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Joint Subcarrier and Power Allocation in NOMA: Optimal and Approximate Algorithms

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Abstract—Non-orthogonal multiple access (NOMA) is a promising technology to increase the spectral efficiency and enable massive connectivity in 5G and future wireless networks. In contrast to orthogonal schemes, such as OFDMA, NOMA multiplexes several users on the same frequency and time resource. Joint subcarrier and power allocation problems (JSPA) in NOMA are NP-hard to solve in general. In this family of problems, we consider the weighted sum-rate (WSR) objective function as it can achieve various tradeoffs between sum-rate performance and user fairness. Because of JSPA’s intractability, a common approach in the literature is to solve separately the power control and subcarrier allocation (also known as user selection) problems, therefore achieving sub-optimal result. In this work, we first improve the computational complexity of existing single-carrier power control and user selection schemes. These improved procedures are then used as basic building blocks to design new algorithms, namely OPT-JSPA, ε -JSPA and GRAD-JSPA. OPT-JSPA computes an optimal solution with lower complexity than current optimal schemes in the literature. It can be used as a benchmark for optimal WSR performance in simulations. However, its pseudo-polynomial time complexity remains impractical for real-world systems with low latency requirements. To further reduce the complexity, we propose a fully polynomial-time approximation scheme called ε -JSPA. Since, no approximation has been studied in the literature, ε -JSPA stands out by allowing to control a tight trade-off between performance guarantee and complexity. Finally, GRAD-JSPA is a heuristic based on gradient descent. Numerical results show that it achieves near-optimal WSR with much lower complexity than existing optimal methods.

I. INTRODUCTION

In multi-carrier multiple access systems, the total frequency bandwidth is divided into subcarriers and assigned to users to optimize the spectrum utilization. Orthogonal multiple access (OMA), such as orthogonal frequency-division multiple access (OFDMA) adopted in 3GPP-LTE and also 5G New Radio Phase 1 standards [1], only serves one user per subcarrier in order to avoid intra-cell interference and have low-complexity signal decoding at the receiver side. OMA is known to be suboptimal in terms of spectral efficiency [2].

The principle of multi-carrier non-orthogonal multiple access (MC-NOMA) is to multiplex several users on the same subcarrier by performing signals superposition at the transmitter side. Successive interference cancellation (SIC) is applied at the receiver side to mitigate interference between superposed signals. MC-NOMA is a promising multiple access

technology for 5G and beyond mobile networks as it can achieve higher spectral efficiency than OMA schemes [3], [4].

Careful optimization of the transmit powers is required to control the intra-carrier interference of superposed signals and maximize the achievable data rates. Besides, due to error propagation and decoding complexity concerns in practice [5], subcarrier allocation for each transmission also needs to be optimized. As a consequence, joint subcarrier and power allocation problems (JSPA) in NOMA have received much attention. In this class of problems, weighted sum-rate (WSR) maximization is especially important as it can achieve different tradeoffs between sum-rate performance and user fairness [6].

Two types of power constraints are considered in the literature. On the one hand, cellular power constraint is mostly used in downlink transmissions to represent the total transmit power budget available at the base station (BS). On the other hand, individual power constraint sets a power limit independently for each user. The latter is often considered in uplink scenarios [7], [8], nevertheless it can also be applied to the downlink [9], [10].

It is known that the equal-weight sum-rate maximization is strongly NP-hard if we consider individual power constraints in both OFDMA [11] and MC-NOMA systems [10], [12]. Nevertheless, several algorithms have been developed to perform subcarrier and/or power allocation for MC-NOMA and this type of constraints. Fractional transmit power control (FTPC) is a simple heuristic that allocates a fraction of the total power budget to each user based on their channel conditions [3]. In [7] and [8], heuristic user pairing strategies and iterative resource allocation algorithms are studied for uplink transmissions. A time efficient two-step heuristic is introduced in [9] to solve the problem with equal weights. Reference [10] derives an upper bound on the optimal WSR and proposes a Lagrangian duality and dynamic programming (LDDP) scheme. This scheme achieves near-optimal result, assuming the power budget is divided in J equal parts to be allocated. It mainly serves as benchmark due to its high computational complexity when J is large in practical systems, which may not be suitable for low latency requirements.

If we consider now cellular power constraints without individual power constraints, the equal-weight sum-rate maximization is polynomial time solvable in OFDMA [13]. To the best of our knowledge, it is unknown whether WSR maximization in MC-NOMA under this type of constraints is polynomial time solvable or NP-hard. However, the aforementioned LDDP solves it in pseudo-polynomial time depending on J . Therefore, JSPA with cellular power constraint can only be *weakly* NP-hard at most (in contrast to *strongly* NP-hard).

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Only a few papers have developed optimization schemes in this setting, which are either heuristics with no theoretical performance guarantee or algorithms with impractical computational complexity. For example, a greedy user selection and heuristic power allocation scheme based on difference-of-convex programming is proposed in [14]. In reference [15], a matching algorithm is developed to perform subcarrier allocation. A minorization-maximization algorithm is used in [16] to compute precoding vectors of a MISO-NOMA system. The authors of [17] employ monotonic optimization to develop an optimal resource allocation policy, which serves as benchmark due to its exponential complexity. The LDDP scheme of reference [10] can also be applied to cellular power constraint scenarios as discussed previously, but it has high complexity as well.

We note that, to the best of our knowledge, no polynomial-time approximation scheme (PTAS) has been proposed in the literature. Although PTAS is interesting for practical considerations of NP-hard problems, as it provides theoretical performance guarantees with controllable computational complexity. Motivated by this observation, we extend the framework of our previous paper [18] with a fully polynomial-time approximation scheme (FPTAS) for the WSR maximization problem with cellular power constraint. In [18], we developed the following algorithms: two basic building blocks SCPC and SCUS which solve respectively the single-carrier power control and single-carrier user selection problems in polynomial time; and a heuristic JSPA scheme based on projected gradient descent, SCPC and SCUS, denoted here by GRAD-JSPA. Our contributions are as follows:

- 1) We improve SCPC and SCUS by performing precomputation to avoid repeated operations each time they are executed. This reduces their computational complexity by a factor proportional to the number of users.
- 2) The above precomputation also speeds up GRAD-JSPA, which now has low and practical computational complexity. In addition, numerical results show that GRAD-JSPA achieves near-optimal WSR, as well as significant improvement in performance over OMA.
- 3) We develop a new optimal algorithm, called OPT-JSPA, suitable for use as a benchmark for optimal WSR performance in simulations. We show that OPT-JSPA has lower computational complexity than existing optimal schemes [10], [17].
- 4) We propose a FPTAS, which is denoted by ϵ -JSPA. Its design is based on the improved SCPC and SCUS, as well as techniques from the multiple choice knapsack problem [19]. By definition of FPTAS, its performance is within a factor $1 - \epsilon$ of the optimal, for any $\epsilon > 0$. Moreover, it has polynomial complexity in both the input size and $1/\epsilon$. Since, no approximation has been studied in the literature, ϵ -JSPA stands out by allowing to control a tight trade-off between performance guarantee and complexity.

The paper is organized as follows. In Section II, we present the system model and notations. Section III formulates the WSR problem. We consider two single-carrier subproblems in Section IV that were previously solved using

SCPC and SCUS in [18]. We propose improved versions of these algorithms, namely i-SCPC and i-SCUS, which perform precomputation to reduce their complexity. Based on these basic building blocks, we develop a low complexity gradient descent based heuristic (GRAD-JSPA), a pseudo-polynomial time optimal algorithm (OPT-JSPA) and a FPTAS with ϵ -approximation guarantee (ϵ -JSPA) in Section V. We show in Section VI some numerical results, highlighting our solution's WSR performance and computational complexity. Finally, we conclude in Section VII.

II. SYSTEM MODEL AND NOTATIONS

We define in this section the system model and notations used throughout the paper. We consider a downlink multi-carrier NOMA system composed of one base station (BS) serving K users. We denote the index set of users by $\mathcal{K} \triangleq \{1, \dots, K\}$, and the set of subcarriers by $\mathcal{N} \triangleq \{1, \dots, N\}$. The total system bandwidth W is divided into N subcarriers of bandwidth W_n , for each $n \in \mathcal{N}$, such that $\sum_{n \in \mathcal{N}} W_n = W$. We assume orthogonal frequency division, so that adjacent subcarriers do not interfere each other. Moreover, each subcarrier $n \in \mathcal{N}$ experiences frequency-flat block fading on its bandwidth W_n .

Let p_k^n denotes the transmit power from the BS to user $k \in \mathcal{K}$ on subcarrier $n \in \mathcal{N}$. User k is said to be active on subcarrier n if $p_k^n > 0$, and inactive otherwise. In addition, let g_k^n be the channel gain between the BS and user k on subcarrier n , and η_k^n be the received noise power. For simplicity of notations, we define the normalized noise power as $\tilde{\eta}_k^n \triangleq \eta_k^n / g_k^n$. We denote by $\mathbf{p} \triangleq (p_k^n)_{k \in \mathcal{K}, n \in \mathcal{N}}$ the vector of all transmit powers, and $\mathbf{p}^n \triangleq (p_k^n)_{k \in \mathcal{K}}$ the vector of transmit powers on subcarrier n .

In power domain NOMA, several users are multiplexed on the same subcarrier using superposition coding. A common approach adopted in the literature is to limit the number of superposed signals on each subcarrier to be no more than M . The value of M is meant to characterize practical limitations of SIC due to decoding complexity and error propagation [5]. We represent the set of active users on subcarrier n by $\mathcal{U}_n \triangleq \{k \in \mathcal{K} : p_k^n > 0\}$. The aforementioned constraint can then be formulated as $\forall n \in \mathcal{N}, |\mathcal{U}_n| \leq M$, where $|\cdot|$ denotes the cardinality of a finite set. Each subcarrier is modeled as a multi-user Gaussian broadcast channel [5] and SIC is applied at the receiver side to mitigate intra-band interference.

The SIC decoding order on subcarrier n is usually defined as a permutation over the active users on n , i.e., $\pi_n : \{1, \dots, |\mathcal{U}_n|\} \rightarrow \mathcal{U}_n$. However, for ease of reading, we choose to represent it by a permutation over all users \mathcal{K} , i.e., $\pi_n : \{1, \dots, K\} \rightarrow \mathcal{K}$. These two definitions are equivalent in our model since the Shannon capacity (2) does not depend on the inactive users $k \in \mathcal{K} \setminus \mathcal{U}_n$, for which $p_k^n = 0$. For $i \in \{1, \dots, K\}$, $\pi_n(i)$ returns the i -th decoded user's index. Conversely, user k 's decoding order is given by $\pi_n^{-1}(k)$.

In this work, we consider the optimal decoding order studied in [5, Section 6.2]. It consists of decoding users' signals from the highest to the lowest normalized noise power:

$$\tilde{\eta}_{\pi_n(1)}^n \geq \tilde{\eta}_{\pi_n(2)}^n \geq \dots \geq \tilde{\eta}_{\pi_n(K)}^n. \quad (1)$$

User $\pi_n(i)$ first decodes the signals of users $\pi_n(1)$ to $\pi_n(i-1)$ and subtracts them from the superposed signal before decoding its own signal. Interference from users $\pi_n(j)$ for $j > i$ is treated as noise. The maximum achievable data rate of user k on subcarrier n is given by Shannon capacity:

$$R_k^n(\mathbf{p}^n) \triangleq W_n \log_2 \left(1 + \frac{g_k^n p_k^n}{\sum_{j=\pi_n^{-1}(k)+1}^K g_k^n p_{\pi_n(j)}^n + \eta_k^n} \right),$$

$$\stackrel{(a)}{=} W_n \log_2 \left(1 + \frac{p_k^n}{\sum_{j=\pi_n^{-1}(k)+1}^K p_{\pi_n(j)}^n + \tilde{\eta}_k^n} \right), \quad (2)$$

where equality (a) is obtained after normalizing by g_k^n . We assume perfect SIC, therefore interference from users $\pi_n(j)$ for $j < \pi_n^{-1}(k)$ is completely removed in (2).

III. PROBLEM FORMULATION

Let $\mathbf{w} = \{w_1, \dots, w_K\}$ be a sequence of K positive weights. The main focus of this work is to solve the following JSPA optimization problem:

$$\begin{aligned} & \underset{\mathbf{p}}{\text{maximize}} && \sum_{k \in \mathcal{K}} w_k \sum_{n \in \mathcal{N}} R_k^n(\mathbf{p}^n), \\ & \text{subject to} && C1: \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} p_k^n \leq P_{max}, \\ & && C2: \sum_{k \in \mathcal{K}} p_k^n \leq P_{max}^n, \quad n \in \mathcal{N}, \\ & && C3: p_k^n \geq 0, \quad k \in \mathcal{K}, \quad n \in \mathcal{N}, \\ & && C4: |\mathcal{U}_n| \leq M, \quad n \in \mathcal{N}. \end{aligned} \quad (\mathcal{P})$$

The objective of \mathcal{P} is to maximize the system's WSR. As discussed in Section I, this objective function has received much attention since its weights \mathbf{w} can be chosen to achieve different tradeoffs between sum-rate performance and fairness [6]. Note that $C1$ represents the cellular power constraint, i.e., a total power budget P_{max} at the BS. In $C2$, we set a power limit of P_{max}^n for each subcarrier n . This is a common assumption in multi-carrier systems, e.g., [11], [13]. Constraint $C3$ ensures that the allocated powers remain non-negative. Due to decoding complexity and error propagation in SIC [5], we restrict the maximum number of multiplexed users per subcarrier to M in $C4$. For ease of reading, we summarize some system parameters of a given instance of \mathcal{P} , for all $n \in \mathcal{N}$, as follows:

$$\mathcal{I}^n = (\mathbf{w}, \mathcal{K}, W_n, (g_k^n)_{k \in \mathcal{K}}, (\eta_k^n)_{k \in \mathcal{K}}).$$

Let us consider the following change of variables:

$$\forall n \in \mathcal{N}, \quad x_i^n \triangleq \begin{cases} \sum_{j=i}^K p_{\pi_n(j)}^n, & \text{if } i \in \{1, \dots, K\}, \\ 0, & \text{if } i = K+1. \end{cases} \quad (3)$$

We define $\mathbf{x} \triangleq (x_i^n)_{i \in \{1, \dots, K\}, n \in \mathcal{N}}$ and $\mathbf{x}^n \triangleq (x_i^n)_{i \in \{1, \dots, K\}}$.

