green power. Similarly, the achieved EE for the proposed EE designs also saturates. On the other hand, the SRM design shows a different trend, where the achieved sum-rates grow with the increase of P_{max}. However, this sum-rate improvement is attained with exponential growth in power consumption, which as a result, causes a severe degradation in the achieved EE. Based on these observations, we can conclude that the proposed EE design offers a reasonable trade-off between the sum-rate and the power consumption for transmission and thus, strikes a good balance between them.

Next, we investigate the performance of the proposed EE maximization resource allocation technique against different P_{idle} values. Fig. 4 shows the achieved EE for the proposed EE resource allocation technique against a wide set of P_{idle} values (between 0.1 and 0.9). In particular, the performance is studied when P_t = 1.5 W for two different γ values, namely 0.75 and 0.95. As expected, the achieved EE through the proposed EE maximization resource allocation technique is significantly improved with the increase of the idle probability P_{idle}. This can be justified because the higher values of P_{idle} resulting in



(a) The achieved sum-rate against the available power budget $P_{\max}$ for all designs



(b) The total required power for transmission P_t against the available power budget $P_{\max}$ for all designs

Fig. 3: Performance comparison between EE and the benchmarks designs, with P_{idle} = 0.5.

a higher number of available idle channels. The number of successful transmission increase considerably with the increase of P_{idle}. This, as a result, can explain the many-fold EE improvement observed in Fig. 4.

Furthermore, Fig. 5 compares the achieved EE of the proposed EE maximization resource allocation technique against the available power budget $P_{\max}$ for different P_{idle} values. Generally, the green power threshold remains constant with different P_{idle} values, as seen Fig. 5. However, the corresponding maximum EE increases with the increase P_{idle}.

Finally, we demonstrate the convergence of the proposed Dinkelbach's algorithm to solve the original optimization problem **P1**. Fig. 6 represents the variations of the non-negative variable ξ against the number of iterations for several channel realizations. With these results, we confirm that the proposed Dinkelbach's algorithm to solve the EE maximization problem in **P1** converges to the solution within a

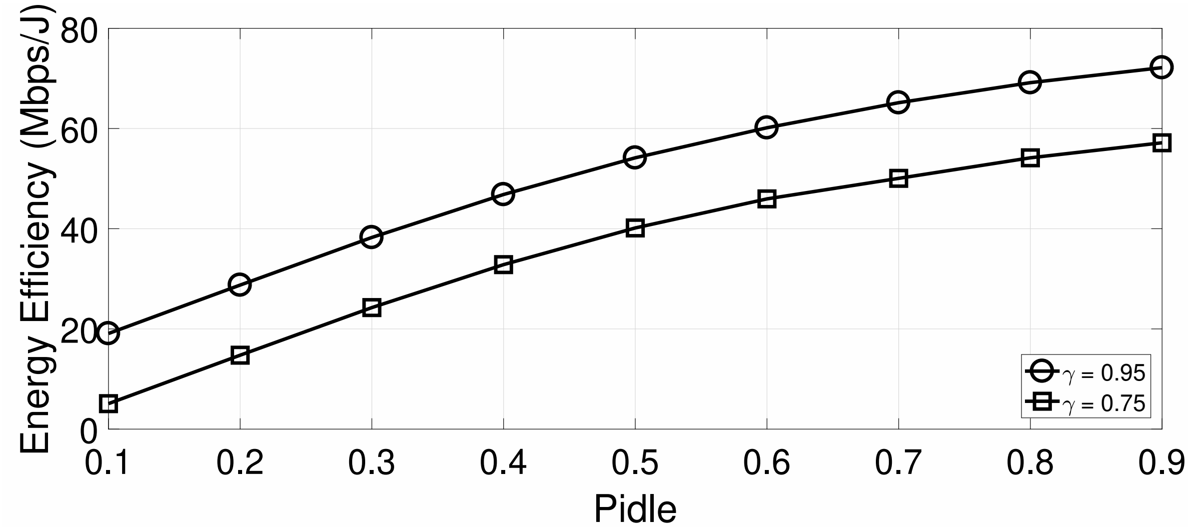


Fig. 4: The achieved EE for the proposed EE design versus P_{idle} with different γ.