Lemma 1 (Equivalent problem \mathcal{P}').

Problem \mathcal{P} is equivalent to problem \mathcal{P}' formulated below:

$$\underset{\mathbf{x}}{\text{maximize}} \quad \sum_{n \in \mathcal{N}} \sum_{i=1}^K f_i^n(x_i^n) + A, \quad (\mathcal{P}')$$

$$\text{subject to} \quad C1': \sum_{n \in \mathcal{N}} x_1^n \leq P_{max},$$

$$C2': x_1^n \leq P_{max}^n, \quad n \in \mathcal{N},$$

$$C3': x_i^n \geq x_{i+1}^n, \quad i \in \{1, \dots, K\}, \quad n \in \mathcal{N},$$

$$C3'': x_{K+1}^n = 0, \quad n \in \mathcal{N},$$

$$C4': |\mathcal{U}'_n| \leq M, \quad n \in \mathcal{N},$$

where for any $i \in \{1, \dots, K\}$ and $n \in \mathcal{N}$, we have:

$$f_i^n(x_i^n) \triangleq \begin{cases} W_n \log_2 \left(\left(x_1^n + \tilde{\eta}_{\pi_n(1)}^n \right)^{w_{\pi_n(1)}} \right), & \text{if } i = 1, \\ W_n \log_2 \left(\frac{(x_i^n + \tilde{\eta}_{\pi_n(i)}^n)^{w_{\pi_n(i)}}}{(x_i^n + \tilde{\eta}_{\pi_n(i-1)}^n)^{w_{\pi_n(i-1)}}} \right), & \text{if } i > 1, \end{cases}$$

and where $\mathcal{U}'_n \triangleq \{i \in \{1, \dots, K\} : x_i^n > x_{i+1}^n\}$. The constant term $A = \sum_{n \in \mathcal{N}} w_{\pi_n(K)} \log_2 \left(1 / \tilde{\eta}_{\pi_n(K)}^n \right)$ is chosen so that \mathcal{P} and \mathcal{P}' have exactly the same optimal value.

Proof: See Appendix A. \square

The advantage of this formulation \mathcal{P}' is that it exhibits a separable objective function in both dimensions $i \in \{1, \dots, K\}$ and $n \in \mathcal{N}$. In other words, it can be written as a sum of functions f_i^n , each only depending on one variable x_i^n .

IV. SINGLE-CARRIER OPTIMIZATION

In this section, we focus on a simpler problem, in which there is a single subcarrier $n \in \mathcal{N}$ and a power budget \bar{P}^n is given for this subcarrier:

$$\begin{aligned} F^n(\bar{P}^n) &= \max_{\mathbf{x}^n} \quad \sum_{i=1}^K f_i^n(x_i^n) + A^n, && (\mathcal{P}'_{SC}(n)) \\ & \text{subject to} && C2-3': \bar{P}^n \geq x_1^n \geq \dots \geq x_K^n \geq 0, \\ & && C4': |\mathcal{U}'_n| \leq M, \end{aligned}$$

where $A^n = w_{\pi_n(K)} \log_2 \left(1 / \tilde{\eta}_{\pi_n(K)}^n \right)$. $C2-3'$ is obtained by combining $C2'$, $C3'$ and $C3''$. $F^n(\bar{P}^n)$ denotes its optimal value. Algorithms SCPC and SCUS have been introduced in our previous paper [18] to tackle respectively the single-carrier power control and single-carrier user selection sub-problems that arise from $\mathcal{P}'_{SC}(n)$. We provide technical details of these algorithms below, and we show how precomputation can further improve their computational complexity. They will be used as basic building blocks in Section V to design efficient algorithms GRAD-JSPA, OPT-JSPA and ε -JSPA, for the joint resource allocation problem.

A. Analysis of the Separable Functions f_i^n

We introduce auxiliary functions to help us in the analysis of f_i^n and the algorithm design. For $n \in \mathcal{N}$, $i \in \{1, \dots, K\}$ and $j \leq i$, assume that the consecutive variables x_j^n, \dots, x_i^n are all equal to a certain value $x \in [0, \bar{P}^n]$. We define $f_{j,i}^n$ as:

$$\begin{aligned} f_{j,i}^n(x) &\triangleq \sum_{l=j}^i f_l^n(x), \\ &= \begin{cases} W_n \log_2 \left(\left(x + \tilde{\eta}_{\pi_n(i)}^n \right)^{w_{\pi_n(i)}} \right), & \text{if } j = 1, \\ W_n \log_2 \left(\frac{(x + \tilde{\eta}_{\pi_n(i)}^n)^{w_{\pi_n(i)}}}{(x + \tilde{\eta}_{\pi_n(j-1)}^n)^{w_{\pi_n(j-1)}}} \right), & \text{if } j > 1. \end{cases} \end{aligned}$$

This simplification of notation is relevant for the analysis of SCPC and SCUS in the following subsections. Indeed, if users $j, \dots, i-1$ are not active (i.e., $j, \dots, i-1 \notin \mathcal{U}'_n$), then $x_j^n = \dots = x_i^n$, therefore $\sum_{l=j}^i f_l^n$ can be replaced by $f_{j,i}^n$ and x_{j+1}^n, \dots, x_i^n are redundant with x_j^n . If constraint $C4'$ is satisfied, up to M users are active on each subcarrier. Thus, evaluating the objective function of $\mathcal{P}'_{SC}(n)$ only requires $O(M)$ operations.

We study the properties of $f_{j,i}^n$ in Lemma 2. Note that $f_i^n = f_{i,i}^n$, therefore Lemma 2 also holds for functions f_i^n . Fig. 1 shows the two general forms that can be taken by $f_{j,i}^n$.

Lemma 2 (Properties of $f_{j,i}^n$).

Let $n \in \mathcal{N}$, $i \in \{1, \dots, K\}$, and $j \leq i$, we have:

- If $j = 1$ or $w_{\pi_n(i)} \geq w_{\pi_n(j-1)}$, then $f_{j,i}^n$ is increasing and concave on $[0, \infty)$.
- Otherwise when $j > 1$ and $w_{\pi_n(i)} < w_{\pi_n(j-1)}$, $f_{j,i}^n$ is unimodal. It increases on $(-\tilde{\eta}_{\pi_n(j-1)}, c_1]$ and decreases on $[c_1, \infty)$, where

$$c_1 = \frac{w_{\pi_n(j-1)}\tilde{\eta}_{\pi_n(i)} - w_{\pi_n(i)}\tilde{\eta}_{\pi_n(j-1)}}{w_{\pi_n(i)} - w_{\pi_n(j-1)}}.$$

Besides, $f_{j,i}^n$ is concave on $(-\tilde{\eta}_{\pi_n(j-1)}, c_2]$ and convex on $[c_2, \infty)$, where

$$c_2 = \frac{\sqrt{w_{\pi_n(j-1)}\tilde{\eta}_{\pi_n(i)}} - \sqrt{w_{\pi_n(i)}\tilde{\eta}_{\pi_n(j-1)}}}{\sqrt{w_{\pi_n(i)}} - \sqrt{w_{\pi_n(j-1)}}} \geq c_1.$$

Proof: See Appendix B.

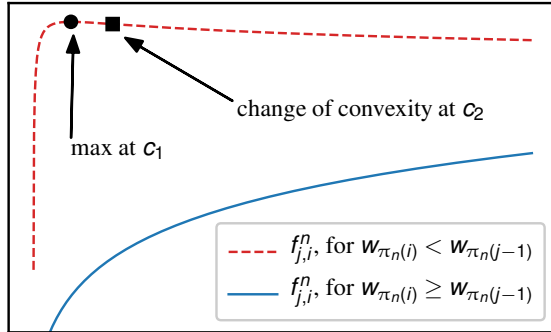


Fig. 1. The two general forms of functions $f_{j,i}^n$.

Algorithm 1 Compute maximum of $f_{j,i}^n$ on $[0, \bar{P}^n]$

function ARGMAX $f(j, i, \mathcal{I}^n, \bar{P}^n)$

- 1: $a \leftarrow \pi_n(i)$
- 2: $b \leftarrow \pi_n(j-1)$
- 3: **if** $j = 1$ or $w_a \geq w_b$ **then**
- 4: **return** \bar{P}^n
- 5: **else**
- 6: **return** $\max\left\{0, \min\left\{\frac{w_b\tilde{\eta}_a - w_a\tilde{\eta}_b}{w_a - w_b}, \bar{P}^n\right\}\right\}$
- 7: **end if**

end function

We present in Algorithm 1 the pseudocode ARGMAX f which computes the maximum of $f_{j,i}^n$ on $[0, \bar{P}^n]$ following the result of Lemma 2. ARGMAX f only requires a constant number of basic operations, therefore its complexity is $O(1)$.

B. Single-Carrier Power Control

The single-carrier power control problem $\mathcal{P}'_{SCPC}(n)$ is equivalent to problem $\mathcal{P}'_{SC}(n)$, with the exception that a fixed user selection \mathcal{U}'_n (or equivalently \mathcal{U}_n) is given as input instead of being an optimization variable. It is defined below:

$$\begin{aligned} & \underset{x^n}{\text{maximize}} && \sum_{i=1}^K f_i^n(x_i^n) + A^n, && (\mathcal{P}'_{SCPC}(n)) \\ & \text{subject to} && C2-3' : \bar{P}^n \geq x_1^n \geq \dots \geq x_K^n \geq 0. \end{aligned}$$

We denote its optimal value by $F^n(\mathcal{U}'_n, \bar{P}^n)$.

Since inactive users $k \notin \mathcal{U}_n$ have no contribution on the data rates, i.e., $p_k^n = 0$ and $R_k^n = 0$, we remove them for the study of this sub-problem. Without loss of generality, we index the remaining active users on subcarrier n by $i_n \in \{1_n, \dots, |\mathcal{U}'_n|_n\}$. For example, if $\mathcal{U}'_n = \{4, 7, 10\}$, then $1_n = 4$, $2_n = 7$ and $3_n = 10$. For simplicity of notation, we add an index $0_n = 0$, which does not correspond to any user. From the definition of \mathcal{U}'_n , variables x_l^n with index from $l = (i-1)_n + 1$ to i_n are equal, for any $i \geq 1$. In the above example, we would have $x_1 = x_2 = x_3 = x_4 > x_5 = x_6 = x_7 > x_8 = x_9 = x_{10}$. Thus, the objective function of $\mathcal{P}'_{SCPC}(n)$ can be written as:

$$\sum_{i=1}^K f_i^n(x_i^n) + A^n = \sum_{i=1}^{|\mathcal{U}'_n|} f_{(i-1)_n+1, i_n}^n(x_{i_n}^n) + B^n, \quad (4)$$

- where $B^n = A^n$ if the last active user's index is $|\mathcal{U}'_n|_n = K$, and $B^n = f_{|\mathcal{U}'_n|_n+1, K}^n(0) + A^n$ otherwise. For $1 \leq j \leq i \leq K$, we simplify some notations as follows:

$$\begin{aligned} \tilde{f}_{j,i}^n(\mathcal{U}'_n, \cdot) &\triangleq f_{(j-1)_n+1, i_n}^n(\cdot), \\ \text{ARGMAX}_{\tilde{f}}(j, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n) &\triangleq \\ &\text{ARGMAX}_f((j-1)_n+1, i_n, \mathcal{I}^n, \bar{P}^n). \end{aligned}$$

We reformulate the problem as:

$$\begin{aligned} & \underset{x_{i_n}^n}{\text{maximize}} && \sum_{i=1}^{|\mathcal{U}'_n|} \tilde{f}_{i,i}^n(\mathcal{U}'_n, x_{i_n}^n) + B^n && (\mathcal{P}'_{SCPC}(n)) \\ & \text{subject to} && C2-3' : \bar{P}^n \geq x_{1_n}^n \geq \dots \geq x_{|\mathcal{U}'_n|_n}^n \geq 0. \end{aligned}$$

Algorithm 2 presents the SCPC method proposed in [18]. The idea is to iterate over variables $x_{i_n}^n$ for $i = 1$ to $|\mathcal{U}'_n|$, and compute their optimal value $x^* = \text{ARGMAX}_{\tilde{f}}(i, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ at line 3. If the current allocation satisfies constraint $C3'$, then $x_{i_n}^n$ gets value x^* . Otherwise, the algorithm backtracks at line 6 and finds the highest index $j \in \{1, \dots, i-2\}$ such that $x_{j_n}^n \geq \text{ARGMAX}_{\tilde{f}}(j+1, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$. Then, variables $x_{(j+1)_n}^n, \dots, x_{i_n}^n$ are set equal to $\text{ARGMAX}_{\tilde{f}}(j+1, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ at line 10. The optimality and complexity of SCPC are presented in Theorem 3.

Theorem 3 (Optimality and complexity of SCPC).

Given subcarrier $n \in \mathcal{N}$, a set \mathcal{U}'_n of M active users and a power budget \bar{P}^n , algorithm SCPC computes the optimal single-carrier power control. Its worst case computational complexity is $O(M^2)$.

Proof: See Appendix C. □

Algorithm 2 Single-carrier power control algorithm (SCPC)

```

function SCPC( $\mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n$ )
1: for  $i = 1$  to  $|\mathcal{U}'_n|$  do
2:    $\triangleright$  Compute the optimal of  $\tilde{f}_{i,i}^n$ 
3:    $x^* \leftarrow \text{ARGMAX}_{\tilde{f}}(i, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ 
4:    $\triangleright$  Modify  $x^*$  if this allocation violates constraint C3'
5:    $j \leftarrow i - 1$ 
6:   while  $x_{j_n}^n < x^*$  and  $j \geq 1$  do
7:      $x^* \leftarrow \text{ARGMAX}_{\tilde{f}}(j, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ 
8:      $j \leftarrow j - 1$ 
9:   end while
10:   $x_{(j+1)_n}^n, \dots, x_{i_n}^n \leftarrow x^*$ 
11: end for
12: return  $x_{1_n}^n, \dots, x_{|\mathcal{U}'_n|_n}^n$ 
end function

```

In multi-carrier resource allocation schemes, such as GRAD-JSPA and ε -JSPA, it is often required to compute the optimal single-carrier power control and WSR for many different values of power budget \bar{P}^n . In this cases, running many times SCPC is actually not efficient in terms of computational complexity, since several computations may be repeated. To avoid this, we propose in Algorithm 3 an improved SCPC algorithm (i-SCPC). The idea is to perform precomputation before runtime by calling SCPC($\mathcal{I}^n, \mathcal{U}'_n, P_{max}$) and storing its result $x_{1_n}^n, \dots, x_{|\mathcal{U}'_n|_n}^n$ as a global variable (also called lookup table). Any subsequent evaluation with input $\mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n$, where $\bar{P}^n \leq P_{max}$, can be obtained as in line 1.

Algorithm 3 Improved SCPC algorithm with precomputation

```

input:  $\mathcal{I}^n, \mathcal{U}'_n, P_{max}$ 
global variable:  $x_{1_n}^n, \dots, x_{|\mathcal{U}'_n|_n}^n$ 
initialization:  $x_{1_n}^n, \dots, x_{|\mathcal{U}'_n|_n}^n \leftarrow \text{SCPC}(\mathcal{I}^n, \mathcal{U}'_n, P_{max})$ 
function i-SCPC( $\bar{P}^n$ )
1: return  $\min\{x_{1_n}^n, \bar{P}^n\}, \dots, \min\{x_{|\mathcal{U}'_n|_n}^n, \bar{P}^n\}$ 
end function

```

Theorem 4 (Optimality and complexity of i-SCPC).

Given subcarrier $n \in \mathcal{N}$ and a set \mathcal{U}'_n of M active users, the precomputation of i-SCPC has complexity $O(M^2)$. Any subsequent evaluation costs $O(M)$. Hence, for C different power budgets, algorithm i-SCPC computes their respective optimal single-carrier power control with overall complexity $O(M^2 + CM)$.

Proof: See Appendix D. \square

Remark. Note that SCPC and i-SCPC returns $|\mathcal{U}'_n|$ values $x_{1_n}^n, \dots, x_{|\mathcal{U}'_n|_n}^n$ representing only the active users' variables. These values are sufficient to compute the optimal power allocation and WSR of $\mathcal{P}'_{SCPC}(n)$ as shown in Eqn. (4). If needed, the full vector \mathbf{x}^n can be obtained by the following procedure in $O(K)$ operations:

```

1: for  $i = 1$  to  $|\mathcal{U}'_n|$  and  $l = (i - 1)_n + 1$  to  $i_n$  do
2:    $x_l^n \leftarrow x_{i_n}^n$ 
3: end for
4: for  $l = |\mathcal{U}'_n|_n + 1$  to  $K$  do
5:    $x_l^n \leftarrow 0$ 
6: end for

```

C. Single-Carrier User Selection

Unlike in the previous subsection, we consider here furthermore the user selection \mathcal{U}'_n optimization under multiplexing and SIC constraint $C4'$, i.e., we solve $\mathcal{P}'_{SC}(n)$. In [18], a dynamic programming (DP) is proposed to solve $\mathcal{P}'_{SC}(n)$. Here, we first develop a similar DP procedure in Algorithm 4 (SCUS). Then, we propose an improved version (i-SCUS) which performs SCUS as precomputation.

The idea of SCUS is to compute recursively the elements of three arrays V, X, U . Let $m \in \{0, \dots, M\}$, $j \in \{1, \dots, K\}$ and $i \in \{j, \dots, K\}$, we define $V[m, j, i]$ as the optimal value of the following problem $\mathcal{P}'_{SC}[m, j, i]$:

$$\begin{aligned}
 V[m, j, i] &\triangleq \max_{\mathbf{x}^n} \sum_{l=j}^K f_l^n(x_l^n), \quad (\mathcal{P}'_{SC}[m, j, i]) \\
 &\text{subject to} \quad C2', C3', C3'', \\
 &\quad C4' : |\mathcal{U}'_n| \leq m, \\
 &\quad C5' : x_j^n = \dots = x_i^n.
 \end{aligned}$$

This problem is more restrictive than $\mathcal{P}'_{SC}(n)$. The objective function only depends on variables x_j^n, \dots, x_K^n . $C4'$ limits the number of active users to m . Moreover, variables x_j^n, \dots, x_i^n are equal according to $C5'$.

It is interesting to note that $V[M, 1, 1]$ is the optimal value of $\mathcal{P}'_{SC}(n)$, since the objective function is $\sum_{l=1}^K f_l^n(x_l^n)$ for $j = 1$ and constraint $C5'$ becomes trivially true for $j = i$. Let $x_j^{n*}, \dots, x_K^{n*}$ be the optimal solution achieving $V[m, j, i]$. We define $X[m, j, i] \triangleq x_i^{n*}$, which is also equal to $x_j^{n*}, \dots, x_{i-1}^{n*}$ due to constraint $C5'$. The idea of SCUS is to recursively compute the elements of V through the following relation:

$$V[m, j, i] = \begin{cases} v_{act}, & \text{if } v_{act} > v_{inact} \\ & \text{and } x^* > X[m-1, i+1, i+1], \\ v_{inact}, & \text{otherwise,} \end{cases} \quad (5)$$

where $x^* = \text{ARGMAX}_{f(j, i, \mathcal{I}^n, \bar{P}^n)}$, and v_{act} (resp. v_{inact}) corresponds to allocation where user i is active (resp. inactive):

$$\begin{aligned}
 v_{act} &= f_{j,i}^n(x^*) + V[m-1, i+1, i+1], \\
 v_{inact} &= V[m, j, i+1].
 \end{aligned}$$

During SCUS's iterations, the array U keeps track of which previous element of V has been used to compute the current value function $V[m, j, i]$. This allows us to retrieve the entire optimal vector \mathbf{x}^n at the end of Algorithm 4 (at lines 28-35) by backtracking from index $(M, 1, 1)$ to \emptyset , where \emptyset is set at initial indices (see lines 5 and 11) to indicate the recursion termination. To sum up, X and U have two different recurrence relations depending on the cases in Eqn. (5).

If $V[m, j, i] = v_{act}$, then:

$$\begin{aligned}
 X[m, j, i] &= x^*, \\
 U[m, j, i] &= (m-1, i+1, i+1).
 \end{aligned}$$

If $V[m, j, i] = v_{inact}$, then:

$$\begin{aligned}
 X[m, j, i] &= X[m, j, i+1], \\
 U[m, j, i] &= (m, j, i+1).
 \end{aligned}$$

Algorithm 4 Single-carrier user selection algorithm (SCUS)

```

function SCUS( $\mathcal{I}^n, M, \bar{P}^n$ )
1:  $\triangleright$  Initialize arrays  $V, X, U$  for  $m = 0$  and  $i = K$ 
2: for  $i = K$  to 1 and  $j = i$  to 1 do
3:    $V[0, j, i] \leftarrow f_{j,K}^n(0)$ 
4:    $X[0, j, i] \leftarrow 0$ 
5:    $U[0, j, i] \leftarrow \emptyset$ 
6: end for
7: for  $m = 1$  to  $M$  and  $j = K$  to 1 do
8:    $x^* \leftarrow \text{ARGMAX}_f(j, K, \mathcal{I}^n, \bar{P}^n)$ 
9:    $V[m, j, K] \leftarrow f_{j,K}^n(x^*)$ 
10:   $X[m, j, K] \leftarrow x^*$ 
11:   $U[m, j, K] \leftarrow \emptyset$ 
12: end for
13:  $\triangleright$  Compute  $V, X, U$  for  $m \in [1, M]$  and  $j \leq i \leq K - 1$ 
14: for  $i = K - 1$  to 1 and  $m = 1$  to  $M$  and  $j = i$  to 1 do
15:    $x^* \leftarrow \text{ARGMAX}_f(j, i, \mathcal{I}^n, \bar{P}^n)$ 
16:    $v_{act} \leftarrow f_{j,i}^n(x^*) + V[m - 1, i + 1, i + 1]$ 
17:    $v_{inact} \leftarrow V[m, j, i + 1]$ 
18:   if  $v_{act} > v_{inact}$  and  $x^* > X[m - 1, i + 1, i + 1]$  then
19:      $V[m, j, i] \leftarrow v_{act}$ 
20:      $X[m, j, i] \leftarrow x^*$ 
21:      $U[m, j, i] \leftarrow (m - 1, i + 1, i + 1)$ 
22:   else
23:      $V[m, j, i] \leftarrow v_{inact}$ 
24:      $X[m, j, i] \leftarrow X[m, j, i + 1]$ 
25:      $U[m, j, i] \leftarrow (m, j, i + 1)$ 
26:   end if
27: end for
28:  $\triangleright$  Retrieve the optimal solution  $x^n$ 
29:  $x_1^n, \dots, x_K^n \leftarrow 0$ 
30:  $(m, j, i) \leftarrow (M, 1, 1)$ 
31: repeat
32:    $x_j^n, \dots, x_i^n \leftarrow X[m, j, i]$ 
33:    $(m, j, i) \leftarrow U[m, j, i]$ 
34: until  $(m, j, i) = \emptyset$ 
35: return  $x^n$ 
end function

```

When $m = 0$, no user can be active on this subcarrier due to constraint $C4'$. Therefore, V, X, U can be initialized by:

$$\begin{aligned} V[0, j, i] &= f_{j,K}^n(0), \\ X[0, j, i] &= 0, \\ U[0, j, i] &= \emptyset. \end{aligned}$$

For simplicity, we also extend V, X and U on the index $i = K$ and $j \leq K$ and initialize them as follows:

$$\begin{aligned} V[m, j, K] &= f_{j,K}^n(x^*), \\ X[m, j, K] &= x^*, \\ U[m, j, K] &= \emptyset. \end{aligned}$$

A detailed analysis is given in Appendix E.

Theorem 5 (Optimality and complexity of SCUS).

Given a subcarrier $n \in \mathcal{N}$, a power budget \bar{P}^n and $M \geq 1$, algorithm SCUS computes the optimal single-carrier power control and user selection of $\mathcal{P}'_{SC}(n)$. Its worst case computational complexity is $O(MK^2)$.

Proof: See Appendix E. \square

We present i-SCUS in Algorithm 5, which performs pre-computation to avoid repeating the DP procedure when multiple evaluations are required. The algorithm precomputes vectors V, X, U from SCUS($\mathcal{I}^n, M, P_{max}$) before runtime, at line 1. Then, in lines 2-5, it retrieves the active users set \mathcal{U}'_n and optimal solution x_1^n, \dots, x_K^n of each $V[M, 1, i]$, $i \in \{1, \dots, K\}$, and stores them in *collection*. Any subsequent evaluation with a lower budget $\bar{P}^n \leq P_{max}$, can be obtained by searching the best allocation among the K possibilities in *collection* (lines 6-7). Each allocation is truncated as in i-SCPC(\bar{P}^n) to satisfy budget \bar{P}^n . The optimality and complexity of Algorithm 5 are given in Theorem 6.

Algorithm 5 Improved SCUS algorithm with precomputation

```

input:  $\mathcal{I}^n, M, P_{max}$ 
global variable: collection
initialization:
1: Get  $V, X, U$  from SCUS( $\mathcal{I}^n, M, P_{max}$ )
2: for  $i = 1$  to  $K$  do
3:   Retrieve the active users set  $\mathcal{U}'_n$  of  $V[M, 1, i]$  and its
   optimal solution  $x_1^n, \dots, x_K^n$ 
4:   Add  $(\mathcal{U}'_n, x_1^n, \dots, x_K^n)$  to collection
5: end for
function i-SCUS( $\bar{P}^n$ )
6: Get  $(\mathcal{U}'_n, x_1^n, \dots, x_K^n)$  in collection that maximizes
    $F^n(\mathcal{U}'_n, \bar{P}^n) = \sum_{l=1}^{|\mathcal{U}'_n|} \tilde{f}_{l,l}^n(\mathcal{U}'_n, \min\{x_l^n, \bar{P}^n\}) + B^n$ 
7: return  $\min\{x_1^n, \bar{P}^n\}, \dots, \min\{x_K^n, \bar{P}^n\}$ 
end function

```

Theorem 6 (Optimality and complexity of i-SCUS).