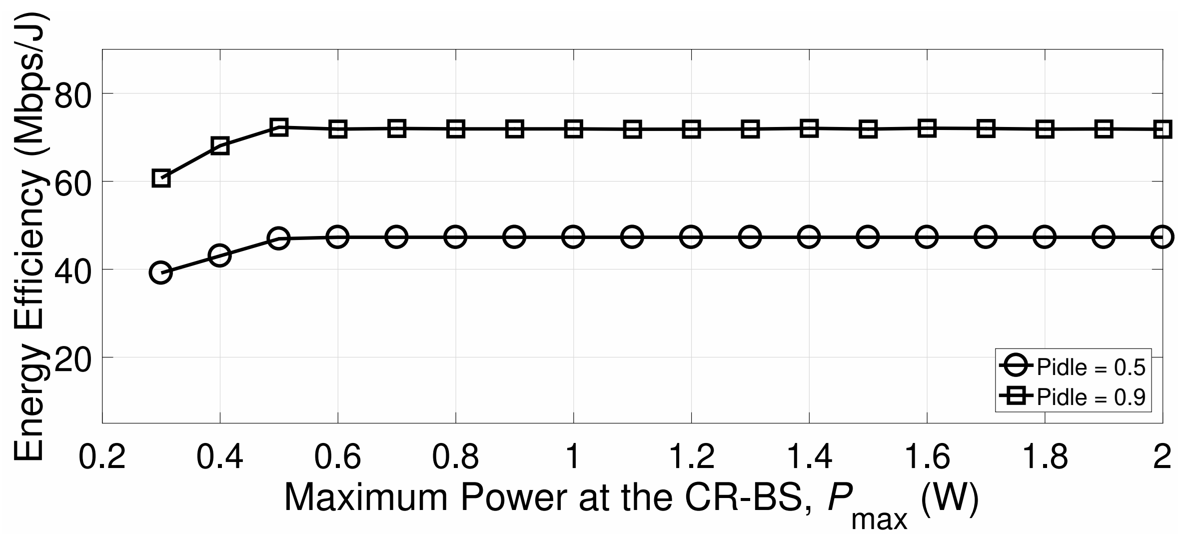


Fig. 5: The achieved EE for the proposed EE design with different P_{idle}.

few iterations.

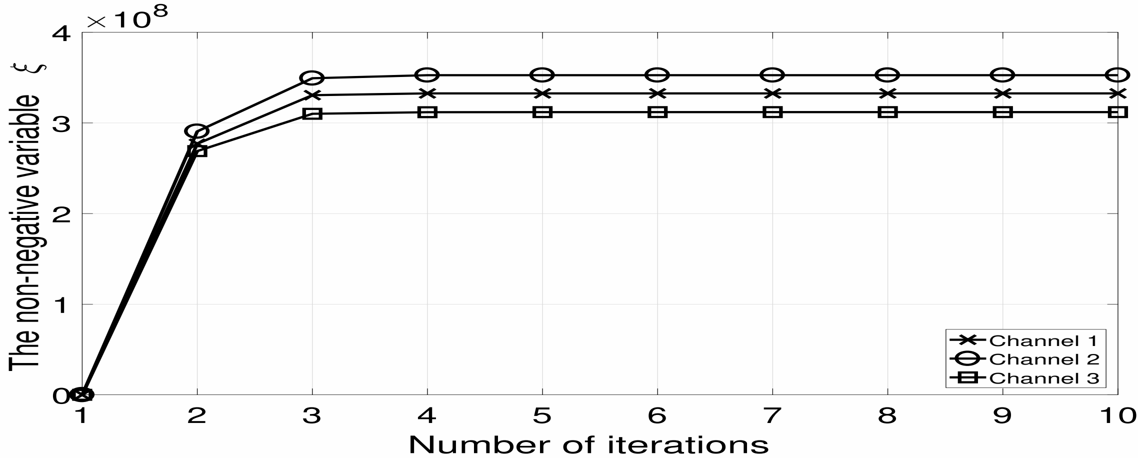


Fig. 6: The convergence of the proposed Dinkelbach's algorithm for different channel realizations, with $P_{\text{max}} = 1.5$ W and P_{idle} = 0.9.

V. Conclusions

In this paper, an energy-efficient resource allocation technique for a multi-carrier NOMA CR-based system was proposed. The proposed resource allocation technique aimed to maximize the achieved EE of the system while satisfying a set of NOMA and CR constraints. We provided a feasibility check to examine the feasibility of the EE maximization problem before solving it. To overcome the fractional non-convex nature of the developed EE maximization framework, we employed the Dinkelbach's algorithm with SCA approach to handle these issues and solved the problem. The simulation results revealed that the proposed EE maximization resource allocation technique outperforms the conventional SRM and P-min resource allocation techniques in terms of the achieved EE while striking a good balance between the achieved sum rate and the transmit power. Furthermore, simulation results were provided to demonstrate the performance of the proposed EE resource allocation technique against different design parameters.

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