Given a subcarrier $n \in \mathcal{N}$, a power budget \bar{P}^n and $M \geq 1$, the precomputation of i-SCUS has complexity $O(MK^2)$. Any subsequent evaluation costs $O(MK)$. Hence, for C different power budgets, i-SCUS computes their respective optimal single-carrier power control and user selection $\mathcal{P}'_{SC}(n)$ with overall complexity $O(MK^2 + CMK)$.

Proof: See Appendix F. \square

Table I summarizes the complexity of the single-carrier algorithms developed in this section. They will be used as basic building blocks to design JSPA schemes in Section V.

TABLE I
SUMMARY OF THE SINGLE-CARRIER RESOURCE ALLOCATION SCHEMES

Algorithm	Complexity to perform C evaluations
SCPC [18]	$O(CM^2)$
i-SCPC	$O(M^2 + CM)$
SCUS [18]	$O(CMK^2)$
i-SCUS	$O(MK^2 + CMK)$

V. JOINT SUBCARRIER AND POWER ALLOCATION

Recall that $F^n(\bar{P}^n)$ is the optimal value of $\mathcal{P}'_{SC}(n)$ with power budget \bar{P}^n . We have $F^n(\bar{P}^n) = \sum_{i=1}^K f_i^n(x_i^n) + A^n$, where x_1^n, \dots, x_K^n is the output of i-SCUS(\bar{P}^n). Using this notation, the JSPA problem \mathcal{P}' can be simplified as:

$$\begin{aligned} &\underset{\bar{P}}{\text{maximize}} && \sum_{n \in \mathcal{N}} F^n(\bar{P}^n) && (\mathcal{P}'_{MC}) \\ &\text{subject to} && \bar{P}^n \in \mathcal{F}, \end{aligned}$$

where \bar{P}^n , for $n \in \mathcal{N}$, are intermediate variables representing each subcarrier's power budget. $\bar{\mathbf{P}} \triangleq (\bar{P}^1, \dots, \bar{P}^N)$ denotes the power budget vector. The feasible set

$$\mathcal{F} \triangleq \{\bar{\mathbf{P}}: \sum_{n \in \mathcal{N}} \bar{P}^n \leq P_{max} \text{ and } 0 \leq \bar{P}^n \leq P_{max}^n, n \in \mathcal{N}\}$$

is chosen to satisfy $C1'$ and $C2'$ in \mathcal{P}' .

A. Gradient Descent Based Heuristic

GRAD-JSPA is an efficient heuristic based on projected gradient descent. Its principle is to perform a two-stage optimization as presented in Fig. 2. The first-stage is a projected gradient descent on $\bar{\mathbf{P}}$ in the search space \mathcal{F} . The evaluations of each function F^n and its derivative are done by i-SCUS in a second-stage optimization.

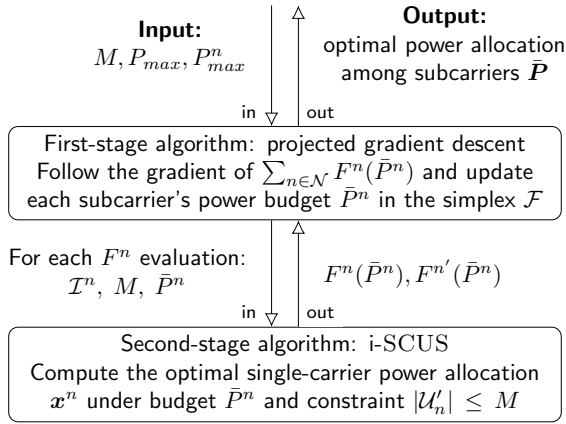


Fig. 2. Overview of GRAD-JSPA

We denote the derivative of F^n at \bar{P}^n by $F^{n'}(\bar{P}^n)$. Lemma 7 shows how to compute it.

Lemma 7 (Derivative of F^n).

Let x_1^n, \dots, x_K^n be the output of i-SCUS(\bar{P}^n). The left derivative of F^n at \bar{P}^n , can be computed as follows:

$$F^{n'}(\bar{P}^n) = \frac{W_n w_{\pi_n(l)}}{(x_l^n + \tilde{\eta}_{\pi_n(l)}^n) \ln(2)} = \frac{W_n w_{\pi_n(l)}}{(\bar{P}^n + \tilde{\eta}_{\pi_n(l)}^n) \ln(2)},$$

where l is the greatest index such that $x_l^n = \bar{P}^n$, and $\ln(2)$ is the natural logarithm of 2.

Proof: See Appendix G. \square

The pseudocode of GRAD-JSPA is described in Algorithm 6. Input ξ corresponds to the error tolerance at termination, as we can see at line 8. The search direction at lines 4-5 is the gradient of $\sum_{n \in \mathcal{N}} F^n$ evaluated at $\bar{\mathbf{P}}$. Since F^1, \dots, F^N are independent, it is equal to the vector of $F^{1'}(\bar{P}^1), \dots, F^{N'}(\bar{P}^N)$. Note that the step size α at line 6 can be tuned by backtracking line search or exact line search [20, Section 9.2]. We adopt the latter to perform simulations. The projection of $\bar{\mathbf{P}} + \alpha\Delta$ on the simplex \mathcal{F} at line 7 can be computed efficiently [20, Section 8.1.1], the details of its implementation are omitted here.

We showed in our previous work [18] that GRAD-JSPA worst case complexity is $O(\log(1/\xi)NMK^2)$ when SCUS is

Algorithm 6 Gradient descent based heuristic (GRAD-JSPA)

function GRAD-JSPA($(\mathcal{I}^n)_{n \in \mathcal{N}}, M, P_{max}, P_{max}^n, \xi$)

- 1: Let $\bar{\mathbf{P}} \leftarrow \mathbf{0}$ be the starting point
 - 2: **repeat**
 - 3: Save the previous vector $\bar{\mathbf{P}}' \leftarrow \bar{\mathbf{P}}$
 - 4: Determine a search direction Δ
 - 5: $\Delta \leftarrow (F^{1'}(\bar{P}^1), \dots, F^{N'}(\bar{P}^N))$
 - 6: Choose a step size α
 - 7: Update $\bar{\mathbf{P}} \leftarrow$ projection of $\bar{\mathbf{P}} + \alpha\Delta$ on \mathcal{F}
 - 8: **until** $\|\bar{\mathbf{P}}' - \bar{\mathbf{P}}\| \leq \xi$
 - 9: **return** $\bar{\mathbf{P}}$
- end function**

used to evaluate functions F^n , $n \in \mathcal{N}$. We show in Theorem 8 that the complexity of GRAD-JSPA can be reduced by the use of i-SCUS.

Theorem 8 (Complexity of GRAD-JSPA).

Let ξ be the error tolerance at termination. Algorithm GRAD-JSPA has complexity $O(NMK^2 + \log(1/\xi)NMK)$ when i-SCUS is used to evaluate functions F^n , $n \in \mathcal{N}$.

Proof: See Appendix G. \square

Although i-SCUS (or equivalently SCUS) is optimal, the returned $F^n(\bar{P}^n)$ is not necessarily concave in \bar{P}^n . As a consequence, GRAD-JSPA is not guaranteed to converge to a global maximum. Nevertheless, we show by numerical results in Section VI that it achieves near-optimal WSR performance with low complexity.

B. Pseudo-Polynomial Time Optimal Scheme

The JSPA problem as formulated in \mathcal{P}'_{MC} has real variables \bar{P}^n on a continuous search space \mathcal{F} . However, the study of NP-hard optimization problems and their approximation requires parameters and variables to be represented by a bounded number of bits [21], i.e., with bounded precision. This is also a reasonable assumption in practice since MC-NOMA systems are subject to minimum transmit power limitation at the BS and floating-point arithmetic precision of the hardware. As a consequence, we discretize the search space \mathcal{F} , in the same way as in [10]. Let δ be the minimum transmit power such that the variables \bar{P}^n can only take value of the form $l \cdot \delta$, for $l \in \{0, 1, \dots, \lfloor \frac{P_{max}}{\delta} \rfloor\}$. We denote the number of non-zero power values as $J = \lfloor \frac{P_{max}}{\delta} \rfloor$. The feasible set then becomes

$$\mathcal{F}' \triangleq \{\bar{\mathbf{P}}: \sum_{n \in \mathcal{N}} \bar{P}^n \leq P_{max} \text{ and } 0 \leq \bar{P}^n \leq P_{max}^n, n \in \mathcal{N}, \text{ and } \bar{P}^n = l \cdot \delta, l \in \{0, \dots, J\}, n \in \mathcal{N}\}.$$

We rewrite problem \mathcal{P}'_{MC} with search space \mathcal{F}' as follows:

$$\begin{aligned} & \underset{\bar{\mathbf{P}}}{\text{maximize}} && \sum_{n \in \mathcal{N}} \sum_{l=1}^J c_{n,l} y_{n,l} && \text{(MCKP)} \\ & \text{subject to} && \sum_{n \in \mathcal{N}} \sum_{l=1}^J a_{n,l} y_{n,l} \leq P_{max}, \\ & && \sum_{l=1}^J a_{n,l} y_{n,l} \leq P_{max}^n, n \in \mathcal{N}, \end{aligned}$$

$$\sum_{l=1}^J y_{n,l} \leq 1, \quad n \in \mathcal{N},$$

$$y_{n,l} \in \{0, 1\}, \quad n \in \mathcal{N}, \quad l \in [1, J],$$

where $c_{n,l} = F^n(l \cdot \delta)$ and $a_{n,l} = l \cdot \delta$. The discretized JSPA problem, denoted by MCKP, is known as the multiple choice knapsack problem [19]. It has N disjoint classes each containing J items to be packed into a knapsack of capacity P_{max} . Each item has a profit $c_{n,l}$ and a weight $a_{n,l}$, representing respectively the WSR and power consumption of this allocation on subcarrier n . The binary variable $y_{n,l}$ takes value 1 if and only if item l in class n is assigned to the knapsack. The problem consists in assigning at most one item from each class to maximize the sum of their profit. We denote its optimal value by F_{MCKP}^* .

The discrete problem MCKP can be solved optimally by *dynamic programming by weights* studied in [19, Section 11.5]. Based on this idea, we propose OPT-JSPA (see Algorithm 7) to solve optimally \mathcal{P}'_{MC} . We first transform \mathcal{P}'_{MC} to problem MCKP: from line 1 to 5, every item's profit $c_{n,l}$ is computed using i-SCUS. Then, we perform dynamic programming by weights at lines 6-7. We summarize the optimality and complexity of OPT-JSPA in Theorem 9. Detailed analysis of the dynamic programming can be found in Appendix H.

Algorithm 7 The pseudo-polynomial time optimal scheme

function OPT-JSPA($(\mathcal{I}^n)_{n \in \mathcal{N}}, M, P_{max}, P_{max}^n, \delta$)

- 1: \triangleright Compute the parameters of MCKP
- 2: **for** $n \in \mathcal{N}$ and $l \in [0, J]$ **do**
- 3: $a_{n,l} \leftarrow l \cdot \delta$
- 4: $c_{n,l} \leftarrow F^n(l \cdot \delta)$
- 5: **end for**
- 6: **return** optimal allocation from the *dynamic programming by weights* [19]

end function

Theorem 9 (Optimality and complexity of OPT-JSPA).

Given a minimum transmit power δ , algorithm OPT-JSPA computes the optimal of \mathcal{P}'_{MC} on the discrete set \mathcal{F}' . Its computational complexity is $O(NMK^2 + JNMK + J^2N)$, which is pseudo-polynomial in J .

Proof: See Appendix H. \square

OPT-JSPA is said to be pseudo-polynomial since it depends on the total number of power values J , whereas all system's parameters and variables are encoded in $O(\log(J))$ bits. As a consequence, in practical systems, the contribution of J to the computation time is way higher than parameters N, K, M .

C. Fully Polynomial-Time Approximation Scheme

We develop a FPTAS to avoid the pseudo-polynomial complexity in J that is inherent to the optimal schemes OPT-JSPA and LDDP [10]. According to [22], an algorithm is said to be a FPTAS if it outputs a solution within a factor $1 - \varepsilon$ of the optimal, for any $\varepsilon > 0$. Moreover, its running time is bounded by a polynomial in both the input size and $1/\varepsilon$. A FPTAS is the best trade-off one can hope for an NP-hard optimization

problem in terms of performance guarantee and complexity, assuming $P \neq NP$.

The proposed FPTAS, called ε -JSPA, is described in Algorithm 8. First, we compute an estimation U of MCKP's optimal value, such that $U \geq F_{MCKP}^* \geq U/4$. We explain the estimation procedure in Appendix I. Then, instead of computing all JN profit values $c_{n,l}$, we only consider the subset L_n of items on each subcarrier n such that:

$$L_n \triangleq \{l \in \{0, \dots, J\} : c_{n,l} \geq \frac{\varepsilon U}{4N} > c_{n,l-1}\}.$$

This can be seen as considering only one profit value per interval of the form $[(l-1) \cdot \varepsilon U/4N, l \cdot \varepsilon U/4N]$, for $l \in \{1, \dots, 4N/\varepsilon\}$. Each L_n , for $n \in \mathcal{N}$, can be obtained by multi-key binary search [23]. All function evaluations required by the multi-key binary search are done by i-SCUS.

Finally, we apply the *dynamic programming by profits* [19, Section 11.5] in lines 5-6. It is known that the optimal solution obtained by dynamic programming by profits considering only items in L_n , differs from F_{MCKP}^* by at most a factor $1 - \varepsilon$. The performance and complexity of ε -JSPA are summarized in Theorem 10. We provide more details on the estimation U in Appendix I and the dynamic programming by profits in Appendix J.

Algorithm 8 The proposed FPTAS (ε -JSPA)

function ε -JSPA($(\mathcal{I}^n)_{n \in \mathcal{N}}, M, P_{max}, P_{max}^n, \delta, \varepsilon$)

- 1: Compute an estimation U of F_{MCKP}^*
- 2: **for** $n \in \mathcal{N}$ **do**
- 3: Get $a_{n,l}, c_{n,l}$, for $l \in L_n$ by multi-key binary search
- 4: **end for**
- 5: **return** ε -approximate allocation from the *dynamic programming by profits* [19]

end function

Theorem 10 (Performance and complexity of ε -JSPA).

Given a minimum transmit power δ and an approximation factor ε , algorithm ε -JSPA computes an ε -approximation of \mathcal{P}'_{MC} on the discrete set \mathcal{F}' . The algorithm is a FPTAS with complexity $O\left(NMK^2 + (\log(\frac{J\varepsilon}{N}) + 1) \frac{N^2MK}{\varepsilon} + \frac{N^3}{\varepsilon^2}\right)$.

Proof: See Appendix J. \square

D. Comparison of JSPA Algorithms

In Table II, we compare the performance and complexity of the proposed algorithms with JSPA schemes in the literature. Reference [17] studied an optimal monotonic optimization framework, which has exponential complexity in K and N . The authors of [10] introduced a Lagrangian duality and dynamic programming algorithm (LDDP) with complexity $O(J^2NMK)$. Both LDDP and the proposed OPT-JSPA are optimal. However, OPT-JSPA has lower complexity than LDDP. Indeed, the right term J^2N is lower by a factor MK , the middle term $JNMK$ by a factor J . The left term NMK^2 also improves the complexity, since reference [9] shows that in practical systems $J \geq \Theta(\min\{K, MN\})$. This result is verified by simulation in Section VI. ε -JSPA is the proposed FPTAS. Its complexity is polynomial in N/ε and

TABLE II
COMPARISON OF SOME JSPA SCHEMES PROPOSED IN THIS WORK AND IN THE LITERATURE

Algorithm	Performance guarantee	Complexity for J discrete power values
Monotonic optimization with outer polyblock approximation [17]	Optimal	Exponential in K and N
LDDP [10]	Optimal	$O(J^2 N M K)$
OPT-JSPA	Optimal	$O(N M K^2 + J N M K + J^2 N)$
ϵ -JSPA	FPTAS, i.e., its performance is within a factor $1 - \epsilon$ of the optimal, for any $\epsilon > 0$	$O\left(N M K^2 + \left(\log\left(\frac{J\epsilon}{N}\right) + 1\right) \frac{N^2 M K}{\epsilon} + \frac{N^3}{\epsilon^2}\right)$
GRAD-JSPA	Heuristic	$O(N M K^2 + \log(J) N M K)$

$\log(J)$. If $N/\epsilon < J$, it has a lower complexity than OPT-JSPA. Otherwise, if $N/\epsilon \geq J$, its complexity exceeds OPT-JSPA's complexity. Thus OPT-JSPA can be applied instead to achieve optimal result. Finally, GRAD-JSPA is a heuristic. Its performance is evaluated through simulation in the next section. When applied in a discrete setting, the error tolerance or precision ξ is related to $\delta = 2\xi$. Hence, its complexity is proportional to $\log(J)$, which is way lower than the optimal schemes with pseudo-polynomial complexity due to J .

VI. NUMERICAL RESULTS

We evaluate the WSR and computational complexity of OPT-JSPA, ϵ -JSPA and GRAD-JSPA through numerical simulations. We compare them with the optimal benchmark scheme LDDP introduced in [10]. We consider a cell of diameter 1000 meters, with one BS located at its center and K users distributed uniformly at random in the cell. The users' weights are generated uniformly at random in $[0, 1]$. The number of users K varies from 5 to 60, and the number of subcarriers is $N = 20$. We assume a system bandwidth of $W = 5$ MHz and $W_n = W/N$ for all n . The minimum transmit power is $\delta = 0.01 W$. The cellular power budget is $P_{max} = 10$ W, therefore the number of power values is $J = 10^3$. Each point in the following figures is the average value obtained over 1000 random instances. Only Fig. 6 and 7 represent a single instance. The simulation parameters and channel model are summarized in Table III.

TABLE III
SIMULATION PARAMETERS

Parameter	Value
Cell radius	1000 m
Min. distance from user to BS	35 m
Carrier frequency	2 GHz
Path loss model	$128.1 + 37.6 \log_{10} d$ dB, d is in km
Shadowing	Log-normal, 10 dB standard deviation
Fading	Rayleigh fading with variance 1
Noise power spectral density	-174 dBm/Hz
System bandwidth W	5 MHz
Number of subcarriers N	20
Number of users K	5 to 60
Total power budget P_{max}	10 W
Minimum transmit power δ	0.01 W
Number of power values J	10^3
Error tolerance ξ	10^{-4}
Parameter M	1 (OMA), 2 and 3 (NOMA)

Fig. 3 shows the WSR performance of OPT-JSPA and LDDP, for $M = 1, 2$ and 3 . We only simulate LDDP for $K = 5$ to 30 , due to its high running time complexity. We see that OPT-JSPA and LDDP achieve the same WSR

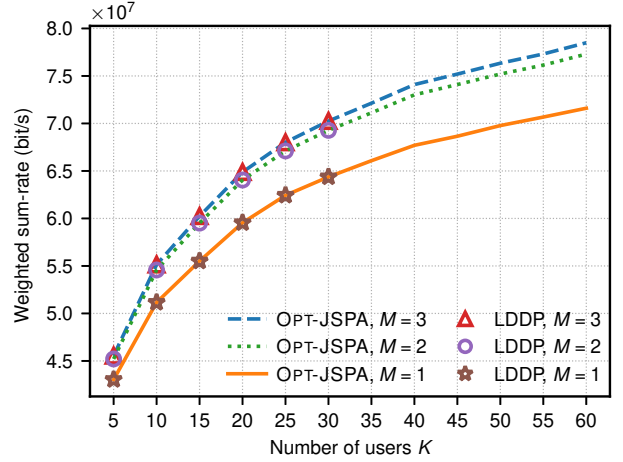


Fig. 3. WSR of the optimal schemes for different number of users K

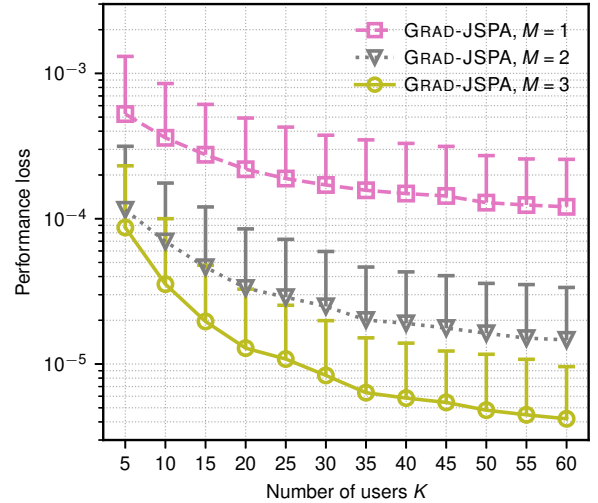


Fig. 4. Performance loss of GRAD-JSPA compared to the optimal WSR

performance, which is consistent with the fact that they are both optimal. The performance gain of NOMA with $M = 2$ (resp. $M = 3$) over OMA (i.e., $M = 1$) is about 8% (resp. 10%), for $K = 60$.

Fig. 4 illustrates the performance loss of GRAD-JSPA compared to the optimal, for $M = 1, 2$ and 3 . The performance loss is defined as:

$$\frac{\text{Optimal WSR} - \text{GRAD-JSPA WSR}}{\text{Optimal WSR}}$$

The markers represent the average performance loss, while the upper intervals indicate the 90th percentile. For example, for $K = 10$ and $M = 1$, 90% of GRAD-JSPA results have less than 9×10^{-4} of performance loss. We observe that the

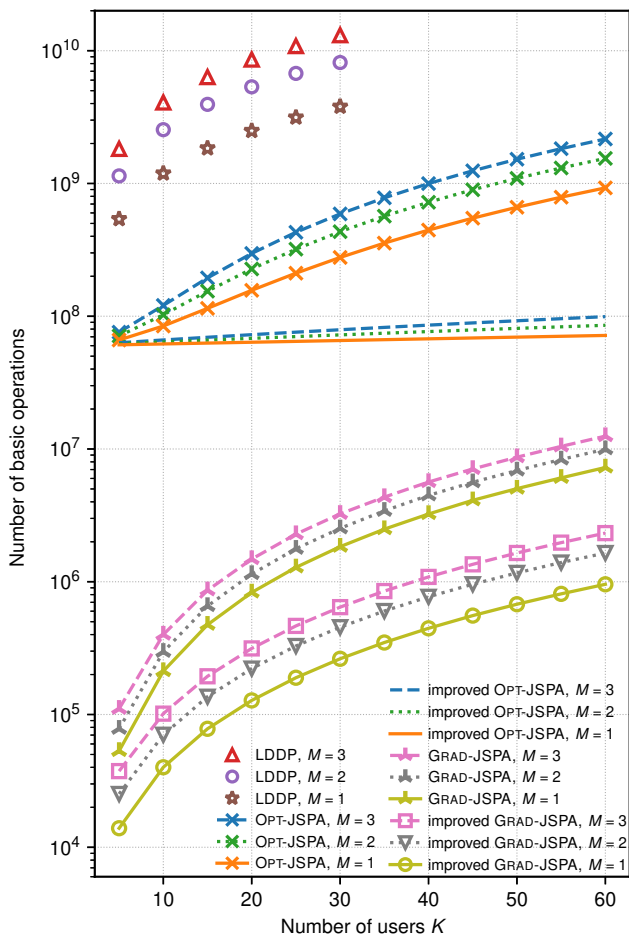


Fig. 5. Number of basic operations performed by each algorithm versus K average performance loss is always below 6×10^{-4} . Hence, our proposed heuristic GRAD-JSPA achieves near-optimal solutions in these simulation settings. It is also suitable for large systems, since the performance loss decreases as K or M increases.

In Fig. 5, we count the number of basic operations (additions, multiplications, comparisons) performed by each algorithm, which reflects their computational complexity. The term “improved” in the legend represents the complexity of OPT-JSPA and GRAD-JSPA when using i-SCPC and i-SCUS instead of SCPC and SCUS. There is a significant speed up by employing i-SCPC and i-SCUS as basic building blocks. Indeed, for $K = 60$ and $M = 1, 2$ or 3 , there is a factor of at least 10 between OPT-JSPA and its improved version. Besides, the improved OPT-JSPA outperforms LDDP in terms of complexity. For instance, OPT-JSPA reduces the complexity by a factor 330, for $K = 30$ and $M = 3$. Finally, GRAD-JSPA has low complexity, which makes it a good choice for practical implementation.

Fig. 6 and 7 present the WSR and complexity of ϵ -JSPA versus N/ϵ . Here, we simulate a single instance with $K = 60$ users to show how ϵ -JSPA behaves as a function of ϵ . In Fig. 6, we also present its performance guarantee. Recall that the performance guarantee is $1 - \epsilon$ times the optimal. As expected, ϵ -JSPA is always above its performance guarantee. As N/ϵ increases, the approximation guarantee tends to the optimal. In this instance, the algorithm already achieves a

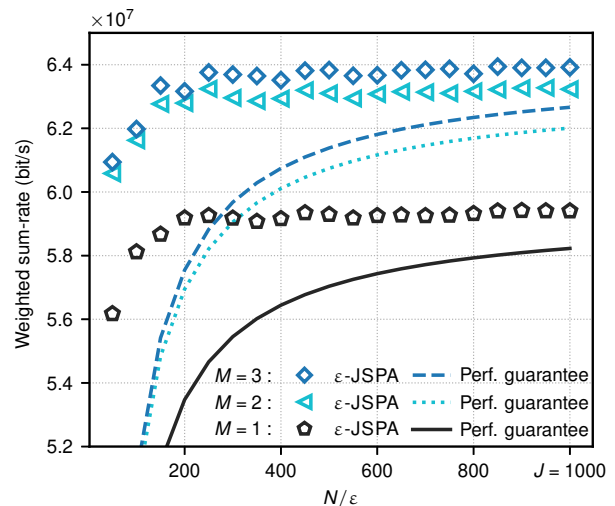


Fig. 6. WSR of ϵ -JSPA and its guaranteed performance bound versus N/ϵ

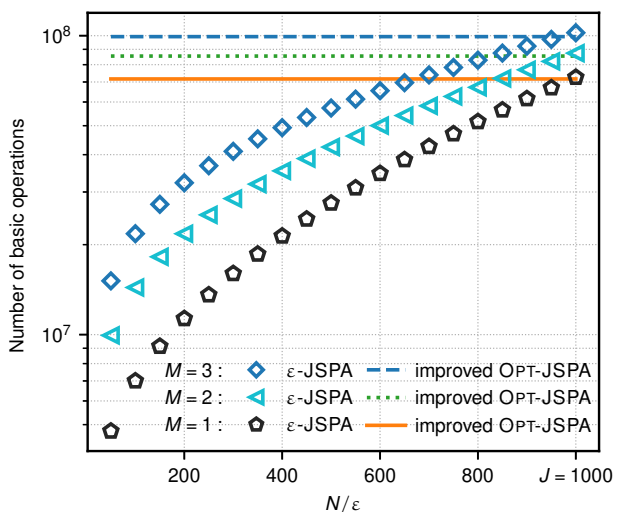


Fig. 7. Number of basic operations performed by ϵ -JSPA versus N/ϵ

near-optimal solution for $N/\epsilon = 200$, i.e., $\epsilon = 10^{-1}$. In Fig. 7, we also plot the complexity of the improved OPT-JSPA for comparison. As explained in Section V-C, the complexity increases with N/ϵ and becomes (asymptotically) equal to that of OPT-JSPA for $N/\epsilon = J$. At this point, there is no benefit of using ϵ -JSPA, since OPT-JSPA achieves the optimal with the same complexity. Here, we are talking about asymptotic complexity, i.e., written in big- O notation. In practice, we can see that for $N/\epsilon = J$, ϵ -JSPA has slightly more operations than OPT-JSPA. This is due to the computation of U (see Appendix I), which is negligible compared to the rest of the algorithm. In summary, ϵ -JSPA allows us to control the trade-off between WSR and complexity with ϵ .

VII. CONCLUSION

In this work, we investigate the WSR maximization in MC-NOMA with cellular power constraint. We improve the complexity of the single-carrier power control (SCPC) and user selection (SCUS) procedures using precomputation. These improved schemes are denoted by i-SCPC and i-SCUS. We develop three algorithms to solve the JSPA problem, based on i-SCPC and i-SCUS. Firstly, OPT-JSPA gives optimal results with lower complexity than current state-of-the-art optimal

schemes. Secondly, ϵ -JSPA is a FPTAS. It achieves a controllable and tight trade-off between approximation guarantee and complexity. OPT-JSPA and ϵ -JSPA are both suitable for performance benchmarking. Finally, GRAD-JSPA is a heuristic. We show by simulation that it has near-optimal WSR with low and practical complexity.

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APPENDIX

We first provide in Lemma 11 an important property on the solution maximizing $\sum_{l=1}^i \tilde{f}_{l,l}^n$ subject to $C2-3'$, for $i \leq |\mathcal{U}'_n|$. This Lemma will be used in Appendices C and G.

Lemma 11.

Assume we are given a subcarrier $n \in \mathcal{N}$, a set \mathcal{U}'_n of active users, a power budget \bar{P}^n , and an index i . Let $x_{1_n}^n, \dots, x_{i_n}^n$ be the allocation maximizing $\sum_{l=1}^i \tilde{f}_{l,l}^n(\mathcal{U}'_n, x_{1_n}^n)$, while also satisfying $C2-3'$, i.e., $\bar{P}^n \geq x_{1_n}^n \geq \dots \geq x_{i_n}^n \geq 0$. $x_{1_n}^n, \dots, x_{i_n}^n$ can be partitioned into sequences of consecutive terms with the same value. That is, sequences of the form $x_{q_n}^n, \dots, x_{q'_n}^n$, where $x_{q_n}^n = \dots = x_{q'_n}^n$ and $1 \leq q \leq q' \leq |\mathcal{U}'_n|$, $q = 1$ or $x_{(q-1)_n}^n > x_{q_n}^n$, $q' = |\mathcal{U}'_n|$ or $x_{q'_n}^n < x_{(q'+1)_n}^n$. Any such sequence satisfies:

$$x_{q_n}^n = \dots = x_{q'_n}^n = \text{ARGMAX} \tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n).$$

Proof: In this proof, we simplify notation $\tilde{f}_{l,l}^n(\mathcal{U}'_n, \cdot)$ as $\tilde{f}_{l,l}^n(\cdot)$. Let $x_{q_n}^n, \dots, x_{q'_n}^n$ be a sequence of consecutive terms with the same value, as defined in Lemma 11. Assume, for the sake of contradiction, that $x_{q_n}^n = \dots = x_{q'_n}^n \neq x^*$, where $x^* = \text{ARGMAX} \tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$. Without loss of generality, we consider the case $x_{q_n}^n < \text{ARGMAX} \tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ and $q > 1$. Let $y_{1_n}^n, \dots, y_{i_n}^n$ be an allocation defined as:

$$y_{l_n}^n \triangleq \begin{cases} \min\{x_{(q-1)_n}^n, x^*\}, & \text{if } q \leq l \leq q', \\ x_{l_n}^n, & \text{otherwise.} \end{cases} \quad (6)$$

We have the following inequalities:

$$\sum_{l=1}^i \tilde{f}_{l,l}^n(y_{l_n}^n) = \sum_{l \notin \{q, \dots, q'\}} \tilde{f}_{l,l}^n(x_{l_n}^n) + \tilde{f}_{q,q'}^n(y_{l_n}^n), \quad (7)$$

$$> \sum_{l \notin \{q, \dots, q'\}} \tilde{f}_{l,l}^n(x_{l_n}^n) + \tilde{f}_{q,q'}^n(x_{l_n}^n) = \sum_{l=1}^i \tilde{f}_{l,l}^n(x_{l_n}^n). \quad (8)$$

Equality (7) comes from the definition in (6). According to Lemma 2, $\tilde{f}_{q,q'}$ is increasing on $[0, x^*]$, which implies inequality (8). In summary, $y_{1_n}^n, \dots, y_{i_n}^n$ satisfies $C2-3'$ by its definition in (6), and it achieves greater value of $\sum_{l=1}^i \tilde{f}_{l,l}^n$ than $x_{1_n}^n, \dots, x_{i_n}^n$. This is a contradiction, therefore it must be that

$$x_{q_n}^n \geq \text{ARGMAX} \tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n). \quad (9)$$

If $q = 1$, the same reasoning can be applied by replacing $\min\{x_{(q-1)_n}^n, x^*\}$ by \bar{P}^n in Eqn. (6). We can perform a similar proof by contradiction on the case $x_{q_n}^n > \text{ARGMAX} \tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ to deduce that:

$$x_{q_n}^n \leq \text{ARGMAX} \tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n). \quad (10)$$

The desired result follows from (9) and (10). \square

A. Proof of Lemma 1

The objective of \mathcal{P} can be written as:

$$\begin{aligned}
& \sum_{k \in \mathcal{K}} w_k \sum_{n \in \mathcal{N}} R_k^n(\mathbf{p}^n) = \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} w_k R_k^n(\mathbf{p}^n), \\
& \stackrel{(b)}{=} \sum_{n \in \mathcal{N}} W_n \sum_{i=1}^K w_{\pi_n(i)} \log_2 \left(\frac{\sum_{j=i}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(i)}^n}{\sum_{j=i+1}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(i)}^n} \right), \\
& \stackrel{(c)}{=} \sum_{n \in \mathcal{N}} W_n \sum_{i=1}^K \log_2 \left(\frac{\left(\sum_{j=i}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(i)}^n \right)^{w_{\pi_n(i)}}}{\left(\sum_{j=i+1}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(i)}^n \right)^{w_{\pi_n(i)}}} \right), \\
& \stackrel{(d)}{=} \sum_{n \in \mathcal{N}} W_n \left[w_{\pi_n(1)} \log_2 \left(\sum_{j=1}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(1)}^n \right) \right. \\
& \quad \left. + \sum_{i=2}^K \log_2 \left(\frac{\left(\sum_{j=i}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(i)}^n \right)^{w_{\pi_n(i)}}}{\left(\sum_{j=i}^K p_{\pi_n(j)}^n + \tilde{\eta}_{\pi_n(i-1)}^n \right)^{w_{\pi_n(i-1)}}} \right) \right. \\
& \quad \left. + w_{\pi_n(K)} \log_2 \left(\frac{1}{\tilde{\eta}_{\pi_n(K)}^n} \right) \right].
\end{aligned}$$

Equality (b) comes from the definition in (2). At (c), the weights $w_{\pi_n(i)}$ are put inside the logarithm. Finally, (d) is obtained by combining the numerator of the i -th term with the denominator of the $(i-1)$ -th term, for $i \in \{2, \dots, K\}$.

By applying the change of variables shown in (3), we derive the equivalent problem \mathcal{P}' . The constant term is $A = \sum_{n \in \mathcal{N}} w_{\pi_n(K)} \log_2 \left(1/\tilde{\eta}_{\pi_n(K)}^n \right)$. Constraints $C1'$ and $C2'$ are respectively equivalent to $C1$ and $C2$ since $x_1^n = \sum_{j=1}^K p_{\pi_n(j)}^n = \sum_{k \in \mathcal{K}} p_k^n$, for $n \in \mathcal{N}$. Constraints $C3'$ and $C3''$ come from $C3$ and the fact that $x_i^n - x_{i+1}^n = p_{\pi_n(i)}^n$, for any $i \in \{1, \dots, K\}$ and $n \in \mathcal{N}$. In the same way, the active users set in $C4'$ is defined as $\mathcal{U}'_n \triangleq \{i \in \{1, \dots, K\} : x_i^n > x_{i+1}^n\}$. \square

B. Proof of Lemma 2

We study the first and second derivatives of $f_{j,i}^n$, denoted by $f_{j,i}^{n'}$ and $f_{j,i}^{n''}$. If $j = 1$, then we have:

$$f_{1,i}^{n'}(x) = \frac{W_n w_{\pi_n(i)}}{\left(x + \tilde{\eta}_{\pi_n(i)}^n\right) \ln(2)}, \quad (11)$$

which is strictly positive and decreasing for $x \geq 0$. Hence, $f_{1,i}^n$ is increasing and concave. For $j > 1$, the first and second derivatives are as follows:

$$\begin{aligned}
f_{j,i}^{n'}(x) &= \frac{W_n}{\ln(2)} \left(\frac{w_{\pi_n(i)}}{x + \tilde{\eta}_{\pi_n(i)}^n} - \frac{w_{\pi_n(j-1)}}{x + \tilde{\eta}_{\pi_n(j-1)}^n} \right), \\
f_{j,i}^{n''}(x) &= \frac{W_n}{\ln(2)} \left(\frac{w_{\pi_n(j-1)}}{\left(x + \tilde{\eta}_{\pi_n(j-1)}^n\right)^2} - \frac{w_{\pi_n(i)}}{\left(x + \tilde{\eta}_{\pi_n(i)}^n\right)^2} \right).
\end{aligned}$$

We know that $\tilde{\eta}_{\pi_n(j-1)}^n \geq \tilde{\eta}_{\pi_n(i)}^n$ by construction of the optimal decoding order in Eqn. (1). If, in addition, we have $w_{\pi_n(i)} \geq w_{\pi_n(j-1)}$, then $f_{j,i}^{n'}(x) \geq 0$ and $f_{j,i}^{n''}(x) \leq 0$ for all $x \geq 0$. We deduce that $f_{j,i}^n$ is increasing and concave. This proves the first point of Lemma 2. Now suppose that $w_{\pi_n(i)} < w_{\pi_n(j-1)}$

instead. Values c_1 and c_2 defined in Lemma 2 are the unique roots of the first and second derivatives, i.e., $f_{j,i}^{n'}(c_1) = 0$ and $f_{j,i}^{n''}(c_2) = 0$. $f_{j,i}^{n'}$ is positive on $(-\tilde{\eta}_{\pi_n(j-1)}^n, c_1)$ and negative on (c_1, ∞) . This implies that $f_{j,i}^n$ is unimodal and has a unique global maximum at c_1 for $x > 0$. Similarly, $f_{j,i}^{n''}$ is negative on $(-\tilde{\eta}_{\pi_n(j-1)}^n, c_2)$ and positive on (c_2, ∞) . Therefore, $f_{j,i}^n$ is concave before c_2 and convex after c_2 . This proves the second point of Lemma 2. \square

C. Proof of Theorem 3

The complexity and optimality proofs of SCPC are presented below.

Complexity analysis: At each for loop iteration i , the while loop at line 6 has at most i iterations. Thus, the worst case complexity is proportional to $\sum_{i=1}^{|\mathcal{U}'_n|} i = O(|\mathcal{U}'_n|^2) = O(M^2)$.

Optimality analysis: Without loss of generality, we can suppose that the $x_{i_n}^n$'s are initialized to zero. We will prove by induction that at the end of each iteration i at line 10 of Algorithm 2, the following loop invariants are true:

$H_1(i)$: $\sum_{l=1}^i \tilde{f}_{l,l}^n$ is maximized by $x_{1_n}^n, \dots, x_{i_n}^n$,

$H_2(i)$: $C2-3'$ is satisfied, i.e., $\bar{P}^n \geq x_{1_n}^n \geq \dots \geq x_{i_n}^n \geq 0$.

Basis: For $i = 1$, x^* computed at line 3 is indeed the optimal of $\tilde{f}_{1,1}^n$. The while loop has no effect since $j = 0 < 1$, therefore $x_{1_n}^n \leftarrow x^*$ and statements $H_1(1)$ and $H_2(1)$ are both true.

Inductive step: Assume that $x_{1_n}^n(i-1), \dots, x_{(i-1)_n}^n(i-1)$ are the variables verifying $H_1(i-1)$ and $H_2(i-1)$ at iteration $i-1 < K$. Let the variables at iteration i be $x_{1_n}^n, \dots, x_{i_n}^n$. We consider two cases:

i) We first suppose that:

$$x^* = \text{ARGMAX}_{\tilde{f}(i,i,\mathcal{I}^n,\bar{P}^n)} \leq x_{(i-1)_n}^n(i-1). \quad (12)$$

In this case, Algorithm 2 sets $x_{i_n}^n = x^*$ and $x_{l_n}^n = x_{l_n}^n(i-1)$, for all $l < i$. The induction hypothesis $H_2(i-1)$ states that $\bar{P}^n \geq x_{1_n}^n \geq \dots \geq x_{(i-1)_n}^n \geq 0$. By taking into account Eqn. (12), this inequality becomes $\bar{P}^n \geq x_{1_n}^n \geq \dots \geq x_{(i-1)_n}^n \geq x^* = x_{i_n}^n \geq 0$. Thus, $H_2(i)$ is satisfied. In addition, we know from $H_1(i-1)$ that $x_{1_n}^n, \dots, x_{(i-1)_n}^n$ maximizes $\sum_{l=1}^{i-1} \tilde{f}_{l,l}^n$. Since, the objective is separable and $x_{i_n}^n = x^*$ maximizes $\tilde{f}_{i,i}^n$ by construction, $H_1(i)$ is true.

ii) Now, suppose that we have the opposite:

$$x^* = \text{ARGMAX}_{\tilde{f}(i,i,\mathcal{I}^n,\bar{P}^n)} > x_{(i-1)_n}^n(i-1). \quad (13)$$

In this case, the allocation mentioned above would violate constraint $C2-3'$. The algorithm finds the highest index $j \in \{1, \dots, i-2\}$ such that $x_{j_n}^n(i-1) \geq \text{ARGMAX}_{\tilde{f}(j+1,i,\mathcal{I}^n,\mathcal{U}'_n,\bar{P}^n)}$ in the while loop at line 6. Such an index exists since all variables are upper bounded by \bar{P}^n and $x_{1_n}^n = \bar{P}^n$ due to Lemma 2. Let us show by contradiction that $H_1(i)$ and $H_2(i)$ are only satisfied if $x_{(j+1)_n}^n = \dots = x_{i_n}^n$. If it is not the case, let $k > j+1$ be the last index such that $x_{k_n}^n = x_{(k+1)_n}^n = \dots = x_{i_n}^n$ and $x_{(k-1)_n}^n > x_{k_n}^n$. We know from the while condition that $x_{(k-1)_n}^n < x^{*'}$, with $x^{*'} = \text{ARGMAX}_{\tilde{f}(k,i,\mathcal{I}^n,\mathcal{U}'_n,\bar{P}^n)}$. According to Lemma 2, $\tilde{f}_{k,i}^n$ is increasing on $[0, x^{*'}]$. Therefore, we can

improve the objective function by setting $x_{k_n}^n, \dots, x_{i_n}^n \leftarrow x_{(k-1)_n}^n$. This is a contradiction with $x_{(k-1)_n}^n > x_{k_n}^n$, we have thus $x_{(j+1)_n}^n = \dots = x_{i_n}^n$. Furthermore, at the termination of the while loop, we have $\text{ARGMAX}\tilde{f}(j+1, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n) \leq x_{j_n}^n(i-1)$, which can be treated as in case i). Hence, variables $x_{(j+1)_n}^n, \dots, x_{i_n}^n$ are set equal to $\text{ARGMAX}\tilde{f}(j+1, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ at line 10, and it satisfies $H_1(i)$ and $H_2(i)$.

We proved that, in both cases i) and ii), the allocation $x_{1_n}^n, \dots, x_{i_n}^n$ computed by Algorithm 2 satisfies $H_1(i)$ and $H_2(i)$. Therefore, by mathematical induction, the allocation returned at line 12 satisfies $H_1(|\mathcal{U}'_n|)$ and $H_2(|\mathcal{U}'_n|)$. We note that $H_1(|\mathcal{U}'_n|)$ and $H_2(|\mathcal{U}'_n|)$ are equivalent to an optimal solution of $\mathcal{P}'_{SCPC}(n)$, which concludes the proof. \square

D. Proof of Theorem 4

Optimality analysis: Let $x_{1_n}^n, \dots, x_{|\mathcal{U}'_n|_n}^n$ be the optimal allocation of SCPC with budget P_{max} . We consider now a lower budget $\bar{P}^n \leq P_{max}$. At each iteration i of the loop in SCPC($\mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n$), the value $\text{ARGMAX}\tilde{f}(j, i, \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ can be replaced by $\min\{\text{ARGMAX}\tilde{f}(j, i, \mathcal{I}^n, \mathcal{U}'_n, P_{max}), \bar{P}^n\}$, since they are equal by definition. One can show, by mathematical induction on i_n , that the function $\text{SCPC}(\mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$ returns $\min\{x_{1_n}^n, \bar{P}^n\}, \dots, \min\{x_{|\mathcal{U}'_n|_n}^n, \bar{P}^n\}$. Therefore, the latter allocation is also optimal.

Complexity analysis: The initialization consists in running SCPC, with complexity $O(M^2)$ (see Theorem 3). Each subsequent evaluation requires to compute $\min\{x_{i_n}^n, \bar{P}^n\}$, for $i \in \{1, \dots, |\mathcal{U}'_n|\}$, with complexity $O(M)$. \square

E. Proof of Theorem 5

Complexity analysis: The complexity mainly comes from the computation of V , X and U in the for loop from lines 13 to 27, which requires $M \sum_{i=1}^{K-1} (i) = O(MK^2)$ iterations. Each iteration has a constant number of operations. Thus, the overall worst case computational complexity is $O(MK^2)$.

Optimality analysis: We will prove by induction that at any iteration $m \in \{0, \dots, M\}$, $j \in \{1, \dots, K\}$ and $i \geq j$ of Algorithm 4, the construction of $V[m, j, i]$ is the optimal value of problem $\mathcal{P}'_{SC}[m, j, i]$. It follows directly that $V[M, 1, 1]$ is the optimal value of $\mathcal{P}'_{SC}(n)$.

Basis: For $m = 0$, no user can be active due to constraint $C4'$. Thus, $V[0, j, i] = f_{j,K}^n(0)$ and $X[0, j, i]$ is initialized to zero. Furthermore, $U[0, j, i] = \emptyset$ to indicate that there is no previous index in the recursion. For simplicity of the algorithm, V, X, U are also initialized for $j \leq i = K$ as explained in Section IV-C.

Inductive step: Let $m \in \{1, \dots, M\}$ and $1 \leq j \leq i \leq K-1$. Assume that $V[m', j', i']$ is the optimal value of $\mathcal{P}'_{SC}[m', j', i']$ for any $m' \leq m$, $j' \geq j$ and $i' > i$. We denote the optimal solution of problem $\mathcal{P}'_{SC}[m, j, i]$ by x_j^n, \dots, x_K^n . Let v_{act} (resp. v_{inact}) be the optimal value of $\mathcal{P}'_{SC}[m, j, i]$, given that user i is active (resp. inactive). Let $x_{(i+1)_n}^{n*} = X[m-1, i+1, i+1]$ be the optimal value of $x_{(i+1)_n}^n$ in $\mathcal{P}'_{SC}[m-1, i+1, i+1]$. If $x^* \leq x_{(i+1)_n}^{n*}$, then we can prove as in case ii) of Appendix C, that user i is inactive in the optimal solution.

In this case, $V[m, j, i] = v_{inact}$. Otherwise, the optimal is $V[m, j, i] = \max\{v_{act}, v_{inact}\}$. Values v_{act} and v_{inact} are computed as follows:

- Case v_{inact} : Suppose that the optimal solution of problem $\mathcal{P}'_{SC}[m, j, i]$ is achieved when user i is inactive, then we have $x_i^n = x_{i+1}^n$ by definition of \mathcal{U}'_n . It follows from $C5'$ that $x_j^n = \dots = x_{i+1}^n$. We obtain, by definition, $V[m, j, i] = V[m, j, j+1]$, which we denote by v_{inact} .
- Case v_{act} : Suppose now that user i is active. Since $x^* > x_{(i+1)_n}^{n*}$ satisfies $C3'$, and the objective is separable, the optimal is obtained when maximizing independently $f_{j,i}^n$ and $\sum_{l=i+1}^K f_l^n$ with $m-1$ active users. That is, $V[m, j, i] = v_{act} \triangleq f_{j,i}^n(x^*) + V[m-1, i+1, i+1]$, where $x^* = \text{ARGMAX}f(j, i, \mathcal{I}^n, \bar{P}^n)$ in line 15.

Hence, $V[m, j, i]$, as computed in (5), corresponds to the optimal of $\mathcal{P}'_{SC}[m, j, i]$.

We derive, by mathematical induction, that $V[M, 1, 1]$ is the optimal value of $\mathcal{P}'_{SC}[M, 1, 1] = \mathcal{P}'_{SC}(n)$. The corresponding optimal allocation x^n is retrieved in lines 28 to 35. \square

F. Proof of Theorem 6

Optimality analysis: Let y_1^n, \dots, y_K^n be the optimal solution of $\mathcal{P}'_{SC}(n)$ subject to a power constraint \bar{P}^n . Let $i \in \{1, \dots, K\}$ be the unique index such that $y_1^n = \dots = y_i^n$ and $y_i^n > y_{i+1}^n$. We know from Lemma 2 that $y_1^n = \dots = y_i^n = \bar{P}^n$. Therefore, y_{i+1}^n, \dots, y_K^n are all strictly less than \bar{P}^n . Let x_1^n, \dots, x_K^n be the optimal solution of $\mathcal{P}'_{SC}[M, 1, i]$ in the execution of SCUS($\mathcal{I}^n, M, P_{max}$), i.e., subject to a power budget P_{max} . According to Lemma 2, $x_1^n = \dots = x_i^n = P_{max}$. We deduce from f 's unimodality in Lemma 2, that y_{i+1}^n, \dots, y_K^n is the optimal solution of $\mathcal{P}'_{SC}[M, i+1, i+1]$ given any power budget no less than \bar{P}^n . In particular, we have $x_l^n = y_l^n$, for all $l \in \{i+1, \dots, K\}$. Hence, x_1^n, \dots, x_K^n and y_1^n, \dots, y_K^n correspond to the same user selection \mathcal{U}'_n , and we derive $y_{l_n}^n = \min\{x_{l_n}^n, \bar{P}^n\}$, for $1 \leq l \leq |\mathcal{U}'_n|$.

We proved above that, for any $\bar{P}^n \leq P_{max}$, there exists $(\mathcal{U}'_n, x_1^n, \dots, x_K^n)$ in *collection*, such that the optimal allocation subject to the power constraint \bar{P}^n is $\min\{x_1^n, \bar{P}^n\}, \dots, \min\{x_{|\mathcal{U}'_n|_n}^n, \bar{P}^n\}$. Thus, the optimal user selection and power control is the one maximizing $F^n(\mathcal{U}'_n, \bar{P}^n) = \sum_{l=1}^{|\mathcal{U}'_n|} \tilde{f}_{l,l}^n(\mathcal{U}'_n, \min\{x_{l_n}^n, \bar{P}^n\}) + B^n$ over all elements in *collection*, as shown at line 6.

Complexity analysis: The initialization consists in running SCUS, with complexity $O(MK^2)$ (see Theorem 5). Each subsequent evaluation has complexity $O(MK)$. Indeed, for each of the K possible active users set \mathcal{U}'_n in *collection*, we compute $F^n(\mathcal{U}'_n, \bar{P}^n)$ with complexity $O(|\mathcal{U}'_n|) = O(M)$. \square

G. Proofs of Lemma 7 and Theorem 8

Let x_1^n, \dots, x_K^n be the output of i-SCUS(\bar{P}^n), and \mathcal{U}'_n the corresponding active users set. For $i \in \{1, \dots, K\}$, there exists $q \leq i$ and $q' \geq i$, such that $x_{q_n}^n = \dots = x_{q'_n}^n = \text{ARGMAX}\tilde{f}(q, q', \mathcal{I}^n, \mathcal{U}'_n, \bar{P}^n)$, according to Lemma 11. We have:

$$\tilde{f}_{q,q'}^n(\mathcal{U}'_n, \min\{x_{q_n}^n, \bar{P}^n\}) = \begin{cases} \tilde{f}_{q,q'}^n(\mathcal{U}'_n, \bar{P}^n), & \text{if } \bar{P}^n \leq x_{q_n}^n, \\ \tilde{f}_{q,q'}^n(\mathcal{U}'_n, x_{q_n}^n), & \text{if } \bar{P}^n > x_{q_n}^n. \end{cases}$$

We consider it as a function of \bar{P}^n . Its left derivative at $\bar{P}^n = x_{q_n}^n$ is 0, according to Lemma 2. Its right derivative at $\bar{P}^n = x_{q_n}^n$ is 0, as it is constant for $\bar{P}^n > x_{q_n}^n$. Hence, $\tilde{f}_{q,q'}^n(\mathcal{U}'_n, \min\{x_{q_n}^n, \cdot\})$ is continuously differentiable on $[0, P_{max}]$.

Let l be the greatest index such that $x_l^n = \bar{P}^n$. The function $F^n(\mathcal{U}'_n, \bar{P}^n)$ can be written as $f_{1,l}^n(\bar{P}^n) + \sum_{i=l+1}^K f_{i,i}^n(x_i^n) + B^n$. Its derivative can be obtained by applying Eqn. (11) of Appendix B as follows:

$$F^{n'}(\mathcal{U}'_n, \bar{P}^n) = f_{1,l}^{n'}(\bar{P}^n) = \frac{W_n w_{\pi_n(l)}}{(\bar{P}^n + \tilde{\eta}_{\pi_n(l)}^n) \ln(2)}. \quad (14)$$

As $F^n(\bar{P}^n) = \max_{\mathcal{U}'_n} \{F^n(\mathcal{U}'_n, \bar{P}^n)\}$, where max is taken over all active users set in *collection* of i-SCUS, and the max operator only preserves semi-differentiability, Eqn. (14) is the left derivative of F^n . This proves Lemma 7.

In addition, the second left derivative of F^n satisfies:

$$\beta \leq F^{n''}(\bar{P}^n) = \frac{-W_n w_{\pi_n(l)}}{(\bar{P}^n + \tilde{\eta}_{\pi_n(l)}^n)^2 \ln(2)} \leq \alpha < 0, \quad (15)$$

where β and α are constant and defined as:

$$\beta = \frac{-W_n w_{\pi_n(l)}}{(\tilde{\eta}_{\pi_n(l)}^n)^2 \ln(2)}, \quad \alpha = \frac{-W_n w_{\pi_n(l)}}{(P_{max} + \tilde{\eta}_{\pi_n(l)}^n)^2 \ln(2)}.$$

Although F^n is only semi-differentiable at some points, it is twice differentiable on each interval where the optimal user selection \mathcal{U}'_n does not change. Appendix F shows that there are K such intervals. Eqn. (15) implies that F^n is piece-wise twice differentiable, α -strongly concave and β -smooth. Therefore, the projected gradient descent on a convex set converges in $O(\log(1/\xi))$ iterations, according to [24, Section 2.2.4]. This proves Theorem 8. \square

H. Proof of Theorem 9

Optimality analysis: Reference [19] proves that dynamic programming by weights is optimal for MCKP. Since problems \mathcal{P}'_{MC} and MCKP are equivalent, the proposed OPT-JSPA based on dynamic programming by weights is also optimal for \mathcal{P}'_{MC} .

Complexity analysis: Let us first briefly explain the principle of dynamic programming by weights. Let Z be a 2D-array such that $Z[n, l]$ is defined as the optimal value of MCKP restricted to the first n classes and with restricted capacity $l \cdot \delta$. It is initialized as $Z[0, l] = 0, l = 0, \dots, J$. For $n \in \mathcal{N}$ and $l = 0, \dots, J$, the recurrence relation is $Z[n, l] = \max_{l' \leq l} \{Z[n-1, l-l'] + c_{n,l'}\}$. In Algorithm 7, we first transform \mathcal{P}'_{MC} to problem MCKP: from line 1 to 5, every item's profit $c_{n,l}$ is computed using i-SCUS in $O(NMK^2 + JNMK)$. Then, we perform dynamic programming by weights at lines 6-7. According to [19], its complexity is $O(J^2N)$, which is the number of items $N(J+1)$ multiplied by the number of possible power values $J+1$. Therefore, the overall complexity is $O(NMK^2 + JNMK + J^2N)$. \square

I. Estimation U in Algorithm 8

In this section, we denote by $F_{MCKP}^*(P_{max})$ the optimal value of MCKP with cellular power budget P_{max} . We provide some properties in Lemma 12 that will be used for the analysis of the estimation procedure.

Lemma 12 (Monotonicity and sublinearity of F_{MCKP}^*). F_{MCKP}^* is a non-decreasing and sublinear function of P_{max} . That is, for any $P_1 < P_2$, $F_{MCKP}^*(P_1) \leq F_{MCKP}^*(P_2)$ and $F_{MCKP}^*(P_1 + P_2) \leq F_{MCKP}^*(P_1) + F_{MCKP}^*(P_2)$.

Proof: We first prove the monotonicity of F_{MCKP}^* . Let \mathcal{F}'_1 and \mathcal{F}'_2 be two feasible sets of \mathcal{P}'_{MC} with power budget P_1 and P_2 respectively. Assuming $P_1 < P_2$, then any solution of \mathcal{F}'_1 is also a solution of \mathcal{F}'_2 , i.e., $\mathcal{F}'_1 \subset \mathcal{F}'_2$. Since \mathcal{P}'_{MC} is a maximization problem over \mathcal{F}' , we have $F_{MCKP}^*(P_1) \leq F_{MCKP}^*(P_2)$. This proves that F_{MCKP}^* is non-decreasing.

Now, let us tackle its sublinearity. We first prove that the $f_{j,i}^n$ are sublinears. If $j = 1$ or $w_{\pi_n(i)} \geq w_{\pi_n(j-1)}$, then $f_{j,i}^n$ is concave according to Lemma 2. Therefore, it is also sublinear. Otherwise, $f_{j,i}^n$ is concave before c_2 and decreasing after $c_1 \leq c_2$. In this case, $f_{j,i}^n$ is thus also sublinear. Secondly, for any subcarrier n and user selection \mathcal{U}'_n , $\mathcal{P}'_{SCPC}(n)$ consists in maximizing a sum of separable sublinear functions $f_{j,i}^n$ subject to a budget constraint \bar{P}^n . Hence, $F^n(\mathcal{U}'_n, \bar{P}^n)$ is sublinear in \bar{P}^n . Thirdly, the optimal of $\mathcal{P}'_{SC}(n)$ can be seen as the best allocation over all possible user selections, i.e., $F^n(\bar{P}^n) = \max_{\mathcal{U}'_n} \{F^n(\mathcal{U}'_n, \bar{P}^n)\}$. The max operator preserves sublinearity. Therefore, $F^n(\bar{P}^n)$ is sublinear in \bar{P}^n . Finally, F_{MCKP}^* is sublinear in P_{max} , since \mathcal{P}'_{MC} is a separable sum maximization of F^n subject to budget constraint P_{max} . \square

Let us introduce a variant of MCKP, denoted by MCKP'. The differences are as follows. Its cellular power budget is $2P_{max}$. The item's weights can only take value of the form $a_{n,l} = l \lfloor J/N \rfloor \delta$ for $n \in \mathcal{N}$, $l \in \{0, \dots, 2N\}$. The profits values are defined similarly as $c_{n,l} = F^n(a_{n,l})$. Consequently, MCKP' only contains $2N + 1$ items per class. The idea of the proof is to show that a greedy solution of MCKP' is a constant factor approximation of MCKP optimal value. The value of U is then easily obtained using the greedy Dyer-Zemel algorithm [19, Section 11.2]. In this case, the complexity is independent of J and negligible compared to the rest of the algorithm. One could also get an estimation by applying the Dyer-Zemel algorithm directly to MCKP. However, the complexity would be proportional to $O(J)$ which is against the idea of polynomial-time approximation.

Let $y_{n,l}^*$, for $n \in \mathcal{N}$, $l \in \{0, \dots, 2N\}$, be an optimal solution of this problem. In addition, we denote by $y'_{n,l}$ for $n \in \mathcal{N}$, $l \in \{0, \dots, 2N\}$, a $1/2$ -approximation given by the Dyer-Zemel algorithm. On the one hand, we have:

$$\sum_{n \in \mathcal{N}} \sum_{l=1}^{2N} c_{n,l} y'_{n,l} \geq \frac{1}{2} \sum_{n \in \mathcal{N}} \sum_{l=1}^{2N} c_{n,l} y_{n,l}^*, \quad (16)$$

$$\geq \frac{1}{2} \sum_{n \in \mathcal{N}} F^n \left(\left\lceil \frac{\bar{P}^n}{\lfloor J/N \rfloor \delta} \right\rceil \left\lfloor \frac{J}{N} \right\rfloor \delta \right), \quad (17)$$

$$\geq \frac{1}{2} \sum_{n \in \mathcal{N}} F^n(\bar{P}^{n*}) = \frac{1}{2} F_{MCKP}^*(P_{max}), \quad (18)$$

where \bar{P}^{n*} is the power allocated to subcarrier n in $F_{MCKP}^*(P_{max})$. The 1/2-approximation of $y'_{n,l}$ translates into Eqn. (16). The right term of Eqn. (17) corresponds to a valid allocation of MCKP', with item $l = \lceil \bar{P}^{n*} / (\lfloor J/N \rfloor \delta) \rceil$ allocated in class n . Indeed, by definition of the ceiling and floor functions, we have:

$$\bar{P}^{n*} \stackrel{(e)}{\leq} \left\lceil \frac{\bar{P}^{n*}}{\lfloor J/N \rfloor \delta} \right\rceil \left\lfloor \frac{J}{N} \right\rfloor \delta < \bar{P}^{n*} + \left\lfloor \frac{J}{N} \right\rfloor \delta \leq \bar{P}^{n*} + \frac{P_{max}}{N}.$$

Therefore,

$$\sum_{n \in \mathcal{N}} \left\lceil \frac{\bar{P}^{n*}}{\lfloor J/N \rfloor \delta} \right\rceil \left\lfloor \frac{J}{N} \right\rfloor \delta < \sum_{n \in \mathcal{N}} \left(\bar{P}^{n*} + \frac{P_{max}}{N} \right) = 2P_{max}.$$

In other words, the power budget is also satisfied. As it is a valid allocation for MCKP', it must have a total profit not greater than the optimal profit $\sum_{n \in \mathcal{N}} \sum_{l=1}^{2N} c_{n,l} y_{n,l}^*$, which proves inequality (17). We derive Eqn. (18) from inequality (e) and the monotonicity of F^n (see Lemma 12).

We have, on the other hand:

$$\sum_{n \in \mathcal{N}} \sum_{l=1}^{2N} c_{n,l} y'_{n,l} \leq \sum_{n \in \mathcal{N}} \sum_{l=1}^{2N} c_{n,l} y_{n,l}^*, \quad (19)$$

$$\leq F_{MCKP}^*(2P_{max}), \quad (20)$$

$$\leq 2F_{MCKP}^*(P_{max}). \quad (21)$$

The optimality of $y_{n,l}^*$ implies Eqn. (19). Eqn. (20) comes from the fact that the items of MCKP' is a subset of MCKP items, given a budget $2P_{max}$. Eqn. (21) follows from the sublinearity of F_{MCKP}^* (see Lemma 12).

Let $U \triangleq 2 \sum_{n \in \mathcal{N}} \sum_{l=1}^{2N} c_{n,l} y'_{n,l}$. We derive from inequalities (18) and (21) the desired approximation bound:

$$U \geq F_{MCKP}^*(P_{max}) \geq U/4. \quad \square$$

J. Proof of Theorem 10

Complexity analysis: We divide the complexity analysis of Algorithm 8 in four parts as follows. The overall complexity can be obtained by summing the complexity of each part.

i. Precomputation: The precomputation required for setting up i-SCUS on each subcarrier has complexity $O(NMK^2)$.

ii. Line 1: The estimation procedure presented in Appendix I, consists in $O(N^2)$ function evaluations and $O(N^2)$ iterations of the Dyer-Zemel algorithm. Each function evaluation is computed by i-SCUS, therefore the complexity of this part is $O(N^2MK)$.

iii. Lines 2-4: Each L_n , for $n \in \mathcal{N}$, is obtained by multi-key binary search [23] which performs $O(N/\varepsilon (\log(J\varepsilon/N) + 1))$ function evaluations. Indeed, for each L_n , we need to find $4N/\varepsilon$ keys in an array $\{c_{n,1}, \dots, c_{n,J}\}$ of length J . Multiplied by the complexity of each function evaluation on each subcarrier, we obtain $O((\log(J\varepsilon/N) + 1) N^2MK/\varepsilon)$.

iv. Lines 5-6: Let us first briefly explain the dynamic programming by profits [19]. Let Y be the DP array such that $Y[n, q]$ denotes the minimal weight, i.e., minimal power budget,

required to achieve WSR $q \cdot \varepsilon U / 4N$ when problem MCKP is restricted to the first n classes. It is initialized as $Y[0, 0] = 0$ and $Y[0, q] = +\infty$, for $q = 1, \dots, \lfloor 4N/\varepsilon \rfloor$. For $n \in \mathcal{N}$ and $q = 0, \dots, \lfloor 4N/\varepsilon \rfloor$, the recurrence relation is:

$$Y[n, q] = \min_{l \in L_n} \begin{cases} Y \left[n-1, q - \left\lfloor \frac{4c_{n,l}N}{\varepsilon U} \right\rfloor \right] + a_{n,l}, \\ \text{if } \frac{q \cdot \varepsilon U}{4N} \geq c_{n,l}, \\ +\infty, \text{ otherwise.} \end{cases} \quad (22)$$

This recursion has complexity $O(N^3/\varepsilon^2)$, which is the number of all considered items $\sum_{n \in \mathcal{N}} |L_n| = 4N^2/\varepsilon$ multiplied by the number of comparisons in Eqn. (22), $|L_n| = 4N/\varepsilon$.

Approximation analysis: As proved in [19, Section 11.9], the optimal solution obtained by dynamic programming by profits considering only items in L_n , differs from F_{MCKP}^* by at most a factor $1 - \varepsilon$.

In summary, ε -JSPA achieves ε -approximation with polynomial complexity in $1/\varepsilon$ and N, M, K . Therefore, ε -JSPA is a FPTAS, which concludes the proof. \square